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Processing surface electromyographical signals for myoelectric control

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1. Introduction

Myoelectric control is the most widely used approach for the control of upper limb prostheses (Ping et al., 2006); (Light et al., 2002); (Chan & Englehart, 2005). When used as control input, the myoelectric signal has dominated because it has several advantages over other input types. Among these advantages are 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 (Parker et al., 2006).

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, as Soares et al. (2003) mention, 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 were the sensor is applied, the surface of the skin and the tissues between de skin and the muscle (Soares et al., 2003) determine the complexity of the surface electromyographical (SEMG) 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 electromyographical signals used in myoelectric control. In this chapter few of them will be described and some results will be presented. The remainder of this chapter is organized as follows. Section 2 is dedicated to pattern-recognition based methods, different approaches are presented and two examples are given. Section 3, reviews few non-pattern recognition based methods. The chapter concludes with a comparison of the methods presented and with an outline of promising directions for future research.

2. Processing of surface electromiographical signal based on pattern recognition

2.1 Short description

The surface myoelectric signals provide rich information about the neuromuscular activity from which they originate and, as a consequence, about the intention to achieve a certain movement. The analysis of myoelectric signals has generated useful information used in clinical diagnosis, as well as in control systems for assistive devices.
The objective of SEMG analysis is to extract meaningful features from the SEMG signals, which can find their use in myoelectric control systems for rehabilitation devices or assistive robots.
The first investigator to study electromyographical (EMG) signals is considered H. Piper using a string galvanometer. The EMG signal began to be used in clinical diagnosis since 1928 and it was in the 1960s when a team of experts presented the first myoelectric prosthesis. Myoelectric control has seen an incremental evolution since then. Still, the complexity of the EMG signal represents the greatest challenge in its application.
There are two different classes of myoelectric control systems: pattern recognition based and non-pattern recognition based. In the former, classifiers are used for discriminating the desired classes from signal patterns. Non-pattern recognition based controllers are mainly constructed on finite state machines or threshold control. Over the last years, as classification algorithms have become more and more complex, the greatest success in myoelectric control has been realized by pattern recognition based control systems. The idea is to associate the different patterns found repeatedly in the EMG signal with the corresponding member movements.

2.2 Segmentation of data

As myoelectric based control systems must meet certain real-time requirements, segments are usually used in EMG analysis. A segment is a time section considered for analysis and feature extraction. Various windowing techniques can be used for these tasks, but all should respect the assumption that, considering real-time constraints, the response time of the control system should be equal or less than 300 ms (Oskoei & Hu, 2007)
There are two basic major windowing techniques used in data segmentation, the adjacent windowing and the overlapped windowing. The adjacent windowing technique uses custom length adjacent segments for analysis and feature extraction, as shown in Fig. 1.
Because of high-speed processors, usually, the processing time is less than the duration of each time segment, so, for each segment, there remains a certain amount of idle time. In the overlapping windowing technique, this idle time of the processor is used for acquiring more data to be processed. The technique is making full use of the processor, and each time segment slides over the one before, as Fig. 2 illustrates. The technique, applied by Englehart and Hudgins (2003) achieves the best performance using continuous segmentation and a segment length of 32 ms. Majority voting was also used as a post-processing method. For a given point majority voting includes a number of *k* last and next decisions to generate a new one based on the greatest number of occurrences. The computing time for making each decision should not be greater than the acceptable delay of the system.

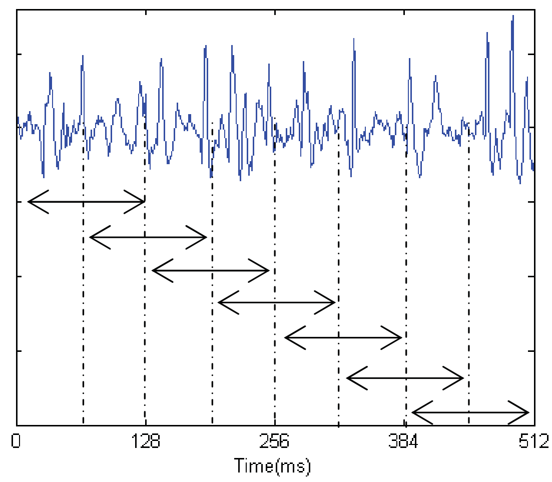

Fig. 1. Adjacent windowing technique

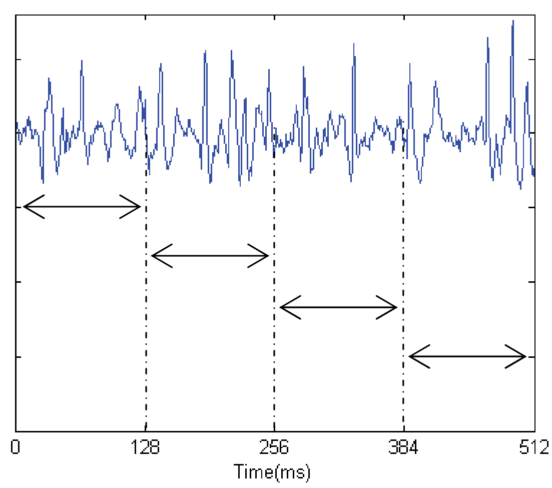

Fig. 2. Overlapped windowing technique

2.3 Feature extraction

The use of row myoelectric signal in a control system is impractical, especially due to the large number of inputs. Noise, randomness of the signal, and the large dimension of the input vector all become real problems in an EMG control system, especially when using embedded systems with limited resources. 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 vector. That is because their controllers must meet very strict real time constraints and the classifiers they implement perform much faster when handling small input vectors. Transformation of the initial input space into a more adequate one, by mapping each input vector into a smaller dimension feature vector, is called *feature extraction*. Over the years, feature extraction has been used in pattern recognition and image processing. Oskoei and Hu (2007) review various feature extraction methods used over the time in myoelectric control systems. Based on their classification time domain, frequency domain and time-scale domain features will be analyzed and compared in next section, with focus on using the results for creating a robust control scheme for myoelectric control.

2.3.1 Time domain features

The accessibility and the computational simplicity make time domain features the most popular tools for generating outputs for the myoelectric control system. They are based on time-amplitude representation of the signal, and can indicate measures like signal energy force and duration. Hudgins et al. (1993) and Herle et al. (2008) studied a set of five features and used the results for generating inputs for an neural network based classifier, to achieve a classification rate between 90 and 96.67%. The set they used contains five representative features for time domain representation:

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

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

where: $i = 1 \ldots I$ is the segment number; S is the number of samples for a segment and x_m is the m^{th} sample in the segment i. MAV usually provides a maximum estimation of amplitude when the signal is modeled as a Laplacian process, the alternative being Root Mean Square (RMS) (witch better estimates Gaussian processes). Farina and Merletti (2000) provided a comparative review of the two.

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

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

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

Zero Crossings is a measure of frequency which can be obtained by counting the number of times the waveform crosses zero. A threshold was included in order to reduce the noise-induced zero crossings. The zero crossing counter is incremented if the condition described by Eq. 3 is satisfied for two consecutive samples x_m and x_{m+1}.

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

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

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

Eq. 5 indicates a measure of the waveform amplitude, frequency and duration in a single parameter called waveform length:

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

where:

$$\Delta x_m = x_m - x_{m-1} \tag{6}$$

Time domain features are also used in combination with other techniques to produce a high classification rate. Chan and Englehart (2005) used the combination of autoregressive coefficients and RMS and obtained a classification rate about 94.6 %.

2.3.2 Frequency domain features

Up until now, we have discussed features extracted from time domain representation of signal. Another class of features, mostly used in fatigue study, are frequency domain features. The power spectrum of a signal represents the contribution of every frequency of the spectrum to the power of the overall signal. It is useful because many signal processing applications, such as noise cancellation and system identification, are based on frequency-specific modifications of signals. The frequency content of a stationary signal is derived from the Fourier transform of the signal, defined by

$$FT_x(f) = \int x(t) e^{-2\pi j f t} dt \tag{7}$$

$$X(t) = \int FT(f) e^{2\pi j f t} df \tag{8}$$

Spectral analysis is the process of identifying component frequencies in data. Power spectral density (PSD) is a positive real function of a frequency variable associated with a stationary stochastic process, or a deterministic function of time and plays a major role in spectral analysis. PSD describes how the power of a signal or time series is distributed with frequency and is defined as the Fourier transform of the autocorrelation function of a signal. The mean frequency and the median frequency are characteristic variables of PSD intensively used in EMG signal analysis, especially in fatigue, force and angle or torque studies (Gerdle & Karlsson, 1994). Peak frequency, mean power and total power are also spectral parameters used in EMG analysis. PSD estimation techniques can involve parametric or non-parametric approaches, and may be based on time-domain or frequency-domain analysis. For example, a common parametric technique involves fitting the observations to an autoregressive model. A common non-parametric technique is the periodogram. In the autoregressive method, the main problem is the determination of the model order. With the periodogram, other problems, such as large estimation variance and small frequency resolution, still remain a challenge. Also, with all PDS estimation methods we lose the information regarding the time at which each event took place.

2.3.3 Time-frequency features

The coefficients X(f) from the Fourier Transform denote the frequency domain distribution of a signal with no temporal resolution and, as a consequence, they do not reflect the transient proprieties of a signal. Time frequency representations (TFR) preserve information regarding both the time structure and frequency structure of a signal. They combine the above-mentioned methods of analysis to yield a clearer picture of a signal’s spectral characteristics at very precise temporal localizations. Image processing, speech recognition or geo-acoustic applications, all found the utility of TFR representations. TFR are divided in two groups: linear TFRs (Fourier and wavelet transform) and quadratic TFRs (Wigner-Ville distribution). As the extracted features are usually used in real time applications and the quadratic methods are based on complex, time consuming algorithms, in the next section we will concentrate on the former. The central concept of linear methods is that of decomposing a signal into time frequency atoms (Eq. 9):

$$x(t) = \sum_{i=1}^{N} c_i \beta_i(t) \tag{9}$$

where $\beta_i(t)$ are the so called basis functions and c_i the corresponding coefficients. The basis function must offer good time frequency localization and also, be computationally efficient. In the following section we will discuss three TFRs: the short time Fourier transform, the wavelet transform and the wavelet packet transform.

2.3.3.1 The Short Time Fourier Transform

The short time Fourier transform (STFT) is a two dimensional function of time and frequency. The central idea of STFT is to partition the time axis through a limited window, and assume that the signal is stationary over short periods of time. If $w(\tau\text{-}t)$ is the windowing function, the STFT equation is:

$$STFT(t,f) = \int x(\tau) w^*(\tau - t) e^{-2\pi j f \tau} d\tau \tag{10}$$

It is important to observe that the information provided by STFT is limited by the size of the analysis window. The choice of $w(t)$ is the main factor on which the time frequency resolution depends. It is important to know that the product between time and frequency resolution must be lower bounded by $1/4\pi$ according to the time-bandwidth uncertainty principle.

2.3.3.2 The Wavelet Transform

Wavelet theory was first described in the early 20th century. It occurred as the next logical step: a windowing technique with variable-sized regions. Wavelet analysis allows the use of long time intervals where we want more precise low-frequency information, and shorter regions where we want high-frequency information. Wavelet analysis reveal particularities of data that other signal analysis techniques miss, like discontinuities in higher derivatives, trends and breakdown points. Wavelet analysis can also compress or de-noise a signal without appreciable degradation.

The continuous wavelet transformation (WT) can be defined as:

$$CVT(a,t) = \frac{1}{\sqrt{a}} \int x(\tau) \psi^*\left(\frac{\tau - t}{a}\right) d\tau \tag{11}$$

and determines the correlation of the signal with a shifted and scaled mother wavelet. The term scale is preferred to the term frequency when using WT because time-scale view is a very natural way to view data deriving from a great number of natural phenomena. A high scale shows slowly changing features, with low frequency, and a low scale illustrates the high frequency details of a signal.

2.3.3.3 The Wavelet Packet Transform

The wavelet packet transformation (WPT) is a generalization of wavelet decomposition that offers a richer range of possibilities for adapted signal analysis. It uses a configurable tiling of the time-frequency space, so the partitioning of the axis may take many forms to suit the application. The main difference between STFT, WT and WPT is the manner in which they partition the time frequency or the time scale plane. A STFT use a plane composed of cells with identical aspect ratio in time and in frequency. A WT offers a variable tiling of time scale plane, as frequency resolution is proportional with the center frequency, allowing greater frequency resolution at lower frequencies and better time resolution at high frequencies.

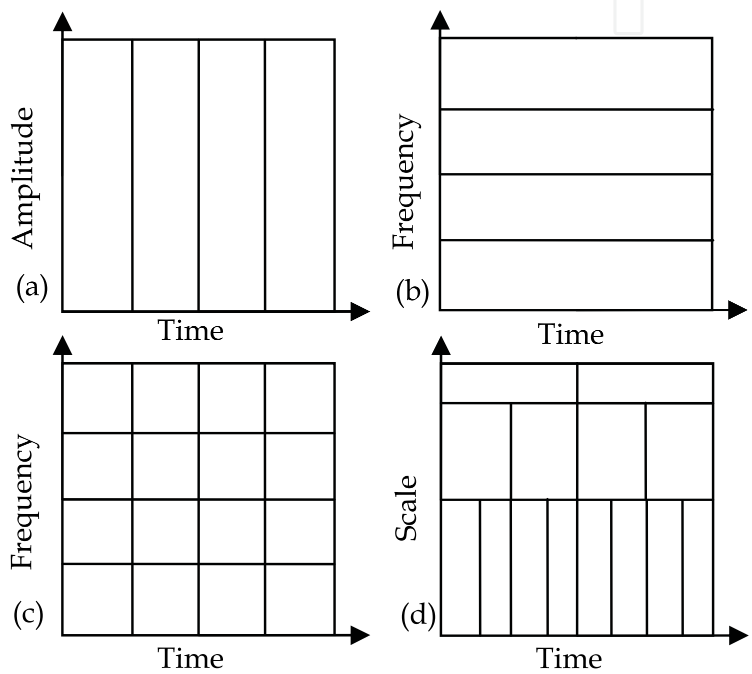

Fig. 3. Four partition methods: (a) Time domain (Shannon), (b) Frequency, Domain (Fourier), (c) STFT (Gabor), (d) Wavelet analysis

The arbitrary segmentation of the frequency axis is provided by WPT. This allows a selection procedure for providing the best set partition for a specific application.
Fig. 3 illustrates the way each technique partitions the corresponding representation plane.

2.3.4 Dimensionality reduction

The methods mentioned above transform the initial input space in a more adequate one, but not necessary in a smaller dimension. The dimensionality reduction's role is to retain the most important information for class discrimination and discard what is irrelevant for the purpose of classification. It is easier to analyze and build a classifier with fewer inputs. This information selection can be achieved by selecting an optimal feature set. Feature selection and feature projection are two fundamentally different approaches to determining the beast feature set.

Feature selection, also known as variable subset selection, is the technique of selecting a subset of relevant features according to some criterion. It requires a search strategy such as sequential forward or backward selection, simulated annealing or Genetic algorithms.
Feature projection methods try to achieve minimal loss of information while describing the data as concisely as possible. Principal component analysis (PCA) and linear discriminate analysis techniques are two of the mapping functions used for feature projection. For instance, PCA will generate components ranked according to the information they contribute to the data, in a mean square error sense. Different feature projection techniques can also be used together for obtaining better results. K. Englehart et al. (1999), investigated feature projection techniques in time-frequency features and achieved the highest classification rate using the WTP/PCA/LDA combination. Also a self-organizing feature map was used in addition to PCA by Chu et al. (2005), leading to significant improvements.

2.4 Classification

As Fig. 4 illustrates, the classification of EMG signal is a multi stage process, and the actual classification algorithm is only the last of the stages. As already seen, signal representation, achieved by feature extraction, and 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.

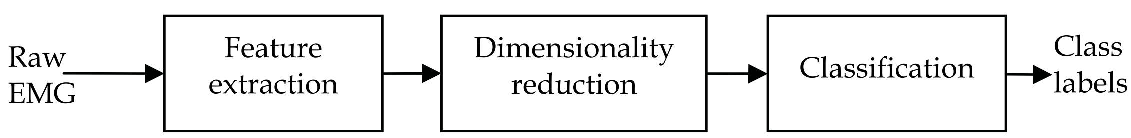

Fig. 4. The stages of the classification problem

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.

2.4.1 Neural networks based classifiers

Neural networks are structures composed of elements inspired by biological nervous systems. As in nature, the connections between elements largely determine the network function. In the last decade, NNs have been intensively used for modelling linear and non linear relationships from a finite number of samples. Once the model is obtained from the training data, it can be used to predict the output values corresponding to the input vector. One of the main advantages in using NNs is that they require no a prior information about the process, and still yield high classification rates.
For example, Soares et al. (2003), have used a multi-layer perceptron (MLP) in combination with an AR technique for feature extraction, and have obtained a very high rate of success. Kuruganti et al. (1995) used two channels with five time domain features per channel to classify four functions with an NN classifier and 90% classification. Chaiyaratana et al. (1996) have used two different types of radial basis function NN. Also, Englehart et al. (1999) used a combination of time scale features, principal component analysis and a MLP classifier to obtain a high rate of success (over 90%). Also time-delayed artificial neural network had been used by Au and Kirsch (2000) in combination with time domain features.

2.4.1.1 Multi-layer perceptron

Multi-layer perceptron is the most commonly used NN architecture for pattern classification.
MLP is composed of neurons or nodes, which usually employ a sigmoid nonlinearity or a linear function. Fig. 5 illustrates the architecture of a typical MLP network:

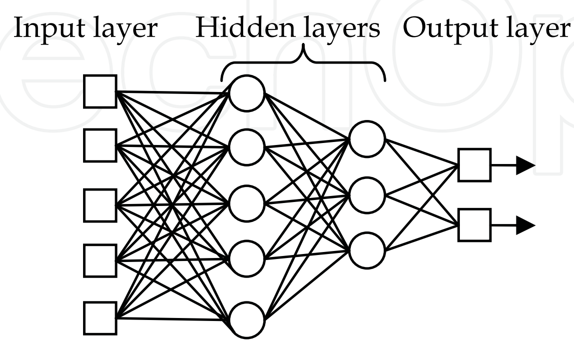

Fig. 5. MLP network architecture

Its fundamental computational unit is the perceptron. Its role is to form a weighted sum of the components of the input vector and to add a bias value. The result is then passed through nonlinearity as *logistic sigmoid* or *hyperbolic tangent sigmoid.*
In the training process, the network weights are adapted so as to provide suitable mapping of input vectors in a set of desired responses. The most used training algorithm for MLP is the backpropagation algorithm. It is a stochastic approximation of the steepest descent algorithm, in which the network weights are moved along the negative of the gradient of the performance function. The process of computing the gradient and adjusting the weights is usually stopped when a certain stopping criteria is achieved. A minimum value of the magnitude of the gradient, or of the sum squared error is common stopping criterions.
The input vector feeds into the first layer and each node of the output layer corresponds to a class in a pattern recognition problem The MLP architecture may contain multiple hidden layers, but according to Haykin (1998), given sufficient neurons, a single hidden layer is enough to approximate arbitrary functions.
Karlik et al. (1994), Ito et al. (1991) and Kelly et al. (1990) published early studies on using MLP as a myoelectric classifier. Recently, Zhao et al. obtained an accuracy of 95% by applying MLP to recognize six motion patterns.

2.4.2 Fuzzy classifiers

Fuzzy logic approaches exploit the partial truth and uncertainty, which make them popular in bio-signal classification and processing. Fuzzy logic systems can discover patterns difficult to detect, and can tolerate contradictions in data. One can also create a fuzzy system to match any set of input-output data. The values detected by the EMG sensors are transformed by the fuzzyfier into linguistic variables, that is, variables whose values are words rather than numbers.
In (Micera et al., 2000) authors evaluated the performance of a variety of neural and fuzzy classifiers: self-organizing maps (SOM), fuzzy c-means (FCM), multi-layer 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. Also, in (Leowinata et al.,1998) a fuzzy logic classifier was used on data collected from an array of electrodes, and in (Weir et al., 2003), authors also proposed a fuzzy logic based prosthesis controller.

2.4.3 Neuro-fuzzy classifiers

Neuro-fuzzy is a way to exploit the advantages of both techniques by combining fuzzy logic and neural networks. Neuro-fuzzy techniques have been widely used for data analysis and decision-making (Nauck & Kruse, 1997). A neuro-fuzzy system can be viewed as a feed forward neural network where the first layer represents input variables, the middle (hidden) layer represents fuzzy rules and the third layer represents output variables (Nauck et al., 1997). Neuro-adaptive learning techniques provide a method for the fuzzy modeling procedure to learn information about a data set. Fig. 6 presents a typical structure of a neuro-fuzzy system.

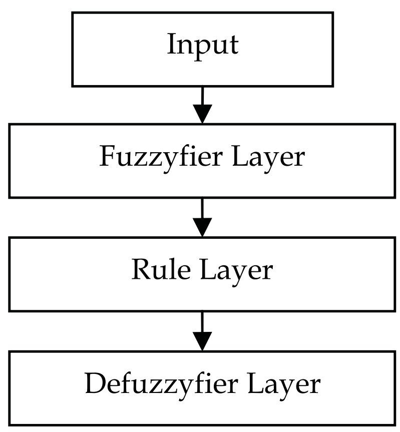

Fig. 6. Structure of a neuro-fuzzy system

(Hussein & Granat., 2002) uses a neuro-fuzzy inference system (ANFIS) on atoms obtained with the Gabor matching pursuit algorithm. He used a generalized bell function (Eq. 12) as the membership function for the Sugeno type fuzzy classifier and the least-squares error Eq. 13 as a cost function for adjusting the coefficients.

$$\mu(x) = \frac{1}{1 + \left|\frac{x - c}{a}\right|^{2b}} \tag{12}$$

$$\varepsilon(n) = \frac{1}{2}\sum_{i=1}^{N} e_i(n)^2, \; e_i(n) = d_i(n) - y_i(n) \tag{13}$$

Where $d_i(n)$ is the desired output and $y_i(n)$ is the actual output of the network. He obtained a 95% rate of classification.

In (Karlik et al., 2003), authors presented a comparative study of the classification accuracy of myoelectric signals using three classifiers: MLP NN, conic section function NN and fuzzy clustering NN. They obtained the highest classification rate (98.3%) with the fuzzy clustering NN. A 6 class motion recognition system was proposed in (Kiguchi et al., 2003), applied on time features extracted from 11 channels data, based on a neuro-fuzzy classifier.

2.5 Examples

The next section will present the development of two multifunction myoelectric classifiers. Different types of features and different classifier schemes will be used.

2.5.1 Example 1

The first example will describe a myoelectric classifier based on a multi-layer perceptron. The inputs provided to the network are the autoregressive coefficients. The classification performance of the feature sets was investigated for four classes of movement. The system architecture is presented in Fig. 7.

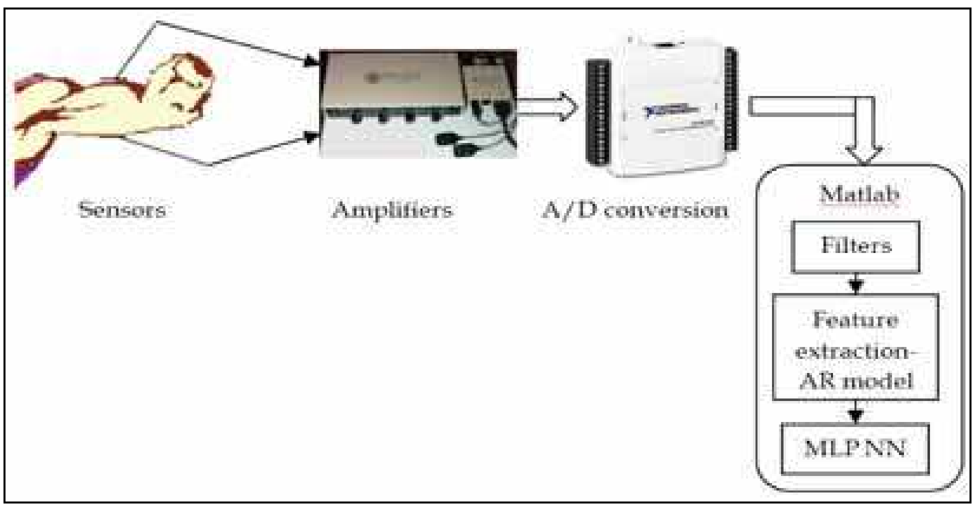

Fig. 7. System architecture based on neural network classifier

Bagnoli 4 system from Delsys Inc. was used for data acquisition, in combination with NI USB-6009 AD card from NATIONAL INSTRUMENTS, The system offers a gain factor between 0 and 10000 and a bandwidth of 20-450 Hz ±10%.

The signals were acquired from the biceps ant the triceps muscles using two differential sensors and a amplification of 1000. Adjacent segments with lengths of 256 samples each were processed. The forearm movements were detected using a goniometer, like the one in Fig. 8 and each class of movement have been associated with a correspondent segment of the myoelectric signal.

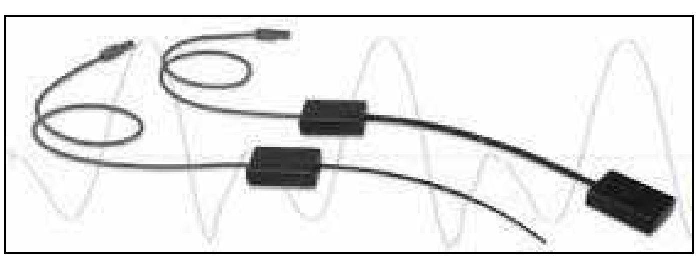

Fig. 8. The goniometer

As the power spectrum of the signal is concentrated in the 20-500Hz range (Soares et al. 2003), first step in signal processing is applying a Butterworth band-pass filter with cut-off frequencies of 20 Hz (low) and 450 Hz (high).
Soares et al. (2003) had shown the fact that AR modeling of the EMG signal offers very good performance in MES classification. It also leads to a small dimension feature vector and therefore to a reduced processing time.
Autoregressive model is commonly used to parameterize linear systems. AR model attempt to predict an output $\overline{x(n)}$ of a system based on the previous outputs (*x(n-1), x(n-2),…)*. AR model is based on the Eq. 14:

$$\overline{x(n)} = \sum_{i=1}^{M} a_i x(n-i) + e(n), n = 0..N-1 \tag{14}$$

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 $\overline{x(n)}$, the samples of the modeled signal. AR methods are widely used for spectral estimation, as they are determined by considering x(n) as the output of a system characterized by the transfer function Eq. 15:

$$G(f) = \frac{1}{1 + \sum_{i=1}^{N} a_i e^{-2\pi jft}} \tag{15}$$

with Gaussian noise used as input.
The power spectral density of $x(n)$ can, therefore, be expressed as Eq. 16 illustrates. The estimation of power spectrum consists of the AR parameters determination according to a proper algorithm.

$$P_{xx} = \sigma_w{}^2 G(f)^2 \tag{16}$$

Studies have shown that an AR model of a sufficiently large, but finite order *M,* might approximate, with a specified degree of accuracy, any model (Hefftner et al., 1988). In calculating the AR coefficients we followed the steps suggested in (Akay, 1996) :

- initialize the filter coefficients.
- calculate the predicted value of the input signal

$$\overline{x(n)} = \sum_{i=1}^{M} a_i x(n-i) \tag{17}$$

estimate the prediction error

$$e(n) = x(n) - \overline{x(n)} \tag{18}$$

update the AR-coefficients using the constant of convergence μ

$$a_i(n+1) = a_i(n) - 2\mu e(n) x(n-i) \tag{19}$$

An ideal value for the constant of convergence cannot be found, and it is not practical to look for a specific value of μ for every single EMG signal to be processed. Based on multiple tries, we used μ=0.01, as it provided the best approximation for most of the signals used.
Farina and Merletti (2000) showed that a model of order 10 works appropriately for any segment length. Soares et al. (2003), concluded that a fourth order model can adequately represent the EMG signal. We searched a best approximation in models with orders between 4 and 10. As the results didn't show improvements when using a higher model order, order 4 was the choice for calculating the AR coefficients.
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.

2.5.2 Example 2

Herle et al. (2008) presented the architecture of a rehabilitation system able to assist the patient. They used a neural network classifier to classify time domain features. Four motions of the forearm: extension, flexion, pronation and supination were controlled using a feed-forward neural network (FFNN) based classifier.
Feeding the SEMG signal as a time sequence, directly into the classifier, is not a feasible approach, because of the complexity of SEMG signal, 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 in order to reduce the delay between signal detection moment and the effective actuation of the device. One solution is to map the initial sequence into a smaller dimension vector, called the feature vector.
Over the years many features were suggested for myoelectric classification. The amplitude of a SEMG signal and its related features are often investigated in time-domain analysis. Time-domain features are the most popular in myoelectric classification due to their computational simplicity.
Features were extracted from a window of two hundred samples (200 ms) of the SEMG signal, even if the length of the recorded signal was one second. The 200 ms window was empirically selected. It is better to use, however, first 200 ms after onset moment. The two hundred samples were divided into five segments, each one having a length of 40, as Figure 9 show. 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) (Hudgins et al., 1993).

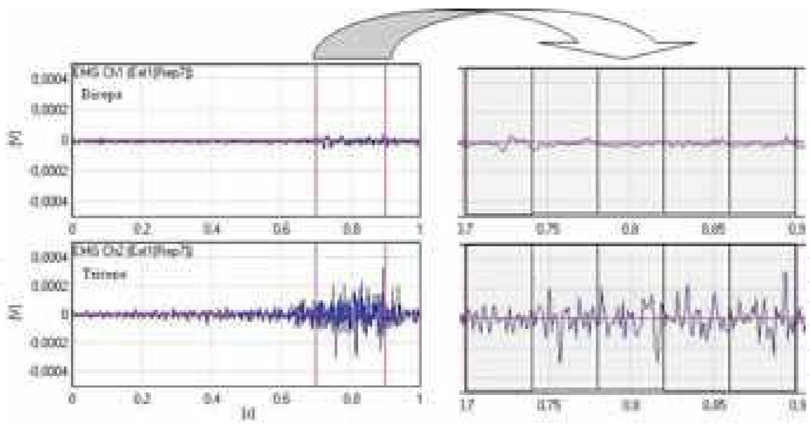

Fig. 9. Waveform segmentation. a) The SEMG signal from biceps (up) and triceps (down) during 1 second. b) Five segments of 40 ms used for feature extraction (Herle et al., 2008)

Subasi et al. (2006) used an extra segment beside the five segments. The features for the sixth segment were calculated as the arithmetic mean of the values computed for the first five segments.

A set of 60 features (5 features/segment x 6 segments x 2 channels) were computed for each movement (Herle et al., 2008). Using the 60 features as inputs for the neural network classifier conducted to a rate of discrimination around 90%. Previous studies showed that by reducing the set of features and choosing the best features according to some criteria, the classifier performance can be improved. The classifier architecture was modified using a neural network with ten neurons on the input layer, two hidden layers each one having ten neurons, and one output layer with four neurons. The transfer function of the hidden layers was a sigmoid and that of the output layer was linear. After the training session, the classifier was tested with features extracted from signals that never been used. The meaning of the outputs' values, used to discriminate among the four motions is presented in Table 1. Figure 10 illustrate the classifier performances.

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

Table 1. Codification of the four movements

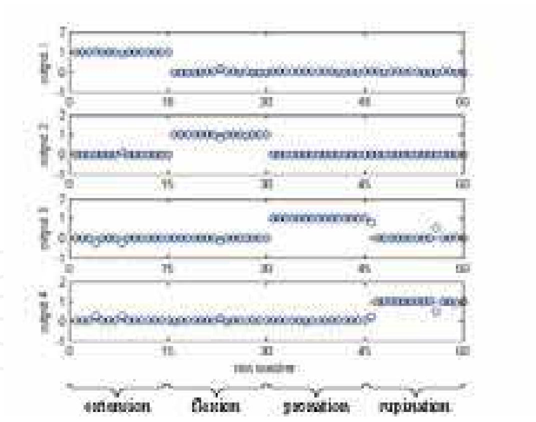

Fig. 10. Classifier responses to 60 test movements (Herle et al., 2008)

The rate of recognition increased from about 90%, when 60 inputs were used, to 96.67% when 10 inputs were used.
This example show that a satisfactory rate of discrimination can be achieved using an easy to implement classifier. The main disadvantage of this approach is the computational time required by the classifier.
Actually there is a trade between the computational time and the performance of the classifier.

3. Processing of surface electromyographical signals using non-pattern recognition based methods

Non-pattern recognition-based methods can be applied in myoelectric control. These methods are used in rehabilitation field for specific applications like wheelchair control (Moon et al., 2005); (Felzer & Freisleben, 2002), upper and lower limb prosthesis control, etc. Different types of control systems can be implemented based on these methods. Thus proportional control, threshold control, onset analysis and finite state machines are approaches included in the category of non-pattern recognition based methods. These approaches will be presented in the remaining of this section. The main drawback of these methods is the limited number of functions that can be implemented, comparing with the pattern-recognition based methods. In some cases non-pattern recognition based methods are combined with pattern-recognition based methods, resulting in a more efficient method in terms of computational power and time required.

3.1 Proportional control

In proportional control, the level of contraction of a muscle is used to control the speed or force of a prosthetic limb. Due to the complexity of SEMG signal it is mandatory to preprocess the signal acquired by sensors before using it as input for the proportional controller. Proportional control is usually used in conjunction with other non-pattern recognition-based method or pattern recognition-based method. This combination will increase the accuracy of positioning and force level.

3.2 Threshold control

Like proportional control, threshold control can be used in conjunction with other pattern recognition-based methods. In threshold control a signal level is used to discriminate between two states. For example if the amplitude of the EMG signal is over a threshold, a given action will take place, based on the command generated. Figure 11 illustrates this mechanism. This type of control is suitable only for discrete actions like *"open hand"* or *"close hand"*.

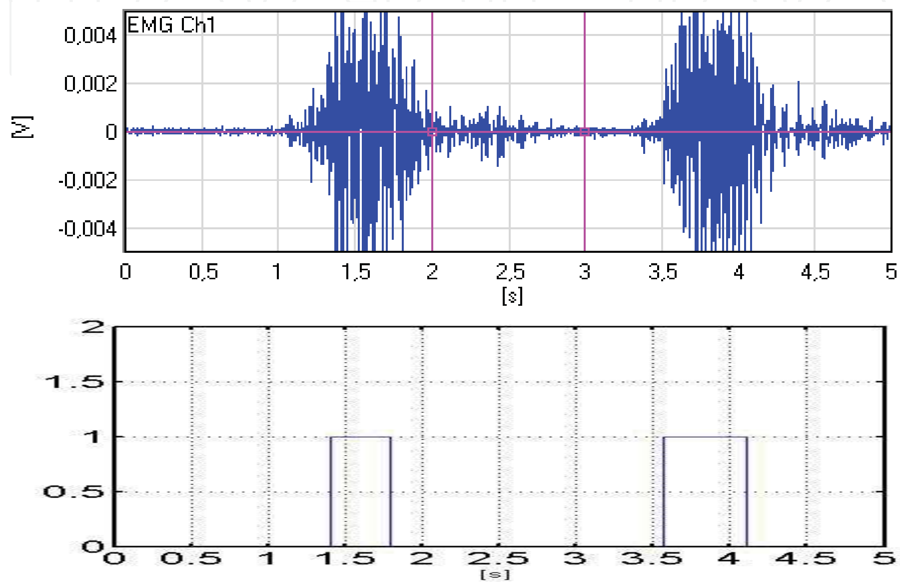

Fig. 11. Threshold control command generated

3.3 Onset analysis

Due to the complexity of the SEMG signal, it is better to use some characteristics of it. Using temporal characteristics like *onset time* and *offset time*, muscle activation and deactivation can be detected. A controller structure based on onset analysis is illustrated in Figure 12. Onset detection can be obtained using different methods. The performance of these methods is evaluated in terms of bias and variance of estimated onset time. Also, the sensitivity to the signal-to-noise ratio (SNR) is a measure of detection quality.

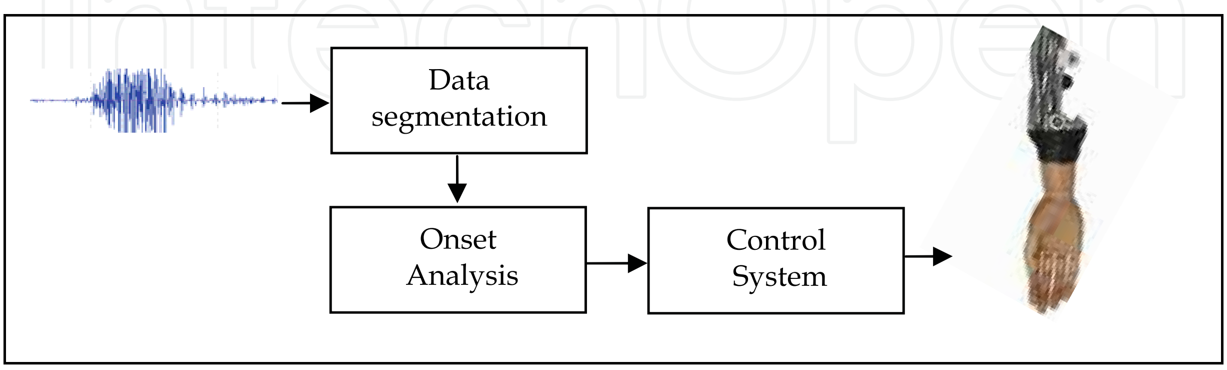

Fig. 12. Onset analysis based myoelectric control system

Single-threshold and double-threshold are the most used methods. In single-threshold method rectified raw signals are compared with some thresholds. These thresholds are obtained based on the mean power of background noise. This method is simple and very fast, but its main drawback is related to the excessive sensitivity to the SNR. In order to overcome this disadvantage the following improvement is possible.
Instead of using instant values of the SEMG signal, a time enveloped signal is used. This improved single-threshold method can be implemented using the Marpel-Hovart and Gilbey algorithm (Sun et al., 2005). In this algorithm two adjacent windows called leading and trailing windows are used to slide over a sequence of data. The lengths of the two windows are the same. For the leading window, the mean absolute value of the signal is computed and compared with the signal in the trial window. Accordingly with the hypothesis that the maximum differences of the two mean absolute value, computed for leading and trailing window, occur when one window contains a muscle contraction and the other doesn't, onset and offset time can be determined.
Another approach was presented by Sun et al. (2005). They use a maximum value detection algorithm, assuming that a muscle is in contraction if the signal acquired show a peak value greater than a given threshold, within a segment of acquired signal. The segment length depends on the EMG sensors and on the tissue. Even this improved method has some disadvantages. It is possible that noise signals to be interpreted as correct signals.
Bonato et al. (1998) reported an improved method used for gait analysis. The double-threshold method based detector operates directly on the raw myoelectric signal. Its performances are fixed by the values of 3 parameters, namely, false-alarm probability, detection probability, and time resolution. The false alarm probability represents the probability that a noise sample to be wrong interpreted as a signal. The detection probability represents the probability that a noises affected signals to be correctly recognized. The time resolution parameter characterizes the length of the observation window. The improvement of this double-threshold method is represented by the possibility to independently adjust the three above parameters.
Another way to improve onset time detection is to use sensor fusion as in section 2 was presented. We used a goniometer mounted at the elbow joint and synchronized the signal detected by this with the signal detected by the EMG sensors mounted on the biceps and triceps in a flexion extension movement. Thus onset time can be detected with very little computation and very fast.

3.4 Finite state machine based control

In finite state machine based control, finite number of states, transition between them, and commands describe the control. The states, state transition roles and the output commands have to be defined. In the case of upper limb prosthesis, the states often represent predefined motion commands like *open, close, rotate inside, and rotate outside.* Transition roles are usually associated with the signal features. The block diagram of a myoelectric controller based on finite state machines is shown in Figure 13.

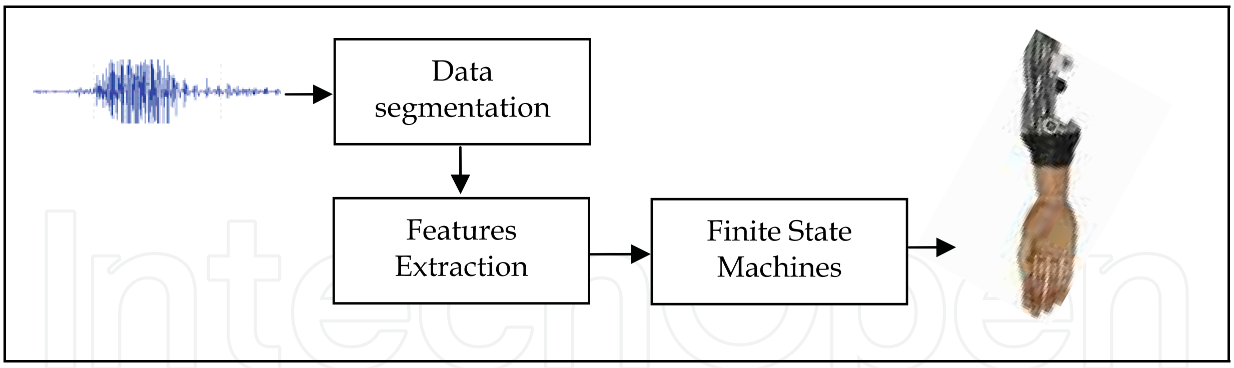

Fig. 13. Finite state machine based control architecture

Finite state machine based myoelectric control was applied by many researchers to drive rehabilitation devices like wheelchair (Felzer & Freisleben, 2002); (Moon et al., 2005), upper and lower limb prosthesis, assistance robots (Zhang et al., 2008), etc. The results reported by Felzer and Freisleben (2002), Moon et al. (2005) show that this method is still limited for wheelchair control. They reported an increase of necessary time to control the wheelchair by 50%, comparing with the case when a joystick was used to drive.

Based on the idea proposed by Moon et al., we developed a myoelectrical control system used to control for motions of a prosthetic hand. The motions controlled are: *open hand, close hand, rotate inside,* and *rotate outside.* Two EMG sensors, placed over the biceps and triceps are used to detect the intention of movement. The biceps sensor commands two motions *close hand* and *rotate inside*, and the triceps sensor commands *open hand* and *rotate outside* motions. Because each sensor commands two movements, it is necessary to discriminate between these movements. Therefore two modes are used. In mode 1 *open* and *close* motion are executed. In mode 2, *rotate inside* and *rotate outside* motions are executed. In order to switch between the two modes, both sensors have to be activated simultaneously, which correspond to a simultaneous contraction of biceps and triceps.

Figure 14 illustrate the state transition diagram that describes the controller functions, where *b* stands for biceps and *t* for triceps.

The indicator *1* codes the presence of a contraction, and *0* its absence.

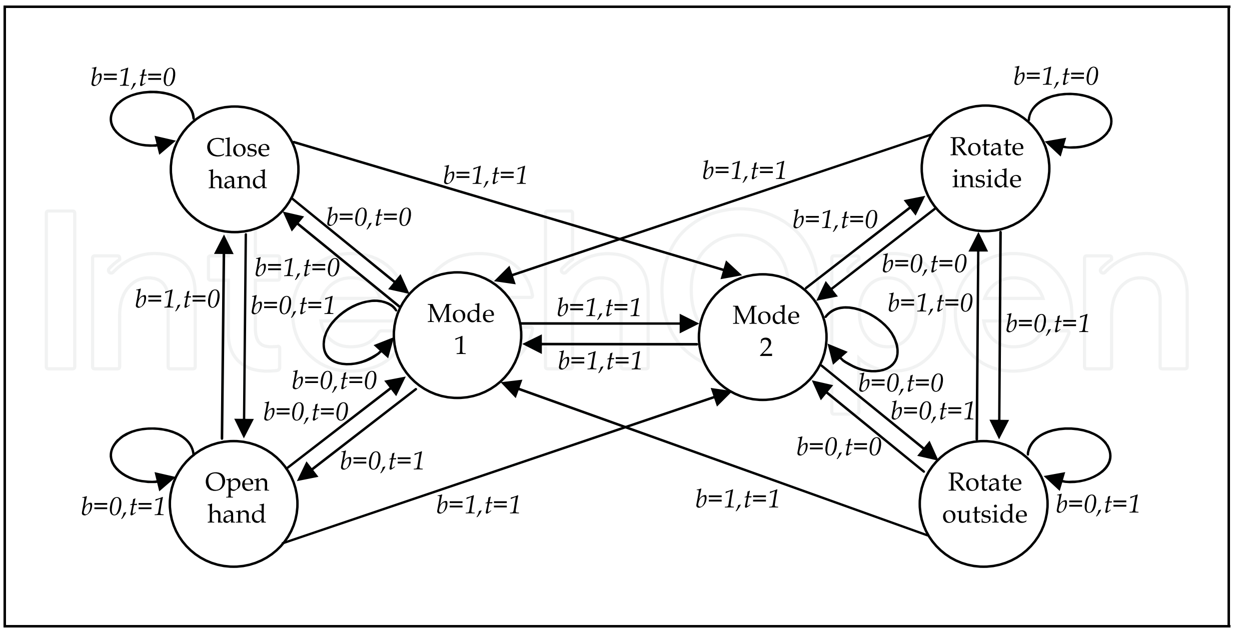

Fig. 14. Finite state machine control architecture for a prosthetic hand

4. Conclusions

As has been mentioned SEMG signals can not 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. For example, time-frequency features yield better results when using a linear discriminant analysis classifier, and time-domain features lead to better results when using neural network based classifiers.

Even a lot of work has been done on this challenging field, still remains problems that must be overcome.

One drawback of myoelectric control is related to its open loop architecture. It is known that open-loop control systems are not so reliable, comparing with close-loop ones. More over open loop myoelectrical control systems requires a great mental effort, especially during the first months after fitting.

In order to reduce this effort hybrid controllers are more suitable. These types of controllers combine myoelectrical control with classical closed loop control. 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. Combining information from different type of sensors like SEMG sensors, force sensors, goniometers, pressure sensors, or other feedback elements, better closed loop controllers could be implemented.

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Population ageing has major consequences and implications in all areas of our daily life as well as other important aspects, such as economic growth, savings, investment and consumption, labour markets, pensions, property and care from one generation to another. Additionally, health and related care, family composition and life-style, housing and migration are also affected. Given the rapid increase in the aging of the population and the further increase that is expected in the coming years, an important problem that has to be faced is the corresponding increase in chronic illness, disabilities, and loss of functional independence endemic to the elderly (WHO 2008). For this reason, novel methods of rehabilitation and care management are urgently needed. This book covers many rehabilitation support systems and robots developed for upper limbs, lower limbs as well as visually impaired condition. Other than upper limbs, the lower limb research works are also discussed like motorized foot rest for electric powered wheelchair and standing assistance device.