Using Background EEG to Predict Baseball Batting Performance

by

Anthony Pluta III
BSc Psychology, University of Phoenix, 2013

A Thesis Submitted in Partial Fulfillment
of the Requirements for the Degree of

Master of Science

in the School of Exercise Science, Physical and Health Education

Supervisory Committee

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Abstract

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In this thesis, I sought to determine whether frequency bands in the human electroencephalogram could be used to predict baseball batting performance. Past electroencephalographic (EEG) studies have found that alpha power in the human electroencephalogram predicts subsequent performance. Specifically, Mathewson and colleagues (2012) found that background brain activity, in particular, frontal alpha, had a direct correlation with one's ability to learn a video game. Here, we decided to see if a similar result would hold true for baseball batting performance. We used a portable electroencephalographic (EEG) data collection system to record EEG data prior to batting practice. Participants sat quietly in a room with the portable EEG unit affixed to their head. Participants then stared in silence at a fixation cross in the center of a computer screen for 30 seconds and then counted backwards from 1000 by 7's for 30 seconds as a masking task while background EEG was recorded. Player's were then immediately given live batting practice and with performance judged by three different coaches on four different criteria. The four criteria were: batting mechanics, power, contact, and the batter's ability to recognize good and bad pitches. Post-hoc, a frequency decomposition was performed on each participant's EEG data to obtain power in all frequency bands. A correlation analysis of EEG power and batting performance showed that beta power and not alpha power predicted the subsequent performance of the batter. Importantly, a high correlation and

significance show that predicting a batter’s performance with a portable EEG system, specifically the MUSE Headband, is highly plausible.

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List of Abbreviations Used

%	percent
ANOVA	analysis of variance
BC	British Columbia
EEG	electroencephalography
ERP	event related potential
ERSP	event-related spectral perturbation
FFT	fast Fourier transform
Hz	hertz, oscillation frequency, cycles/second
MLB	Major League Baseball
ms	milliseconds
p	significance level
PECOTA	Player Empirical Comparison and Optimization Test Algorithm
PSP	postsynaptic potential
RA	research assistant
s	seconds
SD	standard deviation
Sig	significance
μV	microvolt

Acknowledgements

I would like to acknowledge the help and kind support of my supervisor, Dr. Olav Krigolson who not only convinced me to join his lab and pursue a MSc in Kinesiology but unlocked a new-found love of science. Without him none of this would be possible. I would also like to thank the other members of my committee, Dr. John Meldrum, who showed me that researching baseball was possible and Dr. Gordon J Binsted, who came from the Okanagan for my oral defence, for their time and effort.

A special thanks to all members of the Krigolson Lab who took time out of their lives to assist in all aspects of this research: Dr. Francisco Colino, Cameron Hassall, Chad Williams, Robert McCulloch, Steffanie Fisher, Harvey Howse, Bryn Grey, Stephen Luehr, Robert Trska, Shannon Fitzpatrick, Emily Jackson, Lena Walther, Linsey Tabish, Marie Schulze, Brianna Beaudry, Rose Leishmann and Meagan Pelletier.

Thank you to my parents and brother for not only encouraging me to do what I loved to do, but for lending me support when I needed it.

Thank you to Roland Hemmond and the Association of Professional Ball Players of America for providing the scholarship I desperately needed to complete my Bachelor of Science in Psychology which led me to where I am today.

To the Hindles, especially Jim, for taking me not only into his house but into his family and being a driving force behind completing my degree.

Thank you to my 3 children; Kara, Xenia and Annika for understanding why I wasn’t home some nights and missed practices and games from studying and writing.

Finally, I would like to thank my wife, Jennifer. Truly none of this would be possible without you. You have been my biggest supporter since the beginning in every way possible and I love you with all my heart.

Dedication

To my amazing wife Jennifer and family

CHAPTER ONE: INTRODUCTION AND LITERATURE REVIEW

1.1 An Overview

This research assesses a novel approach to predicting baseball performance – analysis of electroencephalographic (EEG) data prior to baseball batting. Previous work has shown that different frequency ranges in the human electroencephalogram predict motor performance. Almost all the research that has been conducted on frequency power in EEG spectra predicting human motor performance, has been done in a laboratory setting and rarely related to the sport world. Furthermore, EEG studies of cognitive motor movements with regards to sport and predicting performance, prior to this study, have only researched closed motor skills. Closed sports/skills are described as self-paced, predictable and relatively consistent (Wang et al., 2013). Examples of closed sports/skills as outlined in the literature review below are: shooting a basketball from the same position on a court, putting from a controlled distance on the same hole, and shooting rifles and pistols at targets. In these examples, the person performing the skill decides when to execute the action and with no influence from the environment. Open sport/skills are unpredictable, influenced and paced by the environment and dynamically changing (Wang et al., 2013). In this thesis, I focus on the skill of hitting a thrown baseball. The skill of hitting a thrown baseball is an open skill and a skill that is considered by many researchers, athletes, fans and others to be one of, if not the most difficult skill in any sport. The thrown ball is coming toward the batter at variable speeds and at varying locations. The ball may have unintentional or intentional movement which is unpredictable by the batter. This skill is influenced by the environment and unpredictable. Here, I show that we can use EEG technology in the field to predict performance of an open motor skill (baseball batting).

The basis behind wanting to assess if predicting the performance of a baseball batter was viable was influenced by Mathewson et al. (2012). Mathewson et al.'s (2012) research outlined the relationship between frontal alpha and alpha and delta event-related spectral perturbations (ERSPs) and their subsequent ability to predict performance as well as predict an individual's rate of learning. Mathewson and colleagues (2012) used the computer game Space Fortress (Donchin, Fabiani, & Sanders, 1989), a complex motor task, to test whether the engagement of high-level attention control mechanisms at the onset of training could predict individuals' rate of subsequent learning in a Space Fortress training regime. Mathewson et al. (2012) confirmed their initial hypothesis that brain activity associated with cognitive control, as indexed by the level of frontal EEG alpha power, can predict learning rate. They also found that ERSP measures also predicted improvements in tasks requiring processes similar to or overlapping with those used in Space Fortress, such as task switching and working memory. As such, based on this work, I was curious to see whether or not, EEG could be used to predict performance of an open sport skill akin to Mathewson et al.'s (2012) findings.

In the first chapter of this thesis, I will present relevant background information and rationale supporting EEG as a predictor of performance. A brief review will be presented on EEG, brain frequencies, Fast Fourier Transforms, portable EEG devices and other methods of predicting performance as well as the physiological and psychological demands required to hit a baseball. Finally, a summary of research on predicting performance through EEG will be presented. Chapter 2 will outline the methods used to collect the data, the groups being studied and the qualifications of the coaches doing the grading. Chapter 3 discusses the results I found. Chapter 4 dissertates the results, limitations and future research and potentials. Chapter 5 concludes this thesis.

1.2 Predicting Performance

The ability to predict performance, especially an athlete's performance is an equation that has taken many forms over the years. The most common themes are through psychological and physiological tests and assessments. Dr. Lorena Martin, a data scientist, researcher and competitive athlete outlined a majority of these themes in her online book *Sports Performance Measurement and Analytics: The Science of Assessing Performance, Predicting Future Outcomes, Interpreting Statistical Models, and Evaluating the Market Value of Athletes (2016)*. Detailed in her book are ways to first understand appropriate measures to define and assess performance which is integral in one's ability to then predict the now outlined performances. Once performance is defined predicting that performance is possible through statistical analysis, specific psychological and physiological tests and more recently the use of EEG.

The Baseball Swing

Before identifying the specific ways to predict performance let's first look at what is involved both physiologically and psychologically in the fundamentals of a baseball swing. Dr. David Fortenbaugh, in his (2011) PhD dissertation, did the most rigorous study to date on the biomechanics of a baseball swing. Fortenbaugh (2011) studied 43 AA-Level Minor League baseball players in an indoor laboratory. The analysis included 28 kinematic measurements and six ground reaction force measurements computed for 2 pitches (fastball and change-up) in 5 pitch locations (high in, high out, low in, low out and middle). The swing was broken down into six phases (stance, stride, coiling, swing initiation, swing acceleration and follow through) and five events (lead foot off, lead foot down, weight shift commitment, maximum front foot vertical ground reaction force and bat ball contact). All aforementioned movements are what take place for the kinetic chain of a batter to move energy from the lower body into the upper body and then into the bat for contact to occur.

Reaction Time for a Baseball Swing

Psychologically, the largest factors in batting performance are reaction time and anticipation. Reacting to a thrown ball takes less time than it does to blink. A pitcher stands on a mound 60 feet 6 inches away from home plate. Once the pitcher strides and releases the ball he is anywhere from five to six feet closer to home plate. To put that into perspective, if a pitcher throws a baseball at 90 mph from approximately 54.5 feet away, the batter has 413 ms before it reaches the contact point. A swing takes approximately 150 ms from start to point of contact (Adair, 1995; Breen, 1967; Katsumata, 2006; Race, 1961). This 150 ms only considers the swing itself and not the other factors needed to be a successful batter. The brain takes 80-100 ms to process an image and another 12 ms to gauge the pitch and decide to swing. And 25 ms for the brain to send a signal to the body to swing. Thus, a batter has approximately a 13ms window between success and failure. In a game situation, a batter also has to account for fear, anxiety, mood and fatigue as contributing factors to performance.

Psychological Methods for Performance Prediction

In line with the physiological and psychological factors listed above, multiple studies have been done to account for both. Psychological examples of predicting performance include ones' mood or personality. According to a meta-analyses by Beedie, Terry & Lane (2008), 16 studies found performance predictors from the Profile of Mood States (POMS). POMS identify various mood states (e.g. fatigue, confusion, vigor, anger, depression, etc…) Another example of predicting performance through psychological measures is with the five-factor model of personality with an adaption for coaching developed by Piedmont, Hill and Blanco, 1999. The five factors being assessed are: coachability, athletic ability, game performance, team playerness and work ethic. Piedmont, Hill, & Blanco (1999) looked at 79 female NCAA Division I soccer players using their adapted five-factor model and the bipolar adjective scale developed by McCrae & Costa (1985, 1987) and found significance in being able to predict performance.

George (1994) looked at self efficacy as a predictor of performance for baseball players. Fifty-three intercollegiate and interscholastic baseball players completed self report measures over a nine-game period. Twenty-Five baseball players came from two different universities that compete in the Big Ten Conference, and 28 high school players from two different teams that compete in the same Connie Mack summer league. The self reported measures were based on Bandura's (1977) recommendations as well as using the Competitive State Anxiety Inventory-2 (CSAI-2), which is a 27-item self-report measure developed by Martens, Burton, Vealey, Bump, and Smith (1990). George (1994) made minor modifications to the instrument items in the CSAI-2 to be specific to hitting. For example, the statement, "I am concerned about this competition," was modified to, "I am concerned about my hitting in this competition." Subjects indicated how they felt just prior to hitting using a Likert type scale, ranging from 1 (not at all) to 4 (very much so). This assessment has nine somatic and nine cognitive anxiety questions. Included in the CSAI-2 and Bandura's (1977) recommendations, players self reported on: perceptions of self efficacy, competitive state anxiety, effort expenditure, and objective hitting performance. George (1994) found that those players with higher self efficacy played with greater effort and with higher hitting performance in seven out of the nine games, thus being able to predict a player's effort and performance through measures of self efficacy.

Although the ability to predict performance was prevalent in these studies, one's ability to immediately and quantitatively predict an individual's performance is not possible using these methods. These studies require the athlete to self-reflect using tests and assessments. These tests and assessments take time for the athlete to figure out and answer and could be difficult to administer in a dugout prior to an at bat or game. In some cases, needing the coach to assess each player's personality and mood could distract the coach from his or her routine and or strategies prior to a game. The same could be said for players and taking paper tests and its effects on changes in routine prior to a game or an at bat. Although these psychological methods have shown to predict the performance of a batter in a game, the actual implementation of these methods could be difficult to introduce knowing the time they take.

Physiological Methods for Performance Prediction

Another method studied by researchers to predict performance is through physiological methods and tests. One physiological factor used to predict performance in baseball players is through anthropometric means according to Hoffman, Vazquez, & Tanenbaum (2009). Hoffman, et al. (2009) assessed 343 professional baseball players during a two-year period. Each player was assessed for height, weight, body composition, grip strength, vertical jump power, 10-yard sprint speed, and agility (2009). Hoffman, et al. (2009) found athletes at more advanced levels of team play performed better than athletes at lower levels. Retrospectively, MLB players performed better in the assessments than players in each lower level of their minor-league counterparts. Homeruns, slugging percentage and total bases all had a significant positive correlation with a player's grip strength. lean body mass, and vertical jump peak and mean power. Hoffman et al. (2009) concluded that agility, speed, and lower- body power to be the greatest predictive power of baseball-specific performance. Bailey, Sato, and Hornsby (2013) predicted offensive performance of baseball players through isometric force production characteristics. Bailey et al. (2013) performed isometric mid-thigh pull strength testing to assess kinetic variables from force plate data and found moderate to large statistically significant correlations between homeruns and slugging percentage with all kinetic variables. These findings mirrored those of Hoffman, et al. (2009) in that lower body power was the most significant predictor of batting performance.

Cardiovascular indexes of challenge and threat were shown by Blascovich, Seery, Mugridge, Norris, and Weisbuch (2004) to be able to predict performance as well. This study consisted of 27 collegiate batters from both baseball and softball that wore impedance cardiography , electrocardiography, and continuous blood pressure monitors. The study instructed participants to deliver one of two different two minute speeches one of which was sport related, the other was not. All participants delivered both speeches but not all in the same order. After the first two-minute speech, the participants were asked to sit in a comfortable arm chair imagining their team competing in regional playoffs in a pressure situation. The participants were then asked specific questions guided by the researcher about their perceived feelings during portions of the visualization. After the visualization period, participants then delivered the second of the one minute speeches. The participants were not told any results and researchers analyzed each participant's statistics at the end of the season for correlation of results. These physiological methods of predicting performance are similar to the psychological methods listed above in that, the data needed to predict performance takes large amounts of time to collect and is not an immediate predictor of performance but rather a predictor for the season.

Statistical Methods for Performance Prediction

Statistics, specifically in the form of sabermetrics, Player Empirical Comparison and Optimization Test Algorithms (PECOTA), and other statistical test algorithms is an increasingly popular way for the prediction of performance. Sabermetrics is a phrase that is generally used to describe any mathematical or statistical study of baseball. Bill James, the founder of sabermetrics (1980) defines sabermetrics as the search for objective knowledge about baseball. James also coined the name sabermetrics to honor the Society of American Baseball Research. Currently, very few studies exist using sabermetrics to predict performance. Beneventano, Berger, and Weinberg (2012), Mangine et al. (2013) are two examples of researchers using sabermetrics to predict the performance of baseball players. Beneventano et al. (2012) used sabermetrics to predict run production and run prevention during a baseball season. Beneventano et al. (2012) used statistics of each team over a year and compared those over-all statistics to individual statistics to explain the “worth” of a player and predict run production and run prevention for a team in any given year. Mangine et al. (2013) used a combination of sabermetrics and anthropometric measures to predict fielding performance of professional baseball players. Mangine et al. (2013) tested 22 professional baseball players with the Texas Rangers professional baseball organization. The anthropometric testing used in this study was: height, body mass, body composition, grip strength, vertical jump, anaerobic power measures, speed, agility, and 300-yard shuttle. Mangine et al. (2013) paired the anthropometric data with statistical data from the previous year from all teams, specifically the ultimate zone-rating extrapolation (UZR/150). The UZR/150 rates fielding performance by runs saved or cost within a zone of responsibility in comparison with the league average of 150 games for a position. What Mangine et al. (2013) found was that anthropometric tests similar to the ones outlined previously were good predictors of fielding performance when compared to a player’s and league’s previous year’s statistics.

PECOTA was developed by the Baseball Prospectus in 2003. There are three purposes of PECOTA. The first purpose is with major league equivalencies, which allows teams to use minor-league statistics to project how a player will perform in the major leagues. The second purpose of PECOTA is baseline forecasts, which use weighted averages and regression to produce an estimate of a player's true talent level. The third and final purpose of PECOTA is career-path adjustment which uses the statistics from comparable players to predict how a player's statistics will change over time (Baseball Prospectus, 2017).

Divergently, from methods listed above, the use of statistics to predict performance would be quicker although gathering the proper statistics before hand would take some time. The collection of data, depending on the algorithm used would need to follow a player for a full year before any predictions could be made. However, in spite of this, there is still no current method for accurately predicting performance in "real-time" (i.e., right before sport competition) other than coach or self-assessment.

Given this, there is some evidence that suggests electroencephalography (EEG) might be able to be used to predict subsequent performance. Indeed, electroencephalographic data has been shown to predict performance in many scenarios. The scenarios examined have traditionally focused on closed skills and very rarely left the laboratory to test in the field. For example, there are numerous studies done on putting a golf ball, other studies on shooting a basketball, some on video games and some on various body movements and shooting at targets. No study has been done on predicting the performance of baseball batters while at the field using electroencephalography until now. Electroencephalographic studies predicting performance are listed in detail below in section 1.7.

1.3 Electroencephalography

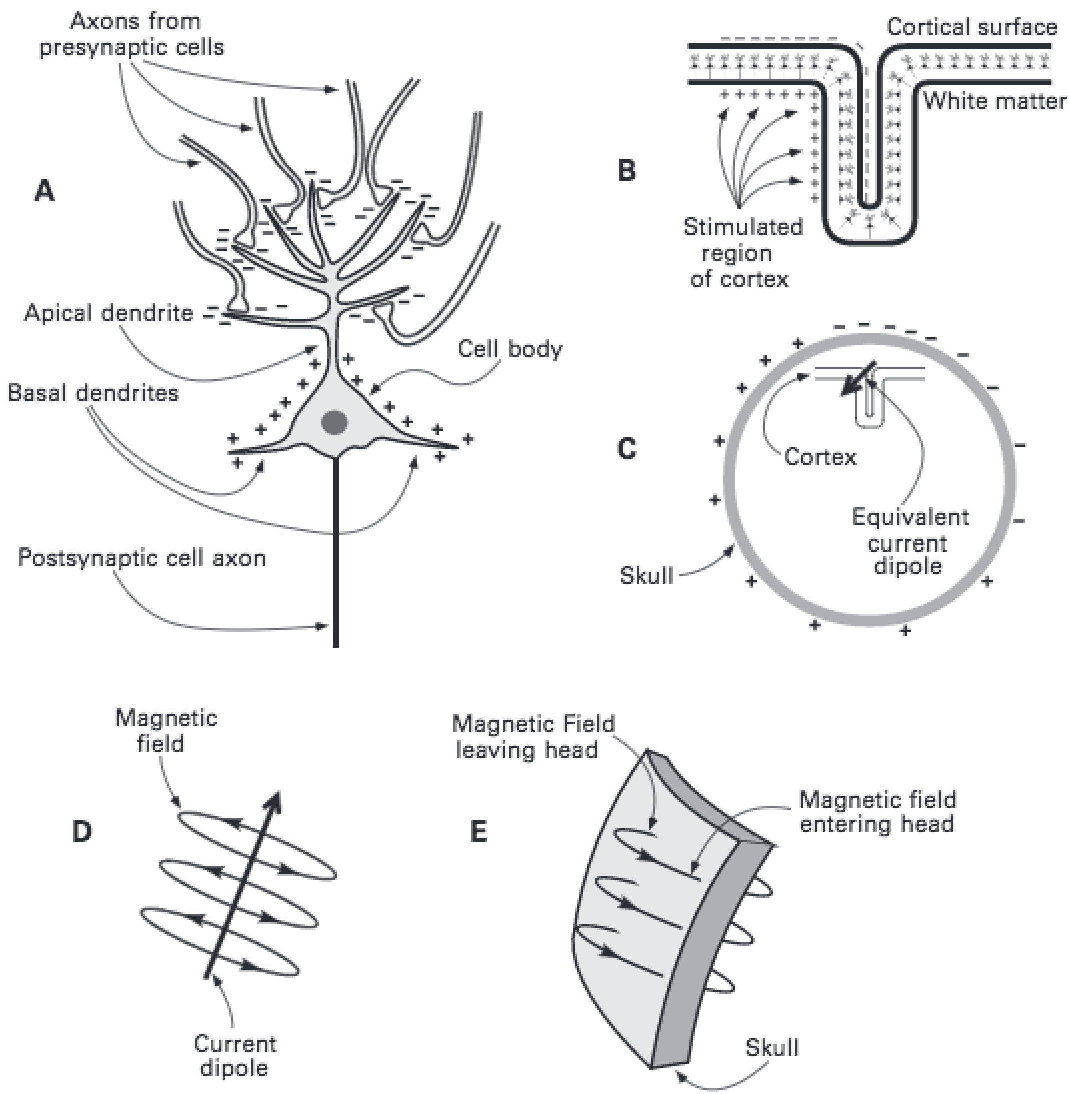
Before being able to predict performance using an electroencephalogram it is imperative to understand what EEG is, how data is collected and why it can predict performance. Luck

(2014) describes EEG with history, citing Hans Berger (1929) and his discovery of the first human brain wave. EEG records electrical activity from the cerebral cortex of the brain in the central nervous system (Rowan & Tolunsky, 2003; Schomer, & Da Silva, 2012) Brain waves are measured by placing electrodes on the scalp at standardized positions (Rowan & Tolunsky, 2003), which allows for interpretation of EEG to be done in one laboratory and the collection to be done in another (Rowan & Tolunsky, 2003) as well as all allowing consistency in literature. The standardized positions of the electrodes were established by Dr. Herbert Jasper and are labeled as the 10-20 electrode system of the International Federation (Rowan & Tolunsky, 2003). Electrodes are non-invasive, non-reactive metal discs that conduct the electrical signals of the brain to an amplifier which is connected to a computer or recording machine. Electrodes measure voltages resulting from the electrical activity of the human brain in microvolts (µV). These voltages then need to be amplified by a million before they can be displayed on a computer screen (Rowan & Tolunsky, 2003).

The electrical activity of brain waves is generated by the billions of neurons in our brains communicating with each other. Specifically, neurons produce two main types of electrical activity, action potentials and postsynaptic potentials. Action potentials are rarely detected by scalp electrodes (Luck, 2014) so only postsynaptic potentials (PSPs) will be described. PSPs occur on the membrane of the postsynaptic cell when neurotransmitters bind to receptors causing ion channels to open or close and leading to a graded change in the voltage across the cell membrane. PSPs can only be recorded on the scalp when dipoles from many thousands of similarly oriented neurons sum together. A dipole as defined by Luck (2014) is a pair of positive and negative electrical charges separated by a small distance. When the dipoles summate the PSPs last tens or even hundreds of milliseconds making recording them at a great distance, such as the scalp, possible. The electrical current does not occur in a singular place but rather a group or area and the electrical current must travel from its starting place to a reference. EEG is always recorded as a potential for current to pass from one electrode (active electrode) to some other specific place (reference). Described in Figure 1 below is how EEG is generated under the scalp and collected by electrodes on the scalp.

Figure 1

An example of how EEG is generated under the scalp



Picture from Luck, 2014, *An Introduction to the Event-Related Potential Technique*

1.4 Frequency Bands

The EEG spectra is typically divided into five main frequency bands: Delta (1 to 3 Hz), Theta (4 to 7 Hz), Alpha (8 to 12 Hz), Beta (12 to 30 Hz) and Gamma (31 to 100 Hz) as well as other frequencies such as lambda and mu (Rowan & Tolunsky, 2003; Schomer, & Da Silva, 2012). In this research study, only the first four frequency bands were used (Delta, Theta, Alpha and Beta) were analyzed in part because of methodical considerations with the MUSE. Each frequency band correlates to a specific physical, mental and/or emotional activity. Alpha and beta waves are believed to have been discovered by Hans Berger, the man responsible for the invention of electroencephalography in humans, in 1924 simultaneously (Buzsáki, G., 2006). Berger termed the larger amplitude, slower frequency waves seen while a participant had their eyes closed as alpha and the smaller amplitude, faster frequency waves that replaced alpha while the participant had their eyes open as beta (Buzsáki, G., 2006). The discovery of theta and delta frequencies came after alpha and beta and all frequencies are continually researched and debated upon as to what each frequency is responsible for in the human body (Rowan &Tolunsky, 2003; Buzsáki, G., 2006).

The following is a description of the physical, mental, emotional characteristics and when they appear most frequently associated with each of the four brain waves used in this study. Given the debated correlations found in research, the following is a sample of some of those works.

Delta (0-4Hz) frequencies are associated with deep, restorative sleep and are the slowest of the frequencies. Indeed, it is impossible to summarize everything that delta has been shown to be sensitive to within the scope of this thesis (NB, this is also true for theta, alpha, and beta). Delta can increase in someone who is experiencing difficult mental activities requiring concentration (Başar, Başar-Eroglu, Karakaş, & Schürmann, 2001; Porjesz, Jones, & Begleiter, 2004). Recent studies have shown delta frequencies to be both stimulus informative (Montemurro et al., 2008) and linked to attentional selection (Lakatos et al., 2008; Cheron et al., 2016). Theta (4-8Hz) frequencies are associated with relaxation and intuition and occur typically when sleeping as well. Although, Delta and Theta frequencies are more prevalent while sleeping, there are instances where they can be seen when awake. Theta will increase in brief intervals during emotional responses to frustrating events or situations (Başar, Başar-Eroglu, Karakaş, & Schürmann, 2001; Porjesz, Jones, & Begleiter, 2004). Theta can also be seen when someone is fatigued (Cheron et al., 2016). Theta power has shown to increase in fast ballistic movements (Ofori, Coombes, and Vaillancourt, 2015) and Baumeister et al. (2008) showed higher theta power associated with expert golfer's performance and higher alpha power associated with a novice golfer's performance.

Alpha (8-12Hz) frequencies are always found when someone's eyes are closed (Buzsáki, György, 2006) but higher alpha frequencies can be associated with being awake but relaxed in an almost meditative state. Numerous studies link high alpha frequencies to positive performance in closed sport skills. For example, (Cheron et al., 2016) found a relaxed but a well focused athlete would demonstrate large alpha amplitude before the accomplishment of a motor task. Interestingly, Del, Percio et al. (2009) found that elite athletes presented less alpha during pistol shooting performance than non-athletes. These findings present links to the possibility of why alpha was not the most significant frequency in this thesis.

Lastly, Beta frequencies are visible in individuals exerting specific mental effort or in those that are generally focused and alert. Beta oscillations also contribute to memory and problem solving (Güntekin, Emek-Savaş, Kurt, Yener, & Başar, 2013). Wróbel (2000) found a link between beta and visual attention and Senkowski, Molholm, Gomez-Ramirez, & Foxe (2006) used beta to predict response speed during a multisensory audiovisual reaction time test.

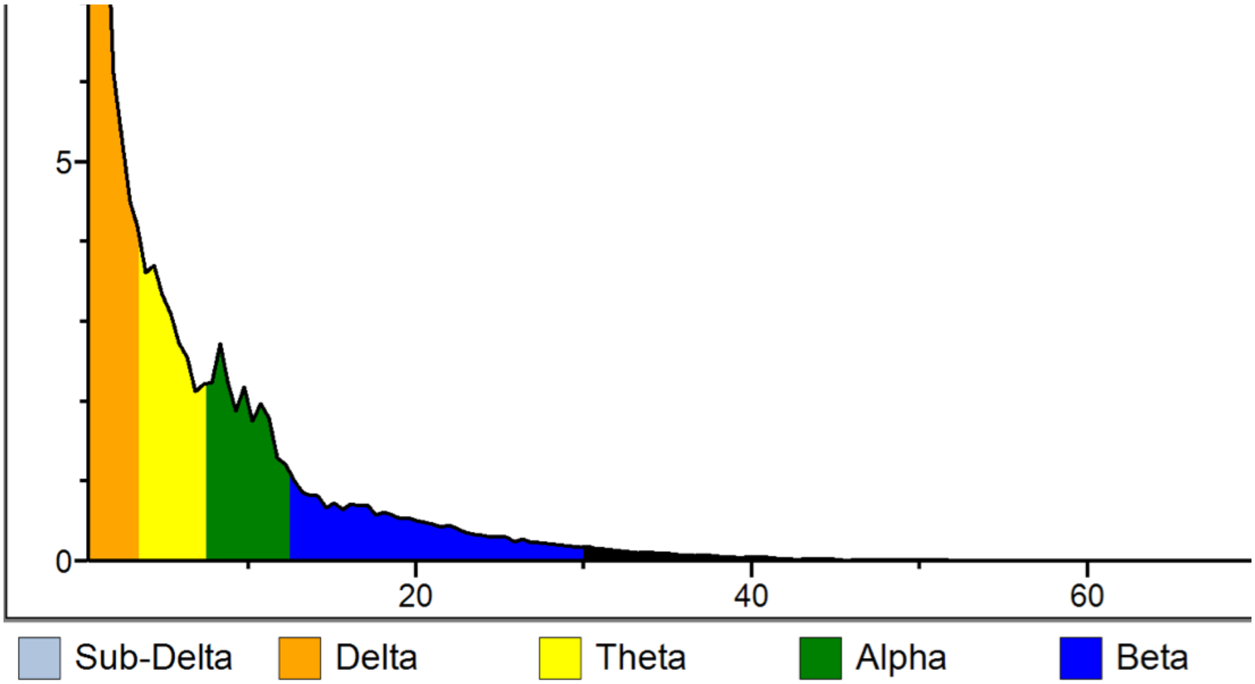
1.5 Fast Fourier Transform

To extract frequency data from raw EEG data, it is customary and appropriate to use a Fourier Theorem. A Fourier Theorem is a mathematical algorithm that breaks down an entire waveform into sine waves. Fourier Transform gets its name from French mathematician, Joseph Fourier. Fourier Transform (FFT) is defined as a linear operator that transforms time domain EEG into Frequency (Thieu, Yang, Kim, & Oh, 2015). There are 5 types of Fourier Transforms. The type used in this research was a Fast Fourier Transform. Fast Fourier Transform is an algorithm to compute discrete Fourier transform and breaks down a signal into constituent sinusoids of different frequencies (Shaker, 2007; Valipour, Shaligram, & Kulkarni, 2013). In other words, FFT decomposes a continuous signal into individual parts. Each of these individual parts relate to a specific frequency band. When looking at frequency data there are certain frequencies of interest which are colour coded according to the ranges.

An example of the colour coding of certain frequencies can be seen in Figure 2 below. This graph represents the amount of each frequency observed during the computerized task.

Figure 2

An example of Fast Fourier Transform from Brain Vision Analyzer 2



1.6 Portable EEG

The ability to record EEG data outside of a laboratory is a phenomenon that did not exist until recently but has advanced quickly in terms of technology and ease of use. A traditional 64 channel EEG system is quite large and takes between 30 to 45 minutes to apply the electrodes and check signal impedances. With the invention of portable EEG, a researcher can take the equipment traditionally found in a laboratory to the field to conduct research. The length of time needed for setup of with a portable EEG varies but takes significantly less time than its big system counterpart. Part of the reason that portable EEG systems require significantly less amounts of time for setup is the smaller amounts of electrodes used in the portable system. Portable EEG systems vary in total numbers of electrodes and how the electrodes are placed on the scalp to conduct a signal but have all shown that the EEG data collected is comparable to traditional big system machines as shown by Krigolson, Williams, Norton, Hassall, and Collino (2017) and Reinecke et al. (2011).

Before portable EEG is further explained one must understand why a portable EEG system is more convenient than a traditional EEG system. Traditional EEG systems use electrodes attached to a cap placed on the participant's head. Once the cap is in place with electrodes inserted, gel is then applied to each of the electrodes through a syringe. As the gel is being applied, the impedances are being monitored. The application of the gel and impedance checks is the most time-consuming portion of data collection with a traditional EEG. Other than the amount of time needed for set up, traditional EEG systems need to be wired into an amplifier which is in turn wired into a computer rendering many movements impossible and forcing participants to typically be seated when collecting data. Portable EEG systems allow participants more freedom in their movements and are easily applied and in some cases without the use of gel, making set up time understandably quicker.

Advancements in technology for portable EEG devices continues to progress at a rapid pace with some systems able to collect good signals in less than five minutes (Krigolson et al., 2017). Some portable EEG systems resemble the traditional system in that the participant wears a cap with electrodes implanted and wires attached to an amplifier and collection device attached to the participants clothing. Other portable systems do not resemble traditional systems at all in that there are no wires and data is being streamed wirelessly via Bluetooth for collection. With one system in particular, the EEG electrodes are embodied in designer sunglasses and data is wirelessly streamed via Bluetooth to a tablet or phone (Smith Lowdown Focus Mpowered by MUSE, 2017).

Krigolson et al. (2017) and Reinecke et al. (2011) both researched the accuracy of portable EEG devices outside of a laboratory and in a field setting. Krigolson et al. (2017) sought to test whether or not the MUSE EEG system (InterAxon, Inc.) could be used to quickly collect EEG data that would yield observable and quantifiable ERP components without the use of event-markers, specifically the N200, P300, and reward positivity. Krigolson et al. (2017) had 60 participants perform two tasks, an oddball and a reward-learning task, on a laptop computer. These tasks were compared to a matched number of randomly selected participants whose data was collected on a traditional EEG system. Krigolson et al. (2017) predicted they would be able to quantify ERPs with data collected from the MUSE without relying on event-markers and that the data would be the same as the data collected on a traditional system. The results of the study concluded that the MUSE system could collect quantifiable ERP data in less than 10 minutes and away from a laboratory.

Reinecke et al. (2011) used EEG data from laboratory studies of golfers performing the action of a putt and compared it to data that was collected at a golf course using a portable EEG. Eleven male, University of Paderborn students, who were part of the universities' golf team, volunteered for the study. The participants were studied first studied in a laboratory setting one week prior to field testing. The participants were tasked with putting on a carpet inside of the laboratory that resembled a medium to medium fast green. The size of the hole and distance from the hole was standard in both the field and laboratory trials. After participants were comfortable with the practice trials in the laboratory and after one week from start time, they were brought to a golf course directly outside of the laboratory. The green at the golf course was flat with no slopes and all putts were attempted from a three-metre distance. In both the laboratory and field tasks, the participants were told to wait until they were comfortable and ready to putt. Results from this study showed that the data collected in the laboratory setting was similar to the data collected in the field setting.

1.7 A Review of EEG Studies Predicting Performance

There is a small but interesting and related body of work examining the use of EEG to predict performance of simple motor tasks. However, most of this research took place in a laboratory setting and was focused on predicting performance of closed skill tasks. For example, Mathewson, et al. (2012) determined that predicting one's ability to play a video game as well as predicting their ability to learn was possible through alpha. Initially, Mathewson was looking for correlation between learning and being able to predict the rate at which an individual will learn. He did this through the observation of individuals playing Space Fortress while EEG data was collected. The experiment consisted of 39 individuals (12 male and 27 female) from the University of Illinois who indicated that they had played less than three hours of video games a week for the last two years. Participants first watched a 20-minute video explaining the Space Fortress game followed by participants watching a 5-minute video that summarized the most important rules of the game. Participants than played 24 3-minute games to get acquainted with the controls and game physics. No EEG data was collected during this time. The next task involved the participants playing 10 3-minute games while EEG data was recorded. Included in the previous task, participants performed a secondary "auditory oddball" task instructing them to silently count and report back at the end of each trial the number of high tones heard.

In the subsequent days following the second task, 20 hr of game training was completed. A post-training session was completed at the end of training. Before and after the training program, participants were also presented with a battery of cognitive tasks, testing attention, cognitive, control, and working memory. The battery of tasks was used to measure the improvement in performance in tasks requiring processes that overlap with those important for the Space Fortress game.

In conclusion and in line with their hypothesis, Mathewson et al. (2012) found that alpha power predicts a person's learning rate. Significance was found with alpha power correlating across all in game events with $p<.05$ or better in all events. Mathewson et al. (2012) also found that alpha power correlated with processes that overlap with those important for the Space Fortress game and with how well a participant would play the game, thus leading me to believe that alpha power could predict the performance of a baseball batter.

Meyer, Peters, Zander, Schölkopf, and Grosse-Wentrup (2014) found that they could predict the motor learning performance of reaching. Six right handed participants, three male and three female, were hooked up to an EEG in a laboratory setting and had a seven degrees of freedom robot arm attached to their right arm. They then performed a series of four tasks: baseline, planning, go, and return to start. The first task was the baseline task which involved the participant doing nothing but staring at a blank screen for 5 s. The second task was the planning task. During this task the participants saw the 3D goal on the computer screen for which they needed to move the robot arm to (blue ball) and the starting position from where to move (yellow ball). This task took between 2.5 and 4 s. Task 3 was the go, or reaching task. The target ball changed from yellow to green and the participant then reached for the green ball. The last task was to return to the starting position which then became the green ball and the participants current position on the screen became the blue ball. Meyer et al. (2014) found that through Alpha power, they were able to predict the second and subsequent trials of the reaching task.

Besserve, et al. (2008) studied 15 participants using experimental protocol designed to study mental fatigue induced by cognitive tasks. Three cognitive tasks were performed successively during one day. The three experiments were the Stroop color word test, the Sternberg-derived test and a spatial stimulus-response compatibility task (Ragot and Renault, 1981). For the spatial stimulus-response compatibility task participants sat in a chair one metre from a screen and were asked to react to a stimulus on the screen. The stimulus was an arrow that appeared for 700ms during the one second trial. The stimulus appeared either on the left or right side of the screen and the participant was asked to point in the direction in which the stimulus appeared. During this and the other two tasks, EEG data was continuously being recorded. Besserve et al. (2008) only analyzed three frequencies during these tasks. Theta, Alpha and Beta were the frequencies analyzed. Besserve et al. (2008) did not use high frequency bands due to them being too sensitive to muscle artifacts to be used in single trial analysis. What was found was that alpha and beta increased with better performance leading to the researchers to be able to predict performance in subsequent trials.

In a study predicting the success of a golfer’s putt, Babiloni, et al. (2008) studied 13 (7 men and 5 women) expert, right handed, golfers. These 13 people had been practicing golf for the last eight years, practiced at least 5 times a day and regularly competed in national and international competitions. These golfers stood on a stabilometric force platform while continuous electroencephalographic (EEG) and electromyographic (EMG) data was collected. Once on the platform, with proper data being collected, the golfers performed a series of putts to a hole 2.1 meters away. The hole varied in size between a standard 108mm to an 80mm, or 60mm hole. Golfers were given a preliminary training phase in which they were able to familiarize themselves with the simulator and for the researcher to ascertain the hole size necessary for testing. The hole diameter associated with more than 30% unsuccessful putts was used. During the putting tasks, participants were told to take their time and putt when they were ready.

What Babiloni et al. (2008) was specifically looking for was whether frontal alpha and beta rhythms of the two hemispheres of the brain are implicated in fine motor control and balance, by simultaneously examining EEG and stailometric data. The results showed that upright balance did not explain the success of the putts. Babiloni et al. (2008) also ruled out low frequency alpha and low and high frequency beta after finding no statistical significance in both hemispheres. What was found as significant was high frequency alpha in successful putts. Due to these findings, Babiloni et al. (2008) states that high frequency alpha is a predictor of performance for a golf putt.

Ahmadian, Cagnoni, & Ascari (2013) conducted a mini review of 10 studies outlining the capabilities of a non-invasive EEG and predicting performance. Four studies looked at the possibilities of predicting the onset of movements. In all four studies, the researchers were able to predict movement onsets. The researchers were not looking to predict the direction of the movement only the intention to move. Three studies examined the possibility of predicting the direction of movement. Two of these studies looked at left vs. right movement. One study looked at up vs. down movement. In all three studies the researchers were able to predict the type of movement, more specifically, Wang and Makeig (2009) found that EEG signals obtained from the posterior parietal cortex before the movement onset carry information about the direction of the intended movement. In Wang and Makeig's (2009) study they looked at left vs. right movement prediction.

The last three studies in Ahmadian, Cognoni, & Ascari's (2013) mini review examined the ability to predict the type of movement that will be performed or the body part that will move. Two out of the last three studies looked at left vs. right finger and hand movements in a typing task. The third study predicted the movement of a participants left hand, right hand, tongue, and right foot. This occurred by telling the participants which body part they were going to be moving and waiting at least two seconds before a “go” cue allowed the participant to move that body part. Before the movement of each body part, there were specific event-related synchronizations and desynchronizations that had statistical significance in predicting which body part would be moved. This mini review did not specify the frequencies of the EEG that predicted each movement or movement initiation. What was identified was if each of the studies were able to predict performance based on either event related desynchronizations (ERD), event related synchronizations (ERS), Bereitschaftspotential (BP), rediness potential (RP), or a contingent negative variation (CNV). For more information and further understanding of these predictors, refer to Ahmadian, Cagnoni, & Ascari (2013).

1.8 Summary

As outlined above, previous research has demonstrated that the prediction of human performance is possible. The method in which performance is predicted as well as what predicts the performance are extremely variable. Past research outlines statistical, physiological, psychological, and electroencephalographic ways that performance can be predicted. Statistical, physiological and psychological methods have shown to predict performance but these means cannot provide immediate performance as the data needs to be collected over a longer period of time. In other words, retrospectively these methods can be used to predict performance but their ability for real time performance prediction is limited.

However, EEG research has proven the ability to predict performance as well but the data has mixed results with beliefs that different brain frequencies predict subsequent behaviour. In these studies, the performance skills took place in a laboratory and focused on skills that could be controlled with no influence of outside variables. The applications of previous EEG studies do not relate to the predictability of a baseball batter but provide valuable insight into possible potentials. Using portable EEG equipment, specifically the MUSE headband, an almost real time prediction of performance could be possible. With the advancement of this type of technology and what is previously understood regarding predicting performance using EEG, the opportunities are seemingly endless. As noted above, there is evidence this can be done – the use of EEG to predict performance. For example, Mathewson et al. (2012) showed that brain activity associated with cognitive control, as indexed by the level of frontal EEG alpha power, can predict learning rate. They also found that ERSP measures also predicted improvements in tasks requiring processes similar to or overlapping with those used in Space Fortress, such as task switching and working memory.

The purpose of this these was to identify if Mathewson, et al's (2012) manuscript is relatable in a real-world context with an open motor skill – baseball batting. Specifically, here, I sought to examine whether or not predicting a batter's performance prior to an at bat is possible using portable electroencephalographic measures. In terms of specific hypotheses, I predicted based on Mathewson et al.'s (2012) work that the amount of a player's frontal alpha power would subsequently predict a batter's success in an at bat immediately following the analysis. Note, this is a prediction also in line with other previous authors. For example, the higher the alpha power score the better statistical probability that the batter will have a successful at bat. However, given the unique nature of the task used here it was not possible to rule out other EEG frequency bands predicting performance.

CHAPTER TWO: METHODS

2.1 Participants

All participants were males between the age of 15 and 21 (mean = 18.24, SD +/- 1.5). Participants were recruited from various high performance baseball programs on the lower mainland of Vancouver, British Columbia, Canada and the Greater Victoria area of Vancouver Island. Participants were also solicited from the varsity baseball programs at the University of British Columbia and Douglas College. The only specific requirement needed by the participant is they must be a part of a high-performance baseball program and have their primary position involve batting. All participants had no known neurological impairments, volunteered for the study and provided informed consent approved by the Human Research Ethics Board at the University of Victoria (BC15—355). The study followed ethical standards as prescribed in the 1964 Declaration of Helsinki.

Sixty-seven high performance baseball players participated in the study. Upon examination of the raw EEG data and after attempts at saving said data, 11 participants were not included in subsequent analysis. These participants either had data that was too noisy or a minimal number of usable segments as identified by a post-hoc examination of the EEG data. Noisy data occurs from various factors such as a poor electrode positioning and/or contact with the MUSE or ambient noise. Subsequently six further participants were eliminated due to an outlier analysis after EEG data analysis was completed which placed their EEG power scores more than three standard deviations above or below the mean (e.g., if a participant's delta, theta, alpha, or beta power score was outside of this range the participant was discarded). Altogether 50 total participants were included in the analyses presented below. All but two participants had normal or corrected-to-normal vision. Two participants had colour blindness but were kept in the analysis.

2.2 Apparatus

The portable EEG device used in this research was the MUSE EEG headband with preset AD (Version 1, 500 Hz sampling rate, no onboard data processing: InteraXon, Ontario, Canada; see http://developer.choosemuse.com/hardwarefirmware/hardware-specifications for full technical specifications). The MUSE EEG headband contains five electrodes located at electrode positions AF7, AF8, Fpz, TP9 and TP10 with electrode Fpz being utilized as the reference electrode. All data from the MUSE EEG system was streamed to either a 11” MacBook Air or 13” or 15” MacBook Pro (Apple Inc., California, U.S.A.) via Bluetooth. On board the laptops, the MUSE Research SDK was used to convert the data to the open sound control (OSC) protocol via the muse-io interface (see http://developer.choosemuse.com/research-tools/museio). Data was then read into MATLAB using software developed by the Neuroeconomics Laboratory (see http://www.neuroeconlab.com/muse.html for all software, acquisition methods, setup and configuration). All MUSE headbands come with on board signal processing which was disabled for this task via a research preset (AD) that also changed the sampling rate to 500Hz. Quality assurance of the incoming signal was assessed on board via custom code written in MATLAB by the Neuroeconomics Laboratory and available at http://www.neuroeconlab.com/musedata-collection.html. Good versus Bad signal quality was determined through inspection of the variance of the EEG signal, computed on a one-second window. Specifically, for each of the four EEG channels the variance was calculated and displayed. Pilot testing in the Neuroeconomics Laboratory and a recent methods paper (Krigolson et al., 2017) suggests that the variance per second needs to be less than 200 μV^2 for decent signal quality. To assist in judging data quality, the variance per second was displayed on screen during calibration and the raw EEG waveforms were colour coded (green = variance below 200 μV^2, red = variance above 200 μV^2). Once the research assistant identified that all variances were in the target range, the quality of the data was deemed acceptable and data recording began.

2.3 Procedure and EEG Task

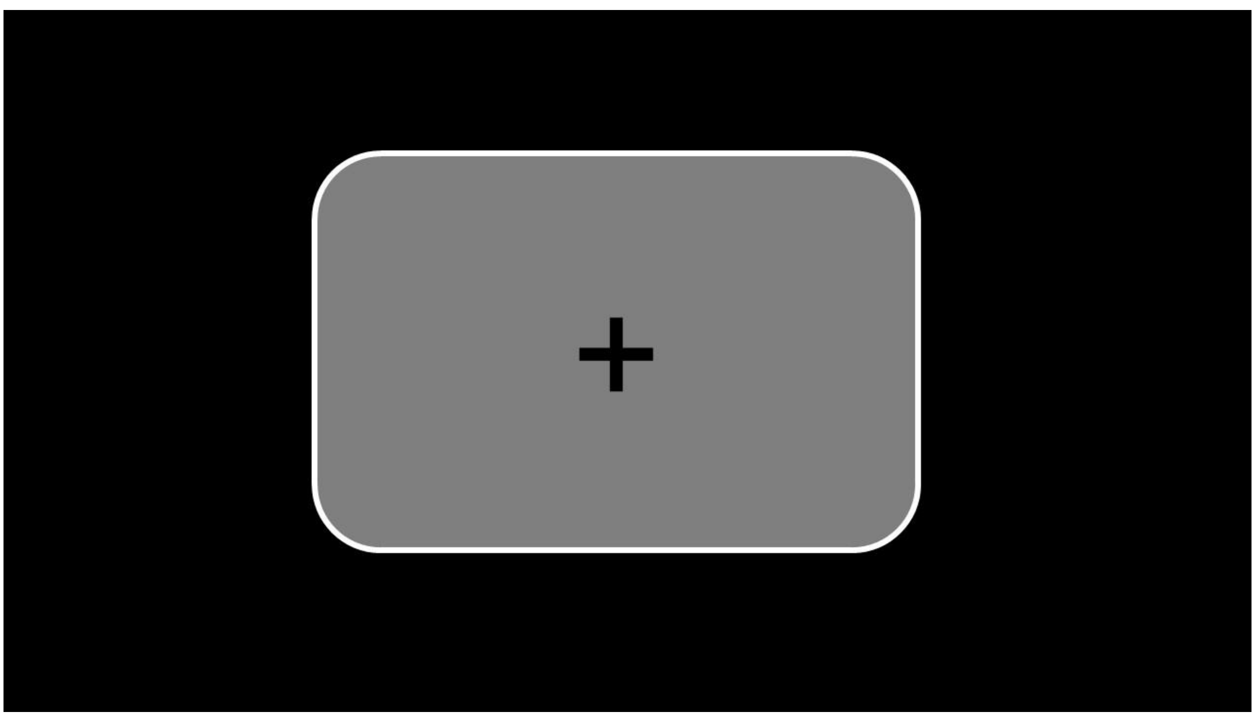
Participants were put into groups of four and paired with a research assistant (RA) who administered the task and affixed the portable, non-invasive, MUSE EEG system to each participant. Once paired with an RA, participants were escorted to a table in an area separate from but near where the batting task would take place. At the table participants were briefed on the study, what to expect during the task and given a consent form. After the participant agreed to participate and signed the consent form, the MUSE EEG system was placed on the participant's forehead and data quality was assessed as outlined above (variance measures were checked to ensure they were below the level criteria 200 μV^2 and MUSE positioning was adjusted until this was so). Once the variances were copacetic, the research assistant pressed the "a" key to accept the transmission and to prompt the first task.

At this time the instructions for the first task appeared onscreen. The instructions advised the participant to stare quietly at a fixation cross in the centre of the screen for 30 seconds while trying not to blink. The participants sat at a comfortable distance from the screen approximately 2-3 feet from the screen. Once satisfied with instructions and prepared for the task, the participant pressed a command key to start the experiment and have their EEG recorded. At the end of the first task a second set of instructions appeared onscreen. These instructions stated that another fixation cross would appear similar to the first but instead of staring quietly the participant would count backwards from 1000 by 7s, simultaneously trying not to blink.

Mirroring the start of the first task, the participant once satisfied with the instructions pressed the same command key to start the task and have their EEG data recorded. The purpose of these two tasks was to allow collection of background EEG data from participants prior to batting practice. By providing instructions, we hoped to ensure participants were focused on something specific to establish a baseline between participants (i.e., they were not mind wandering).

I note here that participants completed two other tasks to adhere to the Neuroeconomics Laboratory's larger laboratory evaluation of ERPs for cognitive assessment consistency between experiments. However, this data was not analyzed as a part of this thesis.

Figure 3:
Example of fixation cross used in the cognitive assessment task performed by the participants both in this study and in every study done in the Neuroeconomics Laboratory.



2.4 Batting Task

Participants remained in their pre-established groups of four from EEG data collection. Immediately following the administering of the EEG protocol the participants were given batting practice thrown by a coach approximately 15 m from the batter's position in the batter's box. The coach throwing the batting practice was instructed to deliver pitches to the batter the same way that they would during a normal batting practice. This entailed the coach attempting to throw baseballs at a speed that is easily batted. The coach was instructed that each pitch should be straight and close to the batter's "strike zone." The strike zone as described by the Official Rulebook of Major League Baseball, 2017:

> *"The STRIKE ZONE is that area over home plate the upper limit of which is a horizontal line at the midpoint between the top of the shoulders and the top of the uniform pants, and the lower level is a line at the hollow beneath the kneecap. The Strike Zone shall be determined from the batter's stance as the batter is prepared to swing at a pitched ball."*

Due to performance variability and the potential of performance anxiety of the coach throwing pitches to the batter, batters were asked to only swing at balls thrown into the strike zone. Only pitches that were swung at counted towards the batter's total number of swings in each round. Each batter was given three rounds of eight swings. At the end of each participant's round they would rest and observe the remaining batters in the group before proceeding with their subsequent rounds. Batters were not provided with any feedback or critiques before or during their testing rounds from any of their coaches, the researcher, player evaluators, or their teammates. Part of each participant's informed consent was them being made aware of the areas in which they would be evaluated. Participants were given a copy of the evaluation sheet prior to signing consent and were reminded of the criterion before their first round of batting practice.

2.5 Evaluation Tool and Evaluator Credentials

The tool used to evaluate each batter was based on the ability and skill needed for a batter to be successful in a game situation. To date, there are very few formal tools for current talent evaluation other than coach opinion. The tool developed for use with this project was based on four criteria: the batter's ability to recognize if the thrown ball will be in the strike zone, the form of the batter, the power displayed upon contact with the baseball and the batter's ability to contact the thrown ball. A more in-depth definition of each of the four criteria are as follows.

The form of each of the batters was objectively evaluated versus the perceived skill level of players in the same high performance league and age level. For the player to receive a score of a 10 out of 10 they would have to have a swing without any perceived flaws. The average score for a batter's form was 6.41 with a standard deviation of +/- 0.98. A score of 6 out of 10 would be given to a batter that moved their larger muscles and body parts well (hips, legs, arms) but had flaws with some of their smaller muscles and body parts (head position, hand position, bat position at contact and follow through, and direction of force not being in fair territory). A score of 4 out of 10 or less would be given to batters with flaws in all smaller muscles and body parts as well as 1 or more big muscles and body parts.

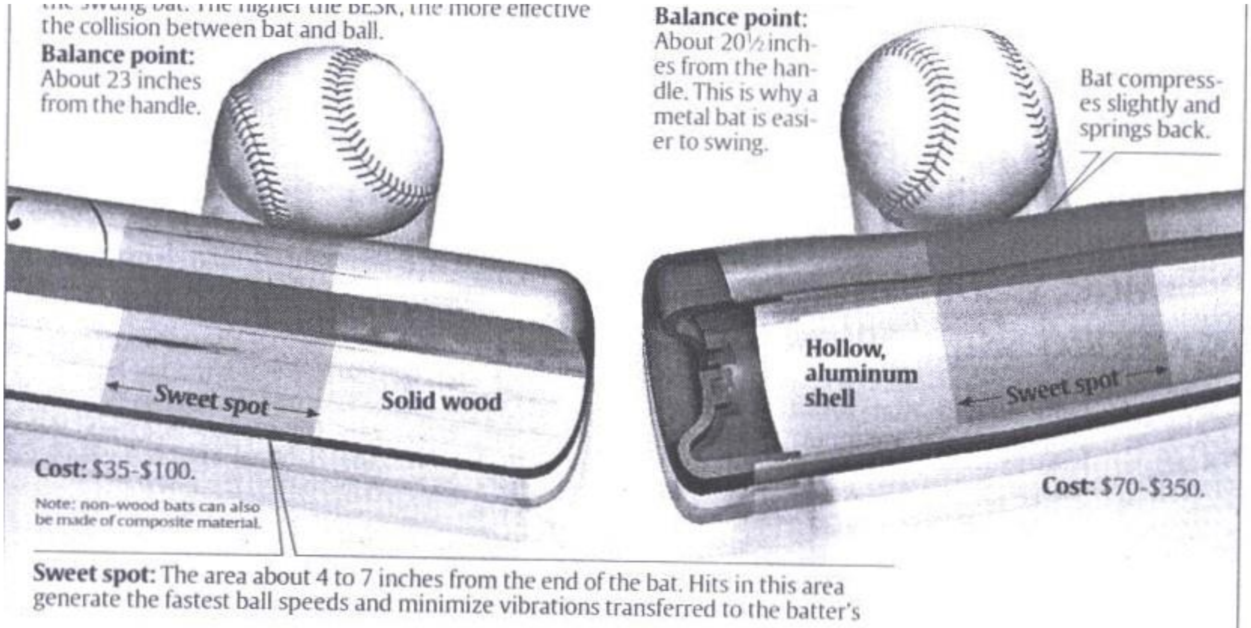
Contact was defined in this study as any batted ball on the ground, that landed in "fair territory," meaning inside of the foul lines, past either first or third base after being contacted by the barrel of the bat. Batted balls hit in the air needed to go past the pitcher and in fair territory. The average score for contact was 6.41 with a SD of +/- 0.93. A score of 6 out of 10 would equate to a player hitting 6 out of ten balls on the barrel of the bat and into fair territory, in the air and/or on the ground. Similarly, a batter with a score of 4 out of 10 would have only contacted 4 out of 10 baseball on the barrel of the bat and into fair territory, in the air and/or on the ground.

Power was described as the perceived rate of speed at which the batted ball exits the barrel ("sweet spot") of the bat on a ball hit on a line or on a ball hit in the air that would likely be caught by an outfielder. The "sweet spot" or radius of gyration in engineering terms, is the point where the most impact energy will be delivered to the ball and the bat rebounds straight back and opposite to the ball's line of flight and without any torqueing, end for end, as rotation is developed as defined by U.S. Patent No. 5,180,163 (1993). For an example of where the "sweet spot" on the bat is located see Figure 4 below.

A 10 out of 10 evaluation would only be possible if the batter demonstrated the ability to contact the ball on the "sweet spot" of the bat causing the ball to exit the barrel at a high rate of speed, on a line or well hit in the air, on every trial. The average score for power was 5.98 with a SD of +/- 1.12. A score of 6 out of 10 would mean a batter contacted the ball on the "sweet spot" of the bat at a perceived high rate of speed on a line or well hit in the air 6 out of 10 times. Similarly, a score of 4 out of ten was given to batters who only hit 4 balls out of ten on the "sweet spot" of the bat, on a line or in well hit in the air.

Figure 4:

The "sweet spot" of a baseball bat (Carey, 2007)



Recognition was described as the batter's ability to recognize whether or not the pitch was in the strike zone before swinging. A perfect 10 out of 10 score would mean in each of the batter's ten swings, he only swings at balls in the strike zone. The average score for recognition was 6.43 with a SD +/- 0.82. Batter's received a 6 out of 10 score for recognition if they swung at 4 pitches that were not in the strike zone out of the 10 balls thrown. Similarly, batters received a 4 out of 10 for swinging at 6 pitches out of the strike zone.

Each of the criteria listed had a 1 to 10 grading scale with 1 being the worst possible score and 10 being the best possible score. Each batter was graded by three different coaches on each criterion after each of the batter's three rounds. In total the player would have three numerical values in each of the four batting criteria. Thirty-six numbers in total were assigned to each batter. The numbers were then averaged for each of the criteria and for each of the coach's scores, thus each batter would have twelve scores averaged over the four criteria.

Two out of the three evaluators at each testing time were at minimum regionally and provincially certified coaches in the National Coaching Certification Program (NCCP), a nationwide coaching certification program in Canada. The third evaluator in each instance was a coach solicited from the high-performance team or college program being tested that day. All evaluators played high performance baseball either in post secondary programs or professionally. Importantly, we also established the reliability of the batting performance evaluation tool (see below).

2.6 Data Analysis

The EEG data was recorded in MATLAB (Release R2015a, Mathworks, Natick, USA) using the Psychophysics Toolbox Extension (Brainard, 1997; Pelli, 1997) as outlined above but was converted for offline processing using a custom MATLAB script into a format that was importable into Brain Vision Analyzer 2 software (Version 2.1.1, Brainproducts, GmbH, Munich, Germany) using methods previously employed by the Neuroeconomics Laboratory (see http://www.neuroeconlab.com/data-analysis.html).

Once data was uploaded to Brain Vision Analyzer 2 an “analysis tree” was established to extract power in each of the four frequencies of interest (delta, theta, alpha, beta). The first step was to filter the data. Data was filtered using a zero-phase shift Butterworth filter with a passband of 0.1 Hz to 30 Hz in addition to a 60 Hz notch filter. Next, the frontal EEG channels were re-referenced to an average of channels TP9 and TP10. Note, channels TP9 and TP10 were not re-referenced as they were already referenced to a frontal channel (FPz). Following re-referencing, the data were pooled into a common or average frontal channel (AF7, AF8) and a common or average posterior channel (TP9, TP10). The data were then segmented into two segments – one for the first thirty seconds (fixation) and one for the next thirty seconds (counting). These two large epochs were then subdivided into 2000 ms “trials” with a 1900 ms overlap. An artifact rejection algorithm was then implemented on each trial. As a result of this procedure segments that had gradients of greater than 10µV/ms and /or an absolute difference of more than 100µV were discarded. The average amount of segments removed per participant was 44%. A Hanning Window with a length of 10% was applied and an FFT was then conducted using maximum resolution, to produce non-complex power output on the full spectrum. The FFT was periodic at a resolution of 0.48 Hz and corrected for variance. Segments were zero-padded for length of 2048 ms generating 1024 points. From this, power was extracted and averaged for each frequency (1 to 30 Hz) for each participant. Finally, average power was computed for each of the frequency bands (delta: 1 to 3 Hz, theta: 4 to 7 Hz, alpha: 8 to 15 Hz, beta: 16 to 30 Hz) for each of the pooled channels for each task for each participant. These data were then submitted for statistical analysis (see below).

CHAPTER THREE: RESULTS

3.1 Test Reliability, Coach Evaluations

Coaches ratings for form, contact, power, and pitch recognition were tested for reliability by examining the correlations between ratings for the three coaches (e.g., correlation between Coach One and Coach Two for form, correlation between Coach One and Coach Three for form, etc.) yielding an overall mean reliability of $r = 0.60$ ($p < .001$). Table 1 includes a summary of all the individual reliability correlations between each of the coaches for all four of the batting performance ratings. Given the overall correlation suggesting that the ratings were reliable (and the individual reliability correlations), I went forward and created mean ratings for form, contact, power, and pitch recognition for each of the athletes remaining in the analysis. Further, I created an overall batting performance rating for each player by taking the mean of the four individual ratings (form, contact, power, pitch recognition). Note, all of these correlations are statistically significant (p's <.001).

Table 1

Inter-coach Reliability- mean coaching scores across all 5 evaluated areas averaged between coaches for correlation and reliability

	Form	Contact	Power	Recognition
Coach 1 vs Coach 2	0.743***	0.610***	0.662***	0.477***
Coach 1 vs Coach 3	0.677***	0.637***	0.601***	0.637***
Coach 2 vs Coach 3	0.660***	0.327***	0.722***	0.413***
Average	0.694***	0.525***	0.662***	0.509***

3.2 Frequency Band Correlation – Frontal Electrodes During Fixation

Pearson r correlation values (and significance tests) were then conducted between each of the five batting performance ratings (form, contact, power, pitch recognition, average) and each of the four EEG frequency bands of interest (delta, theta, alpha, beta) (see Table 2 and Figures 5-

9) for the frontal electrodes during the fixation task. Interestingly, these analyses revealed that there were no correlations between power in the delta, theta, and alpha frequency bands and any of the batting performance ratings (form, contact, power, pitch recognition, average), all *p*'s > .05 (see Table 2). However, we did find that power in the beta band did correlate with all five of the batting performance ratings (form [r = -.391, p < .001], contact [r = -.547, p = .005], power [r = -.365, p < .001], pitch recognition [r = -.405, p = .009], and average [r = -.465, p = .004]). In sum, these results reveal that batting performance was better if power in the beta band was reduced in the EEG data recorded prior to batting.

Table 2

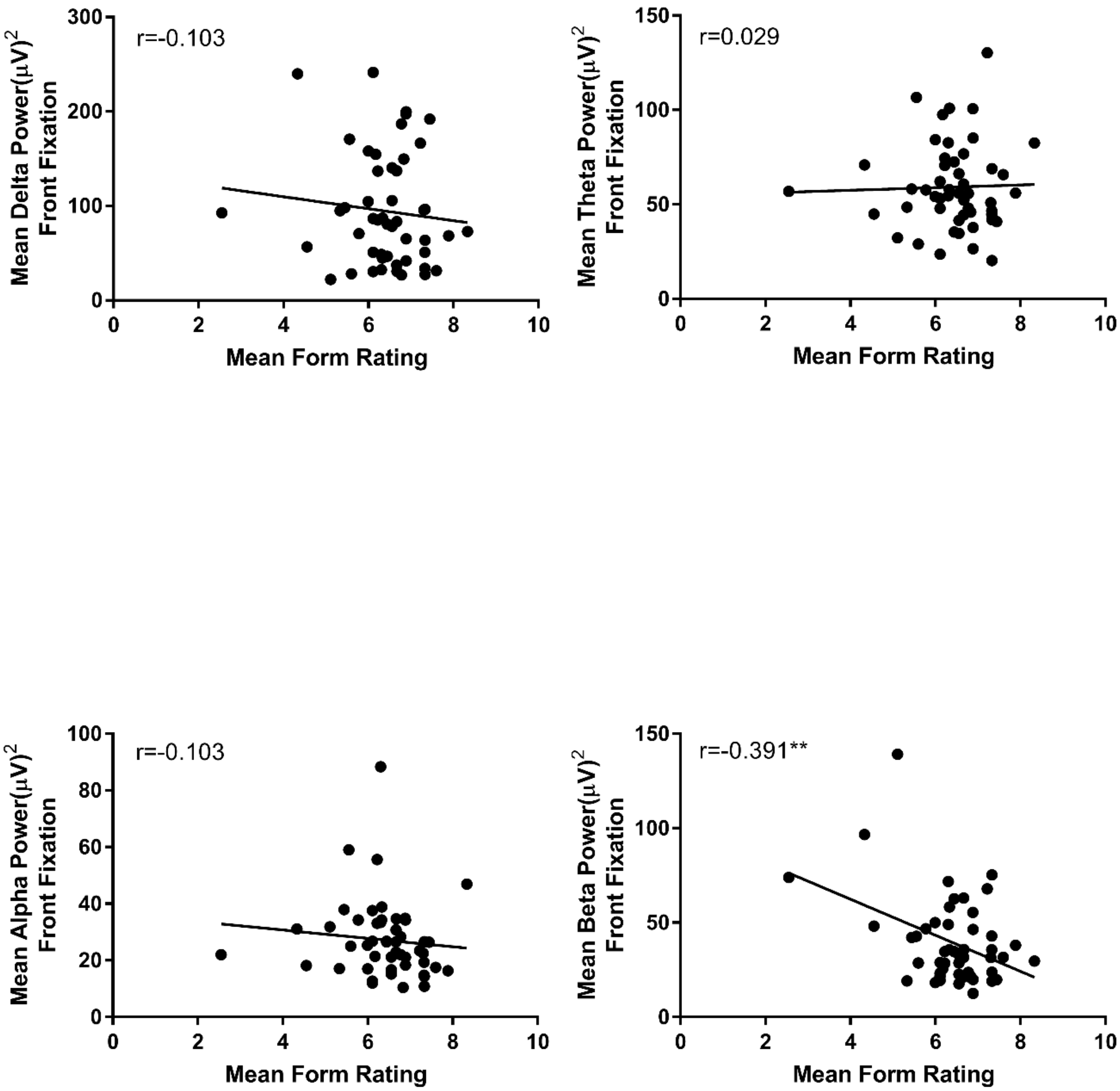
Pearson correlation of the frontal fixation task - frequencies vs evaluation criteria

	Form	Contact	Power	Recognition	Average
Delta	-0.102	0.081	-0.017	0.121	0.011
Theta	0.029	0.018	0.129	0.141	0.083
Alpha	-0.103	-0.173	-0.049	-0.133	-0.122
Beta	$-.391^{**}$	-0.547^{***}	$-.365^{**}$	$-.405^{**}$	-0.465^{***}

Two tailed significance: *p<.05. ***p*<.01. ****p*<.001

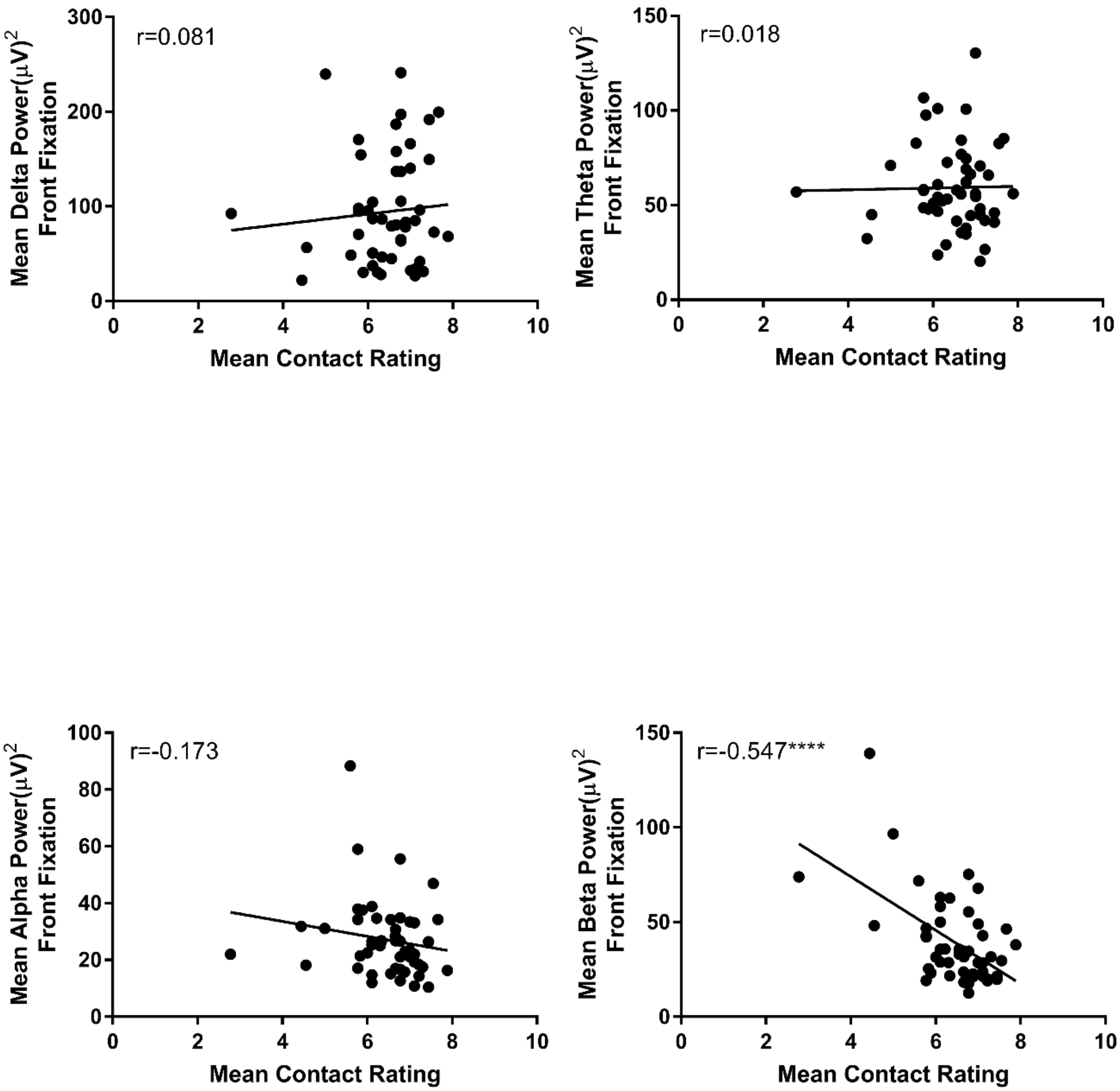
3.2 Figure 5:

Coaching Scores vs. Frequency Bands- xy correlation scatter plots representing brain frequencies (delta, theta, alpha, beta) for form and frontal fixation task.



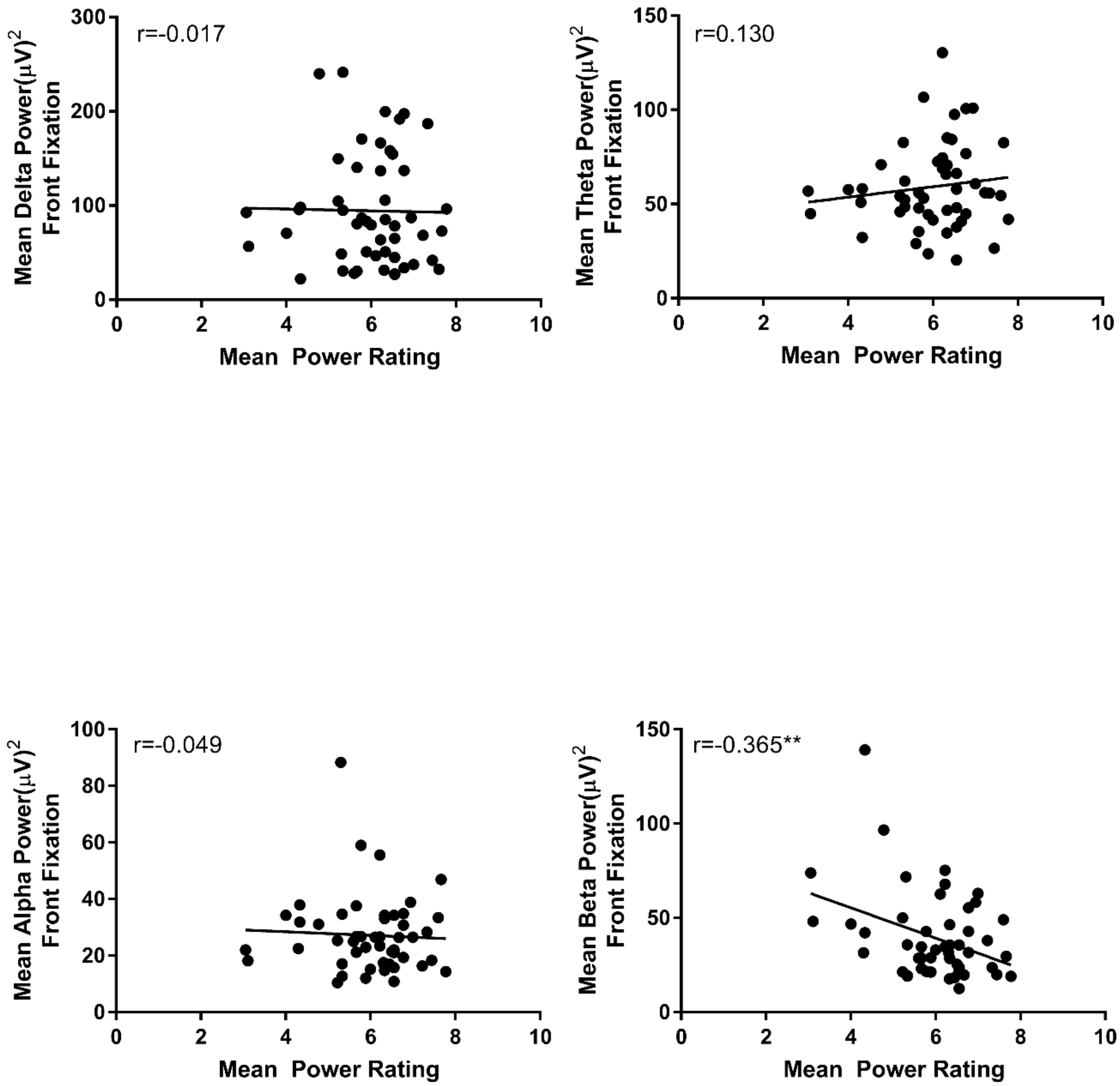
3.2 Figure 6:

Coaching Scores vs. Frequency Bands- xy correlation scatter plots representing brain frequencies (delta, theta, alpha, beta) for contact and frontal fixation task.



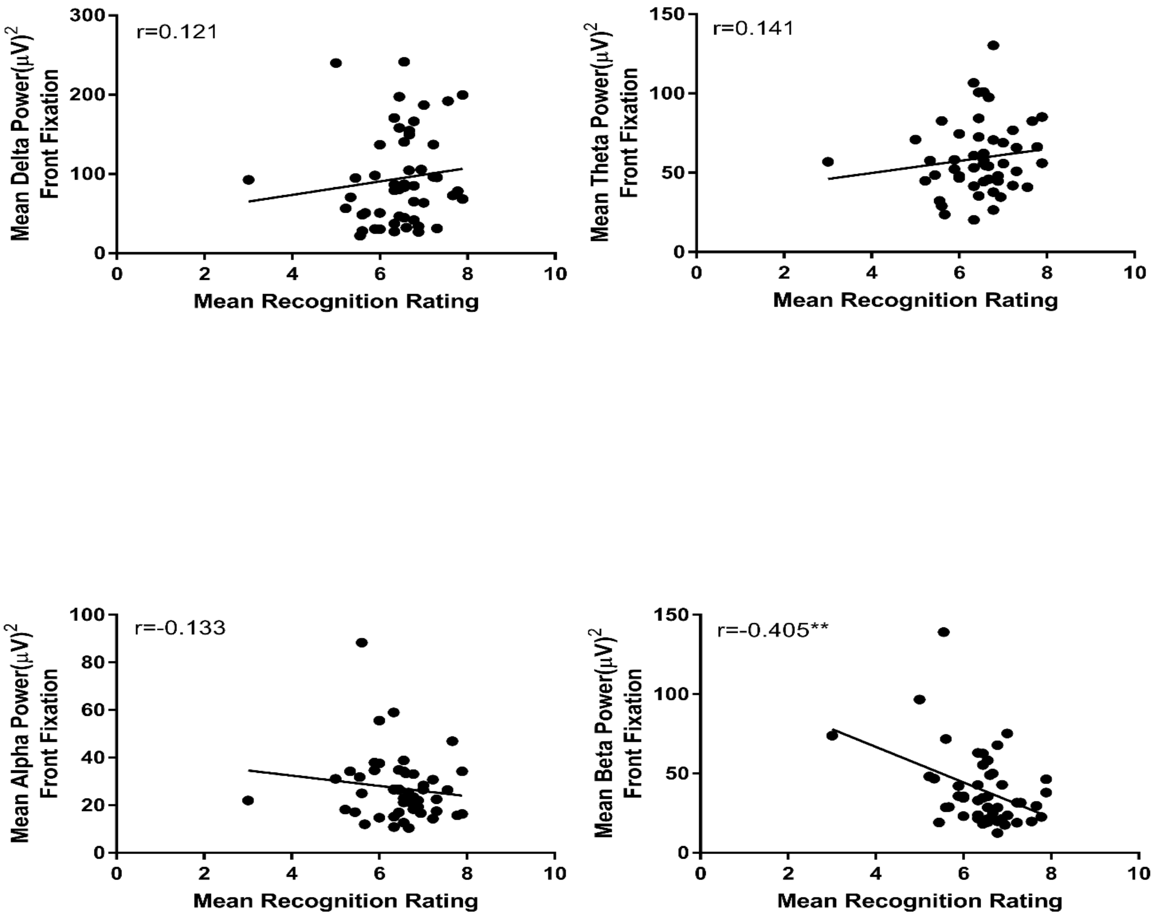
3.2 Figure 7:

Coaching Scores vs. Frequency Bands- xy correlation scatter plots representing brain frequencies (delta, theta, alpha, beta) for power and frontal fixation task.



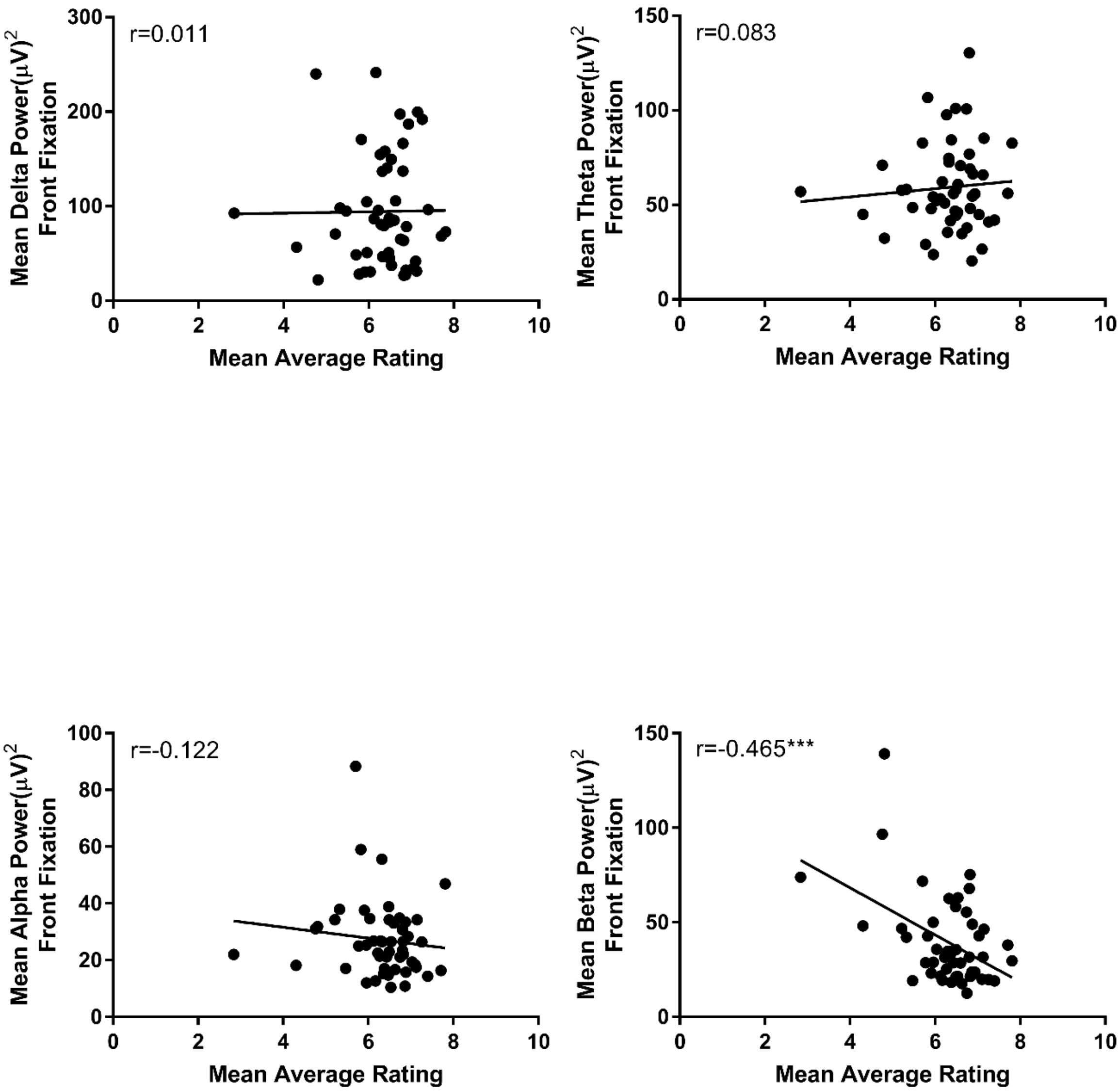
3.2 Figure 8:

Coaching Scores vs. Frequency Bands- xy correlation scatter plots representing brain frequencies (delta, theta, alpha, beta) for recognition and frontal fixation task



3.2 Figure 9:

Coaching Scores vs. Frequency Bands- xy correlation scatter plots representing brain frequencies (delta, theta, alpha, beta) for the average of all scores and frontal fixation task.



3.3 Frequency Band Correlations – Posterior Electrodes During Fixation

Pearson *r* correlation values (and significance tests) were also conducted between each of the five batting performance ratings (form, contact, power, pitch recognition, average) and each of the four EEG frequency bands of interest (delta, theta, alpha, beta) (see Figures 5-9) for the posterior electrodes during the fixation task. As with the analysis of the frontal electrodes during fixation, no correlations between power in the delta, theta, and alpha frequency bands and any of the batting performance ratings (form, contact, power, pitch recognition, average) were observed, all *p*'s > .05 (see Table 3, Figures 10 to 14). Power in the beta band did correlate with one of the batting performance ratings – power, [r = -.331, p = .019], but not with any of the other performance ratings (all *p*'s > .05).

Table 3

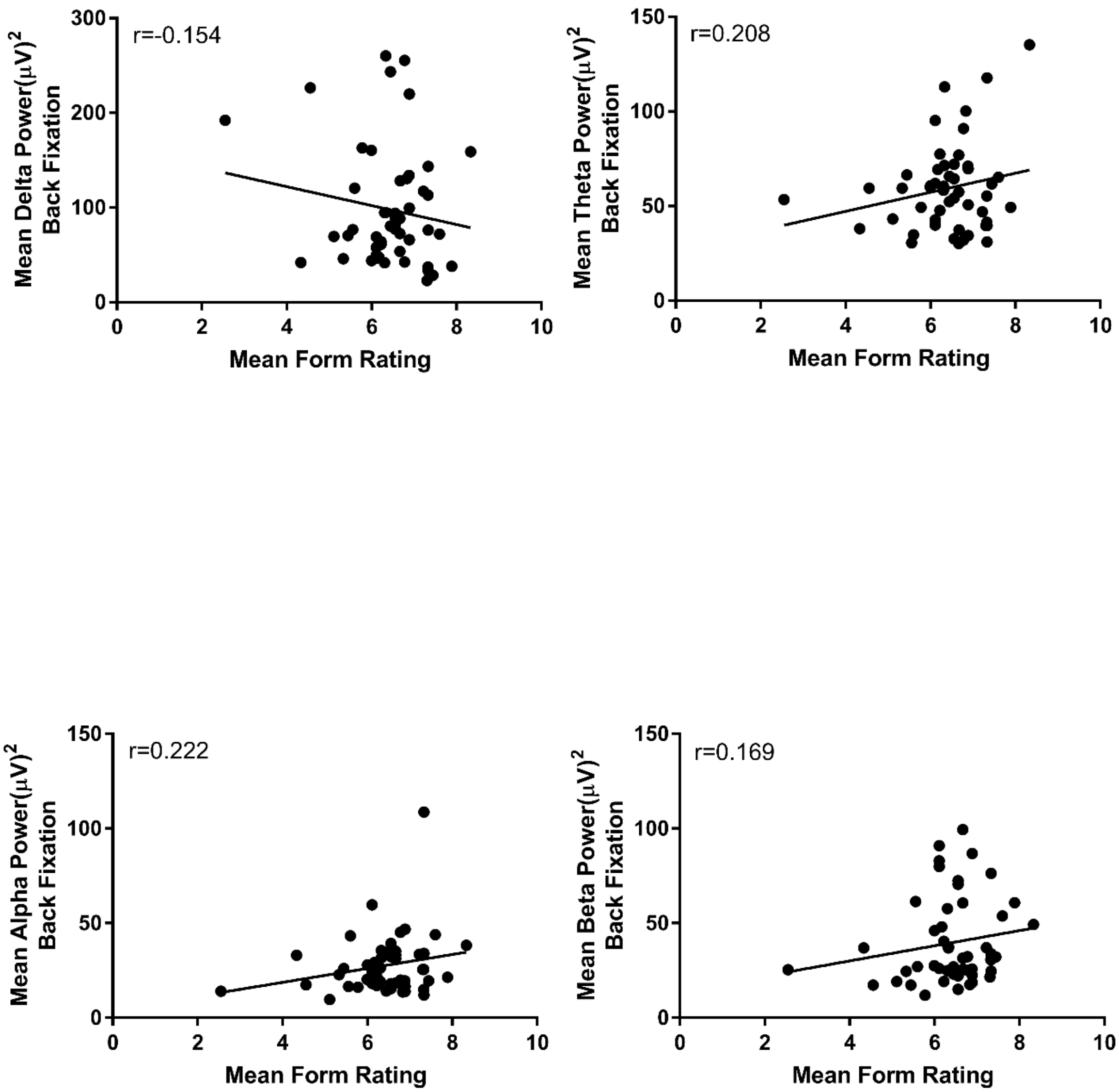
Pearson correlation of the posterior fixation task - frequencies vs evaluation criteria

	Form	Contact	Power	Recognition	Average
Delta	-0.154	-0.218	-0.069	-0.167	-0.163
Theta	0.208	0.172	0.175	0.166	0.197
Alpha	0.222	0.193	0.172	0.208	0.215
Beta	0.169	0.128	0.331*	0.228	0.236

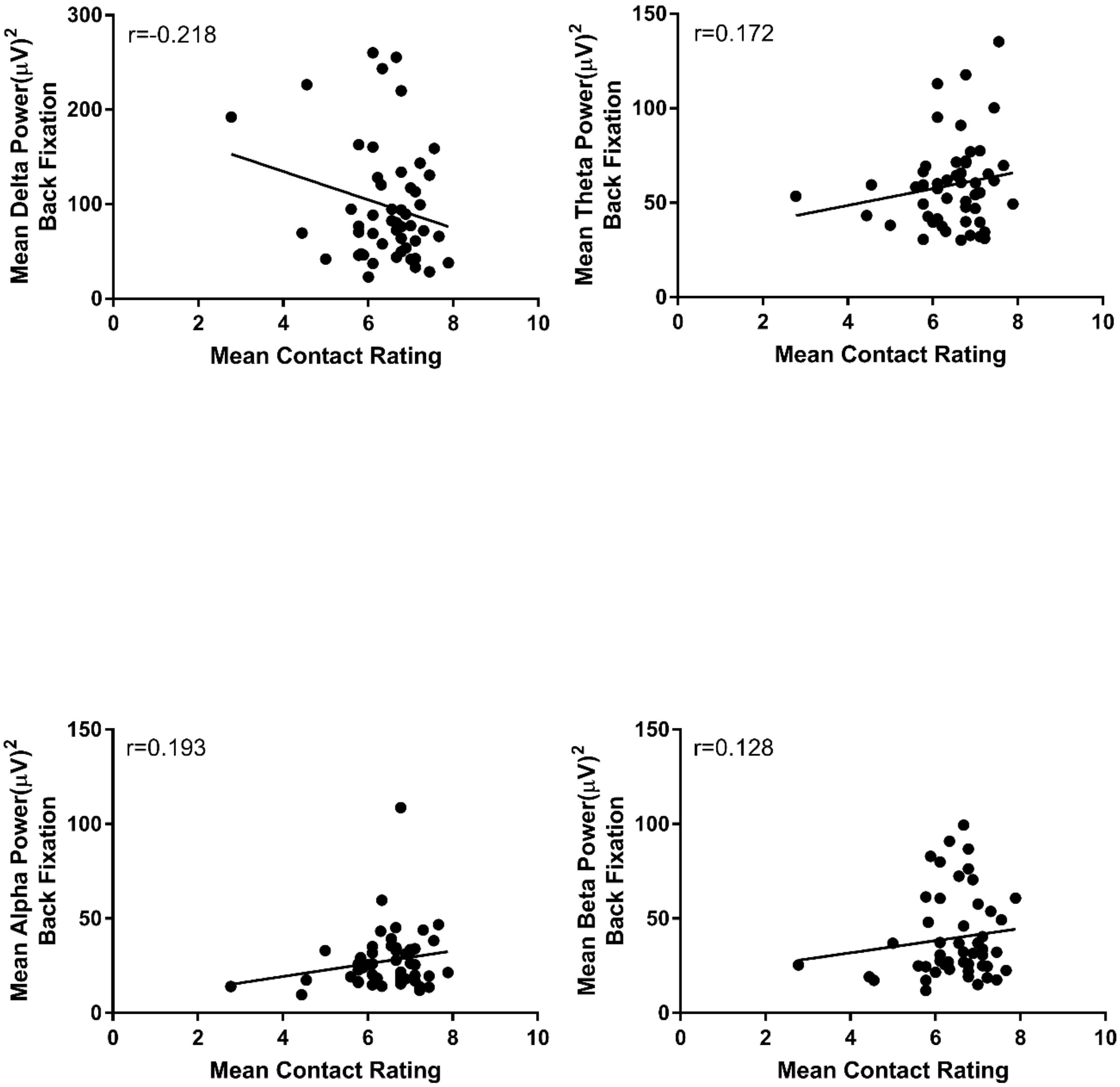
two tailed significance p<.05*; p<.01**; p<.001***

3.3 Figure 10:

Coaching Scores vs. Frequency Bands- xy correlation scatter plots representing brain frequencies (delta, theta, alpha, beta) for form and posterior fixation task.

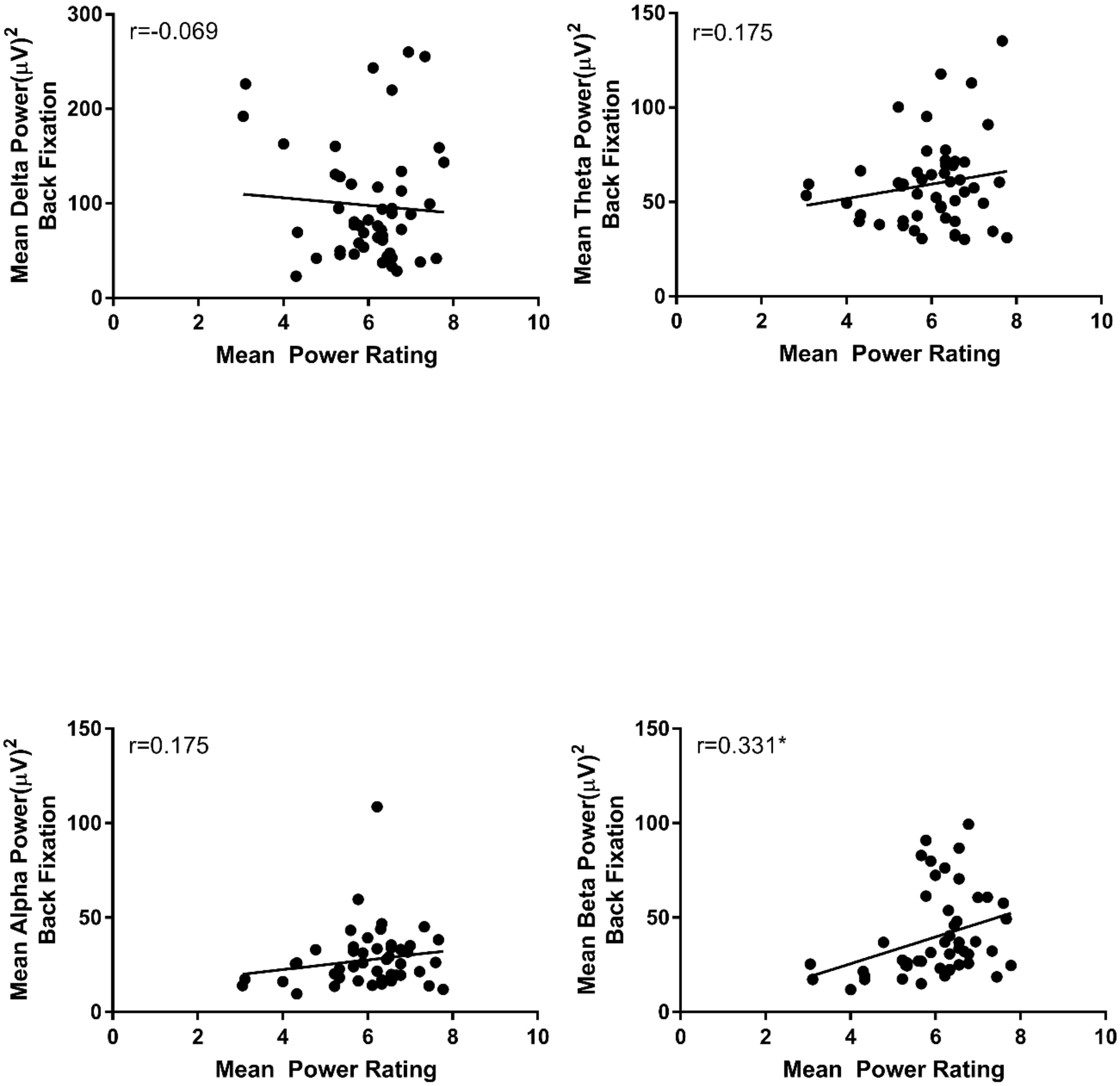


3.3 Figure 11:
Coaching Scores vs. Frequency Bands- xy correlation scatter plots representing brain frequencies (delta, theta, alpha, beta) for contact and posterior fixation task.



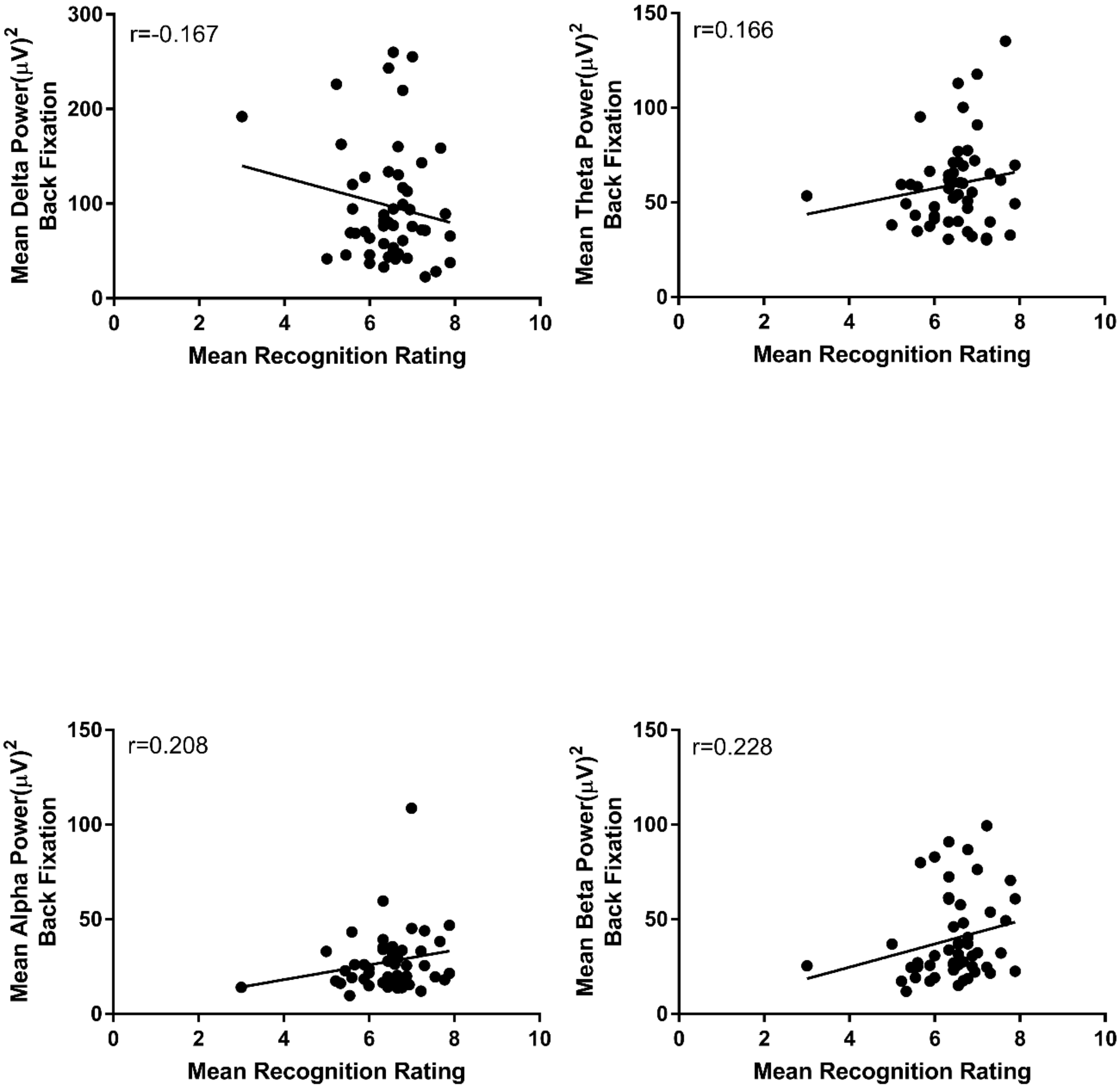
3.3 Figure 12:

Coaching Scores vs. Frequency Bands- xy correlation scatter plots representing brain frequencies (delta, theta, alpha, beta) for power and posterior fixation task.

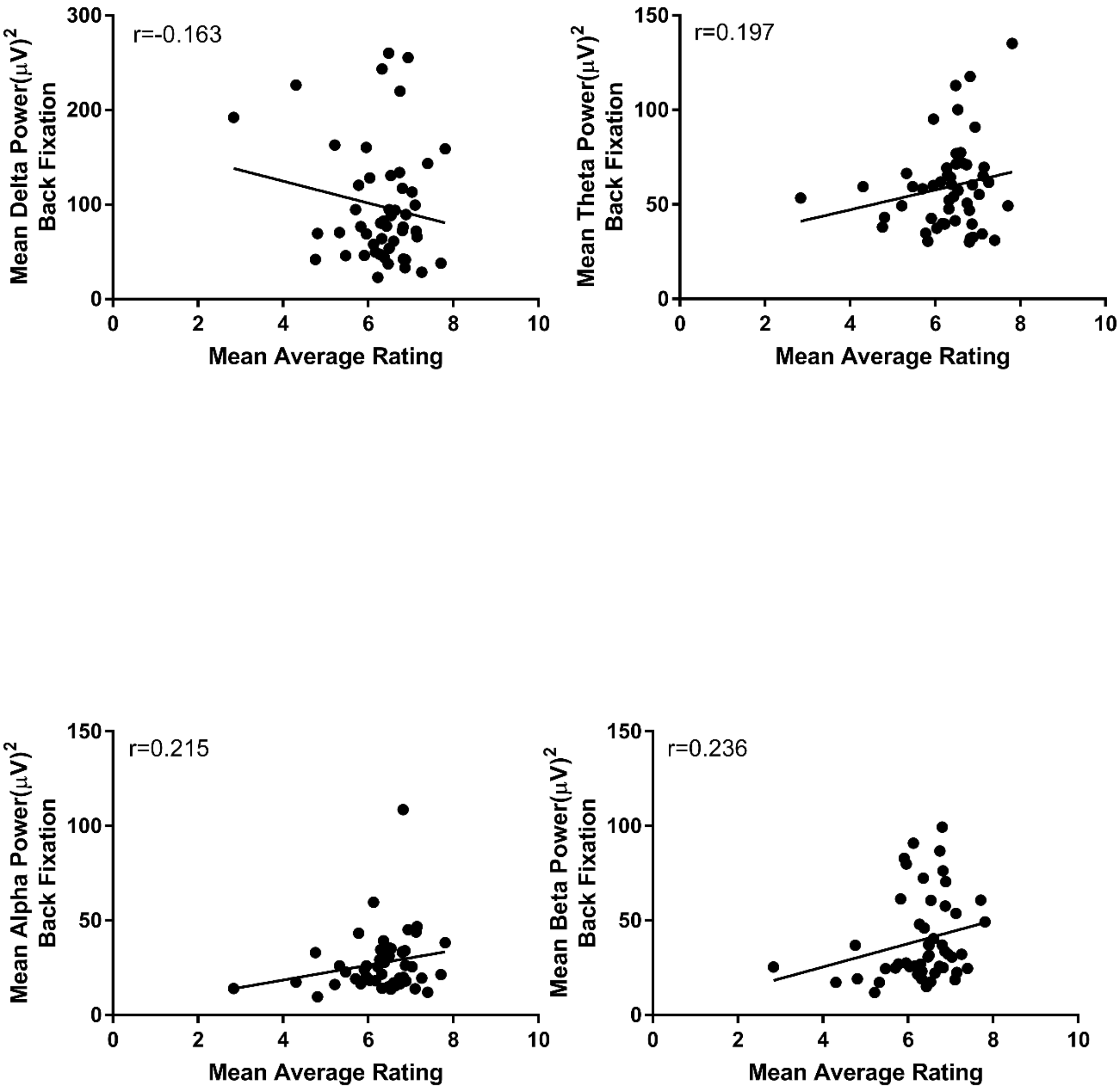


3.3 Figure 13:

Coaching Scores vs. Frequency Bands- xy correlation scatter plots representing brain frequencies (delta, theta, alpha, beta) for recognition and posterior fixation task.



3.3 Figure 14:
Coaching Scores vs. Frequency Bands- xy correlation scatter plots representing brain frequencies (delta, theta, alpha, beta) for the average of all scores and posterior fixation task.



3.4 Frequency Band Correlations – Frontal Electrodes During Counting

The relationship between power in the EEG spectra and performance ratings was also examined during the counting task (see Table 4, Figures 15 to 19) for the frontal electrodes. Similar to the pattern we observed during the fixation task there were no correlations between delta, theta, and alpha power and any of the batting performance ratings (all *p*'s >.05). However, as with the fixation task I did find that two of the batting performance ratings (power [r = .373, p

= .008], average [r = .298, p = .036]) were correlated with power in the beta range. The other batting performance ratings were not correlated with power in the beta range (p's > .05).

Table 4

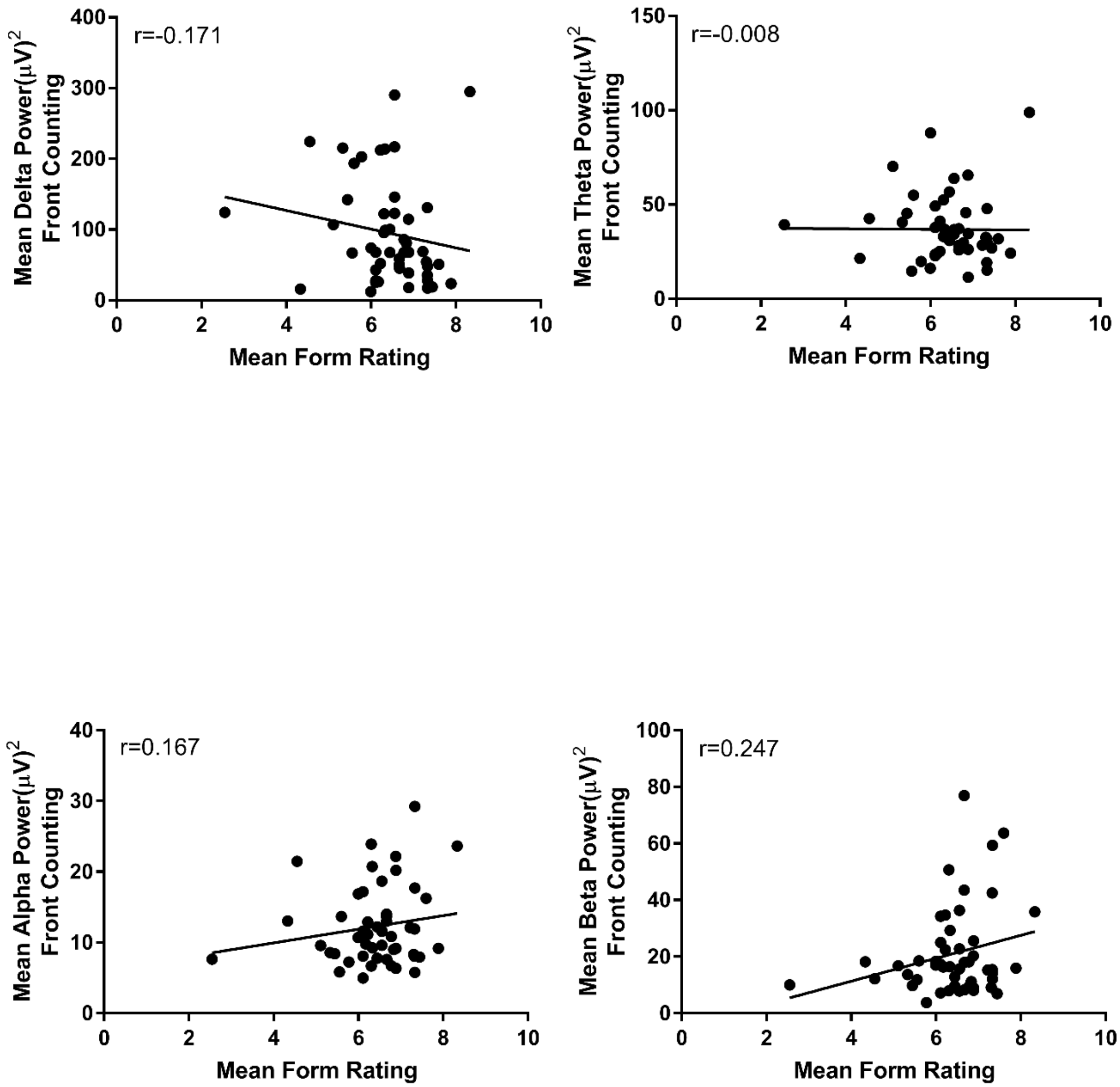
Pearson correlation of the frontal counting task - frequencies vs evaluation criteria

	Form	Contact	Power	Recognition	Average
Delta	-0.171	-0.13	-0.153	-0.14	-0.165
Theta	-0.008	-0.02	0.0224	-0.042	-0.01
Alpha	0.167	0.193	0.196	0.163	0.196
Beta	0.247	0.199	0.373**	0.258	0.298*

two tailed significance p<.05*; p<.01**; p<.001***

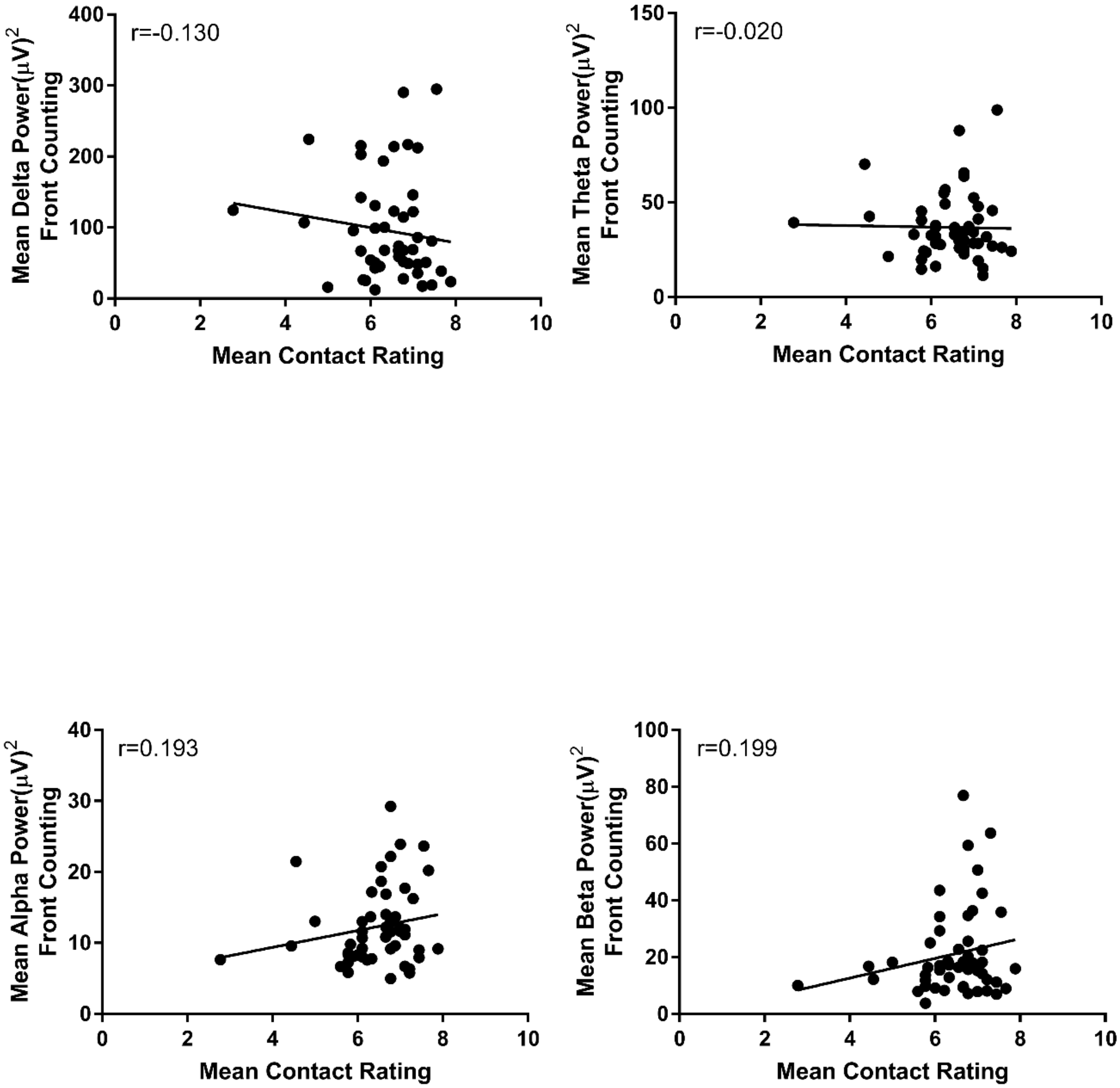
3.4 Figure 15:

Coaching Scores vs. Frequency Bands- xy correlation scatter plots representing brain frequencies (delta, theta, alpha, beta) for form and frontal counting task.



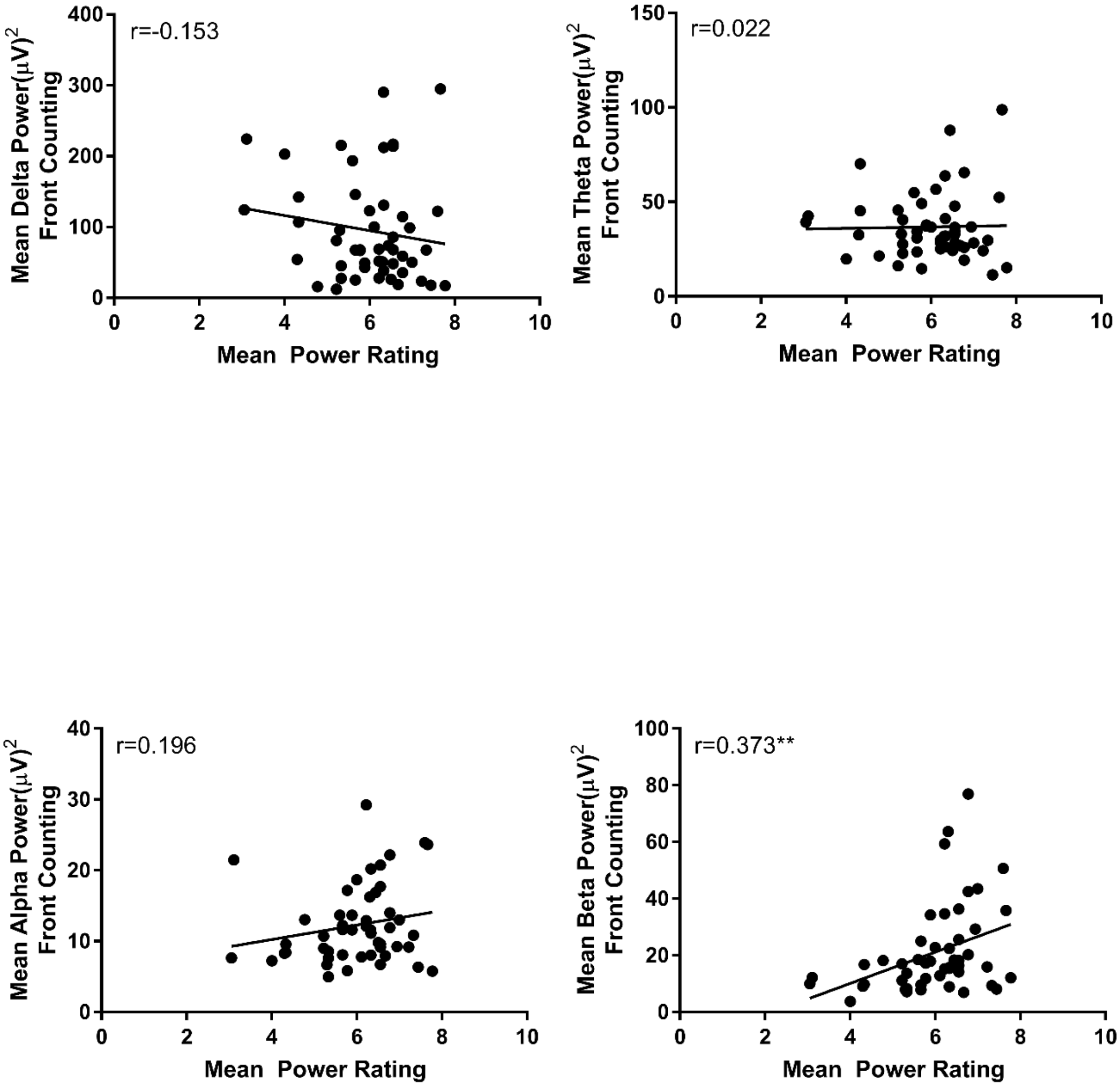
3.4 Figure 16:

Coaching Scores vs. Frequency Bands- xy correlation scatter plots representing brain frequencies (delta, theta, alpha, beta) for contact and frontal counting task.



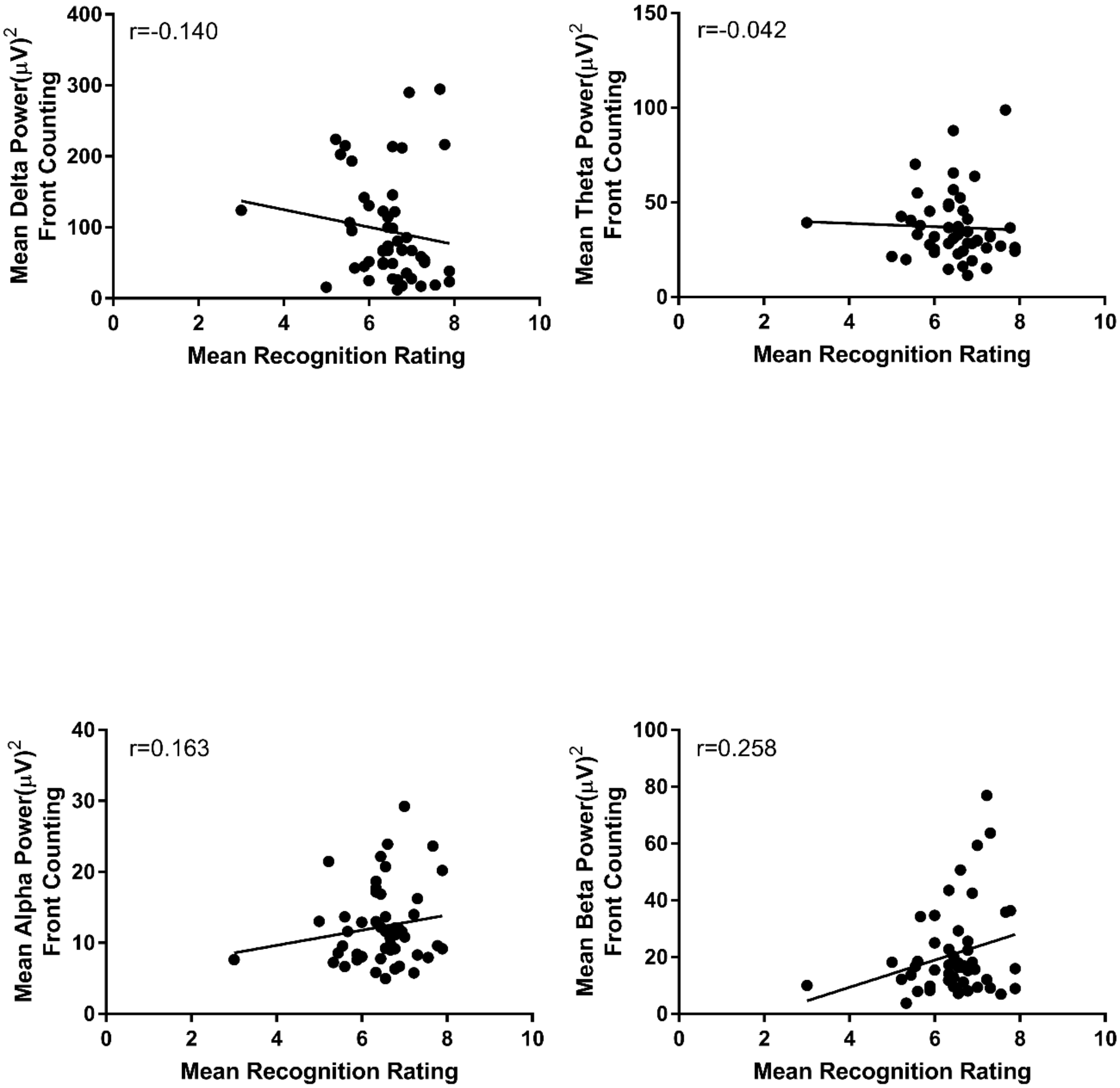
3.4 Figure 17:

Coaching Scores vs. Frequency Bands- xy correlation scatter plots representing brain frequencies (delta, theta, alpha, beta) for power and frontal counting task.

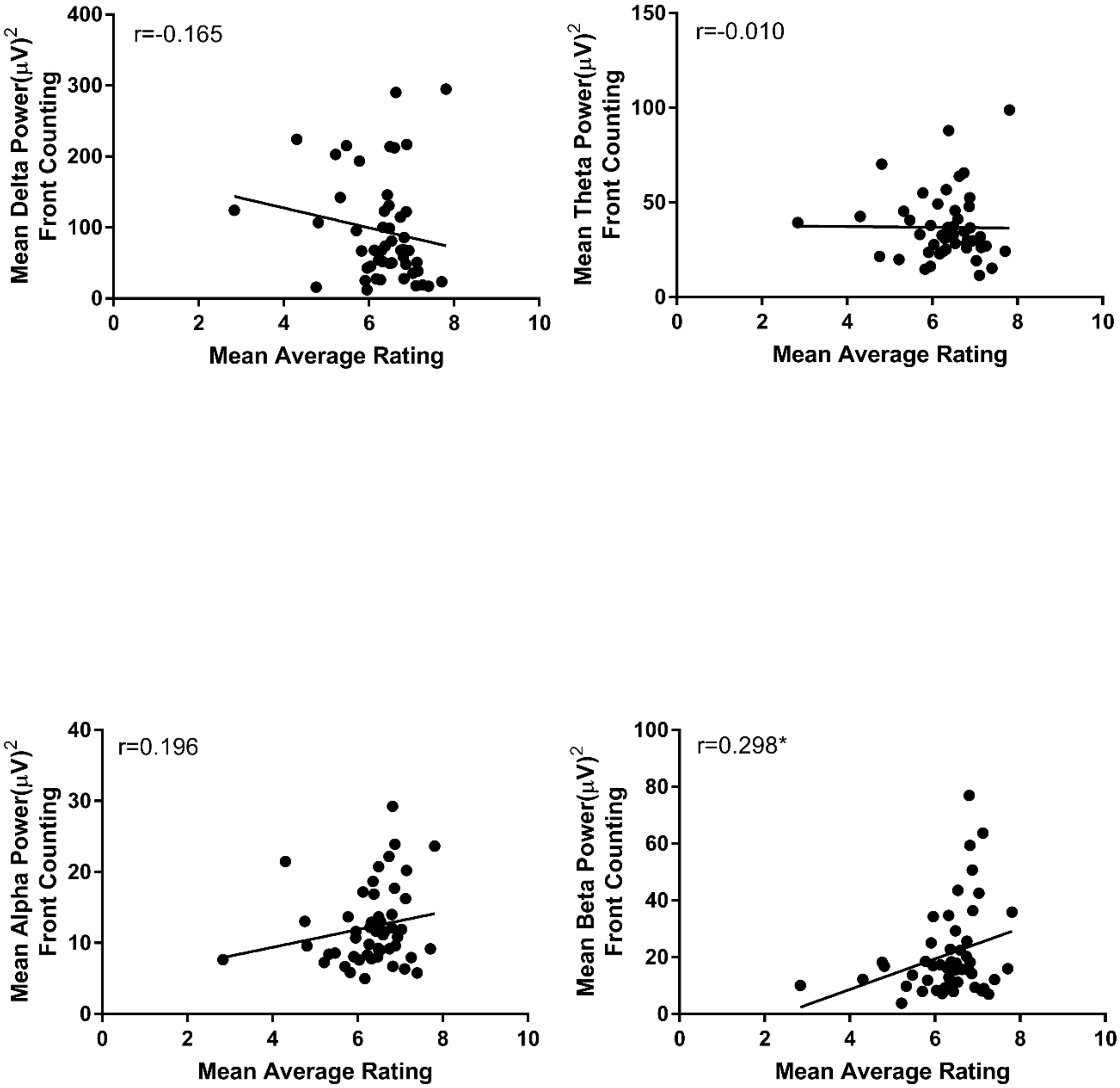


3.4 Figure 18:

Coaching Scores vs. Frequency Bands- xy correlation scatter plots representing brain frequencies (delta, theta, alpha, beta) for recognition and frontal counting task.



3.4 Figure 19:
Coaching Scores vs. Frequency Bands- xy correlation scatter plots representing brain frequencies (delta, theta, alpha, beta) for the average of all scores and frontal counting task.



3.5 Frequency Band Correlations – Posterior Electrodes During Counting

I also examined the relationship between power in the EEG spectra and batting performance ratings (see Table 5 and Figures 20 to 24). Interestingly, we did observe a correlation between batting power and alpha power [r = .282, p = .047]. We also observed a correlation between batting power and average batting performance and beta power [r = .321, p

= .023; r = .280, p = .049]. No other relationships between batting performance and power in the EEG spectra were observed (p's > .05).

Table 5

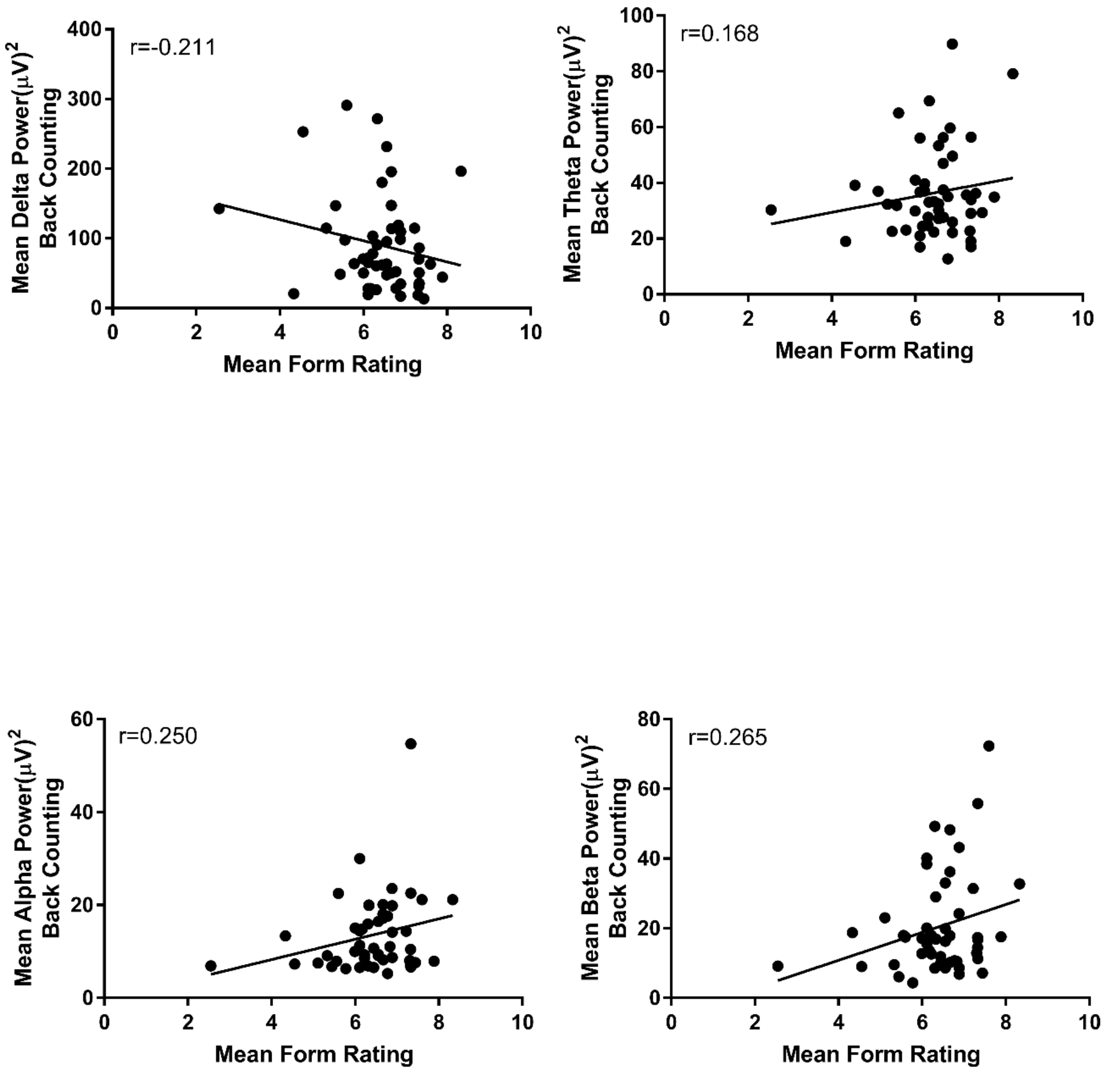
Pearson correlation of the posterior counting task - frequencies vs evaluation criteria

	Form	Contact	Power	Recognition	Average
Delta	-0.211	-0.249	-0.112	-0.236	-0.216
Theta	0.168	0.176	0.217	0.099	0.186
Alpha	0.25	0.209	0.282*	0.201	0.261
Beta	0.265	0.183	0.321*	0.245	0.280*

two tailed significance p<.05*; p<.01**; p<.001***

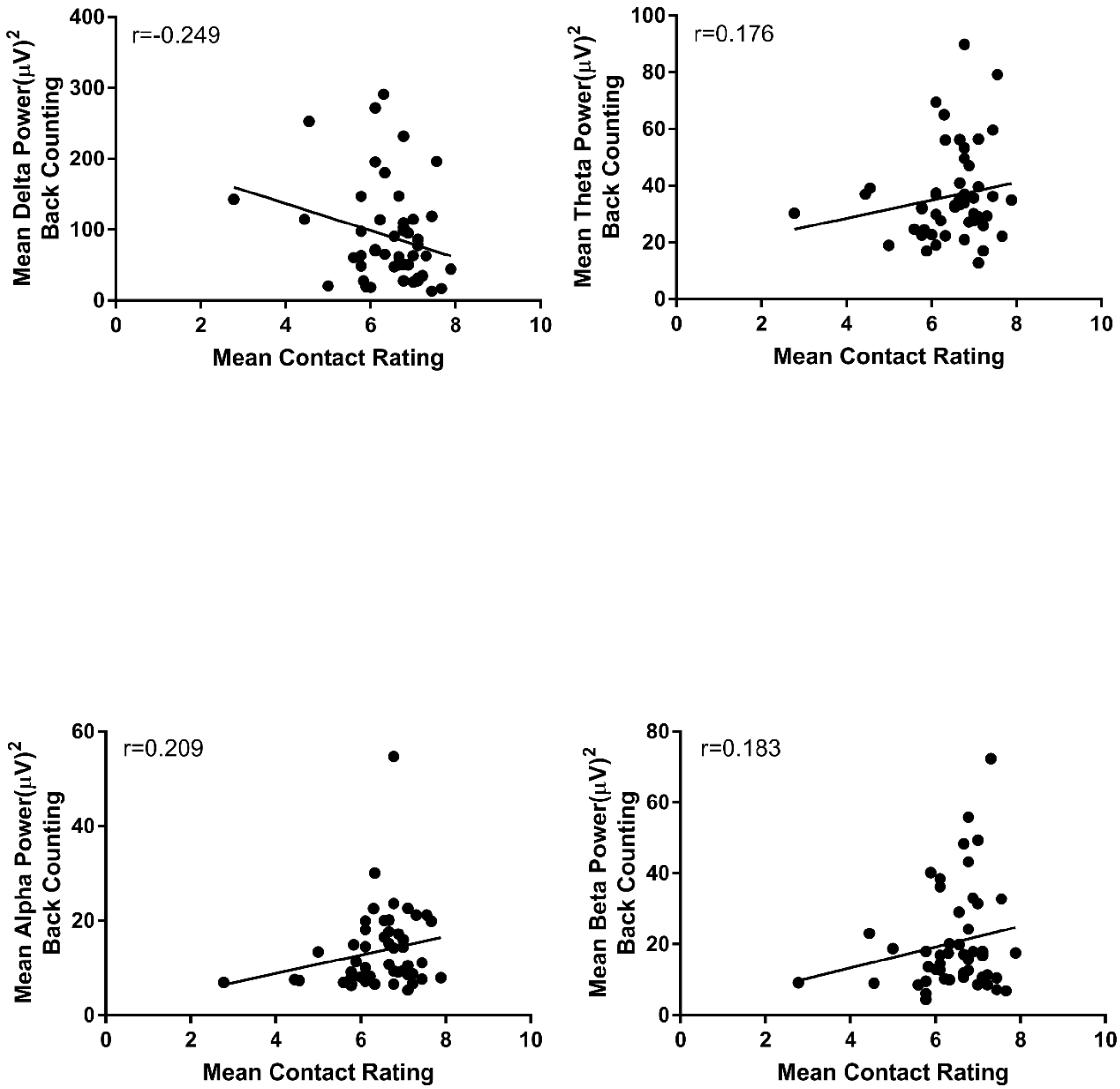
3.5 Figure 20:

Coaching Scores vs. Frequency Bands- xy correlation scatter plots representing brain frequencies (delta, theta, alpha, beta) for form and posterior counting task.



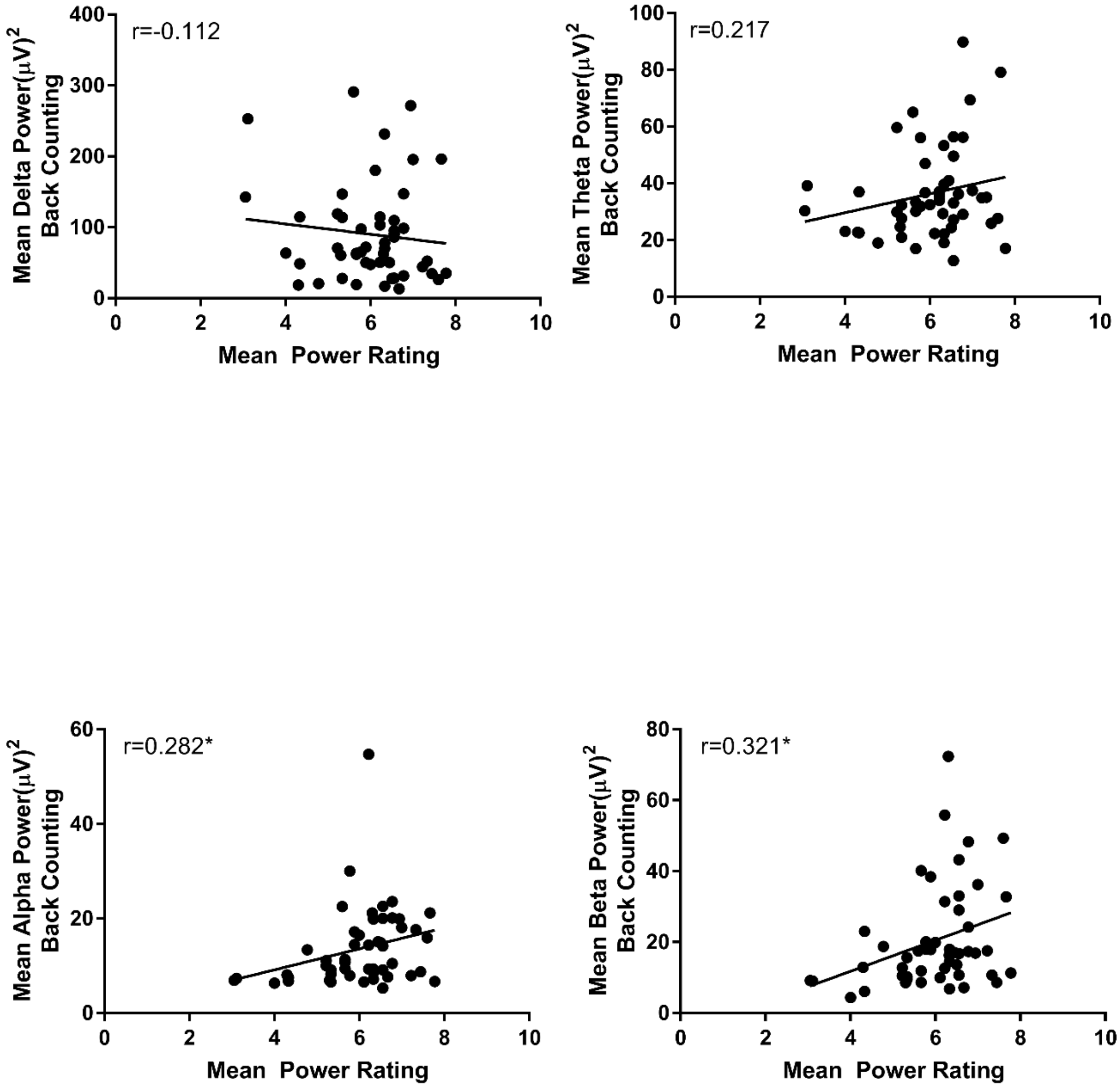
3.5 Figure 21:

Coaching Scores vs. Frequency Bands- xy correlation scatter plots representing brain frequencies (delta, theta, alpha, beta) for contact and posterior counting task.



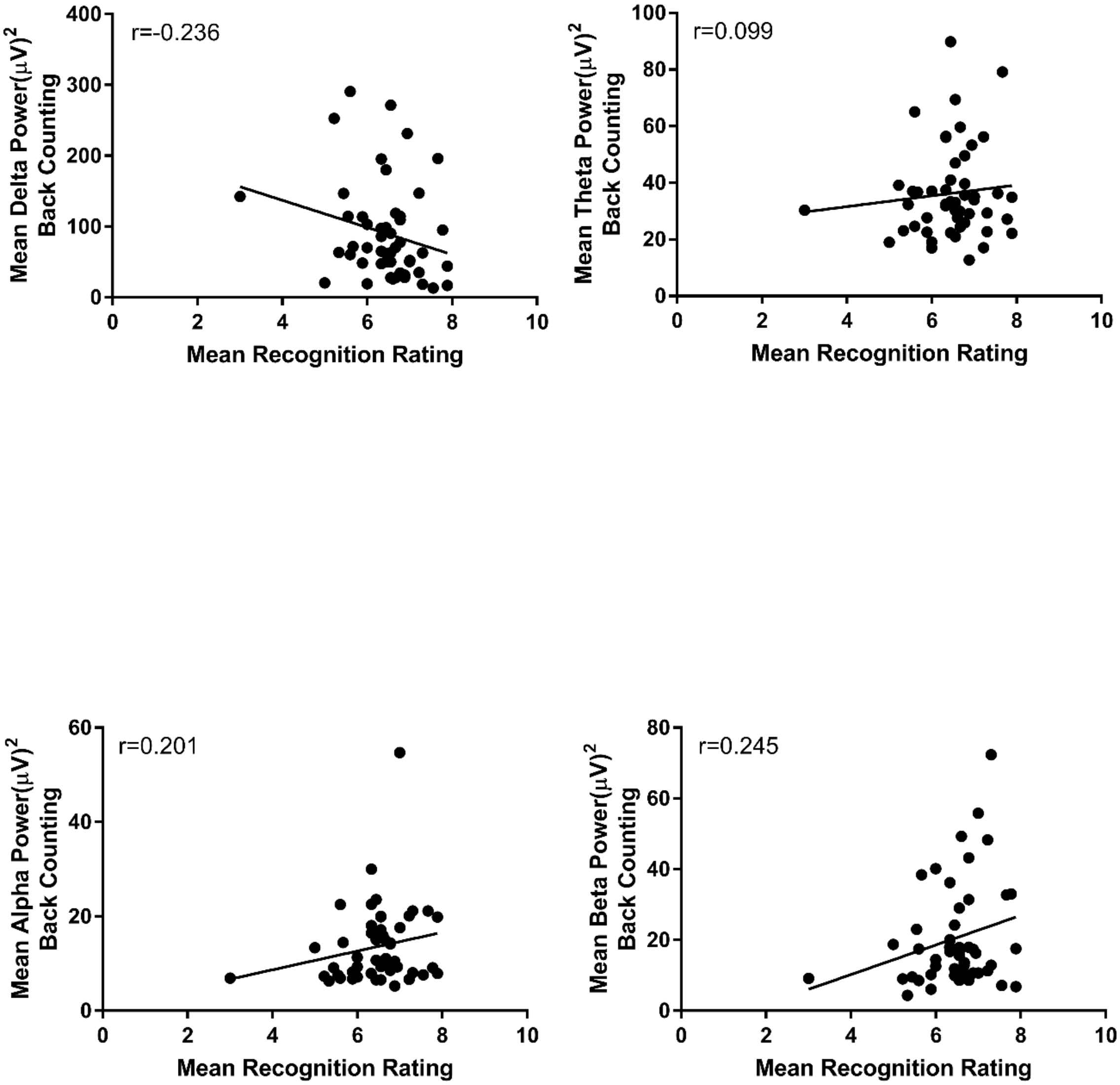
3.5 Figure 22:

Coaching Scores vs. Frequency Bands- xy correlation scatter plots representing brain frequencies (delta, theta, alpha, beta) for power and posterior counting task.

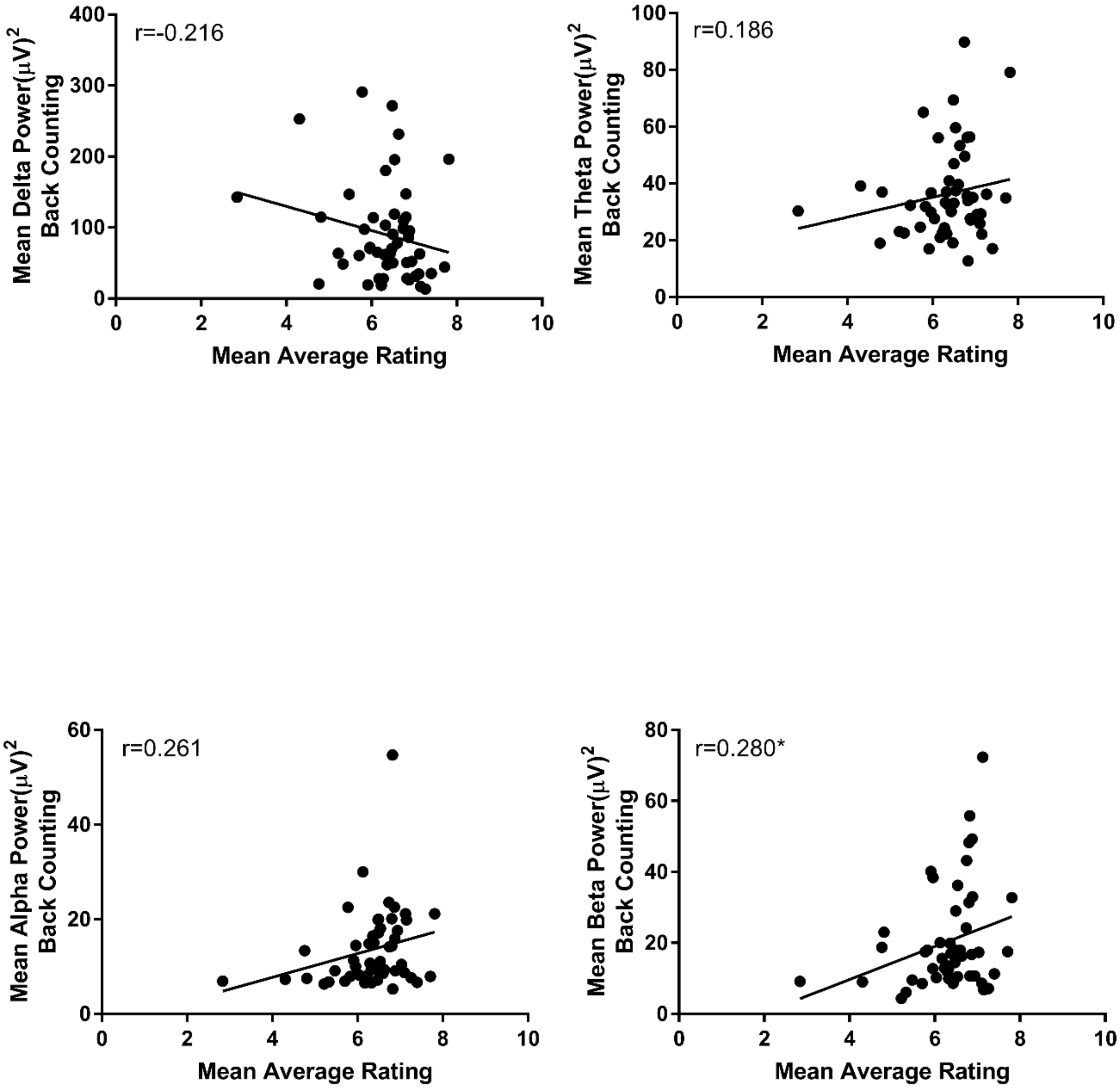


3.5 Figure 23:

Coaching Scores vs. Frequency Bands- xy correlation scatter plots representing brain frequencies (delta, theta, alpha, beta) for recognition and posterior counting task.



3.5 Figure 24:
Coaching Scores vs. Frequency Bands- xy correlation scatter plots representing brain frequencies (delta, theta, alpha, beta) for the average of all scores and posterior counting task.



CHAPTER FOUR: DISCUSSION

4.1 Baseball Performance Ratings

The baseball performance ratings were close on each of the four criteria by all three coaches. Two out of the three coaches stayed consistent for all but one day of testing. On the last day of testing only one out of the three coaches evaluated all trials. Only one small issue was apparent during the rating of baseball performance. Two out of the three coaches out of every trial were nationally certified. The third coach in every trial was solicited from the team being evaluated and had no accreditation and could have presented some bias when grading his own players. Although there was a grading difference in the performance ratings, when the scores were averaged for all trials and between all coaches, the overall mean reliability yielded a significance of $r = 0.60$ ($p < .001$). If all coaches remained the same and all had the highest level of accreditation the possibility of a higher reliability could exist.

4.2 Frontal and Posterior EEG Power during Fixation and Counting

Fixation Task

During the fixation task, in both the frontal and posterior pooled channels, the electrode results showed beta power to have a significant correlation with batting scores. All batting scores during the frontal fixation task yielded significant correlation with beta. Beta power only had significant correlation with power in the posterior fixation results. These results were different than initially hypothesized. My initial hypothesis was that alpha power would have significant correlations with all batting scores, which was in-line with other studies researching performance prediction with EEG.

The lack of a correlation between alpha power and any of the performance measures for batting was quite surprising. Perhaps this relates to the nature of the task itself – the skill used here was an open-motor skill and previous studies have examined closed-motor skills. For example, pistol shooting, putting on artificial or predictable surfaces or shooting a free throw from the same position on a basketball court are all closed motor skills, meaning they are self paced and for the most part predictable (Wang et al., 2013). Hitting a baseball thrown by an individual is an open skill meaning it is paced by the environment and less predictable (Wang et al., 2013). The high correlation between beta and batting performance may also occur due to the batter's need for a quick reaction time to contact the baseball and his or her decision to swing (Go/Nogo). For more information on the relationship between beta and reaction time as well as open motor skill for a Go/Nogo task, see below.

Counting Task

The counting task yielded results in-line with previous studies (e.g., Mathewson et al., 2012) for posterior electrodes in that there was a significant alpha score for power during the posterior counting task. Indeed, this result is in line with my original hypothesis. If you recall, previous work has shown that alpha power can predict subsequent performance (Babiloni et al., 2008; Besserve et al., 2008**;** Mathewson et al., 2012; Meyer et al., 2014). As such, this result is in line with previous work. However, what is unclear is why alpha power only correlated with power and only during counting.

Numerous other articles not discussed in this paper show alpha as the dominate brain frequency in certain aspects of sport performance in closed motor tasks but none that I found focused on open motor tasks. In the studies mentioned above, all data was collected in a laboratory and had the participants perform a closed skill task. In some of the other articles not mentioned in this study, only alpha was looked at as a correlate for the task due to previous findings pointing to that. Posterior alpha power did show to have a significant correlation with a batter's power during the counting task. There was no other correlation in any of the other tasks.

The reason for this is potentially because the data was collected in a field setting and using a portable EEG device.

As with the results for the fixation only task, frontal and posterior beta in the counting task significantly predicted batting power.

4.3 Why Beta Power?

A significant correlation was found between each of the coaches scores and beta power. Beta power significance was not what was expected but a good find none the less. In sum, these results reveal that batting performance was better if power in the beta band was reduced in the EEG data recorded prior to batting.

After tedious searching, no published research was found to determine why beta predicted performance and not alpha. Potential conclusions can be drawn from other EEG research such as Gilbertson et al,. 2008 and elevated beta power correlating with slowed voluntary movements and lower beta power correlating with faster voluntary movements. Gilbertson et al. studied two tasks with two sets of ten individuals. The two tasks were a reaction time paradigm and finger stretch reflex paradigm. Subjects for the reaction time paradigm were ten right handed healthy subjects, eight men and two women. Subjects for the finger stretch reflex paradigm were ten right handed healthy subjects all of which were males.

During the reaction time paradigm participants were seated with their forearms supported on a table with both their left and right index fingers slightly abducted and tonically extended against gravity. Subjects were instructed to abduct their right index finger as quickly as possibly on illumination of a light emitting diode. The light was delivered at both triggered and random cues.

During the finger stretch paradigm participants were situated in the same position as the reaction time paradigm. Instead of the light diode, participants were asked to resist force put onto their finger by a sudden tangential force on their right index finger. Force was applied both with triggered and random cues. The results of both studies showed elevated beta oscillations slowed movement and lower beta oscillations increased movement speed.

Batters need a fast reaction time to make contact with a pitched baseball and multi stimuli are presented when a batter is attempting to make contact. It is because of this that I presume beta and not alpha had the most significant correlation in this thesis.

Another possible reason behind the findings is deciding to swing and ultimately making contact with a thrown ball is a Go/Nogo reaction. Baseball players have to decide if the pitch that is thrown will be a strike and if it is a strike they need to swing. If the pitch thrown is not a strike than the player needs to stop his or her swing. For further information on Go/Nogo reaction of baseball players see Muraskin, Sherwin, and Sajda (2015); Nakamoto and Mori (2008) and Yamashiro et al. (2015). All of the aforementioned studies look specifically at the Go/Nogo task with regards to baseball batters. Neither study looked for beta specifically although Muraskin, Sherwin and Sajda, 2015 looked at alpha and found no significant correlation between alpha and reaction time and the Go/Nogo task.

4.4 Use of portable EEG to predict performance

This study exposes yet another way to predict performance using portable EEG. Similar to Krigolson et al. (2017) the time needed to affix the portable EEG, assess impedances and to start collecting good data took less than 10 minutes and the data quality was comparable to a traditional system. One of the main differences between this study and other studies that predict performance is that this experiment could predict an open task in hitting a thrown baseball.

Another difference was that this study took place in the field, no where near the laboratory. With advancements in technology, i.e. brain wave frequency streamed directly to a smart phone or tablet, immediate prediction of performance would be possible. As this is the first study to use EEG to predict the performance of a baseball batter in a field setting and with the positive results found, more studies need to be done.

4.5 Overview of Current Results

With more research comes more opportunity. Professional and collegiate sports teams are always looking for an edge and if they had the ability to know who to put in the lineup on any given day, their odds of winning would increase. In theory, a total of less than 10 minutes would be needed to affix the MUSE headband, complete the baseline and counting task and know how well a batter will do in a coming at bat. With the portability of the MUSE and minimal time needed to run an experiment, professional and/or collegiate baseball teams would only need a few MUSE systems accompanied by a tablet for each to be able to predict the performance of a batter in an upcoming at bat. We know that beta power has significant correlations with a batter's form, his or her ability to make good contact with a pitch, hit a pitch with power and recognize if the pitch that is thrown is going to be in the strike zone. All a coach would need to do is compare the beta power of the batters on the team to know who should be in the starting lineup or who should pinch hit.

4.6 Limitations

Despite the well thought out and planned views the present thesis revealed, there are, unavoidably, limitations that must be admitted. The assessment of batters took place in a batting cage and not on a field. Ultimately, the performance we want to predict is in live game scenarios. Batting practice was delivered by a coach approximately two thirds of the distance from home plate, on flat ground and at a speed that was well below major league average. In this, reaction times would be different than in a game situation. Only fastballs were thrown with the coach presenting pitches with the mindset of allowing the batter to make contact. In a game situation, the batter will see a pitcher from a further distance, elevated on a mound, throwing harder than in batting practice with not all pitches being straight and the pitchers mindset on getting the batter out. Understanding the difference but also equating for batter expertise and general agreeance of batting practice as an appropriate pregame tool, predicting a batter's ability to have successful batting practice will result in successful game scenarios.

The coach evaluation tool in part was reliant upon coach expertise and unbiased evaluation of the batter. Form and Power were both judged using the coach's perception and understanding of proper mechanics and the ability to identify the amount power vs the batter's age and level of play. With access to the tools and technology of Major League Baseball this area would be more quantifiable with zero emphasis placed on the coach's judgment. Although all potential professional and collegiate players are rated by a human with scores based on individual bias, with tools such as high speed cameras and software that provides ball exit velocity and distance, human bias would be removed and a more quantifiable approach available. Separating groups based on level of play would help account for differences in age, maturity (both mental and physical) and skill level and potentially yield better results. Due to the restraints of this study on recruiting of participants, and to have a large enough sample size, all athletes had to be grouped together.

Lastly, although this study found a negative correlation between beta frequency power and batting performance, there is no magic beta number that encompasses all performance as a predictor. Each day and with each performance, both successful and not, a person's beta power changes. To be able to find the appropriate beta score for an individual to be successful one would need to compare an individual's beta state to their beta trait. What this means is that an average beta power score over time (beta trait) would need to be established and compared to an individual's beta power prior to each successful and non-successful at bat (beta state). In conclusion, predicting performance using a portable EEG device is possible but an individual's beta power trait and state need to be established first to allow for real time predictions.

4.7 Future Research and Potential

Interest from MLB teams could allow analysis of a larger number of participants with a greater skill level and use of better technology and equipment. With research completed and validated on predicting the performance of a batter, research on the potential of predicting the performance of a pitcher would become possible. Similar studies could be done on other sports by predicting the effectiveness of quarterbacks, a hockey or soccer goalie's ability to block shots etc. Using this research to identify brain frequency as a predictor of performance, more research could be done on the potentials of neurofeedback training and helping a batter get into a better beta state.

In the current state of the research an MLB or collegiate team could organize their batting lineups to reflect players with the greatest probability of getting a hit. Alternatively, a team would know which players coming off the bench in a pinch-hit scenario would have the highest probability of getting a hit.

In any follow-up study done one should make sure to recruit a larger sample size from differing age groups and expertise to improve the data quality and assess if there is any difference between the brain frequencies and the differences in age and skill level.

CHAPTER 5: CONCLUSION

The ability to predict performance using a portable EEG device, in a field setting, with external variables present is now possible. Significant correlations from beta oscillations was found in all five coaches scores. This raises the question of if beta is present as a predictor of performance in a field setting can beta or other brain waves be present in taking past laboratory research into the field. Another question that presents itself after this research is why beta and not alpha being the brain frequency that predicts performance. More research is needed to properly find the answer. More research is also needed to test this theory in other settings and more research is needed to find an individuals beta trait and beta state to affectively predict performance in real time with a portable EEG device.

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APPENDICES

Appendix A: University of Victoria Approval

University of Victoria | Office of Research Services | Human Research Ethics Board
Administrative Services Building Rm B202 PO Box 1700 STN CSC Victoria BC V8W 2Y2 Canada
T 250-472-4545 | F 250-721-8960 | uvic.ca/research | ethics@uvic.ca

Certificate of Approval

PRINCIPAL INVESTIGATOR:	**Anthony Pluta**	**ETHICS PROTOCOL NUMBER** Minimal Risk Review - Board members	**15-355**
UVic STATUS:	**Master's Student**	ORIGINAL APPROVAL DATE:	11-Jan-16
UVic DEPARTMENT:	**EPHE**	APPROVED ON:	11-Jan-16
SUPERVISOR:	**Dr. Olave E. Krigolson**	APPROVAL EXPIRY DATE:	10-Jan-17

PROJECT TITLE: **The Brain's Background Noise and its Effect on the Success of Baseball Players**

RESEARCH TEAM MEMBER Dr. Olave Krigolson (Advisor, UVic); Chad Williams (Research Assistant, UVic); Rob McCulloch (Master's Student, UVic); Cameron Hassall (PhD Student, UVic)

DECLARED PROJECT FUNDING: **UVic Startup Funds; Neuroeducation Research Funds**

CONDITIONS OF APPROVAL

This Certificate of Approval is valid for the above term provided there is no change in the protocol.

Modifications
To make any changes to the approved research procedures in your study, please submit a "Request for Modification" form. You must receive ethics approval before proceeding with your modified protocol.

Renewals
Your ethics approval must be current for the period during which you are recruiting participants or collecting data. To renew your protocol, please submit a "Request for Renewal" form before the expiry date on your certificate. You will be sent an emailed reminder prompting you to renew your protocol about six weeks before your expiry date.

Project Closures
When you have completed all data collection activities and will have no further contact with participants, please notify the Human Research Ethics Board by submitting a "Notice of Project Completion" form.

Certification

This certifies that the UVic Human Research Ethics Board has examined this research protocol and concluded that, in all respects, the proposed research meets the appropriate standards of ethics as outlined by the University of Victoria Research Regulations Involving Human Participants.

Dr. Rachael Scarth
Associate Vice-President Research Operations

Certificate Issued On: 11-Jan-16

15-355 Pluta, Anthony

Appendix B: Consent Form

Consent Form

University of Victoria | Neuroeconomics Laboratory

Principal Investigator: Anthony Pluta
Department of Exercise Science, Health & Physical Education
University of Victoria

Lab: McKinnon Room 0026
Phone:
Email:

The Brain's Background Noise and its Effect on the Success of Baseball Players

Introduction

We invite you to take part in a research study being conducted by Anthony Pluta, who is a graduate student of Dr. Krigolson at the University of Victoria and a Victoria based baseball coach. Your participation in this study is voluntary and you may withdraw from the study at any time. If you play for Anthony Pluta, your performance evaluation will not be affected if you decide not to participate. The study is described below. This description tells you about the risks, inconvenience, or discomfort that you might experience. You should discuss any questions you have about this study with the research assistant who will be testing you.

Purpose of the Study

You are being invited to take part in this study because it is important to understand if correlations between brain waves and performance on the field can be determined. At present we are interested in studying your brain waves and how you perform on field. In particular, we are interested in understanding if there is any relationship between background brain activity and physical performance.

Study Design

In this study you will be performing a simple computer-based task while we record electrical activity generated by your brain from electrodes fitted to a portable device you will wear on your head. The experiment will consist of a 15 minute testing session. The 15 minute session includes the time we need to get you prepared for testing, the experiment, and a clean-up and debriefing period.

Who Can Participate In The Study

Any amateur baseball player that plays in a high performance league whose primary position involves batting.

Who Will Be Conducting The Research

The experiment you will be taking part in will be conducted by Anthony Pluta, a graduate student, or by a research assistant working for Dr. Krigolson.

What You Will Be Asked To Do

The study will take place at the field prior to practice and will take 15 minutes. In this study you will be asked to perform a simple computer-based task. In particular, you will be asked to play a game where possible reward is varied.

You will be fitted with a portable EEG machine which will record electrical activity at the scalp. Your task will be completed on a computer. You will participate in a learning task that will include a series of trials in which you will receive feedback on your performance. You will learn to select presented stimuli to maximize reward.

We will be recording brain waves while you complete the learning task. The brain wave recording process will involve the application of recording electrodes in a portable EEG machine in which the electrodes are mounted. These electrodes will allow us to measure the activity in your brain while you perform the task. Following application of the electrodes, you will complete the learning task. During the performance phase, practice will be observed and graded by 3 coaches. At the conclusion of EACH testing session, the research assistant will explain the study in detail, including a description of the results we hope to find. The research assistant will also answer any questions you have at any time during the testing session. At each of the sessions, participants will be reminded that participation is optional and that they can withdraw at any time without penalty.

Possible Risks And Discomforts

There are no known health risks associated with recording brain wave data using a portable EEG machine.

Possible Benefits

Your participation is beneficial to the scientific community as a whole as well as Major League Baseball. The data we gain from testing you may help improve our understanding of who will be successful when brought into a game from the bench. There will be no specific benefit to you.

Compensation

There is no compensation for taking part in this study.

Anonymity And Confidentiality

Your participation in this study will not be anonymous, however, neither your name nor any other personal identifier will be associated with the data we collect from you. Instead, your data will be identified with a code number. However, a file with your code number and initials will be kept by the researcher for 2 months after your participation such that your data can be removed from the study if you decide you do not want us to use it. Additionally, you will not be identified in any reports and publications that stem from this research.

Your confidentiality will be respected. All of our data will be stored in a locked room with limited access on a password protected computer. Only Anthony Pluta or research assistants working for Dr. Krigolson will have access to your data. Following completion of the study, and publication of the results, your data will be kept on the same secure computer for five years. After five years, your data will be destroyed. A copy of any poster presentation or written paper will be provided to participants if requested.

PRINCIPAL INVESTIGATOR'S RELATIONSHIP TO PARTICIPANTS

Players will not be penalized, and treated or evaluated differently by Mr. Pluta regardless of whether they join the study.

Questions

If you have any questions about the study, at any time, you may contact us by phone at or by email at

Problems or Concerns

If you have any difficulties with, or wish to voice concerns about, any aspect of your participation in this study, you may contact:

Dr. Krigolson directly at or

The Human Research Ethics Board at the University of Victoria:
By phone:

By email: ethics@uvic.ca

If you have any concerns or complaints about your rights as a research participant and/or your experiences while participating in this study, contact the Research Participant Complaint Line in the UBC Office of Research Ethics at 604-822-8598 or

if long distance e-mail < > or call toll free
1-877-822-8598.

Signature Page

Study Title: A Hierarchical System for Learning and Control

I, the participant, have read the explanation about this study. I have been given the opportunity to discuss it and my questions have been answered to my satisfaction. I hereby consent to take part in this study. However I realize that my participation is voluntary and that I am free to withdraw from the study at any time.

Participant Signature Date

Participant Name (printed)

PARENT/GUARDIAN SIGNATURE DATE

PARENT/GUARDIAN NAME (PRINTED

Investigator Signature Date

Investigator Name (printed)

A copy of this consent form will be left with you and a copy will be taken by the researcher.

Appendix C: Coach Evaluation Form

Evaluation Form

Each player will be given a grade between 1 and 10 with 10 being the highest or best possible score and 1 being the lowest or worst possible score. The players will be graded by three knowledgeable baseball coaches in 4 categories. The 4 categories are: Form, Contact, Power, and Ability to recognize if the pitch is a ball or a strike. During the batting practice round the player will be thrown 10 pitches varying in speed and type.

Form

1 2 3 4 5 6 7 8 9 10

Contact

1 2 3 4 5 6 7 8 9 10

Power

1 2 3 4 5 6 7 8 9 10

Recognizing Pitches

1 2 3 4 5 6 7 8 9 10

Notes

Appendix D: Strike Zone