An EMG-driven Musculoskeletal Model of the Human Lower Limb for the Estimation of Muscle Forces and Moments at the Hip, Knee and Ankle Joints in vivo

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Abstract. This work presents the design of a novel neuromusculoskeletal model (NMS) of the human lower limb to estimate muscle forces and moments about the hip, knee and ankle joints. This research shows it is possible to use electromyographic (EMG) signals recorded from 16 muscles to drive 34 musculotendon actuators and constrain their operation to simultaneously satisfy the production of moments across several degrees of freedom (DOF) including: hip adduction-abduction, hip flexion-extension, knee flexion-extension, ankle dorsi-plantar flexion. Past research proposed the use single-DOF NMS model to estimate muscle forces and joint moments. However, these models do not properly allow muscles to operate with respect to all the DOFs associated to the joints they span. This leads to unrealistic estimations of muscle activation patterns and force production dynamics. Our proposed model was able to generate muscle forces that properly satisfied the moments generated at hip, knee and ankle joints during a variety of dynamic motor tasks.

Keywords: muscle force, joint moment, musculoskeletal model, human-machine interface

1 Introduction

Muscles are the main joint actuators in the human body [13]. Understanding how they activate and generate force about multiple joints to propel the human body towards a specific motion would significantly influence several research areas ranging from physical therapy to neuro-rehabilitation, from computer animation to robotics [13]. Research in rehabilitation robotics strongly relies on

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Proceedings of SIMPAR 2010 Workshops
Intl. Conf. on SIMULATION, MODELING and PROGRAMMING for AUTONOMOUS ROBOTS
Darmstadt (Germany) November 15-16, 2010
ISBN 978-3-00-032863-3
pp. 137-146

the integration of information about the human physiology into assistive device control systems for improving the interaction between the human and the machine [4, 8]. As an example, the design of intelligent assistive devices such as powered orthoses or exoskeletons requires a deep understanding of which forces the patient's muscles are able to produce. Such knowledge would allow better defining the dynamics of joint support the machine should provide the user with [5, 6]. Research on humanoid robots is also increasingly influenced by musculoskeletal research. The new generation of humanoid robots will have highly complex skeletal structures and actuator systems that even more resemble the human musculoskeletal system. Understanding how the human body is actuated by muscles will therefore allow designing motion and balance controllers to actuate humanoids in a more sophisticated way. This work presents the design and development of a dynamic NeuroMusculoSkeletal (NMS) model of the human lower limb. This model aims to be used as an innovative human-machine interface (HMI) for the control of assistive devices such as powered orthoses for the lower limb. The potential for this research is to develop more intuitive assistive devices control systems to improve disabled people's physical capabilities and to advance the study and understanding of human movement and muscles dynamics. This work shows, for the first time, it is possible to use EMG signals to estimate forces for a large number of muscles in the lower limb and moments produced at multiple joints. This research suggests that the correct estimation of muscle forces requires to consider all DOFs of the joints spanned by a muscle. Past research proposed models for the estimation of forces and moments about one DOF only [10, 9, 8, 1, 5, 2, 6, 12]. For instance, past knee NMS models estimated the forces of the muscles involved in the production of knee flexion-extension (FE) moments only [9, 1, 10, 14, 6, 12]. However, most of the muscles spanning the knee span the hip and the ankle joints too. Therefore, the forces these muscles generate for the production of knee FE moment also have to generate the moments about hip and ankle joints.

Our proposed model constrains the operation of muscles to all DOFs of the joints they span. This produces more accurate estimations of muscle forces. In addition, the proposed NMS model has time performances suitable for applications with real-time constraints. The proposed NMS model will allow designing assistive devices control systems for the simultaneous actuation of multiple joints and the support of an even wider range of movements. This is a crucial requirement when the assistive device is to be used for the support of the lower limb. In fact, all functional motor activity such as walking and climbing stairs involve the simultaneous actuation of hip, knee and ankle. The possibility to estimate more accurate muscle forces is an important result that will allow a better understanding of how the human nervous system activates muscle to generate movement.

2 Methods

One healthy, male subject volunteered for this investigation (age: 28 years, height: 183 cm, mass: 67 kg). The subject was taken through the testing proto-

ISBN 978-3-00-032863-3
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cols and informed consent was obtained prior to data collection. The subject was asked to perform repeated trials of 9 tasks including: walking, fast walking, jogging, running, sidestepping and crossover cutting maneuvers, squats, step jumps and lateral hops. These tasks were chosen as they involve the activation of all the lower limb muscles and the subsequent production of moments across all joints. A subset of these motor tasks was used to calibrate the model. The remaining motion trials were used to validate the model operation.

2.1 Data Collection

Retro-reflective markers were fixed to lower limb landmarks that enabled three-dimensional segmental movements to be recorded using a twelve-camera, 250 Hz VICON motion analysis system (Oxford Metrics Inc.). Appropriate joint centers and axes of rotation were computed. Electromyographic (EMG) data were recorded at 2000 Hz from a 16-channel EMG system (Motion Lab Systems) that was connected to the VICON motion analysis system. Bipolar surface electrodes (Ag-AgCl 3M Red Dot) were placed on the following 16 muscles; Gluteus Maximus, Gluteus Medius, Tensor Fascia Latae, Semimembranosus, Biceps Femoris, Rectus Femoris, Sartorius, Gracilis, Adductor Magnus, Vastus Medialis, Vastus Lateralis, Lateral Gastrocnemius, Medial Gastrocnemius, Tibialis Anterior, Peroneus Longus, Soleus. An in-ground force plate was used to measure the ground-reaction forces (GRF) generated by the foot in contact with the ground during the human motion. GRF were recorded at 2000 Hz.

2.2 Motion Modeling

OpenSim was used to generate a subject-specific motion simulation [3].

Marker trajectories recorded during a static pose were used to scale a generic musculoskeletal model to the subject's real dimensions. The scaling process adjusts a number of variables including: 1) length of each bone and muscle, 2) position of the centre of mass of each bone, 3) mass of each segment, i.e. mass of a specific bone and all of the attached muscles. This process starts with a generic OpenSim musculoskeletal model[5] which has predefined weight, height, inertia and position of centre of mass for each body segment. A scaling factor for each segment is then calculated and used to linearly scale length and mass of the generic OpenSim model. Scaling factors are obtained by computing the ratio between the subject's segments mass and dimension and the generic OpenSim model segment mass and dimension. The dimension of the subject's segments are estimated by computing the distance between the centres of the joints the segment is connected to. In the case of the femur for instance, the length of the segment has been calculated by computing the distance between hip and knee joint centres. The mass of each segment is derived from the subject total mass using anthropometric tables. The scaling process is an OpenSim

[5] Available from the Neuromuscular Models Library: https://simtk.org/home/nmblmodels/

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built-in tool. Marker trajectories recorded during dynamic movements are used to drive the scaled musculoskeletal model. Inverse Kinematics (IK) is used to derive three-dimensional joint angles. GRFs were used in conjunction with the thee-dimensional joint angles computed through IK to derive the experimental joint moments. This is usually done by performing standard Inverse Dynamics (ID). However, this method does not provide optimal solutions. Due to limitations in marker trajectory acquisition and processing, there is an inherent mismatch between the recorded trajectories and the recorded GRF. Therefore, the moments computed via ID do not match the motion computed via IK. In this work we used Residual Reduction Analysis (RRA) to minimize the mismatch between trajectories and GRF. RRA is an optimization procedure that slightly changes the recorded kinematics until an optimum match with GRF is obtained.

3 Neuromusculoskeletal Model

The proposed Neuromusculoskeletal (NMS) model is a digital representation of the human musculoskeletal organization. It reproduces the transformations that take place from the generation of the EMG signal to the production of muscle forces and joint moments at the hip, knee and ankle joints. The proposed model has been developed starting from a well-established EMG-driven model that has been used as a baseline [10, 9, 1, 14, 12, 11]. The initial baseline model estimated the forces of the 13 muscles crossing the knee and the knee flexion-extension torque only. The model described in this work estimates 34 muscle forces (Table 1) and the joint moments about the following 6 DOF: *hip adduction-abduction (HAA)*, *hip flexion-extension (HFE)*, *hip internal-external rotation (HROT)*, *knee flexion-extension (KFE)*, *ankle dorsi-plantar flexion (AFE)*, *ankle subtalar-angle (ASA)*.

Five main blocks compose our NMS model (Fig. 1). The NMS model we propose in this work is implemented in C++. OpenSim is only used to generate experimental joint moments and angles to be used as input data (Section 2.2).

Muscle Activation. Raw EMG signals recorded from 16 muscles are the input for the model and are used to compute the activations of 34 muscles. Muscle activation is a percent value that indicates how much the muscle is activated toward the generation of force in a specific time instant. Raw EMG signals are distributed to all 34 muscles according to the location of the innervation of each musculotendon actuator. That is, muscles that are innervated in the same location and share the same nerve can be assumed to produce similar electromyographic activity and contraction patterns. In the case of muscles that are innervated in two points, a linear combination of the EMG signals associated to the two innervations locations is used. The EMG signals recorded from the adductor muscle group are used to drive the following musculotendon actuators: adductor magnus 1, adductor magnus 2, adductor magnus 3, adductor brevis and adductor longus. The EMG signals recorded from the gluteus maximus muscle are

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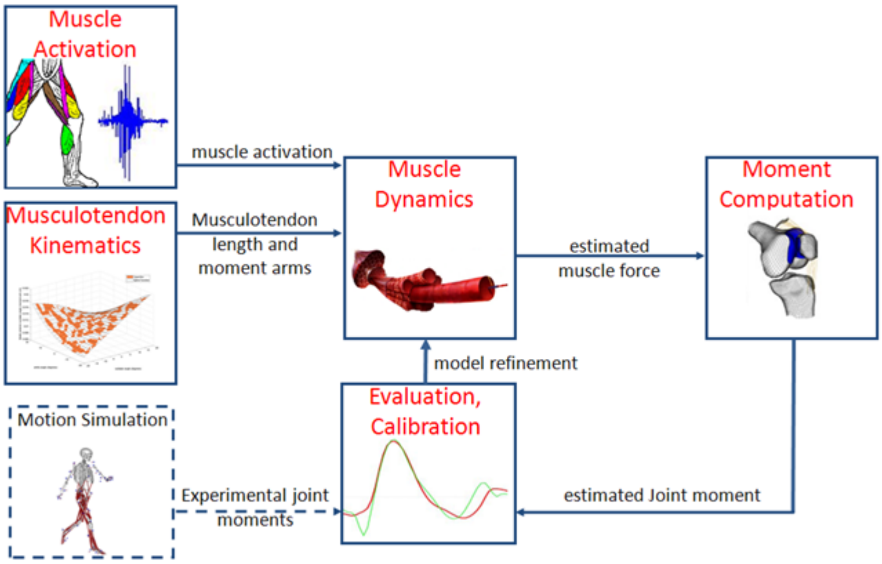

Fig. 1. Structure of the NMS model. The blocks in solid line are the actual components of the NMS model (Section 3) and are implemented in C++. The **motion simulation** block (dotted line block) is implemented using OpenSim. It is not part of the NMS model and is only used to provide the experimental joint moments and angles (Section 2.2).

used to drive 3 musculotendon actuators including: gluteus maximum 1, gluteus maximum 2, gluteus maximum 3. EMG signals from the gluteus medius muscles are used to drive the gluteus medius 1, gluteus medius 2 and gluteus medius 3 muscutotendon actuators. EMG signals for the gluteus minimus muscle are derived as a linear combination of the raw EMG signals recorded from the gluteus maximus and gluteus medius muscle. EMG signals from the peroneus muscles are used to drive the following musculotendon actuators: peroneus brevis, peroneus longus, peroneus tertis. EMG signals from the biceps femoris muscle are used to drive both the biceps femoris long head and the biceps femoris short head muscle. The EMG signals from the hamstrings muscle group are used to drive both the semimembranosus and the semitendinosus musculotendon actuators. EMG signals for the vastus interioris are derived as a linear combination of the raw EMG signals recorded from the vastus medialis and vastus lateralis muscle. The illiacus and psoas muscles are not driven by EMG signals and their activation is not computed in this current implementation of the model. Future version of the NMS model will feature a predictive algorithm for the estimation of the activation of these two muscles with no EMGs. Although the activation of the psoas and illiacus muscles is not computed, those muscles still contribute to the production of force at the hip joint because the passive force generated dur-

ISBN 978-3-00-032863-3
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ing stretching and compression can still be calculated by the Muscle Dynamics component.

Musculotendon Kinematics. The musculotendon kinematics model estimates lengths and three-dimensional moment arms for the musculotendon actuators included in the model. Using the OpenSim musculoskeletal model, a set of nominal values are established for the length of each musculotendon actuator at predefined joint angles. A multidimensional spline function is then used to fit the experimental data and derive a multivariate function that can estimate values in between the experimental nominal values. Muscle moment arms are obtained by differentiating the musculotendon length spline function with respect to the generalized coordinate of interest.

Muscle Dynamics. It uses the values computed in the previous two blocks to calculate the force developed by each musculotendon unit in the model. The muscle model is based on a normalized Hill-type model [7]. The model accounts for changes in pennation angle and uses generic force-length and force-velocity curves for each muscle to estimate muscle fibre force. These curves are normalized to maximum isometric muscle force, optimal fibre length, maximum muscle contraction velocity, and tendon slack length.

Moment Computation. This component evaluates the moments produced at all the DOFs of each joint included in the model. The estimated muscle forces are combined with the corresponding moment arms to calculate the torque about a specific DOF.

Model Validation. To validate a model, it is usually desirable to compare the output of that model with data measured empirically. Unfortunately, the methodological difficulties in measuring individual muscle forces prevent any direct validation of the NMS model on humans, although there are possibilities of measuring muscle forces using an animal model in the future. An indirect process was therefore designed to validate and calibrate the model to an individual. The validation process involves comparing the net moments from muscles crossing the hip, knee and ankle joints with the net moments measured experimentally. If the muscle forces are accurate, then net joint moments estimated by the model should be equal to the external moments measured experimentally.

Model Calibration. The calibration process is critical for the proper operation of the model. It defines how muscles activate in response to EMG signals and generate moments about multiple DOFs. The aim of the calibration process is to obtain a set of parameters for an individual to accurately estimate the net moments at the hip, knee, and ankle across all corresponding DOFs. The calibration process uses a set of calibration trials to learn the muscle dynamics across a wide range of muscle contractile conditions. An optimization

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procedure has been designed to alter the initial uncalibrated parameters so that the moments estimated by the NMS model fit the net joint moments measured experimentally minimizing the root mean squared error (RMSE). The adjustable parameters used in the calibration process were divided into two groups. One group included activation parameters, chosen from the Muscle Activation model and the other group were muscle parameters from the Muscle Dynamics model. The calibration process has been designed to assure that muscles satisfy the moments across all DOFs associated to the joints they span. Biarticular muscles crossing the hip and knee joints for instance, have to produce a force that satisfy four moments altogether (HROT, HAA, HFE and KFE). The calibration process repeatedly calls an optimization routine using different objective functions and different sets of muscles depending on the degree of freedom that has to be calibrated. Each call uses the parameter set generated by the previous optimization routine call. Muscles crossing the knee joint are first calibrated. The objective function to minimize is the RMSE between experimental and predicted knee FE moments. Muscles crossing the hip are then calibrated. The objective function in this case is the summation of the RMSE between the experimental and predicted hip FE moments and the RMSE between the experimental and predicted knee FE moments. The process is repeated until the operation of muscles satisfy the joint moments across all DOFs. Once the calibration process is completed the subject-specific calibrated parameters allow producing good estimates of muscle forces and joint moments while the subject is moving. It is worth noting that, once it is calibrated, the NMS model only requires EMG signals and joint angles as inputs. GRF and experimental joint moments are only needed during the calibration step. Furthermore, once the model parameters have been calibrated, the NMS model can be used to predict muscle force and joint moments during novel motor tasks that have not been used to calibrate the model itself.

4 Results

The moments generated at the hip, knee and ankle joints were predicted using the proposed multi-DOF NMS model as well as using the baseline single-DOF NMS model for motor tasks including: walking (WLK), running (RN), sidestepping (SS), crossover (CO). The motion trials used for the validation of the multi-DOF model as well as for the individual single-DOF models were novel trials that were not used during the calibration process. Five motion trials were performed per motor task (i.e. WLK, RN, SS and CO) and the following joint moments were computed: HAA, HFE, KFE, AFE. The proposed multi-DOF model was able to concurrently predict the joint moments preserving the accuracy of the single-DOF models. Table 2 reports average results for each motor task. The multi-DOF model estimated HAA joint moments with the same accuracy of the single-DOF moments during WLK and SS tasks. A substantial improvement was observed for the CO task. The HAA joint moments during the RN task were better predicted by the single-DOF model. The multi-DOF model estimated HFE joint moments with comparable accuracy to the single-DOF model during the WLK,

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Table 1. The 34 muscles included in the model and joints they span

Hip	Knee	Ankle	Hip-Knee	Knee-Ankle
Adductor brevis	Vastus interioris	Peroneus brevis	Biceps femoris long head	Lateral gastrocnemius
Adductor longus	Vastus lateralis	Peroneus longus	Biceps femoris short head	Medial gastrocnemius
Abbuctor magnus 1	Vastus medialis	Peroneus tertis	Graclis	
Adductor magnus 2	Soleus	Rectur femoris		
Adductor magnus 3	Tibialis anterior	Sartorius		
Gluteus maximus 1	Semimembranosus			
Gluteus maximus 2	Semitendinosus			
Gluteus maximus 3	Tensor fascia latea			
Gluteus medius 1				
Gluteus medius 2				
Gluteus medius 3				
Gluteus minimus 1				
Gluteus minimus 2				
Gluteus minimus 3				
Iliacus				
Psoas				

RN and SS tasks. During the CO task the single-DOF model achieved better accuracy. The multi-DOF model produced better estimates of KFE moments for WLK and CO tasks while the single-DOF model behaved better during the RN and SS tasks. The multi-DOF model produced significantly better results in the estimation of the AFE joint moments. Figure 2 shows the results relative the 5 sidestepping trials. Results show the Multi-DOFs NMS model was able to constrain the operation of all muscles to produce forces that satisfy the moments generated simultaneously at the hip, knee, and ankle joints. The muscle activations and muscle forces predicted by the Multi-DOF model significantly differed from those estimated by the 4 individual single-DOF models. Force patterns predicted using the Multi-DOF NMS model were different showing a earlier production of force for both quadriceps and hamstrings.

5 Discussion

This research work developed a novel EMG-driven neuromusculoskeletal model of the lower limb that uses EMG signals recorded from 16 muscles to derive the activity of 34 muscles and estimate moments about hip, knee and ankle joints. The proposed model was able to predict joint moments with the same accuracy of individual single-DOF EMG-driven models. Furthermore, results demonstrated that the proposed model was able to generate muscle forces that satisfy multiple DOF simultaneously. The proposed NMS model has great potentials to predict more physiologically accurate muscle forces than those estimated by single-DOF models. Findings obtained within this research work will be applied for the design

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Table 2. Mean absolute error and standard deviation between predicted and experimental joint moments (Nm). Numbers have been bolded to highlight the cases in which the multi-DOF model provided same or better joint moment estimates.

Multi-DOF EMG-driven Model				
	HAA	HFE	KFE	AFE
WLK	**11.8 ± 1.6**	**34.0 ± 1.2**	**12.5 ± 1.7**	**12.0 ± 4.6**
RN	46.2 ± 2.6	**34.1 ± 8.5**	26.2 ± 5.7	17.1 ± 4.7
SS	**22.6 ± 4.4**	**18.6 ± 4.7**	32.3 ± 7.3	**13.1 ± 3.1**
CO	**28.6 ± 4.4**	46.4 ± 7.7	**17.6 ± 3.2**	**13.5 ± 4.5**

Single-DOF EMG-driven Model				
	HAA	HFE	KFE	AFE
WLK	11.8 ± 1.5	33.4 ± 1.8	13.3 ± 0.8	29.4 ± 1.1
RN	38.1 ± 8.3	37.3 ± 1.9	17.2 ± 4.6	4.6 ± 4.9
SS	20.1 ± 7.3	17.3 ± 5.8	26.6 ± 6.2	19.5 ± 2.1
CO	36.2 ± 4.7	30.9 ± 4.7	19.1 ± 2.7	13.3 ± 2.2

of more intuitive assistive devices control systems for the simultaneous actuation of multiple joints and the support of an even wider range of movements. This is a critical requirement for assistive device supporting the lower limb motion.

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ISBN 978-3-00-032863-3
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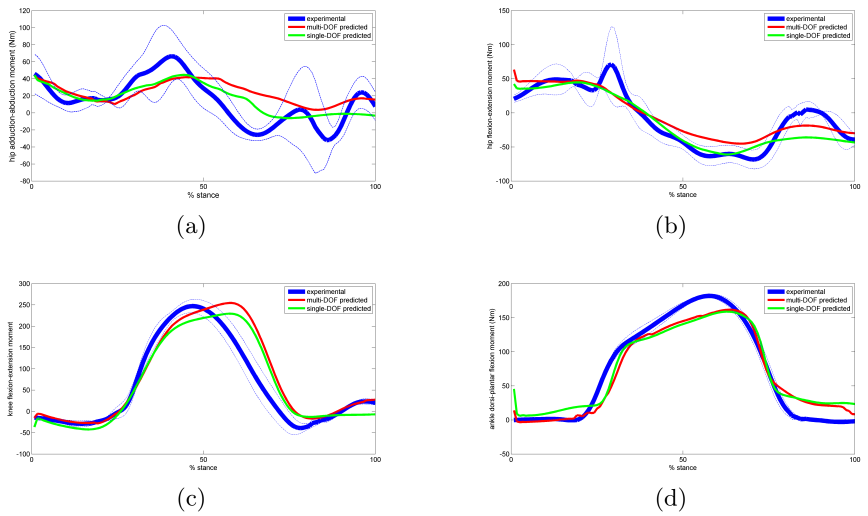

Fig. 2. Data from each trial were time-normalized and the joint moment ensemble average was obtained. The dotted line represents the standard deviation of the experimental mean joint moments. The blue curve is the experimental moment. The red and green curves are the predicted moments obtained using the multi-DOF and single-DOF NMS models respectively. (a) hip adduction-abduction moment, (b) hip flexion-extension moment, (c) knee flexion-extension moment, (d) ankle plantar-dorsi flexion moment.

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