RESEARCH ON ELECTROMYOGRAPHIC SIGNAL PROCESSING FOR CONTROLLING BIOMECHANICAL SYSTEMS

SUMMARY

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INTRODUCTION

Myoelectric control is the most widely used approach for the control of upper limb prostheses. When used as control input, the electromyographic signal has dominated because it has several advantages over other input types. Among these advantages is the detection of the signal on the skin surface without any injury for the patient, the small magnitude of the muscle activity required to provide control signals, which resemble the effort required of an intact limb, and the possibility to use the signal for proportional control with relative ease.

The functionality requirement of the prosthesis increases with the level of amputation, and this demands more effort to control the device. To compensate for the burden, the challenge is to develop control systems that are able to assist the patient in using the prosthesis. As the myoelectric prostheses use biological signals to control their movements, it is expected that they should be much easier to be used by a patient. Contrary to this idea, the prosthesis control is very unnatural and requires a great mental effort, especially during the first months after fitting.

Various factors such as the anatomical and physiological properties of muscles, the characteristics of the instrumentation used for detection and processing, the position where the sensor is applied, the surface of the skin and the tissues between the skin and the muscle determine the complexity of the surface electromiographic (EMG) signal. Therefore, a precise detection of the SEMG signal is an important issue. Due to the small amplitude of the SEMG signal, the accuracy of the acquired signal is affected by noise.

Several methods have been developed to process the surface electromiographic signals used in myoelectric control of prosthetic devices. The present work addresses three important areas in EMG signal processing:

1. The analysis of the best location for electrode placement with the help of high density EMG.
2. The filtering process of EMG signals in both time and space domains.
3. The classification of EMG signals into classes which correspond to the user’s intention.
4. The analysis of visual feedback to the EMG classification process and it’s implication for different training types for prosthesis users.

First chapters are dedicated to a better understanding of EMG generation and acquisition processes, then various methods for EMG classification are presented followed by studies made using high density EMG techniques. The last part is reserved to a study analyzing the influence of visual feedback and the last chapter presents the conclusions of the thesis.

EMG GENERATION AND ACQUISITION

The EMG signal represents the electrical manifestation associated with a muscle contraction. The origin of the signal lays deep in the motor cortex of the human brain, where an electrical impulse is generated (Fig. 1). From here, the impulse is transported through neural fibers until it reaches the motor neuron located in the spinal cord. From this point, afferent and efferent fibers drive impulses towards and from the muscle in a complex scheme, to provide a precise control of the force generated by the muscle and leading to the possibility of controlling the position and movement speed of the limb. The single motor neuron and the muscle fibers it innervates is named motor unit and it represents the basic control structure involved in muscle contraction.

The signal collected over a period of time is related to the force developed by the muscle. By studying the correlation between finger pressure and EMG activity of the forearm, patterns in EMG signal could be associated with a certain finger action and hence, those signals could be used in a system like prosthesis or in keyboard commands for disabled people.

The acquisition of EMG signals can be done by so called EMG sensors, which usually are electrodes of Ag and AgCl placed intramuscular or at the surface of the skin. To provide the reference potential, a so called patient reference electrode is placed over a zone with little or no muscular activity.

Figure 1. The generation of the EMG signal: (a) an impulse is generated at the motor cortex level and transmitted to the motoneuron in the spinal cord where, based on the command impulse and other information collected from the muscle through receptors, a control strategy implements the movement; (b) the motor unit consists of a motoneuron and the muscle fibers it innervates.
EMG CLASSIFICATION

As Fig. 2 illustrates, the classification of EMG signal is a multi stage process, and the actual classification algorithm is only the last of the stages. Signal representation, achieved by feature extraction (in some cases assisted by dimensionality reduction), are vital for obtaining meaningful information for classification. The classifier’s role is to use this information and generate distinctive classes corresponding to the desired motions.

The recognition of the signal characteristics has been performed using a number of soft-computing approaches, such as neural networks (NN), fuzzy logic or neuro-fuzzy.

Four studies were performed to test how different conditions and structures used in each of the four stages represented in Fig. 2 influence the performance of the whole classification process.

First of the studies tests a **classification structure based on autoregressive model coefficients and neural network classifier** in distinguishing between four classes of movement that correspond to four forearm movements (flexion, extension, pronation and supination).

The AR model attempts to predict an output of a system based on the previous outputs (x(n-1), x(n-2),...). AR model is based on the Eq. 1:

\[
\overline{x(n)} = \sum_{i=1}^{M} a_i x(n - i) + e(n), n = 0..N - 1
\]  

(1)
where $a_i$ are the AR coefficients, $M$ is the model order and $N$, the size of the segment considered for analysis, $x(n)$ are the samples of the actual signal and $\tilde{x}(n)$ are the samples of the modeled signal.

A three-layered feed-forward neural network was used in the next step for classifying the obtained AR coefficients into the four classes of motion. There were recorded a set of 200 patterns for each of four classes of motion for training the network. Also, typically, the backpropagation algorithm had been used in the training process. The number of epochs set for the training stage was 200. This value had been chosen considering the use of Levenberg-Marquardt method for backpropagation algorithm, which appears to be the fastest method for training moderate-sized feed-forward neural networks. After trained, the neural network was presented with a new set of EMG pattern. The test set was represented by 200 patterns for each of four classes of motions. A 91.50% classification rate was achieved. The recognition rates varied between 90% and 92.50% as follows: 90% for flexion, 92.50 for extension, 92% for pronation and 91.50 for supination.

The next step was to develop a graphical user interface (GUI) capable of acquiring and processing the EMG signal. The GUI was created in Matlab (Matworks Inc.) software. It was designed to acquire process and display information about the muscular activity and the finger force. The application is consisting in 7 different sections which allow the user to perform different acquisition types, to save and to visualize the data, to train and test classification structures etc..

The second study was dedicated to determination the best feature-classification structure pair in sense of performance in classification of data that correspond to flexion isometric effort of each finger (except the thumb). For this test Surface EMG signals were collected from the forearm muscles (Flexor Digitorum Superficialis and Profundus) of seven healthy male volunteer subjects (age: 26.7±3.9 years). All subjects were right-handed, were informed about the details of the experiment and signed an informed consent form. All the measurements were done with the approval of the local ethical committee. After cleaning the skin with water and abrasive gel, four linear arrays with four electrodes each were placed on the ventral part of the forearm. The location of the electrodes was previously determined using a matrix of 128 electrodes. The places with the highest EMG activity (in terms of RMS amplitude over 250 ms data blocks) during the flexion of each finger (index, medium, ring and little) were selected for electrode placement. The subject was then seated in front of a computer and his hand was placed in a wooden platform on which force sensors were placed (Figure 2). The EMG signals were collected using a 16-channel EMG amplifier (EMG16 – LISIn-OT-Bioelettronica) in differential mode at a sample rate of 2048 Hz. A National Instruments 6024E data acquisition card was used to sample the signals on a computer with Matlab (Matworks Inc.) software installed.

Four different features (time domain: root mean square, average rectified value, frequency domain: mean frequency and median frequency) and several classifiers were tested for classifying the four feature sets: nearest neighbor analysis (KNN), discriminant analysis
(DA), naive Bayes algorithm (NB), neural network (NN) and adaptive neuro-fuzzy inference system (ANFIS).

The study concluded that the use of time domain features in the classification process yielded smaller classification error when compared with frequency domain based features. The best combination feature-classifier was found to be the RMS – KNN when 12 channels of EMG data were used. It has been shown that, when using features computed based on time domain representation of the signal, KNN and NN classifiers achieve a high rate of success (over 98%) in classifying the isometric flexion effort of the hand fingers. The ARV – NN combination seems as the best choice for the classification of finger movements, both from accuracy and computational cost perspective.

Based on the same protocol, a third study investigated if the number of the electrodes used in acquisition process (when the placement and the structure remains the same) has a influence on the classification rate. The study analyzed the influence of the use of linear array electrodes in the classification process and it was concluded that the use of linear electrodes arrays leads to a lower error rate for each classifier with an average decrease of 3.5% for the minimum error in each classifier. The use of multiple electrodes arrays enhanced the classification rate especially when used in combination with frequency based features. This can be due to the increased spatial resolution which leads to the capability of the system to identify MUAPs from different muscle parts.. The results of the study can be used as starting point in developing prosthetic device as the computations required by the classifier can be implemented on an embedded controller. This provides a basis for developing a more complex control system for hand prosthesis with improved functionality and accuracy.

The study of the influence of filtering in the classification process revealed that even if not the whole spectrum of the signal is taken into account in the classification process the results of the classification can be preserved at a very high level. It has been proved that using filters with pass band dimension of around 150-200 Hz the classification performance remains very close to the one obtained in the case all spectrum of the EMG signal is considered.

HIGH DENSITY ELECTROMYOGRAPHY

Multichannel electromyography represents the technique in which a large (>1) number of electrodes are used to record electrical activity from a skin surface. If the number of electrodes is high enough so called EMG maps can be created (Fig. 3) and the activity of different muscle or different muscle regions can be identified.

A study was prepared to find if surface electromiographic signal recordings from forearm locations can be used to identify different compartments Flexor Digitorum Superficialis (FDS) muscle.
Figure 3. If a number of electrodes are placed over a muscle (a) a large number of signals can be acquired (b) and processed so that image (c) of the muscular activity can be created. Various types of electrode configuration can be used (d).

The study was able to confirm the location of the muscular activity at places which corresponded to the location of different compartments of FDS by three different methods:

- The sum of normalized maps
- The product of normalized maps
- A new method based on the barycenter variation

The results showed a high correlation with the location of the compartments as indicated by anatomical studies. The results can be future used estimation the load share of some of the forearm muscles in finger movements, in identification of the best location for placing the electrodes in prosthetic control or the location of innervation zones for medical procedures like botulinum toxin injection.

The study was continued with an investigation over the best spatio-temporal filter structure with best separate the EMG maps which correspond to different finger flexion. To find these parameters a optimization problem was defined both with and without restrictions. The result of this investigation leaded to the conclusion that the most important contribution in separating the EMG maps is the one of the longitudinal electrodes of a spatial filter and the third coefficient of the temporal filter.

THE INFLUENCE OF VISUAL FEEDBACK IN EMG

The influence of visual feedback in EMG was analyzed in a study in which 6 subjects were involved in a study concerning in observing if, in a scenario where subjects are provided information about the accomplishment of a specific task, this information could help them to decrease the response time in generating the right EMG inputs to a classifier which recognizes the isometric flexion effort of different fingers. An application was created for the classification of the EMG signals acquired from the forearm muscles in classes corresponding to finger activations.
The experiment was focused on the flexion of the fingers (index, medium, ring and little finger) at the interphalangeal joint (mainly actuated by the Flexor Digitorum Superficialis muscle). The subject was sitting with his hand placed in a wooden support in which the force sensors were placed. The EMG amplifier and the force conditioning circuit were connected to a PC (Fig. 6).

The subject was asked to perform the MVC for five seconds with all fingers except the thumb, one at a time. During the signal acquisition the subjects received verbal encouragement and visual feedback of the recorded force. After a rest period of at least two minutes, the subject was asked to perform flexion efforts with each of the four fingers, 10 seconds each contraction, trying to match a target set at 40% MVC for each finger. After each contraction, a pause of 30 s was taken. The entire session was repeated after a two minutes break, with a randomized order of the fingers. Also, two sets of signals were acquired during two periods when the subject’s hand was in a rest state. After acquiring the data (which will be referred as training data) the artificial neural network was trained to classify the acquired EMG signals into classes corresponding to each finger flexion. After training the network, the subject was asked to perform three tests in order to compare different parameters of classification process. Each test was performed for 60 s.

The results showed a classification rate of approximately 80% in a real time use of the system. The interface of the applications allows multiple tests to be taken in order to determine different parameters of the subject’s capabilities in controlling the output of the classifier.

CONCLUSIONS

As has been mentioned SEMG signals cannot be used directly as inputs for a controller. Therefore pre-processing techniques are required to extract meaningful information from the raw signal. This information is used by the classifiers that provide input signals to the controller. The performance of the control system is highly dependent on the processing methods used. Unfortunately there is always a trade-off between the performance of the classifier, as interface between the EMG sensors and the controller, and the computational power required. Better results can be obtained if proper features extraction methods and suitable classifiers are used.

The personal contributions of the author to this thesis can be summarized as this:

1. Theoretical contributions:
   a. The development of an algorithm used to identify the EMG activity in an EMG map based on barycenter variation.
   b. The development of a strategy for finding the best parameters of an spatio-temporal filter used to separate muscle activity.
   c. The design and implementation of a classification structure based on neural networks and autoregressive model coefficients.

2. Experimental contributions:
a. Multiple applications for processing EMG signals
b. 5 different protocols for collecting EMG signal from over 20 subjects
c. Different devices designed and developed for EMG acquisition and conditioning
d. Development of several graphical user interfaces for EMG data acquisition and processing.