Development and Evaluation of Human-Computer Interface based on Facial Motor Unit Activity

Carlos M. M. Queiroz[1], Slawomir J. Nasuto[2] and Adriano O. Andrade[1]
[1]*Faculty of Electrical Engineering, Federal University of Uberlândia, Av. João Naves de Ávila, 2121, Uberlândia, Brazil*
[2]*School of Systems Engineering, University of Reading, Reading, U.K.*

1 STAGE OF THE RESEARCH

Interfaces that enable human-computer interaction have progressed significantly. In the past decade a lot of effort has been directed to the development and improvement of perceptual interfaces, i.e., interfaces that promote interaction with the computer without the use of conventional keyboard or mouse. This type of interface combines the understanding of natural human capabilities (e.g., communication, motor, cognitive and perceptual skills) with the use of these for interaction with the computer, taking into account the ways in which people naturally interact with each other and with the world. The search for more natural forms of interaction has directed recent research for the study of biological signals that have the potential to encode control strategies adopted by the central nervous system (CNS). In this context, information obtained through the activity of motor units - such as firing rate, waveform of action potentials and recruitment strategy - can be used in the development of human-computer interfaces. Therefore, this research proposes in an unprecedented manner, the development and evaluation of a human-computer interface based on information extracted from motor units (MUs). The interface development will consist of two steps: i) preparation of a flexible sensor array capable of detecting activity of MUs of facial muscles; ii) implementation of tools for signal processing capable of extracting information from MUs and translation of this information into control signals. The evaluation of the interface will consider: i) the quantification of learning related to the use of the interface; ii) the analysis of the correlation between learning and the dynamics of neural oscillation obtained by means of electroencephalographic signals; iii) the comparison of the new proposed interface with the *Muscle Academy* (Andrade et al., 2012), which is a myoelectric interface recently developed by our research group. The current stage of this study is described below.

1.1 The Choice of the Biosignal Acquisition System

The experiments that will be carried out in this research require the use of a large number of input channels. Since we will be collecting simultaneous information from EMG sensor array together with brain activity (EEG) it was necessary to find commercial equipment, flexible enough to deal with particularities of distinct biosignals and also with the requirement of a large number of channels.

a) b)

Figure 1: The designed box to accommodate the acquisition system board. a) Front view with cover open; b) Back view.

Based on the analysis of a number of available commercial systems it was verified that the RHD2000-series amplifier (Intan Technologies, USA) would be suitable for the research. The main features of this signal conditioner are: A/D converter of 16 bits; support of up to 256 input channels (configurable to distinct types of biopotential according to their inherent characteristics); possibility of sampling rates varying from 1 kS/s to 30 kS/s; and finally, customizable multi-platform software based on the C++/Qt graphical user interface. Figure 1 shows a box designed to accommodate the printed circuit board and the acquisition system and via connectors provide access to some input and output signals (analog and digital). Figure 2 shows an example of the main screen of the graphical user interface during the acquisition of several EMG signals.

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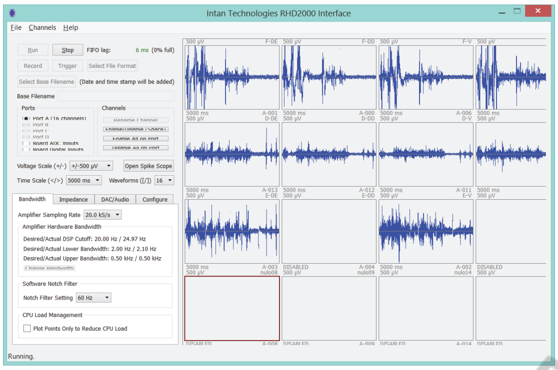
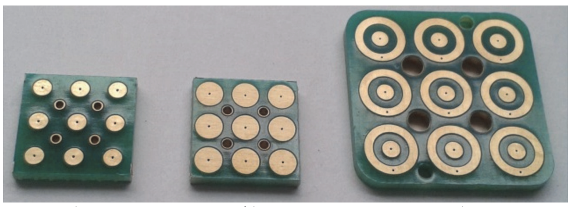


Figure 2: Main screen shot of the graphic user interface control software (Intan Technologies, USA).

1.2 EMG Sensor Array

The development of a human-computer interface based on the activity of MUs requires sensors with contact areas of adequate size to provide the selectivity required to detect isolated action potentials of MUs. However, this selectivity should not require high accuracy in repositioning the sensor near the MU of interest which would prevent everyday usage of the interface for non-technical people. Thus, taking into account these aspects, we developed the sensor arrays in two shapes: circular and concentric surface. This current design was made on a rigid surface and it is illustrated in Figure 3.



a) b) c)

Figure 3: The three sensors array designed. a) Circular sensor array (diameter of 2mm and distance between electrodes (DE) of 4mm); b) Circular sensor array (diameter of 3mm and DE of 4mm); c) Concentric sensor array (internal diameter of 2mm, external diameter of 6m and DE of 7mm).

To avoid the repositioning difficulties of circulars arrays between usage sections, the pairs of bipolar sensors (electrodes) in arrays were spatially distributed in such way to facilitate the alignment of at least one couple in the direction of the muscle fibers. Figure 4 shows the two adopted forms of distribution for bipolar channels. In both settings the electrode pairs were oriented at 45° but with different distances between electrodes.

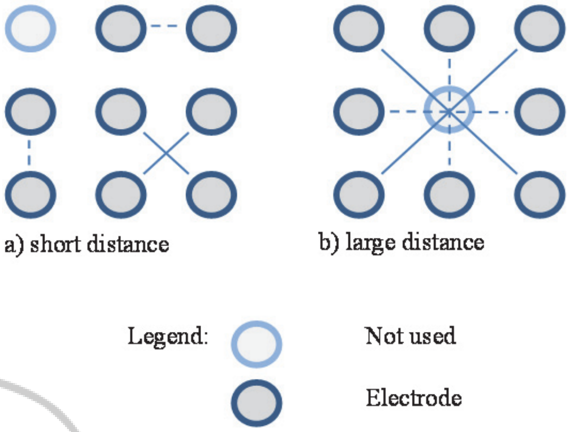
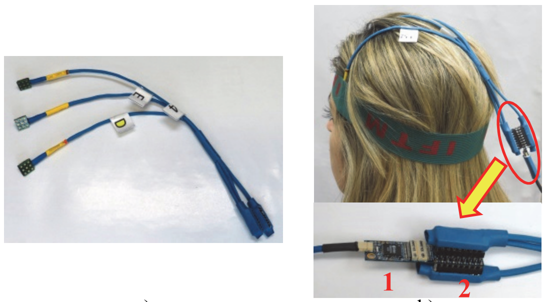


Figure 4: Scheme of distributing the pair of electrodes (bipolar) oriented every 45° with different distances between electrodes. b) Short distance b) Large distance.

The capture of input signals of the proposed human-computer interface is composed of three arrays, one for the Frontal and two for the Temporal muscles. To design this set of arrays, we explored the fact that the conditioning circuit and the digital converter are miniaturized, so it is possible to place them closer to the detection region, aiming to capture data with better signal to noise ratio. Figure 5a shows a set of sensor array and Figure 5b shows its use by an individual. The signal conditioner and digital converter circuit (1) and the connector (2) are highlighted in the figure.



a) b)

Figure 5: a) Set of sensor arrays used to capture EMG signals from facial muscles. b) Set of sensor arrays in use by an individual. The signal conditioner and digital converter circuit (1) and the connector (2) are highlighted.

2 OUTLINE OF OBJECTIVES

The general objective of this research is to develop and evaluate a human-computer interface based on facial motor unit activity.

The specific objectives to achieve this goal can be divided into: i) develop and evaluate a flexible array sensor fabricated by using silver ink, composed of nano-silver particles of high purity, developed by researchers at the Institute of Chemistry, Federal University of Uberlândia; ii) evaluate and implement techniques of multidimensional signal processing capable of mapping the MU activity of facial muscles in commands necessary for human computer interaction; and iii) evaluate the learning of a user while a user employs the human-computer interface activated by facial movements.

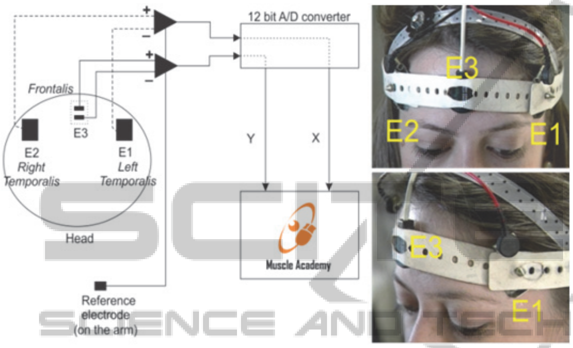


Figure 6: Human-computer interface based on electromyography of facial muscles. Source: extracted with permission from (Andrade et al., 2012).

3 RESEARCH PROBLEM

Recently, our group developed and evaluated a human-computer interface (Andrade et al., 2012) called Muscle Academy that allows complete control of a computer cursor through the activation of the frontal and temporal muscles.

The use of this interface has already been evaluated by healthy individuals and people with disabilities of upper limbs motor. Figure 6 presents a basic schematic about how the sensors are positioned on the facial muscles. The system evaluation was performed by analysis of three different protocols with progressive levels of difficulty.

The evaluation results showed that there is a user learning curve during the interface usage in five different experimental sessions for all protocol types (see Figure 7). However, there is a significant discrepancy among the learning curve protocol 3 (with greater difficulty) and other protocols. This reflects the difficulty of users access the smaller objects in a computer interface, and also the difficulty of fine motor control while performing this task.

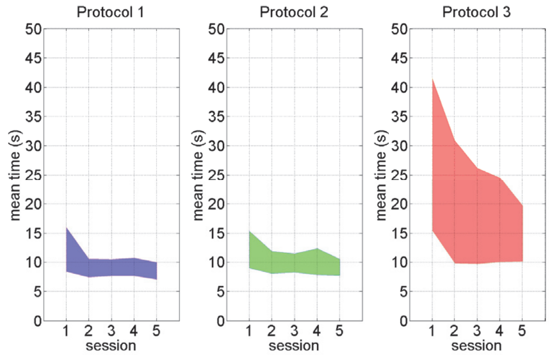


Figure 7: Results related to the learning to use the "Muscle Academy". The mean time in seconds is the unit of measure used to quantify the learning. Source: extracted with permission from (Andrade et al., 2012).

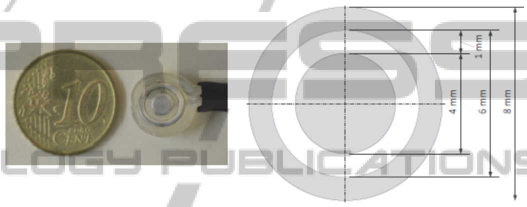


Figure 8: Concentric sensor used in detection of Motor Units Action Potentials developed by our research group (Júnior, 2013).

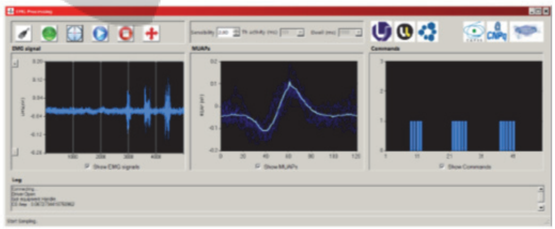


Figure 9: Graphical interface illustrating sequences of action potentials extracted in real time and translation of them into commands (Júnior, 2013).

In order to solve this problem and allow the user greater control interface, we developed a second control strategy based on the detection of the activity of MUs of only one facial muscle. For this purpose we designed a concentric sensor (see Figure 8) able to detect activities of MUs and a strategy to translate this information in commands similar to those reported in (Andrade et al., 2012). Examples of the activity of MUs detected by the concentric sensor are shown in Figure 9.

The results of the evaluation of this new interface, illustrated in Figure 10, show that the incremental learning over experimental sessions, and that the discrepancy of learning is less among the three protocols when compared to the results shown in Figure 7. Thus, the problem of fine control detected in Muscle Academy was largely solved. However, from a practical standpoint, the use of this interface is limited due to the great difficulty of positioning of the sensor in the proximity of MUs of interest.

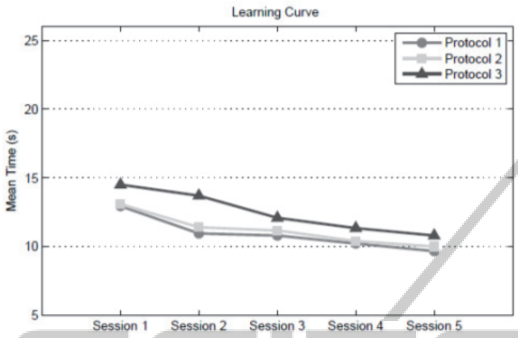


Figure 10: Results concerning on learning of the use of the system based on analysis of motor activity detected by concentric electrode (Júnior, 2013). The mean time in seconds is the unit of measure used to quantify the learning.

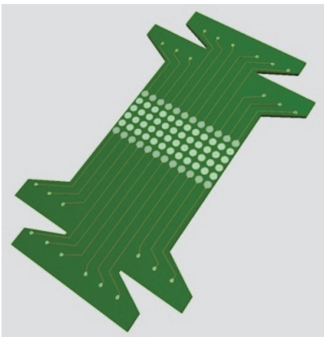


Figure 11: Prototype of flexible sensor array for detection of motor unit activity.

Given this context, the main purpose of this research is to propose, implement and evaluate a new control strategy based on processing of the myoelectric activity from the facial MU detected by sensor array (see an example of the prototype flexible sensor array in Figure 11). It is expected that whit this new control strategy, the sensor placement problem is solved by expanding the contact area of the sensor, and, also, that the learning on how to use the interface is facilitated.

4 STATE OF THE ART

With the advancement of perceptual interfaces, i.e. interfaces that promote interaction with the computer without using keyboard or mouse conventional, each time more research and technologies have emerged in order to understand the natural human capabilities (e.g., communication, motor, cognitive and perceptual skills) and to consider them in the process of human-computer interaction (Oviatt and Cohen, 2000).

The use of perceptual interfaces is of particular interest, but not limited to the field of rehabilitation and assistive technology. Patients suffering motor or cognitive limitations can benefit by the use of this technology to facilitate and encourage interaction with the environment and especially with computers. Such interaction is each more present in our lives, for example, television sets and video games can now be controlled by body movements.

Currently there are many strategies that can be used to obtain user information from a perceptive interface. The basic idea is to convert information from user input into commands that can be interpreted by an application (Oviatt and Cohen, 2000); (Turk and Robertson, 2000).

The strategies can be broadly divided into the following categories with respect to the type of sensor used for the detection of the input signal (Higginbotham et al., 2007): (i) pressure / touch (Bourhis et al., 2002), (ii) motion and gesture recognition (Javanovic and MacKenzie, 2010), (iii) speech recognition (Majewski and Kacalak, 2006) and (iv) biopotentials (Chin et al., 2008).

The main motivation for using biopotentials is, unlike on-off approaches, the possibility to obtain a more natural and proportional control of the human-computer interface (Higginbotham et al., 2007); (Ahsan et al., 2009). An evaluation of review studies (Andrade et al., 2011); (Tai et al., 2008) that have been published recently about the applications of different types of biopotentials (e.g., electroencephalogram, electromyogram, electro-oculogram) in human-computer interaction suggests that the use of electromyographic (EMG) is probably the most common and the reason may be the great success of the use of this signals acting as the input informations of interfaces that control prosthetic devices (Englehart et al., 2001); (Hargrove et al., 2007); (Huang et al., 2005); (Jiang et al., 2009).

5 METHODOLOGY

For the development and evaluation of human-computer interface is proposed an experimental scheme with appropriate resources to enable the use of the interface by two distinct groups and the recording of data from central and peripheral nervous system.

5.1 Definition of Experimental Groups and Criteria for Inclusion and Exclusion

In total, 20 individuals of both genders, from different ages groups, divided into two groups, will be recruited to participate in the experiments proposed in this research.

Experimental group 1 (G1): it will be composed of 10 healthy subjects (i.e. without disabilities in upper limbs), of both genders, aged over 18 years.

Experimental group 2 (G2): it is composed of individuals over 18 years, both genders, with motor disorders of the upper limbs (i.e. paralysis, amputations, congenital malformations, changes in motoneuron) that prevents the individual to move the mouse with his hands. Individuals should not present neurological disorders which disturb the concentration or physical limitation that prevents the contraction of the muscles Temporal and Frontal. Subjects who are unable to perform the contraction of these muscles will be excluded from the experimental group.

The subjects of the experimental group G1 will be recruited randomly in the population, whereas subjects in the experimental group G2 will be recruited in institutions that serve people with neuromotor disabilities. All individuals participate voluntarily in this study. The procedures of this research will be previously explained to the subjects for their full awareness about what will be accomplished. Each individual and/or his legally responsible will fill in and sign an Informed Consent Form proving that will be aware about the protocols and research, and also, that agrees to perform the experiment, without receiving any charge for participation. The confidentiality and personal information of research participants will be maintained.

5.2 Definition of Training Protocols and Data Collection

The training protocol and evaluation of human-computer interface of this research is similar to that used in the evaluation of the Muscle Academy (Andrade et al., 2012). The main difference is that this protocol will include the recording of brain activity (electroencephalogram detected as standard 10-20) simultaneously to the MU activity (detected by arrays of flexible sensors, placed on facial muscles) in order to provide a more detailed evaluation of the learning process due to the use of the interface. This type of analysis will be performed off-line and it is detailed in the next section.

The system evaluation will be performed in acclimatized room, with only the presence of the evaluator and the subject (with the accompanying, if necessary) and equipment to carry out the research.

This study is divided into three protocols varying the size of the buttons to be clicked according to each protocol (Protocol 1, buttons 2 cm x 2 cm, Protocol 2 buttons 1 cm x 1 cm and protocol 3, buttons 0.5 cm x 0.5 cm), and each button has a different colour (GREEN, YELLOW, RED and BLUE) being arranged in a cross shape (Figure 12).

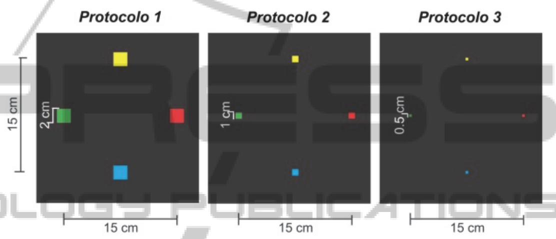


Figure 12: Interface of experimental protocols with different difficulty levels. Source: (Andrade et al., 2012).

The distance between the centers of the buttons in the 3 protocols is constant, and its area varies from one protocol to another, thereby increasing the difficulty as decreases the area of the buttons.

The goal of this interface is to allow the subject to control the cursor, and so, the learning can be quantified, considering the time taken to perform the specific tasks as a good parameter to measure learning progress. The following tasks will be requested to the subjects:

1. Clockwise: move the cursor to the green button and click, move the cursor to the yellow button and click, move the cursor to the red button and click, move the cursor to the blue button and click, and finally move the cursor to the green button and click;
2. Counterclockwise: move the cursor to the green button and click, move the cursor to the blue button and click, move the cursor to the red button and click, move the cursor to the yellow button and click, and finally move the cursor to the green button and click;

Figure 13 shows a schematic which includes the main elements involved in data collecting where muscle and brain activities are simultaneously recorded and stored on a workstation with high performance for offline analysis. The standard 10-20 will be used for the positioning of EEG sensors. The MU activity, detected by sensor arrays on facial muscles, is converted in real time by software available in a high-performance laptop in commands that enable the control of a cursor for interacting with the graphical interface shown in Figure 12. The user will receive continuous feedback audible and visual interaction.

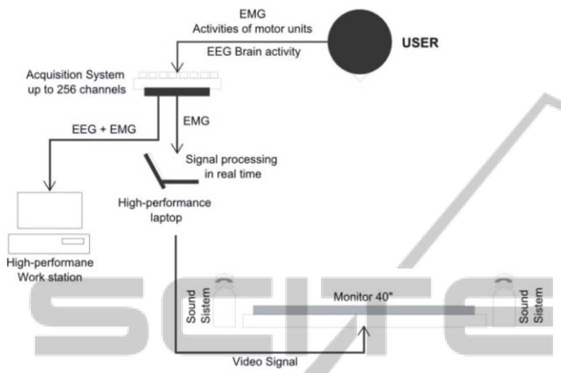


Figure 13: Main components involved in data collection and analysis.

5.3 Analysis of Learning through the Record of Muscle and Brain Activities

During the interaction with the graphical interface, shown in Figure 12, the activities of the MUs and brain (EEG) will be recorded simultaneously. The purpose of this registry is to perform offline analysis in order to understand the correlation between motor learning and brain dynamics, arising from the use of the interface. This analysis will enable the development of alternative indices that can quantify and characterize learning in human computer interaction. These indices will be confronted with the traditional for the measurement of runtimes tasks illustrated in Figures 7 and 10.

The analysis of the correlation between muscle, brain and learning activities will be studied using the technique of signal processing PLS (Partial Least Squares), which is a multivariate statistical tool widely used in studies with the aim of verifying correlations between brain activity and behaviour (Martínez-Montes et al., 2004, Krishnan et al., 2011).

6 EXPECTED OUTCOME

Considering the main objective of this doctoral work is to develop and evaluate a human-computer interface based on MU activity of the facial muscles and taking into account the methodology adopted, it is expected to achieve some goals.

A first expected practical outcome is the development of a flexible sensor array based on an ink composed of nanoparticles of pure silver capable of detecting biopotentials which has numerous applications in rehabilitation, neurology, assistive technology, and others. This type of technology can integrate tools used in the assessment of the neuromuscular system, for the purpose of diagnosing diseases that affect nerves and muscles. The great advantage of using this technology is its low cost and ease of application. This approach eliminates the usage of sophisticated and expensive technologies to silver deposit on surfaces and allows the sensors production with different shapes so adapting to various muscles.

Once we have the right conditions to capture the desired biopotentials, another important achievement is to obtain a computer program which implements a human-computer interface capable of interpreting the MU activity. When compared to other existing technologies, it is expected that this enables the user to more precise control of the interface through the more subtle and natural movements, and thus reduce the incidence of muscle fatigue and discomfort to the user. Whereas the developed interface is independent of the system or device to be controlled, then the same has applications in games (serious games) used for rehabilitation purposes, control environments (e.g., smart homes), automated wheelchairs, bioefeedback systems to control stress or emotions.

Finally, because of the need to evaluate the interface developed, it is expected the development of a neuromotor learning index capable of quantifying and evaluating the learning of individuals using the human-computer interface. The main innovation of this index is take into account components of the central nervous system (brain - EEG) and peripheral (muscle - EMG), and not only the user´s response time. From a practical perspective, this index can be used to measure the contribution level of the central and peripheral nervous system on learning. Furthermore, it can be used for assessment of human-computer interface, because this index can help diagnose of learning disabilities that do not have standardized tests.

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