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Design and Validation of a Myoelectric Cursor Control System for Trans-Radial Amputees

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Abstract— **In this study, a computer cursor controlled by electromyography (EMG) signals has been developed to improve upon currently existing assistive input technologies and to give trans-radial amputees ability to control analog directions and to adjust the speed of the mouse cursor. A Linear Discriminant Analysis (LDA) classifier was used to decode 6 predetermined gestures, and a pattern recognition-based control was used to translate these gestures into cursor movements. Two able-bodied subjects performed a series of center-out tasks with a 30-second time limit for each task, and the data were analyzed using multiple performance metrics and a Fitts' law model to investigate the feasibility of the *Myoelectric Cursor*. Subjects achieved an overall mean success rate of 93.4±8.5% and an overall overshoot of 0.13±0.07. This EMG-computer interface shows promise of improved computer accessibility to trans-radial amputees.**

I. INTRODUCTION

Since the 1970s, the mouse has been a standard input device for operating computers. Despite the success of the mouse-centric computer interfaces today, such interfaces are still kept from being easily accessible by people with motor disabilities or upper-limb amputations [1]. In America, there are over 1.6 million amputees. Surveys estimate that 10-30% of these amputees have upper-limb amputations [2], which could cause difficulties in accessing a computer. Recent efforts have focused on developing a variety of alternative devices, such as trackball, vocal joysticks, and mouth operated joysticks. However, many such devices offer limited functionality, require manipulation by an external physical object, or are costly.

A different approach for a mouse alternative device seeks to drive the manipulation of the computer cursor from myoelectric signals [3]. The direct interface between user and machine via electromyography (EMG) uses subtle difference in muscle activity in amputees' residual limb to identify different EMG patterns to enable the cursor control [4, 5]. In this paper, we present a system called the *Myoelectric Cursor* as a potential solution to overcome the challenges faced by the state-of-the-art mouse alternative devices and enable two-dimensional motion and clicking of a cursor. We use a pattern recognition-based control that learns associations between recorded EMG signals and predetermined gestures as a control strategy. Unlike conventional threshold-based control, which restricts users to operating only 1 or 2 degrees-of-freedom (DOF), the pattern recognition algorithm allows classification of multiple classes to provide more functionality [6-8]. The key benefit of the *Myoelectric Cursor* is that it allows users to control analog directions and to adjust the speed of the cursor by utilizing a finite set of phantom wrist gestures.

II. METHODS

A. Experimental Setup

Two able-bodied subjects (A1,A2) participated in this study. The subject group consisted of 1 male and 1 female both aged 20 years. The study was performed with approval from the Johns Hopkins University Institutional Review Board and with informed consent from each of the participants.

The dominant arm was chosen as the site of electrode placements. The site, typically 2-3 inches below the elbow, was cleaned with an abrasive gel (D.O. Weaver & Co., Aurora, CO) prior to electrode placement to increase conductivity. Subjects then wore a compressive silicone cuff containing eight bipolar pairs of equidistantly arranged dome electrodes (Liberating Technologies INC., Holliston, MA) to collect surface EMG signals. Lastly, an additional electrode (Conmed Corporation, Utica, NY) was placed on the participant's elbow, specifically the olecranon, as a grounding electrode.

The electrodes were connected to differential amplifiers (MYOBOCK, Otto Bock Health care, Minneapolis, MN), which constructed 8 differential EMG signals from the original 16 channels. Amplified outputs were transmitted through an electric isolation device and an I/O connector block (SCC-68, National Instruments, Austin, TX) that were then connected to a data acquisition card (PCI-6040E, National Instruments, Austin, TX) on a computer. A computer configured as an xPC Target (Mathworks, Nattick, MA) was used for real time data acquisition and signal processing.

B. Experiment Task and Procedure

Subjects participated in an initial movement repetition task to generate a set of myoelectric data for training a movement classifier. Subjects performed 6 gestures (Figure 1) in response to visual cues on a computer screen. Subjects held each of the 6 gestures for 3 seconds before returning to

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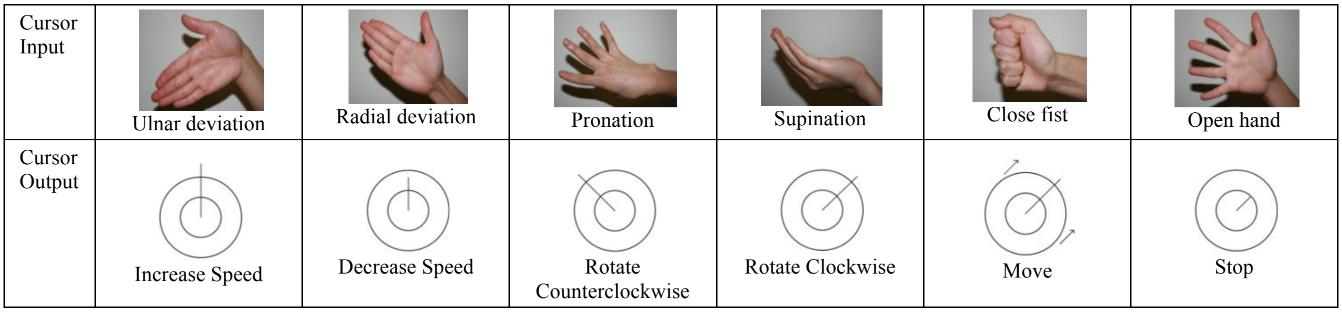

Figure 1 The input source for the Myoelectric Cursor is presented along with corresponding cursor output. This Decision Algorithm translates gestures predicted by the LDA classifier into preliminary commands, which is presented in the GUI for the control of the cursor's movement. Specifically, pronation and supination gives users analog control, and radial and ulnar deviation allows users to adjust the cursor's speed (accelerative control). The close fist set the cursor in motion when its speed was above zero, or clicked on targets when the speed was zero. The open hand stops the cursor's motion entirely.

a neutral relaxed hand position for 2 seconds. Each cue was presented 10 times in a pseudorandom order.

Following the training session, a myoelectric decoder was trained and the subjects participated in a 2-dimensional center-out cursor control task. The cursor took the form of a 2-dimensional vector depicted as a line segment extending from the center of a circle. The angle and magnitude of the vector changed in response to the user's myoelectric commands. These representational elements of the vector indicated to the user the direction and velocity, respectively, that the cursor would travel upon being given a "move" command. A second concentric circle within the original circle indicated a dead-zone. If the vector did not extend beyond this circle, the cursor would not move upon receiving a "move" command.

The graphical user interface (GUI) consisted of a square workspace with dimensions of 20 by 20 arbitrary units (AU). Each trial consists of a presentation of one single circular target in one of 3 potential sizes with radii of 0.4, 0.8, or 1.2 AU. The target was presented 8 AU from the center of the GUI screen, and occupied one of 8 potential locations starting at 0 degrees to the horizontal and evenly spaced in 45-degree increments. This resulted in 24 unique sets of trial parameters. A single experimental session consisted of the presentation of all 24 unique trials in pseudorandom order. Each trial allowed the subject 30 seconds in which to successfully complete the trial. A trial was deemed successful if the subject was able to reach and click a target within the time limit, and deemed unsuccessful if the subject was not able to reach and click a target within the designated time limit.

Each subject performed the aforementioned cursor task in two different ways: once using a keyboard to control the cursor and once using EMG to control the cursor. In the keyboard-controlled cursor section, the cursor was fully controlled by specific key presses from a numeric keypad. In the EMG-controlled cursor section, the cursor was controlled through classification of myoelectric signals generated by the user.

Both the keyboard-controlled and the EMG-controlled cursor tasks consisted of a tutorial that instructed users how to control the cursor along with 2 subsequent practice center-out control sessions to allow the users to become acquainted with the system. The keyboard section consisted of a tutorial, 2 practice sessions, and 3 experimental sessions. The EMG-controlled section consisted of an initial training session, a tutorial, 2 practice sessions, and 12 experimental sessions. To reduce muscle fatigue, subjects were given an optional 5-minute break between practice and experimental sessions as well as between every third experimental session.

C. EMG Classification

The eight channels of myoelectric data were bandpass filtered between 30 and 300 Hz using a fourth order Butterworth filter. The amplified differential myoelectric data was sampled at a rate of 1000 Hz. Features were extracted using a 200 ms long sliding analysis window with 20 ms slide size which was chosen based on established literature regarding optimal classification performance and delay. Three features, the mean absolute value, the waveform length, and the 4th order autoregressive model, were independently extracted from each channel to classify the six predetermined gestures [9]. In this experiment, a LDA algorithm was used as a classification method to decode the intended gesture from the extracted features [10].

D. Data Analysis

The experiment was performed to collect data and evaluate the ability of users to accurately and effectively select an appropriate movement class as well as maintain control over the direction and speed of the intended movement.

In this study, the success rate (SR) is defined as the fraction of all the trials that were successfully completed by the subject and the completion time (movement time or MT) is defined as the time taken to click the target from the moment the subject began to direct the cursor. Unsuccessful trials were excluded when calculating completion time. The mean was calculated by averaging the values across all sessions for each of the input sources, keyboard cursor and the *Myoelectric Cursor*.

For purposes of comparison with other computer interfaces, it is important to use a metric that is independent of the specific task parameters such as size and distance, as these parameters can affect the performance metrics. Fitts' law is the International Organization for Standardization (ISO) standard for the evaluation of computer pointing devices that transforms the experimental measurements to a metric that is independent of the specific task parameters. This allow the empirical comparison generalizable to task parameters beyond those tested in the experiment [11].

According to Mackenzie's variation of Fitts' law [11], there exists a relationship:

$$MT = a + b * ID. \quad (1)$$

$$ID = \log_2(D/W + 1). \quad (2)$$

a = regression coefficient; start/stop time of the device
b = regression coefficient; inherent speed of the device
D = distance from the center of the cursor to a target
W = width of the target

MT is the movement time of the cursor to a target in seconds, index of difficulty (ID) is the task difficulty in bits, the index of performance (IP), reciprocal of b, is the information capacity of the motor system in bits per second (bps). By keeping the same target distance, the difference in ID values were only caused by variations in target size, which resulted in 3 ID values: 2.11, 2.58, and 3.46 bits (2). These values were plotted against the average MT of each subject to obtain an individual subject's IP for each input source.

To measure the accuracy, which is not shown in previously stated metrics, the overshoot score is calculated. The overshoot is defined as the number of occurrences of the cursor being on target and then leaving the target before the cursor can click, divided by the total number of targets. While this metric affects IP, it also indicates the user's ability to accurately control cursor velocity. The higher the overshoot score, more occurrences of cursor exiting the target were observed [12].

Different trajectories between keyboard control sessions and EMG control sessions were visually inspected to provide information that could not be obtained through performance metrics. Using recorded coordinates of cursor positions, a subject's cursor trajectories for the 3 keyboard sessions (Session 1-3) and the 3 EMG sessions (Session 4-6) were presented in Figure 3.

An unpaired t-test was applied to each of the metrics to test for a difference in the performance between keyboard and EMG controlled cursor of both users and the performance between two subjects in EMG-controlled cursor. The results we report as significant are at $p < 0.05$ level, unless otherwise specified.

III. RESULTS

The experimental data is summarized in Table 1. The performance between keyboard and EMG cursor control in both users were found to be significantly different except for SR (p=0.179) and R^2 (p = 0.707), while the performance between two subjects using EMG cursor control was found to be not significantly different except for MT ($p < 0.001$). The overall mean SR across users was 93.4±8.5% for the EMG section and 100.0±0.0% for the keyboard section, while the overall mean MT was 10.3±2.0 seconds and 5.8±0.6 seconds, respectively. The mean MT varied for both types of input sources, yet, the keyboard-controlled cursor always had a shorter MT and smaller deviations than that of the EMG-controlled cursor. Using the Fitts' law model and linear regression, the EMG section had an overall IP of 0.63±0.14 bps while the keyboard section had an overall IP of 2.23±0.95 bps. Figure 2 illustrates the

TABLE 1. SUMMARY OF PERFORMANCE METRICS

Metrics	Input Source	Overall Average	A1	A2
SR (%)*	EMG	93.4±8.5	98.6±2.6	87.8±14.4
	Keyboard	100.0±0.0	100.0±0.0	100.0±0.0
MT (Sec)*	EMG	10.3±2.0	7.26±1.7	13.3±2.3
	Keyboard	5.8±0.6	5.13±0.27	6.50±0.94
IP (bps)	EMG	0.63±0.14	0.727	0.528
	Keyboard	2.23±0.95	2.904	1.555
R^2	EMG	0.94±0.07	0.888	0.999
	Keyboard	0.97±0.18	0.969	0.966
Overshoot	EMG	0.13±0.07	0.091	0.185
	Keyboard	0.03±0.003	0.028	0.042

* Success rate and MT are averaged across all sessions, prior to being averaged across all subjects.

relationship between ID and average MT of both subjects. Two subjects had noticeable difference in slope for EMG-controlled cursor.

The graph displays a very tight relationship between ID and MT with a R^2 value close to 1 for both input sources and shows that MT essentially increased in proportion to ID. This validates that the subjects performed the best for the biggest sized target and the worst for the smallest sized target, which agrees with the Fitts' law's speed-accuracy trade-off.

The overshoot on the performance of the *Myoelectric Cursor* is calculated to be 0.13±0.07 and the keyboard-controlled cursor is 0.03±0.003. Trajectories from keyboard and EMG control sessions from both of the subjects are presented in Figure 3. Whereas the trajectories of the keyboard-controlled cursor resembled the most efficient path, trajectories of the EMG-controlled cursor showed bigger deviations from the efficient path. Subject A2 who had a lower SR and higher MT displayed a smaller overshoot and greater path efficiency.

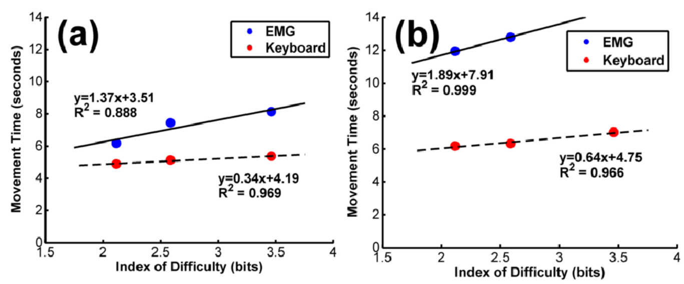

Figure 2. (a) Relationship between the MT and the ID of Subject A. (b) Relationship between the average MT and the ID of Subject B. Bigger slope in EMG section indicates that IP is smaller for EMG section.

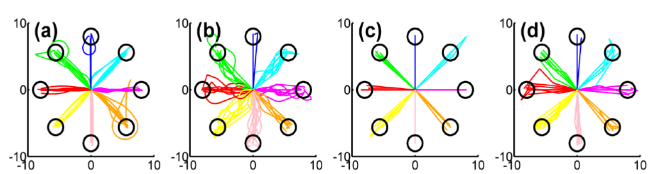

Figure 3. The trajectories are color coded for different target locations and the targets with 1.2 radius are represented in black circles. Trajectories start from the coordinate (0,0). (a)/(c) Subject A1's/A2's trajectories for all 3 keyboard-controlled cursor sessions. (b)/(d) Subject A1's/A2's trajectories for 3 of 12 EMG-controlled cursor sessions.

IV. DISCUSSION

Both subjects showed sufficient ability to control a cursor using the *Myoelectric Cursor*, as demonstrated by the high mean SR. The keyboard-controlled cursor, which was designed to simulate perfect classification accuracy of the *Myoelectric Cursor*, had 100.0% overall mean SR and almost half the MT of the *Myoelectric Cursor*. This indicates that the *Myoelectric Cursor* has the potential to reach performance that is close to the keyboard-controlled cursor once higher EMG classification is achieved. The significant difference between the average MT of 2 subjects is the result of the individual's ability to generate easily separable EMG patterns and to adapt to a new control method for the computer interface.

For evaluation using Fitts' law, the target performance of the *Myoelectric Cursor* was the IP of the mouse. The results show that the IP of the *Myoelectric Cursor* (0.63 bps) and the keyboard-controlled cursor (2.23 bps) are smaller than that of a conventional mouse, which ranges from 1.1 to 5.0 bps [13]. One reason for the lower efficiency may in part be due to the fact that a mouse only requires a point and click motion, while a keyboard or an EMG-controlled cursor experience involves an increase in muscle tension, which may make pointing more difficult [14]. Despite the limitation, the obtained IP of the *Myoelectric Cursor* is greater than the commercial assistive input device called Brainfinger (IP=0.39 bps) [15] or facial EMG computer cursor (IP=0.31 bps) [3] which suggests that the *Myoelectric Cursor* is a better alternative to these assistive devices for upper-limb amputees. Even though the IP of the *Myoelectric Cursor* is smaller than that of the vocal joystick (IP=1.65 bps) [1] or trackball (IP=1.50 bps) [16] due to its slow MT, the EMG-based control has an advantage in providing users with the ability to perform smaller, precise cursor movements [3]. Given that the *Myoelectric Cursor* is an assistive device that relies solely on EMG activity and no manipulation by an external physical object, this technology shows promising future for an alternative interface [1].

During the EMG section, both subjects mentioned their difficulty in stopping the cursor which resulted in an increase in overshoot that is four times more than the overshoot in the keyboard section. As seen in Figure 3, the *Myoelectric Cursor* movements exhibited greater deviation from the straight path towards the target, while the keyboard-controlled cursor movements were mostly directed straight towards the target with minimum overshoot. In recent literature, motor learning in stroke recovery patients has been proved to be effective with repetitive, sustained practice [16]. We suspect that a user's repetitive practice in isolating different EMG patterns can increase both the speed and the accuracy of the *Myoelectric Cursor*. As an immediate solution, our future works will allow the user to control the threshold for classification accuracy of the *Myoelectric Cursor*. The user would be able to set the cursor to have low cursor speed and high threshold for classification accuracy to gain more familiarity with the system. As he/she becomes more experienced with the interface through long-term practice, the threshold can be modulated to achieve a shorter MT and a higher IP.

V. Conclusion

The *Myoelectric Cursor* allowed the user to feasibly control analog directions and to adjust the speed of the cursor using a limited number of wrist gestures with high SR in a 30-second time limit. The obtained IP value is comparable to commercially available assistive input devices and this EMG-computer interface exhibited overshoot less than 0.15. According to these results, the *Myoelectric Cursor* has the potential to be used as a viable alternative to the traditional mouse and enhance computer accessibility for upper limb amputees. The results from the subjects were very promising and warrants further analysis from a greater number of able-bodied and amputee subjects.

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