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Acquisition and analysis of EMG signals to recognize multiple hand movements for prosthetic applications

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Abstract. One of the main problems in developing active prosthesis is how to control them in a natural way. In order to increase the effectiveness of hand prostheses there is a need in better exploiting electromyography (EMG) signals. After an analysis of the movements necessary for grasping, we individuated five movements for the wrist-hand mobility. Then we designed the basic electronics and software for the acquisition and the analysis of the EMG signals. We built a small size electronic device capable of registering them that can be integrated into a hand prosthesis. Among all the numerous muscles that move the fingers, we have chosen the ones in the forearm and positioned only two electrodes. To recognize the operation, we developed a classification system, using a novel integration of Artificial Neural Networks (ANN) and wavelet features.

Keywords: EMG signals, pattern recognition, wavelet network, neural networks

1. Introduction

The target of our research is a feasibility study of a new hand prosthesis that can offer more mobility to the user without the need of complex controllers and with a non invasive interface. In fact, to increase the effectiveness of hand prostheses, we intend to exploit myoelectric signals further than in the usual control of hand opening/closing. A companion objective is to develop a cheap solution to introduce actuated prostheses in developing countries.

Our target is to discriminate between six movements, namely open and close hand, wrist flexion up or down, abduction, and adduction of the thumb. The resulting prosthesis will give the user a more natural grasping movement, allowing also moving the wrist to better align the hand to the object to grasp. The challenge is to extend the same technology of the gripping prosthesis to discriminate between more movements [1, 18]. We are not discussing here about the mechanical construction of the hand; we proposed already some ideas in [13].

Small electrical currents are generated in the muscle fibers before the muscle contraction is produced. These currents are due to the ionic exchange across the membranes of the neural-muscular junctions, which propagate through the resistive surrounding tissues and generate small potential differences.

These signals, called electromyographical (EMG), represent fibers contraction, and can be used as a muscular activity indicator and, therefore, be interpreted to control an external electromechanical device.

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Muscles consist of muscle fibers, activated by motoneurons. Impulses from the spinal cord arrive to the motoneuron and trigger a group of several muscle fibers, called motor unit. To produce a movement, each muscle fiber composing the muscle contracts, carries the contraction to the whole muscle and achieves the desired action. In most of the cases, even for a fine movement, several muscles are simultaneously involved to accomplish that action.

The electrical response of a motor unit is the motor unit action potential (MUAP). A train of MUAP form an EMG signal [24]. There are many classes of MUAP in an EMG signal, and our task is not to find them out but to globally classify the EMG signal using the hypothesis that the same MUAPs are summed up when the same movement is done, so the EMGs of similar movements should show similarities. Those similarities can be exploited to build a classifier [2, 9, 15].

The choice of the electrodes is crucial. For prosthetic use the implanted electrodes present problems in duration and user acceptability [18]. For this reason the surface electrodes are our choice, even though the signals detected by surface electrodes are more difficult to understand than signals obtained by needle electrodes [22]. The surface electrodes are large, they cover an area that corresponds to the activities of several tens of motor units, increasing the cross talking of the signals. Since muscles are deep from skin the power spectrum of EMG is limited to 500 Hz [20, 28].

A few papers presenting results in the classification of EMG signals are available. Some [1, 6] have applied fuzzy rules, others developed ANN, as [12]. Our work partially originates from Hudgins and co-workers [16] who obtained a classifier able to recognize four class labels with a performance around 90%.

In our approach we introduce two novel ideas: the position of electrodes and the method of data classification.

- About positioning the electrodes, we decided to set them on the lower arm and not on the biceps and triceps muscles as used in [16].
- About the classification of the acquired signals we introduced the techniques of wavelet and auto-correlation to extract relevant features able to characterize the signal. Our method uses a neural classifier in cascade after wavelet analysis.

Wavelets [8, 11] have been introduced in the area of arbitrary functions approximation, and mainly used for signal representation and classification in the acoustic domain [26, 27]. Some use of wavelets in the EMG domain (for a different classification problem [21]) has already appeared.

In the following Section 2 we present the general problems of the prosthetic field, then we describe our project and in particular the two main building blocks for the controller: the acquisition of EMG signals, and the classifier.

2. The prosthetic field

The available hand prostheses are passive or active. Our interest is about active prostheses. They can be divided into:

- Prostheses moved by the patient.
- Prostheses with external source of energy, either electronic command or myo-electric command.

All the active prostheses use electrical motors powered by batteries. The controller uses a geared automatic transmission to move to a low transmission rate when a sensor signals the grasping of an object. The velocity of gripping is about 300 mm/s. Well known products are from Otto Bock [1], (see Fig. 1), RSLSteeper, and SPS.

The controller of an actuated prosthesis is usually based on EMG, the electric activity of activated muscles, measured from electrodes.

A better use of the EMG signal is a big challenge in today prosthetic development, as indicated in [18]. Other user needs emerge from user questionnaires.

Fig. 1. MyoHand (from Otto Bock website).

[1] http://www.ottobock.com/

In September 1992, The Institute for Rehabilitation and Research (TIRR) in Houston sent more than 6,600 one-page surveys to individuals with upper-limb loss or absence, throughout the United States. The results of the survey indicated such necessary improvements in the design of upper-limb prosthesis as additional wrist movement, better control mechanisms, greater fingers movement, the ability to make coordinated motions of two joints, and improved reliability for the hand and its electrodes [3].

In another survey (2002), seventy Australian upper limb amputees responded to a postal questionnaire asking how often they wore their prostheses and their level of satisfaction. Only 44% of amputees reported wearing their prosthetic limbs half the time or more. These low levels of use might be partly due to dissatisfaction with the prostheses regarding the discomfort of them. Prostheses were rarely used for dressing tasks, while they were used more frequently in domestic and work activities [10].

The research direction is to improve the automatic activity of the prostheses, and to make the movement more natural. Ideally the controller should be able to reproduce the natural controller exerted on the limb by the nervous system. This is still problematic, since the myoelectric signal cannot be used to send a feedback to the muscle that generated it. Without a feedback from muscles, the only feedback can be generated from vision, and so the resulting system is different from the natural one, as illustrated in Fig. 2.

New solutions to give a feedback can be devised, for instance tactile stimuli can inform the user about the activity going on; however no valid solutions have been provided so far.

3. EMG data and movements to recognize

To define the signal acquisition device we need to understand which muscles are relevant and how they are connected to the movements. there are many of them devoted to move the wrist and the hand, as described in [14], and located in the forearm.

Since the hand has more than 20 degrees of freedom and it is impossible to control all of them in a simple way, we look only at the movements that allow the patient to manipulate common objects.

The movements available in commercial prosthesis are two, namely opening or closing the hand. We will add four more movements, i.e. extension and flexion of the thumb, extension and flexion of the wrist.

Since the muscles that move the thumb are very deep, we will only consider thumb extension and leave the control of thumb flexion to a heuristic controller. Finally the five movements we want to discriminate from the EMG signal are illustrated in Fig. 3.

EMG signals are the expression of impulses which are initially generated in the central nervous system and then travel to their final destination, where they produce the desired result. The potential differences

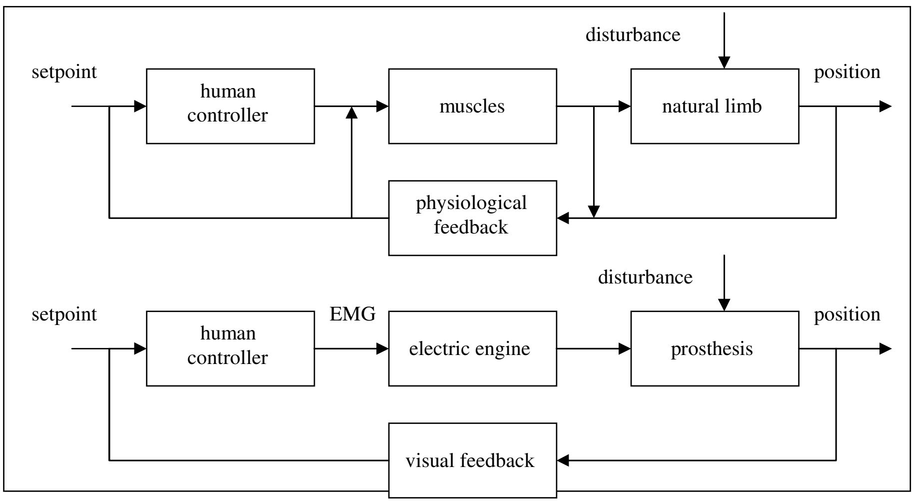

Fig. 2. Comparison of the controller of a natural limb (upper) and of EMG prosthesis (lower).

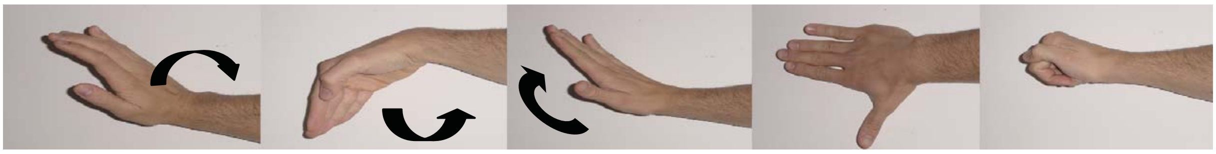

Fig. 3. The five movements to discriminate: wrist extension and flexion, thumb flexion, hand opening, hand closing.

generated in muscles due to these impulses not only generate muscular contraction, but also propagate to the surrounding tissues, which make it possible to measure them by applying specially designed electrodes.

There are two main kinds of electrodes that might be used for measuring EMG signals: surface and inserted. Inserted electrodes are very thin wires or needles that are inserted inside muscles and, due to their proximity to the signal origin, allow acquiring precise and high quality signals. The problems about them are many; they could be painful, are not removable without surgery, and there are no records about their time duration [18].

Due to those factors we chose surface electrodes, in particular bipolar electrodes, to measure the voltage difference between two specific points with two electrodes connected to the inputs of a differential amplifier. In addition, a third electrical connection must be used to set the reference, what is known as “Right Leg Drive” (RLD).

Since the muscles responsible of hand motion are deeply placed on the forearm, when measuring the myoelectric signals with surface electrodes it is not possible to exclusively register the signal of the involved muscle, but we obtain the superimposition of every signal generated between the point of interest and the detection surface. This phenomenon is known as “Cross-talk” [20]. By using bipolar electrodes, the “common” information registered by both electrodes is mostly eliminated by a differential amplifier (next section). Anyway, due to the geometrical configuration between both electrodes, it is not necessarily true that the signal registered in each one of them encloses Cross-Talk due to the same signals as the other one; that is why the output of the differential amplifier doesn’t necessarily represents an exact subtraction of both signals.

Therefore we decided to place both electrodes diametrically opposed on the forearm, assuming that for each interesting movement the cross-talk content will be mostly the same for each signal. The utilized electrodes are made of metal and covered with a thin coat of silver chloride (AgCl). A conductive solution is also used to enhance the conductivity between skin and electrode. The choice of the electrodes has been restricted to the ones commercially available for electro-stimulation.

As said before, we decided to acquire the signals from two electrodes installed in the front and back side of the lower arm, as indicated in Fig. 4. In this case all the muscles acting in the movement are globally considered; the signal contains different patterns for the different movements, and our goal will be to characterize those patterns [5, 16, 29].

The measured signal contains noise and an offset signal; not all the sequences are measured properly since the electrode is in practice a low-pass filter and distorts some spectral components of the signal. The cut frequency for an electrode of 5 mm diame-

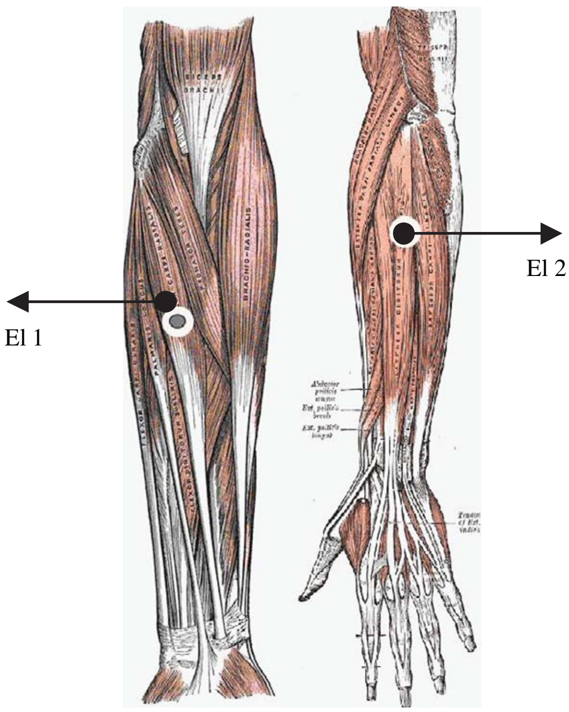

Fig. 4. The position of the two electrodes.

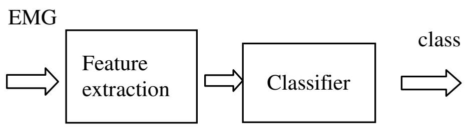

Fig. 5. Feature extraction and pattern recognition.

ter is about 360 Hz, for a 20 mm diameter is about 100 Hz.

Our controller uses a pattern recognition approach, as illustrated in Fig. 5; it will acquire and classify data from a single channel. The classifier should output the class in a time compatible with a natural control loop. The maximum delay tolerable by the user between the commanded movement (generated after signal classification) and the instant when the prosthesis moves is about 300 ms. This time constraint will impose severe restrictions on software

4. Development of the electro-myograph

The different modules that build up the process of acquisition of EMG signals are shown in Fig. 6.

Due to the EMG characteristics, the current flowing through the inputs of the differential amplifier is low, some micro-amperes. In presence of muscular activity, the EMG signal is picked up by the couple of electrodes located on the forearm. This signal is amplified by the "Preamplifier" to achieve adequate voltage levels to prevent electrical interferences. Then there is a "Band pass filter" stage, to obtain a signal into the frequency range of interest and to eliminate most of the noise that affects the myoelectric signal. The third stage, the "Amplifier", raises the voltage levels up to the TTL standard, an indispensable requirement for processing data in a computer. The last phase is the "Analogue-to-digital conversion" of the signal that is then transmitted to the computer for data processing. A User Interface is used for debugging and training.

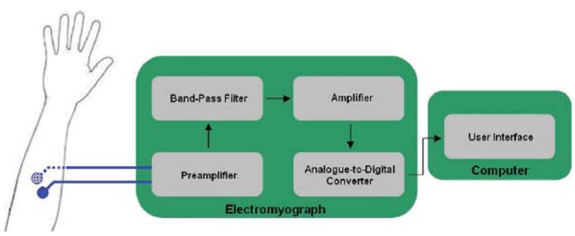

Fig. 6. The modules of the electromyography.

4.1. Noise suppression

Noise is any electrical perturbation that interferes on signals. Myoelectric signals are not an exception; in fact, due to their weak potency, there are several factors that affect them, as [24, 25]:

- Inherent noise of the electronic components in the equipment: this noise has frequency components from 0 Hz to several 1000 Hz. This noise cannot be eliminated; it can only be reduced by using high quality electronic and construction techniques.
- Ambient noise: we are continually exposed to electro-magnetic radiations. The dominant concern for ambient noise arises from the radiation from power sources (50 or 60 Hz, depending on the country), whose magnitude may be even 5 orders greater than the EMG signal [24].
- Motion artifacts: There are two main sources of motion artifacts: one from the interface between the detection surface of the electrode and the skin, the other from movement of the wire connecting the electrode to the amplifier. The electrical signals of both noise sources have most of their energy in the frequency range from 0 to 20 Hz, and can be reduced by proper design of the electronics circuitry.

As practically tested, the most important noise is caused by electrical power sources. To prevent this we utilize shielded wires to connect the electrodes with the amplifier. The shield of each of the leads is connected to the circuit and through it to the reference; in this way, perturbations find a fixed potential shield that avoids them to affect the myoelectric signal in the centre of the leads.

A second way is to consider that two myoelectric signals are received for each electrode; as both leads travel approximately the same distance from the electrode to the differential amplifier, and assuming that both measure points are exposed to the same electromagnetic ambient noise, the total amount of noise on each signal when entering the circuitry is almost the same. Then, the pure difference between both registered myoelectric signals suppresses the noise component. The quality with which a differential amplifier attains such operation is the Common Mode Rejection Ratio parameter (CMRR): the higher CMRR, the more precise the subtraction between inputs and, consequently, the better the noise suppression.

4.2. Power supply

Myoelectric signals produce positive and negative voltages, what compels to provide, despite the input voltage, positive power supply, negative power supply and "ground" (reference). Applying the concept of "Virtual Ground" we establish an arbitrary voltage level as the ground for all the components. To implement the virtual ground we selected the TLE2426 from Texas Instruments.

4.3. Implementation of the modules

The preamplifier has an important role. Bipolar electrodes arrangements are used with a differential amplifier to subtract the potential of one electrode from that of the other, then the difference is amplified suppressing the signals common to both electrodes. The common mode rejection ratio (CMRR) provides an index on the extent to which common signal components are attenuated; a value of 120 dB is recommended.

To avoid the attenuation of the EMG signal, the input impedance of the pre-amplifier should be at least 100 times larger than that of the skin-electrode system, which is about 50 kΩ. In order to bias a circuit, we need an adequate difference of potential as well as a certain amount of current. The current flowing through the inputs of the differential amplifier, coming from EMG, is just some micro-amperes. One drawback with high input impedance is that power line noise and Radio Frequency noise are introduced in the lead wires: the higher the input impedance of the pre-amplifier, the greater the impact of noise from lead wires. Increasing the length of the leads increases the parasitic capacitance, thus the coupled noise. In other words, long lead and high impedance of the pre-amplifier result in reduced signal to noise ratio. It is recommended to include the pre-amplifier stage directly into the electrodes housing or to utilize electrode-leads no longer than 10 cm. This requirement is adequate for the hand-prosthesis, where electrodes are located on the forearm.

It is important that pre-amplifier circuits have strong D/C component suppression circuitry. There are D/C components caused by skin impedance and the chemical reactions between skin, electrode, and gel. Any difference in the D/C potential measured at each of the electrode is also amplified, which can lead to instability or saturation. Our preamplifier is a differential amplifier (INA128 of the Texas Instruments.) with these characteristics [24]:

- High common-mode input impedance;
- CMRR greater than 85 dB;
- Noise (short-circuited inputs) less than 1.5 µV (rms);
- Bandwidth from 15 to 500 Hz.

In order to avoid sampling outside the frequency range of EMG signals (15–500 Hz), an active band pass filter is connected to the pre-amplifier's output.

It is necessary to have a reference circuit on the body to serve as a feedback. Any time that body temperature changes or signals change, this circuit will be in charge of keeping the right voltage level. This concept is known as RLD (Right Leg Drive), because this reference is normally connected to the right leg, but it can be located anywhere.

To avoid electrical noise, the cable connecting the electrodes to the electromyograph is shielded. The conductor that shields the leads carrying the myoelectric signal is also connected to the preamplifier circuit.

The gain at the output of the preamplifier is regulated by external resistances. Because of the EMG signals amplitude, it would be desirable a gain of about 1000 times. However in presence of noises larger then the signal itself, the differential amplifier saturates easily. Therefore, we apply an amplification of 500 times. The presence of noises and perturbations in this same frequency range, with amplitudes much larger than the EMG signal itself, makes it necessary to filter the signal; the selected option was the "Sallen Key Filter"[2], and the chosen operation amplifier the OPA4131 from Texas Instruments.

4.4. Final board

For our board there are three fundamental requirements to fulfill: small size, low power consumption and reduced cost.

We decided to use the microcontroller PIC18F452 of Microchip which includes up to 8 analogue-to-digital converters. A stable energy supply to the PIC is provided by the voltage regulator TPS71550 (Texas Instruments), which receives a positive voltage from the power supply and gives 5 V in output. As in this

[2] http://en.wikipedia.org/wiki/Sallen_Key_filter

way the conversion range is from 0 V up to 5 V, it is then necessary to adjust the EMG signal at the output of the amplifier to be compatible with this range. Since the signal oscillates between -2.5 V and +2.5 V, it is enough to add to it a constant component of 2.5 V. This is achieved by using an operational amplifier.

About low consumption of electrical energy, this involves using batteries and therefore considering the time between charges. The power consumption doesn't exceed 70 m-amperes, including the A/D conversion that requires approximately 70% of this value. AA type alkaline batteries have a nominal voltage of 1.5 V and a capacity of 2.4 Ampere/hour. A 15 V power source is achieved by serially connecting ten AA batteries. In these conditions, until reaching the minimum proper-working voltage of 12 V, the device can operate for approximately 20 hours.

About small size, the electromyograph is a rectangle measuring 3.9 × 4.55 centimeters. The final printed circuit with surface mounting components is in Fig 7. After calibration an example of the EMG signal is in Fig. 8.

About cost, the cost of all components in our prototype is about 23 USD.

5. The multiclass classifier of EMG signals

Since morphological models that explain in detail the effect of a given EMG on a muscle are where complex to model, we will consider the relations between

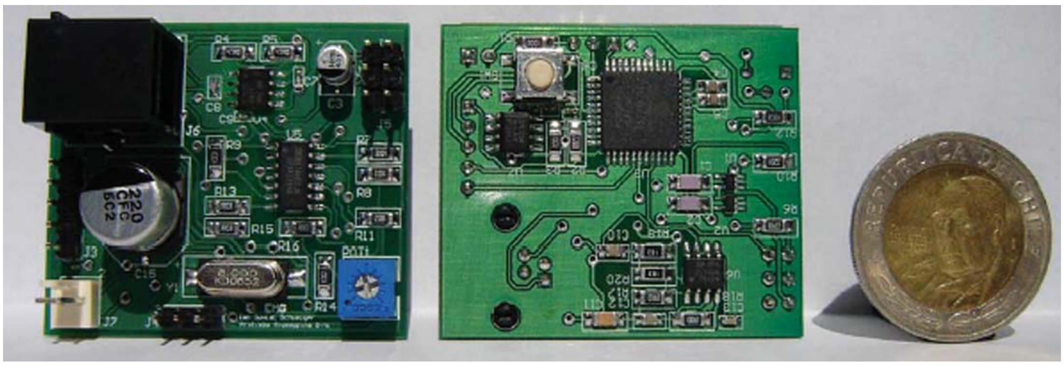

Fig. 7. The circuit compared with 1 euro coin.

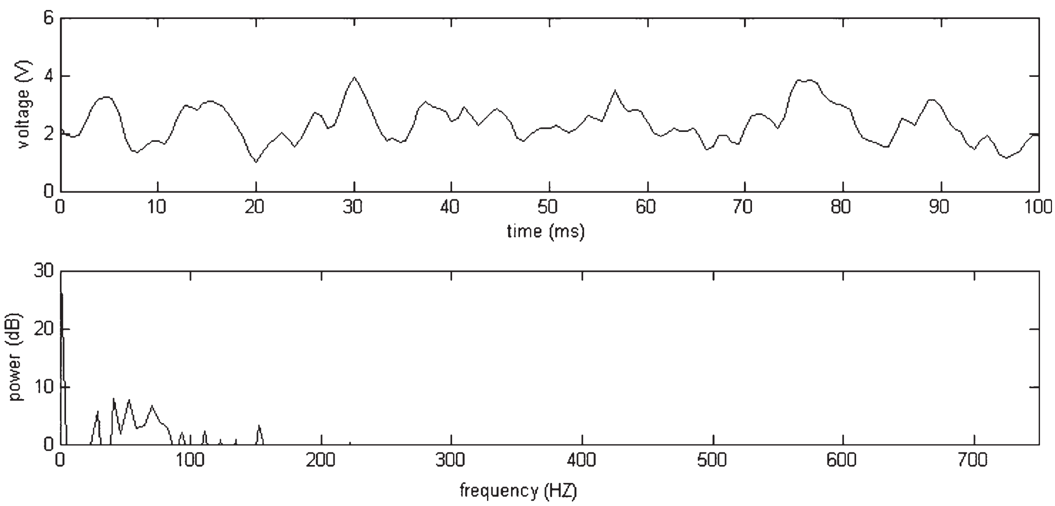

Fig. 8. An example of output of the device. In the upper part the EMG signal after calibration and amplification in the 0–5 V range; in the lower part the principal frequency components are visible.

EMG and the joint movement as a black box, and derive it with statistical methods [16, 25].

The architecture we devised for the classifier is based on a fully connected multilayer artificial neural network. After training, the recall time of a trained NN is very low, but the time to extract the features from the unknown signal should be compatible with the 100 ms time window. For this reason we have chosen a set of statistical parameters that are easy and fast to compute. To improve performance we also introduced 2 wavelet features.

5.1. Feature extraction

We chose a temporal approach, where features are directly extracted from the temporal sequence. According to [16] we have to characterize the time sequence with some parameters; we extract the following five statistical features:

1. Mean Absolute Value (MAV)

$$\overline{X}_i = \frac{1}{N}\sum_{k=1}^{N}|x_k| \tag{1}$$

   the average on the i-segment made of k samples. This parameter will be used also by the controller to set the velocity of movement of the prosthesis, since the velocity is linearly correlated to MAV.

2. Difference between the MAV of two samples

$$\Delta\overline{X}_i = \overline{X}_{i+1} - \overline{X}_i \tag{2}$$

3. Zero count, i.e. number of times the signal passes through zero. To cut the noise we use a threshold of 0.01 V, corresponding to a noise of 4 μV amplified 5000 times. The counter of zero-passing is incremented if the sign of x_k is different from the sign of x_{k+1} and

$$|x_k - x_{k+1}| \geq 0.01V \tag{3}$$

4. Sign changing; given 3 consecutive samples we increment a counter if

$$x_k > x_{k-1} \text{ and } x_k > x_{k+1} \quad \text{and} \\ |x_k - x_{k+1}| \geq 0.01V \tag{4}$$

   or

$$x_k < x_{k-1} \text{ and } x_k < x_{k+1} \quad \text{and} \\ |x_k - x_{k-1}| \geq 0.01V \tag{5}$$

5. Length of the signal

$$l_o = \sum_{k=1}^{N}|x_k - x_{k-1}| \tag{6}$$

Wavelets are one of the several mathematical transformations to extract information from signals. The particularity of Wavelet Transformation is that its result is a signal representation in the time frequency space, i.e., it is possible to know when a certain phenomenon occurs with a specific frequency [19].

Wavelet is a series decomposition of the signal in a set of functions ψ(t), that are different both in the scale factor (a) and in the time shift (b).

$$Wf(a,b) = \int_{-\infty}^{+\infty} f(t)\frac{1}{\sqrt{2}}\psi\left(\frac{t-b}{a}\right)dt \tag{7}$$

Since using directly a and b as features in the classifier does not improve the performance, we adopted a solution proposed in [26]. We train a neural net, with one hidden layer, that takes as input the time t and gives back the signal $s(t)$. The activation functions are wavelet and the output is the sum, as we see in Fig. 9. After training, the scale and shifts values (a and b) associated with the maximum weights of the net are used as additional features for the movements classifier.

5.2. The classifier network

Many methods have been proposed to classify EMG signals [5, 6, 7, 9, 29, 30] are some relevant examples. Our classifier has been devised as a Multi-layered Neural Network, whose inputs are the features extracted, and whose output is the class label, 1 through 5.

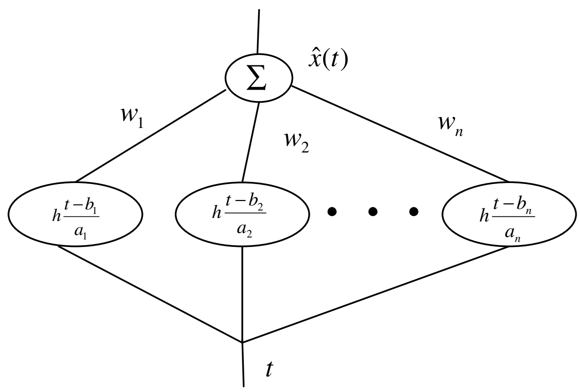

Fig. 9. The wavelet network.

The training and testing data have been acquired using the procedure described in the next section. The five statistical features of the signal have been computed on two consecutive segments of 100 ms each of the registered EMG signal; wavelets features have been computed on 200 ms of the signal, obtaining a total of 12 input features.

Since a net with one hidden layer is a universal approximator, we chose this basic architecture. To estimate the number of neurons in the hidden layer we used a trial procedure since there are no general rules to compute it. It should be as small as possible to simplify the computation and to reduce the risk of over fitting. We have also tried different learning algorithms, as the gradient descent with Newton or moments.

To find the right number of epochs we used the Early Stopping Criterion. We divided the training data in 70% for training and 30% for internal validation, and we continued the training while the error was reducing on the validation set, and stopped when the error started increasing. We used also another technique, Weight Decay, to maintain low the network weights and therefore to avoid discontinuities in the output [4].

As transfer function we tried both Tangent and Sigmoid functions.

We developed a full series of experiments using two kinds of nets:

a) TYPE 1 – Considering that the input data are continuous, we produce a continuous output, and then transform it into a class label. In this case we need to minimize the output error

$$E = \sum_{n=1}^{N} (y_n - t_n)^2 \tag{8}$$

where t is the true output and y is the obtained output.

b) TYPE 2 – Alternatively we can see the classification in c classes (here $c = 5$) as the problem of computing the probability of a given series on input x^n to belong to the class t^n.

$$p(t^n \mid x^n) = \prod_{k=1}^{c} (y^n)^{t_k^n} \tag{9}$$

In this case we minimize the cross entropy:

$$E = -\sum_n \sum_k t_k^n \ln\left(\frac{y_k^n}{t_k^n}\right) \tag{10}$$

The transfer function is sigmoid for the inner layer, normalized exponential for the output layer (since the sum of all the probabilities should be 1). The derivative of the error is the difference between true and obtained values.

6. Data collection and classification results

To collect data we used two volunteers without amputations; this may represent a limitation for practical uses nevertheless it is a good start point for our study of feasibility. The data of each user have been used to create different classifiers for that user. The best classifier was then kept.

The procedure for data acquisition and model training is as following.

- two electrodes where applied on the lower arm and a third on the wrist to close the electric circuit;
- each of the 5 movements are consecutively repeated 10 times, and the EMG signal recorded for 300 ms each;
- each set of 10 movements constitutes a sequence, which is stored in a Matlab file;
- so 50 files with the myoelectric signals, for a total of 500 data sets, are obtained;
- data in each file are squared and the 10 movements are separated and individually saved;
- as only the information contained in the first 200 ms of a movement execution is essential, every signal is segmented into two windows of 100 ms each and features are extracted, while the last 100 ms are discharged; wavelets are computed on the whole 200 ms signal;
- the total amount of extracted features is divided in three groups: one for the training process (3/5 of the totality), another one for the validating process (1/5) and a last one (1/5) for external testing process.

Data have been acquired twice from each person with a different position of the electrodes: lower (CD) or higher (CP) on the arm. The frequency of acquisition is 500 Hz.

We systematically trained the networks in 4 categories, according to the combination of methods used to avoid overfitting (validated entropy or regulated entropy) and to the error measure (MSE validated, so using early stopping or MSE regulated, so using weight decay). The networks with the best performances have

Table 1
Performance of the best classifiers on the data of two subjects. Note the different number of neurons in the hidden layer of the net, and the different position of the electrodes

Data from	ANN method used	Performance (%)	Hidden neurons
Subject 1 CP	MSE and Weight Decay	86%	15
Subject 1 CD	Entropy and Weight Decay	75%	19
Subject 2 CP	Entropy and Weight Decay	90.16%	22
Subject 2 CD	Entropy and Weight Decay Decay	96.77%	15

been chosen, and the results are reported in Table 1, where we see the accuracy of the recognition on the external test set.

We may observe that the recognition rate is quite high and that the generalization capability of the network is good. However we may observe that the generalization is only for the same person. Using a network trained for one user to classify movements from another user gives no good results.

We note that the results for subject 2 are much better. In fact subject 2 is a trained person active in rehabilitation tasks, while subject 1 is an occasional user.

In comparison with other published results, we can conclude that our results are good; at least they are better than the ones reported by Hudgins. The comparison is not easy since every paper presents a different kind of patient disorders to study, a different organization of the electrodes, and a different set of movements to discriminate.

7. Conclusions

Our target is to develop a controller based on a classification stage as a part of a controller for prosthesis.

In this paper we have presented a method to classify EMG signals into multiple classes. Our approach uses a 2-stage network, where the first net is used together with the computation of the features, and extracts the size and shift values of the most relevant wavelet present in the signal. The second net uses the extracted features to recognize one of the five possible movements. The trained networks have been saved for further recalling.

The results indicate that, after a short training, the user can easily control the movement to have high repeatability. We may expect that the same can happen also with amputees if the muscles of the lower arm are maintained. In this case we will obtain a good recognition capability and we may expect that some heuristics can help in making a reliable controller.

Since the relationship between the EMG signal variance and the muscle fibers firing rate is proved [18], we may control also the velocity with which the prosthesis executes its movements. To estimate the variance, the MAV can be used, a parameter that is already calculated during feature extraction. When using this value as an indicator of the velocity of activation of muscle fibers, it can be concluded that the higher the mean absolute value of an EMG signal, the higher the number of muscle fibers involved in a movement. Since the number of fibers implicated in a particular action is directly proportional to the rapidity of a movement's muscular execution, it follows that the higher the mean absolute value of the acquired myoelectric signal, the higher the velocity of the prosthesis movement. This factor has to go along with an adequate control algorithm to manage the velocity and the limits, both temporal and spatial, of movements.

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