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From the Classification of EMG Signals to the Development of a New Lower Arm Prosthesis

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Abstract: The main challenge in today prostheses is the control; the user needs a simple and powerful way to move the prostheses without the need of additional hardware and training. Since the most used way to control, the hand is to classify EMG signals, we explore in this paper how feasible is the multiclass classification of the signals acquired by a miniaturized acquisition board. The goal is to create an association between a predefined set of hand/wrist motion patterns and the corresponding EMG signals generated by the forearm muscles. Our classifier recognizes up to seven different movements of the lower arm. The movements are chosen with the aim of producing a valid base for complex manipulation tasks. They involve only a few of the hand and wrist joints making so possible to design prosthesis with a reduced number of controlled degrees of freedom, and therefore controllable with modern under-actuated techniques.

Keywords: EMG signal analysis, limb prosthesis, wavelet, classifiers, mobile devices.

1. INTRODUCTION

The hand is the terminal part of the forearm and its multiple functions make it an important organ of the human body: people can use it to sense, manipulate and communicate. Therefore it has a primary role also in social activities, which makes its cosmetics even more important. It is easy to understand how the loss of the hand has significant consequences both from a psychological and functional point of view, in a person's life.

Prosthetic implants are the most common solution for the upper limb replacement, but since commercial devices suffer of low controllability, low functionality and low cosmetics, they are far away from being the biomimetic artificial hand we are looking for. The ideal prosthesis would be easy to control, comfortable to wear and aesthetically pleasing (Lai et al, 2006).

This work is concerned with finding solutions to the first of the three objectives mentioned above, using a novel approach: since it is not easy to extract from the residual neural activity the commands we first explore how to obtain an EMG controller able to classify several basic movements of hand and wrist, then we could design a controllable prosthesis using the set of commands discriminated. It is well known that the movements of the single fingers cannot be extracted from the EMG signal, so it is not worth pursuing a design with too many degrees of freedom if it is not possible to move them according to the user command.

The EMG control is the most used approach in today's prosthetic devices, because it is non-invasive compared with other methods. Its goal is to create an association between a predefined set of hand motion patterns and the corresponding EMG signals generated by the forearm muscles, in order to control a prosthetic hand in a realistic way.

To the authors' knowledge, the best recognition accuracies obtained by other researchers range between 97% and 99.5% (Jun-Uk 2007 and Naik 2007) on a set of motion patterns going from six to eight, and using four acquisition channels. In these works the most of the patterns recognised is related with the motion of the wrist, while the hand can be controlled just with an open/close movement. Other approaches (Maier 2008) are based on the increase of the number of channels, in order to control all the fingers individually.

Our work collocates in the middle between the two types of approaches presented above: a method which guarantees a high accuracy on the classification of seven motion patterns, which mostly involve the finger motions instead of the wrist, in order to provide the prosthesis with the capability of executing a sufficient amount of complex tasks.

In the following Sections we will analyze several common problems that a good hand-prosthesis has to solve in order to be accepted, then our hardware and software solution for creating the input to the controller, and finally our proposal for the hand design to execute the range of movements that can be correctly classified.

2. AMPUTEE'S NEEDS

In order to understand the extent of the upper-limb amputation phenomenon, a deep analysis has been performed by NHI in United States in 1988 and 1996. At that time, there was an average of 133,735 hospital discharges for amputation per year: in contrast with lower extremities amputations, which were mainly due to vascular causes, upper-limb amputations had been mostly trauma-related (68% out of all the trauma-related). The second reason for an upper-limb amputation is cancer (23.9% out of all the cancer cases), then the vascular one (3% out of all the vascular cases). More than half of the trauma-related upper-limb amputations occurred at finger level, then at the thumb (12%), at the trans-radial level (2%) and finally at the trans-humeral one (1.5%). Moreover, considering the congenital losses, in 1996 the incidence is of 1,500 over 10,000 live births: the 58% out of all the discharges is related to the upper-limb, of which the 27% is at the longitudinal hand level (MacKenzie 2002).

Currently it has been estimated that in the U.S.A., there are approximately 1.7 million people living without a limb: one out of every 200 people has had an amputation (Ziegler-Graham 2008).

There are approximately 1,908 upper-limb amputations a year versus 56,912 lower-limb amputations: the upper-limb amputee's population is much smaller. Therefore, it is often noted that upper-limb amputees feel isolated from their peers. The upper-limb amputees often reject their prosthetic devices; therefore researchers are questioning about the resources needed to enable the patients to cope with their limb loss and eventually with their prosthesis. It has been found that individuals with upper-limb loss who are fitted within 30 days of amputation are more likely to accept prostheses than those fitted after 30 days. Also differences between unilateral and bilateral amputees have an important consequence on acceptance. Unilateral amputees tend to master tasks with one hand, rejecting prostheses, as opposed to bilateral amputees, who require prostheses for some prehensile activities.

In a 2002 survey, seventy Australian upper limb amputees responded to a detailed postal questionnaire asking how often they wore their prostheses and their level of satisfaction with both their prostheses and their functional abilities. According to (Davidson 2002) 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 cosmetic, discomfort of the harness and strong pain.

Looking at the kinds of hand prosthesis available on the market, we can observe that even the most advanced ones provide five separately actuated fingers but a maximum of two commands (open or close). Different grip positions are manually obtained changing the position of the thumb, improving the versatility of the prosthetic device. No degree of freedom on the wrist is provided. Controllers based on EMG are common, but the only commands in use are open/close. Figure 1 shows one of the most advanced prosthesis, iLimb.

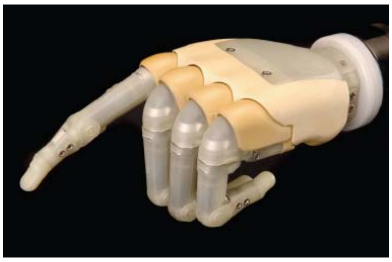

Fig. 1. The ilimb hand, from Touch Bionics

3. NATURE AND CLASSIFICATION OF EMG SIGNALS

The neuromuscular system is an association of several functional units, called motor units(MUs), constituted by an alpha motoneuron and the sum of the muscle fibres it innerves. Nervous and muscular cells react to external events and have electrical polarity on both sides of their cytoplasmatic membrane. The measured membrane potential is stable within -70mV and -90mV. After excitation, cells react with a transitory variation depolarization of the electrical polarity of the membrane that is called the action potential (AP). APs are always identical in duration and characteristics; propagate along the membrane of nervous cells from the axons to the muscle cells via the motor end plate, a chemical unit using neurotransmitters. A single axon is subdivided at its end into branches, innerving many fibres. Muscles are associated with many MUs. When a motoneuron is activated, an AP is generated and propagated along the axon and its branches to muscle fibres; each muscle fibre generates a signal, called MFAP (muscle fibres action potential). The algebraic sum of MFAPs of the single motor unit defines the MUAP (motor unit action potential).

Surface EMG techniques (sEMG) detect a large number of MUAP, so it's considerable as the spatial and temporal integration of a signal composed of several identical signals. Detecting the single contribution of each motor unit is a well known problem called cross-talking.

Many sources in literature establish that the amplitude of the EMG signal is stochastic in nature, and can be represented by a Gaussian distribution function. The amplitude of the signal ranges from 0 to 10mV (peak-to-peak) or 0 to 1;5mV (rms). The usable energy of the signal is limited to a specific frequency range (0 to 500Hz), with the frequencies that most suit our purposes centred in a range between 50 to 150Hz. EMG signals present two main issues that strongly influence the quality of the signal: the signal to noise ratio, and the distortion of the signal. Noise may emanate from a wide range of sources: electrical components, which can be eliminated through intelligent circuit design, the ambient (external disturbances), the body itself (cross talking, endogenous disturbances) or movement artifacts. Motion artifacts can be limited reducing signal cables length, while it is still partially unresolved how to deal with the noise generated by our body.

Multifunction single-channel systems are able to recognize more than one function by means of just one channel. The approach is usually based on pattern recognition methods, or on artificial neural networks (ANN) that receive in input a few statistic features: the mean absolute value, the mean absolute value slope, the zero crossing, the slope sign changes and the waveform length (Hudgins 1993).

Multifunction multi-channel systems try enhancing the EMG control systems using more channels: other electrodes have to be positioned on the forearm. A two-channel system used a neural network to classify four functions, with a performance of 90% (Doershuk 1983). Four channels were used to extract five time-domain features per channel, in order to train a network on six functions and 99.5 performances using wavelet coefficient features (Xiao wen Zhang et al, 2005).

In 2004 an investigation was carried on about increasing classification performance with number of channels. The performance in classifying 10 functions with a linear discriminant classifier increased with the number of channels, reaching 94% at sixteen channels. The performance at eight and four channels dropped to 93% and 87% respectively (Parker et al, 2006).

Another system using Wavelet Packet Transform is able to recognize nine hand motions from four-channels (Jun-Uk 2007). In 2008 a new learning method was proposed, which can detect extension and flexion of all human fingers, as well as sideways movements (abduction/adduction) using lower arm surface EMG with ten channels (Maier et al, 2008).

An interesting and potentially effective approach to independent simultaneous control is Independent Component Analysis and blind source separation. Applied to the signals generated by a group of muscles and detected by an array of electrodes, it is theoretically possible, under certain conditions, to recover the individual muscle signals for control purposes (Naik et al, 2007.)

4. HARDWARE AND SOFTWARE SOLUTION

Since this work is a feasibility study about the real possibility to integrate in an active prosthesis a controller based on a multiclass classifier, the decision was to program the whole project in Matlab and later export it into a programming language suitable for a microcontroller. Work is in progress to port the system on a NVIDIA tegra hardware using Python and C languages.

This paper shows the results of the feasibility study, therefore only the accuracy and theoretical results are presented, while considerations about speed and other implementation aspects are left to future works. Previous work is described in (Arvetti et al, 2007)

4.1. EMG acquisition

In the current work the recording of the EMG signal is carried out by means of three different channels in bipolar configuration (6 electrodes plus one reference), which are positioned respectively along the Extensor Carpi Ulnaris, the Extensor Digitorum Communis, and along the group of flexor muscles, while the reference is on the elbow. Since the electrodes have a big surface (5cm X 5cm), they are prone to detect also the contractions of muscles nearby the ones mentioned above. Because of this configuration we expect Channel 1 and Channel 2 to detect stronger signals when extension movements are performed and Channel 3 to detect more accurately the flexion movements. The positions are illustrated in Figure 2. The electrodes send the signals to a computer through a small acquisition board, designed and realized at Politecnico di Milano (Figure 3).

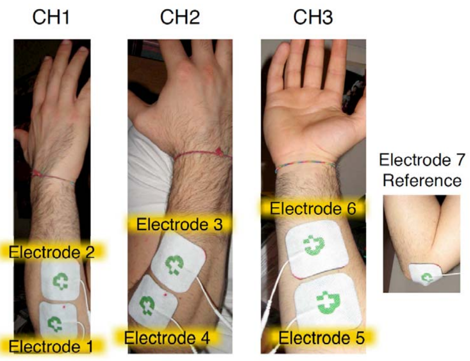

Fig. 2. The positions of the electrodes for acquisition

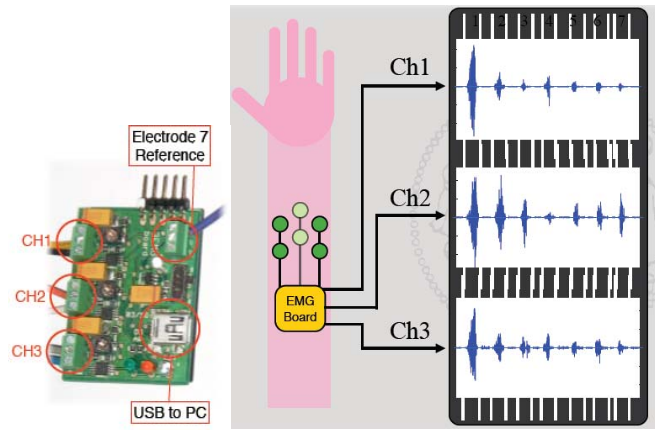

Fig. 3. The acquisition board and the 3 EMG signals.

4.2. Burst extraction

The acquisition system is able to record the whole muscle activity, which comprehends the relaxation and contraction phase, but we need just the parts of the signal related to the muscle contraction (burst). To extract them, each incoming signal is rectified, enveloped and subject to a dynamic threshold (modified *moving average*). Since the signals come from three different sources, their segmentation is characterized by parallelism issues: these are solved by dynamically selecting, at each burst, the leading channel (the one with the strongest signal), which "decides" when a contraction starts and ends, consistently for all the three channels.

4.3. Feature Extraction

The features extraction module has the role of identifying particular numeric parameters from the single signal burst. Such parameters are called features, and the whole set of features is called feature vector. The temporal approach to signal analysis is based on parameters like mean absolute value (MAV), mean absolute value slope, slope sign changes, and waveform length. The above temporal features do not help much in recognizing the hand motion, with the exception of MAV which can be loosely related to the signals energy. Also we build the linear envelope, often referred to as the integral EMG (iEMG) of the rectified burst. MAV and iEMG are the first two features.

Extracting information contained in time-frequency domain needs the use of spectrum analysis. Fourier Transform (FT) and its inverse provide a relation between the time domain and the frequency domain; it is an optimal solution when there is no frequency change with time. However, it does not give any information on a time localization of the frequency component of the signal. Time-frequency analysis based on short-time Fourier transform (STFT) treats time and frequency simultaneously. The basic idea of STFT is to divide a signal into short pieces and apply FT to each piece. STFT is a very useful mathematical method. However, there are many sorts of signals in nature that are non-stationary, non-periodic, ”fractal” or seemingly chaotic.

Since EMG-signals are typically non-stationary and irregular, new methods of analysis could supplement the traditional ones. The best known of these new tools is the wavelet analysis. The basic idea underlying wavelet analysis consists of expressing a signal as a linear combination of a particular set of functions, obtained by shifting and scaling the mother wavelet. The decomposition of the signal into the basis of wavelet functions implies the computation of the inner products between the signal and the basis functions, leading to a set of coefficients called wavelet coefficients. The Continuous Wavelet Transform (CWT) is here used.

Computing the CWT of a single burst composed by 270 samples produces a matrix of size 5x270; it has five rows because of the empirical choice to make the scale vary between 1 and 5. The dimensions of the matrix are reduced to 5x1through the Singular Value Decomposition (SVD) method. So the vector of the extracted features has seven elements. In this way a feature vector representing a hand movement is composed by seven features per channel, for a total of 21 elements.

An Artificial Neural Network (ANN) is then trained to associate each feature vector with the corresponding hand movement (Fig 4).

4.4. Movement Classification

Often classifiers are black box models, trained to learn associations between a specified set of input-output pairs. Actually, each training sample is labelled by a human, according to its corresponding abstract class (supervised learning). Then in the training phase the classifier learns how to associate each training input to its target output. After being trained, the classifier is able to predict the class of membership of a whatsoever unlabelled input taken from a test set.

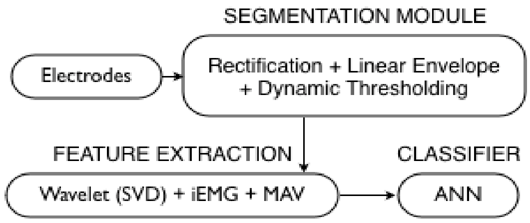

Fig. 4: Schematic representation of the system

ANN is the technique selected to perform supervised learning. This method is very flexible and general (since it makes only the assumption that the mapping function to learn is non-linear), but as a shortcoming it requires a trial and test approach to build the classifier. The net is designed to recognize the following seven simple motions:

1) hand closing;
2) hand opening;
3) wrist extension;
4) wrist flexion;
5) thumb abduction;
6) thumb opposition;
7) index extension.

To obtain good performance the same user who provides the signals for training will use the trained net. In the developed protocol for network training, the user makes sessions to acquire signals for each movement repeated ten times. The signals are divided into training set, validation set, and test set in the proportions 3/5, 1/5, 1/5.

After trials, it came out that the best classification performance is obtained by a feed-forward network with 7 input neurons (the feature vector described in 4.3), 7 output neurons corresponding to the movements, and one hidden layer composed by 35 neurons. Activation function is Tan-Sigmoid, and the Levenberg Marquardt algorithm is used for training. The network outputs are linear, thus binary encoding is needed. For example if the first neuron output is the nearest to 1, then all the other outputs are set to 0. The resulting binary string, in this particular case, represents the event “Hand closed” [1 0 0 0 0 0 0]. Each of the seven movements has its own binary encoding.

5. RESULTS

The general idea behind this project was to work in a different way compared to the majority of works present in literature: i.e. starting from the analysis of the signal and its problems in order to define the specifics for a final robotic hand prototype. This approach permits to identify a set of movement that will be recognized by the control system with good performances, avoiding realizing a complex prosthesis that is impossible to correctly actuate or a simple hand unable to exploit the capability of the actual signal classification devices.

In order to evaluate the performance of our acquisition and classification system, we collected four sound subjects, and asked them to attend some acquisition sessions, in order to collect a sufficient amount of data to produce some statistics.

All the subjects performed the seven movements (*close hand, open hand, wrist extension, wrist flexion, thumb abduction, thumb opposition and index extension*), repeating each one ten times before taking a break. Each train of ten repetitions has been performed twice by subjects A & B, and twice by subjects C & D, for a total of 30 repetitions for movement in subjects A & B and 20 for subjects C & D. Each train has been acquired slightly shifting the position of the electrodes, in order to improve the independence from each session, and to avoid an excessive rising of the muscular fatigue.

A MATLAB(R) script has been developed to analyze collected data and produce some statistics to evaluate the general behaviour of the proposed system. The whole collected dataset for each subject has been divided into two sets, one dedicated to train the ANN (training and validation sets) and the other to test it (test set). The number of repetitions of the same movement to recognize in the test set was 6 for the first two subjects and 4 for the last two.

For each subject a net was trained and tested. Results in table I show that the movement recognition rate of a trained net using our system is very high, with a mean for all movement of near 100%. The two errors are in recognizing wrist extension or thumb abduction for the last two subjects, namely a teenager fat boy and a middle aged woman; for both the muscular tone is low.

Table I. Number of errors in recognition of movements in four subjects. In bold the errors.

BEST	**Sub A**	**Sub B**	**Sub C**	**Sub D**
Mov 1	0/6	0/6	0/4	0/4
Mov 2	0/6	0/6	0/4	0/4
Mov 3	0/6	0/6	**1/4**	0/4
Mov 4	0/6	0/6	0/4	0/4
Mov 5	0/6	0/6	0/4	**1/4**
Mov 6	0/6	0/6	0/4	0/4
Mov 7	0/6	0/6	0/4	0/4

A second MATLAB script was developed to assess the independence of the results from the choice of input data to train the nets. This script tests cyclically generates different partitions of training/test data and tests them. In this way, all data entered at least once the test data set for some nets; the results indicate the stability of the approach.

In table II, results produced by the second script indicate that the error hit rate increases, but proportionally to the increase of the number of movement tested, maintaining the ratio quite stable.

This suggests that the proposed system is stable on the dataset, and shows a good independence on the training set used to train the ANN classifier.

Table II. Number of errors in recognition of movements in four subjects. In bold the biggest errors.

AVERAGE	**Sub A**	**Sub B**	**Sub C**	**Sub D**
Mov 1	1/120	1/120	0/40	1/40
Mov 2	5/120	**6/120**	**3/40**	0/40
Mov 3	0/120	4/120	240	1/40
Mov 4	1/120	0/120	0/40	1/40
Mov 5	6/120	7/120	0/40	**3/40**
Mov 6	3/120	2/120	0/40	0/40
Mov 7	**9/120**	2/120	2/40	1/40

Eventually, the influence of other factors, like muscle fatigue, patient's concentration, motivation and training level was also analyzed, leading to the conclusion that a patient needs to be well trained and prepared before the customization of his own prosthetic controller, as well as motivated and assisted. This topic deserves further investigation.

It is also important to make few considerations on the utility of the motion patterns that the system is able to recognise. Combining them in the right way it is possible to reproduce many complex grips, described by Cutkosky. (1989). *Lateral Pinch, Small Diameter, Disk, Sphere, Thumb-Index Finger, Tripod, Platform and, the index point.*

To create the abstract mapping between the seven basic movements recognized by the classifier and the complex patterns taken from the Cutkosky's taxonomy, we will develop a high level controller, here presented in an abstract way. The first task is to create the following commands:

1. *hand closing detected*: all the DC motors in the metacarpophalangeal joint, plus the flexion/extension DC motor of the thumb start to flex the fingers;
2. *hand opening detected*: all the DC motors in the metacarpophalangeal joint, plus the flexion/extension DC motor of the thumb start to extend the fingers;
3. *wrist extension detected*: the single motor in the wrist performs the extension;
4. *wrist flexion detected*: the single motor in the wrist performs the flexion;
5. *thumb abduction detected*: if the hand is in the *"opened"* configuration, then the thumb can be abducted by its abduction/opposition DC motor ;
6. *thumb opposition detected*: if the hand is in the *"open"* configuration, then the thumb can be opposed by its abduction/opposition DC motor;
7. *index extension detected*: flexion/extension DC motor of the index finger starts to extend, while all the other flexion/extension DC motors in the fingers, thumb included, start to flex.

Hereafter, from different concatenations of these basic movements the high level controller has to produce complex motion patterns. The whole process is described in Figure 5 for the wrist; it uses only the two wrist commands as state transitions, and for the hand, that uses the other five commands.

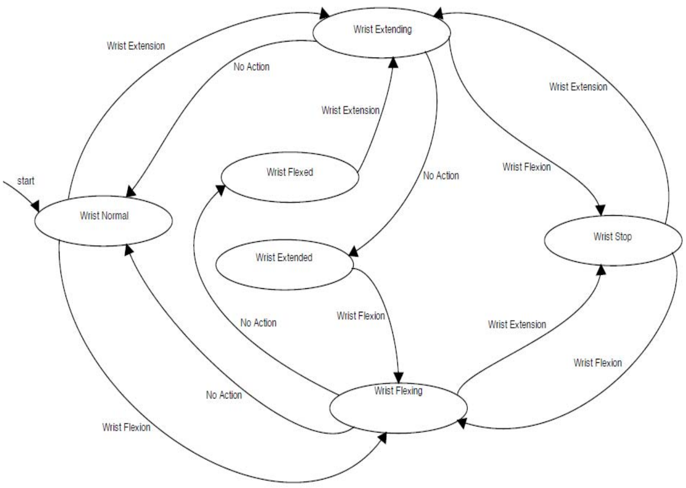

Fig. 5: Wrist state diagram

6. CONCLUSIONS

In this work we establish the basis for the design of a brand new prosthesis, since the whole prosthetic control relies on the EMG signal analysis.

The performances (98.6%) that the system is able to achieve are really promising, considering that it is able to recognize seven motion patterns with the use of just three channels. These seven basic patterns are then fed into a high level controller which is able to produce six different complex movements, like *key, power, precision, tripod grips*, plus *platform grasp* and *index point*. In this way the dexterity and the reliability of the hand are improved with respect to previous works on the subject. Moreover we were able to understand that factors like electrode displacement, fatigue, body structure, concentration, motivation and the training of the patient can influence the whole system.

Of course, for the patient's sake the reliability and the recognition rate of such a product should be of 100%. This goal is reachable just if the patient is well trained, motivated and concentrated. This means that he needs a trainer who helps him to overcome both the psychological and technical issues related to the acquisition phase and to the training phase.

As a practical result, we have developed a complete hardware/software system to classify EMG signals into seven movements, with an accuracy of the classifier which is comparable to the best results obtained in other studies.

Our results suggest that the control of prostheses with more movements that the open/close is not only worth investigation but definitively promising.

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