Discrete vs. continuous surface electromyographic interface control

Meredith J. Cler, Carolyn M. Michener, Cara E. Stepp, *Member, IEEE*

***Abstract*— Over 50% of the 273,000 individuals with spinal cord injuries in the US have cervical injuries and are therefore unable to operate a keyboard and mouse with their hands. In this experiment, we compared two systems using surface electromyography (sEMG) recorded from facial muscles to control an onscreen keyboard. Both systems used five sEMG sensors to capture muscle activity during five distinct facial gestures that then mapped to five cursor commands: move left, move right, move up, move down, and click. One system used a discrete movement and feedback algorithm, in which the user would make one quick facial gesture, causing a corresponding discrete movement to an adjacent button. The other system was continuously updated and allowed the user to move in any 360º direction smoothly. Information transfer rates (ITRs) in bits per minute were high for both systems. Users of the continuous system showed significantly higher ITRs (average of 68.5; $p < 0.02$) compared to users of the discrete system (average of 54.3 bits/min).**

I. Introduction

An estimated 273,000 individuals in the U.S. [1] and 770,000 to 7.84 million [2] individuals worldwide have spinal cord injuries (SCI). Of these individuals, 54.1% have cervical injuries (e.g. C1-C7), and are therefore unable to use their arms and hands to use a mouse and keyboard [3]. This impacts many aspects of quality of life, including the ability to maintain employment [4].

There are a variety of systems that allow these users to control an on-screen cursor in real-time. The most common classes of devices in use clinically are voice-activated designs, mouth sticks, machines that track head movement, eye-trackers, and sip-and-puff designs [4]. Each of these systems has downsides: often they are fatiguing to the user, not appropriate for people with a wide range of physical abilities, difficult to calibrate, or expensive [5]. Brain controlled devices using electroencephalography (EEG) are accessible to individuals with a wide range of disabilities, but are very slow for practical use [6].

Individuals with high spinal cord injuries have unimpaired facial musculature, because these muscles are innervated by cranial nerves that are unaffected by the spinal cord injury. In this paper, we describe two systems that take advantage of this spared muscle function by using facial surface electromyography (sEMG). sEMG requires intact muscle control, but has a much higher signal to noise ratio than EEG [7]. Further, sEMG is noninvasive, simple to apply, and provides real-time information about muscle activation.

We tested the ability of healthy individuals to use facial sEMG to move a cursor to spell words using one of two systems. One system used a discrete algorithm for processing one facial gesture at a time that caused a corresponding discrete movement of the cursor to an adjacent button. The other system continuously monitored the signals coming from each electrode and recalculated cursor velocity at a much shorter time scale, allowing the user to move the cursor in any 360º direction and control the speed of the cursor movement based on the relative magnitude of the sEMG signals. We predicted that the discrete system would be easier to learn due to its simplicity, but that the greater degree of flexibility of the continuous system would allow users to spell words more quickly. We measured the speed and efficiency of the systems in information transfer rate (ITR) [8].

II. Methods

A. Participants

Participants were 14 healthy adults who reported no history of speech, language, or hearing disorders and were fluent speakers of American English. Participants were pseudorandomly assigned to one of two experimental groups: discrete or continuous. The average age of the seven individuals (two males) in the discrete group was 20.0 years (SD = 1.0) and the average age of the seven individuals (two males) in the continuous group was 20.0 years (SD = 1.2). All participants completed written consent in compliance with the Boston University Institutional Review Board.

B. Experimental Setup

The participants had one training session that lasted approximately 90 minutes and included skin preparation, sEMG sensor application, calibration, and 45 trials of interaction with one of the sEMG keyboard systems. Each trial consisted of using the sEMG system to spell out one of 45 common American English five-letter words, using the interface shown in Fig. 1. After each trial, the user was presented with their ITR from that trial as feedback.

Five single differential sEMG sensors were placed parallel to the underlying muscle fibers of the left risorius and orbicularis oris, right risorius and orbicularis oris,

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M.J. Cler is with the Graduate Program for Neuroscience-Computational Neuroscience, Boston University, Boston, MA 02215 USA (e-mail: mcler@bu.edu).

C.M. Michener is with the Department of Speech, Language, and Hearing Sciences, Boston University, Boston, MA 02215 USA (e-mail: cmich@bu.edu).

C.E. Stepp is with the Departments of Speech, Language, and Hearing Sciences and Biomedical Engineering, Boston University, Boston, MA 02215 USA (phone: 617-353-7487; fax: 617-353-5074; e-mail: cstepp@bu.edu).

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frontalis, mentalis, and orbicularis oculi (see Fig. 1 and Table I). Each of these electrodes was placed over one or more muscles that are activated during a particular facial gesture; the sEMG recorded during these movements was then mapped to a cursor movement (see Table I). We chose these muscles and movements because healthy individuals are able to activate them independently and concurrently at will, and because the facial placement of the electrodes corresponds to the movement of the cursor. That is, when the user contracted muscles at the top of her face, the cursor moved up. When she contracted muscles on the left of her mouth, the cursor moved left.

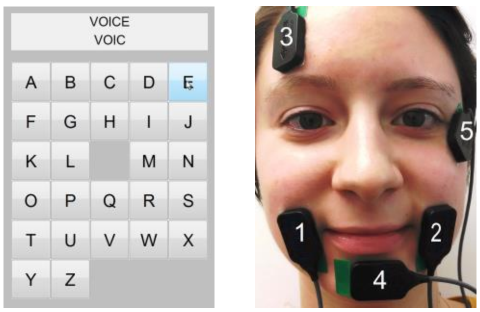

Figure 1. Left: User interface. Five letter stimulus is presented at the top of the screen and each letter the user types appears below. Right: Electrode placement (see Table I).

TABLE I. ELECTRODE PLACEMENT

Electrode Number	Electrode Placement	Muscle Group	Facial Gesture	Cursor Action
1	Left of mouth	Risorius and orbicularis oris	Left cheek movement, similar to half a smile	Move left
2	Right of mouth	Risorius and orbicularis oris	Right cheek movement, similar to half a smile	Move right
3	Above eyebrow	Frontalis	Eyebrow raise	Move up
4	Chin	Mentalis	Chin contraction	Move down
5	Side and slightly below eye	Orbicularis oculi	Hard wink or blink	Click

The sEMG signals were preamplified and filtered using three Bagnoli-2 EMG systems (Delsys, Boston, MA) set to a gain of 1000 with a band-pass filter with roll-off frequencies of 20 and 450 Hz. Simultaneous sEMG signals were recorded digitally with National Instruments hardware and custom MATLAB (Mathworks, Natick, MA) software at 1000 Hz.

C. Data Acquisition and Calibrations

Prior to use of the interface, data from four "calibration runs" was collected. For each calibration run, the user was asked to make each facial gesture twice (i.e., left left; right right; up up; down down; blink blink). The maximum RMS from each electrode was averaged across calibrations and used to calculate thresholds. These thresholds were set using multipliers determined during pilot testing and represented the activation required for the system to recognize the sEMG signal as indicating a deliberate gesture. For example, the threshold multiplier for the blink electrode was 0.7; each participant was therefore required to produce an activation that was at least 70% of the average maximum blink RMS from his own four calibrations in order for the system to register a blink. The threshold multiplier for the left, right, up, and down electrodes was 0.6 in the discrete condition and ranged from 0.3 to 0.5 per electrode for the continuous condition. The threshold multiplier for the blink electrode was 0.7 for both conditions.

Information from the calibrations was used to determine a movement interval for the discrete condition. After each calibration, the maximum duration of sEMG activation across all facial gestures was calculated. Participants had mean movement durations across calibrations ranging from 407 ms to 1150 ms (mean = 669 ms, SD = 249 ms). Each participant's own mean movement duration was used as her movement interval. Personalizing these movement intervals allowed participants with quicker facial movements to move more quickly, but prevented those with slower facial movements from overshooting the target.

D. Discrete Condition

The discrete system allowed the user to move one button at a time using only one quick facial movement, analogous to using the arrow keys on a keyboard. The maximum RMS from the signal from each electrode during the user-specific movement interval was compared to thresholds in order to determine whether the user intended to click or move the cursor.

If the RMS of the signal from the blink electrode went over threshold at any point during the personalized window, the cursor was 'clicked' to select a letter and then returned to the center of the keyboard. If the RMS of the signal from the blink electrode did not go over threshold, the algorithm next checked if the RMS of the signal from one of the other electrodes went over threshold. If the signal from only one electrode went over threshold in that length of time, the cursor was moved from the center of one button to the center of the next (see Fig. 1). However, if the maximum RMS in more than one of the channels went above threshold, the cursor was not moved and the user was informed that there was an error by a red box appearing around the keyboard.

E. Continuous Condition

The continuous system allowed the user to move in any 360º direction by using isolated facial gestures as in the discrete condition, or by combining facial gestures together. In this system, the cursor moved smoothly in small increments, rather than jumping from button to button as in the discrete case. The RMS was calculated from each electrode every 60 ms. If the RMS of the signal from the blink electrode was higher than the blink threshold, the cursor was 'clicked' to select a letter and then returned to the center of the keyboard.

The x and y movement of the cursor was calculated using (1) and (2). The RMS values from the left, right, up, and down electrodes (RMS_R, RMS_L, RMS_U, RMS_D) were divided by their respective thresholds from calibrations, and then squared to determine the magnitude of the cursor movement [9]. Then the magnitude of the left was subtracted from the right, and the up was subtracted from down. Values were then multiplied by a scalar (speed in (1) and (2); identical for all participants), to convert the magnitudes to changes in the x and y cursor position.

$$\Delta x = [(RMS_R/threshold_R)^2 - (RMS_L/threshold_L)^2]\times speed \quad (1)$$

$$\Delta y = [(RMS_D/threshold_D)^2 - (RMS_U/threshold_U)^2]\times speed \quad (2)$$

F. Performance Measure

The information transfer rate was calculated for each trial in bits per minute using Wolpaw's method shown in (3) [8]. This method used bits per selection, in which N was 26, the number of targets on the screen, and A was accuracy from 0 to 1. Bits per selection (3) was converted to ITR in bits per minute by multiplying by the selection rate: the number of selections (5 letters) divided by the time the user took to spell the word. Participants were shown their ITR after each trial and told to try to maximize it in upcoming trials.

$$bits / selection = \log_2(N) + A \times \log_2(A) + (1 - A) \times \log_2((1 - A) / (N - 1)) \quad (3)$$

G. Statistical Methods

Statistical analysis was performed using Minitab Statistical Software (Minitab Inc, State College, PA). An unpaired two-sample Student's t-test was performed to determine the effect of system type on mean ITR. An F-test of equality of variances was also performed to determine if within-group variability was equivalent.

III. Results

A. Overall Performance

Over all the trials, participants had individual mean ITRs between 37.6 and 77.1 bits/min, with a mean of 61.4 bits/min (SD=11.5). Participants generally had higher ITRs closer to the end of the session. The average over the last fifteen trials was 72.4 (SD=13.0). Fig. 2 shows mean performance per individual over the entire session and over the final fifteen trials.

B. Group Effects

The group of participants using the discrete system had a mean individual performance score of 54.3 bits/min (SD 12.0), whereas the group of participants using the continuous system had a mean individual performance score of 68.6 bits/min (SD 4.8). A two-sample t-test showed that these groups were significantly different ($p < 0.02$). Further, the inter-participant variability was significantly different between the two groups (F-Test, $p < 0.05$). Over the last fifteen trials, participants using the discrete system had a mean individual performance score of 64.0 (SD 12.6), and continuous users had a mean score of 80.7 (SD 3.9).

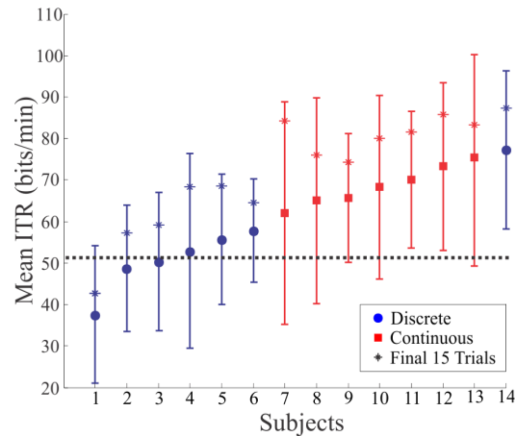

Figure 2. Mean information transfer rate over all 45 trials in bits per minute. Error bars are SD. Asterisk indicates subject's mean performance on last 15 trials. Horizontal dotted line shows maximum ITR from other sEMG systems [9-12] (see Table II).

IV. Discussion

A. Comparisons to Other Systems

Continuous users had faster performance than discrete users (continuous: 18.5 letters/min; discrete: 14.7 letters/min). Both groups of subjects had mean ITRs that were much higher than invasive and non-invasive BCIs. ITRs were also much higher in this study than in other sEMG studies that use continuous muscle control [9-12] (see Fig. 2). ITRs were comparable to eye-tracking systems (see Table II).

Eye tracking requires high illumination, stable head positions, complete control over eye movements, and users cannot look away from the screen without an error [13]. Some head tracking systems do not require specific lighting or position [9], but users with very high spinal cord injuries may not be able to control their head position well enough to use these systems, as some required muscles (e.g. sternocleidomastoid) are innervated by cervical nerves.

TABLE II. Comparisons to Other Systems

System	ITR Range (bits/min)	Example References
Eye-tracking (+ predictive methods)	60-222	[14-17]
Mechanical Switch (+ predictive methods)	96-198	[15]
Head tracking and orientation devices	78	[9]
sEMG systems (continuous muscle control)	5.4-51	[9-12]
Invasive BCIs	5.4-69	[18, 19]
Non-invasive BCIs	1.8-24	[19-22]

sEMG systems do not require any particular lighting, and a user can be in any position as long as they can clearly see the computer screen. The systems described in this paper use visual feedback and therefore also require some intact vision, but alternate systems could be adapted for users with visual impairments [23].

B. Limitations

sEMG systems require careful setup and calibration. In this study, two participants were unable to obtain clean calibrations and therefore did not attempt the task. These participants were unable to separate the five facial gestures, either due to coactivation (i.e. some participants tensed both right and left orbicularis oris when attempting to isolate the right gesture) or due to individual differences in facial geometry (i.e. one participant was not noticeably blinking during left facial gesture, but the electrode placed over the orbicularis oculi picked up muscle activation from this gesture).

C. Future improvements

In the future, these sEMG systems could be modified for use by individuals with a wide variety of capabilities. The classifier in these systems is simple and relies mostly on the user to learn to control their own muscle activation. If users have voluntary, independent control over at least five distinct muscle groups, they could use any of those groups to control the cursor, with no modification of the software. If users do not have independent control over five distinct muscle groups, a machine learning algorithm could be implemented to recognize patterns of muscle movements as representing each of the intended movements. Further, this type of algorithm could allow the system to use fewer than five electrodes, significantly cutting down on cost and setup time.

Other changes could maximize the ITRs from these systems including training protocols and predictive direction and text models. Users in both groups had higher ITRs in the final trials as compared to the entire session (Fig. 2), and other studies show that training increased their users' ITRs by nearly 50% [16]; Additionally, adding a language prediction model could improve the final ITRs by as much as 100% [24, 25].

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