An EMG-Based Human-Machine Interface to Control Multimedia Player

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***Abstract*—The electromyogram signals generated by muscles are used in numerous fields such as augmented reality, biomedical, Kinematics, gaming, 3D animations and Human-Machine Interfaces. The latter are especially used in helping people with reduced mobility or for persons having specific needs to control machines!!. In this paper, we present a novel EMG-based system that aims to control multimedia player in simple, efficient and flexible manner. A real implementation of our proposed approach was realized in order to achieve experiments and to conduct performance analysis. Our approach uses pattern recognition and contraction duration to derive four predefined actions. Our experiment results show the capacity of our system to achieve good detection accuracy of user EMG-based commands and to transform these commands in action in media player system.**

***Index Terms*—ElectroMyoGram (EMG), muscles contractions, signal processing, media player, Human-Machine Interface (HMI)**

I. Introduction

The ElectroMyoGram (EMG) signals provide an intelligent and natural way of a Human Machine Interaction (HMI), which can be a good solution to replace conventional control interfaces. It provides to some categories of users the opportunity to use and exploit new technologies, for example, in augmented reality, we can create a virtual human user, which has a total control of his body members by placing electrodes in different places at his body, such as his feet, legs, arms, hands and face. EMG signals are also used in the Control Command field, where in nuclear power plants or in the big factories, some critical and dangerous tasks are achieved through the use of robots controlled by EMG signals for more security and safety.

Amputation and deformity still an open problem in our society. More than one million individuals in the United States today are living with limb amputations [1], in which there are thousands patients with an upper limb amputation. According to [2] approximately 8% of physical disables, or 2.26 million people, live with limb amputations in China alone. Natural disasters and accidents have been making this number increase. For this reason, over the years many searchers have focused on the creation of artificial limbs and the realization of Human Machine Interfaces controlled by the EMG signals. The use of EMG is not limited to a specific field or to a specific task, which explains the diversity of existing applications controlled by EMG signals.

Several existing researches and applications had exploit the EMG signals to achieve different tasks, such as facial expressions recognition (happiness, sadness and stress) and uterine contractions detection (for pregnant woman). In fact, various studies have been made on EMG data acquisition, signal processing, features extraction and features classification into many classes.

Our study is focused on the EMG signals generated by muscles activations from forearm contraction. We aim to develop an application to control a multimedia player system through the use of EMG signals from the forearm. The electrical potential generated during forearm contraction allows to start/stop a video or switch between a set of media. Our proposed system has been implemented and tested as remote control system based on EMG signals. The objective was to provide efficient control system seeking to simplify the life of hand amputee persons by allowing them to control the media player through the muscles contractions.

The rest of this paper is organized as follows. Section II reviews relevant related works and different existing approaches for exploiting the EMG signals. Section III presents our proposed approach to control medial player through the use EMG signals. Section IV discusses the evaluation of our approach and analyze its performances. Finally, sction V concludes this paper and presents our future work.

II. Related works

Various approaches have been proposed in the area of EMG-based applications. Authors in [3] showed that the EMG allows to measure the facial electrical activity of muscles via electrodes placed on the face. The acquired signal can be used for expressions recognition, where we can distinguish a stress state from agitation state as the first one causes an increase of muscular activities and many others expressions as negative valence, etc.

Author in **??**pproach consists to realize a simulation platform for job interviews, which is based on a set of sensors which are used to acquire physiological signals (EMG, ECG,.etc). These signals are processed as follows (extraction, characteristics, classification and performance evaluation of classifiers). The purpose of this platform is to improve the candidate's behavioral skills and training him to manage his emotional state by using the data that is gathered from him.

The system can give a misinterpretation of the user's face, but in general it remains a good work that brings a new solution that did not exist before, which can be very handy if some improvements were added.

The EMG signal can enable better monitoring of the contraction's evolution during the pregnancy [4] .

Indeed, the precocious detection of premature birth is the key of prevention. The treatment method of EMG uterine for detecting and identifying the pertinent events is based on the wavelet packets. The author propose two approaches for an EMG uterine decomposition, discrete wavelet decomposition which consists to decompose the EMG signal according to the scale levels. this scale interprets any change in frequency or energy signal. And the second approach is the wavelet packet decomposition which is based on the construction of sub-basic functions organized into packets. These approachs permit to choose the most pertinent packages for the good detection and classification of an EMG uterine. Furthermore, we can use other types of frequency wavelet that are more selective.

Several methods in [5] are successively applied on the EMG signals so it can be interpreted. The important step is to extract the most discriminative features. Then, various types of classifiers may be used, each one of them presents advantages and disadvantages. None of them for the moment won unanimously. The objective of these classifiers is to choose a reliable and fast learning mechanism, a way to be adapted to control a hand prosthesis.

These classifiers are poorly adapted to the changes of the signals occurring from different operators over the time.

Author in [6] treat the problem of EMG signal decomposition based on the observation from a single sensor. According to it and to [7], the decomposition consists in the restitution of pulse train for each motor unit corresponding, and enables the subsequent analysis of muscle motor units proprieties, providing an interpretation of the neural roles in the muscle. The decomposition process is performed in two steps: pretreatment for segmenting the EMG signal and provide an approximation of the shapes of elementary waves, followed by a "Bayesian decomposition" that use the stochastic simulation approach, (MCMC). The strength of this solution is that, unlike existing methods, no human manipulation is involved in this process, both steps are fully automatic. This work is bringing a new solution, however it lacks a technical implementation in addition to simulation that has been achieved.

Authors in [8] propose a new method that allow users to control an anthropomorphic robot arm in a 3D space, by developing an interface between the user and the robot arm which is controlled by EMG signals. The efficacy of this proposition is that the experiments are done in real time, including random arm motions with variable hand speed profiles, and those arm motions are not affected by EMG changes with respect to time, and that is done by using a switching model in such a way that it compensated for the EMG changes. This solution is very convenient but the only problem is that the use of robots is not within the reach of everyone and it can be very expensive.

Studies in [9] describes a new hand gesture recognition system based on both multi-channel surface EMG sensors and 3D ACC (accelerometer) to realize a flexible interaction between human and computers. The set of defined hand gestures include both finger actions and circular hand movements of various orientations. To evaluate their system they implemented an application that allow to control Virtual Rubik's Cube game. This work is very interesting because it combines two sensing techniques for hand gestures recognition, thus, precision and efficiency are enhanced. However, this application is not that practical for people whom cannot move their hands in a proper way (circular movements of various orientations).

Authors in [10] propose an interface of "control command" between the prosthetic hand and the human. The human communicates with the prosthetic by sending commands "to keep a hand open, to keep pincer position, keep a encompassing entry position,..etc. On the other hand, the prosthetic hand communicates with the human by displaying messages that are:

Send error messages (when the system does not know the signal value). Raise an alarm in case of fatigue. View the status of the battery.

This solution allows creation of a simple and useful prosthetic hand which is easy to use. But the main problems that we can encounter, is when error messages are displayed on the screen in the case of a co-contraction (contraction of two muscles in the same time), when the prosthetic receives an unknown signal, and when the amplitude of the signal does not indicate a weak nor a strong contraction (between the two).

In addition this solution is not optimal nor flexible because when we want to move from an encompassing state to a pinching state , we have to go through an open state.

Finally, this work has not been implemented yet, so we cannot know what technical problems that can be encountered.

In this paper, we aim to develop an application that control set of medias by using EMG signal with hand force. The electrical potential generated during a contraction of muscles arm permit to switch between this set of medias. Our proposed system has developed in the purpose of helping person with reduced mobility.

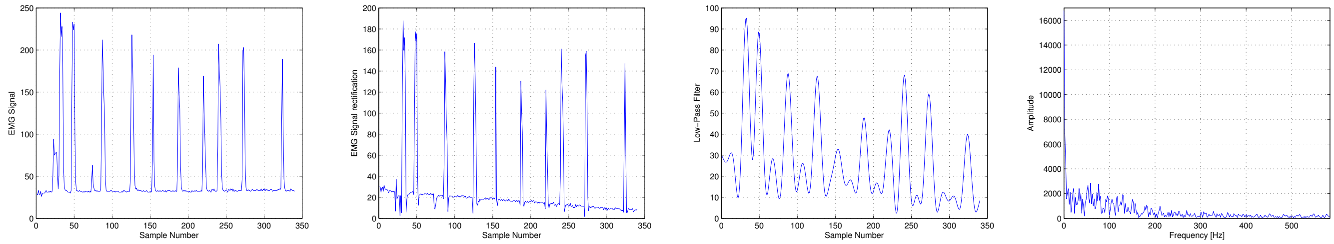
III. Proposed Approach

The control strategies of the application use three electrodes placed on the skin surface overlying the muscles of the arm in order to gather the EMG signals. In this section we explain the signal processing in details. Then, we describe the implementation of the system.

Herein, we present the analysis of the EMG data that we have achieved on the data collected from the arm muscle by three surface electrodes placed on the skin.

The EMG signals acquired from muscles require advanced methods for processing which are as follows (loading, rectification, filter, linear envelope and fourier transform) showed in figure 2. The purpose of this treatment is to turn the signals into a usable form for registration or correlation purposes.

1) Loading the EMG data: this step is a presentation of the data without processing, except an amplification of the signal that can be added by the electrode. The raw signal is



(a) (b) (c) (d)

Fig. 1: (a) EMG Data; (b) EMG signal Rectification; (c) Linear envelope & low-pass filter; (d) Power Spectrum

presented in figure 1.a in this graph we can see the highest peak which represents a muscle contraction that have a value comprised between (30 and 240) and 30 represents the muscle rest period.

2) Rectification of the EMG signal: a full rectification generates the absolute value of EMG signal. Two phases can be distinguished to obtain the rectified signal as follows: eliminate the shift signal and calculate the absolute value of the signal. the results are showed in figure 1.b, we see that the value of each peak is lower than the previous step.

3) Filter and Linear envelope of the EMG signal : Filtering the signal serve to eliminate unwanted noise, there are three types of noise in the EMG signal which are,

Bio-electric noise: that produced by biological functions like, heartbeat, breathing, blood flow velocity and measured skin temperatures, this noise can be minimized with good placement of the electrode and high quality instruments.

Equipment noise: movement of the cable connecting the electrode to the amplifier and the interface between the detection surface of the electrode and the skin creates motion artifacts. Muscle fibers generate electric activity whenever muscles are active. This noise can be reduced by using high quality electronic components and by low pass filter at 20 Hz.

The outside noise: it represent all electrical and electromagnetic interference. It can be minimized with a grounding (GND).

Filter reduces the amplitude of the signal at a given frequency (cutoff frequency), we have used a butter low pass filter for our treatment of EMG signal (a butter filter is a type of linear filter is designed to obtain a constant gain as possible in its bandwidth). The results achieved by using the following equation :

[b,a]=butter(n,w,ftype)

[b,a]= transfer function coefficients of the filter, returned as row vectors n = filter order w= cutoff frequency/sampling frequency ftype= filter type

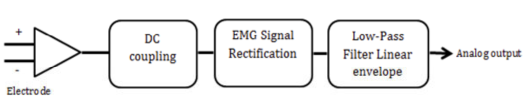


Fig. 2: EMG signal processing diagram

The cutoff frequency low-pass is often set at around 250 Hz for surface electrode, the linear envelope is the result of a full rectification and low-pass filtering at sampling frequency 1000 Hz, the filter of order 5 and filter type is 'low' we can see the results in figure 1.c, we note a decrease in the amplitude of the signal through the filter and the shape of the signal resembles the curve voltage through the linear envelope.

4) Fourier Transform (FFT) of the EMG signals: the power distribution of the EMG signal can be calculated by the âĂIJFast Fourier TransformationâĂİ (FFT) and graphically presented as a total power spectrum of the EMG signal in figure 1.d, which shows the frequency power distribution (Y-axis) in ratio to the amplitude (X-axis), the surface EMG frequency power is located between 0 and 200 Hz as we can see in the graph. The purpose of this treatment step is to analyse muscle fatigue.

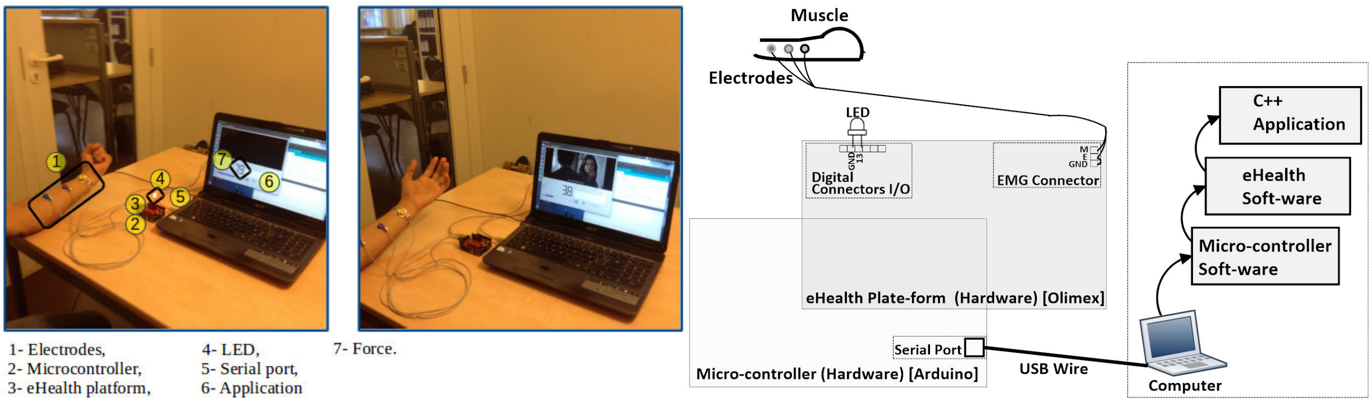
The user of the application should place three electrodes in his arm, which consists to acquire and amplifie the EMG signal gathered from muscles. The signal is processed and filtered, then during a contraction, we can find different values depending to the strength of the contraction. First to show the contractions to the user we have used a "LED", which turns "ON" in case of a contraction, and "OFF" otherwise.

Then we developed a basic mediaplayer, controlled by the same principle of the LED with just one command allowing to star a media. In other words when the user make a contraction, there is signal sent into the application and get started the media. Figure 3.a show an exemple of use of the application.

Figure 3.b shows the architecture of our system:

So here the user launches the command to start the media, we can see also the different components of the interface : a progress bar and an LCDNumber for displaying the signal strength of the user, a button to choose the media, and the media viewer.

To enhance the application and to make it more flexibale and useful, we have added a lot of options. So first, we have done studies on some existing methods allowing an intuitive detection of the location of electrodes and their adaptation with the arm of the user. This step is very important, because The shape and the amplitude of the EMG signal are influenced by the location of the electrodes. Therefore the amplitude of the recorded signal decreases exponentially with respect



(a) (b)

Fig. 3: (a) Example of use case (b) System architecture

to the distance between the electrodes and the source of electrical activity. This required setting up a correction method to simplify the eletrodes placement, in our case we opted for clustering algorithmes (K-means).

The users (man, woman and child) do not have the same EMG signals strength, in addition it may be that the same user does not have the same force when he is fit and when he is tired. Which requires a learning phase that permits the adaptation of the strength threshold with the proper user. So the user -before commanding the application- has to do some tests in order to know to which cluster he belongs. In this phase we also used k-means for the classification of the individual. And, once the category of the user is determined, the system adapts the threshold according to the user.

Then, several fonctionalities were added, like stop media, change it, come back to the previous one,.etc, while, at the same time, keeping the user-friendly side of the system. Thus, creating other commands was realised according to three parameters : "Force", "Timing" and "Contraction frequency". So in our application we need to create four commands, C1 : to start the first media or to get the following ones, C2 : to return to the previous media, C3: to pause the media or to continue, C4 : to stop the media.

		Timing			
		<T	>T	<T	>T
Force	W	F=1 C1	F=1 C3		
	S		F=1 C4		
	W	F=2 C2	F=2 C2	F=1 + F=1 C2	F=1 + F=1 C2
	S	F=2 C2	F=2 C2		

TABLE I: Commands classification

Table I shows the combination of different parameters allowing the creation of new commands. Where the Force can take two values "Strong" and "Weak", the Timing can take two intervales "[0,T[" and "[T,+inf[" where T is the time (in seconds) of maintaining the contraction, and F1, F2 are respectively Frequency = 1 and Frequency = 2. We have defined "t" the maximum period between two frequencies to make the difference between "one command with two frequencies" and between "two different commands", "t" hase been defined based on many tests (detailed on **??**). With this combination of parameters, we have created four commands (six fonctionalities) without any ambiguity. So we can interpret the table as follows : C1(Start|Next) = W + <T, C2(Previous) = (2W|2S|S+W)+(<T|T>) which "|" means "or", C3(Pause|Continue) = W + >T, Finally C4(Stop) = S + >T.

Then, for a more simplicity, especially for people who cannot move their fingers, we can use a dynamic media list, by creating a file or a database containing links (URLs) downloaded and updated automatically from the Internet.

Finally, we made our tests by using wired electrodes that will be replaced later by wireless electrodes, which gives more flexibility, light weight and robustness to our system.

IV. Evaluation and discussion

A. Experimental framework

In our application, we have used 3 modules: Gui for building the graphical interface, Core module which contains core non-GUI functionalities and finally, phonon module for multimedia applications. To understand the application's architecture, the following class diagram provided in Figure 4 describes the multimedia application structure. The "main" class is associated with the "QApplication" and the "control" class which inherits from the "QObject" and is associated with the "QSerialPort" and the "Thread" classes. The "Thread" class inherits from the "QWidget" class and is associated with the "QThread" and the "scene" classes. Finaly, the "scene" class inherits from the "Ui::scene" and the "QMainWindow" classes and is associated with the "phonon" and the "multimedia" classes .

To evaluate the designed application, we used it on a men of 24 years old having 70 kg of weight and 1.80 m of heigh. The experimentation have lasted more than 2 minutes, where the subject realized 5 contractions at different strengths. The strengths of the contraction over time are presented in Figure 5. The latter highlights also the thresholds used for the evaluation.

B. Evaluaion results

For the approach evaluation we use ROC curves. The different statistics necessary for ROC curve computing are obtained as follows:

- False positive: obtained where the subject do not do a contraction but the sensors (electrodes) sense a strength greater than the threshold T.
- True positive: obtained where the subject do a contraction and its strength is more than T.
- False negative: obtained where the subject do a contraction but its power is less than T.
- True negative: obtained where the subject do not do a contraction and the sensors do not sense a strength greater than T.

Figure 6 represents the ROC curve of the described experimentation's results. We can note that the drawn curve is always widely on top of the bisector, which proves the system's good performances. In fact, the Area Under Curve (AUC) of the described ROC is equal to 0.858. The AUC value of a ROC curve reflects the detection performance of the evaluated system. Closer is the AUC to 1, better is the detection, which witness of our system's effectiveness.

V. Conclusion and Future Works

In this paper, we proposed an approach to control a media player by using the EMG signals. Before exploiting the EMG signals, it has to go through some specific processing steps in order to have better results. The approach is designed to provide a control interface destined especially for people with reduced mobility. Thus we have provided a real implementation of the application. To create commands, we have combined different parameters in order to get a performed interface without any ambiguity in control functions. Our experimental results show that this proposed approach realizes an intuitive and user-friendly human machine interface. They also witness of its effectiveness and good performances.

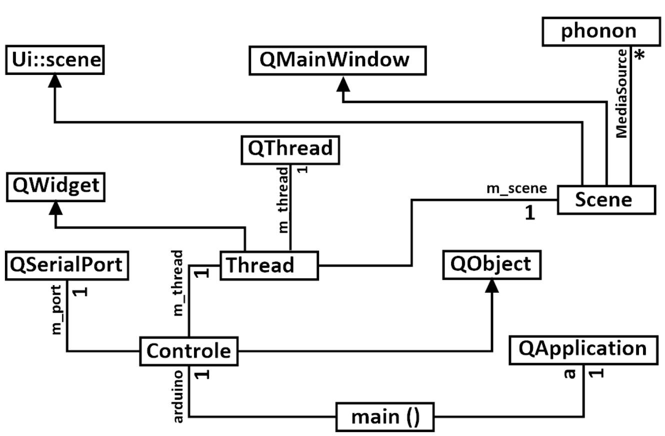


Fig. 4: class diagram of the application

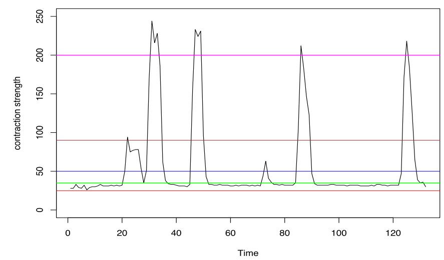


Fig. 5: class diagram of the application

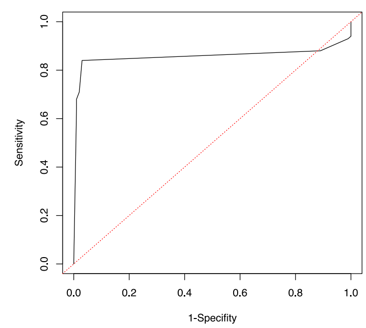


Fig. 6: ROC curve of the obtained results

Our future works will focus on (1) the experimentation of the application on a large population of subjects with different ages and health status. (2) the adaptation of this remote on handling multiple applications at once, such as controlling a TV, turn ON and OFF the light of the room, start the robotic vacuum cleaner,.etc, while, at the same time, keeping the flexibility of the system.

References

[1] e. a. Patricia F. Adams, "Current estimates from the national health interview survey," *Vital and Health Statistics*, pp. 1–203, 1996.

[2] G. Li, *Electromyography Pattern-Recognition-Based Control of Powered Multifunctional Upper-Limb Prostheses*. INTECHOPEN, 2011, ch. 6, pp. 99–116.

[3] H. Hamdi, P. Richard, A. Suteau, and P. Allain, "Emotion assessment for affective computing based on physiological responses," in *Proceedings of IEEE International Conference on Fuzzy Systems (IEEE-FUZZ)*, 2012, pp. 1–8.

[4] M. Chendeb, "Detection et classication des signaux non stationnaires par utilisation des ondelettes. application aux signaux electromyographiques uterins," *Medical Signals and Sensors*, pp. 15–30, Fevrier 2010.

[5] S. Huet, "Classification de signaux electromyographiques en vue de la commande automatique d'une main artificielle," no. 6, 2004.

[6] E. L. c. Di GE, "Mcmc pour la decomposition automatique de signal emg," *Institut de Recherche en Communications et CybernÃl'tique de Nantes*, no. 4, p. 2, Mars 2010.

[7] M. e. X. de Luca, Lefever, “Control scheme governing concurrently active human motor units during voluntary contractions,” pp. 129–142, 1982.

[8] P. Artemiadis and K. Kyriakopoulos, “An emg-based robot control scheme robust to time-varying emg signal features.” *Information Technology in Biomedicine, IEEE Transactions*, vol. 14, no. 3, pp. 582–588, May 2010.

[9] Z. Xu, C. Xiang, W. Wen-hui, Y. Ji-hai, V. Lantz, and W. Kong-qiao, “Hand gesture recognition and virtual game control based on 3d accelerometer and emg sensors,” *The ACM guide to computing literature*, no. 5, pp. 1–4, 2009.

[10] C. N. M. Atieh, P.Y Glorennec, “Commande myoelectrique d’une prothese de main communicante et intelligente,” *4 th International Conference: Sciences of Electronic, Technologies of Information and Telecommunications*, pp. 1–6, March 2007.