Myoelectric Control Strategies for a Human Upper Limb Prosthesis

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Abstract: Myolectric control is nowadays the most used approach for electrically-powered upper limb prostheses. The myoelectric controllers use electromyographic (EMG) signals as inputs. These signals, collected from the surface of the skin, have to be preprocessed before being used as inputs for the controller. In this paper we present a classifier for surface electromyographical signals based on an autoregressive (AR) model representation and a neural network, and two myoelectric control strategies based on Finite State Machine. The results have shown that combining a low-order AR model with a feed-forward neural network, a rate of classification ranging from 91% to 98% can be achieved, while keeping the computational cost low. One of the main advantages of the proposed strategy is the reduced effort required to the patient for controlling the prosthetic device.

Keywords: EMG signal, myoelectric control, finite state machine, neural network, autoregressive model

1. INTRODUCTION

The noninvasive detection of the signal on skin surface, with no need of surgery for the patient, and the relatively small muscle activity required to provide control signals are benefits that make myoelectric control the most widely used approach for the control of upper limb prostheses (Huang et al.,2005), (Ping et al., 2006), (Chan et al., 2005), (Light et al., 2002). In order to detect the movement intention of the patient, many devices can be used such as: surface electromyographic (SEMG) sensors, cortical and peripheral nerve implants, implantable myoelectric sensors, etc. The easiest way to detect the movement intention is to use SEMG sensors.

Although the myoelectric prosthesis uses biological signals to control its movements, a great mental effort is required especially during the first months after fitting (Soares et al., 2002). This happens because the prosthesis control is very unnatural; signals collected from a reduced number of muscles are used to activate movements that are normally controlled by other nervous signals. Moreover, the effort required to control myoelectric prostheses increases with the level of amputation.

We propose two myoelectric control strategies capable of reducing the required effort. Our control strategies are based on a hierarchical controller. The higher level of the controller, implemented using Finite State Machine, is presented in this paper.

In the case of the first control strategy four elementary motions of the prosthesis: *open hand*, *close hand*, *rotate inside* and *rotate* outside, can be initiated directly by the patient using SEMG signals collected from sensors mounted on *extensor communis digitorum* and *flexor carpi radialis* muscles.

In the case of the second control strategy six motions of the prosthesis: *lower arm flexion*, *lower arm extension*, *rotate hand inside*, *rotate hand outside*, *close hand*, and *open hand,* can be initiated by the patient using SEMG signals collected from *biceps*, *triceps* and *pectoralis major* muscles.

The first control strategy can be used for patients with an amputation at wrist level and the second control strategy for patients with an amputation at the lower arm level. For both strategies the lower level of the controller finalizes these motions using a local closed loop. Since the patient must only initiate a movement, the effort required to control the prosthesis will decrease. As the following sections will show, the proposed strategies can be applied to patients with a reduced muscular activity.

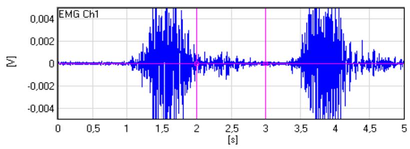
In designing myoelectric controllers, two main approaches are used: the non-pattern recognition- and the pattern-recognition based approach (Oskoei et al., 2007).

In the category of non-pattern recognition-based methods are included, among others, proportional control (Parker et al.,2006), finite state machines (Moon et al., 2005), (Felzer et al., 2002), or threshold control (Sun et al., 2005).

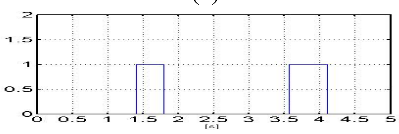
Proportional control uses the level of contraction of a muscle to alter the speed or force of a prosthetic limb. Due to the complexity of SEMG signal it is mandatory to preprocess the signal acquired by sensors before using it as input for the proportional controller. Even if it is easy to implement, it requires a great effort for the patient to permanently control the prosthesis. Therefore, this type of control is not suitable for patient with low muscular activity. Proportional control is typically used in conjunction with other non-pattern recognition-based or pattern recognition-based methods to increase the accuracy of positioning.

Finite State Machine-based myoelectric control was applied by many researchers to drive rehabilitation devices like wheelchairs (Moon et al., 2005), (Felzer et al., 2002), upper and lower limb prostheses, assistance robots (Zhang et al., 2009), etc. Using the finite state machine method, the controller is described by a finite number of pre-defined states, transitions between them, and commands. The main drawback of this approach is the reduced number of actions that can be implemented. However, the reduced number of motions performed by upper-limb prosthesis makes this approach suitable for implementation.

In threshold control, a signal level is used to discriminate between two states. If the amplitude of the surface EMG signal is over a threshold, a command will be generated. Fig. 1 illustrates this mechanism.



(a)



(b)

Fig. 1. (a) SEMG signal recorded,
(b) Threshold control command generated

The performance of this type of controller can be affected by many factors like the characteristics of the acquisition system used to detect and process the electromyographic signals, the anatomical and physiological properties of muscles, the position of the sensors on the skin and the muscle fatigue (De Luca, 1997) etc.

The classification of EMG signals is a very important problem to be addressed for any myoelectric controller. It has the role of achieving a certain class label for each input (e.g. flexion, extension, etc.). Many classification algorithms based on pattern-recognition methods were proposed in recent years. The greatest success in myoelectric control has been realized by pattern recognition based controllers using neural networks (NN) (Engelhart et al., 1999), fuzzy logic (Micera et al, 2000) and neural-fuzzy systems (Karlik et al.,2003).

Because the real-time constraints are an important issue, there is a trade-off between the robustness, required time for classification and the computational power required.

The remainder of this paper is organized as follows. Section 2 describes the architecture and the functionality of the control system proposed. The data acquisition system and the procedures used to acquire the surface EMG signals are presented in Section 3. The implemented classifiers used in our control architectures are presented in Section 4. Section 5 will present the high-level controller's architectures. The performance of our approaches is analyzed in Section 6, and the final conclusions are presented in Section 7.

2. THE ARCHITECTURE OF THE MYOELECTRIC CONTROLLER

Our control strategies are implemented using the myoelectric control system architecture presented in Fig.2.

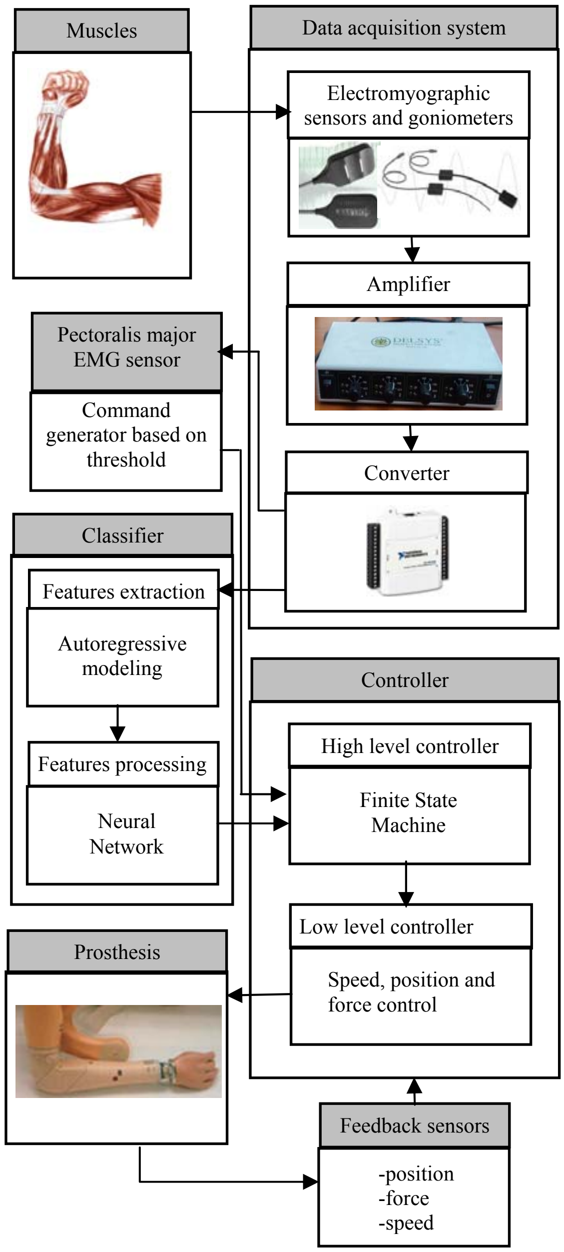


Fig. 2. Myoelectric control system architecture

The data acquisition system comprises SEMG sensors, an amplifier and a converter. The SEMG signals are collected using single differential SEMG sensors. The signals are amplified, filtered and converted from analog to digital.

Because of the complexity of SEMG signal, it is not feasible to identify a movement directly from the acquired signal. Therefore, first a dimensionality reduction has to be applied, using the feature extraction module of the classifier. The purpose of this module is to extract a set of features characterizing the signal. They are further used as inputs for the feature processing module that will discriminate four classes of signals. A detailed description of these classes will be presented in Section 4.

In the case of the first control strategy the four outputs of the classification block are applied to the high level module of the controller. In the case of the second strategy additionally to the four outputs of the classification block, an output from the pectoralis major muscle is applied to the high level module of the controller. Then, the high level controller computes commands for the low level controller. The low level controller will control according with the patient intention, the movements of the prosthesis device using a closed loop control scheme.

3. DATA ACQUISITION SYSTEM

Fig. 3 illustrates the components of the Bagnoli 4 data acquisition system (www.delsys.com) used in our work.

Fig. 3. Bagnoli 4 acquisition system for SEMG signals:
-top right: the main amplifier; -bottom left; the input module;
-top left: the converter.

The amplifier unit (Fig. 3, top right) has a gain factor adjustable from 0 to 10000 and a bandwidth between 20 and 450 Hz ±10%. The single-differential SEMG sensors, illustrated in Fig.4, were connected to the amplifier using an input module (Figure 3, bottom left) which is an interface between sensors and the amplifier. The amplified signals are fielded into the converter represented by a NI USB-6009 DAQ card (Figure 3, top left) from NATIONAL INSTRUMENTS. The DAQ was set to use a 1000 Hz sampling frequency.

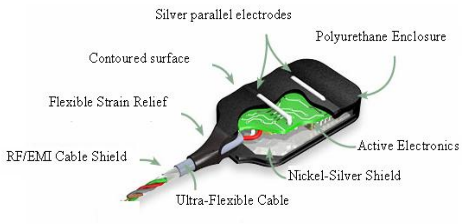


Fig. 4 Single-differential SEMG sensor

Due to the small amplitude of the SEMG signal (μV to mV), the acquired signal is affected by noise. In order to increase as much as possible the accuracy of the signals acquired the noise was carefully considered. A 2nd order notch filter was implemented for suppressing the 50 Hz frequency noise generated by the main line. The distance between the electrodes can also affect the quality of the signal detected (Merletti et al., 2004). To eliminate this problem, the sensors' manufacturer used a fixed distance of 10 mm between electrodes. The SEMG signals were amplified by a factor of 1000.

3.1 The SEMG signal acquisition for the first control strategy

The positions of the sensors on the upper limb are illustrated in Fig. 5 and Fig. 6.

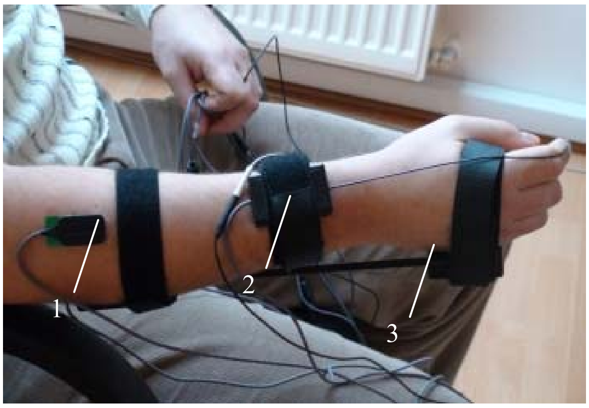


Fig. 5. Position of the sensors (outside view of the forearm): 1- SEMG sensor 1, 2-small goniometer, 3-large goniometer.

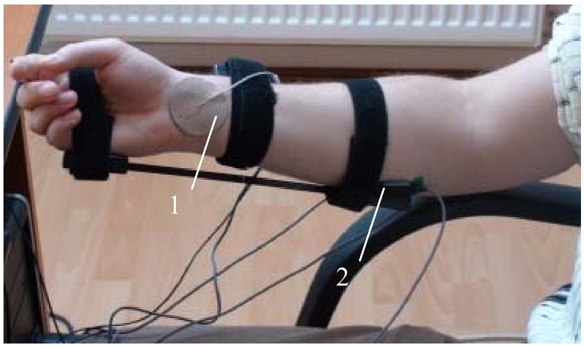


Fig. 6. Position of the sensors (inside view of the forearm): 1- reference electrode , 2- SEMG sensor 2

One SEMG sensor was placed at a distance of 40 mm from the elbow, on the external side of the forearm (Fig. 5) in order to detect myoelectrical signal from *extensor communis digitorum*. The second SEMG sensor was positioned on the internal face of the forearm at a distance of 70 mm from the elbow (Fig. 6) and was used to collect signal from *flexor carpi radialis*.

We chose these two muscles after many trials, because they are the most important contributors to the flexion-extension movements of the hand. In order to differentially detect the SEMG signals, a reference electrode was necessary. This electrode is recommended to be placed away from the SEMG sensors. Therefore, we placed the reference electrode away from the two EMG sensors, on the joint of the hand (Fig. 6).

Because surface electromyographic signals are affected by many disturbances it is very important to know when a movement is initiated, in order to know the starting point for the acquired signal considered for classification. There are several methods used nowadays for this reason. The simplest one is the use of a threshold. Unfortunately, the value of the threshold is chosen empirically; therefore that value cannot work in all cases. Other methods, like video detection of the movement, or the use of a pushbutton that has to be pressed when the patient intend to make a movement, can also be applied.

We used two additional goniometers to detect the beginning of a movement. Using the goniometers, the information from these devices can be used for the implementation of the closed-loop low-level controller too.

One of them was placed on the joint of the hand in order to detect flexion-extension movements. The second goniometer was placed along the small finger in order to detect the closing of the hand.

As Fig. 5 illustrates we placed the goniometers on the same hand on which we placed the SEMG sensors, because we collected data from able-bodies subjects. In the case of the persons with amputations at the wrist level, the goniometers will be mounted on the other hand. During the data collection session the patient will simultaneously make the requested movement with both the healthy and the ill hand. We consider that using this strategy the patient will be encouraged to control both hands.

For the implementation of the first control strategy, we used data collected from five able-bodied subjects, after receiving their informed consent.

Three movements (hand flexion, hand extension and tight closing of the hand) were used during the acquisition of the signals, in order to discriminate three states: both muscles contracted, one contracted, the other relaxed and vice versa. The acquired signals plus the signals recorded from the two muscles when none of the three movements was performed (the repose state) were used to control four movements of the prosthetic device: rotate inside; rotate outside, close hand, open hand.

Each of the three movements was performed 75 times by each subject. Also, 75 data sets were recorded from each subject in the case when no movement was performed. A total of 1500 movements resulted ((3 movements x 75 times +75 data sets corresponding to the case when no movement was performed) x 5 subjects). Because for each movement, data were collected from two muscles, a total of 3000 signals were processed by the classifier.

During the acquisition session the subject sat down with the elbow leaning on a chair arm in order to better isolate the contractions of the muscles for each motion.

3.2 The SEMG signal acquisition for the second control strategy

The positions of the sensors on the arm are illustrated in Fig. 7 (the sensor on triceps not visible in the picture).

One SEMG sensor was placed at a distance of 80 mm from the elbow joint over the biceps muscle. The second SEMG sensor was positioned on the triceps at a distance about 110 mm from the elbow. The third SEMG sensor was positioned over the pectoralis major muscle.

We chose the biceps and triceps muscle because they are the most important contributors to the flexion-extension movements of the forearm. Also the pectoralis major muscle was chosen because it is a large muscle, meaning that even small contractions will be detected by the sensor reducing the patient’s effort. The reference electrode was placed on the joint of the hand.

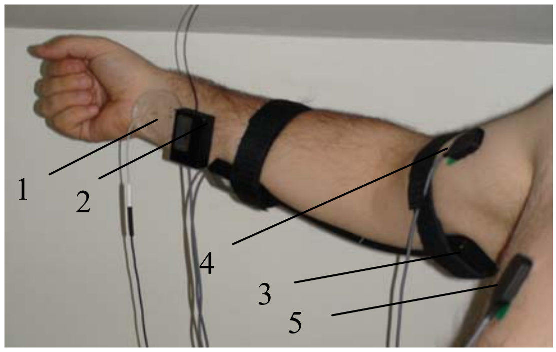


Fig. 7. Position of the sensors on the upper limb: 1-reference electrode, 2-the goniometer for pronation-supination, 3-the goniometer for flexion-extension, 4-SEMG sensor on biceps, 5-SEMG sensor on pectoralis major

Like for the first control strategy, as illustrated by Fig. 7, the two goniometers were placed on the same upper limb as the SEMG sensors, because we collected data from able-bodies subjects.

For the second control strategy, data were collected, like for the first control strategy, from five able-bodied subjects after receiving their informed consent.

Four movements of the forearm (*flexion*, *extension*, *pronation* and *supination*) were performed during the acquisition of the signals.

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 of the four movements was performed 77 times by each subject. A total of 1540 movements resulted ((4 movements x 77 times) x 5 subjects). Performing a large number of motions for each movement type results in collecting signals even where muscles become fatigue, which correspond better to the latter use of a real prosthesis. Because for each movement, data were collected from two muscles, a total of 3080 signals were processed by the classifier.

4. THE ELECTROMYOGRAPHIC CLASSIFIER

As Fig. 2 illustrates, the electromyographic classifier has two modules: the feature extraction module and the feature processing module.

In order to reduce the processing time it is important to extract relevant features from the raw signals, a task that is performed by the feature extraction module. This step is necessary because feeding the SEMG signal as a time sequence, directly into the classifier, excessively increases the processing time. The feature extraction algorithms attempt to preserve from the raw signal only the information that is relevant for classification and to remove redundant information.

The feature processing module is used to classify the features extracted by the first module, into distinctive classes that correspond to the desired motion patterns.

4.1 Feature extraction module

When developing a control system for a prosthetic device an important factor is the real-time implementation. The generally accepted delay between initiating a move command at the mental level and the start of that movement is approx. 300 ms. (Oskoei et al, 2007). In order to respect this constraint, acquired data have to be segmented, and then segments will be processed one by one. The length of the time segment depends on the sampling frequency used in acquisition and on the computational power of the system. We tested the performance of the classification algorithm when using segments ranging from 32 to 256 data set values. We observed that the classification performance is directly related to the length of the segment, the 256 values data sets yielding the lowest error rate in classification. Based on this observation we choose to work on 256 ms time segments corresponding to 256 data set values, since we used a sampling frequency of 1000 Hz.

As the structure of the electromyographic signal is a complex one (Oskoei et al, 2007) and the signal is strongly related to the subject's muscle and tissue structure, a simple threshold based algorithm does not offer sufficient information for the classification of the signal in different movement classes. Different approaches (time domain, frequency domain and time-scale domain analysis) were used previously for feature selection (Hudgins et al., 1993), (Herle et al., 2008), (Karlsson et al., 1999), (Karlsson et al., 2000).

In this paper we used an autoregressive based algorithm for feature extraction. The autoregressive (AR) modeling of the SEMG offers very good performances in myoelectric signals classification. One of the main advantages is that it combines two stages: feature extraction and dimensionality reduction.

This leads to a small size feature vector, and in addition, to a reduction of the processing time.

Equation (1) describes the AR model:

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

where a_i are the AR coefficients, N is the dimension of the time segment, M is the model order, *x(n)* are the samples of the signal, and $\overline{x(n)}$ are the samples of the modeled signal. Studies have shown that an autoregressive model of a finite order (sufficiently large) can approximate any system with a specified degree of accuracy (Parker et al, 2006). The algorithm for the autoregressive coefficients calculation suggested by (Soares et al.,2002) follows the steps bellow:

i. initialize the coefficients
ii. calculate the predicted value of the signal

$$\overline{x(n)} = \sum_{1}^{M} a_i x(n-i) \tag{2}$$

iii. estimate the error

$$e(n) = x(n) - \overline{x(n)} \tag{3}$$

iv. update the coefficients

$$a_i(n+1) = a_i(n) - 2\mu e(n) x(n-i) \tag{4}$$

Using this short algorithm for the n values of the signal, we find the coefficients a of an M^{th} order model. The term μ is the convergence coefficient. Based on multiple trials we used a value μ=0.01. The appropriate model order cannot be found analytically. Farrina and Merletti (Farina et al., 2007) found that a model of order 10 works for most of the segment lengths considered, and Soares et al. (Soares et al., 2003) showed that a fourth model order can adequately represent the structure of the EMG signal. We searched for the best approximation in models with orders between 2 and 12 and found that a fifth order model offers the best classification performance.

AR modeling provides us with two main advantages concerning the classification problem. The first advantage in using the autoregressive model is the dimension of the feature vector that is feed into the neural network based classifier. In our case, the 2x256 data points had been replaced by 2x5 values. This allows the classifier to perform much faster and with a higher degree of accuracy. The second advantage, the robustness is necessary due to the complexity of the EMG signal. As mentioned above, the EMG signal is directly dependent of the muscle structure, the skin thickness and the fatigue of the muscle. An amplitude based feature like a threshold value or a mean value is not necessarily directly related to the level of contraction (Oskoei et al., 2007) and therefore cannot reflect the structural properties of the EMG.

Once the features were extracted, they were classified using the feature processing module, in order to discriminate the upper limb movements.

4.2 Feature processing module

A. The feature processing module for the first control strategy

The features extracted using the above mentioned algorithm (i.e. the coefficients of the autoregressive model) were used in training a classifier to discriminate between 4 different classes: (i) *flexor contracted and extensor relaxed,* (ii) *flexor relaxed and extensor contracted,* (iii) *both muscles contracted,* and (iv) *no movement.* The outputs patterns of the classifier are *1000*, *0100, 0010, and 0001* corresponding to the four classes A two layer neural feed-forward network classifier was used for classifying the autoregressive coefficients into these four classes of movement. In training the classifier, a set of 200 of patterns (from the total of 300) was used for each subject. The rest of 100 patterns for each subject (a total of 500 patterns for the five subjects) were used for testing the classifier. We tuned the number of neurons in the hidden layer. After multiple tries, we concluded that a layer with 13 neurons offers the best classification and still avoids the phenomenon of overtraining, which would lead to a worse classification rate on unseen data.

After training, a testing set of signals was presented to the neural network. A 91% recognition rate was achieved for the four movement classes, ranging from 90% to 95% depending on the movement. Fig. 8 illustrates the expected results and the classifier's output.

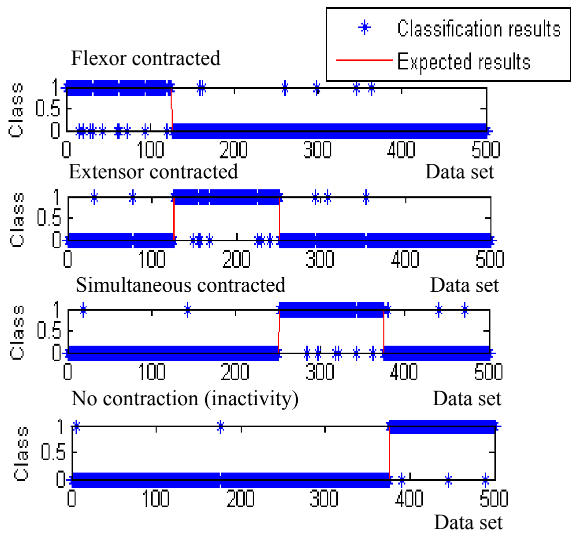


Fig. 8. Comparition between the expected and the obtained results

B. The feature processing module for the second control strategy

For the biceps and triceps muscles, the coefficients of the autoregressive model were used in training a classifier to discriminate between 4 different classes: (i) *flexion,* (ii) *extension,* (iii) *pronation,* and (iv) *supination,* based on a two layer feed-forward neural network.

The classifier was trained using a set of 216 patterns (from the total of 308) for each subject. Thus, a total number of 1080 patterns were involved in the training action. The rest of 92 patterns for each subject (a total of 460 patterns for the five subjects) were involved in testing the classifier. After multiple tests, we concluded that a hidden layer of the neural network, with 14 neurons offers the best classification and still avoids the phenomenon of overtraining, which would lead to a worse classification rate on unseen data. The output patterns of the classifier (neural network) are *1000*, *0100, 0010, and 0001* corresponding to the four classes: *flexion*, *extension*, *pronation* and *supination.* The testing sets of signals were presented to the neural network after training. A 98% recognition rate was achieved for the four movement classes. Fig. 9 illustrates the expected results and the classifier's output.

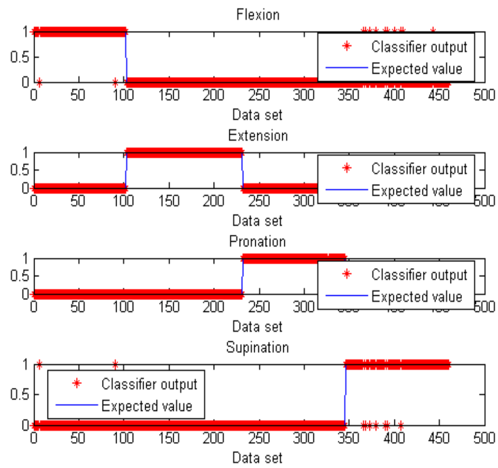


Fig. 9. The classifier outputs. Comparison between the expected and the obtained results

Though we need to know if the pectoralis major muscle is contracted or not, a special classifier is not required for this purpose. A threshold was used in this case.

5. THE HIERARCHICAL CONTROLLER

As Fig. 2 already illustrated, the controller has two levels. The purpose of the high level controller is to transform the classes discriminated by the classifier into the inputs for the low-level controller. The high level module is implemented using finite state machine.

5.1 The high-level controller used in the first control strategy

In Fig. 10 is illustrated the state transition diagram that describes the controller functions, where *f* stands for *flexor carpi radialis* and *e* for *extensor communis digitorum*. The indicator *1* codes the presence of a contraction, and *0* its absence.

The motions controlled are: *open hand, close hand, rotate inside,* and *rotate outside.* The signal from *flexor carpi radialis* muscle is used to commands two motions *close hand* and *rotates inside.* The signal from *extensor communis digitorum* is used to command the *open hand* and the *rotate outside* motions. Because each muscle 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 muscles have to be simultaneously contracted.

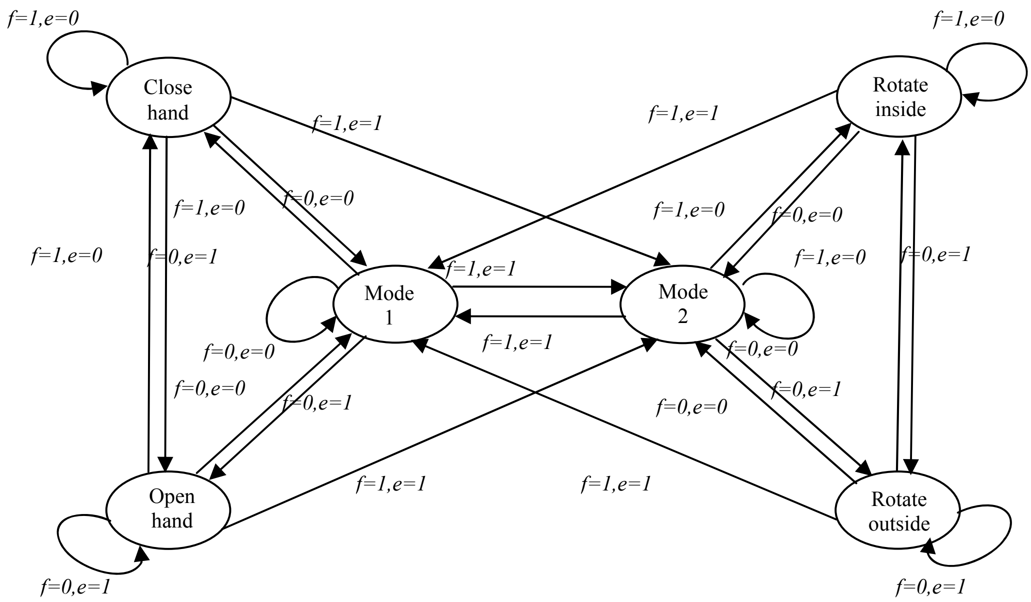


Fig.10 State transition diagram of finite state machine based controller for hand prosthesis

5.2 The high-level controller used in the second control strategy

For the second control strategy the high level controller transform the classes discriminated by the classifier (*flexion, extension, pronation,* and *supination*) into actual six movements of the prosthesis. Because the finite state machine used to implement the high level controller needs a condition to keep a state, and because the classifier implemented can not offer such a condition we tried to modify the classifier using a threshold instead of a goniometer for detection of the start of the movements. The recognition rate of the classifier was around 81% as fig. 11 shows.

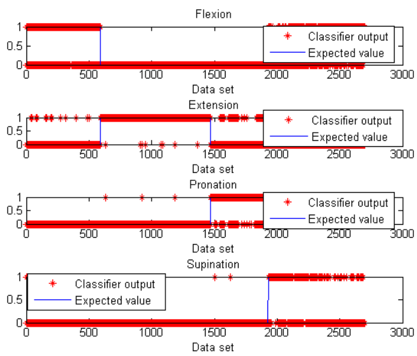


Fig. 11. Comparison between the expected and the obtained results of the classifier when a threshold was used

Moreover, an increased number of data were necessary for the classifier since a threshold was used to identify a movement. Therefore we decided to preserve the performance of the original classifier for the four movements of the forearm and to consider the signal from the pectoralis major muscle as a conditional signal to jump from one state to another.

Figure 12 illustrates the state transition diagram that describes the controller functions, where the conditions to switch from one state to another are coded in the following way:

if $f=1$ and $pm=1$ then a

if $e=1$ and $pm=1$ then b

if $pm=0$ then c

if $p=1$ and $pm=1$ then d

if $s=1$ and $pm=1$ then e

where f stands for *flexion*, e for *extension, p* for *pronation, s* for *supination*, and pm for *pectoralis major*.

The indicator *1* encodes the presence of a contraction, and *0* its absence. For each joint of the prosthesis one mode is defined. The suffixes *ls* and *hs* stand for *low speed*, and *high speed*.

The motions controlled are: *forearm flexion, forearm extension*, *hand pronation*, *hand supination*, *close hand,* and *open hand.*

From mode 1 the flexion and extension of the elbow joint can be controlled using the flexion and extension movements detected by the classifier and the signal from the pectoralis major.

In mode 2, the flexion and extension commands from the classifier are used in conjunction with the signal from the pectoralis major to control the pronation and supination movements of the prosthetic hand.

In mode 3, the flexion and extension outputs of the classifier are used in conjunction with the signal from the pectoralis major to control the close and open movements of the prosthetic hand.

The pronation and supination outputs of the classifier are used in conjunction with the signal from the pectoralis major to switch between modes. Each of the six movements can be controlled using two levels of speed. In this way, if the patient desires to increase the speed of a movement he or she has to repeat once again the condition that allows the execution of that movement.

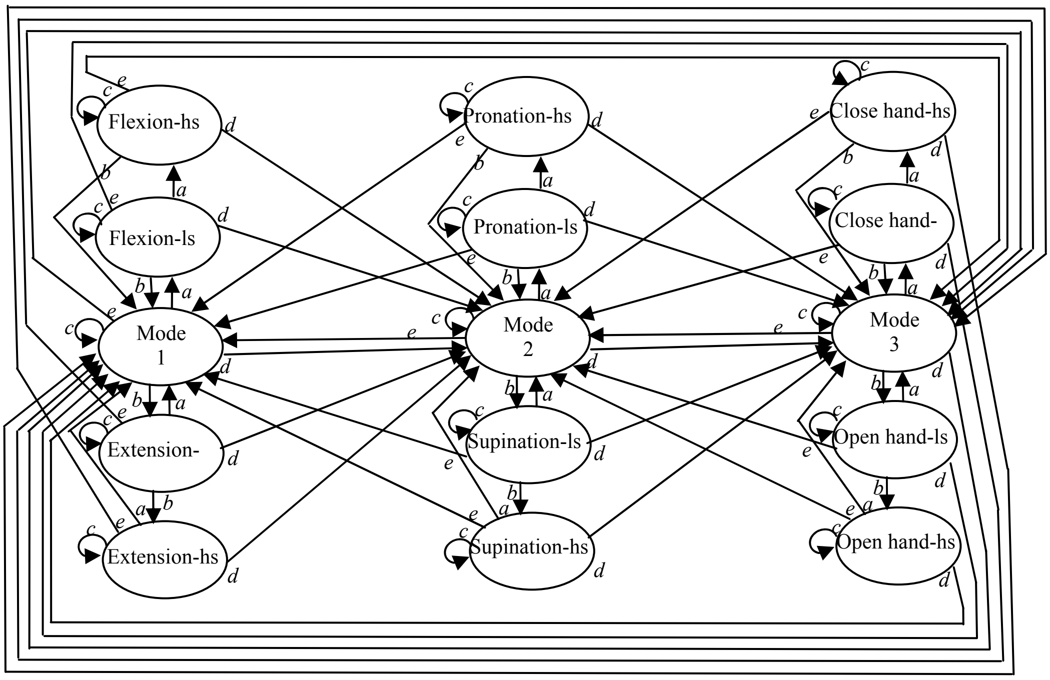


Fig.12 State transition diagram of a finite state machine based controller for an upper-limb prosthesis

6. DISCUSSION

The recognition rate of 91% achieved by the first control strategy is smaller than in our previous study (Herle et al., 2008). The additional signal recorded when no movement was performed altered the performances of the classifier, but this additional signal was necessary to maintain the finite state machine in a certain state. However, there is a trade of between the robustness, required time for classification and the rate of recognition. Using this approach the classification time was drastically reduced. The total time between the moment when the raw EMG signal was presented to the classifier and the moment when the high level controller released a command was around 16 ms, when the test were made on a PC Intel dual core at 2.66 GHz. In order to improve the performance of the classifier, without increasing the processing time we implemented the second control strategy that not only increase the recognition rate to 98% but allows also controlling a prosthetic device with more degrees of freedom using different levels of speed. The total time between the moment when the raw EMG signal was presented to the classifier and the moment when the high level controller released a command was around 19 ms, when the test were made on the same computer like that one used for the first control strategy.

Since 300 ms is considered to be the maximum time between the intention of a movement and the start of it, and taking into account our results, we consider that our approach is feasible for implementation into a real prosthesis. Combining this classification strategy with a finite state machine based high level controller will reduce significantly the effort required to control a real prosthesis. The high-level controller allows the users with a reduced muscular activity to easily control the prosthesis, because the patient must only initiate or stop a movement and the low-level controller will effectively control that movement using information from the local sensors (e.g. force or pressure sensors). Using goniometers, instead of threshold-based methods, we ensured a high robustness of the classifier and a reduced computational time.

7. CONCLUSIONS

In this study we proposed an approach for SEMG signal classification and two hierarchical controllers for a prosthetic upper-limb. We used a classifier based on autoregressive model combined with a neural network to detect of movement intentions. By using goniometers, instead of methods based on thresholds, we ensured a high robustness of the classifier.

Our future work will be focused on the implementation of the low level controller. Since we used goniometers we intend to extract not only information related to the start of the movement, but also information related to the speed.

This information will be useful for the low level controller in order to adjust continuously the speed of the prosthetic device according to the intention of the wearer. This is an advantage with respect to most of the current commercial prostheses, which only perform movements with constant speed.

Another improvement for the classifier will be the use of the online training of the neural network. This will increase the adaptability of the algorithm to each individual user.

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