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Functional Near Infrared Detection of Real and Imagined Finger Taps Using Support Vector Machine, Linear Discriminant Analysis, and Decision Tree Classification Methods

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by

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ABSTRACT

FUNCTIONAL NEAR INFRARED DETECTION OF REAL AND IMAGINED FINGER TAPS USING SUPPORT VECTOR MACHINE, LINEAR DISCRIMINANT ANALYSIS, AND DECISION TREE CLASSIFICATION METHODS

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This study investigates the thesis that given cerebral response samples of an individual's left, right, both, and imagined finger tapping, continuous wave (CW) functional Near Infrared (fNIR), unregistered with fMRI, can differentiate between any two of the four categories.

Fifty subjects were outfitted with a single source/detector attached to a single, square pad, affixed to their heads using devices such as elastic bands and caps for light shielding. Slides depicting arrows pointing left, right, both directions, or made of dashed lines were presented to each subject, with a slide of text interspersed between each. Subjects tapped with their left finger, right finger, both left and right finger, or imagined tapping, depending on the type of arrow. Text was presented in between each tapping slide and was read with no tapping. Each slide was presented for twenty seconds and each type of tapping occurred three times in an eight minute, 20 second period.

Classification was performed using Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), and decision tree algorithms. Results indicated that left finger tapping can be distinguished from right, both, and imagined right finger-tapping with error rates ranging from 24.92% to 29.51% (SVM), 40.05% to 42.69% (LDA), and 23.34% to 28.85% (decision tree). The decision tree algorithm produced results, on an

individual trial basis, with greater than 95% confidence that the results were not due to chance.

These results were obtained with no screening out due to individual characteristics such as hair thickness. The generalizations included the use of a large sample of subjects for which the selection criteria only included statutory minimum and maximum ages.

This study also produced validation of a method of mitigating hair effect. Raising the sensor was shown to still produce valid results that could not be attributed to chance at a confidence level of 95%.

The results are directly applicable to brain-computer interfaces in a number of areas. These relate to validating the ability to classify data collected by a device with a single source/detector, from non-prescreened individuals, with real-time algorithms in a normal environment.

This thesis is dedicated to all the people who may one day benefit from a brain computer interface.

ACKNOWLEDGMENTS

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NOMENCLATURE

Biaucular	Distance from one preauricular to the other
Bilateral	Both sides of the brain
BOLD	Blood Oxygenation Level Dependent
Channel	Combination of IR source and detector; sometimes includes wavelength
Contralateral	Opposite side of the brain
Cutaneous	Sensing through the skin
CW	Continuous Wave
EEG	Electroencephalography
fMRI	Functional Magnetic Resonance Imaging
fNIR	Functional Near Infrared
Handedness	The hand (left or right) whose use dominates the other
ICA	Independent Component Analysis
Inion	The protrusion at the rear of the skull at which the neck meets the skull
IR	Infrared
Ipsilateral	Same side of the brain
KNN	K Nearest Neighbor
Kinesthesis	Sensing through muscles, tendons, and joints
LDA	Linear Discriminant Analysis
Ms	Millesecond; one one-thousandth of a second
Nasion	The top of the bridge of the nose
Oximeter	An instrument that measures oxygen in blood
PCA	Principal Component Analysis
PMC	Primary Motor Cortex

Preauricular	The point of a protruding bone in front of the ear opening
Proprioceptive	Stimulated from within the body
SMA	Supplementary Motor Area
SVM	Support Vector Machine

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CHAPTER 1

INTRODUCTION

This study is for the investigation of the use of Continuous Wave (CW) functional Near Infrared (fNIR) to measure the cerebral response of real and imagined finger tapping over the course of time and analyze the results using Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), and decision tree algorithms. The CW fNIR will be used without coregistering locations with functional Magnetic Resonance Imaging (fMRI)[1].

1.1 Purpose

With this study, tailored, supervised classification algorithms are used to show that finger tapping and finger-stationary states can be differentiated (1) on an individual (vice collective group) basis, (2) using a continuous wave (CW) fNIR system, (3) with only one set of source/detectors, (4) without a priori knowledge of an individual's brain geometry.

1.2 Thesis Statement and Gaps Addressed

Given single source/detector CW fNIR cerebral response samples during an individual's left finger tapping, right finger tapping, both (right and left) finger tapping, and imagined finger tapping; a real-time capable supervised classification algorithm such as SVM can differentiate between any two of the four categories, even if the individual's brain has not been registered using fMRI.

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[1] The figures, tables, and references in this dissertation were formatted using the IEEE Transactions and Journals Style.

Four key components of this hypothesis are:

- Only one set of CW source/detectors is required (*i.e.*, measure a single location).
- Prior knowledge of an individual's brain geometry is not required.
- Preprocessing and classification can be accomplished with algorithms that have the potential to execute in real time.
- Classification can be accomplished on an individual (vice collective group) basis.

The hypothesis components address gaps in the current state of technology and lead to the benefits described in Table 1.

TABLE 1. HYPOTHESES GAPS AND VALUE

Hypothesis Component	Benefit
One set of CW source/detectors	Less hardware on person's head; More affordable BCI
Prior knowledge of individual brain geometry not required	Eliminates pre-registration with fMRI, reduces cost, allows widespread application
Distinguish between two finger tapping states	Minimum requirement of a Brain Computer Interface (BCI)
Preprocessing and classification with algorithms with real-time potential	Essential for BCI
Individual basis versus group basis	BCIs normally require individual interface

Although not part of the hypothesis, this study will show that preprocessing steps that convert raw data to concentrations of oxygenated and deoxygenated concentrations may not be necessary for effective classification.

1.3 Theoretical Background

Functional Near Infrared (fNIR) is a noninvasive neuroimaging method that can detect concentrations of oxygenated hemoglobin (oxy-Hb) and deoxygenated hemoglobin (deoxy-Hb) [1]. Decreases in deoxy-Hb and increases in oxy-Hb and total-Hb can reflect neural activation [2]. Near-Infrared light can pass through body tissues such as the scalp and skull but is absorbed by hemoglobin (or more specifically, the chromophores in hemoglobin). An activation in the brain causes oxygenation (metabolism of oxygen), followed by deoxygenation. Cerebral blood flow increases, causing the oxygenation levels (*i.e.*, concentrations) to exceed the deoxygenation levels.

fNIR is absorbed to different degrees by oxygenated and deoxygenated blood and these differences vary by the wavelength of the infrared light. By shining infrared light of different wavelengths through the brain and measuring the amount returned, the relative concentrations of oxygenated and deoxygenated blood can be determined [3].

fNIR has been used to measure brain activations at various cerebral locations while subjects perform various tasks and actions. Each combination of location/action that has been studied has both theoretical and applied importance. They are of importance because a mapping of a cerebral activation location to a simultaneous task can further knowledge of how the various parts of the brain function. They are of applied significance because a mapping of cerebral location to task being performed could help in the design of prosthetics and in the creation of brain-computer interfaces, as well as potential applications in diagnostics and therapy.

1.4 Method and Procedure

The study consisted of data collection, preprocessing, classification, and interpretation. Fifty subjects were each presented with stimuli for which they were instructed to either tap their right finger, left finger, both fingers, imagine tapping, or read text. A Spire fNIR oximeter with one light source and one detector was used to obtain measurements of four wavelengths of light at a rate of 10 samples per second. The data were preprocessed by using a moving average filter, then classified using a support vector machine supervised classification algorithm and two additional algorithms – Linear Discriminant Analysis (LDA) and decision tree.

1.5 Outline of the Document

Chapter 1 provides an overview of the thesis statement, theoretical background, and the methodology. Chapter 2 describes details of the theoretical background. Chapter 3 reviews current literature, Chapter 4 describes the methodology, and Chapter 5 describes the data collection and preprocessing of the data. Chapter 6 analyzes the results of the classifications. Chapter 6 provides concluding remarks, including contributions to fNIR research and future directions.

CHAPTER 2

THEORETICAL BACKGROUND

Functional Near Infrared (fNIR) is a noninvasive neuroimaging method that can detect concentrations of oxygenated hemoglobin (oxy-Hb) and deoxygenated hemoglobin (deoxy-Hb) [1]. Decreases in deoxy-Hb and increases in oxy-Hb and total-Hb can reflect neural activation [2]. Near-Infrared light can pass through body tissues such as the scalp and skull but is absorbed by hemoglobin (or more specifically, the chromophores in hemoglobin). An activation in the brain causes oxygenation (metabolism of oxygen), followed by deoxygenation. Cerebral blood flow increases, causing the oxygenation levels (*i.e.*, concentrations) to exceed the deoxygenation levels. Fig. 1, adapted from research of Abdelnour shows the rise in oxygenated hemoglobin, followed by a rise in deoxygenated hemoglobin [4]. The data are from a left handed subject tapping with left hand for 20 seconds, initiating a neural activation. Note the approximately five second lag in the rise after tapping begins and an even longer persistence after tapping has ceased; however, there is a wide variance among individuals in both the timing and extent of the changes.

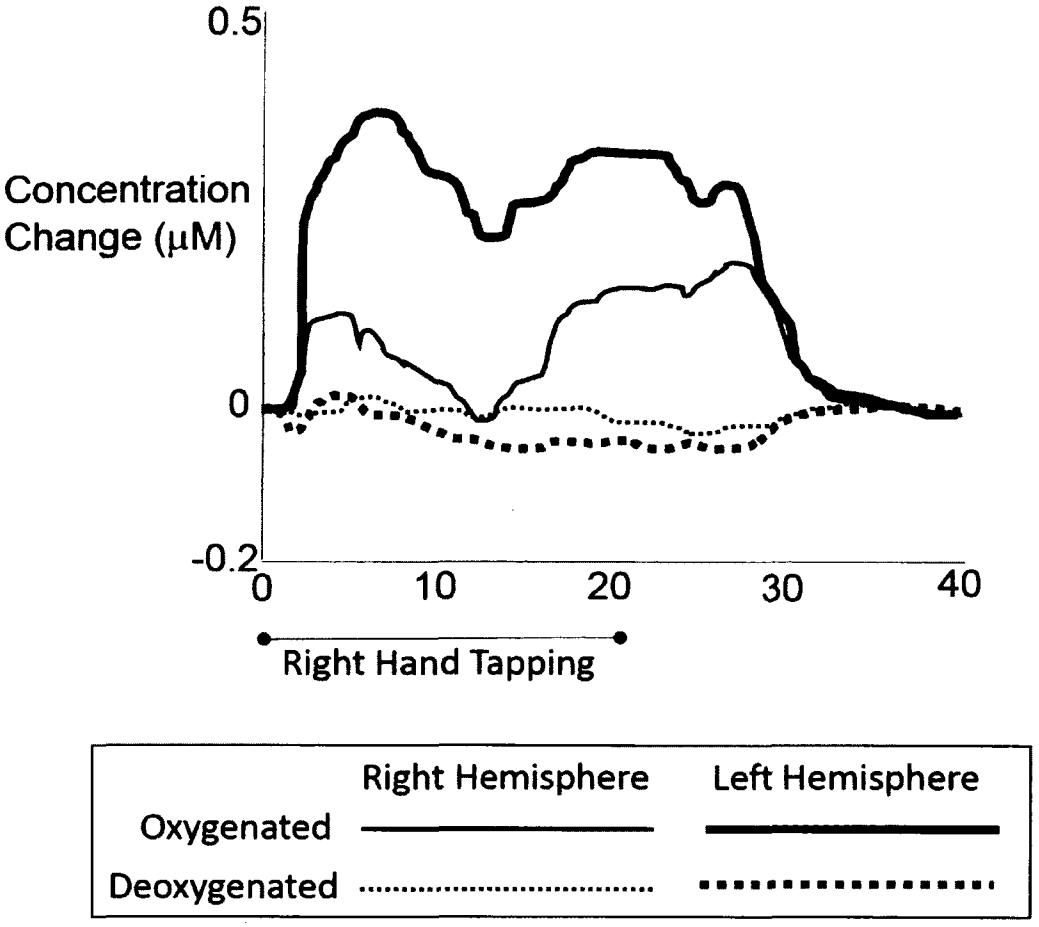

Fig. 1. Oxygenation/deoxygenation change (adapted from Abdelnour [4])

fNIR is absorbed to different degrees by oxygenated and deoxygenated blood and these differences vary by the wavelength of the infrared light. By shining infrared light of different wavelengths into the brain and measuring the amount of each wavelength that is reflected back after passing through the brain, the relative concentrations of the oxygenated and deoxygenated hemoglobin that flowed can be calculated, allowing neural activations to be detected [3]. The degree to which material such as hemoglobin absorbs light is based on the material's absorption coefficient, the amount of material the light passes through, and the wavelength of the light passing through the material. Fig. 2,

modification of a figure from a Spire oximeter manual, depicts how the absorption coefficient for a particular degree of oxygenation varies by wavelength [5]. In general, the shorter the wavelength, the greater the variability of the absorption coefficient and therefore, of the readings.

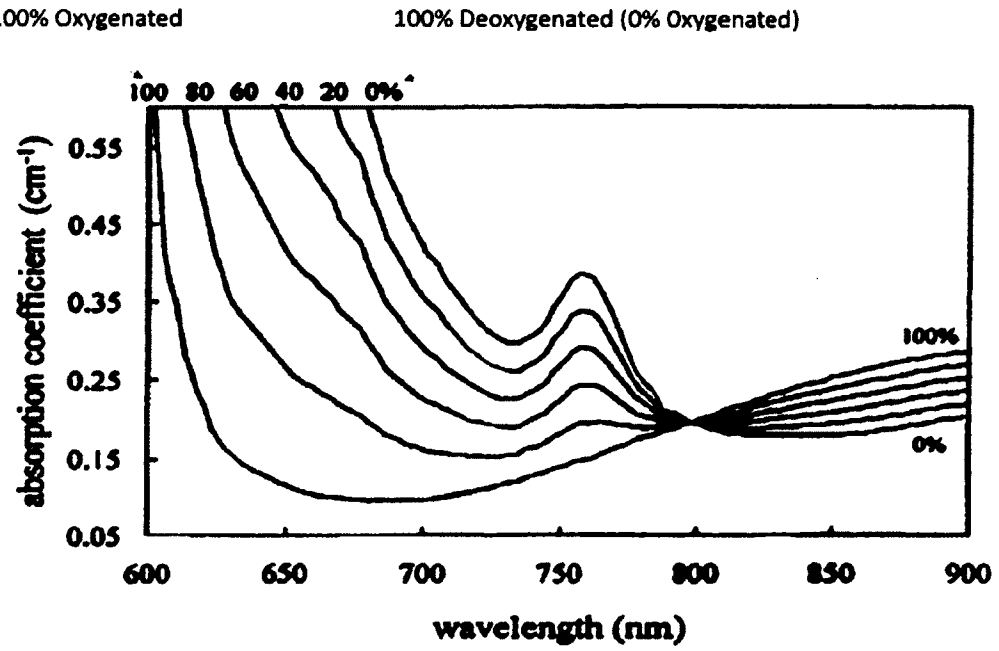

Fig. 2. Absorption by oxygenation and wavelength (adapted from Spire manual [5])

Note that the 100% oxygenation line on the chart is the lowest line for all wavelengths below approximately 800 nm but it is the highest wavelength above 800 nm. By using an oximeter with one light with a wavelength below 800 nm and one light above 800 nm, the amount of light of light of each wavelength that is returned can be compared, allowing the absorbance coefficient to be determined. Once the coefficient is known, the chart allows the percent oxygenation (*i.e.*, which line on the chart) to be determined. For example, if more light was returned from a 650 nm light than an 850 nm

light, then the applicable line on the chart would be one that is lower at the 650 nm point than at the 850 nm point (keeping in mind that more light passing through equates to less absorption). The line would thus be one toward the higher oxygenation levels.

An oximeter is an fNIR device that measures oxygenation. The most accurate type has a pulsed light source, which allows the origination time of the pulse to be compared to the detected time of the pulse, thus allowing the time of flight of the pulse to be determined. Knowing this time period allows the length of the path through the brain to be calculated for a given material (*e.g.*, hemoglobin), thus allowing the particular depth of the underlying neural activation to be bounded and the particular concentration of the material to be known and neural activations detected.

A CW oximeter is another type of fNIR device, in which a continuous infra-red source is used. The length of the path cannot be accurately calculated and must be approximated. Exact concentrations of material cannot be determined; however, relative concentrations can be calculated and these approximations are sufficient to detect activations. CW oximeters are the more prevalent type used in current research. One such instrument, a Spire CW oximeter, has a light source with four wavelengths and is the one which was used in the research for this dissertation.

2.1 Physiological Model

Knowledge of which portion of the brain affects what functionality is also important with regards to determining where to place sensors/detectors. Once the physical area is identified, the location on a particular individual has to be determined, as locations vary among individuals. Currently, locations of functional areas of interest are typically estimated or determined in real time by analysis of sources/detectors placed at

multiple locations. Predetermination is typically accomplished by MRIs of the subjects but other methods can be used. In research by Lee, nerve stimulation measurements were used [6]. The areas of interest have tended to be either motor areas, somatosensory areas, or areas within the cerebellum; however, effects for the specific areas conflict among studies per a metastudy by Witt [7]. For the study in this dissertation, only one source/detector is used; therefore, the placement would optimally be on one of the areas for which there is agreement.

2.2 Finger Tapping Physiological Model

Finger tapping is one of the more common motor tasks for experiments. It is performed in many different manners, including sequentially tapping each finger to the thumb, tapping a finger to a surface, moving a finger without tapping, or different combinations of left/right handed people tapping with the dominant/nondominant hand. Tapping can be performed to an external stimulus (auditory or visual) or can be continuously performed at a self-determined rate, without a stimulus. Rates vary from experiment to experiment and can be a fixed rate, subject's maximal rate, or subject's comfortable rate [8]. Each combination of these factors can result in a different brain activation signature, indicating the potential for a complex mental model [9]. Different parts of the brain would be required in different methods of tapping and tapping control. For example, proprioception provides knowledge of a finger's location, there is a sensation when a finger touches an object, and auditory or visual functions might be required for monitoring related timing stimuli.

Finger tapping activates numerous areas of the brain. The particular areas and their degree of activation can be affected by the method of pacing (external stimulus or

continuous); the type of source stimulus (visual or audible), what is tapped (external surface, other fingers, or nothing), and handedness. Fig. 3 depicts Pinel's theoretical view of some, but not all, of these areas [10]. The locations of the areas are noted. Neither the areas nor their relationships are meant to be exhaustive, nor are they all necessarily supported by empirical evidence. The drawing was created based on text that described major inputs and outputs of selected areas and is designed to facilitate an understanding of how functions and relationships of locations might be related to finger tapping.

One area that is involved in finger tapping but not depicted is the cerebellum. Its function with regard to finger tapping is not well understood although there are finger tapping – related connections between the cortex and cerebellum [11]. Anatomically, there are pathways that loop between the cortex and cerebellum. Functionally, areas in the cerebellum have been shown to be connected to the motor and somatosensory cortices. Its location is not easily accessible via the current fNIR.

In the particular theoretical model this chart depicts, signals travel from the sense receptors to the thalamus, then on to an area of the cortex for the particular sense type – auditory, visual, or somatosensory (body) cortex. From there, the association cortex integrates signals from the different senses and sends a signal to the motor cortex. The motor cortex then sends signals to whatever body parts are to be controlled. As previously noted (and as shown in subsequent paragraphs), this model is only one view, has understated complexity, and may not be empirically supported.

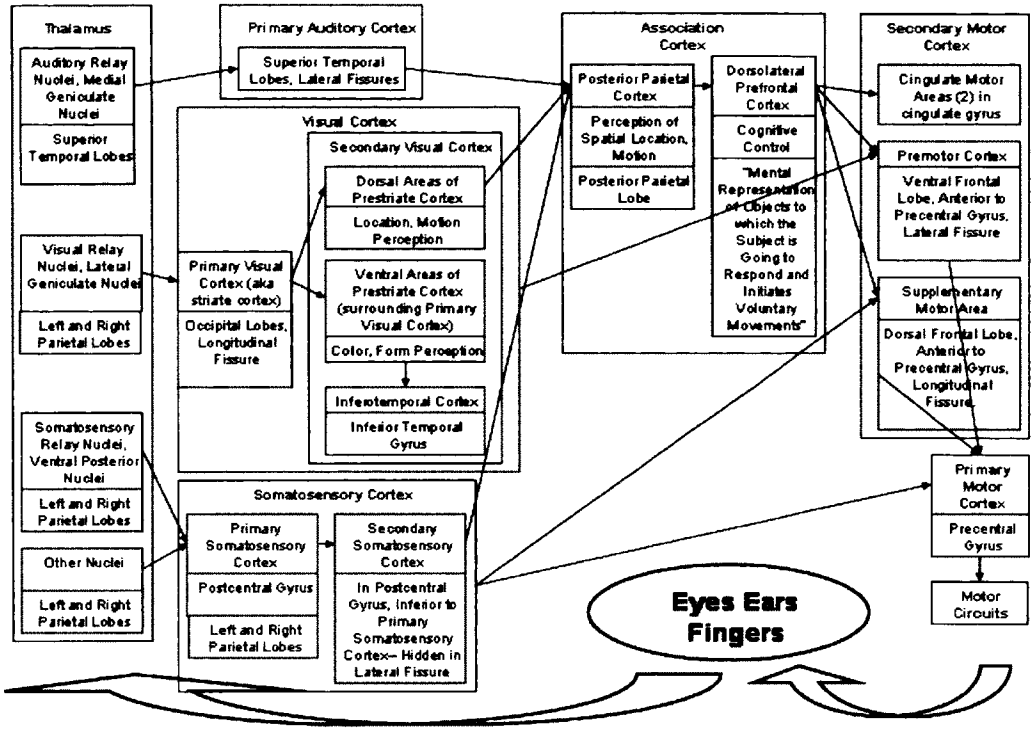

Fig. 3. Notional model of finger tapping signal flow [10]

2.3 Interconnections

The interconnections among some of these areas, particularly the motor-related areas, have been researched through such methods as stimulating an area and observing movement of particular parts of the body (*e.g.*, fingers). The interconnections, as well as the involvement of the areas in motor functions, have also been researched through imaging (*e.g.*, fMRI, EEG, fNIR) in both humans and primates. The research of Dun and Strick has conflicting results regarding the division of the areas as well as their interconnections [12, p. 20]. The following paragraphs describe some of this research, especially among the areas within the primary and secondary motor cortices. This research is generally supportive of the primary and secondary motor connections depicted

in Fig. 3 as well as some of the other areas. The research; however, suggests many more connections among the areas and subareas than the diagram depicts as well as bidirectional connectivity among some of the parts.

The research of Dun and Strick references research (based on connections to the primary motor cortex) that indicates the secondary motor cortex consists of three cingulate motor areas, a ventral, and a dorsal premotor area, and the supplementary area; hence, a different anatomical division than that of Fig. 3 [12, p. 13]. The same source cites research that the premotor cortex has corticospinal neurons that project directly to the spinal cord as well as to the primary motor cortex, suggesting each can directly influence movement [12, p. 10]. In a monkey with the primary motor cortex removed, stimulation of the supplementary motor area still evoked movement – using currents in the preremoval range [12, p. 17]. In other words, after the primary motor cortex had been removed, responses could still be evoked, indicating the existence of a pathway that bypassed the primary motor cortex in normal operation. Had an increase in current been required, the effect could have been attributed to the higher level forcing a path not normally used.

This research tends to confirm some of the connections of Fig. 3 but adding new connections, thus convoluting the flow of activity. Excitation of the secondary motor cortex (specifically, the supplementary motor area) has a higher threshold than excitation of the primary motor cortex [13]. In fact, exciting the primary motor cortex with electrical stimulation has been shown to have a lower threshold than any other area of the cortex [12, p. 4]. These differing thresholds add further complexity, not indicated by the simplified diagram. Padoa-Schioppa cites research showing that many of the premotor

areas project to the spinal cord, including the dorsal premotor area, ventral premotor area, supplementary motor area, and three or four cingulated motor areas [14]. Research also provides evidence that connections exist from both the primary and secondary somatosensory cortices, but removal of these areas does not keep proprioceptive responses from traveling to the primary motor cortex [12, pp. 21-23]. These studies provide evidence that just because connections exist, there is not necessarily a rote use of them – more argument against the existence of a simple, straightforward functional flow diagram. There is research indicating that only the cingulate and premotor cortex receive signals from the dorsolateral prefrontal cortex whereas Fig. 3 depicts signals traveling the supplementary motor area as well [12, p. 27]. There is also research from Dum to support connections among each of the areas in the secondary motor cortex (cingulate motor areas, premotor cortex, and supplementary motor areas) and of two of these areas (premotor cortex and supplementary motor areas) to the primary motor cortex [12, pp. 21-24].

Connections between the premotor cortex and primary motor cortex appear to be essential to map a visual cue to a motor response [15]. Monkeys whose dorsal premotor cortex was removed were not able to choose the correct motor response for a task (open a lit or unlit box). Monkeys without the dorsal premotor cortex removed were able to do the task. In another study, removing monkeys' dorsal and ventral premotor cortex resulted in the monkeys not being able to relearn a visually-cued task to operate a handle [15]. The connections between the inferiotemporal cortex and the ventral and orbital prefrontal cortex also appear to be used for visual-to-motor mapping. Monkeys whose connections were severed were slower to perform such mapping tasks but they were able

to learn the tasks [15]. The posterior parietal cortex has been shown to not be needed for mapping involving color (agreeing with Fig. 3). Even lesions of the dorsal prefrontal cortex have been shown not to disrupt this mapping, again agreeing with the diagram.

2.4 Areas Related to Finger Tapping

An item of interest to this dissertation is the location to place sources/detectors. While the primary motor cortex is an obvious candidate for finger tapping studies, there are other candidate areas depending on research objectives, equipment, and methodology. The metaanalysis of Witt included 38 studies (22 fMRI and 16 PET) and gives some insight into various factors involved in finger tapping and how, for example, auditory and visual pacing can activate different hemispheres [7]. The source studies of the metaanalysis had differences in their experimental methods, making comparisons difficult. Witt's study performed three distinct analyses of right handed finger tapping: (1) all the studies, (2) groups based on type of stimulus – auditory, visual, or none, and (3) groups based on tapping complexity [7]. Table 2 depicts areas in which the papers had agreement for each of the three groups. Of note is the premotor cortex, which did have agreement but task-dependent agreement. For example, visual pacing resulted in bilateral agreement while auditory pacing and self-pacing did not.

For all the finger tapping tasks, paced and unpaced, there were areas of some agreement in primary sensorimotor cortex, supplementary motor area, basal ganglia, and cerebellum. Studies of auditory and visual stimuli have reported different areas activated for these types of stimuli; but the results were inconsistent. The studies had differences in their experimental methods, making comparisons difficult.

TABLE 2. EFFECT OF STIMULUS TYPE ON AREA ACTIVATED

	Auditorially-paced	Visually-paced	Self-paced
Dorsal Premotor Cortices (task-dependent laterality)	X (right)	X (bilateral)	X (left)
Right Dorsolateral prefrontal Cortex		X	X
Right Inferior Parietal Lobe		X	X
Bilateral Claustrum (task-dependent laterality)	X		X
Bilateral Insula		X	
Right Inferior Frontal Gyrus		X	
Bilateral Occipital Lobe		X	
Left Posterior Cerebellum		X	
Brodmann's area 44	X		
Left Ventral Premotor Cortex			X
Right Posterior Cerebellum			X

2.5 Functions of Areas

Per the same metastudy referenced above, the following are functions thought to be performed by the various motor-related areas [7]. Of particular note are the executive area for simple voluntary movements, motor learning, selection of movement, visual cuing, sustained attention, finger movements, and imagined movements.

- Primary sensorimotor cortex.
    - Executive area for simple voluntary movements.

- Processing of complex sequential tapping.

- Supplementary motor area.
  - Executive area for simple voluntary movements.
  - Higher motor processing.
    - Initiation of movement.
    - Motor programming.
    - Motor planning.
    - Readiness to move.
    - Motor learning.
    - Complexity of movement.
    - Responsiveness to internal cueing.
    - Selection of movement.

- Cerebellum.
  - Preparation.
  - Execution.
  - Timing.
  - Externally-cued movements.
  - Internally-cued movements.

- Basal gaglia.
  - Single repetitive movements.
  - Complex sequential movements.

- Premotor cortex.
  - Transformation of sensory data into movement.

- Execution of movements under sensory guidance.

- Lateral premotor cortex.
  - Dominance over internally-guided movements.
- Medial premotor cortex.
  - Dominance over externally-guided movements.
- Ventral premotor cortex.
  - Visually-guided movements.
- Dorsolateral prefrontal cortex.
  - Lateral.
    - Visual-cuing.
    - Sustained attention.
  - Medial.
    - Self-paced cuing.
- Inferior parietal lobe.
  - Sequence-specific data.
  - Sensorimotor integration.
- Right cerebellar pyramis.
  - Possible third homunculus.
- Inferior frontal gyrus.
  - Finger movements.
  - Imagined movement.
  - Motor learning.
  - Motor observation.

2.6 Somatotopic Mapping

Somatotopic maps relate specific physical areas of the brain to areas of the body controlled by that part of the brain. Such maps have been identified in many motor-related areas. One method used to create these maps is by tracing corticospinal neurons from the primary motor cortex and the secondary motor cortex areas. The neurons that go to cervical segments of the spinal cord control neck and arm movements while those that go to lumbarsacral segments control the leg. The origins of the cervical vs. lumbar neurons did not have significant overlap and also corresponded with the locations of neurons that projected to equivalent areas of the primary motor cortex.

Of interest to this dissertation is a finding by Dum that the amount of primary motor cortex area projecting to the upper cervical segments (neck, elbow, shoulder control) was the same as the amount projecting to the lower cervical segments (hand, wrist control), suggesting a disproportionate amount of the brain used to control the wrist and hand, perhaps allowing more complex movements. Also, the upper and lower origin areas were segregated, similar to the cervical/lumbar segregation. Within the cingulated motor areas; however, a degree of overlap was found. Research has established that each of the areas in the premotor cortex has a somatotopic organization, although they are not all complete representations (*e.g.*, one of the premotor cortex areas does not have a face representation) [12, pp. 11-20].

fMRI has also been used to investigate somatotopic mapping. With respect to differentiating areas involved with the different fingers, an fMRI study by Kleinschmidt and Toni showed great overlap among the areas for each finger [16]. In fact for any hand or finger movement there was complete and continuous activation of the entire cortical

hand area. Their work contrasted the movement of each finger with the same finger at rest and showed more overlap than when the finger movement was contrasted with a different movement. One reason posited was that less specific effects could be occurring during rest (an example of draining vasculature was offered); another reason posited was that the finger had to be stabilized while at rest, perhaps canceling the effects occurring while not at rest. The strongest activations were found in the contralateral primary motor cortex, although in many cases an ipsilateral response was also noted. In experiments involving a determination of handedness effects, there were conflicting results. In some, handedness had no effect on contralateral versus ipsilateral effects. In other experiments, handedness did have an effect. For example in one study the use of the non-dominant hand had less contralateral effect [16]. In another study, by Dane, a relationship was found between handedness and the intraocular pressure of each eye [17]. Right-handed subjects had higher intraocular pressure in the right eye than the left eye but in left-handed subjects there was no difference.

There is also some evidence by Geyer that the arms and hands have two representations in the primary motor cortex [18]. Of particular interest is a finding by Sato that digit I has the largest representation and digits III-V, the smallest [19]. Additionally, the representations of each digit overlapped that of neighboring digits. The implications for this study are that the representation of the finger that is tapping may have two representations or may overlap the area related to a neighboring finger.

CHAPTER 3

LITERATURE REVIEW OF HYPOTHESIS COMPONENTS

This chapter provides the current state of research and knowledge with regards to the four components of the hypothesis. Studies that provide the current state of the components are followed by sections that address particular areas related to the components and to the methodology of this study. Table 3 summarizes the findings, relative to the hypothesis component.

TABLE 3. HYPOTHESES COMPONENTS AND CURRENT STATE

Hypothesis Component	Literature Findings
Prior knowledge of individual brain geometry not required	Currently mitigated by adding source/detectors to increase geographical coverage
One set of CW source/detectors	Most research involves multiple source/detectors
Individual basis versus group basis	Previous gap but addressed by recent research
Classification algorithm to distinguish finger tapping states	Limited research on fNIR classification algorithms
Algorithms with real-time potential	Limited research on application of real-time algorithms to fNIR

Current research addresses these areas but not all simultaneously, specifically use of a single channel CW device in conjunction with a real-time individual-based classification capability.

3.1 Prior Knowledge of Individual Brain Geometry

Functional areas of the brain vary in physical location on each individual; therefore, sensor locations to measure specific functionality are unique for each person. To detect signals from a specific functional cerebral area, the literature describes four methods that are currently used.

Chance described one method – that of first having the individual perform the task while being imaged by fMRI, then using the fMRI results to determine the exact physical locations activated on that individual [20]. A second method addresses differences in individual geometry by averaging signals from multiple individuals with the hope that in enough individuals the sources/detectors will cover the location of interest, such as was done by Suto [21]. Ferrari described the evolution from single source/detector devices to those with multiple sources/detectors [22]. Most fNIR research in motor functions in the last decade, such that of Suto, has addressed individual differences in brain geometry by using numerous source/detector combinations to simultaneously collect data from a wide areas of the brain, mitigating the need to know the exact location of a particular brain area for an individual [21]. By increasing the number of sources and detectors, such as the 16 of each (for 256 combinations) that Abdelnour used, the coverage area increases greatly [4]. Other instances of multiple source/detector sets are noted in the research discussed regarding classification methods. The fourth method is just to estimate the location of interest based on that of an average individual.

The first method, pre-MRI, would work for a brain-computer interface; however, an MRI would be costly and require added time. The second method, averaging

individual responses, is unsuitable for a BCI. Requiring multiple source/detector sets is effective but adds physical complexity and constraints to a BCI. The last method is simpler and this study attempts to show that it may be sufficiently accurate for purposes of detecting motor activity using fNIR.

3.2 One Set of CW Source/Detectors

Most research with CW devices involved multiple sources/detectors. Current research with a single source/detector was scarce. The literature does not provide many instances of the use of a single fNIR source/detector for areas of the head covered by hair. Single source/detector research, such as the studies reported by Ferrari, tends to involve earlier studies or is placed over areas with no hair, such as a study by Mandrick where sensors/detectors were placed over each prefrontal cortex [23] [24].

3.3 Individual Basis versus Group Basis

With regard to motor tasks, results were often analyzed by comparing the average of measurements received from a set of individuals performing a task to another set of individuals not performing the task (or performing it in a different manner). Analysis of the changes occurring over time on an individual basis had not been studied much until recent years such as a study by Sato where sources/detectors were placed over and around the motor cortex area [25]. Current research is now commonly done on an individual basis so this component of the hypothesis is less a discriminating factor than the others. The knowledge of individual changes is essential to the operation of a BCI since BCIs are for individuals, not groups.

3.4 Classification Algorithms for Finger Tapping States

The objective attributes of a classification method for this research are discrete assignment and computational feasibility for real-time use. The discrete assignment will determine which of several discrete actions a subject is taking but not how much of each action is being taken. Although classification for this particular study will not be accomplished in real time, a longer term objective is to be able to perform real-time classification, such as would be necessary for a brain-computer interface.

Overlapping the classification method itself are the related preprocessing steps. If a classification method is to support real time, the preprocessing steps must also.

3.4.1 Supervised and Unsupervised Classification

Classification algorithms can be divided into two types, supervised learning and unsupervised. Supervised learning involves the prespecification of target classes, along with data elements for which the target class is known. These data elements can then be used to determine attributes of each class, which can then be used to classify subsequent data elements [26, p. 3]. Unsupervised classification divides data into naturally occurring clusters without regard to whether the data in a cluster is the same class of data. Since in this study the target classes are known and training data was collected, a supervised algorithm is preferable.

Some methods are the Kalman filter, regression, K-Nearest Neighbors (KNN), Parzen Windows, Support Vector Machine (SVM), decision tree classifier, and Linear Discriminant Analysis (LDA). SVM is the focus of this project and it will be compared with the results of a decision tree classifier and LDA.

3.4.2 Kalman Filter Finger Tapping Classification

The Kalman Filter is a method that makes an estimate based on data from previous trials, then weighs that estimate with information from the current data point to predict the current state. As new data are collected, the values are reweighted. An adaptation of this model by Abdelnour adds knowledge of the timing of stimulus events and it is dependent on a prior knowledge of stimulus timing [4]. The experiment included coupling with a simple classifier algorithm and 79% of finger tapping events were correctly classified as right or left handed "overall for the 3 subjects." A trial was considered overall correct if predictions were correct for over half its data points; therefore, the 79% accuracy reflected that data points were classified greater than 50% correctly. Two of the subjects were right-handed and one was left-handed and they alternated between periods of tapping with the left finger and right finger [4]. This study had six minute periods in which the covariance between data from left and right tapping was obtained. Subsequent trials used the covariance data from the training trial in conjunction with a KNN classification algorithm to classify taps as right or left handed. In the adaptive model that was used, the covariance data were constantly updated as data from subsequent taps occurred. For twenty seconds, the subjects sequentially tapped each finger to their thumb on their right or left hand. Tapping was self-paced and lasted for a 20 second block, with a 20 second rest period between blocks. Subjects appeared to alternate between left and right tapping for each block, although the paper was not clear on this. Data were captured from 56 source-detector combinations placed on the left and right motor areas at a rate of 4 Hz; however, due to transfer and classification restrictions, the data were only classified at 2 Hz. These time points were classified as either left

tapping or right tapping and the resulting classification labels displayed, in real time, to the subjects on their computer screens.

The advantages of this method are several. The use of 56 source-detector combinations allowed for more localization than is possible with only a few source-detector combinations. The use of the Kalman filter factored in some of the expected noise.

A disadvantage of this method is that the adaptive model created a lag of 2-3 seconds in the classification due to the time required for the model to process the data from the previous tap as well as the current tap. The delay tended to result in classification of a finger tap occurring after several subsequent finger taps had occurred. This delay was compounded by relatively slow oxygenation/deoxygenation activation periods, which caused classification of data as finger taps, even after finger tapping had ended and the subject had gone to a resting state. The oxygenation/deoxygenation lag varies among individuals but is on the order of five seconds after task initiation and five seconds after task halting [21] [27]. Note: this same artifact is one of the reasons that the use of any algorithm with a temporal template is somewhat problematic for a real-time application. The results of applying the template are not known until the time period spanned by the template has elapsed.

One shortcoming of this method is that displaying the result to the subjects could bias the subjects. For example, a misclassified result could cause a subject to tap harder to try and increase the accuracy. Providing the result to the subjects also appeared inappropriate because of the classification lag described in the previous paragraph – the subjects were apparently being presented with the classification of the finger tap that

occurred two to three seconds earlier. Regarding the potential for subject bias, the study did note that the subjects' responses were sensitive to their attention to the task. When not fully attentive, brain responses were smaller and more classification errors occurred. The relationship of the attentiveness, error rate, and subject bias could, in my opinion, be that when the subjects were more attentive they would be more likely to be in a state of mind to pay attention to the classification results being displayed and then adjust their tapping to keep errors low.

3.4.3 Regression

This method provides a probable value of an independent (response) variable based on a linear relationship to dependent variables. Recent research by Mandrick in which a pair of sensor/detectors was placed over each prefrontal cortex, shows that a linear regression slope of hemodynamic responses during cognitive tasks showed promise as a differentiator between a subject at rest and performing a cognitive activity [24]. A pattern of increase in oxy-hemoglobin and decrease in deoxy- occurred during task periods in 63.7% of the trials.

3.4.4 Principal/Independent Component Analysis (PCA/ICA)

PCA and ICA, although not classification algorithms, can provide a set of components (*e.g.*, a set of variables, a set of variable values) that can account for maximum difference (entropy) among those components. A potential use in this type application would be to identify the set of sensors that account for differences between the two states, thus allowing subsequent analysis to concentrate on those sensors/values. These are viable means of data reduction and geographical feature extraction with

systems that have many combinations of sensor locations, source locations, and wavelengths.

In this research, there is only one location of the sensors/detectors and four wavelengths, of which three are essential to the study; therefore ICA would not offer added value to this study.

3.4.5 K Nearest Neighbor (KNN)

This algorithm has the potential of being computationally feasible for real-time use, and can be easily modified to allow for a sample to remain unclassified. KNN is a classification algorithm that takes K number of training data elements nearest the sample to be classified, then assigns the sample to the class most prevalent in those K elements.

3.4.6 KNN Classification of Focus Task

One of the end goals of fNIR research is the development of BCIs. Experiments involving such capability were performed by Ayaz using 10 detectors, four sources placed on the forehead, and four wavelengths [28]. Subjects were asked to focus on a bar on a computer screen during tasking periods, which alternated with rest periods. The oxygenation changes of subjects were monitored and used to change the size of the bar. States were classified as either resting or task using a KNN classification algorithm and a Bayes classifier. Training data were collected in the morning and used to classify the afternoon trials. The results of the five subjects were 75.44% correct for the k nearest neighbor and 72.10% for the Bayes.

3.4.7 KNN Classification of Imagined Movement

A study by Mason used a nearest neighbor algorithm (with k=1) to classify EEG signals to determine intent to finger-tap [29]. Subjects consisted of two spinal-cord injured people who could not move their fingers. Ten electrodes were placed over the supplementary motor areas and sensory motor cortices and sampled at 128 Hz. Data were collapsed averaged at 1/8 second intervals and classified every 5/16 of a second. Subjects imagined untimed finger flexions. Subjects reported classification errors using a "sip and puff" switch during a feedback period. Resulting hit rates were from 36-44% with false positive rates less than 1%. A strength of this study is that imagined movement appeared to be detected and the algorithm was not tuned for the particular individuals. However, the self-report method may have spuriously inflated correct detection rates. Error reporting required an action, whereas reporting of a correct classification was passive; *i.e.*, the default and therefore might tend to occur more often. Secondly, since the subjects knew what the "correct" response was, they might have a desire to show "correct" behavior.

3.4.8 Parzen Windows

This algorithm has the potential of being computationally feasible for real-time use, and can be easily modified to allow for a sample to remain unclassified. Parzen Windows is similar to KNN but uses a kernel function to determine the weight of each sample that is within the region defined by the kernel [30]. More weight can be given to neighbors that are closer, which could increase classifier accuracy in cases, such as this dissertation, where classes have high variability.

3.4.9 SVM

SVM is a classification algorithm using the concepts of a decision boundary – a linear separation of classes, and the margin – the distance between any of the data elements and the decision boundary [26, pp. 326-327]. SVM establishes an optimal decision boundary between classes such that the distance from it to the classes is maximized. Classification is then determined by which side of the boundary a sample lies on. A downside of this method is that when the boundaries of training sets overlap, there is no pure decision boundary. Modified versions can use "slack variables" that would allow for overlap of classes [26, 331]. Although SVM is designed for two classes multiple classes can be solved by first solving for a pair of classes, then progressively solving subsets within each pair until the total number of classes has been addressed [31]. Another downside is the complexity of the algorithm – initially establishing the boundary is computationally intensive. It is more computationally intensive than KNN but is more accurate. One solution for the complexity issue is to divide the problem space into subsets and solve each, then progressively combine subset solutions and solve for the combination until in the end the total space has been solved [32]. Another solution for complexity is to recursively eliminate features – attributes of the problems space with potential relevancy to the target classes [33].

3.4.10 SVM Classification of Imagined Movement

Herff led a study that compared 252 channels of fNIR data from subjects speaking (audible), moving their articulatory muscles but not speaking (silent), and imagining moving their articulatory muscles (imagine) [34]. Sources/detectors were placed over the

motor area, forward of the motor area, and over the pre frontal cortices. The results for SVM binary classifications were 80% correct for audible/imagine (standard deviation = 15.0), 72% for silent/imagine (standard deviation = 10.7), and 65% for audible/silent (standard deviation = 23.1).

3.5 Research into Related Areas Other than Classification

Research related to imagined actions, stimuli, and other areas related to this project are discussed below. There is a significant amount of research into imagined movement, including involvement of amputees with phantom limbs, amputees without phantom limbs, and non-amputees.

3.5.1 Imagined Finger Tapping

In a study by Jeannerod there was an increase in metabolic activity in the contralateral primary motor cortex while performing imaginary finger tapping with an amputated right hand [35]. Amputees with phantom hands had higher activations in the contralateral motor and somatosensory cortex than non-amputees. But a woman's phantom limbs (the woman was born without limbs) did not evoke sensorimotor activation. But in the other direction, transcranial magnetic stimulation (TMS) stimulation of the sensorimotor cortex increased her sensations. These studies indicate the potential for imaginary finger tapping to be detected in the study for this dissertation.

3.5.2 Interaction of Real and Imagined Movements

In another study, phase synchronization during EEG was used to demonstrate a degree of interaction (and thus functional connections) that were similar between real and

imagined movements [36]. The phase synchronization methodology analyzed the synchrocity between different areas (increases or decreases in power occurring synchronously between different areas), showing detection of weak nonlinear interactions between them. A key strength of the study was the rigor of the methodology – focusing on a red light to mitigate ocular artifacts, number of trials used (*e.g.*, 130, 220), instructions (*e.g.*, instructed to imagine kinesthetic of movement rather than its imagery), and inclusion of a control session (no movement). Weaknesses included the need for the subjects to practice finger tapping and removal of trials with artifacts (approximately 10% of trails were removed). The results showed similarity in the synchronizations obtained from the imagined and actual tasks. The results also showed some functional connectivity among four pair of the electrodes.

3.5.3 Area- and Time– Related Differences in Oxygenation/Deoxygenation

In an fNIR study of finger-tapping, by Sato (2007), two area-related categories of oxygenation/deoxygenation changes were observed [25]. Five source and four detector probes were used in a configuration that provided 12 measurement points for each hemisphere. The two categories were: (1) oxygenated hemoglobin and total hemoglobin increases over a large area (approximately 80% of a 6 cm x 6 cm region) and (2) deoxygenated hemoglobin decreases in a smaller area (8% same side and 16% contralaterally). The smaller areas of deoxygenated hemoglobin changes were explained by the potential that the levels were smaller, therefore having a smaller signal-to-noise ratio, resulting in a smaller area of statistical significance. This lower signal-to-noise ratio of deoxy-Hb was also related to deoxy-Hb decreases having no laterality. The second case was assumed to be due to motor cortex activation because of similar results

with fMRI. fMRI is a type of magnetic resonance imaging that captures Blood Oxygen Level Dependent (BOLD) signals by measuring differences in magnetic fields per Bestmann [37]. Rack-Gomer and Kwong found that fMRI BOLD signals reflect changes in neural activity by way of changes in oxygenation of blood, cerebral blood flow, cerebral blood volume, and metabolism [38] [39]. Three time-related categories were also noted by Sato: (1) sustained activation in one region; (2) activation only at the beginning in a second region, and (3) cumulative activation in a third area. The first category (sustained activation) was believed due to the finger tapping. This category occurred contralaterally over the points corresponding to C3 and C4 on the international 10-20 system and corresponding to the motor cortex. The second (initial period) occurred over the somatosensory cortex and was believed related to the initial stimulus and decreasing due to habituation. The third (cumulative) occurred over the posterior frontal cortex and superior temporal cortex and was believed to be related to maintenance of a long task.

Variations among onset and amplitude of fNIR responses were also documented by Miezin [40]. Variations occurred among different individuals, among different areas of the brain within a single individual, and at different times within the same individual.

3.5.4 Stimuli – Types and Timing

Neural refractory periods cause the response elicited by a stimulus to be reduced for a subsequent stimulus. For auditory stimuli in an EEG study by Liu (2005), the subsequent stimulus response was reduced and when the interstimulus interval was shorter than 150 ms, the response to the subsequent stimulus was completely inhibited [41]. An optical imaging study by Cannestra (1998) with auditory stimuli also showed

that the greater the duration of a stimulus, the longer this reduced responsiveness period as measured over the sensorimotor cortex [42]. Table 4, recreated from their paper, delineates this effect. With regards to this dissertation, responses to finger taps, after the first tap, may be reduced. Furthermore, tapping rates greater than six/minute may be "completely inhibited".

TABLE 4. EFFECT OF STIMULUS ON INTERVAL OF REDUCED RESPONSIVENESS [42]

Primary Stimulus Duration (seconds)	Interval of Reduced Responsiveness (seconds)
0.5	4.5
1.0	4.25
2.0	4.0
2.25	4.25
2.4	7.1
3.5	7.0
10.0	8.0
15.0	13.5

Another area of interest to this dissertation is what regions might be activated by a directional visual stimulus – in particular, are there activated areas that are either interconnected to, or in close proximity to, premotor or motor areas. A recent fMRI study compared the effects of directional visual stimuli (faces, pointing hand, and arrows [43]). All three types elicited responses in the right hemisphere, attributed to possible spatial or attention processing. All the directional stimuli resulted in activations in the

superior temporal sulcus, the inferior parietal lobule, the inferior frontal gyrus, and the occipital cortices in the right hemisphere. Directional hands and arrows also had responses in the inferior frontal gyrus. Directional arrows resulted in activations of the right inferior and middle temporal gyri and the left superior parietal lobule; attributed to possible cognitive processing.

Also of particular interest to this proposal is the effect the type (visual or auditory) of timing stimuli has on areas activated. The areas involved in integrating a timing stimulus appear to be different for a visual stimulus than for an auditory or no stimulus. This could be due to an audible stimulus being more automatic than visual or the effect could be due to the area of visual integration being also used for attentiveness functions. Perhaps an audible stimulus requires little thought to follow. In one study of the rate of a timing stimulus, rates of 1, 2, 3, 4, and 5 Hz resulted in a linearly increasing Blood Oxygenation Level Dependent (BOLD) response; however at frequencies below 1 Hz, the linearity was disrupted, perhaps because of a different mode of execution. Predictable cuing can have different effects than unpredictable cuing, with greater activation for unpredictable. The amplitude of movements is correlated with the magnitude of an fMRI BOLD response in the primary motor cortex [44]. Generally, rates vary from 0.25 to 4 HZ with little consensus on activation differences within that range [7]. There is also more variance in the effects that result from different stimuli methods than there is in the results from tapping tasks of varying complexity, indicating a lack of understanding in what in the brain differentiates complex tasks from each other. While finger tapping may appear to involve only movement of the fingers (and eyes/ears for the stimulus), other muscles are in fact involved including those of the wrist, elbow and

shoulder [45]. Additionally, this movement is sensed through proprioception, and touching of a surface or other fingers is sensed and transmitted back to the brain. Of note to this particular research is that cutaneous stimulation does not excite the supplementary motor area [46].

In a study where subjects responded to an external stimulus, the results were very similar (except for auditory regions) to the responses of the same subjects subsequently responding without a stimulus (self-paced) [47]. Interestingly, this study used an auditory stimulus and the comment in the previous paragraph regarding the similarity of auditory stimuli and no stimuli begs the question of whether this study would have shown differences had visual stimuli been used. This study also did not indicate whether there was a group of subjects that used the reverse order (non-pacing, followed by audible pacing) to help differentiate whether or not the similarity of activations was due to "learning." Activations for syncopated tapping were evident in a broader area than for synchronized tapping. Activity was greater in the supplementary motor area, left premotor area, right thalamus, bilateral inferior frontal gyri, and cerebellum.

3.5.5 Preprocessing Steps

Many studies used a sequence of steps to process the collected data and prepare the data for subsequent analysis and/or classification. These include a variety of methods to average data over multiple trials or multiple subjects, filter data, estimate hemodynamic response from raw values, and data reduction techniques; however, many of these methods are not amenable to real-time classification or to classification with a single sensor/source. For example, data reduction might be necessary on systems with many combinations of sensor locations, source locations, and wavelengths but not with a

single source/sensor. Some methods are more amenable than others to real-time classifications. For example, any averaging of data from multiple trials or multiple subjects could not be used in real-time classification of a single subject's actions; although they may be useful in developing models for classification. The literature search for this study focuses on finding methods that may be applicable to real-time classification with a single sensor/source.

Low pass filters and averaging are common methods to reduce some contaminating physiological features such as heart beat (1.1 Hz) and respiration (0.2Hz) [48] [49].

In the study by Herff previously discussed under the SVM section, they converted the raw data into optical densities, then converted to oxy- and deoxy-hemoglobin values; detrended the data, extracted features with classification potential, selected features, then classified the data [34]. Optical density is simply taking the amount of light received and making a determination of the density (absorbance) of the material traversed. No explicit rationale was given for any functional need to optical densities or to hemoglobin values. No discussion was provided of how the data were detrended. The features were extracted by subtracting the mean of samples 9 through 15 of each trial from the mean of samples 1 through 7, thus giving two features per trial per channel (252 channels). Feature selection, therefore, was a function of geographic selection. SVM was used for classification and produced a 79-80% accuracy. The optodes were secured to a helmet to prevent movement during the study. The location of the optodes included areas with and without hair, including the motor cortex, areas forward of the motor cortex, and both sides of the prefrontal cortex.

One researcher, Scarpa, tested the use of reference sources to capture a baseline signal [48]. The study placed 14 sources and four sensors over the parietal areas, along with two pair of reference sources/detectors with reduced separation – only one third the separation of the other sources/detectors. The reduced penetration allowed detection of only the scalp, allowing them to capture signals not related to the response of the stimulus. The reference signal was then subtracted from each of the other signals. The results showed an improved contrast to noise ratio.

One method, empirical mode decomposition, decomposes input into "intrinsic mode functions" through an iterative process. This method can isolate elements containing a stochastic component [50] and can work on a single-trial basis but requires post-experiment analysis and is therefore not suitable for this effort.

CHAPTER 4

METHODOLOGY

This section describes the overall methodology, followed by a discussion of the stimulus and collection methods, including subjects, system used, placement of source/detector, stimuli used, and subject tasking. The data collection execution and classification methods are then discussed.

4.1 Subjects

Fifty subjects were solicited through the ODU SONA program, with the only criteria being that they be at least 18 years old and under 65 years old. Fifty subjects, 36 females and 14 males, volunteered. A questionnaire was administered, asking the subject's gender, age, number of caffeine drinks they had had prior to the experiment, and whether they are a drummer. The modified Edinburgh handedness inventory in Table 5 was administered to enable a determination of handedness [51]. The modifications to the Edinburgh inventory included adding the hand used to eat (fork, chopsticks), use a computer mouse, hold a cup of water, use a TV remote, use a light switch, and plug a cord into an electrical outlet; and deleting the hand used to hold scissors, knife, spoon, broom, striking a match, and opening a box with a lid. These changes were made to be more inclusive of multiple cultures and adapt to today's usage of objects. The inventory given to the initial subjects included only the first nine items on the list; the remaining seven were added back to the questionnaire to use for potential new research. For this study only the results from the first nine were used. The

following table depicts the items, which ones were original and whether they were for this research or for future research.

TABLE 5. MODIFIED EDINBURG HANDEDNESS INVENTORY

		On Original Edinburg Inventory	To be Used for This Research	To be Used for Future Research
1	Writing	X	X (original)	
2	Drawing	X	X (original)	
3	Eating (fork, chopsticks)		X (added)	
3	Throwing	X	X (original)	
4	Toothbrush	X	X (original)	
5	Computer Mouse or Touch Pad		X (added)	
6	Hold a glass or bottle of water		X (added)	
7	TV Remote		X (added)	
8	Light Switch		X (added)	
9	Plug cord into outlet		X (added)	
10	Scissors	X		X (original)
12	Knife (without fork)	X		X (original)
13	Spoon	X		X (original)
14	Broom (upper hand)	X		X (original)
15	Striking match (match)	X		X (original)
16	Opening box (lid)	X		X (original)

4.2 System

The fNIR device used was a Spire-NASA LaRC Cerebral Oximeter Model SPI-CerOxim-06A, developed by Spire Corporation for NASA depicted in Fig. 4 and Fig. 5 [5].

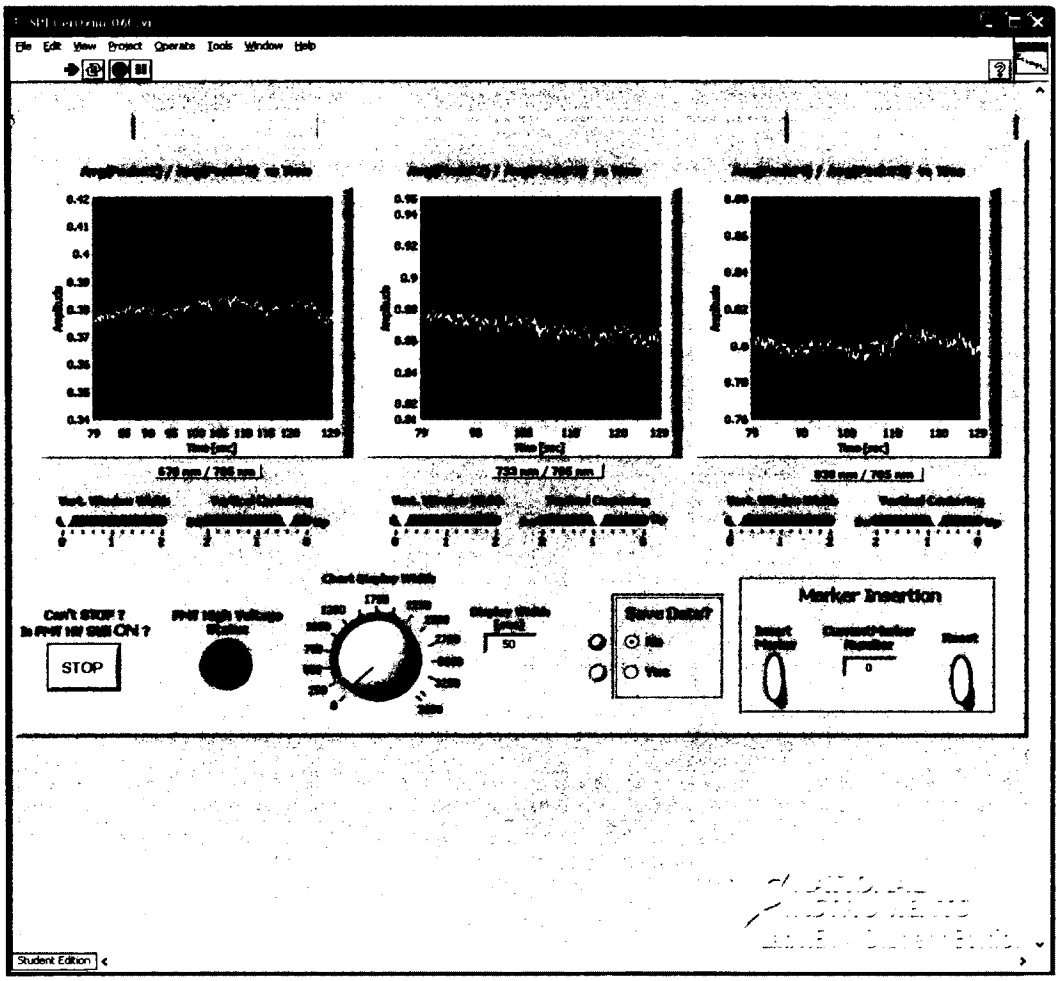

Fig. 4. Spire-NASA oximeter interface

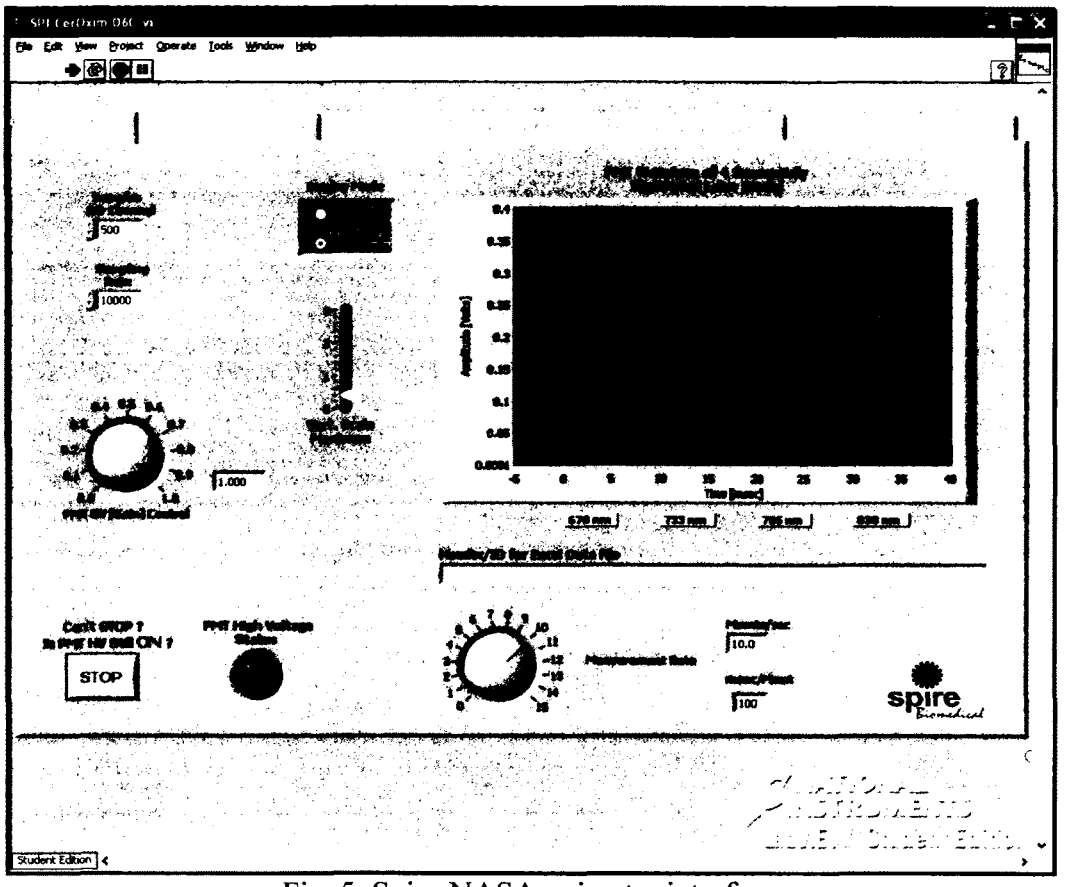

Fig. 5. Spire-NASA oximeter interface

The device contains four infrared emitters, each with a different wavelength: 670 nm, 735 nm, 785 nm, and 830 nm. Light at two of these wavelengths, 670 nm and 735 nm, is absorbed by deoxygenated hemoglobin more so than oxygenated hemoglobin while the opposite is true at 830. At 785 nm, the absorption of oxygenated and deoxygenated hemoglobin is approximately equal. The light emanates from a 1 mm x 1 mm optical prism. As the light passes through the scalp, skull and a portion of the cerebral cortex, it is refracted and absorbed, with a portion of the light making its way back to the scalp. A 1 cm x 1 cm prism gathers this light. The source prism and the detector prism are separated by 2 cm. This separation distance determines the average

penetration depth of the light (*i.e.*, a 2 cm separation leads to a 2 cm penetration depth). More accurately, as depicted Fig. 6, the separation distance determines the predominant depth from which the detector senses the light. The closer together the sensor and detector, the greater the propensity to sense light with a shallow penetration.

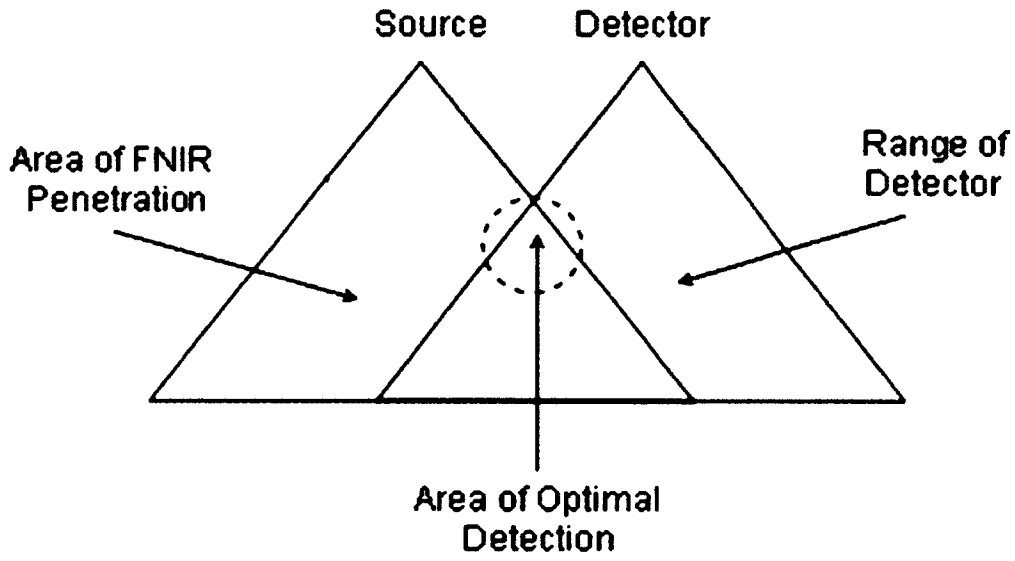

Fig. 6. Detection depth

One of the device's four emitters is turned on for five ms, then turned off. Five ms later a different emitter is turned on and off. After all have been on for five ms and off for five ms, the process is repeated until collection is stopped. The detector readings are sampled at 10000 Hz which equates to 500 samples per emitter on period and 500 per off period. The internal LabVIEW program then averages peak values to provide measurements at 10 Hz.

4.3 Source/Detector Positioning and Calibration

The source/detector was placed over the primary motor cortex on the precentral gyrus. The primary motor cortex is organized somatotopically; therefore, the location responsible for finger movement is known for humans in general; however, the exact location varies from individual to individual. The left cortex was used since subjects had either a dominant right hand or equal dominance of hands and primary motor cortex stimulation results in contralateral muscle movement [10]. The placement on the motor cortex was driven by the following objectives and constraints.

The motor cortex is one of the final brain areas with connection to motor movement, specifically, finger movement and conceivably will be more active for actual movement, as opposed to intentioned movement or decisions related to movement.

The equipment used has a single placement location and the motor cortex has a known location. Furthermore, finger movement appears to be lateralized for people with right hand dominance; therefore, source/detector placement would only need to occur on one hemisphere.

The arrangement of the source/detector on the FNIR equipment used has a fixed detection depth as discussed in Section 4.2; therefore, the target area needed to be near the surface. Some areas, such as the cerebellum are not within the range of this equipment.

4.4 Subject Stimuli and Tasking

Subjects were placed in front of a computer display and continuously responded to stimuli (*i.e.*, arrows, as in Fig. 7, presented for 20 seconds each).

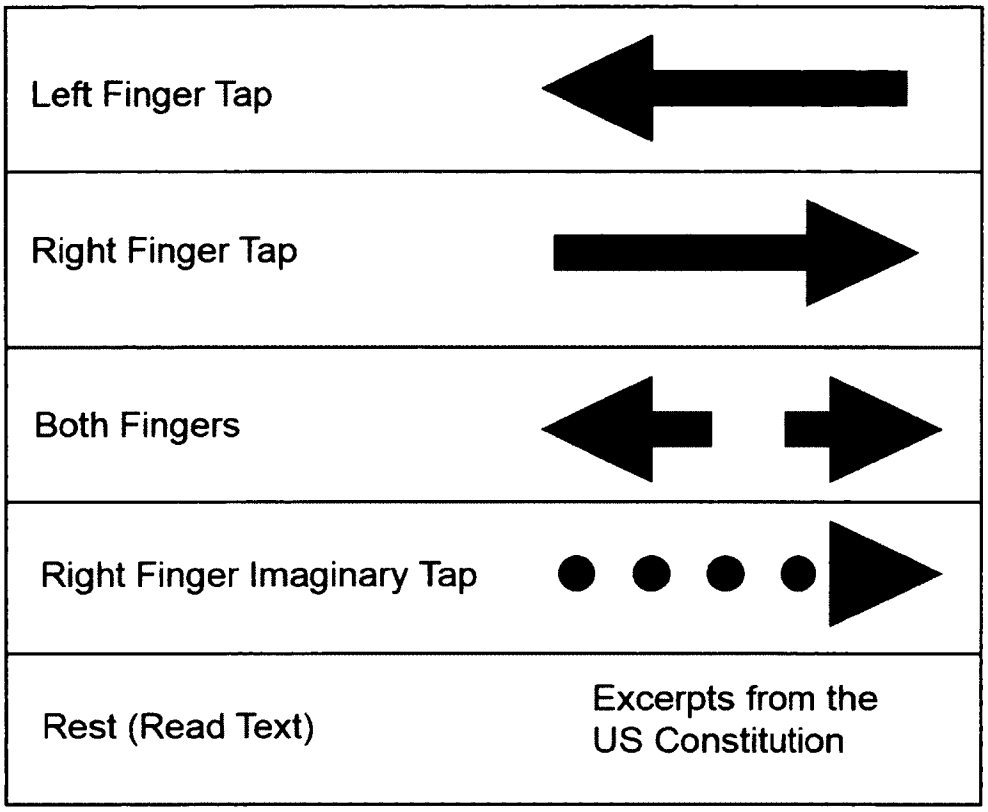

Fig. 7. Stimuli

The subjects were instructed to tap with the left index finger if the stimulus was a solid arrow pointing to the left and tap with the right index finger if the stimulus was a solid arrow pointing to the right. If the stimulus had arrows pointing both left and right, the subject was to tap with both fingers. Since the literature indicated auditory and visual timing elicit additional brain activity, no timing was provided in order to keep ancillary brain activity to a minimum. Subjects were instructed to tap at whatever rate they desired. When a dotted right arrow was presented, the subject was to imagine tapping with the right finger. Text (portions of the United Stated constitution) were

presented for 20 seconds between each type of stimulus, during which time the subjects read the text and did not tap.

The fNIR device was placed on the left side since finger tapping results in contralateral activation. A block design was used, in which subjects were cued with a baseline of text, followed by each of the four tapping stimuli, each interspersed with a block of text. This cycle repeated twice so that each stimulus was presented three times and the interspersed text presented 13 times. The entire sequence took eight minutes and 20 seconds, four minutes for tapping stimuli (1/3 minute x 4 stimuli x 3 cycles) and four minutes, 20 seconds for the baseline (1/3 minute x 13 presentations). This blocked sequence is illustrated in Fig. 8.

Baseline	Stim 1	Baseline	Stim 2	Baseline	Stim 3	Baseline	Stim 4
20 secs	20 secs	20 secs	20 secs	20 secs	20 secs	20 secs	20 secs
Repeat twice, changing order of stimuli and ending with 20 secs of baseline							

Fig. 8. Block protocol of stimuli (Stims) and text baseline

Extensive counterbalancing of stimuli ensured any effects from the order of stimuli were negated. Both the beginning stimulus and the subsequent sequence were varied for the subjects so that a nearly equal number were performed for each permutation of the stimuli. The four tapping stimuli were each used once as one of the first four stimuli, once as one of the second four stimuli, and once as one of the last four stimuli so that each stimuli occurred once during each third of the protocol. The sequence of the four was changed for each third of the protocol so that subjects would not

ever experience the four stimuli in the same order twice. Within those two restrictions, 34 different permutations of sequences were used, as listed in Appendix A, Table 53.

Research previously discussed suggests that the use of directional arrows as a visual stimulus activates areas that are not in either the motor or premotor area. Any resulting nonmotor activity from looking at the arrows was expected to have a short duration since the arrows were static for the entire time a stimulus was presented. The arrows therefore were not expected to negatively affect this research.

4.5 Data Collection

Data were collected at the rate of 10 samples per second using the labVIEW program accompanying the fNIR device. Each sample consisted of four measurements – one for each of the wavelengths. The data were then saved to disk for post analysis.

After all data were collected, three ratios of wavelength data were obtained. The resulting ratios were used for classification of the actions taken by the subjects. Of the four wavelengths, 780 nm is the closest to the crossover wavelength at which higher oxygenation changes from a higher oximeter reading to a lower oximeter reading; therefore, the ratios of the other three wavelengths to 780 nm are good differentiators of relative absorption occurring. Physiological factors such as heart beats could increase overall blood volume and therefore increase the readings from all wavelengths, the ratios should remain relatively constant, negating the need for filtering of respiration and cardiac affects. Additionally, since the data in the four values were effectively captured by the three ratios, the data were reduced by 25 percent, a significant benefit with regards to classification algorithms.

4.6 Classification

The first supervised classification algorithm that was used to analyze the data was SVM due to its posited accuracy. The second was a Linear Discriminant Analysis algorithm and the third was a decision tree.

Ten percent of the data from each individual was designated as training data and used to create training sets. Each of these samples was classified as either right tapping, left tapping, imagined, or stationary, based on the actual state of the subject. The data for these sets were randomly selected from the full data set. The remaining 90% of the data was tested using the three classification algorithms.

CHAPTER 5

DATA COLLECTION AND PREPROCESSING

This chapter describes the execution of the protocol and collection of the data. The findings of an initial look at the data are then presented. The research proposal for this data collection is provided in Appendix B and was approved by Old Dominion Human Subjects IRB, approval number 09-134, November 19, 2009.

5.1 Protocol Execution and Data Collection

The checklist in Appendix C was used for both subject preparation and system setup. All subjects were briefed on the rules and administered the modified Edinburgh handedness inventory. The nasion/inion and preauricular distances were measured and used as references to place the source/detector pad of the Spire-NASA LaRC cerebral oximeter over the primary motor cortex of the left cortex. The oximeter was turned on and adjusted for suitable signal strength. A practice trial was run to ensure subjects understood their tasking. The actual trials then began with each subject being administered the presentation containing the stimuli, while data were captured by the oximeter. Several issues surfaced early on during these trials.

5.2 Collection Issues

Subjects were administered the protocol detailed in the previous section – presented with the stimuli while they responded as instructed, and data were recorded.

One issue that became immediately apparent was that the readings were extremely noisy and/or very weak. This was traced to hair blocking the source/detector

path. Engineers at Spire were contacted and said the oximeter had been used on the front part of the head, where hair is not prevalent and on people without much hair. To mitigate this problem, hair was parted and different articles affixed to the head to try to either directly keep the hair parted or to keep the source/detector pad firmly against the head to maintain the hair part. Swimsuit caps, Velcro straps, elastic bands, and other devices were used.

Even with the use of these devices to maintain the part and stabilize the pad, the oximeter returned negligible or no readings for some subjects. Subjects' hair color, density, and strand thickness appeared to be a factor in the amount of signal attenuation and noise. The darker the color, the denser the hair, and the thicker the strands, the weaker the resulting detected signal and the greater the noise. Collection records for most subjects were annotated with hair color, hair density, and strand thickness for potential analysis value.

In an attempt to get some usable data, pieces of material were inserted under the pad perimeter to raise the pad. The material was covered with black electrical tape to act as a baffle and prevent reflections and resultant false readings. Reading in most cases then became higher. Collection records were annotated with the height of any pad used.

A second issue that arose was undesired movement drift of the sensor pad. The pad would tend to move downward, more so on some subjects than others. This issue was mitigated by using multiple Velcro straps and/or elastic bands. Collection records were annotated with the beginning location and the ending location of the sensor pad.

Fig. 9 depicts the use of Velcro straps for stabilization and a white piece of Styrofoam used to increase the height of the sensor. In cases where only a very small amount of height was needed, a comb would be wedged under one side of the sensor pad.

Fig. 9. Styrofoam and Velcro straps

Fig. 10 depicts the use of a cap to block ambient light. It was used on an as needed basis and was especially useful in cases where the sensor pad did not fit snugly onto the subjects head.

Fig. 10. Cap to block ambient light

Due to the sensor movement and the collected data variations due to hair characteristics, notes were made for many of the subjects, capturing signal quality, hair characteristics, sensor beginning location and ending location.

A third issue that arose is that the data appeared to be truncated. Consultation with the engineers at Spire led to the conclusion that the data were cached and written to disk periodically so that if the machine was turned off prior to the last data being written to disk, the portion of data remaining in the cache would be lost. This problem was temporarily addressed by letting the oximeter run for a period of time prior to turning it off. In parallel, Spire made a software fix and furnished a new release that permanently fixed the problem. The data from the first few subjects were excluded from subsequent analysis.

5.3 Initial Look at Data Quality and Processing Tools

A quick look of the data was taken to validate that the data are plausible, the methodology is viable, the methodology is appropriate, and to make adjustments as needed. A portion of the data was averaged into approximately one-second blocks, per the proposed methodology, to reduce the data to 20 data points per slide. The data were then plotted and reviewed to get an initial look at apparent quality of the data.

Fig. 11 is a plot of the raw values read by each sensor. The y axis is the value of those readings. The legend for the top line incorrectly reflects 810 nm. The correct value is 830 nm. On the first plot, the data do not show, at least to the naked eye, any systematic variability relative to the timing of the slides (*i.e.*, the tick marks). A general downward trend of values is evident.

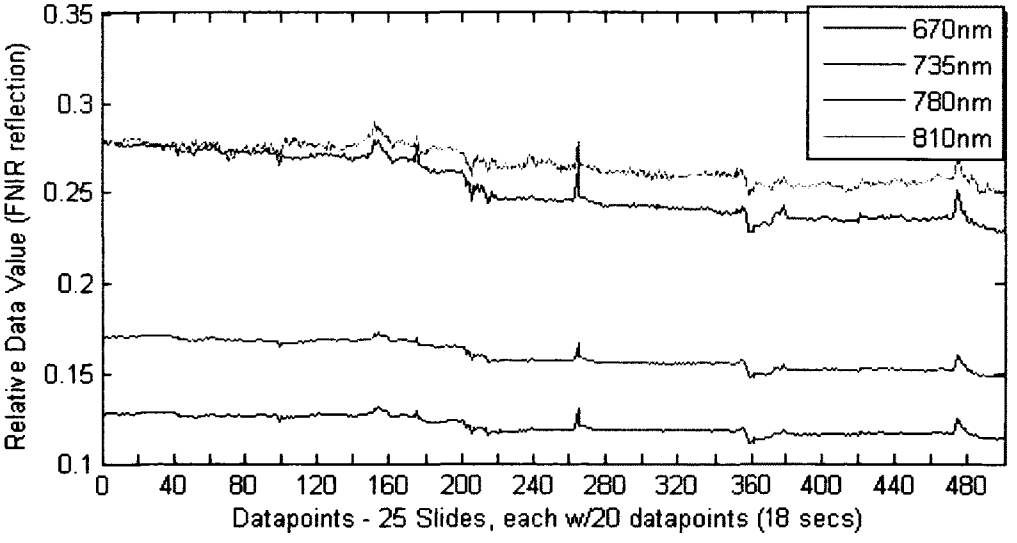

Fig. 11. Raw data values

Fig. 12 has the first 19.6 seconds (subject reading text) of the raw values of all four wavelengths plotted on the same graph. Offsets were added to each wavelength such that the plots were generally overlaid, allowing the differences between the responses of the different wavelengths to be visualized. While the offsets aided in visually comparing the results of the different wavelengths, they were not necessarily of any benefit to classification algorithms.

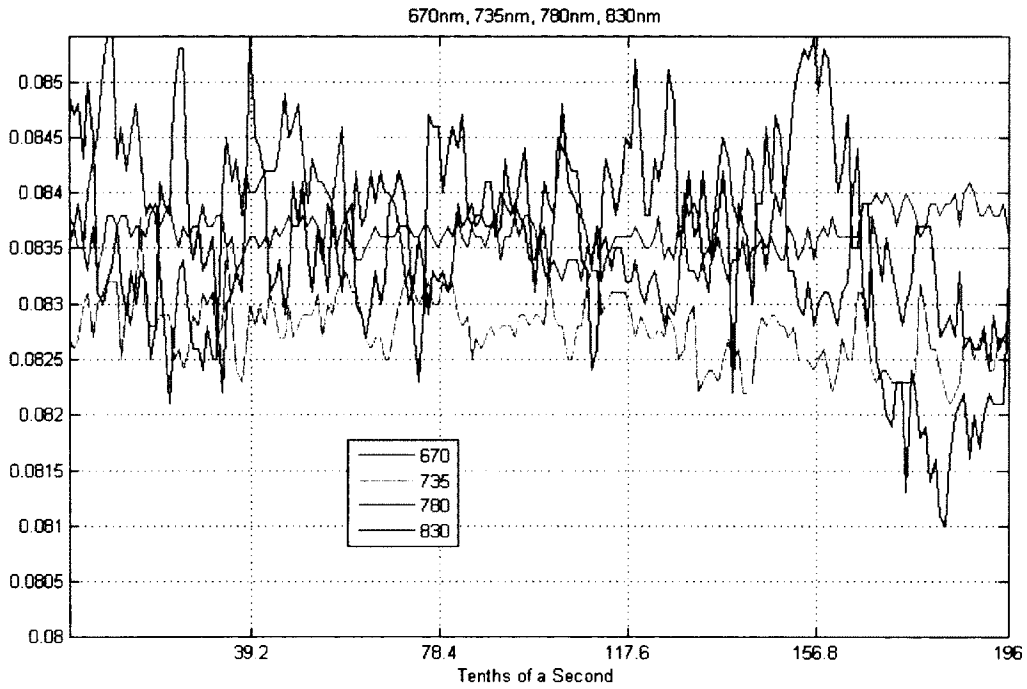

Fig. 12. Raw data values of one baseline presentation

The figure, along with similar figures from other trials, were visually reviewed for any apparent artifacts that might indicate a need for further review prior to continuing to process the data. For example, if the data for any of the wavelengths were to appear to be all zeros or all a constant value, the validity of the data would be suspect. Numerous

abnormal spikes might indicate corruption or contamination of the data. If the variations of each wavelength were to appear constantly similar, the data could be potentially suspect since some degree of continual changes in oxygenation/deoxygenation would be expected and each wavelength would respond differently.

The visual review revealed that each frequency had non-straightline data and each frequency had a different pattern. No two frequencies changed in sync – indicative of responses that affect each frequency differently.

The plots had numerous, relatively mild, spikes, but they were not regular in either frequency or amplitude and did not appear to be even close to a frequency indicative of either heartbeats or breathing. The spikes were therefore likely due to noise. Filtering the data may remove some of the noise although classification routines could arguably be applied without detriment to the unfiltered data.

The data were noisy, even after averaging the data into 20 values per slide (stimulus block) leading to a decision that a method other than block averaging would be more useful for classifying. A supervised classification needs a set of data for training the classifier, and that set needs to include enough good data points to establish a viable training set. If the data were noisy, as this data appeared to be, more points would be required to ensure enough good points were included. In this experiment, each stimulus was presented to a subject three times (three slides), generating only 60 points per stimulus per trial, if averaged into one-second points. Even if twenty percent of the points were held out for training, that is only 12 points for 60 seconds of stimulus presentation, insufficient for this experiment for several reasons. First, 12 points of noisy data will equate to less than 12 accurate points. Second, the oxygenation/deoxygenation

effects have time patterns, necessitating time points that occur during different phases of the pattern. Third, the data showed global trends which will necessitate ensuring training points are selected from different global time phases.

In summary, a filtering method that retains the number of data points, yet produces a smoothing effect, would be more appropriate.

5.3.1 Filter Selection

A moving average filter of length 28 (2.8 seconds) with equal weights was selected, but only after the comparison of a variety of window ranges, discussed below. The filter reduced noise and was, in effect, a low pass filter attenuating cardiac effects.

Variability, presumably noise including physiological effects, was evident in the data from each signal and each ratio suggesting filtering may be beneficial. An initial comparison of filters was made to determine an appropriate filter to use with the results indicating a moving average filter of length 28 and equal weights will suffice. Using the MATLAB filter command, filters were executed for values and ratios, for different weights, and for different moving average lengths. The filters compared were:

- Values and ratios.
- Weights of 3, 2, 2, and 1, and a filter length of 8.
- Weights of 3, 2, 2, and 1, and a filter length of 8.
- Equal weights and a filter length of 8.
- Equal weights and a filter length of 16.
- Equal weights and a filter length of 32.

As the filters progressed to 32x1, the noise became reduced. At 32x1; however, there appeared to be the desired information began being reduced; therefore, a 28x1 filter was selected for the experiment. The filtering of values did not reduce variability any more than the filtering of ratios. Since only three ratios are necessary to capture the information of the four values, filtering ratios is the better method.

5.3.2 Filtering

The collected data consisted of values of four wavelengths, collected at 0.1 second intervals. Each stimulus was presented for 20 seconds; however, due to PowerPoint and cpu timing, the timings varied slightly. The minimum presentation length was 19.0 seconds so each presentation was truncated at 19.0 seconds to make them equal length. The result was 4750 data points per trial, divided into blocks of 190 points. Each stimulus, other than the baseline of reading text, was presented three times, making a total of 570 points per stimulus. Prior to the first presentation, after the last, and in-between the others, a 19.0 second block of baseline data was saved.

The data were multiplied by -1 so that higher number would reflect higher densities of the optical path. MATLAB's polyfit and polyval functions were used to evaluate the data and produce a polynomial of degree 2. The resulting polynomial, overlaid on the data, is shown in Fig. 13.

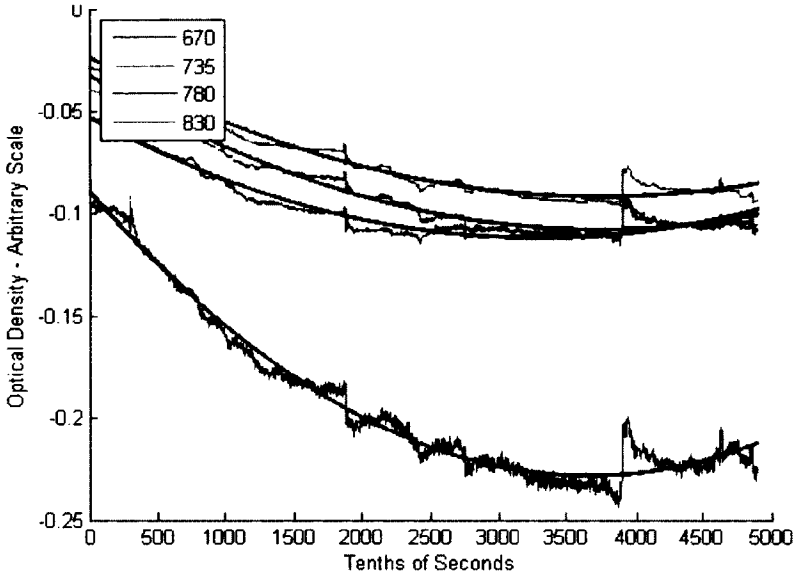

Fig. 13. Polynomials fitted to data

The raw values were then subtracted from this polynomial, resulting in deltas from the polynomial, mitigating any global trend and normalizing the data to a common zero baseline. A plot of these deltas is shown in Fig. 14.

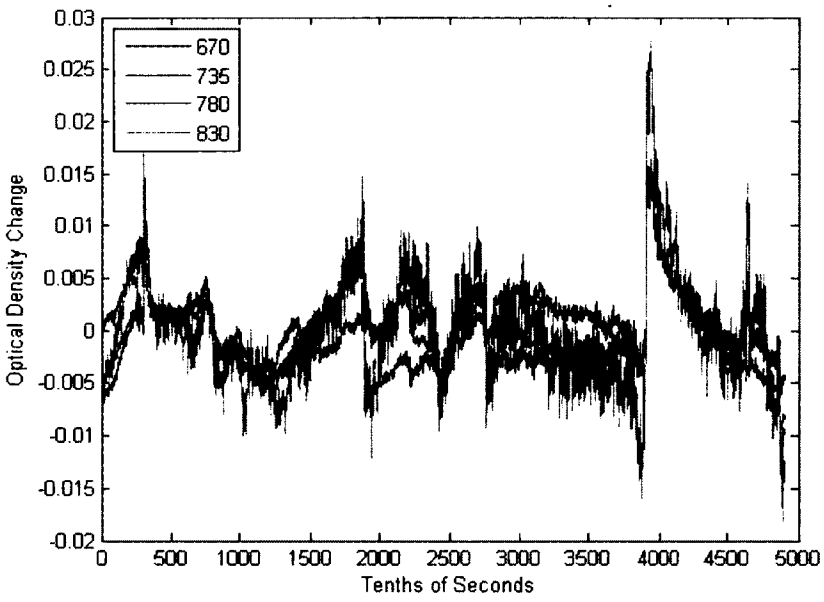

Fig. 14. Data subtracted from polynomials

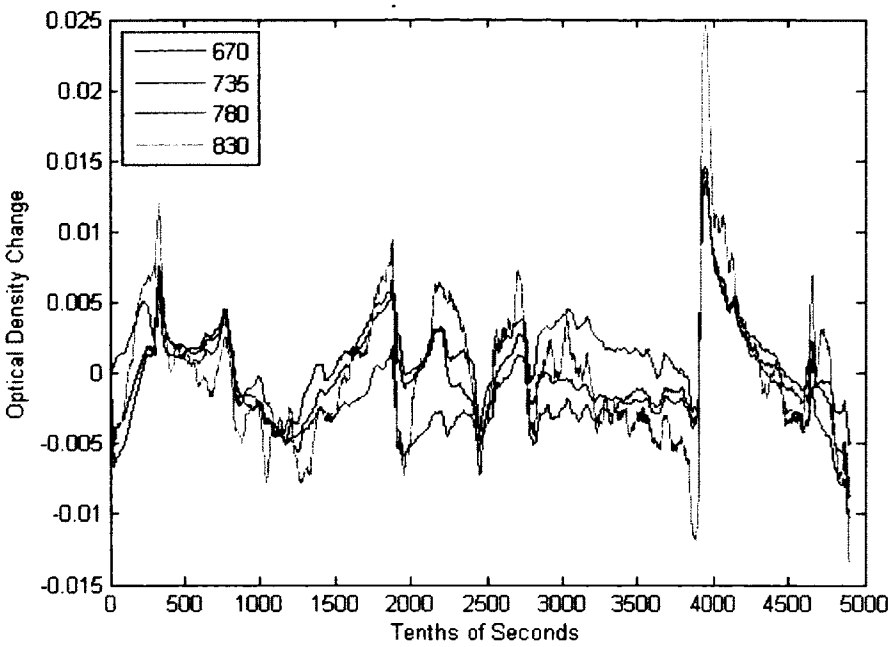

Fig. 15. Filtered polynomial data

The differences in variance among the four baselines remained; changes due to heart beat, overall blood volume, respiration, and movement artifacts also remained.

The data were then filtered using MATLAB's filter function, with a 28 point convolution with equal weights. At each data point, the previous 28 points are averaged and that average is substituted for the current data point. The results are shown in Fig. 15.

All data was put into structures to facilitate subsequent manipulation by subject, stimulus, ratio, or value. The text immediately preceding a stimulus presentation was averaged with the text after a presentation to provide a text baseline for classification uses.

5.3.3 Feature Extraction

Feature extraction was not accomplished for several reasons. The values of feature extraction are to reduce the amount of data to an actionable level and/or to extract meaning from the data, which can then be classified. In this project there is only one source/detector, only four wavelengths (which can be reduced to three ratios), and only ten captures of that data, per second; therefore data reduction is unnecessary. Also, the data already has a meaning – the ratios of the raw values captured of each wavelength indicate ratios of oxygenation/deoxygenation occurrences. While they don't give absolute concentrations of oxygenated and deoxygenated blood, they do give relative values which are sufficient for classification algorithms to act upon.

5.3.4 Classification

The filtered, normalized data were classified using a MATLAB SVM classifier. The SVM was used to classify the data as either "Right" tapping or "Not Right" tapping. "Not Right" included left tapping and reading text. The classifier was trained on 10% of the data (randomly selected), then applied to the remaining 90%. The following two tables, Table 6 and Table 7 show the aggregate results of three classification executions for the subject in Fig. 15 above and the aggregate results for a sample of six subjects. The six subjects were selected as ones having generally less apparent noise than the others.

TABLE 6. CLASSIFICATION OF "NOT RIGHT" AND "RIGHT", ONE SUBJECT

	Classified as "Right"	Classified as "Not Right" (Left or Text)	Correct
Actual "Right"	1067	695	60.56%
Actual "Not Right" (Left or Text)	1351	2177	61.71%
Total	2418	2872	
Error Rate			38.68%

TABLE 7. CLASSIFICATION OF "NOT RIGHT" AND "RIGHT", SIX SUBJECTS

	Classified as "Right"	Classified as "Not Right" (Left or Text)	Correct
Actual "Right"	5429	5143	51.35%
Actual "Not Right" (Left or Text)	9459	11709	55.31%
Total	14888	16852	
Error Rate			46.01%

These results are sufficient to confirm that SVM is an appropriate classification method for this project. The average error rate of 46.01% is slightly better than the 50% that would be expected from a random assignment of classes. These results are with only

ten percent of the data being used for a training set and the remaining 90 percent being held out for actual classification. The confusion tables above, Table 6 and Table 7 show that the amounts of Type I and Type II error are of the same order of magnitude and the amounts classified into each class are also of the same order of magnitude. Such results indicate the hyperplane created by SVM cut through the center of the data, as it should, rather than being placed near the edge of the data. A third positive aspect of these limited results is that this classification was applied "Right" tapping and "Not Right" tapping; which is a total of three classes since "Not Right" tapping included both left tapping and reading text. If only two stimuli are to be differentiated, the accuracy should increase.

CHAPTER 6

CLASSIFICATION

Of all the trials, 60 were suitable for classification. The others had either truncated data or issues with getting a signal through hair. Almost all of the unsuitable trials occurred during the first week of collection. This chapter provides the demographics of those trials, the hypotheses to be tested, and the results of the hypotheses testing. The results of the classification of states using SVM, decision tree, and LDA classifiers are presented, then results of testing the remaining hypotheses are described, and lastly comparison of the classifiers with themselves and with the results of other research is discussed.

6.1 Demographics of Test Trials

The 60 suitable trials were used for all hypothesis testing. The trials were from 29 subjects and contained 17 male and 40 female trials. Of the 29 subjects, one subject had one "left" and four "right and left" boxes checked on the handedness inventory. All the other 28 subjects had only "right" or "right and left" checked, of which only four had four or more "right and left" boxes checked. Summarizing their handedness, 24 of the 29 subjects appeared clearly right handed while five could arguably be considered both handed.

6.2 Hypotheses to be Tested

Hypotheses tested covered discrimination of finger tapping states, gender, age, rate of tapping, and experimental-related attributes. The attributes of the experimental apparatus included the raising of the sensor to obtain a signal, the subjective perception of noisy signals.

6.3 Statistical Method

The data consists of 57 trials, each of which has 513 values (570 – 57 values used for training) that were classified into one of two categories. With only two states per value, each trial could be evaluated as a binomial distribution. As such, the trial data could be compared to a random binomial distribution to determine if a null hypothesis (H_0) were supported. The null hypothesis would posit that the results of the trial could have occurred by chance – that the actual mean of the population was in fact 50% and the sample results deviated from 50% simply because of chance. If H_0 were not supported within a specified level of confidence, typically 95%, we could be assured the results did not happen by chance and therefore the alternative hypothesis is supported – that the algorithm correctly classified the data. This methodology does more than determine that the classifier performed better than chance, it also determines that the mean, which could be far from 50%, was not a random occurrence.

6.3.1 Analysis of a Single Trial

H_0 can be tested using (1) and (2), where n is the number of points in the sample, n_i is the number of correctly classified points, and s is the standard deviation of the sample [52] [53, p. 565].

$$p = n_i / n \quad (1)$$

$$s = \text{squareroot}(p * (1 - p) / n) \quad (2)$$

The first SVM "left" and "right" trial, which had a 40.94% error rate (59.06% correct classification rate) would have a standard deviation calculated as in (3) and (4).

$$p = n_i / n = 303/513 = 0.5906 \text{ (0.4094 error rate)} \quad (3)$$

$$s = \text{squareroot}(0.5906 * (1-0.5906) / 513) = 0.02171 \quad (4)$$

The standard deviation, s, of 0.022 is then compared with a z-score table to find if s is greater than the z score for 0.05. The z score for 0.05 is 1.64, indicating there is less than a 95% probability that true mean error rate of the population from which this sample came is 0.5 or greater. Another way of expressing the statistic is that if 100 trials were performed, less than 5 of them would have a mean error rate of 0.5 or greater.

The performance of the classifier during a single trial could be further measured by calculating a range within which the actual (population) mean might lie, within a specified confidence (again, typically 95%). For example, a sample mean error rate of 23% might have a 95% confidence interval of 16% to 30%, meaning the true mean could lie anywhere between 16% and 30%. This confidence interval can be found with (5) [54]. The latter term (1/2n) is for small samples only (n <= 50) and will be omitted for this analysis.

$$p +/- (s * z_{1-\alpha} 1 / 2n) \quad (5)$$

Applying (5) to the trial just discussed, we have (6) and (7) which gives a confidence interval of 0.56 to 0.63 for correct classification or 0.37 to 0.44 confidence interval for the error rate.

$$p + (s * z_{1-\alpha}\, 1 / 2n) = 0.5906 + (0.02171 * 1.64) = 0.626 \quad (6)$$

$$p - (s * z_{1-\alpha}\, 1 / 2n) = 0.5906 - (0.02171 * 1.64) = 0.555 \quad (7)$$

6.3.2 Analysis of All Trials Combined

The law of large numbers states that as a sample size increases, the mean of that sample converges to the population mean. By this theorem, as the sample size goes from the 513 points of one trial of this experiment, to the 29,241 points of all the trials, the mean is converging toward the population mean.

The 29,241 data points could be analyzed as above – as if they were one binomially distributed sample. The error rate derived from dividing the total misclassifications of all the trials by the total points classified could be tested against H_0. The error rate would be the same as the mean of the individual trial error rates since each trial had an equal number of data points. However, because of the larger sample size, the confidence interval would be narrower than the average of the individual intervals. For example, for the 57 trials for SVM "left" and "right", the error rate was 0.3624 and correct classification rate of 0.6376. Using (5) with the overall rates and with n = 29,241, we have (7), (8), (9), and (10). The confidence interval of the correct classification rate is 0.633 to 0.642 and the error rate is from 0.358 to 0.367.

$$p = n_i / n = 0.6376 \text{ (0.3624 error rate)} \quad (7)$$

$$s = \text{squareroot} (0.6376 * (1 - 0.6376) / 29241) = 0.00281 \quad (8)$$

$$p + (s * z_{1-\alpha} 1 / 2n) = 0.6376 + (0.00281 * 1.64) = 0.633 \quad (9)$$

$$p - (s * z_{1-\alpha} 1 / 2n) = 0.6376 - (0.00281 * 1.64) = 0.642 \quad (10)$$

Using this method, the classification rate and error rate have a narrow interval of confidence, largely due to the high number of samples.

6.3.3 Analysis as a Distribution of Samples and the Central Limit Theorem

Per Sprinthall, the mean of a distribution of samples can be treated as raw scores and use the standard deviation equation of the means [53 p. 150]. Further, the central limit theorem says that the distribution of the means of samples of a population will be approximately normal, regardless of the distribution of any of the samples. The mean of those sample means will approach the mean of the population as the number of samples increase. This knowledge allows the means of the 57 trials of this experiment to be subjected to analyses that are only appropriate for normal distributions, regardless of whether the distributions of the individual trials are normal.

6.3.4 Analysis of Trial Means as Raw Scores – Z-Tests

Since (1) the distribution of trial means is normal (although the underlying distribution may not be), (2) the distribution of trial means is not binomial (although the underlying distribution is), and since the number of trials is large, using a z-test to evaluate the trial results is appropriate. The z-test will show the number of standard errors the distribution mean is from the population mean. For the null hypothesis, the population mean is 0.50 (random); therefore, the mean of the trials will be compared with 0.50.

6.3.5 Statistical Testing

Most of the testing consisted of applying z-tests to determine (1) whether there was a 95% confidence that a sample mean would be less than 50% (random) and (2) whether there was a 95% confidence that one trial would be less than 50%. The mean of the samples is assumed to be normal, as justified by the central limit theorem [53 p. 151].

The z-test was used in two forms, one for a distribution of means and one for a single sample. The first form is the z-test for a mean of a sample distribution of means. This test is appropriate for a distribution of means, which we have and the results speak to the level of confidence in classification on a data point basis. The second z-test is a test for a single sample and therefore treats the distribution of means as a distribution of raw error rates; therefore, the results speak to the level of confidence on a trial basis, not on an individual data point basis. The first test results in a much narrower interval of confidence and is therefore much more likely to attain statistical significance at the 0.05 level, brought about by the high number of samples (data points instead of trials).

The formula used for the first test is in (11), where z is the number of standard errors from the mean, M_bar is the mean of samples, μ is the population mean, s is the standard deviation of the samples, and n is the number of samples [54]. Testing was accomplished using a z-test calculator that was validated with the formula, then used to obtain the results [55].

$$z = (M\_bar - \mu) \; / \; (s \; / \; sqr(n)) \qquad (11)$$

The formula used for the second test is in (12), where z is the standard deviation, M is the error rate of a sample (trial), $\mu$is the population mean, s is the standard deviation

of the samples, and n is the number of samples [54]. Microsoft Excel was used for testing [56] [57].

$$z = (M - \mu) / (s) \quad (12)$$

6.3.6 Z-Test – Two Sample Comparison

The above discussion all related to comparison of one distribution (of means or of samples, but one distribution) to a random distribution in order to test the null hypothesis and determine confidence intervals. Some comparisons in this experiment are of two distributions, such as "raised" to "not raised" and "male" to "female". Like the previous distributions, these also can be treated as normal distributions per the central limit theorem. These comparisons are of samples with different sample sizes and different standard deviations; therefore, a z-test formula that accounts for these differences was used. The formula is very similar to the z-test formula for one sample but includes the statistics (means, standard deviations, and number of samples) for each distribution. he formula used is (13), where M_bar is the mean, σ is the standard deviation and n is the number of samples [58].

$$z = (M\_bar_1 - M\_bar_2) / \text{square root} ((\sigma_1 / n_1) + (\sigma_2 / n_2)) \quad (13)$$

6.3.7 Discrimination of Finger Tapping States

The hypothesis that any two finger tapping states can distinguished from each other using SVM, a decision tree classifier, and LDA was tested. The states tested were "Left", "Right", "Both", and "Imagine". A test SVM classification was conducted using a MATLAB SVM classifier applied to six trials and two classes, "Right" and "Not

Right". The SVM, decision tree, and LDA classifiers were then applied to all sixty trials, testing the classification all combinations of "Left", "Right", "Both", and "Imagine".

6.3.8 Handedness

Since no subjects were left handed, and only a few were both handed, no handedness-related hypotheses were tested.

6.3.9 Gender

The hypothesis that SVM classification of "Left" and "Right" finger states will generate different results, based on gender, was tested.

6.3.10 Age

The hypothesis that SVM classification of "Left" and "Right" finger states will generate different results, based on age, was tested.

6.3.11 Rate of Tapping

The hypothesis that SVM classification of "Left" and "Right" finger states will generate different results, based on rate of finger tapping, was tested.

6.4 Support Vector Machine (SVM)

The first classifier applied was the SVM. A linear SVM was first used, followed by quadratic and polynomial (degree 3) models. All models were used to classify the left tapping and right tapping data from all trials as either "Left" or "Right", followed by all other two-state combinations of "Left", "Right", "Both", and "Imagine".

6.4.1 SVM Classification – "Left" and "Right"

The results for the "Left" and "Right" linear model are shown in

Table 8 and depict an error rate of 36.24% with a standard deviation of 9.68%, much better than the 50% to be expected if the results were due to randomness. The results with the group (sample mean) z-test (Equation 1) were significant; however, the results for the sample (individual trial) z-test were not.

TABLE 8. SVM LINEAR CLASSIFICATION OF "LEFT" AND "RIGHT"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Significant at 0.05?	
					Mean	Ind
Left	Right	57	36.24%	9.68%	Yes z=10.732 one tail p<0.0001	No z=1.42 one tail p=.0778

A look at the individual trials revealed one trial for one subject with an unreasonable error rate, resulting in additional investigation to address the issue. On one trial for one individual, the average error rate was 0.0049% averaged across three MATLAB classification executions. Additional MATLAB executions of this particular trial resulted in similar error rates. A look at the classification results showed all 342 left tapping stimuli were classified correctly and 333 of the right tapping were correctly classified, with nine being incorrectly classified as right tapping. A look at the raw data also indicated nothing out of the ordinary. The preprocessing and classifying of the data

were performed in a batch routine, with all trials for all subjects being subjected to the same code during the same MATLAB execution; therefore, a coding error would be very unlikely. The notes taking during collection indicated the subject had medium blond hair, medium thickness, and medium density, all of which had been properties amenable to good apparent signal strength and quality. The notes did reflect four good signals with no extra height required.

The classification of some of the other states resulted in rates that were not extraordinarily low. Other classification algorithms applied to this trial also resulted in rates that were more reasonable. Since none of this investigation gave reason to believe the data were invalid, and in fact point to a potentially good classification, the trial was included in the analysis and not exempted.

The results of the quadratic model are shown in Table 9 and depict an error rate of 28.01% with a standard deviation of 12.12%. Unlike the SVM linear model, the quadratic results were significant on an individual basis, with a p of 0.0351 (.9649 confidence).

TABLE 9. SVM QUADRATIC CLASSIFICATION OF "LEFT" AND "RIGHT"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Significant at 0.05?	
					Mean	Ind
Left	Right	57	28.01%	12.12%	Yes z=13.6981 one tail p<0.0001	Yes z=1.81 one tail p=.0351

The results of the polynomial model are shown in Table 10 and depict an error rate of 24.92% with a standard deviation of 11.81%. Unlike the SVM linear model, the polynomial results were significant on an individual basis, with a p of 0.0172 (.9828 confidence).

TABLE 10. SVM POLYNOMIAL CLASSIFICATION OF "LEFT" AND "RIGHT"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Significant at 0.05?	
					Mean	Ind
Left	Right	57	24.92%	11.81%	Yes z=16.033 one tail p<0.0001	Yes z=2.12 one tail p=.0.0172

6.4.2 SVM Classification – "Left" and "Imagine"

The results for the "Left" and "Imagine" linear model are shown in Table 11 and depict an error rate of 32.55% with a standard deviation of 13.03%. The results with the group (sample mean) z-test (Equation 1) were significant; however, the results for the sample (individual trial) z-test were not.

TABLE 11. SVM LINEAR CLASSIFICATION OF "LEFT" AND "IMAGINE"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Significant at 0.05?	
					Mean	Ind
Left	Imagine	57	32.55%	13.03%	Yes z=10.1109 one tail p<0.0001	No z=1.34 one tail p=.0901

The results for quadratic model are shown in Table 12 and depict an error rate of 26.00% with a standard deviation of 12.33%. Unlike the SVM linear model, the quadratic results were significant on an individual basis, with a p of 0.0256.

TABLE 12. SVM QUADRATIC CLASSIFICATION OF "LEFT" AND "IMAGINE"

Class 1	Class 2	No Sub	Error Rate	Std Dev	`Significant at 0.05?	
					Mean	Ind
Left	Imagine	57	26.00%	12.33%	Yes z=14.6955 one tail p<0.0001	Yes z=1.95 one tail p=.0256

The results for the polynomial model are shown in Table 13 and depict an error rate of 25.31% with a standard deviation of 12.55%. Unlike the SVM linear model, the polynomial results were significant on an individual basis, with a p of 0.0244.

TABLE 13. SVM POLYNOMIAL CLASSIFICATION OF "LEFT" AND "IMAGINE"

Class 1	Class 2	No Sub	Error Rate	Std Dev	`Significant at 0.05?	
					Mean	Ind
Left	Imagine	57	25.31%	12.55%	Yes z=14.853 one tail p<0.0001	Yes z=1.97 one tail p=.0244

6.4.3 SVM Linear and Quadratic Classification – "Left" and "Both"

The results for the "Left" and "Both" linear model are shown in Table 14 and depict an error rate of 38.34% with a standard deviation of 10.56%. The results with the group (sample mean) z-test (Equation 1) were significant; however, the results for the sample (individual trial) z-test were not.

TABLE 14. SVM LINEAR CLASSIFICATION OF "LEFT" AND "BOTH"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Significant at 0.05?	
					Mean	Ind
Left	Both	57	35.98%	11.67%	Yes z=9.0702 one tail p<0.0001	No z=1.20 one tail p=0.1151

The results for the quadratic model are shown in Table 15 and depict an error rate of 27.46% with a standard deviation of 12.64%. Unlike the SVM linear model, the quadratic results were significant on an individual basis, with a p of 0.0375.

TABLE 15. SVM QUADRATIC CLASSIFICATION OF "LEFT" AND "BOTH"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Significant at 0.05?	
					Mean	Ind
Left	Both	57	27.46%	12.64%	Yes z=13.4631 one tail p<0.0001	Yes z=1.78 one tail p=0.0375

The results for the polynomial model are shown in Table 16 and depict an error rate of 27.21% with a standard deviation of 11.55%. Unlike the SVM linear model, the polynomial results were significant on an individual basis, with a p of 0.0244.

TABLE 16. SVM POLYNOMIAL CLASSIFICATION OF "LEFT" AND "BOTH"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Significant at 0.05?	
					Mean	Ind
Left	Both	57	27.21%	11.55%	Yes z=14.897 one tail p<0.0001	Yes z=1.97 one tail p=0.0244

6.4.4 SVM Classification – "Right" and "Both"

The results for the "Right" and "Both" linear model are shown in Table 17 and depict an error rate of 38.13% with a standard deviation of 11.76%. The results with the group (sample mean) z-test (Equation 1) were significant; however, the results for the sample (individual trial) z-test were not.

TABLE 17. SVM LINEAR CLASSIFICATION OF "RIGHT" AND "BOTH"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Significant at 0.05?	
					Mean	Ind
Right	Both	57	38.13%	11.76%	Yes z=7.6205 one tail p<0.0001	No z=1.01 one tail p=0.1562

The results for the quadratic model are shown in Table 18 and depict an error rate of 30.85 with a standard deviation of 12.72. The results are significant on a group basis but not on an individual basis.

TABLE 18. SVM QUADRATIC CLASSIFICATION OF "RIGHT" AND "BOTH"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Significant at 0.05?	
					Mean	Ind
Right	Both	57	30.85%	12.72%	Yes z=11.3663 one tail p<0.0001	No z=1.51 one tail p=0.0655

The results for the polynomial model are shown in Table 19 and depict an error rate of 29.51 with a standard deviation of 11.55. Unlike the SVM linear model, the polynomial results were significant on an individual basis, with a p of 0.0384. SVM Polynomial Classification of "Right" and "Both"

TABLE 19. SVM POLYNOMIAL CLASSIFICATION OF "RIGHT" AND "BOTH"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Significant at 0.05?	
					Mean	Ind
Right	Both	57	29.51%	11.55%	Yes z=13.3936 one tail p<0.0001	Yes z=1.77 one tail p=0.0384

6.4.5 SVM Classification – "Right" and "Imagine"

The results for the "Right" and "Imagine" linear model are shown in Table 20 and depict an error rate of 36.70% with a standard deviation of 12.37%. The results with the group (sample mean) z-test (Equation 1) were significant; however, the results for the sample (individual trial) z-test were not.

TABLE 20. SVM LINEAR CLASSIFICATION OF "RIGHT" AND "IMAGINE"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Significant at 0.05?	
					Mean	Ind
Right	Imagine	57	36.70%	12.37%	Yes z=8.1174 one tail p<0.0001	No z=1.08 one tail p=0.1401

The results for the quadratic model are shown in Table 21 and depict an error rate of 29.82% with a standard deviation of 12.71%. The results with the group (sample mean) z-test (Equation 1) were significant; however, the results for the sample (individual trial) z-test were not.

TABLE 21. SVM QUADRATIC CLASSIFICATION OF "RIGHT" AND "IMAGINE"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Significant at 0.05?	
					Mean	Ind
Right	Imagine	57	29.82%	12.71%	Yes z=11.9871 one tail p<0.0001	No z=1.59 one tail p=0.0516

The results for the polynomial model are shown in Table 22 and depict an error rate of 27.97% with a standard deviation of 12.62%. Unlike the SVM linear model, the polynomial results were significant on an individual basis, with a p of 0.0175.

TABLE 22. SVM POLYNOMIAL CLASSIFICATION OF "RIGHT" AND "IMAGINE"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Significant at 0.05?	
					Mean	Ind
Right	Imagine	57	27.97%	12.62%	Yes z=13.1793 one tail p<0.0001	Yes z=1.75 one tail p=0.0401

6.4.6 SVM Classification – "Both" and "Imagine"

The results for the "Both" and "Imagine" linear model are shown in Table 23 depict an error rate of 38.26% with a standard deviation of 8.99%. The results with the group (sample mean) z-test (Equation 1) were significant; however, the results for the sample (individual trial) z-test were not.

TABLE 23. SVM LINEAR CLASSIFICATION OF "BOTH" AND "IMAGINE"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Significant at 0.05?	
					Mean	Ind
Both	Imagine	57	38.26%	8.99	Yes z=9.8593 one tail p<0.0001	No z=1.31 one tail p=0.0951

The results for the quadratic model are shown in Table 24 depict an error rate of 29.01% with a standard deviation of 10.39%. The results were significant on an individual basis.

TABLE 24. SVM QUADRATIC CLASSIFICATION OF "BOTH" AND "IMAGINE"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Significant at 0.05?	
					Mean	Ind
Both	Imagine	57	29.01%	10.39%	Yes z=15.2523 one tail p<0.0001	Yes z=2.02 one tail p=0.0217

The results for the polynomial model are shown in Table 25 depict an error rate of 27.81% with a standard deviation of 10.55%. The results were significant on an individual basis.

TABLE 25. SVM POLYNOMIAL CLASSIFICATION OF "BOTH" AND "IMAGINE"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Significant at 0.05?	
					Mean	Ind
Both	Imagine	57	27.81%	10.55%	Yes z=15.8797 one tail p<0.0001	Yes z=2.10 one tail p=0.0179

6.4.7 SVM Classification Summary

All results for both the linear and nonlinear models were significant at 0.05 confidence level for the individual z-test. For the linear model none of the results were significant for the individual z-test; however, for the quadratic model, the results for the individual z-test were significant for three of the five state comparisons but not for the other two. For the polynomial model, all tests were significant.

6.5 Decision Tree Classifier

The second classifier applied was a decision tree classifier, often used with EEG data for feature reduction as well as classification [59]. The combinations of finger states that were used for SVM were also classified by the decision tree. The left tapping and right tapping data from all trials were classified as either "Left" or "Right", followed by all other two-state combinations of "Left", "Right", "Both", and "Imagine".

Initial decision tree classifications were producing trees with too many levels, six or more for some trials. Since there were only three features being classified and those were ratios which have a relationship to each other, the tree appeared to be overfit – providing too much of a match to the training data. An overly high fit on a tree will provide lower error rates on the data used for training but is less likely to maintain that rate on other data. High cross-validation rates also suggested an overfit tree; therefore cross validation was run using different parameters and an optimal minimum leaf size of 25 was obtained. Cross validation provides error rates that would result if trees made from other slices of the data were used to classify the data and therefore provides a good indication if a particular tree is overfit. With less fitting to the data, the trees with the

minimum leaf size of 25 produced a higher error rate on the training data but should be more likely to retain that error rate on test data.

All decision tree executions took a noticeable period of time to execute – on the order of two-three seconds. Whether this amount of time is good, bad, or neither is totally dependent on the intended application. Even for a BCI, any requirement for a minimum latency is driven by the requirements of the BCI.

6.5.1 Decision Tree Classification – "Left" and "Right"

The left tapping and right tapping data from all trials were classified as either "Left" or "Right". The results, shown in Table 26, depict an error rate of 24.98% with a standard deviation of 8.85%, much better than the 50% to be expected if the results were due to randomness. The results for both the group (sample mean) z-test (Equation 1) and the sample (individual trial) z-test were significant. Both the resubstitution error rate and cross validation error rates are shown for this and subsequent decision tree classifications. The resubstitution error rate provides the error rate obtained by the decision tree when applied to the training data and therefore can be considered to be a lower boundary of the classification tree's accuracy. In this case the rate is 20.51%, less than the decision tree's error rate of 24.98%. The cross validation error rate is the error rate when applied to data that was not part of the training set. As such it provides a more realistic indication of the general capability of the tree to accurately classify and can also be used to compare classification methods [60]. The cross validation rate is 25.59% and is only slightly larger than the decision tree's rate of 24.98%, indicating the decision tree's ability to correctly classify may hold up when classifying other data.

TABLE 26. DECISION TREE CLASSIFICATION OF "LEFT" AND "RIGHT"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Resub Error	Cross Val Error	Significant at 0.05?	
							Mean	Ind
Left	Right	57	24.98%	8.85%	20.51%	25.59%	Yes z=21.334 one tail p<0.0001	Yes z=2.83 one tail p=0.0023

6.5.2 Decision Tree Classification – "Left" and "Imagine"

The left tapping and imagined tapping data from all trials were classified as either "Left" or "Imagine". The results, shown in Table 27, depict an error rate of 24.34% with a standard deviation of 10.23%, much better than the 50% to be expected if the results were due to randomness. The results for both the group and individual z-tests are significant at 0.05.

TABLE 27. CLASSIFICATION OF "LEFT" AND "IMAGINE"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Resub Error	Cross Val Error	Significant at 0.05?	
							Mean	Ind
Left	Imagine	57	23.34 %	10.23 %	19.48 %	24.65 %	Yes z=19.67 one tail p<0.0001	Yes z=2.61 one tail p=0.0045

6.5.3 Decision Tree Classification – "Left" and "Both"

The left tapping and both tapping data from all trials were classified as either "Left" or "Both". The results, shown in Table 28, depict an error rate of 26.15% with a standard deviation of 10.41%, much better than the 50% to be expected if the results were due to randomness. These results are very similar to the "Left" and "Imagine" discussed earlier and are also significant at the 0.05 level.

TABLE 28. DECISION TREE CLASSIFICATION OF "LEFT" AND "BOTH"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Resub Error	Cross Val Error	Significant at 0.05?	
							Mean	Ind
Left	Both	57	26.15 %	10.41 %	21.53 %	27.09%	Yes z=19.675 one tail p<0.0001	Yes z=2.29 one tail p=0.011

6.5.4 Decision Tree Classification – "Right" and "Both"

The left tapping and both tapping data from all trials were classified as either "Right" or "Both". The results, shown in Table 29, depict an error rate of 25.52% with a standard deviation of 10.83%, similar to previous results. The results for both the group and individual z-tests are significant at 0.05.

TABLE 29. CLASSIFICATION OF "RIGHT" AND "BOTH"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Resub Error	Cross Val Error	Significant at 0.05?	
							Mean	Ind
Right	Both	57	25.52 %	10.83 %	21.18 %	27.16 %	Yes z=17.056 one tail p<0.0001	Yes z=2.26 one tail p=0.0119

6.5.5 Decision Tree Classification – "Right" and "Imagine"

The left tapping and both tapping data from all trials were classified as either "Right" or "Imagine". The results, shown in Table 30, depict an error rate of 26.90% with a standard deviation of 10.43%, similar to previous results. The results for both the group and individual z-tests are significant at 0.05.

TABLE 30. DECISION TREE CLASSIFICATION OF "RIGHT" AND "IMAGINE"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Resub Error	Cross Val Error	Significant at 0.05?	
							Mean	Ind
Right	Imag-ine	57	26.90 %	10.43 %	22.29 %	28.03 %	Yes z=16.721 one tail p<0.0001	Yes z=2.21 one tail p=0.0136

6.5.6 Decision Tree Classification – "Both" and "Imagine"

The left tapping and both tapping data from all trials were classified as either "Both" or "Imagine". The results, shown in Table 31 depict an error rate of 28.85% with a standard deviation of 9.16%. The results for both the group and individual z-tests are significant at 0.05. Decision Tree Classification of "Both" and "Imagine"

TABLE 31. DECISION TREE CLASSIFICATION OF "BOTH" AND IMAGINE"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Resub Error	Cross Val Error	Significant at 0.05?	
							Mean	Ind
Both	Imag-ine	57	28.85 %	9.16 %	22.81 %	29.85 %	Yes z=17.432 one tail p<0.0001	Yes z=2.31 one tail p=0.0104

6.5.7 Decision Tree Classification Summary

All results were significant at 0.05 confidence level, with both the group and individual z-test.

6.6 Linear Discriminant Analysis (LDA)

The third classifier applied was LDA. The left tapping and right tapping data from all trials were classified as either "Left" or "Right", followed by all other two-state combinations of "Left", "Right", "Both", and "Imagine".

6.6.1 LDA Classification – "Left" and "Right"

The left tapping and right tapping data from all trials were classified as either "Left" or "Right". The results, shown in Table 32, depict an error rate of 42.69% with a standard deviation of 7.68%, somewhat better than the 50% to be expected if the results were due to randomness. The results with the group (sample mean) z-test (Equation 1) were significant; however, the results for the sample (individual trial) z-test were not.
LDA Classification of "Left" and "Right"

TABLE 32. LDA CLASSIFICATION OF "LEFT" AND "RIGHT"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Resub Error	Significant at 0.05?	
						Mean	Ind
Left	Right	57	42.69%	7.68%	41.08%	Yes z=7.1861 one tail p<0.0001	No z=0.95 one tail p=0.1711

6.6.2 LDA Classification – "Left" and "Imagine"

The left tapping and imagined tapping data from all trials were classified as either "Left" or "Imagine". The results, shown in Table 33 depict an error rate of 40.05% with a standard deviation of 10.81%, somewhat better than the 50% to be expected if the results were due to randomness. The results with the group (sample mean) z-test (Equation 1) were significant; however, the results for the sample (individual trial) z-test were not.

TABLE 33. LDA CLASSIFICATION OF "LEFT" AND "IMAGINE"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Resub Error	Significant at 0.05?	
						Mean	Ind
Left	Imagine	57	40.05%	10.81%	38.81%	Yes z=7.8152 one tail p<0.0001	No z=0.92 one tail p=0.1788

6.6.3 LDA Classification – "Left" and "Both"

The left tapping and both tapping data from all trials were classified as either "Left" or "Both". The results, shown in Table 34, depict an error rate of 41.47% with a standard deviation of 8.39%. The results with the group (sample mean) z-test (Equation 1) were significant; however, the results for the sample (individual trial) z-test were not.

TABLE 34. LDA CLASSIFICATION OF "LEFT" AND "BOTH"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Resub Error	Significant at 0.05?	
						Mean	Ind
Left	Both	57	41.47%	8.39%	39.85%	Yes z=7.6758 one tail p<0.0001	No z=1.02 one tail p=0.1539

6.6.4 LDA Classification – "Right" and "Both"

The left tapping and both tapping data from all trials were classified as either "Right" or "Both". The results, shown in Table 35, depict an error rate of 44.09% with a standard deviation of 9.92%, only slightly better than the 50% to be expected if the results were due to randomness. The results with the group (sample mean) z-test (Equation 1) were significant; however, the results for the sample (individual trial) z-test were not.

TABLE 35. LDA CLASSIFICATION OF "RIGHT" AND "BOTH"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Resub Error	Significant at 0.05?	
						Mean	Ind
Right	Both	57	44.09%	9.92%	42.80%	Yes z=5.4797 one tail p<0.0001	No z=0.60 one tail p=0.2743

6.6.5 LDA Classification – "Right" and "Imagine"

The left tapping and both tapping data from all trials were classified as either "Right" or "Imagine". The results, shown in Table 36, depict an error rate of 42.17% with a standard deviation of 10.01%, again only slightly better than the 50% to be expected if the results were due to randomness. The results with the group (sample mean) z-test (Equation 1) were significant; however, the results for the sample (individual trial) z-test were not.

TABLE 36. LDA CLASSIFICATION OF "RIGHT" AND "IMAGINE"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Resub Error	Significant at 0.05?	
						Mean	Ind
Right	Imagine	57	42.17%	10.01%	41.48%	Yes z=5.9056 one tail p<0.0001	No z=0.78 one tail p=0.2177

6.6.6 LDA Classification – "Both" and "Imagine"

The left tapping and both tapping data from all trials were classified as either "Both" or "Imagine". The results, shown in Table 37, depict an error rate of 42.68% with a standard deviation of 9.21%. The results with the group (sample mean) z-test (Equation 1) were significant; however, the results for the sample (individual trial) z-test were not.

TABLE 37. LDA CLASSIFICATION OF "BOTH" AND "IMAGINE"

Class 1	Class 2	No Sub	Error Rate	Std Dev	Resub Error	Significant at 0.05?	
						Mean	Ind
Both	Imagine	57	42.68%	9.21%	41.16%	Yes z=7.2465 one tail p<0.0001	No z=0.79 one tail p=0.2148

6.6.7 DA Classification Summary

The results of state-by-state classification using LDA are depicted in Table 38. All results with the group (sample mean) z-test (Equation 1) were significant; however, all results for the sample (individual trial) z-test were not.

TABLE 38. LDA STATE-TO-STATE CLASSIFICATION RESULTS

		Right	Both	Imagine
Left	Error Rate	42.69%	41.47%	40.05%
	Standard Deviation	7.68%	8.39%	10.81%
	p (ind)	=0.1711	=0.1539	=0.1788
Right	Error Rate		44.09%	42.17%
	Standard Deviation		9.92%	10.01%
	p (ind)		=0.2743	=0.2177
Both	Error Rate			42.68%
	Standard Deviation			9.21%
	p (ind)			=0.2148

6.7 Classification Comparison – Sensor Pad "Raised" and "Not Raised"

During the collection process the sensor pad was raised approximately 0.63 cm for some trials, using either pieces of Styrofoam or in some cases, a comb. Raising the sensor pad made the signal appear stronger and/or less noisy in many cases, especially in

subjects with dark hair, coarse strands, or with dense hair; therefore this technique was used sometimes when the signal was either very weak or very noisy.

The literature search did not find any mention of this technique, thus raising the question of whether the results would be valid. The literature was also lacking with regards to the effects of hair on infrared light, including color, chemical treatment, density, and strand thickness, on infrared light. Solovey and Tufts (2011) simply noted that hair absorbs light and therefore, most research had involved the prefrontal cortex [61].

Raising the sensor by 0.63 cm would mean the detection depth would be decreased by that amount and would be 1.37 cm instead of 2 cm, still sufficient to penetrate and detect activations of the cortex. The larger question is why the signal was stronger. Without any extra height, the sensor seemed to be blocked by hair – presumably hair that was pushed flat. Perhaps raising the sensor allowed the hair to stand up slightly, providing openings between the strands.

To determine the validity of raising the sensor pad, the results of classifying trials with the sensor pad raised was compared with a random classification. If the method has a likelihood of being valid, the results with a raised pad should have an error rate less than the rate of a random classification (*i.e.*, error rate should be less than 50%), significant at the 95% confidence level. Table 39 shows the results. The error rates were significantly different from 50% with all classifiers.

TABLE 39. COMPARISON OF "NOT RAISED" AGAINST RANDOM 50% ERROR RATE

Class 1	Class 2	No Sub	Type Trials	Classifier	Error Rate	Std Dev	Significant at 0.05?
Left	Right	38	Sensor Pad "Raised"	SVM	39.35%	6.85%	Yes z = 9.58
				Decision Tree	26.89%	8.01%	Yes z = 17.79
				LDA	43.51%	7.28%	Yes z = 5.49

The group with a raised pad would also be expected to have a higher error rate than those without a raised pad because (1) the raising only occurred in trials with greater noise and/or low signal strength; (2) the additional distance above the scalp would decrease the penetration into the brain; and (3) the signal may be subject to absorption, reflection, or refraction by the hair.

The results of the left-right classifications were broken down into those trials for which collection notes indicated the pad was raised and those for which the pad was not raised. The results, shown in Table 40, Table 41, and Table 42, depict an error rate higher for "raised" than "not raised" with all three classifiers. The significance results are for comparisons between the sensor pad "raised" and "not raised". The results were significant for SVM and decision tree, but not for LDA.

TABLE 40. COMPARISON OF "RAISED" AND "NOT RAISED" USING SVM CLASSIFIER

Class 1	Class 2	No Sub	Type Trials	Error Rate	Std Dev	Significant at 0.05?
Left	Right	38	Sensor Pad "Raised"	39.35%	6.85%	Yes z=3.25 two tail
		19	Sensor Pad "Not Raised"	30.01%	11.54%	

TABLE 41. COMPARISON OF "RAISED" AND "NOT RAISED" USING DECISION TREE CLASSIFIER

Class 1	Class 2	No Sub	Type Trials	Error Rate	Std Dev	Significant at 0.05?
Left	Right	38	Sensor Pad "Raised"	26.89%	8.01%	Yes z=2.27 two tail
		19	Sensor Pad "Not Raised"	21.16%	9.41%	

TABLE 42. COMPARISON OF "RAISED" AND "NOT RAISED" USING LDA

Class 1	Class 2	No Sub	Type Trials	Error Rate	Std Dev	Significant at 0.05?
Left	Right	38	Sensor Pad "Raised"	43.51%	7.28%	No z=1.10
		19	Sensor Pad "Not Raised"	41.04%	8.37%	

6.8 Classification Comparison – "Noisy" and "Not Noisy"

During data collection, notes were made as to the subjective quality of the signal, specifically the relative degree of noise in the signals. The results of the previous SVM left-right classification was broken down into those trials for collection notes indicate noise and not noise. The results shown in Table 43 depict an error rate of 31.31% with a standard deviation of 12.58%, less than the 39.58% of "Noisy" trials. These results are significant at 0.05 indicating the ability of an observer to differentiate noisy signals from not noisy signals cannot be attributed to chance. A two tail test was used since the goal was to differentiate whether there would be different results from the two perceptions of noise, not better results. The results indicated that, with a 95% confidence level, the results cannot be attributed to chance – that visually looking at the quality of data as it is collected may provide an indication of the relative value of the subsequent use of the data.

TABLE 43. COMPARISON OF "NOISY" AND "NOT NOISY" USING SVM CLASSIFIER

Class 1	Class 2	No Sub	Type Trials	Error Rate	Std Dev	Significant at 0.05?
Left	Right	22	"Not Noisy"	31.31%	12.58%	Yes z=2.139 two tail p=0.0049
		35	"Noisy"	39.58%	7.11%	

Even when just the results of the noisy signal are analyzed, they cannot be attributed to chance at 0.05 as indicated by the results in Table 44. The conclusion that

can be drawn from these results is that data which appears to be noisy might still be valid data and have retrievable information.

TABLE 44. COMPARISON OF "NOISY USING SVM CLASSIFIER"

Class 1	Class 2	No Sub	Type Trials	Error Rate	Std Dev	Significant at 0.05?
Left	Right	35	"Noisy"	39.58%	7.11%	Yes z=8.6703 one tail p<0.0001

6.9 Rate of Tapping Comparison

During data collection, the rate at which subjects tapped was recorded. The rate was determined by visually watching the subject and counting the number of taps in a representative one minute period. Expected results were that a higher tapping rate would cause a greater activation of motor areas, increasing the difference in results from left tapping and right tapping, thus reducing the classification error rate. A high negative correlation between the tapping rate and error rate would give some credence to this idea.

A linear regression was performed using the results of the previous left-right SVM classification along with the tapping rates. A plot of the tapping rate versus error rate is provided in Fig. 16. The correlation coefficient of 0.2508 shows a correlation, albeit it very weak, but it is a positive correlation. The correlation had a p-value of 0.0599 indicating a 94% confidence level and a slope of 0.0017 as indicated in Table 45.

The higher the tapping rate, the higher the error rate. One possible explanation is that the physical movement introduces noise into the data collection process, through physical movement of the sensor pad, for example.

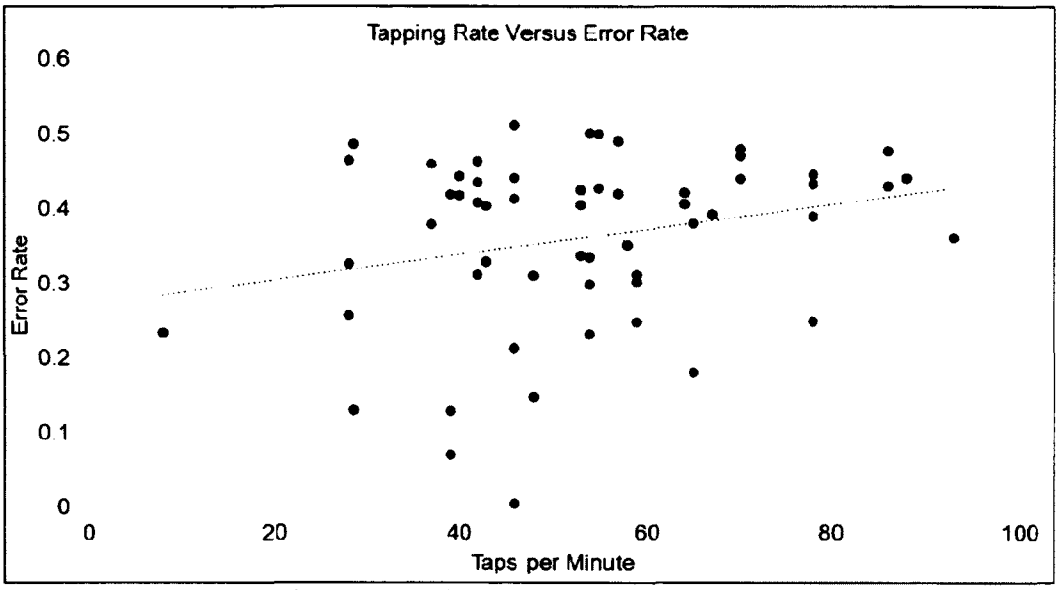

Fig. 16. Tapping rates versus error rates

TABLE 45. TAPPING RATES VERSUS ERROR RATES

Correlation Coefficient	0..2508
R-Squared	0.0629
Y-Intercept	0.2714
Slope	0.0017
P-Value	0.0599
Equation	Error Rate = 0.2714 + 0.0017 * Taps / Minute

6.10 Classification Comparison – "Male" and "Female"

The results of the previous SVM left-right classification were broken down into those trials for males and those for females. The results shown in Table 46 depict an error rate of 36.74% for males, with a standard deviation of 7.67%, only slightly different from the 36.02% of "Female" trials. These results are not significant – they do not show a difference that cannot be attributed to chance.

TABLE 46. COMPARISON OF "MALE" AND "FEMALE"

Class 1	Class 2	No Sub	Gender	Error Rate	Std Dev	Significant at 0.05?
Left	Right	17	M	36.74%	7.67%	No z=0.2889 two tail p=0.7727
		40	F	36.02%	10.49%	

6.11 Age Comparison

During data collection, the age of the subjects was recorded. Expected results due to age were unknown. A linear regression was performed using the results of the previous SVM left-right classification along with ages. The results are shown in Table 47.

TABLE 47. AGE LINEAR REGRESSION RESULTS

Correlation Coefficient	-0.1483
R-Squared	0.02199
P-Value	0.2710
Equation	Error Rate = 0.4017 + 0.0017 * Age

A plot of the age versus error rate is provided in Fig. 17. The correlation coefficient of -0.1483 shows a weak negative correlation. The higher the age, the lower the error rate. The p-value of 0.2710 indicates the confidence level is 82% and not significant at 0.05.

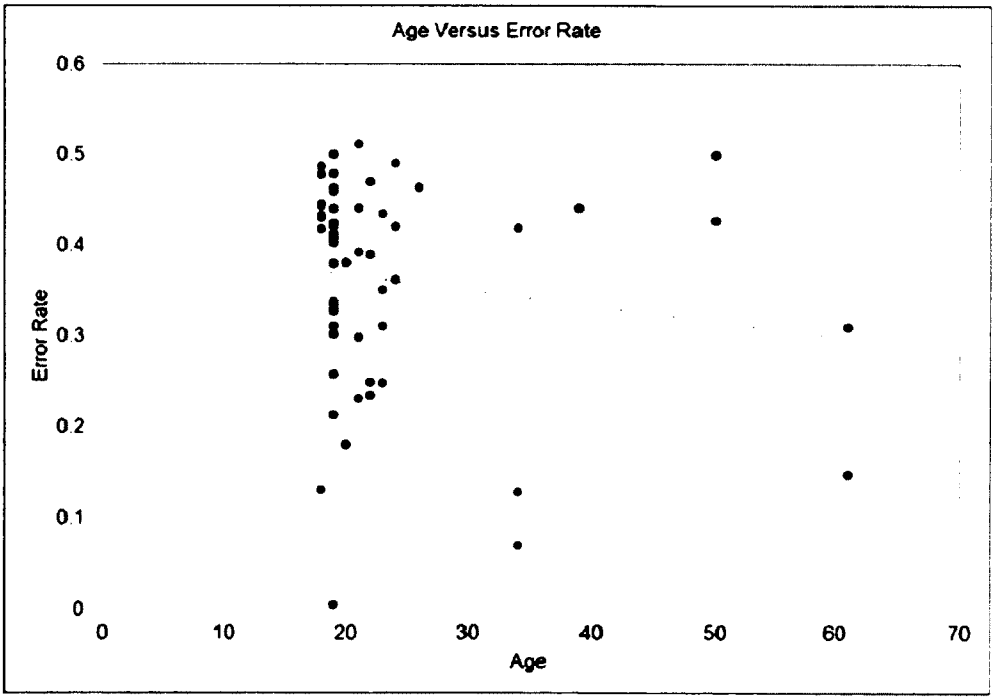

Fig. 17. Age versus error rate of SVM classifier

Linear regressions were also performed separately for ages 19-29 and 30-65. The plots are shown in Fig. 18 and Fig. 19; the regression results are in Table 48 and Table 49. As can be seen, neither had results that showed both a correlation and significance.

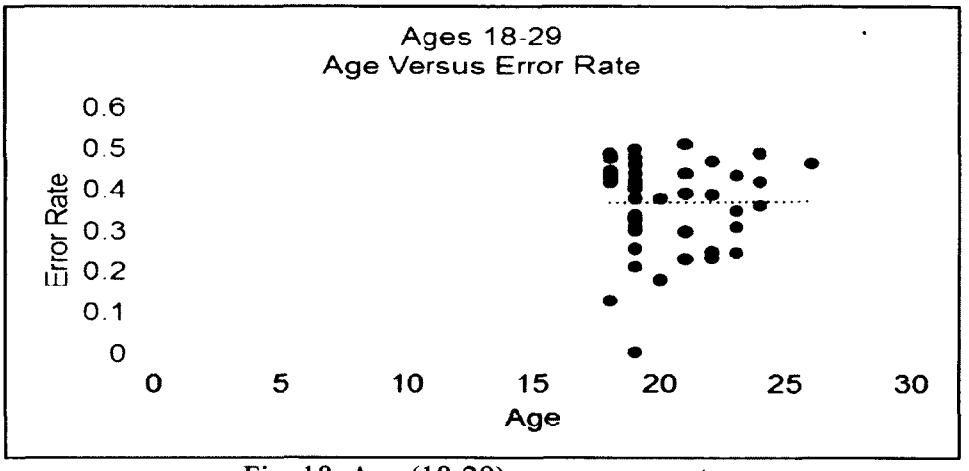

Fig. 18. Age (18-29) versus error rate

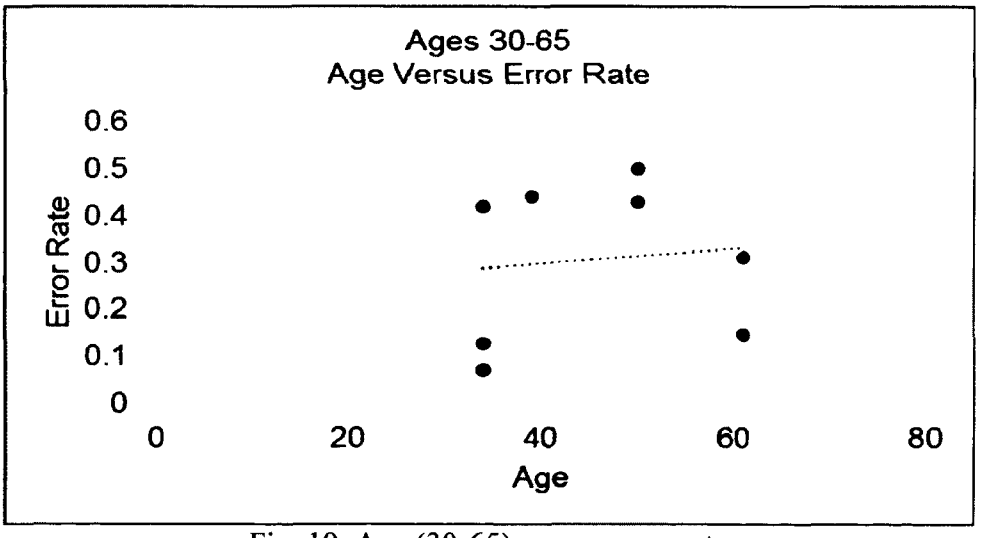

Fig. 19. Age (30-65) versus error rate

TABLE 48. AGE (19-29) LINEAR REGRESSION RESULTS

Correlation Coefficient	0.0069
R-Squared	0.0000
P-Value	0.9623
Equation	Error Rate = 0.3627 + 0.0004 * Age

TABLE 49. AGE (30-65) LINEAR REGRESSION RESULTS

Correlation Coefficient	0.1170
R-Squared	0.0137
P-Value	0.7827
Equation	Error Rate = 0.2293 + 0.0017 * Age

6.12 Comparison of Classifiers

The results of all four classifiers are presented in Table 50. Decision tree classifications had much lower error rates than either SVM or LDA in all state combinations while LDA had much higher error rates in all combinations.

Decision tree classifications had lower error rates than any of the other classifiers in four of the six states; SVM polynomial was lower in the other two states. Decision tree classifications had much lower error rates than either SVM linear or LDA in all state combinations while LDA had much higher error rates in all combinations.

TABLE 50. COMPARISON OF CLASSIFICATION ALGORITHMS

		Right	Both	Imagine
Left	SVM Linear	36.24%	35.98%	32.55%
	SVM Quadratic	28.01%	27.46%	26.00%
	SVM Polynomial	24.92%	27.21%	25.31%
	LDA	42.69%	41.47%	40.05%
	Decision Tree	24.98%	26.15%	23.34%
Right	SVM Linear		38.13%	36.70%
	SVM Quadratic		30.85%	29.82%
	SVM Polynomial		29.51%	27.97%
	LDA		44.09%	42.17%
	Decision Tree		25.52%	26.90%
Both	SVM Linear			38.26%
	SVM Quadratic			29.01%
	SVM Polynomial			27.81%
	LDA			42.68%
	Decision Tree			28.85%

The results of all six classifiers are presented graphically in FIG. 20 and their standard deviations in FIG. 21. Although SVM quadratic and polynomial had low error rates, they both have high standard deviations of error rates for every state combinations, indicating it provides less consistency of classification among different subjects. For four of the six states, LDA had the lowest standard deviation, although it had the highest error rate among the three algorithms.

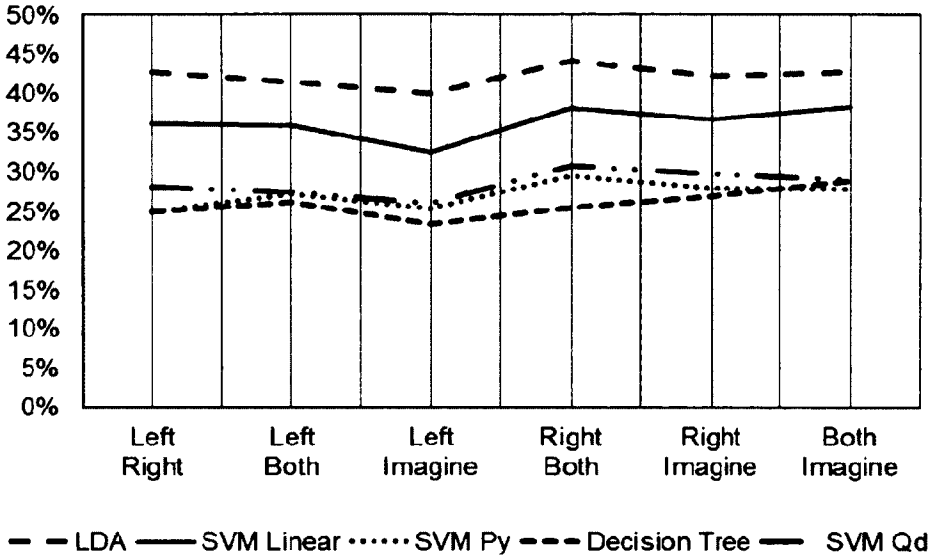

Fig. 20. Comparison of error rates

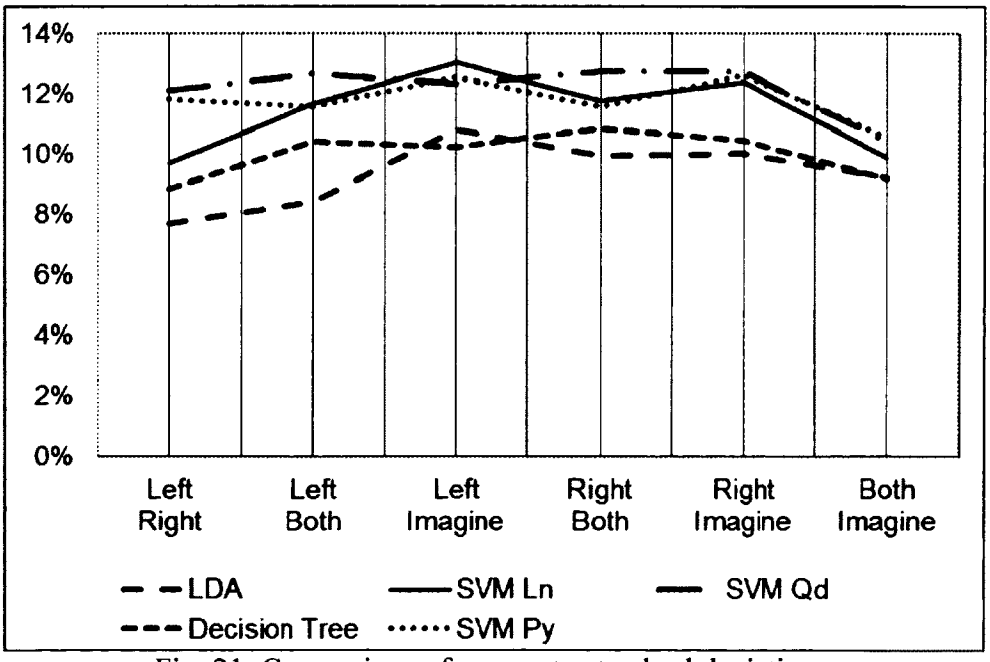

Fig. 21. Comparison of error rate standard deviations

6.13 Comparison of Results to Previous Research

Table 51 compares the results obtained in this study with those of other fNIR studies. The 26% error rate noted in the table is the average of the decision tree error rates, which ranged from 23% to 29%. The error rates the other studies are averages of different classification results. The lowest error rates were those of Abdelnour and Herff, both of which had a large number of channels (source/detector combinations) and only a few trials. Abdelnour had 56 and Herff had 252. None of the three other studies had many subjects. Abdelnour classified an entire stimulus period as correct if over 50% of the classifications in the period were correctly classified.

TABLE 51. ERROR RATES OF OTHER FNIR STUDIES

Study	Method	Ch	Trials	States	Err Rate
This Study	Decision Tree	1	57	Left, Right, Both, Imagined Taps	26%
Abdelnour [4]	Kalman Filter	56	3	Right Taps Left Taps	20%
Ayaz [62]	KNN, Bayes	16	5	Task Rest	28%
Herff [34]	SVM	252	5	Speech Rest	21%

To more closely compare the results from this dissertation with the results Abdelnour obtained, the SVM polynomial was run again against the data. This time the classification results of each stimulus epoch were reviewed and the epoch counted as a correct classification if over 50% of the data points within the epoch were correctly

classified. The results of measuring errors based on epoch performance are shown in Table 52.

TABLE 52. ERROR RATES USING ABDELNOUR'S EPOCH METRIC

States Compared	This Study Error Rate	Abdelnour Error Rate
Left/Right	3%	20%
Left/Both	2%	
Left/Imagine	3%	
Right/Both	4%	
Right/Imagine	4%	
Both/Imagine	4%	

CHAPTER 7

CONCLUSION

This study contributes to the body of knowledge of single source/detector fNIR detection capabilities in the general population. This dissertation's thesis statement was that given single source/detector CW fNIR cerebral response samples during an individual's left finger tapping, right finger tapping, both (right and left) finger tapping, and imagined finger tapping; a real-time capable supervised classification algorithm such as SVM can differentiate between any two of the four categories, even if the individual's brain has not been registered using fMRI.

7.1 Thesis Statement Components

The four components were:

- Only one set of CW source/detectors is required. (*i.e.*, measure a single location).
- Prior knowledge of an individual's brain geometry is not required.
- Preprocessing and classification can be accomplished with algorithms that have the potential to execute in real time.
- Classification can be accomplished on an individual (vice collective group) basis.

7.2 Thesis Statement Evaluation

The methodology used for this study met all the criteria required by the thesis statement, including its components except for the real-time aspect. Specifically, in the study:

The Spire oximeter was a CW device that only had a single source/detector.

There was no a priori knowledge of any of the subject's brain geometry (*i.e.*, no fMRI had been performed on any of them.)

Preprocessing of the data was all amenable to real-time processing, as were the classification algorithms; however, the method of selecting the training sets were not.

The filtering was accomplished by a very low-order filter – a moving average with a 2.8 second window. A real-time moving window that includes future data injects a lag equal to the length of the future data portion of the window. In the research for this dissertation, the window used only current and previous data.

The classification algorithms used were MATLAB's SVM, LDA, and decision tree, all of which can be applied in real time. The decision tree and SVM linear algorithms had results, for individual trials, that were significant at 0.05.

In this particular implementation, the classification was not done in real time. Instead, the training set was derived from data points throughout the individual trial, then used to test the remaining data points, which were also spread throughout the trial. For a real-time application, any future data used in a training set will cause an equal delay in any classification decisions (*i.e.*, a classification result cannot occur until applicable training data has been ingested.) With respect to a BCI, the method of training set selection used in this study means that no BCI actions could be finalized until all tapping

is completed. For a BCI to discriminate states, at least two states would be required. Two states occurred three times each, for 20 seconds each, for a total period of two minutes (three minutes and 40 seconds if the interspersed baseline is included). Therefore using this protocol, after a lag of three minutes and 40 seconds, six decisions could be made.

The classifications were accomplished on individual subject/individual trial basis, not on group averages, not on individual averages, and not on averages of like-stimuli within a trial.

7.2.1 Caveats

Some occurrences during the experiment could have had an effect on the data collection and the subsequent classification results.

As discussed earlier, the sensor was raised in some cases by approximately 0.63 cm, decreasing the detection depth. The data from those trials may have questionable validity. The case was made that the detection depth was decreased to 1.37 cm, from 2 cm, and therefore sufficient penetration made, the literature does not address this situation. The optics and physiology pertinent to light traveling through the hair in those circumstances is not known, nor is the state of the hair under the sensor. The raising may have allowed the hair to stand up, enabling light to pass through but the light could have been reflected back to the detector. A brain computer interface would need to reduce any obstructions between the light source and the head and ensure the distance is minimized.

Classifications occurred for each data point, starting with the presentation of a stimulus. There was a small delay between the time the stimulus was presented and the time the subject began tapping. Once tapping began, there was a further delay for the

oxygenation/deoxygenation responses to begin. A BCI could not depend on classifications occurring during this ramp up period. Additionally the filtering was accomplished with a filter that averaged the previous 2.8 seconds of data; therefore, a BCI using the results of the data would be basing actions on a classification based on data from a time point 1.4 seconds prior to the classification occurring.

Individuals were allowed to set their own tapping pace, which could have introduced motion artifacts into some trials more so than other trials. Subjects with high tapping rates could tire and slow down the tapping.

An attempt was made to position the sensor/detector above the motor cortex; however, exact positioning was not possible on some subjects. On other subjects the initial position was correct but the sensor drifted downward. The results in those instances could therefore be due to activations in areas neighboring the motor cortex or from the motor cortex but not from the finger area.

7.2.2 Lessons Learned

Throughout the experiment, issues were encountered and mitigated in some manner. The following are suggestions that might enable future researchers to avoid some of the pitfalls.

- An algorithm that can train, then test, thus providing a true real time capability is plausible but requires upfront design, especially if subjects cannot be used in preexperimental trials.
- Consider spreading out data collection to allow time to find solutions for any problems prior to collection from additional subjects.

- Have an assistant to help collect the data. Trying to mark the beginning, end, and waypoints of the collection stream, counting subjects' tapping rate, and monitoring/noting movements of the subject became difficult.
- Allow more time per subject. Configuring and stabilizing the hardware on the head at the desired location takes time, especially with equipment tethered with optical cable.
- The data had some artifacts. Attempt to design experiment to reduce movement.
- Find a very secure, safe method for securing the sensor pad. Test with a wide range of head shapes, sizes, and hair color, texture, thicknesses, and densities. Test with people wearing and not wearing glasses.
- Consider securing the head. Some previous researchers have done so. Might reduce artifacts but is a tradeoff with generalizability of results.
- Consider specifying a rate of tapping.
- Find a way to have line of site from sensor to scalp, *e.g.*, shaving, prescreening of subjects, or other method.
- Consider fewer different states (stimuli). Four stimuli plus a baseline state provided a rich set of data for analysis but at the expense of fewer trials of each stimulus type.

7.2.3 Summary

The study produced the results with regards to the thesis statement. The results, on an individual trial basis, using the decision tree algorithm, were significant at the 95% confidence level, thus rejecting the null hypothesis for all state comparisons.

7.3 Contribution to the State of fNIR Research

The study produced a number of results that are directly applicable to brain-computer interfaces. These relate to validating the ability to classify data collected by a device with a single source/detector, from non-prescreened individuals, with real-time algorithms in a normal environment. They also show that classification is viable without converting raw data to absolute concentrations of oxygenated/deoxygenated hemoglobin.

7.3.1 Simplicity of Source/Detector

The results were obtained with a single source/detector attached to a single, square pad affixed to subject's heads using easily available devices such as elastic bands and caps for light shielding.

7.3.2 Generalization to the Population

Unlike almost all studies to date, these results were obtained from non-laboratory conditions with no screening out due to individual characteristics such as hair thickness. The generalizations included:

- A large number of subjects for which the selection criteria only included statutory minimum and maximum ages.

- One period of time for collection. No returning another day to attempt better results. No exclusion of subject data. The only excluded data were from the first week in which no signal could be obtained.
- No detection and removal of specific artifacts, although filtering was used.
- No fixation of the head to make it stationary.
- Use of real-time algorithms. No use of algorithms that require knowledge of future data prior to analysis of present data. For example there was no use of finding an individual's respiration rate, then going back and using that knowledge to filter out respiration.
- No removal of noise with any method requiring a priori knowledge of the data. A moving average was used which is very amenable to real-time processing.

7.3.3 Evidence Supporting Method to Mitigate Hair Effects

This study produced a potential method of mitigating hair effect. Raising the sensor was shown to still produce valid results that could not be attributed to chance at a confidence level of 95%.

7.3.4 Evidence Supporting Validity of Subjectively Assessing Signal Quality and the Validity of Classifying Noisy Data

Evidence was provided that supports the ability to subjectively rate signal quality, important for real-time applications. Additionally, comparison of data rated noisy was shown to be amenable to valid classifications that cannot be attributed to chance at a confidence level of 95%.

7.3.5 Evidence Showing the Degree of Relationships between Subject Attributes

This study produced evidence that does not support differences in motor activations between males and females. The study also produced evidence of a mild correlation between rate of finger tapping and motor area activation.

7.4 Future Directions

There are many areas in which this research can be extended to further the science and application of brain activation research, including the following:

Currently, algorithms are individualized to remove physiological and behavioral artifacts. This research demonstrated that data can be classified without such removal, thus facilitating real-time applications. Future research can address optimization of preprocessing algorithms and generalization of algorithms. For example what filter with what parameters is best for the general population?

Currently, collecting data through hair is difficult. Hair is parted with attempts to keep it parted with mechanically-related means. This research showed the sensor can be raised slightly and still allow for classifiable results. Future research could address the conditions under which raising a sensor is appropriate and what results could be expected. The physiology of light traversing hair with various attributes can be investigated, including absorbance, refraction effects.

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APPENDICES

APPENDIX A: STIMULI ORDER OF PRESENTATION

The permutations used in the experiment are those listed in Table 53.

TABLE 53. STIMULI PERMUTATIONS

	First Third				Second Third				Last Third			
1	B	I	R	L	B	R	I	L	L	R	B	I
2	B	I	L	R	L	R	I	B	B	R	I	L
3	I	R	L	B	I	L	R	B	L	I	R	B
4	R	L	B	I	I	R	B	L	L	I	R	B
5	I	R	L	B	L	B	R	I	R	L	B	I
6	I	L	R	B	L	I	R	B	R	I	B	L
7	I	B	L	R	L	R	B	I	R	I	B	L
8	I	L	R	B	L	I	B	R	I	R	L	B
9	R	I	L	B	L	R	B	I	L	I	R	B
10	R	I	B	L	R	B	L	I	L	R	B	I
11	L	B	R	I	R	L	B	I	L	I	B	R
12	L	B	R	I	R	L	B	I	L	I	B	R
13	R	B	L	I	I	L	R	B	L	I	B	R
14	R	I	L	B	L	R	B	I	I	L	R	B
15	R	I	L	B	L	B	I	R	L	B	R	I
16	L	I	R	B	I	R	B	L	L	B	R	I
17	I	B	L	R	R	L	B	I	I	R	B	L
18	L	I	R	B	L	R	B	I	I	R	B	L
19	B	L	R	I	L	I	R	B	R	L	B	I
20	I	L	R	B	L	I	R	B	L	R	B	I
21	B	L	R	I	B	R	I	L	B	I	L	R
22	R	I	L	B	R	L	I	B	I	L	R	B
23	B	R	I	L	I	B	L	R	I	B	R	L
24	L	R	B	I	R	B	I	L	B	R	L	I
25	B	I	R	L	B	R	I	L	R	L	B	I
26	I	B	R	L	L	B	R	I	B	R	I	L

27	R	B	I	L	L	I	R	B	B	I	R	L
28	L	B	R	I	I	L	B	R	R	L	I	B
29	R	B	I	L	L	B	R	I	L	B	I	R
30	B	R	L	I	I	L	B	R	L	R	B	I
31	R	B	L	I	L	I	B	R	B	L	R	I
32	R	I	L	B	B	I	R	L	R	L	B	I
33	L	I	B	R	I	L	B	R	B	L	R	I
34	B	I	R	L	L	R	I	B	I	L	R	B

APPENDIX B: IRB APPROVAL

No.: 09-134

OLD DOMINION UNIVERSITY
HUMAN SUBJECTS INSTITUTIONAL REVIEW BOARD
RESEARCH PROPOSAL REVIEW NOTIFICATION FORM

TO: Frederic McKenzie — **DATE: November 19, 2009**
Responsible Project Investigator — *IRB Decision Date*

RE: Functional Near Infrared Detection of Real and Imaginary Finger Taps Using K Nearest Neighbor and Parzen Windows Classification
Name of Project

Please be informed that your research protocol has received approval by the Institutional Review Board. Your research protocol is:

___ Approved
___ Tabled/Disapproved
__X Approved, contingent on making the changes below*

George C. Markopoulos — **November 19, 2009**
IRB Chairperson's Signature — *date*

Contact the IRB for clarification of the terms of your research, or if you wish to make ANY change to your research protocol.

The approval expires one year from the IRB decision date. You must submit a Progress Report and seek re-approval if you wish to continue data collection or analysis beyond that date, or a Close-out report. You must report adverse events experienced by subjects to the IRB chair in a timely manner (see university policy).

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* Approval of your research is CONTINGENT upon the satisfactory completion of the following changes and attestation to those changes by the chairperson of the Institutional Review Board. Research may not begin until after this attestation.

* In **the Application:**

- Under 7 c, the investigator should check the box(es) that would indicate if undergraduate and/or graduate students will be enrolled in the study. The investigator should also contact Dr. Mark Scerbo to initiate the procedures required to obtain access to the pool of Psychology students who would participate in the research study. Dr. Justice will send the procedures to Dr. McKenzie that explain how individuals outside of the department may obtain access to the student pool of subjects available.
- Under # 11, the use of the videotaping portion of the study, should be clarified with respect to its intent. Is the investigator planning on videotaping all subjects for purposes of confirming/validating the measure or will only some subjects be videotaped for purposes of disseminating the study findings through platform and poster presentation.

- Under 12C, NO should be checked instead of YES.

In the Informed Consent:

- In the "Description of Research Study" add a statement that will clarify the intent of the videotaping of the subjects (i.e. for validation of the measure or for research presentations at professional conferences) that will be congruent with the application statement. Add a sentence/phrase in the section that describes the laser as similar to a classroom laser pointer.
- In the "Cost and Payments" section add the standard statement from the Psychology Department that states student participation as well as the alternative method for obtaining research credits for those students who prefer not to participate in the study. Also add the $5.00 payment is only offered to subjects who are outside of the Psychology Department research pool.
- Under Compensation fro Illness and Injury" section, change the word "principal" to "project" following Dr. McKenzie's name. Add the Office of Research and phone number (757) 683-3460 as a point of contact in this section.
- (Postscript: the investigators increased the required time from approximately 30 minutes to approximately 45 minutes as noted on the informed consent document)

Attestation

As directed by the Institutional Review Board, the Responsible Project Investigator made the above changes. Research may begin

George C. Maihafer — January 7, 2010

IRB Chairperson's Signature — *date*

INFORMED CONSENT DOCUMENT
OLD DOMINION UNIVERSITY

PROJECT TITLE: Functional Near Infra Red Detection of Real and Imaginary Finger Taps Using K Nearest Neighbor and Parzen Windows Classification

INTRODUCTION
The purposes of this form are to give you information that may affect your decision whether to say YES or NO to participation in this research, and to record the consent of those who say YES.

RESEARCHERS
Responsible Project Investigator: Rick McKenzie, Associate Professor, PhD, Frank Batten College of Engineering and Technology, Electrical and Computer Engineering Department.
Project Investigator: Eugene a. Stoudenmire, Student, MBA, MS, PhD Candidate, Frank Batten College of Engineering and Technology, Electrical and Computer Engineering Department.
Project Investigator: Mark Scerbo, PhD, Professor, Psychology, College of Sciences.

DESCRIPTION OF RESEARCH STUDY
Several studies have been conducted looking into the subject of brain activations during finger tapping. None of them have explained how to effectively and consistently classify types of finger tapping from infrared data.

If you decide to participate, then you will join a study involving research of infra red detection of brain activity resulting from finger tapping. An infra red device, similar to a classroom laser pointer, will be affixed to the top of your head and will measure brain activity by applying laser light, then measuring the scattered light that returns to the device. You will be presented with a computer screen that will have either: a solid left or right arrow, a bar, or a dotted arrow. Each time a solid arrow appears you are to tap your finger (left finger if left arrow and right finger if right arrow). Each time a bar appears you are to do nothing, just rest. Each time a dotted arrow appears you are to imagine tapping the table with your right index finger. Next, you will be presented with two arrows pointing in opposite directions. Each arrow will flash differently. You will be asked to look at one arrow at a time.

You may be videotaped for the purposes of disseminating the study findings through platform and poster presentation.

If you say YES, then your participation will last for approximately 45 minutes at the location of the experiment. Approximately 50 people will be participating in this study.

EXCLUSIONARY CRITERIA
You should be right-handed to participate in this study.

RISKS AND BENEFITS
RISKS: If you decide to participate in this study, then you may face a risk of eye damage if you were to look directly at the lasers. The researcher will reduce this risk by ensuring the device is not turned on until the device is affixed to your scalp and, prior to removal, ensuring the device is turned off. As with any research, there is some possibility that you may be subject to risks that have not yet been identified.

BENEFITS: There is no direct benefit to you for participating in this study. However, this research will potentially further the development of practical brain-computer interfaces that may one day benefit people.

COSTS AND PAYMENTS
If you are part of the Psychology Department research pool and you decide to participate in this study, you will receive 1 Psychology Department research credit, which may be applied to course requirements or extra credit in certain Psychology courses. Equivalent credits may be obtained in other ways. You do not have to participate in this study, or any Psychology Department study, in order to obtain this credit.

If you are outside of the Psychology Department research pool, you will receive five dollars to help defray incidental expenses associated with participation such as parking fees, etc.

NEW INFORMATION
If the researchers find new information during this study that would reasonably change your decision about participating, then they will give it to you.

CONFIDENTIALITY
The researchers will take steps to keep private information, such as photos or videos, confidential by attempting to ensure they contain no personally identifying information. The results of this study may be used in reports, presentations, and publications; but the researcher will not identify you. Of course, your records may be subpoenaed by court order or inspected by government bodies with oversight authority.

WITHDRAWAL PRIVILEGE
It is OK for you to say NO. Even if you say YES now, you are free to say NO later, and walk away or withdraw from the study -- at any time. Your decision will not affect your relationship with Old Dominion University, or otherwise cause a loss of benefits to which you might otherwise be entitled.

COMPENSATION FOR ILLNESS AND INJURY
If you say YES, then your consent in this document does not waive any of your legal rights. However, in the event of harm, injury, or illness arising from this study, neither Old Dominion University nor the researchers are able to give you any money, insurance coverage, free medical care, or any other compensation for such injury. In the event that you suffer injury as a result of participation in any research project, you may contact Dr Rick McKenzie at 757-683-5590, the responsible project investigator or Eugene Stoudenmire, the investigator at 757 857 5670 x509, or Dr. George Maihafer the current IRB chair at 757-683-4520 at Old Dominion University, or the Old Dominion University Office of Research at (757) 683-3460 who will be glad to review the matter with you.

VOLUNTARY CONSENT
By signing this form, you are saying several things. You are saying that you have read this form or have had it read to you, that you are satisfied that you understand this form, the research study, and its risks and benefits. The researchers should have answered any questions you may have had about the research. If you have any questions later on, then the researchers should be able to answer them:

Investigator: Eugene Stoudenmire, 757-857-5670 x509.

If at any time you feel pressured to participate, or if you have any questions about your rights or this form, then you should call Dr. George Maihafer, the current IRB chair, at 757-683-4520, or the Old Dominion University Office of Research, at 757-683-3460.

And importantly, by signing below, you are telling the researcher YES, that you agree to participate in this study. The researcher should give you a copy of this form for your records.

Subject's Printed Name & Signature	**Date**

INVESTIGATOR'S STATEMENT
I certify that I have explained to this subject the nature and purpose of this research, including benefits, risks, costs, and any experimental procedures. I have described the rights and protections afforded to human subjects and have done nothing to pressure, coerce, or falsely entice this subject into participating. I am aware of my obligations under state and federal laws, and promise compliance. I have answered the subject's questions and have encouraged him/her to ask additional questions at any time during the course of this study. I have witnessed the above signature(s) on this consent form.

Eugene A. Stoudenmire	**Date**

Approved Institutional
Review Board - ODU

NOV 19 2009

Expires 1 year from date
Questions: 757-683-3460

APPENDIX C: SUBJECT AND SYSTEM SETUP CHECKLIST

INSTRUCTIONS

1. Read and have sign consent.

2. Fill out questionnaire.

3. Are you a drummer?

ATTACH INSTRUMENTATION

1. Measure Subject Nasion-Inion.

2. Measure Subject Biauricular.

3. Compute PMC, SMA, Premotor Cortex.

4. Attach source/detector to subject – Left Motor Cortex.

5. Cover source/detector.

CALIBRATE

1. Plug in

2. Load "ODU\MSIM897 2008 Spring\NASAfNIR\workspace\SPI=CerOxim-06C.vi".

Note: Use calibrate for data file and log file.

3. Click start arrow.

4. Adjust power to 10.

5. Click "Save Data".

6. Have subject tap finger.

7. Ensure clean signal.

8. Adjust to obtain stronger signal.

9. Measure final location.

10. Adjust power to 0.

11. Stop.

PRACTICE

1. Load practice PowerPoint.

2. Describe instructions.

3. Start PowerPoint.

ARROW EXPERIMENT

1. Load arrow PowerPoint.

2. Write down PowerPoint number.

3. Name data file "RCarrows" plus number of PowerPoint.

Note: if not right cortex, use other letters indicative of location.

4. Adjust power to 10.

5. Click "Save Data".

6. Cue subject.

7. Simultaneously click start button and slide show F5.

8. Insert marker at beginning of each slide.

9. Monitor.

10. Immediately at end, reduce power to 0 and click stop button.

11. Verify data file has correct number of rows.

FLASHING EXPERIMENT

1. Load "FLASHING 001 20100126" PowerPoint.

2. Write down PowerPoint number.

3. Name data file "flashing" plus number of PowerPoint.

4. Adjust power to 10.

5. Click "Save Data".

6. Cue subject.

7. Simultaneously click start button and slide show F5.

8. Monitor.

9. Immediately at end, reduce power to 0 and click stop button.

10. Verify data file has correct number of rows.

VITA

FOR

EUGENE AUSTIN STOUDENMIRE

EDUCATION

Doctor of Philosophy (Engineering with a Concentration in Modeling and Simulation), Old Dominion University, Norfolk, VA, December 2013

Master of Computer Science, College of William and Mary, Williamsburg, VA, May 1993

Master of Business Administration, University of Montana, Missoula, MT, May 1984

Bachelor of Arts, Chapman College, Orange, CA, May 1976

PROFFESSIONAL QUALIFICATIONS AND MEMBERSHIPS

Certified Modeling and Simulation Professional, Project Management Professional (PMP)

Institute of Electrical and Electronics Engineers - Standards Association (IEEE-SA), Simulation Interoperability Standards Organization (SISO)

SELECTED PUBLICATIONS

Eugene Stoudenmire, Michael A. White, Kristen Roy, "Joint Interaction Validation", Simulation Interoperability Workshop, Fall 2007, Orlando FL

Eugene Stoudenmire, Michael A. White, Kristen Roy, "Assessment and Validation of Gaming Technology as Applied to Training: Current State and the Way Ahead", Simulation Interoperability Workshop, Fall 2006, Orlando FL

Eugene Stoudenmire, Michael A. White, Kristen Roy, "Gaming Technology – Complexities of Software and Systems Engineering", Simulation Interoperability Workshop, Fall 2005, Orlando FL

Eugene Stoudenmire, Michael Muuss, et al, "The Remotely Locating of Simulator Display and Controls through High Speed Video Transfer and HLA/RTI", presented at the Fall 1999 SIW Conference, Orlando, FL

Dave Florek, Michael Muuss, Eugene Stoudenmire, et al, "Using HLA/RTI in an Engineering-Level Federation to Support Reconfigurable Simulation", Fall 1999 Simulation Interoperability Workshop Conference, Orlando, FL.