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Signal processing and information fusing algorithms for the synthesis of an alternative electromyogram/eye gaze tracking computer cursor control system

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FLORIDA INTERNATIONAL UNIVERSITY

Miami, Florida

SIGNAL PROCESSING AND INFORMATION FUSING ALGORITHMS FOR THE
SYNTHESIS OF AN ALTERNATIVE ELECTROMYOGRAM/EYE GAZE
TRACKING COMPUTER CURSOR CONTROL SYSTEM

A dissertation submitted in partial fulfillment of the

requirements for the degree of

DOCTOR OF PHILOSOPHY

in

ELECTRICAL ENGINEERING

by

Craig Anthony Chin

2006

To: Dean Vish Prasad
College of Engineering and Computing

This dissertation, written by Craig Anthony Chin, and entitled Signal Processing and Information Fusing Algorithms for the Synthesis of an Alternative Electromyogram/Eye Gaze Tracking Computer Cursor Control System, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

Malek Adjouadi

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Date of Defense: November 14, 2006

The dissertation of Craig Anthony Chin is approved.

Dean Vish Prasad
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University Graduate School

Florida International University, 2006

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DEDICATION

I dedicate this dissertation to the loving memory of my parents. Their loving supervision, encouragement, and emphasis on learning during my formative years prepared me for a lifetime of scholarly pursuits. I also want to dedicate this dissertation to my God and Creator who is revealing to me the true purpose of life and has graced me with the confidence to pursue life's challenges with zeal, knowing that in the end it will all be to His glory.

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ABSTRACT OF THE DISSERTATION

SIGNAL PROCESSING AND INFORMATION FUSING ALGORITHMS FOR THE
SYNTHESIS OF AN ALTERNATIVE ELECTROMYOGRAM/EYE GAZE
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Florida International University, 2006

Miami, Florida

Professor Armando Barreto, Major Professor

This research pursued the conceptualization and real-time verification of a system that allows a computer user to control the cursor of a computer interface without using his/her hands. The target user groups for this system are individuals who are unable to use their hands due to spinal dysfunction or other afflictions, and individuals who must use their hands for higher priority tasks while still requiring interaction with a computer.

The system receives two forms of input from the user: Electromyogram (EMG) signals from muscles in the face and point-of-gaze coordinates produced by an Eye Gaze Tracking (EGT) system. In order to produce reliable cursor control from the two forms of user input, the development of this EMG/EGT system addressed three key requirements: an algorithm was created to accurately translate EMG signals due to facial movements into cursor actions, a separate algorithm was created that recognized an eye gaze fixation and provided an estimate of the associated eye gaze position, and an information fusion protocol was devised to efficiently integrate the outputs of these algorithms.

Experiments were conducted to compare the performance of EMG/EGT cursor control to EGT-only control and mouse control. These experiments took the form of two different types of point-and-click trials. The data produced by these experiments were evaluated using statistical analysis, Fitts' Law analysis and target re-entry (TRE) analysis.

The experimental results revealed that though EMG/EGT control was slower than EGT-only and mouse control, it provided effective hands-free control of the cursor without a spatial accuracy limitation, and it also facilitated a reliable click operation. This combination of qualities is not possessed by either EGT-only or mouse control, making EMG/EGT cursor control a unique and practical alternative for a user's cursor control needs.

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CHAPTER 1

INTRODUCTION

1.1 Objective

The objective of this dissertation is to propose digital signal processing algorithms that will identify patterns in electromyogram (EMG) signals and eye gaze tracking (EGT) paths, which can be produced purposefully by a computer user to control the screen cursor of the computer, without involving the use of his/her hands. This research will also strive to define information fusion approaches that can make use of both sources of information (EMG and EGT) to drive the operation of the computer cursor in an efficient way, within the constraints of the required real-time mode of operation. A secondary objective is to design experiments to assess the levels of system performance when the EMG/EGT system is considered on its own, as well as, when it is compared to other forms of computer cursor control.

1.2 Significance of Research

Typically able-bodied individuals communicate with a computer using standard input devices such as a mouse, trackball, touchpad, or keyboard. The motivation for investigating alternative means for communicating with the computer is that there exists a population of individuals who are unable to use such devices due to some form of physical disability. It is estimated that there are 250,000 – 400,000 individuals in the United States and more than 2 million people worldwide that live with spinal cord injury or spinal dysfunction [1, 2]. In addition, a similar limitation would be experienced by some specialized operators, such as a surgeon, whose hands are committed to higher-priority tasks. Given the increasing pervasiveness of computer-based systems in most of

our daily activities, the increasing levels of communication and social participation that takes place over the Internet, and the potential of increased user productivity that may be realized by increasing the bandwidth of the human-to-computer input channel, it is clear that facilitating access of these individuals to Graphical User Interface (GUI)-driven computer systems is an important technical goal.

With today's GUI-based PC software, most of the human-to-computer interaction is based on selection operations, which consist of two steps:

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

Fulfillment of the research objectives specified will help to enable the aforementioned target users to perform these cursor control operations.

1.3 Problem Statement

To produce the proposed hybrid, hands-free cursor control system, the following technical problems must be solved:

- 1) An algorithm must be created that will accurately translate EMG signals due to facial movements into cursor actions. The accuracy will be determined by classification percentages.
- 2) An algorithm must be created that will recognize an eye gaze fixation, and provide an estimate of the position of the eye gaze.

- 3) An information fusion protocol must be devised to efficiently integrate the two modalities of cursor control.
- 4) Experiments must be designed to evaluate the effectiveness and efficiency of system performance.

Point 4) of the problem statement can be further subdivided into the following sub-problems.

- i. An experiment must test whether EMG/EGT-based input produces a lower error rate in point-and-click trials compared to EGT-based input at different icon sizes.
- ii. An experiment must test whether EMG/EGT-based input produces point-and-click times comparable to EGT-based input for icon sizes large enough for reliable EGT selection.
- iii. An experiment must assess if EMG/EGT-based input will produce a lower error rate than EGT-based input in point-and-click trials when the source of error is exclusively due to unintended gaze-based selections.
- iv. An experiment must investigate whether EMG/EGT-based input can produce point-and-click times comparable (no significant difference) to mouse input at various target sizes and selection distances.

1.4 Introduction to EGT-based Cursor Control

The general mechanism used by the eyes to examine a visual scene consists of two types of eye movements: the saccade and the fixation. A saccade is a rapid, ballistic motion that moves the eye from one area of focus of the visual scene to another. A saccade can take 30 – 120 ms and can traverse a range of 1° – 40° visual angle [3, 4].

Vision is suppressed during a saccade. After a saccade, a period of relative stability follows. This period is called a fixation, and it allows the eye to focus light on an area of the retina called the fovea. Fixations typically last for 200 – 600ms [3-5]. During a fixation, the eyes still exhibit small, jittery motions, usually less than 1° in size. These movements are necessary so as to overcome the loss of vision due to uniform stimulation of the retinal receptors [6]. There are three types of fixational eye movements: tremors, drifts, and microsaccades. A tremor is a wave-like motion of the eyes with a frequency of approximately 90 Hz [6]. Drifts are slow motions of the eye that are interspersed between microsaccade movements. Tremor movements are superimposed over the eye's drift movements. Drift movements will generally cover a dozen photoreceptor widths. Fixational microsaccades or "flicks" are fast, small, jerk-like movements that occur during voluntary fixation. Their range of motion can encompass several dozen to several thousand photoreceptor widths and their duration is approximately 25 ms [6].

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 [3-5, 7-10]. Once the line of gaze is determined, the point of gaze (POG) is found by allowing the line of gaze to intersect with the plane of the scene being viewed (typically the computer screen). The mapping between screen coordinates and eye gaze direction is determined by a calibration procedure.

EGT techniques have been shown to perform faster than a mouse in object selection tests [3, 4]. However, this approach has some disadvantages. One such

disadvantage is the so-called “Midas Touch” problem [5, 8]. This problem originates when eye gaze is used as an object selection technique. During a human-computer interaction session, situations may arise where a user may only desire to stare at an object to examine it, rather than to select it. If this user is utilizing an eye gaze-based object selection technique that issues left-clicks when the point of gaze dwells in a small area, unintended selections may result. Another disadvantage is the limited accuracy of the approach. This limitation results from the fact that the eye only needs to focus incoming light on 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 1° of visual arc [3-5, 10]. This physical constraint limits the accuracy with which the line of gaze can be estimated. Furthermore, if the small jittery motions exhibited by the eye during a fixation were directly translated into cursor movements by an EGT-based input, this would severely deteriorate the computer cursor’s stability. There is also the issue of POG offsets that may occur after the original calibration of the EGT system. These offsets are caused by minor movements of the head from its original calibration position. Morimoto and Mimica have shown experimentally that the calibration mapping of a remote eye gaze tracker decays (becomes less accurate) as the head moves away from its original position [11]. Therefore, the only ways to restore the accuracy of the EGT system is to either place the head of the user back to its original position or to recalibrate the system at the present position of the user’s head.

1.5 Introduction to EMG-based Cursor Control

The process of performing voluntary muscle contractions begins with electrical signals originating from neurons in the contralateral motor cortex. These electrical

signals or “action potentials” travel through the spinal cord until they arrive at the appropriate motor neuron. The motor neuron innervates the muscle fibers of the associated motor unit, and an action potential is transmitted to the muscle fibers via the motor endplates. Upon arriving at a motor endplate, the action potential triggers the release of acetylcholine (ACh) that causes a chemical exchange of sodium and potassium ions inside of a muscle fiber producing an ionic concentration gradient. This gradient produces an action potential that propagates throughout the entire muscle fiber in both directions away from the motor endplate to the tendinous attachments at both ends. The propagation of action potentials throughout the muscle fibers produces a corresponding contraction in the muscle. A more detailed discussion on the anatomy and physiology of skeletal muscles is given in Appendix B.

Electromyography is the study of muscle function through the monitoring of the electrical signals emitted by the muscle [12]. When a surface electrode is placed on the skin above a superficial muscle while it is contracting, it will receive electrical signals emanating from several muscle fibers associated with different motor units. The spatio-temporal summation of these electrical signals results in what is called an electromyogram (EMG) signal. Therefore, the EMG signal provides an effective means of monitoring muscle activity.

EMG signals from muscles in the body have also been used previously for cursor control. This approach has been used in [13-18], with [13, 14] focusing on the use of cranial muscles. The use of EMG signals from cranial muscles is an approach that would be suitable for individuals who would be unable to use their hands because of a motor

disability or because their hands would otherwise be preoccupied with higher priority tasks.

The advantages of this approach are that it provides the user with the ability to perform small, discrete cursor movements, and a robust, stable “clicking” procedure. However, it has been shown that this approach performs slowly compared to a mouse-operated system in object selection tests [13, 14], and could potentially become tiresome if the user is required to make large excursions across the screen with this input approach.

The complementary strengths of EGT and EMG input modalities make them well-suited for integration into a more robust cursor control system that will provide computer access to individuals who are unable to use their hands. Therefore, this project pursued the creation of a bimodal cursor control system that will selectively utilize both types of input from the user to provide a more efficient manipulation of the screen cursor, under a wider range of circumstances. Ideally, the hybrid EMG / EGT system will use the incremental (stepping) positional commands derived from the EMG subsystem to effect small cursor displacements within a restricted neighborhood of the current cursor location. Similarly, only the EMG subsystem will be used to determine when the user commands a click operation. In this way the cursor stability and clicking reliability observed in the evaluation of the EMG subsystem will be inherited by the hybrid system. On the other hand, when the user needs to perform a long cursor displacement on the screen, the EGT subsystem will be employed. This will reduce the time and effort required to perform these types of cursor manipulations.

CHAPTER 2

LITERATURE REVIEW

2.1 Current Unimodal Approaches to Alternative Forms of Cursor Control

A number of approaches exist that seek to address the problem of providing computer cursor control to individuals who are unable to use their hands. Most approaches target the muscular control or motion capabilities still available to the user and provide some means of collecting this muscle control or motion information so that it might be handled by a data-processing algorithm in real-time. The purpose of the data-processing algorithm is to translate the user input information into desired cursor actions.

As described previously, eye gaze tracking (EGT) is an approach that targets the user's ability to direct his eyes to gaze upon objects of attention. It is a non-invasive method of hands free cursor control, because it involves processing the unique orientation of image features of the eye, at particular gaze directions, by using a camera to capture the image data. This orientation of image features is then mapped to a point-of-gaze (POG). The "raw" POG coordinates produced by the EGT system are generally processed further by some form of fixation identification algorithm, which will extract fixation coordinates from the POG coordinates. The fixation coordinates are then used to update the cursor position. Fixation identification algorithms can be classified by the manner in they use spatial and temporal information to identify fixations [19]. A popular fixation identification algorithm utilizes a dispersion-based spatial threshold within a fixed time window (the temporal threshold) to identify the occurrence of a fixation. Selections or clicks may be implemented by using a dwell time threshold or blinks.

Dwell time is more natural to the user [5], and thus is more prevalent in its usage, but has the disadvantages previously discussed.

A seminal work in the field of EGT-based control of the cursor was that of Ware and Mikaelian [10]. The EGT technique that they employed required a dwell time of 400 ms. In their paper, they presented two experiments to investigate the viability of eye gaze tracking as a pointing technique. In experiment 1, selection time was observed as a function of task distance for three different selection techniques: hardware button, dwell time, and on-screen button. The results showed task times of less than 1 s for all techniques and that the data conformed to the Fitts' law model. Experiment 2 investigated the effect of target size on selection time and error rate for the hardware button and dwell time selection techniques. The results showed that task time and error rate increased significantly for target sizes less than 1.5° visual angle.

Hutchinson et al. described an eye-gaze-response interface computer aid (ERICA) in their paper [7]. The EGT-based cursor control system utilized a 2 – 3 s dwell time as a selection criterion, and the testing of their system produced some notable observations. These include: the bright eye effect was not observable in 5% - 10% of the candidates, the head must remain fairly stationary for the eye image to be captured, and there was a limitation in the accuracy of the system.

The work of Robert J.K. Jacob in this field is also worthy of note [5, 8]. The fixation identification algorithm he used in his eye tracking cursor control technique utilized a 100 ms temporal threshold to determine whether the POG points remained within a 0.5° dispersion threshold. In a preliminary evaluation, his eye tracking

technique was used to perform object selection interactions with a dwell time of 150 – 250 ms. It was found to be quite effective in performing these tasks.

Sibert, in conjunction with Jacob and Templeman, provided a more formal evaluation of Jacob's eye gaze tracking system [3, 4]. The evaluation consisted of two experiments that required participants to select circular targets with the EGT system, as well as, with the mouse. The EGT system used a dwell time of 150 ms as a selection criterion. In experiment 1, the circles were empty, except for the desired target, which was highlighted. In experiment 2, all the circles contained letters and the letter to be selected was indicated by prerecorded audio commands. The mean time selection results for both experiments showed that the EGT system was faster than the mouse and that the difference was statistically significant. Fitts' law analysis of the results showed that the EGT interaction technique was not well represented by the Fitts' law model, in the sense that there was little increase in trial time with the increase in trial distance.

Additional approaches have been suggested for modifying the characteristics of the interface in order to make EGT-based cursor control more resistant to the problems it typically encounters. Specifically, the concept of magnifying the area surrounding each fixation point in high resolution environments has been explored. This concept would lessen complications due to accuracy experienced by users of EGT-based pointing systems.

Lankford proposed two methodologies for making the ERICA system truly functional in a windows environment [9]. The first involves modifying gaze clicking in order to perform single click, drag-and-drop, and double-click operations. This is done by associating specific dwell times to each type of operation. The second modification

involved utilizing a zoom window, which appears at the center of the display, containing a magnified view of the area surrounding the most recent fixation point. To perform an operation in this area the user must use the gaze protocol previously described or he/she may opt to close the window. Unfortunately, Lankford does not perform any user evaluations with his device, but one may surmise that the addition of this software-based protocol will significantly slow the natural speed advantages of EGT-pointing.

Miniotas et al. examined how eye gaze interaction may be enhanced by using expanding targets [20]. The concept of expanding targets involves increasing the size of the target to a “pointing-friendly” size while the user’s gaze is within the boundaries of the target. In addition to target expansion they used a grab-and-hold algorithm (GHA) to minimize the effect of eye jitter on cursor stability. In their experimental evaluations they used three levels of expansion factor (1, 2, 3), and had movement time and error rate as dependent measures. Statistical analysis of the results showed that both movement time and error rate decreased with expansion factor and that these differences were significant. The primary disadvantage of target expansion is that the spatial penalty incurred by using this mechanism is permanent, that is, the extra space consumed during the expansion can only be occupied by non-interactive objects.

Another approach to alternative cursor control makes use of the user’s ability to move his/her head. With head pointing devices, head movements in the horizontal or vertical planes are translated into cursor movements in the corresponding directions on the monitor screen. The manner in which head position information is collected varies, and consequently, so does the accompanying data processing algorithm.

A non-invasive version for monitoring head position uses image processing to locate and track features of the user's face, such as the eyes or the nostrils, and translates the orientation of these features into cursor actions. An example of this is presented by Morris and Chauhan [21], where they processed video data captured by a web camera in order to determine the orientation of the nostrils on the face. The instantaneous location of the nostrils was compared with their at-rest location, and any significant displacement was used to control the mouse pointer's movement.

A commercial system called Headmouse ® Extreme tracks head movement by using infra-red light to illuminate and follow a small reflective target placed on the forehead or glasses [22]. Clicks are performed using dwell time, an adaptive switch, or speech recognition.

Another commercial system called HeadMaster™ by Prentke Romich requires that the user wear a headset containing three ultrasonic sensors. A transmitter placed on the computer sends an ultrasonic signal to the sensors. Information from the sensors is then used to determine the location and orientation of the head in space. Click operation implementation is similar to the previous example.

Evans et al. created a system that used head movement to act as a joystick or a relative pointing device to control the computer cursor [23]. The system used a head-mounted array of infra-red light-emitting diodes (LEDs). It also used a mouse emulation unit, which was connected to the serial port of the computer, to determine head position and to translate it into cursor movements. Click operations were performed by switches. Informal user evaluations showed that they prefer a head-operated device with the

characteristics of a joystick over a head-operated device with the characteristics of a mouse or absolute pointing device.

Formal user evaluations of head pointing devices, specifically the HeadMasterTM, have been performed [24]. The results of the experiments showed that reduced neck range of motion caused increased difficulty in using computer head controls. Specifically, the results showed reduced accuracy, longer task times, and increased Fitts' law slopes for participants with neck range of motion disabilities.

An isometric tongue pointing device called Tonguepoint was created by Salem and Zhai [25]. The device consisted of a mouthpiece with an IBM TrackpointIIITM device fitted to the front of it. The TrackpointIIITM is typically used by the fingers to control the computer cursor of IBM laptops, but was used by the tongue to perform the same operations in this situation. Preliminary tests showed that the tongue was 5 – 50% slower than the finger in using the TrackpointIIITM to perform pointing operations.

A different class of alternative cursor control systems seeks to monitor the electrical activity associated with the muscular movements the user can still perform, and uses these electrophysiological signals to drive the manipulation of the cursor. This class of systems is the EMG-based group of systems previously discussed. EMG-based cursor control systems typically monitor EMG signals from a targeted set of superficial muscles, which are associated with a group of movements that the user can still perform. A number of algorithms can be used to recognize the EMG patterns associated with each movement so as to produce the associated cursor action. Some examples are given in the following paragraphs.

Chang et al. designed a real-time EMG discrimination system in which five distinct motions of the neck and shoulders were used to produce five commands [15]. Real-time discrimination was accomplished by using the cepstral coefficients of the input EMG signals as feature inputs to a modified maximum likelihood distance (MMLD) classifier. A 95% recognition rate and a response time of less than 0.17 s were achieved for the six subjects tested.

Barreto et al. created a real-time system that utilized EMG signals from cranial muscles and electroencephalogram (EEG) biosignals from the cerebrum's occipital lobe to control the two-dimensional movement of the cursor, perform left-clicks, and switch the cursor control function on and off [13, 14]. The system performed periodogram estimations of the power spectral density of the EMG signals over discrete windows. This spectral data was classified by considering amplitude thresholds to determine the onset of a contraction and then using spectral power summations aggregated over specific frequency bands between 8 and 500 Hz to determine which muscle was the source of the contraction. The results of click-point-click tests revealed that, although this form of EMG control was effective, its average task completion time was slow (16.3 s) compared to that of a mouse (1 – 2 s).

The prospect of using EMG signals to control the cursor was investigated by Itou [16], who placed three electrode pairs over muscles in the forearm. The raw EMG signals were processed to produce integrated electromyogram (IEMG) signals. These IEMG signals were stored and used offline to train a backpropagation neural network that would output the relevant cursor actions. The testing of the neural network revealed a 70% recognition rate.

Yoshida presented a cursor control system that monitored EMG signals so as to perform cursor actions in real-time [18]. The raw EMG signals were converted into voltage pulse waves that served as inputs to a PS/2 mouse driver. The results showed that the EMG-based input performs object selection tasks more slowly than the mouse, and that they conformed to Fitts' law.

An EMG-based wheelchair control interface was developed by Han et al. [26]. EMG signals were taken from the sternocleidomastoid muscles in the neck. Integrated absolute values (IAV) and variances were derived from the EMG signals and used as features to train a fuzzy min-max neural network (FMMNN). User evaluations verified that the system provides effective control of a powered wheelchair.

Another EMG-based computer interface geared toward controlling the movement of a wheelchair was presented by Moon et al. [27]. The EMG signals were taken from the shoulder muscles (left and right levator scapulae). Elevating of the left and right shoulders, either independently or in unison, were classified into cursor commands by the use of a novel double threshold method applied to the integrated absolute EMG (IEMG) signals. The results of virtual tests showed that EMG control is comparable to keyboard control in navigating the wheelchair in spacious environments.

Kim et al. introduced an EMG system for cursor control that interprets six pre-defined wrist motions into the cursor actions: left, right, up, down, click and rest. A fuzzy min-max neural network (FMMNN) was used as a classifier [17]. Difference absolute mean values (DAMV) were extracted from the EMG signals and used as training features to the FMMNN. The recognition rate obtained was 97% for the ten people used to test the system.

The electroencephalogram (EEG) is another electrophysiological signal that researchers have used to enable a user to communicate messages or commands to a computer. EEG signals are emitted by the brain of the user, so such devices are often called brain-computer interfaces or BCIs. The formal definition of a brain-computer interface is a communication system that does not depend on the brain's normal output pathways of peripheral nerves and muscles [28]. BCIs are classified as dependent or independent. A dependent BCI does not use the brain's normal output pathways to carry the message, but activity in these pathways is needed to generate the brain activity that does carry it. An example of this is a BCI that relies upon visual evoked potentials (VEPs). A VEP is a voltage change in EEG activity that occurs after the eye detects a visual stimulus. Typically, when VEPs are used to operate a BCI, the user is presented with a matrix of letters that flash one at a time. If the user wants to select a letter, he/she must stare at it while the interface flashes the letters in sequence. The VEP generated for the letter that the user is staring at will be larger than the VEPs of the surrounding letters. Even though a VEP-operated BCI measures EEG patterns, these patterns are dependent on activity in the extraocular muscles and cranial nerves as the user directs his/her gaze. This example shows explicitly that dependent BCIs do not fully satisfy the formal definition given above. However, independent BCIs do satisfy this definition, because they are not in any way dependent on the brain's normal output pathways.

Independent BCIs may be further categorized by the form of EEG signal used as input to the device. The categories include: slow cortical potentials, P300 evoked potentials, mu and beta rhythms, and cortical neuronal action potentials. Slow cortical potentials or SCPs are slow voltage shifts that are generated by the cortex that occur over

time scales of 0.5 – 10.0 s. Negative SCPs are associated with movement or other activities that will produce cortical activation, while positive SCPs are associated with reduced cortical activation. SCPs have been shown to be controllable by individuals and have been used in a “thought translation device” to communicate with a computer [29]. The P300 evoked potential is a positive peak in the EEG signal that occurs approximately 300 ms after an infrequent auditory, visual, or somatosensory stimulus has been presented while embedded within more frequent or routine stimuli. This peak is typically centered over the parietal cortex. The P300 potential can be used to detect a subject’s choice by proposing in turn the possible options. Mu rhythms are a form of EEG activity that occur in the 8 – 12 Hz range and are focused over the somatosensory or motor cortex. Beta rhythms are another form of EEG activity that occur in the 18- 26 Hz range and are also focused over the same regions of the cortex. 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. Cortical neuronal action potentials are the electrical signals produced by individual neurons located within the cortex. Computer control using these action potentials focuses on the individual’s ability to control the firing rates of individual neurons. In order to record this neuronal activity for the purpose of performing computer control, intracortical electrodes must be implanted on the surface of the cortex. Of all the

categories described, much of the emphasis in literature has focused on the use of mu and beta rhythms.

Work by the group from the brain-computer interface laboratory at the Wadsworth center has resulted in a BCI that uses a linear equation to translate mu or beta rhythm amplitudes into one-dimensional or two-dimensional cursor movement at a rate of ten times per second [30].

The group at Graz University has also created a BCI that uses mu and beta rhythms as input [31, 32]. They have experimented with three types of preprocessing methods to derive input features from the EEG signals. These are: the computation of band power in subject-specific frequency bands in intervals of 250 ms; the use of adaptive autoregressive (AAR) parameters estimated for every iteration with the recursive least squares algorithm (RLS); the calculation of common spatial filters (CSP). Two different classification approaches were employed with their BCI: learning vector quantization (LVQ), and linear discriminant analysis (LDA). LVQ was used with band power estimates and LDA was used with both the AAR parameters and the CSPs. The group has demonstrated that their BCI can move the cursor left or right based on planned left or right finger movements respectively [31].

The major advantage of using a BCI system as an assistive technology mechanism for individuals with motor disabilities is that it does not require any kind of motor capabilities to produce its control signals. However, present day BCI systems are primarily limited by speed of operation. Current BCIs have maximum information transfer rates of 10 – 25 bits/min [28].

2.2 EGT-based Systems Supplemented by Additional Modalities

It is also worth noting that there has been work in implementing systems that perform point and click tasks, by integrating eye gaze tracking with another input modality. The motivation for integration is that the other input modality can be used to compensate for some of the shortcomings of the EGT modality (e.g. unintended selections, limited accuracy, calibration offset).

A gaze-speech multimodal interface is a system that can produce improved human to computer interaction if the two input modalities are integrated correctly. A user would be required to adhere to a general protocol in order for an interaction procedure to be recognized by the system. Typically this would mean that a user would gaze at an object of interest then utter a specific word or phrase to initiate a procedure (e.g. click, drag, move, or drop) to be performed on the object. A study on how to optimally integrate these modalities for object selection tasks was performed by Zhang et al. [33]. The selection tasks were performed on a grid of icons. One-, two- and three-word phrases were a part of the speech recognition vocabulary used to describe the objects. Also, five radii for the eye operative region around the fixation point associated with a selection were tested. It was found that one-word phrase used in conjunction with a radius of 1.5 cm resulted in the highest recognition rates and smallest selection times.

A key issue in gaze and speech integration is the synchronization of events from the two input streams. An investigation of the relationship between gaze and speech for the task of moving an object from one location of the computer screen to another was done by Kaur et al. [34]. In tests, subjects were required to move a designated object from a cluster of objects to a specified location using eye gaze in conjunction with the

phrase “Move it there”. Results revealed that the fixation just prior to the word “Move” represented the source object with the highest probability. Using this synchronization criterion, 95% accuracy for source object selection was achieved.

These investigations showed that gaze-speech interfaces can overcome the susceptibility of gaze-based interaction to unintended selections, as well as, improve the accuracy and speed of speech recognition systems, by allowing for simpler vocabularies. However, these interfaces did not improve the limited spatial accuracy inherent in EGT systems.

Zhai et al. produced a bimodal form of cursor control, which used mouse input for small cursor movements, along with click operations, and gaze input to perform large cursor excursions [35]. Their approach was called manual and gaze input cascaded pointing or MAGIC. Two MAGIC pointing techniques were developed: conservative and liberal. These techniques differed only in the location of the cursor relative to the fixation point when a gaze-based cursor update was performed. The two techniques were compared to a mouse input using point-and-click trials. The results showed that the difference between techniques was statistically significant, with mean task completion times of 1.4 s for mouse input, 1.52 s for conservative MAGIC input, and 1.33 s for liberal MAGIC input. The results suggest that the liberal MAGIC technique is faster than the mouse for point-and-click tasks, while not being susceptible to the disadvantages typically associated with gaze-based interaction. The results also showed that the MAGIC techniques matched the Fitts’ law model relatively poorly. This technique again demonstrates that if an EGT-based input is properly integrated with another form of input

they can produce a very efficient form of human-computer interaction. However, this technique is not suitable for individuals who are unable to use their hands.

Surakka et al. have developed an HCI system that utilizes the two modalities of voluntary gaze direction (EGT) and voluntary facial muscle movement (EMG) to perform object pointing and selection tasks [36]. The voluntary facial movement of frowning was used to perform object selection by monitoring the EMG signals from the corrugator supercilii. The analysis revealed that the mouse was faster than the new system in performing object pointing and selection over short distances. However, the regression slopes derived from Fitt's law analysis suggest that the system may be faster than the mouse over long distances, that is, beyond 800 pixels. This approach is similar to gaze-speech interfaces in that it overcomes the unintended selection problem encountered with an EGT system, but does deal with its limited accuracy problem.

Barreto et al. have worked to create a hybrid hands-off human-computer interface that made use of the EMG and EGT modalities to produce an alternative pointing device [37-39]. The interface activated the EGT modality for large cursor excursions, and activated the EMG modality for small cursor excursions and for clicking (object selection). The EMG subsystem was the same as the one developed previously by Barreto et al. [13, 14]. In preliminary studies, the hybrid system, the EMG-only system developed by the group, and a mouse were tested using the same protocol introduced previously for testing the EMG-only system. Test results show that the hybrid system was twice as fast as the EMG-only system in these tests, but was significantly slower than the hand-held mouse. As discussed previously, such a system compensates for both the unintended selection and limited accuracy problems encountered with an EGT-based

system, by using the EMG system for interaction in small areas and for selections, while still taking advantage of the inherent speed of the EGT input. Also, unlike the MAGIC technique, this technique can be utilized by persons who are unable to use their hands.

CHAPTER 3

METHODS

3.1 The Evolution of the EMG/EGT Cursor Control System

The first attempt by our group from the Digital Signal Processing Laboratory at producing an alternative cursor control system involved the collaboration of Barreto, Scargle and Adjouadi [13, 14]. As described previously, this system processed EMG signals to produce two-dimensional control of the cursor (left, right, up, and down), as well as, a left-click action. In addition, it processed EEG signals from the occipital lobe to detect the presence of alpha rhythms when the eyes were closed. In this way, the closing of the eyes would toggle an on/off switch for the system. In both cases, periodogram estimations of the power spectral density of the biosignal channels were calculated over discrete time windows. This frequency data was used to classify the biosignal inputs by using spectral power summations aggregated over specific frequency bands between 8 – 500 Hz for the EMG signals, and a single band of 8 – 12 Hz for the EEG signal. Click-point-click testing revealed that the average task completion time for the EMG system (16.3 s) was significantly slower than that of a mouse (1 – 2 s). It was envisaged at this time that EMG- and EGT-based control could be integrated in such a way that advantages of the individual modalities would be preserved, while minimizing their respective disadvantages. This would result in a more efficient and user-friendly form of cursor control system. Specifically, the hybrid EMG/EGT system would use the EMG subsystem to perform small cursor displacements relative to the current cursor position, as well as, click operations. In addition, the output of EGT subsystem would be used to produce large displacements of the cursor.

An initial prototype of the hybrid EMG/EGT cursor control system was created by Lyons et al. [37]. The EMG subsystem was the same as the one created previously. The uniqueness of this system was found in the manner in which it integrated the streams of EMG and EGT data via a context assessment and effective control algorithm. In this algorithm, EMG-based control has precedence over EGT-based control. Under EMG-based control, the cursor position is updated incrementally relative to the previous cursor position in either the horizontal or vertical dimensions based on the output of the EMG classifier (left, right, up, or down) in accordance with equations (3-1) and (3-2).

$$C_x[n] = C_x[n-1] + \Delta x[n] \quad (3-1)$$

$$C_y[n] = C_y[n-1] + \Delta y[n] \quad (3-2)$$

where C_x and C_y represent the x- and y-coordinates of a cursor position, and n represents a discrete index used to describe the progression of cursor updates through time.

If the user directs his/her gaze a considerable distance from the current cursor position the effective control will switch to EGT-based control, and the cursor will be repositioned to the current location of the user's point of gaze. For this context switching approach, a measurement of the distance between the previous cursor location and the user's current point of gaze must be taken. This measure is called "POG_drive" and is defined by equation (3-3).

$$POG_drive = \sqrt{(POG_x[n] - C_x[n-1])^2 + (POG_y[n] - C_y[n-1])^2} \quad (3-3)$$

The context assessment algorithm will evaluate the POG_drive value every time a classification result is produced by the EMG subsystem (four times per second). If the

output of the EMG subsystem is 0 and the value of POG_drive is greater than a fixed threshold, R, then the cursor position will be updated with the user's current point of gaze. This is represented by equations (3-4) and (3-5).

$$C_x[n] = POG_x[n] \quad (3-4)$$

$$C_y[n] = POG_y[n] \quad (3-5)$$

The click-point-click trials showed that using EMG/EGT control resulted in a dramatic decrease in average trial time (16.3 s to 6.8 s) when compared to EMG control.

Al-Masri completed further software modifications to the hybrid cursor control application [38]. These included a slider dialog box that allowed for the manual manipulation of the PSD amplitude thresholds, and the reading of point of gaze data directly from the serial port of the user's computer.

Despite these improvements, a detailed analysis of the system suggested that better performance could be obtained with either modifications to or the replacement of some of the components of the system. It was proposed that effective operation of the hybrid system required the performance of three basic tasks in a continuous fashion:

- T1. Reliable EMG input assessment – muscular contractions must be correctly identified.
- T2. Reliable EGT fixation estimation – EGT fixations must be properly determined.
- T3. Reliable estimation of the user's intent for cursor manipulation and the resulting effective cursor update in the GUI.

These tasks and their interrelation are described in Figure 3-1.

The remainder of this chapter describes the improvements made to the hybrid system in accordance with the task categorization of Figure 3-1. The resulting enhancement in system performance is described in Chapter 4.

Figure 3-1 Conceptual depiction of the functionality of the hybrid EMG/EGT cursor control system, on the basis of the 3 key tasks (T1, T2 and T3)

3.2 EMG Subsystem Implementation

3.2.1 Shortcomings of the Previous EMG Subsystem

In reviewing the functionality of the original EMG subsystem it was discovered that its main weakness was in detecting and differentiating contractions of the Frontalis and Procerus muscles. Therefore, a fourth electrode, located between the eyebrows, was

added to the configuration. This new electrode was now specifically assigned to monitor EMG signals from the Procerus muscle, while the electrode on the forehead was now placed at a higher location to preferentially sense EMG signals from the Frontalis muscle. This new input configuration required that a new EMG classification algorithm be devised.

3.2.2 Placement of Electrodes

Figure 3-2 displays the placement of the four Ag/AgCl electrodes used on the head of the user. The figure indicates that electrodes were placed over the right frontalis muscle, the left temporalis muscle, the right temporalis muscle, and the procerus muscle, respectively. An electrode was placed over the right mastoid as a reference.

Figure 3-2 Electrode placement for the EMG cursor control system

3.2.3 Hardware Components of the EMG Subsystem

The hardware components of the EMG subsystem are presented in Figure 3-3. The set of four EMG signals were input into Grass® P5 Series AC preamplifiers. These 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 60 Hz notch-filter to each EMG

channel. The ADC64™ DSP/AD board (Innovative Integration, Simi Valley, CA) performed analog-to-digital conversion on each signal at a sampling rate of 1.2 kHz, and then applied the EMG classification algorithm to these digitized signals in real-time. The board was connected to the computer's processor through the PCI bus. The output of the classification algorithm was sent to the host application via hardware interrupts. These interrupts occurred once every 213 ms (256/1200).

Figure 3-3 Block diagram of hardware components of EMG subsystem

3.2.4 The EMG Classification Algorithm for Muscle Contraction Identification

The desired relations between cursor actions, facial movements, and muscle contractions for the EMG subsystem are given in Table 3-1.

The purpose of the new EMG classification algorithm was to determine if a facial muscle contraction had occurred and if so, which specific muscle was the source of this contraction. Given the one-to-one correspondence between muscle contraction and

cursor action shown in Table 3-1, the output of an effective muscle contraction classification algorithm can be used to provide real-time cursor control.

Table 3-1 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 new classification algorithm also used the periodogram estimation of the power spectral density (PSD) of the input EMG signals. PSD estimates were calculated every 256 consecutive samples (213 ms) from each of the four EMG signals. Each PSD estimate indicated how the power of that particular EMG signal was distributed over a frequency range of 0 Hz – 600 Hz.

It had been observed previously that the four muscles being monitored possessed distinct EMG spectral characteristics, and that this spectral information would be useful for performing classifications [13, 14]. Empirical observations suggested that Mean Power Frequency (MPF) values would be a more suitable way of representing the spectral data than partial PSD accumulations for this new input configuration, and it was decided to use MPF values in the new classification algorithm. The MPF is derived from PSD values 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:

$$MPF = \left(\frac{f_0 \times P_0 + \dots + f_k \times P_k + \dots + f_{N-1} \times P_{N-1}}{P_0 + \dots + P_k + \dots + P_{N-1}} \right) \quad (3-6)$$

where $k = 0, 1, 2, \dots, N - 1$, and $N = 256$.

EMG recordings, taken from a test group of five individuals, revealed the each muscle type had a characteristic range of MPF values. The frontalis muscle has the majority of its spectral content below 200 Hz, with an MPF in the range 40 – 165 Hz. The temporalis muscles have a significant portion of their spectral content above 200 Hz, with an MPF in the range 120 – 295 Hz. The procerus muscle has an intermediate spectral content when compared to the frontalis and temporalis muscles, with an MPF in the range 60 – 195 Hz.

The new EMG classification algorithm derived three features from each PSD estimate calculated for each EMG input to assist in determining which muscle(s) was the source of a contraction. These features were: the maximum PSD magnitude, the sum of all the PSD magnitudes for a given estimate, and the MPF value for the estimate. The flowchart of Figure 3-4 provides an overview of how these features were calculated and used by the EMG classification algorithm.

The diamond shapes of Figure 3-4 represent the decision processes of the classification algorithm. These processes can be categorized into two forms: the decision process for unilateral contractions (contractions that involve only one muscle), and the decision process for bilateral contractions (commands involving two muscles contracting simultaneously).

The cursor actions left, right, up and down are produced by unilateral contractions. For a unilateral muscle contraction to be correctly classified by the algorithm, a criterion placed on each feature calculated from the PSD estimate, for the electrode (muscle) in question, must be satisfied. These criteria are:

- i. The maximum PSD magnitude 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 MPF must fall into a range consistent with the muscle associated with the electrode.

The left-click cursor action required the bilateral contraction of the left and right temporalis muscles. The criteria that must be satisfied for the correct classification of this bilateral contraction are as follows:

- i. The maximum PSD magnitude 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 MPFs from both PSDs must fall into a range consistent with the muscles associated with those electrodes.

In addition to two-dimensional directional control, the EMG classification algorithm also provided control of the speed of the cursor in the four directions specified in Table 3-1. The size of the increment that the cursor moved in either the horizontal or vertical directions could be increased if a contraction was maintained continuously for specific time periods. This concept is illustrated in Table 3-2.

Figure 3-4 Flowchart of EMG classification algorithm

Table 3-2 The relationship between contraction time and increment size for cursor speed control

Contraction Time (s)	Cursor Increment Size
0.213 – 0.640	± 1
0.853 – 1.280	± 5
1.493 – 3.413	± 10
> 3.413	± 20

The EMG classification algorithm also provided a double-click function. A double-click was executed by performing a left-click contraction (left and right jaw clench) for 3 consecutive classification epochs or 0.64 s. This double-click functionality was not optimized to allow the user not to perform double-clicks unintentionally and was disabled for the experiments described later in this chapter.

3.3 EGT Subsystem Implementation

3.3.1 Shortcomings of the Previous EGT Subsystem

The primary shortcoming of the previous EGT subsystem was that it compared an individual POG estimate against the context switching threshold (R), and also used the same estimate to determine the area of attention of the user. This estimate was not optimal for two reasons. Firstly, for a single POG estimate to be used as an approximation of the user's new area of interest on the screen, this estimate must occur during a fixation. For a fixation to be identified, a group of POG estimates must be collected and analyzed to verify that they satisfy the spatio-temporal requirements for a fixation. Therefore, if one considers a single POG estimate in isolation one cannot determine whether it is a part of a saccadic or fixational period of eye movement. Secondly, even if a POG estimate has occurred during a fixational epoch, the interplay of micro-saccades and drifts that occur during a fixation would mean that the accuracy with

which this estimate approximates that area of interest would vary. It was because of these two reasons that a fixation identification algorithm was employed for the new implementation of the EGT subsystem. This algorithm would ensure that the approximation of the user's area of interest would only occur after a fixation had been identified. Also, the algorithm would utilize an approximation that would minimize the variability of the POG estimates due to fixational eye movements.

3.3.2 The Hardware Components of the EGT Subsystem

The eye tracking system used for our EGT subsystem was an R6-HS Remote Optics system manufactured by Applied Science Laboratories. This system has the ability to produce POG estimates at 120 Hz, 240 Hz or 360 Hz. Figure 3-5 shows a block diagram of the various components of the EGT subsystem.

The EGT subsystem functioned by allowing a beam from near infrared LED's located on the pan/tilt optics module to illuminate the eye of the user. The eye image that was produced by this illumination was focused and sensed by a video camera also present on the pan/tilt unit. Video image data was fed into the eye tracker control unit which performed optical feature recognition and POG estimation. The POG estimates and pupil diameter values were then sent out to the display PC (the computer that interacted with the user) and the interface PC (the computer that interacted with the experimenter). These values were sent to the serial ports of the respective computers. The cursor control application running on the display PC received these values via hardware interrupts that occurred at a rate of 120 Hz. The eye image captured by the camera was also displayed on the eye monitor via the control unit. The image presented on the subject display monitor was routed to the control unit through a scan converter, which

converted the VGA signal into a video signal. This image was then output to the scene monitor for display. The experimenter controlled and received eye gaze information by using the Eye-Trac 6000 User Interface application that ran on the interface PC.

Figure 3-5 Block diagram of EGT subsystem

3.3.3 The Fixation Identification Algorithm

The fixation identification algorithm utilized temporal and spatial criteria to determine whether or not a fixation had occurred. More specifically, the algorithm

extracted a 100 ms moving window (temporal threshold) of consecutive POG data points (POG_x , POG_y), and calculated the standard deviation of the x- and y-coordinates of these points. If both standard deviations were less than the coordinate thresholds associated with 0.5° of visual angle (spatial threshold), then it was determined that the onset of a fixation had occurred, and the point used to represent the fixation were the coordinates of the centroid of the POG samples received during the 100 ms window analyzed, (F_x , F_y). If it was determined that a fixation had not occurred, then the window was advanced by one data point and fixation identification was performed again. This algorithm is further illustrated in the flowchart of Figure 3.6.

3.4 Information Fusion and Cursor Update Algorithm

3.4.1 Shortcomings of the Previous Information Fusion and Cursor Update Algorithm

In the previous implementation, information fusion and cursor update was accomplished by using a context assessment and effective control algorithm. As previously described, this algorithm gave the EMG subsystem precedence, that is, all data processing was performed within the interrupt handler for the EMG system. Therefore, output values from the ADC64TM DSP/AD board and POG values from the serial port were read only when an interrupt was generated by the board. Under this scheme it would be impossible to implement the fixation identification algorithm previously described. Therefore, it was necessary that the POG information be transferred to the host application via hardware interrupts, and a new algorithm be created to coordinate information fusion and cursor update using the outputs of the two interrupt handlers [$(\Delta x$, $\Delta y)$ and (F_x , F_y)].

Figure 3-6 EGT fixation identification algorithm flowchart

3.4.2 The New Information Fusion and Cursor Update Algorithm

The new information fusion and cursor update algorithm determined the effective cursor position as a merging of the incremental EMG commands (Δx , Δy) and the absolute coordinates of a qualified EGT fixation (F'_x , F'_y):

$$C_x[n] = \begin{cases} C_x[n-1] + \Delta x[n] & , \text{If } EMG \text{ update} \\ F'_x[n] & , \text{If } EGT \text{ update} \end{cases} \quad (3-7)$$

$$C_y[n] = \begin{cases} C_y[n-1] + \Delta y[n] & , \text{If } EMG \text{ update} \\ F'_y[n] & , \text{If } EGT \text{ update} \end{cases} \quad (3-8)$$

where C_x and C_y represent the x- and y-coordinates of a cursor position and n represents a discrete index used to described the progression of cursor updates through time.

The merging of the outputs of the two subsystems implied that the current cursor position ($C_x[n]$, $C_y[n]$) may be updated by either the EMG or EGT subsystem at any time.

An EMG subsystem update involved changing the previous cursor position ($C_x[n-1]$, $C_y[n-1]$) by an increment of Δx or Δy . The size and direction of the increment was determined by the output value of the EMG subsystem as described in Section 3.2.4.

An EGT subsystem update involved replacing the previous cursor position with the absolute coordinates of a qualified fixation (F'_x , F'_y). A qualified fixation was determined by taking every new fixation centroid (F_x , F_y) identified by the fixation identification algorithm, and testing it to determine if it signified a new point of user attention, or if it simply was the continuation of previous fixation. This was done by measuring the distance between the current qualified fixation position (F'_x , F'_y) and the (F_x , F_y) under test. This distance was compared to the Euclidean distance defined by the

standard deviations in x and in y of the POG points that resulted in the new fixation (F_x , F_y). If the distance from (F'_x , F'_y) to (F_x , F_y) was greater than this threshold, then (F_x , F_y) was acknowledged as representing the new point of user attention, and it became the new qualified fixation point (F'_x , F'_y).

3.5 Overview of Alternative Cursor Control Software Application

An alternative cursor control software application was designed to provide the user with three forms of cursor control: EMG-based control, EGT-based control, and EMG/EGT-based control. This allowed user evaluation and experimental testing of each form of control. The graphical user interface (GUI) for this application is shown in Figure 3-7.

Figure 3-7 Alternative cursor control application GUI

The area of the GUI surrounded by the hatched rectangle contains the various controls used for the set up of the EGT subsystem. The data format radio buttons allow the user to specify the format of the EGT data entering the serial port of the display computer. The serial port combo box gives the user the ability to choose which serial port will be read for the EGT data. If the user is also fitted with head tracking equipment, checking the eye-head integration check box will allow the reading of additional eye-head data from the serial port. The streaming mode check box alerts the application that it must be set up to read the serial port at the frequency specified by the eye camera update rate combo box. The fixed baud rate at which data communication will be conducted through the serial port is specified by the default value displayed in the baud rate edit box.

The “Open EMG Threshold Dialog” pushbutton opens a dialog box that allows the user to change the maximum PSD thresholds set for each decision process in the EMG classification algorithm (Refer to Figure 3-4). Figure 3-8 shows that the dialog box contains five sliders which allow the user to set the aforementioned thresholds to values that are optimal for him/her. Each slider can be set anywhere in the range $0.1e6 - 50e6$. The edit box to the right of each slider displays the current threshold value set for that decision process or cursor action. The current settings overwrite those stored previously if the “Ok” button is pressed, or the previous settings are maintained if the “Cancel” button is pressed.

The large hatched ellipse in Figure 3-7 highlights the area of the GUI reserved for the pushbuttons used to activate and deactivate the alternative forms of cursor control. This area also contains buttons to connect (set up) and disconnect the serial port for

communication with the EGT system. As a result, the pushbuttons to start EGT or EMG/EGT control are not enabled until the “Connect Serial Port” pushbutton is pressed.

Figure 3-8 EMG threshold dialog box

The hatched circle highlights the edit boxes that give the x- and y-coordinates of the POG presently being output by the EGT subsystem.

The progression of the EMG subsystem output through time is monitored by the output plot displayed in the lower left corner of the GUI. Integer values are mapped to the cursor actions output by the EMG subsystem and are plotted when the relevant outputs are detected. The mapping between integer values and cursor actions is shown in Table 3-3.

Table 3-3 Mapping between cursor actions and EMG system output plot integer values

Cursor Action	Integer Value
No Action	0
Up	1
Left	2
Right	3
Left-Click	4
Down	5

3.6 The EGT-Only Cursor Control Algorithm

In order to provide comparative performance evaluations between EMG/EGT and EGT cursor control, an EGT-only cursor control algorithm was created. This algorithm was activated whenever the “Start EGT Control” button was pressed. The algorithm detected the onset of a fixation, and calculated the centroid of this fixation in a similar manner to the identification algorithm described in Section 3.3.3. If a fixation onset was detected, the Euclidean distance between the new fixation centroid and the previous fixation centroid was calculated. If this distance was greater than a separation threshold derived from the x and y standard deviations of the previous fixation, then the cursor position was updated with the coordinates of the new centroid. The main difference between this EGT-only control and the EGT subsystem described in Section 3.3 was that, in addition to updating the cursor position, the EGT control algorithm also performed gaze-based left-clicks when a fixation was held for a specified time period beyond the initial 100 ms evaluation period. This was done by collecting more POG data over this time period and evaluating these data points to determine whether or not a fixation was maintained. Specifically, if all of the points in the time window after the initial 100 ms period were within a 1° visual angle of the fixation centroid originally found, then it was determined that the fixation had been maintained and a left-click command was issued. Additionally, if any of the points was more than 1° visual angle away from the centroid, but the mean of these points was within 1° , then it was considered that a fixation had been maintained and a left-click command was also issued.

The size of the gaze-assessment time window was chosen to be 250 ms, resulting in a total gaze time of 350 ms being required for a left-click to be executed. It was found

empirically that if the total gaze time of 150 ms used in Sibert's system [3, 4] was applied to our system, it would result in a large number of unintended selections or false positives. However, when we used the 400 ms gaze time specified for Ware and Mikaelian's system [10], the EGT system seemed slow and somewhat unresponsive. So, the value of 350 ms was chosen because it was found to produce considerably less false positives than when 150 ms was used. Also, this value maintained some of the inherent speed of the EGT mode of interaction.

3.7 Design of Experiments

3.7.1 Preliminary Experiments of EMG Subsystem

As a first step in verifying improvements in performance of the new EMG/EGT system, the performance of the new EMG subsystem was compared to that of the previous EMG implementation. These comparisons were done using Matlab off-line assessments and real-time click-point-click tests.

For the off-line assessments, five able-bodied participants (four men and one woman) were used to test the algorithms. Testing involved recording facial movement sequences for each participant. Each sequence was 190 s in duration. During each sequence, the participant was given verbal cues to perform specific types of facial movements. There were two unique sequences given to each participant, and each sequence was repeated twice. The ordering of the facial movements in the two unique sequences is given in Table 3-4.

It should be noted that sequence 2 includes a period of neck movement. This was included to determine if the classification algorithms could accurately discriminate these EMG signals from those due to the targeted muscle contractions.

In order to perform the real-time click-point-click tests, a program was created in Visual Basic and was displayed on a 17" color monitor. For each click-point-click trial, an 8.5 x 8.5 mm "Start" button was presented in a corner of the screen and a "Stop" button was presented in the center. The "Stop" button had four possible dimensions: 8.5 x 8.5 mm, 12.5 x 12.5 mm, 17 x 17 mm, 22 x 22 mm. Each participant was instructed to click the "Start" button to begin timing a trial, move the cursor to the "Stop" button, and click it as quickly as possible. This would record the total task time for the trial. The participant would then click the "Next" button to display another trial layout with the "Start" button located in a different corner of the screen. Figure 3-9 shows an example layout of a click-point-click trial.

Table 3-4 The ordering of facial movement sequences

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

Six able-bodied male subjects participated in this experiment. Each subject was required to use both the old and new EMG systems to perform the click-point-click trials. The cursor control systems were presented to each subject in separate sessions. During a

session, each unique trial configuration (one of four possible “Start” locations, and one of four possible “Stop” sizes) was presented on three occasions. This resulted in 48 trials per session and 96 trials per subject.

Figure 3-9 Click-point-click trial layout for EMG systems

3.7.2 Design of Experiment 1

Two experiments were designed to resolve the sub-problems associated with testing the effectiveness and efficiency of EMG/EGT system performance stated in Section 1.3. Experiment 1 was designed to test whether the EMG/EGT-based input would produce lower error rates and comparable task times to those recorded for EGT-based input in point-and-click trials. Also, this experiment would use the error rate and

task time measures to compare the performance of EMG/EGT-based input to that of a mouse in completing these trials.

The experiment was created in Visual Basic and each trial was displayed on a 19" monitor. The participant was seated in front of the monitor, such that the eye to screen distance was approximately 29". The layout of an example trial is shown in Figure 3-10. Each layout contained a square icon labeled "HOME" and a circular icon labeled "TARGET". There were three target diameters [48 pixels (0.556" or 1.1°), 66 pixels (0.764" or 1.5°), 96 pixels (1.111" or 2.2°)], three pointing distances [286 pixels (3.310" or 6.5°), 578 pixels (6.690" or 13.0°), 778 pixels (9" or 17.2°)], and four angles of approach (NE, SE, SW, NW) chosen for this experiment. These factors were crossed to produce 36 (3 target diameters x 3 distances x 4 angles) unique trial layouts. The distance between the two icons was spaced in such a way that the center of the screen would always bisect the pointing distance.

There were three cursor control techniques used in the experiment: EMG/EGT, EGT, and mouse. 30 participants were grouped according to the cursor control technique they would use to perform the experiment, that is, 10 participants for each cursor control technique. For a given trial, a subject was instructed to click the home icon, move the cursor to the target icon, and then click the target icon. The movement time and any selection errors (clicking outside the target icon) were recorded for each trial. Each of the 36 unique trial layouts was repeated twice resulting in 72 trials per participant. The layouts were presented in a random order. Also, there was a practice session prior to each experiment to allow the user to gain some familiarity with the cursor mechanism assigned to them.

Figure 3-10 Example point-and-click trial layout for experiment 1

3.7.3 Design of Experiment 2

The purpose of experiment 2 was to show that EMG/EGT-based input could produce a lower error rate than EGT-based input in point-and-click trials, when the source of error was exclusively due to unintended gaze-based selections. For this experiment to be successful, the target size for each trial should be designed to minimize EGT selection errors due to its limitation in accuracy, so that it would mainly assess errors associated with using gaze-based selection as a clicking mechanism. An example of the trial layout used in experiment 2 is shown in Figure 3-11.

Figure 3-11 Example trial layout for experiment 2

Each trial displayed a green circle labeled “START” separated by a center-to-center horizontal distance of 578 pixels (6.69” or 13.0°) from a red target circle. The diameter of each circle was 96 pixels (1.1” or 2.2°). At this size, EGT-based selection errors due accuracy limitations were not expected to be predominant. The red target circle contained either a “Y” or “N” label. For a given trial, the “START” circle was presented on either the left or right side of the screen, with the target circle located on the opposite side. Both circles were equidistant from the center of the screen.

The trial objective was to have the user select the “START” circle, then move cursor to target circle. The user must then select the target only if a “Y” label was displayed within it, but not if an “N” label was displayed. If no target selection was made

within 7 s for either kind of target, then the trial would time out. This trial design required that a user examine the target prior to selecting it. Under these circumstances, it was possible that unintended selections could occur when using gaze-based selection for an EGT-based input.

For a given experiment, the participant was required to use two cursor control techniques (EGT and EMG/EGT) in a repeated measures design. The cursor control techniques were presented to the participants in a random order. There were two sessions of data collection per cursor control technique. Also, the participant was given a practice session prior to using each technique to develop his/her skill in using the technique, and there were 5 minute breaks in between sessions to minimize the effects of fatigue.

In a session, each of the four unique trial layouts was repeated eight times for a total of 32 trials per session. This resulted in a total of (32 trials x 2 techniques x 2 sessions) 128 trials per participant. 15 individuals participated in the experiment.

3.8 Data Analysis Methods

3.8.1 Statistical Analysis

The data acquired from the click-point-click trials using the old and new EMG classification algorithms was analyzed by applying a 4-way (cursor control systems, “Start” icon positions, “Stop” icon sizes, and subjects) analysis of variance (ANOVA) to it. This was done to determine if the difference between the mean click-point-click task times produced by the systems was statistically significant.

The two dependent variables of trial time and error rate were analyzed separately using mixed design ANOVAs. This was done to investigate the effects of the various factors each variable. These analyses were accompanied by orthogonal contrasts of the

cursor control techniques for both error rate and trial time. Also, trial time data was isolated for EMG/EGT and EGT techniques for the largest icon size, and a t-test was conducted to compare the mean trial times under these circumstances. This was done to test whether the EMG/EGT-based input produced point-and-click times comparable to EGT-based input for icon sizes large enough for reliable EGT selection.

For experiment 2, it was found that the data could not be made to satisfy the assumptions required for parametric analysis (normality and homoscedasticity) by performing data transformations and outlier removal. Therefore, it was decided to perform nonparametric tests on the data, since such tests do not require that parametric assumptions to be satisfied prior to analysis. The Friedman test was used to analyze the differences between treatments across the 15 subjects that participated in the experiment. This test involves ranking each row or block of data and analyzing the differences in rank along the columns or treatments. In addition to the Friedman test, a number of Wilcoxon signed-rank tests were performed to allow for pair-wise comparisons of the different treatment conditions. For the data set recorded for experiment 2, the signed-rank test involved taking the difference between a pair of treatment conditions on a subject-by-subject basis, and ranking the results regardless of sign.

3.8.2 Fitts' Law Analysis

One of the most popular methods for evaluating the point-and-click performance of cursor control devices is to use Fitts' law analysis. Fitts proposed that the information processing capacity of the human motor system was analogous to Shannon's formulation of channel capacity used in the transmission of information [40, 41]. Specifically, he

argued that a movement task's difficulty, represented by its index of difficulty (I), could be expressed as:

$$I = \log_2 \left(\frac{2A}{W} \right) \quad (3-9)$$

where A is the distance or amplitude to move to a target, W is the width or tolerance of the target region in which the move terminates, and I is quantified in bits.

Equation (3-9) indicates that there is a direct logarithmic proportionality between I and A, that is, as the distance required for a movement task increases, so does the difficulty of the task and the information content associated with it. Equation (3-9) also indicates that there is an inverse logarithmic proportionality between I and W, that is, as the width of the target region increases, the task's difficulty decreases, along with the information content of that task. On this basis, Fitts conjectured that the average movement time (T) for a set of tasks with different amplitude and width values would be constant, provided I was constant for all these tasks. This concept may be expressed as:

$$\frac{I}{T} = C \quad (3-10)$$

where C is a constant with units of bits per second.

C may be interpreted as the capacity of the human motor system to execute a specific class of motor responses. C later became known as the index of performance, and this value is often used to compare the performance of devices that require motor responses to operate them so that they may execute specific tasks. Fitts extended his analogy to the case where I takes on different values, and suggested that T and I would have a first order relationship expressed mathematically as:

$$T = a + bI \quad (3-11)$$

where a is the T intercept for a task of $I = 0$, and b ($= 1/C$) is the slope of the relationship.

Mackenzie made modifications to Fitts' law so as to improve its accuracy in modeling the performance of input devices in point-and-click tasks [42, 43]. His modifications resulted in a reformulation of I :

$$I_e = \log_2 \left(\frac{A}{W_e} + 1 \right) \quad (3-12)$$

where I_e is called the effective index of difficulty, and W_e is the effective width of the target.

W_e is a modified value for the width of the target derived from the distribution of the selection points about the target center for a number of trials. The equation for W_e is given by:

$$W_e = 4.133 \times S_x \quad (3-13)$$

where S_x is the standard deviation of the distances between the selection points and the target center, resolved along the task axis.

W_e gives a better indication of the spread of user selection points than the fixed dimension W . Therefore, Mackenzie's modified Fitts' law model can be expressed as:

$$T = a + b \log_2 \left(\frac{A}{W_e} + 1 \right) \quad (3-14)$$

When applying Fitts' Law analysis to the evaluation of a cursor control system in point-and-click tasks, a movement time value is obtained by averaging all the movement times taken for tasks of a given I . Provided that there are tasks with different I values,

then a number of (I, T) ordered pairs will be available. These order pairs are used to produce a linear regression line that represents the performance capabilities of that cursor control system.

Fitts' law analysis was used to compare the performances of the old and new EMG systems in the real-time click-point-click tests mentioned previously. In this analysis, the actual target dimension W was utilized due to the unavailability of the selection point coordinates for the previous EMG system. Fitts' law analysis was also applied to the hybrid EMG/EGT system to investigate whether or not it would provide a good model for the evaluation of system performance, and thus provide a means of comparison with other cursor control systems. The uncertainty as to how well the hybrid system performance would match Fitts' model was rooted in the fact that empirical evidence presented in human-computer interaction literature has provided conflicting conclusions as to how well eye tracking matches Fitts' model [3, 4, 10]. However, it has been shown that EMG-based cursor control correlates well with the model [44].

3.8.3 Cursor Measure Analysis

Mackenzie et al. and Keates et al. have proposed cursor measures for measuring the movement characteristics of pointing devices [45, 46]. These measures could possibly be beneficial, because they capture aspects of pointer movement during a trial, and thus have the ability to reveal problems with pointer control.

After careful review of the 13 cursor measures proposed in both their papers, it was determined that target re-entry (TRE) was the cursor measure most appropriate for evaluating if there were any difficulties in cursor movement around the target region when using EMG/EGT input. TRE is defined as the situation when the cursor enters the

target region, leaves, then re-enters the region [45]. Target re-entry is evaluated on a per trial basis, that is, if two occurrences of target re-entry happen during a sequence of ten trials, the TRE value is 0.2 per trial. An example of a target re-entry is given in Figure 3-12.

The TRE values produced by all trials involving EMG/EGT users of experiment 1 were collected and mean TRE values were calculated for each user. A similar procedure was followed for the TRE values produced by mouse users, and the two user groups were compared using an independent-samples t test. This was done for the purpose of examining how well EMG/EGT users were able to control the cursor during the homing phase of the trials compared to the standard performance of a mouse user.

Figure 3-12 Example of a Target Re-entry

CHAPTER 4

RESULTS

This chapter presents the results obtained from the performance of the experiments designed to assess the functionality of the EMG/EGT system and its components, as described in Chapter 3. This chapter focuses on providing the reader with data gathered from the experiments and the immediate statistical analyses performed on those data. The discussion and interpretation of the results are developed in Chapter 5.

4.1 Results of Preliminary Experiments Involving EMG Subsystem

4.1.1 Matlab Off-Line Assessment Results

For the Matlab off-line assessments, both the old and new EMG algorithms were applied to each digital data sequence recorded from the subjects, while they were performing the timed sequence of muscle contractions indicated by predetermined scripts (Table 3-4). 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 4-1.

From this table, it can be inferred that a classification sequence consisted of a series of integers ranging from 0 to 5. An example of a classification sequence is displayed in Figure 4-1. By comparing each classification sequence to the ideal timed sequence of outputs determined by the script of contractions that the user followed, the number of correct and incorrect classifications produced by each algorithm was recorded

for all the classification sequences. Correct and incorrect classification percentages were derived from these values, by averaging the correct and incorrect classifications over the four classification sequences produced by each algorithm for a given subject. These percentages are shown in Table 4-2.

Table 4-1 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 4-1 Example of an output classification sequence produced by the new classification algorithm

Table 4-2 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	75.1	24.9	99.01	0.99
5	72.47	27.53	95.49	4.51
Average	78.43	21.57	98.42	1.58

4.1.2 Real-Time Trial Results

The mean click-point-click task times obtained from the real-time experiment, in which the EMG subsystem was used by the subjects to take the cursor from a screen corner to its center (Figure 3.9), were 22.66 s for the old system and 14.21 s for the new system. The ANOVA results produced by Minitab (Table 4-3) show a significant main effect for algorithm (A), $p < 0.0005$, and a significant main effect for icon size (I), $p < 0.0005$.

For Fitts' law analysis, the data were aggregated across subjects to give one data point for each task condition. The resulting aggregated data is shown in Tables 4-4 and 4-5 for the old and new EMG systems respectively. In both tables: D is the start-stop distance, W is the size (side) of the stop icon, I is the index of difficulty, T is the movement time, and C represents index of performance. This is consistent with their definitions in Equations 3-9 and 3-10.

Table 4-3 EMG System ANOVA table

Source	DF	SS	MS	F	p
Algorithm (A)	1	10290.1	10290.1	84.66	0.000
“Start” Position (P)	3	611.3	203.8	1.68	0.171
A*P	3	221.2	73.7	0.61	0.611
“Stop” Icon Size (I)	3	3073.4	1024.5	8.43	0.000
A*I	3	306.5	102.2	0.84	0.472
P*I	9	833.8	92.6	0.76	0.652
A*P*I	9	603.8	67.1	0.55	0.836
Subject (S)	5	27421.5	5484.3	45.12	0.000
Error	539	65514.2	121.5		
Total	575	108875			

The linear regression equation derived from the results of Table 4-4 was $T = -0.623 + 6.148 \cdot I$, $r^2 = 0.924$, $F(1, 2) = 24.3$, $p < 0.0015$. The linear regression equation derived from the results of Table 4-5 was $T = 2.03 + 3.22 \cdot I$, $r^2 = 0.931$, $F(1, 2) = 27.0$, $p < 0.0012$. The C value for the old system was 0.16 bit/s, while the C value for the new system was 0.31 bit/s. Figure 4-2 shows the linear regression plots for both systems.

Table 4-4 Aggregated point-and-click data for Fitts' law analysis of old system

D (mm)	W (mm)	I (bits)	T (s)	C = I/T (bits/s)
180	8.5	4.47	26.87	0.166
180	12.5	3.94	24.24	0.163
180	17	3.53	19.74	0.179
180	22	3.20	19.80	0.162

Table 4-5 Aggregated point-and-click data for Fitts' law analysis of new system

D (mm)	W (mm)	I (bits)	T (s)	C = I/T (bits/s)
180	8.5	4.47	16.34	0.274
180	12.5	3.94	15.13	0.261
180	17	3.53	12.75	0.277
180	22	3.2	12.63	0.253

Figure 4-2 Fitts' law regression lines for both cursor control systems

4.2 Results from Experiment 1 for the Complete System

4.2.1 Statistical Analysis Results

The trial time and error rate results collected during experiment 1 (described in Section 3.7.2) were arranged separately and analyzed as mixed design ANOVAs. Such

statistical tests are based on the parametric assumptions of normality and homoscedasticity. The normality assumption requires that the data variables be from normally distributed populations, while the homoscedasticity assumption requires that the variability of the scores for a given continuous variable be roughly equal at all the values of another continuous variable. Both the trial time and error rate data were found to be substantially non-normal in their distributions. This resulted in the logarithmic transformations of both the trial time [$\log_{10}(X)$] and error rate [$\log_{10}(X + 1)$] data sets. For the repeated measures analyses performed, the assumption of homoscedasticity reduces to that of sphericity. Sphericity is the assumption that the variances of the differences between treatment levels are roughly equal. This assumption is checked in SPSS using Mauchly's test of sphericity. If this test indicates that the assumption of sphericity has been violated for a specific main effect or interaction, then it is recommended by Field that the Greenhouse-Geisser correction of the F-statistic be used [47].

The trial time data was analyzed first. Table 4-6 shows that Mauchly's test of sphericity was significant for the main effects of angle and distance, as well as, a few interactions.

Table 4-7 displays only the significant main effects and interactions, at a 0.05 level, from the within-subjects effects table produced by SPSS. The table shows that the main effects of target size and task distance were significant. Also, the interactions of size*technique and rep*distance were found to be significant.

Table 4-6 Mauchly's test for sphericity for experiment 1 time data

Measure: time

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon(a)		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
rep	1.000	0.000	0.000	.	1.000	1.000	1.000
size	0.997	0.080	2.000	0.961	0.997	1.000	0.500
angle	0.561	14.879	5.000	0.011	0.807	0.957	0.333
distance	0.509	17.567	2.000	0.000	0.671	0.745	0.500
rep * size	0.942	1.562	2.000	0.458	0.945	1.000	0.500
rep * angle	0.836	4.621	5.000	0.464	0.888	1.000	0.333
size * angle	0.187	41.532	20.000	0.003	0.647	0.825	0.167
rep * size * angle	0.225	36.950	20.000	0.012	0.682	0.879	0.167
rep * distance	0.948	1.393	2.000	0.498	0.950	1.000	0.500
size * distance	0.443	20.711	9.000	0.014	0.767	0.940	0.250
rep * size * distance	0.536	15.872	9.000	0.070	0.788	0.970	0.250
angle * distance	0.310	29.004	20.000	0.090	0.718	0.934	0.167
rep * angle * distance	0.175	43.218	20.000	0.002	0.688	0.888	0.167
size * angle * distance	0.005	120.557	77.000	0.002	0.603	0.906	0.083
rep * size * angle * distance	0.002	138.585	77.000	0.000	0.538	0.777	0.083

Levene's test for homogeneity of variances for the between-subject factor of cursor control technique produced significant effects for 62 out of 72 variables. These violations are not fatal for the analysis, because ANOVAs with equal sample sizes have been found to be robust when such violations occur [48]. The tests of between-subjects effects is shown in Table 4-8, and it reveals a significant effect for cursor control technique. The contrasts for these between-subjects effects (Table 4-9), taken together with the mean values reported in Table 4-10 and displayed in Figure 4-3, reveal that the EMG/EGT technique (level 2 in Table 4-9) is significantly slower than both the mouse (level 1 in Table 4-9) and EGT (level 3 in Table 4-9) techniques. Also, to give the trial time results a "real world" context, the marginal means of cursor control technique for the untransformed trial time data are given in Table 4-11.

Table 4-7 Tests of within-subjects effects for experiment 1 time data

Measure: time

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
size	Sphericity Assumed	14.941	2.000	7.470	164.834	0.000
	Greenhouse-Geisser	14.941	1.994	7.493	164.834	0.000
	Huynh-Feldt	14.941	2.000	7.470	164.834	0.000
	Lower-bound	14.941	1.000	14.941	164.834	0.000
size * Techniq	Sphericity Assumed	2.921	4.000	0.730	16.114	0.000
	Greenhouse-Geisser	2.921	3.988	0.733	16.114	0.000
	Huynh-Feldt	2.921	4.000	0.730	16.114	0.000
	Lower-bound	2.921	2.000	1.461	16.114	0.000
Error(size)	Sphericity Assumed	2.447	54.000	0.045		
	Greenhouse-Geisser	2.447	53.835	0.045		
	Huynh-Feldt	2.447	54.000	0.045		
	Lower-bound	2.447	27.000	0.091		
distance	Sphericity Assumed	10.922	2.000	5.461	44.615	0.000
	Greenhouse-Geisser	10.922	1.341	8.144	44.615	0.000
	Huynh-Feldt	10.922	1.490	7.329	44.615	0.000
	Lower-bound	10.922	1.000	10.922	44.615	0.000
Error(distance)	Sphericity Assumed	6.610	54.000	0.122		
	Greenhouse-Geisser	6.610	36.213	0.183		
	Huynh-Feldt	6.610	40.235	0.164		
	Lower-bound	6.610	27.000	0.245		
rep * distance	Sphericity Assumed	0.394	2.000	0.197	5.569	0.006
	Greenhouse-Geisser	0.394	1.901	0.207	5.569	0.007
	Huynh-Feldt	0.394	2.000	0.197	5.569	0.006
	Lower-bound	0.394	1.000	0.394	5.569	0.026
Error(rep*distance)	Sphericity Assumed	1.912	54.000	0.035		
	Greenhouse-Geisser	1.912	51.323	0.037		
	Huynh-Feldt	1.912	54.000	0.035		
	Lower-bound	1.912	27.000	0.071		

Table 4-8 Tests of between-subjects effects for experiment 1 time data

Measure: time

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	319.805	1.000	319.805	35031.526	0.000
Techniq	1.486	2.000	0.743	81.375	0.000
Error	0.246	27.000	0.009		

Of all the significant interactions found in Table 4-7, the technique*size interaction is of particular interest, because it allows the comparison of the mean $\log_{10}(\text{trial time})$ values for the EMG/EGT and EGT techniques when interacting with targets large enough to be selected reliably by the EGT technique. In this experiment, this target size was 96 pixels or 2.2° . Table 4-12 displays the logarithms of mean trial

times for the various levels of the technique*size interaction, and Figure 4-4 gives the corresponding plot for the dependent variable of $\log_{10}(\text{trial time})$. In addition, Table 4-13 gives the corresponding untransformed descriptive statistics for the technique*size interaction.

Table 4-9 Between-subjects contrast results for time data

Cursor Control Techniques		Averaged Variable
Repeated Contrast		time
Level 1 vs. Level 2	Contrast Estimate	-0.542
	Hypothesized Value	0.000
	Difference (Estimate - Hypothesized)	-0.542
	Std. Error	0.043
	Sig.	0.000
	95% Confidence Interval for Difference	
	Lower Bound	-0.630
	Upper Bound	-0.454
Level 2 vs. Level 3	Contrast Estimate	0.220
	Hypothesized Value	0.000
	Difference (Estimate - Hypothesized)	0.220
	Std. Error	0.043
	Sig.	0.000
	95% Confidence Interval for Difference	
	Lower Bound	0.132
	Upper Bound	0.307

Table 4-10 Marginal means of cursor control technique variable for time data

Measure: time

Cursor Control Techniques	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Mouse	2.977	0.030	2.915	3.039
EMG/EGT	3.519	0.030	3.457	3.581
EGT	3.299	0.030	3.237	3.361

One might observe that the mean trial time reported for the EGT technique for the largest target size (1731 ms in Table 4-13) is significantly larger than the mean trial times of 503.7 ms and 1103.0 ms reported in Sibert's paper [3]. There are two possible reasons for this difference. Firstly, the system tested by Sibert utilized a gaze dwell time of 150 ms to produce a left-click. This was significantly shorter than the 350 ms dwell time chosen (Section 3.6) for the EGT system tested in this experiment. Secondly, the mean times reported by Sibert were the results of a procedure that classified trial times that

occurred outside of 1.5 times the interquartile range as outliers, and removed these outliers from the data set. Her argument for this was that excessively long or short trials were due to momentary equipment problems with the eye tracker. In contrast, the objective of this study was not to determine the idealized performance of an eye tracking system, but to investigate its usability in applications that resembled those found in the real world. Therefore, the complete data set of EGT trial times from this experiment was analyzed.

Figure 4-3 Bar chart of mean $\log_{10}(\text{time})$ values for cursor control techniques (error bars = 95% confidence interval)

Table 4-11 Marginal means of cursor control technique variable for untransformed time data

Measure: time

Cursor Control Techniques	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Mouse	983.918	379.923	204.381	1763.456
EMG/EGT	4684.967	379.923	3905.429	5464.504
EGT	3069.806	379.923	2290.268	3849.343

Table 4-12 Marginal means of cursor control technique*size interaction for time data

Measure: time

Cursor Control Techniques	size	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
Mouse	1.000	3.018	0.034	2.948	3.088
	2.000	2.979	0.031	2.916	3.042
	3.000	2.934	0.032	2.869	2.999
EMG/EGT	1.000	3.631	0.034	3.560	3.701
	2.000	3.524	0.031	3.461	3.587
	3.000	3.402	0.032	3.337	3.466
EGT	1.000	3.454	0.034	3.384	3.524
	2.000	3.287	0.031	3.224	3.350
	3.000	3.156	0.032	3.091	3.221

Figure 4-4 Plot of cursor control technique*size interaction for time dependent variable

Table 4-13 Marginal means of cursor control technique*size interaction for untransformed time data

Measure: time

Cursor Control Techniques	size	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
Mouse	1	1081.871	512.199	30.925	2132.816
	2	986.554	380.953	204.904	1768.204
	3	883.329	409.422	43.264	1723.394
EMG/EGT	1	5675.367	512.199	4624.421	6726.312
	2	4642.654	380.953	3861.004	5424.304
	3	3736.879	409.422	2896.814	4576.944
EGT	1	4881.763	512.199	3830.817	5932.708
	2	2597.058	380.953	1815.408	3378.708
	3	1730.596	409.422	890.531	2570.661

Mauchly's test for sphericity of the error rate data produced violations for all but two of the factors and interactions (Table 4-14). Table 4-15 displays only the significant main effects and interactions, at a 0.05 level, from the within-subjects effects table produced. The table shows that the main effects of target size and task distance were significant. Also the interactions of size*technique, distance*technique, rep*distance and rep*distance*technique were found to be significant.

Table 4-14 Mauchly's test for sphericity for experiment 1 error data

Measure: error

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon(a)		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
rep	1.000	0.000	0.000	.	1.000	1.000	1.000
size	0.663	10.687	2.000	0.005	0.748	0.841	0.500
angle	0.427	21.871	5.000	0.001	0.738	0.866	0.333
distance	0.511	17.471	2.000	0.000	0.671	0.746	0.500
rep * size	0.845	4.381	2.000	0.112	0.866	0.988	0.500
rep * angle	0.693	9.437	5.000	0.093	0.810	0.962	0.333
size * angle	0.043	77.804	20.000	0.000	0.528	0.651	0.167
rep * size * angle	0.100	56.969	20.000	0.000	0.606	0.764	0.167
rep * distance	0.380	25.154	2.000	0.000	0.617	0.680	0.500
size * distance	0.236	36.661	9.000	0.000	0.579	0.683	0.250
rep * size * distance	0.336	27.730	9.000	0.001	0.701	0.849	0.250
angle * distance	0.052	73.035	20.000	0.000	0.539	0.666	0.167
rep * angle * distance	0.116	53.331	20.000	0.000	0.624	0.790	0.167
size * angle * distance	0.000	193.715	77.000	0.000	0.510	0.725	0.083
rep * size * angle * distance	0.000	204.090	77.000	0.000	0.456	0.628	0.083

Table 4-15 Tests of within-subjects effects for experiment 1 error data

Measure: error		Type III Sum of Squares	df	Mean Square	F	Sig.
size	Sphericity Assumed	3.586	2.000	1.793	51.051	0.000
	Greenhouse-Geisser	3.586	1.496	2.397	51.051	0.000
	Huynh-Feldt	3.586	1.681	2.133	51.051	0.000
	Lower-bound	3.586	1.000	3.586	51.051	0.000
size * Techniq	Sphericity Assumed	6.097	4.000	1.524	43.401	0.000
	Greenhouse-Geisser	6.097	2.992	2.038	43.401	0.000
	Huynh-Feldt	6.097	3.362	1.813	43.401	0.000
	Lower-bound	6.097	2.000	3.048	43.401	0.000
Error(size)	Sphericity Assumed	1.896	54.000	0.035		
	Greenhouse-Geisser	1.896	40.387	0.047		
	Huynh-Feldt	1.896	45.390	0.042		
	Lower-bound	1.896	27.000	0.070		
distance	Sphericity Assumed	1.439	2.000	0.719	5.789	0.005
	Greenhouse-Geisser	1.439	1.343	1.071	5.789	0.014
	Huynh-Feldt	1.439	1.492	0.964	5.789	0.011
	Lower-bound	1.439	1.000	1.439	5.789	0.023
distance * Techniq	Sphericity Assumed	2.511	4.000	0.628	5.051	0.002
	Greenhouse-Geisser	2.511	2.686	0.935	5.051	0.006
	Huynh-Feldt	2.511	2.985	0.841	5.051	0.005
	Lower-bound	2.511	2.000	1.255	5.051	0.014
Error(distance)	Sphericity Assumed	6.710	54.000	0.124		
	Greenhouse-Geisser	6.710	36.259	0.185		
	Huynh-Feldt	6.710	40.291	0.167		
	Lower-bound	6.710	27.000	0.249		
rep * distance	Sphericity Assumed	0.332	2.000	0.166	5.870	0.005
	Greenhouse-Geisser	0.332	1.235	0.269	5.870	0.016
	Huynh-Feldt	0.332	1.360	0.244	5.870	0.013
	Lower-bound	0.332	1.000	0.332	5.870	0.022
rep * distance * Techniq	Sphericity Assumed	0.491	4.000	0.123	4.336	0.004
	Greenhouse-Geisser	0.491	2.469	0.199	4.336	0.015
	Huynh-Feldt	0.491	2.720	0.181	4.336	0.012
	Lower-bound	0.491	2.000	0.246	4.336	0.023
Error(rep*distance)	Sphericity Assumed	1.529	54.000	0.028		
	Greenhouse-Geisser	1.529	33.334	0.046		
	Huynh-Feldt	1.529	36.717	0.042		
	Lower-bound	1.529	27.000	0.057		

Levene's test for homogeneity of variances for the between-subject factor of cursor control technique produced significant effects for 71 out of 72 variables. As stated previously, this is not detrimental, and we can regard the results of the between-subjects tests (Table 4-16), which indicate a significant effect for cursor control technique, as valid. The contrasts for these between-subjects effects (Table 4-17), taken together with

the mean values reported in Table 4-18 and displayed in Figure 4-5, reveal that the EMG/EGT technique (level 2 in Table 4-17) can be considered to have a comparable error rate with the mouse technique (level 1 in Table 4-17). Also, the EMG/EGT technique was found to have a significantly smaller error rate than the EGT (level 3 in Table 4-17) technique. Also, the marginal means of cursor control technique for the untransformed error rate data are given in Table 4-19.

Table 4-16 Tests of between-subjects effects for experiment 1 error data

Measure: error

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	1.039	1.000	1.039	263.259	0.000
Techniq	1.615	2.000	0.808	204.611	0.000
Error	0.107	27.000	0.004		

Table 4-17 Between-subjects contrast results for error data

Cursor Control Techniques		Averaged Variable
Repeated Contrast		error
Level 1 vs. Level 2	Contrast Estimate	-0.036
	Hypothesized Value	0.000
	Difference (Estimate - Hypothesized)	-0.036
	Std. Error	0.028
	Sig.	0.206
	95% Confidence Interval for Difference	
	Lower Bound	-0.094
	Upper Bound	0.021
Level 2 vs. Level 3	Contrast Estimate	-0.473
	Hypothesized Value	0.000
	Difference (Estimate - Hypothesized)	-0.473
	Std. Error	0.028
	Sig.	0.000
	95% Confidence Interval for Difference	
	Lower Bound	-0.531
	Upper Bound	-0.415

Table 4-18 Marginal means of cursor control technique variable for error data

Measure: error

Cursor Control Techniques	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Mouse	0.004	0.020	-0.037	0.045
EMG/EGT	0.041	0.020	0.000	0.081
EGT	0.514	0.020	0.473	0.554

Figure 4-5 Bar chart of mean log10(error) values for cursor control techniques (error bars = 95% confidence interval)

Table 4-19 Marginal means of cursor control technique variable for untransformed error data

Measure:error				
Cursor Control Techniques	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Mouse	0.014	0.245	-0.489	0.517
EMG/EGT	0.135	0.245	-0.368	0.637
EGT	3.976	0.245	3.474	4.479

4.2.2 Fitts' Law Analysis Results

It was decided to apply Fitts' law analysis to only the EMG/EGT and mouse data initially, because of the uncertainty as to whether the EMG/EGT data would correlate well with Fitts' model. This is because, it has been argued [3, 4] that EGT systems

operating on their own are not adequately modeled by Fitts' law. The combination of three task distances and three target sizes provided nine unique task conditions for which movement time (T) and effective index of difficulty (I_e) values could be calculated for each cursor control technique. As mentioned earlier, an I_e value is based on an effective width value (W_e), which is in turn derived from the standard deviation of the projections of the selection points unto the task axis [equation (3-13)]. Evaluation of the projection values indicated that there were some selection points that could be due to unintentional selections, because of the large distances between these points and the target center. Furthermore, these points had the effect of making the standard deviation values unexpectedly large, and consequently the W_e values were also unusually large. In order to rectify this situation, it was determined that a criterion be put in place to identify such selection points as outliers and remove them from the data set. The criterion involved calculating 3 times the interquartile range of the data corresponding to a given I_e , as well as, 3 times the target diameter used in the tasks associated with the I_e value. If the projection of a given selection point was found to be greater than the larger of the two measures, then it would be classified as an outlier. This procedure resulted in the removal of 11 points out of approximately 720 for the EMG/EGT data, and three out of approximately 720 for the mouse data.

The tabulated results for the analysis are displayed in Tables 4-20 and 4-21 for the EMG/EGT and mouse techniques, respectively. Also, the (I_e , T) points and the associated linear regression lines are given for the EMG/EGT and mouse inputs in Figures 4-6 and 4-7, respectively.

Table 4-20 Aggregated point-and-click data for Fitts' law analysis of EMG/EGT input

D (pixels)	W _e (pixels)	I _e (bits)	T (s)	C = I _e /T (bits/s)
286	65.522	2.424	4.252	0.570
578	69.011	3.229	7.015	0.460
778	51.009	4.023	5.468	0.736
286	70.165	2.343	3.649	0.642
578	77.491	3.080	4.413	0.698
778	76.810	3.476	4.797	0.725
286	124.406	1.722	3.185	0.541
578	115.967	2.581	3.345	0.772
778	121.056	2.893	3.752	0.771

Table 4-21 Aggregated point-and-click data for Fitts' law analysis of mouse input

D (pixels)	W _e (pixels)	I _e (bits)	T (s)	C = I _e /T (bits/s)
286	37.542	3.107	0.882	3.524
578	35.213	4.122	1.088	3.790
778	37.292	4.450	1.276	3.487
286	45.704	2.859	0.779	3.670
578	44.559	3.804	1.010	3.766
778	47.897	4.108	1.170	3.510
286	68.625	2.369	0.699	3.391
578	87.077	3.524	1.029	3.424
778	74.059	2.893	3.752	0.771

Equations (4-1) and (4-2) give the Fitts' model representations of the EMG/EGT and mouse techniques, respectively.

$$T = 0.945 + 1.217I_e \quad (\text{EMG/EGT}) \quad (4-1)$$

$$T = 0.099 + 0.255I_e \quad (\text{Mouse}) \quad (4-2)$$

Figure 4-6 (I_e , T) data points and Fitts' law regression line for EMG/EGT input

Figure 4-7 (I_e , T) data points and Fitts' law regression line for mouse input

The statistics associated with the EMG/EGT equation ($r^2 = 0.474$, $F(1, 7) = 6.296$, $p = 0.04$) suggest that this cursor control technique does not match well with Fitts' model.

This can be compared to the statistics produced for the mouse ($r^2 = 0.933$, $F(1, 7) = 97.294$, $p < 0.0005$), which indicate that the technique is well matched with the model.

4.2.3. Target Re-entry Results

The TRE data were found to exhibit significant non-normality and were transformed logarithmically [$\log_{10}(X+1)$] to make the distribution more normal. These data were then analyzed using an independent-samples t-test. Table 4-22 indicates that there is a significant difference between the EMG/EGT and mouse techniques in terms of TRE results ($p = 0.004$), with Tables 4-23 and 4-24, along with Figure 4-8 revealing that the EMG/EGT technique is prone to more target re-entries per trial.

Table 4-22 T-test results for TRE analysis

Independent Samples Test										
		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Log10(Mean TRE)	Equal variances assumed	8.723	0.009	-3.665	18.000	0.002	-0.077	0.021	-0.121	-0.033
	Equal variances not assumed			-3.665	10.068	0.004	-0.077	0.021	-0.124	-0.030

Table 4-23 Descriptive statistics for TRE data

Group Statistics					
Cursor Control Technique		N	Mean	Std. Deviation	Std. Error Mean
Log10(Mean TRE)	Mouse	10	.01105	.015754	.004982
	EMG/EGT	10	.08806	.064554	.020414

Table 4-24 Descriptive statistics for untransformed TRE data

Measure: tre

Cursor Control Technique	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
Mouse	0.026	0.044	-0.067	0.120
EMG/EGT	0.238	0.044	0.144	0.331

Figure 4-8 Bar Chart of Log10(Mean TRE) Values for Mouse and EMG/EGT Techniques (Error Bars = 95% Confidence Interval)

To give a more detailed view of how many target re-entries occurred on a per trial basis using the EMG/EGT system, a histogram and a TRE count/trial table were created (Figure 4-9 and Table 4-25). Of the 720 trials under evaluation, the most frequent TRE count/trial value was 0, which occurred 616 times or 85.6% of the time. For TRE count/trial values greater than 0, the frequency of occurrence decreased rapidly with

increasing TRE count/trial value. For example, if one were to consider the frequency occurrence of TRE count/trial values greater than 4, one would find that this occurred on only three occasions or 0.4% of the time. The largest TRE count/trial value produced by any trial was 11.

Figure 4-9 Histogram of TRE count/trial values for the EMG/EGT system

Table 4-25 Table giving frequency of occurrence of TRE count/trial values produced by EMG/EGT data of
experiment 1

TRE Count/Trial	0	1	2	3	4	5	6	7	8	9	10	11
Frequency of Occurrence	616	71	17	8	5	1	1	0	0	0	0	1

Also of interest was how the TRE values were distributed among the ten subjects that used the EMG/EGT system in the experiment. These values are given in Table 4-26. The table shows that the TRE totals per subject ranged from a maximum of 49 to a minimum of 2.

Table 4-26 TRE total distribution among the EMG/EGT subjects

Subject #	TRE Total	TRE value = Total TRE/(Total Trials per subject)
3	6	0.0833
5	27	0.375
7	2	0.028
9	49	0.681
17	5	0.069
18	7	0.097
21	14	0.194
22	23	0.319
28	17	0.236
29	21	0.291

4.3 Results from Experiment 2 for the Complete System

The data collected for experiment 2 (described in Section 3.7.3) were examined to determine how many selections of “N” label targets occurred per session. These selections were interpreted as selection errors, and the total of these errors were divided by the total of “N” label targets presented per session (16). This produced a selection error proportion for each session, which meant that four such treatment values (2 cursor control techniques x 2 sessions) were recorded for each subject participating in the experiment. The results of this pre-processing procedure were then analyzed in SPSS using the Friedman test.

The mean ranks for each treatment condition and the test results are shown in Tables 4-27 and 4-28 respectively. These tables reveal that differences between treatments were significant. Table 4-29 in turn reveals that these differences were due to effects of cursor control techniques, because significant differences were only found between treatments that involved different techniques. Table 4-30 and Figure 4-10 show that mean error rate was lower for the EMG/EGT technique compared to the EGT technique.

Table 4-27 Mean Rank Results for Friedman Test

Ranks	
	Mean Rank
EMG/EGT + Session1 = Error Rate	1.40
EMG/EGT + Session2 = Error Rate	1.63
EGT + Session1 = Error Rate	3.70
EGT + Session2 = Error Rate	3.27

Table 4-28 Friedman Test Result

Test Statistics	
N	15
Chi-Square	38.464
df	3
Asymp. Sig.	.000

Table 4-29 Wilcoxon Signed Ranks Test Results

Test Statistics(c)						
	EMG/EGT + Session2 = Error rate - EMG/EGT + Session1 = Error rate	EGT + Session1 = Error rate - EMG/EGT + Session1 = Error rate	EGT + Session2 = Error rate - EMG/EGT + Session1 = Error rate	EGT + Session1 = Error rate - EMG/EGT + Session2 = Error rate	EGT + Session2 = Error rate - EMG/EGT + Session2 = Error rate	EGT + Session2 = Error rate - EGT + Session1 = Error rate
Z	-0.632	-3.413	-3.417	-3.419	-3.306	-1.364
Asymp. Sig. (2-tailed)	0.527	0.001	0.001	0.001	0.001	0.173

Table 4-30 Descriptive Statistics of the Four Treatment Conditions Used in Experiment 2

Descriptive Statistics					
	N	Mean	Std. Deviation	Minimum	Maximum
EMG/EGT + Session1 = Error rate	15	.01	.035	0	0
EMG/EGT + Session2 = Error rate	15	.020833	.0304969	.0000	.0625
EGT + Session1 = Error rate	15	.425000	.1479020	.1875	.6250
EGT + Session2 = Error rate	15	.366667	.1765661	.0625	.7500

Figure 4-10 Bar Chart of Mean Error Rates for EMG/EGT and EGT Techniques (Error Bars = 95% Confidence Interval)

CHAPTER 5

DISCUSSION

The results of the experiments used to compare the new EMG system to the old EMG system have shown that the effect of adding a fourth EMG input channel and replacing the previous classification algorithm with a new one, resulted in the improved performance of this component of the hybrid system. In particular, the off-line assessments have shown that the new EMG system is more accurate in classifying muscle contractions when compared to the previous implementation (98.42% compared to 78.43%). This improved accuracy has resulted in faster performance in real-time cursor control operations (8.45 s faster for the click-point-click tests), and an increased capacity to process task information (0.31 bit/s compared to 0.16 bits/s).

The statistical analysis of experiment 1 data has formalized some interesting observations regarding the EMG/EGT system. Firstly, it seems that the addition of the EMG-based interaction to the EGT-based interaction has resulted in a reduction of the user's speed in performing cursor control tasks (4685 ms mean trial time for EMG/EGT compared to 3070 ms for mean trial time for EGT). The slowing effect of the EMG-based interaction can be examined more closely when one considers the cursor control technique*size interaction for the dependent variable of trial time (Table 4-12 and Figure 4-4). The target diameters for this experiment were set at values for which only the largest target (96 pixels diameter) was found to be reliably selectable by the EGT input. The lack of reliability for selecting the other target sizes (48 pixels diameter and 66 pixels diameter) was due to the inherent low level of accuracy of EGT-based inputs, coupled with the occurrence of POG offsets due to minor head movements or imperfect

interpolations between the calibration points on the screen. This meant that a user of the EGT system would have to shift his/her gaze around the intended target in order to eventually select it. This compensatory activity performed by the EGT users resulted in a dramatic increase in trial times (1731 ms for 96 pixel target to 4882 ms for 48 pixel target). When EMG/EGT users were confronted with these smaller target sizes, they utilized EMG-based control to make up for the lack of accuracy exhibited by the EGT subsystem, instead of the compensatory eye movements employed by EGT users. Unfortunately, the fact that EMG/EGT users were required to coordinate eye movements with facial movements resulted in a task time penalty being incurred, in addition to the task time associated with eye-based control when it is operating in isolation. The only way to observe the full extent of this task time penalty would be to provide a task of negligible difficulty for users of the EGT input to perform. This would theoretically result in negligible task times for the EGT users, and when these task times are compared to those produced by EMG/EGT users performing the same tasks, an estimate of the task time penalty would be found. The closest available scenario to this theoretical situation was when the target diameter was set to 96 pixels. The difference between EGT mean trial time and EMG/EGT mean trial time in this scenario was -2006 ms (1731 ms – 3737 ms). This implies that the task time penalty incurred by integrating EMG control with EGT control was approximately 2 s.

A review of only the trial time results might lead one to conclude that there would be no benefit to integrating EMG and EGT modalities. However, the benefits of this integration are strongly validated by the error rate results. The mean error rates for the three cursor control techniques were: 0.014 errors/trial for the mouse, 0.135

errors/trial for EMG/EGT, and 3.976 errors/trial for EGT (refer to Table 4-19). These mean values showed that the EMG/EGT system produced significantly less errors than the EGT input ($p < 0.0005$ for contrast in Table 4-17), for the target sizes used in this experiment. In fact, the EMG/EGT input produced an error rate similar to that produced by the mouse input ($p = 0.206$ for contrast in Table 4-17). Again, the large difference in error rate values between the EMG/EGT and EGT inputs can be attributed to the different approaches employed by the users of the respective systems when selecting the smaller target sizes. The unnatural shifting of eye gaze in the region of these smaller targets, which was utilized by EGT users to compensate for its inaccuracy, often resulted in unintended left-clicks being issued in the region surrounding the target. These left-clicks were recorded as errors by the Visual Basic program used to present the trials to the user. The reason for these unintended left-clicks can be traced to the fact that target selection was based on dwell time for the EGT modality. When EMG-based input was used to compensate for the lack of accuracy of EGT-based input, it enabled the user to have incremental control of cursor movement, and it allowed the user to no longer be dependent on eye tracking input to perform selection operations. These two advantages provided by EMG/EGT control resulted in a more reliable icon selection mechanism, especially suited for high resolution environments.

The results of Fitts' law analysis indicated that the ballistic nature of eye movements was not well modeled by this law, and the strong influence of these movements on the EMG/EGT technique made EMG/EGT a poor match for the model ($r^2 = 0.474$). This was despite the fact that the EMG modality on its own had been shown to correlate well with Fitts' model [44]. These findings agree with those presented by Sibert

[3, 4], where she found that the eye movement required for EGT input was not well correlated with Fitts' model ($r^2 = 0.02$). These results suggest that a new model may be required to characterize the cursor control performance of this kind of input system.

Examination of the target re-entry results revealed that, on average, EMG/EGT users were more susceptible to committing target re-entries when compared to users of the mouse (0.238 mean TRE/trial for EMG/EGT as opposed to 0.026 mean TRE/trial for the mouse). This suggests that EMG/EGT users have a lesser ability to control the cursor during the homing phase of a point-and-click trial when compared to mouse users. A closer look at the individual trials completed by the group of ten EMG/EGT users indicated that these trials could be divided into three categories according to the nature of movements that characterized the trials. These three categories are:

- i. An initial EGT-based cursor movement which is terminated by an EMG-based object selection.
- ii. An initial EGT-based cursor movement followed by a succession of EMG-based cursor steps, which is in turn terminated by an EMG-based object selection.
- iii. An initial EGT-based cursor movement followed by a mixture of EMG-based and EGT-based cursor movements, which is eventually terminated by an EMG-based object selection.

Actual trials that exemplify each category are displayed in Figures 5-1 through to 5-3.

Figure 5-1 Example of a category i EMG/EGT trial

Figure 5-2 Example of a category ii EMG/EGT trial

Figure 5-3 Example of a category iii EMG/EGT trial

It can be deduced from the inspection of three figures that it was the category iii trials that produced target re-entries. The interspersing of EGT- and EMG-based cursor movements, unique to category iii trials, may be explained by the user's inability to suppress the natural tendency of his/her eye gaze to wander significantly from the target region while he/she should be using EMG-based movements to home in on the target. The EMG/EGT mean trial time for all target sizes (4685 ms), and especially the mean trial times for the two smaller target sizes (4643 ms and 5675 ms) could be considered unnaturally long times to maintain one's gaze in a specific area, and was probably a contributing factor to the TRE values increasing with decreasing target size. However, the occurrence of target re-entries during a trial was far from regular, with the TRE count/trial of 0 occurring 85.6% of the time. This suggests that the loss of coordination

between eye gaze and facial movements was only a sporadic occurrence for all users. In addition, the distribution of target re-entries across subjects showed that the two individuals with more than one hour's worth of experience had two of the three lowest TRE totals (6 and 2) for the allotment of 72 trials they were each required to perform. This implies that the other users, who only had approximately 30 minutes of training prior to performing the experiment, might require additional training time to become truly proficient in using the hybrid cursor control system. This additional training could potentially result in lower trial times and TRE counts/trial values being recorded from each user, indicating more proficient operation of the EMG/EGT system.

The primary purpose of conducting experiment 2 was to establish, through statistical analysis, that the EMG/EGT system was not as susceptible to gaze-based selection errors as an eye tracking system that used gaze dwell time as the basis for its selection operation. This would seem intuitive, because the selection operation for the EMG/EGT technique was performed by the EMG-monitored action of clenching both sides of the jaw simultaneously and was not dependent on gaze time. The statistical results supported this assumption with the EGT technique producing a mean gaze-based selection error rate of 0.396, and the EMG/EGT technique having 0.017 error rate. A secondary reason for conducting experiment 2 was to see how prone to errors a gaze dwell time selection system would be for tasks that could elicit such errors. This type of experiment had not been conducted previously by the proponents of gaze dwell time-based EGT selection techniques [3, 4, 10]. In their experiments, the targets presented to the user were always required to be selected, that is, no decision was necessary. As discussed previously, the gaze time was set to 350 ms for the EGT system used in

experiment 2. This was empirically found to be the best compromise between the speed of selection and the ability to avoid unintended selections, while remaining within range of gaze times reported by Sibert and Ware, that is, 150 ms to 400 ms. The gaze-based selection error rate produced by this technique was approximately 40%, which implies that EGT techniques that use dwell time to directly issue left-clicks would not be recommended for environments where unintended selections based on gaze are possible.

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE WORK

A hybrid EMG/EGT system was created that has the following key performance features:

- 1) It does not require the use of hands to perform computer cursor operations.
- 2) It provides the ability to modify cursor position on a pixel by pixel basis, that is, the system does not possess a spatial accuracy limitation.
- 3) It provides a reliable left-click operation.

Taken together, these features make the EMG/EGT system a viable option if a user requires a hands-free form of cursor control that is able to execute point-and-click actions in a high resolution Window, Icon, Menu, Pointing Device (WIMP) environment, or in an internet browser application.

Feature 1) is the primary advantage of using the EMG/EGT system instead of a mouse, while features 2) and 3) are the advantages of using the hybrid system in place of an EGT system which utilizes gaze dwell time to execute selections.

The shortcomings of this system are its relatively slow point-and-click speed when compared to a mouse or an EGT system, as well as, its reduced ability to control the cursor during the homing phase of a point-and-click trial. However, the average performance results exhibited by the two subjects with the most experience in using the EMG/EGT system (mean trial time = 3.566 s, and mean TRE value = 0.056) lead to the expectation that the overall performance metrics could be improved if each user was given increased training time.

Though significant steps have been made in enhancing the performance and usability of the EMG/EGT device, there still remains work to be done in making this system accessible to computer users outside a laboratory environment. A major impediment to the real world application of this device is the requirement that the EMG subsystem must be calibrated for each user session as a precursor to functional operation. The calibration procedure for the EMG subsystem requires that five distinct thresholds be set for the maximum PSD magnitudes. These thresholds are used to classify the onset of the five unique muscle contractions. The feature set utilized in the EMG classification algorithm was determined heuristically. Therefore, there remains a possibility that other features of the EMG signal could be used in conjunction with those used previously to create a new feature set for which a generalized solution exists. In other words, if such a new feature set can be used to train a learning classification algorithm (e.g. an artificial neural network) then the convergence value of this algorithm will represent a set of features that will allow any subsequent user to operate the EMG subsystem efficiently without further calibration.

The EGT subsystem has applicability limitations because it requires an initial calibration prior to each user session, and subsequent to the calibration, its accuracy is significantly affected by head motion. The calibration issue may be resolved by applying a learning algorithm to the coefficients of the function used to map the orientation of eye features to POG coordinates (similar to the recommendation for the EMG subsystem). The issue of obtaining an EGT system that produces accurate POG estimates in the presence of large head movements might require modifying or replacing the

aforementioned mapping function and/or creating a new infra-red LED/camera system that has the ability to measure features that are invariant with head motion.

Finally, a series of point-and-click sessions should be conducted on a group of subjects to investigate how their trial time and TRE values performance metrics change with increased usage of the EMG/EGT system. These results might verify the assumption that the present results produced by the EMG/EGT users did not reflect the optimal user performance metrics, because these users needed more training.

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APPENDICES

APPENDIX A - IRB APPROVAL DOCUMENTS

Office of Research Integrity
Research Compliance, MARC 430

MEMORANDUM

To: Dr. Armando Barreto
CC: File
From: Chris Grayson, CIM, Institutional Review Board Coordinator
Date: June 16, 2006
Proposal Title: Signal Processing and Information Fusing Algorithms for the Synthesis of an Alternative Electromyogram/Eye Gaze Tracking Computer Cursor Control System.
Approval # 061306-03

The Institutional Review Board of Florida International University has approved your study for the use of human subjects. Your IRB approval date is **June 13, 2006** and this approval will expire on **June 13, 2007**. As a requirement of IRB approval you are required to:

- 1) Provide immediate written notification to the IRB of:
 - Any additions to, or changes in the procedures involving human subjects.
 - Every serious or unusual or unanticipated adverse event as well as problems with the rights or welfare of the human subjects. Confirmation of receipt of serious AE reports must be made with the IRB office.
- 2) Utilize copies of the date stamped consent document(s) for the recruitment of subjects and receive annual renewal of consent documents.
- 3) **Receive annual review and re-approval prior to your expiration date.**

Special Conditions: N/A

Please note your approval number is indicated above. For further information, you may contact the IRB Coordinator by email at irbjaeuc@fiu.edu or visit the OSRA Human Subjects website at www.osra.fiu.edu.

Consent to Participate in a Research Study

Title: Signal Processing and Information Fusing Algorithms for the Synthesis of an Alternative Electromyogram / Eye Gaze Tracking Computer Cursor Control System

You are asked to participate in a research project listed above to be conducted at Florida International University with Dr. Armando Barreto as the principal investigator. The purpose of this investigation is to determine how effective a new method for controlling the computer cursor is in its ability to perform pointing and selection ("clicking") tasks. The study will include about 50 people.

This new form of computer cursor control will combine two types of inputs, taken directly from the user, and processes them so as to execute cursor actions. The first type of input is the infra-red image of one of the user's eyes. This image is obtained by illuminating the eye with infra-red light and capturing the reflection with a camera. By evaluating the orientation of the eye an instrument can determine approximately where on the computer screen the user is looking. The system that performs the image capture and eye-gaze location estimation is called an eye gaze tracking (EGT) system. The other type of input is electrical signals emitted by muscles when they relax or contract. These signals are called electromyogram (EMG) signals. The EMG system used in this study takes EMG signals from the head of user, with the use of surface electrodes, in order to translate facial movements into five cursor actions: left, right, up, down, and left-click. The cursor action information produced by the EMG and EGT systems are integrated in such a way, that the EGT system output is used to move the cursor into the approximate region of interest of the user, while the EMG system is used to make small modifications to cursor location and perform selections or left-clicks.

If you decide to participate in the study, we will tell you the day and time to come to the DSP laboratory at the Engineering Center of Florida International University. As part of the study, you will be placed in front of a computer screen and will have five surface electrodes connected to your head in order to monitor the EMG signals. You will also have your eye illuminated with low-power infra-red light so as to capture your eye image. You will then be asked to perform an experiment that will require you to move the cursor and select a target on a trial-by-trial basis. Each trial may have a different combination of target size, distance to be traveled by the cursor, and angle of approach of the cursor. You will be asked to perform these trials using either the mouse, the EGT system only, or our new EMG/EGT system. It is estimated that the total time for the experiment, including user set-up, will not last longer than one hour.

The risks involved as a participant of this experiment are minimal. The placement of the electrodes with contact points in the hair region of the user's head may cause some minor discomfort.

You will not receive direct benefits from this study. However, the data acquired from the experiments will allow our group to determine how well our EMG/EGT system worked and what areas of modification are required to improve system performance. This will in turn result in a system that will be more usable to individuals that are unable to use their hands to control the cursor and to those users who desire hands-free cursor control.

The data generated as part of the study will only be identified by subject number. The results in this research will be presented in group form and no names will be disclosed. Your responses are strictly confidential as required by law.

You have the right to ask questions concerning the procedure. You may withdraw your consent and discontinue participation in this research project at any time without any negative consequences. If any new findings are developed during the time that you are in this study which may affect your willingness to continue the study, you will be informed as soon as possible.

If you desire further information about this study, please contact Dr. Armando Barreto, Associate Professor in the Department of Electrical and Computer Engineering and the Department of Biomedical Engineering, at 305-348-3711. If you would like to talk with someone about your rights of being a subject in this study you may contact Dr. Jonathan Tubman, the Chairperson of the FIU Institutional Review Board at 305-348-3024 or 305-348-2494.

Your signature below indicates that all questions have been answered to your satisfaction. You are aware of your rights and you would like to be in the study.

Signature of the Participant Printed Name Date

I have explained and defined in detail the research procedure in which the person named above has agreed to participate and have offered him/her a copy of this informed consent form.

Signature of Witness Date

APPENDIX B - THE ANATOMY AND PHYSIOLOGY OF SKELETAL MUSCLES

B.1 Skeletal Muscle Anatomy

A skeletal muscle is a type of striated muscle that is attached to the skeletal frame of the human body. Typically, these muscles facilitate body movements by applying force to the bones and joints to which they are connected.

Skeletal muscles are composed of numerous muscle fibers that can span the entire length of the muscle. They range from a few mm to 40 cm in length, and 10 to 100 μm in diameter [49]. Muscle fibers can be classified into two groups: slow-twitch (type I), and fast-twitch (type II). Each muscle in the body contains a mixture of these fibers. Slow-twitch fibers typically contract at a rate of less than 25 twitches per second [50]. They possess high concentrations of mitochondria and myoglobin, and a highly developed blood supply. This allows such fibers to support aerobic metabolism and to be fatigue-resistant. Fast-twitch fibers typically contract at a rate greater than 25 twitches per second [50], and are usually utilized for anaerobic metabolism. Fast-twitch fibers can be further categorized into the two sub-groupings: type IIA and type IIB. Type IIA fibers have moderate mitochondria and myoglobin concentrations and are fairly resistant to fatigue. Type IIB fibers have low mitochondria and myoglobin concentrations and are not fatigue-resistant. Each muscle fiber contains several myofibrils. A myofibril is a bundle of protein filaments (called myofilaments) that run from one end of the fiber to the other (refer to Figure B - 1 for a structural decomposition of skeletal muscle).

There are two types of myofilaments: thick and thin. A thick myofilament consists of primarily a myosin protein strand held in place by titin filaments. A thin myofilament consists mostly of the protein actin. The structure of a myofibril is arranged

into segments called sarcomeres (Figure B - 2). A sarcomere segment is bounded by two dark colored areas in the myofibril called Z lines. The sarcomere can be further subdivided into three bands: a central, darkly colored band called the A band, and two surrounding lighter colored bands called I bands. The A band contains primarily the thick, myosin-based myofilaments, while the I bands chiefly contain the thin, actin-based myofilaments. There is also a small region of relatively brighter color located centrally within the A band called the H band. In this region myosin and actin strands do not overlap, and this area appears most prominently when the muscle is in a relaxed state.

Figure B - 1 Decomposition of muscle

During a muscle contraction, the actin myofilaments slide over the myosin filaments toward the central region of the sarcomere. This action causes the sarcomere, and the H band in particular, to shrink in size. This overlapping of actin and myosin filaments will eventually result in the disappearance of the H band in a fully contracted muscle.

Figure B - 2 Sarcomere band layout

B.2 The Motor Unit

A motor unit consists of a motor neuron and the muscle fibers it innervates. Motor neurons are connected to the central nervous system (CNS) resulting in an unbroken electrical pathway from the motor cortex to the muscle fibers. This pathway facilitates voluntary muscle contractions. The number of muscle fibers innervated by a specific motor neuron varies from an innervation ratio of 2000 to 1 for the gastrocnemius

muscle of the leg, to an innervation ratio of 3 to 1 for the extraocular muscles [50]. The individual fibers of each motor unit are located randomly throughout the muscle intermingling with fibers from other motor units.

B.3 The Voluntary Muscle Contraction

Voluntary muscle contractions begin with the firing of neurons in the contralateral motor cortex. The nerve impulses or action potentials that result from this process are conducted through the neurons of the spinal cord until they eventually arrive at the appropriate motor neuron(s). An action potential will propagate through a motor neuron to the muscle fibers via the motor endplate. When the action potential arrives at the endplate it triggers the release of acetylcholine. The acetylcholine will cause a chemical exchange of sodium and potassium ions in the muscle fiber resulting in an ionic concentration gradient. This gradient gives rise to a transmembrane potential in the muscle fiber, beginning at the endplate and propagating through the fiber to the tendinous attachments at both ends. It is this potential propagation throughout the muscle fibers that result in a corresponding muscle contraction.

There are two phenomena that govern the strength of a muscle contraction: the number of motor units recruited for the contraction, and the firing rate of each motor unit. The recruitment process involves activating smaller, inactive motor units initially, and then recruiting progressively larger motor units as the demand for muscle tension increases [12]. If the contraction does not reach the maximum voluntary contraction (MVC) limit, then certain motor units will not be activated. The motor units associated with slow-twitch fibers are recruited first, due to their fatigue-resistant capabilities, followed by motor units associated with the fast-twitch, larger diameter fibers. In

addition, as the force output of the muscle rises, the firing rate of a previously recruited motor unit will increase, even to the point that the force produced by the motor unit will saturate while the firing rate continues to rise.

B.4 The Relationship Between Muscle Contractions and the Electromyogram

The electromyogram (EMG) signal is the result of the spatio-temporal summation of electrical signals received from several muscle fibers associated with different motor units when a surface electrode is placed on the skin above a superficial muscle. During a muscle contraction: motor units are recruited at different times, individual motor units will have different firing rates, and the muscle fibers associated with each motor unit are intermingled. These factors contribute to the complex nature of the EMG signal.

B.5 Facial Muscle Anatomy and Function

The temporalis muscle is one of the many muscles connected to the mandible or jawbone. Its primary function involves raising the mandible for mastication bringing the lower teeth into contact with the upper teeth. Also, if the mandible is horizontally shifted to the right or left, the corresponding temporalis muscle is contracted.

The frontalis muscles span from the coronal suture at the top of the skull to the eyebrows, covering the forehead part of the skull located above the eyesockets and bridge of the nose. When contracted, the left and right frontalis muscles elevate the eyebrows. In order to move the eyebrows vertically downward, several muscles cooperate together in the task including the procerus muscle, the corrugator muscle, and the orbital part of the orbicularis oculi muscle.

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