New Results on Classifying EMG Signals for Interfacing Patients and Mechanical Devices

G. Gini, L. Cavazzana, F. Mutti, P. Belluco and A. Mauri

Abstract In modern days the goal of rehabilitative robotics is to take advantage of robotics-inspired solutions in order to assist people affected by disabilities using physical training assisted by robots. In this way the rehabilitative exercises could be autonomously performed by the patients, with a reduced involvement of the therapist, making high-intensity rehabilitative therapy an affordable reality. Moreover high-precision sensors integrated in rehabilitation devices would allow a quantitative evaluation of the progresses obtained, effectively comparing different training strategies. That would represent a huge scientific achievement in a field where evaluations up to this day are performed only by means of subjective observations. Important results were obtained in rehabilitative robotics, but results in the field of the hand rehabilitation are poorer, due to the high complexity and dexterity of the organ. This chapter proposes to integrate the detection of the muscular activity in the rehabilitation loop. A new EMG analysis tool was developed to achieve a reliable early recognition of the movement. Experimental results confirmed that our system is able to recognize the performed movement and generate the first control variable after 200 ms, below the commonly accepted delay of 300 ms for interactive applications. This shows that it is possible to effectively use an EMG classifier to obtain a reliable controller for a flexible device, able to assist the patient only after having detected his effort.

Keywords Rehabilitative robotics · Arm rehabilitation · EMG signals · Classifiers

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1 Introduction

Each year 800,000 people in the U.S. experience stroke attacks, with 50 % of the survivors left with hemi paresis and 26 % unable to independently perform daily activities (American Heart Association 2011). These statistics make stroke the leading cause of physical impairment, but other pathologies such as multiple sclerosis, cerebral palsy, spinal cord injury, Parkinson disease or bones trauma and ligament degradation are cause of poor quality of life.

Tests show that significant improvement in movement ability can be achieved through proper physical training, but this leads to a strong economic pressure on the health care system. The idea behind rehabilitative robotics is to take advantage of modern robots to assist patients through physical training: from the point of view of the therapist, exercises are highly repetitive, time consuming and physically demanding, the kind of task robots are suited for. So in the last 20 years a great effort was spent in developing devices able to offer a (semi-)autonomous training and in studying better methods to help patients to regain their motor functionalities (robot-aided rehabilitation), or providing active assistance with daily activities (assistive exoskeletons). Currently, robotic therapy programs are offered by some health care centres. The ultimate goal is to make affordable domestic intensive therapy in the near future.

Tests conducted within the Veteran Affairs (VA) hospitals (Lo et al. 2010) show how patients who received high intensity therapy by a robotic device for thirty-six weeks achieved a significant gain in motor functionality, similar to the group which received a training of similar intensity from a human therapist. Both groups had a significantly greater gain if compared to a control group who received the traditional care. The cost for patient was $17,831 for the robotic therapy, $19,098 for usual care, and $19,746 for intensive non-robotic therapy. This indicates that now robotic therapy does not offer better improvements per se, but the possible drop in costs due to mass production could make high-intensity rehabilitation available on large scale. Another advantage of the robotic therapy is the ability to compare different training approaches, today left to subjective considerations of the therapist, making it possible to scientifically monitor the progresses and compare different strategies (Lo et al. 2010; Marchal-Crespo and Reinkensmeyer 2009), promoting consistency and reproducibility of the training.

A key element in rehabilitation is interactivity: the patient must not be simply dragged by the robot (Squeri et al. 2011). The rehabilitative system must promote user's effort giving assistance-as-needed, meaning only after detecting an effort, and providing no more than the force the patient needs to complete the task. This approach also makes the training exercise naturally scale with the condition of the patient, as the robot will gradually step aside as motion capabilities are regained (Wolbrecht et al. 2008).

Problems arise when the patient is unable to perform even the slightest movement, making force-triggered assist-on-need useless. For this reason EMG-triggered therapy was introduced: even if muscular tone makes the patient unable to perform any movement his intentions can still be detected if he is able to generate a minimum amount of nervous activity. Even users with better muscular conditions can exploit the EMG analysis to further anticipate their movements, or check if they are correctly performing.

Although robotic rehabilitation is rapidly developing, hand rehabilitation is relatively less dealt with if compared with the arm or the leg. This is because hand is a very complex organ, composed by 22° of freedom and actuated by nineteen muscles. Moreover muscles are tightly packed in the forearm, making signal detection pretty complex using non-invasive techniques like surface EMG, because of high interferences between muscles (cross-talk). Such complexity makes the realization of a rehabilitative device extremely challenging, both in mechanical design and control strategy.

Our goal here is to show how to improve arm, and in particular hand, rehabilitation through the EMG analysis. In the past we developed a rehabilitative device (Mulas et al. 2005), together with hand design and control strategies (Folgheraiter and Gini 2004; Folgheraiter et al. 2003; Soto Martell and Gini 2007), and an EMG-based controller for hand prosthesis (Arvetti et al. 2007; Gini et al. 2012; Lisi et al. 2011). Starting from those experiences we illustrate how the EMG classification system could meet the real time performance requirements for a smooth interaction with the patient, a key element for any EMG-triggered rehabilitative device.

The chapter is so organized. Section 2 presents an overview of the biological aspects of EMG signal generation. Section 3 gives an overview of the field of technology aided rehabilitation, and summarizes the results of the EMG signal classification for the hand movements. Section 4 discusses our EMG classifier, based on the concept of early detection. Section 5 evaluates the performances. Section 6 summarizes the results and proposes possible future developments.

2 Hand Movements and EMG Signals

The hand is one of the most complex organs, counting 22° of freedom actuated by nineteen muscles and able to perform very dexterous movements. A functional taxonomy (Bullock 2011) considers all the hand/wrist movements obtained by combination of the following basic movements.

1. Hand pronation and supination. From the neutral position with the elbow flexed at 90°, and the axis of the palm perpendicular to the floor, pronation is the rotation of the forearm that makes the palm face down, and supination is the rotation making the palm face up.
2. Wrist extension and flexion. From neutral position, wrist extension is the upward rotation of the wrist, while wrist flexion is the downward rotation.
3. Finger hyperextension and flexion. The neutral position is the open hand with fingers extended in a plane parallel to floor. Finger flexion is bending the

fingertips toward the palm, while finger hyperextension is an unusual movement where finger raises above the palm. The flexion of all fingers results in hand closing, while the motion from the close state to the neutral position is hand opening.

4. Thumb abduction and opposition. The neutral position is with the thumb extended alongside the hand, parallel to the other fingers. Abduction is the movement that moves the thumb away from the palm midline, while the opposition is the flexion on the palm.

All movements are exerted through muscles that contract when stimulated. The force they exert is unidirectional, so more than one muscle is required to perform complex movements. Most of the muscles that move the hand are located in the forearm, and move fingers by means of tendons running through sheaths and leverages (Gray 1918). In this way it is possible to transmit a large force to the fingers relocating the bulky muscles away in the forearm, the so called extrinsic muscles responsible for finger and wrist flexion. In the hand there are however intrinsic muscles.

The most relevant muscles are the flexor digitorum profundus (fdp) and flexor digitorum superficialis (fds), which originate in the proximal part of the forearm and fan out in four tendons that run through the carpal tunnel. Also relevant is the extensor digitorum communis (edc) that from the superficial part of the dorsal side of the forearm fans out in four tendons which insert in the middle and distal phalanxes, contributing to wrist and finger extension. For thumb the flexor pollicis longus (fpl) and abductor pollicis longus and brevis (apl and apb) are important.

A striated muscle, made up of a large amount of parallel fibres, is innervated by a single motor nerve; the connection of the nerve to the muscle consists of the axons of numerous alpha-Moto neurons. An important functional consequence is that the entire set of fibres innervated by an alpha-motoneuron contract in consonance.

Any voluntary movement is jointly undertaken by the motor cortex and other neural systems. The prefrontal cortex prepares the plan for the movement; the frontal cortex receives information from the parietal cortex, which is involved in spatial perception; the secondary motor areas work with the cerebellum to specify the precise time sequence of contractions of the muscles. The primary motor cortex, the brainstem, and the spinal cord produce the contractions of the muscles.

The contraction is initiated by an action potential travelling from the cell body of the alpha-motoneuron to the muscle fibres. Subsequently, the depolarization of the muscle fibre membrane causes a time-varying transmembrane electric current field that evokes potential changes in the extracellular tissue. The ionic currents flowing along the muscular fibres cause the muscle shortening.

The neuromuscular system is an association of several motor units (MUs), constituted by an alpha motoneuron and the muscle fibres it innerves. Nervous and muscular cells have electrical polarity on both sides of their cytoplasmatic membrane. The membrane potential is within −70 and −90 mV; after excitation, cells react with a transitory variation of the electrical polarity of the membrane, the action potential (AP). When a motoneuron is activated, an AP is generated and propagated 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). Those variations in potential generate the electro-myographic signal (EMG) (De Luca et al. 1979; Hogan and Mann 1980).

Using needle electrodes it is possible to register a single MUAP; instead, surface EMG (sEMG) techniques detect a larger number of MUAP. The problem of the single contribution detection is commonly called cross-talking.

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 10 mV or 0 to 1.5 mV. Signal frequency falls within 10–200 Hz: 10–30 Hz for a single motor unit, over 30 Hz for the superposition of multiple MUs.

EMG signals present two main issues that strongly influence their quality: the signal to noise ratio, and the distortion of the signal. Noise emanates from a wide range of sources, as the electronics components, the ambient, our body, movement artifacts. Most of the noise can be reduced by good electronics design and reducing signal cables length, while it is still partially unresolved how to deal with the noise generated by our body.

3 EMG Analysis and Rehabilitation

It is well known that it is possible to improve motor conditions by repetitive training: performing motions helps to improve joint plasticity, while continuous contraction and extension (even if passive) help to regain muscle tone. If the patient is affected by a neurological disorder guiding him through the exercise helps him to associate alternative pathways to help the damaged ones in performing the movement. However recent tests show how simply forcing the patient through a set of movement results in suboptimal improvements from the neuromuscular point of view: better results are achieved when there is an active user effort. So a key element in rehabilitation is the so called “assistance as needed”, meaning the robot must trigger help only after detecting a concrete effort to complete the given task, thus forcing user engagement and promoting motor learning while retaining the voluntary control of the limb; moreover it should provide only the minimum force the patient needs (Dipietro et al. 2005). Another advantage in user-triggered assistance is that the pace of the exercise is determined by the patient itself.

Assistive control algorithms are based on highly backdrivable devices, able to quickly react to the force applied by the patient. Issues arise if the condition of the patient does not allow him to execute even the slightest movement, making the force-control paradigm useless. More recently new approaches based on detecting user’s effort through surface EMG analysis were explored: if the patient is still able to generate some nervous activity his intentions could be detected, and some kinematic parameters could be estimated (Dipietro et al. 2005). An alternative paradigm, named impedance based, consists in letting the patient independently move through the goal, and guiding him applying mechanical impedances when he deviates from the desired trajectory. Studies showed how these strategies for robot-aided therapy can lead to a significant improvement in motor skills (Ho et al. 2011).

Historically the first field of application of EMG control was for arm prostheses. However there are some differences between rehabilitation and prosthesis control: in the first one we must restore the very same pre-accident pattern, so we are interested in a control as natural as possible. In the latter instead the level of amputation could force to map the control over other areas, so what is really important is the repeatability of the signal.

Controlling the device using the EMG signal allows implementing the aforementioned assistance as needed when user's conditions are not suitable for a force control. Plus it offers the most natural control for assistive exoskeletons or prostheses (mapping each actuator on the very same muscle it is meant to assist).

Different approaches to EMG signal analysis were proposed. The simplest technique uses signal threshold (Dipietro et al. 2005): the controller checks when the signal (or his linear envelope) exceeds a fixed value. This control paradigm has limited capabilities since the output is only binary. A more sophisticated approach is to output a continuous value roughly proportional to muscle activity. These algorithms are already employed for prostheses control, but they permits to control only few hand postures. This is due to the limited number of independent signals we can register from the forearm muscles packed in a relatively small volume.

Mixing statistical methods and machine learning provided powerful tools for automatic classification (Raez et al. 2006) and unsupervised cross-talk removal (Naik et al. 2007). A first stage of the EMG signal analysis consists in extracting the most significant features from the burst. The most common time-domain features include mean absolute value (MAV), integral absolute value (IAV), standard deviation (SD), and signal power (SP); frequency-domain features are zero crossing, power spectrum, spectrum centroids, and frequency ratio (Arvetti et al. 2007). More recently time/frequency-domain features were introduced; being the EMG a non-stationary signal, features based on classical Fourier transform can't be effectively applied because of the shifting frequencies over time. A promising technique is the wavelet analysis (Szu et al. 1996); a time-frequency representation of the signal obtained by the convolution with a finite-energy function (wavelet) obtained scaling and stretching the basic wavelet (mother wavelet). The output matrix of wavelet analysis contains a large number of elements, so dimensionality reduction should be performed.

The selected features are the input to a classifier that has to recognize the performed movement. Classification performance depends on several system parameters. The most important factor is the number of gesture under analysis; another is the number of acquired signals (Hudgins et al. 1993). Our previous works achieved 96 % accuracy rate over five gestures with one channel (Arvetti et al. 2007), and the same rate was obtained over seven gestures (grasp, hand extension, wrist flexion and extension, thumb abduction and opposition, index hyperextension) with three channels (Lisi et al. 2011).

As we anticipated, hand rehabilitation isn't very developed. However, among the few exoskeleton devices developed at various Universities we name the polimanus (Mulas et al. 2005), partially activated through EMG.

4 Our Analysis of sEMG Signals

Our project is about using a gesture classifier to control a hand rehabilitation device that assists in basic movements. Starting from our sEMG classifier for prosthesis control (Arvetti et al. 2007; Lisi et al. 2011), we focused on the real-time behaviour of the method. According to empirical analysis the maximum tolerable delay between the user command and the action of the controlled device is 300 ms (Englehart and Hudgins 2003), so the main problem is to meet this time requirement.

The first issue was to determine the number of samples needed for a successful classification. Usually the software acquires big batches of data which are later analysed to extract complete movements to classify. With this approach an online classifier is unfeasible, since it requires the movement to complete before recognizing it. So we analyzed how the movement classification depends on the length of the EMG signal so far acquired. The results have been used to define the architecture of the real time classifier (Fig. 1), implemented in Matlab 7.11:

- interface with the EMG acquisition board that outputs the parsed signal.
- analysis of the signal, designed to work with both continuous online and batch classification.
- interface to the exoskeleton.

The hardware system consists in the Eracle USB electromyograph connected to a PC (P4-2.4 GHz, 4 GB RAM). Eracle (Fig. 2) is a wearable device (Belluco et al. 2011) that provides three bipolar channels plus a common reference, used to remove the common noise between two paired electrodes. Each electrode records the voltage with respect to the common reference; each channel measures the difference between two coupled electrodes. The three resulting signals are amplified, sent through a high-pass filter with cut-off frequency at 1.5 Hz and a Sallen-Key anti-aliasing filter (double pole at 150 Hz). Finally a PIC16F688 microcontroller samples the signal at 237 Hz with 10 bit ADC and outputs an ASCII string. The device is extremely small and lightweight (29 $\times$ 45 $\times$ 9 mm and weights 35 g); it is well suitable for wearable applications.

Our previous sEMG classifier took into consideration complete bursts, which means it had to wait for the movement to complete before identifying it. This is unacceptable for an interactive device, since the control signal would be too late, so we investigated how recognition rate varies using incomplete movements.

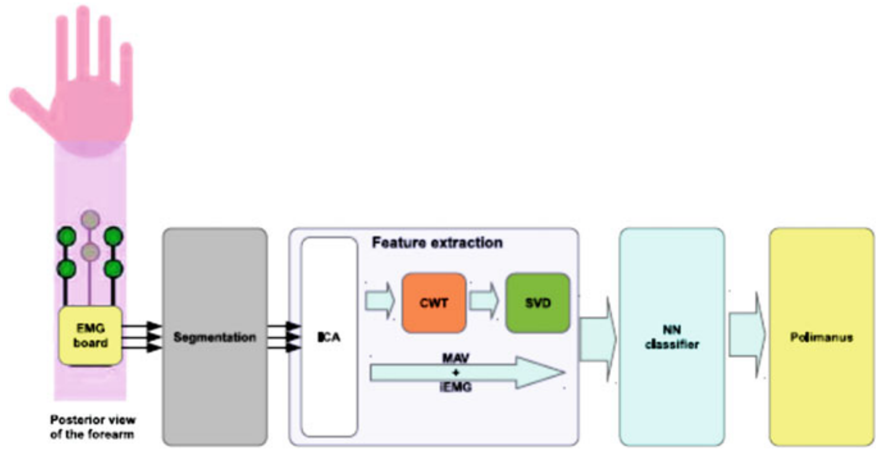


Fig. 1 System architecture

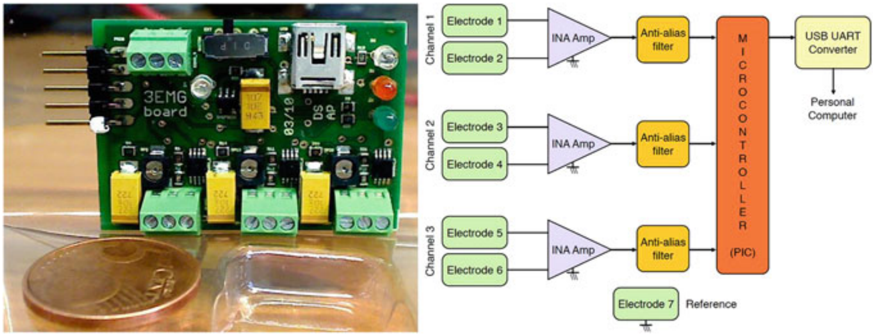


Fig. 2 **a** The Eracle board: picture compared with a 5cents coin; **b** The Eracle structure

We checked the performance of five neural networks trained on sEMG data acquired as in (Lisi et al. 2011); the set was composed by thirty bursts for seven gestures, with an average length of 200 samples each. The classification performances were computed over the testing sub-set, feeding the networks with features extracted from the initial segments of the bursts with increasing lengths.

Figure 3 displays the recognition rate over the percentage of the analyzed burst. After 50 % of the burst the recognition rate dramatically increases reaching performances close to the ones obtained analyzing a complete burst.

The test was repeated using networks trained using only half bursts. Recognition rate reached his maximum with half burst and slightly decreased for longer segments (Fig. 4). The decreasing trend near full burst is due to the fact that the network reaches the peak of his performances over the very same burst length used for his training; as the percentage of the analyzed segment moves from 50 % the

Fig. 3 Recognition rate over burst

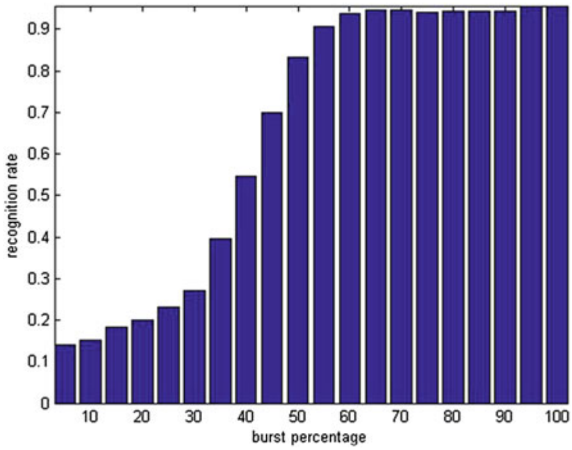
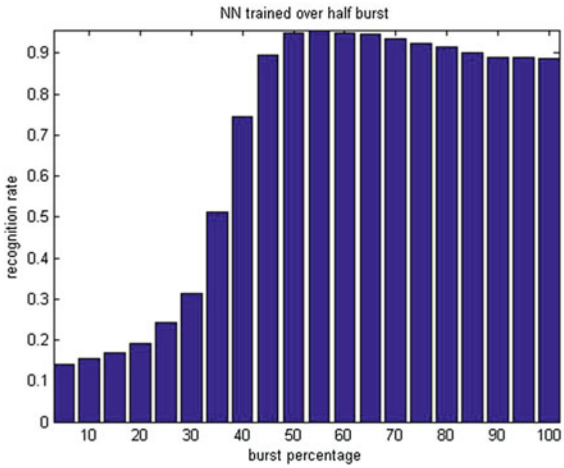


Fig. 4 Recognition rate over half burst



extracted features slightly change, thus scoring under 90 % at the end. Further tests were made training nets over segments even shorter, but no significant result was achieved.

We concluded that it is possible to obtain in an early stage a recognition rate close to the one obtained analyzing full bursts, using features extracted from the preamble and few samples right after the detection of the movement; this is what we call online classifier.

To fully develop the online classifier we selected a new reduced set for rehabilitation purposes of only 3 movements: hand opening, hand closing and precision grasp (pinch). The relevant muscles for those movements are fdp and fds that are responsible of most of the force generated for fingers and wrist flexion, the edc, responsible for fingers and wrist extension, the fpl and apb for thumb movement.

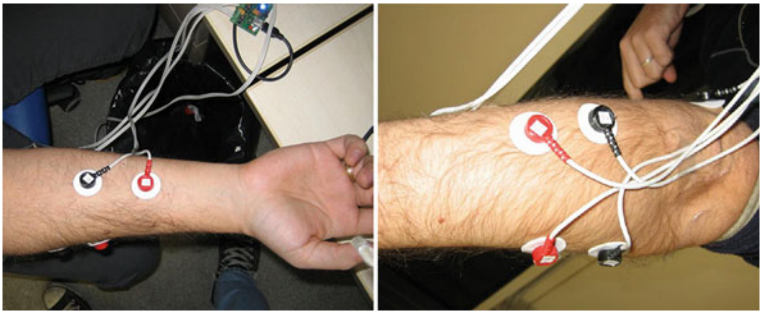


Fig. 5 Electrodes placement

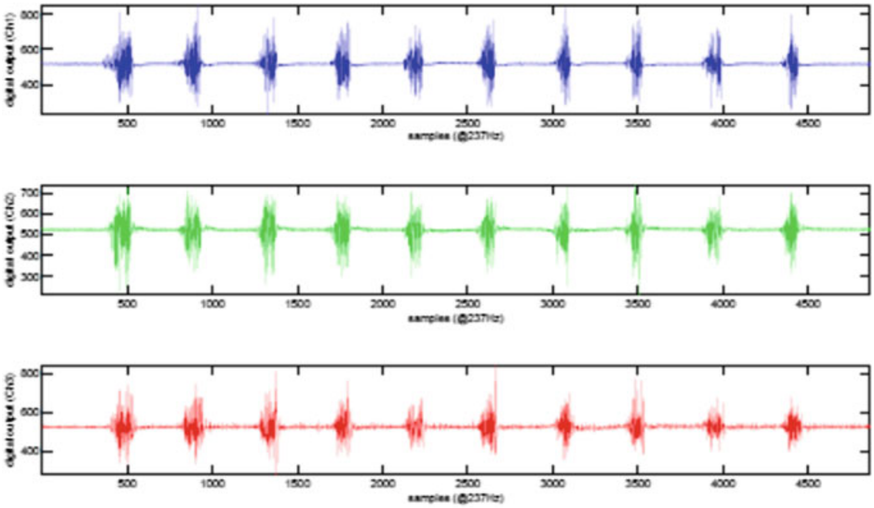


Fig. 6 The parsed signals

The choice for electrodes was intentionally limited to the ones commercially available for electro-stimulation, that are easily available at stores and whose signal keeps an acceptable signal-to-noise ratio even if used multiple times. We opted for 32 mm circular electrodes to reduce the surface and so the crosstalk.

The two electrodes of the first channel were placed in the volar side of the forearm along the fdp and fds, to highlight the muscle activity that leads to hand closing and wrist flexion. The second channel was placed over the edc, to acquire the signal of finger and wrist extension. The third channel could not be placed over the fpl and the apb because these muscles are too small and deep to generate a measurable signal; wee placed it in the internal dorsal part of the forearm (Fig. 5).

The function of Eracle's common reference is to detect the noise from the body (to subtract from the other channels); so its electrode was placed on the elbow, which is far from any involved muscle, and so records noise only.

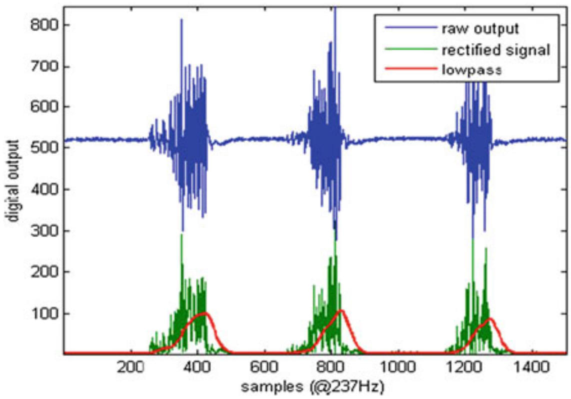


Fig. 7 The result of segmentation over 3 bursts of hand closing on channel 1

We shortly illustrate the main steps of the sEMG classifier.

1. Parsing—The signal is acquired from the board using Matlab's Serial Port Interface and converted from ASCII string to a N $\times$ 3 matrix (Fig. 6), where N is the number of acquired samples; the values are unsigned integer representing the 10 bit encoding of the signal. The input buffer is set to contain up to 1 s of samples.
2. Segmentation—Before identifying a movement we must detect it and define his boundaries. This is done subtracting the signal mean, rectifying the signal, filtering it with a second-order low-pass Butterworth filter (cut-off frequency at 2 Hz). In this way we can determine the beginning of a movement (burst's head) using a fixed threshold and checking his derivative. We consider a movement ended (burst's tail) when the signal or his derivative drops under a fixed value (empirically found). A burst is considered as open while activity in any of the channels is detected, and closed when activity does not satisfy the parameters anymore. See Fig. 7.
3. Independent component analysis (ICA)—We used the FastiICA package with Hyvarinen's fixed-point algorithm ICA allows extracting N independent source signals from at least N samples containing linear mixtures using multivariate statistical analysis. Given enough channels we could theoretically eliminate cross-talk separating the activity of every single muscle. The number of muscles however is much larger than the number of channels, so we couldn't associate a predominant signal to every channel but instead we used ICA for de-noising: we rebuilt the signal with the most significant contributions, applying an adaptive threshold to the matrix of weights. Since the FastICA is a fixed-point algorithm the weighting matrix is stored and used as initial value during further ICA analyses of the same burst, and is reset only after the closing of the burst.
4. Features extraction—The temporal features considered are the mean absolute value (MAV) and his integral (iEMG). They are closely related to signal energy and different gestures generate very different activities on different channels

caused by different patterns in recruitments of MU. For example hand closing generates a strong signal on the channels placed on the volar side, while fingers hyper-extension generates more energy in the dorsal channels. Only using these features we obtained a classification with 80 % accuracy. To improve the performance we considered also the Continuous Wavelet Transform (CWT), which is able to retain the temporal localization of the shifting frequency features. We chosen the Daubechies wavelet family, and empirically set the parameters.

5. Dimensionality reduction—The CWT for an N-samples signal generates an $M \times N$ matrix, where M is the number of scaling coefficients. For an average burst of 200 elements this means 5×200 because of the empirical choice to make the scale to vary between 1 and 5. The dimensionality reduction of the matrix is achieved by singular value decomposition (SVD). Therefore the neural network classifier receives in input a feature vector composed by seven elements: MAV, iEMG and the five singular values.
6. Neural network classification—Among all the techniques available we used ANN because of their ease in the setup process. We defined a feed-forward network with one hidden layer of thirty-five neurons, and tan-sigmoid transfer function. Data was partitioned using 75 % of the data for the training, 15 % of the samples for validation and the remaining 10 % for external testing. As learning algorithm Levenberg-Marquardt was selected, with early stopping.

The modules are automatically called during system execution. A Graphic User Interface was created to guide the user through the acquisition protocol and to automate the training. When the acquisition phase is complete, the interface stores the raw data of each repetition in a text file properly tagged, that is used for training. Offline classification, using the entire batch, is used during the training phase.

On the contrary, the online classifier is used to recognize the movement during the use of the system. During online recognition the EMG board is periodically polled for new samples, the new chunk is appended to the buffer and the updated signal is processed. If a burst is detected during the segmentation, and is at least 120 samples long, then the classifier is called and the resulting command is forwarded to the exoskeleton; if the burst has less than 120 samples only ICA is performed to compute the mixing matrix for the next iterations.

Since we are making a continuous acquisition, before acquiring the next signal segment a part of the old signal may be kept. There are three cases:

- If no burst is detected, the last 100 samples are kept to fill the preamble of any potential new burst.
- If an incomplete movement was detected, the signal is flushed up to the head of the burst.
- If a complete movement was detected, the buffer is flushed to the tail of the burst.

Table 1 Time for a burst classification

Function	Time (ms)
Segmentation	11.4
Feature extraction	14.7
Classification	8.6
Total	34.7

5 Results

The online classifier was tested with to determine the performances of the overall system considering the classification rate to recognize three gestures and the user perceived delay. Tests were performed over a P4-2.4 GHz PC with 4 GB of RAM and running Matlab 7.11 for Windows.

The delay analysis has been performed executing the complete analysis using 100 segments of signals containing a burst. A complete burst classification, as in Table 1, takes an average of 35 ms, which leads to a frequency of 28 analyses per second.

To test performance of the online classifier a new acquisition set was acquired for the three hand movements, for a total of ninety movements, from one subject (26 years old male, with a height of 1.83 m and weighting 73 kg). With this data set a classifier was trained, using cross-validation with 75 % of the samples for training, 15 % for validation and 10 % for external testing. The online classifier was launched and the user was asked to perform a sequence of randomly selected movements while recording the success rate.

The classifier scored an overall recognition rate of 95 %. Hand openings/closings scored a perfect recognition rate of 100 %. Some issues were instead noticed with pinch: this movement generates a mild muscular activity, hard to detect before the fingertips touch and start pushing against each other. In a few cases this movement was mistaken for hand closing because of the relatively similar activation.

The delay recorded between the beginning of the movement and the first response from the classifier was estimated to be around 200 ms (including the delay introduced by the EMG board, the serial communication, the time needed to gather enough samples for a reliable classification and finally the analysis itself), while subsequent cycles produced a new output (confirming the first one) every 20–30 ms until movement completion.

6 Conclusions

In this work we demonstrated the feasibility of an interactive controller for a rehabilitative device based on the classification of the EMG through an early analysis of the burst. We showed how to obtain good classification performances starting the analysis on a limited number of samples from the beginning of the detected movement; this way we reduced the delay under 200 ms, an interval which is under the commonly accepted limit for a smooth interaction. Thanks to the new interactive capabilities the classifier can be integrated into a rehabilitative device, allowing an assist-on-need strategy based on the residual muscle signal. The software is available at http://code.google.com/p/polimiemganalysis.

This result can significantly improve the quality of the rehabilitative training: from tools which force the patient through a set of preprogrammed movements, promoting only joint plasticity, to devices able to detect the user's intentions, quickly reacting to assist whatever movement is trying to perform. This new capability has several implications. Forcing an active effort it helps to regain muscle tone; it allows performing exercises for the rehabilitation of the neuromuscular system; it is also suitable for highly-impaired patients, whose inability to perform any movement would not permit them to benefit from robotic rehabilitation through force-controlled devices.

The new architecture of the system was also conceived to improve his modularity, decoupling the core signal analysis from the specific implementation of the external devices. This allows to easily adapting it to new devices, and reusing the system for applications even outside the field of rehabilitation, such as prosthesis control, teleoperation, and human computer interaction.

Matlab was used because of his high performances and the availability of functions and toolboxes for every application. However better time performances could be achieved porting the code on a microcontroller.

Rehabilitative robotics promises to bring significant improvements into the quality of life of victims of impairing accidents offering high intensity training and allowing to objectively compare the effectiveness of different therapies. Significant results had been achieved, but a solid framework of both knowledge and devices is yet to be established.

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