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MACHINE LEARNING FOR PREDICTION OF MUSCLE ACTIVATIONS FOR A RULE-BASED CONTROLLER

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Abstract **- The inductive learning (IL) technique, radial basis function (RBF) type of artificial neural network (ANN), and the combination of IL and RBF were used to predict muscle activation patterns and sensory data based on the preceding sensory data. The input consisted of the hip and knee joint angles, horizontal and vertical ground reaction forces recorded in an able-bodied human. The output data consisted of the patterns of muscle activities. These patterns were obtained from simulation of walking with a functional electrical stimulation (FES) system. The simulation takes into account the individual biomechanical characteristics of the eventual user having spinal cord injury (SCI). The mappings were tested using numerous data from five minutes of walking previously not used for the training. We illustrate the technique by presenting the estimation of the activations of the equivalent flexor knee muscle and the knee joint sensor for four strides. The correlation is better and tracking errors are smaller when the combination of IL and RBF is used compared to the usage of IL or RBF. We show that the prediction of sensory state is achievable; thus, the delays imposed by the properties of the neuro-muscular system can be minimized.**

Keywords **- Machine learning, FES, Walking, Inductive learning, Radial Basis Function ANN**

I. INTRODUCTION

Despite all of the theoretical advantages of feedback control, most Functional Electrical Stimulation (FES) systems today operate without feedback, the only control input comes from a manually operated switch. Subjects with spinal cord injury (SCI) decide about changes on the basis of visual, auditory, and somatosensory information. In more sophisticated systems the patterns of stimulation follow the known electromyographic profiles (EMG) for able-bodied subjects [1]. These FES systems in some subjects using a rolling walker allowed a walking speed up to 1.1 m/s, and distances over 1 km.

An alternative for gait restoration is the usage of a rule-based controller. In this case the sensory space is mapped to muscle stimulator control commands. For precise tuning of this map the sensory input should be mapped to both the muscle timing, and the level of stimulation. In order to acquire this mapping it is important to take into account the desired kinematics, body parameters and neuro-musculo-tendonal properties of an eventual subject. Simulation study which takes into account all of these elements was recently developed [2], and provides input and output for the mapping. The input are the desired trajectories given as sensory information vs. time, while the output are the profiles of calculated activities of muscles required for optimal tracking vs. time.

The determination of these sensory-motor synergies is simplified due to the development of machine learning and other non-parametric methods for estimation. The usual set of input in a non-parametric system comes from joint angles, joint angular velocities and accelerations, foot pressures, and data recorded from afferent nerves [3,4,5,6,7,8]. The usual output is the estimated EMG pattern or the graded EMG.

The inductive learning (IL) is a well known technique of mapping [9], where the machine learns by examples. In this study IL algorithms are compared for their ability to reconstruct: 1) muscle activation patterns; 2) sensory data, and to predict the timing of sensory data which corresponds to the timing of muscle activity from preceding sensory data. The recognized sensory combination which precedes the muscle activity allows sufficient time to turn on the stimulation, and muscle to contract. The three algorithms are: 1) symbolic (based on minimization of entropy IL [8,10,11]); 2) connectionist (radial basis function type of artificial neural network (ANN) [8,12]); and 3) their combination [8]. The radial basis function (RBF) may also be considered as an IL method because it belongs to supervised learning techniques.

A rule-based IL estimation is explicit, easy to implement, computationally simpler, and easy to comprehend, compared to ANN (although there are methods which extract approximate classification rules from trained ANN, and they contribute to giving readability to the ANN [13]). A rule-based estimation does not work well enough for estimation of the muscle activity level, and ANN does not work well enough for estimation of the muscle timing [8]. ANN gives a continuous, whereas rule-based learning gives discrete output. The best solution is to combine rule-based and ANN methods to get the best from both approaches [8]. In this paper we show that this combination gives the best results for the prediction of sensory states and muscle activations.

II. METHOD

The data for training have two sets: 1) input; and 2) output, and they were prepared using recordings in an able-bodied subject, and the parameters determining the dynamic properties (muscles, tendons, segments, etc.) of a subjects with paralysis of legs. The recorded kinematics was considered as a first approximation of a desired gait pattern.

The kinematic data were recorded during a five minute session, while an able-bodied subject walked on a powered treadmill with a variable speed. The subject used shoe-horn type ankle-foot orthoses in order to stabilize her ankle joints and limit the range of movements at ankle joints. This limitation was introduced to simulate the locomotion with a simple FES system used for gait restoration. The knee and hip joints, and ground reaction forces were measured with flexible goniometers and pressure sensitive transducers [14]. The data were sampled at 100 Hz, and stored for later analysis in a portable custom designed device. The recordings were smoothed at 5 Hz, and digitized to a desired series of levels in order to present them to a training algorithm. The input set used a series of time shifted sensory recordings. The delay between two series was always 10 ms. The data were divided into the learning and testing sets. The learning set was intentionally small, and consisted from only few strides. In the example presented the training set included only three consecutive strides.

A simulation of walking was employed to generate the output. This simulation [2] calculates patterns of muscle activations for a given, desired trajectory using optimal tracking. The simulation includes dynamical specifics of a subject with SCI such as: 1) increased tonic activity of muscles; 2) limited range of movements in joints; 3) modified reflex responses; 4) reduced strength of externally stimulated muscles; 5) activity of antagonistic muscles; 6) body parameters, etc. Hence, the simulation generates a set of muscle activity patterns, that is the output for learning algorithms.

A rule-based inductive learning method based on minimization of entropy was tested. The output (muscle activation and sensory data) were divided using eight fixed levels. The attempt was to estimate quantified levels using the minimization of entropy for the design of one production rule for each level. Rules were designed using the data from a training set, and tested on data from the testing set [3].

The radial basis function type of supervised ANN was used to estimate continuous levels of outputs. This type of ANN was selected because of its characteristic fast training, and capability for generalization. Adjustment of connection weights for ANN was done using data from the same training set used for IL, and the test was done based on test set data.

The third method used both the rule-based IL and RBF methods. The muscle timing (when a muscle is active) was estimated using rule-based IL method, and muscle activation level was estimated using RBF. The connection weights for RBF were calculated based only on elements from the training set that fall in interval in which a muscle was estimated to be active. Sensory data were estimated using mostly RBF because the connection weights for RBF were calculated based on almost whole training set.

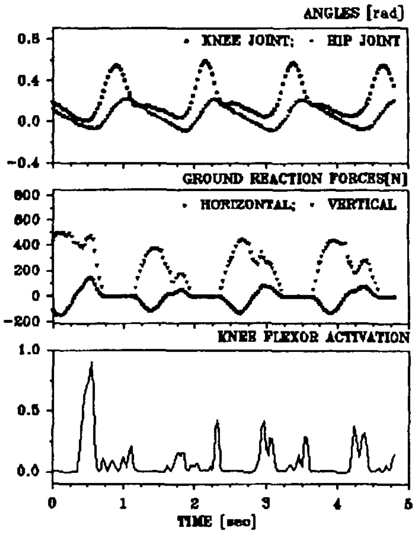

Fig. 1: The testing set consisted of data from four gait strides.

The evaluation of techniques was done by comparing the timing errors (differences between the actual and the estimated muscle timings), cross-correlation between the actual and the estimated muscle activities, cross-correlation between the actual and the estimated value of sensory data, elapsed training and testing time.

The learning algorithms were implemented using the MatLab 4.2c.1 on a PC platform (Pentium 133 MHz, 16 Mb RAM).

III. Results

The estimated activation patterns of the equivalent flexor knee muscle, and estimation of the knee joint angle delayed for 50 milliseconds, for four consecutive strides not used for training is presented.

The representative series of input and output data is shown in Fig. 1. The upper two panels show the joint angles and ground reactions, while the bottom panel shows the simulated activity of the equivalent knee flexor muscle.

Fig. 2 shows results of application of minimum entropy IL technique. The top panel shows the actual simulated activation of the muscle (full line) and the estimated activation (dashed line), the middle panel shows the errors in timing, where the value 1 corresponds to the delay of the estimated activity, while -1 the preceding of the estimate. The bottom panel shows the prediction of the knee joint angle, based on the sensory information which precedes for 50 ms. The differences in predicted sensory value (dashed line) and actual sensory value (full line) are substantial because the number of discrete levels for training was low. If the number of discrete levels is increased, the rules are very complicated

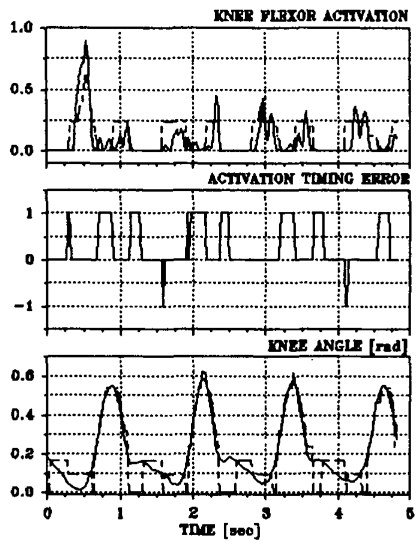

Fig. 2: The results of application of the minimum entropy rule-base generator. The top panel represents the actual and the estimated activation pattern for the equivalent flexor knee muscle. The middle panel represents muscle timing error, and the bottom panel the actual and the estimated angle at the knee joint delayed for 50 ms. Full lines show recordings and simulation, while the dashed lines show the estimated output.

and all of the advantages of this approach are compromised. For the estimation of activity elapsed training time was 31.56 s, and testing time is 0.11 s. For the estimation of sensory data elapsed training time is 31.90 s, and testing time is 0.17 s. Cross-correlation between the actual and the estimated muscle activity is 0.7878, and cross-correlation between the actual and the estimated value of sensory data is 0.9611.

Fig. 3 shows results of application of RBF. This method estimates muscle activity level and sensory data level very well because it gives continuous output (top and bottom panels), but it does not work well for estimation of muscle timing (middle panel). Rules used by RBF are not explicit and comprehensible. For the estimation of activity elapsed training time was 15.82 s, and testing time was 5.5 s. For the estimation of sensory data elapsed training time was 14.44 s, and testing time was 5.49 s. Cross-correlation between the actual and the estimated muscle activity is 0.9248, and cross-correlation between the actual and the estimated value of sensory data is 0.9997.

Fig. 4 shows results of the combined application of both IL and RBF network. This method estimates muscle timing (middle panel), muscle activity level (top panel), and sensory level (bottom panel) very well. The error is small enough to make the full and dashed line hard to distinguish at the bottom panel. For the estimation of activity elapsed training time was 7.03 s, and testing time was 3.07 s. For the estimation of sensory data elapsed training time was 15.66 s, and testing time was 5.22 s. Cross-correlation between the actual and the estimated muscle activity is 0.9081, and cross-correlation between the actual and the estimated value of sensory data is 0.9992.

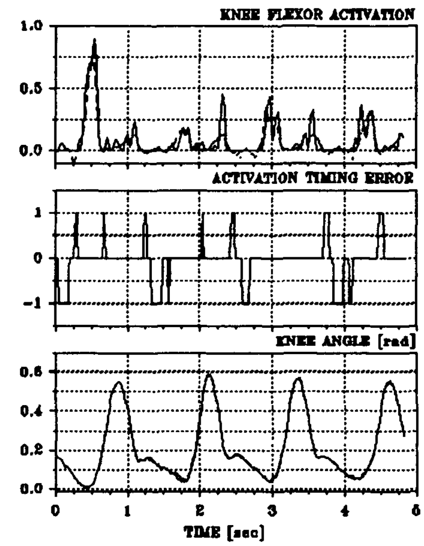

Fig. 3: The results of RBF application (see details in Fig. 2).

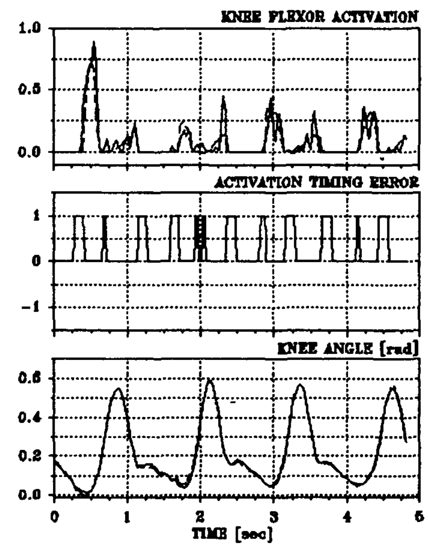

Fig. 4: The results of the application of both minimum entropy rule-base IL and RBF (for details see Fig. 2).

IV. DISCUSSION

In order to judge the acceptability of the timing errors, they should be related to the dynamical characteristics of the musculoskeletal system: the dynamics of muscles can be characterized by rise time of approximately 50-100 ms, depending on the muscle type. The resonance frequency of the skeletal system depends on the phase of the walking cycle (stance or swing), but can be estimated to be lower then 1 Hz. Therefore, timing errors on the order of 50 ms seem to be acceptable.

A possible explanation for the observation that the muscle timing appeared to be reconstructed with sufficient accuracy, but not the muscle activity, is that more information is needed for a good reconstruction of the activity then for a good reconstruction of the timing. Because simulated studies [15] show that the gait pattern is more sensitive to muscle stimulus on/off timing than to stimulus amplitude, and because the aim is reduction of number of used sensors, muscle activity errors seem to be also acceptable. Based on these errors it is possible to identify the most important sensors.

Rule-based inductive learning method based on minimization of entropy can produce only discrete values as output. This is not a problem for the muscle activation pattern which is used to control a muscle stimulator, since the muscle filters out transitions between discrete values. However, dividing muscle activity into several predetermined levels, and attempting to estimate quantified levels, can lead to more complicated rules than if rule-based inductive learning method is used to estimate the muscle timing only. RBF can estimate muscle activation level and sensory data level very well, but it does not work well enough for estimation of the muscle timing. This gives continuous output. The advantage of rule-based learning method is that the rules used are both explicit and comprehensible, whilst the rules used by the RBF are implicit within its structure and not easily comprehended. However, there are methods which extract approximate classification rules from trained ANN, and they help us to evaluate the learned knowledge in light of our knowledge. Furthermore, RBF is computationally intensive. The best solution is to combine these two methods.

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