OPTIMIZATION OF AN EMG PATTERN RECOGNITION SYSTEM BY A SELECTION METHODOLOGY OF ELECTRODE POSITION USING FFT AND ANN ALGORITHMS

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I INTRODUCTION

One of the modern challenges in Biomedical Engineering is to design and build a system that may be used as a man-machine interface for people who have suffered amputations of their upper or lower extremities or that present motor disabilities. This system must be able to recognize and appropriately respond to the person´s desired movements using superficial electrodes as a means of communication or sensing which are placed in the remaining muscles of the person´s amputated extremity or in strategic positions in the case of people with motor disabilities. The signals that the system must acquire, process and analyze are the electric potentials from the neuromuscular activity, better known as electromyografic (EMG) signals; these signals present amplitudes that vary from micro to milli volts and a band-width from 10 to 1000 Hz [1]. There have been great advances in the study of EMG signals, especially in the electric device control applications focused on the rehabilitation of people with amputations through the implementation of myoelectric prostheses in arms [2,3]. These systems use a simple codification scheme of the EMG signal amplitude in order to activate one or more of the prosthesis devices such as the elbow, wrist or hand. Although these systems have been successful, they do not provide enough information to reliably and intuitively control more than one function or multiple functions of the myoelectric prosthesis, which is a problem yet to be solved. One of the techniques that may help solve this problem is applying pattern recognition to the EMG signal processing and analysis [4]. Some of the methods that have been more successful in recognizing or classifying EMG signals include: Bayesian systems [5], artificial neural networks (ANN) [6, 7], Markov maps [8] and fuzzy logic [9].

In this research, an economical EMG system was developed with the idea of assembling it in an embedded device in the near future. The EMG pattern recognition was optimized through a selection methodology of the ideal electrode positions using Fourier´s fast transformation (FFT) and ANN algorithms.

II METHODOLOGY

The objective of our EMG system is to identify a person´s arm movement desired by using two active electrodes placed in the biceps and triceps muscles and another one in the wrist as a reference. The specific movements chosen include: the forearm pronation, forearm supination, hand grasp, and the rest state. For the design and assembly of the EMG system capable of recognizing and classifying the EMG patterns in an efficient manner, a multi-stage methodology was used. Figure 1(a) shows the block diagram of the methodology used; below is a detailed description of each stage:

Stage 1: Electrode Positions

The superficial EMG sensors were placed in the top part of the right forearm using the SENIAM (Surface Electromyography for the Non Invasive Assessment of Muscles) European norm which provides a placement methodology for the electrodes in the biceps and triceps muscles [10]. A study of the peripheral nervous system (PNS) and the arm´s muscular system was also carried out [11]. This allowed nine different places to be considered for electrode positions based on the peripheral nerves: *musculocutaneous*, median, radial, axillary and cubital position, while B varies between the

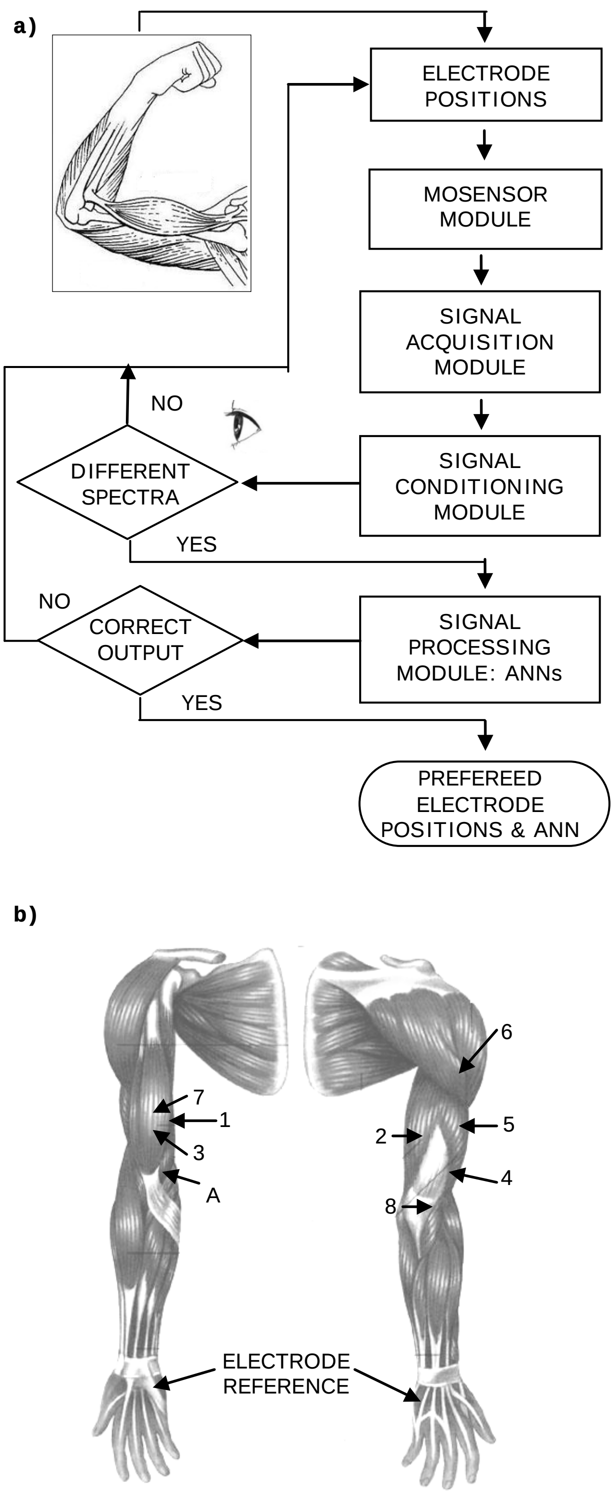


Figure 1: a) Block diagram of the optimization methodology for the EMG system, b) Positions of the electrodes A and B in the biceps and triceps muscles. A Electrode remains in the same

1 and 8 positions. as well as the biceps, triceps and brachialis anticus muscles which take part in the specified movements. Figure 1(b) shows the nine different essential positions for capturing the EMG signals. Electrode A remains in the same position just above of brachialis anticus muscle [10], while B varies between the positions 1 and 8.

Stage 2: Sensor Module

Two superficial bipolar electrodes connected to a differential amplifier with a gain of 1000 (B&L Engineering) and a reference electrode were used to obtain the EMG signals.

Stage 3: Signal Acquisition Module

A six input-six output electromyograph was used to acquire the EMG signals; the electromyograph´s output were sent to a digitalization module (NI DAQ-6211 with a resolution of 16 bits) through a coaxial cable.

Stage 4: Signal Conditioning Module

Each channel was filtered between 20 and 1000 Hz through a Butterworth pass-band digital filter with a 330 phase gain and a CMRR (Common-mode rejection radio) of 95 dB per channel. FFT was used during 1 second periods with a sample rate of 10 kHz in order to generate intensity vs. frequency spectrums from which the coefficient vector to feed the ANNs was obtained. At this stage, it was decided whether the electrode position was acceptable, observing if there exists similarity between the intensity vs. frequency spectra of the different types of movements (the forearm pronation, forearm supination, hand grasp, and the rest state). If they turn out to be similar, new electrode B position is chosen (Stage 1); otherwise, the EMG pattern recognition through the ANNs is begun (Stage 5).

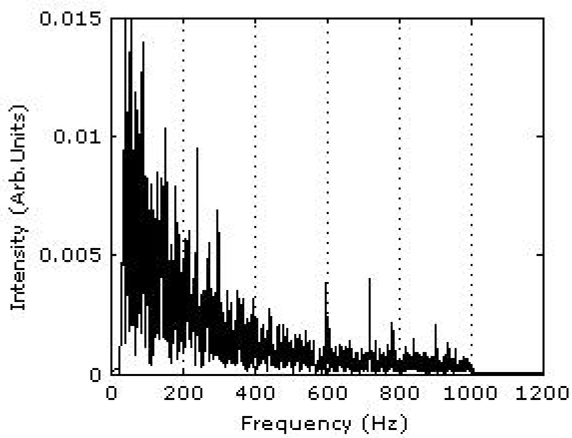
Stage 5: Signal Processing Module

During this stage, the analysis and classification of the EMG patterns through the ANNs was carried out. The ANN Backpropagation (BP) with two hidden layers of 20 neurons and one 4-outputs layer [Ref. Englehart] and an ANN Radial Basis Function (RBF) were used [12]. Other investigators, who have used these ANNs for recognizing EMG patterns, have reported good results [3]. In this stage, the output signals are compared to the person´s specific movement that is made in order to verify that the ANNs are correctly recognizing it; if they do not achieve this, new electrode B position is chosen (Stage 1). In assessing the ANNs´ behavior, the following parameters were also taken into consideration: training algorithm, training time, tests, validations, and computer cost.

RESULTS AND DISCUSSION

The experiments were performed in 20 persons of different ages: 6 children (10-14 years), 7 young (17-28 years) and 7 adults (30-50 years). As explained in the methodology, the experiment starts selecting a position for the electrode B, the electrode A remains in place, Figure 1(b). Figures 2(a) and 2(b) show the spectra of intensity versus frequency for the movements of forearm

a)



b)

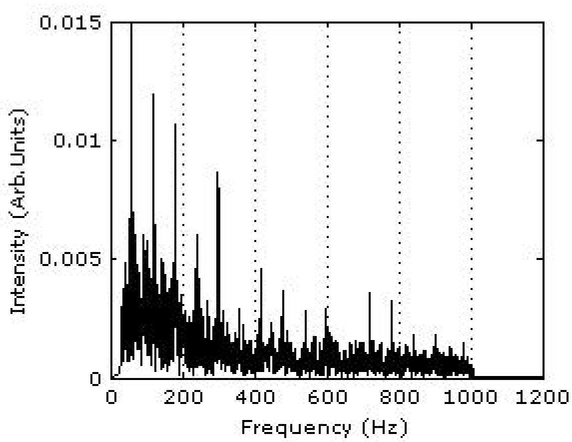
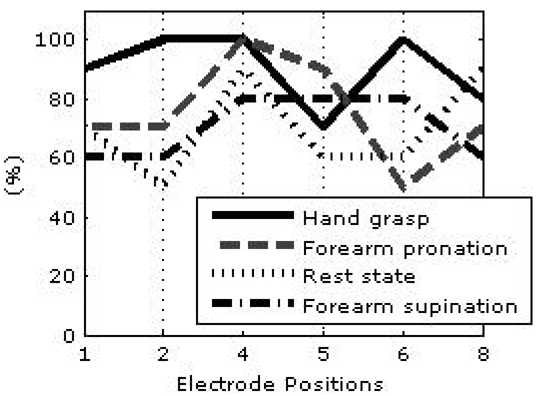


Figure 2: Spectra of intensity versus frequency of the movements a) Hand Grasp, b) Forearm Pronation.

pronation and hand grasp, with the electrode B at position 8 (triceps vastus medialis, just above the radial nerve, Figure 1 (b)).These spectra were obtained using the FFT for periods of 1 second with a sampling rate of 10 kHz. We reviewed how similar are the movements spectra in order to determine if the position of electrode B is suitable for EMG pattern recognition. If the spectra are very similar is probably that ANNs do not perform recognition correctly. As observed in Figures 2(a) and 2(b) the spectra are different. Making a thorough review of all spectra for different movements in the positions 1 to 8 of the electrode B, the positions 3 and 7 were discarded due to their spectra were very similar. Anyway the ANNs showed that positions 3 and 7 are not suitable to recognition.

Figures 3(a) and 3(b) show the average accuracy in the EMG pattern recognition from the three movements and the state of rest for the different positions using the ANN BP (Figure 3(a)) and the RBF ANN (Figure 3(b)). As observed in these figures, the positions 3 and 7 are not plotted due to their average accuracy was less than 50%. We obtained the best average accuracy by both ANNs for positions 4 and 8, also their recognition times were lower compared to the other positions. Recognition times from 1.012 to 2.484 seconds were estimated for the RBF ANN and times ranged from 2 to 10 seconds for BP ANN. The experiments show that position 8 is ideal for a high average accuracy using RBF ANN. It's feasible that these results were obtained because the electrode B is located just above the radial nerve in the position 8, Figure 1(b), thereby the EMG data obtained do not only correspond to muscular activity, also the electric potential of the radial nerve is present. Since it has a large number of differences in the EMG signals it is easier to perform recognition.

a)



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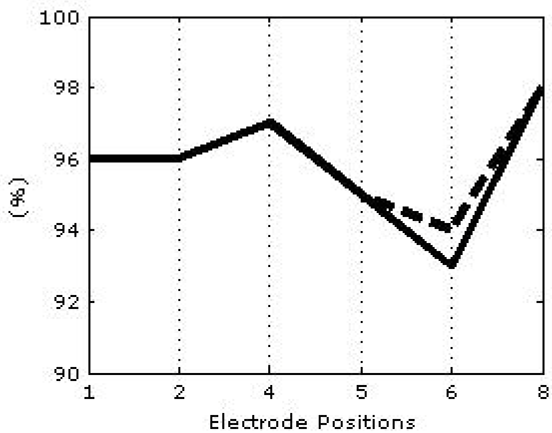

Figure 3: Average accuracy in the EMG pattern recognition from the three movements and the state of rest for the different position a)BP ANN b)RBF ANN.

CONCLUSIONS

This research demonstrates that the selection methodology of electrode positions is an effective technique to optimize an EMG pattern recognition system. The results show that position 8 is ideal for a high average accuracy in EMG pattern recognition using RBF ANN. In the position 8, electrode B is located just above the radial nerve, for this case the EMG signal do not only correspond to muscular activity, also the electric potential of the radial nerve is present. Since the differences in the EMG signals increases, it is easier to perform recognition, which concludes that the electrode positions above nerve paths and muscular activity provide more EMG information and notoriously facilitate the EMG pattern recognition.

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