Classification of EMG signals through wavelet analysis and neural networks for controlling an active hand prosthesis

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Abstract—**In order to increase the effectiveness of active hand prostheses we intend to exploit electromyographic (EMG) signals more than in the usual application for controlling one degree of freedom (gripper open or closed). Among all the numerous muscles that move the fingers, we chose only the ones in the forearm, to have a simple way to position only two electrodes. We analyze the EMG signals coming from two different subjects using a novel integration of ANN and wavelet. We show how to discriminate between more movements, five in this study, using our new classifier. Results show how the methodology we adopted allows us to obtain good accuracy in classifying the hand postures, and opens the way to more functional hand prostheses .**

I. Introduction

THE target of our research is a feasibility study of a new hand prosthesis that could offer more mobility to the user without the need of complex control boxes neither of surgery to install needles. In fact, to increase the effectiveness of hand prostheses, we intend to exploit myo-electric signals more than in the usual well developed application for controlling one degree of freedom of the hand (gripper open or closed).

Imagine we want to discriminate between six movements, namely open and close hand, hand pitch up or down, move the thumb in abduction or adduction. The resulting prosthesis will give the user a more natural grasping movement, allowing also to move the wrist. The challenge is the possibility to use the same technology of the gripping prosthesis to discriminate between more movements [15]. We are not discussing here about the mechanical construction of the hand; we proposed already some ideas in [6, 19].

The electric activity of the muscles allows to understand whether the patient is willing to move his hand. An electromyogram (EMG) is a signal obtained by measuring the electrical activity in a muscle. 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. The electrical response of a motor unit is called motor unit action potential (MUAP). A train of MUAP form an EMG signal [14]. There are many classes of MUAP in a EMG signal, and our task is not to find them out but to globally classify the EMG 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 [8].

For prosthetic use we need to apply only surface electrodes. The signals detected by surface electrodes are more difficult to understand than signals obtained by needle electrodes [13]. The surface electrodes are large, so the area covered is large and corresponds to the activities of several tens of motor units. Since muscles are deep from skin the power spectrum of EMG is limited to 500Hz [10, 18].

A few papers presenting results in a similar task are available. Some have applied fuzzy rules to analyze EMG signals, as [1, 2]. Others developed neural networks, as [5]. Our work partially originates from Hudgins and co-workers [9] who obtained a classifier able to recognize 4 class labels with a performance about 90%. In our approach we introduce two novel ideas: the position of electrodes and the kind 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 by [9].

About the classification of the acquired signals we introduced techniques of wavelet and autocorrelation to extract relevant features able to characterize the signal for classification. Our method uses a neural classifier in cascade after wavelet analysis.

Wavelets [3, 4] have been introduced in the area of arbitrary functions approximation. An arbitrary function on (0, 1) can be represented as a linear combination of waves given by sines and cosines, infinitely long. Since we want to approximate a function in the interval (0, 1) we choose some short waves, i.e. some functions that tend to 0 as x tends to infinity. Those functions are called wavelets.

In wavelet networks, the radial basis functions of RBF-networks are replaced by wavelets. During the training phase, the network weights as well as the degrees of freedom (position and scale) of the wavelet functions are optimized. [16, 17] have used wavelet networks for signal representation and classification applied to the acoustic domain. [12] has already approached the EMG domain for a different classification problem.

In the following sections we will discuss our project development. We present the characteristics of the EMG signals, we illustrate the classification method developed, we discuss its role in the construction of a controller.

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II. THE EMG SIGNAL ACQUISITION

The choices about signal acquisition are about the choice of the muscles to detect in order to discriminate between the movements of the prosthesis and the choice of the electrodes to apply

A. *The muscles acting on the hand*

Since we want to use the muscles of the forearm to control the prosthesis, we list the most important in Table 1, obtained after [7].

TABLE. 1. THE MUSCLES IN THE FOREARM USED TO MOVE THE HAND.

Muscle	Movement	Action
Abductor pollicis longus	Abduction	Abduction of the thumb and of the wrist
Extensor digitorum communis	Extension	Extension of fingers and wrist
Extensor pollicis brevis	Extension	Extension of thumb and wrist abduction
Extensor pollicis longus	Extension	Extension of thumb and wrist abduction
Extensor indicis	Extension	Extension of thumb and abduction of index
Extensor digiti quinti	Extension	Extension of the little finger
Flexor digitorum sublimis	Flexion	Flexion of articulations in wrist, interphalanxes and metacarpophalanxes
Flexor digitorum profundus	Flexion	Flexion of interphalanxes articulations and wrist
Flexor pollicis longus	Flexion	Flexion of the thumb

B. *Kinds of movement for the prosthesis*

Since the hand has too many degrees of freedom (20 considering only the fingers) and it is impossible to reproduce all of them in a simple way, we look only at the movements that can allow the patient to manipulate objects in a sufficient way. The movements available in commercial prosthesis are only two, namely to open or close the hand. We will add three more movements, i.e. abduction of the thumb, and extension or 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 an heuristic controller.

Finally the five movements that we want to discriminate are illustrated in Figure 1.

C. *Electrodes and signal acquisition*

The choice of the electrodes has been restricted to the ones commercially available for electro-stimulation. A conductive gel will reduce the noise and improve the results.

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. 2, while the reference electrode is applied on the other limb. In this case all the muscles acting in the movement are globally considered; the signal obtained should contain different patterns for the different movements, and our goal will be to characterize those patterns [10].

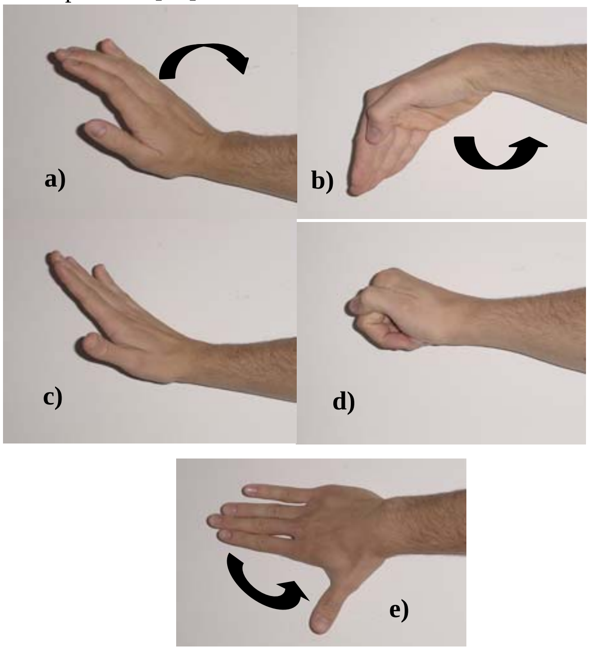

Fig. 1. The 5 movements to discriminate: a) wrist extension b)wrist flexion c)hand opened d)hand closed e) thumb abduction

The measured signal contains noise and an offset signal; moreover not all the sequences are measured properly since the electrode is in practice a low-pass filter and distorts same spectral components of the signal. The cut frequency for an electrode of 5mm diameter is about 360Hz, for a 20mm diameter is about 100Hz.

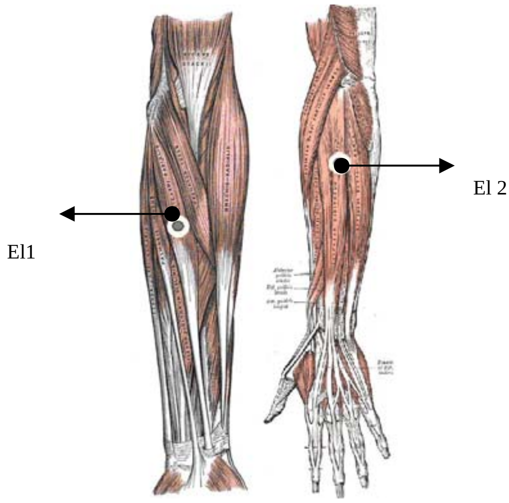

Fig. 2. The position of the electrodes

III. THE CLASSIFIER OF EMG SIGNALS

A. *Basic design and constraints*

The classifier should output the class label in a time compatible with a natural control loop. According to an empirical analysis, the maximum delay, tolerable by the user, between the commanded movement generated by the signal and the instant when the prosthesis starts moving is about 300ms; since the signal acquisition can require 200ms (fixed by hardware constraints), the classifier should operate in the maximum time of 100ms to output the desired movement.

Our controller will use a pattern recognition approach, as illustrated in Fig. 4. It will acquire and classify data acquired on a single channel, obtained from 2 electrodes only.

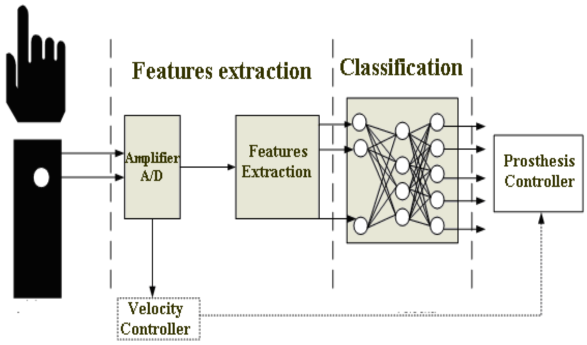

Fig. 4. – An open loop controller based on pattern recognition.

The architecture we devised for the classifier is based on artificial neural network (NN); namely is fully connected multilayer network. The processing time from a trained NN is very low, but the time to extract the features from the unknown signal should be compatible with the 100ms time window, that is the above defined maximum time available to remain inside the window of 300ms. For this reason we have chosen a set of statistical parameters that are easy and fast to compute, and we have separately listed the parameters that require more computer time.

B. Feature extraction

Before classifying the signal, we extract the following features, as already proposed in [9]:

1. Mean Absolute Value (MAV), where the average on the **i**-segment made of **k** samples is $\overline{X}_i = \frac{1}{N}\sum_{k=1}^{N}|x_k|$. This parameter will be used also by the controller to set the velocity of movement of the prosthesis, since the velocity will be linearly correlated to MAV.
2. Difference between the MAV of two samples $\Delta\overline{X}_i = \overline{X}_{i+1} - \overline{X}_i$
3. Zero count, number of times the signal pass through zero. To cut the noise we use a threshold of 0.01V, corresponding to a noise of 4μV amplified 5000 times. The counter of zero-passing is incremented if sign of x_k is different from sign x_{k+1} and $|x_k - x_{k+1}| \geq 0.01V$
4. Sign Changing; given 3 consecutive samples we increment a counter if $x_k > x_{k-1}$ and $x_k > x_{k+1}$ and $|x_k - x_{k+1}| \geq 0.01V$ or $x_k < x_{k-1}$ and $x_k < x_{k+1}$ and $|x_k - x_{k-1}| \geq 0.01V$
$$l_o = \sum_{k=1}^{N}|x_k - x_{k-1}|$$
5. Length of the signal

The following features also were included in our analysis even if, for real time applications, they require high performance computers or dedicated hardware. We will add them as input one at a time after developing networks with the first 5 features to see if they really improve the classifier. In Section 4 we see that the first and the last features of this list are really important.

1. Autocorrelation coefficient, for a signal with finite energy or finite power, computed as
$$R_X(\tau) = \int_{-\infty}^{+\infty} x(t)x(t-\tau)dt$$
$$R_X(\tau) = \lim_{T\to\infty}\frac{1}{T}\int_{-T/2}^{T/2} x(t)x(t-\tau)dt$$
2. STFT (Short-Time Fourier Transform),
3. Wavelet; they measure the correlation of a signal using a principal function that is translated and modified in time. Wavelet is a series decomposition of the signal in a set of functions *ψ(t)*, that are different both in the scale factor (s) and in the time shift (σ).
$$Wf(s,\sigma) = \int_{-\infty}^{+\infty} f(t)\frac{1}{\sqrt{2}}\psi\left(\frac{t-\sigma}{s}\right)dt$$

C. The network architecture

The 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.

In our case the number of input neurons is 5 to 8 for the features above discussed. If we divide the time of registration, 200 ms, in two segments we doubled the input neurons.

Since a net with one hidden layer is a universal approximator, we chosen this basic architecture. To estimate the number of neurons in the hidden layer we need 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 overfitting. We have also tried different learning algorithms, as the gradient descent with Newton or moments, and different transfer functions. To find the right number of epochs we used the Early stopping criterion. We divided the data in 70% for training and 30% for validation, and we continue the training while the error is reduced on the validation set, and stop when the error is increasing, as illustrated in Fig. 5.

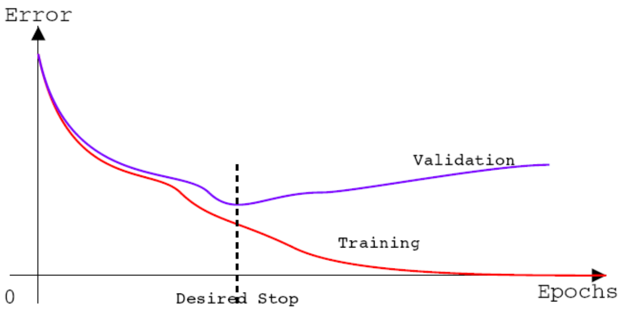

Fig. 5. – The early stopping criterion

We used also another technique, called Weight Decay (WD); in the hypothesis of Gaussian distribution of the weights, this allows to keep the network weight low and therefore to avoid discontinuities in the output [20].

As transfer function we tried both Tangent and Sigmoid functions.

Finally, we developed a series of experiments using two kinds of nets:

a) TYPE 1 NET- Considering that the input data are continuous, we can produce a continuous output too, and transform the real value into a class label after. In this case we need to minimize the output error, given as $E = \sum_{n=1}^{N} (y_n - t_n)^2$, where t is the wanted output and y is the obtained output.

b) TYPE 2 NET- 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.

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

In this case we chose to minimize the cross entropy:

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

that has its zero in $t^n_k = y^n_k$. The transfer function chosen is sigmoid for the inner layer, softmax (normalized exponential) for the output layer (since the sum of all the probabilities should give 1). In this case the derivative of the error is computed as $\frac{\partial E^n}{\partial a_k} = y_k - t_k$

All the networks have been developed in Matlab version 7.

IV. EXPERIMENTAL RESULTS

To collect data we used two volunteers without lesions; this may represent a limitation since we will need to repeat the experiments on amputees, nevertheless it is a good start point for our feasibility study. Two electrodes where applied on the lower arm and a third on the wrist to close the electric circuit. They were asked to repeat 10 times each of the movements, and data have been recorded and labeled. Data have been acquired for 300 ms each, with a different position of the electrodes lower (CD) or higher (CP) on the arm. The sequences of data to elaborate are finally indicated in Table 2.

TABLE 2. THE DATA SETS ACQUIRED FROM 2 PERSONS.

Volunteer	CP	CD
Subject 1	300+300	300
Subject 2	300+300	300

The signal has been acquired at a frequency of 500Hz and amplified with a gain of 5000. An example is illustrated in Fig. 6.

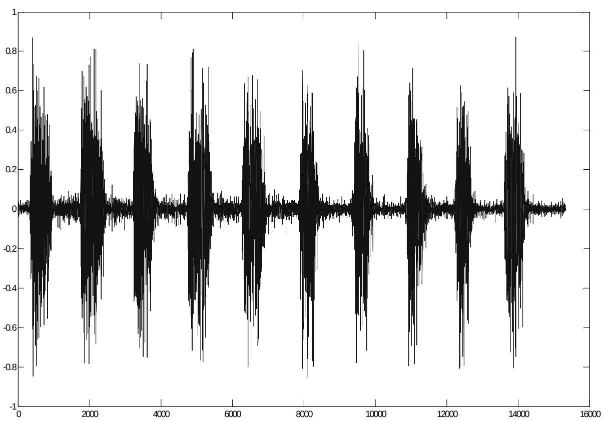

Fig. 6. EMG signal in the ten positions of the same movement, same person.

Data files obtained from the instrument are transformed into different Matlab files containing one movement each. The separation is automatically obtained squaring the signal and setting a threshold. Then we use only the first 200ms of the signal for classification, since this is the maximum time window we can use to discriminate the intended movements.

Moreover we split the data sets in three parts: 3/5 of the data for training, 1/5 for validation, 1/5 for external testing.

We systematically built the networks in 4 categories, according to the combination of methods used to avoid over-fitting (validated entropy or regulated entropy) and to the error measure (MSE validated or MSE regulated). Validated means using early stopping, regulated means using weight decay.

The number of neurons in the hidden layer has been checked between 10 and 30.

A. performance evaluation

An important aspect of our classifier is the wavelet feature. In Matlab the function CWT ( ) gives the matrix represented in Fig. 7 where we see a signal of 500ms for an *s* between 1 and 32; the function CWT() gives back a matrix of 32x500. It is difficult to use all those values directly in the training, where we need instead a limited number of relevant features. So the Matlab solution was discarded.

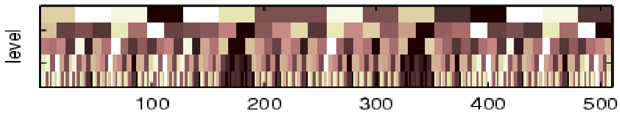

Fig. 7. – the wavelet representation in Matlab, with s on the y axis and σ on the x. Darker colors represent smaller coefficients

To extract the relevant wavelet features we adopted instead a solution proposed in [16]. The idea is to train a neural net that takes as input the time t and gives back the signal s(t). The network has an input layer that uses. After the network is trained, the a and b values of the scale and shifts associated with the maximum weights of the net are used as features for the above discussed classification neural net. In practice the two nets are in cascade, and the output of the first becomes input to the second.

We see in Figure 8 the wavelet network. Since it takes some time to extract the parameters it will be wise to implement the wavelet net in hardware. The weights w_i are modified during training in such a way to learn x(t). In our application we have used 25 neurons.

We started training the classification network using data coming from both the subjects. In table 3 we report the parameters for the network built after wavelet analysis, in table 4 the preliminary results for this experiment. Performances show the rate of correct classifications.

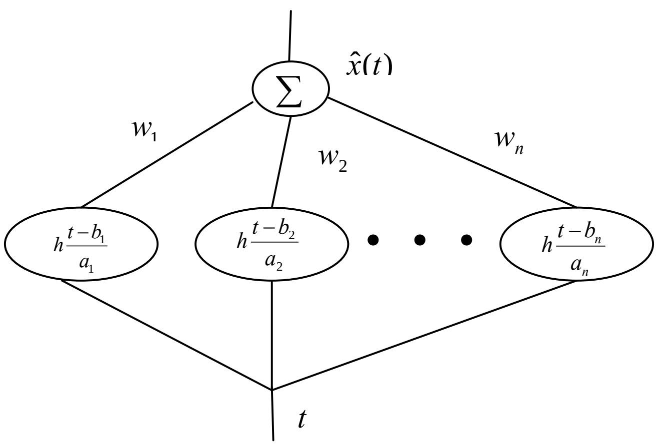

Fig 8 . The wavelet network.

In a first attempt we trained the network using data coming from both the subjects.

TABLE. 3. NETWORK PARAMETERS

Parameter	Value
Windows size	25
Number of windows	4
n. Class	5
Min n. hidden neurons	25
Max n. Hidden neurons	35
n. Epochs	1500
Target Error	0.01

TABLE. 4. BEST PERFORMANCES OF THE CLASSIFIER ON THE DATA OF TWO PERSONS.

Network	Performance	Hidden neurons
Entropy + Early Stop	45.27 %	33
Entropy +WD	55.22 %	25
MSE + Early Stop	49.3 %	28
MSE+ WD	56.21 %	33

Those results are not acceptable. To understand why we can observe that, in this case, the network should adapt to two different subjects and to two different experimental setups. So we changed both the experimental setup and the network construction. In fact we considered a separate network for each single subject, and trained different kinds of network architectures to finally chose the network with the best performances. The solution with a minor number of neurons has been preferred in case of similar performances of two networks, to reduce the computation. We also added in the input the signal autocorrelation. The results are illustrated in Table 5.

TABLE. 5. BEST PERFORMANCES OF THE CLASSIFIER ON THE DATA OF TWO PERSONS.

Data from	ANN method used	Performance	Hidden neurons
Subject 1	MSE + WD	86%	15
Subject 1	Entropy + WD	75%	19
Subject 2	Entropy + WD	90.16%	22
Subject 2	Entropy + WD	96.77%	15

We can observe a substantial improvement especially for subject 2. We should note that subject 2 is a more trained person active in rehabilitation tasks, while subject 1 is an occasional user. Moreover we can observe that the number of repetition of each movement used in training is only 60; a bigger number of training data probably will improve the results.

In comparison to data obtained in other published paper, we can make the following considerations: our results are statistically better than the ones in [9] that reach performances about 90%.

V. CONCLUSIONS

In this paper we have developed a method to classify EMG signals into multiple classes. Our target is to reach a high quality of the classification and to use this classification stage as a part of a controller for a prosthesis. The obtained results are comfortable. 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 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.

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