Control Interfaces to Actively
Support the Arm Function of Men
with Duchenne Muscular Dystrophy

JOAN LOBO PRAT

CONTROL INTERFACES TO ACTIVELY SUPPORT
THE ARM FUNCTION OF MEN WITH
DUCHENNE MUSCULAR DYSTROPHY

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To my father
my best friend and teacher

My main reward is having helped to
improve the quality of life of people with Duchenne

CONTROL INTERFACES TO ACTIVELY SUPPORT
THE ARM FUNCTION OF MEN WITH
DUCHENNE MUSCULAR DYSTROPHY

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SUMMARY

Adults with Duchenne muscular dystrophy (DMD) have very limited or no arm function left due to severe muscular weakness. While their life expectancy has considerably increased over the last five decades, their quality of life still remains very poor. Currently, a considerable group of people with DMD live until their 30's with a strong dependency on care and restrictions to participate in social activities.

Assistive technology can play an important role in increasing the quality of life for adults with DMD by enabling them to independently perform activities of daily living. While the function of legs can be effectively supported with the use of manual or electric wheelchairs, there are few effective solutions to support arm function. Commercially available arm supports present three major limitations: (I) they provide insufficient support to the weakest users, (II) their large dimensions and unattractive looks often stigmatize users, and (III) they use control interfaces (i.e. buttons and joysticks) that require sacrificing the use of one hand or other body part.

The work presented in this dissertation is part of the joint efforts made by the members of the Flexextension A-Gear project to give solutions to the limitations of current arm supports. The aim of the Flexextension A-Gear project was to develop body-bound assistive devices that could be worn underneath clothing and be able to support the arm function for the execution of essential activities of daily living meeting the time-varying needs of individuals with DMD. The development towards the ultimate arm support was divided in two separate functional prototypes: the Passive A-Gear and the Active A-Gear, which are directly related to two levels of assistance. The Passive A-Gear is intended for individuals with DMD that are still able to perform activities of daily living if the weight of the arms is compensated. When the support provided by the Passive A-Gear becomes insufficient, the Active A-Gear provides the extra assistance needed by adults with DMD through motorized joints that react to the intentions of the user. As a parallel strategy, we also developed the A-Arm device, which is a non-wearable two-DOF active arm support that replaces the arm rest of a wheelchair.

A critical component of active arm supports, such as the Active A-Gear or the A-Arm, is the control interface, as is it responsible for the human-machine interaction. My role in the project was the development and evaluation of suitable control interfaces to detect the motion intention of people with DMD and their implementation in the Active A-Gear and in the A-Arm. We assumed that the use of control interfaces that derive the motion intention from implicit commands can result in a natural and intuitive interaction with the assistive device. Electromyography- (EMG) and force-based control interfaces were selected as promising candidates for the detection of the motion intention in adults with DMD. This dissertation presents several studies towards *“the development, evaluation and implementation of EMG- and force-based control interfaces to actively support the arm function of adults with DMD”*.

The following questions were answered during the research process:

- i *What is the state-of-the-art of non-invasive methods to detect motion intention?*

We carried out a comprehensive literature study of non-invasive methods to detect motion intention in active movement-assistive devices. We found that the performance of non-invasive brain-computer interfaces appears to be limited for the control of active movement-assistive devices and are being used in devices for highly paralyzed patients. Muscle-activation interfaces (i.e. surface EMG-based interfaces) are the most common method for operating active upper-extremity prosthetic devices. New techniques such as artificial-learning or surgical procedures are improving its functionality by increasing the number of controllable degrees-of-freedom and intuitiveness. Despite muscle-contraction interfaces (e.g. mechanomyography-based interfaces) are not being implemented in today's clinical practice, these interfaces are showing significant advancements and may find their way to compete with the well-established myoelectric control in the near future. Movement- and force-based control interfaces are often implemented in rehabilitation robots for patients that need training to regain mobility and strength. Finally, we found that control interfaces based on signals from parallel systems are generally a suitable solution to derive the movement intention of highly paralyzed patients and are also implemented in hybrid sensor modalities to expand the sources of information.

ii Are EMG- and Force-based control interfaces feasible for the control of active arm supports in adults with DMD?

We found that both EMG- and force-based control interfaces are feasible for the support of elbow and planar arm movements in adults with DMD with very limited arm function (Brooke 4, 5 and 6). There is a fundamental difference between EMG and force-based control: in force-based control, the measured force signal contains not only the voluntary force of the user, but also the intrinsic forces of the arm such as stiffness, viscosity, inertia and gravitational forces. Therefore, it is crucial to accurately distinguish the voluntary forces of the user from the other force components in people with severe muscular weakness. In this dissertation, joint-stiffness forces were estimated and actively compensated using a measurement-based method, which resulted in an increased functional range of motion in adults with DMD (Brook scores of 5 and 6). Nevertheless, these participants perceived force-based control as fatiguing. In contrast, EMG-based control was not perceived as fatiguing, which indicates that adults with DMD could use the assistive device and their arms for a longer period of time with this control interface. This finding is supported by the study presented in Chapter 5 in which we were able to measure EMG signals in a 37 year-old man with DMD that had lost his arm function 15 years before the study. The measured signals were successfully used as input signal to control a simulated elbow orthosis, which suggests that EMG signals can be used as a control interface for assistive devices in adults with DMD until the last stage of the disease.

The comparative studies between EMG and force-based control interfaces indicated that, in general, EMG-based control interfaces are better suited for adults with DMD than force-based control interfaces as the former are experienced as less fatiguing. Nevertheless, force-based control interfaces with active joint-stiffness compensation can be a better alternative for those cases in which voluntary forces would still be higher than the intrinsic forces of the arms. This conclusion has an indicative value, as it is based on a low number of subjects. In any case, the decision on the most suited interface will have to be taken based on the specificities of each subject.

iii How can the A-Arm and the Active A-Gear tackle the major limitations of existing devices?

The A-Arm and the Active A-Gear have been specially developed to support the arm function of adults with DMD. The A-Arm is a non-wearable two degrees-of-freedom (DOF) active arm support based on a serial two-link mechanism that assists movement in the horizontal plane. The A-Arm becomes inconspicuous by its simplicity and the way it is integrated into the wheelchair. The Active A-Gear is a five-DOF wearable and active exoskeleton designed to provide assistance for the performance of activities of daily living to people with severe muscular weakness. Through the combination of passive and active support, we designed a low-weight (2.5 kg) and close-to-body system (max. of 15 cm away from the body) able to support the weight of the arm (3 kg) and apply high endpoint forces (30-60 N). Both EMG and force-based control interfaces have been implemented in the A-Arm and the Active A-Gear.

The A-Arm and the Active A-Gear tackle the limitations of current arm supports. They can provide support to the weakest users, and have small dimensions that reduce their stigmatizing effect. Moreover, they have control interfaces that use signals implicitly related to the movement intention of the user, which does not require sacrificing the use of any part of the body.

In conclusion, by developing EMG- and force-based control interfaces and implementing them in the A-Arm and Active A-Gear, we succeeded in making a significant step in improving arm supports for adults with DMD. Hopefully these novel concepts of arm supports will be the basis for the development of commercially available active arm supports for people with severe muscular weakness. These control and assistive strategies may also be applicable to other patient groups with muscular weakness.

SAMENVATTING

Vanwege ernstige spierzwakte hebben volwassenen met Duchenne Spierdystrofie (DMD) beperkte, of bijna geen, armfunctie meer. Hoewel hun levensverwachting veel is toegenomen in de afgelopen vijf decennia, blijft hun kwaliteit van leven nog erg achter. Een grote groep mensen met DMD leeft tegenwoordig tot na het dertigste levensjaar, maar met een grote afhankelijkheid van zorg en beperkte deelname in sociale activiteiten.

Ondersteunde technologie zou een belangrijke rol kunnen spelen in het verbeteren van de levenskwaliteit van volwassenen met DMD, door het voor hen mogelijk te maken zonder zorg hun dagelijkse taken uit te voeren. Hoewel de taak van de benen effectief kan worden ondersteund of vervangen door (elektrische) rolstoelen, zijn er nog weinig effectieve oplossingen om de armfunctie te ondersteunen. Commercieel verkrijgbare armondersteuningssystemen lijden aan drie veel voorkomende beperkingen: (I) ze leveren te weinig ondersteuning voor de zwakste gebruikers, (II) hun grootte en onaantrekkelijke uiterlijk werken visueel stigmatiserend voor gebruikers, en (III) ze hebben control interfaces zoals knoppen en joysticks die het gebruik van een hand of ander lichaamsdeel van de gebruiker opofferen.

Het werk gepresenteerd in dit proefschrift is onderdeel van de gezamenlijke inspanning door leden van het Flexextension A-Gear project om oplossingen te vinden voor de beperkingen van de huidige verkrijgbare armondersteuningssystemen. Het doel van het Flexextension A-Gear project was om een draagbare armondersteuning te ontwikkelen, welke onder kleding kan worden gedragen, de arm kan ondersteunen in dagelijkse taken en om kan gaan met de vraag naar toenemende ondersteuning over tijd. De ontwikkeling van de uiteindelijke armondersteuning was opgedeeld in twee functionele prototypes: de Passive A-Gear en de Active A-Gear, welke direct gerelateerd zijn aan twee niveaus van ondersteuning. De Passive A-Gear is bedoeld voor individuen met DMD die zelf nog dagelijkse taken kunnen uitvoeren, mits het eigen gewicht van de arm wordt gecompenseerd. Wanneer deze mate van ondersteuning onvoldoende wordt, kan de Active A-Gear extra ondersteuning bieden via gemotoriseerde gewrichten die adequaat reageren op de intentie van de gebruiker. Ook is in parallel de A-Arm

ontwikkeld; een niet-draagbaar actieve armondersteuning met twee vrijheidsgraden die de armleuning van de rolstoel vervangt.

Een belangrijk onderdeel van actieve armondersteuning, zoals in de Active A-Gear of de A-Arm, is de control interface. Deze is verantwoordelijk voor de mens-machine interactie. Mijn rol in het project was het ontwikkelen, implementeren en evalueren van geschikte control interfaces die de bewegingsintentie van mensen met DMD afleiden uit signalen die impliciet gerelateerd zijn aan de ondersteunde functie. We namen aan dat het gebruik van zulke control interfaces resulteert in natuurlijke en intuïtieve aansturing van het apparaat. Op elektromyografie (EMG) en op kracht gebaseerde control interfaces waren gekozen als kandidaten om de bewegingsintentie te bepalen. Dit proefschrift presenteert onderzoek naar *“de ontwikkeling, evaluatie en implementatie van op EMG en op kracht gebaseerde control interfaces om de armfunctie van volwassenen met DMD te ondersteunen”*.

De volgende vragen zijn beantwoord tijdens het onderzoek:

- i Wat is de state-of-the-art van het niet invasief bepalen van bewegingsintentie?

We hebben een uitgebreid literatuuronderzoek uitgevoerd naar niet invasieve methodes om bewegingsintentie te bepalen voor actieve bewegingsondersteunende apparaten. We vonden dat de prestaties van niet invasieve brain-computer interfaces te beperkt zijn om te gebruiken in actieve bewegingsondersteuning en doorgaans enkel worden gebruikt voor verlamde patiënten. Het meten van spier-activatie (via oppervlakte EMG) is de meest voorkomende methode om armprotheses aan te sturen. Nieuwe technieken zoals machine learning en chirurgische ingrepen bieden verbeteringen in functionaliteit door het uitbreiden van het aantal aanstuurbare vrijheidsgraden en door het intuïtiever aanstuurbaar maken van het systeem. Hoewel spiercontractie interfaces (e.g. via mechanomyography) vandaag de dag (nog) niet gebruikt wordt in klinieken, is de vooruitgang dusdanig veelbelovend dat ze in de nabije toekomst goed zullen kunnen concurreren met huidige myoelektrische aansturing. Op beweging en op kracht gebaseerde control interfaces worden vaak geïmplementeerd in revalidatierobotica om patiënten te helpen bij het trainen om hun bewegingsvrijheid en kracht terug te krijgen. Uiteindelijk merkten we dat control

interfaces die signalen afleiden uit parallelle systemen doorgaans een goede oplossing zijn voor verlamde patiënten en ook kunnen worden gebruikt in een hybride opzet om meer informatie over de intentie van de patiënt af te leiden.

ii Zijn op EMG en op kracht gebaseerde control interfaces bruikbaar voor het aansturen van actieve armondersteuning voor mensen met DMD?

We vonden dat zowel op EMG als op kracht gebaseerde control interfaces bruikbaar zijn om ellenboogbewegingen en bewegingen in het horizontale vlak te ondersteunen bij volwassenen met DMD met beperkte armfunctie (Brooke scores 4, 5 en 6). Er is een fundamenteel verschil tussen op EMG en op kracht gebaseerde aansturing: bij op kracht gebaseerde aansturing meten we niet alleen de vrijwillige krachtsbijdrage van de persoon, maar ook intrinsieke krachten van de arm en het gewricht, zoals stijfheid, viscositeit en zwaartekracht. Daarom is het belangrijk om nauwkeurig onderscheid te maken tussen vrijwillige en andere krachten voor mensen met spierzwakte. In dit proefschrift wordt een methode beschreven waar gewrichtsstijfheid eerst door te meten werd geschat en actief werd gecompenseerd. Dit resulteerde in een vergroot bewegingsbereik voor volwassenen met DMD (Brook scores 5 en 6). Desondanks, vonden de deelnemers de op kracht gebaseerde aansturing vermoeiend. In tegenstelling tot kracht, werd op EMG gebaseerde aansturing niet vermoeiend gevonden. Dit geeft aan dat volwassenen met DMD hun arm met ondersteuning voor een langere aaneengesloten tijd zouden kunnen gebruiken met deze control interface. Deze vondst wordt ondersteund door de studie gepresenteerd in hoofdstuk 5, waarin we EMG metingen laten zien die gedaan zijn bij een 37 jaar oude man met DMD die al 15 jaar geen armfunctie meer heeft. De gemeten signalen zijn succesvol gebruikt als signaal om een gesimuleerde ellenboogorthese aan te sturen. Dit lijkt te suggereren dat EMG signalen tot in een vergevorderd stadium van DMD gebruikt kunnen worden als control interface voor ondersteuningsapparaten. De vergelijkingsstudie gedaan tussen op EMG en op kracht gebaseerde control interfaces geeft aan dat, in het algemeen, op EMG gebaseerde control interfaces beter geschikt zijn voor volwassenen met DMD dan op kracht gebaseerde interfaces. Echter, is een op kracht gebaseerde control interface met actieve gewrichtsstijfheidscompensatie een beter alternatief voor de gevallen waar vrijwillige kracht groter is dan intrinsieke krachten in de arm. Deze con-

clusie is enkel indicatief, omdat deze gebaseerd is op een klein aantal proefpersonen. In ieder geval zal de keuze afhangen van de specifieke (signaal)eigenschappen van elke proefpersoon.

iii Hoe kunnen de A-Arm en de Active A-Gear de grote tekortkomingen van huidige apparaten overwinnen?

De A-Arm en de Active A-Gear waren specifiek ontworpen om de armfunctie van volwassenen met DMD te ondersteunen. De A-Arm is een niet-draagbare actieve armondersteuning met twee vrijheidsgraden, en is gebaseerd op een twee-balk mechanisme die beweging in het horizontale vlak ondersteunt. De A-Arm wordt visueel onopvallend gemaakt door zijn eenvoud en integratie in de rolstoel. De Active A-Gear is een draagbaar en actief exoskelet met vijf vrijheidsgraden, ontworpen om ondersteuning te bieden bij dagelijkse taken voor mensen met ernstige spierzwakte. Door een combinatie van passieve en actieve ondersteuning, hebben we een lichtgewicht (2.5 kg) systeem gemaakt dat dicht bij het lichaam zit (maximaal 15 cm van het lichaam) en de mogelijkheid heeft het gewicht van de arm (3 kg) te ondersteunen en hoge eindpuntkrachten kan genereren (30-60 N). Zowel op EMG als op kracht gebaseerde control interfaces zijn geïmplementeerd in de A-Arm en Active A-Gear. De A-Arm en de Active A-Gear lossen problemen op die huidige armondersteuningen wel hebben. Ze kunnen ondersteuning bieden aan de zwakste gebruikers, en zijn klein genoeg zodat ze minder visueel stigmatiserend zijn. Bovendien hebben ze control interfaces die signalen gebruiken die impliciet gerelateerd zijn aan bewegingsintentie van de gebruiker, zodat geen ander lichaamsdeel daarvoor opgeofferd hoeft te worden.

Door het ontwikkelen van op EMG en op kracht gebaseerde control interfaces, en door deze te implementeren in de A-Arm en Active A-Gear, zijn we geslaagd in het maken van een significante verbeterstap voor armondersteuning voor volwassenen met DMD. Hopelijk zijn deze nieuwe concepten de basis voor de ontwikkeling van commercieel verkrijgbare armondersteuning voor mensen met ernstige spierzwakte. Deze regel- en ondersteuningsstrategieën zouden ook toepasbaar kunnen zijn op patiëntgroepen met andere types spierzwakte.

INTRODUCTION

We continuously use our arms to perform most of our activities of daily living (ADL) and socialize with others. Adults with Duchenne muscular dystrophy (DMD), due to severe muscular weakness, have very limited or no arm function left, which hinders the performance of basic ADL [1, 2]. While their life expectancy has considerably increased over the last five decades, their quality of life still remains very poor [3]. Currently, a considerable group of adults with DMD live until their 30's with a strong dependency on care and restrictions to participate in social activities [4].

Assistive technology can play an important role in increasing the quality of life for people with DMD. The function of legs can be effectively supported with the use of wheelchairs, but there are few effective solutions to support arm function[5, 6]. The work presented in this dissertation is part of the joint effort made by the members of the Flextension A-Gear project [7] to develop new arm supports that better meet the needs of people with DMD.

This part gives a general overview on the pathogenesis, disease progression and treatment of DMD, followed by a brief description of assistive technology used by people with DMD with a special focus on existing arm supports. Finally, the goals of the Flextension A-Gear project, together with a description of the specific goals, research questions, and outline of this dissertation are presented.

1.1 DUCHENNE MUSCULAR DYSTROPHY

1.1.1 *Pathogenesis*

DMD is the most common inherited muscle disorder, affecting 1 in 5000 live born males, and is characterized by progressive muscle wasting and weakness [8]. DMD is caused by defective mutations in the dystrophin gene, which causes the absence or defect of the dystrophin protein. DMD affects mostly males since the mutation is located in the X-chromosome. Females that carry the defective gene rarely show any symptoms but can pass the mutation to their sons [9].

The dystrophin protein plays a key role in the functioning of muscle cells and thus people with DMD suffer from degeneration of skeletal, respiratory and cardiac muscles. In the extremities, muscle weakness affects mainly proximal muscles [10]. DMD does not affect smooth muscles, and thus bladder, gastrointestinal and sexual organs, among others, function normally. Few studies have also reported the preservation of muscle spindles, which are crucial to provide proprioceptive feedback [11]. Small amounts of dystrophin protein are also expressed in the brain, which causes that about one third of individuals with DMD also present mental deficiencies [10].

DMD is part of a larger group of muscular dystrophies including: Becker muscular dystrophy (BMD), Emery-Dreifuss, distal, facioscapulohumeral, oculopharyngeal, and limb-girdle. All of the muscular dystrophies are inherited disorders characterized by variable degrees and distribution of muscle wasting and weakness. Note that BMD is also caused by a defective mutation in the dystrophin gene and the muscle wasting and weakness is similar to that in DMD. However, in BMD the dystrophin protein is partially functional, which makes the course of the disease more benign compared to DMD, with an age of onset around 12 years. The loss of ambulation in people with BMD varies from adolescence onwards, with a life expectancy reaching the fourth or fifth decade [10].

A fundamental difference between DMD (or muscle dystrophies in general) and neurological disorders, such as stroke, cerebral palsy or spinal cord injury, is that in DMD the neural pathways are intact and the motor impairment is present only at the muscle level. Nevertheless, some signs and symptoms of DMD are similar to the ones of neurological disorders due to the muscle weakness and limited mobility of the patients, such as contractures, skeletal deformities, fatigue, balance and coordination problems, increased joint stiffness and joint pain.

Figure 1: Disease Progression and Assistive Technology used by people with DMD as function of time.

1.1.2 Disease Progression and Treatment

Even though people with DMD show a high functional heterogeneity [12], there is a disease progression pattern (Fig. 3). People with DMD start to present upper and lower extremity limitations from the early ambulatory stage and lose independent ambulation around the age of 10 years. This is followed by the development of scoliosis, joint contractures and loss of upper extremity function during their teens. They also develop severe cardiomyopathies and respiratory problems during their twenties, which in most cases will lead to death. Another characteristic pattern of DMD is that proximal muscles, such as shoulder muscles, are affected first, while distal muscles, such as hand and finger muscles, preserve their function for a longer period of time [10, 2].

Currently, there is no cure for DMD. Treatment aims to delay the disease progression and preserve functional abilities. Over the last five decades, the use of corticosteroids and nocturnal ventilation has increased the life expectancy of people with DMD from 14 years in 1960's to 25 years in 1990's [13]. Currently, the mean life expectancy of boys with DMD is estimated to be over 30 years [3] and it is foreseen that with new treatments life expectancy will be prolonged further.

Since the characterization of the mutation that causes DMD [14], much research has focused in developing an effective gene therapy that could cure or diminish the symptoms of the disease. An increasing knowledge of the dystrophin gene (one of the largest genes in the human body) and the role of dystrophin protein in muscle function has indicated ways to genetically manipulate the mutation and the dysfunctional protein [15]. Recent advancements in gene therapy for DMD using the CRISPR/Cas9 technique have shown promising results

Figure 2: Brooke score as function of time (years) for 121 individuals with DMD. Figure reproduced from [18].

in mice for the correction of the genetic mutation [16]. Treated DMD mice performed better on tests of muscle strength than untreated DMD mice but did not perform as good as normal mice [17]. These therapies are still around 10 years away from being tested in humans [16].

International guidelines recommend people with DMD to regularly perform sub-maximal exercises and avoid eccentric and exhausting high-resistance exercises [19]. While it is accepted that sub-maximal physical exercises might delay the secondary functional deterioration as a result of disuse, the number of randomized controlled trials that investigated the effect of physical training in adults with muscle diseases is low [20]. Few (un-controlled) studies that examined the effects of physical training in people with DMD during resistance exercises concluded that although sub-maximal resistance exercises did not cause any harm, they had only limited beneficial effects [21, 22, 23]. In contrast, a recent randomized controlled trial study that investigated dynamic exercises (i.e. assisted bicycle training) in boys with DMD concluded that prolonged physical training can delay the secondary functional deterioration due to disuse [24]. Improved endurance and strength was also found with dynamic exercise in patients with BMD (the milder variant of DMD) [25]. Finally, a feasibility study on the use of arm supports for upper extremity training showed that the trained arm retained more motor function than the untrained arm in four out of six participants [26].

1.2 ARM FUNCTION EVALUATION IN DMD

The most common functional assessment scale of arm function in DMD is the Brooke score [27]. The Brooke score ranges from 1 to 6, where 1 indicates normal arm and hand function, and 6 indicates that no arm and hand function is left. Table 1 gives a description for each of the scores. The Brooke score is determined by asking the subject to perform a series of basic arm movements and evaluating if the movement can or cannot be performed. Figure 2 shows the correlation between age and brooke score of 121 individuals with DMD [18].

Recently, a new arm function scale, the performance of upper limb (PUL) score [28], has been introduced in the clinical community which evaluates a larger number of arm and hand movements with a standardized protocol.

In this dissertation the Brooke score will be used to refer to the level of arm function of people with DMD.

Table 1: Description of the Brooke scores. Table reproduced from [18]

Brooke Score	Description
1	Starting with arms at the sides, the patient can abduct the arms in a full circle until they touch
2	Can raise arms above head only by flexing the elbow (shortening the circumference of the movement) or using accessory muscles
3	Cannot raise hands above head, but can raise a 8-oz glass of water to the mouth
4	Can raise hands to the mouth, but cannot raise a 8-oz glass of water to the mouth
5	Cannot raise hands to the mouth, but can use hands to hold a pen or pick up pennies from the table
6	Cannot raise hands to the mouth and has no useful function of the hands

Figure 3: Disease Progression and Assistive Technology used by people with DMD as function of time.

1.3 ASSISTIVE TECHNOLOGY FOR PEOPLE WITH DMD

Several assistive devices are used by people with DMD to support or preserve their functional abilities, or reduce the physical effort of care givers [19, 29, 30]. Leg orthoses are the first aid that boys with DMD generally wear (first only during the night) to keep their joints flexible and delay the onset of contractures, which can lengthen the ambulatory period. The use of crutches or standing frames is also common to help them stand or walk for some time a day.

When the legs become too weak, people with DMD use wheelchairs for ambulation. At the beginning they can use manual wheelchairs, but when the arms become too weak they require motorized wheelchairs which are usually controlled with a highly sensitive hand joystick [31]. Devices such as transfer boards, electromechanical lifts, stairs or beds are also commonly used to reduce the physical effort of people with DMD and care givers during transfers. Often,

Figure 4: An adult with DMD using the JACO robotic arm as arm support. The subject of the picture decided to use a piece of cloth to hold his arm with the JACO because in this way he felt that the assistance was more natural and he had better control than when interacting with objects directly with the gripper of the robot. This picture illustrates the will of people with severe muscular weakness to keep using their arms instead of using external robotic arms. Currently there is a need for (active) arm supports that can provide assistance to the weakest users.

scoliosis appears when people with DMD start using the wheelchair full time. This deformation of the spine can be prevented by trunk orthoses or custom-made back rests for the wheelchair. In case of severe scoliosis a surgical operation has to be performed to correct the spine curvature with implants. When the diaphragm and other chest muscles become too weak for normal respiration, artificial ventilation devices are used to assist in breathing using first a mask and an invasive tracheostomy latter.

Arm supports are used to assist the arm function and will be described in detail in the next section. External robotic arms, such as the JACO (Kinova, Canada; Fig. 4) [32] or the iARM (Exact Dynamics, Netherlands), are used by people with DMD when they cannot benefit from arm supports anymore. External robotic arms allow adults with DMD to manipulate the environment and bring food or drinks to their mouth, but they do not use their arms at all, which can contribute to the development of complications such as joint contractures, pain, and functional deterioration of the arms [2, 26, 24].

1.4 ARM SUPPORTS

The first arm supports for people with muscular weakness were developed in 1960's [33]. The first designs only supported self-feeding movements, but current devices can assist a wider range of ADL. Currently, a large number of upper-extremity assistive devices have been developed. Most of them are intended as rehabilitation devices, and only few are meant for daily use, commercially available, and used by people with DMD (comprehensive reviews can be found in [5, 33]).

1.4.1 *Classification of Arm Supports*

Arm supports (Fig. 5) can be divided into three subcategories: passive devices (also known as body-powered devices), actively adjustable passive arm supports, and active arm supports (also known as robotic arm supports).

Passive arm supports use elastic elements (i.e. springs) to compensate the weight of the arm. The WREX (JAECO Orthopedic, USA) [34] and the TOP (Focal Meditech, the Netherlands) are passive arm supports that have been in the market for more than 20 years. The WREX (JAECO Orthopedics, USA) is now available in two versions: a metal version that attaches to the wheelchair or to a table, and a wearable version, known as Baby WREX, that combines 3D printed plastic parts and metal parts for ambulatory children [35]. More recent commercially available passive arm supports include the Sling, the Dowling and the Balancer (Focal Meditech, the Netherlands), the VERTICAL M.A.G. (Proteor, France), the Armon Pura and Edero (Microgravity Products, the Netherlands), the Nitzbon Mobility Arm (Nitzbon, Germany), the Saebo MAS (Saebo Inc., USA) and the X-Ar (Talem Technologies, USA).

Actively adjustable passive arm supports have motors to adjust the settings of the gravity compensation mechanism, lock the position of the joints or move the arm vertically and horizontally using buttons and joysticks. While these devices can provide extra assistance with the actuators, the motors are generally intended to be used occasionally and not continuously. Focal Meditech has developed several actively adjustable passive arm supports: the active version of the TOP known as TOP/HELP, the Sling, the Darwing and the Gowing. Other

Figure 5: Examples of commercially available arm supports. **(a)** Baby WREX (JAECO Orthopedic, USA). **(b)** Armon Pura (Microgravity Products, the Netherlands). **(c)** Sling (Focal Meditech, the Netherlands). **(d)** Darwing (Focal Meditech, the Netherlands). **(e)** TOP/HELP (Focal Meditech, the Netherlands). **(f)** Neater Arm Support (Neater Solutions, UK). **(g)** Armeo Power (Hocoma AG, Switzerland). **(h)** MyoPro (MyomoInc., USA). **(i)** Device developed in the ESTA project.

powered arm supports include the Armon Ayura and Elemento (Microgravity Products, the Netherlands) [36], the Zonco Mobile Arm Valet (ZoncoArm, USA), the DAS (Exact Dynamics, the Netherlands) [37] and the Neater Arm support (Neater Solutions, UK) [38].

Active arm supports are in most cases available as rehabilitation devices (e.g. ARMEO Power, Hocoma, Switzerland) and are not intended to provide assistance during ADL. Few devices are available and intended for daily use such as the MyoPro (Myomo Inc., USA), which is an electromyography (EMG) controlled elbow-wrist-hand orthosis, and the H200 (Bioness Inc., USA), which is a device that provides electrical stimulation of hand muscles. However, none of the aforementioned devices for daily use are recommended for people with DMD. There are few active arm supports under development intended to provide assistance during ADL for people with muscular dystrophies. These include the active version of the WREX [39], the device developed in the ESTA project [40] and the device developed in the McArm project [41].

1.4.2 *Effectiveness of Arm Supports*

A recent systematic review on the effect, effectiveness and usability of arm supports concluded from the results of 47 evaluation studies that there was an increased ability to perform activities of daily living and user satisfaction when using an arm support, but that their use at home was low [6]. A recent study of a questionnaire-based evaluation of the WREX concluded that the WREX made a significant improvement in arm function for users while performing ADL. The 60% of the 55 users included in the study continued to use the WREX at the time of the survey. The 69% percent of wheelchair-mounted WREX users continue to use it, and 48% of the body-mounted version continue to use it. Reasons for abandonment included weight, interference with other activities, joint contractures, and imprecise gravity compensation. Users also reported more improvement of arm function with the wheelchair-mounted WREX than with the body-mounted version. Aesthetics, fitting, and reimbursement were identified as areas for improvement [35]. Finally, a user evaluation study with the Neater arm support concluded that the use of the Neater arm support by adults and teenagers with neuromuscular disorders could greatly improve their independence, confidence, and ability to engage in social situations [38].

1.5 PROBLEM DEFINITION

From the aforementioned literature and several discussions (i.e. [42]) with people with DMD, care givers, rehabilitation physicians, and manufacturers of arm supports, three major limitations of current arm supports were identified:

- Passive or actively adjustable arm supports provide insufficient support to the weakest users. These users can barely generate any force to overcome inertia and friction of the device, or their own joint stiffness.
- The large dimensions and unattractive look of arm supports are often stigmatizing to the users.
- The user must sacrifice the use of one hand to operate the device, using buttons or a joystick, if the device is actively adjustable.

1.6 THE FLEXTENSION A-GEAR PROJECT

In order to advance the field of assistive technology the Flexextension Foundation [7] was initiated in collaboration with the Dutch Duchenne Parent Project in 2009. The Flexextension Foundation has the goal to improve the quality of life of people with DMD through the development of new assistive technology. The foundation is a collaboration between several centers in the Netherlands including universities, companies and patient organizations.

In 2011, the first project of the Flexextension Foundation was initiated to give solutions to the limitations of current arm supports: *the Flexextension A-Gear project*. The aim of the Flexextension A-Gear project was to develop body-bound assistive devices that could be worn underneath clothing and be able to support the arm function for the execution of essential activities of daily living meeting the time-varying needs of individuals with DMD (Fig. 6). The development towards the ultimate arm support was divided into two separate functional prototypes: the Passive A-Gear and the Active A-Gear (Fig. 7a,b), which are directly related to two levels of assistance. The Passive A-Gear [43] is intended for individuals with DMD that are still able to perform activities of daily living if the weight of the arms is compensated. When the support provided by the Passive A-Gear becomes insufficient, the Active A-Gear [44] provides the extra assistance needed by adults with DMD through motorized joints that respond to the intentions of

Figure 6: The goal of the Flextension A-Gear project was to develop arm supports that meet the time-varying needs of people with DMD. Therefore, the type of support had to be adapted to the level of muscle strength. At the first stage of the disease people with DMD do not need any arm support, later, passive support that compensates the weight of the arm is provided with the Passive A-Gear, and at the last stage of the disease active support is provided with the motorized joints of the Active A-Gear or the A-Arm.

the user. As a parallel strategy, the A-Arm device was also developed during the A-Gear project (Fig. 7c). The A-Arm is a non-wearable 2-DOF active arm support that assists in tabletop tasks and replaces the arm rest of a wheelchair [45]. Additionally, in order to identify the specific needs and abilities of individuals with DMD at the different stages of the disease, the A-Gear project carried out a clinical study to investigate the functional and physiological consequences caused by the progressive muscle degeneration. The ultimate goal of the Flextension A-Gear project was to develop functional prototypes that demonstrated that the arm function of individuals with DMD could be effectively supported with (wearable) assistive devices. These developments will be further elaborated in future projects initiated as well by the Flextension Foundation.

Figure 7: The prototypes of arm supports developed in the Flextension A-Gear project.

The Flextension A-Gear research team (Fig. 8) was composed of four PhD students working at four different Dutch universities. Under the supervision of Imelda J.M. de Groot (Radboud University Medical Center), Mariska M.H.P Janssen was responsible for the research on the clinical aspects of the project, which mainly focused on the investigation of the user needs, the investigation of the arm function in boys and men with DMD, and the clinical evaluation of the prototypes and working principles. Under the supervision of Just L. Herder (Delft University of Technology), Gerard A. Dunning was responsible for the design and evaluation of the Passive A-Gear and the development of slender spring systems for a close-to-body arm support. Under the supervision of Micha I. Paalman and Ruud Verdaasdonk, Peter N. Kooren (VU Medical Center) was responsible for the integral design, the manufacturing and evaluation of the Passive and Active A-Gear and the A-Arm, and the design of research setups to validate several working principles. Finally, I was responsible for the development and evaluation of suitable control interfaces to detect the motion intention of people with DMD and their implementation in the Active A-Gear and in the A-Arm, under the supervision of Bart F.J.M. Koopman, Arno H.A. Stienen and Peter H. Veltink at the University of Twente .

Figure 8: The Flextension A-Gear research Team together with (almost) all the members of the user committee. Picture taken during the last user committee meeting of the Flextension A-Gear project. From left to right: Nils van Leerdam (Ambroise), Arjen Bergsma (Flextension Foundation), Mirjam Franken (Duchenne Parent Project), Prof. Jaap Harlaar (VUMC), Simone van der Berge (Prinses Beatrix Spierfonds), Paul Verstegen (Focal Meditech), Dr. Imelda de Groot (RadBoud umc), David Spies (Tree Top Design), Micha I. Paalman (VUMC), Prof. Bart Koopman (University of Twente), Joan Lobo Prat (University of Twente), Boudewijn Wisse (InteSpring), Peter Kooren (VUMC), Mariska Janssen (RadBoud umc), Gerard Dunning (TU Delft), Henry van der Valk (STW), Prof. Just Herder (TU Delft).

1.7 OBJECTIVES AND RESEARCH QUESTIONS

Current arm supports do not provide sufficient support for people with severe muscle weakness such as adults with DMD. Active arm supports (such as the Active A-Gear or the A-Arm) can provide extra assistance, and have the potential to enable adults with DMD to continue performing ADL, increasing their independence and participation in social activities. A critical component of active arm supports is the control interface, as it is responsible for the human-machine interaction. Current arm supports use joysticks or buttons as control interface,

which require the user to sacrifice the use of one hand to operate the device. We assumed that the use of control interfaces that derive the motion intention from implicit commands could result in a natural and intuitive interaction with the assistive device. EMG- and force-based control interfaces were selected as promising candidates for the detection of the motion intention in adults with DMD.

The goal of this dissertation is “*the development, evaluation and implementation of EMG- and force-based control interfaces to actively support the arm function of adults with DMD*”. The investigations towards this goal led to the formulation of the following research questions:

Research Questions

- i *What is the state-of-the-art of non-invasive methods to detect movement intention? Part I (Chap. 2)*
- ii *Are EMG- and force-based control interfaces feasible for the control of active arm supports in adults with DMD? Part II (Chap. 3 to 6)*
- iii *How can the A-Arm and the Active A-Gear tackle the major limitations of existing arm supports? Part III (Chap. 7 and 8)*

Figure 9: Diagram of the dissertation’s outline.

1.8 DISSERTATION’S OUTLINE

All Chapters of this dissertation (excluding the introduction and discussion) were written as full journal or conference publications. This causes an overlap between some chapters, but allows the reader to read them individually or out of order. Figure 9 illustrates the outline of this dissertation.

Part I: State of the art of non-invasive control interfaces. This part was dedicated to the review of the state of the art of non-invasive control interfaces for movement-assistive devices. This literature study together with a thorough analysis of the user needs and system requirements was used to evaluate several concepts of control interfaces. From this evaluation, EMG- and force-based control interfaces were selected as the most promising solutions for the control of active arm supports for adults with DMD.

- **Chapter 2** presents a novel systematic classification method to categorize the control interfaces for intention detection in active-movement assistive devices. Each sensing modality is shortly described in the body of the chapter following the same structure used in the classification method. Furthermore, the chapter presents several design considerations, challenges and future directions of the non-invasive control interfaces for active movement-assistive devices.

Part II: Evaluation of EMG and force as control interfaces to support the arm function of adults with DMD. This part focused on carrying out several comparative studies that evaluated the performance, feasibility and user's acceptance of EMG- and force-based control interfaces in healthy subjects and in adults with DMD. These experiments were performed using screen-tracking tasks (Chap. 3) and two experimental arm supports: the Elbow Drive (Chap. 4) and the commercially available UR5 Robotic Arm (Chap. 6). The results of the Elbow Drive experiment indicated that EMG-based control was probably the only feasible solution for the weakest subjects with DMD. Therefore, we performed an exploratory experiment to investigate if EMG signals from a 37 year-old man with DMD were measurable and could be used for control (Chap. 5).

- **Chapter 3** presents a comparative study between EMG, force and joystick as control interfaces for active arm supports. The interfaces were assessed in eight healthy volunteers with a screen-based one-dimensional position-tracking task. The control performance was evaluated in terms of tracking error, gain margin crossover frequency, information transmission rate and effort. This experiment was intended to have a baseline performance measure that would serve as a reference on the potential value of EMG, force and joystick as control interfaces for active arm supports. The joystick-based interface was included in the comparison as an alternative system that is currently used for the adults with DMD to control wheelchairs or external robotic arms.
- **Chapter 4** presents a feasibility study on the use of EMG and force as control interfaces for the operation of active arm supports for men with DMD. An active elbow support controlled with EMG- and force-based interfaces was tested in three adults with DMD (21-22 years) during a discrete position-tracking task.

- **Chapter 5** describes the results of EMG measurements from Biceps and Triceps Brachii muscles of a 37 year-old man with DMD that lost his arm function several years ago. The quality of the EMG signals was evaluated in terms of signal-to-noise ratio and co-contraction ratio. Additionally, the measured EMG signals were used to drive a simulated elbow orthosis to evaluate the feasibility of using the EMG signals for control purposes.
- **Chapter 6** extends the evaluation of the 1-DOF EMG- and force-based control interfaces presented in Chapter 4 to two DOF. Three men with DMD (18-23 years old) with three different levels of arm function (i.e. Brooke scores of 4, 5 and 6) performed a series of planar line-tracing tasks over a tabletop surface using an experimental active arm support. The arm movements were controlled using three different control methods: EMG-based control or force-based admittance control with and without active joint-stiffness compensation. The movement performance was evaluated in terms of task completion rate, tracing error, smoothness and speed. We found that movement performance and subjective preference of the three control methods differed with the level of arm function (i.e. Brooke score) of the participants.

Part III: Implementation of EMG- and force-based Control Interfaces in arm supports for men with DMD. All the studies of the second part showed positive results that indicated that both EMG- and force-based control interfaces were feasible solutions to actively support arm movements in adults with DMD. Therefore, the next step focused on the implementation of EMG- and force-based control interfaces in two proof-of-concept prototypes of arm supports: the A-Arm (Chap. 7) and the Active A-Gear (Chap. 8).

- **Chapter 7** details the design and control of the A-Arm, an inconspicuous and simple planar active arm support for adults with DMD that can be controlled with force- or EMG-based interfaces. The A-Arm is intended to replace the arm rest of the wheelchair and assist during table top tasks such as computer, tablet, or smartphone use, writing and drawing, and the use of the wheelchair's joystick. We performed a pilot evaluation with an adult with DMD (24 years old, Brooke 5) using the same line tracing task as in Chapter 6.

- **Chapter 8** presents the design and control of the Active A-gear, a wearable five degree-of freedom exoskeleton that has been specially developed to assist people with DMD for the performance of ADL. The Active A-Gear is built upon our previous design of the passive A-Gear, thus combining active and passive support. We report the results of the system verification, which included endpoint position bandwidth, workspace, weight, joint speed, endpoint force and joint backlash measurements. A pilot validation was carried out with one healthy subject (27 years old) performing ADL.

Discussion

- **Chapter 9** concludes this dissertation with a discussion section for each of the research questions, and finalizes with a discussion on the approach limitations, next steps in EMG- and force-based control interfaces, and the general conclusions of the Flexension A-Gear project.

Part I

STATE OF THE ART OF NON-INVASIVE CONTROL INTERFACES

NON-INVASIVE CONTROL INTERFACES FOR INTENTION DETECTION IN ACTIVE MOVEMENT-ASSISTIVE DEVICES¹

Abstract: *Active movement-assistive devices aim to increase the quality of life for patients with neuromusculoskeletal disorders. This technology requires interaction between the user and the device through a control interface that detects the user's movement intention. Researchers have explored a wide variety of invasive and non-invasive control interfaces. To summarize the wide spectrum of strategies, this paper presents a comprehensive review focused on non-invasive control interfaces used to operate active movement-assistive devices. A novel systematic classification method is proposed to categorize the control interfaces based on: (I) the source of the physiological signal, (II) the physiological phenomena responsible for generating the signal, and (III) the sensors used to measure the physiological signal. The proposed classification method can successfully categorize all the existing control interfaces providing a comprehensive overview of the state of the art. Each sensing modality is briefly described in the body of the paper following the same structure used in the classification method. Furthermore, we discuss several design considerations, challenges, and future directions of non-invasive control interfaces for active movement-assistive devices.*

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2.1 INTRODUCTION

The ability to move in a controlled and stable manner is an essential trait for the human body. The Human Movement Control System (HMCS) can be modeled as in Figure 10A. The HMCS consists of a mechanical structure, the plant, which represents the skeleton and passive tissues, the actuators, which represent the muscles, and a controller, which represents the central nervous system and receives sensory feedback from the physiological sensors [46, 47]. Movement impairments, due to disease or trauma, can occur at various levels of the HMCS, affecting one or several components of the system: blindness affects the "sensors," while muscular dystrophy affects the "actuators."

Advances in neuroscience, engineering, and computer science have led to an acceleration in the development of biomechatronic systems, capable of actively assisting the impaired motor functions of patients affected by neuromusculoskeletal disorders [47, 49, 50]. Assistive devices have been classified by the International Organization for Standardization (ISO) in the standard ISO 9999:2011 according to their main function. Artificial Movement Control Systems (AMCSs) function in parallel to the impaired HMCS and can be modeled with the same components as the HMCS: a plant representing the mechanical structure and passive elements, such as springs or dampers, and an artificial controller that receives the data measured from the sensors and generates control signals to operate the actuators (Fig. 10B).

Three kinds of interactions between the HMCS and the AMCS can be distinguished [47]: (I) detection of the movement intention of the user; (II) provision of feedback to the user regarding the state of the AMCS, the HMCS or the environment; and (III) exchange of mechanical power between both plants. Note that providing feedback to the user is especially relevant when the human sensory system is disturbed.

Several physiological phenomena occur in every subsystem of the HMCS. Some of these phenomena can be measured and associated to the motion intention of the user and therefore can be exploited for the effective control of an AMCS. Neural signals from the central nervous system, neural activation of the muscles, muscle contraction forces and small movements and forces of the human plant are some examples of signals that are implicitly related to the motion intention. Motion intention can also be derived from explicit commands of the user, for example by pressing command switches, through speech, or through

Figure 10: Schematic block diagram of the Human Movement Control System (A) in parallel with the Artificial Movement Control System (B). Three kinds of interactions between the HMCS and AMCS can be distinguished: (I) detection of the motion intention of the user; (II) provision of feedback to the user regarding the state of the AMCS, the HMCS or the environment; and (III) exchange of mechanical power between plants. Both the human and the artificial systems are depicted as dynamic systems in which both the human muscles and artificial actuators generate forces to transfer power and hence move the combined plant composed of the mechanical structure of the assistive device, the human musculoskeletal system and the environment (depicted as "external load"). Note that the interaction between the actuators and the plant is pictured with a bond graph that represents the energy exchange between them (i.e., movement and force in this particular case). The power 1-junction states a common velocity of all components. The reader is referred to [48] for further information on bond graphs. Modified from [46].

Figure 11: Classification Method. Example of the classification method illustrated with a schematic block diagram. See Table 2 for a full overview.

head, tongue or eye movements. Explicit commands are generated by Parallel Systems, which are defined as systems that function in parallel to the supported system (see Fig. 10A).

Researchers have explored a wide variety of invasive and non-invasive methods to derive the user’s movement intention. However, a comprehensive overview of these methods is not available, which hampers efficient and well-founded selection of a suitable control interface for a given application. To illustrate the wide spectrum of strategies, this paper presents a comprehensive review of non-invasive sensing modalities for motion intention detection in active movement-assistive devices. The strategies are classified in a systematic way that provides a clear overview of the state of the art and a framework in which new sensing modalities can be included. This review is limited to non-invasive interfaces (specifically meaning that the sensors are not implanted in the human body) as these are easier to use with a wide variety of patients [51, 52, 53].

The paper is structured as follows. Review section introduces the classification method used to categorize the control interfaces, briefly describes each of the interfaces and discusses several design considerations. Finally, Conclusions section presents our conclusions and future directions.

2.2 REVIEW

Classification method

The inventory of control interfaces for motion intention detection resulting from the literature search was stratified through a four-level classification (see Table 2 and Fig. 11). The first level was defined according to the subsystems of the HMCS (controller, actuators, plant and parallel systems), and the second level was defined according to the physiological phenomena that occur in every subsystem. The set of signals that can be measured for every physiological phenomenon defines the third level of classification, and the sensors used to measure these signals define the fourth level. For each sensor/signal, its transduction principle, interface with the body, area of application, and key references were indicated. Note that the inventory of control interfaces using Parallel Systems is illustrative and not complete and has been added as an additional subsystem of the HMCS in the first level of the classification.

Table 2: Stratified inventory of non-invasive control interfaces used for motion intention detection in active movement-assistive devices

Human system	Physiological phenomena	Signal	Sensor	Transduction principle	Interface with the body	Application	Key reference
Controller	Brain Activity	Electric current	EEG	Electrode	Skin contact	C/P/O/E	[54, 55, 56, 57, 58, 59]
			MEG	MEG machine	No contact	C/O	[60, 61]
	Hemodynamics	fMRI	MRI machine	Induction	No contact	C/E	[62, 63]
		NIRS	Spectrometer	Photoelectric	Near-infrared illumination of the brain	C/E	[64, 65]
Actuators	Muscle Activation	EMG	Electrode	-	Skin contact	O/P/E	[66, 67, 68, 69]
					Targeted muscle reinnervation*	P	[70, 71]
	Vibration	MMG	Microphone	Induction	Skin contact	P	[72, 73, 74, 75]
				Piezoelectric			
			Accelerometer	Piezoelectric	Skin contact	P	[74, 75, 76]
			Hall-effect sensor	Induction	Magnet on the skin	P	[77, 78]
	Muscle contraction	MK	Pneumatic sensor	Resistive Capacitive	Skin contact	P	[79, 80]
			Encoder	Optical	Skin contact	O	[81]
			Ultrasound scanner	Piezoelectric	Skin contact	P	[82, 83, 84]
			Electric impedance	-	Electric current to skin	P	[85]
	Radial force and stiffness	MT/MK	Force-sensitive resistor	Resistive	Skin contact	O/P	[86, 87, 88]
			Piezoelectric transducer	Piezoelectric	Skin contact	O/P	[89]
Hemodynamics	Force	Force	Strain gauges	Resistive	Tunnel muscle cineplasty*	P	[90]
		NIRS	Spectrometer	Photoelectric	NIR illumination of the muscle	P	[91, 92, 93, 94]

	Body segment movement	Body segment movement	IMU	Piezoelectric	Skin contact	P/O	[95, 96]
Plant	Relative Joint movement	Body segment movement	Camera	Photoelectric	No contact	E	[97]
	Movement	Joint rotations	Goniometer	Resistive	Skin contact	P/O	[98, 99, 100, 101]
	Force / Pressure	Deformation	Force/Torque sensor (strain gauges)	Resistive	No contact	P/O/E	[104, 105, 106]
	Eye movement	Corneal reflection	Video camera	Photoelectric	NIR illumination of the cornea	P/E	[110]
Parallel systems	Head movement	EOG	Electrode	-	Skin contact	P/E	[111, 112]
	Tongue movement	Contact with palate / Movement	Induction coil	Induction	Ferromagnetic material at the tip of the tongue	E/C	[118, 119, 120]
	Speech	Sound	Microphone	Induction Piezoelectric	No contact	P/E	[121, 122, 123]
	Hand movement	Angle	Joystick (potentiometers)	Resistive	Skin contact	O/E	[124, 125, 32]

Interfacing with the controller: brain computer interfaces

Current noninvasive brain-computer interfaces (BCIs) derive the user's movement intention from electrical and hemodynamic signals from the brain.

Electrical brain activity: Electroencephalography (EEG) and magnetoencephalography (MEG) are well-established non-invasive methods that measure the average dendritic currents of a large proportion of cells from the scalp [84]. Several brain signals have been used for BCIs, including slow cortical potentials, low-frequency changes in field potentials (such as P300) and α and β rhythms. Furthermore, BCIs can exploit signals related to external sensory stimulation such as auditory or visual stimuli (i.e., evoked potentials), or voluntary mental activity, such as imagining a movement. Even though MEG provides a higher signal quality than EEG and does not require the attachment of scalp electrodes, the latter is portable (i.e. does not require a shielded room) and less expensive. Consequently, EEG-based BCIs are currently commercially available (e.g., by intendiX, g.tec medical engineering GmbH, Schiedlberg, Austria) for personal use to operate spelling and domestic devices. While most current research on EEG- and MEG-based BCIs focus on providing basic communication control to people suffering from severe motor impairments [54, 60], researchers have also been exploring their capabilities for providing control of orthotic [57, 58, 61, 126, 127, 128] (see Fig. 12 and Additional file 1), prosthetic [55], and external movement-assistive devices [53, 56, 129]. The main drawbacks of current EEG-based BCIs include the long training periods to learn to modulate specific brain potentials, the need to attach multiple electrodes to the scalp -both a time and cosmetic issue- the low information-transmission rate due to the filtering properties of the skull, low spatial resolution and high variability of the brain signals due to changes in background activity (e.g., motor, sensory, and cognitive activity) and learning processes [130, 131]. All these factors limit the applicability of BCIs as control interfaces of active movement-assistive devices. Today, BCI research is focused on the development of practical systems and their evaluation outside of the laboratory environment by end-users [59, 132, 133].

Figure 12: EEG-based interface. An EEG-based BCI used for the control of the Mind-walker lower-extremity exoskeleton [57, 128]. In this setup the BCI is controlled using Steady State Visually Evoked Potentials (SSVEP). The glasses that the user is wearing stimulate the retina with several flashing lights at different frequencies, and depending on which flashing light the users looks at, the brain will generate electrical activity at the same (or a multiple) frequency as the visual stimulus. With this method, different control states are assigned to the electrical brain signals with specific frequencies. Additional file 1 shows this EEG-based BCI controlling the Mindwalker lower-extremity exoskeleton. Figure courtesy of Mindwalker project.

Brain hemodynamics: Besides electric activity, hemodynamic signals from the brain are also used in BCIs. These signals are measured with functional magnetic resonance imaging (fMRI) or near infrared spectroscopy (NIRS). Both methods rely on the measurement of the task-induced blood oxygen level-dependent (BOLD) response, which was proven to be strongly correlated to the electrical brain activity [134]. Most studies using fMRI- and NIRS-based BCIs focused on their application to neurofeedback [135, 136, 137], and only a few studies have aimed to develop interfaces for communication [62, 138, 139], cursor control [140], environmental control [64, 141], and external robotic arm control [63, 65]. As for EEG, NIRS is also portable and both less expensive and less cumbersome than fMRI. Furthermore, in contrast to fMRI, when using NIRS, subjects can be examined in a sitting or standing position without movement constraints. However, the depth of brain tissue that can be measured using NIRS is 10 to 30 mm, which limits the measurements to cortical regions [134]. While these functional imaging methods are promising for non-invasive recording of activity across the entire brain (or cortical regions in the case of NIRS) at high spatial resolution [134], they suffer from a very poor information transfer rate [142, 143] that limits their functionality. NIRS-based BCIs are still in the early phases of research and development, and therefore their future potential value as control interfaces remains uncertain [144].

Interfacing with the actuators: muscle activation interfaces

The recording of the electrical signals from muscle activation is known as electromyography (EMG). From a biomechatronic perspective, the muscle can be conceived as a biological signal amplifier of the low-amplitude electric potential from the motor neurons. The large majority of active prostheses that exist today, including commercially available devices, are controlled using surface EMG signals [130, 145].

Commercially available myoelectric upper-extremity prostheses are generally operated using proportional or on/off controls by measuring EMG from two independent residual muscles, or by distinguishing different activation levels of one residual muscle. Switching techniques such as muscle co-contraction or the use of mechanical switches or force-sensitive resistors are commonly implemented for enabling the sequential operation of several degrees of freedom (DOF) [130, 145, 146]. Lower-extremity prostheses and upper- and lower-

extremity orthoses are commonly controlled estimating the joint angles or torques from EMG signals of muscles that mainly contribute to the supported motion [66, 67, 147, 148].

EMG-based control interfaces are widely used because of its easy access and generation, and its direct correlation to the movement intention. An EMG-based interface presents several drawbacks: It requires significant signal processing before it can be used as control signal due to its broad bandwidth and low amplitude; many patients have difficulties generating isolated and repeatable contractions [130]; and finally, the filtering properties of the limb tissue and the movement of the skin beneath the electrode notably affect long-term recordings [149]. All these factors make the control challenging for the user. To overcome these limitations, researchers are developing muscle synergy-based algorithms, motor neuron spike train decomposition algorithms, and new surgical procedures.

The increasing number of DOF in active prosthetic and orthotic devices to achieve higher functionality has been pushing the scientific community to develop EMG-based control interfaces capable of controlling multiple DOF in an intuitive and natural way. The identification of interactions between multiple muscles, commonly known as muscle synergies, using pattern recognition or regression algorithms is showing promising results toward achieving natural multifunctional control of prosthetic and orthotic devices [150].

EMG pattern-recognition algorithms are based on the assumption that humans can generate different yet repeatable muscle-activation patterns that are associated to specific movements, such as different grasping configurations. During the training of the algorithm, each programmed movement is linked to a stable muscle-activation pattern that is described by a set of features. These features should be repeatable across trials of the same movement and discriminative between different movements [151]. Once the training is completed, the algorithm extracts features from windowed raw EMG data and classifies them into the programmed movements. Many different variations of each of these steps have been investigated [152] trying to find a suitable tradeoff between speed and performance [153]. Pattern-recognition algorithms recently became commercially available (Coapt LLC., Chicago, USA). This technique has the potential to eliminate the need for isolated muscle activation and allow for the control of multiple degrees of freedom [130]. However, an important limitation of pattern-recognition algorithms is that they are only capable of classifying

movements in sequence and not simultaneously and lack proportional controllability, which limits user acceptance [151]. EMG regression algorithms, which are based on non-negative matrix factorization, artificial neural networks, or linear regressions, present a functional improvement since they allow for simultaneous and proportional control of multifunctional prostheses [146]. Regression algorithms require a training data set for which a continuous relationship between EMG signals and plant kinematics or dynamics is known. Several studies have reported proportional and simultaneous control of two or more DOF in upper-extremity prosthetic [68, 154, 155] and orthotic [69, 156] devices. An additional movie file shows an amputee operating an upper-extremity prosthesis using both simultaneous and sequential EMG-based control during functional tasks (see Additional file 2).

Targeted muscle reinnervation (TMR) is a surgical procedure developed by Kuiken et al. [70] that consists of rerouting the nerves that originally innervated the amputated limb to residual chest or upper-arm muscles (Fig. 13). TMR is a one-time invasive method that allows a more intuitive control of a larger number of DOF [157] than standard EMG methods, since the prosthesis is controlled by EMG signals from the residual muscles that are activated by the nerves that previously controlled the amputated limb. Moreover, there is evidence that cutaneous sensory feedback of the amputated hand can be regained by reinnervating skin near or overlying the target muscles with residual afferent nerve fibers of the amputated hand [70]. TMR appears to be more suitable for high-level amputations [158] and current implementations still experience some difficulties separating the EMG signals from the different chest muscles. Recent studies aim at combining TMR with muscle synergies-based algorithms [71, 159], developing new targeted sensory reinnervation techniques [160], applying TMR for the control of lower-extremity prostheses [66, 161, 162], and implementing intramuscular EMG electrodes [163].

Finally, a recent approach that may lead to a new EMG-based control strategy is the use of high-density electrode grids that can extract spike trains of motor neurons and provide information on muscle-discharge patterns. The decomposition of EMG signals into spike trains of motor neurons can be used for proportional control of assistive devices and has shown a higher accuracy when estimating muscle force compared to conventional surface EMG recordings [151].

Figure 13: EMG-based interface. An amputated patient using a Targeted Muscle Reinnervation (TMR) EMG-based interface for the control of an active prosthetic arm [157]. With the TMR EMG-based interface, the patient could control a 6 DOF prosthesis consisting of shoulder flexion, humeral rotation, elbow flexion, wrist rotation, wrist flexion, and hand opening/closing control. The movement performance of this 6 DOF prosthesis (right arm) controlled with TMR EMG-based interface was evaluated and compared to the commercially available prosthesis (left arm) with 3 DOF (body-powered elbow and wrist rotation, and active terminal device) during several timed tasks: **A)** cubbies, **B)** cups, **C)** Box and blocks, and **D)** clothespin relocation task. The participant could control up to 4 DOF simultaneously, reach a larger workspace and perform some of the timed tasks faster using the TMR EMG-based interface. Figure reused with permission from Elsevier.

Interfacing with the actuators: muscle-contraction interfaces

Several signals derived from the muscle-contraction phenomena have been used to detect motion intention: muscle vibration, dimensional change, radial muscle force and stiffness, longitudinal muscle force and muscle hemodynamics. The main advantage of muscle contraction-interfaces (MCIs) is that they are free from electromagnetic noise and may have a lower cost compared to EMG based interfaces. MCIs have only been used for the control of prosthetic devices.

Muscle vibration: The mechanical vibration that is generated when the muscles contract can be measured with microphones [72, 73], accelerometers [76], or a combination of both [74, 75]. This method is known as phonomyography (PMG), acoustic myography (AMG), or mechanomyography (MMG).

Orizio et al. reported a linear relationship between the root-mean-square (RMS) values of MMG signals recorded from the biceps brachii and the force of the contraction between 20 to 80 percent of the maximum voluntary contraction [164], which makes MMG potentially suitable for prostheses control. MMG offers several advantages over conventional EMG, including robustness to changes on skin impedance, less specific sensor placement, and reduced sensor cost [72, 74]. However, microphones and especially accelerometers are highly prone to limb-movement artifacts that compromises signal detection and classification [73]. To overcome this major problem, Silva and Chau [75] developed a coupled microphone-accelerometer sensor (embedded in silicone) that fuses data from both transducers to reduce dynamic noise. In their design, the accelerometer is used as a dynamic reference sensor to determine the source of the measured vibration (muscle contraction or limb movement). Recently, Posatskiy and Chau [165] developed a novel microphone with cylindrical and conical acoustic chambers that improves the robustness to limb-movement artifacts.

Muscle dimensional change: When the muscle contracts, dimensional changes also occur: the muscle shortens and consequently its cross-section area increases. The measurable signals resulting from this phenomenon are known as myokine-metric (MK) signals. MK signals have been measured with Hall-effect sensors, tendon-activated pneumatic (TAP) foam sensors, angular encoders, ultrasound scanners, and with electrodes that detect changes in electrical impedance.

Evidence from [77, 78] suggests that MK signals are inherently low in noise and that their magnitude can be directly used for control, avoiding any kind of signal processing. The study by Kenney et al. [77] developed a sensor that measured radial displacements of the muscle bulge with a Hall-effect transducer. They found that the MK signals of six upper-limb amputees could be generated with sufficient accuracy to perform a one-dimension tracking task with a low tracking error, and therefore had potential for the control of active upper-limb prostheses. However, it was also found that the MK signals were susceptible to socket slippage with time, as well as socket re-donning. The study by Heath [78] improved the sensor interface and proved the feasibility of using MK signals for proportional position control of prosthetic fingers.

The TAP sensors developed by Abboudi et al. [79] measured pressure differences at the skin surface generated by tendon displacements when finger flexor or extensor muscles contracted. TAP sensors presented a linear relation to finger force. Trials on three upper-limb amputees showed that the TAP sensors could provide effective control of individual finger movement and grasping. Since the performance of the TAP control interface is highly dependent upon accurate sensor placement and specific movement resolution at each sensor location, Curcie et al. [80] developed a pressure vector decoder able to discriminate specific finger flexion commands in real-time. This decoder decreased the dependence on sensor location, offering a more robust and reliable control of the TAP-based interface.

The study by Kim et al. [81] presents the development of a sensor that can measure muscle circumference changes using an angular encoder that was attached to an elastic arm band with a wire. The authors developed a calibration procedure and a biomechanical model to estimate the elbow torques from the measurements of the muscle circumference.

Recent studies propose the use of ultrasound scanners [82, 83, 84, 166] to measure changes in muscle thickness for the control of prosthetic devices. This method is known as sonomyography (SMG). SMG presents a linear relationship between ultrasound image features of the human forearm and the hand and wrist kinematic configurations [82, 167], suggesting that simple proportional control could be implemented for the operation of active movement-assistive devices. A recent study by Gonzalez and Castellini [84] shows that a linear relationship also exists between specific image features and fingertip forces. Furthermore the study by Shi et al. [166] shows that SMG can be implemented

in real-time using a two-dimensional logarithmic search algorithm. While it has been demonstrated that SMG could be potentially used for the control of active prosthetic devices, the current system used for the SMG measurements (i.e., standard ultrasound scanner) is not suitable for practical implementation because it is expensive and cumbersome [83].

Another signal derived from dimensional changes of the muscle was examined in the early 1970s by Kedefors and Olsson [85]. The study investigated electrical impedance as a measure of motion intent for the control of a robotic hand. The electrical impedance measured on the skin above a muscle varied when the dimensions of the muscle changed due to its contraction (among other factors). A recent study by Silva et al. [168] shows evidence that relates muscle activity and tissue resistivity changes and suggests that this information could be used for the control of assistive devices.

Radial muscle force and muscle stiffness: The stiffness of muscle tissue increases when it contracts. The measured force signals resulting from this phenomenon are known as myotonic (MT) [78] or myokinetic (MKT) [86] signals. These signals have been measured using arrays of force-sensitive resistors (FSRs) [86] or strain gauges [87, 169]. A recent study by Castellini and Koiva [88] used a tactile sensor placed between the arm and the table to measure changes in pressure distribution at the ventral side of the forearm while performing a variable force task with the fingertip. The authors report that the fingertip forces could be estimated with a high degree of accuracy from the pressure distribution measured at the forearm.

Recently, a study by Han et al. [89] presented a novel muscle stiffness sensor that could be worn over clothing, based on the measurement of the muscle resonance frequency. This sensor measured muscle stiffness by generating and sensing resonance vibrations using a piezoelectric transducer: As the muscle became stiffer, the resonance frequency became higher.

Muscle-stiffness-based interfaces are still in the early phases of research and development, and therefore their potential value as control interfaces for active movement-assistive devices remains unclear. None of the aforementioned studies reported results from experiments implementing this sensing modality in an assistive device and testing it with people with movement impairments.

Muscle force: Direct muscle force control by muscle tunnel cineplasty (MTC; Fig. 14) was first performed in the early 1900s, becoming popular after World War II [90, 170]. The major advantage of this one-time invasive method is that is capable of providing tactile and proprioceptive feedback from the terminal device back to the user complying with the concept of extended physiological proprioception (EPP) [90, 171]. However, such procedures lost favor in the 1970s due to the advent of clinically available myoelectric prostheses, which do not require any surgery. Moreover, MTC presented the disadvantage that patients sometimes lacked sufficient muscle force to power their prosthesis [170].

While traditionally MTCs provided both the control and the actuation of the prosthetic prehensor [172], Weir et al. [90] proposed a hybrid method where the MTC provided the control signal for the prosthetic prehensor, but the grasping force was supplied by an external power source. The authors of the study suggested that the implementation of multiple miniature forearm MTCs could be potentially used as control signals for independent multi-finger control. However, to the best of our knowledge, no further advancements on this method have been made up to date.

Muscle hemodynamics: NIRS has also been used to measure optical changes due to muscle contraction for the operation of active prostheses. Several physiological phenomena have been reported as responsible for the muscle optical changes, including blood perfusion [91, 173], muscle shortening [92], and muscle fiber direction [93]. Numerous studies show that NIRS signals are qualitatively similar to EMG signals in both magnitude and duration for different levels of contraction [91, 92, 94], with the particular difference that isometric and isotonic contractions can be distinguished from NIRS signals [93]. Furthermore, Herrmann et al. [173] proposed to combine EMG and NIRS signals to improve the pattern classification algorithm for the control of a prosthetic hand.

Interfacing with the plant: movement interfaces

The human body moves as a result of the interaction between the forces generated by the muscles and the configuration of the skeletal system. Measurements of relative joint rotations and motion of body segments with respect to a fixed reference have been used to detect motion intention.

Figure 14: Muscle-force-based interface. The prosthesis is controlled by pulling on cables that mechanically link the tendons attached to the tunnel muscle cineplasty to a force transducer mounted to the thumb of the prosthetic hand. An artificial controller measures the tendon force produced by the muscle to operate the opening and closing of the hand. **A)** schematic representation of the prosthesis and the control interface, **B)** an early version of the prototype without a cosmetic hand glove, and **C)** the final prototype of the prosthesis with a cosmetic hand glove. Figure modified from [90]

Body segment movement: Body segment motion has been measured with inertial measurement units (IMUs) and camera-based systems. In a study by Thomas and Simon [95] and in one by Moreno et al. [96] IMUs were used to control an active knee joint during walking. The study by Jiang et al. [97] presented a hand-gesture recognition interface system based on two Microsoft Kinect cameras (Microsoft; Redmond, Washington) for the control of external robotic arms. The interface was specifically developed for individuals with upper-level spinal cord injuries (SCIs) to perform a variety of simple object-retrieval tasks. One camera was used to interpret the hand gestures and locate the operator's face

for object positioning. The other camera was used to automatically recognize different daily living objects for test subjects to select. A similar interface was developed by Martin et al. [174] and used several infrared sensors to measure hand movements to control an active arm support for patients suffering from muscular weakness.

Relative joint movement: Angular displacement between two adjacent body segments has been measured using electrogoniometers, that are attached to two adjacent body segments and produce an electrical signal proportional to the angle. Several kinds of electrogoniometers have been used to measure angular displacements. Early goniometers used simple angular potentiometers. Doubler and Childress [98] and Gibbons et al. [99] used these sensors to investigate the EPP concept in the control of active upper-extremity prostheses. Recent studies also investigated the performance of controlling prosthetic arms with the residual shoulder motion measured with a two-DOF joystick [100, 101] (see Fig. 15 and Additional file 3). Although potentiometers can measure rotations about only one axis and the accuracy of the measurements depends on their alignment with the human joint, these sensors are still a common component in active movement-assistive devices [175, 176]. Another common solution for measuring angular displacement to control active prosthetic and orthotic devices is the use of angular encoders [103] or bending sensors [102, 177]. The control strategy developed by Wang et al. [178] estimates the location of the body center of mass in the sagittal and frontal plane using IMUs and angular encoders to measure the weight shift and trigger the stepping movement of a lower-extremity exoskeleton.

Interfacing with the plant: force interfaces

The human plant can exert forces to the environment that can provide information about the motion intention of the user. Force-based interfaces have been implemented using force-torque sensors [104, 105, 106] or simple FSRs for the control of active upper-extremity orthoses [107, 40, 108, 109] and prostheses [100]. These kind of interfaces generally implement control strategies where the output motion is related to the input force [179]. An advantage of force-based interfaces is that force sensors can be embedded in the mechanical structure of the assistive device, avoiding any preparation for the placement of

Figure 15: Joint-rotation-based interface. 2 DOF joystick used for the control of a prosthetic arm (shoulder flexion-extension, shoulder internal-external rotation) with the residual shoulder motion. **A)** Diagram of the control interface used to measure the residual shoulder motion, **B)** close-up of the prototype, **C)** shoulder elevation produces shoulder flexion, **D)** shoulder depression produces shoulder extension, **E)** shoulder protraction produces internal shoulder rotation, **F)** shoulder retraction produces external shoulder rotation. Additional file 3 shows an amputee using this shoulder-joystick-based interface to control the shoulder motions of an active prosthesis. Figure modified from [100].

the sensors on the user. Recently, Ragonesi et al. [104] reported measurements of gravitational and joint stiffness torques in patients with muscle weakness with the end goal of obtaining a robust model that could be used for the control of an active arm support. The authors found that voluntary forces of individuals with muscular weakness were very hard to measure since gravitational forces were much larger. Subject-specific models were suggested as a strategy to optimize the identification of voluntary forces. The study by Lobo-Prat et al. [106] demonstrated that an adult man with Duchenne muscular dystrophy with no arm function left, could successfully control an active elbow orthosis using the low-amplitude force (and EMG) signals that still remained measurable (Fig. 16). In the aforementioned study, the gravitational and joint stiffness forces were measured during a calibration procedure in which the orthosis together with the relaxed forearm of the participant slowly moved across its range of motion. The gravitational and joint stiffness forces measured during this calibration procedure were subtracted from the actual measured force to compensate them. Additional movie files show an adult man with Duchenne muscular dystrophy with no arm function left performing the calibration procedure used to measure the gravitational and joint stiffness forces (see Additional file 4), and using the force-based control interface to perform a discrete position-tracking task (see Additional file 5).

In patients with severe movement and force limitations, it is very challenging to use movement- and force-based interfaces. These type of control interfaces are more often implemented in rehabilitation robots where patients need training to regain mobility and strength [148, 180].

Interfacing with parallel systems

Apart from deriving the motion intention from signals that originate from the supported systems, several methods have been proposed that exploit signals from parallel systems such as the eyes, the mouth or the head to derive the movement intention of the user. This section reviews six groups of common interfaces that derive the intent of the user through signals generated by parallel systems.

Figure 16: Force-based interface. An adult man with Duchenne muscular dystrophy with no arm function left using a force-based interface to operate an active elbow orthosis [106]. The force sensor measures the interaction force between the orthosis and the user, which is used as a control input for an admittance controller. A critical aspect for the usability of this interface is the accurate identification of the gravitational and joint stiffness forces (which are pose-dependent) required to distinguish the low-amplitude voluntary forces of the user. Additional file 4 shows the force calibration procedure used to identify the gravitational and joint stiffness forces. Additional file 5 shows a man with Duchenne muscular dystrophy performing a discrete tracking task using the force-based interface to control the active elbow orthosis. Figure courtesy of FlexTension project.

Eye interfaces: Eye tracking systems are a common method for the control of spelling devices or computer cursors in patients with severe movement impairments. Several eye-trackers have been developed, including camera-based methods, which measure changes in corneal reflection while infrared light is projected to the eye [181], and electrical-based methods that measure the electrooculographic (EOG) potential from surface electrodes.

Duvinage et al. [111] proposed an innovative system based on EOG and a programmable central pattern generator to control a lower-limb prosthesis. The control method was composed of two steps: First, an EOG-based eye-tracking

system generated high-level control commands (such as faster, slower, or stop), according to specific eye movement sequences executed by the user; and second, a pattern generator, following the high-level commands derived from the user's eye motion, provided the low-level commands for the control of the actuators.

In the study by Chen and Newman [112], EOG was used to control two-dimensional movements of an external robotic arm that resembled the human arm configuration. Eye movement patterns such as saccades, fixation, or blinks were detected from the raw eye gaze movement data by a pattern-recognition algorithm and converted into control signals according to predefined protocols. The authors suggested that one option to extend the movement control to three-dimensional space was to switch between predefined action planes in which the EOG control would still be two-dimensional.

While eye movement interfaces proved to be very accurate in two-dimensional space, three-dimensional gaze-tracking is more challenging [182]. The three-dimensional gaze-tracking problem consists of mapping pupil coordinates for left and right eye to a three-dimensional point referenced to the user's head coordinated. A recent study by Abbott and Faisal [110] presents an ultra-low-cost binocular three-dimensional gaze tracking system, which the authors plan to use to control wheelchair navigation or end point control of robotic arms.

Tongue interfaces: Tongue movement has been interfaced using electrical switches [183], Hall-effect sensors [184], pressure sensors [185], and by measuring changes in the inductance of an air-cored induction coil, by moving a ferromagnetic material attached to the tongue into the core of the coil [118, 120, 186].

The tongue-movement-based control interface developed by the research group of Prof. M. Ghovanloo at the GT-Bionics Lab (Georgia Institute of Technology, USA) is a wireless, unobtrusive, and wearable assistive technology that enables SCI patients to control computers and powered wheelchairs [118, 119] (see Fig. 17 and Additional file 6). This system has an inductive coil mounted at the lateral part of the mouth and a ferromagnetic material attached at the tip of the tongue. The users generate control commands by moving the tongue to one of the user-defined locations, such as touching a particular tooth with the tongue's tip. This control interface was tested in 13 high-level SCI patients during a navigation task with a powered wheelchair. The study reported that the subjects were able to perform the experimental task with 82 percent accuracy [187].

Figure 17: Tongue-movement-based interfaces. The tongue-movement-based interface developed by [119]. This system has two inductive coils mounted at the lateral parts of the mouth and a ferromagnetic material attached at the tip of the tongue. The users generate control commands by moving the tongue to one of the user-defined locations. Tongue movement interfaces take advantage of the fact that highly paralyzed patients generally have tongue control and they can move it very rapidly and accurately within the oral space. Additional file 6 shows a SCI patient performing a driving task with a wheelchair that is controlled with this tongue-movement-based interface. Figure courtesy of Dr. Maysam Ghovanloo.

The tongue interface developed by Struijk et al. [120] integrated the induction coils under the palate, where 18 sensors allowed real-time proportional control of both speed and direction similar to a conventional joystick. The system's functionality was demonstrated in a pilot experiment with one healthy subject, where a typing rate of up to 70 characters per minute was obtained with an error rate of 3 percent. Recently, two alternative sensor designs based on the previously described system have been proposed in order to reduce the size of the sensor pad and increase the comfort of the oral interface [188].

Head interfaces: Head movements are generally measured using accelerometers and used to control powered-wheelchairs [113, 114, 115, 189, 190]. The direction of the head inclination controls the wheelchair's direction and the velocity of the wheelchair is proportional to the inclination angle. Artificial neu-

ral networks are usually implemented in the control interface to detect with higher accuracy the movement intention of the user [113]. However, all the research studies found were tested with healthy subjects, which does not provide reliable evidence of its actual usability in patients with severe movement impairments.

Alternative sensors include ultrasonic sensors [117] and camera-based interfaces [40, 116]. An important disadvantage of camera-based interfaces is that their functionality largely depends on the light conditions that result in the need of repetitive calibrations during the day [191].

Speech interfaces: In speech-based interfaces, the voice commands of the user are recorded using conventional microphones and translated into control signals through speech-recognition algorithms. Generally, speech-recognition requires training, which consists of the recording of the voice commands and their subsequent manual classification.

Fan and Li [121] developed a speech-based interface for the control of an upper-extremity prosthesis that could recognize 15 different voice commands with an accuracy of 96 percent. Speech has been also used to control powered wheelchairs [122] or external robotic arms [123]. The main drawback of speech-based interfaces is their high sensitivity to ambient noise, which compromises signal detection and classification. The recognition accuracy of the speech-based interface developed by Lv et al. [192] for the control of a robot was decreased by 30 percent when ambient noise was present.

Hand interfaces: Hand joysticks are generally implemented for the control of powered wheelchairs [125] and external robotic arms [32, 193]. The study by Johnson et al. [124] controlled the end-point position of a five-DOF upper-extremity orthosis with a joystick operated with the contralateral hand.

Other interfaces with parallel systems: Some of the control interfaces described previously in sections Interfacing with the Plant and Interfacing with the Actuators have also been used to measure signals from parallel systems. For instance, EMG signals measured from muscles of the upper-extremity have been used to control electrically powered wheelchairs [194, 195, 196]. Another example are the force-based interfaces used to control power-assisted wheelchairs [197] in which the wheelchair detects and amplifies the force applied by the user's arm on the wheel.

Hybrid control interfaces:

Each of the methods described in this review present unique capabilities and limitations. A recent approach to take advantage of this functional heterogeneity is the development of hybrid control interfaces, which fuse data from several sensors. The concept behind hybrid control interfaces is to exploit the advantages and diminish the limitations of each individual system by combining them. Hybrid approaches can improve accuracy, reliability, and robustness compared to individual use of control interfaces [198]. Moreover, hybrid control interfaces have the potential advantage of adapting better to the needs and capabilities of the user since they can rely on several information sources. For instance, if the user gets fatigued and EMG signals present poor quality, the hybrid system could adapt and give priority to other information sources. EEG-EMG-based control interfaces are an example of a hybrid system that has been extensively used to operate active prostheses, orthoses, and robotic wheelchairs [198]. In active lower-extremity prostheses, hybrid interfaces combine EMG and mechanical inputs to identify the phase of the gait cycle and actions like sitting or standing [199, 200, 201]. Other examples include the combination of EMG with foot switches [202], IMUs [203] and video cameras [204].

Evaluation of control interfaces

While there is a large variety of control interfaces, a small number of studies have focused on their formal performance evaluation and comparison [205, 206, 207, 208, 209, 210, 211, 212]. The performance of control interfaces is rarely evaluated consistently, which prevents an objective evaluation and comparison. The information provided in most cases is insufficient to determine the advantages and limitations of a given control interface compared to the current state of the art. A significant step toward the standardization of outcome measures has been made by the American Academy of Orthotics & Prosthetics, which provides comprehensive recommendations for the evaluation of upper-limb prostheses [213].

A better understanding of the limitations and capabilities of the different control interfaces, through objective and quantitative evaluations during functional tasks, can provide relevant information for the selection of the most suited control interface for a specific application. One-dimensional screen-based

position-tracking task experiments [205, 212] have been used to evaluate the performance of EMG-, force-, joystick- and wrist angle-based control interfaces in terms of tracking error, information transmission rate, human-operator bandwidth or crossover frequency, and effort. Guo et al. [206] compared SMG-, EMG-, force- and wrist angle-based interfaces during a series of screen-based discrete tracking tasks with and without a simultaneous auditory attention task. Even though these studies do not evaluate the interface performance during functional tasks, they can provide insight on their potential value as control interfaces for active movement-assistive devices. Other common evaluation methods are tests based on the Fitts' Law paradigm in two- or three-dimensional space to compare the performance of different control strategies [207, 211, 214]. Recently, Simon et al. [215] developed the Target Achievement Control test, a real-time virtual test environment that closely resembles reality and allows the evaluation of upper-extremity movement control of multifunctional prostheses. The Target Achievement Control test is being used by several research groups to compare the performance of different control algorithms [216, 217].

Physiological and artificial learning

A common issue in all of the interfacing modalities described in this review is the fact that the user must learn how to use the control interface. Artificial learning is an alternative approach that aims at relieving the user from the training period by rapidly identifying individualized signal patterns that are associated to a specific intention. Casadio et al. [218] developed a control interface for highly paralyzed patients optimizing a subject-specific mapping of residual voluntary movements with control inputs for assistive devices. In practice, this approach is translated into a mutual adaptation in which both user and assistive device learn from each other [131]. Several studies have shown that including artificial learning in BCIs accelerates the adaptation process [56, 219, 220]. Artificial learning/intelligence has also been used for the development of shared-controlled algorithms that aim to combine the intelligence of the human and the assistive device to reduce the concentration effort [131, 221]. With this approach, low-level functions are controlled by the assistive device, and the role of the user is reduced to only give high-level commands, supervise and fine tune the functioning of the system.

In addition to artificial learning, researchers have also been investigating the physiological learning capabilities of the human-controller when subjects are asked to interact with control interfaces that have intuitive and non-intuitive mappings between EMG signals and cursor or device movement. Radhakrishnan et al. [222] and Pistohl et al. [223] found that subjects could learn non-intuitive mappings with a final performance nearly equal to the intuitive mappings using both virtual and real prosthetic control environments. In addition, the recent study by Antuvan et al. [224] extended the aforementioned studies investigating the influence of previously learned mappings on new control tasks. They found that learning curves transferred across subsequent trials have the same mapping, independent of the tasks to be executed, which suggests that maximal performance may be achieved by learning a constant, arbitrary mapping rather than using the common approach of subject- and task-specific mappings.

Design considerations

Intuitiveness: A control interface should be intuitive, enabling the user to operate their active movement-assistive device subconsciously (i.e. the way healthy people control their limbs) with a short training period and to think and do other things while using the device. Control interfaces may require proprioceptive feedback (i.e., EPP; [171]) in cases where sensory feedback has been lost (such as in amputees), to not only rely on visual feedback, which requires considerable mental effort [225].

The reviewed literature shows that most control interfaces are tested in laboratory environments in which users can concentrate on the experimental task with minimal distractions. However, "real-world" users must deal with much more complex situations, where mental effort cannot be entirely (or even primarily) dedicated to the control of the assistive device, as they have to interact with other people and the environment. Therefore, considering that many processes run simultaneously in the brain, it is plausible to conjecture that noninvasive-BCIs would require a considerable effort of concentration to generate those specific brain signals required for the control of an active movement-assistive device. On the other hand, peripheral signals such as force or EMG are more closely linked to the control of movement. Consequently, control interfaces using these signals would appear to be more natural and intuitive for

the user than noninvasive-BCIs. Nevertheless, as previously presented in section Physiological and Artificial Learning, shared-control strategies can reduce the concentration effort of BCIs.

Information source for the control interface: A second consideration in the design of a control interface required to gain both user and clinical acceptance of active movement-assistive devices, is that the control interface should avoid the sacrifice of "useful" body functions from parallel systems (e.g. eye, head or tongue movement) for deriving the motion intention of the user. Nevertheless, signals from parallel systems can be used for "supplementary control," such as tuning control settings or switching on and off control modalities. Note that supplementary control is used on an occasional basis and therefore, does not require continuous attention of the user and never implies the sacrifice of the parallel system functionality.

Response time: Another essential feature of the control interface that has a determinative effect on the performance of the assistive device is the response time or delay [226]. A tradeoff between speed and accuracy exists regarding the control delay. Large delays increase accuracy of the motion intention detection, but at the same time, decreases responsiveness (and therefore performance) of the active assistive device. Farrell and Weir [226] concluded that controller delays should be kept around 100 and 175 ms for proper control of myoelectric prostheses.

Robustness: The system should be robust to disturbances so that variability of sensor placement during donning, slow signal changes due to variation of environmental conditions (e.g. temperature, humidity, or light), user fatigue or external forces with low (e.g., gravity) or high frequencies (e.g. automobile vibrations), do not compromise its performance. Several researchers have identified signal stability and robustness as one of the most critical requirements of control interfaces [130, 151, 227, 228].

Coordination of the degrees of freedom: From a functional point of view, a control interface for active movement-assistive devices should be able to coordinate multiple DOF simultaneously in an effective way. The importance and feasibility of simultaneous control has been investigated using several control modalities such as EEG- [229], EMG- [68, 207] and head movement-based in-

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terfaces [211]. Apart from functional advantages, coordinated movements give a more natural appearance than if every DOF is controlled separately. Nevertheless, the user may also need to control an individual DOF when performing a precision task such as unlocking a door or clicking the buttons of a computer mouse.

Independence: Ideally, an active movement-assistive device should not require assistance from other people (e.g., caretakers or family) for the preparation of the equipment, such as installing the sensors in the correct location or calibrating the system. Control interfaces that use implantable sensors or sensors integrated in the artificial plant inherently offer a clear advantage in this respect. Most of the active prosthetic devices can be self-donned [145], and recent studies focus on simplifying the training of control methods such as pattern recognition by developing interfaces that guide the user during the training of the algorithm [230].

Customization: Control interfaces for active movement-assistive devices need to be customized to the characteristics of the pathology, the available physiological signals, morphology of the body, and the mechanical configuration of the device. In this respect, the control interface (and maybe the rest of the device) should be able to adapt to the changing needs and capabilities of the user. Note that changes can occur over the short term (during a day) as well as over a longer term (years) periods. The monitoring of specific biomechanical descriptors could give an indication of the user's changes and adapt the assistive device to the new situation. Moreover clinicians could use this information to evaluate a disease's progression.

2.3 CONCLUSIONS

This paper presented a comprehensive review of the existing non-invasive control interfaces used to operate active movement-assistive devices. A novel systematic classification method is presented to categorize the inventory of existing control interfaces. This method is based on classifying the control interfaces depending on the source of the signal, that is, which subsystem of the HMCS is the signal coming from, which physiological phenomena is generating the signal and which sensors have been used to measure the signal. We found that

the classification method could successfully categorize all existing control interfaces providing a comprehensive overview of the state of the art. The classification method also represents a framework in which new sensing modalities can be included. Each method was shortly described in the body of the paper following the same structure as the classification method.

Current non-invasive BCIs appear to be limited in speed, accuracy, and reliability for the control of active movement-assistive devices. However, researchers are improving their performance by implementing artificial learning algorithms, shared-control strategies and combining BCI with other sensor modalities. Myoelectric-based interfaces are nowadays the most common method for operating active prosthetic and orthotic devices. Advanced myoelectric-based techniques, such as TMR and muscle synergy-based algorithms, are overcoming important functional limitations of standard myoelectric control. Despite the fact that muscle contraction-based interfaces are not being implemented in today's clinical practice, these interfaces are showing significant advancements and in the future may find their way to compete with the well-established myoelectric control. Although movements and forces are the natural way for the human to interact with the environment, interfaces based on these phenomena are very challenging to use in patients with severe movement and force limitations. Movement- and force-based control interfaces are more often implemented in rehabilitation robots where patients need to train to regain mobility and strength. Finally, control interfaces based on signals from parallel systems are generally a suitable solution to derive the movement intention of highly paralyzed patients. Recently, interfaces based on parallel systems have also been implemented in hybrid sensor modalities to expand the sources of information. In this respect, artificial learning is a promising strategy to make use of these extra sources of information and to give some degree of autonomy and adaptability to the artificial controller. In addition, a better understanding on how the human-controller works and learns will have a great impact on how control interfaces are designed.

Regarding the comparison and evaluation of the existing control interfaces, we have found that while many different control interfaces have been developed, their respective performance capabilities and limitations remain unclear. There is a need for a basic consensus on the evaluation methodology to be able to compare control interfaces and select the most suitable for a specific application. An important step toward the standardization of evaluation methods is

specially being made in the field of upper-extremity prostheses by the American Academy of Orthotics & Prosthetics. Furthermore, it is clear that most of the studies presenting novel control interfaces lack tests outside the laboratory environment. In this context, it is important for future studies to validate new developments by conducting experiments with real end users in an everyday life situation.

All the reviewed control interfaces (in combination with the rest of the assistive system) are still far below the performance of the human movement control system, which inevitably hinders their user's acceptance. However, the high rate at which these technologies are advancing is a clear indication that there is global interest in developing natural and intuitive control interfaces for active movement-assistive devices.

Part II

EVALUATION OF EMG AND FORCE AS CONTROL INTERFACES TO SUPPORT THE ARM FUNCTION OF ADULTS WITH DMD

EVALUATION OF EMG, FORCE AND JOYSTICK AS CONTROL INTERFACES FOR ACTIVE ARM SUPPORTS¹

Abstract: *The performance capabilities and limitations of control interfaces for the operation of active movement-assistive devices remain unclear. Selecting an optimal interface for an application requires a thorough understanding of the performance of multiple control interfaces. In this study the performance of EMG-, force- and joystick-based control interfaces were assessed in healthy volunteers with a screen-based one-dimensional position-tracking task. The participants had to track a target that was moving according to a multisine signal with a bandwidth of 3 Hz. The velocity of the cursor was proportional to the interface signal. The performance of the control interfaces were evaluated in terms of tracking error, gain margin crossover frequency, information transmission rate and effort. None of the evaluated interfaces was superior in all four performance descriptors. The EMG-based interface was superior in tracking error and gain margin crossover frequency compared to the force- and the joystick-based interfaces. The force-based interface provided higher information transmission rate and lower effort than the EMG-based interface. The joystick-based interface did not present any significant difference with the force-based interface for any of the four performance descriptors. We found that significant differences in terms of tracking error and information transmission rate were present beyond 0.9 and 1.4 Hz respectively. Despite the fact that the EMG-based interface is far from the natural way of interacting with the environment, while the force-based interface is closer, the EMG-based interface presented very similar and for some descriptors even a better performance than the force-based interface for frequencies below 1.4 Hz. The classical joystick presented a similar performance to the force-based interface and holds the advantage of being a well established interface for the control of many assistive devices. From these findings we concluded that all the control interfaces considered in this study can be regarded as a candidate interface for the control of an active arm support.*

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3.1 INTRODUCTION

Several active arm supports are currently available and used to increase the independence and the quality of life for patients suffering from neuromusculoskeletal disorders [231, 5]. The operation of these active devices is mediated by a control interface that detects the user's movement intention. The design of the control interface in response to specific user needs and capabilities is crucial for the usability and success of the device.

Electromyography-based interfaces are the most common method used for the control of active prostheses and orthoses [232, 233, 234, 235, 67]. Myoelectric prostheses are controlled by measuring electromyographic (EMG) signals from two independent residual muscles or by distinguishing different activation levels of one residual muscle. Switching techniques such as muscle co-contraction or the use of mechanical switches or force-sensitive resistors are implemented for the sequential operation of several degrees of freedom (DOF) [145]. In the case of active orthoses, these are controlled by estimating the muscular joint torques from the EMG signals of the muscles that mainly contribute to the supported motion [67, 233, 232]. Recently, innovative pattern recognition algorithms [234] and surgical procedures such as targeted muscle re-innervation [71] are being developed in order to improve the functionality of EMG-based interfaces.

Force-based interfaces have been used in assisted-powered wheelchairs [197] where the wheelchair detects and amplifies the force applied by the user. Recent studies implemented six-DOFs force-torque sensors [105, 104], or simple force sensor resistors for the control of active upper-extremity orthoses [107] and prosthesis [100]. These kind of interfaces generally implement admittance control strategies where the output acceleration, velocity or position is related to the input force [179]. Haptic force-based control interfaces are very often implemented in rehabilitation robots where patients need to train to regain control, mobility and strength [148, 180].

Joysticks have been used for the control of powered wheelchairs [125] and external robotic arms [32, 193]. Recent studies also investigated the performance of controlling prosthetic arms with the residual shoulder motion measured with a two-DOF joystick [100, 101]. Furthermore, Johnson et al. [124] developed a five-DOF upper-extremity orthoses, in which the position of the end point was controlled with a joystick operated by the contralateral hand.

While there is a large variety of control interfaces, only few studies have focused on their formal performance evaluation and comparison [205, 206, 147]. As a consequence, there is a lack of knowledge as to which one is the most suitable for a specific type of impairment and task. Currently, there is no basic consensus on how to evaluate the performance of control interfaces, which prevents their objective evaluation and comparison.

The selection of the most suited control interface for a specific application requires a better understanding of the limitations and capabilities of the different control strategies, through objective and quantitative evaluations during functional tasks. One example of this approach is the study by Corbett et al. [205], which compared wrist control of angle, force, and EMG as interfaces for upper-extremity prosthesis during a one-dimensional position-tracking task. The control interfaces were evaluated at 1 Hz, which according to the authors it is a tracking frequency optimal for direct-position control. The results of the study showed that EMG and force interfaces did not outperform their golden standard angle-based interface in all the performance descriptors considered (tracking error, bandwidth and information transmission rate). But they did show that EMG was significantly better than force in terms of tracking error.

While wrist control is appropriate to evaluate interfaces for the operation of active hand prostheses, the control of active arm supports is preferably achieved by interfacing with signals from more proximal joints. Therefore, our ultimate interest in developing active arm supports for individuals with muscular weakness required extending the aforementioned work [205] with a comparative study of the performance, learning characteristics and subjective preference of control interfaces that used signals from either elbow or shoulder joints. Additionally, we were interested in evaluating the control interface performance for a bandwidth beyond 1 Hz in order to capture the limitations of the human-operator.

Here we report tests performed by eight healthy subjects using a screen-based one-dimensional position-tracking task. Healthy individuals were chosen to provide a baseline performance measure and to serve as a reference on the potential value of the control interfaces for active arm supports.

3.2 METHODS

We compared control interfaces based on physiological signals from the elbow muscles -EMG and force- because they are intrinsically related to the arm movement, and added a joystick interface as an alternative system that is more familiar to patients. The selected physiological signals were EMG signals from the muscles that mainly contribute to elbow flexion-extension and the force signals resulting from the activation of elbow flexion-extension muscles. Signals from the elbow muscles were preferred over those at the shoulder as they are easier to access with surface EMG.

Our motivation to test a classic hand-joystick is based on the fact that this type of interface is commonly used by individuals with severe muscular weakness to control electric wheelchairs, domestic devices and external robotic arms. Therefore, it makes sense to consider the option of also using this control interface to operate an active arm support. Comparing a classic hand-joystick to new interfaces (from a patient's point of view) is especially relevant for the targeted patient group, as the performance of a new control interface needs to represent a meaningful improvement and worth the effort of learning and adapting to it.

The performance of each control interface was evaluated in terms of tracking error, gain margin crossover frequency, information transmission rate and effort. The learning characteristics were evaluated by analyzing the tracking error along a series of training trials. A model of the human-interface system was fitted to its estimated frequency response function (FRF) to evaluate the delay and gain parameters of each control interface. Finally, the eight participants were asked to list the control interfaces in order of preference.

Participants

A total of eight healthy males aged between 22 to 29 years participated in this study. All participants gave written informed consent, were right-arm dominant and had no experience with EMG- or force-based control interfaces. The experimental protocol was in accordance with the Research Ethics Guidelines of the Department of Biomechanical Engineering of the University of Twente (Enschede, The Netherlands).

Experimental setup and protocol

A one-dimensional position-tracking task was presented to the subjects on a computer screen by means of a C# (Microsoft Visual Studio, Microsoft Corporation, USA) graphical user interface. The subjects remained in a sitting position during all the experiment with the arm immobilized as shown in Figure 18. With the elbow flexed at 90 degrees, the forearm was securely strapped to a rigid structure using a padded brace around the styloid processes. During the experiment, the participants were asked to keep the cursor (yellow circle in Fig. 18 and 19) as close as possible to the center of a dynamic target (magenta square in Fig. 18 and 19), which moved according to a predefined multi-sine signal with a flat velocity spectrum (i.e. all frequency components of the target velocity had the same amplitude). The experimental task is represented in a block diagram form in Figure 19. The participant visually perceived the target (w) and cursor (x) positions, and in order to minimize the error (e) between them, the participant generated a control signal (u) using one of the interfaces (i.e. EMG, force or joystick), which was mapped to the velocity of the cursor and subsequently integrated to obtain the cursor position. Figure 20 shows a sample of the target and cursor positions and the corresponding control signals for each control interface.

The participants were asked to execute the tracking task with the three different control interfaces. The order in which the subjects tested each interface was randomized. For each interface, 10 training trials of 30 seconds and 3 evaluation trials of 180 seconds were performed. Training trials allowed the subjects to become familiar with the control interface and to get as close to their maximum performance as possible before starting the evaluation trials. The experimenter informed the participants after each training trial about the tracking error and encouraged him/her to improve it.

Signal acquisition and conditioning

The 30 seconds position signal of the moving target (x) was generated from 10 sinusoidal signals with (i) logarithmically distributed frequencies between 0.1 and 3 Hz; (ii) amplitudes inversely proportional to frequency; (iii) and randomly assigned phases for each trial. The design of the input signal was adapted

Figure 18: Experimental setup. **Top)** Picture of the experimental setup. **Bottom)** Schematic diagram of the experimental setup. The forearm of the participants was securely strapped to a rigid structure using a padded brace around the styloid processes. The EMG electrodes were placed at the biceps and triceps muscles. The resulting forces from the biceps and triceps activation were measured with a 1DOF force sensor located at the wrist. The joystick was located in front of the subject.

Figure 19: Block Diagram of the position-tracking task. The subject visually perceived the target (w) and cursor (x) positions. In order to minimize the error (e) between them, the human generated a control signal (u), using one of the control interfaces, which was mapped to the velocity of the cursor and subsequently integrated to obtain the cursor position.

from the classical work of McRuer [236] who did extensive research on the modeling of human-machine systems.

The isometric EMG signals were measured from the biceps and the triceps brachii, where the activation of the biceps moved the cursor up and the activation of the triceps moved the cursor down. Two 99.9% Ag parallel bars (contact: 10 mm x 1 mm each) spaced 1 cm apart (Bagnoli DE-2.1, Delsys; Boston, Massachusetts) were placed in parallel with the muscle fibers according to the SENIAM (Surface ElectroMyoGraphy for the Non-Invasive Assessment of Muscles) recommendations [237]. The signals were amplified with a Delsys Bagnoli-16 Main Amplifier and Conditioning Unit (Delsys; Boston, Massachusetts) with a bandwidth of 20 to 450 Hz and a gain of 1000.

Forces resulting mainly from elbow flexion-extension muscles were measured at the forearm, using a custom made one DOF load cell attached between the padded brace and the ground. During the training trials subjects were instructed to use biceps and triceps muscles, avoiding the generation of force from shoulder or trunk movements. A force upwards (elbow flexion) moved the cursor up and a force downwards (elbow extension) moved the cursor down. For each subject, the offset force resulting from the weight of the arm was corrected at the beginning of the experiment.

Figure 20: Interface, target and cursor signals. **Left)** EMG (blue), force (green) and joystick (red) signals measured by the control interfaces. The interface signals, which are proportional to the velocity of the cursor, were generated by one of the participants attempting to track the target. **Right)** Target and cursor position signals for each control interface resulting from the interface signals shown in the left part of the figure.

Both the EMG and force signals were sent to a real-time computer (xPC Target 5.1, The MathWorks Inc; Natick, Massachusetts) by means of a National Instruments card (PCI-6229; Austin, Texas), which performed the analog-to-digital conversion with a sampling frequency of 1 KHz and 16-bits resolution. The controller was also running in the real-time computer and was connected through a local area network using TCP/IP protocol to a computer with Windows operating system (Microsoft Corporation, USA) which was displaying the tracking task by means of the C[#] graphical user interface.

For the joystick-based control interface we used the joystick of the PlayStation 3 controller (Sony Computer Entertainment; Miniato, Tokyo, Japan) which presents a similar range of motion than the joysticks used to control electric

wheelchairs. A forward tilt of the joystick moved the cursor up and a backward tilt of the joystick moved the cursor down. The digital signal was sent to the real-time computer by means of a USB interface.

Signal processing and normalization

In order to obtain the envelopes, the EMG signals were full-wave rectified and smoothed using a second order low-pass Butterworth filter with a cutoff frequency of 5 Hz as in [205, 156]. Preliminary analysis revealed that a cutoff frequency of 5 Hz represents a good tradeoff between noise removal and control bandwidth. No filter was applied to the force and joystick.

Before starting the tracking task, subjects were asked to perform three maximal voluntary contractions (MVC) of three seconds for both biceps and triceps muscles. Both EMG and force signals were measured simultaneously during the MVCs and used to normalize the EMG and force signals respectively. Normalizing the signals with the subject specific MVC provided a relative measure of muscle activation and force that made intra-subject comparison possible. In the case of the force-based control interface, upward forces were normalized using the mean measured force during the MVC of the biceps and downward forces were normalized using the mean measured force during the MVC of the triceps. The joystick signal was normalized to its maximum output.

For the tracking task, the velocity of the cursor was set to zero if the EMG or force signals were below a threshold of 2.5% of their MVC. This dead zone prevented that measurement noise could move the cursor. No threshold was required for the joystick control interface.

The sign of the force and joystick signals were used to determine the direction of the cursor's movement. In the case of the EMG-based control interface the channel that presented the highest amplitude was used to control the cursor, i.e. when the biceps muscle was most active the cursor moved up and when the triceps muscle was most active the cursor moved down.

After all the aforementioned signal processing, to ensure appropriate velocity control of the cursor and to prevent fatigue, the EMG and force signals were amplified by a fixed gain that ensured that the subjects had to produce a maximum of 25% of their MVC at the peak velocity of the target in order to follow it. In the case of the joystick-based interface the angle signal was amplified with

a fixed gain that resulted in the same cursor velocity at the maximum joystick angle as the EMG or force signals at 25% of their MVC.

Data analysis

The control interfaces were evaluated analyzing the characteristics of the closed-loop system, which can be approximated by a linear transfer function (Fig. 19). These characteristics will vary according to the operator's ability to adapt to the dynamics of the controlled elements, influencing the stability and performance of the entire closed-loop system. The time records of the target ($w(t)$), cursor ($x(t)$) and error ($e(t)$) position signals along time, and the control signal produced by the human-interface system ($u(t)$) were used to evaluate the performance of the three control interfaces. First, the time records ($w(t)$, $x(t)$, $e(t)$, $u(t)$) were transformed to the frequency domain ($W(f)$, $X(f)$, $E(f)$, $U(f)$) via a fast Fourier transform (FFT) function and were used to estimate the power spectrums:

$$\begin{aligned}
 \hat{S}_{wx}(f) &= W^*(f)X(f) \\
 \hat{S}_{ww}(f) &= W^*(f)W(f) \\
 \hat{S}_{xx}(f) &= X^*(f)X(f) \\
 \hat{S}_{eu}(f) &= E^*(f)U(f) \\
 \hat{S}_{wu}(f) &= W^*(f)U(f)
 \end{aligned} \tag{1}$$

where $\hat{S}$ denotes the estimated power spectrums (the hat denotes estimate) and the asterisk (*) denotes the complex conjugate. With an observation time of 30 seconds the resultant frequency resolution is $\Delta\omega=0.0333$ Hz. Note that the time records ($w(t)$, $x(t)$, $e(t)$, $u(t)$), which lasted 180 seconds for the evaluation trials, were averaged over each subsequent block of 30 seconds for a total of 6 times in order to reduce the variance while maintaining sufficient frequency resolution.

The FRFs (H_{xy} ; Eq. 2) and the coherence functions ($\hat{\gamma}_{wx}^2$; Eq. 3) of the closed-loop system were estimated only for the 10 frequencies of the multisine signal ($f_k, k = 1, \dots, 10$), which is known to ensure unbiased spectral estimators and relatively low variances [238].

$$\hat{H}_{wx}(f_k) = \frac{\hat{S}_{wx}(f_k)}{\hat{S}_{ww}(f_k)},$$

$$\text{where } f_k = [0.100 \ 0.134 \ 0.200 \ 0.300 \ 0.467 \ 0.667 \ 0.967 \ 1.4 \ 2.067 \ 3.00] \text{ Hz} \quad (2)$$

$$\hat{\gamma}_{wx}^2(f_k) = \frac{|\hat{S}_{wx}(f_k)|^2}{\hat{S}_{ww}(f_k)\hat{S}_{xx}(f_k)}, \quad (3)$$

The coherence function is a measure of the signal to noise ratio and thus of the linearity of the dynamic process. By definition, this function equals one when there is no non-linearity and no time-varying behavior, and zero in the opposite case. These procedures used to estimate the FRFs and the coherence functions are common within system identification theory [238].

Four performance descriptors were chosen to evaluate the control interfaces: tracking error, gain margin crossover frequency, information transmission rate and effort. Furthermore, a model of the human-interface system was fitted to its estimated frequency response functions to evaluate the delay and gain parameters of each control interface.

Tracking error: The tracking error was calculated as the area under the power spectrum of the error signal ($\hat{F}_{ee}$) from 0 to 3 Hz using the following equation:

$$\hat{F}_{ee} = \sum_{i=1}^n \hat{S}_{ee}(f_i) \Delta\omega, \text{ where } n = \frac{f_{max}}{NT} \text{ and } \hat{S}_{ee}(f_i) = \hat{S}_{ww}(f_i) - \hat{S}_{xx}(f_i) \quad (4)$$

where N is the number of samples, T is the sampling time, $\Delta\omega$ is the frequency resolution and f_{max} is the maximum frequency for which the tracking error was calculated (i.e. 3 Hz). This method of calculating the tracking error in the frequency domain is equivalent to the common mean squared difference between the cursor and target position signals along time [205]. A high value of F_{ee} indicates that the frequency content of the target and the cursor signals are different, while a low value of F_{ee} indicates that the frequency content of the target and the cursor signals are similar. This tracking error measure was also used to analyze the learning characteristics during the training trials.

Information transmission rate: The information transmission rate (Eq. 4) quantifies the amount of information that is contained in the output signal of a communication channel, relative to the input signal [239]. In this type of studies the human-interface system can be conceived as a communication channel where the human has to transmit a movement intention through the interface [98]. We estimated the information transmission rate ($\hat{I}$; Eq. 6) of the human-interface system for each evaluation trial by integrating Shannon's channel capacity over the disturbed frequencies (f_k ; Eq. 5). The same method to calculate the information transmission rate was used in [205, 240, 241, 98].

$$I = \int \log_2 \left(1 + \frac{S(f)}{N(f)} \right) df \quad (5)$$

$$\hat{I} = \frac{1}{NT} \sum_k \log_2 \left(\frac{\hat{S}_{xx}(f_k)}{\hat{S}_{xx}(f_k) - |\hat{H}_{wx}(f_k)|^2 \hat{S}_{ww}(f_k)} \right),$$

where $\frac{\hat{S}_{xx}(f_k)}{\hat{S}_{xx}(f_k) - |\hat{H}_{wx}(f_k)|^2 \hat{S}_{ww}(f_k)} = 1 + \frac{S(f_k)}{N(f_k)}$ (6)

Gain margin crossover frequency: The gain margin crossover frequency indicates the maximum frequency at which the human can properly track the target. The gain margin crossover frequency was defined as the first frequency where the estimated phase of $\hat{H}_{wx}$ dropped below -180 degrees. This parameter is commonly used in control engineering to analyze the stability margin of closed-loop systems.

Effort measure: The root mean square (RMS) of the velocity signal (u) was used to compare the required average level of velocity input during the control task between interfaces. The RMS was calculated for each period of the multisine signal, which had a duration of 30 seconds. The RMS value was interpreted as a measure of effort; assuming that when the subject produced less EMG, force or joystick movements, to complete the tracking task, the effort was lower. The increase in RMS of EMG in relation to the level of effort has been reported in several studies [242, 243]. Note that the measure of effort in the case of the joystick-based interface cannot be compared to the EMG- and force-based inter-

faces in terms of actual physical effort as the effort required to move the joystick is not comparable to the one needed to produce the equivalent control signal using the EMG or the force interface. Nevertheless, it is still relevant to analyze with which of the control interfaces the subjects were able to produce a control signal closest to the ideal control signal needed to complete the tracking task.

Learning characteristics: The learning characteristics were analyzed calculating the tracking error for each training trial. An exponential function was fitted to the mean tracking error values as a function of trial number. We selected the first training trial as a reference to identify significant reduction of the tracking error. A performance plateau was identified when no significant reduction of the tracking error was found in all subsequent trials.

Human-interface model: To model the human-interface system (H_{eu}) we implemented the McRuer Crossover Model [236], which is a mathematical function that describes the human controller capacities in terms of gains and time delays. According to the classic work of McRuer, during a velocity-controlled task (meaning that the plant is a first order system) the human-interface system (H_{eu}) can be described with the following equation:

$$H_{mod}(s, p) = ke^{-\tau s} \quad (7)$$

where k and τ represent a gain and a delay respectively, s is the Laplace transform variable and p is the parameter vector $p = [k, \tau]$. The values of p were estimated for each subject and interface from the FRF of the human-interface system by solving a non-linear least squares optimization problem using the following error cost function:

$$E(p) = \sum_k \gamma_{wx}^2(f_k) \left| \ln \left(\frac{\hat{H}_{eu}(f_k)}{H_{mod}(f_k, p)} \right) \right|^2, \text{ where } \hat{H}_{eu}(f_k) = \frac{\hat{S}_{wu}(f_k)}{\hat{S}_{eu}(f_k)}. \quad (8)$$

This cost function, which has been previously used in [244, 245], compares the FRFs of H_{mod} with H_{eu} in order to find the gain and delay parameters that give the lowest error. Note that by using the logarithm of the FRFs we are compensating for the gain variations over the frequency spectrum [238]. Additionally, the model errors are weighted with the coherence to reduce emphasis on less reliable frequencies of the FRFs.

The fidelity of the model fit of each human-interface system was evaluated calculating the variance accounted for (VAF; Eq. 9) in the time domain using the mean estimated parameters of each interface.

$$\text{VAF} = \left(1 - \frac{\text{var}(\hat{y} - y)}{\text{var}(y)} \right) 100\% \quad (9)$$

where $\text{var}(i)$ indicates variance of i , y indicates the measured output, and $\hat{y}$ indicates the simulated output using the model.

Statistical analysis: We carried out a two-way repeated measures analysis of variance (RMANOVA) for each performance measure, defining the interface and the order in which the control interfaces were tested as fixed factors. Statistical test were performed with IBM SPSS software (IBM Corp. Released 2012. IBM SPSS Statistics for Windows, Version 21.0. Armonk, NY).

The testing order was not significant for any of the performance descriptors ($p > 0.78$) suggesting that the training protocol was effective and cross-over learning effects were not present. The potential influence of the order was further investigated with a correlation analysis between EMG and force signals during EMG and force tasks. The correlation coefficients showed a mean value of 23% ($\pm 10\%$ SD), which suggested that the EMG and force tasks were considerably different and therefore the order in which the subjects tested the interfaces could not introduce a significant bias to the interface performance evaluation.

Since the order did not show significant influence on the evaluation, one-way RMANOVAs were performed for each performance measure. We used $\alpha = 0.05$ (probability of Type I error) as the level of significance. A Bonferroni test was applied for pairwise comparisons.

The learning characteristics were tested with a one-way RMANOVA where each training trial was defined as a fixed factor. The influence of the order was tested for the first training trial in a similar way as in the performance evaluation and did not show any significant differences. A Sidak test was applied for pairwise comparisons as the number of fixed factors was high (i.e. 10) for this test.

Figure 21: Estimated frequency response and coherence functions of the closed-loop system ($\hat{H}_{wx}$). From top to bottom: magnitude, phase and coherence functions of the EMG- (blue), force- (green) and joystick-based (red) control interfaces, all as function of frequency. The solid lines indicate the mean values and the area in faded colors indicate ± 1 SD. The vertical lines in the magnitude plot indicate the mean estimated gain margin crossover frequencies of each interface.

3.3 RESULTS

The estimated FRFs and coherence values of the closed-loop system ($\hat{H}_{wx}$) for each interface are shown in Figure 21. The coherence values are high ($\hat{\gamma}_{wx}^2 > 0.8$) for all three interfaces, meaning that the estimated FRFs are reliable and that the relationship between input and output is linear.

Performance evaluation

All the performance descriptors presented significant differences for the RMAN-OVA test. However, not all pairwise comparisons between interfaces were significant (Fig. 22). The EMG-based interface presented significantly lower tracking error ($p < 0.05$) compared to force- and joystick-based interfaces (Fig. 22A). Fur-

Figure 22: Performance evaluation. (A) Boxplots of the tracking error for each interface. The dashed horizontal lines indicate reference values of the tracking error. (B) Boxplots of the gain margin crossover frequency for each interface. (C) Boxplots of the information transmission rate for each interface. (D) Boxplots of the RMS of the velocity signal for each interface. The dashed horizontal line indicates the RMS of the optimal u signal. Stars indicate statistically significant differences. (*) indicates $p < 0.05$, (**) indicates $p < 0.005$ and (***) indicates $p < 0.001$.

thermore, the EMG-based control interface showed a significantly higher gain margin crossover frequency ($p < 0.001$) than the force- and the joystick-based interfaces (Fig. 22B). We also found that force-based interface provided significantly higher information transmission rates ($p < 0.05$) than the EMG-based interface (Fig. 22C). Finally, we found that the RMS values of the control signal u were significantly lower ($p < 0.05$) for the force-based interface compared to the ones obtained with the EMG-based interface (Fig. 22D).

Figure 23 shows the tracking error and the information transmission rate as function of frequency measured accumulatively and per frequency. Note that the progression of these quantities as function of frequency is affected by the fact that the multisine signal used as input (w) presented larger power at low frequencies. As a result the tracking error and the information transmission rate presents larger magnitudes at low frequencies when measured per frequency, and they rise quickly at low frequencies when measured accumulatively. We emphasize that the aim of Figure 23 is not to provide a relative comparison of the quantities along the frequency spectrum but to compare the quantities between the three interfaces for specific frequencies. The accumulative tracking error of the EMG-based interface becomes significantly lower compared to the force- and joystick-based interfaces beyond 0.9 Hz (Fig. 23A). The accumulative information transmission rate of the EMG-based interface becomes significantly lower ($p<0.05$) compared to the force-based interface beyond 1.4 Hz (Fig. 23C). The tracking error per frequency of the EMG-based interface is significantly lower at 0.6 ($p<0.05$) and 0.9 ($p<0.001$) Hz, and significantly higher ($p<0.001$) at 2.06 Hz compared to the force- and joystick-based interfaces (Fig. 23B). The information transmission rate per frequency of the EMG-based interface is significantly lower ($p<0.05$) at 0.9, 1.4 and 2.06 Hz compared to the force-based interface (Fig. 23D).

Learning characteristics

Figure 24 shows the learning curves obtained from fitting an exponential function to the mean values of the tracking error of each training trial. For the EMG-based control interface there was a significant reduction of tracking error ($p<0.05$) relative to the first training trial at the 6th trial, while the force-based interface presented a significant reduction ($p<0.05$) in the 3rd trial. The joystick-based interface did not show any significant reduction of the tracking error. The learning curves also show that all interfaces reached a performance plateau before the end of the training.

Figure 23: Tracking error and information transmission rate as function of frequency of the EMG- (blue), force- (green) and joystick-based (red) control interfaces. **(A)** Accumulative tracking error as function of frequency for each control interface. **(B)** Accumulative information transmission rate as function of frequency for each interface. **(C)** Tracking error per frequency of each control interface. **(D)** Information transmission rate per frequency for each interface. The solid lines indicate the mean values and the area in faded colors indicate ± 1 SD. The dashed vertical lines indicate from which frequency the parameter presents statistically significant differences. The solid vertical lines indicate at which frequencies the parameter present statistically significant differences. Stars indicate statistically significant differences. (*) indicates $p < 0.05$ and (**) indicates $p < 0.001$. The text on top of the vertical lines indicate between which of the interfaces the differences were statistically significant.

Figure 24: Learning curves. Tracking error along the ten training trials for the EMG-, force- and joystick-based control interfaces. An exponential function was fitted to the mean tracking error of each training trial. The first training trial was used as a reference to identify significant reductions of tracking error. The green markers indicate significant reduction of tracking error ($p < 0.05$) relative to the first trial. The red markers indicate non-significant reduction of tracking error ($p > 0.05$) relative to the first training trial. The vertical lines indicate the trial in which the performance plateau was identified. The error bars indicate ± 1 SD. Stars indicate statistically significant differences. (*) indicates $p < 0.05$.

Human-interface model

The results of the parameter estimation of k and τ are shown in Figure 25. We found a VAF measure of 98.8%, 96.7% and 82.9% for the EMG-, force- and joystick- based interfaces respectively. The high VAF values indicate that the observed behavior is well described by the model within the measured frequency range. While we did not find a significant difference between the estimated gain parameters (k), the EMG-based interface presented significantly lower delay ($p < 0.001$) than the force- and the joystick-based interfaces .

Figure 25: Estimated parameters of the human-interface model ($\hat{H}_{eu}$). **(A)** Boxplots of the gain parameter for each interface. **(B)** Boxplot of the delay parameter for each interface. Stars indicate statistically significance differences. (***) indicates $p < 0.001$.

Participant's opinion

The results from the questionnaire show that six out of eight participants preferred the force-based interface followed by EMG- and joystick-based interfaces. The other two participants preferred EMG-based interface the most, followed by force- and joystick-based interfaces.

3.4 DISCUSSION

The amplitude range of the joystick interface was smaller compared to the other two interfaces, for which the amplitude limits were set according to the maximum force or EMG signal that the subject could generate (i.e. MVC). This very sensitive and limited range of the joystick might be the cause of the reduced user acceptance. Nevertheless, the performance of the joystick interface was similar to the force-based interface for all the performance descriptors (Fig. 22). Our motivation to test a classic hand-joystick with small input range was that this type of interface is commonly used by individuals with severe muscular weakness to control electric wheelchairs, domestic devices and external robotic arms. Therefore, it makes sense to consider the option of also using this control interface to operate an active arm support. Comparing a classic hand-joystick to new interfaces (from a patient's point of view) is especially relevant for the targeted patient group, as the performance of a new control interface needs

to represent a meaningful improvement and worth the effort of learning and adaption.

In accordance with the results by Corbett et al. [205] we also found that the EMG-based interface presented a significantly lower tracking error than the force-based interface. Interestingly the tracking error per frequency of the EMG-based interface becomes significantly higher at 2 Hz compared to the force- and joystick-based interface (Fig. 23B). This performance change might be caused by the significant decrease of information transmission rate of the EMG-based interface beyond 1.4 Hz (Fig. 23C).

Regarding the performance measure of the gain margin crossover frequency, the participants were able to track frequencies up to 1.7 Hz when using the EMG-based control interface, while they were able to track frequencies only up to 1.3 Hz with the other two interfaces (Fig. 22B). From the parameters estimation of the human-interface system we can conclude that the larger gain margin crossover frequency of the EMG interface is possible due to its low delay (Fig. 25B). Note that the EMG signals are measured earlier than their resultant force or motion signals, which pass through the muscle and skeleton dynamics. Despite having a higher gain margin crossover frequency, the EMG-based interface presented a significantly lower information transmission rate beyond 1.4 Hz (Fig. 23C) due to its lower signal to noise ratio (see also lower coherence in Figure 21) compared to the force and joystick signals.

Figure 23C shows that, unlike found in [205], significant differences between EMG- and force-based interfaces in terms of information transmission rate appear beyond 1.4 Hz. We conjecture that the study by Corbett et al. [205] could not find equivalent significance due to the limited bandwidth (1 Hz) of the used tracking task.

The results of the effort comparison showed that the force-based interface had significantly lower RMS value of the control signal compared to the EMG- and joystick-based interfaces (Fig. 22D). An analysis of the EMG data during both EMG and force tasks indicated that the difference in RMS values was caused by the higher presence of co-contraction when using EMG as control interface.

The VAF measures indicated that the parameters found for the EMG- and force-based interfaces described the human-interface system with very high fidelity. However, this was not the case for the joystick-based interface, for which the model could explain 83% of the measured data. These results suggest that a

slightly different model should be used to describe the joystick-based interface more precisely.

With regard to the learning curves, we can observe, as expected, that as the training proceeded, the subjects learned and the tracking error became smaller indicating that the frequency content of the target and the cursor became increasingly similar. The results showed that despite the fact that the EMG-based interface is far from the natural means to interact with the environment while the force-based interface is closer, the difference in terms of learning cost was small: the participants were able to reach a performance plateau with the EMG-based interface after the 6th training trial, which is only three trials after the same plateau was reached with the force-based interface (Fig. 24). Regarding the joystick-based interface, we did not find any significant improvement of the tracking error after the 10th training trial. The lack of a significant learning effect with the joystick could be a consequence of the prior experience of the participants with these type of devices, thus no further detectable improvement was achieved during the experiment.

3.5 CONCLUSIONS

In the context of the wide variety of invasive and non-invasive control interfaces for active movement-assistive devices [246, 247, 130], our study characterizes and compares the performance, learning characteristics and subjective preference of EMG, force and hand joystick as control interfaces for active arm supports using a one-dimensional screen-based position-tracking task.

None of the evaluated interfaces was superior in all of the four performance descriptors that we have analyzed (Table 3). EMG-based interface was superior in terms of tracking error and gain margin crossover frequency compared to the force- and joystick-based interfaces. The force-based interface was superior in terms of information transmission rate and effort compared to the EMG-based control interface. While the results of the tracking error are in accordance with the findings reported by [205], the significant differences found in terms of information transmission rate were unnoticed in the aforementioned study probably because these are present beyond 1.4 Hz only. Strictly speaking, the joystick was always tied with the force-based interface in all four performance descriptors, although our results were close to significance for considering the joystick as the worst option in terms of gain margin crossover frequency and effort.

Our modeling of the human-interface system revealed that the high gain margin crossover frequency of the EMG-based interface was related to its low delay. This finding should be especially considered in interfaces where high bandwidths are required, such in the case of empowering exoskeletons in which target bandwidths are in the order of 2 Hz [248].

Probably because of being a well-known device, with which all participants had already some experience, the joystick showed no learning effects in these experiments. The other two interfaces were not hard to learn, with the force-based interface showing the fastest learning curve. Surprisingly, despite being the most familiar interface, the joystick was the least preferred interface because participants disliked its high sensitivity over the small amplitude range.

In practice, the performance descriptors should be weighted according to the requirements of the specific application to select the most suitable interface for a particular case. In the context of our specific application of controlling an arm support for people with muscular weakness, tracking error and the effort measure should be weighted heavily. Also, criteria such as preference and learning are likely to show significant differences among patients with different pathologies.

Table 3: Overview of the performance, learning and preference evaluation

	EMG	Force	Joystick
Tracking Error	1	2	2
GM Crossover Freq.	1	2	2
ITR	2	1	–
Effort	2	1	–
Learning	2	2	1
Preference	2	1	3

The ranking of the interfaces for each performance descriptor is indicated with numbers where 1 indicates the best interface for a specific performance descriptor. GM Crossover Freq.: gain margin crossover frequency ITR: information transmission rate.

From these results we conclude that all of the control interfaces considered in this study can be regarded as a candidate interface for the control of an active arm support in patients with muscular weakness. Our future work will have to consider testing them all using a functional task closer to an activity of daily living, (e.g. a two- or three-dimensional reaching-retrieving task). Apart from the performance criteria evaluated in this study, we will consider additional design requirements, such as ease of use, portability and comfort.

IMPLEMENTATION OF EMG- AND FORCE-BASED CONTROL INTERFACES IN ACTIVE ELBOW SUPPORTS FOR MEN WITH DUCHENNE MUSCULAR DYSTROPHY: A FEASIBILITY STUDY¹

Abstract: *While there is an extensive number of studies on the development and evaluation of electromyography- (EMG) and force-based control interfaces for assistive devices, no studies have focused on testing these control strategies for the specific case of adults with Duchenne muscular dystrophy (DMD). This paper presents a feasibility study on the use of EMG and force as control interfaces for the operation of active arm supports for men with DMD. We have built an experimental active elbow support, with a threefold objective: (I) to investigate whether adult men with DMD could use EMG- and force-based control interfaces, (II) to evaluate their performance during a discrete position-tracking task, and (III) to examine users' acceptance of the control methods. The system was tested in three adults with DMD (21-22 years). Despite all three participants had not performed any voluntary movements with their arms for the past 3-5 years, all of them were 100% successful in performing the series of tracking tasks using both control interfaces (mean task completion time EMG: 6.8 ± 4.8 s, force: 5.1 ± 1.8 s). While movements with the force-based control were considerably smoother in Subject 3 and faster in Subject 1, EMG based-control was perceived as less fatiguing by all three subjects. Both EMG- and force-based interfaces are feasible solutions for the control of active elbow supports in adults with DMD and should be considered for further investigations on multi-DOF control.*

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4.1 INTRODUCTION

Duchenne muscular dystrophy (DMD) is the most common form of muscular dystrophy in children, with an incidence of 1 in 5,000 male live births [8]. Defective mutations in the dystrophin gene result in progressive degeneration of skeletal, respiratory and cardiac muscles leading to loss of independent ambulation by the age of ten years, followed by the development of scoliosis and loss of upper extremity function [10, 2]. The mean life expectancy of boys with DMD used to be no more than twenty years [3], but in the last five decades, long-term survival has improved substantially due to improvements in drugs and the introduction of home care technology, such as, artificial ventilators. As a result, currently, there is a considerable group of adults with DMD living with severe physical impairments and a strong dependency on care up to their 30's [1]. Commercially available arm supports, which mainly provide passive gravity compensation [5], become insufficient to support the arm function of adults with DMD [105]. Active arm supports, which can provide extra assistance, could enable adults with DMD to continue performing basic activities of daily living and participate in social activities.

In order to operate active arm supports, the user needs to communicate his motion intention to the device through a control interface. The selection of the control interface, in response to specific user needs and capabilities, is a crucial determinant of the usability of the assistive device. We consider that surface electromyography (EMG) and force-based interfaces are two promising strategies to achieve a natural control of active arm supports as they have been widely implemented in prostheses and orthoses/exoskeletons [249, 33].

The clinical standard EMG-based control strategy implemented in upper limb prosthetics is a simple amplitude-based dual site control approach also known as direct control [145]. This method measures EMG from two independent residual muscles, or by distinguishing different activation levels of one residual muscle. Switching techniques such as muscle co-contraction are commonly implemented for enabling the sequential operation of different degrees of freedom (DOF). More advanced EMG-based control strategies for operating active prostheses and orthoses/exoskeletons are based on estimating joint angles or torques from the EMG signals of the muscles that mainly contribute to the supported motion. Common estimation methods include pattern-recognition-based algorithms [152] and regression-based algorithms [68, 155, 250].

Force-based interfaces have been used in assistive-powered wheelchairs [197], in which the wheelchair detects and amplifies the force applied by the user. Other studies implemented force-torque sensors, or simple force sensor resistors for the control of active upper-extremity orthoses [105, 39, 107] and prostheses [100]. Force-based interfaces generally implement control strategies where the output motion is proportional to the input force. Additionally, haptic force-based control interfaces are often implemented in rehabilitation robots where patients need training to regain motor control, mobility and strength [33]. The advantage of implementing haptic interfaces, such as admittance or impedance control, in human-interactive robots is that the apparent dynamics of the robot can be modified to enhance the interaction.

While there is an extensive number of studies on the development and evaluation of EMG- and force-based control interfaces for prostheses and orthoses/exoskeletons [212, 205, 211, 215, 207], no studies have focused on testing these control strategies for the specific case of men with DMD. The selection of the most suitable control interface to operate an active arm support for adults with DMD required a better understanding of the limitations and capabilities of EMG- and force-based control interfaces through objective and quantitative evaluations during functional tasks.

This paper presents a feasibility study on the use of EMG and force as control interfaces to operate active arm supports for adults with DMD. We built an experimental active elbow orthosis, the Flexextension Elbow Drive (Fig. 26), with a threefold objective: (I) to investigate whether adult men with DMD with very limited arm function could use EMG- and force-based control interfaces, (II) to evaluate their performance during a discrete position-tracking task, and (III) to examine users' acceptance of the control methods. The system presented in this paper is a research platform for the evaluation of EMG- and force-based control interfaces and does not represent an early prototype of an actual arm support for daily use.

4.2 METHODS

Participants

Three adults with DMD participated in this study. Participants were carefully selected considering that they should have been users of passive arm supports

Figure 26: Top) An adult man with DMD using the Flexion Elbow Drive system during the control interface evaluation. 1) EMG electrodes. 2) Force sensor. 3) Motor housing. 4) Display of the experimental task. 5) Emergency stop. **Bottom)** Schematic drawing of a subject using the Elbow Drive system and performing the discrete position-tracking task. The Elbow Drive generates an assistive torque (τ_{mot}) that helps the subject to reach from the start position the target angle (θ_{tar}) with his forearm (θ_{cur}). Note that in reality the axis of the motor is tilted vertically to align the movement of the elbow to a comfortable/natural orientation.

and have experienced severe difficulties using them due to muscular weakness and increased joint stiffness. All subjects were not able to perform any voluntary movements with their arms for the past 3-5 years. Subject's demographic information is shown in Table 4.

Subject 1 (S1) presented no arm function and limited hand function (Brooke scale: 5, [251]) that allowed him to do some writing and drive an electric wheelchair using a hand joystick. Subject S1 was not able to actively flex or extend his wrist. Using the Elbow Drive with only passive weight compensation subject S1 was still able to move his elbow over a range of motion of 15 degrees. Subject S1 suffered from sever scoliosis which was surgically corrected at the age of 12.

Subject 2 (S2) presented no arm function and limited hand function (Brooke scale: 5), that only allowed him to use a computer mouse (using a passive arm support) and drive an electric wheelchair using a hand joystick. However, subject S2 was not able to write or actively flex or extend his wrist. Subject S2 suffered from sever scoliosis which was surgically corrected at the age of 14.

Subject 3 (S3) presented no arm function and limited hand function (Brooke scale: 5), which did not enable him to write or use a computer mouse. Subject S3 was still able to control an electric wheelchair using a hand joystick. Subject S3 used an artificial ventilator and did not suffer from severe scoliosis.

The Medical Ethics Committee of the Radboud University Nijmegen Medical Center approved the study design, protocols and procedures, and informed consent was obtained from each subject.

Setup: The Elbow Drive System

The Elbow Drive was designed to investigate different control interfaces while performing a challenging yet simple and functional movement. Elbow flexion-extension movements against gravity were chosen considering that it resembles a functional movement needed when eating, drinking or face scratching, and that individuals with muscular weakness specially need support in upward movements. The Elbow Drive (Fig. 26 and 27) has one active rotational DOF aligned with the elbow joint of the user which rests on the table surface. Perpendicular to the motor axis an aluminum beam extends along the forearm in which the hand of the user is fixated with an ergonomic hand interface made of thermoplastic.

The interaction forces between the human and the device were measured with a one DOF force sensor (LSB200 - 5lb, FUTEK Advanced Sensor Technology Inc., USA) located between the plastic hand cup and the aluminum lever. The attachment of the force sensor was designed in such a way that only forces acting perpendicular to the aluminum lever are measured (see close-up image in Fig. 27). The muscle activation signals were measured from the biceps

Table 4: Summary of the participants' characteristics

Subject's Code	Age (years)	Brooke Scale	Preferred Arm	ROM (deg)	Pas. Sup. ROM (deg)	E_{mvic_b} (mV)	E_{mvic_t} (mV)	F_{mvic_f} (N)	F_{mvic_e} (N)
1	22	5	Right	58.5	15	0.09	0.02	0.94	2.7
2	21	5	Right	60.5	5	0.004	0.004	0.80	1.47
3	22	5	Right	48.0	5	0.002	0.001	0.55	0.82

Note: ROM, passive range of motion reached when the forearm is moved by a therapist; Pas. Sup. ROM, range of motion that the subject can reach when using passive support for gravity compensation of the forearm; E_{mvic_b} , EMG amplitude during maximal voluntary isometric contraction of the biceps; E_{mvic_t} , EMG amplitude during maximal voluntary isometric contraction of the triceps; F_{mvic_f} , force amplitude during maximal isometric voluntary contraction of the biceps; F_{mvic_e} , force amplitude during maximal isometric voluntary contraction of the triceps. Note that the values of E_{mvic_b} and E_{mvic_t} do not indicated the maximum EMG electrical potential measured but the maximum signal value after the envelop detection. The EMG envelopes during rest (i.e. noise level) presented maximum values of 0.0007 mV in all subjects.

and triceps branchii muscles, which are the muscles that mainly contribute to the elbow flexion-extension movements. Two single differential-surface EMG dry-electrodes (Bagnoli DE-2.1., Delsys, USA) were placed parallel to the muscle fibers according to the SENIAM (Surface ElectroMyoGraphy for the Non-Invasive Assessment of Muscles) recommendations [237] and manual muscle exploration. The EMG signals were amplified by a Delsys Bagnoli-16 Main Amplifier and Conditioning Unit with a bandwidth of 20 to 450 Hz and a gain of 1000. The Elbow Drive was also equipped with a one DOF hand-joystick with the only purpose of letting the participants familiarize with the system dynamics and the tracking task.

All the signals from the sensors were sent to a real time computer (xPC Target 5.1, MathWorks Inc., USA) by means of a National Instruments card (PCI-6229; National Instruments Corp., USA), which performed the analog-to-digital conversion with a sampling frequency of 1 KHz and 16-bit resolution. The controller was also running on the real-time computer and was sending the pulse width modulated (PWM) control signals to the motor driver (UK1122-L298 Dual H-Bridge 4A, Cana Kit Corp., Canada) through the same National Instruments card. Further details on the design requirements, mechanics, actuation, sensors and safety measures of the Elbow Drive system are described in [106].

Signal Processing

The envelope detection of the EMG signals was performed applying a full-wave rectification and a second order low-pass Butterworth filter with a cut-off frequency of 3 Hz. The filter settings were chosen considering previous studies on EMG control [67, 232] and pilot trials on our setup. The normalized EMG signals, $E_{nor,k}(i)$, and the resultant EMG control signal, $u_{emg}(i)$, were obtained using (Eq. 10) and (Eq. 11) respectively:

$$E_{nor,k}(i) = \frac{E_{env,k}(i) - E_{res,k}}{E_{mvic_k}} \quad (10)$$

$$u_{emg}(i) = E_{nor,b}(i) - E_{nor,t}(i) \quad (11)$$

Figure 27: Components of the Elbow Drive system. The Elbow Drive system was build to investigate if subjects with DMD could use EMG- and force-based interfaces to operate an active arm support. A DC motor drives the lever through a mechanical torque limiter that prevents high torques to be transmitted to the elbow joint. The wrist of the participant is attached to the Elbow Drive system using an anatomically shaped plastic interface (in the figure the shape of the interface is simplified). The interaction forces between the user and the Elbow Drive system are measured with a one DOF force sensor mounted between the wrist cup and the lever arm. We used a linear slide bearing to prevent discomfort due to misalignment between the elbow joint and the motor axis.

where subscript k represents the abbreviations of the biceps (b) and triceps (t) muscles, $E_{env,k}(i)$ denotes the processed EMG signal at the i^{th} time step, $E_{res,k}$ represents the average signal amplitude of the EMG envelopes during 3 s at rest, and E_{mvic_k} represents the mean maximum magnitude of $E_{env,k}(i)$ during two seconds of maximum voluntary isometric contraction (MVIC; see Table 4).

To properly detect the movement intention of the user in force-based interfaces, it is critical to distinguish the voluntary forces from any other force, such as gravity or joint stiffness forces. Note that in Fig. 29 the measured force (F_{sen}) is the combination of the muscle torque (τ_{mus}) and the intrinsic/passive torques of the arm (τ_{pas}). In the Elbow Drive system, the estimated voluntary forces of the user, $\hat{F}_{vol}(i, \theta)$, and the resultant force control signal, $u_{for}(i, \theta)$, are obtained using (Eq. 12) and (Eq. 13) respectively:

$$\hat{F}_{vol}(i, \theta) = F_{sen}(i) - \hat{F}_{com}(\theta) \quad (12)$$

$$u_{for}(i, \theta) = \begin{cases} \frac{\hat{F}_{vol}(i, \theta)}{F_{mvic_f}}, & \text{if } \hat{F}_{vol}(i, \theta) > 0 \\ \frac{\hat{F}_{vol}(i, \theta)}{F_{mvic_e}}, & \text{if } \hat{F}_{vol}(i, \theta) < 0 \end{cases} \quad (13)$$

where $F_{sen}(i)$ denotes the measured force signal at the i^{th} time step, $\hat{F}_{com}(\theta)$ represents the estimated compensation force measured at angle θ , and F_{mvic_f} and F_{mvic_e} represents the mean maximum magnitude of $\hat{F}_{vol}(i, \theta)$ during biceps (flexion) and triceps (extension) MVIC respectively. The $\hat{F}_{com}(\theta)$ was obtained by measuring the forces during a slow and constant descending movement (0.05rad/s) from the upper limit to the lower limit of the elbow support with the arm of the subject relaxed and attached to the system (Fig. 28). A 10th order polynomial function was then fitted to the measured force to reduce any possible disturbances during the measurement. Pilot trials showed that this measurement-based method was able to accurately estimate gravity and joint stiffness forces along the range of motion of the elbow. A video showing the compensation force measurement can be found in [249] as additional file 4.

Control

Figure 29 shows the control diagram of the physiological (i.e. man with DMD) and the assistive system (i.e. Elbow Drive). The objective of the participant is to reach the target angle (θ_{tar}) with the arm. The arm muscles of the participant are too weak to generate the muscular torque (τ_{mus}) necessary to move the passive human arm dynamics and therefore an assistive device is used. The Elbow Drive can use either the interaction torque (τ_{int}) between the user and the Elbow Drive (measured with a force sensor, F_{sen}) or EMG signals (E_{sen}) to detect the motion intention of the user and support the movement towards the target angle. After processing the EMG and force signals as described in Section 4.2, the resulting control signals (u_{for} or u_{emg}) are filtered by a second order transfer function ($H_{id}(s)$) that represents the virtual dynamics of a mass-damper system:

$$H_{id}(s) = \frac{1}{0.5s^2 + 0.5s}. \quad (14)$$

Figure 28: Top) Representative data of a compensation force measurement from one of the participants. For the measurement of the gravity and joint stiffness forces ($\hat{F}_{com}$), the Elbow Drive moved with a low constant speed (0.05 rad/s) across the ROM of the elbow while the subject was relaxed. In blue the force measured over the elbow's ROM in one of the subjects. In red the curve fitted with a 10th order polynomial function. **Bottom)** The u_{emg} signal of the same subject during the compensation force measurement. This signal was used to supervise if the subject was relaxed during this procedure.

The specific values of the parameters of the interface dynamics function were chosen from pilot trials with men with DMD. Note that the parameters of the interface dynamics are effectively scaled to the MVIC values by the normalization of the control signals u_{for} and u_{emg} . The angle reference signal resulting from the virtual dynamics (θ_{ref}) is send to a low-level position feedback controller

(i.e. PD controller) that operates the motor. The torque generated by the DC motor (τ_{mot}) together with the interaction torque (τ_{int}) move the passive dynamics of the Elbow Drive system, which assists the user to move his arm making possible for the participant to perform elbow flexion/extension movements (θ_{cur}) and eventually reach the target angle (θ_{tar}).

Experimental Protocol

After a detailed explanation of the purpose and procedure of the experiment, the ROM of the setup, the elbow alignment and the amount of padding on the hand cup were adjusted to the convenience of the participant. The participants first used the one DOF joystick, operated with the contralateral hand, to control the Elbow Drive in order to familiarize themselves with the movement of the arm and the tracking task.

A one-dimensional discrete position-tracking task was presented to the participant on a computer screen by means of a custom-made C# (Microsoft Visual Studio, Microsoft Corporation, USA) audiovisual interface (Fig. 26). The participant was asked to bring a yellow circular cursor (θ_{cur}), which represented the angle of the elbow, as close as possible to the center of a purple circular target (θ_{tar}) and remain inside the target zone (i.e. ± 2 degrees) for two seconds as predefined dwell time. When the cursor was inside the target zone, a beeping sound was played in order to inform the participant that he was in the correct position. Three target angles were linearly distributed over the elbow's ROM of the participant. Note that from this distribution of target angles two movement lengths can be distinguished: long movements, from minimum to maximum ROM, and short movements, from minimum or maximum to half of the ROM. The target angles located near the limits of the ROM were placed, within the ROM, 5 degrees from the limits in order to prevent collisions with the mechanical end-stops placed at the limits of the ROM. A video of one of the participants performing the discrete position-tracking task using the force-based control interface can be found in [249] as additional file 5.

For each interface the participant had 5 minutes to perform free movements, followed by 12 training trials and 36 evaluation trials. Each trial represented a single tracking task to a target angle. The target angles of the training and evaluation trials were ordered with the same number of long and short movements (i.e. 18 movements) and same number of ascending and descending movements.

Figure 29: Control Diagram of the physiological and assistive system. Either Force (F_{sen}) or EMG signals (E_{sen}) are used to derive the motion intention of the user and control the Elbow Drive system. The interaction torque (τ_{int}), which is a combination of the muscular torque (τ_{mus}) and the passive/intrinsic human arm torque (τ_{pas}) is measured by a force sensor (F_{sen}) at a distance r from the axis of rotation of the elbow joint. The task of the user is to reach the target angle (θ_{tar}) with the Elbow Drive (θ). The subject has visual feedback of the elbow and target angle. After the signal processing and the virtual dynamics (H_d), the resulting angle reference signal (θ_{ref}) is sent to a low-level position feedback controller that operates the motor. The resulting torque (τ_{res}) generated by the DC motor (τ_{mol}) together with the interaction torque (τ_{int}) moves the passive Elbow Drive's and Human Arm dynamics.

For all participants, the free-movements and the training trials were performed using first the EMG-based interface and afterwards the force-based interface. Subsequently, the subject rested for 10 minutes and performed the evaluation trials first with the EMG-based interface, and secondly with the force-based interface, with a resting period of 10 minutes in between the evaluation of the two control interfaces.

Questionnaire

To evaluate the experience of the participants and the acceptance of the EMG- and the force-based control interfaces, each participant was asked to answer 7 questions (see Table 6) after completing the experimental protocol.

Data Analysis

Data analysis was performed on metrics derived from the elbow angle displacements as function of time while reaching towards the short and long targets. We measured 18 evaluation trials for each of the three subjects using EMG- and force-based control interfaces. The first two evaluation trials were removed from the analysis since they showed clear start-up effects, thus the dataset resulted in a total of 16 trials for each subject, control interface and target distance. The movement performance was evaluated in terms of task completion time (TCT) and rate (TCR), overshoot (OS), trajectory efficiency (TE), and smoothness (SM; see Table 5 for definitions). Additionally, to better understand the metric of task completion time, this metric was divided in two parts: rising time (RT) and settling time (ST). Short and long movements were analyzed separately since they present different index of difficulty [252]. The chosen performance descriptors are common measures used in studies that evaluate the performance of control interfaces [211, 215, 207].

Departure from normality and severe heteroscedasticity that was not alleviated by transformation were present in the distribution of all metrics, which prevented the use of multi-way repeated measures ANOVA to test for significance of the grouping by control system and subjects. We thus used a suite of non-parametric Friedman tests with a level of significance fixed at $p < 0.05$. A more detailed inspection of the distribution of all metrics by control system for

each subject and target distance was performed through box plots combined with non-parametric Wilcoxon rank-sum tests (significance level: $p < 0.05$). In the box plots, the data points above or below 1.5 times the interquartile range (IQR) are shown as outliers with a '+' symbol. Furthermore, we explored the distribution of trials in all bivariate planes among all metrics in search of patterns related to control interfaces and subjects. The statistical tests were performed with R software (R Development Core Team 2015).

4.3 RESULTS

Figure 30 presents the average and $\pm 1SD$ of the elbow angle displacements and the task completion rates as function of time using the EMG- and the force-based control interfaces of subjects S1, S2 and S3. While the movements with EMG-based control were considerably slower in subject S1 and less smooth in subject S3, subjects present similar movements with force-based control.

Table 5: Performance Metrics

Performance metric	Description
1. Rising Time (s):	Time needed to move the elbow from the start position to the target area.
2. Settling Time (s):	Time needed to stabilize the elbow from the first time that the elbow reaches the target area to the completion of the task.
3. Task Completion Time (s):	Total time needed to complete the task.
4. Task Completion Rate (%):	Number of trials completed over the total number of trials in function of time.
5. Overshoot (%):	Maximum normalized distance traveled outside of the target area during a trial.
6. Trajectory Efficiency (%):	Shortest distance to the target angle divided by the total distance traveled by the elbow during a trial.
7. Smoothness (NZC):	Number of times that the elbow angle changed direction i.e. number of zero crossings (NZC) of the velocity signal from the time that the elbow leaves the previous target area, and excluding the last two seconds of dwell time.

Figure 30: Average (solid line) and ± 1 SD (area with faded color) of the elbow angle displacements, and task completion rate as function of time of the 32 evaluation trials of subjects S1 (red), S2 (green) and S3 (blue) using the EMG- (top) and the force-based (bottom) control interfaces while reaching towards the long (norm. angle = 1) and short (norm. angle = 0.5) target angles (grey solid line). Three slow trials of subject S3 [long targets: (1),(2); short targets:(4)] and one of subject S1 [long targets: (3)] using EMG-based control have been excluded from this figure for clarity. The slow trials can be seen in Fig. 34 in Supplementary Material.

Task Completion Rate and Time

Average task completion rate of all trials at 15 s was higher for force-based control (100 %) than for EMG-based control (95.8 ± 5.1 %). Actually, a rate of 100 % was already achieved at 9 s with force-based control, while 85.4 ± 19.6 % was achieved with EMG-based control at the same time span (Fig. 30). For Subject 3, 35 s were necessary to achieve a 100 % task completion rate with the EMG-based control due to two slow trials. Average task completion time of all trials was 6.8 ± 4.8 s and 5.1 ± 1.8 s for EMG- and force-based control respectively. For more details of the elbow angle displacements and task completion rates as function of time of each subject, control interface and target distance, see Figure 34 in Supplementary Material.

Friedman Tests

Table 7 in Supplementary Material presents the results of the significance of grouping trials by control interface and subjects for all metrics. Significance was much higher (p -value much lower) for grouping by subjects than by control systems in all metrics. The only metric that showed a significant difference among control methods was overshoot ($p = 0.0011$). Significant differences between subjects were found for all metrics ($p < 0.001$).

Box Plots and Wilcoxon Rank-Sum Tests

Subject S1 presented a significantly longer task completion time ($p = 0.0007$) for EMG-based control (7.6 ± 2.8 s) due to a longer rising time (5.2 ± 2.2 s, $p = 0.0002$) compared to force-based control (TCT: 4.9 ± 1.1 s, RT: 2.7 ± 1 s; Fig. 31 and Table 8 in Supplementary Material). For short targets, the trajectory efficiency was significantly higher ($p = 0.019$) in EMG-based control (89.7 ± 9.1 %) than in force based-control (78.5 ± 13.5 %; Fig. 32 and Table 9 in Supplementary Material). Subject S2 showed significantly higher task completion time (EMG: 4.3 ± 0.8 s, force: 4.8 ± 0.7 s, $p = 0.039$) due to a significantly higher rising time (EMG: 1.9 ± 0.4 s, force: 2.5 ± 0.6 s, $p = 0.003$) for the movements towards the long targets when using force-based control compared to EMG-based control. Subject 2 also presented a significantly higher number of zero crossings for the long targets (EMG: 5.6 ± 1.6 , force: 7.3 ± 0.7 , $p = 0.0008$) when using force-based control. Subject S3 presented large significant differences ($p = 1.2 \times 10^{-6}$) in the smoothness of the movement. The number of zero crossings for this subject were nearly two-fold higher in EMG-based control (37.4 ± 2.6) than in force-based control (18.1 ± 0.9), which compromised trajectory efficiency (EMG: 67.2 ± 2.6 %, force: 81 ± 11.1 %, $p = 0.04$) and overshoot (EMG: 12.1 ± 6.2 %, force: 2.9 ± 4.9 %, $p = 0.0002$) of the movements when using EMG-based control. In Subject S3, differences in trajectory efficiency were larger for the movements towards the short targets ($p = 0.004$), for which EMG-based control presented a significantly higher task completion time than force-based control (EMG: 9.7 ± 4.1 s, force: 5.3 ± 1.5 s, $p = 0.0007$; Fig. 32).

Figure 31: Boxplots for each movement performance metric of subjects S1, S2 and S3 using the EMG- (blue) and the force-based (red) control interfaces during the tracking of the long target. Outlier (1) has the value of 32 s and outlier (2) of 25 s. (*) indicates $p < 0.05$. (**) indicates $p < 0.01$. (***) indicates $p < 0.001$.

Figure 32: Boxplots for each movement performance metric of subjects S1, S2 and S3 using the EMG- (blue) and the force-based (red) control interfaces during the tracking of the short target. (*) indicates $p < 0.05$. (**) indicates $p < 0.01$. (***) indicates $p < 0.001$.

Figure 33: Distribution of trials in all bivariate planes among all metrics: performance metrics task completion time, overshoot, trajectory efficiency and smoothness. All 16 trials from long and short targets of subjects S1 (red), S2 (green) and S3 (blue) using EMG- (full circle) and force-based (empty circle) control are included. The vertical dashed line indicates the time limit of 15s used to distinguish the slow trials.

Bivariate Plots

Figure 33 shows that trials cluster in three groups according to smoothness, and that this grouping is mainly by subjects: trials corresponding to subject S2 at one extreme, trials corresponding to subject S3 with EMG-based control to

the other extreme, and a third cluster in the middle including both the trials corresponding to subject S1 and those corresponding to S3 with force-based control only. Smoothness is minimum (maximum number of zero crossings) for trials done by subject S3 using EMG control and maximum (minimum number of zero crossings) for trials done by subject S2, while trials done by subject S1 are intermediate. It is worth to note that while trials done by subject S3 with EMG-based control have a very low smoothness, those performed by the same subject with force-based control have similar levels of smoothness than those of subject S1.

As a summary, the analysis of the performance metrics indicated that there is more, and more consistent variability among subjects than between control interfaces, with subject S2 presenting a higher movement performance than subjects S1 and S3. For subjects S1 and S2 both control interfaces were equally performant, but the force-based control system clearly performed better for subject S3.

Questionnaire

The results of the questionnaire are summarized in Table 6. While subjects S1 and S3 showed a clear preference for EMG- and force-based control respectively, subject S2 did not. All subjects agreed that EMG-based control was least fatiguing. For the rest of the questions, the answers of the participants showed different preferences.

4.4 DISCUSSION

Feasibility, Performance and Acceptance

In the context of assistive devices, the performance descriptor that we consider most meaningful is the task completion rate with a reasonable time limit, which clearly captures the ability of subjects to perform the task. Additionally, descriptors that measure accuracy and efficiency of the movement, such as trajectory efficiency, overshoot and smoothness become relevant to analyze and compare the movement performance between control methods in more detail. Results of

questionnaires provide additional insights on usability and acceptance of the technology.

Despite all three participants had not been able to perform any voluntary movements with their arms for the past 3-5 years, all of them were able to perform 100 % of the series of tracking tasks with both control modalities (mean task completion time EMG: 6.8 ± 4.8 s, force: 5.1 ± 1.8 s). These results indicate that EMG- and force-based interfaces are feasible solutions for the control of active elbow supports in adults with DMD. While healthy individuals perform the tabletop to mouth movement within a second, the task completion times achieved by the participants of this study were considerably longer. We expect that the task completion time of adults with DMD would decrease with training and make this technology acceptable.

All participants were capable to continuously control the amplitude of their EMG and force signals to perform the series of discrete position-tracking tasks with a high overall movement performance. Even though the EMG and force signals of the participants presented a very low-amplitude (see MVIC values in Table 4; compared to signals of healthy individuals [212]), they were measurable with standard signal acquisition equipment, and contained meaningful information of their motion intention. In a recent uncontrolled exploration, we

Table 6: Questions and preferences of the participants

	EMG Preference	Force Preference	No Preference
1. Which interface could control the Elbow Drive most accurately?	S1	S2 S3	
2. Which interface could control the Elbow Drive fastest?	S1 S2	S3	
3. Which interface was the easiest to control (did react best to your motion intention)?	S1	S2 S3	
4. Which interface was least fatiguing to use?	S1 S2 S3		
5. Which interface was the easiest to set up/install?		S1 S2	S3
6. Which interface was the most comfortable to use?	S2		S1 S3
7. Which interface has your overall preference for controlling the Elbow Drive?	S1	S2 S3	

detected that a 37 year-old man with DMD was still able to generate usable EMG signals with his biceps and triceps muscles.

The relative performance of the control interfaces depended on the subject (Table 7 in Supplementary Material). For subject S2, the differences on performance between both methods were small for all metrics: small but statistically significant for task completion time and smoothness, and even not significant for trajectory efficiency and overshoot. The movements of subject S1 were considerably faster with the force-based interface, while the rest of performance metrics presented similar results for both control interfaces. Finally, all metrics (specially smoothness) clearly indicated that subject S3 performed better with force-based control than with EMG-based control (Tables 8 and 9 in Supplementary Material).

The large performance differences found between the control methods in subject S3 resulted from the lower signal-to-noise ratio of the EMG compared to the other subjects (S3 E_{mvic_t} : 0.001 mV, S1 E_{mvic_t} : 0.004 mV). The envelope of the EMG signal while resting (i.e. noise level) presented maximum peaks of 0.0007 mV for all three subjects, which clearly affected the EMG-based control of subject S3 since the amplitude of the signal noise was equivalent to 70 % of his E_{mvic_t} . Jerkiness of the movements performed when using the EMG-based control interface could have been improved by fine-tuning the system for subject S3: modifying the cut-off frequency of the filter used to detect the EMG envelope, or increasing the mass constant of the interface dynamics (H_{id}). We decided not to manipulate the parameters of the interface dynamics during the experiment in order to keep the experimental conditions consistent among participants.

The results of the questionnaire showed mixed preferences between participants which indicates that both EMG- and force-based control were perceived as possible solutions for the control of active arm supports.

Fatigue and Joint Stiffness

All three participants indicated in the questionnaire (Table 6 question 4) that EMG-based control was less fatiguing than force-control. One fundamental difference between EMG and force-based control is that in the latter the measured force signal also contains static and dynamic components (i.e. intrinsic forces) of the arm such as stiffness, viscosity, inertia and gravitational forces. Distin-

guishing the voluntary component of the force signal requires proper estimation of the other components. Gravity and joint stiffness forces are challenging to estimate accurately due to their non-linearity, time-variance and pose dependency [253, 254, 104]. Additionally, the low voluntary forces of adult men with DMD, which are several orders of magnitude smaller than their arm's weight, and the increase of joint stiffness due to disuse of the arms [255] make the distinction of the voluntary forces even more challenging. The higher fatigue levels experienced by the participants when using the force-based control interface might be due to small errors on the estimation of the gravity and joint stiffness compensation force.

Force- vs EMG-based control

Taking into account the aforementioned difficulties of the force-based control interface to detect the voluntary forces of the user, we think that force-based control interfaces are appropriate for people that still have enough force to partially overcome the intrinsic forces of the arm. While EMG-based control might be less intuitive (specially for multi-DOF movements) than force-based control, since force is closer to the natural way of interacting with the environment, EMG signals are not affected by the intrinsic forces of the arm. Therefore we presume that EMG signals can better represent the movement intention of people with voluntary forces below the intrinsic forces of the arm. On the other hand, EMG-based interfaces present several practical issues, including the poor long term stability of the measurements, the high sensitivity to electrode location, the time required to place the electrodes and the uncomfortable feeling that the multiple electrodes may produce in contact with the skin for a long period of time.

Participants and Experimental Protocol

Due to the low density of men with DMD [256] and the legal/ethical constraint that they can only participate in one study at the same time, the access to suitable subjects was limited. In the allowed time window of this study, we had access to three participants that met all criteria, and were able and willing to participate. Being the main goal of this study to investigate the feasibility of

EMG and force as control interfaces using a research platform, we performed the tests with three participants, which allowed for an exploratory assessment of the limitations and capabilities of the control interfaces. Therefore, our results indicate, but cannot demonstrate at population level the feasibility of both control interfaces for the operation of active elbow supports for adults with DMD.

Adults with DMD experience strong training and fatigue effects due to the disuse of their arms. Therefore, the experimental protocol balanced the amount of training and evaluation trials: the protocol allowed the participants to learn how to control the Elbow Drive and perform the tracking task while having a considerable number of evaluation trials per condition (i.e. 36 trials) and keeping the overall length of the experiment below two hours to minimize fatigue. Due to the small number of participants included in this study and the high functional variability between adult men with DMD [1], randomizing the order of the control methods would not have been effective.

Implications

Several arm supports that compensate the weight of the arms are commercially available [5] and have shown to increase the independence and quality of life for people with muscular weakness [6, 35]. However, in adults with DMD, the decrease of muscle force combined with an increase of passive joint-stiffness [104, 255], due to the disuse of the arms, reduces the effectiveness of passive arm supports [105]. Table 4 presents the range of motion reached by the three participants using only passive weight compensation in the Elbow Drive. Subject S1, which was the strongest, could achieve only 15 degrees of elbow flexion with his maximum effort. At the last stage of the disease people with DMD can benefit more from active arm supports, which can provide extra assistance.

Compared to the large number of active arm prosthetic devices available for amputees [145], few active devices have been developed for supporting upper-extremity function of people with severe muscular weakness [39, 40, 7]. This feasibility study is the first step towards the development of a control interface specially designed to control active arm supports for people with DMD.

The results show a higher variability between subjects than between control interfaces (Table 7 in Supplementary Material), which indicates that it is likely that the control interfaces have to be customized for each individual with DMD.

This customization should include signal-filtering parameters, interface dynamics, sensor placement, but also the physiological signals (i.e. EMG, force or combination) used to derive the motion intention of the user.

First One-DOF Control

Upper-extremity assistive devices that support the performance of activities of daily living require multiple-DOF. It is part of our continued investigations to determine how many DOF are needed and what is the most suitable way to control them. There are no studies that evaluated the feasibility of EMG and force as control interfaces in adults with DMD. Hence, our strategy was to carry out an evaluation with a one-DOF active elbow support to focus on the control capabilities of men with DMD before integrating the complexity of a multi-DOF assistive device.

Extension to Multi-DOF Control

The extension of the control interfaces to a device with multiple DOF will increase their complexity, which might lead to clear performance differences between the two control interfaces. While the calibration-based method proved to be effective for the distinction of the user's voluntary force to control the elbow movement, it might become too cumbersome for the compensation of gravity and joint stiffness in a multi-DOF arm support where the arm can acquire a large variety of poses. We have performed preliminary measurements of joint stiffness forces in the horizontal plane [257] that can be used for their compensation.

Several studies have shown simultaneous and proportional control of two-DOF in arm prosthesis by means of regression-based algorithms [97, 155] and three-DOF using intramuscular EMG electrodes [258]. Furthermore, there are studies that have correlated shoulder EMG to arm kinematics [233, 259]. We are currently working on the extension of the one-DOF proportional EMG-based control used in the Elbow Drive system, to multiple-DOF, and the implementation of regression-based control methods for arm prosthesis to active arm supports for people with DMD. Preliminary results of a proportional and simultaneous two-DOF EMG-based control interface for assisting planar movements

in task-space, can be found in [260]. In [260], EMG signals from biceps/triceps were mapped to right/left translations of the hand and EMG signals of deltoid anterior/posterior were mapped to forward/backward translations of the hand.

4.5 CONCLUSIONS

This study presents a feasibility and performance evaluation of EMG- and force-based interfaces during a one DOF discrete position-tracking task with adults with DMD. All subjects were able to complete 100 % of the series of tracking tasks with both control interfaces with an average task completion time of 6.8 ± 4.8 s and 5.1 ± 1.8 s for the EMG- and force-based control respectively. While movements with the force-based control were considerably smoother (difference between means: 19 zero crossings; $p < 0.001$) in Subject 3 and faster in Subject 1 (difference between means: 2.5 s; $p < 0.001$), EMG-based control was perceived to be less fatiguing by all three participants. In conclusion, we found important variability among subjects in terms of performance of EMG- and Force-based interfaces, and both methods are feasible for the control of one DOF active elbow supports in men with DMD with very limited arm function. Both EMG- and force-based interfaces should be further investigated for the control of multi-DOF active arm supports.

SUPPLEMENTARY MATERIAL

Table 7: p-values of Friedman Tests

	TCT	OS	TE	SM
Control	NS	**	NS	NS
Interface	0.31	0.0011	0.15	0.67
Subject	***	***	***	***
	1.0×10^{-6}	0.0003	1.4×10^{-15}	2.2×10^{-16}

Note: TCT: task completion time; OS: overshoot, TE: Trajectory efficiency; SM: smoothness. (NS) indicates no significant. (*) indicates $p < 0.05$. (**) indicates $p < 0.01$. (***) indicates $p < 0.001$.

Table 8: Performance of movements towards long targets

Performance Descriptor	Subject	EMG control		Force control		Wilcoxon tests	
		Mean	SD	Mean	SD	p-value	
Rising Time (s)	S1	5.15	2.21	2.71	0.99	0.0002	***
	S2	1.85	0.39	2.51	0.60	0.003	**
	S3	1.87	0.38	2.50	0.62	0.004	**
Settling Time (s)	S1	2.40	0.95	2.21	0.62	0.61	NS
	S2	2.47	0.69	2.25	0.46	0.40	NS
	S3	6.18	8.11	3.08	1.32	0.34	NS
Task Comp. Time (s)	S1	7.55	2.78	4.92	1.06	0.0007	***
	S2	4.32	0.76	4.76	0.67	0.039	*
	S3	8.05	8.08	5.59	1.45	0.87	NS
Overshoot (%)	S1	3.49	3.85	2.13	2.30	0.17	NS
	S2	2.74	3.59	2.30	2.51	0.96	NS
	S3	12.09	6.18	2.90	4.91	0.0002	***
Traj. Efficiency (%)	S1	93.55	6.78	93.24	6.27	0.67	NS
	S2	89.73	7.00	92.66	5.49	0.20	NS
	S3	67.24	21.61	81.03	11.11	0.04	*
Smoothness (NZC)	S1	16.56	3.98	19.06	2.17	0.052	NS
	S2	5.56	1.63	7.25	0.68	0.0008	***
	S3	37.44	2.58	18.12	0.89	1.2×10^{-6}	***

Note: NZC, number of zero crossings. (NS) indicates no significant. (*) indicates $p < 0.05$. (**) indicates $p < 0.01$. (***) indicates $p < 0.001$.

Table 9: Performance of movements towards short targets

Performance Descriptor	Subject	EMG control		Force control		Wilcoxon tests	
		Mean	SD	Mean	SD	p-value	
Rising Time (s)	S1	3.55	2.21	1.78	0.57	0.0003	***
	S2	1.43	0.52	1.92	0.59	0.012	*
	S3	1.79	0.72	2.00	0.64	0.30	NS
Settling Time (s)	S1	2.28	0.76	2.59	0.60	0.04	*
	S2	2.52	0.95	2.33	0.50	0.77	NS
	S3	7.96	4.09	3.28	1.58	0.0003	***
Task Comp. Time (s)	S1	5.83	1.64	4.36	0.52	0.004	**
	S2	3.94	0.88	4.25	0.69	0.052	NS
	S3	9.74	4.45	5.28	1.54	0.0007	***
Overshoot (%)	S1	5.77	4.25	6.80	6.52	0.51	NS
	S2	4.88	6.23	5.13	7.54	0.93	NS
	S3	26.89	15.10	11.54	22.75	0.0008	***
Traj. Efficiency (%)	S1	89.70	9.08	78.54	13.45	0.019	*
	S2	81.14	11.87	86.80	10.97	0.20	NS
	S3	39.64	16.34	64.03	17.50	0.0004	***
Smoothness (NZC)	S1	18.56	5.25	21.12	2.13	0.17	NS
	S2	6.19	2.20	6.94	1.84	0.23	NS
	S3	39.81	3.25	19.56	1.82	1.35e-6	***

Note: NZC, number of zero crossings. (NS) indicates no significant. (*) indicates $p < 0.05$. (**) indicates $p < 0.01$. (***) indicates $p < 0.001$.

Figure 34: Elbow angle displacements and task completion rate (solid grey area) as function of time during the 16 evaluation trials of subjects S1, S2 and S3 using the EMG- (blue) and the force-based (red) control interfaces while reaching towards the short (right) and long (left) target angles (black solid line). The dashed black line indicates the limits of the target area. The trial number is indicated with a color intensity gradient. Task completion time of the slow trials: (1) 32 s, (2) 25 s, (3) 15 s and (4) 20 s.

SURFACE EMG SIGNALS IN VERY LATE-STAGE OF DUCHENNE MUSCULAR DYSTROPHY: A CASE STUDY¹

Abstract: *Robotic arm supports aim at improving the quality of life for adults with Duchenne muscular dystrophy (DMD) by augmenting their residual functional abilities. A critical component of robotic arm supports is the control interface, as is it responsible for the human-machine interaction. Our previous studies showed the feasibility of using surface electromyography (EMG) as a control interface to operate robotic arm supports in adults with DMD (22-24 years-old). However, in the biomedical engineering community there is an often raised skepticism over adults with DMD at the last stage of their disease having EMG signals that can be measured and used for control. In this study EMG signals from Biceps and Triceps Brachii muscles were measured for the first time in a 37 year-old man with DMD (Brooke 6) that lost his arm function 15 years ago. The EMG signals were measured during maximal and sub-maximal voluntary isometric contractions and evaluated in terms of signal-to-noise ratio and co-activation ratio. Beyond the notorious deterioration of the muscles, we found that EMG signals from both Biceps and Triceps muscles were measurable in this individual, although with a maximum signal amplitude 100 times lower compared to EMG from healthy subjects. Despite the low EMG amplitude and a considerable level of muscle co-activation, simulations of an elbow orthosis using the measured EMG as driving signal indicated that the EMG signals of the participant had the potential to provide control of elbow movements. These findings offer promising perspectives to the use of EMG as an intuitive and natural control interface for robotic arm supports in adults with DMD until the last stage of the disease.*

¹ This chapter has been submitted as: J. Lobo-Prat, M.M. Janssen, H.F.J.M. Koopman, A.H.A. Stienen, I.J.M. de Groot "Surface EMG signals in very late-stage of Duchenne muscular dystrophy: a case study," August. 2016 (under review).

5.1 INTRODUCTION

People with Duchenne muscular dystrophy (DMD) lose independent ambulation by the age of ten years, followed by the development of scoliosis and loss of upper extremity function during their teens, and develop severe cardiomyopathies and respiratory problems during their twenties [261]. Life expectancy of people with DMD has substantially improved over the last five decades, due to improvements in care, drugs, and the introduction of home care technology, such as artificial ventilators[3]. As a result, there is currently a considerable group of adults with DMD living with severe physical impairments and a strong dependency on care up to their 30's [4].

Several arm supports that compensate the weight of the arms are commercially available and have shown an increase of independence and quality of life for teenagers with DMD [6]. However, in adults with DMD, the decrease of muscle force combined with an increase of passive joint-stiffness [255], reduces the effectiveness of current arm supports [105, 104]. More advanced robotic arm supports can provide extra assistance, and have the potential to enable adults with DMD to continue performing activities of daily living, increasing their independence and participation in social activities.

In order to operate robotic arm supports, the user needs to communicate his motion intention to the device through a control interface. Currently, the only control interface available for adults with DMD are hand joysticks and switches, which are used to control wheelchairs and external robotic arms. We consider that the use of control interfaces that detect the motion intention from physiological signals that are implicitly related to the supported motion can result in a more natural and intuitive interaction with the robotic arm support. In this direction, we have developed and evaluated force- and surface electromyography-(EMG) based control interfaces [249, 262].

The ability for adults with DMD to use EMG-based control, a well-established control interface in upper-extremity prosthetics [130], depends on the availability and quality of their EMG signals. EMG signals have been used for decades in DMD patients for diagnosis and carrier detection [263]. These studies are mostly based on invasive needle EMG recordings. Studies with EMG in boys and men with Duchenne are less common and most of them report measurements of lower extremity, facial or oral muscles [264, 265, 266]. From a comprehensive literature review we found that Priez et. al. [267], Bowen et. al [268],

Kumangai and Yamada [269], Fascarelli et al. [270], and Janssen et al. [271] measured EMG signals from upper extremity muscles in subjects with DMD aged between 5 to 22 years. To the best of our knowledge there are no published studies that report the measurement of upper-extremity EMG signals in men with DMD older than 24 years, which is the period when robotic arm supports are most needed.

In a previous study [262], we showed that both EMG- and force-based control interfaces were feasible solutions for the control of elbow movements in adults with DMD (22-24 years-old). Force-based control was experienced as fatiguing by all participants, a fact that indicates that EMG-based control is probably the only viable interface for adults with DMD at the last stage of the disease. However, in the biomedical engineering community there is an often raised skepticism over adults with DMD at the last stage of their disease (>24 years old) having EMG signals that can be measured and used for control. As a consequence, development of assistive devices for this group of patients is getting low attention. We think that this skepticism might be based on a wrong pre-conception and that it is thus important to investigate if EMG signals from upper-extremity muscles of men with DMD at the last stage of the disease are measurable and can be used for control.

DMD patients at the last stage of their disease are very rare and getting them involved in any study is difficult and delicate, because they easily get overwhelmed by the exercises. As a consequence, conducting tests with even just a few of these subjects is very unlikely and general conclusions will have to be drawn from a number of independent studies. We were able to get the kind collaboration of a 37 year-old man with DMD for this study to evaluate his EMG signals from upper-extremity biceps and triceps muscles. Albeit results from only one subject are insufficient to draw general conclusions, they are relevant to be communicated because of their exceptional nature and will encourage similar studies.

While we hypothesized that the neural activation of the muscle is still measurable in men with DMD that have lost their arm function long time ago (DMD is a disease affecting the contraction of the muscle cells only), we expected their EMG signals to have a much lower amplitude than in the case of healthy individuals: the infiltration of fatty and connective tissue in the muscle is known to increase the electrical impedance [272]. The quality of the EMG signals was evaluated in terms of signal-to-noise ratio (SNR) and co-activation ratio (CAR).

Additionally, we evaluated the feasibility of EMG-based control by simulating the control of an active elbow orthosis using the measured EMG signals as input signal.

5.2 METHODS

Participant

A 37 year-old man with DMD participated in this study. The participant was classified according to the Brooke upper extremity function scale [27] with a score of 6 (i.e. no arm/hand function was left) and lost his arm function long time ago: shoulder movements more than 20 years ago, and elbow flexion-extension more than 15 years ago. He was able to control an electric wheelchair with a highly sensitive joystick and several push buttons that were operated using residual motion of the fingers of both hands. No other functional tasks were possible with his arms or hands. The participant also presented joint contractures caused by the disuse of the arms, which severely limited the range-of-motion of all the upper-extremity joints.

Signal acquisition and processing

The EMG signals were measured from the Biceps Brachii and Triceps Brachii muscles of the right arm, which originally was the dominant arm. Two 99.9 % Ag parallel bars electrodes (contact: 10 mm x 1 mm each) spaced 10 mm apart (Bagnoli DE-2.1. Delsys; Boston, Massachusetts) were placed in parallel with the muscle fibers following to the SENIAM recommendations [237] and manual muscle exploration, after the skin was shaved and scrubbed clean. The signals were amplified with a Delsys Bagnoli-16 Main Amplifier and Conditioning Unit (Delsys; Boston, Massachusetts) with a bandwidth of 20 to 450 Hz and a gain of 1000.

The EMG signals were measured with a data acquisition card with a sampling frequency of 1 KHz and 16 bit resolution. The offset of the raw EMG signals was removed on-line using a fourth-order Butterworth high-pass filter with a cutoff frequency of 20 Hz. Subsequently the signals were full-wave rectified and smoothed using a second-order low-pass Butterworth filter with a cutoff

frequency of 1 Hz to obtain the signal envelope. The envelopes were used for the visual feedback during the maximal voluntary isometric contractions (MVIC) and sub-maximal voluntary isometric contractions (SVIC), for the analysis of the CAR, and for the simulation of the elbow orthosis.

Measurement protocol

The participant was asked to perform a series of MVICs and SVICs with his biceps and triceps muscles. Since the participant had not been able to voluntarily flex and extend his elbow joint for a long time, the examiner passively moved his elbow joint and applied pressure against the intended movement to familiarize the subject with the task. For the MVIC measurements the researcher asked the participant to maximally flex and extend his elbow during three seconds, three times for each muscle. For the SVIC measurements the subject was asked to reach three activation levels (20 %, 40 % and 80 % of MVIC) during three seconds for each muscle. Note that the actual activation levels achieved by the participant were slightly different from these target levels (see Results section). Having three activation levels, only one run for each level could be performed to avoid overwhelming the participant with too long a session. All measurements were guided with real-time visual feedback of the EMG envelopes displayed on a computer screen. For the SVICs the researcher pointed at three levels on the computer screen used for visual feedback. Between each muscle contraction the participant rested during five to ten seconds and between each series of MVIC or SVIC tasks the participant rested during five to ten minutes.

Data analysis

The quality of the EMG signals was evaluated in terms of the SNR and the CAR. Additionally, the measured EMG signals were used to drive a simulated elbow orthosis to evaluate the feasibility of using the EMG signals for control purposes.

Signal-to-noise ratio

The SNR of the biceps (SNR_b) and of the triceps (SNR_t) was calculated by taking the ratio between the power of the root-mean-squared amplitude of the raw

EMG signal (RMS_b , RMS_t) during the three MVIC and SVIC measurements, and the power of the RMS amplitude of the raw EMG signal during a resting period, which represented the noise level (RMS_{nb} , RMS_{nt}):

$$SNR_b = \left(\frac{RMS_b}{RMS_{nb}} \right)^2, \quad SNR_t = \left(\frac{RMS_t}{RMS_{nt}} \right)^2. \quad (15)$$

The highest RMS value found within the three repetitions of the MVIC measurement was used to normalize the EMG signals of the biceps and triceps muscles for the CAR calculation.

Co-activation Ratio

Similarly to the SNR, we evaluated the involuntary activation of the antagonistic muscle by calculating the CAR of the biceps (CAR_b) and triceps (CAR_t). The CAR was defined as the ratio between the RMS amplitude of the normalized EMG signal envelope of the agonist muscle (RMS_{Nb} , RMS_{Nt}), and the RMS amplitude of the normalized EMG signal envelope of the antagonist muscle (RMS_{Nt} , RMS_{Nb}) during the three MVIC and SVIC measurements (Eq. 16). A high CAR value indicates a high level of co-activation while a low CAR value indicates that a low level co-activation is present.

$$CAR_b = \frac{RMS_{Nt}}{RMS_{Nb}}, \quad CAR_t = \frac{RMS_{Nb}}{RMS_{Nt}} \quad (16)$$

The normalized signal envelopes of the biceps (RMS_{Nb}) and triceps (RMS_{Nt}) were calculated by dividing the RMS value of the signal envelope (RMS_{Eb} , RMS_{Et}) by the RMS value of the signal envelope of the MVIC ($RMS_{Eb_{MVIC}}$, $RMS_{Et_{MVIC}}$; Eq. 17). Note that the RMS value of the noise envelope (RMS_{Enb} , RMS_{Ent}) was subtracted from signal envelopes before calculating RMS_{Nb} and RMS_{Nt} .

$$RMS_{Nb} = \frac{(RMS_{Eb} - RMS_{Enb})}{RMS_{Eb_{MVIC}} - RMS_{Enb}}, \quad RMS_{Nt} = \frac{(RMS_{Et} - RMS_{Ent})}{RMS_{Et_{MVIC}} - RMS_{Ent}} \quad (17)$$

Elbow orthosis simulation

To evaluate the feasibility of using the measured EMG signals for control purposes, we performed an off-line simulation (i.e. open-loop control) of a EMG-controlled elbow orthosis. This method was chosen because the high intrinsic stiffness and contractures present in the elbow joint of the participant prevented the use of a real robotic elbow orthoses.

The control method implemented in the simulation and described in this subsection was the same used in our previous study [262]. An estimation of the elbow torque ($\hat{\tau}_e$) was obtained by multiplying the signal envelopes of the biceps and triceps EMG signals (E_b , E_t) by a mapping gain (K_b , K_t) and subsequently subtracting the triceps signal from the biceps signal:

$$\hat{\tau}_e = E_b K_b - E_t K_t. \quad (18)$$

Note that a fix offset resulting from the EMG signal noise was removed from the signal envelopes to obtain E_b and E_t . The offset value was calculated by taking the mean value of the signal envelope during three seconds while the participant was relaxed. For the simulation, one MVIC of the biceps ($MVIC_b$ 1) and one of the triceps ($MVIC_t$ 3; shown in Fig. 35) were concatenated and used as E_b and E_t . For this simulation, the aforementioned MVICs and the mapping gains ($K_b = 2$, $K_t = 0.72$) were chosen to obtain a symmetric elbow flexion-extension movement.

The estimated elbow torque was then used as input for an admittance model that rendered the dynamics of a mass-damper system and had as output the elbow angle (θ_e):

$$\theta_e(s) = \frac{1}{(I_v s^2 + B_v s)} \hat{\tau}_e(s), \quad (19)$$

where I_v and B_v represent the virtual mass and damping parameters of the admittance model respectively, and s is the Laplace transform variable. Note that in a real elbow orthosis, the elbow angle (θ_e ; or the angular velocity) resulting from Eq. (20) would be used as reference signal for a low-level position (or velocity) controller of the elbow orthosis as in [262]. The simulation was done with $I_v = 4 \cdot 10^{-3}$ Kg m² and $B_v = 1 \cdot 10^{-3}$ Nm s/rad respectively, which resulted in a

Figure 35: Raw EMG signals during three maximal voluntary isometric contractions (MVIC) of biceps and triceps muscles. **A)** Agonist contractions of biceps in blue; signal of antagonist muscle (triceps) in red. RMS values for each MVIC of the biceps: $MVIC_{b1}=0.0021$ mV, $MVIC_{b2}=0.0016$ mV, $MVIC_{b3}=0.0019$ mV. **B)** Agonist contractions of triceps in red; signal of antagonist muscle (biceps) in blue. RMS values for each MVIC of the triceps: $MVIC_{t1}=0.0024$ mV, $MVIC_{t2}=0.0026$ mV, $MVIC_{t3}=0.0025$ mV.

motion close to the natural range of the elbow joint. In a real elbow orthosis the interface dynamics and the mapping gains would be chosen to the convenience of the user.

5.3 RESULTS

Maximal voluntary isometric contractions (MVIC)

The raw EMG signals of the MVICs during three seconds presented maximum amplitudes of 0.01 and 0.015 mV for biceps and triceps muscles respectively (Fig. 35). The RMS values of the EMG signals of the agonist muscle were higher for the triceps ($MVIC_t$ in Fig. 35) than for the biceps ($MVIC_b$ in Fig. 35) in all three repetitions, with an average value of 0.0025 mV for the triceps and 0.0019 mV for the biceps. Also, the mean SNR (Fig. 38A) of the triceps during MVIC was double than that of the biceps ($SNR_t : 4.16 \pm 0.5$; $SNR_b : 2.17 \pm 0.5$; Fig. 38A).

Figure 36: Envelope of the EMG signals during sub-maximal voluntary isometric contractions of biceps muscles. **A)** Envelope of the EMG signals measured during the SVIC of the biceps muscle in blue. Envelope of the antagonist muscle (triceps) in dashed red. **B)** Boxplots of the 3000 data points (i.e. 3 seconds) measured for each of the SVIC levels. In blue the boxplots of the biceps EMG signals and in faded red the boxplots of the antagonist muscle (triceps). Note that the noise level of the EMG signal during relaxation is also shown.

Both RMS and SNR values were lower for the biceps than for the triceps which could indicate a higher muscle atrophy of the biceps (infiltration of fatty and connective tissue in the muscle, which degrades the EMG signal).

Mean CAR values for both muscles during the MVICs were 0.55 ± 0.2 for the biceps and 0.44 ± 0.2 for the triceps (CAR_b and CAR_t respectively in Eq. 16), which indicated notorious co-activation of the antagonist muscle, even more so for the biceps than for the triceps (38B).

Figure 37: Envelope of the EMG signals during sub-maximal voluntary isometric contractions of triceps muscles. **A)** Envelope of the EMG signals measured during the SVIC of the triceps muscle in red. Envelope of the antagonist muscle (biceps) in dashed blue. **B)** Boxplots of the 3000 data points (i.e. 3 seconds) measured for each of the SVIC levels. In red the boxplots of the triceps EMG signals and in faded blue the boxplots of the antagonist muscle (biceps). Note that the noise level of the EMG signal during relaxation is also shown.

Sub-maximal voluntary isometric contractions (SVIC)

When performing the SVICs, the participant was able to generate EMG signals that followed the level of effort demanded by the task (Fig. 36 and 37), indicating that the participant could voluntarily modulate the required level of muscle

activation. The SNR of the SVICs increased for both biceps and triceps muscles with the increase of SVIC level (Fig. 38A), as expected because of the raise in signal amplitude. In agreement with the results of the MVICs, the SNRs of the triceps muscle were higher than the ones of the biceps muscle for all conditions.

The CARs of the biceps muscle were higher than the CARs of the triceps muscle for all levels of SVIC (Fig. 38B). While the CARs of the triceps muscle presented values close to 0.5 for all SVICs (with the exception of the 20 % SVIC level) the CARs of the biceps muscle presented more variability over activation levels: the CAR of the 20 % SVIC level was above 1.5, the CAR of the 40 % SVIC level and of 100 % was close to 0.5, and the CAR of the 80 % SVIC level was close to 1.

Elbow orthosis simulation

Figure 39A and B show the raw and the envelope of the EMG signals respectively used as input for the simulation. Figure 39C shows the estimated muscle torque calculated by multiplying the signal envelope with the mapping gains K_b and K_t . Note that after applying the mapping gains, the biceps signal is larger than the triceps signal for the first half of the movement and the triceps signals is larger then the biceps signal for the second half of the movement. Figure 39D shows the estimated elbow torque resulting from the difference between the biceps and triceps muscle torques. Figure 39E presents the output of the admittance controller and shows that the simulated system responded with a positive angular velocity during the first part of the movement (biceps activation) and a negative angular velocity during the second part (triceps activation). The integral of this angular velocity is shown in Fig. 39F, which indicates that the simulated orthosis would successfully support an elbow flexion and extension movement of 1 rad in 20 s with a maximum speed of ± 0.2 rad/s under the control of the realistic EMG signals shown in Fig. 39A. Note that the apparent delay between the muscle activation signal and the initiation of the movement is due to the phase lag of the second order dynamics of the admittance model Eq. (20).

Figure 38: Signal-to-noise ratio (SNR) and co-activation ratio (CAR) for the biceps and triceps EMG signals as function of activation level. **A)** Signal-to-noise ratios of the biceps (blue) and triceps (red) EMG signals during the three SVIC and MVIC. **B)** Co-activation ratios of the biceps (blue) and triceps (red) EMG signals during the three SVIC and MVIC. Note that the error bar is only shown for the MVIC as this measurement was repeated three times.

5.4 DISCUSSION

Our results revealed the notorious deterioration of the upper-extremity muscles of the 37-year-old man with DMD. The maximum amplitudes of the EMG signals of the participant were 100 times lower than those typical of healthy individuals (i.e. our measurements of 0.01 mV vs. the 1 mV measured in healthy individuals [273]). These low signal amplitudes implied low SNRs. We also found notorious involuntary activation of the antagonistic muscle as revealed by the measured CARs, which could be caused by the disuse of the arms. Note that

Figure 39: Simulation of the EMG-controlled elbow orthosis. **A)** Raw EMG signals used as input for the simulation. Specifically the first ($MVIC_b1$) and third ($MVIC_t3$) MVIC attempts of the biceps (blue) and triceps (red). **B)** Envelopes of the raw EMG signals of the biceps (blue) and triceps (red). **C)** Estimated muscle torque of the biceps (blue) and triceps (red) obtained by multiplying the envelopes multiplying by the mapping gains K_b and K_t . **D)** Estimated elbow torque calculated by subtracting the estimated triceps torque from the estimated biceps torque (Eq. 18). **E)** Angular velocity resulting from the admittance model (Eq. 20). **F)** Elbow angle displacement resulting from the integral of the angular velocity (Eq. 20).

arm immobilizations of 12 hours are sufficient to significantly reduce motor performance in healthy subjects [274].

Despite the deterioration, we cannot underestimate the fact that EMG signals from the biceps and triceps muscles were still measurable in a 37-year-old man with DMD that presented considerable muscle deterioration since 20 years ago and completely lost his arm function 15 years ago. Our results also indicate that the participant was able to adjust his voluntary isometric contractions as demanded by the exercises.

The relevance of detecting measurable upper-extremity EMG signals in adults with DMD at the late-stage of the disease extends beyond its clinical interest. EMG signals can be used to detect the users' motion intention and control rehabilitation or assistive devices, which have the potential to delay the disease progression and increase the quality of life for men with DMD [24, 26]. On this regard, our simulation, which used the measured EMG signals as input, indicated that, if the high degree of stiffness and joint contraction were not present, the participant could control an active elbow orthosis to perform flexion-extension movements with a simple proportional EMG-based control method. The angular velocity and displacement calculated by the simulation indicates that it was possible to detect the elbow flexion/extension intention of the user when contracting the biceps and the triceps muscle.

Currently, the use of a robotic elbow orthoses in adults with DMD in the last stage of the disease is not an option due to the high intrinsic stiffness and joint contractures. However, the use of robotic arm supports, would allow adults with DMD to keep using their arms and therefore contribute to the delay of the functional deterioration. We expect that in the future, boys and men with DMD will use arm supports from an early age, which would preserve the range of motion of their joints and enable them to use EMG-controlled arm supports until the last stage of the disease.

5.5 CONCLUSIONS

The results of the present case study indicate that EMG signals from the biceps and triceps muscles were very deteriorated but still measurable in a 37 year-old man with DMD that lost his arm function several years ago. Also, the participant was able to adjust his muscle activation level as demanded by the exercises. To the best of our knowledge this is the first time that EMG signals from a man

with DMD older than 24 years were measured and reported. Despite the muscle deterioration, the measured signals could be successfully used as input for the control of a simulated elbow orthosis. These results offer promising perspectives to the use of EMG as an intuitive and natural control interface for assistive devices in adults with DMD until the last stage of the disease, provided that the use of assistive devices since an early stage of the disease reduce joint stiffness and contractures.

Results from only one subject are insufficient to draw general conclusions, but the difficulties to involve participants with DMD in the last stage of the disease makes the inclusion of several patients in one single study highly complicated. Thus, sufficient evidence should come by integrating independent studies performed in different laboratories. We hope that the results presented in this Short Report will start breaking the current general opinion that EMG signals are too weak in DMD patients at the last stage of the disease to be used for control, and will encourage similar studies in other parts of the world, finally leading to better assistive devices for adults with DMD.

COMPARISON BETWEEN EMG AND FORCE AS CONTROL INTERFACES FOR SUPPORTING PLANAR ARM MOVEMENTS IN ADULTS WITH DUCHENNE¹

Abstract: *Adults with Duchenne muscular dystrophy (DMD) can benefit from devices that actively support their arm function. A critical component of active arm supports is the control interface as it is responsible for the human-machine interaction. Our previous work indicated that surface electromyography (EMG) and force-based control with active gravity and joint-stiffness compensation were feasible solutions for the support of elbow movements (one degree of freedom). In this paper, we extend the evaluation of EMG- and force-based control interfaces to simultaneous and proportional control of planar arm movements (two degrees of freedom). Three men with DMD (18-23 years-old) with differing levels of arm function (i.e. Brooke scores of 4, 5 and 6) performed a series of line-tracing tasks over a tabletop surface using an experimental active arm support. The arm movements were controlled using three control methods: EMG-based control, force-based control with stiffness compensation (FSC), and force-based control with no compensation (FNC). The movement performance was evaluated in terms of task completion rate, tracing error, smoothness and speed. For subject S1 (Brooke 4) FNC was the preferred method and performed better than FSC and EMG. FNC was not usable for subject S2 (Brooke 5) and S3 (Brooke 6). Subject S2 presented significantly lower movement speed with EMG than with FSC, yet he preferred EMG since FSC was perceived to be too fatiguing. Subject S3 could not successfully use neither of the force-based control methods (i.e. FNC and FSC), while with EMG he could reach almost his entire workspace. Our results indicate that, EMG-based control interfaces are better suited for adults with DMD than force-based control interfaces as they are experienced as less fatiguing. Nevertheless, force-based control interfaces with active gravity and joint-stiffness compensation can be a better alternative for those cases in which voluntary forces are higher than the intrinsic forces of the arms.*

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6.1 INTRODUCTION

Duchenne muscular dystrophy (DMD) is an X chromosome-linked recessive neuromuscular disease, which affects mainly males. It is diagnosed in childhood with an incidence of 1:5000 male live births [8]. Defective mutations in the dystrophin gene result in progressive degeneration of skeletal, respiratory and cardiac muscles. Generally people with DMD lose independent ambulation by the age of ten, followed by the development of scoliosis and deterioration of the upper extremity function during their teens, and develop severe cardiomyopathies and respiratory problems during their twenties [10, 2]. Over the last five decades, the lifespan of men with DMD has increased from 20 to 35 years due to improvements in health care and the introduction of home care technology, such as artificial ventilators [13]. As a result, there is currently a considerable group of adults with DMD living with severe physical impairments and a strong dependency on care [1].

People with DMD can benefit from commercially available passive arm supports that compensate for the weight of their arms [6, 35]. By the time they reach their twenties, the decrease of muscle force combined with the increase of passive joint-stiffness [255, 4] generally makes gravity compensation insufficient to support their arm function [105]. At that point, adults with DMD may benefit more from active arm supports, which can provide extra support and augment their residual capabilities. Active arm supports could enable them to continue performing basic activities of daily living and maintain social participation.

To control such devices, the user needs a way to communicate his motion intention to the device through a control interface [249]. In our previous work [262] we investigated the feasibility of using surface electromyography (EMG) and force-based control with active gravity and joint-stiffness compensation. Three adults with DMD (Brooke score 5) performed a series of discrete position-tracking tasks using a one degree-of-freedom (DOF) active elbow support. Despite all three participants not having performed any voluntary movements with their arms for the past 3-5 years, all of them were 100% successful in completing the series of discrete position-tracking tasks with a reasonable average completion time using both control interfaces. These results indicated that both methods were feasible for the control of one-DOF active elbow supports by adults with DMD who have very limited arm function.

This paper extends the feasibility study on the use of EMG and force as control interfaces from one to two DOF². The goals of this study were: (I) to investigate whether adults with DMD can use EMG-based control, force-based control with stiffness compensation (FSC) and force-based control with no compensation (FNC) to perform planar arm movements; (II) to evaluate their movement performance during a line-tracing task; and (III) to examine users' acceptance of the control methods.

EMG- and Force-based Admittance Control

In [262], both force- and EMG-based control interfaces were used in combination with an admittance model (Eq. 20) that mapped the estimated force of the user ($\hat{F}_{vol}$), to the intended motion of the arm support (v_{ref}). Using this control method, the interface dynamics of the device can be modified by changing the virtual parameters of the admittance model, which is usually composed of mass (M_{vir}), damping (D_{vir}), and stiffness (K_{vir} ; not used in our application).

$$H_{adm}(s) = \frac{v_{ref}(s)}{\hat{F}_{vol}(s)} = \frac{1}{M_{vir}s + D_{vir}} \quad (20)$$

In order to have a control interface that is highly responsive to the low amplitude signals of people with DMD, the admittance model should have M_{vir} and B_{vir} as low as possible (i.e. highest admittance possible).

Figure 48 shows a simplified control diagram of EMG- and force-based admittance control. To perform a movement the man with DMD generates neural commands (C_{nrl}) with his central nervous system, which result in muscle activation (i.e. from where EMG signals (E_{sen}) are measured) and muscle contraction that generates voluntary muscle force (F_{vol}). The muscle force, together with the force from the passive dynamics of the arm (H_{pas} , Eq. 32), results in the interaction force between the device and the user (F_{int}), which is measured by the force sensor.

$$H_{pas}(s) = \frac{F_{pas}(s)}{v_{sup}(s)} = M_{pas}s + D_{pas} + \frac{K_{pas}}{s}. \quad (21)$$

Figure 40: EMG- and Force-based Admittance Control. Simplified control diagram of the physiological system and the assistive system. To perform a movement the man with DMD generates neural commands (C_{cnt}) with his central nervous system (CNS), which result in muscle activation (i.e. from where EMG signals E_{sen} are measured) and muscle contraction that generates voluntary muscle force (F_{vol}). Either Force (F_{int}) or EMG signals (E_{sen}) are used to derive the motion intention of the user and control the assistive system. **A)** The interaction force (F_{int}), which is a combination of the voluntary muscle force (F_{vol}) and the passive/intrinsic human arm force (F_{pas}) is measured by a force sensor (F_{int}). An estimation of the voluntary force of the user is obtained by actively compensating the intrinsic arm force ($\hat{F}_{com}$). **B)** EMG signals from the arm muscles of the user are measured and a voluntary force is estimated from them. In both control methods the estimated voluntary force is used as input for an admittance model. The resulting velocity reference signal (v_{ref}) is send to a low-level velocity feedback controller that operates the actuator. The resulting force (F_{res}) generated by the actuator (F_{act}) together with the interaction force (F_{int}) moves the passive robot and human arm dynamics.

When using force-based control (Fig. 48A) the force sensor measures the interaction force (F_{int}), which contains not only the voluntary force of the user (F_{vol}), but also the intrinsic (or passive) forces of the arm (F_{pas}). Thus, to assist the movement intention of the user it is crucial to distinguish the voluntary force from the other components. In order to have an estimate of the voluntary force of the human ($\hat{F}_{vol,f}$), the “Active Compensation Method” subsystem in Fig. 48A estimates the intrinsic arm forces ($\hat{F}_{com}$) using information of the arm movement (v_{sup}). The estimated compensation force is then subtracted from the measured interaction force:

$$\hat{F}_{vol,f} = F_{int} - \hat{F}_{ine}(v_{sup}s) - \hat{F}_{dmp}(v_{sup}) - \hat{F}_{stf}(v_{sup}/s), \quad (22)$$

where F_{ine} indicates the arm inertia force, F_{dmp} indicates the joint-damping force and F_{stf} indicates the joint-stiffness force. Note that an active arm support with force-based control with no active compensation (i.e. FNC) of the intrinsic force of the human arm resembles the behavior of a passive arm support with a certain mass (M_{vir}) and damping (D_{vir}).

The active compensation of human inertia and damping forces has been investigated by Aguirre-Ollinger et al. in several studies [275, 276, 277]. Furthermore, in our previous work [257, 262] we have investigated measurement- and state-machine-based methods for the active compensation of gravity and joint-stiffness forces, which are the dominant components in low-frequency arm movements. In this study we will investigate force-based control with active compensation of joint-stiffness force (i.e. FSC) over two degrees of freedom.

In the case of EMG-based control (Fig. 48B), the voluntary force of the user ($\hat{F}_{vol,e}$) is directly estimated from the EMG signals. Several methods have been developed to estimate the voluntary force of the user [249] from EMG signals. Note that, in contrast to force-based control interfaces, the EMG signals are not affected by the passive arm dynamics, and therefore, do not require any compensation method. However, EMG-based control presents several practical limitations, including poor long-term signal stability, the time required to place the electrodes on top of the specific muscles, and probably a lower intuitiveness compared to force-based control [249].

METHODS

The feasibility of using EMG and force-based control interfaces for supporting planar movements in adults with DMD was evaluated with three participants and using a commercial robotic manipulator as experimental arm support during a series of line-tracing tasks.

Participants

Three adults with DMD participated in this study (18-23 years old). Participants were carefully selected considering that they should have diverse levels of arm function with Brooke scores [251] of 4, 5 and 6. We choose participants with diverse arm function to explore the feasibility of the control interfaces in different stages of the disease. Demographic information of the subjects is shown in Table 10.

The Setup

The UR5 Robotic Arm (UR5, Universal Robots, Denmark) was used as a research platform to provide active support for planar arm movements (Fig. 41). A plastic forearm scale from the Darwing arm support (Focal Meditech, Tilburg,

Table 10: Demographic and arm function information of the participants.

Subject's Code	Age (years)	Brooke score	Preferred Arm	Maximum Force (N)	Arm Function
1	22	4	Right	22	can raise hands to mouth, but cannot raise 200 g to mouth
2	18	5	Right	6	cannot raise hands to mouth, but can use hands to hold a pen or to pick up coins
3	23	6	Right	3	cannot raise hands to mouth and has no useful function of the hands

The Netherlands), with a custom-made wrist support was attached to the end-point of the robot. Between the arm scale and the end-point of the robot, a 6-DOF force/torque sensor (ATI mini 45, Industrial Automation, USA) was mounted to measure the interaction force and torque between the user and the robot (${}^s\mathbf{W}_{int}$ in Fig. 42). Four differential-surface EMG wireless electrodes (Trigno Lab, Delsys, USA) were used to measure EMG signals (E_{sen_k} in Fig. 42) from four arm muscles: biceps, triceps, deltoid anterior and deltoid posterior. A metal rod with a marker attached at the end of it was mounted on the last segment of the UR5 Robotic Arm and served as a pointer for the tracing task.

Both the EMG- and the force-based interfaces controlled the horizontal linear velocities of the pointer (${}^g\dot{\mathbf{p}}_{ref_{x,y}}$) in the global reference frame (ψ_g in Fig. 41). In both control methods, the rotational velocity of the pointer around the vertical axis (${}^g\dot{\theta}_{ref_z}$) was actively driven by the interaction torque between the subject's arm and the robot. In this way, the task of the experimental subject was reduced to controlling the position of the pointer in the plane (i.e. two-DOF tasks), and the orientation of the arm was automatically given by the musculoskeletal constraints acting on the human arm. The UR5 robot controller was programed to control the velocity of a virtual end-point that was set to coincide with the endpoint frame (ψ_e in Fig. 41). The remaining three DOF of the robot's virtual endpoint were locked (${}^g\dot{\mathbf{p}}_{ref_z} = 0; {}^g\dot{\theta}_{ref_{x,y}} = [0, 0]^3$).

The analog signals from the force/torque sensor and the EMG signals were measured by a real-time computer (xPC Target 5.1, MathWorks Inc., USA) by means of a National Instruments card (PCI-6229; National Instruments Corp., USA), which performed the analog-to-digital conversion at a sampling frequency of 1 kHz and 16-bit resolution. The controller was also running on the real-time computer and was sending the velocity commands (using the URscript function *speedl* [278]) at 125 Hz through UDP communication to a Windows PC, which at the same time was communicating with the UR5 robot via TCP/IP communication at a frequency of 125 Hz. The Windows PC that interfaced between the robot controller and the real-time computer was required because TCP/IP communication was not supported by the real-time computer.

Signal Processing and Control

The participants performed a line-tracing task with the goal of reaching the end point of the target line ($\mathbf{p}_{tar}$). The central nervous systems received propriocep-

Figure 41: The research setup. Subject S1 controls the active arm support during the evaluation of the control interfaces. The task of the subject was to trace the target path with the pointer, which was connected to the endpoint of the UR5 Robotic Arm. The UR5 Robotic Arm was used as an active arm support which could be controlled with EMG- and force-based control interfaces.

tive and visual information about the current pointer position ($\mathbf{p}_{cur}$) and the target position, and sent neural commands ($\mathbf{C}_{nrl}$) to the arm muscles in order to perform the task. The intention of the user was detected in two ways: (I) by measuring EMG signals ($\mathbf{E}_{sen}$); or (II) by measuring the interaction force and torque, between the user's arm and the active arm support (${}^s\mathbf{W}_{int}$).

EMG-based control: For the EMG-based control, the acquisition of the EMG signals' envelopes ($\mathbf{E}_{env}$) was performed by using a full-wave rectification and filtering with a 2nd order Butterworth filter with a cut-off frequency of 3 Hz. The filter settings were chosen in line with previous studies on EMG control [67, 232, 262, 260] and pilot trials on our setup to find a fair tradeoff between signal bandwidth and phase-lag. The voluntary ($\mathbf{E}_{vol}$) and the normalized ($\mathbf{E}_{nor}$) EMG signals were derived using:

$$E_{nor_k} = \frac{E_{vol_k}}{E_{mvic_k}}, \text{ where } E_{vol_k} = E_{env_k} - E_{res_k}, \quad (23)$$

subscript k represents the abbreviations of the biceps (b), triceps (t), deltoid anterior (da) and deltoid posterior (dp) muscles, E_{env_k} denotes the processed EMG envelope signal, E_{res_k} represents the average of the processed EMG envelope signal during rest, and E_{mvic_k} represents the mean maximum magnitude of E_{env_k} over three seconds of maximum voluntary isometric contraction (MVIC). The normalized EMG signals were used to derive the force estimations for the two controlled DOF (${}^g\hat{F}_{vol,e_x}$, ${}^g\hat{F}_{vol,e_y}$) of the endpoint using:

$${}^g\hat{F}_{vol,e_x} = E_{nor_b} - E_{nor_t} \text{ and } {}^g\hat{F}_{vol,e_y} = E_{nor_{da}} - E_{nor_{dp}}, \quad (24)$$

where the $\hat{}$ denotes that a value is estimated, and the superscript g denotes that the estimated force is expressed in the global coordinate frame (ψ_g in Fig. 41).

Force-based control: For the force-based control interface, the interaction force and torque, denoted with a wrench (${}^s\mathbf{W}_{int}$), were measured with the force/torque sensor (${}^s\mathbf{W}_{int} = [{}^s\boldsymbol{\tau}_{int}^T, {}^s\mathbf{F}_{int}^T]^T$) and expressed in the sensor frame (ψ_s). The measured wrench was transformed to the endpoint coordinate system (ψ_e) using standard rotation and transformation matrices and rotated to match the orientation of the global coordinate system (ψ_g). With the measured wrench expressed in the global frame (${}^g\mathbf{W}_{int}$), the estimated joint-stiffness compensation force (${}^g\hat{\mathbf{F}}_{stf_{x,y}}({}^g\mathbf{p}_{cur_{x,y}})$) was subtracted from the horizontal measured force (${}^g\mathbf{F}_{int_{x,y}}$) to obtain an estimate of the voluntary force applied by the user (${}^g\hat{\mathbf{F}}_{vol,f_{x,y}}$). The estimated joint-stiffness compensation force was obtained by performing a force measurement during a slow movement of the arm along a predefined grid that covered the participant's workspace (see Figure 43). The arm of the participant was moved by the robot in position control mode while the user was relaxed. After this measurement a two-dimensional linear interpolation was applied (using the Matlab function *interp2*) to achieve a force field with a uniform resolution (i.e. 50×50 points).

Figure 42: The control diagram implemented in the active arm support. The upper section represents the physiological system (user), while the lower section represents the assistive system (active arm support).

Figure 43: Graphical representation of the path made by the robot across the participant's workspace (dashed square) and used to obtain the joint-stiffness force field.

The force field was then used for the force-based control with stiffness compensation (i.e. FSC) by subtracting the interpolated values of the force-field for a specific x and y position of the endpoint (${}^g\mathbf{p}_{cur_{x,y}}$):

$${}^g\hat{\mathbf{F}}_{vol,f_{x,y}} = {}^g\mathbf{F}_{int_{x,y}} - {}^g\hat{\mathbf{F}}_{stf_{x,y}}({}^g\mathbf{p}_{cur_{x,y}}). \quad (25)$$

For the force-based control with no compensation (i.e. FNC), the force expressed in the global reference frame was equal to the estimated voluntary force (${}^g\mathbf{F}_{int_{x,y}} = {}^g\hat{\mathbf{F}}_{vol,f_{x,y}}$). A more detailed description of the joint-stiffness force-field interpolation method can be found in [45].

Depending on which control method was used, the estimated force resulting from the EMG-based or the force-based control (i.e. ${}^g\hat{\mathbf{F}}_{vol,f_{x,y}}$ or ${}^g\hat{\mathbf{F}}_{vol,e_{x,y}}$) was mapped to linear velocities (${}^g\dot{\mathbf{p}}_{ref_{x,y}}$) using an admittance model (i.e. H_{adm_e} or H_{adm_f}). The admittance model represented the dynamics of a mass-damper system. The torque signal around the vertical axis (${}^g\tau_{sen_z}$) was also mapped to angular velocities (${}^g\dot{\theta}_{ref_z}$) using an admittance model (H_{adm_t}) that modeled the dynamics of an inertia-damper system:

$$H_{adm_c} = \frac{1}{A_c s + B_c}. \quad (26)$$

where subscript c stands for the type of control input: torque (t), EMG (e) or force (f). The values of the parameters of the force and torque interface dynamics (Table 11) were chosen from pilot trials with two men with DMD and were set as low as the robot could handle without becoming unstable in contact with the passive human arm dynamics. The EMG interface dynamics were also chosen from pilot trials with men with DMD and note that these are effectively scaled to the MVIC values as in [262]. In both cases the admittance parameters were chosen with the criteria that the interaction with the robot had to be safe (i.e. no instabilities or fast movements that could injure the arm).

The vector of the linear reference velocities (${}^g\dot{\mathbf{p}}_{ref_{x,y}}$) was combined with the rotational velocity reference (${}^g\dot{\theta}_{ref_z}$) and sent to the UR5 robot. The velocity controller of the UR5 robot made the motors apply a wrench (${}^s\mathbf{W}_{mot}$) that in combination with the interaction wrench (${}^s\mathbf{W}_{int}$) moved the passive dynamics of the robot and of the human arm.

Experimental Protocol

The participants were invited to the Rehabilitation Department of the Radboud University Medical Center. After a detailed explanation of the purpose and procedure of the experiment, the participants placed their wheelchair in front of a height-adjustable table that was used to present the tracing task to the subjects. A comfortable position of the arm scale and the amount of padding was adjusted to the convenience of the participants. Afterwards, the EMG electrodes were placed and the EMG signals were checked. The MVIC for each muscle was measured with the arm attached in the arm scale and instructing the participant to perform three seconds of MVIC for each of the four targeted muscles. The participant had visual feedback of the raw EMG signals and the envelopes

Table 11: Admittance transfer function parameters

	A_c	B_c
H_{adm_e}	10 kg	10 Ns/m
H_{adm_f}	15 kg	5 Ns/m
H_{adm_t}	2 kgm ²	1 Nms/rad

of the EMG signals during the measurement of the MVIC. Consequently, the passive range of motion (ROM; shown as black lines in Fig. 45 and 44) of the participants was defined using the active arm support in force-based admittance control with a high virtual damping (i.e. $B_f = 20 \text{ Ns/m}$) while the researcher moved the arms of the participants along the target lines. Once the MVIC of the EMG signals and the passive ROM were measured, the training for the EMG-based control started.

EMG-based Control: First, movements along the x direction were trained for a maximum of 15 minutes. Subsequently, movements in the y direction were trained for the same amount of time, and finally movements in both x and y directions simultaneously were trained for 15 minutes while practicing the line-tracing task. The line-tracing task consisted of tracing the five target lines (see black lines in Figure 41) as accurate and fast as possible in a clock-wise direction, i.e. starting from the line pointing towards the subject's left side and finishing with the line pointing to the subject's right side. After the training phase, the subject performed the evaluation trials, which consisted of tracing the five lines three times (i.e. 15 trials). Once the evaluation trials with the EMG-based control interface were finished, the participant had a break of 45 to 60 minutes.

Force-based Control: After the break, the FSC and FNC were evaluated. First, the participant was relocated to the same position in front of the height-adjustable table. Subsequently, the subject trained with FNC for 15 minutes while practicing the line-tracing task. Once the training phase was completed, the subject performed the evaluation trials. After completing the evaluation trials with FNC, the subject relaxed for approximately 5 minutes while the measurement of the joint-stiffness force field was performed. After the measurement of the joint-stiffness force field the subject trained for 15 minutes with FSC while practicing the line-tracing task. Once the training phase was complete, the subject performed the evaluation trials.

Questionnaire: To evaluate the experience of the participants and the acceptance of the EMG, FNC and FSC control interfaces, each participant was asked to answer 7 questions (see Table 13) after completing the experimental protocol.

Data Analysis

Data analysis was performed on metrics derived from the end-point trajectories as function of time while tracing the five target lines. The movement performance was evaluated in terms of task completion rate (TCR), tracing error (TE), smoothness (SM) and speed (SP; see Table 12 and Fig. 44 for definitions). The chosen performance descriptors are common measures used in studies that evaluate the performance of control interfaces [211, 215, 207]. For every metric, its mean value through all the trials per interface and per subject was calculated together with the median and the standard deviation (see Table 14). The task completion rate and the tracing error were calculated using:

$$TCR = \frac{\text{Active Maximum Distance}}{\text{Passive Maximum Distance}}, \quad (27)$$

$$TE = \frac{\sum_{i=1}^n \text{Tracing Error}_i}{n}. \quad (28)$$

The smoothness metric was adopted from Balasubramanian et al. [279]. The authors developed a smoothness metric based on the spectral arc length (SPARC)

Table 12: Performance metrics

Performance Metric	Description
1. Task Completion Rate (%):	Ratio between the maximum active distance and the maximum passive distance for each of the five directions
2. Tracing Error (cm):	Mean distance between the points of the end-point's trajectory and the target line.
3. Smoothness (-):	Spectral arc length (SPARC). The length of the frequency spectrum of the speed profile of a movement. [279].
4. Speed (cm/s):	The mean speed of a movement.

Figure 44: Graphical explanation of the performance metrics. **A)** Illustration of the raw movement trajectory (green) and the distances used to calculate the task completion rate (TCR) the tracing error (TE). **B)** Illustration of the spectral arc length (SPARC) derived from the Fourier magnitude spectrum of the speed profile. The green and red curves illustrate the speed profiles in time (left) and frequency (right) domain of two movements with different duration. Since the SPARC measure calculates the spectral arc length with an adaptive frequency threshold (ω_c) the smoothness measure is independent of the movement duration.

of the speed profile. We calculated the SPARC for the Euclidean norm of the movement velocity using:

$$SPARC \triangleq - \int_0^{\omega_c} \sqrt{\left(\frac{1}{\omega_c}\right)^2 + \left(\frac{d\hat{V}(\omega)}{d\omega}\right)^2} d\omega, \quad \hat{V}(\omega) \triangleq \frac{V(\omega)}{V(0)}, \quad (29)$$

$$\omega_c \triangleq \min\{\omega_c^{max}, \min_{\omega}\{\omega | \hat{V}(r) < \bar{V} \forall r > \omega\}\}, \quad (30)$$

where $V(\omega)$ is the Fourier magnitude spectrum of the speed profile ($v(t)$), and ω_c is the frequency bandwidth for which the SPARC is measured. The ω_c is adaptively selected based on a chosen threshold $\bar{V}$ and it is limited to a chosen maximum frequency (ω_c^{max}). This makes possible the comparison of movements with different duration (e.g. green and red curves in Fig. 44B) [279]. The parameters chosen in our analysis where $\bar{V}=0.01$ and $\omega_c^{max}=20\pi$. The value for ω_c^{max} was chosen following the recommendations in [279], and the value of the threshold ($\bar{V}$) was chosen after observing the magnitude spectrum of the velocity. By definition the SPARC metric has a negative value and values closer to zero indicate smoother motion.

A detailed inspection of the distribution of all metrics by control system for each subject was performed. This was illustrated through box plots combined with non-parametric Wilcoxon rank-sum tests with a level of significance fixed at $\alpha = 0.0167$ after applying the Bonferroni correction (i.e. $\alpha = 0.05/3$). In the box plots, the data points above or below 1.5 times the inter-quartile range are shown as outliers with a '+' symbol. The statistical tests were performed with R software (R Development Core Team 2015).

A representation of the trajectories was done by illustrating the raw trajectories, the reachable ROM, and the task completion rate as function of time for each subject and control interface. The representation of the reachable ROM was done by finding the smallest polygons that contained all the data points of the movement trajectories. The *convhull* function from Matlab was used to create the polygons.

6.2 RESULTS

Figure 45 illustrates the joint-stiffness force fields, the raw endpoint trajectories, the reachable ROMs and the task completion rates over time during the line-tracing tasks using EMG, FNC and FSC. For all subjects, the endpoint stiffness forces presented a maximum magnitude of 6 N at the upper-left corner of the participant's workspace. In all subjects we also found a region of low endpoint stiffness force going from the center of their chest to the right upper side of their workspace.

Subject S1 - Brooke score: 4

S1 performed the maximum amount of trials with all three methods (15 trials with each method). The trajectories of subject S1 showed a high task completion rate with all control methods (FNC: 90.5 ± 6.5 %, FSC: 88.2 ± 5.6 %, EMG: 93.9 ± 5.3 %; Fig. 46). While trajectories with EMG presented the highest mean task completion rate, with a significant difference ($p = 0.004$) compared to FSC, the mean tracing error tended to be larger (but not significant $p = 0.25$) compared to FSC and FNC. The trajectories using FNC show the highest smoothness (-3.2 ± 0.3) with a significant difference compared to FSC (-3.8 ± 0.8 ; $p = 0.0164$). The mean speed of the trajectories presented significant differences ($p < 0.005$) between all control methods: EMG was the slowest (2.1 ± 0.5 cm/s), FNC was the fastest (3.3 ± 0.4 cm/s) and FSC was in between the other two (2.7 ± 0.4 cm/s). The results of the questionnaire showed a clear preference for FNC with the exception of speed, for which subject S1 indicated that he could move the fastest with FSC.

Subject S2 - Brooke score: 5

Subject S2 performed only 5 trials with the FNC method and 15 trials with the other two methods. Subject S2 showed a significantly ($p < 0.01$) worse performance in terms of task completion rate and tracing error when using FNC compared to FSC and EMG-based control. While trajectories with FSC and EMG showed a task completion rate close to 100 % (FSC: 96.5 ± 3.4 %, EMG: 95.9 ± 3.2 %), FNC showed a task completion rate significantly lower (80.3 ± 14.9 %; $p < 0.005$) with minimum values reaching 58 %. The tracing error of subject S2 was more than two-fold higher using FNC (1.78 ± 1.04 cm) than with FSC (0.54 ± 0.34 m; $p = 0.002$) or EMG (0.71 ± 0.35 cm; $p = 0.007$). No significant differences were found for the smoothness metric, for which all methods presented mean values around -3 (Fig. 46). While EMG based control presented a performance similar to FSC in terms of tracing error, task completion rate and smoothness, the mean speed when using EMG (2 ± 0.3 cm/s) was significantly lower than with FSC (3.5 ± 0.2 cm/s; $p = 1.29 \cdot 10^{-8}$) or with FNC (3.4 ± 0.7 cm/s; $p = 9.02 \cdot 10^{-4}$). The results of the questionnaire showed a clear preference for EMG with the exception of “being easy to set up”, for which subject S2 indicated that FNC was the easiest.

Subject S3 - Brooke score: 6

Subject S3 performed 1 test trial with FNC (not used for the data analysis and not shown in Fig. 46), 5 trials with FSC and 10 trials with EMG. The trajectories of subject S3 tended towards a lower (non-significant $p > 0.09$) mean task completion rate and speed with FSC (TCR: 73.7 ± 15.3 %; SP: 1.5 ± 0.04 cm/s) compared to EMG (TCR: 85 ± 7.1 %; SP: 2 ± 0.6 cm/s). The mean values of the tracing error and smoothness were similar between FSC and EMG (Table 14). The results of the questionnaire showed a clear preference for EMG, with the exception of accuracy and easy to control, for which subject S3 indicated that he preferred FSC. Additionally subject S3 indicated that FNC was the easiest to set up.

Table 13: Questions and preferences of the participants. The codes of the subjects are color-coded.

Which interface...	EMG Preference	FNC Preference	FSC Preference
1. could control the arm support most accurate?	S2	S1	S3
2. could control the arm support fastest?	S2 S3		S1
3. did react best to your intention?	S2	S1	S3
4. was least fatiguing to use?	S2 S3	S1	
5. was the most easy to set up/install?		S1 S2 S3	
6. was the most comfortable to use?	S2 S3	S1	
7. has your overall preference?	S2 S3	S1

Figure 45: Joint stiffness force-fields, raw trajectories, reachable ROM and task completion rate over time. Data is presented for each subject (columns) and each metric (rows).

Figure 46: Box Plots and Wilcoxon Rank-Sum Tests of the performance metrics. Data is presented for each subject (columns) and each performance metric (rows). The number of repetitions is indicated at the bottom of the figure. (**) indicates $p < 0.0167$.

Table 14: Summary of the means with standard deviations and the Wilcoxon Rank-Sum tests. Bold *p* – values indicate a significant difference.

Metric			S1	S2	S3
TCR (%)	Interface	FNC	90.5(±6.5)	80.3(±14.9)	-
		FSC	88.2(±5.6)	96.5(±3.4)	73.6(±15.3)
		EMG	93.9(±5.3)	95.9(±3.2)	85(±7.1)
	Wilcoxon Test	FNC-FSC	<i>p</i> = 0.366	p = 0.002	-
		FSC-EMG	p = 0.004	<i>p</i> = 0.389	<i>p</i> = 0.099
		EMG-FNC	<i>p</i> = 0.089	p = 0.005	-
TE (cm)	Interface	FNC	0.92(±0.26)	1.78(±1.04)	-
		FSC	0.91(±0.25)	0.54(±0.34)	1.92(±0.46)
		EMG	1.56(±1.13)	0.71(±0.35)	2.01(±0.58)
	Wilcoxon Test	FNC-FSC	<i>p</i> = 0.967	p = 0.002	-
		FSC-EMG	<i>p</i> = 0.249	<i>p</i> = 0.115	<i>p</i> = 0.953
		EMG-FNC	<i>p</i> = 0.216	p = 0.007	-
SM (-)	Interface	FNC	-3.2(±0.34)	-3.19(±0.47)	-
		FSC	-3.83(±0.75)	-3.02(±0.26)	-3.37(±0.15)
		EMG	-3.5(±0.68)	-3.29(±0.52)	-3.35(±0.69)
	Wilcoxon Test	FNC-FSC	p = 0.016	<i>p</i> = 0.394	-
		FSC-EMG	<i>p</i> = 0.486	<i>p</i> = 0.148	<i>p</i> = 0.594
		EMG-FNC	0.148	<i>p</i> = 0.932	-
SP (cm/s)	Interface	FNC	3.27(±0.39)	3.35(±0.7)	-
		FSC	2.70(±0.38)	3.48(±0.2)	1.49(±0.35)
		EMG	2.13(±0.53)	2(±0.3)	2.02(±0.57)
	Wilcoxon Test	FNC-FSC	p = 1.79 · 10⁻⁶	<i>p</i> = 0.93	-
		FSC-EMG	p = 0.002	p = 1.29 · 10⁻⁸	<i>p</i> = 0.129
		EMG-FNC	p = 1.55 · 10⁻⁷	p = 9.02 · 10⁻⁴	-

6.3 DISCUSSION

Performance and Users' Acceptance

The results of the movement performance metrics and subjective preference of the three control methods differed with the level of arm function (i.e. Brooke score) of the participants. Subject S1 (Brooke 4) showed a high overall performance with all three control methods with the best movement performance when using the FNC method. The low number of repetitions, the low task completion rate, and the high tracing error of FNC clearly indicated that subject S2 (Brooke 5) performed better with FSC and EMG than with FNC. Even though the movements of subject S2 presented significantly lower speed with EMG than with FSC, he preferred EMG over FSC since the latter was perceived to be fatiguing. Finally, subject S3 (Brooke 6) was not able to effectively use neither of the force-based control interfaces (i.e. FNC and FSC) and he showed a better performance in terms of task completion rate and speed with EMG and could reach almost his entire workspace. The results of the questionnaire indicated that S2 and S3 had a clear preference for EMG, and subject S1 preferred FNC. The subjective preferences of the participants were in accordance with the results of the performance metrics.

Participants and Experimental Protocol

Any study dealing with testing assistive devices for subjects with DMD is severely conditioned by the low density of available candidates. In our case, the limitation of subjects was also a consequence of our commitment to cause the least inconveniences to the subjects, and strictly observing the legal and ethical constraint that restricts the participation of any given subject to one single study at the same time.

In the framework of this limitation, considering that our main goal was the investigation of suitable control interfaces for the support of arm movements in adults with DMD, we chose to carry out an exploratory assessment of several working principles at the expense of testing with a low number of participants (i.e., 1-3 subjects), rather than a systematic assessment of few working principles with a large number of subjects. Systematic studies should be carried in future studies, once the exploratory phase has been completed and few, se-

lected and relatively optimized control methods are ready for testing on larger samples.

Adults with DMD experience strong training and fatigue effects due to the disuse of their arms. Therefore, the present experimental protocol was designed to balance the amount of training and evaluation trials: the protocol allowed the participants to learn how to use the control interfaces and perform the experimental task, while having a sufficient number of evaluation trials per condition, but keeping the overall length of the experiment within five hours (including breaks) to minimize mental and physical fatigue. Reaching this balance was challenging and future studies must pay particular attention to the design of suitable protocols.

Passive vs. Active Support

As we already mentioned in the Background section, the FNC method resembles the dynamics of passive planar arm supports with a certain mass (M_{vir}) and damping (D_{vir}). FNC was only usable for subject S1 (Brooke 4), FSC was usable for subject S1 and S2 (Brooke 5), and EMG control was usable for subjects S1, S2 and S3 (Brooke 6). These results suggest that men with a voluntary force above the joint-stiffness forces can benefit from passive planar arm supports (i.e. FNC), and when voluntary forces decrease below the intrinsic force of the arm the effective use of passive arm supports is considerably reduced as these will hardly react to their intention (see maximum planar forces in Table 10). Thus, weaker subjects can benefit more from active arm supports that either actively compensate joint-stiffness force, or are EMG-controlled.

Force vs. EMG-based Control

The use of force-based control interfaces for people with severe muscular weakness requires the distinction of the voluntary force of the user from the intrinsic force of the arm, or external disturbances from the environment. In this study the joint-stiffness forces were estimated and actively compensated using a measurement-based method that created a two-dimensional force field (see Figure 45). Our results showed an increase in the functional ROM of subject S2 and S3 when using FSC compared to FNC (S2: 409 vs. 557 cm²; S3: 132 vs.

248 cm²). Subjects S2 and S3 showed a clear benefit in terms of ROM since their maximum forces (S1: 20N; S2: 6N; S3: 3N) were equal or below the joint-stiffness forces (see Fig. 45). However, both subjects also reported that FSC was too fatiguing for them, as we also found in [262]. Differently, for subject S1, the active compensation of the joint-stiffness forces made the control of his movements less stable and smooth than with FNC, which forced him to reduce the movement speed to keep a low tracing error. Additionally, subject S1 also reported a lower effort/fatigue when using FNC, which suggests that probably he had to actively increase his joint impedance and effort when using FSC.

The EMG signals are not affected by the intrinsic forces of the arm (Fig. 42) and therefore we presume that they can better represent the movement intention of people with voluntary forces below the intrinsic forces of the arm. While we found that functional ROM of all subjects when using EMG was similar to or larger than when using FSC, EMG was reported by subject S1 and S3 as less intuitive and required longer training than force-based control. Additionally, EMG-based control presented a significantly lower movement speed compared to force-based control methods in subject S1 and S2. However, it is worth noting that the differences in speed between EMG- and force-based control are probably caused by the difference in the admittance parameters.

In the context of assistive devices for people with severe muscular weakness such as DMD, we consider that the usability of the device is highly affected by the fatigue of the user. The results of this study and the ones from [262] indicated that EMG-based control allows the performance of one- and two-DOF arm movements with lower levels of fatigue compared to force-based control. Therefore, EMG-based control has our preference as control interface for arm supports in adults with DMD with voluntary forces below the intrinsic forces of the arm. Force-based control interfaces with active gravity and joint-stiffness compensation can be a better alternative for those cases in which voluntary forces would still be higher than the intrinsic forces of the arms.

Embodiment

Embodiment refers to the ability of the brain to integrate an external device to its own control scheme. One of the subjects that participated in the pilot trials experienced some sort of embodiment at the end of the experiment: while one of the researchers was moving the robot using a joystick, the participant felt

that his arm was moving, even though he was far from the UR5 and his arm was resting on his wheelchair. Recent studies showed that embodiment can be enhanced with practice [280] and can reduce the cognitive burden of controlling an active assistive device [281]. Based on this anecdotal experience with one of the participants, we speculate that in adults with DMD embodiment may start fast (only after a few minutes of training) due to the preservation of sensory feedback [11, 281, 282], and that embodiment may improve the performance of both EMG- and force-based control interfaces.

Implementation

The assistance of planar arm movements can enable the performance of table-top tasks such as computer/phone/table use, writing or drawing, or the control of the wheelchair's joystick. We have recently developed a two-DOF active arm support known as A-Arm [45], which assists movement in the horizontal plane and replaces the normal arm rest of a wheelchair. In the A-Arm we have implemented the same control interfaces as the ones evaluated in this study. Preliminary pilot evaluations with one adult with DMD (Brooke 5) indicated that assisting planar arm movements with the A-Arm enabled him to switch from different devices (action that he could not do without the A-Arm), which was perceived by the subject as a significant increase of autonomy.

6.4 CONCLUSIONS

We were able to evaluate the feasibility, performance and users' preference of EMG-based control, force-based control with stiffness compensation (FSC) and force-based control with no compensation (FNC) during planar line-tracing tasks in adults with DMD. Movement performance and subjective preference of the three control methods differed with the level of arm function (i.e. Brooke score) of the participants. In conclusion, our results indicate that, EMG-based control interfaces are better suited for adults with DMD than force-based control interfaces as they are experienced as less fatiguing. Nevertheless, force-based control interfaces with active gravity and joint-stiffness compensation can be a better alternative for those cases in which voluntary forces are higher than the intrinsic forces of the arms.

Part III

IMPLEMENTATION OF EMG- AND FORCE-BASED CONTROL INTERFACES IN ARM SUPPORTS FOR ADULTS WITH DMD

DESIGN AND CONTROL OF THE A-ARM: AN ACTIVE PLANAR ARM SUPPORT FOR ADULTS WITH DUCHENNE MUSCULAR DYSTROPHY¹

Abstract: *Adults with Duchenne muscular dystrophy (DMD), due to their severe muscular weakness, cannot benefit from passive arm supports that only compensate for the weight of their arms. Active arm supports can potentially enable adults with DMD to perform activities of daily living, improving their independence, and increasing their participation in social activities. In this paper we present the A-Arm, an inconspicuous and simple planar active arm support for adults with DMD that can be controlled with force- or EMG-based interfaces. The A-Arm is intended to replace the arm rest of the wheelchair and assist during table top tasks such as computer, tablet, or smartphone use, writing and drawing, and the use of the wheelchair's joystick. In the force-based control interface we have implemented active compensation of the joint-stiffness forces using a measurement-based method to obtain an estimation of the voluntary forces of the user. A pilot evaluation with an adult with DMD (24 years-old, Brooke 5) has shown that the A-Arm was able to increase the functional workspace of the arm (from 100 cm² to 190-200 cm²). We found that while force-based control was experienced by the participant as more fatiguing than EMG-based control, the movements with EMG-based control were less accurate. These preliminary results give promising perspectives for the use of simple active arm supports to increase the independence of people with DMD.*

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7.1 INTRODUCTION

Duchenne muscular dystrophy (DMD) is the most common form of muscular dystrophy in children, with an incidence of 1 in 5,000 male live-births [8]. People with DMD suffer from progressive degeneration of skeletal, respiratory, and cardiac muscles, which leads to loss of independent ambulation by the age of ten, followed by the development of scoliosis and loss of upper extremity functions during their early teens [261]. The mean life expectancy of boys with DMD used to be no more than twenty years [3], but in the last five decades, long-term survival has improved substantially due to improvements in medicine and the introduction of home care technology such as artificial ventilators. As a result, currently, there is a considerable group of adults with DMD living with severe physical impairments and a strong dependency on care up to their 30's [1, 4].

Several arm supports that compensate the weight of the arms are commercially available [5] and have shown to increase the independence and quality of life for people with muscular weakness [6, 35]. However, in adults with DMD, the decrease of muscle force combined with an increase of passive joint-stiffness [104, 255], due to the disuse of the arms, reduces the effectiveness of passive arm supports [105, 262]. Active arm supports, can provide extra assistance, and could enable adults with DMD to continue performing activities of daily living (ADLs) and participate in social activities.

From several discussions with adults with DMD, we have concluded that ADLs in the horizontal plane that are related to social and work activities, such as laptop, tablet and smartphone use, writing or drawing, are important for their quality of life. However, only planar passive arm supports are commercially available [283, 284, 285]. We have developed the A-Arm (Fig. 47), a planar active arm support for adults with DMD to assist during tabletop tasks. In this paper we present the design and control of the A-Arm, several performance verification results and a pilot evaluation with an adult with DMD.

7.2 BACKGROUND

To control active movement-assistive devices the user needs a way to communicate his motion intention to the device through a control interface [249]. In previous studies we have shown that adults with DMD could use electromyography (EMG) and force-based control interfaces to operate one degree of freedom

Figure 47: A healthy subject using the A-Arm, the dashed lines represent the passive (green) and active (red and blue) degrees of freedom.

(DOF) elbow movements [262] and two-DOF horizontal movements [257, 260]. Figure 48 shows simplified diagrams of (A) force- and (B) EMG-based control. To perform a movement the man with DMD generates neural commands (C_{nrl}) with his central nervous system (CNS), which result in muscle activation (i.e. from where EMG signals E_{sen} are measured) and muscle contraction that generates voluntary muscle force (F_{vol}). Both force- and EMG-based control interfaces are used in combination with an admittance model (Eq. 31) that maps the estimated force of the user ($\hat{F}_{vol}$), to the intended motion (i.e. velocity) of the arm support (v_{ref}). The admittance (or impedance) of the device can be modified by changing the virtual parameters of the admittance model, which is

Figure 48: Simplified diagram of a force-based (A) and EMG-based (B) control model of a support system for a man with DMD. The admittance models generate a support velocity (v_{sup}) based on the estimated voluntary force ($\hat{F}_{vol}$). An essential difference between force and EMG-based control is that in force-based control, the measured signal (F_{int}) is a combination of the voluntary force of the user F_{vol} and the intrinsic forces of the arm F_{pas} , while in EMG-based control, the measured signal E_{sen} is not affected by the intrinsic forces of the arm.

usually defined with mass ($\mathbf{M}_{vir}$), damping ($\mathbf{D}_{vir}$), and stiffness ($\mathbf{K}_{vir}$; not used in our application) parameters. The admittance model should have mass and damping values that are as low as possible (i.e. highest admittance possible) in order to be highly responsive to the low amplitude control signals of people with DMD.

$$\mathbf{H}_{adm}(s) = \frac{\mathbf{v}_{ref}(s)}{\hat{\mathbf{F}}_{vol}(s)} = \frac{1}{\mathbf{M}_{vir}s + \mathbf{D}_{vir}}. \quad (31)$$

The admittance model converts the $\hat{\mathbf{F}}_{vol}$ to a reference endpoint velocity ($\mathbf{v}_{ref}$) that the arm support must reach. The $\mathbf{v}_{ref}$ is sent to the low-level velocity feedback controller (i.e. PI control), which supplies current ($\mathbf{I}_{mot}$) to power the actuators. The actuators generate an actuation force ($\mathbf{F}_{act}$) that, in combination with the interaction force, results in a total force ($\mathbf{F}_{tot}$) that interacts with the passive arm support dynamics. These dynamics are modeled as an admittance system, and will output the support velocity ($\mathbf{v}_{sup}$) which interacts with the human arm dynamics ($\mathbf{H}_{pad}$), which is modelled as an impedance system:

$$\mathbf{H}_{pad}(s) = \frac{\mathbf{F}_{pad}(s)}{\mathbf{v}_{sup}(s)} = \mathbf{M}_{pad}s + \mathbf{D}_{pad} + \frac{\mathbf{K}_{pad}}{s}. \quad (32)$$

When using force-based control (Fig. 48A) for assisting movements, since the force sensor measures the interaction force ($\mathbf{F}_{int}$), it is crucial to distinguish the voluntary force ($\mathbf{F}_{vol}$) from the intrinsic forces of the arm ($\mathbf{F}_{pad}$)

$$\mathbf{F}_{pad} = \mathbf{F}_{ine} + \mathbf{F}_{dmp} + \mathbf{F}_{stf} + \mathbf{F}_{gra}, \quad (33)$$

where $\mathbf{F}_{ine}$ indicates the inertia forces, $\mathbf{F}_{dmp}$ indicates the joint-damping forces, $\mathbf{F}_{stf}$ indicates the joint-stiffness forces and $\mathbf{F}_{gra}$ the gravity forces. In order to have an estimate of the voluntary force of the human, the intrinsic arm forces need to be estimated and actively compensated (i.e. subtracted) from the measured interaction force:

$$\hat{\mathbf{F}}_{vol,f} = \mathbf{F}_{int} - \hat{\mathbf{F}}_{ine} - \hat{\mathbf{F}}_{dmp} - \hat{\mathbf{F}}_{stf} - \mathbf{F}_{gra}. \quad (34)$$

Note that an active arm support with force-based control without active compensation of the intrinsic forces of the human arm resembles the behavior of a passive arm support with a certain mass ($\mathbf{M}_{vir}$) and damping ($\mathbf{D}_{vir}$). The

Figure 49: Cross-sectional view of the mechanics showing the belt and pulley system. The DOFs are color coded, the parts are shaded, and the arm links and arm scale are shown only partially.

active compensation of human inertia and damping forces have been investigated by Aguirre-Ollinger et al. in several studies [275, 276, 277]. Furthermore, in our previous work [262, 257] we have investigated measurement- and state-machine-based methods for the active compensation of gravity and joint-stiffness forces, which are the dominant components in low-frequency arm movements. In this paper we extend the one-DOF measurement-based active compensation of gravity and joint-stiffness forces used in [262] to two-DOF.

In the case of EMG-based control (Fig. 48B), the estimated voluntary force of the user ($\hat{F}_{vol,e}$) is estimated from the EMG signals. This estimation can be done with different methods [249]. Note that, in contrast to force-based control interfaces, the EMG signals are not affected by the intrinsic arm properties, and therefore directly represent the motion intention of the user. On the other hand, disadvantages of EMG-based control include the poor long-term signal stability, the time required to place the electrodes on top of the specific muscles, and probably a lower intuitiveness compared to force-based control.

7.3 THE A-ARM

System Overview and Mechanics

The A-Arm is a planar active arm support intended to be used by people with DMD that cannot benefit any more from passive arm supports (Fig. 47). The A-Arm is composed of a two-link mechanism driven by two brushless DC motors (EC 20 flat 5W, Maxon Motor ag, Switzerland) in combination with planetary gearboxes (GP 20C, Maxon Motor ag, Switzerland) driven by motor controllers (EPOS2 24/2, Maxon Motor ag, Switzerland). The Actuators are placed at the base of the A-Arm and transmit their power through a pulley-belt system (Fig. 49). Motor 1 actuates link 1, and motor 2 actuates link 2 by having its axis going through the hollow axis of link 1. The joint angles are measured by Hall sensors integrated in the motors which provide joint position information with a resolution of 24 ticks per revolution (before the gearbox). The actuators can deliver a maximum endpoint force, ranging from 4 N to 15 N, depending on the orientation of link 1 and link 2. The endpoint position bandwidth is 1 Hz for a movement amplitude of ± 75 mm, and the maximum endpoint velocity is $0.2 \text{ m}\cdot\text{s}^{-1}$.

The user physically interacts with the A-Arm through an arm scale, which can freely yaw 360° and pitch 10° around its mounting point. The arm scale is connected to the endpoint of the two-link arm through a six-DOF force/torque sensor (ATI Nano25; ATI Industrial Automation, Apex NC, USA), which measures the interaction forces between the user and the device. Note that only two channels from the sensor, corresponding to the planar forces, are used for the control of the A-Arm. For the EMG-based control, a wireless EMG measurement system (Trigno Wireless EMG System; Delsys Inc., Natick MA, USA) was used to record the surface EMG signals from four different muscles: biceps, triceps, deltoid anterior, and deltoid posterior.

The analog signals of the force/torque and EMG sensors are sent to a real-time computer (cRIO 9082, National Instruments Corp., Austin, TEX, USA) by means of a data acquisition module (NI 9205), which performs the analog-to-digital conversion with a sampling frequency of 100 Hz and a 16-bit resolution. The Hall sensor position data from the two motors is sent from the motor controllers to the real-time computer via CANopen protocol by means of a high-speed CAN module (NI 9853). The reference velocity signals are sent via the

same CAN module to the motor controllers. The programming of the controller was done in Labview 2014.

Signal Processing and Control

In the A-Arm we have implemented force-based control interface with active joint-stiffness compensation, and EMG-based control interface (Fig. 48).

Force-based control: The interaction forces between the man with DMD and the A-Arm are measured by the force sensor ($\mathbf{F}_{int}$). To estimate the voluntary force of the user ($\hat{\mathbf{F}}_{vol}$), we have developed and implemented the Force-Field Interpolation (FFI) method to actively compensate for the joint-stiffness forces, which is an extension of the measurement-based method from [262]. With the FFI method the joint-stiffness forces of the user are estimated by moving the user's arm with the A-Arm at a low velocity along a virtual grid within a pre-defined workspace while the user is relaxed. The measured forces along this grid are interpolated to form a two-dimensional force field of the forces in both x- and y-directions. This measurement has to be done before using the A-Arm. During its use, the required joint-stiffness compensation force is calculated on-line and in real-time by interpolating the estimated joint-stiffness force from the force field, based on the position of the endpoint ($\mathbf{p}_{end}$).

For the measurement of the force field a mesh of x- and y-positions is created, using the Matlab function *meshgrid()*:

$$[\mathbf{X}, \mathbf{Y}] = \text{meshgrid}(x_{min}:dx:x_{max}, y_{min}:dy:y_{max}) \quad (35)$$

Here, dx and dy define the density of the grid along those axes. This density will influence both the calculation time needed for the interpolations as well as the accuracy of the interpolations. For these interpolations, the measured position ($\mathbf{x}_{pth}, \mathbf{y}_{pth}$) and the x- and y-forces ($\mathbf{F}\mathbf{X}_{pth}, \mathbf{F}\mathbf{Y}_{pth}$) are used as well as the $\mathbf{X}$ and $\mathbf{Y}$ meshes, to create two force fields. This is done for the x- and y-forces separately using the function *griddata()*, which is a triangulation-based linear interpolation function (Eq. 36). Before $\mathbf{x}_{pth}, \mathbf{y}_{pth}$, and $\mathbf{F}\mathbf{X}_{pth}$ are used, they are

down-sampled to reduce the calculation time and create a uniform distribution of data over the workspace.

$$\mathbf{FX} = \text{griddata}(\mathbf{x}_{pth}, \mathbf{y}_{pth}, \mathbf{FX}_{pth}, \mathbf{X}, \mathbf{Y}) \quad (36)$$

For the online compensation, the $\text{interp1}()$ function is used to find the estimate of the joint-stiffness forces ($\hat{\mathbf{F}}_{stf}$):

$$\hat{\mathbf{F}}_{stf}(p_{end}) = \begin{bmatrix} \text{interp1}(\mathbf{X}, \mathbf{Y}, \mathbf{FX}, \mathbf{p}_{end_x}, \mathbf{p}_{end_y}) \\ \text{interp1}(\mathbf{X}, \mathbf{Y}, \mathbf{FY}, \mathbf{p}_{end_x}, \mathbf{p}_{end_y}) \end{bmatrix} \quad (37)$$

The error between the measured force and $\hat{\mathbf{F}}_{stf}$ was determined to be 0.1 N. For this test we used a known spring element attached to the force sensor and we used the FFI method to actively compensate for the stiffness of the spring. $\hat{\mathbf{F}}_{stf}$ needs to be subtracted from the measured interaction force to obtain an estimate of the user's voluntary force:

$$\hat{\mathbf{F}}_{vol,f}(p_{end}) = \mathbf{F}_{int} - \hat{\mathbf{F}}_{stf}(p_{end}) \quad (38)$$

EMG-based control: For the EMG-based control, the measured EMG signals (E_{sen}) are processed to obtain their envelopes using the standard rectification and low-pass filtering method with a second-order Butterworth with 2 Hz cut-off frequency. As in [260] the envelopes of the agonist/antagonist muscle pair's signals (biceps/triceps and deltoid posterior/anterior) are then combined by subtracting the antagonist muscle activation from the agonist muscle activation to obtain an estimate of the voluntary forces ($\hat{\mathbf{F}}_{vol,e}$):

$$\hat{\mathbf{F}}_{vol,e} = \begin{bmatrix} \hat{F}_{vol,e_x} \\ \hat{F}_{vol,e_y} \end{bmatrix} = \begin{bmatrix} E_{bi} \cdot K_{bi} - E_{tr} \cdot K_{tr} \\ E_{da} \cdot K_{da} - E_{dp} \cdot K_{dp} \end{bmatrix} \quad (39)$$

E_i represents the EMG envelopes (bi: biceps; tr: triceps; da: deltoid anterior; dp: deltoid posterior) and K_i is the gain used to map the subject's muscle activation to the voluntary force. This gain was tuned to the convenience of the user.

7.4 PILOT EVALUATION

Purpose, Participant, and Setup

The purpose of the pilot evaluation was to evaluate the performance of the control methods in terms of reachable range of motion (ROM). We evaluated three conditions: force-based control without active joint-stiffness compensation (i.e. passive support), force-based control with active joint-stiffness compensation, and EMG-based control. The participant was a 24 year-old man with DMD (Brooke 5) who had no arm function left and only some residual finger function that enabled him to use devices such as the wheelchair joystick, the computer, and his mobile phone. The Medical Ethics Committee of the Radboud University Nijmegen Medical Center approved the study design, protocols, and procedures, and an informed consent was obtained from the subject prior to the evaluation.

The A-Arm was mounted on the fixation plate of the right arm rest of the participant's wheelchair (see Fig. 47). For comfort reasons the seat of the wheelchair was tilted backwards around 10° , which meant that the A-Arm was tilted equally. A tablet (Cintiq 13 HD; Wacom Technology Corp., Vancouver WA, USA) was placed in front of the subject (Fig. 50) and its tracking pen functioned as the cursor of which the position was recorded over time by a Matlab (Matlab 2014a; MathWorks, Natick MA, USA) script.

Experimental Task and Protocol

After a detailed explanation of the purpose and procedure of the experiment, the participant's arm was placed in the arm scale of the A-Arm and a comfortable position of the A-Arm was defined as initial position for all the tracing tasks. Using an admittance control with a virtual damping of $25 \text{ N}\cdot\text{s}\cdot\text{m}^{-1}$, the researcher moved the arm of the subject to find the passive workspace limits for safety. After, the tracing task was displayed on the tablet (see Fig. 50 and Fig. 51) and the subject was asked to trace it a minimum of three times and a maximum of five times with the three conditions. Before starting the tracing tasks the participant was given 15 minutes to familiarize with each control method and to tune the control gains of the admittance model and the EMG gains according to the participant's feedback. The trials with the force-based

Figure 50: Overview of the setup, with the subject holding the tracking pen. The figure that he has to trace is shown on the tablet in front of him.

control without joint-stiffness compensation were carried out first with the seat of the wheelchair and the A-Arm horizontal (not tilted backwards) to prevent that gravity forces could affect the measurement. The seat was tilted backwards for the other two conditions since the participant preferred that seating position. Before performing the trials with the force-based control with joint-stiffness compensation the measurement of the stiffness forces was done with the FFI method.

7.4.1 Results

The force field produced by the FFI method is shown in Fig. 52. Note that due to the inclination of the wheelchair the measured forces not only originate from joint-stiffness but also from gravity. Since gravity forces also depend on the arm configuration, they can be subtracted together with the stiffness forces using the same strategy.

The reachable ROM was found to be 100 cm^2 , 190 cm^2 , and 200 cm^2 for the passive support, the active joint-stiffness compensation, and the EMG-based control respectively (Fig. 51). The reachable ROM was two fold lower with

Figure 51: Comparison of the reachable ROM with the A-Arm using: passive support or force-based control without stiffness compensation (red), force-based control with active joint-stiffness compensation (green), and EMG-based control (blue). The black lines present the target trajectories that had to be traced by the participant.

the passive support than with the force-based control with active joint-stiffness compensation or the EMG-based control. While no differences were noticeable in terms of ROM between the movements made with the EMG-based and compensated force-based control, the movements with the EMG-based control presented more deviations from the target lines. Note that the trajectories of Fig. 51 result from the combined performances of the mechanics and the control.

For both force-based tracing task, the maximum voluntary forces the subject could exert were found to be around 1 N. At the bottom left corner the surface area of the tablet was too small to measure the actual distance the subject could move to. The subject was not able to move to the bottom right corner with the compensated force-based control probably due to a wrong FFI measurement.

After the experiment, the subject was asked to give feedback on the use of the A-Arm in terms of fatigue and intuitiveness. The participant mentioned that: "Force control was much more fatiguing, with or without joint-stiffness compensation, than EMG-based control", and that "It was more intuitive to use force-based control than EMG-based control but I think that with more

Figure 52: The interpolated force fields created with the FFI method and used for the online calculation of $\hat{\mathbf{F}}_{stf}$ during the pilot evaluation.

training I would get used to EMG control with no problem”. The subject was also asked to give his opinion regarding the usability of the A-Arm in ADLs and he mentioned the following: "The A-Arm would allow me to switch from my mobile phone to my laptop or to my wheelchair’s joystick, without asking anyone to do it for me. This would be a great improvement for me”.

7.5 DISCUSSION

In this paper we have presented the design and control of the A-Arm, a planar active arm support for adults with DMD that can be controlled through a force- or EMG-based interfaces. A preliminary evaluation of the A-Arm with a man with DMD has shown that the assistive device increased the functional workspace of the user’s arm. The A-Arm was perceived by the participant as a usable device to independently switch between devices within his workspace area: from a laptop to a mobile phone or the wheelchair’s joystick. The results give promising perspectives for the use of a planar active arm supports by men with DMD.

The development of the A-Arm was part of our continued investigation to determine how many DOF are needed to assist people with DMD and what is the

Figure 53: Frontal view of the A-Arm mounted to the participant's wheelchair. The profile of the A-Arm is comparable to that of his standard arm support.

most suitable control interface for them. The A-Arm is less complex than a fully actuated arm exoskeleton, yet it is able to support planar movements which can have a considerable impact on the quality of life for adults with DMD. Another advantage of the simplicity of the A-Arm with respect to an arm exoskeleton, is that it is inconspicuous (Fig. 53), which is an important requirement for the users (specially for teenagers).

The FFI method was used to estimate, and actively compensate for, the joint-stiffness forces of the user during the force-based control. Compared to uncompensated force-based control, the workspace of the participant almost doubled in size (from 100 cm^2 to 190 cm^2) when using the actively compensated force-based control or EMG-based control. The force-based control was perceived as fatiguing by the participant compared to the EMG-based control, which was also observed in the evaluation of the one-DOF active elbow support [262].

From the pilot evaluation, we have concluded that stronger actuation is required to overcome the gravity forces when the wheelchair is tilted backwards. Furthermore, we are considering the addition of a third DOF to the A-Arm to support hand to mouth movements.

DESIGN AND CONTROL OF THE ACTIVE A-GEAR: A WEARABLE 5 DOF ARM EXOSKELETON FOR ADULTS WITH DUCHENNE MUSCULAR DYSTROPHY¹

Abstract: *Adults with Duchenne muscular dystrophy (DMD) can benefit from active arm supports that augment the residual motion capabilities of their arms. While there is a considerable number of active exoskeletons commercially available for rehabilitation purposes, no active exoskeletons for supporting the arm function during the performance of activities of daily living (ADL) are available. In this paper, we present the Active A-gear, a wearable five degree-of-freedom exoskeleton that has been specially developed to assist people with DMD for the performance of ADL. The Active A-Gear is built upon our previous design of the passive A-Gear, thus combining active and passive support. The Active A-Gear can be controlled using force-based (admittance) control. We report the results of the system verification, which included endpoint position bandwidth, workspace, weight, joint speed, endpoint force and joint backlash measurements. A pilot evaluation was carried out with one healthy subject (27 years-old) performing ADL. The results of the verification and evaluation tests indicate that with some modifications the Active A-Gear is a suitable platform to test the functional performance and feasibility of a wearable and active support for adults with DMD.*

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8.1 INTRODUCTION

Duchenne muscular dystrophy (DMD) is the most common form of muscular dystrophy in children, with an incidence of 1 in 5,000 male live births [8]. Defective mutations in the dystrophin gene result in progressive degeneration of skeletal, respiratory and cardiac muscles leading to loss of independent ambulation by the age of ten years, followed by the development of scoliosis and loss of upper extremity function during their early teens [261]. The mean life expectancy of people with DMD used to be no more than twenty years, but in the last five decades, long-term survival has improved substantially due to improvements in drugs and the introduction of home care technology such as artificial ventilators [3]. As a result, currently, there is a considerable group of adults with DMD living with severe physical impairments and a strong dependency on care up to their 30's [4].

Commercially available arm supports, which mainly provide passive gravity compensation [5], become insufficient to support the arm function of adults with DMD [262, 257]. They can barely generate forces to overcome inertia and friction of passive devices, or their own joint stiffness. Active arm supports, which can provide extra assistance, could enable adults with DMD to perform basic activities of daily living and participate in social activities.

While there is a considerable number of active exoskeletons commercially available for rehabilitation [33, 5, 286], no active exoskeletons for supporting the arm function during activities of daily living (ADL) are available. Few active arm supports are currently under development, such as the active version of the WREX [39], the device developed in the ESTA project [40] or the device developed in the McArm project [41].

This paper presents the design of the Flexension Active A-Gear, a wearable arm exoskeleton with five degrees-of-freedom (DOF), specially developed for assisting adults with DMD during the performance of ADL. We report several verification tests of the device and a pilot evaluation with one healthy subject.

8.2 DESIGN OF THE ACTIVE A-GEAR

The Active A-gear is intended to support the arm function of adults with DMD that are too weak to benefit from passive arm supports. The Active A-Gear aims at providing active assistance to support the arm function during basic ADL,

Figure 54: The Active A-Gear worn by a healthy subject. The Active A-Gear is build upon our previous design of the passive A-Gear, thus combining active (motorized joints) and passive support for gravity compensation (blue elastic bands). The Active A-gear is controlled using a force-based interface with admittance control.

such as eating/drinking, personal hygiene and using communication technology (i.e. laptops or phones).

The Active A-Gear was designed to fulfill a number of requirements. Firstly, the device needs to increase the arm function of the user. Preferably, the arm will have a complete functional range of motion (ROM). Controlling the exoskeleton should be intuitive, the device should be easy to put on and off, and should be comfortable. For users it is also important that the product is not obtrusive and silent, so that they do not feel stigmatized. Finally, the device must be safe for the user and bystanders (Table 15).

Passive Mechanics

The Active A-Gear is built upon our earlier work on the Passive A-Gear arm support [43]. To provide the required freedom of motion the exoskeleton has five rotational pin joints in series mimicking the biomechanics of the human trunk and arm (Fig. 55): one next to the hip, three pointing at the approximated center of rotation of the shoulder complex and one aligned with the elbow joint. The user, which is wheelchair bound, is sitting on the base of the exoskeleton and the reaction forces from the arm support are redirected to the wheelchair through the seat and not to the trunk, which could hamper breathing or cause discomfort. The weight of the user's arm and of the exoskeleton is passively compensated using springs (blue rubber bands in Fig. 54) as in [43] implementing the method described in [287]. The weight compensation force can be adjusted by either modifying the number of elastic bands or by adjusting the location of the attachment points of the springs. The device is safe in case a rubber band snaps, since every spring bundle consists of multiple bands.

Driving system

The strategy of combining passive weight support with actuation presents the advantage that the motor size and power required to move the user's arm and the exoskeleton is considerably reduced (i.e. $\approx 70\%$). Although the envisioned product consists of five motorized joints, the first prototype that has been built

Table 15: Requirements

Requirement	Target
Increased arm function	Natural ROM. Shoulder elevation up till 90°. Able to perform ADLs.
Intuitively controlled	No extra mental effort
Comfortable	During full day
Unobtrusive	Underneath clothing
Safe	No risks
Silent	Max whispering sound
Easily to put on/off	<10min a day

Figure 55: Kinematic Architecture of the Active A-Gear. The black lines represent the mechanical structure, the red areas represent the interfaces with the body, the green cylinders represent the motorized joints and the blue lines represent the elastic bands.

does not include a motorized hip joint (q_1). The three shoulder (q_2 , q_3 and q_4) joints and the elbow joint (q_5) are actively driven. Flat brushless DC motors are used (EC flat, Maxon motors, Switzerland) in combination with planetary gear-boxes (GP, Maxon motors, Switzerland) driven by motor controllers (EPOS2 24/2, Maxon Motors, Switzerland, see Table 16). Criteria such as play, allowable gear torque, motor power and output torque determined the choices of the motor/gear combinations.

Alternatives for DC motors were considered: the exoskeleton could have been driven by brushed motors, pneumatic cylinders, pneumatic artificial muscles,

hydraulic cylinders or artificial muscles, by shape memory alloys or electroactive polymers. When choosing the actuation method, not only the actuators were taken into account, but the total power system, including power supply, pressurized tank or generator if necessary, the actuator itself, and the transmission. Overall, we found that brushless DC motors with gears, drivers and battery matched best with the requirements of this device.

Since this prototype was intended as a proof-of-concept, the motors of the second and third joints are oriented following the joint axes, which was easier and quicker to implement than orienting them alongside the body. In a market product we envision these motors to be alongside the trunk link (see Discussion section).

The motors driving the fourth and fifth joints are located alongside the body and integrated inside in the upper arm tube. Since these motors are perpendicular to the joint axis, the motor torque needs to be redirected over a 90° angle. This is done with bevel gears (steel, ratio 1:3, module 1, 15 and 45 teeth, SDP/SI, USA).

The electric power needed to drive the exoskeleton is taken from the wheelchair battery, which does not require extra volume for energy storage. The power required for arm motion is low compared with the power required for over-ground transport. Therefore, we expect the battery not to deplete much faster than without the Active A-Gear in use.

Sensors and Signal Acquisition

A 6 DOF force/torque sensor (Nano 25, ATI Industrial Automation, Apex, USA) is attached in between the forearm link and the arm scale to measure the in-

Table 16: Requirements

Joint	Motor Power	Gear(s)	Torque [Nm]
q_2	5W	GP 370:1	2,75
q_3	15W	GP 246:1	6,27
q_4	5W	GP 370:1 and Bevel 3:1	8,25
q_5	5W	GP 370:1 and Bevel 3:1	8,25

teraction forces/torques between the user and the Active A-Gear. Additionally, the Active A-Gear is equipped with hall-sensors integrated in the flat brushless DC motors, which provide joint position information with a resolution of 24 ticks per revolution times the gear box ratio. The analog signals of the force/torque sensor are sent to a real-time computer (cRIO 9082, National Instruments, Texas, USA) by means of a data acquisition module (NI 9205), which performs the analog-to-digital conversion with a sampling frequency of 100 Hz and a 16-bit resolution. The hall-sensor position data from the four motors is sent to the real-time computer via CANopen protocol by means of a high-speed CAN module (NI 9853). The reference velocity signals are sent via the same CAN module to the motor controllers.

Control

Forward Kinematics: We assume a 3-DOF shoulder joint. The rotation matrix of the upper arm “frame” with respect to the fixed shoulder frame (superscript 0) is described by:

$$\begin{aligned}
 {}^0\mathbf{R}_{ua} &= {}^0\mathbf{R}_2(q_2){}^2\mathbf{R}_3(q_3){}^3\mathbf{R}_4(q_4), \\
 {}^0\mathbf{R}_2(q_2) &= \mathbf{R}_z(10^\circ)\mathbf{R}_y(-10^\circ)\mathbf{R}_z(q_2)\mathbf{R}_y(56^\circ), \\
 {}^2\mathbf{R}_3(q_3) &= \mathbf{R}_z(q_3)\mathbf{R}_y(56^\circ), \\
 {}^3\mathbf{R}_4(q_4) &= \mathbf{R}_z(q_4){}^2\mathbf{R}_y(56^\circ),
 \end{aligned} \tag{40}$$

where $\mathbf{R}_y$ and $\mathbf{R}_z$ are standard rotations around the local x and y axes. The constant angles in (Eq. 40) correspond to the fixed angles of the three-DOF gimbal mechanism ($10^\circ, -10^\circ, 56^\circ$) used to recreate a virtual spherical joint. A full description of the gimbal mechanism can be found in [12].

Figure 56: Definition of the swivel angle (ϕ_s), vectors and the coordinate systems used for the forward and inverse kinematics.

The upper arm unit vector is then given by:

$$\mathbf{u}_{ua} = \mathbf{R}_{ua} \hat{\mathbf{x}}, \quad (41)$$

with $\hat{\mathbf{x}} = [1, 0, 0]^T$. The elbow location (${}^0\mathbf{p}_e$) is then directly found with the length of the upper arm (l_u) to be:

$${}^0\mathbf{p}_e = \mathbf{u}_{ua} l_u. \quad (42)$$

The end-point (hand; ${}^0\mathbf{p}_h$) is then found by:

$${}^0\mathbf{p}_h = {}^0\mathbf{p}_e + {}^0\mathbf{R}_4 \mathbf{R}_z(q_5) \hat{\mathbf{y}} l_{fa}, \quad (43)$$

where l_{fa} the length of the forearm.

Figure 57: Diagram of the force-based admittance control implemented in the Active A-Gear. Active stiffness and gravity compensation are implemented to obtain an estimate of the voluntary force of the user ($\hat{\mathbf{F}}_{vol}$).

Swivel Angle: We defined the swivel angle (see Fig. 56) as the angle between the normalized projection of the negative z axis on the plane with the normal vector ${}^0\mathbf{u}_w$, and ${}^0\mathbf{u}_{ua}$:

$${}^0\mathbf{u}_w = \frac{{}^0\mathbf{p}_h}{\|{}^0\mathbf{p}_h\|}. \quad (44)$$

The normalized projection of the negative z on the plane given by ${}^0\mathbf{u}_w$ is given by:

$${}^0\mathbf{u}_{-z,w} = \frac{{}^0\mathbf{u}_w \times (-\mathbf{z} \times {}^0\mathbf{u}_w)}{\|{}^0\mathbf{u}_w \times (-\mathbf{z} \times {}^0\mathbf{u}_w)\|}. \quad (45)$$

Similarly, the normalized projection of the upper arm unit vector $\mathbf{u}_{ua}$ on the plane of ${}^0\mathbf{u}_w$ is given by:

$${}^0\mathbf{u}_{ua,w} = \frac{{}^0\mathbf{u}_w \times ({}^0\mathbf{u}_{ua} \times {}^0\mathbf{u}_w)}{\|{}^0\mathbf{u}_w \times ({}^0\mathbf{u}_{ua} \times {}^0\mathbf{u}_w)\|}. \quad (46)$$

By construction ${}^0\mathbf{u}_w$ and ${}^0\mathbf{u}_{-z,w}$ are now orthogonal, and have an orthogonal complement:

$${}^0\mathbf{u}_v = {}^0\mathbf{u}_w \times {}^0\mathbf{u}_{-z,w}. \quad (47)$$

The swivel angle, down being 0° and clockwise around ${}^0\mathbf{u}_w$ positive (seen from the user), is then given by:

$$\phi_s = \arccos({}^0\mathbf{u}_{-z,w} \cdot {}^0\mathbf{u}_{ua,w}) \operatorname{sgn}({}^0\mathbf{u}_v \cdot {}^0\mathbf{u}_{ua,w}). \quad (48)$$

The addition of the sign-function ensures proper distinction between positive and negative angles around $\phi_s = 0$. This representation is singular if 1) ${}^0\mathbf{p}_h = 0$ the hand is inside the shoulder, or 2) the hand is directly above or below the shoulder, which is a configuration that cannot be reached with the design of the gimbal mechanism.

Differential Inverse Kinematics: We implemented differential inverse kinematics since our motor controllers were velocity controlled. The differential kinematics of the arm are given by:

$${}^0\dot{\mathbf{p}}_h = \mathbf{J}\dot{\mathbf{q}} = \begin{pmatrix} \frac{\partial {}^0\mathbf{p}_h}{\partial \mathbf{q}} \\ \frac{\partial \phi_s}{\partial \mathbf{q}} \end{pmatrix} \begin{pmatrix} \dot{q}_2 \\ \dot{q}_3 \\ \dot{q}_4 \\ \dot{q}_5 \end{pmatrix}, \quad (49)$$

with $\frac{\partial {}^0\mathbf{p}_h}{\partial \mathbf{q}}$ a 3×4 matrix, and $\frac{\partial \phi_s}{\partial \mathbf{q}}$ a 1×4 row vector. The position part of the Jacobian is readily found by:

$$\begin{aligned} \frac{\partial {}^0\mathbf{p}_h}{\partial \mathbf{q}} &= [{}^0\mathbf{R}_2\hat{\mathbf{z}} \times {}^0\mathbf{p}_h \quad {}^0\mathbf{R}_3\hat{\mathbf{z}} \times {}^0\mathbf{p}_h \quad {}^0\mathbf{R}_4\hat{\mathbf{z}} \times {}^0\mathbf{p}_h \quad \mathbf{J}_4], \\ \mathbf{J}_4 &= {}^0\mathbf{R}_5\hat{\mathbf{z}} \times ({}^0\mathbf{p}_h - {}^0\mathbf{p}_e). \end{aligned} \quad (50)$$

It is hard to find an analytic solution to the last row of the Jacobian, $\frac{\partial \phi_s}{\partial \mathbf{q}}$, and therefore we approximate this last row by a finite difference:

$$\frac{\partial \phi_s}{\partial q_j} \approx \frac{\phi_s(\mathbf{q} + \mathbf{u}_j \delta q) - \phi_s(\mathbf{q})}{\delta q}, \quad j = 2, \dots, 5, \quad (51)$$

with $\delta q = 10^{-8}$ rad, and $\mathbf{u}_j$ a unit vector with the j^{th} element 1 and the rest 0. The total inverse kinematics algorithm to get the reference velocity for the joint angles from the hand and swivel reference velocities is found by inverting the square matrix $\mathbf{J}$ in non-singular configurations:

$$\dot{\mathbf{q}}_{ref} = \mathbf{J}^{-1} \begin{pmatrix} {}^0\dot{\mathbf{p}}_{h,ref} + \mathbf{K}_p({}^0\mathbf{p}_{h,ref} - {}^0\mathbf{p}_h) \\ \dot{\phi}_{s,ref} + K_\phi(\phi_{s,ref} - \phi_s) \end{pmatrix}, \quad (52)$$

where feedback gain $\mathbf{K}_p$ is a diagonal 3×3 matrix, and K_ϕ is a scalar. These gains ensure convergence to the required configuration. Using the described method the error between the inverse and forward kinematics was below $5 \cdot 10^{-6}$ m for the position of ${}^0\mathbf{p}_h$ and $1 \cdot 10^{-3}$ rad for the angle of ϕ_s .

Admittance Control: In previous studies we have shown that adults with DMD could use force-based control interfaces using admittance control to operate one-DOF elbow movements [262] and two-DOF horizontal movements [257]. In admittance control the device reacts with a displacement (i.e. velocity, v) to forces exerted to it (F). The admittance (or impedance) of the device can be modified by changing the virtual parameters of the admittance model (H_{adm}), which is usually defined with mass ($M_v ir$), damping ($D_v ir$) and stiffness ($K_v ir$, not used in our application):

$$v(s) = H_{adm}(s)F(s) = \frac{1}{M_v ir s + D_v ir + K_v ir / s} F(s). \quad (53)$$

The active compensation of inertial and damping forces have been investigated by Aguirre-Ollinger et al. in several studies [276, 275, 277]. Furthermore, in our previous work [257, 262] we have investigated the active compensation of gravity and joint-stiffness forces, which are the dominant components in low-speed and low bandwidth arm movements. An estimate of the voluntary force of the user ($\hat{F}_{vol}$) can be obtained by subtracting the estimated intrinsic forces from F_{int} :

$$F_{int} = F_{stf} + F_{dmp} + F_{int} + F_{gra} + F_{vol}. \quad (54)$$

Figure 57 shows a diagram of the control implemented in the Active A-Gear. The interaction forces and torques, denoted here with a wrench ($\mathbf{W}_{int}$), are measured with the force/torque sensor (${}^s\mathbf{W}_{int} = [{}^s\boldsymbol{\tau}_{int}^T, {}^s\mathbf{F}_{int}^T]^T$) and expressed in the sensor frame (ψ_s). The measured wrench is transformed to the hand coordinate system (ψ_h) using standard rotation and transformation matrices and rotated to match the orientation of the global coordinate system (ψ_0). The four motorized joints of the Active A-Gear allow the control of four DOF of the end-point: three translations in Cartesian space (${}^0\mathbf{p}_h = {}^0p_{h_x}, {}^0p_{h_y}, {}^0p_{h_z}$) and a rotation around the swivel axis (ϕ_s).

Currently, in the Active A-Gear, we have implemented active gravity and joint-stiffness compensation. For the active gravity compensation we estimate the weight of the arm by asking the subject to relax and measuring the vertical force. For the active joint-stiffness compensation we use the force field interpolation (FFI) method, which is a measurement-based method that measures the joint-stiffness forces along a predefined grid across the three-dimensional (3D)

workspace of the arm and creates a 3D force field by interpolating the measured data. This measurement needs to be performed before using the Active A-Gear with joint-stiffness compensation. Once the measurement of the 3D force field is completed, an online and real-time interpolation is done to determine the active joint-stiffness compensation force for the current position of the arm. Further details on the FFI method can be found in [45]. The estimated gravity and joint-stiffness compensation forces are subtracted from the measured force to obtain the estimated voluntary force of the human. The estimated voluntary forces are used as input for the admittance model that outputs the linear velocities in task space. From the measured torques (${}^0\tau_{int}$), the torque around the swivel axis ${}^0\mathbf{u}_w$ (see Fig. 56), is calculated with (Eq. 55) and used also as input for the admittance model. Active compensation of the stiffness was not yet implemented for the torques.

$$\tau_s = {}^0\tau_{int} \cdot {}^0\mathbf{u}_w \quad (55)$$

The end-point reference velocities (${}^0\dot{\mathbf{p}}_{h,ref}, \dot{\phi}_{s,ref}$) obtained from the admittance model are transformed to joint velocities using the differential inverse kinematics algorithm (described in section II.D.3) and sent to the motor controllers, which perform the low-level feedback velocity control. The torques (τ_{res}) resulting from the combination of the motor's wrench (τ_{mot}) together with the interaction torques (τ_{int} and the balancing torques (τ_{bal}) provided by the elastic bands, interact with the passive mechanics of the Active A-Gear (modeled as an admittance system in Fig. 57) and provide assistance velocity ($\dot{\mathbf{q}}_{ass}$) to the passive human arm dynamics (modeled as an impedance system in Fig. 57).

Performance Verification

The performance of the Active A-Gear has been evaluated in terms of ROM, endpoint position bandwidth, endpoint force, joint and endpoint play, endpoint velocity, weight and distance from the body (Table 17). For the endpoint bandwidth and speed measurements the Active A-Gear was tested with a 1 kg weight attached to the arm scale.

The ROM was defined with the standard clinical definitions of the shoulder and elbow rotations. The endpoint position bandwidth has been measured using a chirp signal of 300 seconds as reference endpoint velocity with frequencies

ranging from 0.1 Hz to 1 Hz and constant amplitude of 0.1 m/s. The system was perturbed in the global y direction from a neutral position with the upper arm segment pointing down and the elbow flexed 90 degrees. Due to the play at the joints the position data from the hall sensors was not reliable, and therefore an external position sensor (Cintiq 13HD Tablet, Wacom Co., Ltd.) was also used to directly measure the endpoint position by attaching the tablet's pen to the endpoint of the Active A-Gear. The position data from both sensors was used to estimate the frequency response functions. The maximum bandwidth was defined as the frequency when the gain dropped below -3 dB or when the phase crossed -180 degrees. We found that the estimated endpoint position bandwidth using both the hall sensor data and the external sensor was around 1 Hz with ± 17 mm amplitude.

8.3 PILOT EVALUATION

The prototype is intended to be evaluated with people with DMD. However, at this point, the prototype has been preliminarily tested with a healthy individual to evaluate whether the functionality and safety of the device were acceptable to proceed with the patient tests.

While wearing the Active A-Gear, the healthy subject performed the following activities: grabbing, reaching, shaking hands and drinking. These activities were captured on video (see submitted video). During the evaluation it was observed that the user had a large ROM of the arm while using the exoskeleton that enabled him to perform all the aforementioned tasks. Since the test subject was healthy, improvement of arm functionality could not be evaluated. It took around 15 seconds to put on the device, the exoskeleton felt comfortable to the user and it was intuitively controlled. Functionality was not fully robust yet, due to occasional control instabilities with low admittance parameters (i.e. $M_{vir} < 10$ kg and $D_{vir} < 5$ Ns/m).

8.4 DISCUSSION

In this paper we have presented the design and control of the Active A-Gear, an active arm exoskeleton to assist people with muscular weakness during ADL. To the best of our knowledge the Active A-Gear is the lightest and most slender

actuated upper-extremity exoskeleton currently developed [39, 5, 41, 40, 33]. Excluding the real-time controller and the fixed frame the Active A-Gear weighs 2.5 kg and has a maximum distance from the body of 150 mm, and 80 mm if motor 2 and 3 are excluded.

The prototype still displays a significant amount of play in the drive chains, which is known to have influence on the stability of admittance control [276].

Table 17: Technical Specifications of the Active A-Gear

Performance Metric		Measured Value
ROM [deg]	Plane of shoulder elevation	-50 to 75 (45) ^a
	Shoulder elevation (front)	-75 to 110
	Shoulder elevation (side)	0 to 40
	Internal/External rotation	-50 to 75 (45) ^a
	Elbow flexion	20 to 160 (140) ^a
Estimated endpoint position bandwidth from hall-sensor data [Hz]		1 Hz (17 mm) ^b
Estimated endpoint position bandwidth from external sensor [Hz]		1 Hz (17mm) ^b
Endpoint Force [N]	Z: Up/Down	60
	Y: Forward/back	40
	X: Left/Right	30
Endpoint Play [mm]	Z: Up/Down	20
	Y: Forward/back	30
	X: Left/Right	30
Joint Play [deg]	q_2	2
	q_3	1
	q_4	2
	q_5	2
Max. Endpoint velocity [m/s]		0,2 ^b
Weight (excluding cRIO and fixation frame) [kg]		2.5 ^c
Maximum Distance away from body [mm]		150 mm (80 mm disregarding motor 2 and 3)

a: Values in brackets indicate the human ROM limits; b: Measured with a 1kg mass attached to the arm scale; c: Includes the Active A-Gear from joint 2, with motors, controllers, gears and elastic bands.

Furthermore, the endpoint deviation from its ideal position (i.e. without play) causes active gravity compensation errors due to the uncertainty of the endpoint orientation with respect to gravity. Joints exhibit 2-3 degrees of play, which results in 20-30 mm of play at the endpoint. The play is mainly caused by the multiple staged planetary gearboxes and the bevel gears. The bevel gears may be modified by adding pretension in the joint to reduce the play. Apart from the play, other causes of the occasional instability of the system could be the high apparent inertia of the motors in q_4 and q_5 (due to the high gear ratio), and non-optimal PI gains of the low level controllers.

In the current prototype we have implemented force-based control. Nevertheless, the device can be adapted to use EMG-based control as well to detect the motion intention of the user. EMG-based control presents the advantage that the EMG signals are not influenced by the intrinsic arm forces. Moreover, EMG has shown to be less fatiguing for people with DMD [262]. On the downside, currently, a maximum of three DOF have been controlled simultaneously and proportionally [288], which is less than the controllable DOFs of the Active A-Gear. Furthermore, the EMG signals might be affected by artifacts due to collisions between the electrodes and parts of the Active A-Gear.

In a next version of the Active A-gear we plan to locate the motors of q_2 and q_3 on the back of the user and transmit the power to the corresponding joints by cables via pulleys and/or Bowden cables.

In conclusion, the results of the verification and evaluation tests indicate that with some modifications the Active A-Gear is a suitable platform to test the functional performance and feasibility of a wearable and active arm support for adults with DMD.

DISCUSSION

This dissertation presented several studies towards *“the development, evaluation and implementation of EMG- and force-based control interfaces to actively support the arm function of adults with DMD”*. The following questions were answered during the research process:

Research Questions

- i *What is the state-of-the-art of non-invasive methods to detect movement intention?* Part I (Chap. 2)
- ii *Are EMG- and force-based control interfaces feasible for the control of active arm supports in adults with DMD?* Part II (Chap. 3 to 6)
- iii *How can the A-Arm and the Active A-Gear tackle the major limitations of existing arm supports?* Part III (Chap. 7 and 8)

9.1 SUMMARY OF RESULTS AND CONCLUSIONS

Adults with DMD can benefit from active arm supports that augment their residual functional capabilities. However, intuitively controlled and fully actuated arm supports are currently not commercially available and adults with DMD are limited to use external robotic arms which contribute to the disuse of their arms. To fill this gap in the field of arm supports, we have developed EMG- and force-based control interfaces that have been implemented in two new active arm supports: the A-Arm and the Active A-Gear. We found that both EMG- and force-based control interfaces are feasible solutions for the control of active arm support for adults with DMD that have lost their arm function a long time ago. The comparative studies between EMG and force-based control interfaces indicated that, in general, EMG-based control interfaces are better suited for adults with DMD than force-based control interfaces as they are experienced as less fatiguing. Nevertheless, force-based control interfaces with active gravity and joint-stiffness compensation can be a better alternative for those cases in which voluntary forces would still be higher than the intrinsic forces of the arms. This conclusion has an indicative value, as it is based on a low number of subjects. In any case, the decision on the most suited interface will have to be taken based on the specificities of each subject. In conclusion, by developing these new control interfaces and implementing them in new active assistive devices, we made a significant step in improving arm supports for adults with DMD. Hopefully, these novel concepts of arm supports will be the basis for the development of commercially available active arm supports for people with severe muscular weakness. The control and assistive strategies developed in the Flexextension A-Gear project may be applicable to other patient groups with muscular weakness.

9.2 STATE-OF-THE-ART OF CONTROL INTERFACES FOR MOVEMENT-ASSISTIVE DEVICES

i *What is the state-of-the-art of non-invasive methods to detect motion intention?*

Chapter 2 presents a comprehensive overview of the current methods used to detect the motion intention in active movement-assistive devices.

Non-invasive brain-computer control interfaces appear to be limited in speed, accuracy, and reliability for the control of active movement-assistive devices [131, 130]. However, researchers are improving their performance by implementing artificial learning algorithms [56, 219, 220], shared-control strategies [131, 221] and combining brain-computer interfaces with other sensor modalities [198].

Myoelectric-based control interfaces are currently the most common method for operating active upper-extremity prosthetic devices [145, 130]. The clinical standard myoelectric-based control strategy is a simple amplitude-based dual site control approach also known as direct control, which measures electromyography (EMG) signals from two independent residual muscles, or by distinguishing different activation levels of one residual muscle. In this dissertation, direct EMG-based control has been successfully implemented in active arm supports to assist one- and two-DOF arm movements of adults with DMD. Direct myoelectric-based control methods are robust but require the user to generate independent EMG signals, which can be mentally fatiguing and provide a limited number of simultaneously controlled DOF [130]. Advanced myoelectric-based techniques, such as targeted muscle reinnervation [289] and muscle synergy-based algorithms [151, 68, 69], are increasing the number of controllable DOF and intuitiveness of standard myoelectric control.

Despite the fact that **muscle contraction-based control interfaces** [72, 77, 86, 90, 91] are not being implemented in today's clinical practice, these interfaces are showing significant advancements in the laboratories and may find their way to compete with the well-established myoelectric control in the near future¹.

¹ We performed a pilot measurement of mechanomyographic (MMG) signals in one adult with DMD (24 years old, Brooke 5) using the sensors described in [290]. It was not possible to distinguish signal from noise from the measurement and we concluded that MMG signals were not a feasible

Movement- and force-based control interfaces are challenging to use in patients with severe movement disorders. Force and movement signals are generally disturbed by the impairments of the users or by intrinsic or external disturbances such as joint stiffness and gravity. In this dissertation we have developed force-based control interfaces that estimated and actively compensated gravity and joint-stiffness forces (see Chap. 4 and 6). These type of interfaces are often implemented in rehabilitation robots for patients that need training to regain mobility and strength [33, 148, 180].

Finally, we found that **control interfaces based on signals from parallel systems** (i.e. systems that function in parallel to the supported system; see Chap. 2) are generally a suitable solution to derive the movement intention from highly paralyzed patients [112, 118, 113, 121, 125]. Interfaces based on parallel systems have also been implemented in hybrid sensor modalities [198] to expand the sources of information.

Although many different control interfaces have been developed, their respective performance capabilities and limitations remain unclear. There is a need for a basic consensus on the evaluation methods to be able to compare control interfaces and select the most suitable for a specific application. The studies presented in chapter 3 and in [205] are examples of evaluation methods based on continuous position-tracking tasks that can be used to systematically characterize the performance of control interfaces. An alternative would have been the use of evaluation methods based on the Fitts' Law paradigm with screen-based discrete position-reaching tasks in one-, two- or three-dimensions [207, 211, 214, 291].

Current control interfaces (in combination with the rest of the assistive system) are still far below the performance of the human movement control system. This difference in performance does not meet the expectations of users in many cases, which inevitably hinders the acceptance of assistive devices. However, the large number of research studies aiming at improving the performance of assistive devices (Chap. 2) is a clear indication that there is global interest in developing natural and intuitive control interfaces for people with functional disabilities.

signal to detect the motion intention of adults with DMD. We conjecture that interfaces based on this phenomena are not viable options since DMD affects the muscle contraction.

9.3 EVALUATION OF EMG AND FORCE AS CONTROL INTERFACES TO SUPPORT THE ARM FUNCTION OF ADULTS WITH DMD

ii *Are EMG- and Force-based control interfaces feasible for the control of active arm supports in adults with DMD?*

While there are several studies on the development and evaluation of EMG- and force-based control interfaces [205, 215, 292, 217, 293], no studies focused on testing these control strategies for the specific population of adults with DMD. The selection of the most suitable control interface to operate an active arm support for adults with DMD required a better understanding of the limitations and capabilities of EMG- and force-based control interfaces through objective and quantitative evaluation methods during functional tasks. Chapters 3, 4 and 6 present studies that investigated the feasibility, performance and user's acceptance of EMG- and force-based control interfaces in one- and two-DOF tasks.

Firstly, we performed a comparison between EMG, force and joystick (i.e. interface used by adults with DMD) using a screen-based position-tracking task with healthy subjects to have a baseline performance measure (see Chapter 3). The results of this first experiment showed that all three control methods presented an acceptable performance and could be regarded as potential solutions for the control of arm supports. Therefore, we proceeded to carry out feasibility studies using experimental active arm supports (i.e. the Elbow Drive and the UR5 Robotic Arm; Fig. 58) with adults with DMD. While we also implemented joystick-based control in the experimental devices (besides EMG- and force-based control interfaces), we decided to exclude the joystick-based interface from the comparative studies as this interface requires the use of the contralateral hand and is not a viable solution if both arms are supported. Instead, the joystick-based interface was used to let the participants with DMD familiarize themselves with the experimental tasks and the device.

Chapter 4 and 6 investigated the feasibility of EMG- and force-based control interfaces for the support of elbow (Chap. 4) and planar arm movements (Chap. 6) in adults with DMD with very limited arm function (Brooke 4, 5 and 6). During the evaluation of these control methods, we found several differences that are described in the following paragraphs and summarized in Table 18.

Figure 58: Research Platforms used to evaluate EMG- and force-based control interfaces. **a)** Elbow Drive system used to actively support elbow movements during a discrete position-tracking task. **b)** UR5 Robotic Arm used to actively support planar arm movements during line tracing tasks.

Force-based control interfaces fundamentally differ from EMG-based control interfaces in the fact that the measured force signal also contains information on the intrinsic forces of the arm, such as stiffness, viscosity, inertia and gravitational forces (Fig. 59). Therefore, the use of force-based control interfaces by people with severe muscular weakness requires an accurate distinction between the voluntary forces of the user and the intrinsic forces of the arm or external disturbances from the environment. We estimated and actively compensated gravity and joint-stiffness forces using a measurement-based method which resulted in an increase of the functional range of motion in adults with Brooke scores of 5 and 6 (Chap. 4, 6 and 7). We also developed adaptive methods for the active gravity and joint-stiffness compensation that were not measurement dependent [257]. These methods were based on the estimation of the compensation force using a low-pass filter and switching of control parameters using a finite state machine. Even though these strategies were also able of increasing the functional workspace of the arm, adults with DMD considered them as inconvenient because switching the controller resulted in intermittent movements, and because the system had to be relaxed every time to update the compensation force.

EMG-based control interfaces are not affected by the intrinsic forces of the arm and therefore do not require a method to distinguish the voluntary compo-

Figure 59: Simplified diagram of EMG- and force-based control interfaces. **A)** The interaction force (F_{int}), which is a combination of the voluntary muscle forces (F_{vol}), and the intrinsic human arm forces (F_{pas}) is measured by a force sensor. An estimation of the voluntary force ($\hat{F}_{vol,f}$) is obtained by actively compensating the intrinsic forces of the arm. **B)** EMG signals from the arm muscles are measured, and a voluntary force ($\hat{F}_{vol,e}$) is estimated from them.

nent from other signal components. Yet EMG-based control interfaces require a method to map the EMG activity to movement. We implemented direct EMG control that maps the activity of a pair of agonist-antagonist muscles to an estimated joint torque, or force in a certain direction. In Chapter 6, the EMG signals were measured from muscles that were not directly related to the supported movement but controlled the arm movements in tasks-space, which can compromise intuitiveness. Even though it has been shown that humans can quickly

adapt to non-intuitive mappings of EMG to movements [150], the use of an exoskeleton as arm support, such as the Active A-Gear, would allow the mapping of the EMG signals to joint torques (as in Chap. 4) which could improve the level of control intuitiveness.

Adults with DMD perceived EMG-based control interfaces as less intuitive than force-based control interfaces (specially for multi-DOF movements; Chap. 6), probably because force is closer to the natural way of interacting with the environment. Nevertheless, EMG-based control had the advantage of being less fatiguing. We presume that since EMG signals are not affected by the intrinsic forces of the arm, they better represent the movement intention of people with voluntary forces below the intrinsic forces, and therefore require less effort.

In the context of assistive devices for people with severe muscular weakness such as DMD, we consider that the usability and performance of the device is highly affected by fatigue. Despite the fact that all our evaluation studies (Chap. 4, 6 and 7) show that subjects with Brooke scores of 5 were able to perform arm movements using force-based control interfaces when gravity and joint-stiffness were compensated, all subjects also reported high levels of fatigue. In contrast, EMG-based control was not perceived as fatiguing and thus would allow adults with DMD to use the assistive device and their arms for longer periods of time not only along the day but also along the progression of the disease. This conjecture is supported by the study presented in Chapter 5, in which we were able to measure EMG signals in a 37 year-old man with DMD that had lost his arm function 15 years before the study. The measured signals were successfully used as input signal to control a simulated elbow orthosis, which supports that EMG signals can be used as control interface for assistive devices in adults with DMD until the last stage of the disease.

Table 18: Relative comparison of EMG- and force-based control interfaces based on the results of Chapters 4, 6 and 7.

	Intuitiveness	Ease of Donning	Fatigue	Speed & Accuracy
EMG-based control	-	-	-	+/-
Force-based control	+	+/-	++	+

Regarding the ease of donning, force-based control interfaces present the advantage that they can be integrated in the active arm support eliminating the need for manually placing the sensor in a specific location as in the case of EMG electrodes. Nevertheless, force-based control interfaces probably will require a measurement of the joint stiffness forces across the workspace, which can increase the time of donning, especially if this measurement has to be repeated several times along the day due to changes in joint stiffness. EMG-based control interfaces present other practical issues (Chap. 2), including the time-variability of the measurements, the high sensitivity to electrode location, and the uncomfortable feeling that the multiple electrodes may produce in contact with the skin for a long period of time. Additionally, the combination of EMG electrodes with a close-to-body structure such as the one of the Active A-Gear can compromise signal quality due to artifacts caused by collisions between the electrodes and the structure.

The movement performance (i.e. speed and accuracy) presented a high variability among the test subjects. Movements with EMG based control interfaces were generally slower and less smoothness than with force-based control interfaces. We consider that the lower speed and smoothness of EMG-based control could be improved by training and fine-tuning of the control gains.

In conclusion, we found that both EMG- and force-based control interfaces are feasible solutions for the control of active arm support for adults with DMD that have lost their arm function a long time ago. The comparative studies indicated that, in general, EMG-based control interfaces are better suited for adults with DMD than force-based interfaces as they are experienced as less fatiguing. Nevertheless, force-based control interfaces with active gravity and joint-stiffness compensation can be a better alternative for those cases in which voluntary forces would still be higher than the intrinsic forces of the arms.

9.4 ARM SUPPORTS FOR PEOPLE WITH SEVERE MUSCULAR WEAKNESS

iii *How can the A-Arm and the Active A-Gear tackle the major limitations of existing arm supports?*

Fully passive or actively adjustable passive arm supports are in most cases not effective for people with severe muscular weakness such as adults with DMD [42]. This specific group of people are generally too weak to use arm supports since they cannot generate the forces needed to overcome the intrinsic forces of their arms, or the inertia and friction forces of the device [105, 104]. Accordingly, the results from Chapter 4 and 6 indicated that people with a maximum strength similar to or below the joint-stiffness forces can benefit more from (force- or EMG-controlled) active arm supports than from passive arm supports. However, active arm supports for people with severe muscular weakness are not commercially available, and this group of people is limited to use external robotic arms such as the JACO arm (Kinova, Canada) [32]. External robotic arms enable adults with DMD to interact with the environment and perform basic activities of daily living (ADL) such as self-feeding, but they do not use their arms at all, which can contribute to the development of complications such as joint contractures, pain, and functional deterioration of the arms [2, 26, 24].

The A-Arm (Chap. 7, Fig. 60a) and the Active A-Gear (Chap. 8, Fig. 60b) were developed with the aim to solve the three limitations of current arm supports: (I) they provide insufficient support to the weakest users, (II) they have large dimensions and an unattractive look that are often stigmatizing the users, and (III) they are operated with a joystick and buttons, which require sacrificing the use of one hand. In the Flexextension A-Gear project we decided to tackle these shortcomings by developing the Active A-Gear, a five-DOF wearable arm support that can be controlled with signals that are implicitly related to the movement intention of the user. In parallel, we decided to investigate an alternative design, the A-Arm, which is a planar and non-wearable active arm support that becomes inconspicuous by its simplicity and the way it is attached to the wheelchair and to the user's arm. In accordance with the feasibility studies (Chap. 3, 4 and 6), both EMG- and force-based control interfaces were viable solutions for supporting arm movements in adults with DMD. Thus, both control

(a) A-Arm

(b) Active A-Gear

Figure 60: Prototypes of arm supports in which EMG and force-based control interfaces were implemented. **a)** The A-Arm, a planar active arm support that provides assistance in tabletop tasks. **b)** The Active A-Gear, an active and wearable five-DOF upper extremity exoskeleton.

methods were implemented in the A-Arm and the Active A-Gear. Compared to the use of joysticks and buttons for the operation of arm supports, EMG- or force-based control interfaces present the advantage that they derive the control commands from signals that are implicitly related to the movement intention, and do not require the use of any other part of the body. Additionally, in the ideal case that adults with DMD use one active arm support for each arm, the use of control interfaces that derive the motion intention from implicit commands becomes necessary for the interaction with the assistive device.

The concept of **the A-Arm** came up from several discussions with adults with DMD and physicians who highlighted the importance of tabletop tasks such as computer, phone or table use, writing or drawing, and the control of the wheelchair's joystick. In order to support these type of tasks, we developed the A-Arm, a simple two-DOF active arm support based on a serial two-link mechanism that assists movement in the horizontal plane. The A-Arm can be controlled with EMG- and force-based control interfaces, and replaces the normal

armrest of a wheelchair, which makes it inconspicuous. In contrast to existing planar arm supports [283, 284, 285] that are passive and cannot assist people with severe muscle weakness, the A-Arm can provide extra assistance with the actuators increasing the functional range of motion of the users. Additionally, the A-Arm has control interfaces that do not require the use of the other arm or hand (to operate joysticks or buttons), which results in a natural interaction with the assistive device. Preliminary results with a 24 year-old adult with DMD (Brooke 5) indicated that the assistance provided by the A-Arm enabled the user to switch from different devices (mobile, computer and wheelchair's joystick), which was perceived as a considerable increase of autonomy (Chap. 7).

The Active A-Gear is an active exoskeleton designed to provide assistance for the performance of ADL in people with severe muscular weakness. It is build upon the Passive A-Gear [43] and differs from existing arm supports in its kinematic structure that closely mimics the biomechanics of the arm and trunk. Thanks to the implementation of the balancing mechanism described by [294], we were able to design a wearable and close-to-body kinematic architecture that balances the weight of the arm in every position and orientation without using parallelograms. Another characteristic of the Active A-Gear arm support is the addition of a DOF at the hip level. This DOF was perceived by the test subjects [43, 295] as “very beneficial” since they had the freedom to lean forward and back and did not feel restricted to the wheelchair. This restriction is for example a drawback of the popular WREX [34] which is rigidly attached to the wheelchair and does not allow trunk movements. The combination of passive and active support made it possible for us to design the Active A-Gear as a low-weight (2.5 kg) device capable to support the weight of the arm (≈ 3 kg) and apply high endpoint forces (30-60 N). In contrast to the MyoPro (Myomo. Inc., USA), an EMG-controlled elbow-wrist-hand orthosis, we developed the Active A-Gear to support almost all the DOF of the arm (three-DOF at the shoulder and one-DOF at the elbow) to allow users to perform a complete set of basic activities of daily living. Note that the assistance of shoulder movements is crucial in people with DMD as proximal muscles are affected first and hand or wrist muscles remain functional for a longer period of time.

It has been part of our investigations to determine how many DOF are needed for the optimal support of the arm function in adults with DMD. After testing the A-Arm and the Active A-Gear, we believe that an optimal balance between functionality and complexity exists between these two concepts. On one hand,

the A-Arm could be extended to three DOF to support hand to face movements, which would expand its functionality to basic ADL such as eating and drinking or face and head scratching. On the other hand, reducing the number of active DOF of the shoulder in the Active A-Gear could reduce its complexity while preserving most of its functionality. Future research should further analyze this trade off between complexity and functionality to find an optimal balance.

In conclusion, by developing the A-Arm and the Active A-Gear and implementing EMG- and force-based control interfaces, we made a significant step in improving arm supports for adults with DMD: the A-Arm and the Active A-Gear provide support to the weakest users, have small dimensions to reduce their stigmatizing effect, and use control interfaces that use signals implicitly related to the movement intention of the user. Hopefully these novel concepts of arm supports will be the basis for the development of commercially available active arm supports for people with severe muscular weakness.

9.5 FUTURE DIRECTIONS

In this section, we note the main limitations of our approach and suggest future research directions to overcome them, with a particular section for the increase of controllable DOF.

Approach Limitations

Low number of subjects: Any study dealing with testing assistive devices for subjects with DMD is severely conditioned by the low density of available candidates. In our case, the severe limitation of subjects was also a consequence of our commitment to cause the least inconveniences to the subjects, and strictly observing the legal and ethical constraint that restricts the participation of any given subject to one single study at the same time.

In the framework of this limitation, considering that our main goal was the investigation of suitable control interfaces for the support of arm movements in adults with DMD, we chose to carry out an exploratory assessment of several working principles at the expense of testing with a low number of participants (i.e., 1-3 subjects), rather than a systematic assessment of few working principles with a large number of subjects. Systematic studies should be carried out

now, once the exploratory phase has been completed and few, selected and relatively optimized control methods are ready for testing on larger samples.

Fatigue: Adults with DMD experience strong training and fatigue effects due to the disuse of their arms. Therefore, the experimental protocols had to be designed to balance the amount of training and evaluation trials: the protocols allowed the participants to learn how to use the control interfaces and perform the experimental task, while having a sufficient number of evaluation trials per condition, but keeping the overall length of the experiment within a reasonable time frame to minimize mental and physical fatigue. Reaching this balance was challenging and future studies must pay particular attention to the design of additional protocols.

Heterogeneity: DMD shows a high functional heterogeneity [12] and any assistive device for this population should be personalized and adjusted to the specific anatomical characteristics, capabilities and limitations of every user. However, the personalization of the control parameters to each individual was limited during the comparative studies due to time constraints and the need for keeping consistent experimental conditions among participants. Future research should investigate the personalization of the control interfaces, which could include signal-filtering parameters, interface dynamics and sensor location.

Simplified tasks: While the comparative studies presented in this dissertation were based on arm movements that are related to ADL, the experimental tasks were simplified to make the quantification of the performance metrics easier. Future research should evaluate the performance and robustness of the control interfaces during fully functional tasks and in everyday life situations. Additionally, it is needed to investigate long-term performance of the EMG- and force-based control interfaces, which might be affected by learning, fatigue or poor long-term signal stability.

Limited Evaluation of Prototypes: The evaluation of the A-Arm and the Active A-Gear was limited due to time constraints. Preliminary test with the A-Arm and the Active A-Gear revealed that several aspects of the design could be improved. Future work should improve these prototypes and perform tests with several adults with DMD.

9.5.1 *Next Steps in EMG- and Force-Based Control Interfaces*

This dissertation has presented studies that implemented and evaluated EMG- and force-based control interfaces of one (Chap. 3 and 4) and two DOF (Chap. 6 and 7). The extension to operate three or more DOF (e.g. four in the Active A-Gear) presents challenges for both control methods, as well as for invasive alternatives.

Force-based control interfaces: the control of three or more DOF using force-based control interfaces would require the extension of the measurement-based method that we developed for the active compensation of gravity and joint-stiffness forces to more dimensions. The implementation and preliminary testing of the active compensation of joint-stiffness and gravity forces in three DOF with the Active A-Gear revealed a considerable increase of the time needed to perform de measurement of these forces compared to the two-DOF measurements performed with the UR5 (Chap. 6). This increase of the measurement time would probably hinder user's acceptance. An alternative approach would be to model the gravity and joint-stiffness forces (as proposed in [104]) to reduce the duration of the measurement. In any case, force-based control interfaces would always be compromised by the challenging detection of the low-amplitude voluntary forces of the user.

Besides the challenge of accurately distinguishing the voluntary forces of the user from the intrinsic forces of the arm, force-based control interfaces also need to take into account the user-environment interaction. For instance, in the case of tasks such as picking up and placing objects, the force-based control interface should be able to detect the intention of picking or dropping an object and the compensation of its weight.

Force-based control interfaces provide assistance to the users by actively reducing their impedance or the effect of external forces such as gravity forces. In our studies, we have actively reduced the impedance of the arm by actively compensating the joint-stiffness forces. The active compensation of joint-damping or inertia forces of the arm would further reduce the impedance and provide extra assistance to the users. Aguirre-Ollinger et al. have investigated the active compensation of limb inertia and damping forces in several studies [296, 275, 277]. The goal of these active compensation strategies is to render negative virtual impedance with a robotic device that interacts with the positive impedance

of the human. As a result, the overall human-robot impedance stays positive yet lower than the one of the human on its own. These compensation strategies are challenging to implement due to the inherent instability of the robotic device when rendering negative virtual impedance.

EMG-based control interfaces: the EMG-based control methods implemented are similar to the clinical standard EMG-based control strategies known as direct control or proportional control and implemented in upper limb prosthetics. Direct EMG-based control interfaces are robust but require the user to generate independent EMG signals, which can be mentally fatiguing and provide a limited number of simultaneously controlled DOF [130, 207]. More advanced EMG-based control methods such as regression-based algorithms [68, 291] have been implemented in upper extremity prosthetics showing simultaneous and proportional control over two DOF with surface EMG signals, and over three DOF with intramuscular EMG signals. These methods do not require isolated EMG signals as they can learn to map complex activation patterns to specific movements, and provide proportional and simultaneous control of several DOF. Besides the control of movements or forces of the assistive device, regression-based algorithms can also be used to modulate the joint or end-effector impedance [297], which is known to be fundamental for the interaction with the environment [298].

A preliminary implementation and evaluation of regression-based algorithm using an artificial neural network (ANN) was carried out by Jolein van der Sluis in her BSc graduation project [299]. The goal was to design an ANN to map EMG signals to forces for the control of active arm supports. The ANN was trained to map EMG activity from arm and chest muscles to forces at the forearm in an isometric neutral position, and was validated with the same experimental task and setup as the one used in Chapter 6 with one healthy subject: the subject had to perform planar line tracing tasks in several directions using the UR5 robotic manipulator as active arm support. While the subject was able to trace the lines in all five directions of the horizontal plane during the evaluation of the ANN, the subject experienced high levels of effort when trying to reach in the directions that were far away from the location used during the isometric training of the ANN. These results suggested that an ANN was useful for finding complex mappings between EMG signals and intended forces, but that the training strategy of the ANN should be improved to make movements

easier in all directions. Future research should focus on the development of a better training protocol and explore unsupervised and on-line learning techniques that take the arm position into account and can be used by people with DMD.

As mentioned in Chapter 8 and in Section 9.3, the combination of surface EMG electrodes with close-to-body structures is challenging since the EMG signals are highly sensitive to movement artifacts and collisions. EMG sensing technology integrated in textile [300] or implanted underneath the skin [301] could possibly improve the usability (i.e. donning) and robustness of EMG-based control interface.

Hybrid EMG-force-based control interfaces: now that we have a comprehensive overview of the capabilities and limitations of EMG- and force-based control interfaces, the design of an interface that integrates the information from both control interfaces taking the best of each system seems a logical continuation. For instance, an EMG-force hybrid interface could use EMG signals to distinguish voluntary from un-voluntary forces, and force signals for the control of the direction and amplitude of the movements. Hybrid approaches have been shown to improve accuracy, reliability or robustness in comparison to individual use of control interfaces [198].

Invasive control interfaces: with the development of wireless devices for invasive recordings that remain operational for long periods of time, and stable decoders that give robust performance without daily retraining, invasive control interfaces, could become a way to increase independence and the quality of life for many people with neuromuscular disorders. Invasive control interfaces can be based on either intracortical or peripheral signals. Recent studies on invasive brain-computer interface have shown that people with tetraplegia can control robotic arms (up to 10 DOF) using signals recorded by intracortical electrodes [302]. Additionally, a recent study [303] showed how intracortical signals could be linked in real-time to muscle activation via surface electrical stimulation to restore movement in a paralyzed subject. The subject was able to continuously control isolated finger movements and six different wrist and hand motions. It has to be noted that invasive brain-computer interfaces still presents many practical and safety challenges for its implementation in clinical practice [304]. Nevertheless, the high information content of intracortical sig-

nals allows the decoding of a high number of independent control signals thus enabling the support of complex movements.

In contrast to neurological disorders, in muscular dystrophies the neural pathways are not affected and therefore the control commands can also be decoded from invasive nerve [305] or muscle [301] recordings using implantable electrodes. Signals from the peripheral nervous system such as nerve or muscle recordings might be more specific and have a higher signal to noise ratio compared to intracortical signals. Furthermore, the risks of implanting electrodes in arm muscles or nerves are lower than implanting electrodes in the brain.

9.6 GENERAL CONCLUSIONS FROM THE FLEXTENSION A-GEAR PROJECT²

The goal of the Flexextension A-Gear project was to develop an inconspicuous and natural arm support that can support ADL and adapt to the growing needs of people with DMD. As a result of the development of this arm support we reached the following conclusions:

Adaptive Support

DMD is a progressive disease and therefore the level of support should increase along the course of the disease. The strategy of the Flexextension A-Gear project was to develop first a passive system (the Passive A-Gear [43]) and then upgrade it to an active system with motorized joints and a control interface (the Active A-Gear [44]).

We have developed and implemented EMG- and force-based control interfaces for the Active A-Gear [262, 44]. Comparative studies between EMG and force-based control interfaces indicated that, in general, EMG-based control interfaces are better suited for adults with DMD than force-based control interfaces, because the former are experienced as less fatiguing. Nevertheless, force-based control interfaces can be a better alternative for those cases in which voluntary forces would still be higher than the intrinsic forces of the arms.

² This section is based on the overall work carried out by the Flexextension A-Gear Research Team (www.flexextension.nl)

Inconspicuousness and Natural Support

The aesthetic appearance of arm supports plays an important role in users' acceptance [35, 42, 105]. Therefore, our strategy was to make a slender arm support, with the long-term goal that could be worn underneath clothing. In addition, we chose to make an "exoskeleton-like" arm support that could mimic the biomechanics of the arm and trunk allowing natural movements. We found that the design of "close-to-body" structures was challenging as it compromised balancing quality of the weight compensation mechanism, proper alignment of the human joints with the device, and range of motion.

Through the development of the A-Arm [45], a non-wearable and planar active arm support, we investigated an alternative strategy. We found that inconspicuousness could also be reached by simplifying the design and integrating the arm support in the wheelchair of the user. Finally, natural support was also addressed by using EMG- and force-based control interfaces, which derive the movement intention from signals that are implicitly related to the intended movement.

Translating Clinical Knowledge into Design Requirements

In order for an arm support to be accepted, design requirements should match user wishes and needs. Upper extremity function of boys and men with DMD, over the course of the disease, was studied using questionnaires and quantitative outcome measures, such as 3D motion analysis, muscle force, surface electromyography, muscle ultrasound and the Performance of Upper Limb scale. These studies showed that arm function starts decreasing in an early stage of the disease. Activity limitations already occur before boys with DMD become non-ambulant, and muscle forces deviate from those of healthy subjects before activity limitations are actually observed [2]. In addition, we found that upper extremity muscles deteriorated at a different pace, which requires the development of adaptive arm supports that are able to provide different levels of assistance.

Taking these findings into account, we believe that starting to use an arm support early in the course of the disease is beneficial. The use of an arm support stimulates boys to keep using their arms, which can lead to a training effect, reduction of disuse, and slower deterioration of arm function [24].

Evaluation of Arm Supports

Despite several arm supports are commercially available [5], no studies had focused on systematically comparing their performance and identifying their advantages and limitations. Few publications [34, 43, 36, 37] describe the design and performance of a specific arm support, yet these never compare the proposed design with other devices, nor use similar performance metrics that allow their comparison. As a consequence, there is a lack of knowledge as to which device or working principle is the most suitable for a specific type of impairment and task. Within the Flexextension A-Gear project, we have evaluated prototypes using both subjective and objective outcome measures [43, 295] and we carried out several comparative studies [212, 262] that evaluated the feasibility, performance and user's acceptance of EMG- and force-based control interfaces. These studies assessed the suitability of different arm supports and control methods for DMD with diverse levels of arm function. Similar studies should be carried out to evaluate the performance of current and new arm supports, with the goal of making evidence-based clinical recommendations for the use of any given arm support. User requirements such as aesthetics and fatigability should always be taken into account.

Future Perspectives

Although the assistive technology developed in the Flexextension A-Gear project focused on the specific needs of the DMD population, people with other neuromuscular disorders may benefit from many of our findings. Passive gravity compensation and active assistance using force and EMG-based control have been successfully used by people with different neuromuscular disorders [306, 307, 308, 250, 34, 309].

The goal of the Flexextension A-Gear project was to develop arm supports that can be used in daily life. In the course of this project, however, we could not test the prototypes in an "at home" situation due to time constraints. Future studies should be carried out to test the effectiveness of the prototypes over longer periods of time in "at home" situations. The first steps in this direction are being made in the "A-Gear @ Home" project.

BIBLIOGRAPHY

- [1] Bartels B, Pangalila RF, Bergen MP, Cobben NAM, Stam HJ, Roebroek ME. Upper limb function in adults with Duchenne muscular dystrophy. *Journal of Rehabilitation Medicine: Official Journal of the UEMS European Board of Physical and Rehabilitation Medicine*. 2011 Sep;43(9):770–775.
- [2] Janssen MMHP, Bergsma A, Geurts ACH, Groot IJMd. Patterns of decline in upper limb function of boys and men with DMD: an international survey. *Journal of Neurology*. 2014 Apr;261(7):1269–1288.
- [3] Eagle M, Bourke J, Bullock R, Gibson M, Mehta J, Giddings D, et al. Managing Duchenne muscular dystrophy. The additive effect of spinal surgery and home nocturnal ventilation in improving survival. *Neuromuscular Disorders*. 2007 Jun;17(6):470–475.
- [4] Rahbek J, Steffensen BF, Bushby K, de Groot IJM. 206th ENMC International Workshop: Care for a novel group of patients: adults with Duchenne muscular dystrophy Naarden, The Netherlands, 23-25 May 2014. *Neuromuscular Disorders*. 2015 Sep;25(9):727–738.
- [5] Heide LAVd, Nindhuis Bv, Bergsma A, Gelderblom GJ, Pijl DJvd, Witte LPd. An overview and categorization of dynamic arm supports for people with decreased arm function. *Prosthetics and Orthotics International*. 2014 Aug;38(4):287–302.
- [6] van der Heide LA, Gelderblom GJ, de Witte LP. Effects and effectiveness of dynamic arm supports: a technical review. *American Journal of Physical Medicine & Rehabilitation / Association of Academic Physiatrists*. 2015 Jan;94(1):44–62.
- [7] Flexextension;. Available from: <http://www.flexextension.nl/>.
- [8] Mendell JR, Lloyd-Puryear M. Report of MDA muscle disease symposium on newborn screening for Duchenne muscular dystrophy. *Muscle & Nerve*. 2013 Jul;48(1):21–26.
- [9] Kornberg A, Yiu E. Duchenne muscular dystrophy. *Neurology India*. 2008;56(3):236.
- [10] Emery AEH. The muscular dystrophies. *Lancet*. 2002 Feb;359(9307):687–695.

- [11] Skuk D, Goulet M, Tremblay JP. Preservation of muscle spindles in a 27-year-old Duchenne muscular dystrophy patient: importance for regenerative medicine strategies. *Muscle & Nerve*. 2010 May;41(5):729–730.
- [12] Desguerre I, Christov C, Mayer M, Zeller R, Becane HM, Bastuji-Garin S, et al. Clinical Heterogeneity of Duchenne Muscular Dystrophy (DMD): Definition of Sub-Phenotypes and Predictive Criteria by Long-Term Follow-Up. *PLOS ONE*. 2009 Feb;4(2):e4347.
- [13] Eagle M, Baudouin SV, Chandler C, Giddings DR, Bullock R, Bushby K. Survival in Duchenne muscular dystrophy: improvements in life expectancy since 1967 and the impact of home nocturnal ventilation. *Neuromuscular Disorders*. 2002 Dec;12(10):926–929.
- [14] Hoffman EP, Brown RH, Kunkel LM. Dystrophin: the protein product of the Duchenne muscular dystrophy locus. *Cell*. 1987 Dec;51(6):919–928.
- [15] van Deutekom JCT, van Ommen GJB. Advances in Duchenne muscular dystrophy gene therapy. *Nature Reviews Genetics*. 2003 Oct;4(10):774–783.
- [16] Mendell JR, Rodino-Klapac LR. CRISPR/Cas9 treatment for Duchenne muscular dystrophy. *Cell Research*. 2016 Mar;.
- [17] Kaiser J. CRISPR helps heal mice with muscular dystrophy. *Science*. 2015 Dec;.
- [18] Jung IY, Chae JH, Park SK, Kim JH, Kim JY, Kim SJ, et al. The Correlation Analysis of Functional Factors and Age with Duchenne Muscular Dystrophy. *Annals of Rehabilitation Medicine*. 2012 Feb;36(1):22–32.
- [19] Bushby K, Finkel R, Birnkrant DJ, Case LE, Clemens PR, Cripe L, et al. Diagnosis and management of Duchenne muscular dystrophy, part 2: implementation of multidisciplinary care. *The Lancet Neurology*. 2010 Feb;9(2):177–189.
- [20] Voet NB, van der Kooi EL, Riphagen II, Lindeman E, van Engelen BG, Geurts AC. Strength training and aerobic exercise training for muscle disease. *The Cochrane Database of Systematic Reviews*. 2010;(1):CD003907.
- [21] Scott OM, Hyde SA, Goddard C, Jones R, Dubowitz V. Effect of exercise in Duchenne muscular dystrophy. *Physiotherapy*. 1981 Jun;67(6):174–176.
- [22] de Lateur BJ, Giacon RM. Effect on maximal strength of submaximal exercise in Duchenne muscular dystrophy. *American Journal of Physical Medicine*. 1979 Feb;58(1):26–36.

- [23] Vignos PJ, Watkins MP. The effect of exercise in muscular dystrophy. *JAMA*. 1966 Sep;197(11):843–848.
- [24] Jansen M, van Alfen N, Geurts ACH, de Groot IJM. Assisted bicycle training delays functional deterioration in boys with Duchenne muscular dystrophy: the randomized controlled trial "no use is disuse". *Neurorehabilitation and Neural Repair*. 2013 Dec;27(9):816–827.
- [25] Sveen ML, Jeppesen TD, Hauerslev S, Køber L, Krag TO, Vissing J. Endurance training improves fitness and strength in patients with Becker muscular dystrophy. *Brain: A Journal of Neurology*. 2008 Nov;131(Pt 11):2824–2831.
- [26] Jansen M, Burgers J, Jannink M, van Alfen N, Groot IJM. Upper Limb Training with Dynamic Arm Support in Boys with Duchenne Muscular Dystrophy: A Feasibility Study. *Int J Phys Med Rehabil*. 2015;3(256):2.
- [27] Brooke MH, Griggs RC, Mendell JR, Fenichel GM, Shumate JB, Pellegrino RJ. Clinical trial in duchenne dystrophy. I. The design of the protocol. *Muscle & Nerve*. 1981;4(3):186–197.
- [28] Mayhew A, Mazzone ES, Eagle M, Duong T, Ash M, Decostre V, et al. Development of the Performance of the Upper Limb module for Duchenne muscular dystrophy. *Developmental Medicine and Child Neurology*. 2013 Nov;55(11):1038–1045.
- [29] Pandya S, Andrews J, Campbell K, Meaney FJ. Rehabilitative technology use among individuals with Duchenne/Becker muscular dystrophy. *Journal of Pediatric Rehabilitation Medicine*. 2016 Feb;9(1):45–53.
- [30] Stuberger W. Home Accessibility and Adaptive Equipment in Duchenne Muscular Dystrophy: A Case Report. *Pediatric Physical Therapy Winter* 2001. 2001;13(4):169–174.
- [31] Pellegrini N, Guillon B, Prigent H, Pellegrini M, Orlikovski D, Raphael JC, et al. Optimization of power wheelchair control for patients with severe Duchenne muscular dystrophy. *Neuromuscular disorders: NMD*. 2004 May;14(5):297–300.
- [32] Maheu V, Archambault PS, Frappier J, Routhier F. Evaluation of the JACO robotic arm: Clinico-economic study for powered wheelchair users with upper-extremity disabilities. In: 2011 IEEE International Conference on Rehabilitation Robotics (ICORR); 2011. p. 1–5.
- [33] Maciejasz P, Eschweiler J, Gerlach-Hahn K, Jansen-Troy A, Leonhardt S. A survey on robotic devices for upper limb rehabilitation. *Journal of NeuroEngineering and Rehabilitation*. 2014 Jan;11(1):3.

- [34] Rahman T, Sample W, Seliktar R, Scavina MT, Clark AL, Moran K, et al. Design and Testing of a Functional Arm Orthosis in Patients With Neuromuscular Diseases. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2007 Jun;15(2):244–251.
- [35] Gunn M, Shank TM, Eppes M, Hossain J, Rahman T. User Evaluation of a Dynamic Arm Orthosis for People With Neuromuscular Disorders. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2015;PP(99):1–1.
- [36] Herder JL. Development of a statically balanced arm support: ARMON. In: *Rehabilitation Robotics, 2005. ICORR 2005. 9th International Conference on*; 2005. p. 281 – 286.
- [37] Kramer G, Romer GRBE, Stuyt HJA. Design of a Dynamic Arm Support (D ∞ AS ∞) for gravity compensation. *IEEE*; 2007. p. 1042–1048.
- [38] Kumar A, Phillips MF. Use of powered mobile arm supports by people with neuromuscular conditions. *The Journal of Rehabilitation Research and Development*. 2013;50(1):61–70.
- [39] Ragonesi D, Agrawal S, Sample W, Rahman T. Series elastic actuator control of a powered exoskeleton. *Conference proceedings: Annual International Conference of the IEEE Engineering in Medicine and Biology Society IEEE Engineering in Medicine and Biology Society Conference*. 2011;2011:3515–3518.
- [40] Baklouti M, Guyot PA, Monacelli E, Couvet S. Force controlled upper-limb powered exoskeleton for rehabilitation. In: *IEEE/RSJ International Conference on Intelligent Robots and Systems, 2008. IROS 2008*; 2008. p. 4202.
- [41] Motion Controlled Arm Support (McArm);. Available from: <http://www.mcarm.eu/>.
- [42] Bergsma A, Lobo-Prat J, Vroom E, Furlong P, Herder JL. 1St workshop on upper-extremity assistive technology for people with duchenne: state of the art, emerging avenues, and challenges. *Neuromuscular Disorders*. 2016 Apr;.
- [43] Kooren PN, Dunning AG, Janssen MMHP, Lobo-Prat J, Koopman BFJM, Paalman MI, et al. Design and pilot validation of A-gear: a novel wearable dynamic arm support. *Journal of NeuroEngineering and Rehabilitation*. 2015 Sep;12(1):83.
- [44] Kooren PN, Lobo-Prat J, Keemink AQL, Janssen MMHP, Stienen AHA, Groot IJMd, et al. Design and Control of the Active A-Gear: a Wearable 5 DOF Arm Exoskeleton for Adults with Duchenne Muscular Dystrophy. In: *Biomedical Robotics*

- and Biomechatronics (2014 5th IEEE RAS EMBS International Conference on. vol. (submitted). Singapore: IEEE; 2016. .
- [45] Straathof PTC, Joan Lobo-Prat, Frank Schilder, Peter N Kooren, Micha I Paalman, Arno H A Stienen, et al. Design and Control of the A-Arm: an Active Planar Arm Support for Men with Duchenne Muscular Dystrophy. In: Biomedical Robotics and Biomechatronics (2014 5th IEEE RAS EMBS International Conference on. vol. (submitted). Singapore: IEEE; 2016. .
 - [46] Veltink PH. Sensory feedback in artificial control of human mobility. *Technology and Health Care*. 1999;7(6):383–391.
 - [47] Veltink PH, Koopman HF, van der Helm FC, Nene AV. Biomechatronics—assisting the impaired motor system. *Archives of physiology and biochemistry*. 2001 Feb;109(1):1–9.
 - [48] Borutzky W. Bond Graph Methodology: Development and Analysis of Multidisciplinary Dynamic System Models. Springer; 2010.
 - [49] Dollar AM, Herr H. Lower Extremity Exoskeletons and Active Orthoses: Challenges and State-of-the-Art. *IEEE Transactions on Robotics*. 2008 Feb;24(1):144–158.
 - [50] Front Matter. In: Pons JL, editor. *Wearable Robots*. John Wiley & Sons, Ltd; 2008. p. i–xix.
 - [51] Nicolas-Alonso LF, Gomez-Gil J. Brain Computer Interfaces, a Review. *Sensors*. 2012 Jan;12(2):1211–1279.
 - [52] Zecca M, Micera S, Carrozza MC, Dario P. Control of multifunctional prosthetic hands by processing the electromyographic signal. *Critical Reviews in Biomedical Engineering*. 2002;30(4-6):459–485.
 - [53] McFarland DJ, Wolpaw JR. Brain-Computer Interface Operation of Robotic and Prosthetic Devices. *Computer*. 2008 Oct;41(10):52–56.
 - [54] Kubler A, Birbaumer N. Brain-computer interfaces and communication in paralysis: Extinction of goal directed thinking in completely paralysed patients? *Clinical Neurophysiology*. 2008 Nov;119(11):2658–2666.
 - [55] Muller-Putz GR, Pfurtscheller G. Control of an Electrical Prosthesis With an SSVEP-Based BCI. *IEEE Transactions on Biomedical Engineering*. 2008 Jan;55(1):361–364.

- [56] Galan F, Nuttin M, Lew E, Ferrez PW, Vanacker G, Philips J, et al. A brain-actuated wheelchair: Asynchronous and non-invasive Brain-computer interfaces for continuous control of robots. *Clinical Neurophysiology*. 2008;119(9):2159–2169.
- [57] Gancet J, Ilzkovitz M, Motard E, Nevatia Y, Letier P, de Weerdt D, et al. MIND-WALKER: Going one step further with assistive lower limbs exoskeleton for SCI condition subjects. In: 2012 4th IEEE RAS EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob); 2012. p. 1794–1800.
- [58] Looned R, Webb J, Xiao ZG, Menon C. Assisting drinking with an affordable BCI-controlled wearable robot and electrical stimulation: a preliminary investigation. *Journal of NeuroEngineering and Rehabilitation*. 2014 Apr;11(1):51.
- [59] Leeb R, Perdakis S, Tonin L, Biasiucci A, Tavella M, Creatura M, et al. Transferring brain-computer interfaces beyond the laboratory: successful application control for motor-disabled users. *Artificial Intelligence in Medicine*. 2013 Oct;59(2):121–132.
- [60] Mellinger J, Schalk G, Braun C, Preissl H, Rosenstiel W, Birbaumer N, et al. An MEG-based brain-computer interface (BCI). *NeuroImage*. 2007 Jul;36(3):581–593.
- [61] Buch E, Weber C, Cohen LG, Braun C, Dimyan MA, Ard T, et al. Think to move: a neuromagnetic brain-computer interface (BCI) system for chronic stroke. *Stroke; a Journal of Cerebral Circulation*. 2008 Mar;39(3):910–917.
- [62] Sorger B, Reithler J, Dahmen B, Goebel R. A Real-Time fMRI-Based Spelling Device Immediately Enabling Robust Motor-Independent Communication. *Current Biology*. 2012 Jul;22(14):1333–1338.
- [63] Lee JH, Ryu J, Jolesz FA, Cho ZH, Yoo SS. Brain-machine interface via real-time fMRI: preliminary study on thought-controlled robotic arm. *Neuroscience Letters*. 2009 Jan;450(1):1–6.
- [64] Sagara K, Kido K. Evaluation of a 2-channel NIRS-based optical brain switch for motor disabilities' communication tools. *IEICE Transactions on Information and Systems*. 2012;E95-D(3):829–834.
- [65] Misawa T, Goto K, Takano S, Hirobayashi S. A development of NIRS-based brain-computer interface for robot control. *IEEE Transactions on Sensors and Micromachines*. 2012;132(10):355–361.

- [66] Hargrove LJ, Simon AM, Lipschutz R, Finucane SB, Kuiken TA. Non-weight-bearing neural control of a powered transfemoral prosthesis. *Journal of Neuro-Engineering and Rehabilitation*. 2013 Jun;10(1):62.
- [67] Lenzi T, De Rossi SMM, Vitiello N, Carrozza MC. Intention-based EMG control for powered exoskeletons. *IEEE transactions on bio-medical engineering*. 2012 Aug;59(8):2180–2190.
- [68] Jiang N, Rehbaum H, Vujaklija I, Graitmann B, Farina D. Intuitive, Online, Simultaneous, and Proportional Myoelectric Control Over Two Degrees-of-Freedom in Upper Limb Amputees. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2014 May;22(3):501–510.
- [69] Artemiadis PK, Kyriakopoulos KJ. EMG-Based Control of a Robot Arm Using Low-Dimensional Embeddings. *IEEE Transactions on Robotics*. 2010 Apr;26(2):393–398.
- [70] Kuiken TA, Marasco PD, Lock BA, Harden RN, Dewald JPA. Redirection of cutaneous sensation from the hand to the chest skin of human amputees with targeted reinnervation. *Proceedings of the National Academy of Sciences*. 2007 Dec;104(50):20061–20066.
- [71] Kuiken TA, Li G, Lock BA, Lipschutz RD, Miller LA, Stubblefield KA, et al. Targeted Muscle Reinnervation for Real-Time Myoelectric Control of Multifunction Artificial Arms. *JAMA : the journal of the American Medical Association*. 2009 Feb;301(6):619–628.
- [72] Barry DT, Leonard JA Jr, Gitter AJ, Ball RD. Acoustic myography as a control signal for an externally powered prosthesis. *Archives of physical medicine and rehabilitation*. 1986 Apr;67(4):267–269.
- [73] Posatskiy AO, Chau T. The effects of motion artifact on mechanomyography: A comparative study of microphones and accelerometers. *Journal of Electromyography and Kinesiology*. 2012;22(2):320–324.
- [74] Silva J, Heim W, Chau T. A Self-Contained, Mechanomyography-Driven Externally Powered Prosthesis. *Archives of Physical Medicine and Rehabilitation*. 2005 Oct;86(10):2066–2070.
- [75] Silva J, Chau T, Naumann S, Helm W, Goldenberg AA. Optimization of the signal-to-noise ratio of silicon-embedded microphones for mechanomyography. In: *Canadian Conference on Electrical and Computer Engineering*, 2003. IEEE CCECE 2003. vol. 3; 2003. p. 1493 – 1496 vol.3.

- [76] Antonelli MG, Beomonte Zobel P, Giacomini J. Use of MMG Signals for the Control of Powered Orthotic Devices: Development of a Rectus Femoris Measurement Protocol. *Assistive Technology*. 2009;21(1):1–12.
- [77] Kenney LPJ, Lisitsa I, Bowker P, Heath GH, Howard D. Dimensional change in muscle as a control signal for powered upper limb prostheses: a pilot study. *Medical Engineering & Physics*. 1999 Oct;21(8):589–597.
- [78] Heath GH. Control of proportional grasping using a myokinematic signal. *Technology and Disability*. 2003 Jan;15(2):73–83.
- [79] Abboudi RL, Glass CA, Newby NA, Flint JA, Craelius W. A biomimetic controller for a multifinger prosthesis. *IEEE Transactions on Rehabilitation Engineering*. 1999 Jun;7(2):121–129.
- [80] Curcie DJ, Flint JA, Craelius W. Biomimetic finger control by filtering of distributed forelimb pressures. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2001 Mar;9(1):69–75.
- [81] Kim WS, Lee HD, Lim DH, Han JS, Shin KS, Han CS. Development of a muscle circumference sensor to estimate torque of the human elbow joint. *Sensors and Actuators A: Physical*. 2014 Feb;208:95–103.
- [82] Zheng YP, Chan MMF, Shi J, Chen X, Huang QH. Sonomyography: Monitoring morphological changes of forearm muscles in actions with the feasibility for the control of powered prosthesis. *Medical Engineering & Physics*. 2006 Jun;28(5):405–415.
- [83] Chen X, Zheng YP, Guo JY, Shi J. Sonomyography (smg) control for powered prosthetic hand: A Study with normal subjects. *Ultrasound in Medicine and Biology*. 2010;36(7):1076–1088.
- [84] González DS, Castellini C. A realistic implementation of ultrasound imaging as a human-machine interface for upper-limb amputees. *Frontiers in Neurobotics*. 2013;7:17.
- [85] Kedefors R, Olsson T. Electrical impedance as a source of information in man-machine systems. *Proceedings of the IEEE*. 1972 Jun;60(6):724–725.
- [86] Wininger M, Kim NH, Craelius W. Pressure signature of forearm as predictor of grip force. *Journal of Rehabilitation Research and Development*. 2008;45(6):883–892.

- [87] Moromugi S, Koujina Y, Arika S, Okamoto A, Tanaka T, Feng MQ, et al. Muscle stiffness sensor to control an assistance device for the disabled. *Artificial Life and Robotics*. 2004 Sep;8(1):42–45.
- [88] Castellini C, Koiva R. Using a high spatial resolution tactile sensor for intention detection. In: 2013 IEEE International Conference on Rehabilitation Robotics (ICORR); 2013. p. 1–7.
- [89] Han H, Han H, Kim J. Development of real-time muscle stiffness sensor based on resonance frequency for physical Human Robot Interactions. In: 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC); 2012. p. 2367–2370.
- [90] Weir RF, Heckathorne CW, Childress DS. Cineplasty as a control input for externally powered prosthetic components. *Journal of rehabilitation research and development*. 2001 Aug;38(4):357–363.
- [91] Bianchi T, Zambarbieri D, Beltrami G, Verni G. NIRS monitoring of muscle contraction to control a prosthetic device. vol. 3570; 1999. p. 157–163.
- [92] Cen L, Han H, Kim J. Optical muscle activation sensors for estimating upper limb force level. In: 2011 IEEE Instrumentation and Measurement Technology Conference (I2MTC); 2011. p. 1–4.
- [93] Chianura A, Giardini ME. An electrooptical muscle contraction sensor. *Medical & Biological Engineering & Computing*. 2010 Jul;48(7):731–734.
- [94] Schneider DM, Ripplinger CM, Gilbertson K, Katti R, Schroeder MJ. Optically-based control of a Prosthetic Device. Key Biscayne, Florida; 2003. .
- [95] Thomas G, Simon D. Inertial thigh angle sensing for a semi-active knee prosthesis. In: *Proceedings of the IASTED International Symposia on Imaging and Signal Processing in Health Care and Technology, ISPHT 2012*; 2012. p. 119–124.
- [96] Moreno JC, de Lima ER, Ruiz AF, Brunetti FJ, Pons JL. Design and implementation of an inertial measurement unit for control of artificial limbs: Application on leg orthoses. *Sensors and Actuators B: Chemical*. 2006 Oct;118(1-2):333–337.
- [97] Jiang H, Wachs JP, Duerstock BS. Integrated vision-based robotic arm interface for operators with upper limb mobility impairments. In: 2013 IEEE International Conference on Rehabilitation Robotics (ICORR); 2013. p. 1–6.

- [98] Doubler JA, Childress DS. An analysis of extended physiological proprioception as a prosthesis-control technique. *Journal of rehabilitation research and development*. 1984 May;21(1):5–18.
- [99] Gibbons DT, O’riain MD, Philippe-Auguste S. An Above-Elbow Prosthesis Employing Programmed Linkages. *IEEE Transactions on Biomedical Engineering*. 1987 Jul;BME-34(7):493–498.
- [100] Lipschutz RD, Lock B, Sensinger J, Schultz AE, Kuiken TA. Use of two-axis joystick for control of externally powered shoulder disarticulation prostheses. *Journal of rehabilitation research and development*. 2011;48(6):661–667.
- [101] Losier Y, Englehart K, Hudgins B. Evaluation of shoulder complex motion-based input strategies for endpoint prosthetic-limb control using dual-task paradigm. *Journal of Rehabilitation Research and Development*. 2011;48(6):669–678.
- [102] Takagi M, Iwata K, Takahashi Y, Yamamoto SI, Koyama H, Komeda T. Development of a grip aid system using air cylinders. In: *IEEE International Conference on Robotics and Automation*, 2009. ICRA ’09; 2009. p. 2312–2317.
- [103] Font-Llagunes JM, Arroyo G, Serrancoli G, Romero F. A powered lower limb orthosis for gait assistance in incomplete spinal cord injured subjects. In: *ACM International Conference Proceeding Series*; 2011. .
- [104] Ragonesi D, Agrawal S, Sample W, Rahman T. Quantifying anti-gravity torques in the design of a powered exoskeleton. *Conference proceedings: Annual International Conference of the IEEE Engineering in Medicine and Biology Society IEEE Engineering in Medicine and Biology Society Conference*. 2011;2011:7458–7461.
- [105] Rahman T, Ramanathan R, Stroud S, Sample W, Seliktar R, Harwin W, et al. Towards the control of a powered orthosis for people with muscular dystrophy. *Proceedings of the Institution of Mechanical Engineers, Part H: Journal of Engineering in Medicine*. 2001 Mar;215(3):267–274.
- [106] Lobo-Prat J, Kooren PN, Keemink AQL, Paalman MI, Hekman EEG, Veltink PH, et al. Design and control of an experimental active elbow support for adult Duchenne Muscular Dystrophy patients. In: *Biomedical Robotics and Biomechanics (2014 5th IEEE RAS EMBS International Conference on)*; 2014. p. 187–192.
- [107] Abbruzzese K, Lee D, Swedberg A, Talasan H, Paliwal M. An innovative design for an Assistive Arm Orthosis for stroke and muscle dystrophy. In: *Bioengineering Conference (NEBEC)*, 2011 IEEE 37th Annual Northeast; 2011. p. 1–2.

- [108] Huo W, Huang J, Wang Y, Wu J. Control of a rehabilitation robotic exoskeleton based on intentional reaching direction. In: 2010 International Symposium on Micro-NanoMechatronics and Human Science (MHS); 2010. p. 357–362.
- [109] Nilsson M, Ingvast J, Wikander J, von Holst H. The Soft Extra Muscle system for improving the grasping capability in neurological rehabilitation. In: 2012 IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES); 2012. p. 412–417.
- [110] Abbott WW, Faisal AA. Ultra-low-cost 3D gaze estimation: an intuitive high information throughput compliment to direct brain-machine interfaces. *Journal of Neural Engineering*. 2012 Aug;9(4):046016.
- [111] Duvinage M, Castermans T, Dutoit T. Control of a lower limb active prosthesis with eye movement sequences. In: 2011 IEEE Symposium on Computational Intelligence, Cognitive Algorithms, Mind, and Brain (CCMB); 2011. p. 1–7.
- [112] Chen Y, Newman WS. A human-robot interface based on electrooculography. In: 2004 IEEE International Conference on Robotics and Automation, 2004. Proceedings. ICRA '04. vol. 1; 2004. p. 243–248 Vol.1.
- [113] Craig DA, Nguyen HT. Wireless real-time head movement system using a personal digital assistant (PDA) for control of a power wheelchair. In: *Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the*; 2006. p. 772–775.
- [114] Fusco DA, Balbinot A. Prototype for managing the wheelchair movements by accelerometry. *Sensors and Transducers*. 2011;126(3):31–41.
- [115] Hinkel III JB. Head-guided wheelchair control system. In: *ASSETS'10 - Proceedings of the 12th International ACM SIGACCESS Conference on Computers and Accessibility*; 2010. p. 313–314.
- [116] Baklouti M, Monacelli E, Guitteny V, Couvet S. Intelligent Assistive Exoskeleton with Vision Based Interface. In: Helal S, Mitra S, Wong J, Chang CK, Mokhtari M, editors. *Smart Homes and Health Telematics*. No. 5120 in *Lecture Notes in Computer Science*. Springer Berlin Heidelberg; 2008. p. 123–135.
- [117] Coyle ED. Electronic wheelchair controller designed for operation by hand-operated joystick, ultrasonic noncontact head control and utterance from a small word-command vocabulary. In: *IEE Colloquium on New Developments in Electric Vehicles for Disabled Persons*; 1995. p. 3/1–3/4.

- [118] Huo X, Wang J, Ghovanloo M. A Magneto-Inductive Sensor Based Wireless Tongue-Computer Interface. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2008;16(5):497–504.
- [119] Kim J, Park H, Bruce J, Sutton E, Rowles D, Pucci D, et al. The Tongue Enables Computer and Wheelchair Control for People with Spinal Cord Injury. *Science Translational Medicine*. 2013 Nov;5(213):213ra166–213ra166.
- [120] Struijk JJ, Lontis ER, Bentsen B, Christensen HV, Caltenco HA, Lund ME. Fully integrated wireless inductive tongue computer interface for disabled people. In: *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2009. EMBC 2009; 2009. p. 547–550.
- [121] Fan BH, Li KY. The speech control system of intelligent robot prosthesis. In: *Proceedings - 2010 2nd WRI Global Congress on Intelligent Systems, GCIS 2010*. vol. 2; 2010. p. 407–409.
- [122] Simpson RC, Levine SP. Voice control of a powered wheelchair. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2002 Jun;10(2):122–125.
- [123] Rogalla O, Ehrenmann M, Zollner R, Becher R, Dillmann R. Using gesture and speech control for commanding a robot assistant. In: *11th IEEE International Workshop on Robot and Human Interactive Communication*, 2002. *Proceedings*; 2002. p. 454–459.
- [124] Johnson GR, Carus DA, Parrini G, Marchese S, Valeggi R. The design of a five-degree-of-freedom powered orthosis for the upper limb. *Proceedings of the Institution of Mechanical Engineers, Part H: Journal of Engineering in Medicine*. 2001 Mar;215(3):275–284.
- [125] Dicianno BE, Cooper RA, Coltellar J. Joystick Control for Powered Mobility: Current State of Technology and Future Directions. *Physical medicine and rehabilitation clinics of North America*. 2010 Feb;21(1):79–86.
- [126] Pfurtscheller G, Guger C, Muller G, Krausz G, Neuper C. Brain oscillations control hand orthosis in a tetraplegic. *Neuroscience letters*. 2000 Oct;292(3):211–214.
- [127] Do AH, Wang PT, King CE, Chun SN, Nenadic Z. Brain-computer interface controlled robotic gait orthosis. *Journal of NeuroEngineering and Rehabilitation*. 2013 Dec;10(1):111.
- [128] Wang S, Wang L, Meijneke C, van Asseldonk E, Hoellinger T, Cheron G, et al. Design and Control of the MINDWALKER Exoskeleton. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2014;PP(99):1–1.

- [129] Kaufmann T, Herweg A, Kubler A. Toward brain-computer interface based wheelchair control utilizing tactually-evoked event-related potentials. *Journal of NeuroEngineering and Rehabilitation*. 2014 Jan;11(1):7.
- [130] Schultz AE, Kuiken TA. Neural Interfaces for Control of Upper Limb Prostheses: The State of the Art and Future Possibilities. *PM&R*. 2011;3(1):55–67.
- [131] Millan JdR. Brain-Computer Interfaces. In: Farina D, Jensen W, Akay M, editors. *Introduction to Neural Engineering for Motor Rehabilitation*. John Wiley & Sons, Inc.; 2013. p. 237–252.
- [132] Allison BZ, Dunne S, Leeb R, Millán JdR, Nijholt A. Recent and Upcoming BCI Progress: Overview, Analysis, and Recommendations. In: Allison BZ, Dunne S, Leeb R, Millán JdR, Nijholt A, editors. *Towards Practical Brain-Computer Interfaces*. Biological and Medical Physics, Biomedical Engineering. Springer Berlin Heidelberg; 2013. p. 1–13.
- [133] Perdakis S, Leeb R, Williamson J, Ramsay A, Tavella M, Desideri L, et al. Clinical evaluation of BrainTree, a motor imagery hybrid BCI speller. *Journal of Neural Engineering*. 2014 Jun;11(3):036003.
- [134] Sitaram R, Caria A, Birbaumer N. Hemodynamic brain-computer interfaces for communication and rehabilitation. *Neural Networks*. 2009 Nov;22(9):1320–1328.
- [135] Kanoh S, Murayama YM, Miyamoto K, Yoshinobu T, Kawashima R. A NIRS-based brain-computer interface system during motor imagery: system development and online feedback training. *Conference proceedings : Annual International Conference of the IEEE Engineering in Medicine and Biology Society IEEE Engineering in Medicine and Biology Society Conference*. 2009;2009:594–597.
- [136] Weiskopf N. Real-time fMRI and its application to neurofeedback. *NeuroImage*. 2012 Aug;62(2):682–692.
- [137] Weiskopf N, Veit R, Erb M, Mathiak K, Grodd W, Goebel R, et al. Physiological self-regulation of regional brain activity using real-time functional magnetic resonance imaging (fMRI): methodology and exemplary data. *NeuroImage*. 2003 Jul;19(3):577–586.
- [138] Naito M, Michioka Y, Ozawa K, Ito Y, Kiguchi M, Kanazawa T. A Communication Means for Totally Locked-in ALS Patients Based on Changes in Cerebral Blood Volume Measured with Near-Infrared Light. *IEICE - Trans Inf Syst*. 2007 Jul;E90-D(7):1028–1037.

- [139] Sorger B, Dahmen B, Reithler J, Gosseries O, Maudoux A, Laureys S, et al. Another kind of BOLD Response: answering multiple-choice questions via online decoded single-trial brain signals. In: Steven Laureys NDSaAMO, editor. *Progress in Brain Research*. vol. Volume 177. Elsevier; 2009. p. 275–292.
- [140] Yoo SS, Fairney T, Chen NK, Choo SE, Panych LP, Park H, et al. Brain-computer interface using fMRI: Spatial navigation by thoughts. *NeuroReport*. 2004;15(10):1591–1595.
- [141] Ayaz H, Shewokis PA, Bunce S, Onaral B. An optical brain computer interface for environmental control. In: *Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE*; 2011. p. 6327–6330.
- [142] Ward BD, Mazaheri Y. Information transfer rate in fMRI experiments measured using mutual information theory. *Journal of neuroscience methods*. 2008 Jan;167(1):22–30.
- [143] Power SD, Kushki A, Chau T. Towards a system-paced near-infrared spectroscopy brain-computer interface: differentiating prefrontal activity due to mental arithmetic and mental singing from the no-control state. *Journal of neural engineering*. 2011 Dec;8(6):066004.
- [144] Shih JJ, Krusienski DJ, Wolpaw JR. Brain-Computer Interfaces in Medicine. *Mayo Clinic Proceedings*. 2012 Mar;87(3):268–279.
- [145] Spires MC, Kelly BM, Davis AJ. *Prosthetic Restoration and Rehabilitation of the Upper and Lower Extremity*. Demos Medical Publishing; 2013.
- [146] Roche AD, Rehbaum H, Farina D, Aszmann OC. Prosthetic Myoelectric Control Strategies: A Clinical Perspective. *Current Surgery Reports*. 2014 Mar;2(3):1–11.
- [147] Jimenez-Fabian R, Verlinden O. Review of control algorithms for robotic ankle systems in lower-limb orthoses, prostheses, and exoskeletons. *Medical Engineering & Physics*. 2012;34(4):397–408.
- [148] Anam K, Al-Jumaily AA. Active Exoskeleton Control Systems: State of the Art. *Procedia Engineering*. 2012;41:988–994.
- [149] Muzumdar A, editor. *Powered Upper Limb Prostheses: Control, Implementation and Clinical Application*. 1st ed. Springer; 2004.
- [150] Ison M, Antuvan CW, Artemiadis P. Learning efficient control of robots using myoelectric interfaces. In: *2014 IEEE International Conference on Robotics and Automation (ICRA)*; 2014. p. 2880–2885.

- [151] Farina D, Jiang N, Rehbaum H, Holobar A, Graimann B, Dietl H, et al. The Extraction of Neural Information from the Surface EMG for the Control of Upper-Limb Prostheses: Emerging Avenues and Challenges. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2014 Jul;22(4):797–809.
- [152] Scheme E, Englehart K. Electromyogram pattern recognition for control of powered upper-limb prostheses: state of the art and challenges for clinical use. *Journal of Rehabilitation Research and Development*. 2011;48(6):643–659.
- [153] Smith LH, Hargrove LJ, Lock BA, Kuiken TA. Determining the Optimal Window Length for Pattern Recognition-Based Myoelectric Control: Balancing the Competing Effects of Classification Error and Controller Delay. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2011 Apr;19(2):186–192.
- [154] Muceli S, Jiang N, Farina D. Extracting Signals Robust to Electrode Number and Shift for Online Simultaneous and Proportional Myoelectric Control by Factorization Algorithms. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2014 May;22(3):623–633.
- [155] Rehbaum H, Jiang N, Paredes L, Amsuess S, Graimann B, Farina D. Real time simultaneous and proportional control of multiple degrees of freedom from surface EMG: Preliminary results on subjects with limb deficiency. In: 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC); 2012. p. 1346–1349.
- [156] Cavallaro EE, Rosen J, Perry JC, Burns S. Real-Time Myoprocessors for a Neural Controlled Powered Exoskeleton Arm. *IEEE Transactions on Biomedical Engineering*. 2006 Nov;53(11):2387–2396.
- [157] Miller LA, Lipschutz RD, Stubblefield KA, Lock BA, Huang H, Williams III TW, et al. Control of a Six Degree of Freedom Prosthetic Arm After Targeted Muscle Reinnervation Surgery. *Archives of Physical Medicine and Rehabilitation*. 2008 Nov;89(11):2057–2065.
- [158] Bueno Jr RA, French B, Cooney D, Neumeister MW. Targeted Muscle Reinnervation of a Muscle-Free Flap for Improved Prosthetic Control in a Shoulder Amputee: Case Report. *The Journal of Hand Surgery*. 2011 May;36(5):890–893.
- [159] Tkach DC, Young AJ, Smith LH, Rouse EJ, Hargrove LJ. Real-Time and Offline Performance of Pattern Recognition Myoelectric Control Using a Generic Electrode Grid With Targeted Muscle Reinnervation Patients. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2014 Jul;22(4):727–734.

- [160] Hebert JS, Olson JL, Morhart MJ, Dawson MR, Marasco PD, Kuiken TA, et al. Novel Targeted Sensory Reinnervation Technique to Restore Functional Hand Sensation After Transhumeral Amputation. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2014 Jul;22(4):765–773.
- [161] Souza JM, Fey NP, Cheesborough JE, Agnew SP, Hargrove LJ, Dumanian GA. Advances in Transfemoral Amputee Rehabilitation: Early Experience with Targeted Muscle Reinnervation. *Current Surgery Reports*. 2014 May;2(5):1–9.
- [162] Hargrove LJ, Simon AM, Lipschutz RD, Finucane SB, Kuiken TA. Real-time myoelectric control of knee and ankle motions for transfemoral amputees. *JAMA*. 2011 Apr;305(15):1542–1544.
- [163] Smith LH, Hargrove LJ. Intramuscular EMG after targeted muscle reinnervation for pattern recognition control of myoelectric prostheses. In: 2013 6th International IEEE/EMBS Conference on Neural Engineering (NER); 2013. p. 1155–1158.
- [164] Orizio C. Muscle sound: bases for the introduction of a mechanomyographic signal in muscle studies. *Critical reviews in biomedical engineering*. 1993;21(3):201–243.
- [165] Posatskiy AO, Chau T. Design and evaluation of a novel microphone-based mechanomyography sensor with cylindrical and conical acoustic chambers. *Medical Engineering & Physics*. 2012 Oct;34(8):1184–1190.
- [166] Shi J, Chang Q, Zheng YP. Feasibility of controlling prosthetic hand using sonomyography signal in real time: preliminary study. *Journal of rehabilitation research and development*. 2010;47(2):87–98.
- [167] Castellini C, Passig G. Ultrasound image features of the wrist are linearly related to finger positions. In: 2011 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS); 2011. p. 2108–2114.
- [168] Silva OL, Sousa THS, Hoffman IO, de Camargo EDLB, de Moura FS, Martins ARC, et al. A proposal to monitor muscle contraction through the change of electrical impedance inside a muscle. In: *Biomedical Robotics and Biomechatronics (2014 5th IEEE RAS EMBS International Conference on)*; 2014. p. 763–767.
- [169] Moromugi S, Kumano S, Ueda M, Ishimatsu T, Feng MQ, Tanaka T. A sensor to measure hardness of human tissue. In: *5th IEEE Conference on Sensors*, 2006; 2006. p. 388–391.
- [170] Childress DS. Presentation highlights: Tunnel cineplasty. *Journal of Rehabilitation Research and Development*. 2002;39(3 SUPPL.):9–10.

- [171] Simpson DC. The choice of control system for the multimovement prosthesis: extended physiological proprioception (epp). The control of upper-extremity prostheses and orthoses. 1974;p. 146–150.
- [172] BRAV EA, FLETCHER MJ, KUITERT JH, LEONARD F, LUSCOMBE HB, MACDONALD WF, et al. Cineplasty; an end-result study. The Journal of bone and joint surgery American volume. 1957 Jan;39-A(1):59–76.
- [173] Herrmann S, Attenberger A, Buchenrieder K. Prostheses Control with Combined Near-Infrared and Myoelectric Signals. In: Moreno-Diaz R, Pichler F, Quesada-Arencibia A, editors. Computer Aided Systems Theory - EUROCAST 2011. No. 6928 in Lecture Notes in Computer Science. Springer Berlin Heidelberg; 2012. p. 601–608.
- [174] Martin H, Chevallier S, Monacelli E. Fast calibration of hand movement-based interface. In: ESANN 2012 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium): ESANN; 2012. p. 573–578.
- [175] Blaya JA, Herr H. Adaptive control of a variable-impedance ankle-foot orthosis to assist drop-foot gait. IEEE Transactions on Neural Systems and Rehabilitation Engineering. 2004 Mar;12(1):24–31.
- [176] Herr H, Wilkenfeld A. User-adaptive control of a magnetorheological prosthetic knee. Industrial Robot: An International Journal. 2003 Feb;30(1):42–55.
- [177] Orengo G, Giovannini L, Latessa G, Saggio G, Giannini F. Characterization of piezoresistive sensors for goniometric glove in hand prostheses. In: 1st International Conference on Wireless Communication, Vehicular Technology, Information Theory and Aerospace Electronic Systems Technology, 2009. Wireless VITAE 2009; 2009. p. 684–687.
- [178] Wang L, Wang S, van Asseldonk EHF, Van Der Kooij H. Actively controlled lateral gait assistance in a lower limb exoskeleton. In: 2013 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS); 2013. p. 965–970.
- [179] Zeng G, Hemami A. An overview of robot force control. Robotica. 1997;15(05):473–482.
- [180] Lo HS, Xie SQ. Exoskeleton robots for upper-limb rehabilitation: State of the art and future prospects. Medical Engineering & Physics. 2012 Apr;34(3):261–268.

- [181] Betke M, Gips J, Fleming P. The Camera Mouse: visual tracking of body features to provide computer access for people with severe disabilities. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2002 Mar;10(1):1–10.
- [182] Morimoto CH, Mimica MRM. Eye gaze tracking techniques for interactive applications. *Computer Vision and Image Understanding*. 2005 Apr;98(1):4–24.
- [183] Clayton C, Platts RGS, Steinberg M, Hennequin JR. Palatal tongue controller. *Journal of Microcomputer Applications*. 1992 Jan;15(1):9–12.
- [184] ; Apparatus for controlling peripheral devices through tongue movement, and method of processing control signals. US5460186 A; 1995. International Classification: A61F4/00; H01H36/00; H01H3/14 U.S. Classification: A61F4/00; H01H3/14.
- [185] Wakumoto M, Masaki S, Honda K, Ohue T. A pressure sensitive palatography: application of new pressure sensitive sheet for measuring tongue-palatal contact pressure. In: *The 5th International Conference on Spoken Language Processing, Incorporating The 7th Australian International Speech Science and Technology Conference*, Sydney Convention Centre, Sydney, Australia, 30th November - 4th December 1998; 1998. .
- [186] Struijk LNSA. An Inductive Tongue Computer Interface for Control of Computers and Assistive Devices. *IEEE Transactions on Biomedical Engineering*. 2006 Dec;53(12):2594–2597.
- [187] Huo X, Ghovanloo M. Evaluation of a wireless wearable tongue-computer interface by individuals with high-level spinal cord injuries. *Journal of Neural Engineering*. 2010 Apr;7(2):026008.
- [188] Lontis ER, Andreasen Struijk LNS. Alternative design of inductive pointing device for oral interface for computers and wheelchairs. In: *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*; 2012. p. 3328–3331.
- [189] Joseph T, Nguyen H. Neural network control of wheelchairs using telemetric head movement. In: *Engineering in Medicine and Biology Society, 1998. Proceedings of the 20th Annual International Conference of the IEEE*. vol. 5; 1998. p. 2731–2733.
- [190] Taylor PB, Nguyen HT. Performance of a head-movement interface for wheelchair control. In: *Proceedings of the 25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2003*. vol. 2; 2003. p. 1590–1593 Vol.2.

- [191] Bergasa LM, Mazo M, Gardel A, Barea R, Boquete L. Commands generation by face movements applied to the guidance of a wheelchair for handicapped people. In: 15th International Conference on Pattern Recognition, 2000. Proceedings. vol. 4; 2000. p. 660–663 vol.4.
- [192] Lv X, Zhang M, Li H. Robot control based on voice command. In: IEEE International Conference on Automation and Logistics, 2008. ICAL 2008; 2008. p. 2490–2494.
- [193] Romer GRBE, Stuyt HJA, Peters A. Cost-savings and economic benefits due to the assistive robotic manipulator (ARM). In: 9th International Conference on Rehabilitation Robotics, 2005. ICORR 2005; 2005. p. 201–204.
- [194] Felzer T, Freisleben B. HaWCoS: The "Hands-free" Wheelchair Control System. In: In Proc. ASSETS 2002. ACM Press; 2002. p. 127–134.
- [195] Han JS, Zenn Bien Z, Kim DJ, Lee HE, Kim JS. Human-machine interface for wheelchair control with EMG and its evaluation. In: Proceedings of the 25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2003. vol. 2; 2003. p. 1602 – 1605 Vol.2.
- [196] Moon I, Lee M, Chu J, Mun M. Wearable EMG-based HCI for Electric-Powered Wheelchair Users with Motor Disabilities. In: Proceedings of the 2005 IEEE International Conference on Robotics and Automation, 2005. ICRA 2005; 2005. p. 2649 – 2654.
- [197] Cooper RA, Corfman TA, Fitzgerald SG, Boninger ML, Spaeth DM, Ammer W, et al. Performance assessment of a pushrim-activated power-assisted wheelchair control system. IEEE Transactions on Control Systems Technology. 2002 Jan;10(1):121–126.
- [198] Lalitharatne TD, Teramoto K, Hayashi Y, Kiguchi K. Towards Hybrid EEG-EMG-Based Control Approaches to be Used in Bio-robotics Applications: Current Status, Challenges and Future Directions. Paladyn, Journal of Behavioral Robotics. 2013 Nov;0(0):11–18.
- [199] Simon AM, Fey NP, Ingraham KA, Young AJ, Hargrove LJ. Powered prosthesis control during walking, sitting, standing, and non-weight bearing activities using neural and mechanical inputs. In: 2013 6th International IEEE/EMBS Conference on Neural Engineering (NER); 2013. p. 1174–1177.

- [200] Huang H, Zhang F, Hargrove LJ, Dou Z, Rogers DR, Englehart KB. Continuous Locomotion-Mode Identification for Prosthetic Legs Based on Neuromuscular-Mechanical Fusion. *IEEE transactions on bio-medical engineering*. 2011 Oct;58(10):2867–2875.
- [201] Zhang F, Huang H. Decoding movement intent of patient with multiple sclerosis for the powered lower extremity exoskeleton. In: 2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC); 2013. p. 4957–4960.
- [202] Resnik L, Borgia M, Latlief G, Sasson N, Smurr-Walters L. Self-reported and performance-based outcomes using DEKA Arm. *Journal of Rehabilitation Research and Development*. 2014;51(3):351–362.
- [203] Carbonaro N, Anania G, Bacchereti M, Donati G, Ferretti L, Pellicci G, et al. An Innovative Multisensor Controlled Prosthetic Hand. In: Romero LMR, editor. XIII Mediterranean Conference on Medical and Biological Engineering and Computing 2013. No. 41 in IFMBE Proceedings. Springer International Publishing; 2014. p. 93–96.
- [204] Dosen S, Cipriani C, Kostic M, Controzzi M, Carrozza MC, Popovic DB. Cognitive vision system for control of dexterous prosthetic hands: Experimental evaluation. *Journal of NeuroEngineering and Rehabilitation*. 2010;7(1).
- [205] Corbett EA, Perreault EJ, Kuiken TA. Comparison of electromyography and force as interfaces for prosthetic control. *The Journal of Rehabilitation Research and Development*. 2011;48(6):629.
- [206] Guo JY, Zheng YP, Kenney LPJ, Bowen A, Howard D, Canderle JJ. A Comparative Evaluation of Sonomyography, Electromyography, Force, and Wrist Angle in a Discrete Tracking Task. *Ultrasound in Medicine & Biology*. 2011 Jun;37(6):884–891.
- [207] Wurth SM, Hargrove LJ. A real-time comparison between direct control, sequential pattern recognition control and simultaneous pattern recognition control using a Fitts-law style assessment procedure. *Journal of NeuroEngineering and Rehabilitation*. 2014 May;11(1):91.
- [208] Kaufmann T, Holz EM, Kubler A. Comparison of tactile, auditory, and visual modality for brain-computer interface use: a case study with a patient in the locked-in state. *Frontiers in Neuroscience*. 2013 Jul;7.

- [209] Simon AM, Stern K, Hargrove LJ. A comparison of proportional control methods for pattern recognition control. Conference proceedings: Annual International Conference of the IEEE Engineering in Medicine and Biology Society IEEE Engineering in Medicine and Biology Society Annual Conference. 2011;2011:3354–3357.
- [210] Koyama S, Chase SM, Whitford AS, Velliste M, Schwartz AB, Kass RE. Comparison of brain-computer interface decoding algorithms in open-loop and closed-loop control. *Journal of Computational Neuroscience*. 2010 Aug;29(1-2):73–87.
- [211] Williams MR, Kirsch RF. Evaluation of Head Orientation and Neck Muscle EMG Signals as Command Inputs to a Human-Computer Interface for Individuals With High Tetraplegia. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2008 Oct;16(5):485–496.
- [212] Lobo-Prat J, Keemink AQ, Stienen AH, Schouten AC, Veltink PH, Koopman BF. Evaluation of EMG, force and joystick as control interfaces for active arm supports. *Journal of NeuroEngineering and Rehabilitation*. 2014 Apr;11(1):68.
- [213] Hill W, Kyberd P, Norling Hermansson L, Hubbard S, Stavdahl O, Swanson S. Upper Limb Prosthetic Outcome Measures (ULPOM): A Working Group and Their Findings:. *JPO Journal of Prosthetics and Orthotics*. 2009 Oct;21(Supplement):P69–P82.
- [214] Scheme EJ, Englehart KB. Validation of a Selective Ensemble-Based Classification Scheme for Myoelectric Control Using a Three-Dimensional Fitts' Law Test. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2013 Jul;21(4):616–623.
- [215] Simon AM, Hargrove LJ, Lock BA, Kuiken TA. Target Achievement Control Test: Evaluating real-time myoelectric pattern-recognition control of multifunctional upper-limb prostheses. *The Journal of Rehabilitation Research and Development*. 2011;48(6):619.
- [216] Ortiz-Catalan M, Hakansson B, Branemark R. Real-Time and Simultaneous Control of Artificial Limbs Based on Pattern Recognition Algorithms. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2014 Jul;22(4):756–764.
- [217] Young AJ, Smith LH, Rouse EJ, Hargrove LJ. A comparison of the real-time controllability of pattern recognition to conventional myoelectric control for discrete and simultaneous movements. *Journal of NeuroEngineering and Rehabilitation*. 2014 Jan;11(1):5.

- [218] Casadio M, Pressman A, Acosta S, Danzinger Z, Fishbach A, Mussa-Ivaldi FA, et al. Body machine interface: Remapping motor skills after spinal cord injury. In: 2011 IEEE International Conference on Rehabilitation Robotics (ICORR); 2011. p. 1–6.
- [219] Bradberry TJ, Gentili RJ, Contreras-Vidal JL. Reconstructing Three-Dimensional Hand Movements from Noninvasive Electroencephalographic Signals. *The Journal of Neuroscience*. 2010 Mar;30(9):3432–3437.
- [220] Kim HK, Biggs SJ, Schloerb DW, Carmenta JM, Lebedev MA, Nicolelis MAL, et al. Continuous shared control for stabilizing reaching and grasping with brain-machine interfaces. *IEEE transactions on bio-medical engineering*. 2006 Jun;53(6):1164–1173.
- [221] Cowan RE, Fregly BJ, Boninger ML, Chan L, Rodgers MM, Reinkensmeyer DJ. Recent trends in assistive technology for mobility. *Journal of NeuroEngineering and Rehabilitation*. 2012 Apr;9(1):20.
- [222] Radhakrishnan SM, Baker SN, Jackson A. Learning a Novel Myoelectric-Controlled Interface Task. *Journal of Neurophysiology*. 2008 Oct;100(4):2397–2408.
- [223] Pistohl T, Cipriani C, Jackson A, Nazarpour K. Abstract and proportional myoelectric control for multi-fingered hand prostheses. *Annals of Biomedical Engineering*. 2013 Dec;41(12):2687–2698.
- [224] Antuvan CW, Ison M, Artemiadis P. Embedded Human Control of Robots Using Myoelectric Interfaces. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2014 Jul;22(4):820–827.
- [225] Farrell TR, Weir RF, Heckathorne CW, Childress DS. The effects of static friction and backlash on extended physiological proprioception control of a powered prosthesis. *Journal of rehabilitation research and development*. 2005 Jun;42(3):327–341.
- [226] Farrell TR, Weir RF. The Optimal Controller Delay for Myoelectric Prostheses. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2007 Mar;15(1):111–118.
- [227] Gijssberts A, Bohra R, Sierra Gonzalez D, Werner A, Nowak M, Caputo B, et al. Stable myoelectric control of a hand prosthesis using non-linear incremental learning. *Frontiers in Neurorobotics*. 2014 Feb;8.

- [228] Collinger JL, Boninger ML, Bruns TM, Curley K, Wang W, Weber DJ. Functional Priorities, Assistive Technology, and Brain-Computer Interfaces after Spinal Cord Injury. *Journal of rehabilitation research and development*. 2013 Apr;50(2):145–160.
- [229] McFarland DJ, Sarnacki WA, Wolpaw JR. ELECTROENCEPHALOGRAPHIC (EEG) CONTROL OF THREE-DIMENSIONAL MOVEMENT. *Journal of neural engineering*. 2010 Jun;7(3):036007.
- [230] Lock BA, Simon AM, Stubblefield K, Hargrove LJ. Prosthesis-Guided Training For Practical Use Of Pattern Recognition Control Of Prostheses. 2011;.
- [231] van Nieuwenhuis B, van der Heide LA, Jansen JW, Gysen BLJ, van der Pijl DJ, Lomonova EA. Overview of Actuated Arm Support Systems and Their Applications. *Actuators*. 2013 Oct;2(4):86–110.
- [232] Rosen J, Brand M, Fuchs MB, Arcan M. A myosignal-based powered exoskeleton system. *IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans*. 2001;31(3):210–222.
- [233] Gopura RARC, Kiguchi K, Li Y. SUEFUL-7: A 7DOF upper-limb exoskeleton robot with muscle-model-oriented EMG-based control. In: *IEEE/RSJ International Conference on Intelligent Robots and Systems, 2009. IROS 2009; 2009*. p. 1126–1131.
- [234] Fougner A, Staudahl O, Kyberd PJ, Losier YG, Parker PA. Control of upper limb prostheses: Terminology and proportional myoelectric control: a review. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. 2012;20(5):663–677.
- [235] Parker P, Englehart K, Hudgins B. Myoelectric signal processing for control of powered limb prostheses. *Journal of Electromyography and Kinesiology*. 2006;16(6):541–548.
- [236] McRuer DT, Jex HR. A Review of Quasi-Linear Pilot Models. *IEEE Transactions on Human Factors in Electronics*. 1967 Sep;HFE-8(3):231 – 249.
- [237] Hermens HJ, Freriks B, Merletti R, Stegeman D, Blok J, Rau G, et al. European recommendations for surface electromyography. *Roessingh Research and Development The Netherlands*; 1999.
- [238] Pintelon R, Schoukens J. *System Identification: A Frequency Domain Approach*. John Wiley & Sons; 2004.

- [239] Shannon CE. A mathematical theory of communication. SIGMOBILE Mob Comput Commun Rev. 2001;5(1):3–55.
- [240] Chan RB, Childress DS. On information transmission in human-machine systems: channel capacity and optimal filtering. IEEE Transactions on Systems, Man and Cybernetics. 1990 Oct;20(5):1136–1145.
- [241] Elkind JI, Sprague LT. Transmission of Information in Simple Manual Control Systems. IRE Transactions on Human Factors in Electronics. 1961;HFE-2(1):58–60.
- [242] Stokes IAF. Relationships of EMG to effort in the trunk under isometric conditions: force-increasing and decreasing effects and temporal delays. Clinical biomechanics (Bristol, Avon). 2005 Jan;20(1):9–15.
- [243] Sogaard K, Gandevia SC, Todd G, Petersen NT, Taylor JL. The effect of sustained low-intensity contractions on supraspinal fatigue in human elbow flexor muscles. The Journal of Physiology. 2006 Jun;573(2):511–523.
- [244] van der Helm FCT, Schouten AC, de Vlugt E, Brouwn GG. Identification of intrinsic and reflexive components of human arm dynamics during postural control. Journal of Neuroscience Methods. 2002 Sep;119(1):1–14.
- [245] Schouten AC, de Vlugt E, van Hilten JJB, van der Helm FCT. Design of a torque-controlled manipulator to analyse the admittance of the wrist joint. Journal of Neuroscience Methods. 2006 Jun;154(1–2):134–141.
- [246] McFarland DJ, Wolpaw JR. Brain-computer interfaces for communication and control. Commun ACM. 2011;54(5):60–66.
- [247] Navarro X, Krueger TB, Lago N, Micera S, Stieglitz T, Dario P. A critical review of interfaces with the peripheral nervous system for the control of neuroprostheses and hybrid bionic systems. Journal of the Peripheral Nervous System. 2005;10(3):229–258.
- [248] Perry JC, Rosen J, Burns S. Upper-Limb Powered Exoskeleton Design. IEEE/ASME Transactions on Mechatronics. 2007 Aug;12(4):408–417.
- [249] Lobo-Prat J, Kooren PN, Stienen AH, Herder JL, Koopman BF, Veltink PH. Non-invasive control interfaces for intention detection in active movement-assistive devices. Journal of NeuroEngineering and Rehabilitation. 2014 Dec;11(1):168.

- [250] Vogel J, Bayer J, van der Smagt P. Continuous robot control using surface electromyography of atrophic muscles. In: 2013 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS); 2013. p. 845–850.
- [251] Brooke MH, Fenichel GM, Griggs RC, Mendell JR, Moxley R, Florence J, et al. Duchenne muscular dystrophy: patterns of clinical progression and effects of supportive therapy. *Neurology*. 1989 Apr;39(4):475–481.
- [252] Fitts PM. The information capacity of the human motor system in controlling the amplitude of movement. *Journal of Experimental Psychology*. 1954;47(6):381–391.
- [253] Formica D, Charles SK, Zollo L, Guglielmelli E, Hogan N, Krebs HI. The passive stiffness of the wrist and forearm. *Journal of Neurophysiology*. 2012 Aug;108(4):1158–1166.
- [254] Drake WB, Charles SK. Passive Stiffness of Coupled Wrist and Forearm Rotations. *Annals of Biomedical Engineering*. 2014 Jun;42(9):1853–1866.
- [255] Cornu C, Goubel F, Fardeau M. Muscle and joint elastic properties during elbow flexion in Duchenne muscular dystrophy. *The Journal of Physiology*. 2001 Jun;533(2):605–616.
- [256] Bergen van den JC, Koeks Z, Straathof CSM, Ginjaar HB, Groot de I, Kooi van der A, et al. P.7.8 The national Dutch dystrophinopathy patient registry. *Neuromuscular Disorders*. 2013 Oct;23(9–10):775–776.
- [257] Lobo-Prat J, Keemink AQL, Koopman BFJM, Stienen AHA, Veltink PH. Adaptive gravity and joint stiffness compensation methods for force-controlled arm supports. In: 2015 IEEE International Conference on Rehabilitation Robotics (ICORR); 2015. p. 478–483.
- [258] Smith LH, Kuiken TA, Hargrove LJ. Real-time simultaneous myoelectric control by transradial amputees using linear and probability-weighted regression. In: 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC); 2015. p. 1119–1123.
- [259] Au ATC, Kirsch RF. EMG-based prediction of shoulder and elbow kinematics in able-bodied and spinal cord injured individuals. *IEEE Transactions on Rehabilitation Engineering*. 2000 Dec;8(4):471–480.
- [260] Nizamis K, Lobo-Prat J, Keemink AQL, Carloni R, Stienen AHA, Koopman BFJM. Switching proportional EMG control of a 3D endpoint arm support for people

- with duchenne muscular dystrophy. In: 2015 IEEE International Conference on Rehabilitation Robotics (ICORR); 2015. p. 235–240.
- [261] Yiu EM, Kornberg AJ. Duchenne muscular dystrophy. *Journal of Paediatrics and Child Health*. 2015 Aug;51(8):759–764.
- [262] Lobo-Prat J, Kooren P, Janssen M, Keemink A, Veltink P, Stienen A, et al. Implementation of EMG- and Force-based Control Interfaces in Active Elbow Supports for Men with Duchenne Muscular Dystrophy: a Feasibility Study. *IEEE transactions on neural systems and rehabilitation engineering*. 2016 Feb;.
- [263] Liguori R, Fuglsang-Frederiksen A, Nix W, Fawcett PR, Andersen K. Electromyography in myopathy. *Neurophysiologie Clinique = Clinical Neurophysiology*. 1997 Jun;27(3):200–203.
- [264] Eckardt L, Harzer W. Facial structure and functional findings in patients with progressive muscular dystrophy (Duchenne). *American Journal of Orthodontics and Dentofacial Orthopedics: Official Publication of the American Association of Orthodontists, Its Constituent Societies, and the American Board of Orthodontics*. 1996 Aug;110(2):185–190.
- [265] Armand S, Mercier M, Watelain E, Patte K, Pelissier J, Rivier F. A comparison of gait in spinal muscular atrophy, type II and Duchenne muscular dystrophy. *Gait & Posture*. 2005 Jun;21(4):369–378.
- [266] van den Engel-Hoek L, Erasmus CE, Hendriks JCM, Geurts ACH, Klein WM, Pillen S, et al. Oral muscles are progressively affected in Duchenne muscular dystrophy: implications for dysphagia treatment. *Journal of Neurology*. 2013 May;260(5):1295–1303.
- [267] Priez A, Duchene J, Goubel F. Duchenne muscular dystrophy quantification: a multivariate analysis of surface EMG. *Medical & Biological Engineering & Computing*. 1992 May;30(3):283–291.
- [268] Bowen RC, Seliktar R, Rahman T, Alexander M. Surface EMG and motor control of the upper extremity in muscular dystrophy: a pilot study. In: *Proceedings of the 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2001. vol. 2; 2001. p. 1220–1223 vol.2.
- [269] Kumagai K, Yamada M. The Clinical Use of Multichannel Surface Electromyography. *Pediatrics International*. 1991 Apr;33(2):228–237.
- [270] Frascarelli M, Rocchi L, Feola I. EMG computerized analysis of localized fatigue in Duchenne muscular dystrophy. *Muscle & Nerve*. 1988 Jul;11(7):757–761.

- [271] Janssen MMHP, Harlaar J, de Groot IJM. Surface EMG to assess arm function in boys with DMD: a pilot study. *Journal of Electromyography and Kinesiology: Official Journal of the International Society of Electrophysiological Kinesiology*. 2015 Apr;25(2):323–328.
- [272] Kuiken TA, Lowery MM, Stoykov NS. The effect of subcutaneous fat on myoelectric signal amplitude and cross-talk. *Prosthetics and Orthotics International*. 2003 Apr;27(1):48–54.
- [273] Semmler JG, Tucker KJ, Allen TJ, Proske U. Eccentric exercise increases EMG amplitude and force fluctuations during submaximal contractions of elbow flexor muscles. *Journal of Applied Physiology*. 2007 Sep;103(3):979–989.
- [274] Moisello C, Bove M, Huber R, Abbruzzese G, Battaglia F, Tononi G, et al. Short-Term Limb Immobilization Affects Motor Performance. *Journal of motor behavior*. 2008 Mar;40(2):165–176.
- [275] Aguirre-Ollinger G, Colgate JE, Peshkin MA, Goswami A. A 1-DOF assistive exoskeleton with virtual negative damping: effects on the kinematic response of the lower limbs. In: *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2007. IROS 2007; 2007. p. 1938–1944.
- [276] Aguirre-Ollinger G, Colgate JE, Peshkin M, Goswami A, others. Inertia compensation control of a one-degree-of-freedom exoskeleton for lower-limb assistance: initial experiments. *Neural Systems and Rehabilitation Engineering, IEEE Transactions on*. 2012;20(1):68–77.
- [277] Aguirre-Ollinger G, Nagarajan U, Goswami A. An admittance shaping controller for exoskeleton assistance of the lower extremities. *Autonomous Robots*. 2015;p. 1–28.
- [278] UR Download | Support Site | Universal Robots;. Available from: <http://www.universal-robots.com/download/>.
- [279] Balasubramanian S, Melendez-Calderon A, Roby-Brami A, Burdet E. On the analysis of movement smoothness. *Journal of NeuroEngineering and Rehabilitation*. 2015;12(1):1–11.
- [280] Gallagher P, Desmond D, MacLachlan M. *Psychoprosthetics*. March; 2008.
- [281] Hellman RB, Chang E, Tanner J, Helms Tillery SI, Santos VJ. A robot hand testbed designed for enhancing embodiment and functional neurorehabilitation of body schema in subjects with upper limb impairment or loss. *Frontiers in human neuroscience*. 2015;9(February):26.

- [282] Marasco PD, Kim K, Colgate JE, Peshkin MA, Kuiken TA. Robotic touch shifts perception of embodiment to a prosthesis in targeted reinnervation amputees. *Brain*. 2011;134(3):747–758.
- [283] Table Mount MAS - Jaeco Orthopedic;. Available from: <http://jaecoorthopedic.com/products/products/Table-Mount-MAS-.html>.
- [284] M.A.G.; Available from: http://assistive.technology.proteor.com/scripts/famille.php?id_fam_pdt=128.
- [285] Ergorest;. Available from: <http://www.ergorest.fi/>.
- [286] Gopura RARC, Bandara DSV, Kiguchi K, Mann GKI. Developments in hardware systems of active upper-limb exoskeleton robots: A review. *Robotics and Autonomous Systems*. 2016 Jan;75, Part B:203–220.
- [287] Lin PY, Shieh WB, Chen DZ. A theoretical study of weight-balanced mechanisms for design of spring assistive mobile arm support (MAS). *Mechanism and Machine Theory*. 2013 Mar;61:156–167.
- [288] Smith LH, Kuiken TA, Hargrove LJ. Real-time simultaneous and proportional myoelectric control using intramuscular EMG. *Journal of Neural Engineering*. 2014 Dec;11(6):066013.
- [289] Kuiken TA, Miller LA, Lipschutz RD, Lock BA, Stubblefield K, Marasco PD, et al. Targeted reinnervation for enhanced prosthetic arm function in a woman with a proximal amputation: a case study. *The Lancet*. 2007;369(9559):371–380.
- [290] Fara S, Vikram CS, Gavriel C, Faisal AA. Robust, ultra low-cost MMG system with brain-machine-interface applications. In: 2013 6th International IEEE/EMBS Conference on Neural Engineering (NER); 2013. p. 723–726.
- [291] Smith LH, Kuiken TA, Hargrove LJ. Evaluation of linear regression simultaneous myoelectric control using intramuscular EMG. *IEEE Transactions on Biomedical Engineering*. 2015;PP(99):1–1.
- [292] Wurth SM, Hargrove LJ. Real-time comparison of conventional direct control and pattern recognition myoelectric control in a two-dimensional Fitts' law style test. In: 2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC); 2013. p. 3630–3633.
- [293] Guo JY, Zheng YP, Xie HB, Chen X. Continuous monitoring of electromyography (EMG), mechanomyography (MMG), sonomyography (SMG) and torque output during ramp and step isometric contractions. *Medical Engineering and Physics*. 2010;32(9):1032–1042.

- [294] Lin PY, Shieh WB, Chen DZ. A theoretical study of weight-balanced mechanisms for design of spring assistive mobile arm support (MAS). *Mechanism and Machine Theory*. 2013 Mar;61:156–167.
- [295] Dunning, A G . Slender Spring Systems, for a close-to-body dynamic arm support for people with Duchenne muscular dystrophy [PhD Thesis]. TU Delft. Delft; 2016.
- [296] Aguirre-Ollinger G, Colgate JE, Peshkin MA, Goswami A. Active-Impedance Control of a Lower-Limb Assistive Exoskeleton. In: *IEEE 10th International Conference on Rehabilitation Robotics*, 2007. ICORR 2007; 2007. p. 188–195.
- [297] Ison M, Artemiadis P. Multi-directional impedance control with electromyography for compliant human-robot interaction. In: *2015 IEEE International Conference on Rehabilitation Robotics (ICORR)*; 2015. p. 416–421.
- [298] Blank AA, Okamura AM, Whitcomb LL. Task-dependent impedance and implications for upper-limb prosthesis control. *The International Journal of Robotics Research*. 2014 May;33(6):827–846.
- [299] Jolein Van Der Sluis. Fine-Tuning of Artificial Neural Networks to Improve EMG to Force Mapping [Bachelor Thesis]. University of Twente. Enschede; 2015.
- [300] Farina D, Lorrain T, Negro F, Jiang N. High-density EMG E-Textile systems for the control of active prostheses. In: *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*; 2010. p. 3591–3593.
- [301] Ortiz-Catalan M, Branemark R, Hakansson B, Delbeke J. On the viability of implantable electrodes for the natural control of artificial limbs: Review and discussion. *BioMedical Engineering OnLine*. 2012 Jun;11:33.
- [302] Wodlinger B, Downey JE, Tyler-Kabara EC, Schwartz AB, Boninger ML, Collinger JL. Ten-dimensional anthropomorphic arm control in a human brain-machine interface: difficulties, solutions, and limitations. *Journal of Neural Engineering*. 2015 Feb;12(1):016011.
- [303] Bouton CE, Shaikhouni A, Annetta NV, Bockbrader MA, Friedenberg DA, Nielson DM, et al. Restoring cortical control of functional movement in a human with quadriplegia. *Nature*. 2016 May;533(7602):247–250.
- [304] Courtine G, Micera S, DiGiovanna J, del R Millán J. Brain-machine interface: closer to therapeutic reality? *The Lancet*. 2013 Feb;381(9866):515–517.

- [305] Micera S, Citi L, Rigosa J, Carpaneto J, Raspopovic S, Di Pino G, et al. Decoding Information From Neural Signals Recorded Using Intraneural Electrodes: Toward the Development of a Neurocontrolled Hand Prosthesis. *Proceedings of the IEEE*. 2010 Mar;98(3):407–417.
- [306] Stein J, Narendran K, McBean J, Krebs K, Hughes R. Electromyography-Controlled Exoskeletal Upper-Limb-Powered Orthosis for Exercise Training After Stroke:. *American Journal of Physical Medicine & Rehabilitation*. 2007 Apr;86(4):255–261.
- [307] Wolbrecht ET, Leavitt J, Reinkensmeyer DJ, Bobrow JE. Control of a pneumatic orthosis for upper extremity stroke rehabilitation. *Conference proceedings: Annual International Conference of the IEEE Engineering in Medicine and Biology Society IEEE Engineering in Medicine and Biology Society Conference*. 2006;1:2687–2693.
- [308] DiCicco M, Lucas L, Matsuoka Y. Comparison of control strategies for an EMG controlled orthotic exoskeleton for the hand. In: *2004 IEEE International Conference on Robotics and Automation, 2004. Proceedings. ICRA '04. vol. 2; 2004. p. 1622–1627 Vol.2*.
- [309] Gijbels D, Lamers I, Kerkhofs L, Alders G, Knippenberg E, Feys P. The Armeo Spring as training tool to improve upper limb functionality in multiple sclerosis: a pilot study. *Journal of NeuroEngineering and Rehabilitation*. 2011;8:5.

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Joan Lobo Prat

Nijmegen, July 2016

BIOGRAPHY

Joan Lobo Prat was born on October 14th of 1988 in Barcelona (Spain). He studied Industrial Design Engineering at ELISAVA Barcelona School of Design and Engineering and received his MSc. degree (cum laude) in Biomedical Engineering from the Technical University of Catalonia and the University of Barcelona. During his MSc. degree in Barcelona he completed a six month Erasmus exchange program at the Technical University of Delft (The Netherlands). He carried out his master graduation project in the Hospital of Neurorehabilitation “Institut Guttmann” (Barcelona, Spain) in collaboration with the Technical University of Catalonia and the National Institute of Physical Education of Catalonia. The title of the project is: “A new kinematic and dynamic model for clinical evaluation of the upper extremity motion during an activity of daily living in subjects with neurological disorders”. After graduating he decided to continue studying at the Technical University of Delft (The Netherlands) where he completed another MSc. degree in Biomedical Engineering. At the end of his study program, Prof. Bart F.J.M. Koopman, Prof. Peter H. Veltink and Arno H.A. Stinen offered him the opportunity to carry out a PhD at the Department of Biomechanical Engineering of the University of Twente working on the Flexextension A-Gear project. This dissertation on the development of control interfaces to actively support the arm function of adults with Duchenne muscular dystrophy is the result of his work in the Flexextension A-Gear project. Since April 2016 he is working at Focal Meditech (Tilburg, The Netherlands) in the department of Research and Development. His work at Focal Meditech deals with the development of force-based control interfaces for active arm supports. After his work at Focal Meditech, thanks to a Balsells grant, he will work as a Postdoctoral researcher at the Biorobotics Lab (UCI, Irvine, California, USA) with Prof. David J. Reinkensmeyer. There, he will be developing a robotic device that assists people with stroke in manual wheelchair propulsion.

PUBLICATIONS

JOURNAL PUBLICATIONS

8. **J. Lobo-Prat**, K. Nizamis, M.M. Janssen, A.Q.L. Keemink, P.H. Veltink, H.F.J.M. Koopman, A.H.A. Stienen **“Comparison between sEMG and Force as Control Interfaces to Support Planar Movements in Adults with Duchenne,”** June 2016 (under review).
7. **J. Lobo-Prat**, M.M. Janssen, H.F.J.M. Koopman, A.H.A. Stienen, I.J.M. de Groot **“Surface EMG signals in very late-stage of Duchenne muscular dystrophy: a case study,”** Aug. 2016 (under review).
6. A. Bergsma[§], **J. Lobo-Prat**[§], Elizabeth Vroom, Pat Furlong, J.L. Herder **“1st Workshop on Upper-Extremity Assistive Technology for People with Duchenne: state of the art, emerging avenues, and challenges,”** Elsevier Journal of Neuromuscular Disorders, April. 2016.
5. **J. Lobo-Prat**, P.N. Kooren, M.M. Janssen, P.H. Veltink, A.H.A Stienen, H.F. J.M. Koopman **“Implementation of EMG- and force-based control interfaces in active elbow supports for people with Duchenne muscular dystrophy: a Feasibility Study,”** IEEE Transactions on Neural Systems and Rehabilitation Engineering, Feb. 2016.
4. P.N. Kooren, G. Dunning, M.M. Janssen, **J. Lobo-Prat**, H.F.J.M. Koopman, M. Paalman, I.J.M. de Groot, and J.L. Herder **“Design and validation of A-gear: a novel wearable dynamic arm support,”** Journal of NeuroEngineering and Rehabilitation, Sept. 2015.
3. **J. Lobo-Prat**, P.N. Kooren, A.H.A Stienen, J.L. Herder, H.F.J.M. Koopman, and P.H. Veltink, **“Non-invasive control interfaces for intention detection in active movement-assistive devices,”** Journal of NeuroEngineering and Rehabilitation, vol. 11, no. 1, p. 168, Dec. 2014.

§ indicates equal contribution

2. **J. Lobo-Prat**, A.Q.L. Keemink, A.H.A Stienen, A.C. Schouten, P.H. Veltink, and H.F.J.M. Koopman, “**Evaluation of EMG, force and joystick as control interfaces for active arm supports,**” *Journal of NeuroEngineering and Rehabilitation*, vol. 11, no. 1, p. 68, Apr. 2014.
1. **J. Lobo-Prat**, J.M. Font-Llagunes, C. Gomez-Perez, J. Medina Casanovas, and R.M. Angulo-Barroso, “**New biomechanical model for clinical evaluation of the upper extremity motion in subjects with neurological disorders: an application case,**” *Computer Methods in Biomechanics and Biomedical Engineering*, vol. 17, no. 10, pp. 1144–1156, Nov. 2014.

INTERNATIONAL PEER-REVIEWED CONFERENCE PUBLICATIONS

10. P.N. Kooren[§], **J. Lobo-Prat[§]**, A.Q.L. Keemink, M.M. Janssen, M.I. Paalman, A.H.A. Stienen, and H.F.M. Koopman, “**Design and Control of the Active A-Gear: a Wearable 5 DOF Arm Exoskeleton for Adults with Duchenne Muscular Dystrophy,**” in 2016 IEEE International Conference on Biomedical Robotics and Biomechatronics (BioRob), Singapore, 2016, (accepted).
9. A.Q.L. Keemink, R.I.K. Fierkens, **J. Lobo-Prat**, J.S.F. Schorsch, D.A. Ab-bink, J.B.J. Smeets, and A.H.A. Stienen, “**Using Position Dependent Damp-ing Forces Around Reaching Targets for Transporting Heavy Objects: A Fitts’ Law Approach**” in 2016 IEEE International Conference on Biomed-ical Robotics and Biomechatronics (BioRob), Singapore, 2016, (accepted).
8. P.T.C. Straathof[§], **J. Lobo-Prat[§]**, F. Schilder, P.N. Kooren, M.I. Paalman, A.H.A. Stienen, and H.F.M. Koopman, “**Design and Control of the A-Arm: an Active Planar Arm Support for Men with Duchenne Muscular Dys-trophy,**” in 2016 IEEE International Conference on Biomedical Robotics and Biomechatronics (BioRob), Singapore, 2016, (accepted).
7. T. Desplenter, **J. Lobo-Prat**, A.H.A. Stienen and A. Luisa Trejos, “**Exten-sion of the WearME Framework for EMG-driven Control of a Wearable Assistive Exoskeleton**” in 2016 IEEE International Conference on Ad-vanced Intelligent Mechatronics (AIM), Banff, 2016, (accepted).

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6. K. Nizamis, **J. Lobo-Prat**, A.Q.L. Keemink, R. Carloni, A.H.A. Stienen, and H.F.J.M. Koopman, **"Switching proportional EMG control of a 3D end-point arm support for people with duchenne muscular dystrophy,"** in 2015 IEEE International Conference on Rehabilitation Robotics (ICORR), Singapore, 2015, pp. 235–240.
5. **J. Lobo-Prat**, A.Q.L. Keemink, H.F.J.M. Koopman, A.H.A. Stienen, and P.H. Veltink, **"Adaptive gravity and joint stiffness compensation methods for force-controlled arm supports,"** in 2015 IEEE International Conference on Rehabilitation Robotics (ICORR), Singapore, 2015, pp. 478–483.
4. **J. Lobo-Prat**, P.N. Kooren, A.Q.L. Keemink, M.I. Paalman, E.E.G. Hekman, P.H. Veltink, A.H.A. Stienen, and H.F.J.M. Koopman, **"Design and control of an experimental active elbow support for adult Duchenne Muscular Dystrophy patients,"** in 2014 IEEE International Conference on Biomedical Robotics and Biomechatronics (BioRob), Sao Paulo, 2014, pp. 187–192.
3. R.L.Smith, **J. Lobo-Prat**, H. van der Kooij, and A.H.A. Stienen, **"Design of a perfect balance system for active upper-extremity exoskeletons,"** in 2013 IEEE International Conference on Rehabilitation Robotics (ICORR), Seattle 2013, pp. 1–6.
2. S. Ates, **J. Lobo-Prat**, P. Lammertse, H. van der Kooij, and A.H.A. Stienen, **"SCRIPT Passive Orthosis: Design and technical evaluation of the wrist and hand orthosis for rehabilitation training at home,"** in 2013 IEEE International Conference on Rehabilitation Robotics (ICORR), Seattle, 2013, pp. 1–6.
1. **J. Lobo-Prat**, J.M. Font-Llagunes, J. Medina-Casanovas, and R.M. Angulo-Barroso, **"Clinical evaluation of the upper-extremity motion in subjects with neurological disorders,"** Proceedings of ESB2012 - 18th Congress of the European Society of Biomechanics, Lisbon, Journal of Biomechanics, vol. 45, Supplement 1, p. 291, Jul. 2012.

PROPOSITIONS

accompanying the dissertation

CONTROL INTERFACES TO ACTIVELY SUPPORT THE ARM FUNCTION OF MEN WITH DUCHENNE MUSCULAR DYSTROPHY

by Joan Lobo Prat

1. Direct interaction with users must be the first step of any design process: the engineer will identify needs that were not thought of previously (this dissertation).
2. What works for healthy people will probably not work for people with Duchenne; and what works for people with Duchenne will probably not work for healthy people (this dissertation).
3. Every person with a disability, and in particular a person with Duchenne, is different and changes over time (this dissertation).
4. Do not fear failing: success is based on experience but experience is based on failure.
5. A simple solution will rarely solve a complex problem completely, but sometimes can be a significant improvement.
6. Measuring voluntary forces from people with severe muscle weakness is as challenging as listening to a soft melody in a cocktail party (this dissertation).
7. Team work in a collaborative environment is far more efficient than isolated work under competitive pressure.
8. During an engineering PhD/research, the priorities of product development and scientific research should be properly balanced.
9. Results of research that has been funded with public resources should be freely accessible.
10. Collaboration with and knowledge transfer to commercial partners is necessary for the utilization of the results.

These propositions are regarded as opposable and defensible, and have been approved as such by the promoters Prof.dr.ir. Bart F.J.M. Koopman and Prof.dr.ir. Peter H. Veltink.