Artificial Neural Network closed loop control technique for FES applications

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Introduction

FES (Functional Electrical Stimulation) is a promising technique to restore motor functions in patients with upper motor neuron lesions, through the artificial activation of the peripheral nervous system.

A crucial point for a large application of this technique is the development of control strategies able to reproduce efficiently as physiologically as possible the muscle activation pattern. The biological systems and the musculo-skeletal system in particular, present characteristics such as non-linearity, time variability (principally muscular fatigue) and redundancy, which make the control problem difficult. For this reason, robust and efficient control strategies are required in order to obtain repeated functional movements.

Existing control strategies for FES are both open and closed loop. Currently an improvement on the traditional feedforward and feedback systems has been achieved by *model based* control strategies, which include a physiological model of the system to be controlled into the control scheme. The model can either be used as a direct model or inverse model according to its position in the whole control scheme. However the various model parameters are very difficult to be determined experimentally, and need specifically designed protocols. Moreover, these procedures need to be repeated frequently because of the change of muscular response, especially in Spinal Cord Injury (SCI) patients. As an alternative to the physiological model, it is possible to consider a non-linear black box model able to approximate an arbitrarily complicated input/output relationship. Such a model can be represented by Artificial Neural Networks (ANNs) [3]. In the literature, a growing number of researchers applied this approach to the control of FES. For example, Sepulveda et al. [2] developed a neural controller for the restoration of gait cyclic movements and Chang et al. [1] designed a neural controller combining an ANN inverse model with a traditional Proportional Integrative derivative (PID), for the knee joint movement. This kind of feedback controller, optimal solution for linear and time-invariant problem, needs continuous identification of its parameters, during the same movements as well as during different sessions. Moreover, delay introduced in the control corrupts performances during repeated sequences of movements.

The aim of this paper is to create a neural strategy able to control the leg flex extension movements produced by FES. ANNs, in analogy with the biological structures, possess good learning and generalization abilities and so they can cope with system complexity and non-linearity. The innovative aspect of this analysis concerns the possibility of using ANN generalization capability both in order to identify a complex inverse model and to deliver a stable adjustment in the feedback control signal.

Methods

The developed system (figure 1) is designed to control knee joint flex-extension movements in accordance with desired trajectories, through the electrical stimulation of quadriceps muscle. The simplicity of the chosen movement has been already adopted in literature [1], [3], [4], allowing more attention to be placed on innovative control techniques. The strategy includes an inverse model of the system to be controlled in the feed forward path (AIM block in fig. 1) and a neural network trained to compensate the fatigue effects in the feedback loop (NIF block in fig. 1).

In order to simulate the lower limb of a subject, a complex model proposed by Riener [5] implemented in Simulink® has been adopted. In this model (Plant in figure 1) five muscle groups spanning the human knee joint are considered: biarticular (biceps femoris long head, semitendineous, semimembranosus) and monoarticular (biceps femoris short head) knee flexor muscles, biarticular and monoarticular knee extensor muscles (rectus femoris and vasti muscles, respectively) and biarticular ankle plantarflexors (lateral and medial gastrocnemius). The model includes the muscular fatigue simulation according to the equation proposed by Riener [5]. Inputs to the plant are the modulated pulse widths (PW) and the pulse frequency, which is maintained fixed at 20 Hz, produced by the stimulator and delivered to each muscle through surface electrodes. The plant output is the computed knee joint position resultant from the stimulation of different muscle groups or alternatively from the only passive oscillations.

One of the crucial points in developing any controller for FES is the reduction of or compensation for muscle fatigue phenomenon. Especially in the case of surface electrodes FES, the artificial stimulation, hardly exploits the correct, i.e. physiological, sequence of fibre recruitment, hence it quickly tires the subject. This effect is enormously amplified in the case of stimulating SCI patients.

The neural network (AIM in fig.1), which simulates the nominal (i.e. without the fatigue effects) inverse model of the system to be controlled, is a multilayered feed forward perceptron. It has ten input neurons, twenty neurons in the hidden layer and one neuron in the output layer. The number of neurons in hidden layer is chosen in order to obtain optimal generalization performance. Net inputs are the actual knee angle and velocity and in the four previous instants. Activation functions are hyperbolic tangent for the hidden layer and sigmoid in the output neuron. The net computes the pulse width of the stimulation impulses normalized between 0 and 1. Training data for this network was obtained from a group of single knee movements, induced by a defined set of control signals (triangular and pseudo-sinusoidal PW added with a white noise, whose variance is proportional at the max PW delivered). The feedback network (NF in fig. 1) is again a multilayered perceptron with ten input neurons, eight neurons in the hidden layer and one in the output layer. The activation function is the hyperbolic tangent for both the hidden and the output layer. The NF training set is built as follows. The NF inputs are the actual knee angle and knee angular error samples and their four previous instants. The NF output is built by an auxiliary block. The actual output of the plant ($q_{obt}, \dot{q}_{obt}$, fig. 1) are inputs to a copy of the AIM inverse model. The calculated output, (pw_{fat}), represents the pulse width which would have considered the fatigue effect. Indeed, in the case of no fatigue, q_{obt} would be equal to q_{des}, except for model error, thus pw_{fat} is the same as pw_{ff}. In the case of fatigue, the difference between the pw_{ff} and pw_{fat} is used as training output of NF. This way, given an error in angular trajectories (Δq), NIF is trained to produce the extra pulse width (Δpw) required to compensate for fatigue.

Results

In order to evaluate the stability and the fatigue compensation delivered by the proposed control strategy, a repeated knee flex extension, in accordance with an artificial sinusoidal angular trajectory, has been simulated. In the upper panel of figure 2, one trial of 27 seconds, which comprises 8 working cycles, is reported. This panel allows the comparison between the desired trajectories (solid line) and those obtained by the AIM (dotted line), used as feedforward controller, and by the AIM & NF controller (dashed line). The lower panel shows

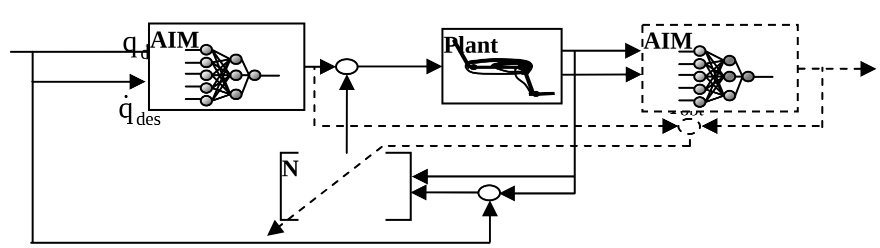

Figure 1: *The control scheme where AI M is the ANN Inverse Model and NF is the Neuro Feedback block. The dashed lines show the Neuro Feedback training method.*

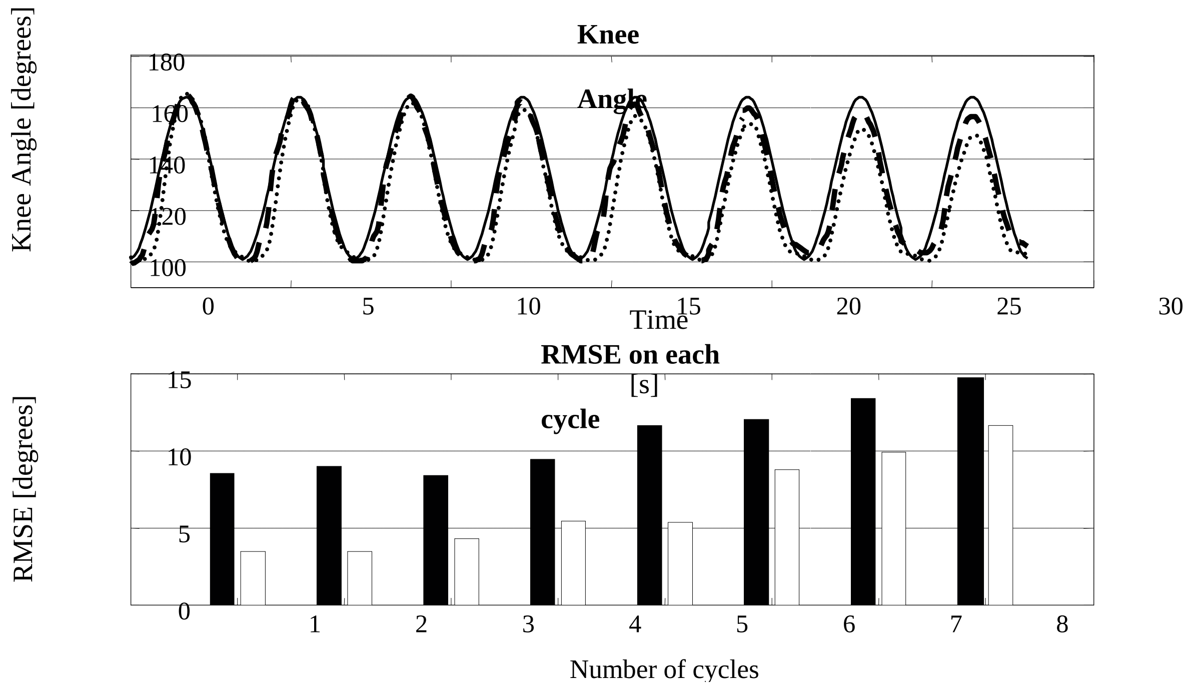

Figure 2: *Angular trajectories obtained by the tested control strategies (upper panel). Quantitative analysis in terms of RMSE (lower panel).*

the RMSE, between the desired and the obtained angular trajectories, calculated on each cycle. The black bars are related to the feedforward AIM controller, while the white ones to the AIM & NF control strategy.

Discussion

The good results point out the importance of the neural control strategy proposed. The potentiality of the feedback neural network is that it behaves as a sort of predictor: it is pre-trained in order to produce the appropriate pulse width correction corresponding with the current knee angle. This way the NeuroFeedback (NF), due to its generalization ability, can compensate at least partially for fatigue.

Its effects were principally identified in a reduction of the maximal muscular force, and in a growing delay in its response. The controller described here compensates well for the delay during the repeated movement, whereas the increase in the maximum pulse delivered is able to increase the muscular force necessary for the desired extension only in the first four cycles. As shown in the histogram reported in figure 2, the RMSE of the new control strategy naturally increases during the simulation task, but its maximum value remains inferior to 10 degrees until the seventh cycle, although the muscular fatigue does not allow the limb to completely track the desired trajectory, in particular in accordance to the maximum extension.

The developed control strategy can compensate for the fatigue time varying phenomenon through a non-adaptive system which exploits in a predictive way, the generalization ability of the neural network placed in the feedback loop. This improvement in performance is coupled with the very important simplification of net training versus PID parameters identification in terms of experimental protocols.

The results suggest a further development of the work. It would be possible to make the NeuroFeedback adaptive, i.e. the neural network can adjust its weights through an adaptive training algorithm in real time. In such a way the control action would be more sensitive to the time varying characteristics of the system analysed.

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