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Adaptive Neuro-Fuzzy Logic Analysis Based on Myoelectric Signals for Multifunction Prosthesis Control

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***Abstract*—The myoelectric signal is a sign of control of the human body that contains the information of the user's intent to contract a muscle and, therefore, make a move. Studies shows that the Amputees are able to generate standardized myoelectric signals repeatedly before of the intention to perform a certain movement. This paper presents a study that investigates the use of forearm surface electromyography (sEMG) signals for classification of five distinguish movements of the arm using just three pairs of surface electrodes located in strategic places. The classification is done by an adaptive neuro-fuzzy inference system (ANFIS) to process signal features to recognize performed movements. The average accuracy reached for the classification of five motion classes was 86-98% for three subjects.**

I. Introduction

THE development of systems managed by myoelectric signals with the intention to reproduce the human arm movement still is target of many investigations [3]. In recent years, there has been an explosion of interest in computational intelligence (CI) as evidenced by the numerous applications in health, biomedicine, and biomedical engineering. CI techniques are computing algorithms and learning machines, including artificial neural networks, fuzzy logic, genetic algorithms, and support vector machines [1]-[13].

Many studies are being conducted in able-bodies subjects to verify the feasibility and performance of different algorithms for pattern recognition using EMG signals from the forearm muscles [1]-[13]. In these studies are usually employed a high number of electrode pairs, ranging for 4 to 12. Using classification patterns techniques such as LDA [3],[11], fuzzy logic [2],[5],[6],[7],[12], among others, was found high accuracies (>90%) for the classification of different moves ranging between four to ten. This suggests that it is possible to achieve high accuracy using several pairs of electrodes.

A recent study estimated that for twelve pairs of electrodes was possible to classify ten different movements with an accuracy of 81.2% and decreasing the number of pairs of electrode to eight, the classification accuracy dropped 1-3% [3]. This study also produced an average classification accuracy of 88.5% reducing the motion classes to six and using four channels of sEMG.

It is important to notice that almost all of the previous studies used at least four pairs of electrodes to evaluate the performance of the pattern recognition algorithms. On the other hand, a prior study has shown that Artificial Neural Network was able to classify six movement classes with an average accuracy of 78% with just three pairs of surface electrodes [13]. The proposed system in this paper also uses three pairs of electrodes for signals acquisition, and processes these signals with an adaptive neuro-fuzzy system for recognition of performed movements.

II. Methods

A. Experimental Procedures

The data was collected from three able-bodies subjects over three consecutive trials: calibration, adaptation and performance test.

The calibration is an important step because its aims to check if the electrodes are positioned correctly and also to determine a threshold value that will be used later to detect the occurrence of a movement. This procedure involves capturing the muscle signal during one second at a time of relaxation and in a moment of maximum voluntary contraction (MVC). If one of the electrode's pairs were not correctly positioned, the signal received will have low quality compared to the baseline signal and would be necessary to do the reposition of the electrodes until the signal to noise ratio reaches at least a rate greater than 10, based on the value established in tests of the signal acquisition previously performed. A percentage ranging from 15 to 30% of the average peak values, acquired from the MVC movement, is also used as threshold which indicated whether occurred or not a muscle contraction.

The adaptation's trial has the function to adapt the system for each subject, once it depends on the variability due to different muscle activities that each person can make. The trial consists in a session with five repetitions for each chosen movement to train the pattern classification algorithm.

In order to verify the feasibility and accuracy of the system is accomplished the performance test. The sEMG data were collected over 10 sessions. A session consists in

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three repetitions of each of the five determined moves, in random order. This represents a total of 150 movements.

For every trial, demonstrations of each movement were shown in a LCD screen and subjects were instructed to perform the movements that appear in random order, as shown in Figure 1. Between consecutives movements was determined an interval ranging from 3-5 seconds.

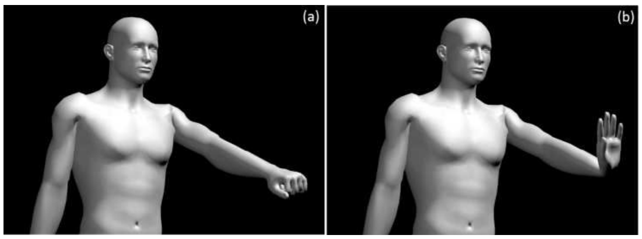

Figure 1. Pictures of the movements of the virtual arm interface: (a) hand contraction and (b) wrist extension.

B. SEMG Data Acquisition

For every subject 3 pairs of bipolar surface electrodes with passive configuration were placed in specific locations on the arm. The choice of recording sites for muscle activity is motivated by the relevance of the chosen muscles to the gestures that must be classified. For this study, the captured signals belong to three muscles: Flexor Carpi Ulnaris (channel 1), Extensor Carpi Radialis Longus (channel 2) and Biceps (channel 3) – see Figure 2. Also, an electrode was placed on the forehead for ground.

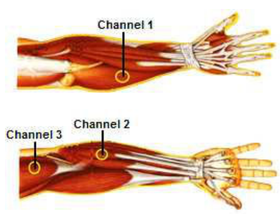

Figure 2. Non-invasive placement of electrodes. Freely adapted from [14].

In this study five classes of hand, wrist and forearm motion plus a no movement class were characterized. The five chosen movements were hand contraction, wrist flexion and extension, and forearm flexion and rotation – Figure 3.

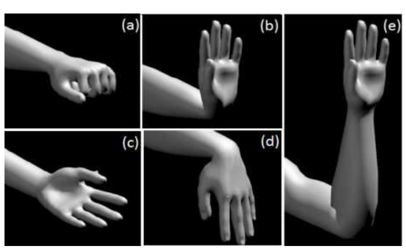

Figure 3. Pictures of the movements characterized by the developed system: (a) hand contraction, (b) wrist extension, (c) forearm rotation, (d) wrist flexion and (e) forearm flexion.

The sEMG signals were amplified and band-pass filtered (20–500 Hz), sampled at a frequency of 1 kHz, and acquired with a National Instrument's USB 6008 acquisition board.

C. SEMG Preprocessing and Feature Extraction

Before the pattern classification of the signal acquired it is necessary to perform a preprocessing. The sEMG preprocessing consists in four steps: offset signal removal, signal full rectification, extraction of the interest signal and RMS value computation on the extracted signal.

The extraction of the interest signal is performed by determining the moment when the muscle contraction begins and ends. This determination is based on the threshold calculated during the calibration of the system. The data is verified to find the first and the last peak value above the threshold. Then, this portion of the signal is extracted and this RMS value is calculated. The RMS value of the moment occurs muscle contraction of each channel is used as input in the step of sEMG pattern classification.

D. SEMG pattern Classification

For recognizing sEMG patterns a neuro-fuzzy approach was applied. Neuro-adaptive learning techniques provide a method for the fuzzy modeling procedure to *learn* information about a data set. The technique known as Adaptive Neuro-Fuzzy Inference System (ANFIS) was select to be analyzed in the present study. The ANFIS uses Sugeno-type inference system. A typical rule in Sugeno has the form:

$\mathbf{R}^i$: If x_1 is MF_1^i and x_2 is MF_2^i and … x_j is MF_j^i
Then $z^i = s_0^i + s_1^i x_1 + s_2^i x_2 + \ldots + s_j^i x_j$

where $\mathbf{R}^i$ (i=1,2,..,L) denotes the i^{th} fuzzy rules, x_j (j=1,2...n) is the j^{th} input and z^i is the output of i^{th} fuzzy rule, finally MF_j^i is fuzzy membership function for i^{th} rules.

The ANFIS constructs a fuzzy inference system whose membership function parameters are adjusted using a hybrid method. ANFIS employs backpropagation algorithm for the parameters associated with the input membership functions and LMS estimation for the parameters associated with the output membership functions. The MF used is the bell membership function, which depends on three parameters *a*, *b*, *c* as shown:

$$MF(x) = \frac{1}{1 + \left|\frac{x - c}{a}\right|^{2b}}$$

The output level z_i of each rule is weighted by the firing strength w_i of the rule $\mathbf{R}^i$, as given by:

$$w_i = \prod_{j=1}^{n} MF_j^i(x_j)$$

where n is the number of inputs. The final output of the system is the weighted average of all rule outputs, computed as:

$$y = \frac{\sum_{i=1}^{L} w_i z_i}{\sum_{i=1}^{L} w_i}$$

where L is the number of rules. For this study, was designed a fuzzy structure of Sugeno-type with order three. This structure is represented in the Figure 4.

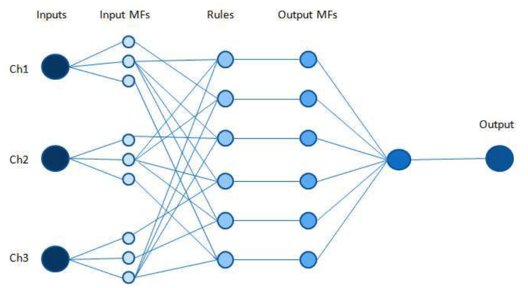

Figure 4. Structure of fuzzy system with three inputs and one output.

To design the system, was used “prod” as AND method, “probor” as OR method and “weight average” as deffuzification method. The system has three inputs, six fuzzy rules and one output, where Ch1 is the first input and so on for others inputs. Table I represents these rules with linguist expression. These expressions were applied from lower range to upper range of inputs as low, average and high. The output represents the characterized movement. Each output is obtained by combining all inputs.

TABLE I
REPRESENTATION OF THE FUZZY RULES

IF			THEN
sEMG Ch1	sEMG Ch2	sEMG Ch3	Output
Average	Average	Low	Hand Contraction
High	Average	Low	Wrist Extension
Average	High	Low	Wrist Flexion
Average	Average	High	Forearm Flexion
Average	Average	Average	Forearm Rotation
Low	Low	Low	None

E. Statistical Analysis

Many experiments involve more than two factors. For statistical validation methodology was used the “Design and analysis of three-factor experiments – Three-Factor Fixed Effects Model” [15]. Consider the three-factor-factorial experiment, with underlying model:

$$Y_{ijkl} = \mu + \tau_i + \beta_j + \gamma_k + (\tau\beta)_{ij} + (\tau\gamma)_{ik} + (\beta\gamma)_{jk} + (\tau\beta\gamma)_{ijk} + \epsilon_{ijkl} \quad \begin{cases} i = 1,2,\dots,a \\ j = 1,2,\dots,b \\ k = 1,2,\dots,c \\ l = 1,2,\dots,n \end{cases}$$

where μ is the overall mean effect, τ_i is the effect of the ith level of factor A (three subjects), β_j is the effect of the jth level of factor B (five movements: wrist flexion, wrist extension, hand contraction, forearm flexion, forearm rotation, forearm rotation and hand contraction), γ_k is the effect of the kth level of factor C (three different muscles or three channels 1-3), $(\tau\beta)_{ij}$ is the effect of the interaction between A and B, $(\tau\gamma)_{ik}$ is the effect of the interaction between A and C, $(\beta\gamma)_{jk}$ is the effect of the interaction between B and C, $(\tau\beta\gamma)_{ijk}$ is the effect of the interaction between A, B and C and ϵ_{ijkl} is a random error component having a normal distribution with mean zero and variance σ^2. Notice that the model contains three main effects (A, B and C), three two-factor interactions, a three-factor interaction, and an error term. This experimental design is a ***completely randomized design***. The hypotheses are:

(a) $H_0: \tau_1 = \tau_2 = \cdots = \tau_a$ no main effect of factor A *or* H_1: at least one $\tau_i \neq 0$

(b) $H_0: \beta_1 = \beta_2 = \cdots = \beta_b$ no main effect of factor B *or* H_1: at least one $\beta_j \neq 0$

(c) $H_0: \gamma_1 = \gamma_2 = \cdots = \gamma_c$ no main effect of factor C *or* H_1: at least one $\gamma_k \neq 0$

(d) $H_0: (\tau\beta)_{11} = (\tau\beta)_{12} = \cdots = (\tau\beta)_{ab}$ no interaction or H_1: at least one $(\tau\beta)_{ij} \neq 0$

(e) $H_0: (\tau\gamma)_{11} = (\tau\gamma)_{12} = \cdots = (\tau\gamma)_{ac}$ no interaction or H_1: at least one $(\tau\gamma)_{ik} \neq 0$

(f) $H_0: (\beta\gamma)_{11} = (\beta\gamma)_{12} = \cdots = (\beta\gamma)_{bc}$ no interaction or H_1: at least one $(\beta\gamma)_{jk} \neq 0$

(g) $H_0: (\tau\beta\gamma)_{111} = (\tau\beta\gamma)_{112} = \cdots = (\tau\beta\gamma)_{abc}$ no interaction or H_1: at least one $(\tau\beta\gamma)_{ijk} \neq 0$

The F-test on main effects and interactions follows directly from the expected mean squares. These ratios follow F distributions under the respective null hypotheses. We will use $\alpha = 0.05$ (significance level). The analysis of variance for a three-factor experiment showed that the main effects due to the three channels, three subjects and five movements are significant, in other words, there is a strong evidence to conclude that H_0 is not true. Thus, it is possible to say that the output rms for each one of the three channels, three subjects and five movements are quite distinct from each other, and thus, the myoelectric signals are also distinct and so can be treated as distinct channels by the developed adaptive fuzzy logic analysis model. The results of this model showed that the interactions are true, i.e. $(\tau\beta), (\tau\gamma), (\beta\gamma)$ and $(\tau\beta\gamma)$ are significant. However, the ANOVA doesn't identify which means are different. Methods for investigating this issue are called multiple comparisons methods. In this study we used the Fisher's least significant difference (LSD) method. From this analysis, we see that there are significant differences between all pairs of means.

III. Experimental Results

The signal processing was performed with three individuals and the system performance was verified for five distinct movements in terms of accuracy over ten trials. All subjects participated in the same process of raining and system testing. The threshold used was 30% in respect to the correspondent channel's MVC.

In order to validate the experiment, a statistical analysis based on Fisher's method was computed. Analyzing the results, it can be stated that the average values of the myoelectric signals (data in RMS) are significant. As an example, Figure 5 presents a possible relationship to the experimental data. It's interesting to notice that the subject 2 has the lower average RMS for all movements, except for hand contraction. The subject 2 also has the lower performance in terms of the average classification accuracy (86.6%) compared with the subject 1(98.6%) and subject 3 (94.6%).

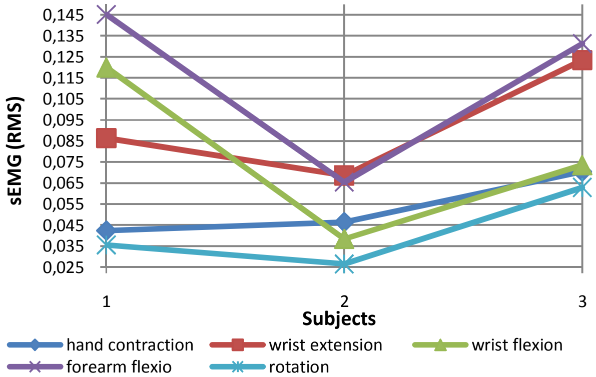

Figure 5. Relationship between the average of the myoelectric signal for three different subjects and muscles.

As shown in Figure 6, the system's results were satisfactory, except to the motion of wrist flexion on the Subject 2. The error occurred in the movement aforementioned must have been caused by an error in electrode placement on the skin, or some kind of bad contact.

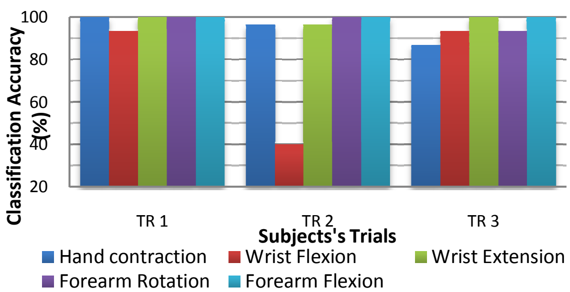

Figure 6. Classification accuracy for 5 movement classes over three subjects.

The average accuracy over all three subjects was 93.3%. Wrist flexion classification accuracies (75.5%) were significantly lower than forearm flexion (100%), and were more variable.

IV. Conclusion

The proposed system had the purpose to use a limited number of acquisition channels of myoelectric signal and with the help of a robust digital signal processing verify the validity of its performance. As can be noticed in the results, some movements achieved a lower hit rate. This may occur due to poor signal quality and the number of movement repetitions during the training of the ANFIS, since some movements had the answer in terms of RMS value very similar. The neuro-fuzzy system exhibit very good results as the minimum average accuracy obtained was 86.6%, a little lower than the average accuracy on the other studies cited in this paper [1]-[12]. However, only three pairs of surface electrodes were used in this study. Also, comparing with [13], the system has shown an improvement of accuracy in the use of the pattern recognition technique ANFIS above Artificial Neural Network, with an increment of 10% in the average accuracy. The results can be considered only preliminary and need further corroboration. To achieve a solid statistical inference additional tests are being conducted with able-body subjects and also with subjects with partial amputation of the upper limb.

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