Neuro-Fuzzy Extraction of Angular Information from Muscle Afferents for Ankle Control during Standing in Paraplegic Subjects: An Animal Model

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***Abstract*—This paper is part of a project whose aim is the implementation of closed-loop control of ankle angular position during functional electrical stimulation (FES) assisted standing in paraplegic subjects using natural sensory information. In this paper, a neural fuzzy (NF) model is implemented to extract angular position information from the electroneurographic signals recorded from muscle afferents using cuff electrodes in an animal model. The NF model, named dynamic nonsingleton fuzzy logic system is a Mamdani-like fuzzy system, implemented in the framework of recurrent neural networks. The fuzzification procedure implemented was the nonsingleton technique which has been shown in previous works to be able to take into account the uncertainty in the data. The proposed algorithm was tested in different situations and was able to predict reasonably well the ankle angular trajectories especially for small excursions (as during standing) and when the stimulation sites are far from the registration sites. This suggests it may be possible to use activity from muscle afferents recorded with cuff electrodes for FES closed-loop control of ankle position during quite standing.**

***Index Terms*—ENG signal processing, functional electrical stimulation (FES), muscle afferents, natural sensors, neural fuzzy systems.**

I. Introduction

FUNCTIONAL electrical stimulation (FES) has proven to be a valuable technique to restore motor function in spinal cord injured persons due to the remaining excitability of the peripheral nerves distal to the lesion level. Unfortunately, the highly nonlinear and time-variant characteristics of the effector system (the neuromuscular system) have made the use of open-loop control techniques inadequate in terms of stimulation efficacy and acceptability for the final users. This problem can be solved by using closed-loop control techniques, but this requires reliable sensory information about the ongoing motor task. Artificial external sensors have been widely used as a source of information during the stimulation of the neuromuscular system but they present problems such as the need for frequent calibration, subject encumbrance, and cosmetic unacceptability due to sensor dimensions and appearance. Thus, natural sensors are receiving growing attention as an alternative means to provide the necessary feedback information. For example, cutaneous afferents have been used for the control of grasp force in quadriplegics [1] and for the correction of footdrop in hemiplegics [2], while muscle afferents have been used for ankle angular control in animal models [3], and for bladder control [4]. In the above cases, the efficacy of the approach was strictly related to the possibility of extracting the relevant information from the signals recorded from the afferent nerves. This is the most important requirement for their use and many efforts are currently being made to implement better processing algorithms for the different applications [5]–[7]. To this end, emerging techniques such as artificial neural networks (ANNs) and fuzzy systems (FSs) can be valuable tools for natural sensory signal interpretation.

ANNs and FSs are two processing techniques whose efficacy has been proven in many applications [8], [9]. Their most important characteristic is the numerical-model-free structure which is important when the system under study is complex. Moreover, in the last few years, many attempts have been made to integrate the advantages of these two complementary algorithms (namely, the learning and generalization capability of the ANNs; and the ability of the FSs to incorporate human knowledge) to obtain hybrid systems often named neural fuzzy (NF) networks [10].

A. Goals

This paper is part of a project whose aim is to implement closed-loop control of ankle angular position during standing in paraplegic subjects using muscle afferent information [11]–[14] (see Fig. 1 for a schematic of the overall system).

Different aspects are to be addressed; namely, 1) the need for better characterization of the behavior of natural sensors during posture control; 2) extraction of the kinematic and dynamic information from the natural sensors; and 3) the implementation of a real-time control system. This paper presents the first attempt to solve problem 2) using the above mentioned properties of NF systems. Here, we illustrate the application of a NF network to extract angular information from muscle afferent electroneurographic (ENG) signals recorded using implanted whole nerve cuff electrodes.

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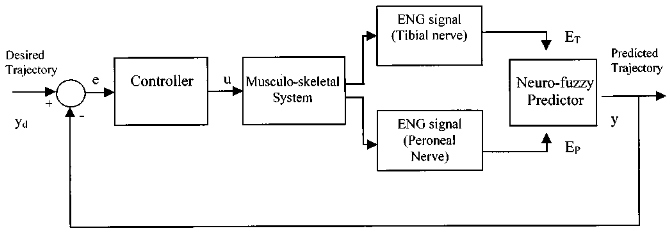


Fig. 1. Diagram of the implementing system for standing control using natural sensory information. The information extracted from the ENG signals recorded from muscle afferents will be used to modify the stimulation parameters in a closed-loop paradigm.

The system implemented for this purpose was a recurrent ANN whose structure was used to implement a set of fuzzy rules [15], [16]. Moreover, this network used a nonstandard algorithm for the fuzzification (the transformation of real data into fuzzy data) of the input signals, named "nonsingleton" fuzzifier, which is very useful when the processing data are noisy [15].

II. Methods

A. Experimental Setup

1) Animal Preparation: Acute experiments were performed using four female rabbits[1] (identified by progressive numbers). The animals were initially relaxed using an intramuscular injection of 2.0-mg/kg Midazolam (Dormicum) and then anesthetized using 0.095-ml/kg Fetanyl and 0.30-mg/kg Fluranison (combined in Hypnom). Supplemental intramuscular injections were administered every 20 min to maintain the anesthesia during the experiments. Two tripolar, whole nerve cuff electrodes were implanted: one around the tibial nerve and the other around the peroneal nerve (which are major branches of the sciatic nerve) in the rabbit's left leg. The cuff lengths were approximately 20 mm and the inner diameters were 2 and 1.8 mm for the tibial and peroneal nerves, respectively. The cuff electrodes were produced according to the procedure described in [17], except that a straight cut was used as a closing method. The sural nerve was cut immediately distal to the peroneal cuff to minimize recording unwanted cutaneous afferent activity during the experiments. In the case of trajectories #2 and #4 (see Table I for a description of the different trajectories), two wires were inserted in the lateral head of the lateral gastrocnemius (LG) muscle for bipolar electrical stimulation (0.1 mm in diameter, approximately 3-mm deinsulated; separation between the electrodes approximately 3 mm). In Fig. 2, a schematic of the implantation sites for the cuff electrodes is presented (similar rabbit preparations have been used in other experiments, see [12]–[14]).

2) Apparatus: In all the experiments, the equipment used consisted of a computer controlled servomotor to passively rotate the rabbit's ankle in the sagittal plane (see [12]).

A support and fixation device equipped with four strain gauges was used as torque transducer (sensitivity 10 Nm/V). An optics-based rotation transducer was used to record the position of the ankle during the movements (sensitivity $= 10°$/V). The

[1]The Danish Committee for Ethical use of Animals in Research approved all procedures used in the experiments.

TABLE I
SUMMARY OF THE DIFFERENT TRAJECTORIES USED DURING THE SIMULATIONS. FOR EACH TRAJECTORY THE INITIAL POSITION OF THE RABBIT ANKLE, THE EXCURSION (PEAK TO PEAK), AND THE PRESENCE (OR ABSENCE) OF THE LG MUSCLE STIMULATION ARE GIVEN

Traj	Profile	Initial Pos	Excursion	LG Stimul
♯1	Standing (Normal Subject)	70°	3°	No
♯2	Standing (Normal Subject)	70°	3°	Yes
♯3	Standing (Paraplegic Subject)	70°	20°	No
♯4	Standing (Paraplegic Subject)	70°	20°	Yes
♯5	Ramp and Hold Profile (♯1)	80°	5°	No
♯6	Ramp and Hold Profile (♯2)	100°	30°	No
♯7	Sinusoid	80°	5°	No

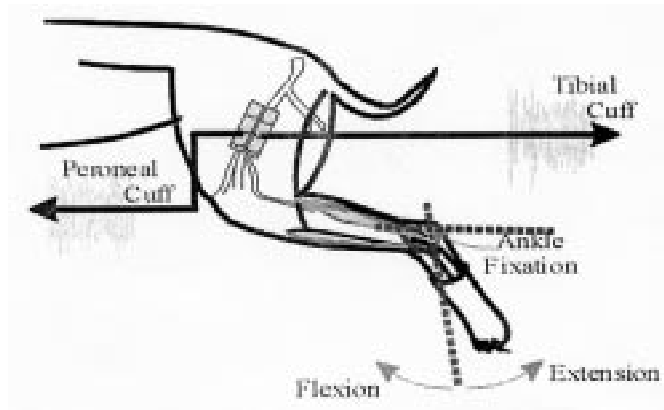


Fig. 2. Schematic illustration of the implantation sites. The cuff electrodes were used to record the ENG signals from the tibial and peroneal nerve while the ankle joint of the Rabbits was rotated by using a servo-motor.

position and torque signals were sampled at 500 Hz. The rabbit was placed on its right side, and the left foot was mounted in a cradle. The knee and ankle joints were also fixated during the experiment.

An detailed description of the experimental apparatus can be found in [14]. The whole nerve cuff recordings were pre-amplified 200 000 times, bandpass filtered using a second-order Butterworth analog filter (500 Hz–5 kHz), and sampled at $f_s = 10$ kHz (12-bit National Instruments analog-to-digital board) [2].

3) Movement Trials and Stimulation Protocol: The rabbit's ankle joint was rotated passively by the servomotor using seven different trajectory profiles, while the ENG signals from the tibial and peroneal nerves were recorded. In Table I, the different trajectories are summarized.

Four of the seven position profiles were used in the experiments with Rabbits #1 and #2 and mimicking movement of the ankle joint of both a normal and a paraplegic subject during standing as follows. A male subject with no known neurological disorders participated in this study. He was instructed to keep his knees and hips extended and to primarily use the calf muscles to initiate and maintain body sway about the ankle joint while the movement was recorded. In addition, postural sway about the ankle joint was recorded from a male T4/T5 paraplegic subject, but in this case, standing was initiated and maintained with open-loop electrical stimulation of the quadriceps muscles. The paraplegic subject stood quietly until fatigue of the quadriceps occurred. The fatigue caused increased knee and ankle flexion.

When the subject could no longer maintain standing, he sat down. In all the experiments with the normal and paraplegic subjects, the ankle angle was recorded using an electrogoniometer XM110 (Biometrics ltd, Gwent, U.K.).

When the rabbit's ankle joint was rotated, flexion of the joint simulated forward sway of the human subject, and extension simulated backward sway. A description of the protocol for the human standing and the rabbit model is given in [12]. In trajectories #1 and #3, the rabbit's ankle joint was rotated using the angular position profiles recorded during standing of the normal and paraplegic subjects, respectively. In trajectories #2 and #4, the same profile of trajectories #1 and #3 was imposed while continuously stimulating the LG muscle. The stimulation frequency was chosen to be 80 Hz, at which fused contraction was obtained for both muscles. The duration of the rectangular stimulus pulses was 100 μs. The amplitude was adjusted for each rabbit to obtain recruitment levels equal to 25% of the maximal force.

Two ramp-and-hold profiles constituted for the fifth and sixth angular trajectories and were used during the experiments with Rabbits #3 and #4. For the fifth trajectory, the ankle was moved from an initial position of 80° with an excursion of 5° and a velocity of 10°/s. For the sixth trajectory, the ankle was moved from an initial position of 100° with an excursion of 30° and a velocity of 20°/s. The trajectory was chosen to assess the robustness of the NF model when the excursion of the ankle is large (e.g., when the ground reaction force vector in a standing human goes behind the knee, causing it to bend). The last trajectory used was a sinusoid causing the ankle joint to be rotated from an initial position of 100° with a peak-to-peak excursion of 5°. The frequency of the sinusoidal wave was 0.5 Hz. This trajectory was used during the experiments with Rabbits #3 and #4. Three trials were recorded for each movement.

4) ENG Data Processing: All ENG recordings were rectified and bin integrated during a 9-ms window regardless of whether electrical stimulation was applied or not. When stimulation was applied, the window duration allowed periods of artifact free ENG to be obtained in between the stimulus artifacts that occurred every 12.5 ms [18]. In this way, artifacts did not interfere with the recordings. The position and torque data were low-pass filtered at $f_s = 100$ Hz (twelfth-order digital Butterworth filter) [12]. All data were normalized as follows:

$$y_n = \frac{y - \min(y)}{\max(y) - \min(y)} * 0.8 \tag{1}$$

where y_n is the normalized variable, and y is the original data point.

5) Afferent Nerve Response Characterization: The ENG signals recorded during different passive movements have been used to characterize the response of the muscle afferents in different conditions. The results are extensively described in [14] and can be summarized as follows.

- While passively rotating the ankle at a velocity of 30°/s through a 60° excursion [from a fully extended (130°) to a fully flexed ankle (70°)], the tibial and peroneal nerves showed a reciprocal behavior (see Fig. 3). The former was active during the flexion ramp movement while the latter was active during the extension ramp.

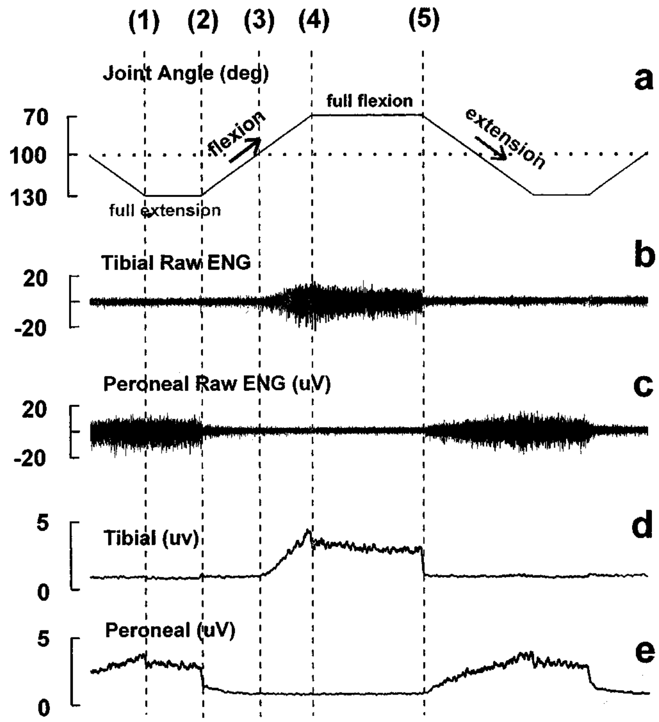


Fig. 3. The ENG signals recorded from the tibial and peroneal nerves during passive trapezoidal ankle movements. Trace (a) indicates the profile imposed to the rabbit ankle. Traces (b) and (c) show the raw ENG signals recorded from the two nerves. Traces (d) and (e) show the rectified and integrated activities of the two nerves. (Reproduced with permission from R. Riso *et al.*[14].)

- Reciprocal activity was confirmed also for other passive movements.
- The afferent origin of the ENG signals recorded during the different ankle movements was demonstrated when the recorded nerve was transected distal to the recording cuff (see Fig. 4).

B. *The Inverse Model Problem*

The problem in question here is the well-known "inverse model problem." Here, we had an unknown variable y (the ankle joint position), and two derived and known variables x_1, x_2 (the ENG signals recorded from the muscle afferents) whose relation with y can be expressed as follows:

$$[x_1(t),\, x_2(t)] = f(y(t)) \tag{2}$$

where in our case the function f represents the coding of position information implemented by the peripheral nervous system.

A NF model was implemented to solve the inverse model problem, i.e., to find an approximation to the function f^{-1} to extract the unknown variable

$$y(t) = f^{-1}(x_1(t),\, x_2(t)). \tag{3}$$

NF models have been shown to be able to adequately approximate dynamic systems [19], [20]. They can be very useful when traditional quantitative techniques of systems modeling have significant limitations. In most cases, in fact, it is quite difficult to adequately describe the behavior of a nonlinear system by mathematical models, especially when the structure of the system is unknown. Even if one knows

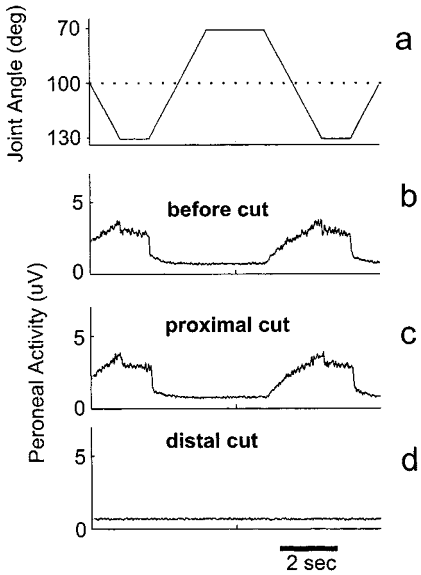


Fig. 4. Experiments to verify the afferent origin of the ENG signals recorded. Trace (a) indicates the profile imposed to the rabbit ankle. Trace (b) indicates the peroneal nerve recorded activity before any transection. Trace (c) indicates the peroneal nerve recorded activity after a transection proximal to the cuff. Trace (d) indicates the peroneal nerve recorded activity after a transection distal to the cuff. (Reproduced with permission from R. Riso *et al.*[14].)

the structure, numerical model representations usually become irrelevant and computationally inefficient as the complexity adds making impossible its use in real-time applications. Moreover, some soft-computing models (beside being faster) have been shown to work much better than descriptive models of the neuromuscular system [21], [22]. Finally, the NF models can incorporate the *a priori* knowledge (see Section II-C) in the fuzzy rules (as the FSs).

All these considerations make the use of a NF recurrent model very appealing with respect to the approach previously proposed (i.e., the use of a look-up table [3]) which is not able to deal with the complexity of the system we want to model, especially the system's time-variance.

C. The Neural-Fuzzy Model

A FS is generally composed of four different subsystems: the fuzzifier; the fuzzy rule base; the inference engine; and the defuzzifier as described in Fig. 5 [10].

1) Fuzzifier: In order to use fuzzy logic properties, the real data $\mathbf{x} = (x_1, \ldots, x_m)$ have to be transformed into a set of new "subjective" input values characterized by a membership function. The proposed NF model uses a "nonsingleton" procedure. In this case, the input value x_i is transformed into a fuzzy membership function $\mu_{A_x}(x_i')$ which is equal to one for $x_i' = x_i$ and decreases from one to zero, as x_i' moves away from x_i. This means that x_i is the most likely value to be correct, but because of the presence of noise in the data, the neighboring points are also likely to be the correct ones even if to a lesser degree. This fuzzification procedure has been shown to be able to take into account the uncertainty in the data [15]. Gaussian-like membership functions were implemented for the fuzzification. This choice allowed us to use simple equations to implement the NF model, as described in [16].

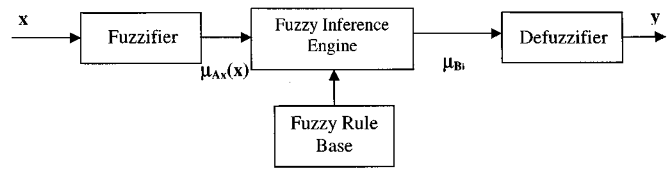


Fig. 5. Diagram of a FS. A FS is composed by four subsystems: 1) the fuzzifier which tranforms real data into subjective fuzzy values; the fuzzy rule base which represents the core of the FS incorporating the knowledge used (in this application) to extract the angular information; the inference engine which is used to infer the fuzzy rules with respect to the fuzzified data; and the defuzzifier which transforms fuzzy variables into real data.

2) Fuzzy Rule Base: FSs are composed of several IF *antecedent*—THEN *consequent* rules. In particular, the implemented NF model is a Mamdani-like FS, i.e., both the antecedent and the consequent parts of the IF–THEN rules are expressed using fuzzy membership functions [23]. The structure of the IF–THEN rules in the case of multiple-input–single-output is the following (the generalization to the multioutput case is straightforward):

$$R^i: \quad \text{IF } x_1 \text{ is } A_1^i \text{ and } x_2 \text{ is } A_2^i, \ldots, \text{ and } x_m \text{ is } A_m^i \text{ THEN } y^i \text{ is } B^i \tag{4}$$

where A_j^i and B^i are the jth input membership functions ($j = 1, \ldots, m$) and the output membership function in the ith rule ($i = 1, \ldots, N$), respectively.

3) Inference Engine: The engine is based on a compositional rule of inference [10]. In this case the membership function of the *consequent* for a particular *antecedent* can be obtained as follows:

$$\mu_{B^i} = \mu_{A_x} \circ \mu_{R^i} = \sup_x (\mu_{A_x}, \mu_{R^i}) \tag{5}$$

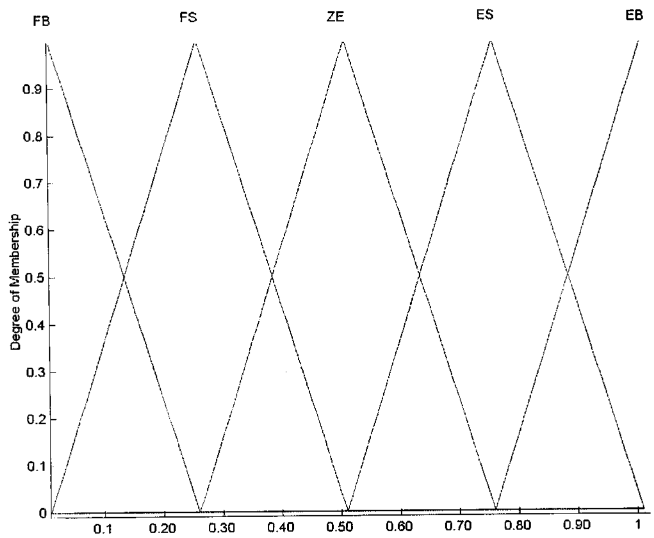
where μ_{R^i} is the membership function of the ith rule obtained, in our case, with the product operation, and $\circ$ is the composition operator. It is worth noting that by using the "nonsingleton" fuzzifier, the membership functions are not evaluated in x_i but in a new point $x_{i,\sup}$, as described in [15] (for "singleton" fuzzification $x_{i,\sup} = x_i$).

4) Defuzzifier: The last component of a FS is the defuzzifier. Its aim is to transform the fuzzy output obtained after the inference of the fuzzy rules into a crisp output which can be used in the "real" world. In the proposed NF systems, we implemented the modified height defuzzifier [24] as follows:

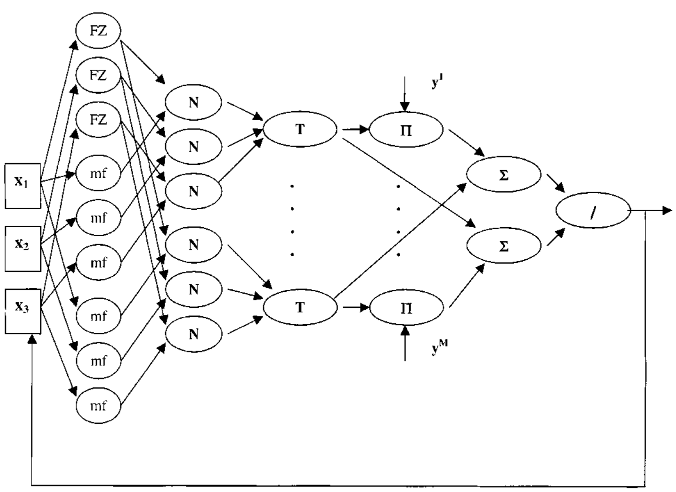
$$y = \frac{\sum_{i=1}^{N} \overline{y}^i \mu_{B^i} / (\delta^i)^2}{\sum_{i=1}^{N} \mu_{B^i} / (\delta^i)^2} \tag{6}$$

where

- y output of the NF network;
- $\overline{y}^i$ point where $\mu_{B^i}(\overline{y}^i)$ reaches the maximum value [24];
- δ^i measure of the uncertainty that $\overline{y}^i$ is close to the point where $\mu_{B^i} = 1$ (it is equal to the standard deviation for Gaussian-like membership functions);
- μ_{B^i} membership function of the ith rule after its inference.



(a)



(b)

Fig. 6. (a) Scheme of the membership functions implemented for the inputs of the NF model. (b) The architecture of the NF model implemented as a recurrent network. The "FZ" blocks represent the "nonsingleton" fuzzification procedures, the "mf" blocks represent the membership functions of the different rules for the different variables, the "N" blocks represents the operation to calculate $x_{i,\sup}$ (for i = 1, 2, 3), and the "T" blocks represent the application of the fuzzy operators for the inference of the rules.

5) The NF Model Proposed in this Paper: The structure of the NF system described above has been implemented in the framework of a recurrent neural network as illustrated in Fig. 6.

The inputs to the NF network were the two rectified and bin-integrated (RBI) ENG signals (recorded from the muscle afferents) plus the delayed output of the network (the predicted trajectory) as feedback input, frame by frame [i.e., $x_1(T)$ and $x_2(T)$ are the RBI-ENG signals at time T, while $x_3(T) = y(T-1)$]. The fuzzy rules (before the training procedure described in the next section) were set by using the knowledge about the relationship between the ENG signals extracted from the tibial and peroneal nerves and the ankle angular trajectory. In fact, we know that the tibial nerve activity is related to the dorsiflection of the ankle [14]. Therefore, for the tibial ENG signal, if the membership function with the maximum degree is "greater" in a fuzzy way (e.g., PB is greater than ZE) than the membership function with the maximum degree of the bin-integrated peroneal ENG signal, we can suppose that the ankle angular position is becoming more dorsiflexed, and we can write a fuzzy rule according to this information.

TABLE II

RMS OF THE PREDICTION ERROR (E), MAXIMUM PREDICTION ERROR $e_{\max}$, AND CORRELATION COEFFICIENT ρ BETWEEN THE PREDICTED AND THE ACTUAL ANKLE PROFILE FOR THE TEST SETS OF RABBITS #1–#4

Rabbit	Trajectory	e_{max}	ρ	E
#1	#1 Standing (Normal)	0.72°	0.8892	0.0021
	#2 Standing (Normal)	0.60°	0.8019	0.0028
	#3 Standing (Paraplegic)	7.80°	0.9809	0.0007
	#4 Standing (Paraplegic)	8.00°	0.9435	0.0080
#2	#1 Standing (Normal)	1.00°	0.8542	0.0024
	#2 Standing (Normal)	2.20°	0.7128	0.0046
	#3 Standing (Paraplegic)	5.50°	0.9894	0.0007
	#4 Standing (Paraplegic)	5.70°	0.9839	0.0080
#3	#5 Ramp and Hold (#1)	0.98°	0.9736	0.0013
	#6 Ramp and Hold (#2)	7.50°	0.9506	0.0040
	#7 Sinusoid	1.00°	0.9870	0.0018
#4	#5 Ramp and Hold (#1)	1.00°	0.9954	0.0014
	#6 Ramp and Hold (#2)	3.75°	0.9921	0.0020
	#7 Sinusoid	1.65°	0.9224	0.0030

6) Training Procedure: The training procedure was implemented using the description in [16]. It was stopped when the maximum prediction error was under 0.75°. In this way we could be sure that the prediction error will always be less than 1°, as suggested in [25]. Moreover, this choice allowed us to avoid the overfitting problems (i.e., the network is not able to generalize well during the test phase) which can occur if a stricter training goal is adopted. In any case the simulation was also stopped if the improvement in the maximum prediction error was less than 0.0001. The "leave one out" method is used for validation [26]: one trajectory is randomly excluded and the NF model is trained on the remaining ankle profiles; then, the selected sample is used to test the NF model prediction capability (henceforth named as "test set").

7) Performance Evaluation Criteria: To evaluate the prediction ability of the NF model, the root mean square (rms) of the prediction error e was calculated

$$E = \frac{1}{N}\sqrt{\sum_{n=1}^{N} e(n)^2}. \tag{7}$$

The correlation coefficient ρ between the desired and the actual trajectories, and the maximum prediction error $e_{\max}$ were also used for performance analysis.

III. RESULTS

The prediction ability of the NF model was tested by using the trajectories and the ENG signals as described in the previous section. Prediction results for the test sets of the different Rabbits are summarized in Table II.

Simulated Standing Trajectories—Normal Subject: In both Rabbit #1 and #2, when no stimulation of the LG muscle was applied, the NF model was able to predict the ankle angular

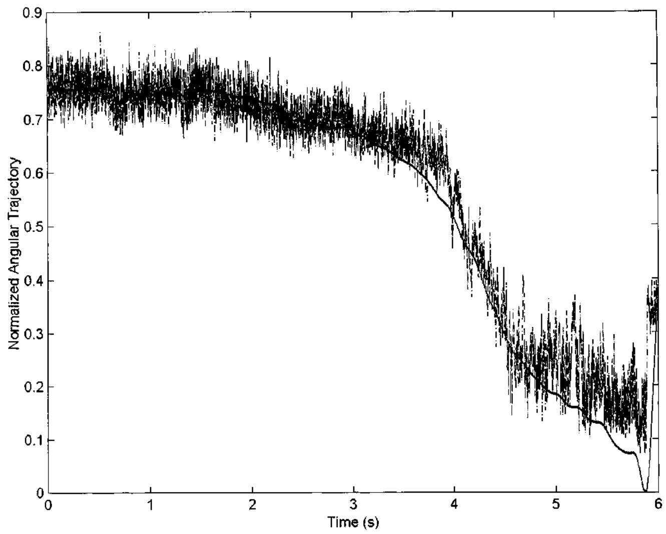


Fig. 7. The predicted ankle profile (dash-dotted line) and the actual one (solid line) for the test set of trajectory #3 (Rabbit #1).

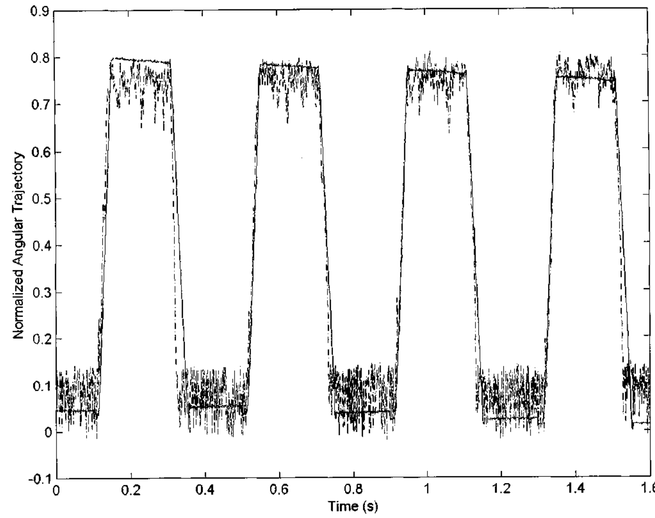


Fig. 8. The predicted ankle profile (dash-dotted line) and the actual one (solid line) for the test set of trajectory #5 (Rabbit #3).

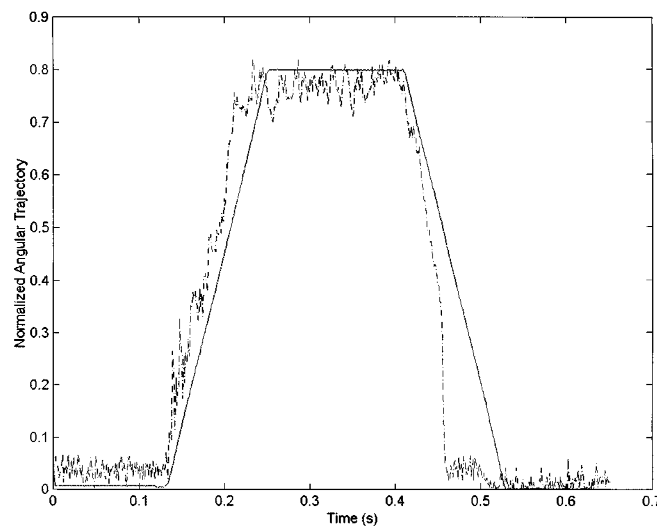


Fig. 9. The predicted ankle profile (dash-dotted line) and the actual one (solid line) for the test set of trajectory #6 (Rabbit #3).

trajectory of the simulated standing profiles recorded during a normal subject sway in accordance with the criterion suggested in [25] (maximum prediction error below 1°) as indicated by the value of the different parameters.

When the LG muscle was stimulated, the performance levels for the NF model were still good for Rabbit #1 while a dramatic deterioration of the performance occurred for Rabbit #2. This was probably caused by some artifacts generated in the recorded ENG signal during the stimulation. In fact, even if we tried to minimize all the possible sources of noise (e.g., by cutting the cutaneous information), we cannot avoid to have some artifacts due to the LG muscle stimulation.

Simulated Standing Trajectories—Paraplegic Subject: For the simulated standing trajectories recorded during standing of a paraplegic subject, the NF model prediction was not satisfactory in terms of maximum error (because it is not below the value suggested in [25]) but was quite good in terms of rms of the prediction error and correlation coefficient for both Rabbits #1 and #2 (see Fig. 7). This shows the robustness of the NF model even in this case, which should not be a common situation since during FES-based closed-loop control of standing we want to stabilize the ankle angular profile about the starting position.

"Ramp-and-Hold" Trajectories: For trajectories #5 and #6 ("Ramp-and-Hold" trajectories), the NF model was able to predict the trajectories quite well as suggested by the values of $e_{\max}$, ρ, and E. From Figs. 8 and 9, it is evident that most of the error is concentrated in the constant part of the profile. This is probably due to the choice of only one input parameter (the rectified and bin-integrated ENG signal) which is not able to give enough information to the NF model related to this part of the trajectory. Additional parameters (such as, the coefficients of a wavelet decomposition of the signal) might be useful as input to the NF model to improve its performance.

For trajectory #5 (large excursion ramp-and-hold profile) the maximum error is quite large especially when the trajectory goes near zero probably due to the normalization procedure we have chosen. However, the network seems to be robust enough in this case as suggested by the favorable values of the other parameters related to prediction error. In fact, in this case the NF model is required to give a rough prediction of the ankle angular trajectory to permit adequate control actions to manage this extreme situation (i.e., when the angle excursion is far from the middle position).

Sinusoidal Trajectory: For trajectory #7 (sinusoidal trajectory), the NF model prediction was satisfactory in terms of maximum error—especially for Rabbit #3 (see Fig. 10).

IV. Discussion and Conclusion

The aim of this paper was to assess the feasibility of using muscle afferent signals to control standing in subjects affected by spinal cord injury. To show this, we recorded different "passive" (i.e., without stimulation during the movements) and "active" (i.e., with LG stimulation during the movements) ankle profiles in an animal model.

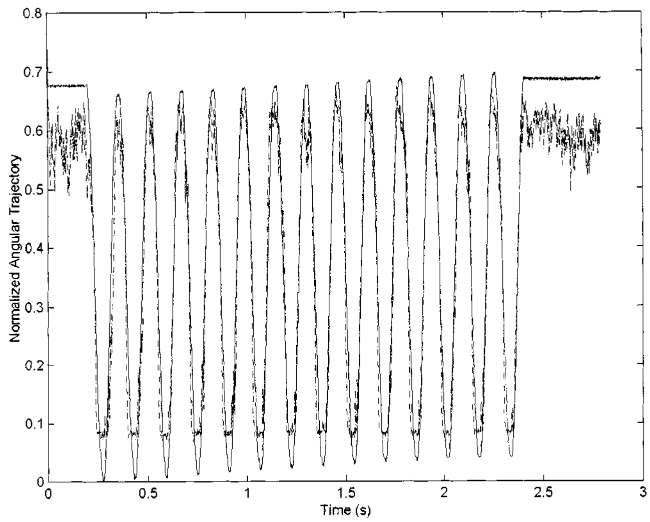


Fig. 10. The predicted ankle profile (dash-dotted line) and the actual one (solid line) for the test set of trajectory #7 (Rabbit #3).

The use of an animal model has permitted us to preliminary test our hypothesis about the feasibility of extracting position information from muscle afferent activities in a very simple and controllable situation (for example, we removed the cutaneous sensory information as described in [14]). Moreover, in the future, we could carry out further studies, e.g., on the possibility of extracting more restrictive sensory information rejecting signals which are not useful (such as the above mentioned cutaneous information). Finally, we tried to make the experimental situation more closely mimic the real condition by applying to the animal model standing trajectories recorded from human subjects (as previously described).

Most of the profiles consisted of a small angular excursion because this is the usual situation during human sway. Moreover, to test the robustness of the implemented system, we also recorded the ankle profile of a paraplegic subject during FES standing as well as ramp-and-hold profiles having a large peak-to-peak excursion.

The proposed NF model showed good performance during the prediction of ankle angular position in the small passive excursion trajectories respecting (or obtaining results very near to) the criterion suggested in [25] (maximum prediction error below 1°) for Rabbits #1 and #2. On the other hand, when these trajectories were replicated in conjunction with the stimulation of the LG muscle (i.e., in trajectory #2), the NF model performance dramatically decreased as for Rabbit #2.

In the large excursion curves, the prediction performances were not as good in terms of maximum error. However, with these large excursions, the NF model still yielded good results as suggested by the high correlation coefficient and the low value of the rms of the prediction error.

Thus, it appears that the NF model proposed in this paper can be used for control purposes in real applications where the movement excursions are small (as during standing), and providing that the FES stimulation sites are far from the nerve recording sites (to avoid the presence of artifacts in the ENG signals we want to use for the prediction). It is worth noting that for control purposes we may not need the exact prediction of the trajectory but only some qualitative information during the movements and this may always be furnished by the NF model as suggested by the good values of the correlation coefficients. A strategy similar to that proposed in [6] may be used for example to keep the Center of Pressure of a disabled person within a region under the foot which can assure his/her stability [27]. Finally, it is worth noting that the prediction of ankle angular information the ENG signals recorded during different trials of the same ankle trajectories seems to be quite similar [14].

Future work will deal with other steps needed to achieve the final goal of this project. For example, we will implement a closed-loop control of the ankle joint will be implemented in a rabbit model. Moreover, to improve the prediction capability of the system, different features extracted from the ENG signals will be tested, and possibly, other models will be evaluated.

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