NEURAL NETWORKS FOR RECONSTRUCTING MUSCLE ACTIVATION FROM EXTERNAL SENSOR SIGNALS DURING HUMAN WALKING

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Abstract

The feasibility of using neural networks for reconstructing muscle activation patterns during human walking on the basis of mechanical sensor information was studied. Joint angle trajectories and foot contact were measured during walking at two speeds. Activation patterns of two muscles were determined from surface EMG. A multi-layer perceptron network was trained using the back-propagation rule. During the training, the sensor data were applied to the input, and the EMG activation patterns were applied to the output.

After the training, the ability of the network to reconstruct muscle activation at each time step from sensor data at that time step and previous time steps was evaluated. The sensor data in this test consisted of trials at both walking speeds, which had not been included in the training set.

The network appeared to be able to reconstruct the activation patterns at both speeds reasonably well. Especially, the timing of the activation bursts was quite accurate. Therefore, these preliminary results indicate that neural networks can be used to predict muscle activation patterns from past sensor signals in a cyclical movement like walking.

Introduction

Skeletal muscles are the motors in generating walking in humans. The activation patterns of the muscles are generated by the central nervous system, using physiological sensors in the muscles and tendons for feedback. We investigated whether a neural network can reconstruct muscle activation at each moment from external sensor signals upto that moment (figure 1).

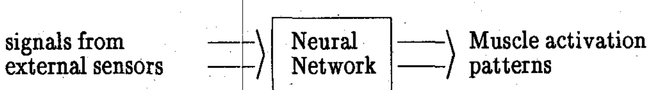

Figure 1. *A neural network for reconstructing muscle activation patterns in the walking cycle on the basis of signals from external sensors, like goniometers, footswitches, etc.*

If neural networks can reconstruct muscle activation patterns in healthy subjects from external sensor data, they might be useful in the control of artificially generated locomotion in paraplegic patients. In these patients, the muscles do not receive the necessary activation patterns, because of a spinal cord lesion. Artificially generated activation patterns can be supplied to the muscles by artificial electrical muscle stimulation. In this way, functional movements, like walking, can be generated. This is called Functional Electrical Stimulation (FES) [1,2].

Control of such a FES-system is still a problem, which is being addressed by several research groups: e.g. Andrews et al. based the control of FES-induced walking on a finite-state description of walking [2]. Another approach would be to generate the muscle activation patterns from the desired joint angle trajectories using an inverse model of the system. This can only be done if an inverse model of the dynamics of the whole biomechanical system can be constructed. It would result in an open loop compensator in front of the actual system. However, it is hard to model the biomechanical system accurately, because such a model is rather complex [3,4], the system characteristics can vary substantially and the identification of all system parameters is difficult. The construction of an inverse model might even not possible in a strict sense, because of causality reasons. However, such an inverse model might in principle be constructed if the desired movement is known in advance upto some time in the future, like is the case in a well-defined cyclical movement.

If the inversion could be done implicitely by a neural network, such an open loop compensator might be constructed. However, the inversion is expected to work only for a limited set of cyclical motions, which were learned by the network.

The current study is limited to the investigation of the principle possibility of reconstructing muscle activation patterns from joint angles and foot contacts in a well defined cyclical walking movement. It was done in a healthy subject. Activation patterns of two leg muscles of the subject were measured by means of Electro MyoGraphy (EMG). Simultaneously, signals from external sensors, like goniometers and foot switches were measured. We investigated whether a neural network could reconstruct these activation patterns on the basis of the sensor signals at two walking speeds. The neural network was trained using measured sensor signals (input) and EMG patterns (output).

Methods

Experimental methods

Experimental data were obtained from walking of a healthy individual. Hip, knee and ankle angles were measured in both legs using Penny & Giles Goniometers. Furthermore, foot contact was measured by monitoring electrical contact between metal contacts under both feet (under heel and toes) and a conducting rubber floor. Muscle activation patterns of the semitendinosus and vastus medialis muscles were determined from EMG measurements using bipolar surface EMG electrodes. The EMG signal was rectfied and presampling filtered using a second order Butterworth low-pass filter with a cut-off frequency of 25 Hz. The goniometer signals and contacts were sampled at 50 Hz and the EMG signals at 200 Hz by an IMB-PC compatible computer with a data acquisition card. The EMG was low-pass filtered using a 57 coefficient FIR filter with a linear phase characteristic and a cut-off frequency of 5 Hz. This filter was derived from the impulse response which corresponds to the ideal frequency response using a Hamming window [5]. After filtering the EMG signal was shifted back in time to compensate for the time delay introduced by the filter.

Walking was registrated at two speeds in order to evaluate the ability of the neural network to generate muscle activation patterns at varying walking speeds. At each speed (comfortable speed and a faster speed) 4 trials of 4 or 5 steps were measured during steady walking.

Neural network reconstruction of muscle activation patterns

The objective of this study is to assess the feasibility of neural networks to generate muscle activation patterns needed for a functional walking movement. A multi-layer perceptron network with supervised learning via backpropagation was used in this study [6]. This network allows for analog input and output signals, and supervised learning. The inputs of the network at each time step consisted of samples of the sensory signals upto that time step (figure 2). The input signals were normalized between -1 and 1. The output of the network consisted of the reconstructed muscle activation patterns. Neural network computations were done on an IMB-PC compatible computer using the software package Neural Works.

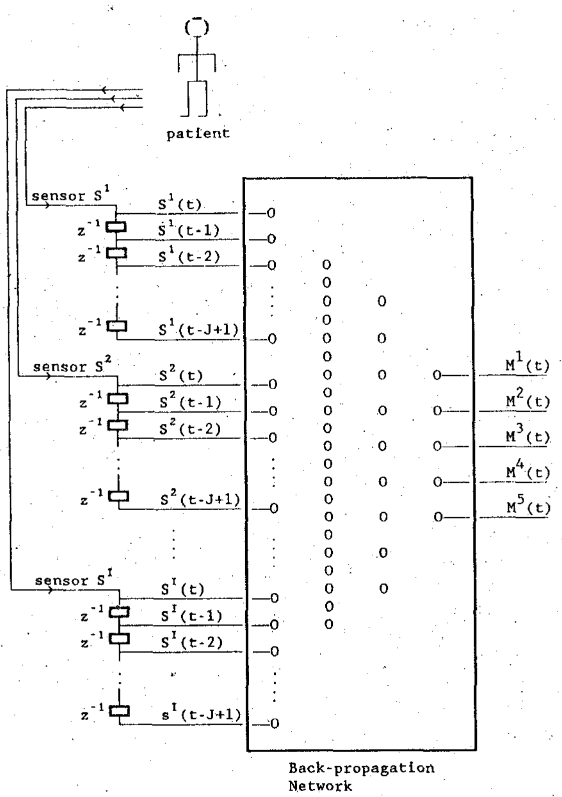

Figure 2. *At each time step t, a number of subsequent samples of the sensory signals upto that time step were used as inputs to the neural network (z^{-1} means a time step delay). The network reconstructs the activation of a number of muscles at time step t.*

First, the relation between the input and output patterns was learned by the network in a training session. At the beginning of the training session the weights of the nodes of the network were initialized randomly between –0.1 and 0.1. The input signals and the corresponding output activation patterns were applied to the network, and the weigths of the nodes were adapted via the backpropagation training algorithm in each time step. The learning coefficient was set to 0.9 and the smoothing factor to 0.6 [7]. The training set was derived from 27 steps in 6 trials (3 trials at each speed). The set consisted of the input and corresponding output patterns belonging to all time steps of these trials in a randomized order. The training set was applied to the network several times (about 50 times).

After the training session the ability of the network to reconstruct muscle activation patterns was evaluated. Sensory input signals of the two trials which were not part of the training set were applied to the network, and the reconstructed activation patterns at the output of the network were compared with the measured EMG patterns. This evaluation was done at both walking speeds.

In this evaluation several parameters were varied: the number of learning steps and the number of nodes in the network. The number of nodes in the first hidden layer was varied between 10 and 50. The ratio between the number of nodes in the first and second hidden layer was always taken 3 to 1. The number of nodes in the input layer depended on the number of sensor signals, and the number of samples per signal used. The number of samples per signal which were applied to the input of the network and the time delay between the samples were varied. Only the goniometer signals of hip and knee of the right leg (same leg as EMG measurements), and contacts of both feet were used as input signals.

Results

Figure 3 shows examples of the normalized signals obtained from walking at two speeds.

When varying the number of nodes in the first hidden layer, a number of 20 nodes appeared to yield the lowest RMS–error between measured and reconstructed activation patterns. The RMS–error was higher for both a lower, and a higher number of nodes. The number of learning cycles (time steps) was varied between 50,000 and 500,000. A continuation of the training process beyond 100,000 cycles did not result in a significant improvement in RMS–error.

Good results of the reconstruction of the activation patterns were found for 4 input signals (hip and knee gonio signals of the right leg, and foot contact at both sides), 15 samples per signal used as input values, 0.02 s time delay between the samples, 20 nodes in the first hidden layer, and 7 in the second hidden layer. The number of input nodes was 60, and the number of output nodes 2. Figure 4 shows the performance of the network in reconstructing the muscle activation patterns at both walking speeds. The typical examples shown in figure 4 were not part of the training set.

The results show a good correspondence between the reconstructed and measured activation patterns. Especially the time of onset and offset of the activation bursts are important in generating a coordinated walking movement. The timing of the reconstructed activation patterns is rather accurate (figure 4). For evaluation of the timing of the activation bursts we determined the time difference of crossing half of the maximum of each measured activation burst. The resulting time differences are given in table 1.

When assuming a relatively slow mechanical system, the momentum (time integral of muscle force) belonging to each activation burst is also important, rather than the exact form of the burst. The time integral of muscle force relates to the time integral of the activation pattern via the nonlinear muscle dynamics [8]. The time integral of the activation patterns are reconstructed reasonably well, except for a few cycles (figure 4). Average values and standard deviations of the differences of the time integral of the activation patterns are given in table 2. Table 2 indicates that the time integral of the reconstructed activation patterns tended be some what higher than the time integral of the measured patterns.

The minimum configuration of the neural network, giving still acceptable results is not yet known. The optimal number of input signals, the number of samples per input signal, the optimal time delay between the samples of the signal, and the optimal number of nodes in the hidden layers for this configuration is looked for at the moment.

Discussion

This study shows that neural networks can be used to reconstruct muscle activation at a certain time in normal waking on the basis of a limited number of sensory signals upto that time: A multi–layer perceptron neural network can learn the relation between signals from external sensors and muscle activation patterns in healthy persons, walking at variable speed. An optimal configuration of the neural network for this application has still to be found.

In principle, this method can be used to predict muscle activation in real time on the basis of sensor signals upto the moment of prediction for well defined cyclical movements with limited variations in e.g. speed. To realize this, a fast system for computing the neural network in real time is needed.

When this method is to be applied for control of FES in paraplegic patients, the network can not be trained from the relation between activation patterns and joint angle and foot contacts in healthy persons, since the system characteristics are different: only a limited number of muscles are stimulated in an inefficient way, and the patient uses crutches or a walking frame to keep balance. An acceptable way of generating a training set, e.g. from stimulation experiments performed at the patient, has to be developed for this purpose.

comfortable walking ($T_{stride} \simeq 1.3$ *s*) *faster walking* ($T_{stride} \simeq 1.2$ *s*)

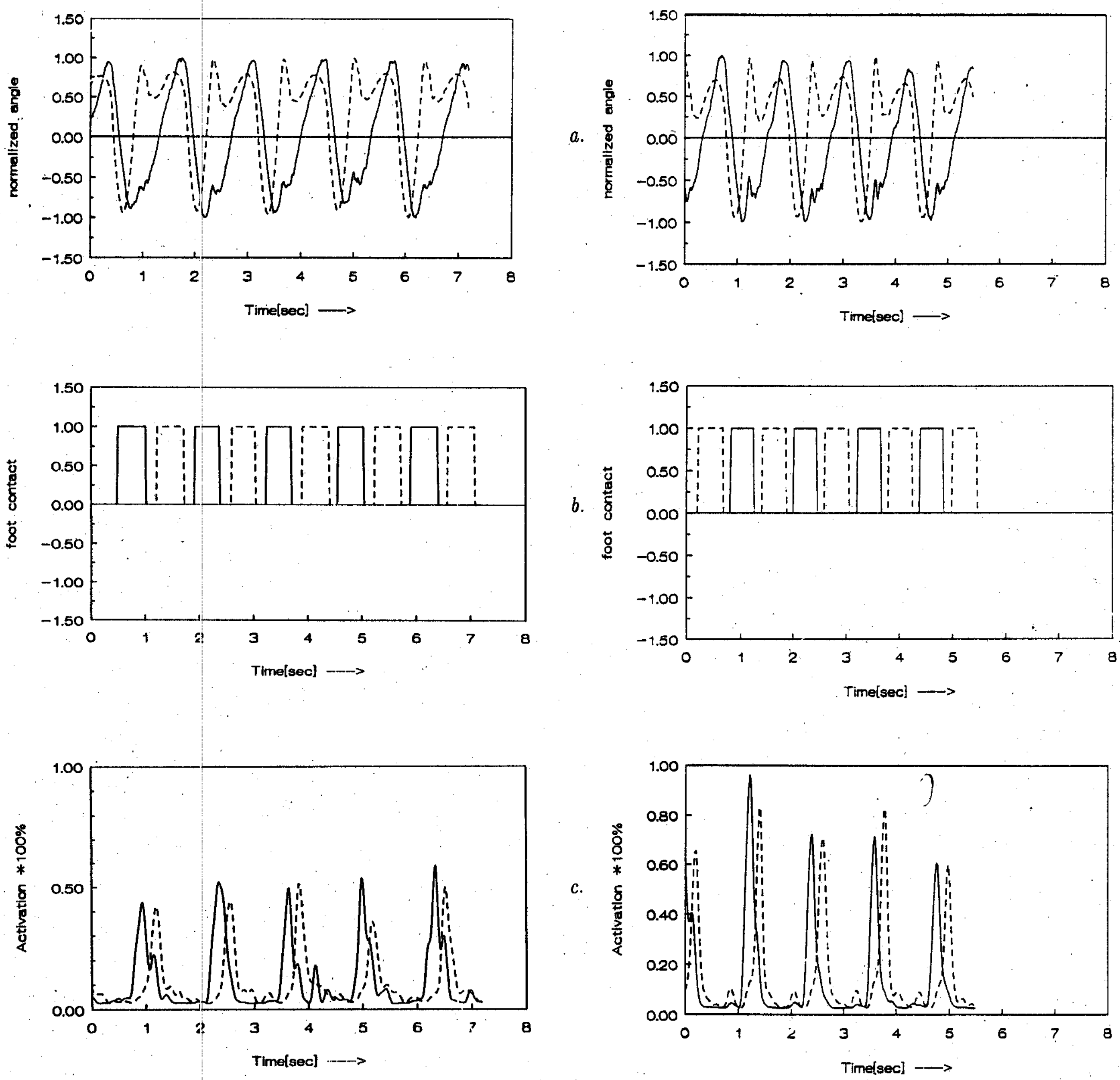

Figure 3. *Signals measured during walking at two speeds. The signals have been normalized.*
a. goniometer signals of right hip (solid line) and right knee (broken line).
b. contactsignals of right foot (solid line) and left foot (broken line) (0 means foot contact, 1 means no foot contact).
c. rectified and filtered EMG patterns of semitendinosus (solid line) and vastus lateralis (broken line) muscles of the right leg.

comfortable walking ($T_{stride} \simeq 1.3$ s) *faster walking ($T_{stride} \simeq 1.2$ s)*

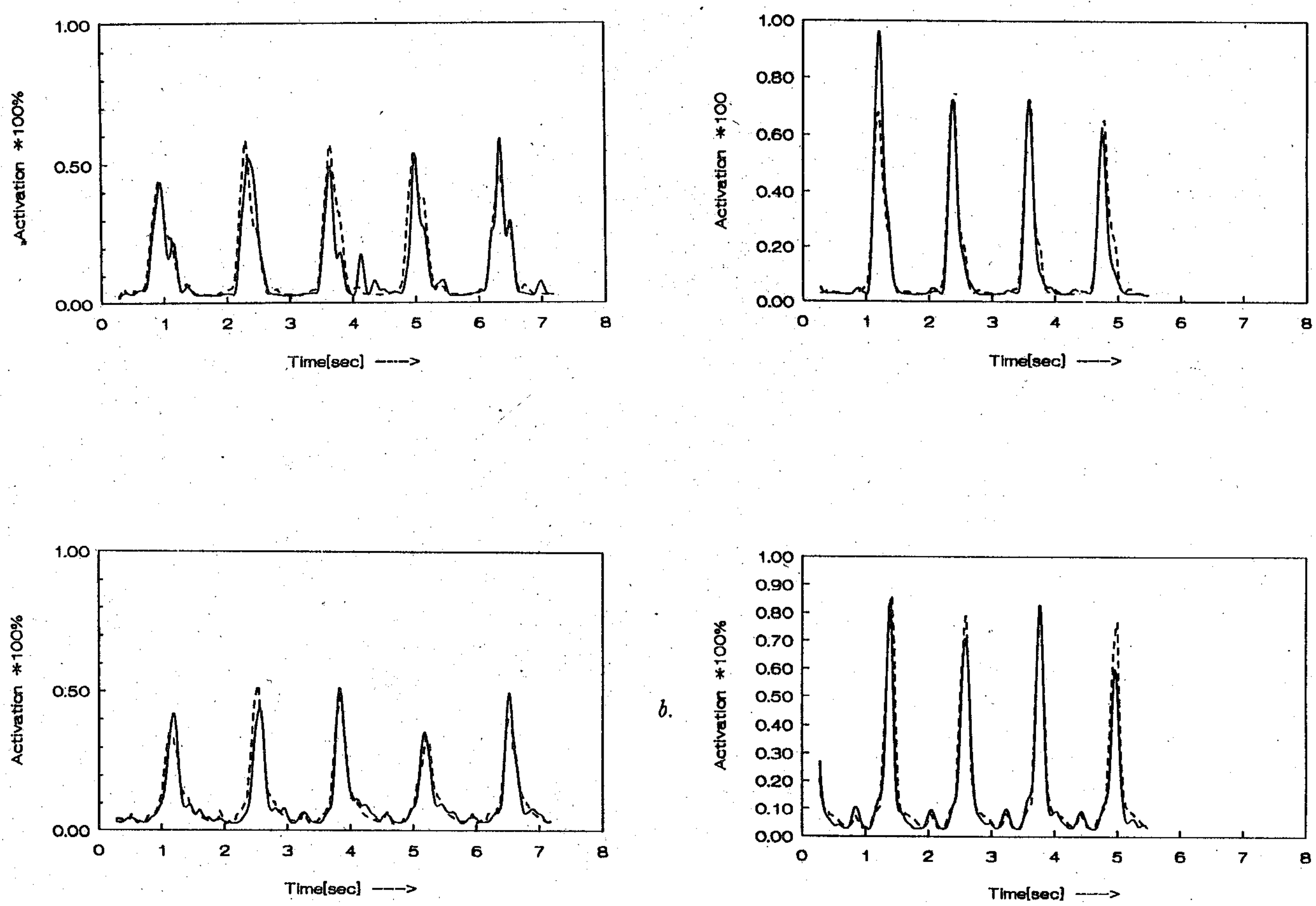

Figure 4. *Typical examples of the activation patterns generated by the neural network compared to the measured activation patterns. The examples were not part of the learning set.*
a. Semitendinosus muscle, b. Vastus medialis muscle.
Parameters: 4 input signals (hip and knee gonio signals of the right leg, and foot contact at both sides), 15 samples per signal used as input values, 0.02 s time delay between the samples, 20 nodes in the first hidden layer, and 7 in the second hidden layer. The number of input nodes was 60, and the number of output nodes 2. The number of training cycles was 100,000.

muscle	walking speed	# steps	time difference (ms) onset	offset
semitendinosus	comfortable	5	−36 ± 17	30 ± 50
vastus medialis	comfortable	5	−24 ± 15	10 ± 12
semitensinosus	faster	4	− 3 ± 10	0 ± 40
vastus medialis	faster	4	−20 ± 14	15 ± 13

Table 1. *Differences in timing of measured and reconstructed activation patterns. Of each activation burst in the examples of figure 4, the time differences of crossing half of the maximum of the measured activation burst was determined. Average and standard deviations are indicated in this table for the differences in times of onset and offset.*

muscle	walking speed	# steps	differences in time integral of activation (%)
semitendinosus	comfortable	5	10 ± 9
vastus medialis	comfortable	5	6 ± 10
semitensinosus	faster	4	5 ± 16
vastus medialis	faster	4	13 ± 10

Table 2. *Differences of the time integral of the EMG activation patterns of the measured and reconstructed activation bursts. The time integral was determined for every walking cycle. Average and standard deviations of these differences are indicated in this table, expressed as a percentage of the average time integral of the measured activation patterns of that trial.*

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