A neuro-adaptive control system was designed to control the knee joint flexo-extension movements in accordance with desired trajectories, through electrical stimulation of quadriceps muscles. This control system consist in an Artificial Neural Network (ANN) used as inverse model and an adaptive ANN trained on PID output which performs a feedback adjustment of control signal. The neuro-adaptive control strategy was tested in several conditions, and its performances resulted better than those of a PID controller alone.

Introduction

FES (Functional Electrical Stimulation) is a promising technique to restore some motor functions in patients with upper motor neuron lesions, through the artificial activation of the peripheral nervous system. However, there are many problems in stimulating, through superficial electrodes, muscles of paralyzed limb, such as rapid fatigue, time varying properties, non-linearity of passive and active muscle characteristics.

Many control strategies have been reported in literature: feed forward, feedback and composition of both, have been examined [2], [5], [6], [7].

An artificial neural network is a valid alternative for the control of non-linear systems because it can approximate an arbitrarily complicated input/output relationship. Not many authors applied this technique to FES control. For example, Chang et al. [4] designed an inverse model neural controller for the movement of the knee joint, and Sepulveda et al. [10] developed a neural controller for the restoration of cyclic movements, like gait. As neural networks for FES control are still in an early stage, further researches and experimental validation on animal and human have the potentiality to provide neural controllers usable in clinical applications.

The aim of this work is to design, starting from a control strategy based on combination of an inverse model and a PID controller [1], an adaptive neural controller, which combines feed-forward and feed-back neural control.

Methods

A. Set up

The performances of the control system have been tested in the control of knee angle during swinging leg movements of seated subject by means of quadriceps stimulation. This specific experimental condition was often adopted [1], [3], [4], [9], because it allows to perform several experimental sessions, in a safety and relatively simple condition. Moreover, the quadriceps muscle plays a fundamental role in the main motor activities (i.e. standing up, walking, standing posture). In figure 1 the experimental set up is shown.

B. Simulation model

In order to simulate lower limb of a paraplegic subject, we adopted a dynamical model previously developed by Rienert et al. [8], [9]. In this model 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). Inputs to the model are the modulated pulse widths (controlled variable) and pulse frequencies (fixed) produced by stimulator. Maximum pulse width was fixed at 500 µs. Model output is the knee angular trajectory as resulting from a given set of stimulation patterns delivered to the different muscle groups.
C. Control strategy

The block diagram of implemented control strategy is illustrated in fig. 2. This control system consists of an ANN, off-line trained to obtain the inverse dynamics of the implant, used as a long-term memory, and another ANN, adapted on-line to follow the adjustments of a PID controller, which works as a short-term memory. The first neural network, once successfully trained, would be used directly for inverse feed forward control.

However, time variant properties of the model related with muscle’s fatigue, and non-perfectly representation of the inverse model dynamics by an ANN, suggests us to use a feedback control. Our strategy performs it using an adaptive neural network that learns from a PID controller. PID Parameters were previously identified using Ziegler and Nichols method.

D. Neural networks topology

The neural network that simulate inverse model is a multilayered feed forward perceptron. It has seven input neurons, fifteen neurons in hidden layer and one neuron in the output layer. Number of neurons in hidden layer was chosen in order to obtain optimal generalization performance. Inputs are the pulse frequency, the actual and two time delayed samples of desired angular trajectory of the knee joint and her derivative (angular velocity). The output was the normalized between 0-1 pulse width. Activation functions are hyperbolic tangent for the hidden layer and sigmoid in the output neuron. Topology of this ANN is shown in figure 3. The adaptive network is also a multilayered perceptron with five input neurons, eight neurons in hidden layer and one in the output layer. Activation functions are hyperbolic tangent for the hidden layer and hyperbolic tangent in the output neuron.

E. Training of neural inverse model

Identification procedure for the neural inverse model was performed using Nguyen-Widrow initialization method and Levenberg Marquardt training algorithm. Examples used to train ANN were collected stimulating the implant model with several triangular and pseudo-sinusoidal pulse widths, sampled at 20 Hz, with a duration variable between 2 and 10 seconds and a maximum value variable between 200 µs and 500 µs.

Results

A. Inverse model mapping

In order to find the best ANN architecture for mapping inverse model, we train several networks with different number of neurons in the hidden layer. In figure 4 were showed numerical results in term of RMSE (Root Mean Square Error) for training data set and for a test set, composed by couple of input/output never seen by networks.

Net with 18 neurons in hidden layer achieves best performance in terms of fitting training data and at the same time generalizing on test ones.

B. Controller Performance

In order to test the neural controller we compare its performances with two other different control schemes: one composed by the inverse model (feed forward) alone and the other with the addition of a PID controller on the feedback line.

Furthermore in order to simulate presence of an external disturbance, we constrained controllers to follow a normal desired angular trajectory, the plant
having an external 1 kg weight positioned near the ankle. In this way we changed the dynamics of the plant and furthermore we could test our systems, when a significant effect of muscles fatigue was present.

In figure 5 is shown the same example of an angular trajectory, chosen from test data set, for free and weighted swinging shank, controlled by our adaptive controller.

![Fig. 5: Repeated sequence of free and weighted swinging shank controlled by neuro-adaptive controller.](image)

RMSE for test trajectories has been computed for both conditions and the results are summarized in figure 6.

![Fig. 6: RMSE for each swing cycle for the three controllers in free and weighted swinging repeated sequences.](image)

Performance of the neural adaptive controller is better than those of other control schemes in both conditions.

The results obtained indicate that a neuro-adaptive feedback is able to map error dynamics and to elaborate an adjustment to the control signal better than a simple PID. The capability to modify on line the control signal learned by the inverse model, allows the system to follow in a good manner, changes in the knee joint dynamics, induced by muscles fatigue.

**Discussion**

In this study a neuro-adaptive control system for the knee joint position during quadriceps stimulation has been developed.

Its performances were tested in free and weighted swinging, and compared with two other kinds of neural controllers. adaptive approach produced better results in both conditions. Furthermore, it was confirmed the need of a feedback line, because the capability to generalize of a feed-forward neural inverse model does not allow to follow changes due to fatigue or to the presence of external disturbance like an additional weight. The adaptive neural network, trained by a PID controller, showed to perform stable adjustments better than the PID alone.

The promising results obtained in computer simulations and presented in this paper open the possibility to perform experiments on paralyzed subjects, that could confirm the applicability of our approach.

**References**


