

Control of Tibialis Anterior FES Envelop for Unilateral Drop Foot Gait Correction Using NARX Neural Network

Neda Kordjazi¹, Hamid R. Kobrai²

Abstract— In this paper a control methodology based on artificial neural networks (ANN) is proposed for control of ankle dorsiflexion in patients with unilateral drop foot. In the presented strategy, the electrical stimulation intensity for the disabled tibialis anterior (TA) muscle is controlled considering the existing coordination patterns between activities of the ipsilateral ankle dorsiflexor muscles and the contralateral ankle plantarflexor muscles during normal gait. Based on this coordination, in each gait cycle the TA muscle of one leg acts in close simultaneity with the calf muscle of the opposite leg. Therefore in this paper a dynamic ANN has been trained in a predictive manner, to forecast the disabled TA muscle activity based on the input from the healthy calf muscle of the opposite leg. The predicted TA activation is then used to control the TA muscle FES intensity in real time. Seven healthy volunteers participated in the experiments. Surface electromyogram was recorded from TA and calf muscle simultaneously on the opposite legs while walking in different gait frequencies. Results obtained from the controller are quite promising and show impressive generalization ability between subjects.

Index Terms— Drop foot, Surface Electromyography (SEMG), Functional Electrical Stimulation (FES), Tibialis Anterior (TA), NARX Neural Network, Muscle activation pattern

I. INTRODUCTION

Unilateral drop foot refers to insufficient activation of the dorsiflexor muscles in one leg, due to weakened selective control and/or calf muscle spasticity [2]. The lack of ability to properly dorsiflex the ankle results in toe dragging, and therefore abnormal gait behaviors, serving to compensate the inadequacies [5]. Functional electrical stimulation (FES) with surface electrodes is a rehabilitation solution, of interest for patients with neuromuscular disorders. Lack of efficient control however, is the major drawback preventing wider usage of FES.

In most unilateral drop foot stimulators (DFS) FES is applied using a trapezoidal FES intensity envelope which results in a tibialis anterior (TA) muscle activation pattern that is extremely different from that observed in natural gait [4, 8]. The FES intensity is linearly ramped up to its

maximum value at toe off. Intensity is then kept constant until heel strike, when it is ramped down to zero. This is quite similar to that first proposed by Liberson in 1961 [4, 7, 8].

A variety of control methods are described in literature for FES systems. ON-OFF control [8], preprogrammed open-loop control (desired trajectory tracking) [6] and sometimes complicated closed-loop control methods being some of them [10, 11].

In this paper the basic idea comes from the fact that bipedal walking is a quasi-cyclic activity where the movements of the ipsilateral and contralateral legs are time shifted for about 50 percent of the gait cycle [12]. Therefore when one leg is in stance, the other leg is in swing phase most of the time [2]. This results in a synergical coordination between the ankle dorsiflexor and plantarflexor muscles in opposite legs which means that during normal gait ipsilateral ankle dorsiflexor muscles act in close simultaneity with contralateral ankle plantarflexor muscles.

We suggest the use of a form of sensory-driven machine learning based predictive controller to improve the gait quality in patients with unilateral drop foot. In the presented control approach a NARX ANN is trained in a predictive manner to learn the existing coordination patterns between the activities of ankle dorsiflexor and plantarflexor muscles in opposite legs during normal gait. Thus the controller can be described as a dynamic model that triggers the appropriate motor actions in the impaired TA muscle based on the true state of the system, provided by the healthy calf muscle activity on the opposite (non-paretic) leg. Using the predicted TA muscle activity, the FES pulse duration is modulated in real time such that the desired muscle activation is achieved.

II. METHODS AND METERIALS

A. Experimental Protocol

Seven healthy male volunteers (27 years \pm 2) participated in the experiments. They were asked to walk on a treadmill wearing comfortable footwear. For each subject the treadmill speed was set in 3 phases, such that they could keep up by taking 60, 80, and 100 steps (30, 40, and 50 gait cycles) per minute (step/min) which are close to drop foot patients' stride frequency range. The stride length was not confined, and the subjects were told to walk with the most comfortable stride length. In order to take into account the day to day and subject to subject variations, each subject

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was asked to conduct three trials on three different days. In every trial subjects were asked to walk for 1 minute at each speed.

Meanwhile surface EMG was recorded from muscles tibialis anterior (TA) on the right leg, and gastrocnemius (GC) on the left leg. We used Skintact pre-gelled Ag/AgCl electrodes in bipolar order, and ADInstruments Dual Bio Amp and multi-channel PowerLab recording system. Skin preparation and electrode placements were in accordance to SENIAM protocol [14].

To obtain a form suitable for usage in ML, recorded data were processed off-line in MATLAB. EMG signals were full-wave rectified, normalized with respect to maximum voluntary contraction (MVC), and filtered using a fourth order Butterworth low pass filter ($f_c=6\text{Hz}$) for envelope extraction. Fig. 1 shows a 10 second time window of both TA and GC muscles activation envelopes in three gait frequencies.

B. Control Strategy

Recurrent Neural Networks (RNNs) are able to symbolize arbitrary nonlinear dynamical mappings, such as those commonly found in nonlinear time series prediction. They are not only of interest for the prediction of time series but also generally for the control of the dynamical systems. “Nonlinear Autoregressive model process with eXogenous input” (NARX), an architectural approach of RNN with embedded memory, is a powerful class of models that has been shown to have favorable qualities for modeling of dynamical systems and forecasting of nonlinear and chaotic time series [13].

Time series prediction can be assimilated to identification of a dynamic process, therefore one major usage of NARX dynamic neural networks is in control

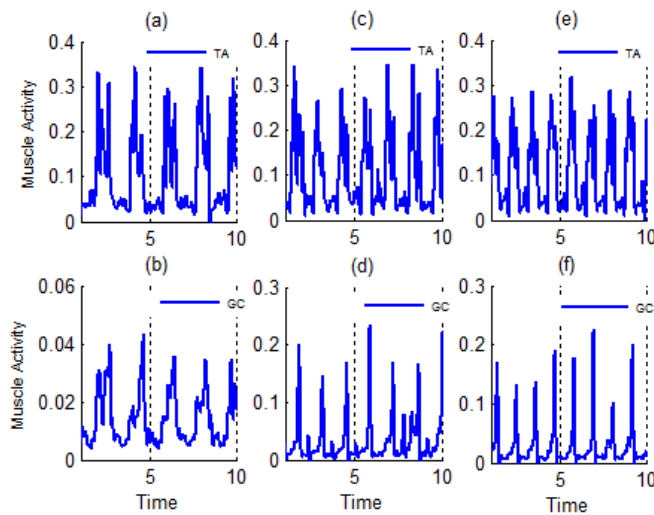


Figure 1. 10 second time window of both TA and GC muscles activation envelopes recorded simultaneously from opposite legs in three gait frequencies. (a), (b) are recorded at 60 step/min, (c), (d) are recorded at 80 step/min and (e), (f) are recorded at 100 step/min. The temporal coordination between the ipsilateral leg TA muscle and the contralateral leg GC muscle activities is quite sensible here.

purposes of dynamical systems. Some outstanding qualities about NARX networks with gradient-descending learning algorithm have been reported: (1) learning is more efficient in NARX networks than in other neural network (the gradient descent is more effective in NARX) and (2) NARX generalizes better and converges much faster than other networks. On the other hand as we are using the NN approach to time series prediction which is non-parametric, there is no necessity to have any information regarding the process that generates the data.

NARX networks include two operational modes; serial-parallel mode (Fig. 2 (a)) and parallel mode (Fig. 2 (b)). The selected training method in this work uses the advantage of availability of the true real output set at the training time. We use the true output instead of the estimated output to train the network which has the feedback connections decoupled (cut). The decoupled network has a common feedforward architecture which can be trained with classical static back-propagation algorithm (serial-parallel mode). During training, the inputs to the feedforward network are just the real/true ones, not estimated ones, and the training process will be more accurate. Training is done using the present and a fixed finite number of past samples of the GC muscle EMG envelop as input. In addition to that a fixed finite number of past samples of TA muscle EMG envelop form the open loop feedback input.

Having been done with the training phase, the NARX network is converted to the parallel mode with closed feedback loop. In the resulting connectionist architecture the network output is fed back to the input to perform the prediction. The predicted desirable TA muscle activity is then used to determine the proper FES intensity in real time.

III. RESULTS

At each gait frequency three successful trials were chosen for the experiments for each subject. Two trials were used for training and one for test which put together a rich training set. To make the training most effective data from different gait frequencies from the same subject were fed to the network in random order. The network was then tested using the unseen data from the same subject. Fig. 3 shows a comparison between the controller output and the target TA muscle activity in 3 gait frequencies. They were compared in terms of correlation coefficient between the predicted TA muscle activity and the desired signal, when time shifted

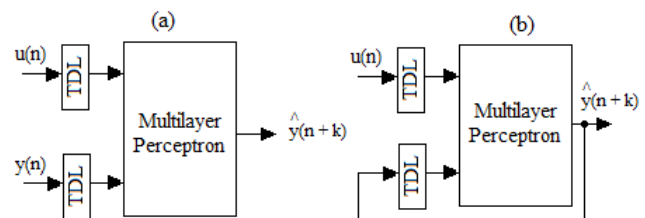


Figure 2. NARX network in serial-parallel mode (a) and parallel mode (b). TDL means Tapped Delay Line

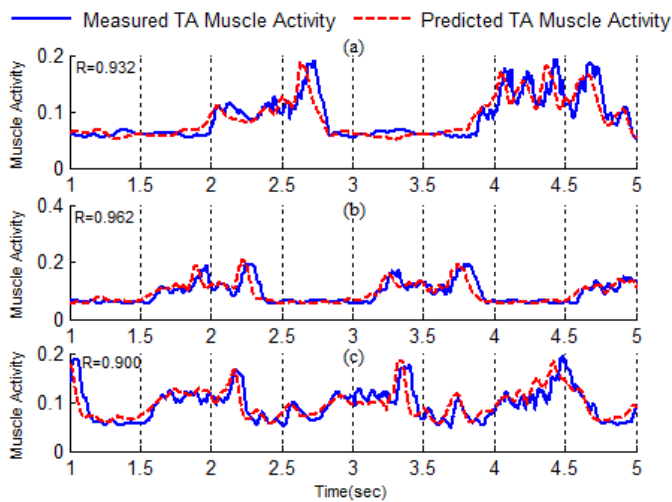


Figure 3. a comparison between the controller output and the target TA muscle activity when trained and tested with data from the same subject in 3 gait frequencies. (a), (b) and (c) correspond to 60, 80 and 100 step/min respectively. Correlation coefficient was calculated between the predicted TA muscle activity and the desired signal, when time shifted 0.04 sec which is the prediction horizon . The prediction was considered desirable if $R \geq 0.9$ was achieved.

0.04 sec which is the prediction horizon (according to FES frequency of 25 Hz). R naturally lies within range of $[-1, 1]$ and the prediction was considered desirable if $R \geq 0.9$ was achieved.

Furthermore to assess the generalization ability of the controller the network was tested when fed with data from a different subject in various gait frequencies (Fig. 4). Again the comparison was done in terms of correlation coefficient. Only here the desirable range for R was considered $R \geq 0.8$. The prediction horizon was set such that the next FES pulse intensity is determined while the

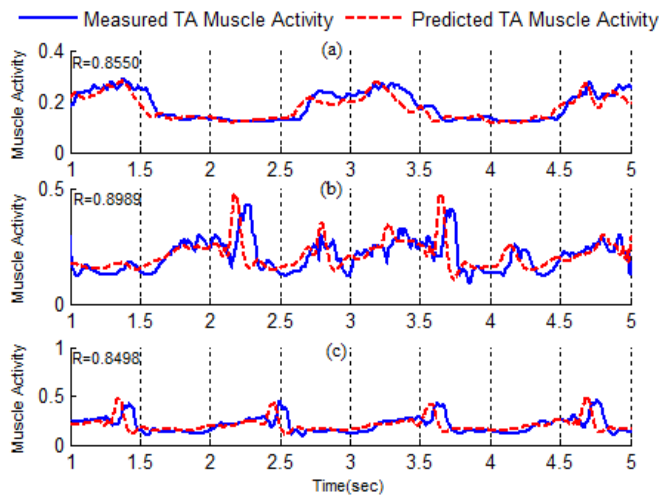


Figure 4. a comparison between the controller output and the target TA muscle activity when trained and tested with data from the different subjects in 3 gait frequencies. (a), (b) and (c) correspond to 60, 80 and 100 step/min respectively. Correlation coefficient was calculated between the predicted TA muscle activity and the desired signal, when time shifted 0.04 sec which is the prediction horizon . The prediction was considered desirable if $R \geq 0.8$ was achieved

previous one is still being applied. In accordance with Parawalk neuromuscular stimulator [9] FES frequency is considered 25 Hz, pulse duration range is 0 to 700 μ sec, and pulse amplitude is considered constant. Using the predicted TA muscle activity, the FES pulse duration is modulated in real time such that the desired muscle activation is achieved (Fig. 5). In practice the maximum FES pulse duration should be set to the maximum intensity that the subject feels comfortable with. Here for the purpose of generality the maximum intensity is normalized to 100%. FES intensity can be altered a maximum of 25 times per second via pulse duration modulation and the FES pulse amplitude is kept constant.

IV. CONCLUSION

With the purpose to be used in unilateral drop foot stimulators, a type of sensory driven machine learning based FES intensity predictive controller is developed. The basic idea in this paper is to retrieve the impaired coordination between the paretic and the non-paretic sides of the body. This goal is achieved by using the close temporal coordination that naturally exists between the ipsilateral leg TA muscle and the contralateral leg GC muscle during gait. This way the movement is constantly being compared with the actual state of the system and accordingly corrected. Results obtained from the controller are quite promising (Fig. 3 and Fig. 4), and show impressive generalization ability (Fig. 4). This can be due to the efficient choice of embedded memory for the NARX network, and rich training sets put together in a way to cover as much walking state variations as possible during gait.

On the other hand using machine learning methods to design the controller turns the FES envelope design into a dynamic modeling problem. This point of view is quite the opposite of desired trajectory tracking methods which offer no flexibility and leave no space for the un-modeled dynamics. Instead this method provides an FES intensity

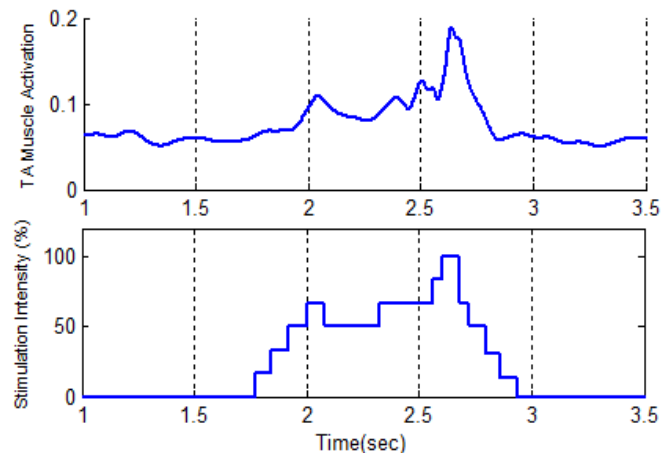


Figure 5. (a) Predicted TA muscle activity. (b) FES envelope designed Using the predicted TA muscle activity via pulse duration modulation. FES intensity is normalized to the maximum intensity as 100%.

envelope which is not pre-programmed, nor a typical ramp up-ramp down. Instead it has the flexibility to adjust itself to walking speed changes and day to day variations. Therefore the FES induced TA muscle activity is potentially more likely to be close to that observed in natural gait, and to retrieve the correct coordination between the two legs during gait.

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