ERACLE: Electromyography System for Gesture Interaction

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Abstract. Gesture interaction is one of the most important topics in the human-computer interaction. In this field, the main research activities are oriented on recognizing and classifying different gestures in order to interact with the computer directly with the body, without using classical mobile devices such as touchpad or trackball. This paper describes the development and the testing of our wearable interaction system that uses surface electromyography (sEMG) signals to recognize and process the gestures of the users. The core of the system is the "Eracle-board" that is a wearable 3-channel board developed in order to acquire the sEMG signals from the user's forearm. The acquired data are subsequently processed by an external device, which allows us to recognize and classify seven different gestures through the implementation of a neural network. Finally, the effectiveness of the system has been evaluated through some tests carried out with users.

1 Introduction

Acquiring and understanding the movement and the posture of the body is the new way to interact with computers. In fact, a large part of the research activities in human-computer interaction is focusing on the study of new modalities to get and to use the information deriving from our body in order to develop interfaces able to interact with computers. Currently there are various technologies for capturing the movement of the body. Today accelerometers are the most frequently devices used to do it, thanks to their availability on the market and to their modest price, but they are still far from being optimal. Actually accelerometers are able to capture only a small part of information posture and motion. Among other modalities for capturing movements, there is the *surface electromyography* (sEMG). This is a technique that derives from the medical field and is able to recognize the electrical activity produced by skeletal muscles. It is called “surface” because in the normal EMG investigation the muscles of the patient are reached by needles inserted directly inside the muscle, while in the sEMG the electrodes pad are used in place of needles. This paper presents a prototype of an sEMG interaction system. We have built a three-channel wearable electromyography. Furthermore we have built specific software that is able to acquire the digital data from the board, classify the movement and train an ANN and store the user's parameters and data in a MySQL DB in order to study how different parameters can

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affect the sEMG signal. In the first part of this paper we introduce how our body generates this specific electric signal and which parts of the body are involved. Afterwards we describe the characteristics of the sEMG information and the difficulties that this kind of technique involves. Then we describe how we have elaborated the signal, the extraction of the features and the classification of the movement, by using two different methods: wavelet analysis and independent component analysis. Next we describe the characteristic of the hardware and software system, and the setup for the system performance evaluation. Finally we show the results and present future developments of the wearable sEMG system.

2 Related Works

The new way to interact with computers or machines in general is by gestures and bodily motion; this originates from the face or hand. Many approaches have been made using cameras and computer vision algorithms to interpret sign languages. The most famous application in gesture recognition is probably the *Wiimote*. Furthermore there are systems based on one or two cameras that recognize a part of the body (typically the hands and the fingers), in which gestures are encoded as command for the computer, e.g. the S*ixthSense* from MIT Media Lab [7] that uses a camera and a tiny projector in a pendant-like device to see what is requested, and visually augment the surfaces or objects with which the user interacts by hand gesture, thanks to colored markers placed on the four fingers. Electromyography is a well-known technique in the medical field; it is used to diagnose pathology such as amyotrophic lateral sclerosis; otherwise it is used to facilitate amputees to command robot prosthesis [3]. Lately the techniques have been improved and now the control is made using not only one single muscle control, but using an entire group of muscles [7]. EMG signals can be used for a variety of applications including clinical applications, such as HCI and interactive computer gaming [4]. Other studies in the domain of bioengineering have concentrated on the use of electromyographic signals for controlling of prosthesis, rehabilitation and computer interfaces for users with motor disabilities [6] [10]. For example Benko and Saponas [1] presented a touch sensing developed through an interactive surface, and muscle sensing via EMG. Another work has been developed by Microsoft Research and Saponas et. al. [8] [9] in which is presented a muscle-sensing interface for always-available input in real-world applications (e.g. to interact with portable music player, videogames, car) able to classify and use in real-time a variety of finger gesture in order to interpret forearm electromyography (EMG) and classify finger gestures on a physical surface. They studied the existing taxonomies of natural human grips to develop a gesture set covering interaction in free space even when hands are busy with other objects.

3 The Electromyography System

The system consists of 3-channel wearable sEMG device that the user wears on his forearm by means of a forearm cover. The device is connected to an external device that provides the signal elaboration and allows the interaction of the user. We have built a prototype of a sEMG developing board, named *Eracle* (see Fig. 1) able to handle 3 different and independent channels (three triplets of electrodes).

It is equipped with PIC16F688 processor. In the first step the signals pass through the INA amplifier (the gain is adjustable from 200dB to 2000dB) and through a high-pass filter (cutoff frequency: 1.5Hz); afterwards an anti-aliasing filter is inserted, which is the Sallen-Key (double pole at 150Hz). This architecture is replicated for each EMG-channel. Then, the analog signals are digitalized from the microcontroller, which has a 10bit ADC (sampling rate: 270 Samples/Second); the samples are transferred to the computer via USB. The Eracle's output is composed of a string that contains for each row the data for each channel.

3.1 Data Elaboration

An external desktop computer performs the elaboration of the signal and the storage of the information that have been acquired. A standard desktop computer runs the software that elaborates the digital signals. It performs the training of the artificial neural network and hosts the MySQL DB, where the information is gathered.

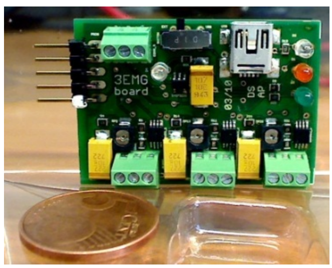

Fig. 1. The Wearable Eracle Acquisition Board compared with 5 cent coin

4 Signal Elaboration

This section presents how the electromyography signal is generated and the strategy developed for movement splitting, the methods for feature extraction and the way for movement classification (see Fig. 2). For elaborating the signals we have used two methods: the wavelet and independent component analysis (FastICA algorithm). The feature extractions have been performed with the same acquisition for both methods. EMG measures the electrical currents that are generated in a muscle during its contraction and represent neuromuscular activities. The neuromuscular system must be considered as an association of several functional units, called motor units (MUs). Nervous and muscular cells (muscle fibers) are excitable cells and their measured potential is stable within -70mV and -90mV. EMG signal detection is a delicate matter, and presents two main issues that strongly influence the fidelity of the signal. The first is the signal to noise ratio, defined as the ration between the energy of the EMG signal to the ratio of noise signal; and the distortion of the signal itself.

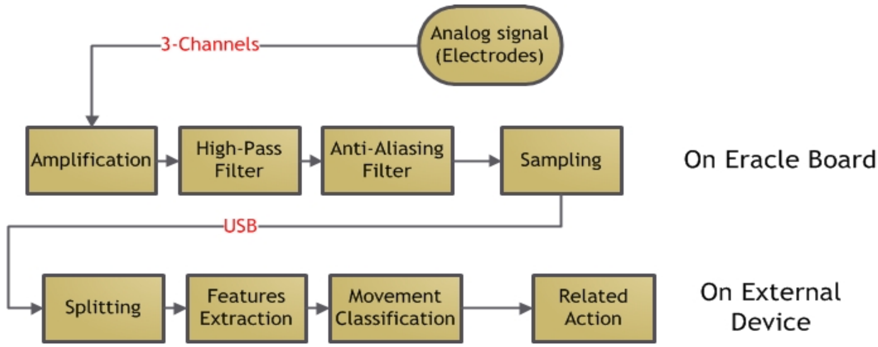

Fig. 2. DataStream of the application. The signal comes from the electrode pads; it passes through the acquisition board and then is acquired from the desktop station.

EMG signal is stochastic (random) in nature, and that 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 generally limited to a specific frequency range (0 to 500Hz), with the frequencies that most suits our purposes centered between 50 to 150Hz. Noise, instead, in the electromyographic techniques, may emanate from a wide range of sources: from the ambient (external disturbances), from our body (cross talking, endogenous disturbances) or from movement artifacts are the general noise related problems, which have to be addressed when working with EMG signal.

4.1 Wavelet Analysis

The wavelet is one of the best known of tool for signal analysis. The first step to perform for understanding the EMG signals is the splitting. The digital signal received from the EMG board is divided in many bursts, each related to a specific contraction in order to understand when a contraction starts and ends. An EMG signal is always made of a deterministic part, which contains the movement, and a part which contains the signal in its baseline configuration, when the muscles are inactive but the electrodes register a sort of basal activity and capture noise from environment. A neat separation using the raw signal is impossible, due to its high frequency oscillation that prevents it from using a fixed threshold to recognize when a movement is being executed. Working on the smoothed signal allows us to easily recognize the movement when it is performed, and so fixing a threshold on the elaborated signal leads to more effective results. This phase consists of three steps:

1. Rectification
2. Linear envelope
3. Segmentation

The feature extraction module has the role of identifying particular numeric parameters from the single signal burst. The integral EMG (linear envelope), moving absolute mean of the whole signal and its skewness has been used as feature as well. The Continuous Wavelet Transform (CWT) is here used. According to empiric observations and results obtained in other works, we have used for our analysis the Morlet mother wavelet [3]. Computing the CWT of a single burst composed by 270 samples produces a matrix of 5X270 size, and using the Singular Value Decomposition (SVD) we extract a vector of features that has seven components.

4.2 FastICA Analysis

In biometrics analysis the ICA methods are mainly employed for denoising. The main problem in using ICA methods with noisy signals is the lack of robustness of the algorithms; however, for sEMG data analysis, these approaches have been used with good results by Naik et al. [13]. From this point of view, ICA is also used to reduce the cross-talking between two or more muscles that are activated in the same contraction, thus the obtained independent components are the real signals generated by each motor unit. First of all the amplitude values of the three signals have been normalized. Moreover the signal sampled on channel 2 that is very noisy, maybe due to crosstalking has been limited by the ICA algorithm. On the contrary, the source signal sampled by channel 1 has been boosted, while the input signal on channel 3 remained virtually unchanged. Removing the noise from the signals it is possible to correctly extract some features, such as the root mean square (RMS), that identify the gesture performed by the user.

5 Software Module

The software module that has been developed for acquiring the electromyographic signal is able to acquire the digital data from board, classify the movements, train an ANN and store the user's parameters and data in MySQL DB in order to study how different parameters can affect the sEMG signal (see Fig. 3). First of all the user inserts his/her parameters in the form. The parameters stored so far are the following: Age, Gender, Height, Weight, Ethnic Group, Body Mass Index, Physical Activity, and Muscular Pathology. After the user data entry, the acquisition can be activated. For each movement, a short movie is presented, which shows how the user must perform the movement in order to improve the quality of the classification, and to avoid as much as possible errors in the signal splitting. After each acquisition the data are stored in a text file, and are automatically divided in a single file for each channel. Then it is possible to see the raw data acquired for each channel (the *"View Ch"* buttons). This is a first way of verifying the quality of the acquisition. Subsequently, it is possible to see the signal after the pre-elaboration (and to compare it with the raw signal), and before the launch of the classification and recognition methods. This elaboration consists in the rectification, the Butterworth filtering (in order to remove the main noise components [14]), the linear envelope of the filtered signal and then the splitting of the signal for each movement. These features allow us to check, straight afterwards every acquisition, if the quality of the data acquired is good. In case the quality is not good, it is possible to repeat the specific movement acquisition. After this we run a MATLAB program that performs the extraction of the features by using wavelet and ICA analysis, the classification of the neural network and the training session in order to test the quality of the whole session. Finally, the user's parameters and data are stored in a MySQL DB, so that it is possible to study how the different parameters can affect the sEMG signal. This is useful during the prototyping phase, because we can identify which are the common features of the target user for a specific application, or if the number of electrode pads are appropriate, or if their position inside the clothes is correct.

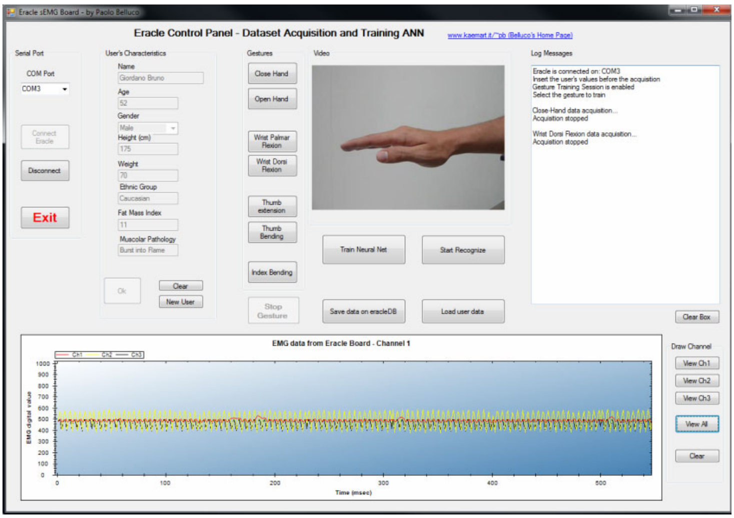

Fig. 2. The Eracle software Graphical User Interface

6 Evaluation Tests

We have organized some evaluation tests of the system. The time dedicated to each test is around 25 minutes, which include the placement of the electrodes, the storing of the users' parameters, the acquisition of the gestures, the elaboration by using the two methods and training of the ANN and finally the test for recognizing the gestures. The movements have been selected among those gestures that are considered easy to perform for a generic user. Particular attention has been devoted to verify that the selected movement performs well with the technology used, the techniques used for signal analysis adopted, and the kind of feature that has been extracted. In order to find a balance between the need of using 'user-friendly' movements and 'easy-to-analyze' movements, several tests have been performed on the same subject by evaluating different movements and estimating both the difficulties and the performances of the ANN in terms of number of movements correctly recognized. Experimentation confirms that the ANN with BP architecture for the classification, used in combination with the wavelets or FastICA, gives good performance for seven different movements, which are:

- open hand;
- close hand;
- wrist dorsi flexion;

- wrist palm flexion;
- thumb extension (only by wavelet);
- thumb bending (only by wavelet);
- index extension (together with the medium finger);

Table 1 shows that the movement recognition rate of a trained net using wavelet is very high, with a mean for all movements over 95%. By using FastICA the results are worse, but the sEMG recording classification is done almost in real-time.

Table 1. Success in percentage of movements recognized, referred to four subjects, computed by our system based on wavelet and FastICA

Movements	Wavelet %	FastICA %
Open	99.1	85
Close	95.6	90.2
Wrist Dorsi Flexion	97.8	92.1
Wrist Palm Flexion	99.3	89.5
Thumb Extension	95	-
Thumb Bending	98.4	-
Index	95.6	72.2

6.1 Discussion about the Results

The analyses conducted on the Eracle board reveal that the output digital signal, elaborated by the sEMG signals by using two different methods, is clean and suitable to our purposes despite the small dimensions of the board. The Eracle board is small enough to be inserted inside the clothes with minimum annoyance for the users. The performances related to the gesture recognition are good and the metaphors, implemented for the interaction, are powerful and intuitive. The movements recognized are easy to perform, and allow the user to act naturally even when he is using one of these movements as a command. Especially the movement related to thumb and index/medium has shown to be a good choice. In fact, the index is often used in the normal life to point at objects, and so it is suitable for commands in those user interfaces that include some kind of pointing action; and the thumb, the most important finger for human being, is often free to be used as a source of command.

7 Conclusion

This paper has presented a novel wearable interaction system based on the electric activity of the human muscles. The system, named Eracle, is a wearable acquisition system based on sEMG signals that allow us to recognize and manage the user's gestures by using two different promising methods (wavelet and FastICA) for features extraction. The effectiveness and performances of the system have been demonstrated through some users' tests. In the future, we will replace the electrodes with another type, which will sewed up inside the clothes, and we will also integrate other different signal acquiring techniques, based on the use of other kinds of sensors, in order to increase the number and the quality of the recognized gestures.

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