Enhancing E-Accessibility of Disabled People Using Low-Cost Technology

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ABSTRACT

E-Inclusion of disabled people and implementation of a lot of e-services requires e-accessibility, which refers to the ease of use of information and communication technologies, such as the Internet, by people with disabilities. In order to enable computer access of disabled people and enhance e-accessibility, this work presents two devices based on low-cost technology to control the mouse cursor.

Decoding upper-limb gestures from electromyography (EMG) could help to develop human-computer interfaces that increase the quality of life and e-inclusion of the disabled or aged people. Thus, was developed an EMG-based computer access device that use biological signals. Another device for computer access was developed based on inertial sensors, which allow capturing motion. From the Fitts' law test carried out, it was obtained an IP of 0.31 bit/s for the EMG-based computer access device and IP of 0.85 bit/s for the inertial sensor-based computer access device.

CCS Concepts

Human computer interaction (HCI), Accessibility technologies.

Keywords

E-Accessibility, Information and Communication Technology, Computer access, E-inclusion, Human-computer interaction.

1. INTRODUCTION

Disability has traditionally been a barrier for millions of people who are not able to benefit from the recent advances in technologies such as the Internet, personal computers and any digital interface commonly used to deliver commercial or government services or information. Taking into account that the overall number of people with disabilities is increasing, and it is estimated at 7% to 10% of the population worldwide [1], it can be concluded that millions of people are excluded from basic constitutional rights, as well as services. These numbers underline the growing demand expressed nowadays for online services and tools that are universally accessible and usable, so that the entire population can benefit.

The United Nations' Convention on the Rights of Persons with Disabilities and European policies support e-accessibility as a fundamental component of our increasingly digital world [2]. E-Accesibility refers to the ease of use of information and communication technologies, such as the Internet, by people with disabilities [2]. The emergence of the Information Society and the Information Society Technologies, signify the transition towards a new form of society based on the production and exchange of information and, in effect, of knowledge. The consequent changes affect not only the interaction in computer-mediated human activities, but also individual human behavior and inclusion of the disabled or aged people. Access to information is a basic right and the increasing amount of publicly available information is even more important for people with disabilities and other groups at risk of exclusion. However, a number of obstacles are to overcome in order for disadvantaged groups to be able to fully benefit from it. Problems of accessibility to computer-based applications and services require products designed for the user with special needs, depending of type of disability.

There are numerous types of impairment that affect computer use. These include:

- Cognitive impairments and learning disabilities, such as dyslexia, attention-deficit hyperactivity disorder or autism.
- Visual impairment such as low-vision, complete or partial blindness, and color blindness.
- Hearing-related disabilities including deafness, being hard of hearing, or hyperacusis.
- Motor or dexterity impairment such as paralysis, cerebral palsy, or carpal tunnel syndrome.

Emerging low-cost technologies enable implementing adaptable products for computer-access, which may decode movements and gestures to control computer-based applications [3].

Gesture recognition is the process by which specific movements executed by a user are used to convey information or to control an external device. Hand gesture recognition has numerous applications for human-computer interaction [4]. Decoding hand gestures based on bioelectrical signals of the body are becoming increasingly important in many applications, such as personalized health systems, robotic assisted physiotherapy, rehabilitation applications, and computer access [5]. Decoding movement intention from electromyography (EMG) has been increasing in the last years [6]. EMG provides a measure of the electrical activity of the muscle during contraction. Classification principle of such control lies in EMG-based motion intention detection. This control uses EMG signals to continuously detect the user's movement intention.

Furthermore, gesture recognition may be carried out using inertial sensors, such as accelerometers, that provides information about specific movements. Inertial sensors are an emerging technology that could be found in smart phones and other devices.

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In the following sections we describe the devices for computer access and experiments of validation. The document is organized as follows: Section 2 focuses on the EMG-based computer access device. Section 3 focuses on the inertial sensor-based computer access device. Section 4 presents experimental results obtained with both systems. Finally, Section 5 outlines the main conclusions and future work.

2. EMG-BASED COMPUTER ACCESS FOR DISABLED PEOPLE

2.1 Electromyography

Electromyography is a technique for recording the electrical activity produced by skeletal muscles [7, 8]. Acquiring and interpreting the electromyographic signals make possible to design systems controlled by voluntary muscle contractions. However, to build such systems several aspects must be considered, from signal acquisition to its processing and muscle onset detection. A relevant difficulty is that EMG signals present several interferences that must be removed [9]. It was considered following three phases: signal acquisition, signal processing and onset detection.

2.2 Acquisition of EMG Signals

It was used the Muscle Sensor v3 (see figure 1) from Advancer Technologies which measures, filters, rectifies, and amplifies the electrical activity of a muscle and produces an analog output signal that can be read by a microcontroller. Taking into account that measured raw EMG potentials range between 500 μV and 5 mV, the amplifier was tuned to increase signal level by a gain factor of 1000 times.

Figure 1. Muscle Sensor v3

A voluntary muscular contraction may be measured using this sensor. Figure 2 shows a bioelectrical signal measured from a muscle.

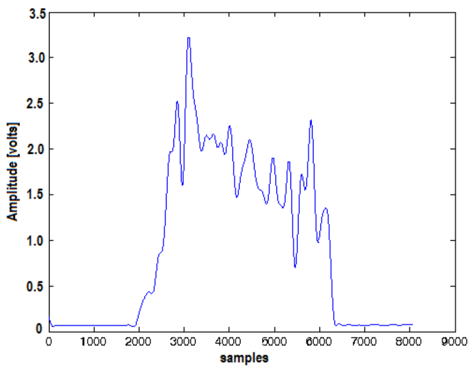

Figure 2. EMG signal from a voluntary muscular contraction

It was used as control unit the Arduino (model Leonardo), which is a very low-cost open hardware system based on a microcontroller. There are multiple hardware choices available; however the Arduino is currently the most flexible and easy-to-use hardware and embedded software platform, with low cost, easy communication, and software running on a computer or other devices [10]. It was connected two muscle sensors to analog input pins (A0, A1) of the Arduino. It was used a sampling frequency of 100 Hz.

2.3 EMG Signal Processing

It was programmed the microcontroller with a firmware that permits:

- To acquire two analog signals from muscle sensors.
- To compare an EMG signal with a threshold for onset detection.
- To implement pattern recognition of EMG signals and detect movements (user's intentions).
- To control a mouse cursor following user's intentions.

The effectiveness of EMG-based pattern recognition algorithm is based on an effective implementation of three modules: pre-processing, feature extraction and classification (see figure 3).

In the pre-processing module, EMG signals were segmented in windows of 200 ms and overlapped in 50 ms, taking into account that delays in myoelectric control for real-time applications must be inferior to 300 ms [11]. It was used the Root Mean Square (RMS) value of EMG signal in the feature extraction module. Finally, the work presented by [11] showed that a simple feature extraction method combined with a LDA (Linear discriminant analysis) classifier may provide a suitable performance for real-time myoelectric control. Taking into account its easy implementation and high performance, this configuration has been widely accepted and was implemented in the present work.

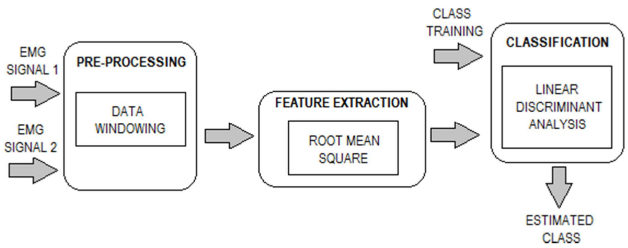

Figure 3. Algorithm for EMG-based pattern recognition

The estimated class in the myoelectric algorithm relates to a specific movement executed by user, according to the training phase. Section 4.1 shows the experimental methods and training of the algorithm.

3. SENSOR-BASED COMPUTER ACCESS FOR DISABLED PEOPLE

3.1 Inertial Motion Capture

The body movement may play an important role in human computer interaction. Motion capture is the process of recording the movement of people [13]. Inertial motion capture technology is based on miniature inertial sensors and sensor fusion algorithms [14, 15]. Benefits of using inertial systems include: low-cost, portability, and large capture areas. These sensors represented a real scientific breakthrough in the medical field and humanmachine interaction, where there is a need for small sensor systems for measuring the kinematics of body segments. Since micromachined sensors such as gyroscopes and accelerometers have become generally available, human movement can be measured continuously outside a specialized laboratory with ambulatory systems.

Gesture and sign language in human-computer interaction may be implemented using inertial motion capture systems. Thus, it was designed and implemented a computer access device using an accelerometer to decode hand gestures that permit to control the mouse cursor.

3.2 Acquisition of Signals

Advances in MEMS (MicroElectroMechanical Systems) enable inertial sensors based systems as alternatives for motion capture. An accelerometer measures the acceleration that the sensor is subject to. An accelerometer is a device that measures its proper acceleration that is the physical acceleration experienced by it relative to a free-fall, or inertial, observer who is momentarily at rest relative to the object being measured.

It was used the accelerometer MMA6361L from Freescale Semiconductor (see figure 4) which is a tri-axial device that could measure ±1.5g.

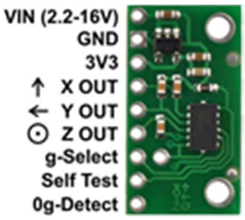

Figure 4. Accelerometer MMA6361L

Accelerometer data is a vector, having 3 axes (x, y, z). This vector permits to measure gravity acceleration and any other acceleration the device is subject to. For instance, figure 5 shows an accelerometer used to calculate a tilt. Figure left (condition a) provides x-axis signal of zero. Figure right (condition b) provides x-axis signal different of zero, according to tilt angle θ.

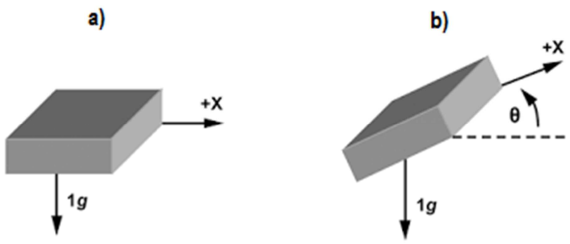

Figure 5. Accelerometer used to calculate a tilt

In order to acquire analog signals provided by the accelerometer, it was used as control unit the Arduino (model Leonardo). It was connected the three axes (x, y and z) signals from accelerometer to analog input pins (A0, A1, A2) of the Arduino. It was used a sampling frequency of 100 Hz.

A glove was instrumented with the accelerometer in order to capture movements of the user. Figure 6 shows the final prototype.

Figure 6. Prototype of the inertial capture system for computer access of the disabled

3.3 Signal Processing

It was programmed the microcontroller with a firmware that permits:

- To acquire three analog signals from accelerometer.
- To implement an algorithm using acceleration signals to detect movements (user's intentions).
- To control a mouse cursor following user's intentions.

The algorithm using acceleration signals is presented in figure 7. In the pre-processing module, it was applied a technique for signal averaging. Classification focused on threshold detection. It was defined an empirical threshold of each signal (x, y and z axis) to detect intention of movement.

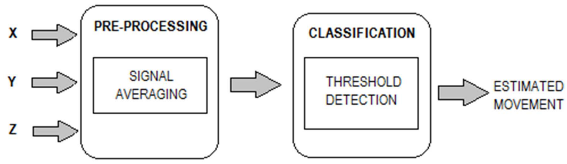

Figure 7. Algorithm for processing the accelerometer data

4. EXPERIMENTAL METHODS

4.1 Training and Validation

EMG signals and accelerometer data were converted to the mouse cursor movement. For training and validation of both algorithms, a set of experiment was carried out. Five healthy adult volunteers were instrumented with surface EMG electrodes following the SENIAM recommendations [12], provided through Ag-AgCl electrodes arranged at locations of the forearm. Two forearm muscles were measured: The wrist flexor carpi radialis and wrist extensor carpi radialis (see figure 8). Furthermore, one accelerometer was coupled to dorsal side of hand. Within each trial, the subject repeated each limb motion three times randomly with movements: flexion and extension of the wrist, pronation and supination of the forearm, and at resting state. The resting state was maintained at the beginning and at the end of each test, and between movements.

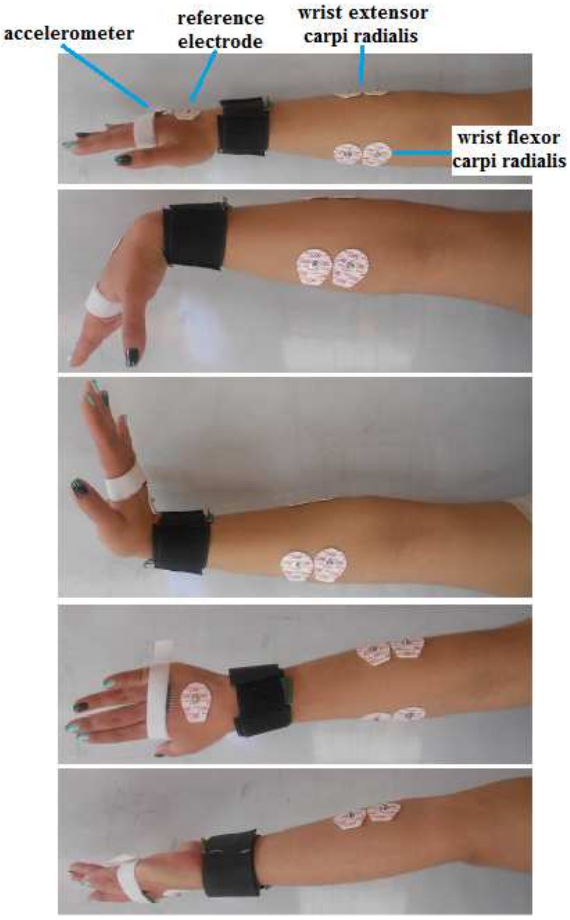

Figure 8. Hand gestures (from top to bottom): rest, wrist flexion, wrist extension, forearm pronation and forearm supination.

The classifier of EMG-based algorithm was trained using data from the first two trials and was tested with data from the last trial, for each subject. The EMG-based pattern recognition algorithm provided an error of classification of 6.7%, which demonstrate that it is a good algorithm for movement detection from EMG signals.

Finally, error of classification of algorithm using accelerometer data was 3.1%, which demonstrate that it is a good algorithm for movement detection.

4.2 Performance Evaluation

It was used the Mouse and Keyboard library functions of Arduino, to control the computer's cursor [16].

The usability and performance evaluation of both systems followed a Fitts' law test [17]. Fitts' law is a model to quantitatively evaluate the effectiveness of a computer pointing device. The efficiency of the computer access device is defined by the index of performance (IP) that represents how quickly pointing and clicking can be done using the device for cursor control. Higher IP values represent larger quantities of information (bits) that can be transferred per second.

Five healthy adult volunteers participated in the study. From the Fitts' law test carried out; it was obtained an IP of 0.31 bit/s for the EMG-based computer access device and IP of 0.85 bit/s for the inertial sensor-based computer access device.

5. CONCLUSIONS

Emerging low-cost technologies promise an alternative for improving the quality of life and e-inclusion of the people with several pathologies of nervous system, amputations and other physical disabilities, through computer access devices. Those devices play an important role in creating an inclusive society, where information is accessible for all, and people with special needs are not excluded.

This paper presented two computer access devices to enhance e-accessibility of motor disabled people, using emerging low-cost technology. It was demonstrated their potential use and performance evaluation using a Fitts' law test.

As future work, it is going to be validated with motor disabled people. Furthermore, it is going to be evaluated for specific applications, such as gaming.

6. ACKNOWLEDGMENTS

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