Signal Processing Approaches for EMG-based Hands-off Cursor Control

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Abstract

There are numerous scenarios in which it would be preferred or necessary to manipulate the screen cursor of a computer's graphic user interface (GUI). Some specialized operators, such as pilots or surgeons may need to interact with computer-based equipment while their hands are committed to tasks with higher priorities. For individuals with severe motor disabilities, who may not be able to perform movements from the neck down, manipulation of a "hand-held mouse for directing the pointing and clicking functions associated with the screen cursor is not possible. These diverse needs have inspired the design and development of interfaces that do not require the usual coordinated movements of the user's hands to drive the screen cursor in the GUI. Part of these efforts have been devoted to the potential use of electrical activity that is generated by the activation of excitable cells in our brain and muscles, to control the movements and functions of the screen cursor. Several groups around the world are actively pursuing the development of interfaces driven by the electroencephalogram (EEG) signals recorded from the head of the user. These interfaces are often referred to as "Brain-Computer Interfaces", or BCIs. For the last 5 years, our group has targeted the development of cursor control approaches that utilize a different biopotential signal: the electromyogram (EMG) from facial muscles, i.e., the electrical signal changes that take place when the user contracts some specific muscles in his/her face. A large proportion of individuals with severe motor disabilities still retain control over these muscles. Initially, an EMG-based cursor control system was created to provide real-time, hands-free cursor control from signals collected through three surface electrodes. This initial 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. It was found, however, that the differentiation between lowering and raising the eyebrows to move the cursor DOWN and UP, respectively, from just one EMG signal was particularly (and maybe unnecessarily) challenging. Accordingly, 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

It is estimated that there are 250,000 – 400,000 individuals in the United States living with spinal cord injury or spinal dysfunction (National Spinal Cord Injury Association, 2005). The quality of life of these individuals along with those afflicted with Amyothrophic Lateral Sclerosis (ALS) could be significantly improved by providing them with a practical, reliable means to use standard Personal Computers. In particular, given the increasing pervasiveness of computer-based systems in most of our daily activities, and the increasing levels of communication and social participation that take part over the Internet, it is clear that facilitating access of these individuals to GUI-driven computer systems is an important technical goal

With today's Graphic User Interface (GUI) – based PC software, most of the human-to-computer interaction is based on selection operations, such as:

- 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 indication to complete the selection of the item associated to the icon at the location of the screen cursor.

There have been a number of approaches that have attempted to make these operations available to individuals with severe motors disabilities. Several of these devices target the motor skills that are still available to some users. The “Tonguepoint” system is based on an IBM Trackpoint III™ pressure sensitive isometric joystick fastened to a mouthpiece so that it can be operated by the user with his /her tongue. The joystick provides cursor-control, while two switches, one being a bite switch and the other a manual switch located outside of the mouth, allow the user to consider left and right button selections (Salem and Zhai, 1997).

Another alternative based on movement is the Headmouse™ (and recently an upgraded system called Headmouse Extreme™) by Origin Instruments. The Headmouse is a pointing device that transforms head movement into cursor movement on the screen. This is accomplished using a wireless optical sensor that tracks a small target with adhesive backing that is placed on the user's forehead or glasses. When combined with an on-screen keyboard, the left and right mouse button operations are triggered either by dwelling over a particular key for a set period of time or by using a remote adaptive switch that can be mechanically altered.

A different class of alternative cursor control approaches seek to drive the manipulation of the cursor from signals that occur “naturally” in the user, such as the person’s electroencephalogram (EEG) or electromyogram (EMG). Frequently, approaches that monitor and process electrophysiological signals from the brain to communicate messages or commands to a computer 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 (Wolpaw, Birbaumer, McFarland, Pfurtscheller & Vaughan, 2002).

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. (Fabiani, McFarland, Wolpaw & Pfurtscheller, 2004), and Pfurtscheller et al. (Pfurtscheller, Flotzinger & Kalcher, 1993) 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 (Wolpaw, Birbaumer, McFarland, Pfurtscheller & Vaughan, 2002).

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 (Hutchinson, White, Martin, Reichert and Frey, 1989) (Jacob, 1991) (Jacob, 1993) (Lankford, 2000) (Sibert & Jacob, 2000). 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 (Sibert & Jacob, 2000). The approach has some disadvantages however. One such disadvantage is the so-called “Midas Touch” problem (Jacob, 1991) (Jacob, 1993). 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 (Jacob, 1991) (Sibert & Jacob, 2000). 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 (Itou, Terao, Nagata & Yoshida, 2001) (Yoshida, Itou and Nagata, 2002), and (Barreto, Scargle &

Adjouadi, 1999) (Barreto, Scargle & Adjouadi, 2000) focused specifically on the use of EMG from 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 (Barreto, Scargle & Adjouadi, 1999) (Barreto, Scargle & Adjouadi, 2000).

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 (Lyons, Barreto & Adjouadi, 2001) (Barreto, Al-Masri & Cremades, 2003). The EMG system used in (Barreto, Scargle & Adjouadi, 1999) (Barreto, Scargle & Adjouadi, 2000) (Lyons, Barreto & Adjouadi, 2001) 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

The montage of four surface EMG electrodes used in the new cursor control system is a direct extension of the three-electrode montage used by our group previously (Barreto, Scargle & Adjouadi, 1999) (Barreto, Scargle & Adjouadi, 2000). An electrode has been added over the procerus muscle to help differentiate the lowering of the eyebrows (in which this muscle is directly involved), from the raising of the eyebrows. The complete four-electrode montage is illustrated in Figure 1. Most importantly, the algorithm used with this four electrode montage is different the one used for the operation of the previous, three electrode cursor control system.

2.1 Placement of Electrodes for the EMG-based 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.

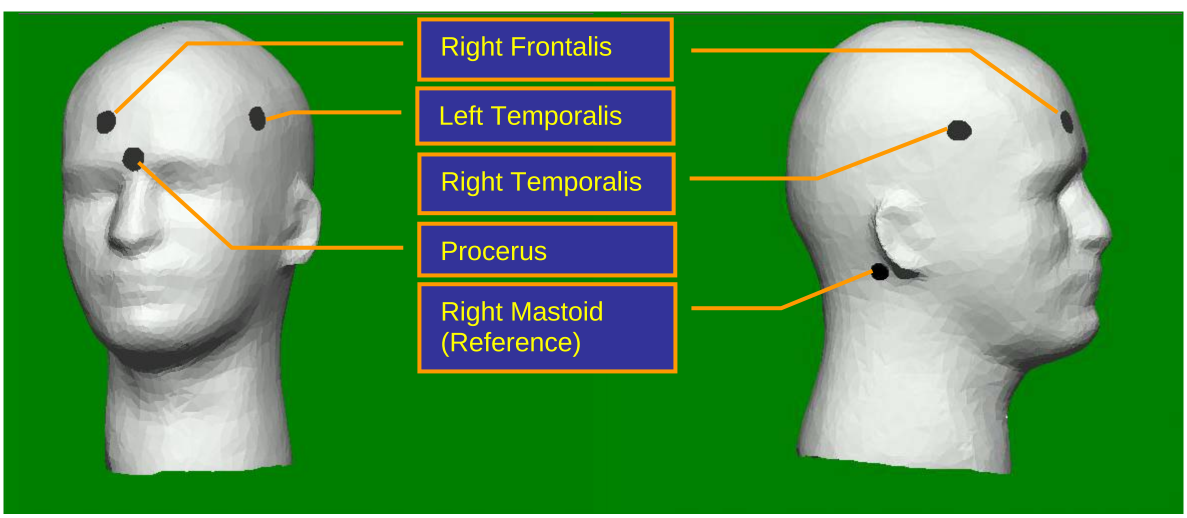

Figure 1: Electrode placement for the EMG cursor control system

2.2 Hardware and Software Components for EMG Signal Processing

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.

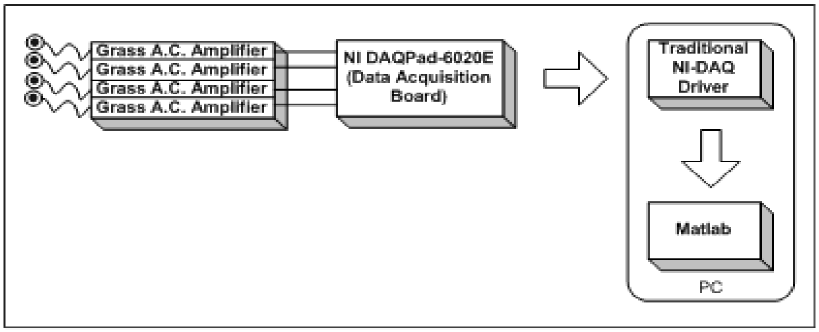

Figure 2: Recording structure for EMG signals

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(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 (Barreto, Scargle & Adjouadi, 1999) (Barreto, Scargle & Adjouadi, 2000) 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 (Barreto, Scargle & Adjouadi, 1999) (Barreto, Scargle & Adjouadi, 2000) 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 (Barreto, Scargle & Adjouadi, 1999) (Barreto, Scargle & Adjouadi, 2000) 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:

$$MPF = \left(\frac{f1 \times P1 + f2 \times P2 + ... + fn \times Pn}{P1 + P2 + ... + Pn} \right), \quad n = 1, 2, \ldots, 250 \qquad (1)$$

It has been observed previously that the spectral content of the four muscles used in this system are distinct (Barreto, Scargle & Adjouadi, 1999) (Barreto, Scargle & Adjouadi, 2000). 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 Evaluation of EMG detection Algorithms

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 obtained from the new, four-electrode algorithm is displayed in Figure 3. An interesting comparison is offered through Figure 4, which represents graphically the classifications determined by the previous, three-electrode system operating on the same test data (of course, using only the three signals that the previous method involves). It can be appreciated by comparing figure 3 and 4, that the old, 3-electrode algorithm was able to identify the contractions of the left and right temporalis muscles (independently or together), but produced hesitant or erroneous results when the desired cursor movements were either UP or DOWN (second and fourth movement segments in the sequence, respectively).

In order to obtain a quantitative notion of the level of improvement achieved with the new approach, the number of correct and incorrect classifications made for each sequence was defined 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**

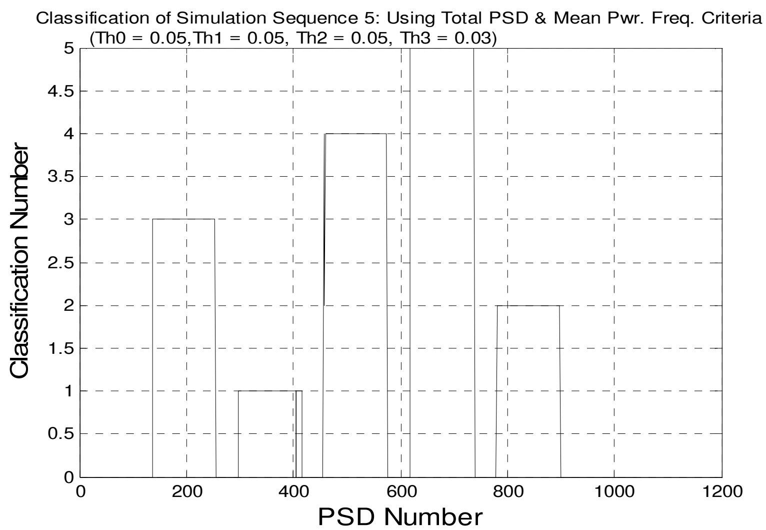

Figure 3: Example of classification sequence produced by the four-electrode classification algorithm

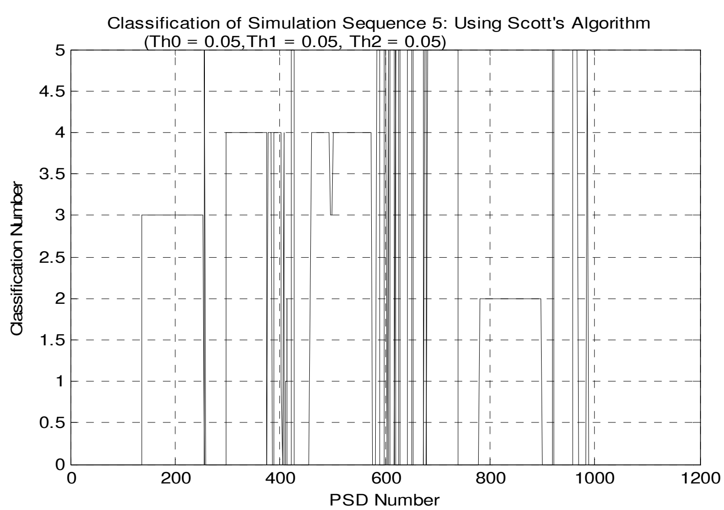

Figure 4: Example of classification sequence produced by the three-electrode classification algorithm, operating on three of the four signals used by the new system to generate the results shown in Figure 3.

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

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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