# Adaptive and Linear Energy Based Detector for a Virtual Mouse Control

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**Abstract.** The paper describes a system for controlling a virtual mouse using the mioelectric signal from voluntary contractions of the masseter and temporal muscles. The average energy of each of the data packets is compared to a threshold, established by a process of personal calibration executed before starting the system. The threshold energy value was computed using two different adaptive techniques: Linear Energy Based Detector (LED) and Adaptive Linear Energy Based Detector (ALED). Two volunteers were submitted to 90 facial contractions in order to control the mouse and test the system with the proposed techniques. The Linear Energy Based detector presented 17% of failures, the adaptive Linear Energy Based Detector presented 15% of failures and the static threshold presented 26% of failures during the commands detection. Thus the preliminary results have shown that adaptive techniques are robust alternatives for threshold events detection.

## 1 Introduction

According to World Health Organization (WHO) [1], approximately 15% of world population has a disability or incapacity. This number of people will increase due to the population growth, aging and medical advances that preserve and prolong life. The motor coordination as well the social integration is degraded by physical and cognitive disabilities. People carrying some type of disability have to face many difficulties every day, in their social, professional and personal life. The reintegration and the promotion of these people are essential for their well-being, as well for their financial and social life. In the last two decades, computers have become essential for daily living of the general population. Nevertheless, people with disabilities find several obstacles to participate and integrate in today's computerized world mainly due to physical difficulties to access conventional input devices. Nowadays many engineers are working to develop alternative approaches to computer access for people with physical disabilities. In most situations, disable people have strong difficulties in controlling conventional man machine interfaces such as the mouse and keyboard. During last years, different methods were proposed in order to interface a mouse to the computer such as eyes or face movement, voice [2], [3] and recently low cost video cameras [4]. Another approach is to use biological signals as the control parameter of devices or sensors such as accelerometers or inclinometers [5]. However, according to Bates [2], the alternative interfaces devices are still not widespread.

The human skeletal muscular system is primarily responsible for providing the forces required to perform various actions. Currently, electromyography (EMG) studies are used for evaluating and diagnosing patients with neuromuscular disorders. The interpretation of EMG readings is usually performed by trained person. Problems arise when there are too few experts to meet the demand of patients and, therefore, it is becoming increasingly important to developed automated diagnostic systems based on EMG readings. The myoelectric signal is the sign of muscle control of the human body that contains the information of the user's intent to contract a muscle and, therefore, make a move. The main goal of this paper is to present the development of a system for controlling the movements of a virtual mouse through the acquisition and characterization of myoelectric signals of the masseter and temporal muscles. Thresholds of the myoeletric signals from two volunteers are computed by three different techniques: Linear Energy based Detector (LED), Adaptive Linear based Energy Detector (ALED) and the regular static average. The results showed that the adaptive techniques LED and ALED have better performance than the regular average threshold approach.

## 2 Experimental Section

Figure 1 present the experimental arrangement developed in this work. Eight surface electrodes (model Meditrace 200 Kendal from The Ludlow Company LP ©Tyco Healthcare) are disposed to capture the biosignals from masseter and temporal muscles on the human face. The second block represents the hardware composed by an 8-channels electromyography (EMG) and the ADC converter (National Instruments USB-6008 – 12 bits – 1kHz sample rate per channel). The EMG includes features such as: 8 bipolar channels, 1000x differential gain, two cascaded second-order low-pass Butterworth filters with a cutoff frequency of 800 Hz; two cascaded high-pass second-order filters with a cutoff frequency of 20 Hz. The third block represents the processing software. The analog signal is collected and the signal is processed for controlling the virtual mouse. Each of the system functions can be tested by a man-machine interface.

After the start command, the data are sent continuously to the ADC USB interface until the stop command. Each time the system is started, the user will be asked to perform a calibration in order to adapt the personal biosignals. In the calibration process, signals are captured and the decision energy threshold is calculated through both techniques: LED and ALED. Also, the simple average energy of each packet is calculated and used as a threshold value.

When the system is executed, the myoelectric signals of the voluntary contraction of masseter and temporal muscles are captured and divided into data packets. If the average energy packet is larger than the reference energy value (obtained by the calibration process) then the software must perform a certain action, otherwise not.

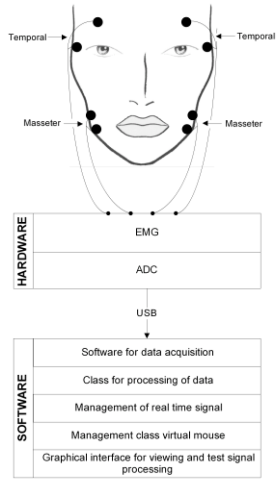



**Fig. 1.** Block diagram of experimental developed apparatus.

The number of samples of the package is computed by:

$$N = (t_{packet})/f_{sample}^{-1} . \qquad (1)$$

where $N$ is the number of samples of a package; $t_{packet}$ the packet size in seconds and $f_{sample}$ is the sampling rate.

### 2.1 Static Threshold Detection

The static energy threshold $E_{static}$ estimates the average noise energy $E_{noise}$ and manually determines a safety margin defined by:

$$E_{static} > k.E_{noise} . \qquad (2)$$

where $k$ (typically $k > 1$) is the safety margin that avoid the system becomes unstable [6].

### 2.2 Linear Energy Based Detector and Adaptive Linear Energy Based Detector

In recent years techniques based on detection of energy have shown increased usage in voice transmission systems [6], [7], [8], [9]. For instance [6], discusses the use of a technique based on energy analysis, called Voice Activity Detection (VAD) in VoIP (Voice over Internet Protocol) systems for bandwidth reduction. This technique has also been employed in systems for voice recognition, voice compression and coding [7]-[9]. Algorithms based on energy analysis techniques usually must provide some of the following criteria [20]: (1) use some physical property of the phenomenon for characterizing a good decision rule such as the signal segments of silence; (2) low sensitivity to non-stationary noise and (3) low computational complexity for real time applications.

These criteria are successfully employed in this work. Consider $X(i)$ the $i^{th}$ sample of the signal. If the length of the data packet is $k$ samples, then the $j^{th}$ packet can be represented in the time domain by a sequence indicated by:

$$f_j > \{X(i)\} \text{ for } i = (j\text{-}1)k\text{+}1 \text{ to } jk \,. \tag{3}$$

where the energy $E_j$ on the $j^{th}$ packet is:

$$E_j = \frac{1}{k}\sum_{i=(j-1)k+1}^{jk} X^2(i) \,. \tag{4}$$

In order to determine if a packet should or not trigger some virtual mouse function, the average energy of the packet is computed. The average energy $E_m$ is defined [9] by:

$$E_m = \frac{1}{N}\sum_0^{N-1}\left(E_{sample}\right)^2 \,. \tag{5}$$

where $E_{sample}$ is the sample energy and $N$ the number of samples in the packet.

The threshold value is an important parameter to distinguish the active signals (maximal voluntary contraction of the myoelectric signals) from the basic noise or the inactive signal. The decision threshold in this work uses the energy of the frame for classifying active and inactive signals, i.e. maximal voluntary contraction from period of silence. If the energy of the packet is greater than the threshold value established on the calibration then an action on the virtual mouse is performed.

Linear Based Energy (LED) is an adaptive threshold detection technique appropriate for determining the energy threshold of non-stationary signals such as myoelectric signal. In this technique, at least two data packets are analyzed [8] and the threshold energy $E_{LED}$ is computed:

$$E_{LED} = (1-p)E_{previous} + pE_{current} \,. \tag{6}$$

where $E_{previous}$ is the last average energy packet; $E_{current}$ is the average energy packet being computed currently and $p$ the step index of the adaptation process (range from 0 to 1). The Z transform of (6) is:

$$E_r(Z) = (1-p)Z^{-1}E_r(Z) + pE_{noise}(Z) \,. \tag{7}$$

and the transfer function:

$$H(Z) = \frac{E_r(Z)}{E_{noise}(Z)} = \frac{p}{1-(1-p)Z^{-1}} \,. \tag{8}$$

Usually, the virtual mouse can be controlled between two events, in a period ranging from 50 to 100ms. Thus $p$ is chosen to correspond to 100 ms or 15 packets per period in order to avoid the fall-time effects $E_r$. The main difference between LED and ALED techniques is the determination of the adaptation step $p$. While on LED the configuration of $p$ is manual, on the ALED technique it depends of the ratio of the energy variance of the actual data packet ($Var_{new}$) and the variance of the last processed data packet ($Var_{old}$), as shown in Table 1 [7].

**Table 1.** Determination of the adaptation step of ALED technique ($x = Var_{new}/Var_{old}$).

| Classification | $P$ |
|---|---|
| $x \geq 1.25$ | 0.25 |
| $1.25 \geq x \geq 1.10$ | 0.20 |
| $1.10 \geq x \geq 1.00$ | 0.15 |
| $1.00 \geq x$ | 0.10 |

### 2.3 System Operation

First the user selects an action to be performed by the virtual mouse. Any action is based on the behavior of the myoelectric signals, i.e. the voluntary contraction of the masseter and temporal muscles. The user interaction with the system is performed by three commands: (a) command 1: contraction of the left and right masseter and temporal muscles simultaneously, i.e., this command is executed when the energy of data packets from both hemifaces has average value greater than the threshold calibrated for both sides; (b) command 2: contraction of the right masseter and temporal, i.e. this command is executed when the energy of the data packets of the right hemiface has average value greater than the threshold calibrated for the right side and (c) command 3: contraction of the left masseter and temporal muscles, i.e. this command is executed when the energy of data packets of the left hemiface has average value greater than the threshold calibrated for the left side.

In order to have these commands correctly identified the user is required to perform a calibration as an initializing procedure. In the calibration process the user must perform the following actions: (a) contraction of left masseter and temporal muscles and (b) contraction of right masseter and temporal muscles.

The actions taken by each of the commands of the system are listed below: (a) command 1: selection of the action emulated by the virtual mouse; (b) command 2: execution of the selected action on command 1 and (c) command 3: emulation of the left click regular mouse action. The actions executed by the virtual mouse are the following: (a) move to left; (b) move to right; (c) move up; (d) move down; (e) left click; (f) double click with left button and (g) click with right button. The real time data acquisition is based on the *National Instruments Measurement Studio 2009 for Visual Studio* API communicating with DAQ USB-6008.

The electromyography data is collected with 1000 samples per second, 256 samples per channel. The data packet is processed when the buffer of each of the four channels reach the number of configured samples. The four data packets are processed and the energy computed, the buffers are cleaned and a new acquisition starts. Additionally a virtual mouse interface was developed in order to facilitate the man to the machine communication (MMI). This interface displays informative messages during calibration and the virtual mouse action.

## 3 Results and Discussion

### 3.1 Data Collection

Both hemifaces need to be contracted simultaneously in order to run the command 1. Figure 2(a) presents an example of collected signals in order to perform command 1. These signals have the same pattern and energy above the calibrated thresholds and are successfully recognized by the software and thus command 1 is executed correctly. Figure 2(b) presents an example of collected signals in order to perform command 2. At the same time there is activity in both channels on the right hemiface while there is only noise on the left hemiface channels. Also, these signals are successfully recognized by the software.

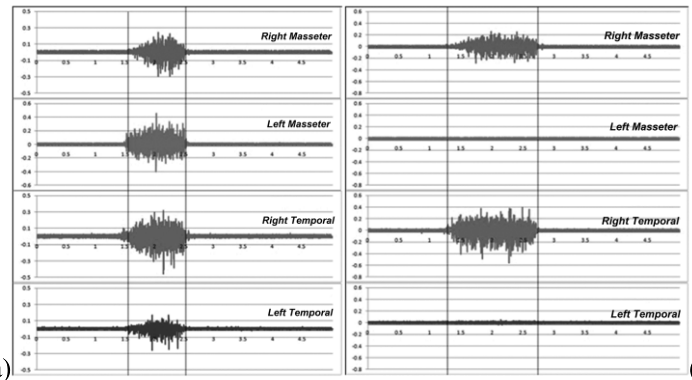
(a)  (b)


**Fig. 2.** Morfology of myoelectric signal for (a) command 1 and (b) command 2.

Several experiments were performed in order to test the commands and the virtual mouse movements with the three techniques described in this article for determining the threshold energy: LED, ALED and static. Two volunteers performed 30 muscle contractions in order to test each of the three techniques, thus totaling 90 contractions each volunteer. In these tests, each contraction is supposed to execute the commands. The commands successfully executed as well the failures are registered.

Three kinds of failures can happen: (a) the system does not execute any command; (b) the system executes the wrong command and (c) the system repeat the right command with wrong number of times. Before the tests, each volunteer used the system for 40 minutes in order to adapt to the commands. After, they conducted the experiments with the three techniques in different order, volunteer 01: LED, static, ALED and volunteer 02: ALED, LED and Static.

The results of techniques LED, ALED and Static are presented in Table 2. The total number of correct commands interpretation of LED technique was 83.3 % while ALED was 85% in 180 performed tests. The tests of static technique were performed with different safety margins for each volunteer. Volunteer 01 used a 10% safety margin (*k*), while volunteer 02 used 30%. The total number of correct commands interpretation of the static threshold detection presented 134 correct interpretations of the commands in 180 tests, i.e. a total success rate of 74.4 %. Table 3 presents a comparative percentage of failures and successes for each of the techniques.

According Table 3, there is a considerable difference between the successful rate of adaptive techniques (ALED and LED), and static threshold detection, which failed for 26% of tests. Furthermore, the static technique presented 50 % failure to command 3 for volunteer 02. This volunteer reported difficulties in controlling the demanded side of the facial muscles for this command. Command 1 presented 47 % failure rate using the static technique for volunteer 01. This volunteer reported difficulties in controlling the demanded side of the facial muscles for this command. The higher failure rate of the adaptive techniques in these last two described cases was 30 %. Thus the results indicate that the adaptive techniques help to improve the system performance for the facial muscles the users have control difficulties. Both volunteers had high rate of correct commands interpretations when the myoelectric signals were demanded by the respective reported easily controlled muscles. The command that requires muscle control of both hemifaces simultaneously also had a high successful rate.

**Table 2.** Results of techniques: LED, ALED and Static.

| Technique | | Command 1 | Command 2 | Command 3 |
|---|---|---|---|---|
| ***LED*** | ***Volunteer*** | ***Correct - Failure*** | ***Correct – Failure*** | ***Correct - Failure*** |
| | 01 | 26 – 04 | 23 – 07 | 27 – 03 |
| | 02 | 25 – 05 | 28 - 02 | 21 – 09 |
| ***ALED*** | ***Volunteer*** | ***Correct - Failure*** | ***Correct – Failure*** | ***Correct - Failure*** |
| | 01 | 27 – 03 | 25 – 05 | 28 – 02 |
| | 02 | 24 – 06 | 26 - 04 | 23 – 07 |
| ***Static*** | ***Volunteer*** | ***Correct - Failure*** | ***Correct – Failure*** | ***Correct - Failure*** |
| | 01 | 25 – 05 | 16 – 14 | 28 – 02 |
| | 02 | 23 – 07 | 27 - 03 | 15 – 15 |

**Table 3.** Technique results.

| | LED | ALED | Static |
|---|---|---|---|
| ***Correct*** | 83% | 85% | 74% |
| ***Failure*** | 17% | 15% | 26% |

## 4 Conclusions

This study demonstrated that it is possible to develop a virtual mouse controlled by the face biosignals of a user using LED and ALED decision threshold techniques. According to both volunteers reports, the longer the system is used, easier became the virtual mouse control, since the longer they could train the masseter and temporal muscles. Moreover, both users reported that after performing a new calibration the system usability is improved. Finally, the experimental results have shown that the adaptive threshold computing techniques ALED and LED have a higher successful rate than the static threshold detection approach. In this work a virtual mouse was developed and 180 experiments were performed by two volunteers. The failures rates of the different approaches were computed. The adaptive techniques LED and ALED had failures rates of 17% and 15%, respectively, while the static threshold detection presented 26% of failure rate. The algorithms based on LED and ALED techniques are simple and show results for quality control applications based on the maximum voluntary contraction of myoelectric signals. In future work the following aspects will be evaluated: (a) investigate whether the failure rate is related to the reduction of skin electrodes impedance; (b) investigate the optimum system time of use them as a function of muscle fatigue; (c) investigate the rate of assertiveness of the LED technique with different steps (parameter $p$) and (d) implement methods to dynamically determine the size of data packets, in order to reduce the failure rate.

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