New Classification Algorithm for Electromyography-Based Computer Cursor Control System

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Abstract

At present, a three-input Electromyography (EMG) system has been created to provide real-time, hands-free cursor control. The system uses the real-time spectral analysis of three EMG signals to produce the following five cursor actions: i) LEFT, ii) RIGHT, iii) UP, iv) DOWN, v) LEFT-CLICK. The three EMG signals are obtained from two surface electrodes placed on the left and right temples of the head and one electrode placed in the forehead region. The present system for translating EMG activity into cursor actions does not always discriminate between up and down EMG activity efficiently. To resolve this problem it was proposed that the three-electrode system be converted into a four-electrode system, using two electrodes in the forehead of the user, instead of one. This paper compares the effectiveness of the four-electrode system to that of the three-electrode system in classifying EMG activity into cursor actions through the use of Matlab simulations. It will be shown that the new four-electrode system produces significant improvements in classification performance.

1. Introduction

The benefits of having the ability to utilize a computer in today's technological world are self-evident. Unfortunately there are a number of individuals that suffer from severe motor disabilities, which render them unable to operate a mouse, trackball, touchpad, or keyboard. It is estimated that there are 250,000 – 400,000 individuals in the United States living with spinal cord injury or spinal dysfunction [11].

There exist a number of approaches that seek to address the problem of providing computer access for people who are unable to use a mouse, trackball, touchpad, or keyboard. One such approach is the use of electrophysiological signals from the brain to communicate messages or commands to a computer. Such devices are called brain-computer interfaces (BCIs). Present day independent BCIs can be classified by the form of physiological signal that they use to determine user intent. These signals include: slow cortical potentials, P300 evoked potentials, mu and beta rhythms, and cortical neuronal activity recorded from electrodes implanted in the scalp [14].

It has been found that movement or preparation for movement is accompanied by a decrease in the mu and beta rhythms, especially in the region of the brain contralateral to the movement. This phenomenon is called "event-related desynchronization" (ERD). In addition, it has been observed that there is mu rhythm increase or "event-related synchronization" (ERS) after a movement and with relaxation. It has also been found that ERD and ERS do not require actual movement but can accompany imagined movement. These facts make mu/beta rhythms suitable for input into a BCI, and work by Fabiani et al. [4], and Pfurtscheller et al. [12] has focused on their use as a source of cursor control.

The major advantage of using a BCI system as an assistive technology for individuals with motor disabilities is that it does not require the brain's normal output pathways to produce its control signals, neither does it require activity in these pathways to generate the control signals. However, present day BCI systems are primarily limited by speed of operation. Current BCIs have maximum information transfer rates of 10 - 25bits/min [14].

Another prominent approach to providing hands-free cursor control is eye-gaze tracking (EGT). EGT techniques seek to determine the user's visual line of gaze by taking video images of the eye in order to establish a relationship between the geometric properties of the eye and the line of gaze. The most popular EGT technique at present uses the relative position of the bright eye (pupil) center and the center of the glint (corneal reflection) to determine the line of gaze [5, 7, 8, 9, 13]. Once the line of gaze is determined, the point of gaze is found by allowing the line of gaze to intersect with the plane of the scene being viewed (typically the computer screen).

This approach has been shown to perform faster than a mouse in object selection tests [13]. The approach has some disadvantages however. One such disadvantage is the so-called "Midas Touch" problem [7, 8]. The problem originates from the use of the eye gaze as an object selection technique. Since there may be situations where a user may only desire to stare at an object to examine it, rather than to select it, an eye gaze-based object selection technique may result in unintended selections. Another disadvantage is the limited accuracy of the approach. This limitation is rooted in the fact that the eye only needs to focus incoming light on an area of the retina called the fovea, in order to see objects clearly. For an object to be focused on the fovea, it must fall within an area covered by approximately one degree of visual arc [7, 13]. This physical constraint limits the accuracy with which the line of gaze can be estimated.

Electromyographic (EMG) signals from muscles in the body have also been used for cursor control. This approach has been used in [1, 2, 6, 15], with [1, 2] focusing on the use of cranial muscles. The use of EMG signals from cranial muscles is an approach that would be suitable for individuals suffering from severe motor disabilities, who are paralyzed from the neck down.

The advantage of this approach is that it provides the user with the ability to perform small cursor movements, unlike EGT systems. However, it has been shown that this approach performs slowly compared to a mouse-operated system in object selection tests [1, 2].

Based on the seemingly complementary characteristics of the EGT and EMG-based modes of cursor control, an EGT/EMG hybrid system was conceived and implemented [3, 13]. The EMG system used in [1, 2, 3, 13] utilized a three-electrode system 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.

After a thorough evaluation of the EMG system, it was found that the three-electrode system was occasionally inaccurate in discriminating between eyebrows up and eyebrows down EMG activity. This paper outlines the development of a new four-electrode system with its associated classification algorithm. Section 2 details how the system was implemented and the methodology behind the classification algorithm. Section 3 details how testing was performed on the two classification algorithms. Section 4 gives tabulated results derived from the tests. Section 5 provides conclusions and recommendations.

2. System Implementation and Methodology

2.1. Electrode Placement for Cursor Control System

Figure 1 displays the placement of the Ag/AgCl electrodes on the head of the subject. Figure 1 indicates that one electrode was placed over the right frontalis muscle, one electrode was placed over the procerus muscle, one electrode over the left temporalis muscle, one electrode over the right temporalis muscle, and one electrode was placed on the right mastoid. The right mastoid electrode was used as a reference.

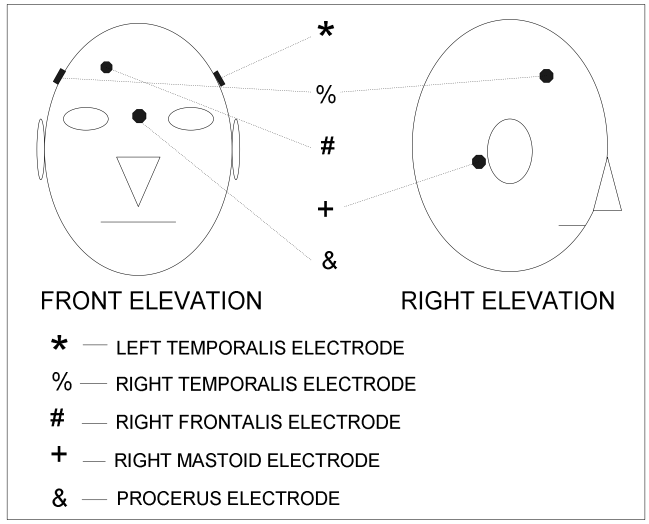

Figure 1. Electrode placement diagram for EMG system

2.2. Recording System for EMG Signals

The recording structure used to capture the EMG signals is shown in Figure 2. The Grass® P5 Series AC preamplifiers were set to preprocess the signals with analog anti-aliasing filters, and with a gain of 10,000 V/V. Each preamplifier also applied a 60Hz notch-filter to each of the four EMG channels. The NI DAQPad-6020E is a data acquisition board that took the amplified EMG analog signals and performed analog-to-digital conversion on each signal at a sampling rate of 1 kHz. The digital data was stored on a PC with the assistance of the "Traditional" NI-DAQ driver. The digital data files collected with this setup were used as the inputs to the two off-line classification algorithms written in Matlab, for the comparison described below.

2.2. The Classification Algorithm

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

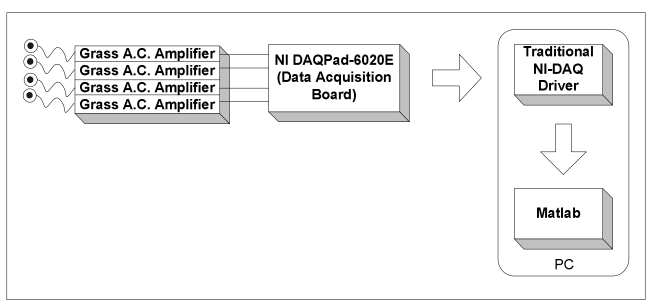

Figure 2. Recording structure for EMG signals

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(s) 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 [1, 2] and the classification algorithm discussed in this paper, made use of the periodogram estimation of the power spectral density (PSD) of the EMG signals recorded. In both cases, the PSD indicates how the power of an EMG signal is distributed over a frequency range of 0Hz – 500Hz. Periodogram PSD estimations were taken every 250 consecutive samples (every 0.25s) from each of the four EMG channels recorded in the digital data file.

Each classification algorithm differed in the way it utilized the PSD estimates to classify the EMG data. Firstly the algorithm of [1, 2] only utilized three electrodes, placed on the left temporalis muscle, the right temporalis muscle, and the right frontalis muscle respectively, to record EMG signals. The classification algorithm adopted for this three-electrode system, calculated partial accumulations over the frequency ranges of 0Hz – 145Hz and 145Hz – 500Hz of the PSDs produced from three EMG channels. These partial accumulations were used to distinguish between the frequency characteristics of a temporalis contraction as opposed to a frontalis contraction. The algorithm of [1, 2] also utilized PSD amplitude thresholds to estimate the strength of contraction from each of the three muscles mentioned previously. The partial accumulation and threshold criteria were used to classify the facial movements: left jaw clench, right jaw clench, eyebrows up, and left and right jaw clench. The eyebrows down movement required a divergent set of classification criteria. The eyebrows down movement used a partial accumulation over the frequency range 88Hz – 250Hz of the PSD calculated from the frontalis electrode. In addition, it was required that the PSD amplitude thresholds of the three electrodes not be exceeded.

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.

It was decided that this new classification algorithm would make use of the Mean Power Frequency (MPF) values as means of distinguishing spectral differences associated with each facial muscle contraction, instead of partial PSD accumulations. This decision was based on the fact that it seemed to produce more robust classification results for the test group used. The MPF is derived from the PSD values. The MPF can be calculated 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:

$$MPF = \left(\frac{f1 \times P1 + f2 \times P2 + \ldots + fn \times Pn}{P1 + P2 + \ldots + Pn} \right) \qquad \text{(eq. 1)}$$

n = 1, 2, …, 250

It has been observed previously that the spectral content of the four muscles used in this system are distinct [1, 2]. We have also confirmed this in new observations made on the five subjects involved in this research. The frontalis muscle has the majority of its spectral content below 200Hz, with an MPF in the range 40Hz – 165Hz. The temporalis muscles have a significant portion of their spectral content above 200Hz, with an MPF in the range 120Hz – 295Hz. The procerus muscle has an intermediate spectral content when compared to the frontalis and temporalis muscles, with an MPF in the range 60Hz – 195Hz.

For a unilateral muscle contraction to be correctly classified by the four-electrode algorithm all the following criteria must be satisfied:

i) The maximum PSD amplitude must exceed the threshold set for that electrode.

ii) The sum of the PSD amplitudes for the given electrode must exceed the PSD sums of the other electrodes.

iii) The mean power frequency calculated from the PSD must fall into a range consistent with the muscle associated with the electrode.

For the classification of the bilateral contraction of the left and right temporalis muscles used to trigger the left-click cursor action, all the following conditions must apply:

i) The maximum PSD amplitude thresholds must be exceeded for both electrodes.

ii) The PSD sums for both electrodes must be greater than the other two PSD sums.

iii) The PSD sums for both electrodes must indicate a fairly balanced bilateral contraction, that is, each PSD sum must be greater than 20% of the total of both PSD sums.

iv) The mean power frequencies calculated from both PSDs must fall into a range consistent with the muscles associated with both electrodes.

3. Testing

Each subject had four active surface electrodes attached to him or her as specified in Fig. 1. These attachments were for the purpose of recording the EMG signals associated with facial movements using the equipment outlined in Fig. 2. Five subjects (4 men, 1 woman, all able-bodied) were utilized in the testing of the classification algorithm. Testing involved recording facial movement sequences for each subject. Each sequence was 190s in duration. During each sequence the subject was given verbal cues to perform specific types of facial movements. There were two unique sequences given to each subject. Each sequence was repeated twice. The ordering of facial movements in the two unique sequences is given in Table 2.

It should be noted that sequence 2 includes a period of neck movement. This is included to determine if the classification algorithm can accurately discriminate such EMG signals from those due to the targeted muscle contractions.

Table 2. The ordering of facial movement sequences

Time	Sequence 1 Facial Movements	Sequence 2 Facial Movements
0s – 20s	No Movement	No Movement
20s – 40s	Right Clench	Right Clench
40s – 50s	No Movement	No Movement
50s – 70s	Eyebrows Up	Eyebrows Up
70s – 80s	No Movement	No Movement
80s – 100s	Left/Right Clench	Left/Right Clench
100s – 110s	No Movement	No Movement
110s – 130s	Eyebrows Down	Eyebrows Down
130s – 140s	No Movement	No Movement
140s – 160s	Left Clench	Left Clench
160s – 170s	No Movement	No Movement
170s – 190s	No Movement	Neck Movement

4. Results

Both the three-electrode classification algorithm and the four-electrode classification algorithm were applied to each digital data sequence. Therefore, for each data sequence, two classification sequences were obtained. The outputs of both classification algorithms were programmed to be one of six integer values (0 – 5) for a given classification. Each integer value represented a specific cursor action. The mapping between classification output values and cursor actions are given in Table 3. Therefore, a classification sequence consists of a series of integers ranging from zero to five. An example of a classification sequence is displayed in Figure 3. The number of correct/incorrect classifications were tabulated for all the classification sequences. Correct/incorrect classification percentages were calculated for each algorithm by averaging over the four classification sequences produced by each algorithm for a given subject. These classification percentages are shown in Table 4.

Table 3 - Mapping between classification algorithm outputs and cursor actions

Classification Algorithm Output	Cursor Action
0	No Action
1	Up
2	Left
3	Right
4	Left-Click
5	Down

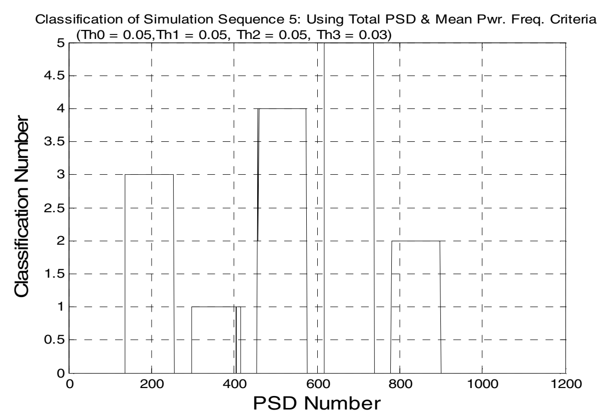

Figure 3. Example of a classification sequence produced by four-electrode classification algorithm

Table 4. Summary of classification percentages on a subject-by-subject basis

Subject No.	Classification Percentages (%)			
	3-Electrode Algorithm		4-Electrode Algorithm	
	Correct	Incorrect	Correct	Incorrect
1	82.38	17.62	99.52	0.48
2	78.36	21.64	99.01	0.99
3	83.85	16.15	99.08	0.92
4	75.10	24.90	99.01	0.99
5	72.47	27.53	95.49	4.51
Average	**78.43**	**21.57**	**98.42**	**1.58**

5. Conclusions and Recommendations

The results show a significant increase in classification performance of the four-electrode system over the three-electrode system. The four-electrode system had an average correct classification percentage of 98.42% with a maximum correct classification percentage of 99.52% and a minimum correct classification percentage of 95.49%. The standard deviation for the correct classification percentages of this algorithm was 1.65%. The three-electrode system had an average correct classification percentage of 78.43% with a maximum correct classification percentage of 83.85% and a minimum correct classification percentage of 72.47%. The standard deviation for the correct classification percentages of this algorithm was 4.79%.

The higher average classification percentage for the four-electrode algorithm suggests that this algorithm provides greater accuracy when compared to the three-electrode algorithm. The smaller standard deviation for the four-electrode algorithm when compared to the three-electrode algorithm implies that the four-electrode algorithm provides a more consistent classification performance for the group of subjects examined. The results also suggest that the four-electrode system has the potential to be a more efficient classifier of EMG signals in a real-time environment.

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