Electromyogram-based Cursor Control System for Users with Motor Disabilities

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An improved hands-free cursor control system suitable for use by individuals with spinal dysfunction or spinal cord injury is introduced. The system uses electromyogram (EMG) signals from facial muscles to produce five distinct cursor actions, namely: left, right, up, down and left-click. The new system is derived from a system previously created by our group. Object selection tests are performed on both systems. We use statistical analysis and Fitts' law analysis of these tests to support our assertion that the new system provides enhanced performance over its predecessor.

1 Introduction

Computer-based systems have become increasingly pervasive in every arena of human activity. Many professions require access to computer-based applications in order for an individual to fulfill job requirements. With the advent of the Internet, the computer has become a portal to a new domain of social interaction, information access, and entertainment. Typically, able-bodied individuals interact with a computer using standard input devices, such as, a mouse, trackball, touchpad, or keyboard. However, there is a considerable segment of the population (e.g., 250,000 – 400,000 individuals in the United States) who are often unable to use such input devices because they live with spinal cord injury or spinal dysfunction [8]. There exists a need to provide such individuals with a more usable means of computer access than these input devices.

With today's GUI-based PC software, most of the human-to-computer interaction is based on selection operations, which consists of two steps:

- Pointing: Positioning the cursor at the desired location of the screen, over the appropriate area or icon.
- Clicking: Executing the Mouse Down/Up function that is interpreted by the computer's operating system as an indicator to complete the selection of the item associated with the icon at the location of the screen cursor.

The cursor control system that we have created facilitates these point-and-click operations through the detection and processing of electromyogram (EMG) signals.

Electromyography is the study of muscle function through monitoring of the electrical signals generated by the muscle [4]. A surface electrode placed on the skin above a superficial muscle will receive electrical signals emanating from several muscle fibers associated with different motor units. The spatio-temporal summation of these electrical signals results in what is called an EMG signal. Therefore, the EMG signal provides an effective means of monitoring muscle activity.

EMG signals have been used previously for cursor control. EMG-based systems have been used in [5], [9] and [2], [3], with [2], [3] focused specifically on the use of EMG signals from cranial muscles. Monitoring the EMG signals of cranial muscles makes this approach suitable for individuals suffering from severe motor disabilities and who are also paralyzed from the neck down.

EMG-based cursor control systems have been shown to perform slowly when compared to a mouse-operated system in object selection tests [2], [3]. However, EMG-based systems have the advantage of allowing for small cursor movements suited for high resolution computer displays. This is a quality that is not possessed by other alternative cursor control approaches, such as some based on eye-gaze tracking (EGT) [1], [6], [7].

The EMG system developed previously by our group [2], [3] utilized three electrodes that measured EMG signals from muscles in the head of the user. The EMG signals were classified into cursor actions by performing real-time spectral analysis of these signals. A previous empirical study of the EMG signals from different muscles revealed that they possessed distinguishing frequency characteristics. An example of this is displayed in Fig. 1

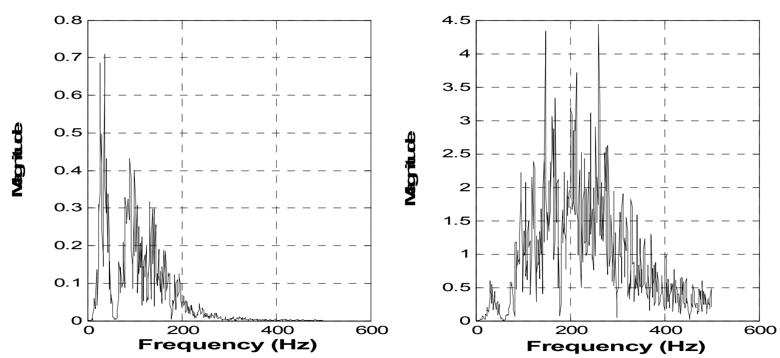

Fig. 1. Spectra observed during a right frontalis contraction (left plot) and a left temporalis contraction (right plot)

After a thorough evaluation of the previous EMG system, it was found that it was occasionally inaccurate in discriminating between the muscle contractions that command up and down cursor movements (eyebrows up and eyebrows down, respectively). To remedy this problem an additional electrode was added to the forehead region, and a new classification algorithm was devised to work with this new input configuration.

Section 2 of this paper details how the new system was implemented and the methodology behind the new classification algorithm. Section 3 also describes the experiment used to obtain object-selection task times, as well as, the data analysis methods used to study these task times. Section 4 provides the results of statistical analysis and Fitts' Law analysis performed on the experimental results. Section 5 presents our conclusions.

2 System Implementation and Signal Processing Methodology

2.1 Placement of Electrodes for the New EMG-based Cursor Control System

Fig. 2 displays the placement of the Ag/AgCl electrodes on the head of the subject. This figure indicates that electrodes were placed over the right frontalis muscle, the left temporalis muscle, the right temporalis muscle, and the procerus muscle, respectively. An electrode was placed over the right mastoid as a reference. This electrode set up differs from the previous EMG-based system only in the addition of the fourth electrode over the procerus muscle.

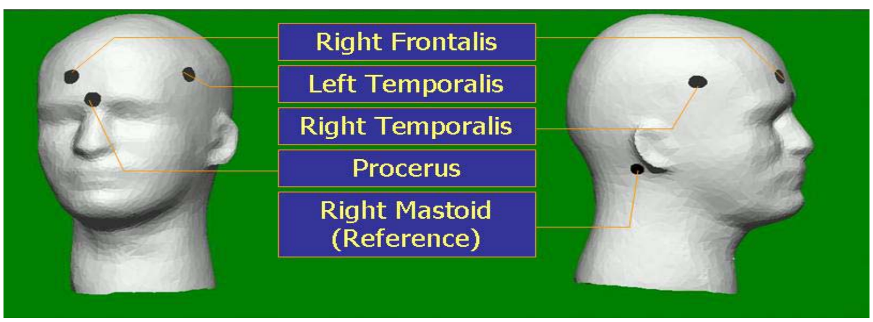

Fig. 2. Electrode placement for the new EMG cursor control system

2.2 Hardware Components of the EMG-Based Cursor Control System

The hardware components of the cursor control system are presented in Fig. 3. Each of the four EMG signals was magnified by a Grass® P5 Series AC preamplifier. Each of these preamplifiers possessed an anti-aliasing filter with a gain of 10,000 V/V and a 60Hz notch-filter. The ADC64TM DSP/AD board (Innovative Integration, Simi Valley, CA) performed analog-to-digital conversion on each signal at a sampling rate of 1.2 kHz, and then applied the classification algorithm to these digitized signals in real-time. The output of the board was a series of TTL-compliant binary voltage sequences consistent with voltage sequences expected from a serial mouse. The Motorola® MC1488C RS-232C driver converted the TTL sequences into RS-232C format and transmitted these sequences into the serial port of the personal computer (PC). The serial mouse driver of this computer communicated with the operating system to produce cursor actions driven by the serial signal created by the DSP board.

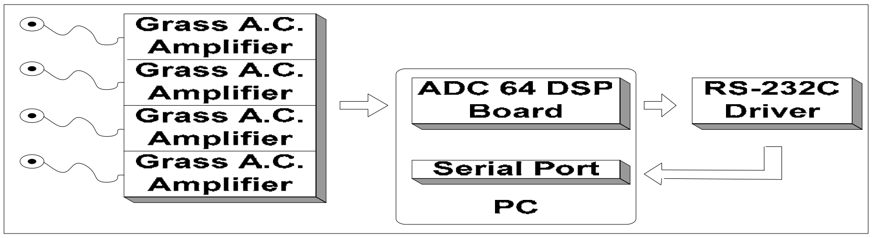

Fig. 3. Block diagram of hardware components of EMG-based cursor control system

2.3 EMG Processing Algorithm for Muscle Contraction Identification

The desired relations between cursor actions, facial movements, and muscle contractions are given in Table 1.

Table 1. Relations between cursor actions, facial movements and muscle contractions

Cursor Action	Facial Movement	Muscle Contraction
Left	Left Jaw Clench	Left Temporalis
Right	Right Jaw Clench	Right Temporalis
Up	Eyebrows Up	Right Frontalis
Down	Eyebrows Down	Procerus
Left-Click	Left & Right Jaw Clench	Left & Right Temporalis

The purpose of the classification algorithm was to determine if a facial muscle contraction had occurred and if so, which specific muscle was the source of this contraction. Given the one-to-one correspondence between muscle contraction and cursor action, the output of an effective muscle contraction classification algorithm can be utilized in a real-time implementation for hands-free cursor control.

Both the classification algorithm of [2], [3] and the new classification algorithm made use of the periodogram estimation of the power spectral density (PSD) of the input EMG signals. In both cases, the PSD indicated how the power of an EMG signal was distributed over a frequency range of 0 Hz – 600 Hz. Periodogram PSD estimations were taken every 256 consecutive samples (every 0.213s) from each of the EMG channels.

The two classification algorithms differed in the way each utilized the PSD estimates to classify the EMG data. The algorithm of [2], [3] only utilized three electrodes placed on: the left temporalis muscle, the right temporalis muscle, and the right frontalis muscle respectively. This algorithm calculated partial accumulations over the frequency ranges of 0 Hz – 145 Hz and 145 Hz – 600 Hz of the PSDs produced from the three EMG channels in order to distinguish between the frequency characteristics associated with the contraction of different muscles (temporalis versus frontalis). This algorithm also utilized PSD amplitude thresholds to estimate the strength of contraction from each of the three muscles mentioned previously.

Testing of this algorithm revealed that it did not always classify the eyebrows down movement efficiently. So it was proposed that an additional electrode be placed over the procerus muscle, because it is one of the muscles directly involved in the eyebrows down facial movement. This new four-electrode input configuration required a new classification algorithm, the details of which are described in the following paragraphs.

The new classification algorithm made use of Mean Power Frequency (MPF) values to distinguish spectral differences associated with each facial muscle contraction, instead of partial PSD accumulations. The MPF is derived from the PSD values as a weighted average frequency in which each frequency component, f, is weighted by its power, P. The equation for the calculation for the MPF is given by:

$$MPF = \left(\frac{f1 \times P1 + f2 \times P2 + ... + fn \times Pn + ... + fN \times PN}{P1 + P2 + ... + Pn + ... + PN} \right). \qquad n = 1,2, \ldots, N. \tag{1}$$

The new classification algorithm used a combination of PSD amplitude thresholds, complete PSD sums, and MPF values to correctly classify muscle contractions. For example, to correctly classify a unidirectional muscle contraction all the following criteria must be satisfied:

1. The maximum PSD amplitude must exceed the threshold set for that electrode.
2. The sum of the PSD amplitudes for the given electrode must exceed the PSD sums of the other electrodes
3. The mean power frequency calculated from the PSD must fall into a range consistent with the muscle associated with the electrode (frontalis: 40 Hz – 165 Hz, temporalis: 120 Hz – 295 Hz, procerus: 60 Hz – 195 Hz).

Detection of a click action requires fulfillment of similar requirements in both temporalis muscles simultaneously.

3 Testing and Data Analysis Methods

The experiment used to determine the point-and-click capabilities of the two systems followed a 2 x 4 x 4 x 6 factorial design with two cursor control systems (old and new), 4 different "Start" icon positions (Upper Left, Lower Left, Upper Right, and Lower Right), 4 different "Stop" icon sizes (8.5 x 8.5 mm, 12.5 x 12.5 mm, 17 x 17 mm, 22 x 22 mm), and 6 different able-bodied male subjects. A program was created in Visual Basic to present the point-and-click interface to each subject and to record the movement times required for each task. The program was displayed on a 17" color monitor. For each point-and-click trial, an 8.5 x 8.5 mm "Start" icon was presented in a corner of the screen and a "Stop" icon was presented in the center. Each subject was instructed to use the EMG-based cursor control system to click the "Start" button to begin timing a trial, move the cursor to the "Stop" button, and click on it as quickly as possible. This would record the total task time for the trial. The subject would then click a "Next" icon to display another trial layout with the "Start" button located in another corner of the screen. Each specific trial configuration ("Start" location, "Stop" size, and algorithm) was repeated three times by each subject resulting in a total of 96 trials executed by each subject.

The statistical analysis involved applying a four-way analysis of variance (ANOVA) of this factorial experiment. The results are given in the following section.

Fitts' law analysis applies Fitts' law to object selection data such as those produced by our experiment. Fitts' law states that there is a linear relationship between the movement time taken for a point-and-click task (MT) and the difficulty of this task (ID). The Fitts' law equation is given by:

$$MT = a + bID \quad (2)$$

where MT is the movement time in seconds, ID is the index of difficulty for the task, in bits. Also, a (seconds) and b (seconds/bit) are the coefficients associated with the linear relationship. ID is given by:

$$ID = \log_2 \left(A/W + 1 \right) \quad (3)$$

where A represents the distance to the target, and W represents the width of the target, which in our case is the "Stop" button.

Fitts' law essentially states that the narrower and further away a target is, the more difficult the task will be and the more time it will take to be completed.

For Fitts' law analysis, a movement time value is obtained by averaging all the movement times taken for a task of a given ID. Provided that there are tasks with different ID values then we will have a number of (ID, MT) ordered pairs. These ordered pairs are used to produce a linear regression line that represents the performance capabilities of that cursor control system. More specifically, the reciprocal of the slope of the regression line is used as performance measure. The name of this measure is the index of performance (IP) and has units of bits/s. The IP value for a point-and-click system indicates the rate of user information processing for that system.

4 Results

The analysis of variance of the data performed in Minitab produced the following table:

Table 2. Four-way ANOVA table

Source	DF	SS	MS	F	P
Algorithm (A)	1	10290.1	10290.1	84.66	0.000
"Start" Position (P)	3	611.3	203.8	1.68	0.171
A*P	3	221.2	73.7	0.61	0.611
"Stop" Icon Size (I)	3	3073.4	1024.5	8.43	0.000
A*I	3	306.5	102.2	0.84	0.472
P*I	9	833.8	92.6	0.76	0.652
A*P*I	9	603.8	67.1	0.55	0.836
Subject (S)	5	27421.5	5484.3	45.12	0.000
Error	539	65514.2	121.5		
Total	575	108875			

Table 2 shows a significant main effect for algorithm (A) with $p < 0.0005$, and a significant main effect for icon size (I), $p < 0.0005$. Therefore we can reject the null hypothesis of H_{o1}: $A_1 = A_2 = 0$, as well as, the null hypothesis H_{o2}: $I_1 = I_2 = I_3 = I_4 = 0$.

The mean point-and-click task times obtained from the real-time experiment were 22.66 s for the old system and 14.21 s for the new system.

The Fitts' law analysis data are shown in tables 3 and 4.

Table 3. Aggregated point-and-click data for Fitts' law analysis of old system

D(mm)	W(mm)	ID(bits)	MT(s)	IP=ID/MT(bit/s)
180	8.5	4.47	26.87	0.166
180	12.5	3.94	24.24	0.163
180	17	3.53	19.74	0.179
180	22	3.20	19.80	0.162

Table 4. Aggregated point-and-click data for Fitts' law analysis of new system

D(mm)	W(mm)	ID(bits)	MT(s)	IP=ID/MT(bit/s)
180	8.5	4.47	16.34	0.274
180	12.5	3.94	15.13	0.261
180	17	3.53	12.75	0.277
180	22	3.20	12.63	0.253

The linear regression equation derived from the results of Table 3 was $MT = -0.623 + 6.148*ID$, $r = 0.924$, $F(1, 2) = 24.3$, $p < 0.0015$. The linear regression equation derived from the results of Table 4 was $MT = 2.03 + 3.22*ID$, $r = 0.931$, $F(1, 2) = 27.0$, $p < 0.0012$. The IP value for the old system was 0.16 bit/s, while the IP value for the new system was 0.31 bit/s. Fig. 4 shows the linear regression plots for both systems.

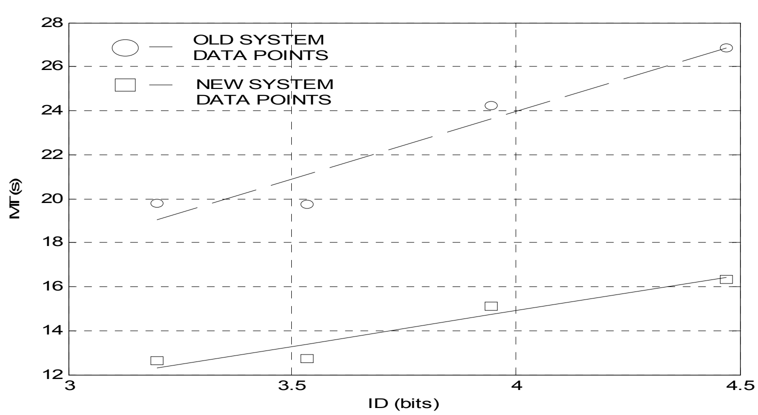

Fig. 4. Fitts' law regression lines for both cursor control systems

5 Conclusion

The results show that mean point-and-click task times are 8.45 s faster for the new system when compared to the old system. The ANOVA results prove that this difference is statistically significant. Therefore, we conclude that the new system provides faster point-and-click operations when compared to the old system.

The Fitts' law data shows that the IP value for the new algorithm is larger than that of the old one (0.31 bit/s compared to 0.16 bit/s). Also the linear regression equations and the corresponding plot indicate that the new system performs 6 - 10 s faster than the old system for a task of a given index of difficulty. One can conclude from these analyses that the new system exhibited a shorter mean object selection time, and allowed a more efficient processing of user input information (larger IP) for enhanced hands-free interaction with the GUI of a personal computer.

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