Neural Control of the Computer Cursor Based on Spectral Analysis of the Electromyogram

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Abstract **– A classification algorithm is developed to translate facial movements into five cursor actions: i) LEFT, ii) RIGHT, iii) UP, iv) DOWN, and v) LEFT-CLICK. The algorithm utilizes the unique spectral characteristics exhibited by electromyogram (EMG) signals obtained from different muscles in the face to assist in the classification process. A previous three-electrode, EMG-based system was utilized in [1, 2] to perform a similar translation of facial movements into cursor actions. This system also made use of spectral analysis to classify muscle activity. It was found that this system does not always discriminate between the EMG activity assigned to UP and DOWN cursor actions efficiently. To remedy this matter, a fourth electrode was added and a new classification algorithm was devised. This paper details the classification algorithm utilized with the four-electrode system. It also compares the effectiveness of the four-electrode system to that of the three-electrode system in classifying EMG activity into cursor actions. This was done through the use of Matlab simulations. It will be shown that the new four-electrode system produces significant improvements in classification performance.**

I. 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 [9].

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). Fabiani et al. [3], and Pfurtscheller et al. [10] have utilized mu and beta rhythms as a source of cursor control.

Another prominent approach to providing hands-free cursor control is based on 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. At present the most popular EGT technique uses the relative position of the bright eye (pupil) center and the center of the glint (corneal reflection) to determine the line of gaze [4, 6, 7, 8, 11]. 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).

Electromyogram (EMG) signals from muscles in the body have also been used for cursor control. This approach has been used in [1, 2, 5, 12], with [1, 2] focusing on the use of cranial muscles. In [1, 2], three EMG signals are obtained from two surface electrodes placed on the left and right temples of the head (right and left temporalis muscle groups) and one electrode placed in the forehead region (the right frontalis muscle). 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 work described in [1, 2] makes use of the distinct spectral characteristics exhibited by muscles in the face to assist in the classification of muscle activity. Fig. 1 displays the spectra exhibited during a frontalis contraction and temporalis contraction respectively. Frequency-based classification was required, because volume conduction would cause significant EMG artifacts from other facial muscles to be observed by an electrode assigned to detect EMG activity from only one facial muscle [1, 2].

After a thorough evaluation of the EMG system in [1, 2], it was found that the three-electrode system was occasionally inaccurate in discriminating between up and 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.

II. System Implementation and Methodology

A. Electrode Placement for Cursor Control System

Fig. 2 displays the placement of the Ag/AgCl electrodes on the head of the subject. Fig. 2 indicates that one electrode was placed over the right frontalis muscle, one electrode was placed over the procerus muscle, two electrodes were placed over the left and right temporalis muscles, and one electrode was placed on the right mastoid. The right mastoid electrode was used as a reference.

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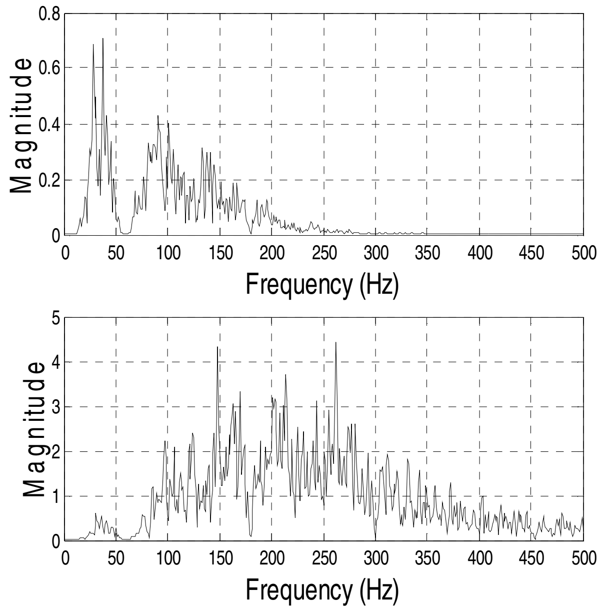

Fig. 1. Spectra observed during a right frontalis contraction (top plot) and left temporalis contraction (bottom plot)

B. Recording System for EMG Signals

The recording structure used to capture the EMG signals is shown in Fig. 3. The Grass® P5 Series AC amplifiers 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 module 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. A digital data file acted as the input to the classification algorithm written in Matlab, for the comparison described below.

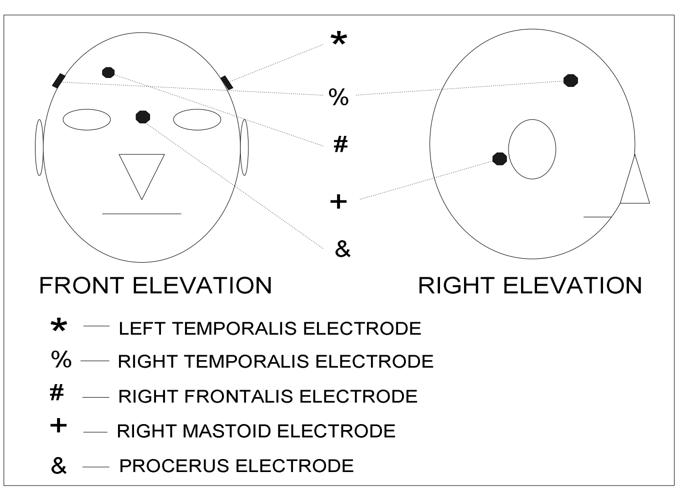

Fig. 2. Electrode placement diagram for EMG system

C. The Classification Algorithm

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

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. A flowchart representing the classification algorithm is given in Fig. 4.

The classification algorithm made use of the periodogram estimation of the power spectral density (PSD) of each of the four EMG signals. The PSD indicates how the power of an EMG signal is distributed over a frequency range of 0 Hz – 500 Hz. 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.

The classification algorithm also made use of Mean Power Frequency (MPF) values derived from the PSD estimates. 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:

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

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

For a unilateral muscle contraction to be acknowledged by the algorithm at a given electrode site, all the following conditions must be satisfied:

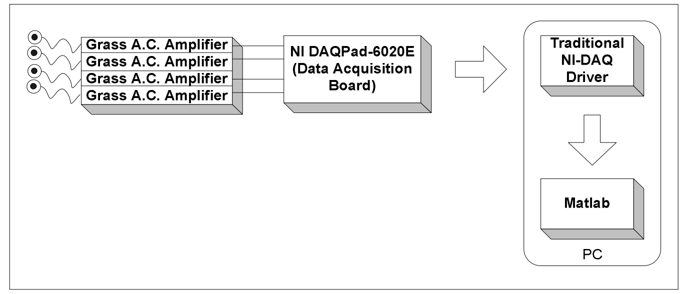

Fig. 3. Recording Structure for EMG Signals

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

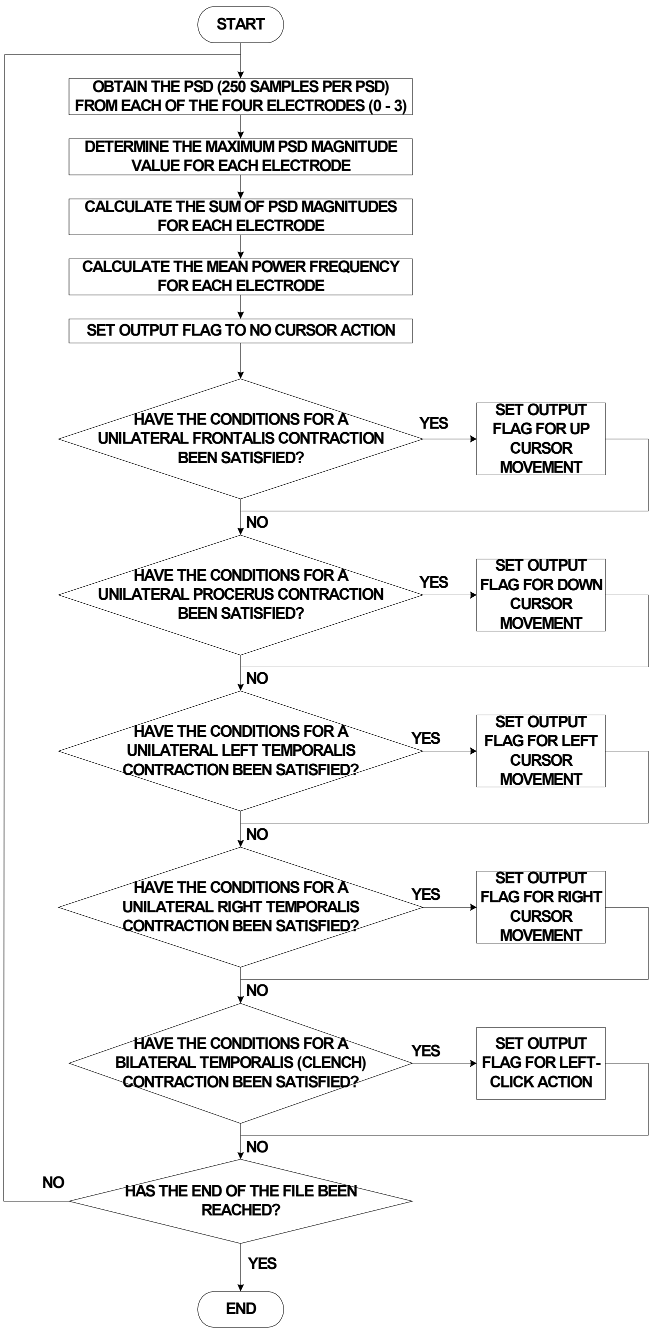

Fig. 4. Flowchart of EMG-based classifcation algorithm

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.

III. Testing

Five subjects (4 men, 1 woman, all able-bodied) were involved in the testing of the classification algorithms. Testing involved recording facial movement sequences for each subject. Each sequence was 190 seconds 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 desired 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

IV. RESULTS

Both the previous three-electrode classification algorithm and the new four-electrode classification algorithm were applied to the recorded digital data sequences. The number of correct/incorrect classifications were tabulated for each sequence, for each subject. Correct/incorrect classification percentages were calculated using the four sequences recorded for each subject. These classification percentages are shown in Table 3.

V. CONCLUSIONS AND RECOMMENDATIONS

The results show that 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 the new algorithm was 1.65%. The results also show that 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 the old algorithm was 4.79%.

The higher average classification percentage for the new algorithm indicates that this algorithm provides greater accuracy when compared to the old algorithm. The smaller standard deviation for the new algorithm when compared to the old algorithm implies that the new algorithm provides a more consistent classification performance for the group of subjects examined. These two facts lead us to conclude that the four-electrode system produces improved classification performance over the previous system and it has the potential to be a more efficient classifier of EMG signals in a real-time environment.

Table 3. Summary of classification percentages on a subject-by-subject basis

Subject No.	Classification Percentages (%)			
	Old Algorithm		New 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

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