2018

Using EEG data to predict engagement in face-to-face conversations

Brooke Maddestra

Edith Cowan University

Copyright Warning

Using EEG Data to Predict Engagement in Face-to-Face Conversations.

Brooke Maddestra

A report submitted in Partial Fulfilment of the Requirements for the Award of Bachelor of Arts (Psychology) Honours, School of Arts and Humanities, Edith Cowan University.

I declare that this written assignment is my own work and does not include:

(i) material from published sources used without proper acknowledgement; or

(ii) material copied from the work of other students.

Signature: Brooke Maddestra

2018

Using EEG Data to Predict Engagement in Face-to-Face Conversations.

Abstract

To date engagement in face-to-face conversation has been studied almost exclusively through the post event measurement of self-reporting surveys or questionnaires. Electroencephalography (EEG) has been used for decades to examine brain activity for both research and diagnostic purposes. Medical grade EEG equipment is both costly and confined to being used within laboratory settings. With the recent advent of off-the-shelf consumer grade portable EEG-devices, novel psychological research on cognitive computations that have traditionally been confined to self-report, is now a reality. Although it is well documented that people use their cognitive abilities during conversations, an extensive literature search found no studies on the use of EEG data to obtain a neurological engagement score during conversation. Consequently, the present study sought to remedy a gap in the literature, and capitalised on the readily available consumer-grade portable EEG equipment. A within-participants quantitative study with 42 participants examined whether EEG predicted engagement during face-to-face getting acquainted conversations. Participants' alpha and beta brain activity were examined from EEG data collected during two separate conversations, and participants also completed a post-hoc self-report on their engagement and attention. The results of the study found a significant difference for participants' alpha brain activity and engagement, but not for the beta activity and engagement. There was also no significant difference found for participants attention and their alpha or beta activity. A surprising additional finding in the present study was a within-participant consistency for both alpha and beta activity across the two conversations, which is consistent with individual differences stability found in other psychophysiological studies. Overall, the present study has found that alpha activity is necessary for neurological engagement during face-to-face getting acquainted conversations. Therefore, future research is warranted on the use of EEG as an additional tool in face-to-face communication to compliment self-report and measure engagement.

Author: Brooke Maddestra
Supervisors: Doctor Shane Rogers and Doctor Craig Speelman

Copyright and Access Declaration

I certify that this thesis does not, to the best of my knowledge and belief:

i. incorporate without acknowledgement any material previously submitted for a degree or diploma in any institution of higher education;

ii. contain any material previously published or written by another person except where due reference is made in the text; or

iii. contain any defamatory material.

Signed: Brooke Maddestra

Dated: 30 October 2017

Acknowledgements

Sincere thanks are extended to my supervisor Doctor Shane Rogers for his endless support throughout the year and suggestions that greatly improved this research and paper. Special thanks, are also extended to Professor Craig Speelman for his support and knowledge in the co-supervision of the study. I would also like to acknowledge the proposal reviewers, Dr Rodrigo Becerra and Dr Ross Hollett, for their suggestions to make the research better. I would also like to thank all the participants who volunteered their time and contributed to the research project.

Special thanks go to my partner, Andrew and children, Jye, Flynn and Darcy who gave me tremendous support and whose encouragement helped me greatly to complete this research project.

Table of Contents

List of Figures

Using EEG Data to Predict Engagement in Face-to-Face Conversations

Introduction

Interpersonal Communication

An ability to communicate effectively is widely held to be a valuable interpersonal skill (Bolton, 1991; Hargie, 2011). There are a variety of complex brain computations required during social interaction involved with attention, working memory, and cognitive control (Amodio & Firth, 2006; Shallice, 1988; Smith & Jonides, 1999; Ybarra et al., 2008). Studies in neuroscience have shown that understanding of others' beliefs and desires during interpersonal communication is associated with heightened activity in the pre-frontal cortex, specifically, the medial and orbitofrontal cortex (Amodio & Firth, 2006; Firth & Firth, 1999; Kuhlen, Bogler, Brennan & Haynes, 2017). These brain regions are also associated with executive functions such as working memory and attention (Firth & Firth, 1999; Royall et al., 2002; Ybarra et al., 2010).

Executive functions have been investigated for decades using electroencephalography (EEG) and event related potentials (ERPs) (Astolfi et al., 2007; Babiloni et al., 2001; 2008; Kuhlen et al., 2017; Nunez, 1995). More recently, advances in technology and the digitisation of EEG equipment have enabled the manufacture and availability of consumer level EEG devices, such as the Emotiv EPOC (Duvinage et al., 2013). Researchers have started to use these devices, and there are several published papers that have examined the effectiveness of the devices, and found them to be viable research tools (Badcock et al., 2013; Duvinage et al., 2013; Fakhruzzaman, Riksakomara, & Suryotrisongko, 2015). This thesis represents an attempt to use the new consumer grade and user-friendly EEG technology in communication research where the implementation of EEG recording has historically been too difficult, and specifically, to examine if EEG measures can be used to predict self-reported engagement in conversation.

Potential Use of a Neurological Engagement Measure in Communication

The discovery of a neurological engagement measure during communication would build on the current knowledge regarding executive functions during communication, and provide benefit in both clinical and non-clinical settings. In a clinical setting the application of a neurological engagement measure could build on current neurofeedback training for psychopathologies such as ADHD (Arns, de Ridder, Strehl, Breteler & Coenen, 2009; Escolano, Navarro-Gil, Garcia-Campayo, Congedo, & Minguez, 2014; Friel, 2007). In a therapeutic counselling context, interpersonal communication between intimate partners could also be measured. This could enable an awareness of a person's engagement during interpersonal communication with their partner (Myers & Young, 2012). A neurological engagement measure within an educational setting could increase students' engagement when communicating, as well as providing an awareness of their own variability of engagement (Myers & Young, 2012; Rukavishnikova, 2016). This could also enable the refinement of interpersonal communication between teacher and student, and between students themselves, maximising social and educational outcomes (Pennings et al., in press). Implementing a neurological engagement measure within the primary and secondary school setting has the potential to address communication deficits at a young age, when social skills are being developed and refined (Sharp, 1981).

Social skills training could also benefit from a neurological engagement measure. Individuals or helping professions, such as nursing, that rely on effective interpersonal skills, could implement a neurological engagement measure into their professional social skills training framework (MacLean, Kelly, Geddes & Della, 2016; Schneider, 1992). Further adoptions of a neurological engagement measure could be within the modern dating scene, as an adaption of face-to-face speed dating (Janz, Pepping & Halford, 2015). This could enable another layer of assessment, by monitoring levels of an individual's own engagement during

interpersonal interactions when selecting potential partners (Pepping, Taylor, Koh, & Halford, 2017). The application of a neurological engagement measure during interpersonal communication, whether within a clinical or non-clinical setting, has the potential to allow for more effective and meaningful communication experiences.

Using Psychophysiological Measures to Complement Self-Report

To date, engagement in conversation has been studied almost exclusively through the post event measurement of self-reporting surveys or questionnaires (Campbell & Atas Akdemir, 2016; Dekeyser, Raes, Leijssen, Leysen, & Dewulf, 2008; McCroskey & McCroskey, 1988; McEwan & Guerrero, 2010). Self-reports can be unreliable when used in isolation due to a participant misinterpreting rating scales and/or questions (McCroskey & McCroskey, 1988; Schwarz, 1999). Although self-reports are subjective and contain assumptions regarding participant understanding of the questions, they are still widely used in psychological research (Schwarz, 1999).

Psychophysiological measurements have been argued to be an effective form of data to complement self-report (McMahan, Parberry & Parsons, 2015). Psychophysiological signals are continuously available from research participants, and can in certain circumstances be collected without the participant's conscious awareness (Freeman, Mikulka, Prinzel, & Scerbo, 1999; McMahan et al., 2015a; Pope, Bogart & Bartolome, 1995). Psychophysiology is defined by Andreassi (1995) as the study of relations between psychological manipulations and resulting physiological responses, to promote understanding of the relation between mental and bodily processes. Measures that are taken by psychophysiologists include: electroencephalogram (EEG), the event related brain potential (ERP), the electromyogram (EMG) to measure muscle activity, pupillometry to measure pupil dilation, electrooculography (EOG), which is a measure of eye movement, electrodermal activity (EDA) for electrical activity at skin surface, heart responses, blood

volume and pressure, respiration, oxygen consumption, salivation and gastric motility (Andreassi, 1995; Cacioppo & Tassinary, 1990).

Over the last 30 years there has been an increase in psychophysiological research studies, particularly psychophysiological studies that relate to brain activity (EEG and ERPs) and human behaviour. The reason for the increase in the research on psychophysiological brain activity is that the brain is central to our behaviour (Cacioppo & Tassinary, 1990). Another reason is the digitisation and advancement of technology through the availability of computerised equipment and processing programs (Andreassi, 1995; Cerquera, Arns, Buitrago, Guiterrez & Freund, 2012; Vincent & Lledo, 2014).

Brain signals and Electroencephalography (EEG)

EEG is a well-recognised and widely used technique that measures cortical activity by recording electrical signals from the scalp (Figure 1) (Aissani, Martinerie, Yahia-Cherif, Paradis & Lorenceau, 2014; Engel & Fries, 2010; Freeman et al., 1999; Ivanovski & Malhi, 2007; McMahon, Parberry & Parsons, 2015; Stern, Ray & Quigley, 2001). These electrical signals are derived from the synchronised activity of large neuronal assemblies, with some patterns appearing random and others periodic (Sanei, 2013; Stern et al., 2001). Electrical activity from the neuronal assemblies is measured in microvolts (Sanei, 2013; Stern et al, 2001). EEG is described by Stern et al. (2001) as being comprised of two parameters; amplitude (size of the signal) and frequency (the speed of the signal cycles). The five most common and easily defined brain wave frequency bands found in EEG data, from low to high frequency are, delta (δ) (0.5-4 Hz), theta (θ) (4-8 Hz), alpha (α) (8-12 Hz), beta (β) (12-30 Hz) and gamma (γ) (30-70 Hz) (Aissani et al., 2014; Avanza et al., 2009; Cohen, 2014; Sanei, 2013; Stern et al., 2001). The characteristics of these identified brain wave frequency bands change during wakefulness and sleep in healthy humans and are also affected by age (Sanei, 2013).

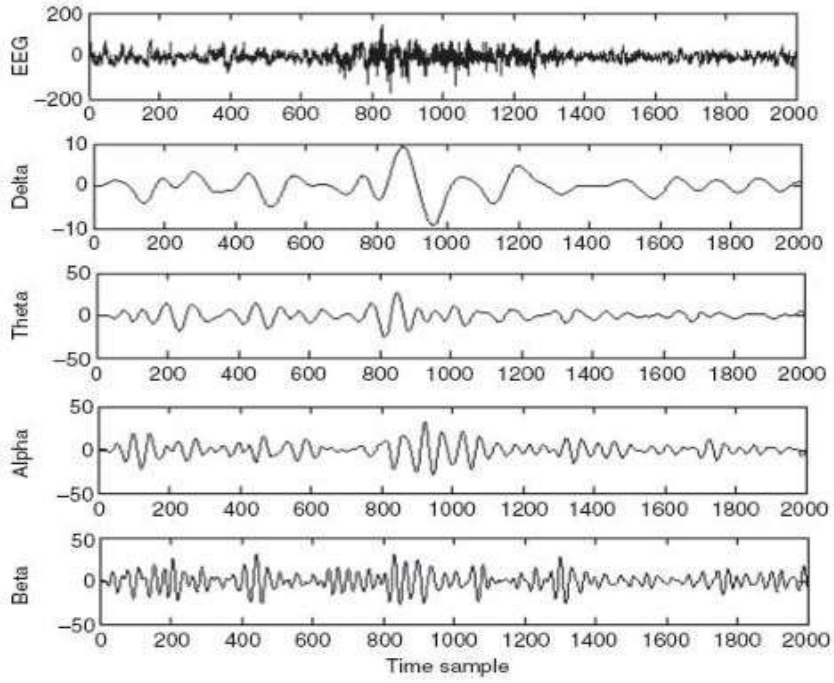


Figure 1. The EEG signal and the four typical and dominant brain normal rhythms, from high to low frequencies, delta, theta, alpha and beta. Adapted from *Adaptive Processing of Brian Signals* (p. 44) by S. Sanei, 2013, Chichester, United Kingdom: John Wiley & Sons. Copyright 2013 by John Wiley & Sons. **Adapted with permission.

The delta band frequency is primarily associated with deep sleep in healthy humans, as well as pathological conditions such as tumours (Lagopoulos et al., 2009; Sanei, 2013; Stern et al., 2001). Delta is also predominant throughout the first two years of life, and is associated with learning, motivational processes and the brain reward system (Engel & Fries, 2010; Stern et al., 2001). The theta band frequency has two distinct psychological states. One state is associated with working memory functions, emotional arousal, problem solving, attention, and fear conditioning (Engel & Fries, 2010; Ivanovski & Malhi, 2007; Stern et al., 2001). The second state is associated with lower levels of alertness or drowsiness, REM (rapid eye movement) sleep, and hypnosis (Ivanovski & Malhi, 2007; Sanei, 2013; Stern et al., 2001; Walter, 1953).

The alpha band frequency is associated with being awake and alert and has two types of characteristic responses. The first is a decrease of the signal, in the occipital brain region, during cognitive processes and sensory input (Ivanovski & Malhi, 2007; Sanei, 2013; Stern et

al., 2001). This has led to alpha interpreted traditionally as a 'cortical idling state', that decreases upon the engagement of cognitive processes and sensory input from the external world. This decrease and/or cessation of the alpha signal is referred to as alpha desynchronisation or alpha blocking (Cahn & Polich, 2006; Jensen & Mazaheri, 2010; Klimesch, Doppelmayr, Russegger, Pachinger & Schwaiger, 1998; Sanei, 2013; Stern et al., 2001; Tuladhar et al., 2007). Secondly, more recently, an increase in the alpha signal, found in the frontal brain region, known as alpha synchronisation, is seen to indicate internal attention, such as, working memory (Cooper, Burgess, Croft & Gruzelier, 2006; Engles & Fries, 2010; Ivanovski & Malhi, 2007; Shaw, 1996).

Effortful cognitive activity in humans is more often characterised in recent EEG literature by higher frequency waves known as the beta band frequency (13-25Hz) and the gamma band frequency (30-70Hz). The beta band frequency occurs when an individual is alert, and is the usual waking rhythm of the brain associated with active thinking, attention, focus on the external environment (responsive to somatic, motor, sensory input) and problem solving (Ivanovski & Malhi, 2007; Sanei, 2013; Stern et al., 2001). Beta is also seen to develop overtime and maintains a "status quo" providing stability to the cognition of decision making and consequent actions (Aissani et al., 2014). Higher levels of beta are associated with excitement (Lubar, 1991).

The gamma band frequency occurs rarely. Assessment of these rhythms is used to detect and confirm certain brain diseases (Sanei, 2013). However, there is also increasing evidence in recent studies that the gamma frequency band is also involved in the brain's ability to integrate a variety of stimuli into a coherent whole, during completion of tasks requiring visual representation and attention. Although these findings are still considered controversial (Berkovich-Ohana, 2017; Rieder, Rahm, Williams & Kaiser, 2010; Rouhinen, Panula, Palva & Palva, 2013).

The alpha and beta band frequencies are both reported to have distinct responses to cognitive processes involving internal and external attention, which are associated with neurological engagement (Anderson et al., 2011; Pope et al., 1995). The theta band frequency and the gamma frequency are also associated with various cognitive processes. However, these signals were not pursued as part of the investigation in this thesis. This is due to the slower wave oscillation of the theta band frequency, as well as its association with drowsiness (Lubar, 1991), and the gamma band frequency requiring further research to consolidate the emerging cognitive hypothesis (Rouhinen et al., 2013).

EEG, Neurological Engagement and Meditation Research

The technological advancement and availability of EEG devices for research purposes, has resulted in an increase in research into new areas (Ahani et al., 2014; Amodio & Firth, 2006; McMahon et al., 2015), such as the neurophysiological processes of individuals during and after meditation (Ivanovski & Malhi, 2007). Research using EEG in experiments on meditation are largely based on two types of meditation, concentrative and mindful. Both types of meditation are seen to draw parallels with psychological domains such as concentration, and sustained attention, and have been used in therapeutic settings for stress reduction (Cahn & Polich, 2006; Chiesa & Serretti, 2010; Lo, Huang & Chang, 2003; Lutz, Slagter, Dunne & Davidson, 2008; Vago & Silbersweig, 2012).

Increases in the alpha signal during mindfulness meditation was one of the main findings of a recent literature review of 56 papers on mindfulness meditation practice (Lomas, Ivtzan & Fu, 2017). Alpha has been consistently observed in meditation, with 67% of the papers reporting this outcome involving healthy participants, including novice and experienced meditators. The literature on alpha and meditation overall supports the finding that the intention of mental activity, or an ‘inner-directed’ attention, such as working memory or attending to

evoked activities is associated with increased alpha power (Cooper et al., 2006; Jensen, Gelfand, Kounios & Lisman, 2002; Lomas et al., 2017; Shaw, 1996).

In contrast, the research on the beta signal in meditation is more limited in comparison to alpha. Traditionally the beta signal has been found to increase when individuals are exposed to auditory, visual and multisensory stimuli (Engel & Fries, 2010; Guntekin et al., 2013; Leventhal et al., 2012). Beta is considered, in the neuroscience literature, to be the signal for alert response and attentiveness, and most of the studies on meditation show a loss or reduction in the beta signal during meditation (Lomas et al., 2017). While the majority of the studies on meditation and beta have found a decrease or no change of the signal, there have been a handful of studies that report an increase during meditation, when the form of meditation is mindfulness, not relaxation (Ahani et al., 2014; Dunn, Hartigan & Milulas, 1999; Lo et al., 2003).

EEG and the Development of Neurological Engagement Indices

EEG has also been used in other areas of research to investigate neurological engagement, and produce objective indices of measurement (Kuhlen et al., 2017; McMahan et al., 2015a). Researchers in the aviation industry have used EEG to study neurological engagement for airline pilots in relation to areas such as fatigue (Caldwell, Hall & Erikson, 2002; Howitt, Hay, Shergold & Ferres, 1978; Hunn, 1993), cognitive behavioural control (Borghini, Astolfi, Vecchiato, Mattia, & Babiloni, 2014), and in automated tasks (Freeman et al., 1999; Pope et al., 1995). Pope et al.'s study is one specific example of the use of EEG on neurological engagement in the aviation industry. Pope et al. investigated if participants could maintain sustained attention and engagement while supervising an automated flight deck system. The study involved the use of an EEG-based index of engagement, that was calculated based on the participant's alpha, theta and beta brain signals, when completing the task. The brain signals were collected via a medical grade EEG device. The study used a closed loop

feedback model that responded to the participant's level of engagement. That is, as the participant's engagement was reduced, the program activated a more mentally demanding task to increase engagement, and vice versa. Pope et al. reported that beta / (alpha + theta) reflected task engagement best in the closed loop feedback model.

In a follow-up to Pope et al.'s (1995) study, Freeman et al. (1999) also used EEG to test participants' responses to visual stimuli in an adaptive automation system (closed loop feedback model). Freeman et al. (1999) used the beta / (alpha + theta) index as well as two further indices, beta / alpha and 1 / alpha ratio. They found that the beta / (alpha + theta) and the beta / alpha engagement indices produce more switching from automated to manual mode under negative feedback, and participants performed well in manual mode. This was not found for the 1 / alpha ratio index. This result suggested that beta activity is necessary to be included when measuring neurological engagement (Freeman et al., 1999).

The study of Neurological Engagement with Commercially Available EEG Devices

Commercially available neuroheadsets, such as the Emotiv EPOC (Emotiv), are marketed and sold with associated EEG data software packages for ease of data analysis. The software calculates EEG algorithms, and produces outputs of levels of cognitive and emotional metrics, such as 'engagement', 'interest', and 'excitement', herein referred to as Emotiv engagement indices (Emotiv, 2013). This presents a limitation for study replication, unless the exact device and software is available for use. This limitation is acknowledged by most of the researchers using these devices, that they cannot provide specific information on the specific mathematical formulas and specific brain signals used to calculate neurological engagement in their studies. The following research studies reflect this limitation, as only the Emotiv engagement indices were reported. However, the offset to this limitation is that the commercially available and user-friendly EEG technology has allowed a wider range of

scientists, with a diverse range of projects in naturalistic settings, to investigate neurological engagement (Stopczynski, Stahlhut, Larsen, Petersen & Hansen, 2013).

Roe, Asponall, Mavros and Coyne (2013) investigated neurological engagement for participants viewing a natural (landscape) scene versus an urban scene. Using the Emotiv, EEG data was collected when participants looked at natural landscape photographs and urban scene photographs in a laboratory setting, and when walking within an urban environment. Natural scenes were found to be associated with strong Emotiv engagement indices. Although stronger Emotiv engagement indices were found for natural scenes in a laboratory setting, lower Emotiv engagement indices were presented by participants in a walking study, when green spaces were encountered in an urban setting (Roe et al., 2013). Participants were also asked to complete self-surveys, and rated natural landscapes more positively than urban scenes. The EEG data also indicated that the Emotiv's engagement index was higher for landscape scenes in comparison to the urban scenes. Roe et al.'s (2013) study concluded the Emotiv could be used to detect emotional change in people to different environmental settings.

A study by Sena, D'Amore, Brandimonte, Squitieri, & Fiorentino (2016) on driver distraction, incorporated the use of the Emotiv to capture participant's neurofeedback (EEG) in a virtual reality adaptive stimulation (a closed loop feedback system). Participants used computer driver simulators, to drive at a safe braking distance behind a lead vehicle, whilst wearing the Emotiv. The neurofeedback from the Emotiv's EEG signals was used to periodically modify the virtual task of driving. The Emotiv engagement indices of 'boredom and engagement' and 'long-term excitement' were used. If a participant's 'boredom and engagement' level was over 70% or under 20% or 'long-term excitement' level was over 80% or under 20% the lead car would brake. Only three participants were involved in the experiment, two males and one female (aged 23-26 years), however the study confirmed that

the Emotiv could measure engagement, boredom, high excitement and low excitement. The study found that with the four neurofeedback measures taken by the Emotiv, all three participants responded to the prescribed activity of braking in response to the lead car braking in the simulation (Sena et al., 2016). The study also confirmed that the Emotiv could be used in conjunction with a virtual reality adaptive simulation to measure neurological engagement.

Neurological engagement was investigated by Wrzesien et al. (2015) in the examination of the effectiveness of avatars used in mental health training for youth in the promotion of emotion regulation strategies. A small sample of twenty-two participants of Spanish nationality (11 boys) took part in the research (M = 13.27 years, SD = 0.47). Participants wore the Emotiv and viewed a scenario in a virtual environment in which an avatar encounters a computer problem that is at first easily resolved, and then is unresolvable, leading to frustration for the avatar who then punches the computer. Finally, the avatar moves away from the computer and begins to breath slowly (Wrzesien et al., 2015). The experimental group viewed the scenario that had an avatar that was a virtual representation of themselves, using specialised 3D modelling software. The control group viewed the same scenario that had an avatar that was a virtual representation with a neutral face. A series of self-report questionnaires was also used to capture data. The results showed a significant increase in negative valence in self-modelled avatar participants, in comparison to the neutral avatar participants. The negative valence was reflected in the EEG data with greater activity in the areas of the brain related to emotion regulation, the limbic and frontal regions, and in the self-report data (Wrzesien et al., 2015). The information from the Emotiv indicated that, in this study, the use of avatars can influence human behaviour, particularly in the context of emotion regulation (Wrzesien et al., 2015).

The Emotiv has also been used to investigate neurological engagement indices, independent of the Emotiv software, in studies of video game experience. Building on the

research of Pope et al. (1995) and Freeman et al. (1999) on an engagement index, McMahan et al. (2015a) measured participants' video game experience in real time. The research aim was to see if differing levels of player neurological engagement would be evident when comparing death scenes versus general play. McMahan et al. (2015a) investigated three different neurological engagement indices: beta / (alpha + theta); frontal theta / parietal alpha; and frontal theta.

McMahan et al. (2015a) found that there was a significant difference between general game play and death events, with higher levels of theta and beta recorded during the death event when using beta / (alpha + theta) and frontal theta. There were no significant findings for frontal theta / parietal alpha. However, the research found that the Emotiv can be used to assess engagement, and that the beta / (alpha + theta) index, was the preferred calculation. This was consistent with other research that has reported increased beta signal when playing video games (Salminen & Ravaja, 2007). McMahan et al. (2015a) noted that further research was needed as their sample size was small and the results were preliminary.

In a second study using the Emotiv, McMahan et al. (2015b) investigated participant brain signals when exposed to various stimulus modalities. The three different stimulus modalities were; a two-picture cognitive task, and as in their previous study, general game play and death events in a video game. The delta and theta bands were not included in the analysis, because of low reliability. The study only examined the beta and gamma signals. The rationale for the focus on beta and gamma was that gamma is associated with cognitive processes such as arousal and top-down modulation of sensory processes, and beta is associated with attention and motor processing (see Sanei, 2013). McMahan et al. reported an increase in both beta and gamma signals in the death scenes compared to the two-picture cognitive task. This signifies a difference in brain signals for the participants when they change their engagement from a low-level impact event (i.e., two-picture cognitive task), to a

high intensity or threat event (i.e., exposed to death scenes in video game play). No statistically significant difference was found between the two-picture cognitive task and the general play. Overall, the study concluded that although the sample size was small (N= 30), and more extensive research is needed, the Emotiv was successful in assessing differences in brain signals when participants experienced various stimulus modalities (McMahan et al., 2015b).

EEG, Neurological Engagement and Communication

The study of neurological engagement and interpersonal communication using EEG, to date, is centred largely on language production (Kuhlen, Allefeld & Haynes, 2012). Studies in psycholinguistics using EEG have concentrated on unidirectional communication such as during a speaking task (e.g., giving a monologue), and when engaged in a listening task, and so has not included face-to-face interactions in natural conversation (De Jaegher, Di Paolo, & Gallagher, 2010; Hari & Kujala, 2009; Kuhlen et al., 2012; Pickering & Garrod, 2004; Wilms et al., 2010). However, neurological engagement and communication has been investigated, by Goldberg, Brawner and Holden (2012), using the Emotiv, between people and a sophisticated interactive computer program with virtual characters.

Goldberg et al. (2012) examined whether computer based tutoring systems (the Intelligent Tutoring Systems) can distinguish varying states (high or low) of engagement in students, in real-time using EEG. Goldberg et al. also compared the Emotiv data with self-reported levels of engagement provided by the participants. In the study, participants conversed with a virtual character that was part of a computer based training platform whilst wearing the Emotiv. The participants (79 cadets at the U.S. Military Academy) were to act as a squad leader and converse with hospital staff following an attack under three different scenarios. Each scenario varied in difficulty with the aim of assessing engagement and

attention when in an interactive conversation, and participants' EEG data for resting states and task execution states were examined (Goldberg et al., 2012).

Goldberg et al. (2012) obtained metrics from the Emotiv Affective Suite that reported participant short-term excitement (STE), long-term excitement (LTE) and engagement during the experiment. It was found that the change from a resting state to a task execution state produced significant increases in engagement levels for the participants, and then stabilised and remained at a consistent level during the remainder of the task execution to completion. When the tasks increased in difficulty participants showed significant differences in both STE and LTE, between the easier and more difficult tasks. Results from the study confirmed the Emotiv can be used to monitor engagement with students in desktop training applications with virtual training characters. Although there are obvious limitations to Goldberg et al.'s (2012) research, such as, the use of virtual agents and reliance on the Emotiv engagement indices, their study has provided preliminary evidence for the use of the Emotiv device to further investigate neurological engagement in a communication context.

The Present Research

As described in the previous section neurological engagement with the Emotiv has been used in research where people interact with a virtual character, but no studies, at the time of writing this thesis, have been published investigating EEG and face-to-face human interaction. The present study seeks to extend upon prior research utilising the Emotiv to obtain neurological engagement indices by examining neurological engagement during natural face-to-face conversations. Understanding how people adapt and coordinate to each other, through an objective neurological engagement index derived from EEG data, would be a valuable addition to the field of psychology (Kuhlen et al., 2012). This research project specifically investigated two research hypotheses: 1) The participants' neurological engagement measures will correspond to the self-reported engagement during face-to-face

conversation; and, 2) participant's that report experiencing more variable attention during face-to-face conversations will have a higher standard deviation for the neurological engagement measure.

Method

Participants

Upon receiving Edith Cowan Human Research Ethics Committee approval recruitment of participants commenced via advertising through the university student portal (Appendix A). Fifty-five Edith Cowan University (ECU) students were recruited and participated in the study. EEG data files for 13 participants did not record properly and could not be used, leaving a final total of 42 participants (M_{age} = 27.74, SD_{age} = 9.07). Seventy three percent of the participants were female. All participants received a Coles/Myer gift voucher for $20, or, if eligible, a credit point towards an undergraduate ECU psychology statistics unit.

The sample size is consistent with the literature on neurological engagement using EEG, the exception being Goldberg et al.'s study (2012) that had 79 participants. The present study has a larger sample size in comparison to studies by McMahan et al. (2015a, 2015b), Sena et al. (2016), Wrzesien et al. (2015), and Roe et al. (2013) who all used samples of no more than 30 participants.

Materials

The Emotiv EPOC. The Emotiv EPOC is an inexpensive wireless and compact consumer-grade EEG headset, and has previously been used to measure neurological engagement successfully (Goldberg et al., 2012; McMahon et al., 2015a; Roe et al., 2013; Sena et al., 2016; Wrzesien et al., 2015). Three Emotiv wireless headsets were used for this

research to capture participants' raw EEG data during face-to-face conversations (see Figure 2). The Emotiv has 14 electrodes (saline sensors), located at scalp positions AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, T7, T8, O1, O2 (see Figure 3a). Two additional sensors serve as reference channels for the left and right hemispheres, CMS/DRL (Emotiv, 2013; McMahan et al., 2015a). The 14 electrodes are data collection channels, and are organised in accordance with the International 10-20 system (see Figure 3b). The sampling rate is 128Hz, with a bandwidth of 0.2-45Hz and digital notch filters at 50Hz and 60Hz. The Emotiv is a 'dry EEG' device as it does not require the lubrication of gels needed for the traditional 'wet EEG' medical devices (Stopczynski et al., 2014). However, saline solution is required and was used to keep the 14 electrode sensors moist for optimal collection of data during the data collection sessions.

Figure 2. Emotiv EPOC headset.

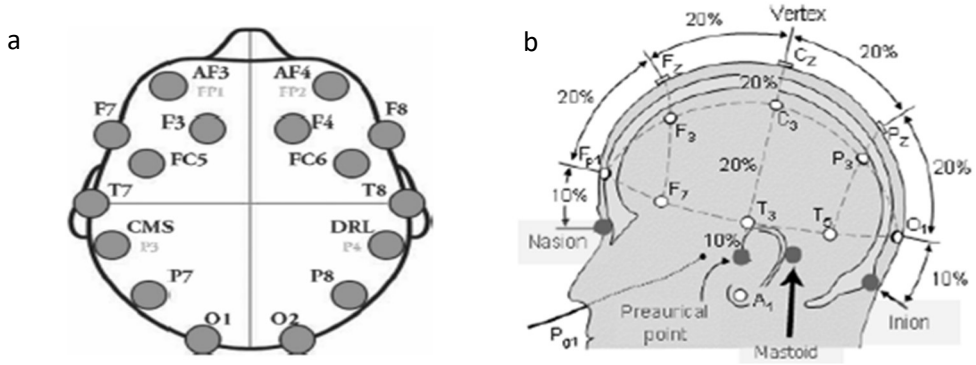


Figure 3. Figure 3a is the 14-electrode placement and two reference sites for the Emotiv EPOC. Figure 3b is the International 10-20 locations for electrode placement when using EEG devices.

Laptops. Three DELL laptops were used to connect to the Emotiv headsets and collect the continuous raw EEG data through the Emotiv Testbench© software. The Emotiv

Testbench© captures the raw EEG data generated by the participant's electrical neural brain activity when wearing the Emotiv (see Figure 4).

Figure 4. Emotiv EEG Testbench© interface that shows the progress of the raw EEG data being collected wirelessly from the Emotiv's 14 electrode sensors.

Self-report Questionnaires. After the completion of both conversations, participants answered two questions that compared the two conversations: 1. "I found the conversation more interesting with: person 1 or person 2" and 2. "My engagement in conversation was more variable with: person 1 or person 2"

Procedure

An information sheet explaining the experimental procedure was provided to participants to explain the details of the research (Appendix B). Participants were also provided with and completed a written consent form prior to participating in the study (Appendix C). Participants were informed that their involvement was voluntary and that they could withdraw their involvement at any time with no consequences. All participants were given a subject ID that rendered their data unidentifiable. Participants were recruited to attend the ECU Cognition Group laboratory in groups of three. The participants in each group were previously unacquainted with each other. Data collection sessions ran for 60 minutes.

The Emotiv devices were fitted to the participants' heads, with all 14 electrodes individually checked to ensure scalp contact. The Emotiv Testbench© software was also used to ensure that all 14 electrodes were signalling green for optimum EEG data collection. Participants were asked to remove all metal hair accessories and for long hair it was gathered into an elastic hair band, and positioned on top of the participant's head, to allow greater access to the scalp to place the electrodes evenly for optimum results.

All EEG recording took place within the ECU Cognition Group laboratory, specifically in the communication laboratory room (see Figure 5), with participants sitting at a desk across from each other (at a distance approximately 1 metre). Participants then engaged in a series of 4-minute conversations, wearing the Emotiv headsets, with a sample rate of 128Hz (~30,000 sample points per conversation). The four-minute time allocation is consistent with prior research investigating getting acquainted communication, where interactions are generally kept to a time duration of three to six minutes (Berrios, Totterdell & Niven, 2014; Carney, Colvin, & Hall, 2007; Dunbar, Duncan & Marriot, 1997; Eaton & Funder, 2003; Korobov, 2011). A repeated measures design was used as each participant had two conversations by rotating in a round robin fashion. Audio and vision of the conversations were recorded as part of a broader research project. As part of this broader project, the laptop that was connected to the participants' Emotiv headset was placed beside the participant to appear in the video recording to allow syncing of the audio/visual recording and the EEG data at a later date (see Figure 5). When not having a conversation, a participant was seated in an adjoining room unable to hear the conversation occurring between the other two participants.

Figure 5. The experimental set up with two participants wearing the Emotiv headsets engaged in 4-minute getting-acquainted conversation. Participants were seated across from each other in the communication laboratory next to the corresponding laptops collecting EEG data from their Emotiv headsets. Apart from the laptops, no other visual or audible stimulus was available to the participants, apart from each other (participants consented to the use of their photographs for use in this research).

On completion of each conversation an EEG raw data file was saved for each individual in Emotiv Testbench©, equating to six EEG data files obtained per session for this research (i.e., two per conversation as each individual across all three conversations had a file recorded). When both conversations were completed, participants answered the two comparison questions on the self-report questionnaire. For more information on the experimental procedure used in this study please see Appendix D.

Results

Data Analysis

Pre-processing Raw EEG Data and Artefact removal. EEG data was captured by the Emotiv devices with Emotiv Testbench©, for each of the forty-two participants' conversation one (C1) and conversation two (C2). The EEG data was pre-processed in the software MATLAB® with two EEG data analytical processing components, the EEGLAB toolbox and EEGLAB's BioSig plugin. EEGLAB is an interactive MATLAB® toolbox, for processing continuous and event related EEG data. The BioSig plugin is an open source software library for biomedical signal processing, for analysis of biosignals such as EEG.

All pre-processing in EEGLAB used a preconfigured file template that enabled the data processing to be set at 14 channels, which is congruent to the Emotiv wireless headset's 14 electrodes. A Basic FIR Filter was used in the pre-processing of all EEG data (Cohen, 2014). The Basic FIR filter was set at the lower edge of the frequency pass band (high-pass filter) at 1Hz as recommended by Widmann, Schroger and Maess (2014) to remove linear trends. This setting allows for a very generous transition region that is a linear phase, which does not distort the signal and removes electrogalvanic signals, that may, for example, be related to sweating (Cohen, 2014). Digital notch filters are automatically applied by the Emotiv EPOC device to remove any electrical interference from mains power sources (Ferdjallah & Barr, 1994).

Pre-processing of EEG data is traditionally used to remove unnecessary artefacts such as muscular movements from eyebrow, forehead and jaw movement, as well as eyeblinks, in research that involves trials lasting milliseconds to seconds in length (Berkovich-Ohana, 2017). However, although these artefacts are seen to impede traditional EEG studies, they are not necessarily a detrimental issue when analysing engagement over longer time periods (McMahan et al., 2015b). In the present research, neurological engagement was investigated in face-to-face conversation that lasts for minutes, and additionally any artefacts produced by muscle contractions are generally outside the frequency range of interest (Salenius, Portin, Kajola, Salmelin & Hari, 1997). For more information on the methodological procedure used in this study for pre-processing the EEG data, please see Appendix E.

EEG Data Processing. The raw processed EEG data was converted into the wave bands of Alpha (8-13Hz) and Beta (15-30Hz) via a fast Fourier transform (FFT), using the MATLAB® Neurophysiological Biomarker Toolbox (NBT). The NBT was created by developers to facilitate integration of multiple biomarkers and to support large scale research in MATLAB® (Hardstone et al., 2012). Research by Pope et al. (1995), Freeman et al.

(1999) and McMahan et al. (2015a, 2015b) all suggest that beta activity should be included to fully measure engagement. Alpha activity was also found extensively in the meditation literature to be associated with neurological engagement via both internal and external attention (Cooper et al., 2006; Ivanovski & Malhi, 2007; Jensen et al., 2002; Lomas et al., 2017; Shaw, 1996). For more information on the methodological procedure used in this study for processing the EEG data, please see Appendix E.

In prior studies of neurological engagement both alpha and beta signals have been found to be active in the frontal region of the brain (Grant, Courtermanche, Duerden, Duncan, & Rainville, 2010; Lazar et al., 2005; Holzel et al., 2011, McMahan et al., 2015a & 2015b). The average and standard deviation of participants' alpha and beta activity was calculated across the eight electrodes, that were located over the participants frontal brain region, AF3, F7, F3, FC5, FC6, F4, F8, and AF4. Muscle artefacts can add noise to the EEG data. In ERP research where the trials are on a small timescale, trials are excluded that are contaminated with muscle artefacts (Cohen, 2014). However, the present study involves the examination of an entire flow of 4-minutes of continuous EEG signal at 128Hz (approx. 30,000 data points).

Therefore, the alpha and beta values were obtained across the whole interaction, creating a larger timescale than ERP research. A further exploratory data analysis was conducted to ensure that outliers, such as possible muscle artefacts, did not affect the means and standard deviations of the participants' alpha and beta values. Therefore, calculations of the final mean and standard deviation values, for alpha and beta, involved removing any outliers in the data, through the use of an outlier labelling rule (Hoaglin & Iglewicz, 1987).

The outlier labelling rule involved using the interquartile range (IQR), IQR = Q4-Q1, with a multiplier of 2.2 (see Hoaglin & Iglewicz, 1987). An exploratory analysis found that due to the very large dataset per conversation for each individual (i.e., ~30,000 data points) the outliers did not affect the means, and only marginally affected the standard deviations for

the sample. All statistical analysis was completed on the filtered and outlier removed data, using IBM SPSS version 24.

Statistical analysis of neurological engagement measurement via EEG and post-hoc self-reported engagement for face-to-face conversations. The participants' individual overall alpha activity and beta activity means that were collected for conversation 1 and conversation 2, constituted the participants' neural engagement during face-to-face communication. Participants' post-hoc self-report on their engagement during the conversations, involved choosing one conversation as the one in which they were more engaged, rendering the other conversation as the less engaged. Thus, the participants' self-report effectively decided on the allocation of the alpha and beta activity means, to either a "most engaged EEG score" or a "least engaged EEG score". For example, for the alpha activity, if a participant marked on their self-report that they found the conversation more interesting with person 1, then the corresponding alpha mean values for conversation 1 were designated the "most engaged EEG score". Conversely, in this example the participant's "least engaged EEG score" would then be derived from the alpha mean values from conversation 2, with person 2. This allocation process was completed for both the alpha means and the beta mean values separately, so that each participant obtained four engagement scores for the two conversations they completed. Two engagement scores were for the alpha signal; a "most engaged EEG alpha score" and a "least engaged EEG alpha score", and two engagement scores were for the beta signal; the "most engaged EEG beta score" and the "least engaged EEG beta score".

A two tailed, paired sample *t*-test with an alpha level of 0.05 was used to compare the alpha most engaged EEG alpha scores ($M = 9.50$, $SD = 4.84$) with the least engaged EEG alpha scores ($M = 8.33$, $SD = 4.45$) for all the participants (Figure 6a). The difference was statistically significant, $t(41) = 2.28$, $p = .03$, and small to medium, $d = .35$. A two tailed,

paired sample *t*-test with an alpha level of 0.05 was also used to compare the beta most engaged EEG alpha scores ($M = 11.05$, $SD = 4.86$) with the least engaged EEG beta scores ($M = 10.37$, $SD = 4.13$) for all the participants (Figure 6b). No statistical difference was found, $t(41) = 1.26$, $p = .22$, and small, $d = 0.19$. The assumptions of normality and normality of difference scores were not violated.

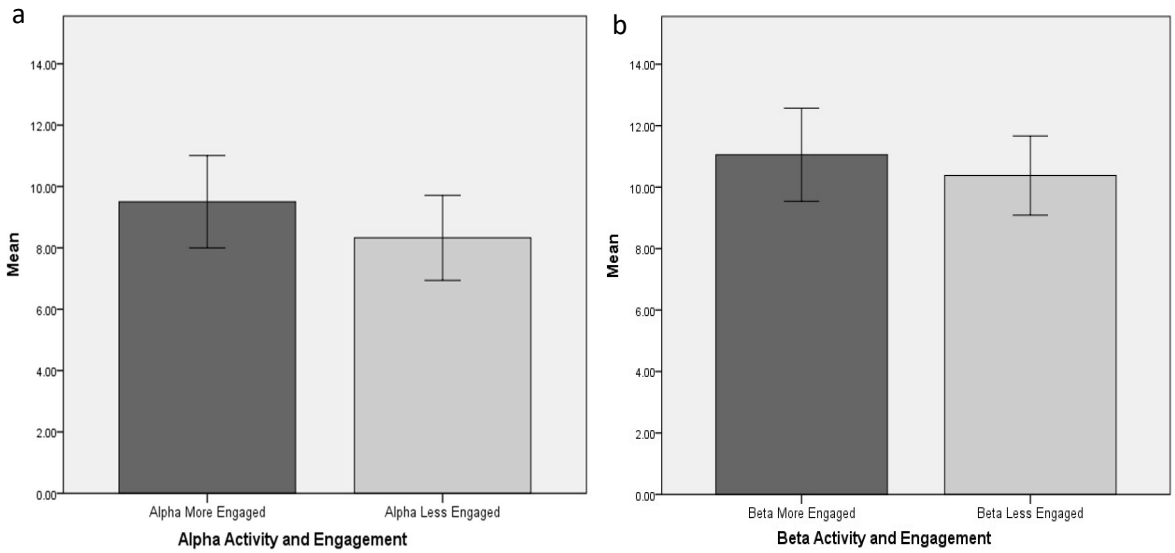


Figure 6. Means of alpha more engaged and less engaged with 95% confidence interval error bars (6a) and means of beta more engaged and less engaged with 95% confidence interval error bars (6b).

Statistical analysis of participants' variability of attention via EEG and post-hoc self-reported variability of attention for face-to-face conversations. The participants' individual overall alpha activity and beta activity means of the standard deviation values, that were collected for conversation 1 and conversation 2, constituted the participants' neural variability of attention during face-to-face communication. Participants' post-hoc self-report on their variability of attention during the conversations, involved choosing one conversation as more variable, rendering the other conversation as less variable. Thus, the participants' self-reports effectively decided on the allocation of the alpha and beta activity standard deviation means to either a "more variable attention EEG score" or a "less variable attention EEG score". For example, for the alpha activity, if a participant marked on their self-report that they found their attention in the conversation was more variable with person 1, then the

participant's corresponding alpha standard deviation mean value for conversation 1 was designated the "more variable attention EEG score". Conversely, in this example, the participant's "less variable attention EEG score" would then be derived from the participant's alpha standard deviation mean value from conversation 2, with person 2. This allocation process was completed for both the alpha and beta standard deviation mean values separately, so that each participant obtained four variability of attention scores for the two conversations they completed. Two scores were for the alpha signal; a "more variable attention EEG alpha score" and a "less variable attention EEG alpha score", and two engagement scores were for the beta signal; the "more variable attention EEG beta score" and the "less variable attention EEG beta score".

A two tailed, paired sample *t*-test with an alpha level of 0.05 was used to compare the alpha more variable attention EEG alpha scores ($M = 5.12$, $SD = 4.26$) with the less variable attention EEG alpha scores ($M = 5.28$, $SD = 4.54$) for all the participants (Figure 7a). There was no statistical significance found, $t(41) = .31$, $p = .76$, and small, $d = .05$. A two tailed, paired sample *t*-test with an alpha level of 0.05 was also used to compare the beta more variable attention EEG beta scores ($M = 5.17$, $SD = 2.65$) with the less variable attention EEG beta scores ($M = 5.85$, $SD = 3.53$) for all the participants (Figure 7b). No statistical difference was found, $t(41) = 1.88$, $p = .07$, and small, $d = 0.29$. The assumptions of normality and normality of difference scores were not violated.

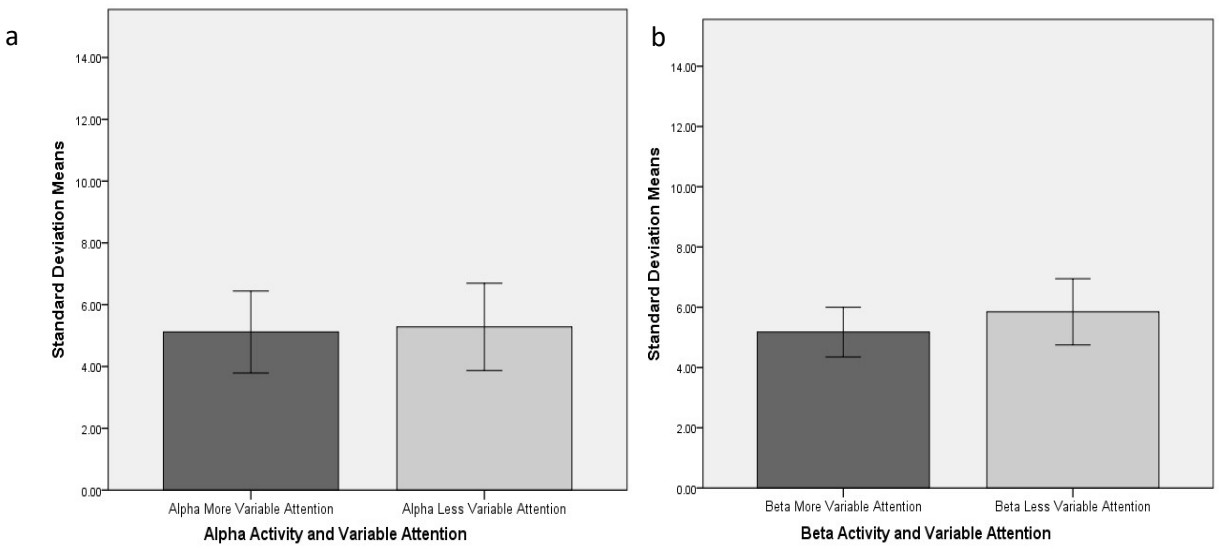


Figure 7. SD-means of alpha more and less variable attention with 95% confidence interval error bars (7a). SD-means of beta more and less variable attention with 95% confidence interval error bars (7b).

Additional findings. On closer inspection of the data a surprising uniformity was found between the separate conversations for both the dependent variables of alpha and beta activity for individual participants. Evidence for within-participant consistency was found across both alpha and beta activity mean scores. The alpha and beta activity SD-means also were consistent across both conversations.

To assess the size and direction of the linear relationship between participants' alpha conversation 1 mean scores, and alpha conversation 2 mean scores (Figure 8), a bi-variate Pearson's product-moment correlation co-efficient (r) was calculated. The bivariate correlation between these two variables was positive and strong, $r(40) = .71$, $p < .001$. Similarly, a bivariate Pearson's product-moment correlation coefficient (r) was calculated for participants' beta conversation 1 mean scores, and beta conversation 2 mean scores (Figure 9). The bivariate correlation between these two variables was also positive and strong, $r(40) = .70$, $p < .001$.

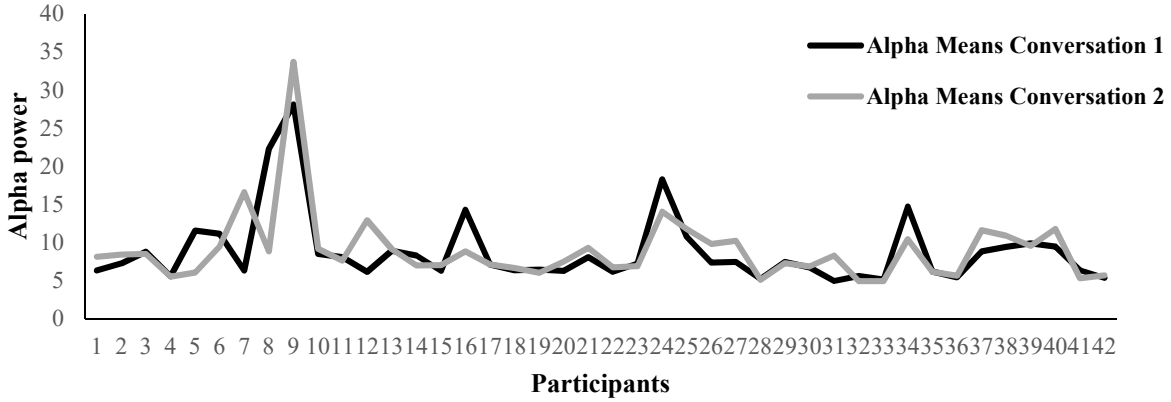


Figure 8. Alpha activity means for participants' conversation one and conversation two.

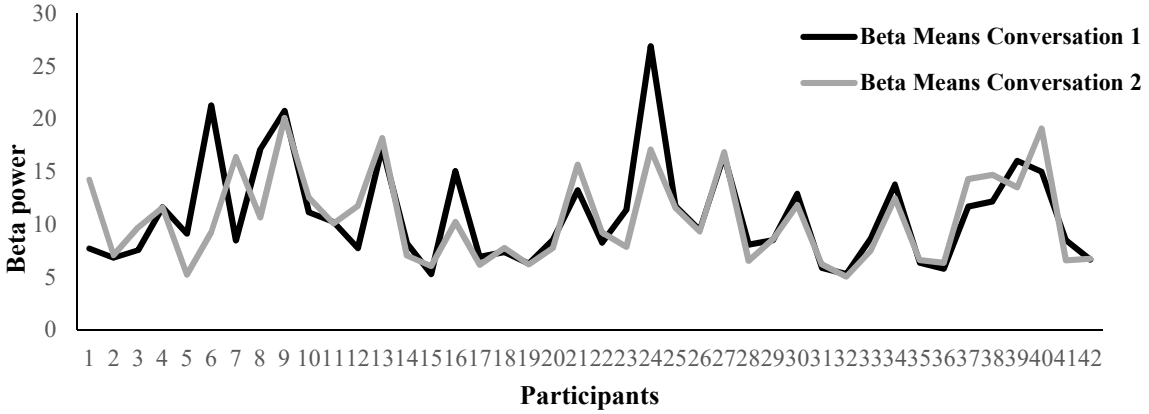


Figure 9. Beta activity means for participants' conversation one and conversation two.

To assess the size and direction of the linear relationship between participants' alpha conversation 1 SD-means scores, and alpha conversation 2 SD-means scores (Figure 10), a bi-variate Pearson's product-moment correlation co-efficient (r) was calculated. The bivariate correlation between these two variables was positive and strong, $r(40) = .69$, $p < .001$. Similarly, a bivariate Pearson's product-moment correlation coefficient (r) was calculated for participants' beta conversation 1 SD-means scores, and beta conversation 2 SD-means scores (Figure 11). The bivariate correlation between these two variables was also positive and strong, $r(40) = .72$, $p < .001$.

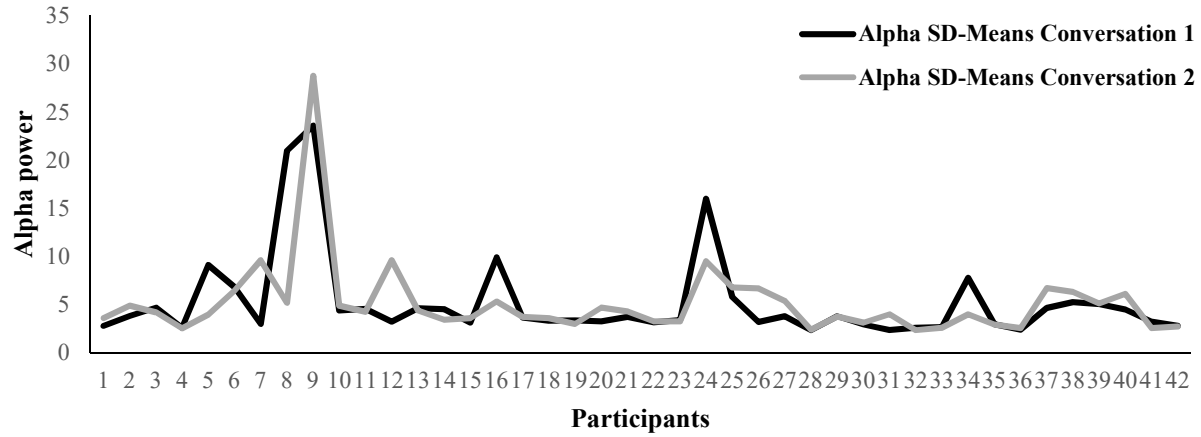


Figure 10. Alpha activity SD-means for participants' conversation one and conversation two.

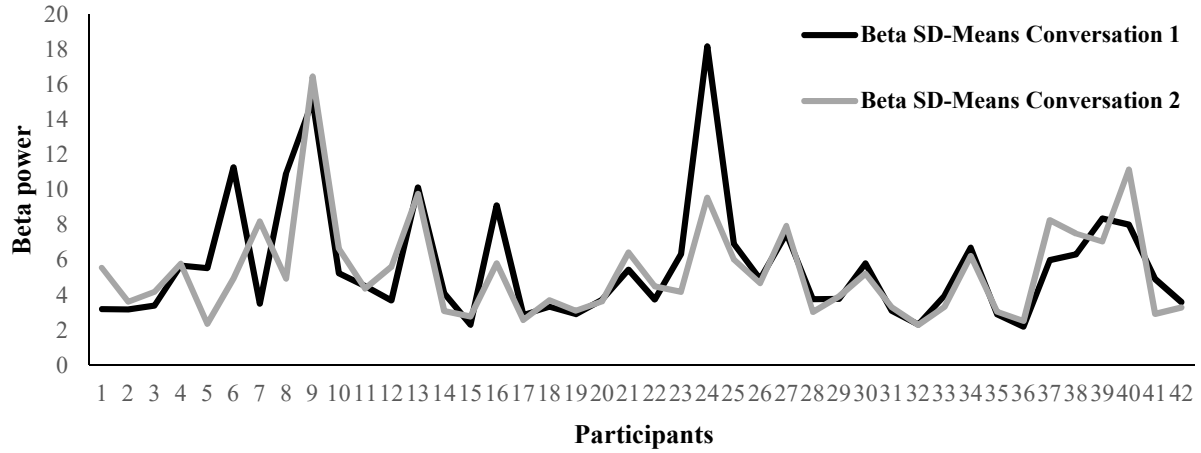


Figure 11. Beta activity SD-means for participants' conversation one and conversation two.

Discussion

The aim of this study was to examine the relationship between objective neurophysiological data (i.e., EEG) and subjective self-reported engagement obtained during and after face-to-face conversations. Participants engaged in two face-to-face conversations while wearing an Emotiv device. As expected, for the conversation that the participant rated as more engaging, their average alpha activity during that conversation was found to be higher in comparison to the conversation rated as less engaging, with a small to medium effect size. There was no significant difference found between the beta signal for participants when involved in more engaged versus less engaged conversations in this study. There was no significant difference found between the variability of attention for both the alpha and beta signal for participants and their self-reported variability of attention during their

conversations in this study. A surprising additional finding in this study was the uniformity in neurological measurements of alpha and beta activity for both conversations across the participants. The within-participants consistency was found for both the neurological measure of engagement and the neurological measure of variability of attention.

Neurological and Self-Reported Engagement During Interpersonal Communication

Previous research has found that neurological measures can be used when exploring engagement in a variety of contexts. Examples of the types of studies that have investigated neurological engagement include during video game play (McMahan et al., 2015a, 2015b), viewing natural versus urban scenes (Roe et al., 2013), when driving a car (Sena et al., 2016), when listening to music (Adamos, Dimitriadis, &Laskaris, 2016), during psychological therapy (Wrzesien et al., 2015), and when communicating (Goldberg et al., 2012).

In the current study the alpha and beta signal were recorded during face-to-face communication, as both signals are reported to have distinct responses to cognitive processes involving internal and external attention, which are associated with neurological engagement (Anderson et al., 2011; Pope et al., 1995). Studies have also used alpha and beta signal activity to measure neurological engagement successfully, such as, during task automation on a simulated flight deck for pilots (Freeman et al., 1999; Pope et al., 1995), and during video game play (McMahan et al., 2015a, 2015b).

Alpha. There are conflicting findings in the literature regarding the role of alpha activity as a marker of engagement. Some studies have reported a decrease in the activity of alpha during cognitive processes and sensory input (Ivanovski & Malhi, 2007; Sanei, 2013; Stern et al., 2001). This has led to alpha interpreted traditionally as a ‘cortical idling state’, that decreases upon the engagement of cognitive processes and sensory input from the external world (Cahn & Polich, 2006; Jensen & Mazaheri, 2010; Klimesch et al., 1998;

Sanei, 2013; Stern et al., 2001; Tuladhar et al., 2007). Other studies have found higher alpha activity during 'inner directed' activities such as during mindfulness meditation (Lomas et al., 2017). Also, higher activity has been shown to occur in athletes prior to executing a physical motor action (Shaw, 1996), and when using working memory to complete a modified Sternberg task (Jensen et al., 2002).

In the present study, alpha activity was found to be higher for conversations rated by the participants as more engaging. This finding is consistent with research using alpha as an indicator of task engagement (Cooper et al., 2006; Jensen et al., 2002; Shaw, 1996). When the participants in the present study reported being more engaged in a face-to-face conversation alpha activity was found to be higher. Face-to-face conversation draws upon attentional resources during listening when deciphering what the other person is saying, and during speaking when formulating utterances (Brennan, Galati and Kuhlen, 2010; Kuhlen et al., 2012). The employment of these attentional resources could be a factor behind the increase in alpha activity, signifying internal attention and demand. However, the precise reasons why alpha activity is associated with engagement is not entirely clear, and future research is needed.

Beta. Higher levels of beta activity have been reported in the literature as a marker of engagement. An increase in beta activity is associated with active thinking, attention and focus on the external environment (Caccioppo & Tassinary, 1990; Ivanovski & Malhi, 2007; Sanei, 2013; Stern 1991). Beta activity has been examined in studies on engagement, such as when using an automated flight deck system (Pope et al., 1995), when responding to visual stimuli in an adaptive automation system (Freeman et al., 1999), and during video game play (McMahan et al., 2015b).

In this study there was no significance found between the participants' subjective self-report of engagement and their beta activity, during face-to-face conversation. This suggests

that when the participants were subjectively more engaged with a conversation, this did not require more mental activity compared to a conversation that participants felt they were less engaged in. This is inconsistent with previous research that suggests beta activity is necessary to be considered in order to fully measure engagement (Freeman et al., Pope et al., 1995; 1999; McMahan et al., 2015b).

Neurological and Self-Reported Variability of Attention During Interpersonal Communication

Prior research has used neurological engagement indices to measure the *extent* of participant engagement. However, in the present research I also took the opportunity to examine if the *variability* of brain activity corresponds to self-reported variability of attention. Pickering and Garrod's (2004) Interactive Alignment Model states that attention is a crucial component of interpersonal communication. There was no significant relationship between participants' neural activity (alpha and beta) and their self-report of variability of attention, during the conversations. Therefore, the variability of both alpha and beta activity did not correspond with participant self-reported difference in variability of attention across the two conversations.

Within-Participant Consistency of Alpha and Beta Activity

In this study, an assumption was that participant EEG would vary substantially between conversations. This was predicted as brain activity was expected to vary, as a consequence of, the overall level of engagement of the participant during the different conversations. Therefore, an unexpected finding in the present study was a high level of within-participant consistency for EEG activity across conversations. That is, there was a strong correlation found between both conversations for all EEG measures: alpha activity, beta activity, alpha variability, and beta variability.

Previous psychophysiological studies using measures such as heart rate and skin conductance responses have also found a similar pattern of within-participant consistency. The stability of individual differences for heart rate response scores to psychological stressors are well documented (Matthews, Rakaczky, Stoney & Manuck, 1987). A study by Manuck and Garland (1980) examined a 13-month stability of heart rate responses and systolic blood pressure associated with completing a frustrating mental task (i.e., a difficult mental arithmetic test). They found a stability of heart rate responses for subjects between sessions, as well as a significant correlation between heart rate response and the accuracy level of the difficult mental arithmetic task. Turner, Carrol, Sims, Hewitt and Kelly (1986) also found stability within individuals when comparing heart rate responses to a video game over a 20-month interval in twins. Another study by Llabre et al. (1993) also reported a stability of individual differences with subjects' responses for heart rate response and a psychological stress response, when completing speech tasks.

Another physiological measure reported to exhibit consistency within-participants is skin conductance (Crider et al., 2004). For example, in a study by O'Gorman and Horneman (1979), subjects' skin conductance response was assessed during relaxation, vigilance and a mental arithmetic task. They found a large main effect size for individual differences. A similar study was completed by Crider et al. (2004) involving; middle-aged male twins, a rest period, a trial period consisting of a series of 1000Hz tones and a digit transformation task. Crider et al.'s study also found a within-participant consistency for both retest stability and cross-task consistency, as reported by O'Gorman and Horneman (1979).

The present study uncovered a within-participant consistency that is comparable with research studies that report a uniformity of psychophysiological measures and individual differences (Crider et al., 2004; Matthews et al., 1987; O'Gorman & Horneman, 1979;

Turner, 1989). The present study is also the first study to have shown within-participant consistency of neurological brain activity across face-to-face conversations.

Limitations

The findings of this study are based on a comparatively larger sample size (n = 42) compared to other similar studies using EEG to investigate neurological engagement. For example, McMahan et al. (2015a, 2015b), Sena et al. (2016), Wrzesien et al (2015), and Roe et al.'s (2013) research all used samples of between 3 and 30 participants. The present study also used a within-subjects design, which has the advantage over a between subject design in terms of increased power due to a reduction in error variance associated with individual differences (Charness, Gneezy & Kuhn, 2012; Rescorla, 2008). However, a limitation in the present study is that only two conversations were held for each participant, which may be the reason why the results reflected similarities for participants' self-reported engagement and beta activity, as well as, their self-reported variability of attention and both alpha and beta activity. Future studies could include more conversations to see if the similarity found in the present study remains or a difference occurs when participants have multiple conversations.

A further limitation of the present study is the use of subjective self-report (McCroskey & McCroskey, 1988; Schwarz, 1999). An aim of the present study was to address the current subjective limitations of self-report, by examining whether EEG could be a complimentary and objective measure of participants' engagement and variability of attention during face-to-face communication. Self-report relies on information from participants that cannot be independently verified and must be taken at face value (Campbell & Atas Akdemir, 2016; Dekeyser et al., 2008). Self-report can also contain participants' personal biases, such as, exaggeration, and or interpretation and understanding of the questions, which may lower the reliability of the data collected (McEwan & Guerrero, 2010). Although self-report is widely used in psychological research, it is important to understand

the limitations, in the present study (Schwarz, 1999). For example, although all possible precautions have been taken, participants' may still misinterpret or misunderstand, the question in the self-report questionnaire regarding their variability of engagement with person 1 or person 2. Therefore, participants could select the wrong person by marking person 1 as the conversation where they experienced more variability of engagement, when in fact they meant to select person 2 (McCroskey & McCroskey, 1988). Another example of how self-report could affect the data in the present study is simply that the wrong person and conversation is selected due to carelessness. Although it is expected to only be a small percentage of participants that would misinterpret the questions or mistakenly chose the incorrect conversation, it is important to know the limitations of self-report regarding participants' potential personal biases when using this form of data collection (Schwarz, 1999).

Future research

The present study involved the collection of EEG data continuously over two, 4-minute face-to-face conversations. Many EEG research studies use time-locked activity or event-related potentials (ERPs) that capture neural activity associated with both sensory and cognitive processes (Astolfi et al., 2007; Babiloni et al., 2001; 2008; Kuhlen et al., 2017; Nunez, 1995; Sur & Sinha, 2009). A more structured design would be to use ERPs that evoke neurological responses during face-to-face conversations with confederates. Confederates have been used successfully to evoke responses in ERP studies on deception (Carrión, Keenan, & Sebanz, 2010) and social conformity (Chen, Wu, Tong, Guan, & Zhou, 2012). Confederates could be used to further examine neurological engagement and variability of attention by acting bored or extremely interested during face-to-face conversations. Confederates could also ask specific questions at designated times to evoke specific responses or emotions from participants. The evoked responses could produce a difference in

alpha and beta activity, when participants talk about different conversational topics, such as good and bad experiences. These conversational topics may also evoke changes in participants' levels of engagement, such as in Goldberg et al.'s study (2012).

An additional finding of the present research was the within-participant consistency for both alpha and beta activity across two conversations. Future research involving a replication of this study that increases the number of conversations and conversational partners (i.e., more data collection points) is recommended, to see if the within-participant consistency found in this study remains constant over several conversations. This would also aid in addressing any potential discrepancy between conversations, as the self-reported engagement and beta activity was similar across the conversations, as was the self-reported variability of attention and both alpha and beta activity for participants. Having more conversations would increase the chances that the participants would have a 'more' or 'less' engaged conversation that could be compared.

An extension of the present study could be to include conversations with close friends to compare against the getting acquainted data. Research by Savitsky, Keysar, Epley, Carter and Swanson, (2011) found that people overestimate their success when communicating with close friends in comparison to strangers, and this is seen as "letting their guard down". In contrast they found that communication with strangers requires active monitoring of strangers' divergent perspectives. Examining Savistsky et al.'s (2011) findings on people's processing of information whilst communicating with strangers and with close friends, could see a difference in the amount of alpha and beta activity for engagement in face-to-face communication for participants. The findings of the present study warrant future research, through an extension or replication, towards a neurological engagement measure during face-to-face communication.

Conclusion

The current study has investigated whether EEG can be used to predict engagement during face-to-face conversations. An examination using self-report and EEG was undertaken on the communication components of engagement and attention, which are both seen to be crucial during interpersonal communication (Pickering & Garrod, 2004). The findings from this study were that the overall alpha activity of participants was higher when they reported more engagement in the conversations, and decreased when reporting less engagement in the conversations. However, there was no significant relationship between beta activity and engagement. There were also no significant relationships found between the participants' variability of attention in their self-reported engagement, and their EEG data across the two conversations. A surprise additional finding of within-participant consistency for both alpha and beta activity across both conversations, is suggestive of a relatively stable level of neurological activity within individuals, during a complex activity such as face-to-face conversation. The within-participant consistency found in this study is consistent with findings of psychophysiological studies involving heart-rate response (Tuner et al., 1986, Llabre et al. 1992, Manuck & Gardner, 1980) and skin conductance response (Crider et al., 2004; O'Gorman & Horneman, 1979). Further investigation into the consistency of neural activity during communication is warranted.

The present study also builds on previous research that EEG is a tool that can be used alongside other tools such as self-report to gather information on the complexities of interpersonal interactions. Understanding an individual's brain signal pattern that occurs when in various states of engagement during interpersonal interactions, as well as, the individual's awareness of their varying states of engagement, has the potential to be of use for both clinical (Arns et al., 2009; Friel, 2007; Myers & Young, 2012) and non-clinical application (Janz et al., 2015; MacLean et al., 2016; Pepping et al., 2017; Schneider, 1992).

References

Adamos, D. A., Dimitriadis, S. I., Laskaris, N. A. (2016). Towards the bio-personalisation of music recommendation systems: A single-sensor EEG biomarker of subjective music preference. *Information Sciences, 94*(108), 343-344.

Ahani, A., Wahbeh, H., Nezamfar, H., Miller, M., Erdogmus, D., & Oken, B. (2014). Quantitative change of EEG and respiration signals during mindfulness meditation. *Journal of Neuroengineering and Rehabilitation*, *87*, 1-11.

Aissani C, Martinerie J, Yahia-Cherif L, Paradis A-L, Lorenceau, J. (2014). Beta, but Not Gamma, Band Oscillations Index Visual Form-Motion. *PLoS ONE, 9*(4): e95541. https://doi.org/10.1371/journal.pone.0095541

Amodio, D. M., & Firth, C. D. (2006). Meeting of the minds: the medial frontal cortex and social cognition. *Nature Reviews Neuroscience*, *7*(4), 268-277.

Anderson, E. W., Potter, K. C., Matzen, L. E., Shepherd, J. F., Preston, G. A., & Silva, C. T. (2011). A user study of visualization effectiveness using EEG and cognitive load. *Computer Graphics Forum*, *30*(3), 791-800.

Andreassi, J. L. (1995). *Psychophysiology: Human Behaviour and Physiological Response.* Hillsdale, N.J: L. Erlbaum Associates.

Arns, M., de Ridder, S., Strehl, U., Breteler, M., & Coenen, A. (2009). Efficacy of neurofeedback treatment in ADHD: the effects of inattention, impulsivity, hyperactivity: a meta-analysis. *Clinical EEG and Neuroscience, 40*(3), 180-189.

Astolfi, L., Toppi, J., De Vico Fallini, F., Vecchiato, G., Salinari, S., Mattia, D., … Babiloni, F. (2010). Neuroelectrical hyperscanning measures simultaneous brain activity in humans. *Brain Topography*, *23*, 243-256.

Babiloni, F., Carducci, F., Cincotti, F., Del Gratta, C., Pizella, V., Romani, G. L., Rossini, P. M.,…& Babiloni, C. (2001). Linear inverse source estimate of combined EEG and MEG data related to voluntary movements. *Human Brain Mapping, 14*(4), 197-209.

Badcock, N. A., Mousikou, P., Mahajan, Y., Lissa, P., Thie, J., & McArthur, G. (2013). Validation of the Emotiv Epoc EEG gaming system for measuring research quality auditory ERPs. *Peer J*, *38*, 1-17.

Berrios, R., Totterdell, P., & Niven, K. (2013). Why do you make us feel good? Correlates and Interpersonal Consequences of Affective Presence in Speed-dating*, European Journal of Personality*, *29*(1)*,* 72–82. doi*:* 10.1002/per.1944.

Berkovich-Ohana, A. (2017). A case study of meditation-induced altered state: increased overall gamma synchronisation. *Phenomenology and the Cognitive Sciences*, *16*(1), 91-106.

Bolton, R. (1991). *People skills: How to assert yourself, listen to others, and resolve conflicts.* Brookvale, Australia: Simon & Schuster.

Borghini, G., Astolfi, L., Vecchiato, G., Mattia, D., & Babiloni, F. (2014). Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness. *Neuroscience and Biobehavioural Reviews, 44*, 58-75.

Brennan, S. E., Galati, A., & Kuhlen, A. K. (2010). Chapter 8 - two minds, one dialog: coordinating speaking and understanding. *Psychology of Learning and Motivation*, *53*, 301-344.

Cacioppo, J. T., & Tassinary, L. G. (1990). Psychophysiology and psychophysiological inference. In J. T. Cacioppo & L. G. Tassinary (Eds.), *Principles of psychophysiology: Physical, social, and inferential elements* (pp. 3-33). New York: Cambridge University Press.

Cahn., B. R., & Polich, J. (2006). Meditation states and traits: EEG, ERP and neuroimaging studies. *Psychological Bulletin, 132*(2), 180-211.

Caldwell, J. A., Hall, K. K., & Erickson, B. S. (2002). EEG data collected from helicopter pilots in flight are sufficiently sensitive to detect increased fatigue from sleep deprivation. *The International Journal of Aviation Psychology*, *12*(1), 19-32.

Campbell, J., & Atas Akdemir, O. (2016). The development of interpersonal communication scale: the study of validity and reliability. *International Periodical for the Languages, Literature and History of Turkish or Turkic, 11*(19), 859-872.

Carney, D., Colvin, R., & Hall, J. A. (2007). A thin slice perspective on the accuracy of first impressions. *Journal of Research in Personality, 41*(5), 1054-1072.

Carrión, R. E., Keenan, J. P., & Sebanz, N. (2010). A truth that's told with bad intent: An ERP study of deception. *Cognition*, *114*(1), 105-110.

Cerquera, A., Arns, M., Buitrago, E., Gutiérrez, R., & Freund, J. (2012, August). Nonlinear dynamics measures applied to EEG recordings of patients with Attention Deficit/Hyperactivity Disorder: Quantifying the effects of a neurofeedback treatment. *Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE* (pp. 1057-1060). IEEE

Charness, G., Gneezy, U., & Kuhn, M. A. (2012). Experimental methods: Between-subject and within-subject design. *Journal of Economic Behavior & Organization*, *81*(1), 1-8.

Chen, J., Wu, Y., Tong, G., Guan, X., & Zhou, X. (2012). ERP correlates of social conformity in a line judgment task. *BMC Neuroscience, 13*(1), 43.

Chiesa, A., & Serretti, A. (2010). A systematic review of neurobiological and clinical features of mindfulness meditations. *Psychological Medicine, 40*, 1239-1252.

Cohen, M (2014). *Analysing neural time series data: theory and practice.* London, England: MIT Press.

Cooper, N. R., Burgess, A. P., Croft, R. J., & Gruzelier, J. H. (2006). Investigating evoked and induced electroencephalogram activity in task-related alpha power increases during an internally directed attention task. *Neuroreport*, *17*(2), 205-208.

Crider, A., Kremen, W. S., Xian, H., Jacobson, K. C., Waterman, B., Eisen, S. A., ... & Lyons, M. J. (2004). Stability, consistency, and heritability of electrodermal response lability in middle-aged male twins. *Psychophysiology*, *41*(4), 501-509.

Dekeyser, M, Raes, Leijssen, M., Leysen, S., & Dewulf, D. (2008). Mindfulness skills and interpersonal behaviour. *Personality and Individual Differences, 44*(5)*,* 1235-1245.

De Jaegher, H., Di Paolo, E., & Gallagher, S. (2010). Can social interaction constitute social cognition? *Trends in Cognitive Science, 14*(10), 441-447.

Dunbar, R., Marriott, A., & Duncan, N. D. (1997). Human conversational behaviour. *Human Nature, 8*(3), 231-246.

Dunn, B. R., Hartigan, J. A., & Mikulas, W. L. (1999). Concentration and mindfulness meditations: unique forms of consciousness. *Applied Psychophysiology and Biofeedback, 24*(3), 147-165.

Duvinage, M., Castermans, T., Petieau, M., Hoellinger, T., Cheron, G., & Dutoit, T. (2013). Performance of the Emotiv Epoc headset for P300-based applications. *Biomedical Engineering Online*, *12*(1), 1-15.

Eaton, L. G., & Funder, D. C. (2003). The creation and consequences of the social world: an interactional analysis of extraversion. *European Journal of Personality, 17*(5), 375-395.

Emotiv. (2014). Emotiv EPOC User Manual. Retrieved from https://emotiv.zendesk.com/hc/en-us/article.../EPOCUserManual2014.pdf

Engel, A. K., & Fries, P. (2010). Beta-band oscillations - signalling the status quo? *Current Opinion in Neurobiology, 20*, 156-165.

Escolano, C., Navarro-Gil, M., Garcia-Campayo, J., Congedo, M., & Minguez, J. (2014). The effects of individual upper alpha neurofeedback in ADHD: an open label pilot study. *Applied Psychophysiology Biofeedback*, *39*, 193-202.

Fakhruzzaman, M. N., Riksakomara, E., Suryotrisongko, H. (2015). EEG wave identification in human brain with Emotiv Epoc for motor imagery. *Procedia Computer Science*, *72*, 269-276.

Firth, C. D., & Firth, U. (1999). Interacting minds - a biological basis. *Science, 286*(5445), 1692-1695.

Freeman, F., Mikulka, P, Prinzel, L., & Scerbo, M. (1999) Evaluation of an adaptive automation system using three EEG indices with a visual tracking task. *Biological Psychology, 50*, 61-76.

Ferdjallah, M., & Barr, R. E. (1994). Adaptive digital notch filter design on the unit circle for the removal of powerline noise from biomedical signals. *IEEE Transactions on Biomedical Engineering, 41*(6), 529-536.

Friel, P. N. (2007). EEG Biofeedback in the Treatment of Attention Deficit Hyperactivity Disorder. *Alternative Medicine Review, 12*(2), 146– 151.

Goldberg, B., Brawner, K., & Holden, H. (2012). Efficacy of measuring engagement during computer-based training with low-cost electroencephalogram (EEG) sensor outputs. *Proceedings of the Human Factors and Ergonomics Society 56th Annual Meeting, 56*(1), 198-202.

Grant, J. A., Courtemanche, J., Duerden, E. G., Duncan, G. H., & Rainville, P. (2010). Cortical thickness and pain sensitivity in zen masters. *Emotion, 10*(1), 43-53.

Guntekin, B., Emek-Savas, D. D., Kurt, P., Yener, G. G., & Basar, E. (2013). Beta oscillatory responses in healthy subjects and subjects with mild cognitive impairment. *Neuroimage: Clinical*, *3*, 39-46.

Hargie, O. H. O. (2011). *Skilled Interpersonal Communication*. Florence: Taylor and Francis. Retrieved from https://ebookcentral.proquest.com/lib/ECU/detail.action?docID=574564

Hardstone, R., Poil, S-S., Schiavone, G., Jansen, R., Nikulin, V. V., …Linkenkaer-Hansen, K. (2012). Detrended fluctuation analysis: a scale-free view on neuronal oscillations. *Frontiers in Psychology, 3*(450), 1-13.

Hari, R., & Kujala, M. V. (2009). Brain basis of human social interaction: form concepts to brain imaging. *Physiological Review, 89*(2), 453-459.

Hoaglin, D. C., & Iglewicz, B. (1987). Fine-tuning some resistant rules for outlier labelling. *Journal of the American Statistical Association, 2*(400), 1147-1149.

Howitt, J. S., Hay, A. E., Shergold, G. R., & Ferres, H. M. (1978). Workload and fatigue-in-flight EEG changes. *Aviation, Space, and Environmental Medicine, 49,* 1197-1202.

Ivanovski, B., & Malhi, G.S. (2007). The psychological and neurophysiological concomitants of mindfulness forms of meditation. *Acta Neuropsychiatrica*, *19*, 76-91.

Janz, P., Pepping, C. A., & Halford, W. K. (2015). Individual differences in dispositional mindfulness and initial romantic attraction: a speed dating experiment. *Personality and Individual Differences, 82*, 14-19.

Jensen, O., Gelfand, J., Kounios, J., & Lisman, J. E. (2002). Oscillations in the alpha band (9-12Hz) increase with memory load during retention in a short-term memory task. *Cerebral Cortex, 12*, 877-882.

Jensen, O., & Mazaheri, A. (2010). Shaping functional architecture by oscillatory alpha activity.: gating by inhibition. *Frontier in Human Neuroscience, 4*(186), 1-8.

Klimesch, W., Doppelmayr, M., Russegger, H., Pachinger, T., & Schwaiger, J. (1998). Induced alpha band power changes in the human EEG and attention. *Neuroscience Letters*, *244*, 73-76.

Korobov, N. (2011). Mate-preference talk in speed-dating conversations. *Journal of Research on Language and Social Interaction, 44*(2), 186-209.

Kuhlen, A., Allefeld, C., & Haynes, J-D. (2012). Content-specific coordination of listeners' to speakers' EEG during communication. *Frontiers in Neuroscience, 6*(266), 1-15.

Kuhlen, A.K., Bogler, C., Brennan, S. E., & Haynes, J-D. (2017). Brains in dialogue: decoding neural preparation of speaking to a conversational partner. *Social Cognitive and Affective Neuroscience*, *12*(6), 871-880.

Llabre, M. M., Saab, P. G., Hurwitz, B. E., Schneiderman, N., Frame, C. A., Spitzer, S., & Phillips, D. (1993). The stability of cardiovascular parameters under different behavioural challenges: one-year follow-up. *International Journal of Psychophysiology, 14*(3), 241-248.

Lagopoulos, J., Xu, J., Rasmussen, I., Vik, A., Malhi, G. S., Eliassen, C. F., …Ellingsen, O. (2009). Increased theta and alpha EEG activity during non-directive meditation. *The Journal of Alternative and Complimentary Medicine, 15*(11), 1187-1192.

Leventhal, D. K., Gage, G. J., Schmidt, R., Pettibone, J. R., Case, A. C., Berke, J. D. (2012). Basal ganglia beta oscillations accompany cue utilization. *Neuron*, *73*(3), 523–536.

Lo, P-C., Huang, M-L., Chang, K-M. (2003). EEG alpha blocking correlated with perception of inner light during zen meditation. *The American Journal of Chinese Medicine, 31*(4), 629-642.

Lomas, T., Ivtzan, I., & Fu, C. H. Y. (2017). A systematic review of the neurophysiology of mindfulness on EEG oscillations. *Neuroscience and Biobehavioural Reviews*, *57*, 401-410.

Lubar, J.F. (1991). Discourse on the development of EEG diagnostics and biofeedback for attention-deficit/hyperactivity disorders. *Biofeedback and Self-Regulation, 16*(3), 201-225.

Lutz, A., Slagter, H. A., Dunne, J. D., & Davidson, R. J. (2008). Attention regulation and monitoring in meditation. *Trends in Cognitive Sciences, 12*(4), 163-169. doi: 10.1016/j.tics.2008.01.005

McCroskey, J. L., & McCroskey, L. L. (1988). Self-report as an approach to measuring communication competence. *Communication Research Reports, 5*(2), 108-113.

McEwan, B., & Guerrero, L. (2010). Freshmen engagement through communication: Predicting friendship formation strategies and perceived availability of network resources from communication skills. *Communication Studies, 61*(4), 445-463.

McMahan, T., Parberry, I., & Parsons, T. D. (2015a). Evaluating electroencephalography engagement indices during video game play. *UNT University of North Texas, Technical Report LARC-2015-03*.

McMahan, T., Parberry, I., & Parsons, T. D. (2015b). Modality specific assessment of video game player's experience using the Emotiv. *Entertainment Computing, 7*, 1-6.

MacLean, S., Kelly, M., Geddes, F., & Della, P. (2017). Use of simulated patients to develop communication skills in nursing education: an integrative review. *Nurse Education Today, 48*, 90-98.

Manuck, S. B., & Garland, F. N. (1980). Stability of individual differences in cardiovascular reactivity: a thirteenth-month follow-up. *Physiology & Behaviour, 24*(3)*,* 621-624.

Matthews, K. A., Rakaczky, C. J., & Stoney, C. M., & Manuck, S. B. (1987). Are cardiovascular responses to behavioural stressors a stable individual difference variable in childhood. *Psychophysiology, 24*(4), 464-473.

Myers, J. E., & Young, J. S. (2012). Brain wave biofeedback: benefits of integrating neurofeedback in counselling. *Journal of Counselling & Development*, *90*, 20-28.

Nunez, P. L. (1995). *Neocortical dynamics and human EEG rhythms*. Oxford: Oxford University Press.

O'Gorman, J. G., & Horneman, C. (1979). Consistency of individual differences in non-specific electrodermal activity. *Biological Psychology*, *9*(1), 13-21.

Pepping, C. A., Taylor, R., Koh, K., Halford, W. K. (2017). Attachment, culture and initial romantic attraction: a speed-dating study. *Personality and Individual Differences, 108*, 79-85.

Pennings, H. J. M., Brekelmans, M., Sadler, P., Claessens, L. C. A., van der Want, A. C., & van Tartwijk, J. (in press). Interpersonal adaption in teacher-student interaction. *Learning and Instruction,* 1-17. http://dx.doi.org/10.1016/j.learninstruc.2017.09.005

Pickering, M. J., & Garrod, S. (2004). Toward a mechanistic psychology of dialogue. *Behavioural and Brain Sciences*, *27*(2), 169-190.

Pope, A., Bogart, E., & Bartolome, D. (1995). Biocybernetic system evaluates indices of operator engagement in automated task. *Biological Psychology*, *40*(1), 187-195.

Rieder, M. K., Rahm, B., Williams, J. D., & Kariser, J. (2011). Human gamma-band activity and behaviour. *International Journal of Psychophysiology, 79*(1), 39-48.

Roe, J., Aspinall, P., Mavros, P., & Coyne, R. (2013). Engaging the brain: The impact of natural versus urban scenes using novel EEG methods in an experimental setting. *Environmental Science, 1*(2), 93-104.

Royall, D. R., Lauterbach, E. C., Cummings, J. L., Reeve, A., Rummans, T. A., Kaufer, D. I., …Coffey, E. C. (2002). Executive control function: a review of its promise and

challenges for clinical research. Journal of *Neuropsychiatry & Clinical Neuroscience, 14*(4), 377-405.

Rouhinen, S., Panula, J., Palva, J. M., & Palva, S. (2013). Load dependence of β and γ oscillations predicts individual capacity of visual attention. *Journal of Neuroscience*, *33*(48), 19023-19033.

Rukavishnikova, E. E. (2016). Specific psychological characteristics of interpersonal relationships in preschool children. *Procedia – Social and Behavioural Sciences*, *233*, 118-122.

Salminen, M., & Ravaja, N. (2007). Oscillatory brain responses evoked by video game events: the case of Super Monkey Ball 2. *CyberPsychology & Behavior*. *10*(3), 330–338.

Salenius, S., Portin, K., Kajola, M., Salemin, R., & Hari, R. (1997). Cortical control of human motoneuron firing during isometric contraction. *Journal of Neurophysiology, 77*(6), 3401-3405.

Sanei, S. (2013). *Adaptive processing of brain signals.* West Sussex, United Kingdom: John Wiley & Sons Ltd.

Savitsky, K., Keysar, B., Epley, N., Carter, T., & Swanson, A. (2011). The closeness-communication bias: Increased egocentrism among friends versus strangers. *Journal of Experimental Social Psychology*, *47*(1), 269-273.

Schneider, B. H. (1992). Didactic methods for enhancing children's peer relations: a quantitative review. *Clinical Psychology Review,* 12, 363-382.

Schwarz, N. (1999) Self reports: how the questions shape the answers. *American Psychologist, 54*(2), 95-105.

Sena, P., D'Amore, M., Brandimonte, M., Squitieri, R., & Fiorentino, A. (2016). Experimental framework for simulators to study driver cognitive distraction: brake reaction time in different levels of arousal. *Transport Research Arena, 14,* 4410-4419.

Shallice, T. (1988). *From neuropsychology to mental structure*, Cambridge: Cambridge University Press.

Sharp, K.C. (1981). Impact of interpersonal problem-solving training on pre-schoolers social competency. *Journal of applied developmental psychology, 2*(2), 129-143.

Shaw, J. C. (1996). Intention as a component of the alpha-rhythm response to mental activity. *International Journal of Psychophysiology*, *24*(1), 7-23.

Smith, E. E., & Jonides, J. (1999). Storage and executive processes in the frontal lobes. *Science*, *283*(5408), 1657-1661. doi: 10.1126/science.283.5408.1657

Stern, R. M., Ray, W. J., & Quigley, K. S. (2001). *Psychophysiological recording*. New York: Oxford University Press.

Stopczynski, A., Stahlhut, C., Larsen., E. J., Petersen, M. K., Hansen, L. K. (2014). The smartphone brain scanner: a portable real-time neuroimaging system. *PLoS ONE, 9*(2), 1-10.

Sur, S., & Sinha, V. K. (2009). Event-related potential: An overview. *Industrial psychiatry journal*, *18*(1), 70.

Turner, J. R., Carroll, D., Sims, J., Hewitt, J. K., & Kelly, K. A. (1986). Temporal and inter-task consistency of heart-rate reactivity during active psychological challenge: a twin study. *Physiology & Behaviour, 38*(5)*,* 641-644.

Turner, J. R. (1989). Individual differences in heart rate response during behavioural challenge. *Psychophysiology, 26*(5), 497-505.

Tuladhar, A. M., Huurne, N., Schoffelen, J-M., Maris, E., Oostenwald, R., & Jensen, O. (2007). Parieto-occipital sources account for the increase in alpha activity with working memory load. *Human Brain Mapping*, *28*(8), 785-792.

Vago, D. R., & Silbersweig, D. A. (2012). Self-awareness, self-regulation, and self-transcendence (S-ART): a framework for understanding the mechanisms of mindfulness. *Frontiers in Human Neuroscience, 6*(296),1-30.

Vincent, J., & Lledo, P. (2014). *The custom-made brain: cerebral plasticity, regeneration, and enhancement*. Retrieved from http://ebookcentral.proquest.com

Walter, W. G. (1953). *The living brain*. New York: Penguin.

Widmann, A., Schroger, E., & Maess, B. (2015). Digital filter design for electrophysiological data – a practical approach. *Journal of Neuroscience Methods, 250,* 34-46.

Wrzesien, M., Rodríguez, A., Rey, B., Alcañiz, M., Baños, R-M., & Vara, M. D. (2015). How the physical similarity of avatars can influence the learning of emotion regulation strategies in teenagers. *Computers in Human Behaviour, 43*, 101-111.

Ybarra, O., Burnstein, E., Winkielman, P., Keller, M. C., Manis, M., Chan, E., Rodriguez, J. (2008). Mental exercising through simple socialising: social interaction promotes general cognitive functioning. *Personality and Social Psychology Bulletin, 34*(2), 248-259.

Appendix A

Recruitment Advertisement

Volunteers sought for EEG conversation study

April 2017

- Downloads
- Information Letter
  PDF, (45.3 KB)

This study seeks to better understand what elements contribute to an enjoyable conversation. Participants will be reimbursed with a **$20 Coles/Myer voucher** to compensate their time/travel. Volunteers are sought to come to the ECU Cognition lab (located at Joondalup campus, building 8) to engage in some conversation with each other.

Participants will wear the Emotiv EPOC a wireless EEG device, that captures electrical neural activity (brain wave patterns of thought) from a person's scalp non-invasively. If you are interested in meeting some other ECU students, and learning about some new research technology, then please email Brooke Maddestra (Psychology Honours Student) for more information. Please put 'EEG conversation study' in the subject heading of the email.

Study participation should take approximately 1 hour. You will be free to ask questions at any time throughout the study, and you are also free to withdraw your participation at any time. The research project has been approved by the ECU Human Research Ethics Committee.

Research Contact: brookemaddestra@our.ecu.edu.au

Research Supervisors

Dr Shane Rogers (lecturer in ECU psychology department)

Email: shane.rogers@ecu.edu.au

Professor Craig Speelman (Professor of Psychology)

Email: c.speelman@ecu.edu.au

AUSTRALIA ECU EDITH COWAN UNIVERSITY
JOONDALUP CAMPUS
270 Joondalup Drive, Joondalup
Western Australia 6027
☎ 134 328
www.ecu.edu.au
ABN 54 361 485 361 CRICOS IPC 00279B

Appendix B

Information Letter

EEG conversation study

Dear Participant,

This study is to examine whether EEG data can be used to predict engagement during face-to-face communication. As a participant you will be fitted with an Emotiv EPOC EEG headset. The non-invasive lightweight wireless device will be placed on your head and 16 points of contact will be placed on your scalp (14 data collection electrodes with saline dampened foam and two rubber reference points) for the duration of the experiment. How the device works will be fully explained by the experimenter, if you have any questions during this explanation, please do not hesitate to ask.

Then you will engage in a series of 4 minute *getting acquainted* conversations with other participants. On completion of your conversations you will answer two questions to rate your experience. Note, these ratings will be completely confidential and will **not** be revealed to the other participants at any time. During the conversations a recording will be made via video camera. The audio-visual recordings will only be examined for compiling statistics to be analysed for research reports and be presented as statistics in charts.

The session should take approximately 45 mins. Participation in this study is entirely voluntary, with no pressure to participate and no consequences for electing not to participate. You are free to ask questions at any time throughout the study and you are also free to withdraw your participation at any time.

All data collected will be stored securely and confidentiality will be maintained. There is also potential that collected data will be used for publication purposes, and reanalysed as part of 4th year or Masters level student research projects. The research project has been approved by the ECU Human Research Ethics Committee. If you have any concerns or complaints regarding the research project and would like to speak to an independent person, please contact the Research Ethics Officer on 6304 2170 or via email research.ethics@ecu.edu.au

Sincerely yours,

Researcher: Brooke Maddestra
ECU Psychology Honours Student
bmaddest@our.ecu.edu.au

Principle Research Supervisor: Dr Shane Rogers
Lecturer @ School of Psychology, Arts and Humanities
Edith Cowan University, Joondalup Campus
Email: shane.rogers@ecu.edu.au | P: +61 8 63045728

Research Co-Supervisor: Professor Craig Speelman
Associate Dean Research
Professor of Psychology
Director of the Cognition Research Group School of Arts and Humanities
Email: c.speelman@ecu.edu.au | P: +61 8 6304 5724

AUSTRALIA ECU EDITH COWAN UNIVERSITY
JOONDALUP CAMPUS
270 Joondalup Drive, Joondalup
Western Australia 6027
☎ 134 328
www.ecu.edu.au
ABN 54 361 485 361 CRICOS IPC 00279B

Appendix C

Consent Form

EEG conversation study

I, _____, have read the information provided in the information letter and I'm satisfied that any questions I have asked have been answered adequately.

I understand that I can choose to withdraw my participation at any time throughout the study. I agree that the data collected will be used for the current study and potentially published in a research article. I also understand that the recordings will be securely stored and may be further analysed at a later date. I understand that my questionnaire responses will be stored with no identifying information and therefore my responses are anonymous. I also understand that the audio/visual recordings will not be used for any other purpose than for compiling statistics to be analysed for research reports. The statistics will be presented in charts instead of the videos being presented in the write up of the research. Any footage of me will NOT be viewed by anyone outside of the ECU Cognition research group, and will NOT be publicly posted or presented anywhere without my express permission (see below).

I consent to participating in this research.

Signed_____ Date_____

Additionally, I consent and give permission that video or images of myself obtained during participation can be used to assist in communication of the research via journal article publications, University lectures, media articles, or social media posts.

Please tick:

☐ Yes, I give permission

☐ No, I only consent to recordings and images to be viewed for research purposes only.

Appendix D

EEG Experiment and Data Capture Using the Emotiv EPOC Procedure

Introduction

The following procedure outlines the initial set-up, EEG data collection and pack-up processes, in numerical order, for the research on EEG predicting engagement during natural conversations. This all EEG data collection from participants engaged in 4-minute face-to-face getting acquainted conversations. All EEG data was captured using the Emotiv EPOC EEG wireless and portable headsets. All the necessary hardware and software for data set-up and capture was available and owned by the Communication Research Laboratory, which is part of the broader Cognition Research Laboratory at Edith Cowan University, for this experiment.

Initial Set-up (Duration is approximately 30 minutes to set-up experiment)

1. Ensure that all foam inserts for the Emotiv EPOC headset are adequately wet with saline solution.
2. Place foam inserts into the electrodes of all of the Emotiv EPOC headsets.
3. Turn on video recorders
4. Turn on laptops and open 'clocks' by using the Wi-Fi, then turn off Wi-Fi.
5. Open Emotiv Testbench onto the lap top screen.
6. Have headsets ready and dongles inserted into USB on laptops prior to participants arriving.
7. Participants then must complete the following forms prior to any involvement in the experiment:
    a. Consent forms
    b. Initial conversation questionnaires.
8. Be familiar and ensure all the points in the introductory instructions to participants are delivered as below:

    Thank you for volunteering in this lab experiment on communication. You will undergo two conversations each in a round robin fashion. Conversations will last four minutes. When you are waiting your turn, you will wait in the common area. On completion of your conversations a self-report survey will be completed.

    So, that we can get the most out of your valuable time we ask that you help with the following:

    Please leave mobile phones in bags outside of research room prior to entering and to turn off wi-fi to limit equipment interference.

    We ask that you do not touch the headsets when they have been set up on your heads.

If you have your hair up in clips or with items that could stop the Emotiv EPOC device from sitting easily on your head can you, please remove for the duration of the experiment.

Thank you.

Conversation EEG data capture (Duration is approximately 1 hour to run the experiment)

9. When placing headsets on all the participants ensure that all electrodes are touching the scalp, move hair out of the away if needed. Participants with long hair are to tie it up into a high 'pony tail' on top of their head out of the way of all the electrodes to make it easier to get electrode-to-scalp contact. Hair ties are supplied by the researchers.
10. Place headsets on all two participants in the designated research room (see Figure 1.) and turn on the headsets.

Figure C1. Designated research room where getting-to-know-you acquaintance conversations EEG data is collected for the experiment between two participants at a time.

11. Place a headset on the third participant in the common area and turn on the headsets.
12. Check headsets are all showing green for the nodes on the required laptops that are situated next to them. See Figure 2 for correct position of nodes.

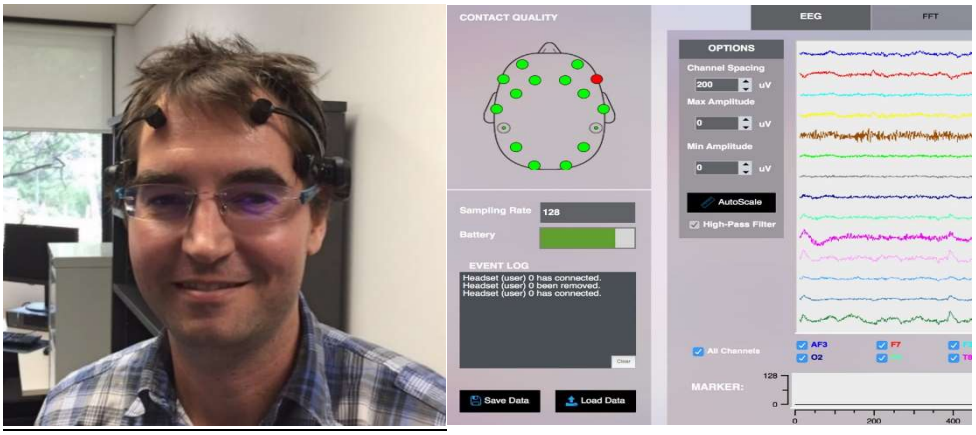


Figure C2. Position of Emotiv EPOC headset on participant and checking all nodes are green on the Emotiv Testbench software.

13. Check that the video cameras are in correct position to capture the laptop and the participant (make sure that the clock is in the frame with the time visible).
14. Remind participants to stay in the same spot once seated at the table so they remain in the video camera frame.
15. Open 'Marker' window in Emotiv Testbench:
    a. Go to ☰ icon located top left-hand corner and select 'Marker'
    b. Then select 'Send Manually Marker'
    c. Input 1 into Name and then input 1 into Value (this only needs to be done once for duration of experiment)
    d. Place this box on top of the Emotiv Testbench Box and leave it open for the duration of the experiment (see Figure 3).

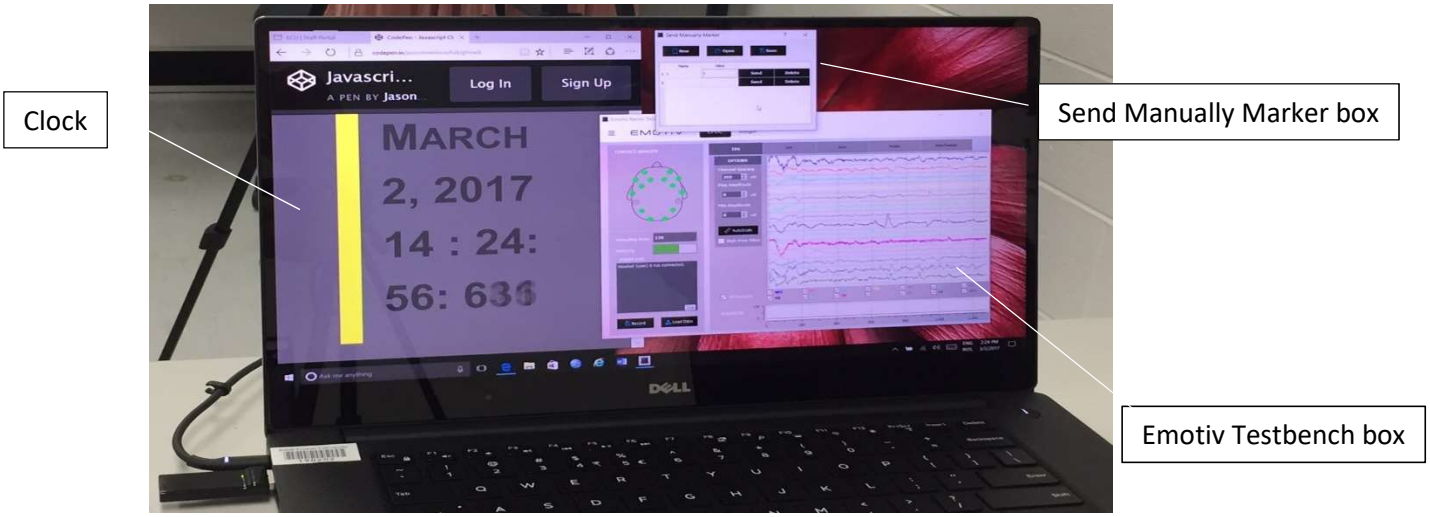


Figure C3. Laptop screen set up for conversation EEG data capture

16. Initial Set-up Record in Emotiv Testbench screen:
    a. Select Record
    b. Press Select (see Figure 4)

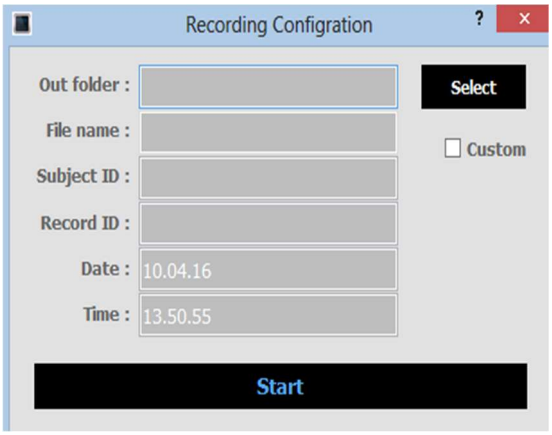


Figure C4. Recording configuration in Emotiv Testbench into EDF format

    c. Open Folder named (Session #_DD.MM.YYYY, e.g. Session 1_08.10.2017)
    d. Then select Subject ID and enter the following:
        i. Participants first letter of first name and numerical value starting with one, e.g. Shane would be s1, subsequent participants with the same first name letter would be s2 and so on.
        ii. Once allocated this does not change for the duration of the experiment.
    e. Select Record ID and enter the following for conversation one and two:
        i. C1
        ii. C2
17. Press record on video cameras
18. Press 'start' on record in Emotiv Testbench (see Figure 4)
19. Press Send in 'Marker' screen (see Figure 5)
20. CLAPBOARD and instruct participants to start 4-minute conversation.
21. Begin 4-min stop watch.
22. After 4-min use CLAPBOARD to end conversation
23. Press 'stop' on record in Emotiv Testbench
24. Stop video camera record
25. Participant 3 to swap out with either participant 1 or 2 and commence round robin of 4-min conversations.
26. Participants self-report to be collected and checked for proper completion.
27. Vouchers or credit points to be allocated to volunteers. All necessary forms to be completed and signed.

END OF DATA COLLECTION

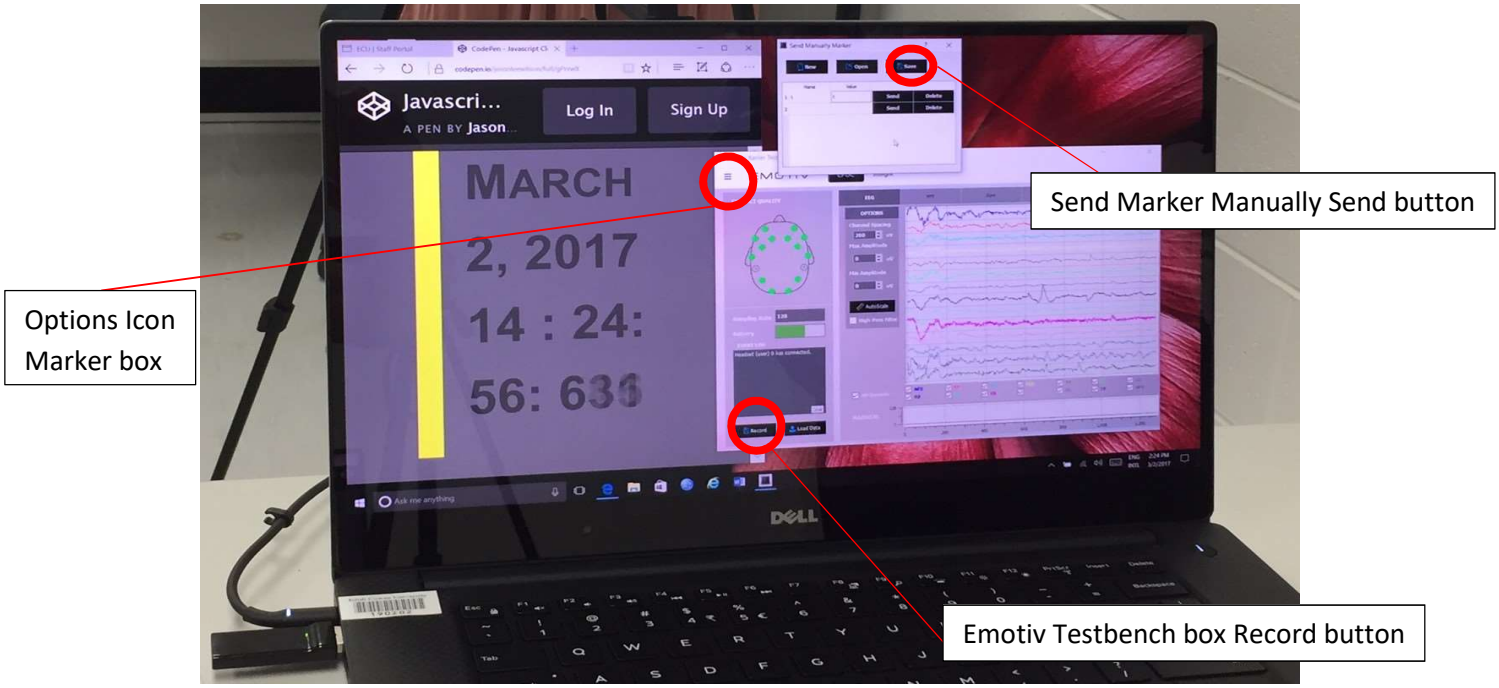


Figure C5. Function areas in Emotiv Testbench

Experiment Equipment Pack-up (Duration is approximately 30 minutes to pack-up experiment)

28. All equipment to be kept in the locked Communication Laboratory located at the Cognition Research Laboratory.
29. All EEG EDF files to be checked that they have been saved to correct session and participant folders.
30. All foam inserts to be removed from headsets and placed in saline solution.
31. All electrodes to be unscrewed from headsets and placed in designated containers. Ensure they are dry to stop corrosion.
32. Headsets and associated dongle to be placed together and the headsets to be charged after each session.
33. Laptops to be powered down and closed and then placed in the locked filing cabinet.

END OF PROCEDURE

Appendix E

EEG Data Pre-Processing and Signal Processing Procedure

Introduction

The following procedure outlines the pre-processing and processing steps, in numerical order, of the raw EEG data captured during research between participants engaged in 4-minute face-to-face getting acquainted conversations. All EEG data was captured using the Emotiv EPOC EEG wireless and portable headsets. All the necessary software for pre-processing and processing was available on the Communication Research Laboratory's computer.

Please note: this procedure can be used in conjunction with three instructional videos that are available on request from Dr Shane Rogers from the Cognition Research Laboratory at Edith Cowan University.

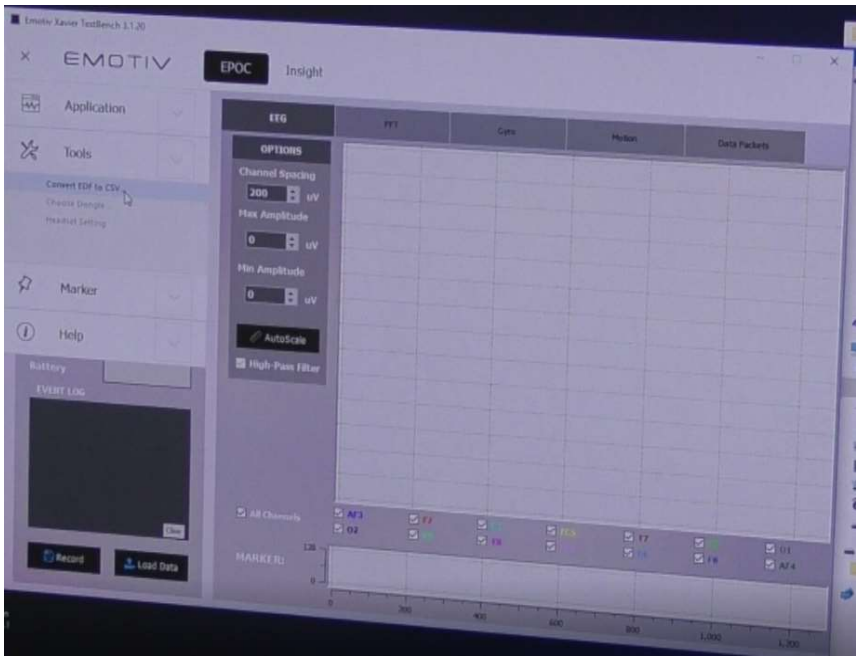
Software List

- Emotiv Testbench Software
- Matlab Software:
  - EEGLAB Toolbox
  - BIOSIG Tool
  - Neurophysiological Biomarker Toolbox (NBT) Pre-processing the data
- Microsoft Excel

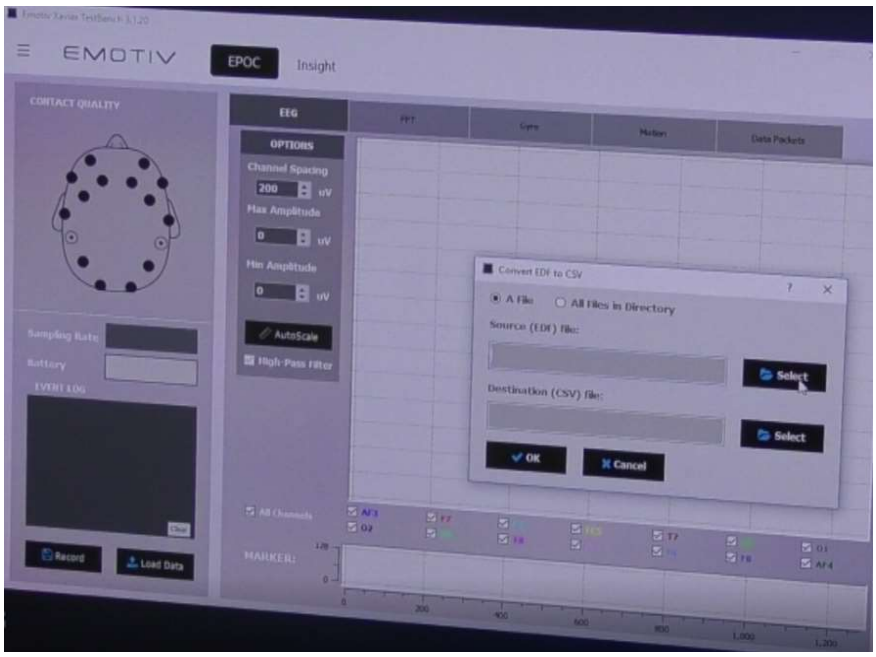
Pre-Processing the data

Converting Raw EEG Data from EDF to CSV using Emotiv Testbench Software

1. All the EEG data is recorded automatically into EDF format. To convert it into CSV format, use the EDF to CSV converter tool in Testbench. Emotiv>Tools>Convert EDF to CSV (see screenshot below).



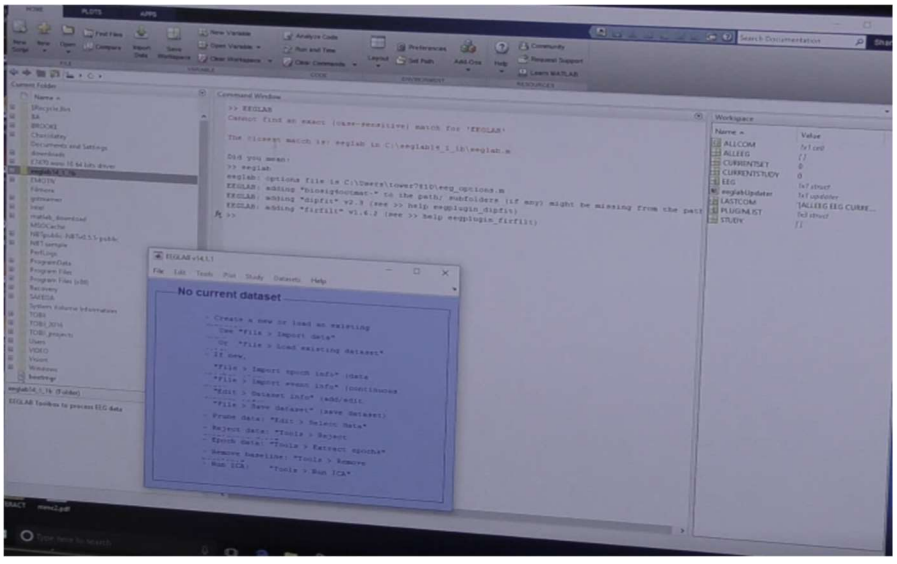
2. Then select the EDF file from the participants folder (see screenshot below) (see companion document the Communication Research Laboratory – EEG Experimental Procedure).



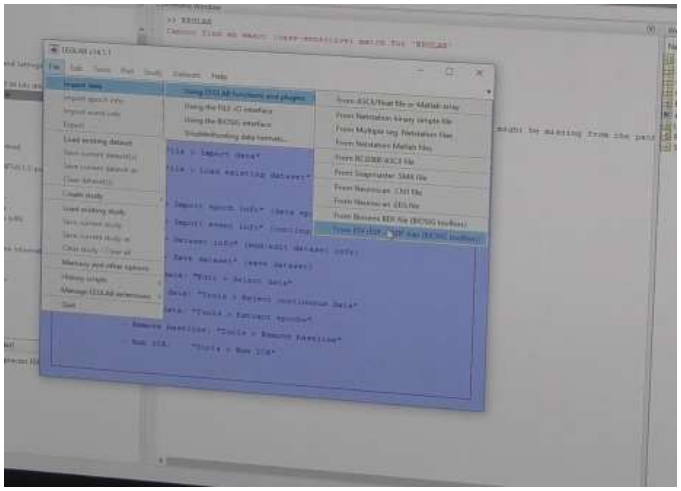
3. Save the CSV files in the same folder as the EDF files using the same naming protocol of session #_ participant first initial_ C1 or C2_DD.MM.YYYY e.g. S1_B_C1_01.10.2017. Note: C1 is conversation 1 and C2 is conversation 2.

Pre-processing: Cleaning Data using Matlab's EEGLAB Toolbox and Biosig Tool

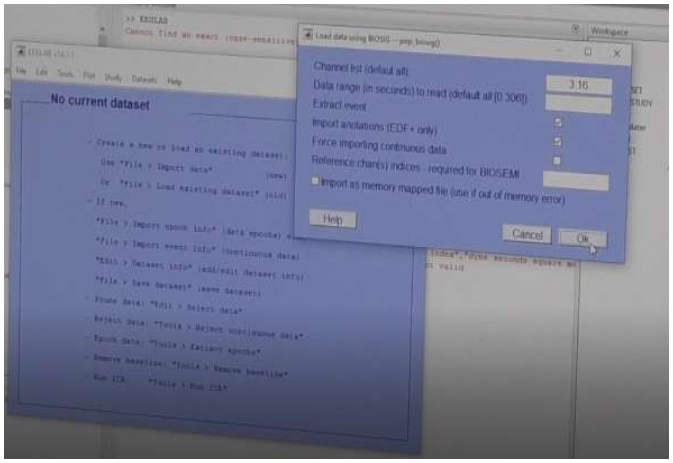
4. Open Matlab.
5. Open Matlab's EEGLAB Toolbox by choosing 'eeg14_1_1b'
6. Choose 'add to path' and then choose 'selected folders'
7. eeglab into the Command Window should look like this >> eeglab
8. No Current dataset window will appear (see screenshot below).



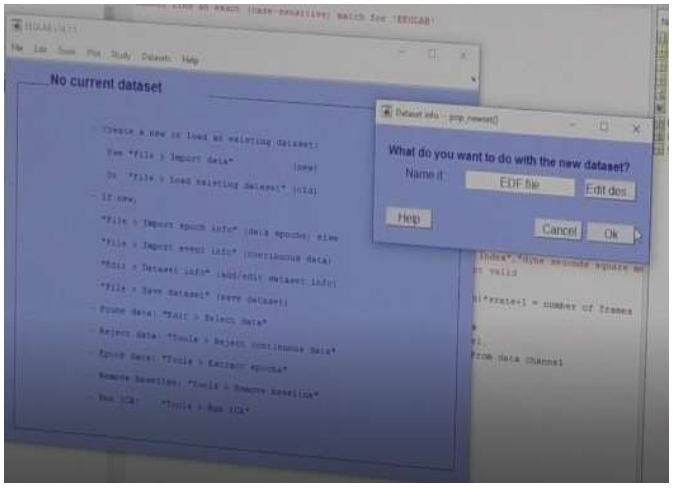
9. Select File>Using EEGLAB functions and plugins>From EDF/EDF + AGDF files (BIOSIG toolbox) (see screenshot below).



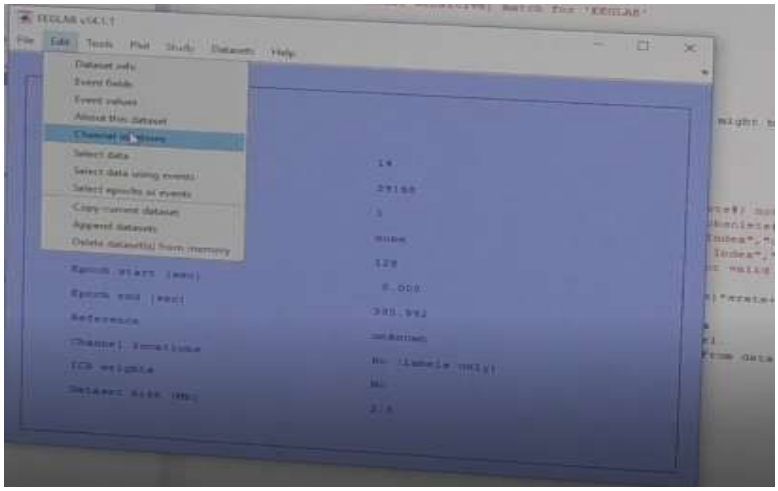
10. Then go to the participant folder and select the correct EDF file for C1 and press ‘open’
11. ‘Load data using BIOSIG window’ will appear, place 3:16 for the Channel list (default all), then click OK (see screenshot below).



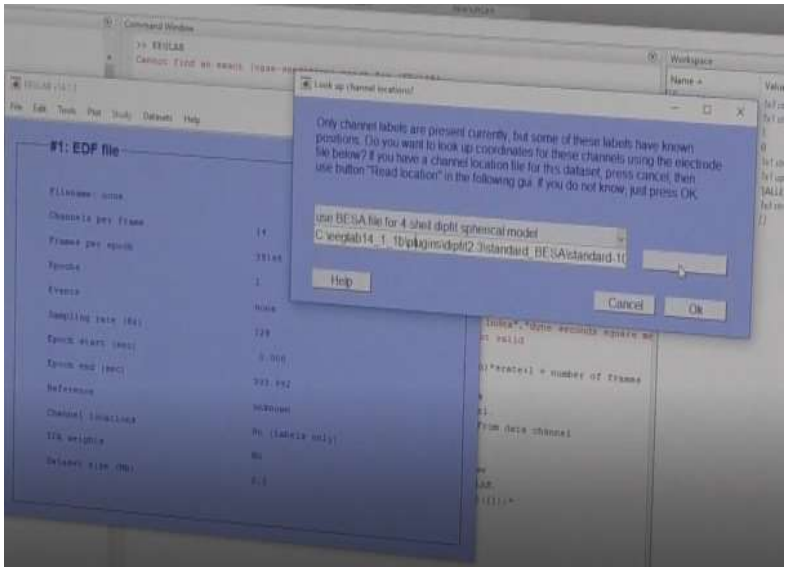
12. Click OK for the ‘What do you want to do with the new dataset’ window (see screenshot below).



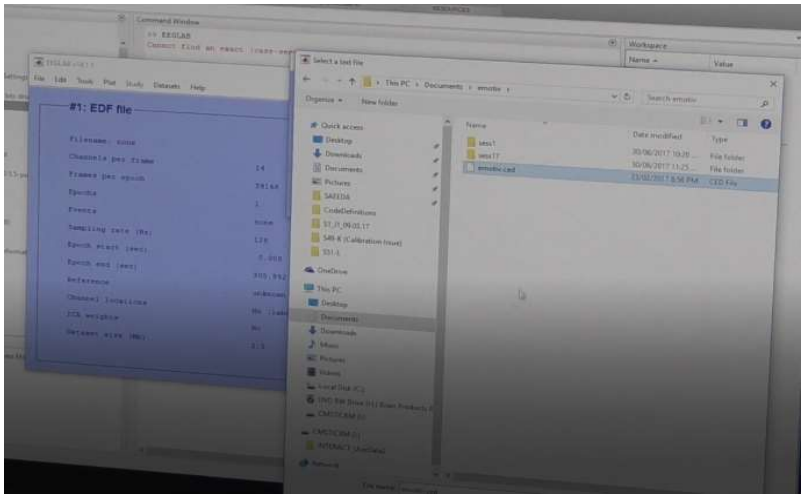
13. On the ‘EDF File window’ select Edit>channel locations (see screenshot below).



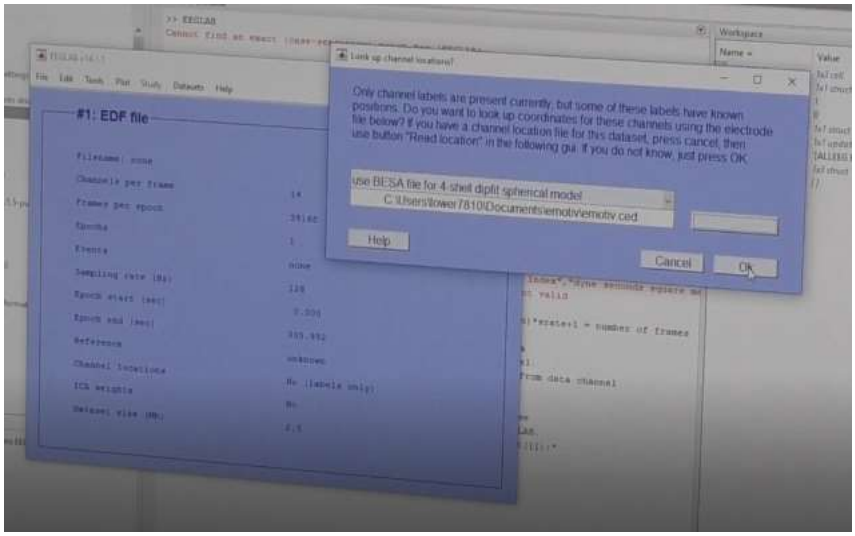
14. In the ‘Look up channel locations?’ window select the blank tab (see screenshot below).



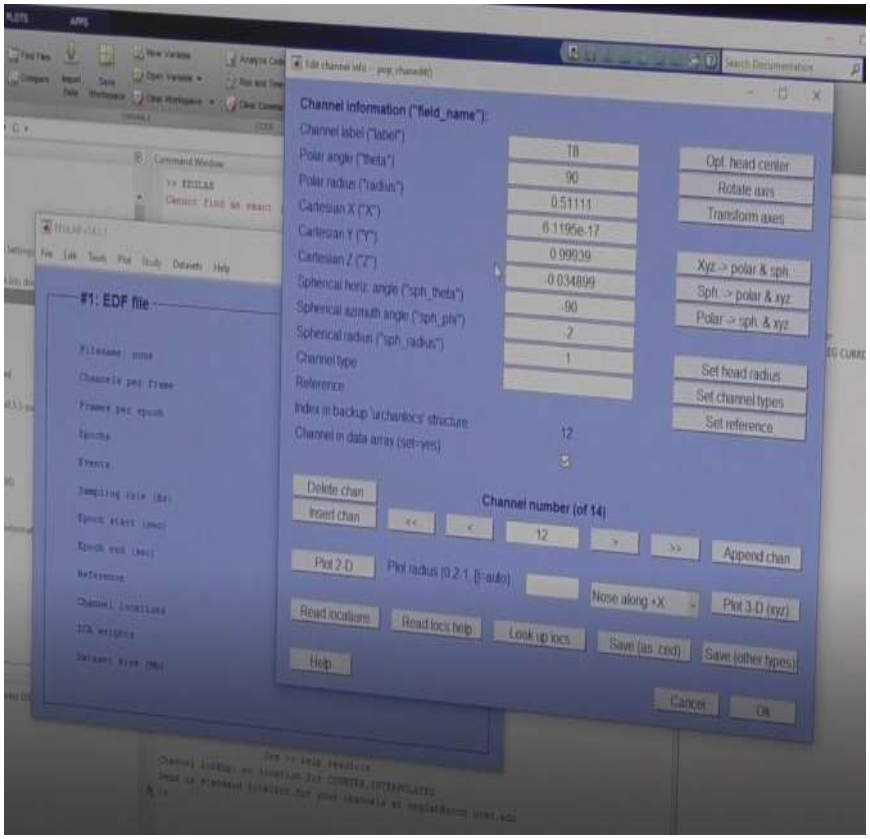
15. Then go into the folder view and select the ‘emotiv.ced’ file and press open (see screenshot below).



16. Then press OK (see screenshot below).

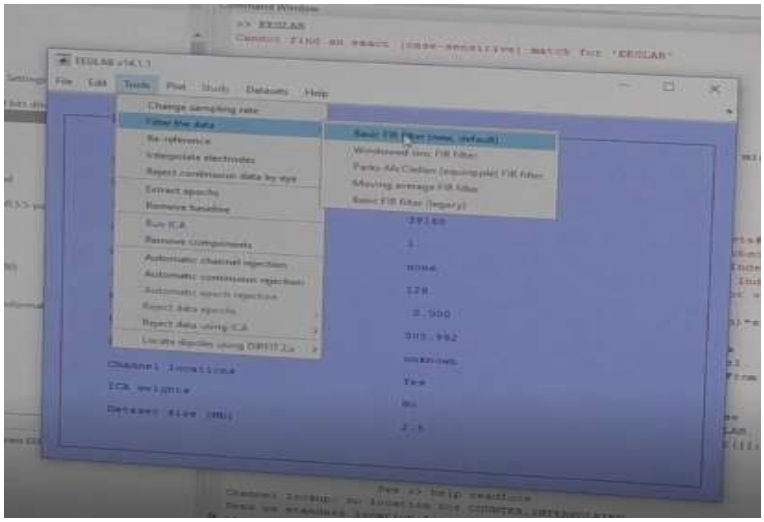


17. Edit channel info will appear, scroll through the channels to number '12' of the 14 channels called 'T8' and remove the negative symbol against the number for the Cartesian Y ("Y") field. It will look like the screen below once moved (see screenshot below).

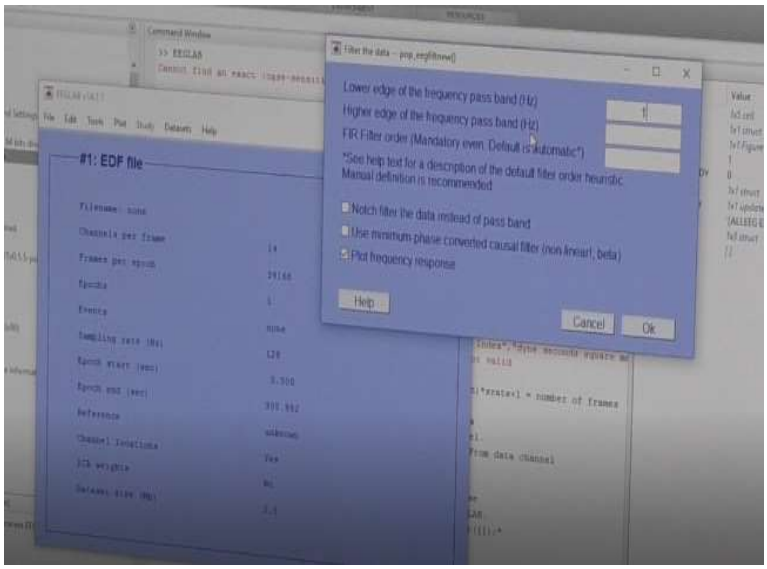


18. Then click OK to exit the Edit channel info window.

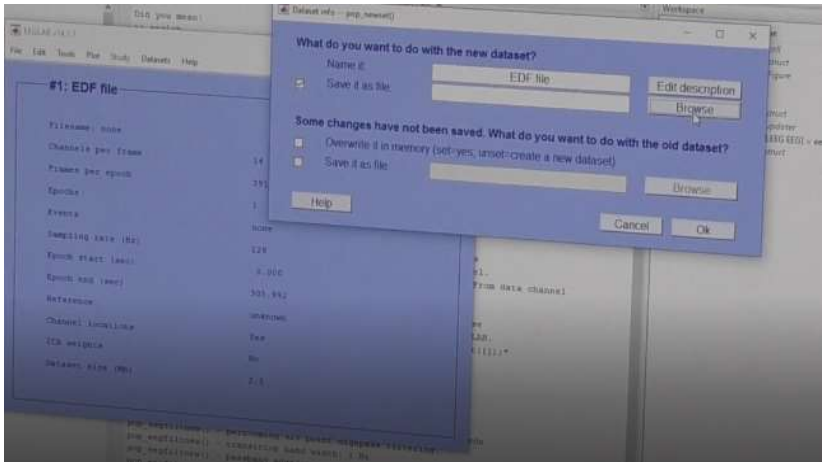
19. Then go to Tools>filter the data>Basic FIR Filter (new, default) (see screenshot below).



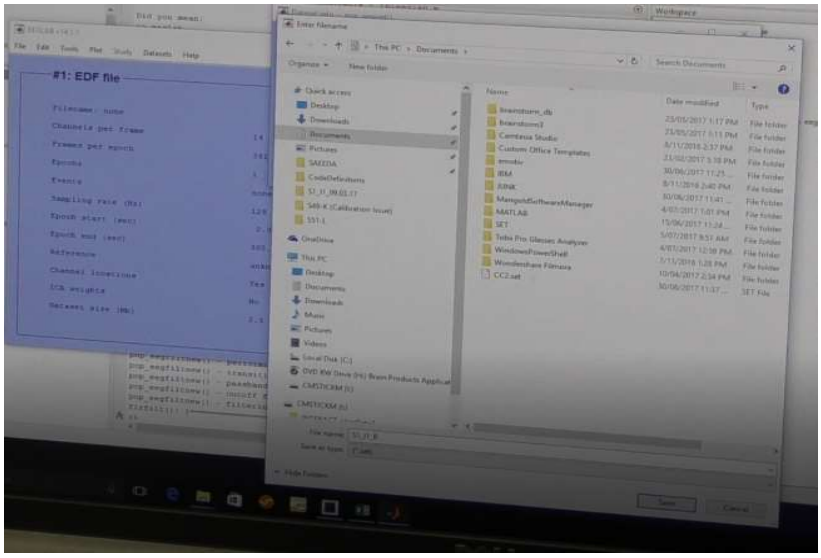
20. Place a 1 in the Filter the data – pop_eegfiltnew() window and then press OK (see screenshot below).



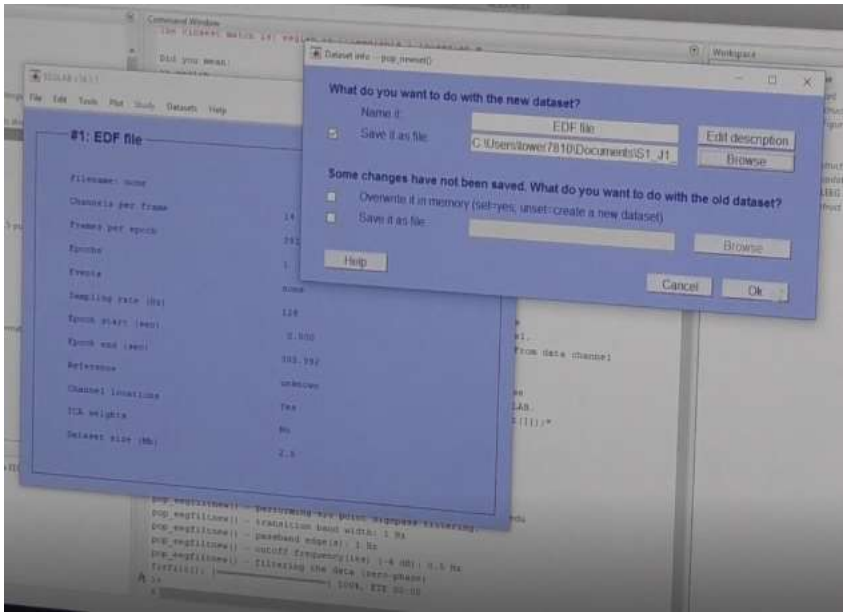
21. Select save it as file and press Browse in the Dataset info – pop_newset() window (see screenshot below).



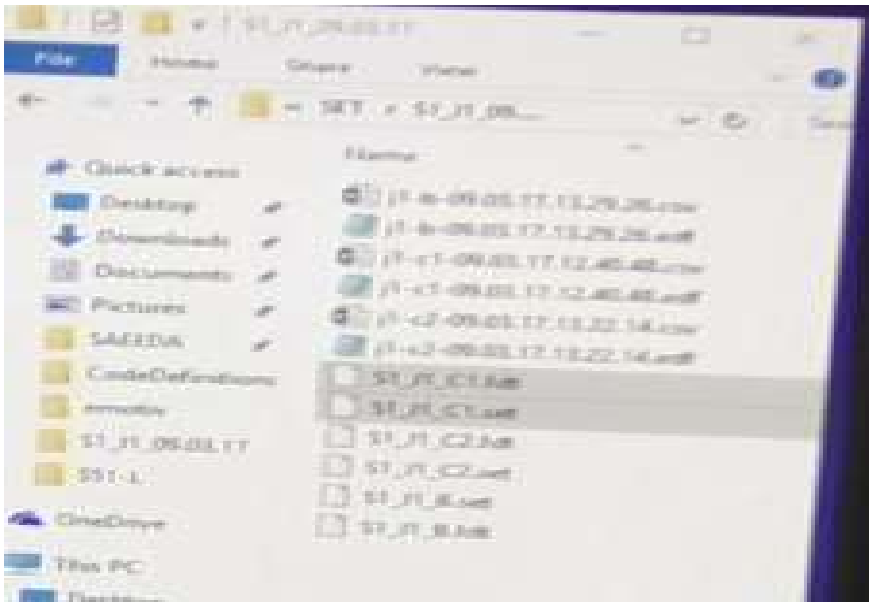
22. Place the new file into ‘Documents’ with the following file naming protocol Session #_Participant initial_C1 then press save button (see screenshot below).



23. Then select OK (see screenshot below).



24. .SET documents are created from the .EDF files for the participant. Remove the saved .SET files for the participant from the 'Documents' folder and save to the original participant folder. So far there should be EDF, CSV, & SET & FDT files for the participants' conversation 1 and conversation 2 (see screenshot below).

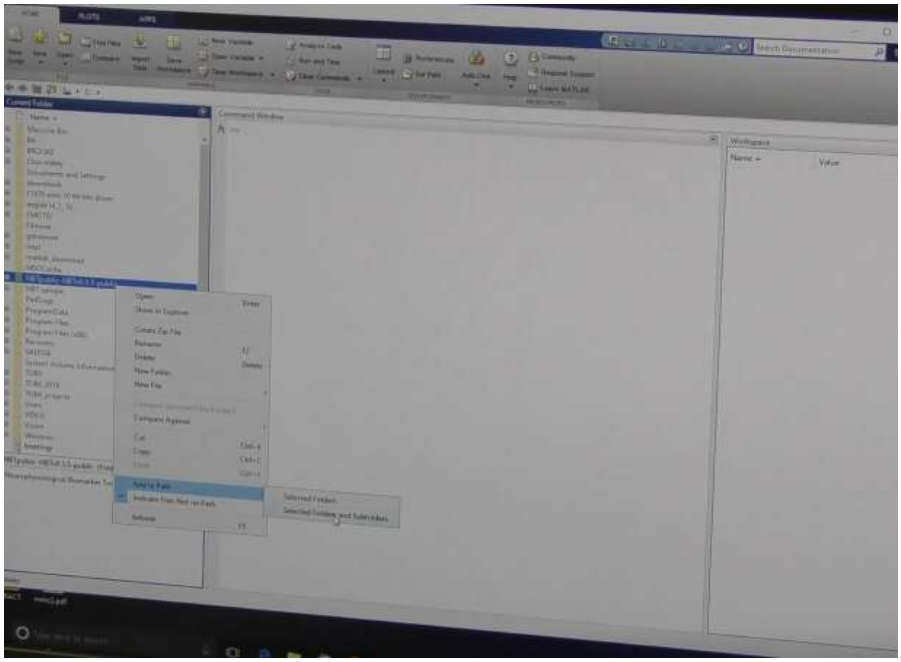


25. Then repeat for the rest of the EDF files for all of the participants, following steps 4-24 of this procedure.

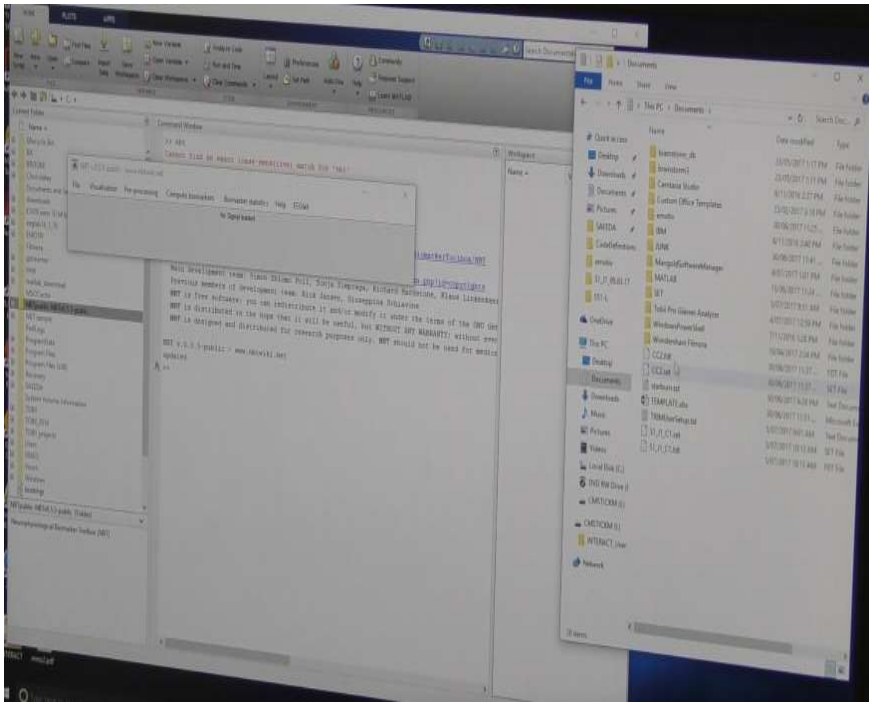
Processing the Data

Converting .SET & .FDT files to .MAT files using Matlab's Neurophysiological Biomarker Toolbox (NBT)

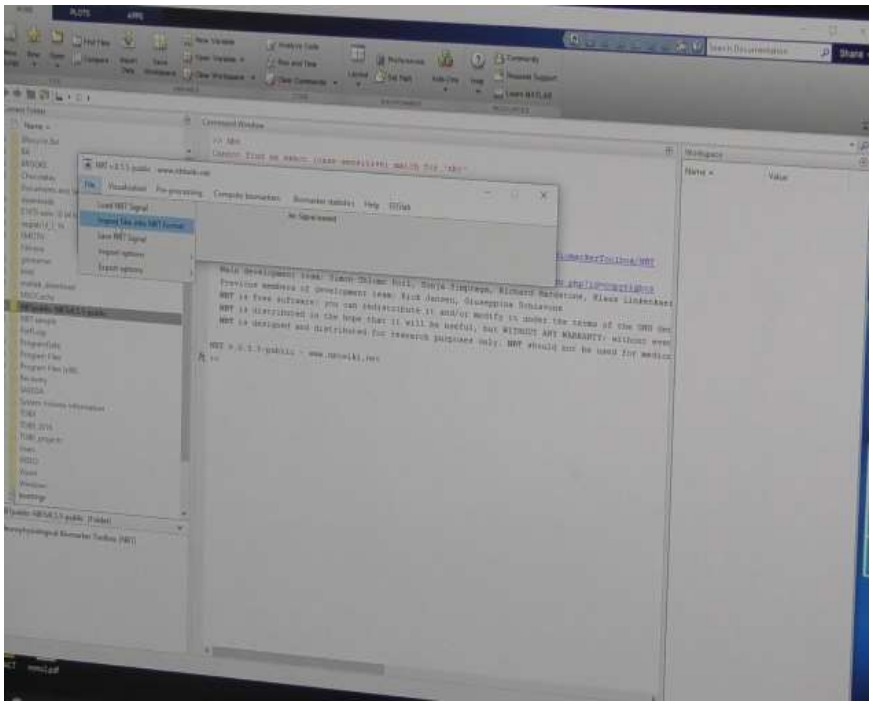
26. Open Matlab (close if already using with EEGLAB, and then re-open) and select NBTpublioc-NBTv0 5.5 – public>Add to path>Selected Folders and Subfolders (see screenshot below).



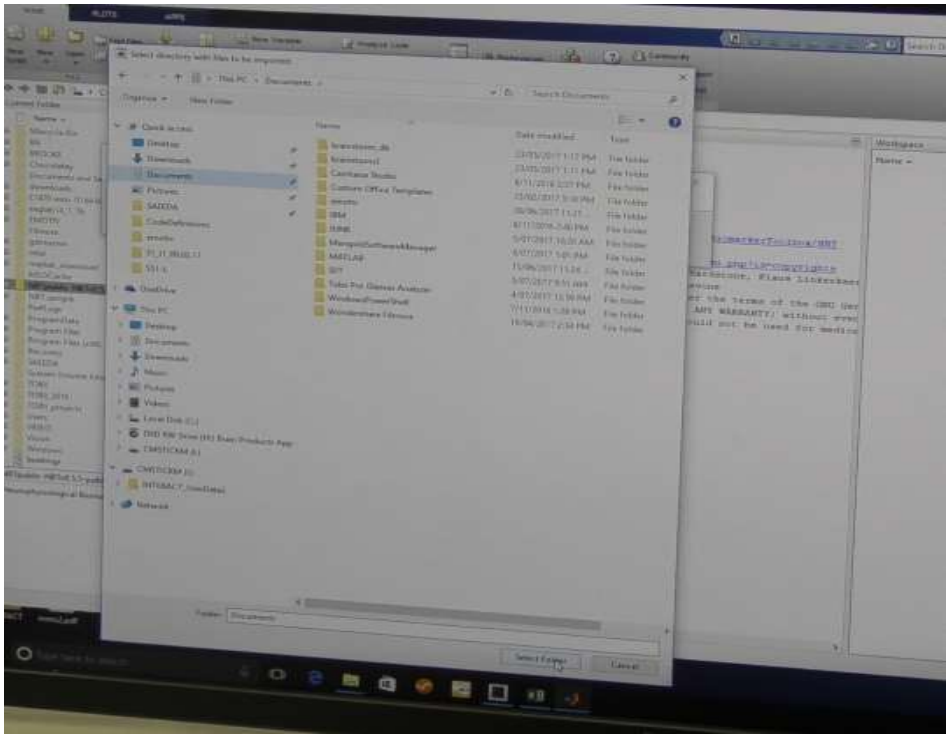
27. Type NBT into the Command Window
28. Go into the participants file and cut the .SET file and .FDT file for conversation 1 and paste them into the 'Documents' folder (NBT will only allow you to access the .SET files from this location). You can copy until you feel confident with this step to cut and paste. You should only have the participants .SET and .FDT files in the 'Documents' folder that you are working on (see screenshot below).



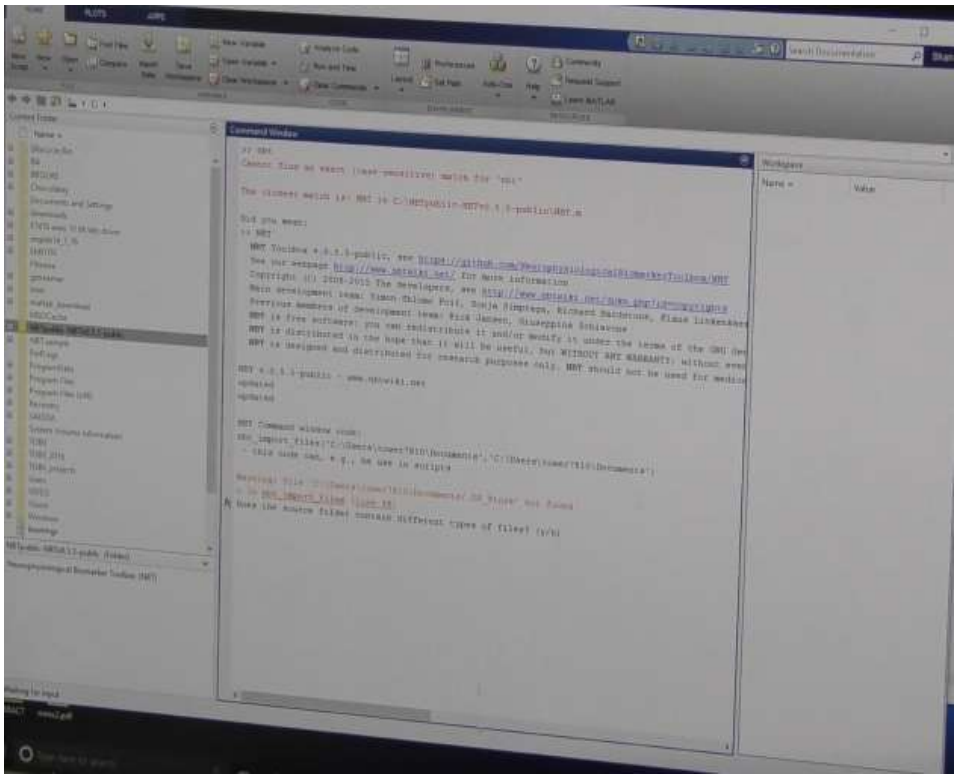
29. In the NBT v0.5.5 public window select File>Import File into NBT Format (see screenshot below).



30. It will take you to the Local Disc (C:) on your computer. Click on Documents then press select folder ***twice.*** You will not see the files in the 'select directory with files to be imported' window (don't panic) it will look like the screen shot below.



31. The command window will then appear and there will be a series of questions that need to be answered (see screenshot below).



32. Complete the information on the screen with the highlighted answers below.

Does the source folder contain different types of files (y/n) y

Please specify target file extention (e.g., raw) .set

File names in NBT should be <ProjectID>.S<SubjectID>.<DateOfRecording [yymmdd]>.<Condition>, for example NBT.S0099.090212.EOR1

Is the filename already according to the NBT convention (y/n) n

Session#_Participant initial_C# for example S1_J_C1. **Hint**: it is the same as the .SET file name.

Generating filename (note use nbt_Rename for automatic renaming:

Please write ProjectID: S1_J_C1

Do you want to downsample the signal (y/n) n

What is the sample frequency? 128

Do you want to read a special channel location file (answer n to use standard channel location file) (y/n) y

Channel location filename: 14

File: S1_J_C1

This field is automatically generated.

Can't use letters here only numbers, just place '1' if there are no subject numbers given.

Subject ID? 1

Date of recording? YYYYMMDD

Condition? q

Need to complete this space place the letter 'q' in as a default for all files unless you want to specify a condition

Notes?

Just press enter no need for any information here.

Converting S1_J_C1.set

Pop_loadset (): loading file C:\Users\tower7810\Documents\S1_J_C1.set

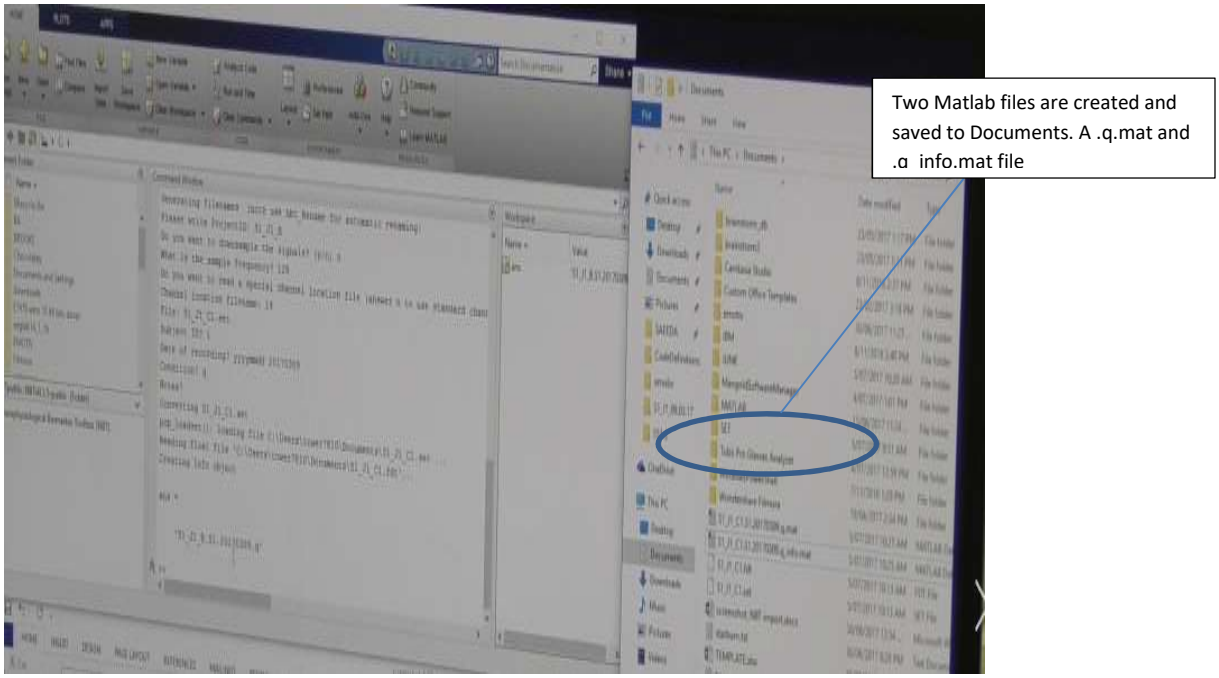
Reading float file 'C:\ Users\tower7810\Documents\S1_J_C1.fdt'…

Creating Info object

ans =

'S1_J_C1.S1.20170309.q'

33. Two Matlab files are created and saved to Documents. A .q.mat and .q_info.mat file (see screenshot below).



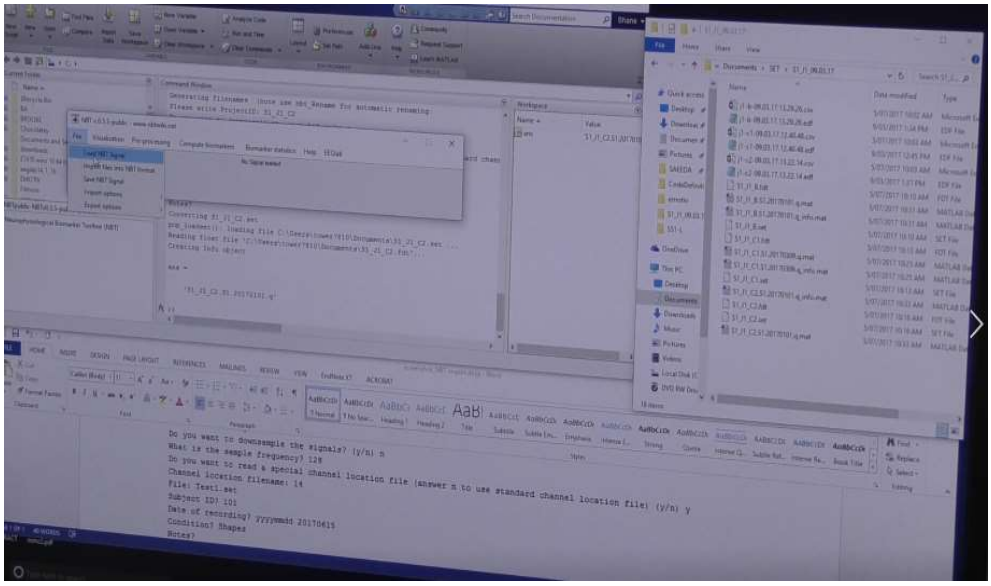
34. Cut and paste the >SET , .FDT and the new matlab files (4 files in total) out of documents folder and into the original participant's folder.

35. Repeat steps 28 to 33 for C2.

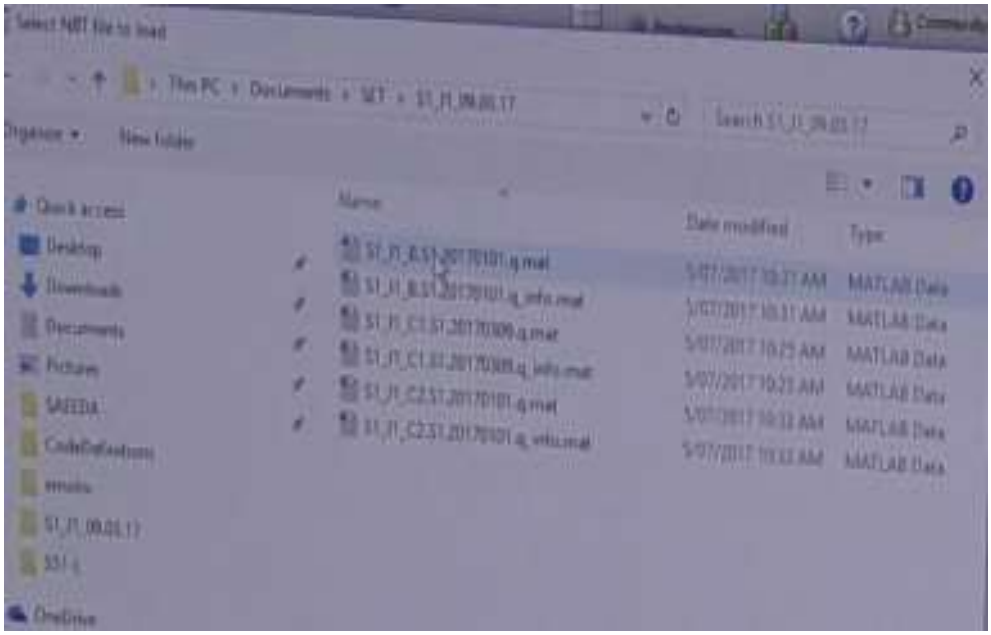
36. Repeat Steps 28 to 34 for all the participants' .SET and .FDT files to covert to .MAT files.

Processing the Data using Matlab's Neurophysiological Biomarker Toolbox (NBT) .MAT files to filter the data for the alpha and beta signals

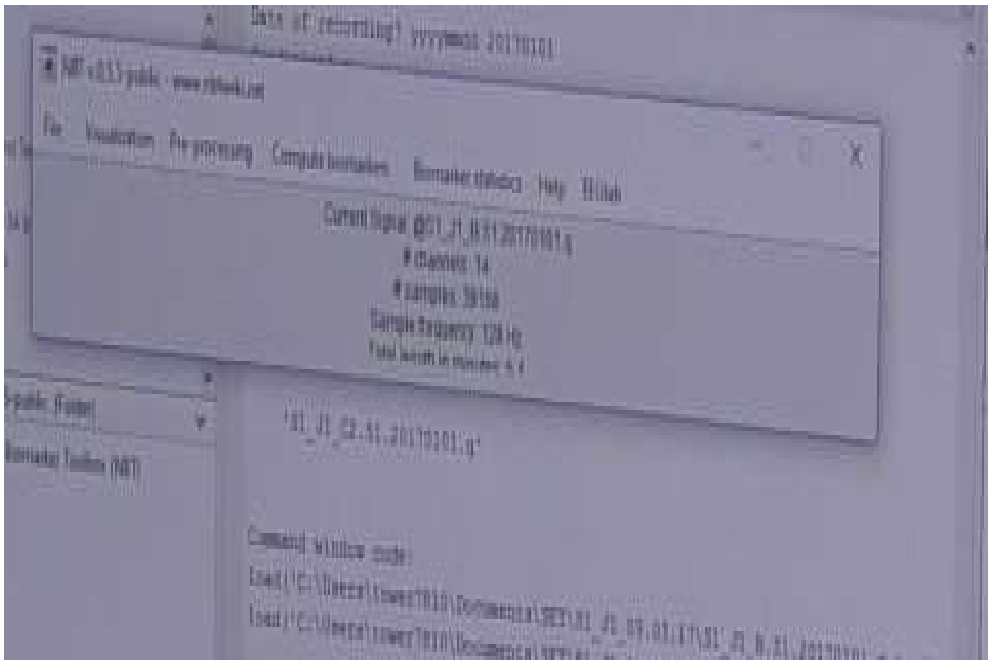
37. Open the NBT window by clicking on the MATLAB icon on the taskbar and select File>Load NBT signal (see screenshot below).



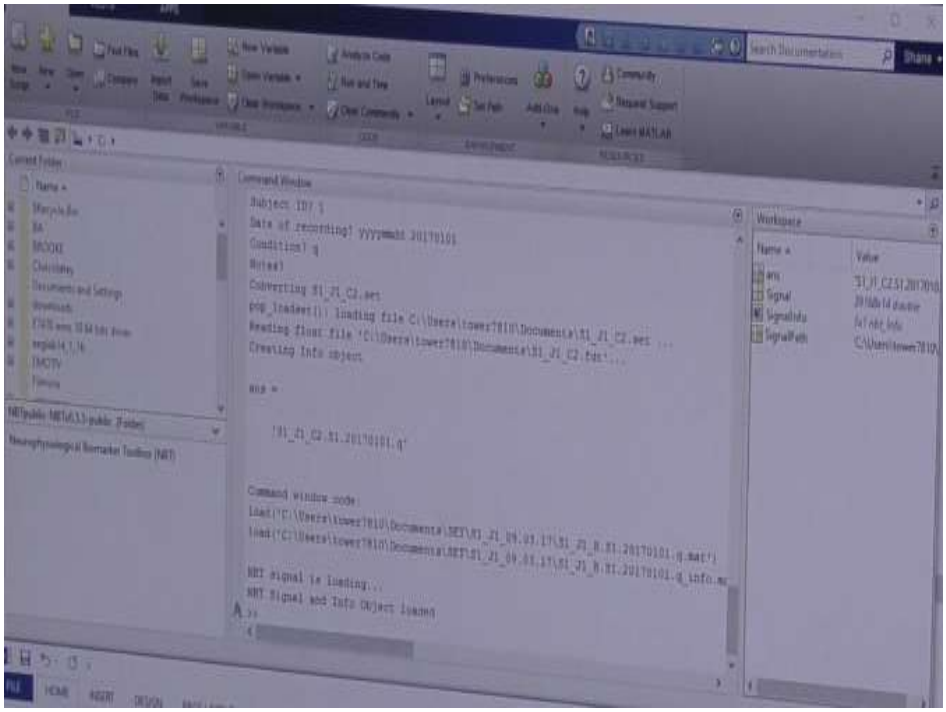
38. Go to the participants original folder where the .MAT files are saved you will only be able to see the .MAT files (see screenshot below).



39. Select the file with in the format ending with .q.mat and press open. You will then see the NBT window with the file name and file information as in the screen shot below.



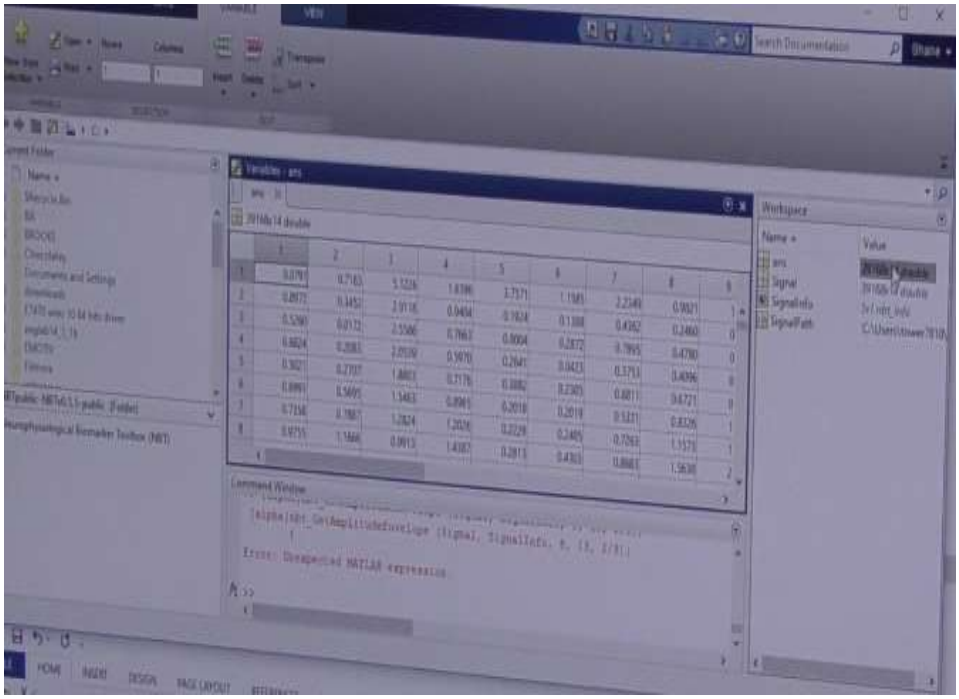
40. The ‘NBT signal and Info Object loaded’ is visible in the command window, (see screenshot below).



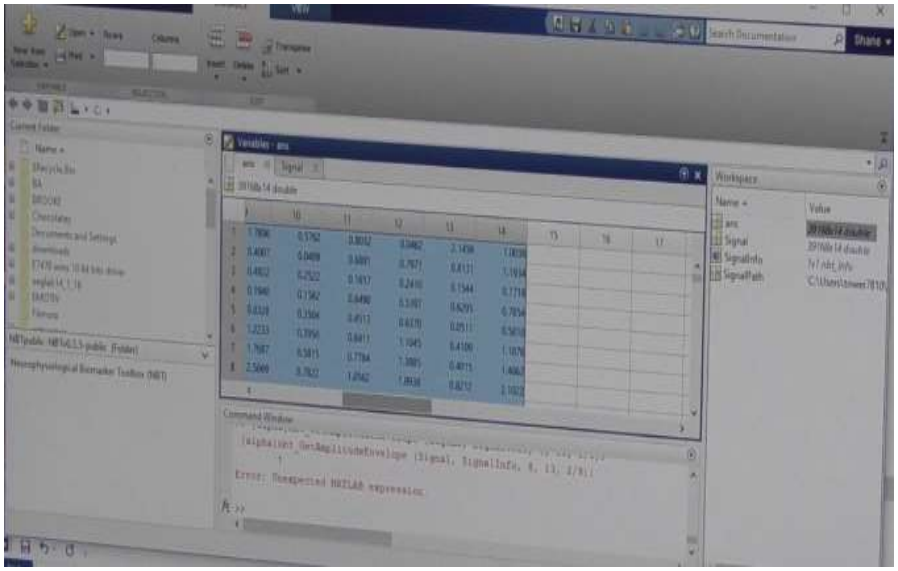
41. Cut and paste the below code into the command window to process the **Alpha** signal for the loaded participants .mat file for the specific conversation. Press enter.

    nbt_GetAmplitudeEnvelope (Signal, SignalInfo, 8, 13, 2/8);

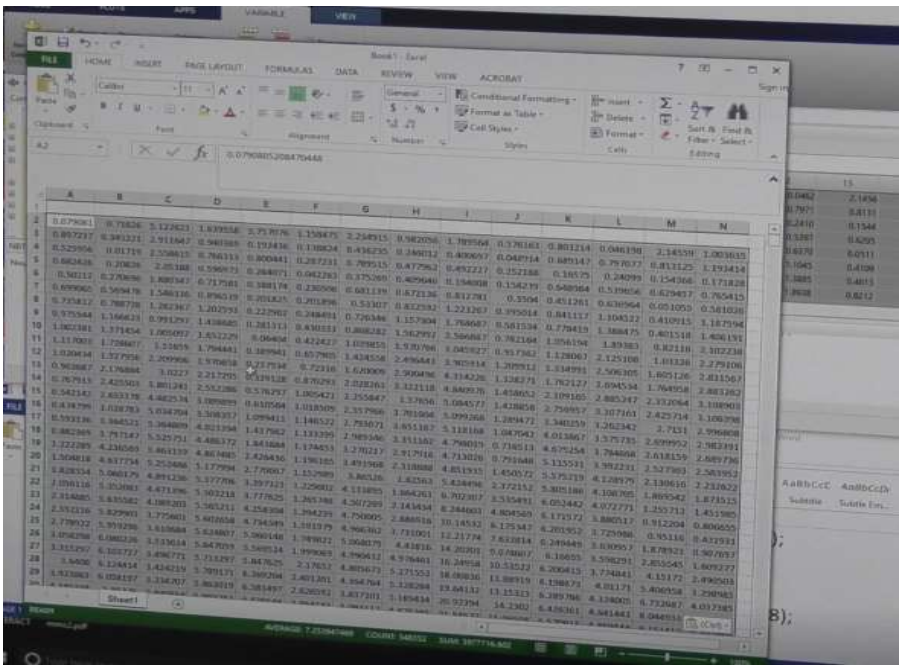
42. Double click on the value for ‘ans’ that is the **alpha** processed data (see screenshot below).



43. Highlight the columns 1-14 and then highlight and capture all of the data and right click copy the data (see screenshot below). This may take some time as the files are large with ~30,000 data points.



44. Then open excel. Open a new document and paste the copied data from Matlab onto the second row (see screenshot below).



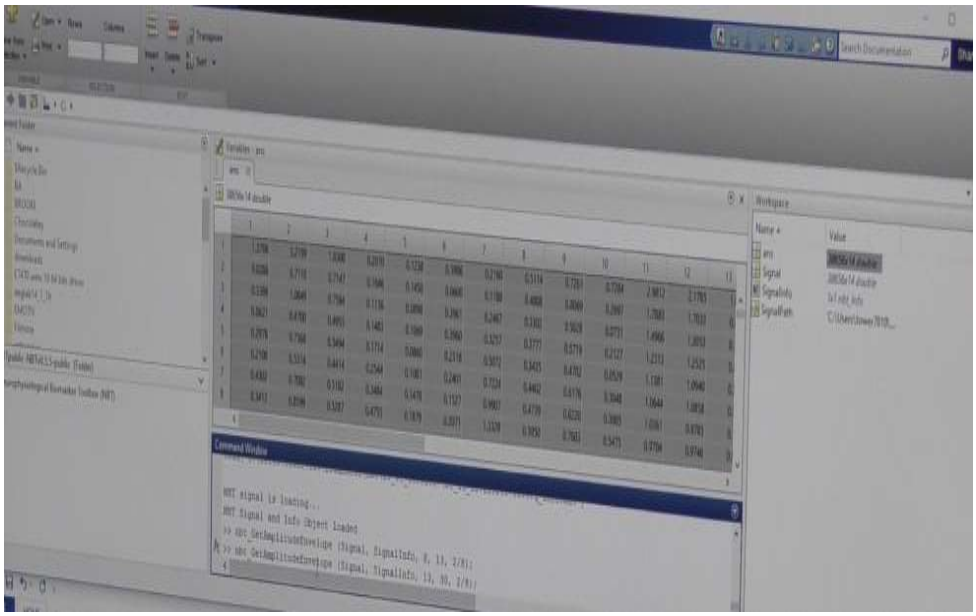
45. Insert a line at the top of the CSV file and copy and paste paste the Emotiv Electrode template into the file (see screenshot below).

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
1	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4	RAW_CQ	GYROX	GYROY	MARKER_	MARKER	SYNC	TIMS_S	TIME_MS

46. Save the file as an excel spreadsheet. Rename the file as session#_participants first intial_C1_**ALPHA.**

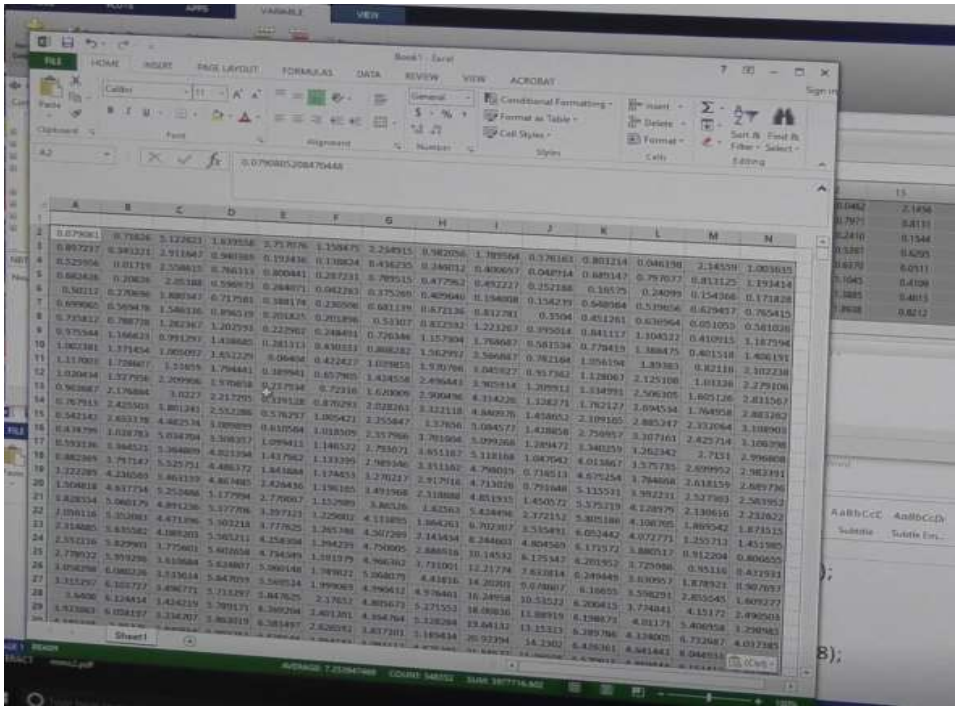
47. You can then use the same loaded file for processing the **beta** signal. Cut and paste the below code into the command window (see screenshot below), to process the **beta** signal for the loaded participants .mat file for the specific conversation. Press enter.

    nbt_GetAmplitudeEnvelope (Signal, SignalInfo, 13, 30, 2/8);



48. The already highlighted values will change to **beta** values. So you can just copy the data, it may take some time to copy due to the large file size.

49. Then open excel. Open a new document and paste the copied data from Matlab onto the second row (see screenshot below).

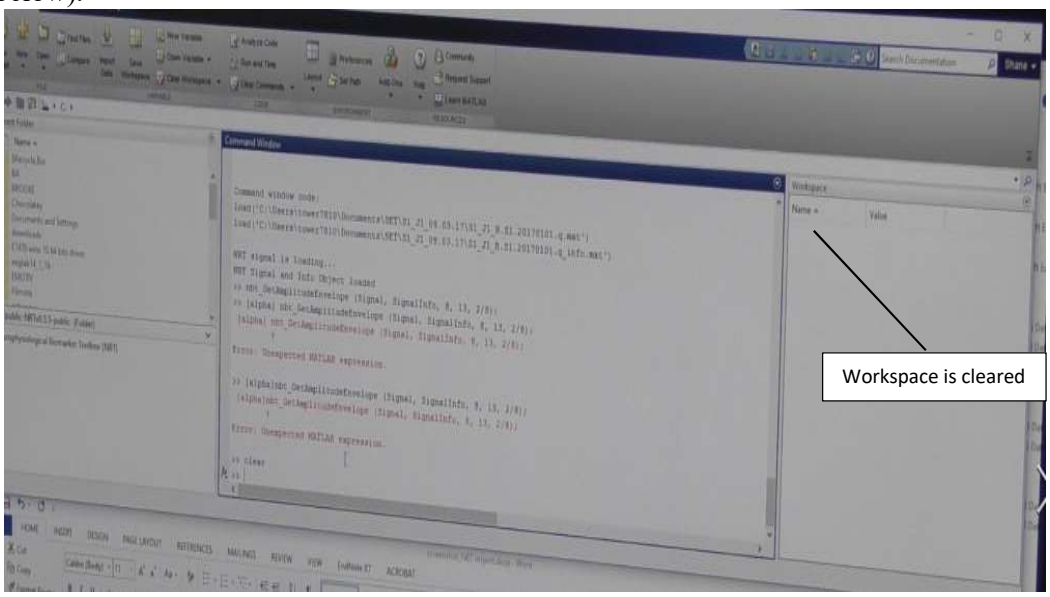


50. Paste the Emotiv Electrode template into the file (see screenshot below).

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
1	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4	RAW_CQ	GYROX	GYROY	MARKER_	MARKER	SYNC	TIMS_S	TIME_MS

51. Save the file as an excel spreadsheet. Rename the file as session#_participants first intial_C1_**BETA.**

52. Go back to Matlab after saving the excel spreadsheet and clear the command window by typing in 'clear'. The workspace should now be cleared for you to work on a new file (see screenshot below).



53. Repeat steps 36 to 52 for all of the participants C1 and C2.

Constructing Data Sheets for the Alpha and Beta Signals for Participants

54. Open the participant's CSV file for C1. Copy the data in the columns Q-X

55. Open the participant's Alpha C1 excel file and paste the data from columns Q-X into the columns O-V. Ensure that all of the data is copied across. Then close the .CSV file (see screenshot below).

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
1	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4	RAW_CQ	GYROX	GYROY	MARKER_	MARKER	SYNC	TIMS_S	TIME_MS

56. Copy the entire first sheet of data into a second sheet and name it 'alpha chop'

57. Look for the markers '1' (start) and '2' (end) in the 'R' column in the excel spreadsheet on the 'alpha chop' sheet. Delete the data prior to the marker 1 and then delete the data after marker 2.

58. Repeat the process for steps 53 to 56 for C1 but for the beta in the beta C1 excel file. Replace all reference of alpha with beta e.g. 'beta chop'.

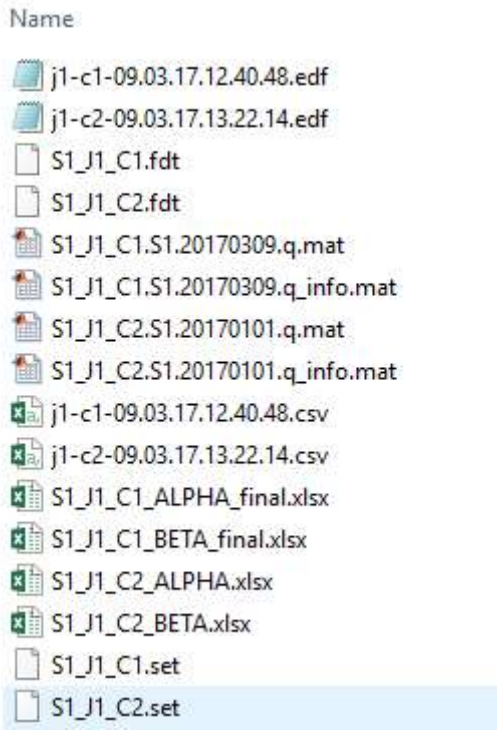
59. Ensure you save the worksheets as you go.

60. Working only in the 'chop' worksheets add a new column named Frontal (column X).

61. To calculate the means of the Frontal use the function tool in excel and enter the formula =AVERAGE(A2:D2,K2:N2). You can double check that you have selected in row 1 data in

columns named AF3, F7, F3, FC5, FC6, F4, F8, AF4). Then filter the formula down for all of the rows.

62. Calculate the total mean then apply =AVERAGE and highlight the X column for all the data points to calculate the total mean.
63. Then calculate the median =MEDIAN and highlight the X column for all the data points to calculate the total median.
64. Then calculate the standard deviation of the means =STDEV.S and highlight the X column for all the data points to calculate the total standard deviation of the means.
65. This is to be repeated for the beta signal and for C2 alpha and beta means.
66. All means and SD-means were then loaded into a master data EEG spreadsheet and then exported into SPSS for statistical analysis.
67. Each participant should have a folder containing the following files (see screen shot below).



END OF PROCEDURE