Postural Sway and Brain Hemispheric Power Spectral Density Under Different Attentional Focus Conditions

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POSTURAL SWAY AND BRAIN HEMISPHERIC POWER SPECTRAL DENSITY
UNDER DIFFERENT ATTENTIONAL FOCUS CONDITIONS

by

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Bachelor of Science in Kinesiology
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2012

A thesis submitted in partial fulfillment
of the requirements for the

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ABSTRACT

The purpose of this study was to determine the differences, if any, in the root mean square error (RMSE) of postural sway and hemispheric power spectral density (PSD) in the alpha and beta bands (8-12Hz and 12-25Hz) during different conditions of attentional focus (i.e., internal focus (IF), and external focus (EF) and a control condition (C)). Previous studies have shown that the adoption of IF and EF significantly alter motor performance and that EF promotes automaticity (Wulf, 2013). Sports performance and balance studies utilizing EEG spectral analyses report increased alpha oscillations during expert performance and stable balance and increased beta oscillations during novice performances and challenging balance tasks. The present study was the first to examine the effects of attentional focus on postural sway and hemispheric PSD of EEG readings. Fifteen participants (N=15) were given instructions (i.e., C, “stand still”; IF, “keep your feet still”; EF, “keep the platform still”) while standing on an unstable, compliant surface. Data were recorded for 3 minutes 45 seconds per condition. Results of the analyses were compared within subject. Postural sway analysis did not reveal differences between conditions but did show higher RMSE values in the anterior-posterior than the medial-lateral directions. The EEG PSD analyses revealed significant Condition x Frequency interaction within the right hemisphere for alpha and beta frequencies. The control condition had more power density than did the external or internal focus conditions. Also, the left hemisphere had more power density in the beta band in the control condition than the other focus conditions. There were not, however, differences between external and internal focus in either hemisphere or frequency band. Possible limitations of the study and suggestions for future inquiries are discussed.
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CHAPTER 1

INTRODUCTION

A line of research began over fifteen years ago providing convincing evidence that a specific focus of attention alters qualities of human movement (Wulf, 2013). Various measures of motor performance and physiological data were collected while participants adopted an internal focus (IF) (i.e., attention on a body movement) compared to an external focus (EF) (i.e., attention on an external effect of the movement) during the execution of a motor task. Findings concluded that the adoption of an EF, when compared to an IF, significantly improved motor skill effectiveness and efficiency. The adoption of an external focus promoted “unconscious, fast, and reflexive control processes” (Wulf, 2013, p. 91) descriptors that are also attributed to expertly learned skills and seemingly automated actions (p.77). These results are analogous to measurements of motor skill effectiveness and efficiency in trained versus untrained individuals.

In sciences concerned with human movement, qualities of automaticity, such as those observed in studies of attentional focus, are often observed in athletic and otherwise physically trained individuals. Analyzing the outcome of task performance or athletic ability remains a practical method to measure movement success, but does little to illuminate the underlying processes. Regarding neural contributions to skilled motor behavior, it has been assumed that if the “performance is automatic, so is the underlying process” (Moors & De Hower, 2006, p. 297). Automaticity of motor behavior is described to be “less dependent on cognitive resources” (p. 297), indicating that well-practiced or learned motor responses are related more to subcortical than conscious
Spectral analyses of electroencephalographic (EEG) data indicate that oscillations at about 8-12Hz (alpha) are related to less effortful and more efficient automated processes, although the relationship of alpha to these processes is complex and only somewhat understood. Recent advancements in accessible technology allow researchers to better analyze neural activity, including the electrical brain activity of motor performance.

The validation of accessible and affordable mobile EEG technology (Badcock, Mousikou, Mahajan, de Lissa, Thie, & McArthur, 2013; Cernea, Olech, & Ebert, 2012; Choudhury, 2012; Ekanayake, 2010; McFarland & Wolfpaw, 2011; Reinecke, Cordes, Lerch, Koutsandreou, Schubert, Weiss, & Baumeister, 2011; Vokorokos, Mados, Ádám, & Baláž, 2012) has allowed a recent expansion of previous explorations of cortical activity during motor skill performance. For example, studies utilizing EEG technology have compared electrical readings of cortical activity from elite, expert, and novice athletes during motor performance (Babiloni, Del Percio, Iacoboni, Infarinato, Lizio, Marzano, ...Eusebi, 2008; Babiloni, Infarinato, Marzano, Iacoboni, Dassu, Soricelli, ...Del Percio, 2011; Collins, Powell, & Davies, 1991; Deeny, Hillman, Janelle, & Hatfield, 2003; Kerick, McDowell, Hung, Santa Maria, Spalding, & Hatfield, 2001). Most studies have utilized tasks that do not require gross bodily adjustments, such as rifle marksmanship (Deeny et al., 2003; Kerick et al., 2001) and golf putting (Babiloni et al., 2008, 2011) in order to avoid excessive perturbation to the signal. Overall, elite and expert athletes showed less overall cortical activity and higher alpha frequencies compared to novices, supporting the notion of underlying automatic neural processes during skilled movement.
To better understand motor control, performance, and learning, additional methods of data collection have included postural sway during balance performance on an unstable surface (Wulf, Landers, Lewthwaite, & Töllner, 2009; Wulf, Töllner, & Shea, 2007; Wulf, Mercer, McNevin, & Guadagnoli, 2004). These studies documented reduced postural sway with the adoption of an external attentional focus (e.g., “keep the platform still”), compared with adoption of an internal attentional focus (e.g., “keep your feet still”), while balancing on a rubber, air-filled disc (Wulf et al., 2004; 2007; 2009). The reduction in postural sway and the efficiency of postural adjustments were indicative of motor behaviors that had become more reflexive and automated (Wulf et al., 2004; 2007; 2009; 2013).

Electromyography (EMG) data, or electrical muscle activity, were collected during dart throwing (Lohse, Sherwood, & Healy, 2010), muscle contractions and bicep curls (Lohse, Sherwood, & Healy, 2011; Marchant, Grieg, & Scott, 2009; Vance, Wulf, Töllner, McNevin, Mercer, 2004), and free-throw shooting in basketball (Zachry, Wulf, Mercer, & Bezodis, 2005). EMG readings reported less activity in muscles when an external focus of attention was adopted during bicep curls and free-throw shooting (Lohse et al., 2010, 2011; Marchant et al., 2009; Vance, et al., 2004; Wulf, 2013; Zachry et al., 2005).

Performance, postural sway, and EMG data have consistently revealed automaticity in motor performance with the adoption of an external focus compared to an internal focus and control condition. This is the first study to analyze the power spectral density (PSD) of EEG data recorded during these same states of attentional focus during a motor task. Postural sway and EEG data were collected while participants balanced on
a force platform with an inflated rubber disk. This same task was used to measure postural sway in previously mentioned attentional focus balance studies (Wulf et al., 2004; 2007; 2009).

PURPOSE OF THE STUDY

The purpose of this study is to determine the differences, if any, in the root mean square error (RMSE) of postural sway and hemispheric power spectral density in the frequency bands of alpha (8-12Hz) and beta (12-25Hz) as a function of different conditions of attentional focus conditions while balancing on a compliant surface.

RESEARCH HYPOTHESES

Hypothesis 1 - Postural sway (RMSE) will be reduced in the external focus condition compared to the internal focus and control conditions.

Hypothesis 2 - Alpha (8-12Hz) power spectral density values will be greater in the EF compared to the IF and C conditions in both the left and right hemisphere, the left having higher PSD values than the right.

Hypothesis 3 - Beta (12-25 Hz) power spectral density values will be greater in the C and IF conditions compared to EF condition in both the left and right hemisphere, the left having higher PSD values than the right.

The hypotheses were formulated from results of previous EEG studies of athletes and other expert performers compared to untrained or non-expert performers, as well as from the similar results of postural sway and EEG readings in stable versus unstable balance conditions.
CHAPTER 2

REVIEW OF RELATED LITERATURE

ATTENTIONAL FOCUS

The implementation of an internal as opposed to an external attentional focus refers to the direction of one’s attention on a bodily aspect during motor performance (e.g., “keep your feet still”), or the effect of the movement on the environment (e.g., “keep the platform still”), respectively. A visual focus is not the consideration, but rather a purposeful direction of conscious attention. Significance in measurable behaviors while adopting EF compared to IF supports the conclusion that a conscious adoption of focus of attention has a direct effect on the body’s unconscious and automatic ability to perform effective and efficient movement (Wulf, 2013). Motor skill learning was also enhanced as indicated by retention tests (p. 77).

In a review article of fifteen years of attentional focus research, Wulf (2013) compiled results of fifty-three published studies on movement effectiveness (e.g., accuracy, consistency, and balance) and twenty-four involving movement efficiency (e.g., speed, endurance, force production, and kinematics). Results consistently reported movement improvement across populations (e.g., children, older adults, athletes, and diseased individuals), skill levels (e.g., novice and experts), tasks (e.g., balance, various golf shots and putting, basketball free-throw, running, swimming, kayaking, dart throwing, and juggling), physiologic (cardiovascular, muscular efficiency, oxygen consumption), and kinematic measures (Wulf, 2013).

The findings have been explained with the constrained action hypothesis (Wulf, McNevin, & Shea, 2001; Wulf & Lewthwaite, 2010), which proposed interference with
motor automaticity when internal focus is utilized (Wulf, 2013, p.91). Findings suggest that an external focus promotes “unconscious, fast, and reflexive control processes” (p. 91). Wulf, McNevin, and Shea (2001) also showed “demonstrations of reduced attentional-capacity demands” when external focus was employed (p.91). Overall, by adopting an external focus, individuals appear to achieve a higher skill level sooner - as demonstrated by greater automaticity, movement effectiveness and efficiency - relative to an internal focus.

**AUTOMATICITY**

Automaticity is associated with a reduction in dependence on frontal brain systems (Gupta & Noelle, 2007, p.405). It is believed that the prefrontal cortex, the premotor supplementary area, and the anterior cingulate cortex (ACC) are active during the acquisition of a motor skill, but not when successfully performing a learned task (p. 405). The prefrontal cortex is associated with executive functioning, planning, and other cognitive activity, while the ACC has been shown to contribute significantly to error detection (Joseph, 2000). Functional magnetic resonance imaging (fMRI) during a standard reaction time key-press task verified these results when reaction time was reduced and activity in the lateral prefrontal regions and the ACC decreased after participants completed three hours of training over several days, compared to pre-training (Poldrack, Sabb, Foerde, Asarnow, Bookheimer, & Knowlton, 2005).

Baseline brain activities in individuals who have practiced motor skills over long periods indicate more efficient general processes, or a general automaticity of motor behavior during skill performance and at rest. EEG data was collected under resting conditions from athletes (Babiloni, Marzano, Iacoboni, Infarinato, Ashieri, Buffi, Cibelli,
Soricelli, & Eusebi, 2010; Nakata, Michiko, Miura, & Kazutoshi, 2010), and physically trained individuals (Lardon & Polich, 1996) compared to non-athletic and untrained individuals. Significance in waveform activity in several spectral bands, including heightened alpha frequencies, was reported as a heightened efficiency of neural processing in elite and expert athletes (Babiloni et al., 2010; Nakata et al., 2010; Lardon & Polich, 1996), and trained persons compared to untrained individuals (Nakata et al., 2010). In an eyes-closed, resting-state condition, dominant alpha waves (8-12Hz) were considered an important predictor of the “efficacy of cortical information processing during cognitive and sensorimotor demands” (Babiloni et al., 2010, p.199).

It is currently accepted that certain brain ‘states’ are generally correlated with less effortful processing. For example, alpha oscillations (8-12 Hz) are indicative of attentional resource management. One study suggested that alpha pulse-inhibition oscillations may indeed be the brain’s way of directing attention by achieving preferential synchrony of neural activity (Mathewson, Lleras, Beck, Fabiani, Ro, & Gratton, 2011). Based on the presented evidence, it is plausible that the brains of trained and athletic individuals experience efficient processing via alpha frequency modulations. This measurable phenomenon is apparent during task performance, while the individual is at rest, and is inactive but aware. It appears that the dynamic state of electrical brain activity is reliant upon internal states (e.g., previous training and practice) as well as external influences (e.g., difficulty of the task).

AUTOMATICITY AND ATHLETES - EEG

A valuable line of motor control inquiry includes several decades of EEG and sporting performance tasks. Reports from studies examining EEG data from several
sports domains reveal that cortical activation is dependent upon the demands of the required motor performance “rather than a rigid neural efficiency strategy” (Babiloni et al., 2010, p.150). Nonetheless, the majority of studies analyzing EEG spectra during sport performance reported increased alpha frequencies in more expert and successful performances (Babiloni et al., 2008; Babiloni et al., 2011; Collins et al., 1991; Crews & Landers, 1993; Deeney et al., 2003; Kerick et al., 2001). These authors reported spectral features in the EEG data recorded from rifle marksmen during the preparatory period (Deeney et al., 2003; Kerick et al., 2001), golfers during the preparatory period of putting tasks (Crews & Landers, 1993), and karate athletes (Collins et al., 1991). These studies reported an overall increase in alpha power in elite but not novice performers (Deeney et al., 2003; Crews & Landers, 1993). Expert marksmen showed higher alpha power during planning and execution phases in an electrode on the left temporal region, but not a symmetrical electrode on the right (Kerick et al., 2001). Collins and associates reported an increase in alpha power, predominantly in the left hemisphere, prior to successful motor performance in karate athletes (1991, p. 313). Increased alpha power in the left temporal region was attributed to a reduction in cortical processing (p.263).

In 2008 and 2011, Babiloni et al. analyzed Event Related Desynchronization (ERD) and Event Related Synchronization (ERS) in the alpha (8-12 Hz) and beta (13-30Hz) oscillations of the sensorimotor cortex. ERS is considered more power in a certain frequency range and ERD less power. In experts’ golf-putting, the area over the right sensorimotor cortical area exhibited more alpha activity prior to successful putts compared to unsuccessful putts. The authors concluded that alpha rhythms over associative, premotor, and non-dominant primary sensorimotor areas “may represent a
basic mechanism underlying… fine motor control” (p. 137). These results contradict earlier studies, a difference that could be explained by electrode array of interest as well as the number of electrodes and quality of systems.

BALANCE AND POSTURAL CONTROL

Bipedal postural control and equilibrium is considered to be a series of complex reflexes including the interaction of visual, vestibular, and somatosensory systems, (Horak, 2006; Mihara, Miyai, Hatakenaka, Kubota, & Sadoka, 2008; Tse, Petrofsky, Berk, Dahler, Lohman, Laymon, & Cavalcanti, 2013). Cortical excitability is reduced with stable balance conditions and balance training (Tse et al., 2013). Electrical brain activity observed during tasks requiring postural control appears to be dependent upon the difficulty of the postural task and the participant’s “postural control system”, which can be affected by age, health, expectations, goals, and prior experiences (Horak, 2006, p.ii7). Indeed, responses to postural instability appear to “require a high hierarchical level…and activation of different brain areas” (Solopova et al., 2003, p.28).

In the pursuit of better understanding of the contribution of the brain during postural control, EEG researchers have recorded electrical brain activity while employing stable and unstable balance conditions (Adkin, Quant, Maki, & McIlroy, 2006; Horak, 2006; Mihara et al., 2008; Slobounov, Hallett, Stanhope, & Shibasaki, 2005; Tse et al., 2013), and low vs. high platform standing (Sibley, Mochizuki, Frank, & McIlroy, 2010). The brain dynamics comparing lying still, standing, and balance performance have been observed in a mobile gantry positron emission tomography (PET) scans (Ouchi, Okada, Yoshikawa, Nobezawa, & Futatsubashi, 1999), functional magnetic resonance imaging (fMRI) (Mihara et al., 2008), and transcranial magnetic stimulation (TMS) (Solopova,
Kazennikov, Deniskina, Levik, Ivanenko, 2003). The results of multiple imaging
technologies, including EEG, indicate the involvement of pre-frontal cortices when tasks
increase in difficulty, and a return to subcortical influences when postural demands are
reduced (Adkin et al., 2006; Horak, 2006; Mihara et al., 2008; Ouchi et al. 1999; Sibley
et al., 2010; Slobounov et al., 2005; Solopova et al., 2003; Tse et al., 2013).

A recent study investigated postural sway and the PSD of EEG recordings using
eight stable and unstable balance tasks comprised of six mixed variables (i.e., feet apart,
feet touching toe to heel, eyes open, eyes closed, standing on a stable surface, standing on
an unstable surface) (Tse et al., 2013). Alpha frequencies were more prevalent when two
conditions of challenge were employed than three or more. Postural sway perturbations
and beta frequencies increased under more challenging conditions (i.e., feet touching toe
to heel, eyes closed, and standing on an unstable surface). These and other results
(Slobounov et al., 2005) verified the increase in cortical activity during static balance
compared to sitting or lying, a shift from alpha to beta as conditions become more
challenging, and an “increase in corticospinal excitability during an unstable stance” (Tse
et al., 2013, p. 184).

It is of interest to note the results of inquiries in human locomotion. With the use
of mobile EEG technology, sciences of Kinesiology (e.g., Biomechanics, Motor Control,
and Exercise Physiology) have embarked upon a better understanding of the underlying
neurological occurrences in the human brain during walking and treadmill running
(Gramann, Gwin, Bigdely-Shamlo, Ferris, & Makeig, 2010; Gwin, Gramann, Makeig, &
Ferris, 2011; Hashimoto, Ushiba, Kimura, Liu, & Tomita, 2010; Presacco, Forrester, &
Contreras-Vidal, 2012). Results indicate a higher level of cortical involvement during
locomotion than was previously assumed, showing “different spatial distributions suggesting distinct neural networks for feed forward and feedback control of gait” (Presacco, et al., 2012, p. 212.).

SPECTRAL BANDS OF ELECTROENCEPHALOGRAPHY

EEG has enjoyed a relatively long history. In 1912, EEG was first used to measure the electrical fluctuation of canine brains. In 1920, Hans Berger began using the new technology on humans (McFarland & Wolfpaw, 2011). Berger observed a consistent waveform at about 10 Hz that was reactive to light, eye closing, and eye opening. Since this was the first and most prominent wave, it was named ‘alpha’ (p. 60). Recording data from scalp electrodes posed confounding obstacles, perhaps the multiple coverings of the brain being the most obvious (p. 60). Electrodes record a summation of signals, making it impractical to easily conclude the specific location, the magnitude, or the timing of event directly from the location of the electrode itself. In other words, recorded EEG signals are the total sum of activity in all source areas. Computer aided data reduction software applications have allowed the application of systematic algorithms to efficiently reduce the data and analyze the results (Delorme & Makeig, 2004).

EEG signals are a culmination of multitudinous action potentials of large populations of pyramidal neurons. In order to record the activity, a summation of potentials must rise through the cortex, skin, skull, dura matter, blood, spinal fluid and pia matter. To make matters more complex, negative and positive potentials cancel each other out in the tightly packed, perpendicular arrays of neuronal columns - six neurons deep - lying below the skull. Indeed, what are being measured through electrodes are the
most robust activities that have stimulated a few millimeters of the outermost cortex (Kaiser, 2005). The activity recorded from scalp EEG is not considered to be a microscopic representation. Additionally, the researcher must always consider that the activity recorded at an electrode cannot be considered a specific measurement at that exact location of the brain, but rather an incomplete representation of the culmination of activities throughout the organ that rises to the level of detection between electrodes.

Even with the inherent complexity, there are now multiple methods to analyze and view EEG data. Each method can be thought of as a unique snapshot of brain activity. Two distinct domains of EEG analyses are Event Related Potentials (ERPs), and spectral and time/frequency analysis (Delorme & Makeig, 2004). Evoked related potentials are transient waveform perturbations that are phase-locked by events (McFarland & Wolpaw, 2011). Oscillatory events are measured in through spectral analysis, and do not have to be time-locked to an event (p. 61). There are multiple methods of EEG spectral analysis. In this study, continuous data will be processed with EEGLAB’s SPECTOPO function (Delorme & Makeig, 2004) for the mean of the alpha and beta frequency magnitude (dB) of all electrodes in the LH array compared to the same in the RH array.

The standard divisions of alpha and beta frequencies and the activity generally associated with their prevalence are as follows:

- Alpha - 8-12 Hz
  - Regional and usually involves entire lobe(s)
  - Active during relaxation, but not a drowsy state
  - Related to automatic movement and processing
  - Often associated with meditative states
• Beta - 12-30Hz
  o Localized signal
  o Indicates alertness, agitation
  o Occurs during mental activity

GENERAL HEMISPHERIC FUNCTIONS

General hemispheric processing has been divided with the left hemisphere being more responsible for language, math and logic, with the right involved in spatial abilities, facial recognition, visual imagery, and music (Joseph, 2007).

Using this information, it is possible to consider spectral information in general hemispheric electrode arrays to better understand the relationship of the electric activity of the brain and motor behavior. By simultaneously measuring postural sway it is possible to analyze the effects of attentional focus on brain activity and motor performance. These combined measures can serve to further illuminate the effects, or lack thereof, of attentional focus conditions.

MOBILE WIRELESS EEG

Mobile scanning devices have encouraged inquiries of dynamic brain activity while the body is in motion. Wireless EEG allows participants to move during data collection in natural, or ‘field’ conditions, as opposed to the traditional laboratory, albeit with limitations (Reinecke et al., 2011). Due to movement artifact, or ‘noise’ in the data caused by eye and head movement, external electrical interference, and other physiological measures (i.e., muscle and cardiac activity), tasks still require some measure of quietude, although improved online and offline processing programs are swiftly providing solutions for artifact filtering and data reduction (Delorme, Mullen,
Technological advances in mobile EEG allow video game players to interact with avatars using an EEG headset. Neurogaming headsets are non-invasive Brain-Computer Interfaces (BCI) (McFarland & Wolfpaw, 2011; Vokorokos et al., 2012). This technology was designed to enrich human-machine interactions by integrating the user’s state (e.g., mood, level of engagement, facial expression, eye movements) with the hardware. The signal provided by these headsets is comprised of EEG signal and muscle movement resulting in EMG signal. The original purpose was for entertainment, but scientists interested in assisting patients who have lost some or all of their ability to move, particularly those with ‘locked-in’ syndrome (i.e., Amyotrophic Lateral Sclerosis (ALS) and tetraplegia), successfully utilized this technology as an avenue of communication and mobility for otherwise unreachable and immobile patients. Although these devices were not intended to compete with standard laboratory and medical grade EEG systems, the headset from Emotiv (Emotiv EPOC®, www.emotiv.com) has been used in several scientific inquiries.

There are recent validation reports and studies using the Emotiv EPOC 14-channel wireless headset (Cernea et al., 2012; Ekanayake, 2010; Badcock et al., 2013; Vokorokas et al., 2012). One validation study had mixed results, reporting that the Emotiv EPOC did not record quality data compared to data collected from standard EEG medical devices (Duvinage, Castermans, Petieau, Hoellinger, & Cheron, 2013). Cernea and colleagues reported that the Emotiv EPOC did record useful but not medical grade data, highlighting the necessity of specific headset placement and continual hydration of the felt electrodes (2012). Ekanayake (2010) concluded that the Emotiv EPOC captured
the ERP P300 (an indicator of cognitive processing), sufficiently for traditional oddball key-press tasks. One study simultaneously utilized a standard research EEG by Neuroscan and an Emotiv EPOC (Badcock et al., 2013). The results showed reliable ERP waveform recordings when the results from the EPOC were compared to the results from the Neuroscan. There are not, however, similar validation studies of the Emotiv device in spectral analyses.

The data recorded from the Emotiv EPOC is extremely ‘noisy’ with EMG artifact. Computational neuroscientists have developed more robust and user-friendly software to remove artifacts, more accurately process non-linear data, and integrate other devices with mobile wireless EEG units. EEGLAB was introduced in 2000 by Scott Makeig, Lead Scientist and Director of the Swartz Center for Computational Neuroscience (SCCN), University of California at San Diego, and Arnaud Delorme, Project Scientist at the same facility (Delorme & Makeig, 2004). EEGLAB is Open Source, providing its software, updates, resources, tutorials, and product support at no cost to the EEGLAB community. Currently, over 2,400 published papers have cited EEGLAB as a utilized processing toolbox. EEGLAB recently added the new toolbox BCILab, to address the limitations of mobile EEG and enhance its potential (Delorme et al., 2011).

SUMMARY

Automaticity of motor performance is often attributed well-learned motor tasks, including stable and upright balance in healthy individuals. Studies have shown that the adoption of an external attentional focus reliably improves motor performance, producing a state of automaticity typically associated with practice. Beneficial effects on adopting an EF, however, are often seen immediately (Wulf, 2013). This discovery has important
implications for those in pursuit of skilled performance as well as the improvement of movement disorders. As well, this knowledge can be considered an important contribution to the understanding of the relationship between brain activity and motor performance.

In attentional focus studies, EEG spectral data has not yet been examined. Therefore, results from quantitative analyses of athletic performances and balance tasks are drawn upon to hypothesize the effects of attentional focus conditions on postural sway and PSD of EEG data. The reviewed literature suggests two general characteristics of spectral activity during successful expert sport performance and stable balance. The first is an increase of alpha and decrease of beta in the LH, a conclusion from studies that employed spectral analysis between opposite hemispheric electrodes (Collins et al., 1991; Crews & Landers, 1993; Deeney et al., 2003; Kerick et al., 2001). The second characteristic is a general reduction of spectral activity during optimal motor performance from electrodes in the area of the pre-motor and motor cortex (Babiloni et al., 2008; Babiloni et al., 2011). Because the fixed arrangement of the electrodes of the Emotiv EPOC did not allow placement over the motor cortex, the first characteristic was tested. The purpose of this study is to measure and analyze postural sway and hemispheric EEG power spectral density (8-12Hz and 12-25Hz) while balancing on an unstable, compliant surface under a control condition and while adopting states of external vs. internal attentional focus.
CHAPTER 3

METHODS

PARTICIPANTS

Fifteen participants (N=15) were recruited from the undergraduate student body at the University of Las Vegas, Nevada (UNLV). They were ages 20-25 (M=22 ± 1.705), with the average weight of 141.73 lbs. (SD = 21.88). Fourteen participants were right-handed and one was left-handed. Ten reported participation in a regular exercise program (at least 150 minutes per week of moderate or 75 minutes a week of vigorous planned physical activity) and five said they did not participate in exercise. All were free from headaches, diabetes, musculoskeletal injury, or neurological conditions. Participants were instructed to avoid unnecessary medication the night prior to or stimulants the day of data collection. Six of the participants had consumed one cup of coffee at least two hours prior and the remaining nine had not consumed any caffeine that day. No one had previous involvement in an EEG or balance study or had previous knowledge of the extant literature in studies of attentional focus and motor learning.

INSTRUMENTS AND TASK

A force platform (Kistler Corp., Amherst, NY, Model #478A01) with a 13 inch-diameter inflated rubber disk (Disc ‘O’ Sit; Perform Better, Cranston, RI) served as the unstable balance surface. To protect the participants in the event of extreme instability or falls, the force platform/disc apparatus was positioned in a corner of the laboratory with a heavily weighted file cabinet positioned on the open side in order to provide a U-shaped alcove of reachable and stable surfaces. From the force platform, center of pressure data were collected using BioWare software and processed in standard laboratory software on
a Toshiba Satellite laptop computer (C75D-A7370).

During the postural tasks, electroencephalographic data were collected with a 14-channel mobile wireless EEG from Emotiv, the EPOC (see Figure 1). The output was collected in the program TestBench (an Emotiv proprietary program) via a USB dongle on a laptop (Toshiba Satellite C75D-A7370), then imported into EEGLAB (Makeig et al., 2004) for processing.

Figure 1. Emotiv EPOC headset from emotiv.com.

The Emotiv headset has 16 electrodes, 14 of which follow the International 10-20 channel names (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4) (see Figure 2). Additionally, one mastoid (M1) sensor is a ground reference point to compare the voltage of all of the other sensors, and the other mastoid (M2) is a feed-forward reference to reduce external electrical signals. The Emotiv headset uses sequential sampling internally at 2,048Hz, with a rate of 128Hz deliverable. The resolution is set at 16 bits (14 bits effective) at 1LSB, equaling 1.95 µV. The dynamic range is 256dBpp. The connectivity is proprietary and operates at a 2.4GHz band. Impedance measurement is defined by Emotiv as being, contact quality using a patented system.
Placement of the EEG headset followed manufacturer guidelines. The felt pads used by the Emotiv EEG were wetted with a generic sterile multi-purpose saline solution, as suggested by the manufacturer.

*Figure 2. Emotiv EPOC channel locations according to International 10-20 channel names.*
Figure 3. Emotiv EPOC specification sheet from emotiv.com/eeg/download_specs.

A stimuli presentation program, Paradigm (Perception Research Systems Incorporated), installed on the same Toshiba laptop, played recorded instructions at 15-second intervals through an external speaker (Jambox by JawBone). Off-line analyses were performed with traditional laboratory software and the open source toolbox, EEGLAB, and associated plugins and toolboxes (Delorme & Makeig, 2004). Statistical analyses were performed in SPSS Version 21.0.0.0 (IBM).
PROCEDURES

After granting written consent, participants were allowed to stand on the force platform/disc apparatus for general familiarization of the task. Participants were instructed to stand on the disc with their feet approximately hip width apart and to attempt to keep their arms hanging at their side. In order to avoid unnecessary head movements, they were instructed to maintain a relatively steady gaze straight ahead. A sample of the recorded instruction was played to familiarize them with the overall sound location and quality. It was also explained that the instructions were recorded in order to ensure consistency and not as a method of performance feedback. After introduction to the balance task, participants were fitted with the EEG headset according to manufacturer recommendations.

Participants performed under three focus conditions with the indicated instruction:

- **Control** - Standing on the platform facing straight ahead, arms down side - Recorded instruction played at fifteen-second intervals - “stand still”.

- **External Focus** - Standing on the platform facing straight ahead, arms down side. Recorded instruction played at fifteen-second intervals -"keep the platform still".

- **Internal Focus** - Standing on the platform facing straight ahead, arms down side. Recorded instruction played at fifteen-second intervals -"keep your feet still".
Care was taken to provide an otherwise quiet environment during trials. No verbal feedback or other instructions were given during data collection.

Participants performed 5 trials under each condition, with the order of conditions counterbalanced between participants (Order 1: C/EF/IF; Order 2: EF/IF/C; Order 3: IF/C/EF). Each participant performed a minimum of 15 trials. In the case of a fall or wall touch, trials were excluded. Up to two additional trials were collected. Participants were asked to avoid falling and/or touching the walls when possible, but in order to avoid feedback that might confound the results, were not told that trials were marked for exclusion during data collection. Four participants included in the analyses exceeded the minimum by two trials. Two participants were removed from analyses due to repeated touching of the walls during data collection. In order to prevent fatigue, a 1-minute break was employed between conditions (5 successive trials per condition). A chair was provided for participants to sit.

A recorded instruction was played at the onset of each trial (i.e., “Please step on the platform”) followed by a silent eight-second period to allow participants to adjust their stance. At the ninth second, recorded focus condition instructions were played three times at 15-second intervals. At the end of the third trial, recorded instructions asked the participant to “please step off the platform.” Force platform data was recorded from the onset of the first focus condition recording to the final instruction (approximately 45 seconds). EEG data was derived from 1 second prior to the first focus condition instruction to the onset of the final instruction (“please step off the platform”). This served to maintain homogeneity of data collection instructions and procedures, and served to mark data in the EEG collection software programs.
At the end of data collection, the participant completed a brief questionnaire:

1. Did you use a strategy or technique to balance during the sessions asking you to “stand still”? 
2. Did you find one instruction assisted you to balance better more than the others (i.e., “stand still”, “keep your feet still”, “keep the platform still”)? 

The information from the final questionnaire was not included in the quantitative (i.e., PSD and RMSE) statistical analyses. The results, however, are reported in Appendix 1 of this document.

DEPENDENT VARIABLES AND STATISTICAL ANALYSIS

POSTURAL SWAY

Although there are various analyses for postural sway, this inquiry used the RMSE of sway distance from the center of pressure (CoP) to ascertain the level of performance while balancing on an unstable surface. The methodology and data analyses were consistent with those of previous studies examining the effects of external vs. internal attentional focus on balance performance. In the previous studies, lower RMSE of sway distance indicated a superior balance performance during an external but not an internal focus (Wulf et al., 2004; 2007; 2009).

Data were converted to ASCII format and imported into traditional laboratory software for analyses. Center of pressure (CoP) data were recorded at 500Hz. Data were adjusted to central coordinates (0,0) then translated from Cartesian to polar coordinates. RMSE was calculated from the magnitude of the vector (Appendix 2). The RMSE
served as a measure of postural sway. The RMSE of the magnitude vector, or a measure of the sway distance, was analyzed in a 3 (focus conditions: C, EF, IF) x 5 (trials) x 3 (condition order) mixed model analysis of variance (ANOVA) with repeated measures on the first two factors. If Mauchly’s Test of Sphericity was violated, the Huynh-Feldt correction, considered to be minimally conservative, was chosen for further analyses.

For a more complete understanding of postural adjustments during the task, additional analyses for the RMSE of CoP sway distance included measurements from the x and y Cartesian coordinates in the anterior-posterior (AP) plane and the medial-lateral (ML) plane. Code for analyses was taken from a review article by Duarte and Freitas (p. 185 & 189, 2010) and is included in Appendix 2. Data were analyzed with a 3 (focus condition: C/EF/IF) x 5 (trials) x 2 (directional plane: AP, ML) x 3 (condition order) mixed model ANOVA.

**EEG PSD**

EEG data were imported as a standard ASCII file into EEGLAB and channel locations were defined. In EEGLAB, a high pass filter (1Hz), and CleanLine - a function that removes line noise above 50Hz - were performed (Delorme et al., 2011). The average channel baseline was removed. An artifact subspace reconstruction (ASR) program, clean_rawdata from EEGLAB’s toolbox BCILab was performed for automatic artifact removal of the continuous data. This function removes flat-line channels, low-frequency drifts, noisy channels, short-time bursts and incompletely repaired segments from the data. Default parameters were used with the exception of the channel criterion, which was set at 0.4, considered a minimally conservative range. This adjustment allowed all channels to be included in the analyses without further processing.
The following left and right hemispheric electrode arrays were averaged for analyses (left hemisphere array: AF3, F3, F7, FC5, T7, P7, and O1; right hemisphere array: AF4, F4, F6, F8, T8, P8, and O2). The EEGLAB function, SPECTOPO, was employed to compute the power spectral density (PSD) in the alpha and beta frequency bands (8-12Hz and 12-25Hz), per trial, from the averaged electrode arrays. Power spectral density (PSD) is the average power distribution of frequency response of a random or periodic signal. SPECTOPO utilized Matlab’s PWELCH function, whereby Fast Fourier Transform (FFT) data were segmented into eight sections with a 50% overlap. A Hamming window was applied. The modified periodograms were then averaged to calculate an estimation of PSD, a method that preserves frequency resolution. Although PSD is often expressed in \((10\log(\text{microvolt}^2)/\text{Hz})\), the output variable, spectra from SPECTOPO, is reported in decibels/Hertz(dB/Hz) and was used for analyses in this study. Code is provided in Appendix 2.

Power Spectral Densities were compared in a 2 (hemisphere: left, right) x 2 (frequency: alpha 8-12Hz, beta 12-25Hz) x 3 (condition: C/EF/IF) x 3 (condition order: C/EF/IF; EF/IF/C; IF/C/EF) repeated measures ANOVA, with hemispheres, frequency bands, and conditions measured within-participants.
CHAPTER 4

RESULTS

POSTURAL SWAY

Significance levels were set at .05 for all analyses. For the 3 x 5 x 3 ANOVA, Mauchly’s test indicated the assumption of sphericity had been violated in the main effects of condition, $\chi^2(2) = 9.745, p = .008$, and trial, $\chi^2(9) = 17.432, p = .045$, and in the interaction of Condition x Trial, $\chi^2(35) = 140.995, p < .001$. The Huynh-Feldt correction for $F$ was utilized. There were no significant results for the main effects of condition, $F(1.573, 18.877) = .560, p > .05$, trial $F(4, 48) = 2.122, p > .05$, or condition order, $F(2, 12) = 1.466, p > .05$. The interaction between Condition x Trial was not significant $F(3.414, 40.965) = 1.017, p > .05$ (see Figures 4.1 and 4.2).

Analyses of the data in AP/ML planes met sphericity assumptions for condition, $\chi^2(2) = 2.005, p > .05$, and for interactions between Direction x Condition, $\chi^2(2) = 2.648, p > .05$. The 3 x 5 x 2 x 3 ANOVA revealed significant difference in the direction main effect, $F(1,12) = 42.510, p < .001$, but not in the condition main effect, $F(2, 24) = 6.16, p > .05$, or in condition order main effect, $F(2,12) = 2.779, p > .05$. There was not significance in the interaction between Direction x Condition, $F(2,24) = .446, p > .05$. These results indicated more adjustments in the anterior-posterior direction ($M = .948, SD = .027$) than the medial-lateral direction ($M = .772, SD = .029$) (see Figure 5).
Figure 4.1. Bar graph showing condition by the mean RMSE of trials.

Figure 4.2. Bar graph showing the mean RMSE of Condition x Condition Order.
Figure 5. Bar graph showing the mean RMSE of conditions in the anterior posterior and medial lateral directions.

EEG PSD

Descriptive analyses on the means of trial data by condition were analyzed and reported (see Tables 1 and 2). Individual trials were plotted for each participant by hemisphere and frequency band (see Appendix 4, Figures 11-14). Significance levels were set at .05 for all analyses. For the 2 x 2 x 3 x 3 ANOVA, Mauchly’s test indicated that the assumption of sphericity was met for all main effects, but had been violated in the interaction of Hemisphere x Frequency x Condition, $\chi^2 (2)= 6.448, p<.001$. The Huynh-Feldt correction for $F$ was utilized. The 3-way interaction Hemisphere x Frequency x Condition was significant ($F(1.769,21.234) = 284.901, p<.001$). Simple effects analyses were performed for the comparisons of interest.
TABLE 1

<table>
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<tr>
<th></th>
<th>Left Alpha Control</th>
<th>Left Alpha EF</th>
<th>Left Alpha IF</th>
<th>Left Alpha Med</th>
<th>Mean 3.992</th>
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<td>3.992</td>
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<tr>
<td>Min</td>
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<td>0.681</td>
<td>1.146</td>
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<tr>
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<td>9.119</td>
<td>9.867</td>
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<tr>
<td>SD</td>
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<td>2.384</td>
<td>2.621</td>
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<tr>
<td>Median</td>
<td>3.419</td>
<td>3.903</td>
<td>3.723</td>
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</table>

TABLE 2

<table>
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<th></th>
<th>Right Alpha Control</th>
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<th>Right Alpha IF</th>
<th>Right Alpha Med</th>
<th>Mean 5.947</th>
</tr>
</thead>
<tbody>
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<td>5.967</td>
<td>5.947</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Min</td>
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<td>2.305</td>
<td>2.847</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Max</td>
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<td>11.594</td>
<td>11.549</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SD</td>
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<td>2.723</td>
<td>2.650</td>
<td></td>
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</tr>
<tr>
<td>Median</td>
<td>9.613</td>
<td>5.562</td>
<td>5.292</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The Condition x Frequency interaction was significant within both left and right hemispheres ($p < .001$). In the left hemisphere at the alpha frequency band, there was not a significant difference in mean PSD among the three conditions ($F(2, 28) = 2.935, p = .070$). In the left hemisphere at the beta frequency band, the mean PSD value was significantly higher in the control condition than the external or internal focus conditions ($p < .001$). There was not a difference between the external or internal focus conditions ($p > .05$) (see Figure 6).
Also in the left hemisphere, mean PSD was significantly different between alpha and beta frequencies at each condition. In the control condition, mean PSD was significantly higher in the beta frequency ($t(14) = -3.395, p = .004$). However, mean PSD was significantly higher in the alpha frequencies in the external focus group ($t_{14} = 4.95, p < .001$) and the internal focus group ($t(14) = 5.12, p < .001$) (see Figure 7).
In the right hemisphere at the alpha frequency band, there was a significant difference in mean PSD among the three conditions \((F(2, 28) = 132.08, p < .001)\). Pairwise comparisons revealed significantly higher mean PSD values in the control condition than the external or internal focus conditions \((p < .001)\). There was not a difference between the external or internal focus conditions \((p > .05)\) (see Figure 8). In the right hemisphere at the beta frequency band, there was a significant difference in mean PSD among the three conditions \((F(2, 28) = 228.03, p < .001)\). Pairwise comparisons revealed significantly higher mean PSD values in the control condition than the external or internal focus conditions \((p < .001)\). There was not a difference between the external or internal focus conditions \((p > .05)\) (see Figure 8).

![Figure 8. Condition comparisons at each frequency in the right hemisphere.](image)

Also in the right hemisphere, mean PSD was significantly higher in the alpha frequency band at each condition \((p < .001)\) (see Figure 9).
The interaction Hemisphere x Frequency was significant at each level of condition ($p < .001$). In the control condition, mean PSD was significantly higher in the right hemisphere at each frequency ($p < .001$). In the left hemisphere, mean PSD was significantly higher in the beta frequency ($p = .004$), and conversely, mean PSD was significantly higher in the alpha frequency in the right hemisphere compared to the left ($p < .001$). In both the external and focus conditions, mean PSD was significantly higher in the right hemisphere at each frequency band ($p < .001$). Mean PSD was significantly higher in the alpha frequencies in both left and right hemispheres ($p < .001$) (see Figure 10).
Figure 10. Hemispheric comparison.

Additional graphs are provided in Appendix D including single trial scatter plots (see Figures 11-14), bar graphs of participant hemispheric PSD means by frequency bands (see Figures 15-20), and SPECTOPO plots illustrating the relative topographic distribution of power at the frequency bands of interest. The plots display three data sets from the study population representing the minimum, mean, and maximum values. These plots simultaneously illustrate frequency, power, and scalp projections (space) (see Figures 21-26).
CHAPTER 5

DISCUSSION

Participants were asked to balance on an unstable, compliant surface while adopting different states of attentional focus. Force platform and EEG data were collected and analyzed to reveal differences, if any, between conditions. It was hypothesized that postural sway (RMSE) would be reduced in the external focus condition compared to the internal focus and control conditions. It was further hypothesized that alpha PSD would be greater in the external focus compared to the internal focus and control conditions in both the left hemisphere and the right hemisphere, and that beta PSD values would be greater in the control and internal focus conditions compared to external focus condition in both the left hemisphere and the right hemisphere. Additionally, it was hypothesized that the left hemisphere would have greater PSD in both frequency bands than the right hemisphere.

Postural sway analysis did not reveal differences between conditions but did show higher RMSE values in the anterior-posterior than the medial-lateral directions. The secondary analysis was performed to further illuminate the characteristics of sway patterns. None of the analyses, however, revealed differences between conditions.

In the left hemisphere at the alpha frequency band, there was not a difference in mean PSD among the three conditions. In the left hemisphere at the beta frequency band, the mean PSD value was significantly higher in the control condition than the external or internal focus conditions. There was, however, not a difference between PSD values in the external or internal focus conditions.
In the right hemisphere at the alpha frequency band, there was a difference in mean PSD among the three conditions. Pairwise comparisons revealed significantly higher mean PSD values in the control condition than the external or internal focus conditions. There was not a difference between the external or internal focus conditions. In the right hemisphere at the beta frequency band, there was a difference in mean PSD among the three conditions. Pairwise comparisons revealed significantly higher mean PSD values in the control condition than the external or internal focus conditions. There was not a difference between the external or internal focus conditions.

Higher PSD alpha values are associated with expert and automatic performance, the same quality of performance observed during the adoption of an external focus. For the purposes of this inquiry, it was hypothesized that alpha frequencies would increase during external focus. Increased PSD in beta bands are associated with challenging tasks and unstable balance conditions, conditions that result in non-optimal motor performance. The results of attentional focus studies strongly support that internal focus and often control conditions result in degraded motor performance when compared to an external focus. Therefore, it was also hypothesized that beta would increase in the control and internal focus conditions. In sports performance studies, greater significance was found in the left hemisphere compared to the right (Collins et al., 1991; Crews & Landers, 1993; Deeney et al., 2003; Kerick et al., 2001) leading to the hypothesis that the left hemisphere would have greater PSD values than the right. Data analyses did not support these hypotheses.

For postural sway, RMSE of distance indicates average deviations from a goal, in this case, stable balance around the center of pressure (CoP) (Wulf et al., 2004). The CoP
is a measure of displacement, expressing “the location of the resultant vector of the ground reaction force” (Duarte & Freitas, p. 186, 2010). Smaller values are associated with a more stable performance and a state of more expert performance. In the current study, the findings of previous inquiries were not replicated. The inability to reproduce similar results may have been influenced by the level of difficulty of the task, the length of time participants were asked to perform, the use of blocked trials, or the equipment.

A 2007 study on attentional focus on balance suggested that the use of external focus is “only beneficial for skills in which errors, or postural instability, tend to be large” (Wulf et al., 2007, p. 263). It is possible that motor tasks with less difficulty do not require profound and measurable cortical involvement are processed in sub-cortical domain. The Constrained Action Hypothesis states that automatic motor performance is degraded when the performer intervenes cognitively, a response that is related to challenging tasks (Wulf, 2013). This task may not have provided enough challenge to produce measurable deviations in performance and resulted in automatic and other well-practiced balance strategies (i.e., one point of visual focus, use of large muscle groups), overriding any effect of the attentional focus instructions.

Postural sway data is often collected for long periods of time in quiet standing. The desired outcome for the participant was to stand quietly, yet data was collected to measure the neuromuscular responses to changes of center of gravity (CoG) and attentional focus under a challenging balance condition. CoG displacement is considered to measure the sway of the whole body and CoP a combination of that whole body sway and the neuromuscular response. For CoP analyses, periods of 30 seconds to 2 minutes are suggested for quiet erect postures. It is suggested that longer periods may lead to a
learning effects and lead to a reduction in postural sway. For tasks measuring balance perturbations, a few seconds before and after can provide sufficient data (Duarte & Freitas, 2010). Participants found a strategy to stay upright early in the task as evidenced by an absence of falls during data collection. Several strategies were reported on the brief questionnaire at the end of data collection with the majority of participants reporting the use of a ‘one point of visual focus’ and contraction of the abdominal muscles or other large muscle group (see Appendix C). Thusly, it can be assumed that a level of familiarization with the task and an adoption of a physiological and neurological strategy may have occurred early in data collection.

The length of time for data collection was 3.75 minutes per condition totaling 11 minutes and 15 seconds. Due to the inherently noisy data collected from the Emotiv EPOC, longer data collection sessions are preferred. Therefore, it is not likely the time of data collection could be significantly shortened in a future similar study - postural sway and EEG continuous data frequency analyses - without adversely affecting the quality of EEG analyses. Future experiments would be required to find a task period that allows optimal EEG spectral and CoP data collection.

The order of conditions was counterbalanced (C/EF/IF; EF/IF/C; IF/C/EF). There were not any significant differences of order. Participants who began their first block of trials with any of the three conditions showed no significant advantage in the RMSE analysis. Randomizing individual trials might illuminate additional differences in balance performance during attentional focus conditions. A future study could alter this aspect of the design while maintaining the other methods.

The disk itself may have confounded the results. The formulas used in CoP
calculations have a variable for height (see Appendix B). For instance, if a carpet is placed on the platform, this variable is to be set to the height of the carpet. The default is set to zero, assuming that the measurements will be taken directly from the surface of the force platform. In this case, the disk - without the stress of the participant’s mass - was 4” high. The variability of elastic deformation of the disk, due to individual mass and foot placement, rendered the use of a constant or normalized value for height untenable. Therefore, the default value, ‘0’, was maintained for height in the analyses. It follows that what was directly recorded from the force platform were the movements of the rubber disk on the surface of the platform rather than the direct CoG and motor adjustments.

The shape and material of the disk may have altered the data. The disk was an ellipse and did not lie flush to the platform. This indicates that adjustments were only recorded where the area of the disk was in direct contact with the platform. It is unknown if the disk was constantly and uniformly distributed across the surface of the platform for each data collection period and for each participant. It also must be considered that movement energy from balance perturbations may not have completely transferred to the force platform, but some was ‘lost’ in the rubber and air of the disk itself. Accounting for the energy lost in elastic deformation is outside of the scope of this inquiry. Future research could utilize only the force platform without the disk and examine the data of quiet standing under attentional focus conditions.

Finally, foot markers on the disk for specific foot placement were not provided. Although this study employed a within participant design, the variability of stance may have altered the difficulty and result of the task. Participants were only asked to use the
same foot placement for each trial. In a 2010 review article, it is stated, “the standardization of feet position is very important for investigating postural control” (Duarte & Freitas, p. 187). The authors continue to say that body stability is also related to a person’s height. For accurate foot placement, variances should ideally be based on anthropometric measures. A more accessible method is to divide the CoP values by the person’s height (Duarte & Freitas, 2010).

Although this inquiry did not find significant differences between the RMSE of postural sway during differing states of attentional focus, previous studies with the same methods have shown significant differences (Wulf et al., 2004; 2007; 2009). Indeed, the increased proficiency of motor behavior in a multitude of tasks, and under the same focus conditions, has been sufficiently validated. The previous discussion poses the possibility that the disk may not be a reliable instrument, however, there are factors that may have produced a robust effect in some earlier studies and not in this one. The most apparent is the amount of air in the disk, which is refillable. The average daily weight of the disk in this study was 8.124 N. The weight of the disk is not reported in previous studies. It is possible the disk was more or less inflated during the previous studies. Foot placement markers or a different instruction for foot placement (e.g., feet in the center of the disk) may have been employed. The average weight and height of participants could have altered the dynamics of the disk on the platform. Data collection trials were not as lengthy (3 and 4 x 15 s trials per condition). The participants in this study were healthy undergraduate students with the majority (N=10) reporting a regular physical activity program. In the 2009 study, participants were individuals with Parkinson’s disease, and in the 2008 study, participants were professional acrobats (Wulf et al.). In one study, a
control condition was not included (Wulf et al., 2004). Any of these factors could have affected characteristics of the data, but similar to the findings of Wulf et al., 2007, the task itself may not have provided enough challenge to produce measurable effects between conditions of attentional focus.

This inquiry is the first of to examine PSD of EEG as a function of attentional focus protocols (Wulf, 2013). Therefore, there are not specific comparable data to refer to in the design, analyses, and interpretations of the results. There is a general agreement in the literature that greater PSD values in the alpha frequencies generally indicate a withdrawal, shift, or modulation of attention and operate independently of respiratory, vascular, or motor responses (Babiloni et al., 2010; Kaiser, 2005; Mathewson et al., 2011). Published literature in sports performance and EEG indicates that during expert motor performance alpha frequencies are greater, and often the most significant difference is found in the left hemisphere (Babiloni et al., 2008 & 2011; Deeny et al., 2003; Kerick et al., 2001). Beta frequencies indicate a higher level of cognitive processing (Kaiser, 2005). It is also agreed that general electrical activity is reduced during more expert, or automated performances (Mathewson et al., 2011; Babiloni et al., 2010). EEG studies in balance also report general conclusions that balance activities that are more challenging show great beta density and those that are less taxing and more automatic are associated with alpha frequencies (Slobounov et al., 2005; Tse et al., 2013). With consideration of the limitations of the equipment, it was from these data the hypotheses were formed.

Because the postural sway data did not have significant differences between conditions and this is the first study to measure EEG PSD, and due to the lack of
validation studies on the EMOTIV headset for spectral analysis, interpretations of the EEG data must be conservative. It is possible the structure of blocked trials may have increased familiarity and reduced the recordable differences between conditions. The task may have lacked enough motor challenge to activate measurably different cortical strategies. Other limitations involve the equipment and choices of data analyses.

The Emotiv EEG headset, released in late 2011, is available to researchers at $750. In comparison, Cohen (2014) discusses the cost of an EEG set up as being approximately $100,000. The Emotiv equipment has been validated in ERP studies (Cernea et al., 2012; Ekanayake, 2010; Badcock et al., 2013; Vokorokas et al., 2012) but PSD studies are not found at this time. The data recorded from this equipment is considered to be ‘noisy’ due to the presence of a large amount of EMG artifact. Still, it detects EEG signal, is accessible for new labs or junior researchers, and allows participants to be studied in active tasks. Algorithms from EEGLAB are specifically designed for this type of noise and were employed in these analyses. Further analyses could compare individual electrodes from the left hemisphere and right hemisphere at specific frequencies rather than a grand average of all frequencies in a band and all electrodes, and a favored approach, Independent Component Analyses (ICA). Whether the data recorded by Emotiv EPOC is of sufficient quality for meaningful ICA interpretation is not currently known.

CONCLUSION

The use of external focus for efficient and effective motor performance is conclusively documented. This study analyzed postural sway and PSD of EEG recordings during attentional focus conditions. The results of the balance task did not
replicate previous studies showing improved performance with the use of an EF. EEG PSD is reported but inconclusive due to lack of prior research and the outcome of the sway analyses. Further research could include the use of an alternative sway measurement task or device, a higher quality EEG system, and further EEG data analyses.
APPENDIX 1: PARTICIPANTS’ ANSWERS TO THE FINAL QUESTIONNAIRE

Question 1. Did you use a strategy or technique to balance during the sessions asking you to “stand still”?

1. I stared at a research poster, found a particular focal point and sort of zoned out. It was easier to balance when I wasn't thinking about much of anything.
2. I tried to focus on one particular object/point in front of me to keep balance. I also imagined a straight line running vertically through my body to keep it straight.
3. Yes, I picked a spot on the wall and looked at it.
4. I tried to focus on my entire body staying still by tightening up my entire body.
5. When it asked me to just stand still I found myself just kind of zoning out and simultaneously tensing my body. I wasn't exactly focusing on anything but when I paid attention I would notice my core and legs quite tense.
6. No I did not.
7. Just focused on the position of my body to try to keep it in a stable position.
8. I tried to relax and not getting so nervous. I could focus on one part of my body that seemed to be moving the most if I relaxed. I also tried to freeze my arms in a comfortable position and steady my eyes so that the focused on the door.
9. Focusing on standing still helped a little, but I felt like I would go off balance quickly so instead I would focus on another object and try not to think about standing still. Once the voice said, "keep the platform still" it was easier to focus on that.
10. Just took the pain in my calves in and didn't let it affect my balance.
11. I found that thinking about the platform as flat worked better for me.
12. I noticed that when I kept my mind clear and focused on a point on the wall that I balanced better.

13. I found a point on the wall and focused my eyes on that exact point throughout the trial. I also tried to not let my mind wander to not lose focus.

14. Yes, when prompted to stand still I focused my center of mass in my hips to remain as stable as possible.

15. Yes, I engaged my core and outer thighs to keep still.

Question 2: Did you find one instruction assisted you to balance better more than the others (i.e., “stand still”, “keep your feet still”, “keep the platform still”)?

1. I found it easier when asked to keep the platform still.

2. I think "stand still" was easier than "keep your feet still" because I'm too focused on moving my feet vs. being able to keep steady generally when the instructions stay "stand still"

3. Yes, I preferred the one that instructed me to keep the platform still.

4. I felt balancing during the instructions "Keep your feet still" was easiest because I just focused on my own feet staying still and making adjustments to my feet.

5. I didn't really prefer one to any of the others and didn’t notice a difference in the level of easiness of the three instructions.

6. No I did not.

7. I felt it was easiest when I was just asked to keep my body still. I was asked to keep a certain area still it was a lot harder to narrow down my focus on keeping that part still.
8. It was easier to get myself to stand still than it was to get the board to stay still. I was able to control myself more than I could control the board.

9. Focusing on keeping the platform still was easier. I was able to balance more steadily than the other instructions.

10. The stand still instruction made it easier to balance.

11. Yes, I found that focusing on the platform made it easier for me to balance.

12. Stand still as by far the easiest one then keep the platform still and lastly keeps feet still.

13. The instruction to "stand still' seemed to help me focus on the balance of my feet rather than balancing the disk.

14. Keep the platform still > stand still > feet still. It was easier to balance during the last (EF) trials due to being able to focus my stability in my hips.

15. Yes, when directed to keep the platform still, I felt better overall balance.
APPENDIX 2: POSTURAL SWAY ANALYSES BATCH CODE

This code was adapted by permission from code written by John Mercer.

%COP sway program
%This program was written to calculate Center of Pressure variables
%clc
clear;
clear all;
fclose('all');
temporary_directory = pwd;
fprintf(1,'\n\nProcessing\n\n');

%SELECT THE NUMBER OF SUBJECTS, CONDITIONS AND TRIALS YOU WISH TO ANALYZE
subjects    = 15;   %number of subjects to process
conditions  = 3;    %number of conditions per subject
trials      = 5;    %trials per condition

startwithsubj   = 1;    %subject number to start with
startwithcond   = 1;    %condition number to start with
startwithtrial  = 1;    %trial number to start with

my_dir = 'C:\Users\';    %directory where data is located
freqlow     = 0.1;    %low end of frequency range to calculate mean power
freqhigh    = 10;    %Frequency indicating the high end of the range
tempdir     = pwd;    %directory where data is located
mpf_high    = 30;    (%Frequency indicating the high end of the range
to calculate mean power frequency over
fc = 15;    %cutoff frequency

%--------------------------------------------------------------
%for all files
headers     = 13;
fs          = 500;

tempdir     = pwd;
datain      = '.txt';
dataout     = '.csv';
precision   = 4;    %output precision

datain      = '.txt';
dataout     = '.csv';    %for each data file -
peakcol     = 6;    %3 channels and time
peakrow = 25000;  %should be about 50 s worth of data

%program variables
filenumber = 0;    %use this to identify row number to put data
sdist = 0;        %sway distance
meanamp = 0;      %mean amplitude
meanpowermag = 0;
precision = 8;    %output precision
tempoutputdata = []; 

%==================================================================

filenumber = 0;

for s = startwithsubj:(startwithsubj+subjects-1)
    for c = startwithcond:(startwithcond+conditions-1)
        for t = startwithtrial:(startwithtrial+trials-1)

%==================================================================

    % Open a file
    %==================================================================

        %create s?c?t? filename
        subj = int2str(s);
        cond = int2str(c);
        tri = int2str(t);

        f_name = ['s' subj 'c' cond 't' tri];
        fprintf(1,f_name); fprintf(1,'n');

        %create filenames
        inputfile = [f_name datain];
        dataout = [f_name dataout];

        %open a file using 'my_open' function
        data = sj_my_fopen(my_dir, inputfile, peakcol, peakrow, headers);

        % time = data(1,1);
        time = data([1250:23750],1);

        % CoPx = data(:,5);
        CoPx = data([1250:23750],5);

        % CoPy = data(:,6);
        CoPy = data([1250:23750],6);
%adjust x and y values to AMP; this will effectively center the data about
%0 for the polar conversion
x = CoPx;
y = CoPy;

%----------calculate parameters----------
%transform x,y coordinates to polar coordinates
[th, r] = cart2pol(x,y);
polar(th,r);

%Calculate sway distance

%parse file
for i = 1:(length(y)-1); %calculate squares up to length-1
    x_2   = (x(i+1)-x(i))^2;
    y_2   = (y(i+1)-y(i))^2;
    dist(i) = (x_2 + y_2)^.5;
    sdist = sdist + dist(i);
end %end parse data set

vector = dist;

%Calculate RMS
rmsvalue = rms(vector) % RMSE of sway distance

%RMS in the AP and ML planes

    RMSap=sqrt (sum(CoPx.^2)/length(CoPx));
    RMSml=sqrt (sum(CoPy.^2)/length(CoPy));

end %end t
end %end c
end %end s
APPENDIX 3: EEG PSD ANALYSES BATCH CODE

clc
close(gcf)
close all
clear
tic

%SELECT THE NUMBER OF SUBJECTS, CONDITIONS AND TRIALS YOU WISH TO
%ANALYZE
subjects = 15;  %number of subjects to process
conditions = 3;  %number of conditions per subject
trials = 5;  %trials per condition

my_dir = ['C:\Users\...'

startwithsubj = 1;  %subject number to start with
startwithcond = 1;  %condition number to start with (there were 6 conditions)
startwithtrial = 1;  %trial number to start with

%open EEGlab
[ALLEEG EEG CURRENTSET ALLCOM] = eeglab;

%create loop counter
counter = 1;

for subjects = startwithsubj:(startwithsubj+subjects-1)
    for conditions = startwithcond:(startwithcond+conditions-1)
        for trials = startwithtrial:(startwithtrial+trials-1)

            %temporary string variables
            es = int2str(subjects);
c = int2str(conditions);
t = int2str(trials);
%temporary number variables
    es_num = str2num(es);
    c_num = str2num(c);
    t_num = str2num(t);

%save name in a string and print to screen
    f_name = ['es' es 'c' c 't' t];
    fprintf(1,f_name); fprintf(1,\n);

%eegh from data import csv file
    temp_fn = sprintf('C:\Users\p25_to_41_copy\columns_removed\%8s.CSV',
                      f_name);
    es_set = sprintf('%2s', es);
    c_set = sprintf('%2s', c);
    t_set = sprintf('%2s', t);
    EEG = pop_importdata('dataformat','ascii','nbchan',0,'data',temp_fn
                          ,'setname',
                          f_name, 'srate',128,'subject',es_set,'pnts',0,'condition',c_set,'xmin',0,'session',
                          t_set);
    [ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG, 0,'gui','off');

%eegh - import marker data from channel 15 and delete channel 15
    EEG = eeg_checkset( EEG );
    EEG = eeg_checkset( EEG );
    EEG = pop_chanevent(EEG, 15,'edge','leading','edgelen',0);
    [ALLEEG EEG] = eeg_store(ALLEEG, EEG, CURRENTSET);

%eegh - read channel locations from emotiv.ced file
    EEG=pop_chanedit(EEG, 'load',{C:\Program Files\emotiv.ced 'filetype'
                                  'autodetect'});
    [ALLEEG EEG] = eeg_store(ALLEEG, EEG, CURRENTSET);

%eegh - high pass filter and save new set
    temp_fn = sprintf('C:\Users\imported_channels_assigned\%8s_hp.set',f_name);
    EEG = pop_eegfiltnew(EEG, [], 1, 424, true, [], 1);
[ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG, 1,'savenew',
temp_fn, 'overwrite', 'on', 'gui', 'off');

% eegh - clean line from 50 to 120 Hz and save new set
temp_fn = sprintf('C:\\Users\\HP_CL_3\\%8s_cl.set', f_name);
EEG = pop_cleanline(EEG, 'bandwidth', 2, 'chanlist', [1:14], 'computepower', 0,
'linefreqs', [50 120], 'normSpectrum', 0, 'p', 0.01, 'pad', 2, 'plotfigures', 0,
'scanforlines', 1, 'sigtype', 'Channels', 'tau', 100, 'verb', 0, 'winsize', 4, 'winstep', 1);
[ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG, 1, 'savenew',
temp_fn, 'gui', 'off');

close (gcf);

% eegh - remove a second of data to force a conversion of markers to strings for further
% processing
cur_set = sprintf('%8s_cl.set', f_name);
EEG = pop_loadset('filename', cur_set, 'filepath', 'C:\\Users\\HP_CL_3\\');
[ALLEEG, EEG, CURRENTSET] = eeg_store( ALLEEG, EEG, 0);
EEG = eeg_checkset( EEG);
EEG = pop_select( EEG, 'noTime', [1 2]);

% eegh - remove times outside of interest and save to events_only file

if c_num == 1
    control_events;  % these sub-routines allowed different event numbers to
                      % be processed appropriately
elseif c_num == 2
    external_events;  % subroutine
elseif c_num == 3
    internal_events;  % subroutine
else
    disp(error);
end

close (gcf);
%temporary variable to hold file name
cur_set = sprintf('%8s_events.set', f_name);
%eegh - remove mean baseline from each channel
EEG = pop_loadset('filename',cur_set,'filepath','C:\Users\events_only\');
[ALLEEG, EEG, CURRENTSET] = eeg_store( ALLEEG, EEG, 0 );
EEG = eeg_checkset( EEG );
EEG = pop_rmbase( EEG, []);
pop_eeplot( EEG, 1, 1, 1);

%temporary variable to hold file name
cur_set = sprintf('%8s_auto.set', f_name);
%eegh - run clean_rawadata and save
EEG = clean_rawdata(EEG, 5, [0.25 0.75], 0.3, 5, 0.5);
EEG = eeg_checkset( EEG );
pop_eeplot( EEG, 1, 1, 1);
EEG = pop_saveset( EEG, 'filename',cur_set,'filepath','C:\Users\clean\');
[ALLEEG EEG] = eeg_store( ALLEEG, EEG, CURRENTSET);

%eegh - spectopo plots
EEG = eeg_checkset( EEG );
figure; pop_spectopo(EEG, 1, [0 inf], 'EEG', 'freq', [8 10 12], 'freqrange', [8 12], 'electrodes','off');
EEG = eeg_checkset( EEG );
figure; pop_spectopo(EEG, 1, [0 inf], 'EEG', 'freq', [13 20 25], 'freqrange', [12 25], 'electrodes','off');

%remove channels for left hemisphere processing
EEG = pop_loadset('filename',cur_set,'filepath','C:\Users\clean\');
[ALLEEG, EEG, CURRENTSET] = eeg_store( ALLEEG, EEG, 0 );
EEG = eeg_checkset( EEG );
EEG = pop_select( EEG,'channel',{'af3' 'f7' 'f3' 'fc5' 't7' 'p7' 'o1'});

%calculate spectra for left alpha & beta
tms_la = find(EEG.times > 0 & EEG.times < inf);
[spectra,freqs,speccomp,contrib,specstd] = ...
spectopo(EEG.data(:, tms_la,:), length(tms_la), EEG.srate);
fr_a = find(freqs > 8 & freqs < 12);
fr_b = find(freqs > 12 & freqs < 25);
la = mean(mean(spectra(:, fr_a), 2));
lb = mean(mean(spectra(:, fr_b), 2));
la_channel = mean(spectra(:, fr_a), 2);
%la_max = max(mean(spectra(:, fr), 2))
lb_channel = mean(spectra(:, fr_b), 2);
%lb_max = max(mean(spectra(:, fr), 2))

% save left set
   temp_fn = sprintf('C:\\Users\\channels_1_7_3\\%s_LEFT_3.set', f_name);
   [ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG, 6, 'savenew', temp_fn, 'gui', 'off');

% remove channels for right
   EEG = pop_loadset('filename', cur_set, 'filepath', 'C:\\Users\\clean\\');
   [ALLEEG, EEG, CURRENTSET] = eeg_store(ALLEEG, EEG, 0);
   EEG = eeg_checkset(EEG);
   EEG = pop_select(EEG, 'channel', {'o2' 'p8' 't8' 'fc6' 'f4' 'f8' 'af4'});

% calculate spectra for right alpha and beta
   tms_ra = find(EEG.times > 0 & EEG.times < inf);
   [spectra, freqs, speccomp, contrib, specstd] = ...
   spectopo(EEG.data(:, tms_ra,:), length(tms_ra), EEG.srate);
fr_a = find(freqs > 8 & freqs < 12);
fr_b = find(freqs > 12 & freqs < 25);
ra = mean(mean(spectra(:, fr_a), 2));
rb = mean(mean(spectra(:, fr_b), 2));
ra_channel = mean(spectra(:, fr_a), 2);
%ra_max = max(mean(spectra(:, fr), 2))
rb_channel = mean(spectra(:, fr_b), 2);
%rb = max(mean(spectra(:, fr), 2))
tms_l = (max(tms_la/EEG.srate));
tms_r = (max(tms_ra/EEG.srate));
close(gcf);
close(gcf);

%save right Fileset
temp_fn = sprintf('C:\Users\channels_8_14_3\%8sRIGHT_3.set', f_name);
[ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG, 1,
'savenew',temp_fn,'gui','off');

%format channel freq for print
left_alpha_by_channel = la_channel';
left_beta_by_channel = lb_channel';
right_alpha_by_channel = ra_channel';
right_beta_by_channel = rb_channel';

% Write DVs to text files
if c_num == 1 && t_num == 1
    first_file_save;   %subroutine
elseif c_num == 3 && t_num == 5;
    last_file_save;   %subroutine
else
    reg_file_save;   %subroutine
end

%increment counter
    counter = counter + 1;
close(gcf);
close(gcf);
close(gcf);
close(gcf);
end %end trials
end %end conditions

end %end subjects
APPENDIX 4: DESCRIPTIVE STATISTICS

Scatter plots: Single trials

Figure 11. Single trial scatter plot displaying the mean of the alpha frequency range in the left hemisphere.

Figure 12. Single trial scatter plot displaying the mean of the alpha frequency range in the right hemisphere.
Figure 13. Single trial scatter plot displaying the mean of the beta frequency range in the left hemisphere.

Figure 14. Single trial scatter plot displaying the mean of the alpha frequency range in the right hemisphere.
Bar graphs: Means of PSD by frequency band, condition and hemisphere

Figure 15. Mean of alpha frequencies by participant in the control condition.

Figure 16. Mean of alpha frequencies by participant in the external focus condition.

Figure 17. Mean of alpha frequencies by participant in the internal focus condition.
Figure 18. Mean of beta frequencies by participant in the control condition.

Figure 19. Mean of beta frequencies by participant in the external focus condition.

Figure 20. Mean of beta frequencies by participant in the internal focus condition.
Internal Focus Alpha

External Focus Alpha

SPECTOPO graphs for participant – alpha levels represent minimum or near minimum values. Z-D scores. Figure 21: Example Participant A: Alpha SPECTOPO graph for minimum values.
SPECTOPO graphs for participant – beta levels represent minimum or near minimum values. 2-D scalp projections reflect power spectral density. Frequency values are on the x-axis and power on the y-axis.

Figure 22. Example Participant A: Beta SPECTOPO graph for minimum values.

Figure 22. Example Participant A: Beta SPECTOPO graph for minimum values.
SPECTOPO graphs for participant – alpha levels represent mean or near mean values. 2-D scalp projections reflect power spectral density. Frequency values are on the x-axis and power on the y-axis.

Figure 24. Example Participant B: Alpha SPECTOPO for mean values.

Figure 25. Example Participant C: Alpha SPECTOPO for mean values.
SPECTOPO graphs for participant – beta levels represent mean or near mean values. 2-D scalp projections reflect power spectral density. Frequency values are on the x-axis and power on the y-axis. Figure 24: Example Participant B: Beta SPECTOPO graph for mean values.
SPECTOPO graphs for participant – alpha levels represent maximum or near maximum values. 2-D scalp projections reflect power spectral density. Frequency values are on the x-axis and power on the y-axis.

Figure 25. Example Participant C: Alpha SPECTOPO graph for maximum values.
Control Beta

External Focus Beta

Internal Focus Beta

SPECTOP graphs for participant – beta levels represent maximum or near maximum values. 2-D scalp projections reflect power spectral density. Frequency values are on the x-axis and power on the y-axis.

Figure 26. Example Participant C: Beta SPECTOP graph for maximum values.
REFERENCES


CURRICULUM VITAE

University of Nevada, Las Vegas
4505 S. Maryland Parkway
Box 453034
Las Vegas, NV 89154-3946
702-895-3946

EDUCATION

2014 
M.S. IN KINESIOLOGY — UNIVERSITY OF NEVADA, LAS VEGAS
PENDING
Thesis: Postural sway and brain hemispheric power spectral density under different attentional focus conditions
Supervisor: Gabriele Wulf, Ph. D.

2012 
B.S. IN KINESIOLOGY — UNIVERSITY OF NEVADA, LAS VEGAS
Summa Cum Laude, 4.0 GPA

RESEARCH EXPERIENCE

2014 
Postural sway and brain hemispheric power spectral density under different attentional focus conditions
Primary Investigator: Gabriele Wulf, Ph. D.

Female blood pressure responses to wearing wet-suits
Co-mentored student for a Summer term research grant from Nevada IDeA Network for Biomedical Research Excellence (INBRE)
Primary Investigator: John Mercer, Ph. D.

An educational survey, including the international physical activity questionnaire: short form, and a gifted pedometer: the effect of social reciprocity on survey response time, pedometer use, and self-reported levels of physical activity in university employee
Primary Investigator: Richard Tandy, Ph. D.

2012 
Brief hypnotic intervention enhances throwing accuracy
Independent study project in my Undergraduate Senior year
Published in the International Journal of Sports Science and Coaching
Primary Investigator: Dr. Gabriele Wulf, Ph. D.
2011 Estrogen Effects after a Crush Muscle Injury and Acute Exposure to Hypobaric Hypoxia
Funded project by the Department of Defense
Undergraduate Student Lab Assistant
Primary Investigator: Barbara St. Pierre-Schneider, Ph. D.

PROFESSIONAL APPOINTMENTS

University of Nevada, Las Vegas
2013- present

THE SOCIAL PSYCHOLOGY OF PHYSICAL ACTIVITY AND SPORT
I redesigned this course as the Milestone Experience course for the Kinesiology Department as part of a University Undergraduate Learning Outcomes (UULOs) General Education program. The Milestone class develops two of the five UULO objectives, inquiry and critical thinking, and communication.

PHYSICAL ACTIVITY AND HEALTH
This course is an introduction to the science and current research regarding health and activity. My proposal for a redesign of this course has been approved as part of the Research-based Course Redesign Project from the Office of Faculty, Policy and Research.

SPECIAL PROBLEMS IN KINESIOLOGY/INDEPENDENT STUDY
I have worked with six students on Independent Study topics related to their field. Two students have submitted Literature Reviews for publication in UNLV’s Students for Science Undergraduate Research Journal and another received a Nevada IDeA Network for Biomedical Research Excellence grant to complete a summer research project.

2013-2014

INQUIRIES AND ISSUES IN HEALTH SCIENCES
This course is the First Year Seminar to introduce students to the UULO objectives as part of the General Education Core Requirements. As a ‘Breakout Group’ Instructor I taught eight sections to develop and present individual research posters.

2012-2014

HUMAN ANATOMY AND PHYSIOLOGY I AND II LABORATORY
These courses review the basic organization of human cells and tissues and the structure and function of the skeletal, muscular, nervous, sensory, digestive, circulatory, urogenital, reproductive, and endocrine systems. As a lab instructor for twenty-two sections, I taught and assisted with microscope and dissection skills, applied cardiorespiratory assessment, model identification, blood typing, and related experiments and procedures.
PUBLICATIONS

Peer Reviewed Publication

2013
Brief hypnotic intervention enhances throwing accuracy.

Other Publications

2014
Exercise and Alzheimer’s Disease
UNLV’s Division of Educational Outreach newsletter

2013
Human thermodynamics: Physiological responses to the ingestion of cold beverages.
Hunter-Newbury donated EEG equipment for my research project as compensation for this literature review. This document was required for obtaining FDA approval for a new product. Approval was granted upon receipt of the article.

AWARDS

2014
CSUN Health Sciences Faculty Award: University of Nevada, Las Vegas

Nominated For Rebel Award: University of Nevada, Las Vegas

SERVICE AND INVOLVEMENT

University of Nevada, Las Vegas 2012-2014

Allied Health Science Faculty Reviewer – Students for Science Journal

Advisor for Kinesiology Registered Student Organization, Kappa Iota Nu

Fitness 4 Finals UNLV collaborative fitness involvement program

Twenty-four guest lectures on Health Science related topics
MEDIA

2014  Interview on exercise adherence - New Year’s Resolution article –

Las Vegas Review Journal

Radio Interviews – The Health Forum Show – CBS 100.5

Rebel TV Interview- Tips on staying healthy for students

OTHER PROFESSIONAL EXPERIENCE

2008-2010  Director of Business Development
            The Sports Performance Institute of Las Vegas
            Director of Marketing
            The Orthopedic and Sports Medicine Institute
            of Las Vegas

2006-2008  General Manager – Bikram Yoga Southwest

2012 - present  Anatomy Instructor - RYT Yoga Alliance Certified Zflow Yoga

2004- present  Bikram Yoga Instructor

2008-2011  Founder and President – Yogis Unite 501c3

2008-2010  Founder and Director of Fitness in the Square
            Weekly free community fitness events at Town Square Park, Las Vegas, NV
            Multi day events promoting fitness and wellness

2008-2010  Community Service Advisory Board – Fighter Relief Fund