Classification of surface electromyographic signals for control of upper limb virtual prosthesis using time-domain features

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Abstract- **The development of a training system in the field of rehabilitation has always been a challenge for scientists. Surface electromyographical signals are widely used as input signals for upper limb prosthetic devices. The great mental effort of patients fitted with myoelectric prostheses during the training stage, can be reduced by using a simulator of such device. This paper presents an architecture of a system able to assist the patient and a classification technique of surface electromyographical signals, based on neural networks. Four movements of the upper limb have been classified and a rate of recognition of 96.67% was obtained when a reduced number of features were used as inputs for a feed-forward neural network with two hidden layers.**

I. Introduction

The myoelectric control seems to be the most used approach for upper limb prostheses. When used as control input, the myoelectric signal has dominated because it has several advantages over other input types, such as in the body-powered mechanical systems. Among these are the detection of the signal on the skin surface without any injury for the patient, the muscle activity required to provide control signals is relatively small and can resemble the effort required of an intact limb, and the possibility to adapt the signal to the proportional control with relative ease [1].

The functionality requirement of the prosthesis increases with the level of amputation, which 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 prosthesis 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, as Soares et al. [2] mention, the prosthesis control is very unnatural and requires a great mental effort, especially during the first months after fitting.

In order to reduce this effort a hybrid controller has been developed by Light et al. [3] to enable different prehensile functions to be initiated directly from the user's myoelectric signal. In this case, the wearer's effort is reduced because he should only initiate the action which is finalized by the controller using information from sensors mounted into the prosthesis. Even this approach is a good one, the control remains unnatural, so the patient needs months of training.

The price of these devices being still high, the access of the people who need those remains reduced. However, even if the price is affordable for some of them, the major problem, adapting to the control of the prosthesis, remains. Many people give up during the training period. In order the increase the rate of acceptance, one idea was to develop a system to assist the patient during the training period.

This paper presents the architecture of a system able to assist the patient and the classification technique used for the surface electromyographic signal as the control input. The goal of the system proposed is to increase the controller performance and the rate of acceptance of the prosthesis by the patients.

The focus was on analyzing and processing the electromyographic signal in order to discriminate among four motions of the forearm: extension, flexion, pronation and supination. A feed-forward neural network (FFNN) was used as a classifier of the four movements.

The inputs of the FFNN have been obtained by processing experimental measurements of SEMG signals from the biceps and triceps of several healthy persons. Due to the capacity of learning, the FFNN can be used to recognize forearm movements of persons who have experienced some form of trauma.

The outputs of the network may be used as control inputs of a virtual prosthesis intended to assist a disabled person in training.

II. System Architecture

The architecture of the system proposed is presented in Fig.1:

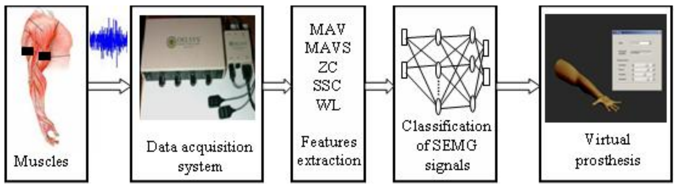

Figure 1. System architecture

The SEMG signals are collected from biceps and triceps using two differential myolectric sensors and preprocessed: amplified, filtered and converted from analog to digital.

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It is not feasible to identify a movement directly from a SEMG signal, due to its complexity. Therefore, in this architecture, it is necessary to extract a set of features characterizing the signal to be used as inputs of a neural network classifier.

The outputs of the classification block are further applied to the virtual prosthesis, in order to visualize the effect of patient's intention.

III. Data acquisition and Feature extraction

A. Data acquisition

A Bagnoli 4 system from Delsys Inc., used for data acquisition is presented in Fig.2 and comprises: four differential SEMG sensors, the main amplifier unit having the possibility of changing the gain factor between 0 and 10000 and an input module which is an interface between sensors and the main amplifier. The bandwidth of the system is 20-450 Hz ±10%. In order to process the signals an AD card PCI-6034E from National Instruments and EMGworks software from Delsys Inc. for signal preprocessing operations were used. The signals are stored as files on a computer and are used for further analysis.

Figure 2. Bagnoly 4 system for SEMG signals acquisition

Various factors such as the anatomical and physiological properties of muscles, the characteristics of the instrumentation used for detection and processing, the position were the sensor is applied, the surface of the skin and the tissues between de skin and the muscle [2] determine the complexity of the SEMG signal. Therefore, a precise detection of a SEMG signal is an important issue. Due to the small amplitude of the SEMG signal (μV to mV), the accuracy of the acquired signal is affected by noise.

In order to increase as much as possible the accuracy of the signals acquired all these factors were carefully considered. The distance between the electrodes can also affect the quality of the signal detected. To eliminate this problem the sensors have a fixed distance of 10 mm between electrodes.

The SEMG signals were acquired using two differential sensors and amplified by a factor of 1000.

After receiving informed consent, seventeen able-bodied male subjects, between 20 and 30 years old, participated in this study.

Fig. 3 illustrates the position of the sensors on the arm and the movements performed by each subject. One sensor was fixed on the biceps at a distance of about 50 mm from the elbow joint while the other one was placed on the triceps. The reference electrode was placed over the bony part of the wrist. Each subject was asked to perform four motions: flexion, extension, pronation and supination of the forearm.

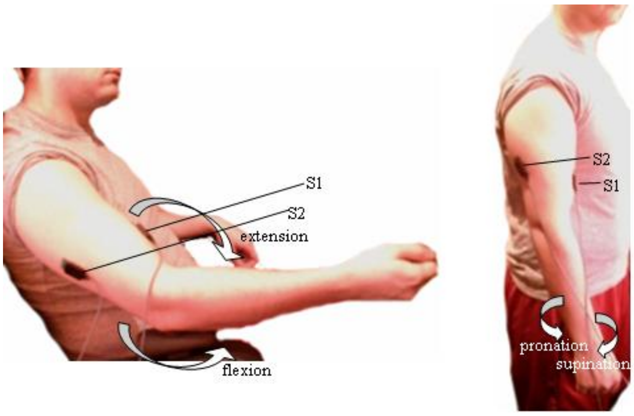


Figure 3. Position of sensors and the movements of upper limb

For the flexion and extension movements, the subject sat down with the upper arm in a position that makes an angle of about 30 degree with the longitudinal axis of the body. The elbow was leaned on a chair arm in order to isolate better the contractions of the muscles for the motions. The flexion movement was around ninety degrees and the extension movement was made as much as was possible by the subject.

For pronation and supination the subject stood up with the arm near the body in an anatomical position. The pronation and supination movements were about ninety degrees toward and outward the body, respectively.

During the acquisition of the SEMG the subjects were encouraged to make movements in a way which was comfortable for them.

Each movement was performed fifteen times. Thus for each subject 60 movements were recorded (4 motions x 15 repetitions/motion) and the total number of movements was 1020 (17 subjects x 60 movements). The signals acquired from two channels (biceps and triceps) identified each movement, hence the total number of signals recorded was 2040 (1020 movements x 2 channels).

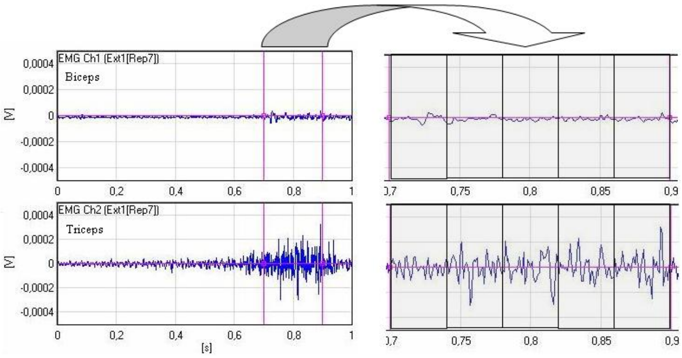
B. Feature extraction

Feeding the SEMG signal as a time sequence, directly into the classifier, is not a good idea, because of its complexity, the large number of inputs and randomness of the signal. Moreover, if the final goal is to use this signal to control a prosthetic device, it is absolutely mandatory to reduce as much as possible the length of the input. One solution is to map the initial sequence into a smaller dimension vector, called the feature vector.

The success of any pattern recognition problem depends critically on the selection and extraction of the features. Over the years many features were suggested for myoelectric classification. Amplitude and power spectrum are two main characteristics of a SEMG signal, frequently used in feature extraction. Amplitude and its related features are often investigated in time-domain analysis. For power study, a frequency domain analysis is more suitable. Englehart et al.[5], [6] applied feature projection to compare the final performance of the classification. They compared the performance of time-domain features [4] with time-scale features comprised of a short-time Fourier transform, wavelet transform and a wavelet packet transform.

Time-domain features are the most popular in myoelectric classification due to their computational simplicity.

In this study the features recommended by Hudgins et al. [4] were used. The signals from biceps and triceps have been acquired with 1000 samples per second. The length of the record was one second, but only a window of two hundred samples (200 ms) was kept for feature extraction. The two hundred samples were divided into five segments, each one having a length of 40 samples as illustrated by Fig. 4.



a) b)

Figure 4. Waveform segmentation. a) The SEMG signal acquired from biceps (up) and triceps (down) during 1 second. b) Five segments of 40 ms used for feature extraction.

For each segment five features have been computed: Mean Absolute Value (MAV), Mean Absolute Value Slope (MAVS), Zero Crossing (ZC), Slope Sign Changes (SSC), and Waveform Length (WL), [4].

MAV represents the mean absolute value of the segment analyzed. Equation (1) is used to compute this value:

$$\overline{x_i} = \frac{1}{S}\sum_{m=1}^{S} \left| x_m \right|, \tag{1}$$

where: $i = 1 \ldots I$ is the segment number; $S = 40$ is the number of samples for a segment and x_m is the m^{th} sample in the segment i.

The Mean Absolute Value Slope is the difference between the Mean Absolute Values computed for two adjacent segments and is calculated from the relation:

$$\overline{\Delta x_i} = \bar{x}_{i+1} - \bar{x}_i, \tag{2}$$

where i and $i+1$ are two adjacent segments and $i = 1 \ldots I-1$.

Zero Crossings is a measure of frequency which can be obtained by counting the number of times the waveform crosses zero. A threshold (ε) was included in order to reduce the noise-induced zero crossings. In our calculations, a value $\varepsilon = 10^{-6}$ was used. The zero crossing counter is incremented if the condition:

$$\begin{aligned}&\{x_m > 0 \text{ and } x_{m+1} < 0\} \text{ or } \{x_m < 0 \text{ and } x_{m+1} > 0\} \\ &\text{and } \left| x_m - x_{m+1} \right| \geq \varepsilon\end{aligned} \tag{3}$$

is satisfied for two consecutive samples x_m and x_{m+1}.

Slope Sign Changes is a feature which provides another measure of frequency content. The Slope Sign Changes counts the number of times the slope changes sign. The same threshold as for the zero crossings was used and for the same reason. The SSC counter is incremented if the condition (4) is true for three consecutive samples, x_{m-1}, x_m, x_{m+1}:

$$\begin{aligned}&\{x_m > x_{m-1} \text{ and } x_m > x_{m+1}\} \text{ or} \\ &\{x_m < x_{m-1} \text{ and } x_m < x_{m+1}\} \text{ and} \\ &\left| x_m - x_{m+1} \right| \geq \varepsilon \text{ or } \left| x_m - x_{m-1} \right| \geq \varepsilon\end{aligned} \tag{4}$$

Waveform Length is used to appreciate the waveform complexity in each segment. Relation (5) indicates a measure of the waveform amplitude, frequency and duration in a single parameter:

$$l = \sum_{m=1}^{S} \left| \Delta x_m \right|, \tag{5}$$

where: $\Delta x_m = x_m - x_{m-1}$; x_m and x_{m-1} are two adjacent samples.

As was suggested by [7] besides these five segments an extra virtual segment was considered, having the features calculated as the arithmetic mean of the values computed for the first five segments.

Thus, a set of 30 features (5 features/segment x 6 segments) were computed for each channel. Because for each motion two channels were used, the total number of features was 60 (30 features x 2 channels).

IV. THE SURFACE ELECTROMYOGRAPHIC CLASSIFIER

The features extracted, need to be classified into distinctive classes that correspond to the desired motion patterns. Due to the nature of myoelectric signals, it is reasonable to expect a large variation in the value of a particular feature. Other external factors, such as changes in electrode position, sweat and fatigue, cause changes in a signal pattern over time. Therefore, a classifier should be able to cope optimally with such varying patterns.

Many approaches were used to implement a classifier. Among these, neural networks [8], fuzzy logic [9], neuro-fuzzy [10], and probabilistic methods [11], were intensively analyzed.

In the present paper, a neural network approach was used because of their success in myoelectric signal classification. The advantage of the neural network is its ability to represent both linear and nonlinear relationships. Moreover neural networks are able to learn those relationships directly from data being modeled. Another important advantage of neural networks is their ability to perform with respect to the real-time constraints.

A feed-forward neural network (FFNN) with back propagation was used in the present paper.

After many trials with various configurations in the number of neurons per layer and the number of layers, the decision was to use a FFNN with two hidden layers. When all the sixty features were fed as the input of the FFNN, the input layer had sixty neurons. Four outputs were used to discriminate among the four motions as presented in Table 1.

TABLE 1. Desired neural network response for the movements

Network's outputs	Forearm movements			
	Extension	Flexion	Pronation	Supination
1	1	0	0	0
2	0	1	0	0
3	0	0	1	0
4	0	0	0	1

It has to be mentioned that for the encoding of four motions two outputs should be enough, but in this study, four neurons on the output layer provided a better response.

The success rate was around 90%, which was not satisfactory in our opinion. Previous studies proposed several approaches intended to increase the classification performance by dimensionality reduction [5], [12]. Feature projection and feature selection were the two main strategies which tried to determine either the best combination of the original values, according to some criteria, or the best subset of features, generally smaller than the original one [12].

Since the FFNN having 60 inputs did not perform reasonably we have tried a much simpler method to reduce the dimensionality of the network. The numerous experiments have indicated that a number of 10 inputs were sufficient for an accurate classification. The features selected as the inputs of the FFNN in this case, were the mean values of each type of feature extracted from the five segments (Fig. 2b), *i.e.* the characteristics of the sixth (virtual) segment were considered, for both of the two channels.

Consequently, the network architecture consisted of ten neurons on the input layer, two hidden layers each one having ten neurons, and one output layer with four neurons, as shown in Fig. 5. The transfer function of the hidden layers was a sigmoid and that of the output layer was linear (Fig. 6).

From the total number of 1020 movements recorded, 960 were used to train the network. The network response to the inputs in the training set is illustrated in Fig. 7.

The network was able to learn very well to recognize the vectors from the training set, with a very few, inherent errors, most probably due to the incorrect movements of the subjects at the time of data acquisition.

A set of 15 input vectors never used in the training phase, for each type of the four movements, have been randomly selected to test the network.

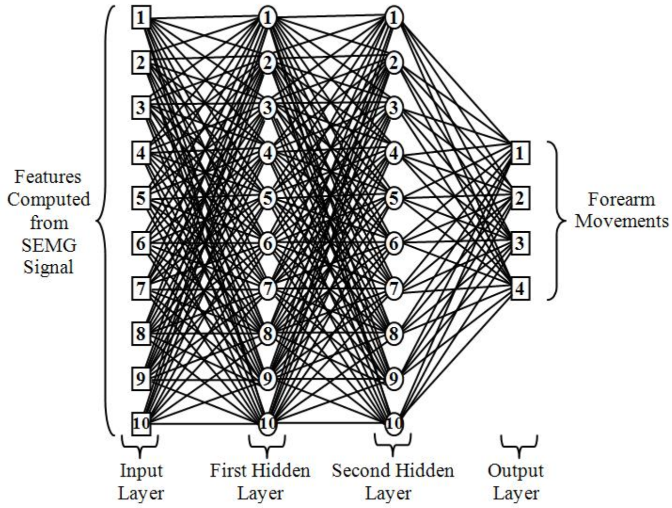


Figure 5. Neural network architecture

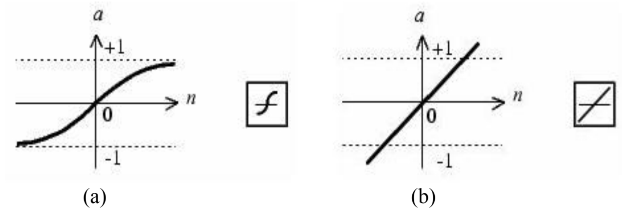


Figure 6. (a) Sigmoid function; (b) Linear function

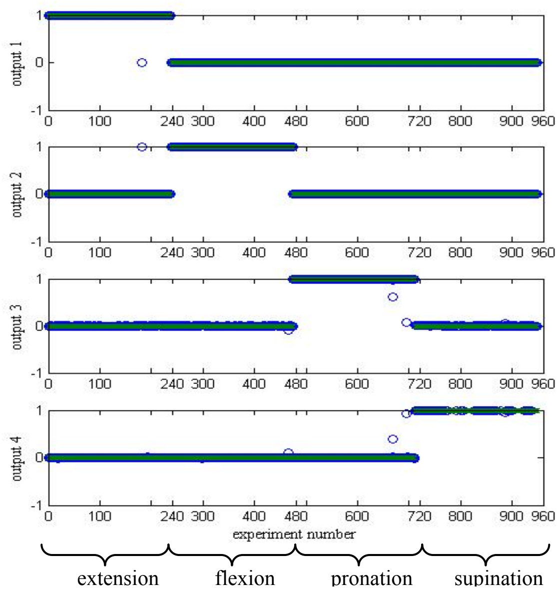


Figure 7. Neural network response after training

As presented in Fig. 8, the network response to the test vectors was accurate. Only two tests failed, out of 60, thus the rate of success was 96.67%.

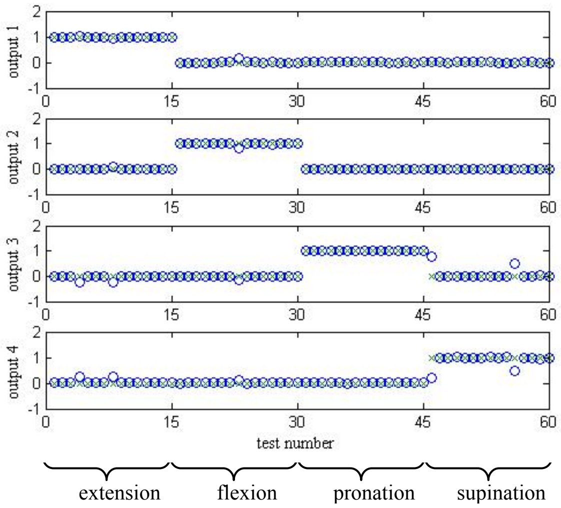


Figure 8. Neural network responses to 60 test movements

The results of the method presented are very encouraging; the neural network classifier proved to be suitable for the sets of patterns recorded from different subjects.

A reduced number of features presented as inputs to the classifier increased the rate of recognition from about 90%, when 60 inputs were used, to 96.67% when 10 inputs were used.

The initial work of Hudgins et al. [4] reported a performance of about 91%, when they used 30 features, acquired from one channel, as inputs for a neural network with one hidden layer. A comparison between feed-forward error backpropagation artificial neural networks (FEBANN) and wavelet neural network (WNN), used for EMG signals classification was made by Subasi et al.[7]. The overall accuracy obtained was 88% for FEBANN and 90% for WNN. Micera et al. [13] evaluated the performance of a variety of neural and fuzzy networks: self-organizing maps (SOM), fuzzy c-means (FCM), multilayer perceptrons (MLP), and Abe-Lan fuzzy network (ALFN) using small-sized training sets. The reported results were: 50% for SOM, 53.33% for FCM, 86.66% for MLP, and 93.33% for ALFN.

Due to the fact that the final intention of this study was to use the network as a classifier for a virtual prosthesis, the constraints related to the calculation speed and memory requirements can be easily obeyed, because both the virtual prosthesis and the control system are implemented on the same computer system.

V. VIRTUAL PROSTHESIS

The output of the neural network is used as input to the virtual prosthesis that can mimic a real one. The initial stages of learning to use a prosthetic device are very frustrating due to the unnatural way in which it is controlled. Therefore, it would be useful for a patient to use a virtual environment for training before deciding to acquire a real prosthesis.

This virtual environment brings benefits not only for the patient, but also for the physicians (prosthetic doctor, surgeon, neurologist, and orthopedist). The system can also be very useful for engineers to test prosthesis control systems.

Fig. 9 illustrates the architecture of the virtual environment, and Fig. 10 the virtual prosthesis.

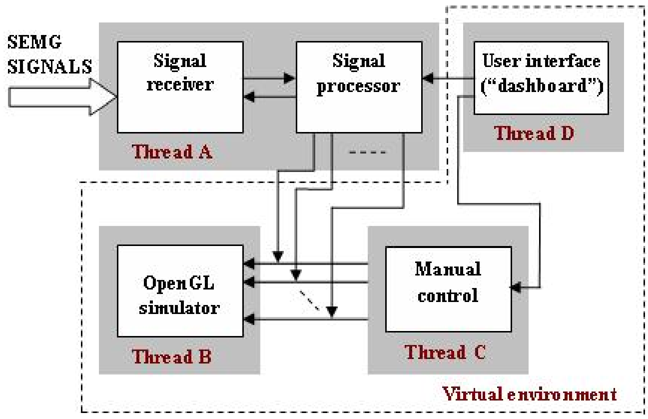


Figure 9. The architecture of the virtual environment

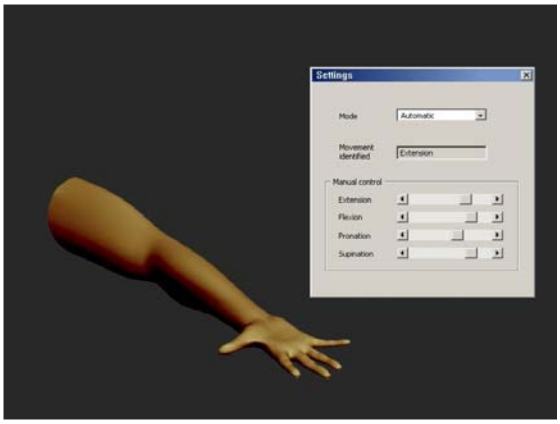


Figure 10. Virtual prosthesis

The application that simulates the whole process consists of 4 threads: *Thread A* for processing external inputs and transferring them to the application, *Thread B* for the actual simulation, *Thread C* to process the manual inputs and *Thread D* for the control panel.

Thread A contains two separate objects; one reads the SEMG signals from files and the other one processes and sends them as commands to the OpenGL simulator. The neural classifier is implemented in the signal processing object.

Thread C, the manual input controller, behaves as *Thread A,* only instead of external commands, it simply processes commands from a user interface (*Thread D*). It uses the same set of control signals towards the simulator as the signal processor in *Thread A*.

Thread D is responsible for controlling the "priority" of *Threads A* and *C*.

Thread B is controlled by the two interfaces (manual control and signal processor). It has a predefined set of commands ("channels") that can be used to move around the 3D model.

The user interface can be operated in two modes: *manual mode* when the movements are made using the slides from the settings window, or in *automatic mode*, when the commands come from the classifier, according to the architecture presented in Fig.9.

VI. Conclusion

This study presents an approach for SEMG signal classification and proposes a virtual prosthesis architecture.

A sufficient amount of data carefully recorded and a correct architecture for the FFNN represent the keys of a very good performance of the classifier. Even if a simple method is used, it was proven that good performance can be achieved when the mean value of each feature, calculated for five segments of 40 ms is used. Khezri and Jahed [14] reported the same performance of the classifier when they used a real-time pattern recognition algorithm for SEMG signals, based on adaptive neuro-fuzzy inference system (ANFIS), integrated with a real–time learning scheme to identify hand motion commands. Even if the results are the same, the amount of time required for training is quite large: 3 to 11 minutes in comparison with our approach when the training time is less then 1 minute. Better results can be obtained as Cui et al. [15] shown, when support vector machine is used in pattern recognition; unfortunately this will increase the computational time. There is a trade between the accuracy of the movement discrimination and the computational time required. Further work will be focused on reducing the computational time for classifier implementation into a real prosthesis. Another important issue will be analyzing SEMG signals in order to extract information regarding the force and the speed of the movement necessary for real prosthesis control.

Acknowledgment

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