Clarifying the Unconscious Mind

By

Jaxon Mitchell

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ABSTRACT

Unconsciousness is defined as the state of being where a person is unable to respond to any stimulus, be it tactile, auditory or otherwise. This plays a big part in surgeries, where doctors use anaesthesia to induce unconsciousness in patients to prevent them from feeling pain during the surgery. However, a known phenomenon is for patients to be able to rouse from unconsciousness mid-surgery, causing complications for both the patient and surgeon. Various tools have been attempted to be made to measure depth of anaesthesia (DOA) over the last 3 decades, but they still aren't used widely in clinical settings due to high variability in results and a lack of interpretability for surgeons to use their judgement when algorithms fail.

This project aimed to expand knowledge surrounding how the unconscious brain works, using a data set that demonstrates participants transitioning from consciousness to unconsciousness. As compared to similar studies, this one is unique as one of the largest sources of noise in brain recordings, skeletal muscle noise, was removed by pharmaceutically paralysing the participant prior to sedation. This data was to be processed to produce spectrograms that could be viewed multiple ways, and a connectivity analysis.

The methods used to generate spectra of the EEG recordings were new to the brain signals laboratory (BSL), designed after the 'multitaper method' of spectrum estimation employed by other papers. It was found that this algorithm had great performance in creating 'smooth' spectra, although using additional methods such as 'smoothing priors' could help advance spectra estimation tools within the BSL further. The spectra and spectrograms generated using this method revealed a lot of hidden gamma activity within the brain during unconsciousness, in addition to recurring landmarks found to approximate LOC.

From the connectivity analysis, it was found that regardless of baseline used, there was a significant number of connections demonstrating information flow towards the temporal regions of the brain. Whilst there is no further evidence to support this theory, it is hypothesised that this could be an intentional inhibitory signal towards the auditory processing centre of the brain.

The project ended by setting up future works to find evidence for a hypothesised 'inhibitory signal' in the gamma band of frequencies that inhibits sensory function during unconsciousness.

DECLARATION

I certify that this thesis:

1. does not incorporate without acknowledgment any material previously submitted for a degree or diploma in any university
2. and the research within will not be submitted for any other future degree or diploma without the permission of Flinders University; and
3. to the best of my knowledge and belief, does not contain any material previously published or written by another person except where due reference is made in the text.

Signature of student 

Print name of student JAXON MITCHELL

Date 16/10/2023

I certify that I have read this thesis. In my opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Biomedical Engineering (Honors / Masters). Furthermore, I confirm that I have provided feedback on this thesis and the student has implemented it fully.

Signature of Principal Supervisor 

Print name of Principal Supervisor KENNETH POPE

Date 16/10/2023

ACKNOWLEDGEMENTS

The work done in this report is a continuation from research performed in a previous thesis done by Dhruti Rathod. Her work is acknowledged and accredited, as the work done by her allowed much of the research done in this paper to be possible.

Regarding much of the MATLAB used during this project, I would like to give thanks and acknowledgement to Kenneth Pope, who assisted me with developing my skills with the programming language.

Finally, I would like to credit the Brain Signals Laboratory (BSL) personnel who have performed the recording of the EEG's used in this thesis from years 2004-2006. Additionally, they have provided some of the MATLAB functions I have used at several points within this project, most prominently with formatting figures for use in documents.

LIST OF FIGURES

INTRODUCTION

Background

Unconsciousness is defined as a state where a person is unable to respond to any stimulus, be it tactile, auditory, or otherwise, in addition to the loss of conscious thought and feeling. Within a medical context, this can be brought on voluntarily, using anaesthesia, or involuntarily as caused by various illnesses and injuries (Medline Plus, n.d.).

During surgical procedures, patients are put under anaesthesia so they neither feel pain, move, or otherwise recognise what is happening during a surgery. This is a vital component of surgery as it reduces risk of mental trauma in patients, the feeling of pain during the operation, and allows surgeons to do their work without interruption (National Institute of General Medical Sciences, 2022). However, it is possible for a patient to arise from unconsciousness during the middle of a surgery, which introduces various complications during the procedure when the patient regains consciousness (Robson D, 2019).

To counteract this phenomenon, there is ongoing work to produce tools that measure depth of anaesthesia (DOA) to assist surgeons by informing them when a patient is at risk of becoming conscious. The goal is that, if a tool can succinctly and accurately predict when a patient is edging towards consciousness, anaesthetists are able to increase dosage of anaesthesia before return of consciousness (ROC). Several tools have been designed and tested so far, as early as 1992 (Devika Rani and Harsoor, 2012) with bi-spectral index (BIS) monitors. They are considered the standard in measuring DOA, although they are still not fully recommended due to their high variance with age and mental health, in addition to being unable to account for different anaesthetics (Mathur Surbhi, 2023). BIS monitors are favourable for clinical use due to their relative low cost and non-invasive (does not penetrate the skin) nature, although a lack of consensus on validation methods for models impedes development in the tool (Devika Rani and Harsoor, 2012).

There are several methods to measure DOA, but they are powered by algorithms and AI, with human understanding in the matter limited. This hampers interpretability of models, which when combined with the closed source nature of commercially available tools, significantly reduces human understanding. However, there is still much research being done to unveil the curtains on unconsciousness.

BSL Data Set

This thesis is a retrospective study, based on EEG recordings done by the Brain Signals Laboratory (BSL) from 2006-2008. These recordings are significant as they contain participants transitioning from consciousness into unconsciousness and can assist in improving our understanding of loss of conscious (LOC) in surgery. The data is also unique as the recorded participants were pharmaceutically paralysed prior to LOC, which removes skeletal muscle noise in the recordings. This is significant to the findings of the project as skeletal muscle noise can completely obstruct brain signals and limit the findings of a study. This data has the capacity to reveal brain signals not commonly found in EEG recordings.

Within this report, these recordings are analysed using a series of signal processing techniques to generate different views of the data, with the goal of gaining more insight into unconsciousness. There were 6 EEG's recorded total under the conditions needed for the work done, however only 5 recordings were used in the study due to issues with one of the recordings. In the original study, each EEG recording was done using the following procedure:

- The participant went through a series of instructed movements to demonstrate the effect on the recording.
- The participant was pharmaceutically paralysed.
- The participant attempted these same movements again, to record how the brain attempts to stimulate the muscles when they cannot move.
- The participant is placed under anaesthesia (using propofol) and brought unconscious until the effects of paralysis have worn off.

The original purpose of these recordings was to study how the brain prepares and executes movement in muscles from an EEG perspective, but the inclusion of LOC within the recordings allows this study to exist. This data is important to be able to validate the findings of recent papers covering the brains transition into unconsciousness. As previous papers recorded the transition, the participants in those studies were not pharmaceutically paralysed, and hence there existed some large amount of muscle artifact from the EEG recordings. By having data of paralysed participants, the analysis performed in this report can be extended into uncovering brain signatures typically hidden by muscle noise.

The first steps of this study were already completed as part of a previous paper written by Dhruti Rathod, where spectrograms of the data were successfully created to visualise different frequencies the brain is operating at, and at what powers. Some of the MATLAB code used for that thesis was adapted for the requirement of this paper. See Appendix A that contains heavily modified code from her original paper.

The work already done by Rathod. D and Pope. K will be continued in this paper, which firstly includes refining the spectrogram outputs already being generated by previous code, and then conducting a ‘connectivity analysis’ of the recordings, which shows information transfer between regions of the brain at various stages of the recording. The refinement of spectrogram outputs within the BSL is needed due to other institutions algorithms being able to produce ‘smooth’ figures that we do not have the algorithms for.

Scope

The scope for this project is limited as follows:

- Only 5 participants are included in the retrospective study and no new data is to be collected.
- No analysis methods outside of a spectral analysis and connectivity analysis will be performed on the data.
- No other methods for generating spectral estimates outside of that mentioned in the methodology will be explored.
- Return of consciousness (ROC) will not be explored in this project due to lack of data.

Any elements of research that go beyond the boundaries of these limitations can be considered out of scope of the project.

Research Gap

As discussed earlier, there is a lack of clinical tools trusted by doctors to measure DOA in patients during surgery. Additionally, with how relatively little is known about the unconscious brain, there is a lack of interpretability in the results of DOA instruments. Hence, the research done for this project aims to increase understandability of EEG results of the brain, and further illuminate what is not known of the brains activity through a connectivity analysis. Hence, the research questions driving this project are:

1) Are the EEG landmarks of unconsciousness reproduceable and are they a good measurement for DOA?
2) With the removal of skeletal muscle noise, what previously unseen activity can be found in the unconscious brain?
3) What connections are found within the unconscious brain?

The current failing of . Interpretability of results is still an issue within

Hence, the research questions for this project are:

1) What landmarks in unconscious EEG are replicable for clinical use?
2) What is revealed in unconscious brain activity without the presence of skeletal muscle noise?
3) Which regions of the brain demonstrate connectivity with each other during unconsciousness?

Research Outcomes

To achieve the overarching goal of furthering the understanding of the unconscious mind, the project was spread out into 3 main objectives to ground the work done in a realistic manner. These project goals were:

1) Improve the tools used within the BSL to generate spectrograms.
2) Re-analyse the 2006-2008 data, to determine whether they either support or challenge other papers findings.
3) Perform a connectivity analysis and see what interactions within the brain are not only statistically significant, but also what they might represent.

The data that this retrospective study is using was recorded in Compumedic's proprietary .cnt format, where the vast majority of analysis tools available today would be able to read it. However, it is assumed that these objectives will be completed using MATLAB, with the EEG3 toolkit for presenting the results. This was done as this thesis is a continuation of a previous student's project, where work was previously done in the MATLAB development environment.

One of the constraints of the project is its small sample size, which reduces the statistical power of the results. Unfortunately, due to the nature of collecting data under paralysis, only a limited number of participants could be recruited, and recruiting more would be a substantial task. Of the ethics approval provided to 8 participants, only 6 were recorded, and 5 were used within this project due to issues with one of the recordings.

Report Structure

Following this section, the thesis details the literature review performed at the beginning of the project, detailing all papers and research that relate to the findings and work done in this field. The research within both helped to interpret the results found during this project, and to illustrate and prove the gap that the project aimed to solve. This document also the tools used and the methodology practiced to obtain results in the 'methodology' section. The section describes both the application of these methods, but to view all the code written for the project, please see Appendices A-D. All figures displaying results are located in the appropriate 'Results' section, in addition to written descriptions and comments on repeatability. The results are compared to existing papers and explained / hypothesised on in the 'Discussion' section. After the concluding remarks made at the end of this paper, there is an additional section named 'Future Research' which provides suggestions on where this project can be continued by students in future semesters, and knowledge gaps raised by this thesis that can be filled in a future project.

LITERATURE REVIEW

Unconsciousness from an EEG Perspective

Currently, there is little to no incidence of being able to monitor the state of an unconscious person using EEG in a clinical environment (John H. et al., 2021). This has a variety of factors that have resulted in this, that being the relatively new research surrounding it and the difficulty in being able to approve the use of a device. However, recent movements have been made to identify this with recent medical research. John H et al. submitted an article to the public library of science detailing using machine learning (ML) to classify states of unconsciousness using specific types of anaesthesia (GABAergic in particular). This is of note for the work to be done for this project as the anaesthesia used for the data collection was propofol, a GABAergic anaesthesia. Their testing from the ML algorithm was proven to be a success with being able to provide better outputs than previous efforts from Ramaswamy S, et al. in 2019 (Ramaswamy M.S et al., 2019). This shows a rapid uptake in the ability to monitor unconsciousness using EEG in recent technological developments.

Similarly, a paper by Li Q. et al. aimed to employ 'sample entropy analysis' to estimate depth of anaesthesia (DOA) using live EEG recordings to help estimate a patients level of unconsciousness during surgery. This is similar in regards to both previous papers discussed as it is aiming to achieve live detection of DOA in a surgical procedure. Whilst like the other two papers it approached a satisfactory level of detection of registering when a patient is at risk of waking up, it also admitted that it has a noticeable time delay in being able to respond to changes in DOA during the experiment. Of note, it uses a bispectral-index as a reference value to quantify DOA. The data obtained for this project did not use a bispectral-index monitor in addition to the EEG cap. This may provide an opportunity for a future project to expand the findings of this paper using BIS to further investigate unconsciousness.

However, reading through the results and discussion of these three papers, it is clear that there is a lack of understanding or interpretability as to what the brain is doing. These papers fail to demonstrate to medical professionals what can be learnt about the brain and how to directly interpret what is being read on screen as an EEG is being recorded. Whilst the intent of this project aims to add to the greater goal of allowing software similar to what John H et al. and Ramaswamy S. et al. have developed, a crucial part of the research that still needs exploration is some human amount of understanding as to what is happening.

One paper that approaches very closely to what is aimed to be accomplished by this project comes from Wong K.F.K et al. in 2012. As such, this paper will be referenced a few times in this review. The paper aimed to investigate signatures of loss and recovery of unconsciousness from propofol (the anaesthesia used in the BSL experiment). Unlike the three papers discussed prior, this one aims to directly show what is going in the brain and hopes to answer how it is performing as it enters and leaves the state of unconsciousness. In its results it uses a variety of views to demonstrate what power each of the different regions of the brain is operating at during unconsciousness. A significant part of the report relevant to the visualisation of data that will be utilised in this project is the averaging algorithm they had used to collate participant data. As can be seen below in figure 1, Wong K.F.K et al had used an averaging algorithm that had made the overall view appear much smoother and have greater clarity than the data that this project has currently produced (See figure 2 for a direct comparison of what the current data looks like).

Figure 1 has been removed due to Copyright restrictions.

Figure 1: An example of the 'smoothing algorithm' in action for a spectral analysis depicting loss of consciousness (LoC), Wong K.F.K, 2012.

Figure 2 has been removed due to Copyright restrictions.

Figure 2: An example of a previous students work in depicting loss of consciousness without a 'smoothing algorithm', Rathod D., 2022

The main difference between this project and the paper described is the data set used. The participants within that study were tasked with responding to stimulus in both verbal and physical to be able to define the exact point of loss of consciousness over the course of this experiment. This project will take those learnings of when to identify the loss and return of consciousness and apply them to the unique data set to be used for this project. As the project data contains significantly less muscle artifact, further understanding of the brain will be gained through this analysis.

A similar paper in scope of the previous papers goals was done by Akeju O. et al. in 2016. Instead of doing the same experiment with propofol, however, it was done with ketamine as an anaesthetic. The reason why this is significant in difference to the propofol paper is because ketamine targets completely different receptors than propofol, resulting in a different brain response to the use of the chemical (Mathur Surbhi, 2023).

Whilst the project for this thesis does not use data that includes participants that have been placed unconscious using ketamine, it does pose an opportunity for future research that involves going through a similar data collection process involving paralysing the participant to remove muscle artifact, but instead using ketamine as the anaesthesia to perform a study that delves deeper into NMDA receptor anaesthesia's. The authors of that paper concur with this, as they discuss in their limitations their results are limited due to it being a retrospective study which did not provide the exact depth of data they wanted.

Improving EEG Analysis

The first goal of this project was to improve the EEG analysis tools used by the BSL. Specifically, an algorithm dubbed internally as the ‘smoothing algorithm’. This ‘smoothing algorithm’ is in reference to a paper created by Wong, K.F.K. et al. (2019) that implements an algorithm that gives greater insight into how each of the EEG channels interact with each other and influence signals. This sort of effect can be found in a few other papers as well, notably with many of the same authors included in them. Within the 2019 paper, it is noted that the paper does not address how the algorithm was created, other than mentioning that the figure was an average between all participants of the study. The closest note the paper makes to revealing what has been done algorithmically is a reference it makes to a paper using ‘Global Coherence Analysis’.

Inside the paper referenced (Cimenser A. et al, 2011), the authors reveal their processing methodology for obtaining similar plots to the 2019 Wong K.F.K. paper. The methodology used begins with a referencing scheme that has each electrode viewed in reference to the average activity of the electrode positions surrounding it. Additionally, findings of the paper showed that taking a surface Laplacian shows the approximation of how electrical current travels across the scalp at each electrode site, for a sufficiently dense EEG reading. However, given the density of the paper and the results already being covered in much greater detail in Wong K.F.K. et al’s 2019 paper, where the definition of the transition into unconsciousness was covered in far greater detail, this 2011 paper didn’t provide much other than indicators as to how to create this algorithm.

Looking further, there was a 2011 study in which Wong K.F.K et al. unpacked Cimenser A. et al's paper, looking at how their methods could have greater use when viewing EEG recordings of participants under anaesthesia. Within this paper (Wong K.F.K et al. 2011), a method was found to improve upon Cimenser A. et al's. work to make it significantly more robust to noise. Their findings demonstrated how, in a series of figures, how their could improve the views of their findings through the removal of large noise artefacts present in their findings. The authors show their methodology which includes equations of taking the cross-spectral matrix of the results, and using the median in place of the mean to make it more robust to noise. As the methods described only apply to the robustness to noise, and not trying to explicitly remove it, this methodology should have no negative impacts on the analysis of the paralysis data given the lack of muscle artifact. And as the methods for this smoothing algorithm is a little more defined, the final question of how to interpret the data must also be answered.

Expectations of Findings

Finally, using all that has been discussed prior, the question must be asked of what is expected to be found by analysing the data set unique to this project. One area that was under explored was how to interpret the results, and what is expected to be found as a result of the data analysis. As such, papers already discussed within this literature review were revisited to observe how each paper went about reporting and analysing their findings. Wong K.F.K et al. in 2019 created a series of spectrograms and visualisations based on defining the loss and returnal of consciousness, with a focus on specific bands of frequencies found at the scalp of the head. These frequencies being 0.1-1 Hz, 8-12Hz, and 25-35Hz. The paper used these to investigate specific frequencies they found relevant from a neuroscience perspective (these frequencies being named low-frequency, alpha and gamma respectively). The paper does make note of beta waves (13-24Hz) but does not provide visualisations of them. Hence, in this study it will be endeavoured to also investigate that band of frequencies.

In Cimenser A. et al.'s 2011 paper, one visualisation of results was seen as particularly useful to one of the goals of the masters thesis, which was to produce a view of different regions of the brain and how they operate during unconsciousness. As seen in figure 3, this was done by generating individual views of each channel, and plot them all against each other, relative to where that channel is located on the scalp.

Figure 3 has been removed due to Copyright restrictions.

Figure 3: A demonstration of how different regions of the brain can be viewed during unconsciousness (Cimenser A. et al. 2011)

The final context of how to interpret results is discussed in Akeju O. et al's 2016 paper. Whilst this paper covers work done to investigate ketamine as an anaesthetic (not particularly useful to this thesis), it does comment on how it analysis the results found through it's study. Their results analysis was formed in investigating repeating patterns in certain frequency bands during the EEG recording. Using this, it is known that a portion of the results discussion should be dedicated to investigating the existence of any rhythmic patterns during the different stages of unconsciousness, and if any begin or cease during the transition between consciousness and unconsciousness,

METHODOLOGY

Implementation of the Multitaper-Method into Existing Code

As shown in the literature review, current methods used to generate spectrograms within the BSL do not match those of the literature and need to be improved upon. A method of spectrum estimation named the ‘Multitaper-Method’ was found to be used in experiments closest to this one, which was able to produce spectrum estimations with a higher frequency resolution than obtained previously (Purdon et al., 2013). The estimation method is performed by using several windows or ‘tapers’ to generate a variety of spectrum estimations, which are then averaged to create a “smooth” spectrum, as visually demonstrated in Figure 4. This process is then repeated multiple times by sliding the windows along the raw data to generate multiple spectra across the recording. Once this is done for the whole recording, all of the generated spectra are concatenated to provide a spectrogram which can be viewed using MATLAB.

Initial tests for the algorithm attempted to utilise the original recordings sampling rate (5000Hz) for the spectrogram, but it was found that MATLAB would not be able to generate spectra at such a high sampling rate. This was found to be caused by an error where an adaptive algorithm made to determine if the spectrum estimate was ‘good enough’ would be stuck in an infinite ‘while’ loop due to the size of the data. Hence, the data was down sampled to 500Hz to prevent issues whilst maintaining a high enough rate to prevent any aliasing in the signal analysis.

Figure 4 has been removed due to Copyright restrictions.

Figure 4: A graph demonstrating the process of the multitaper method. Noisy data has several spectrographs taken of it using different windows (tapers) and is then averaged to create an averaged multi-taper spectrum. This process removes the effects of noise on the data, although at the cost of removal of some features (Prerau et al., 2017).

MATLAB has an implementation of the multitaper-method via the function ‘pmtm’. It takes in a set of data as a basic input, as well as allowing several optional inputs to be able to customise how the multitaper-method is performed. To allow this to integrate with the BSL dataset, a wrapper function was designed to work with the eeg3.eeg data objects in use. The wrapper handled cases where either one or more objects were inputted in addition to any variable amount of channels included in the recording. The wrapper would extract the raw data from each channel in each object and perform the ‘pmtm’ function on it, before packaging the resulting spectra into an eeg3.timefreq object.

The default choice of tapers was left as the MATLAB default choice, discrete prolate spheroidal sequences. With the slide between each window being 0.1 seconds, this again down sampled the final spectrogram to 10Hz. Additionally, with using the function in MATLAB, the spectral resolution in the generated spectrograms became 0.5Hz.

Determining LOC

To analyse unconsciousness using EEG recordings, LOC needs to be identified so that all participant recordings can be aligned. If this is not done, the group cannot have its median taken and as a result general trends are much harder to find. Papers that have studied unconsciousness have used participant activity (responses to stimulants) to determine the point of LOC in participants, and marked the exact time in the recording this was found to be. The BSL data does not have this feature, as both the original study did not call for it and participants had no easy method to respond given their paralysis. Figure 1 demonstrates that LOC can be found as the location where there is a significant increase in power in the beta and gamma frequency bands (Purdon et al., 2013). This was hence used as a benchmark to identify LOC for each participant, with the help of an academic to verify the observed landmark of unconsciousness.

Baseline

Another significant aspect of the process in generating spectrograms is the use of a baseline. Baselines allow researchers to be able to study EEG recordings with respect to a selected time-period of the recording. By using baselines of BSL participants laying down with their eyes closed, interesting components of the recording that deviate from the participants normal state of being is exemplified.

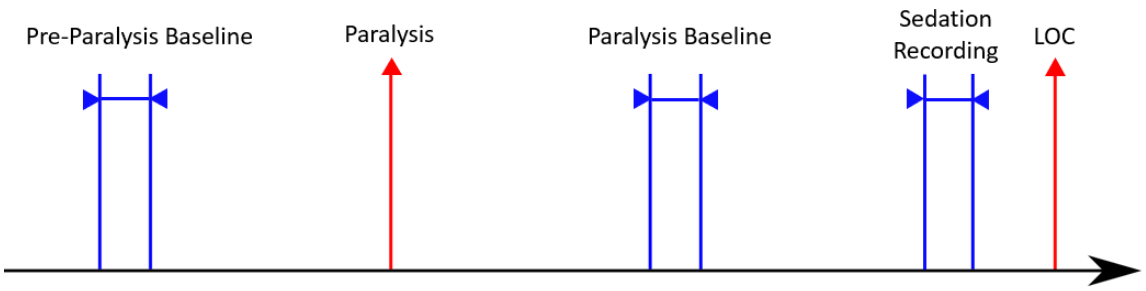

Figure 5: An indicative timeline of the original paralysis experiment, identifying the periods of the time that will be used as a baseline (blue) relative to the major events of the experiment (red).

The baselines that were used for this paper are shown in Figure 5, where two of them were taken during paralysis, and one pre-paralysis. It was hoped that the sedation recording could be used as a baseline due to it most closely matching the state of the participants mind at LOC, but due to the short amount of recording time prior to LOC the results between participants could vary greatly. Hence, an additional baseline was selected further away from LOC, but still part of the paralysis recording to ensure that a baseline of appropriate length and conditions was available. A paralysis baseline was desired as to address the lack of knowledge of the brain's activity with skeletal muscle noise removed. Additionally, a pre-paralysis baseline was also selected from the available recordings. This was done as it most closely matches the data found in both a clinical environment and in other research papers.

Powerbands

It is also interesting to generate other views of the spectrogram data as it may reveal details that are not immediately obvious to the observer. Averaging power over specific frequency bands (delta, alpha, ect.) is useful as these bands vary over time. The code needed to achieve this already exists, written by a previous student (Rathod, 2023). To mirror what was done in previous research, the frequency bands initially used were the delta, alpha and gamma bands, but this was expanded to include theta and beta frequencies to explore what is happening at other notable frequencies.

Topography Generation

As the power in each EEG channel is different, being able to view where channel power varies relative to their location on the head is also useful for data interpretation, as demonstrated in Figure 6. Like with the power bands analysis, the code used to generate these figures was created by a previous student (Rathod, 2023). An EEG topography is achieved by choosing both a time period and frequency range from the spectrogram and averaging the power in that moment for a channel. This is repeated for all channels from which MATLAB will draw the powers of each channel relative to each other in a montage of the head. Unlike in the example below, the code used for this includes topology lines to show the peaks and valleys of the power.

Figure 6 has been removed due to Copyright restrictions.

Figure 6: An example of EEG topographies from a similar paper (Purdon et al., 2013)

The time selected to represent unconsciousness was at the end of the sedation recordings, well past LOC as that represents a stable point of reference of the brains activity during unconsciousness. Instead of one frequency range being selected, multiple were made, selecting bands from delta to gamma frequencies to investigate the differences between bands.

Connectivity Analysis

A connectivity analysis is a series of calculations made to test which parts of the brain are communicating with each other, and in which direction. There are a variety of connectivity measures useful to EEG analysis (Bakhshayesh et al., 2019), and each show different connections based on the question. In this project, 3 measures of connectivity were explored:

1) Transfer Entropy (TE)
2) Symbolic Transfer Entropy (STE)
3) Normalised Transfer Entropy / Symbolic Normalised Transfer Entropy (NTE / SNTE)

As can be observed, all 3 measures explored are variations of transfer entropy. Transfer entropy is a statistical test that measures information shared between two random events. It is a causal test, meaning that it can determine the direction of information flow between channels (Bakhshayesh et al., 2019). To illustrate how transfer entropy is measured, see Figure 7 for a visual guide. To elaborate on what the figure means, first, a signal's current response (Y_t) is estimated using previous data from the same signal ($Y_{t-1:t-1-l}$), as represented by the red shaded region. Then, previous data from a *different* signal ($X_{t-1:t-1-l}$) is then used to estimate the current response of the original signal. The connectivity (information flow) from one channel to another is determined by how much the different signal is able to improve the signal estimation, represented by the green shaded region (Bakhshayesh et al., 2019).

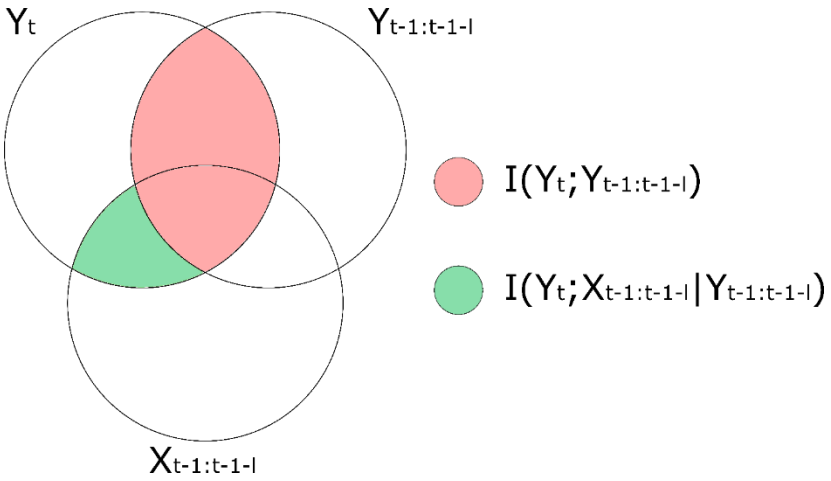

Figure 7: How transfer entropy is measured using prior data. A signal's own ability to predict itself is shown in red, and information flow from one signal to the other is shown in green.

This entire process is calculated using the amplitude of the signal. However, an alternate method of calculating this to instead use numbers that represent the ranks of the amplitudes. This process, named ‘Symbolic Transfer Entropy’ (symbolic TE), was found to be better for fine-tuning parameters on the data as it makes no assumptions about the data (Bakhshayesh et al., 2019). If symbolic TE is found to create a significantly different connectivity result both will be used, otherwise only TE will be explored.

Once the analysis methods have been chosen, the normalised form(s) of TE analysis will then be taken. Normalised TE differs from TE in that instead of measuring just the amount of information flow found between two signals, normalised TE finds this relative to how much information there is in the destination signal. This has the effect of showing connections that would’ve been disregarded otherwise and removes connections that were shown to have a high absolute measure of entropy, but a small relative value. Finally, to interpret the results of the connectivity analysis, the help of a neuroscientist was enlisted to gain insight into the findings.

RESULTS

Initial Spectrograms

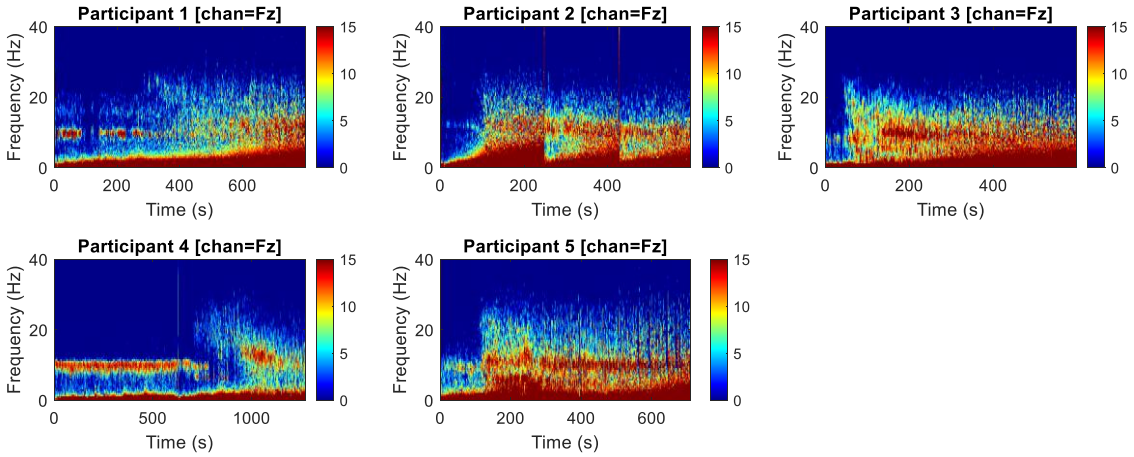

Figure 8: The raw spectrograms of all the original participants. Time has not been aligned such that t=0 represents LOC, and the full recording associated with each participant has been used.

Using the multitaper method as described in the 'methodology' section, all individual participants sedation recordings can now be visualized in a spectrogram, shown in Figure 8. What needs to be noted at this point in data processing is that the data is not aligned to LOC for any of the participants, and that they all need to be set to the same size before any useful comparisons can be made. There is a large spike in power around 0.1 – 2 Hz, which is likely caused from cyclic behaviour in the body, such as breathing and the common heartbeat, but this is considered a normal feature of unconsciousness (Mukamel et al., 2011). The last element that needs to be addressed regarding the initial spectrograms is the unknown artifacts which can be seen around 250 and 400 seconds in participant 2. After discussions with one of the lead scientists from the BSL who performed this experiment, those artifacts seem to be caused by someone poking the participant to see if they were unconscious yet.

Baseline

As shown in Figure 8, creating a spectrogram using the Multitaper-Method did create ‘smoother’ results, due to the increase in both time and frequency resolution (see Figure 24 for a direct comparison). As discussed in the methodology, the times were selected through consensus when reviewing with an academic to find the most likely point of LOC. After aligning all participants to LOC, the data was truncated such that all participants had the exact same recording window, which not only made them easier to compare side-by-side, but also easier to generate a median of all participants data. As can be seen in Figure 9, the median shows a spike in power around 10Hz, which is typical of resting brain landmarks (Mukamel et al., 2011).

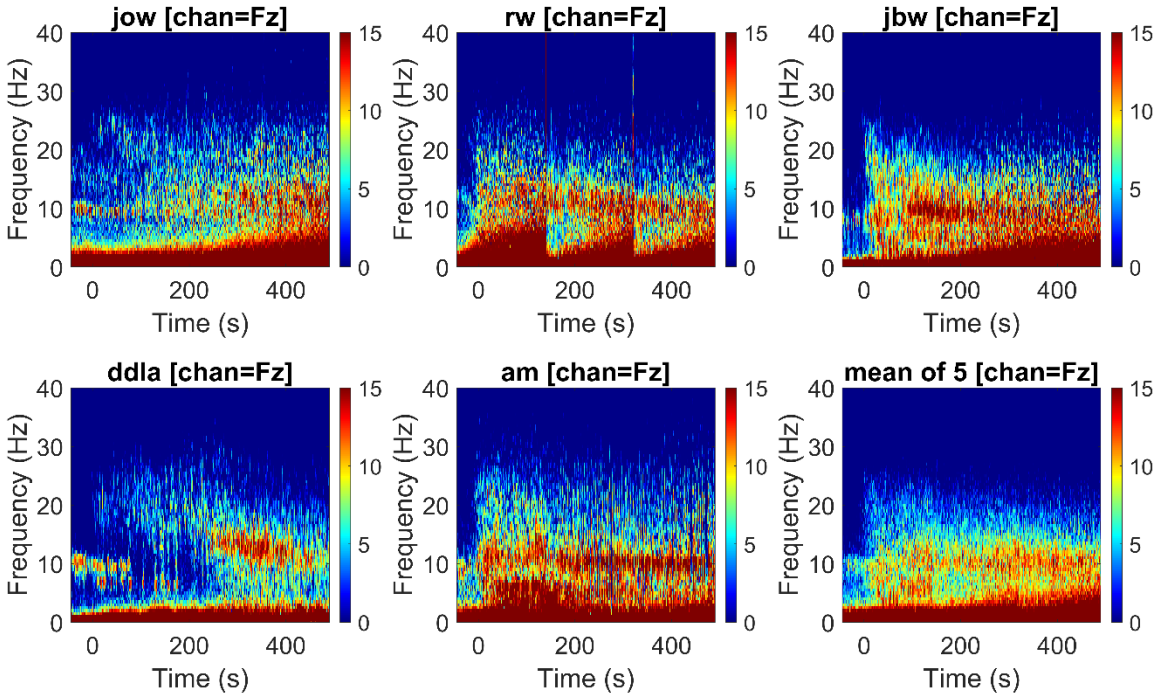

Figure 9: Spectrograms of all participants within the study, including a median of all. The spectrograms have inconsistent noise patterns across participants.

The variance between all participants and their oft hard to find LOC times are of note in manual analysis but given how much an EEG recording can vary with a multitude of factors, this isn’t a surprise (Devika Rani and Harsoor, 2012). However, to get more consistent results across participants, a baseline normalisation was performed, where post-stimulus activity is revealed by comparing post-stimulus data to a period of recorded data with no stimulus (University of Bern, n.d.). For this thesis, 3 baselines were tested to see what would suit the data the best.

The spectrograms made using the sedation baseline can be seen below in Figure 10. As predicted, the short selection time has resulted in three participants (1, 4 and 5) having reduction in alpha band power, whilst two participants (2 and 3) showed a sharp increase in this band. This is likely due to participants tensing prior to sedation and reducing alpha frequency power. As such the sedation baseline was rejected due to inconsistent responses.

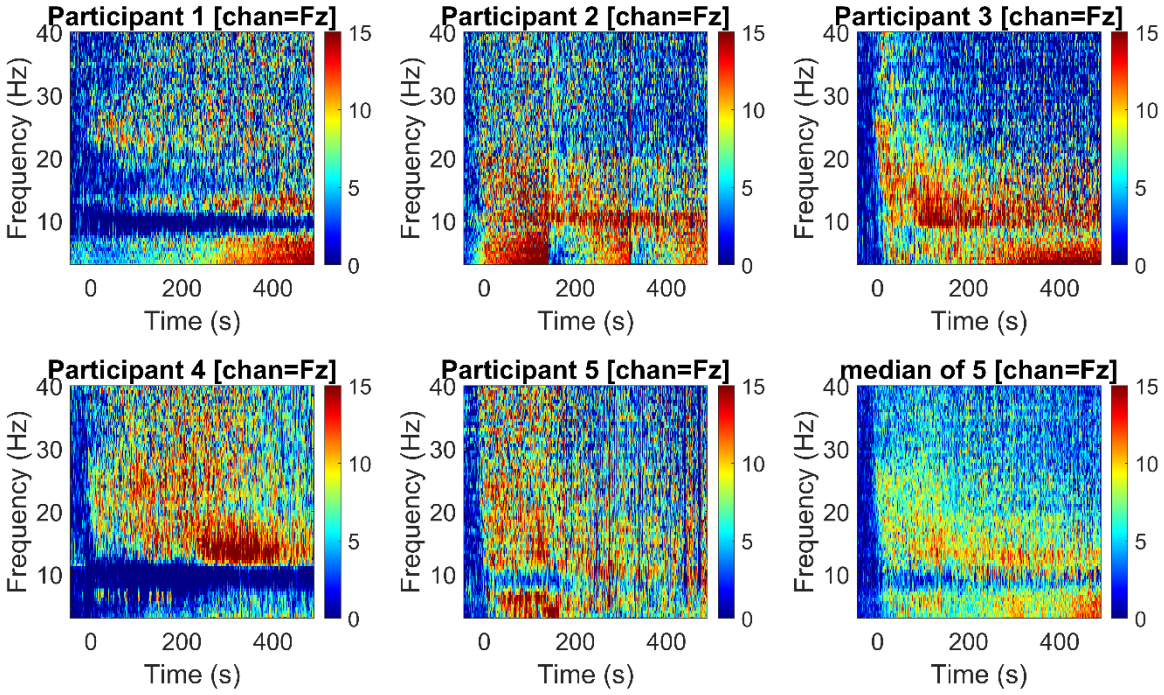

Figure 10: Spectrograms of all 5 participants, in addition to a median of all spectrographs, taken using the multitaper method and using a baseline from the sedation recording, close to LOC. The removal of power in the alpha frequency band can be observed.

The spectrograms generated using the paralysis baseline is shown in Figure 11, which was found to be much more consistent between participants. Only one participant had a notable reduction of alpha frequencies, And all participants showed an increase in low beta / high alpha frequency power. One feature of note is the amount of activity happening in gamma frequencies (25 Hz +).

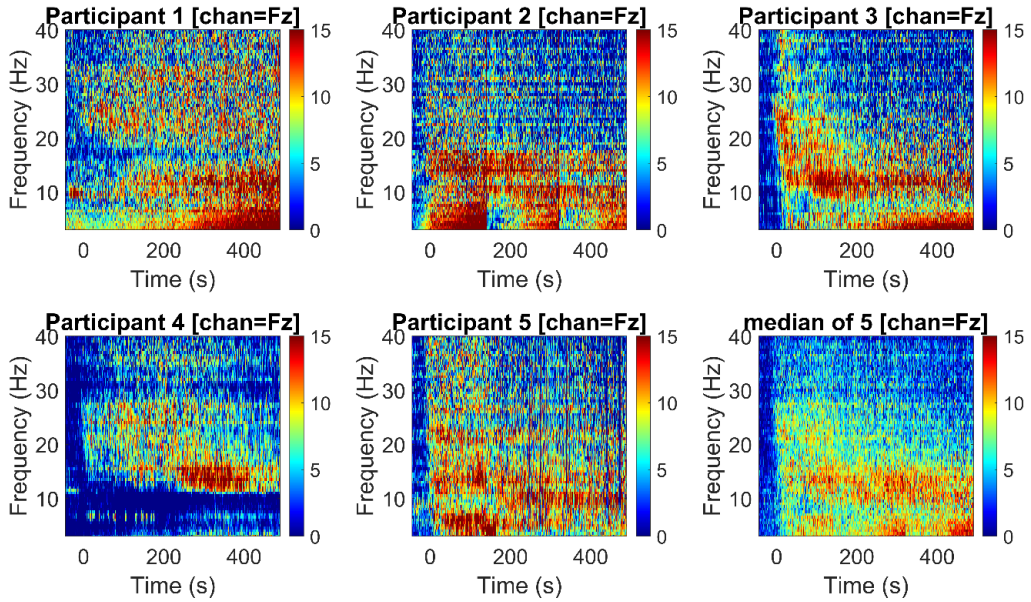

Figure 11: Spectrograms of all 5 participants, with an additional median of all spectrographs. This set of graphs was made using a baseline that was further away from LOC, using a specific ten second 'baseline' recording.

Using a baseline taken prior to paralysis was shown to create a very smooth spectrogram, as can be seen in the median of Figure 12. There is a significant reduction in power in the gamma band, due to the recording being compared to a time where participants weren't paralysed (skeletal muscle activity primarily operating in the gamma band).

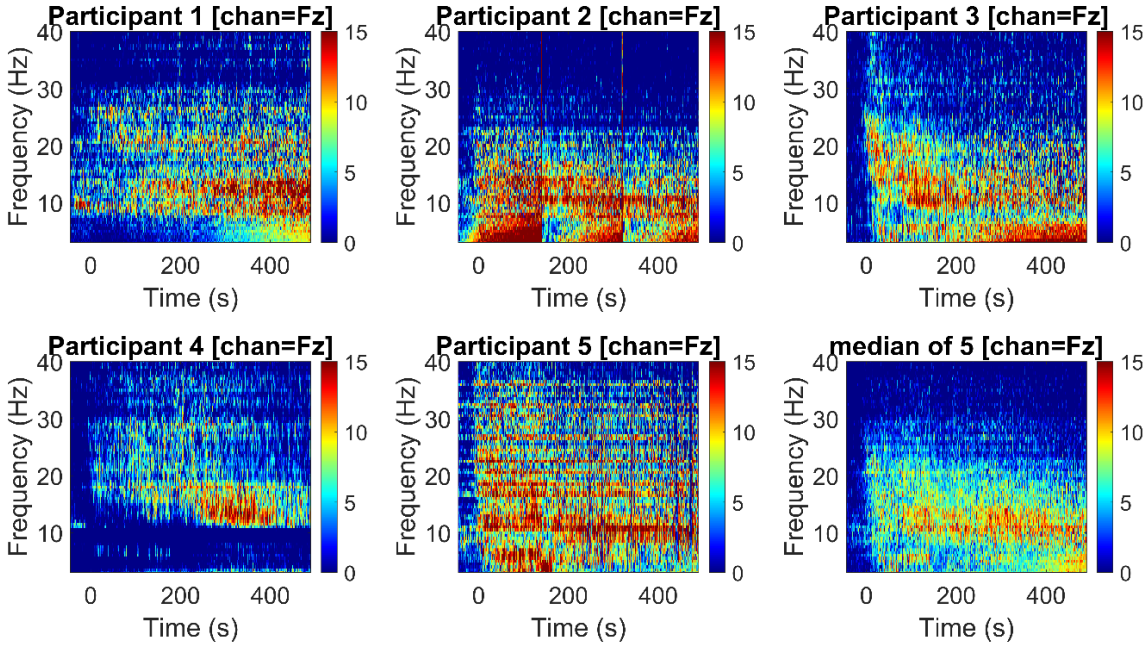

Figure 12: Spectrograms of all 5 participants in addition to a median between them all. The spectrograms were made using a baseline taken pre-paralysis. In the median, the high alpha / low beta landmark can be identified, but not as much the delta landmark.

Relative to Paralysis

The following section contains the produced median figures of all 5 participants. Figure 13 contains the median spectrogram with respect to paralysis, 14 contains the average powerbands from the spectrogram as they vary over time, and figure 15 demonstrates the topography of the EEG cap well after LOC.

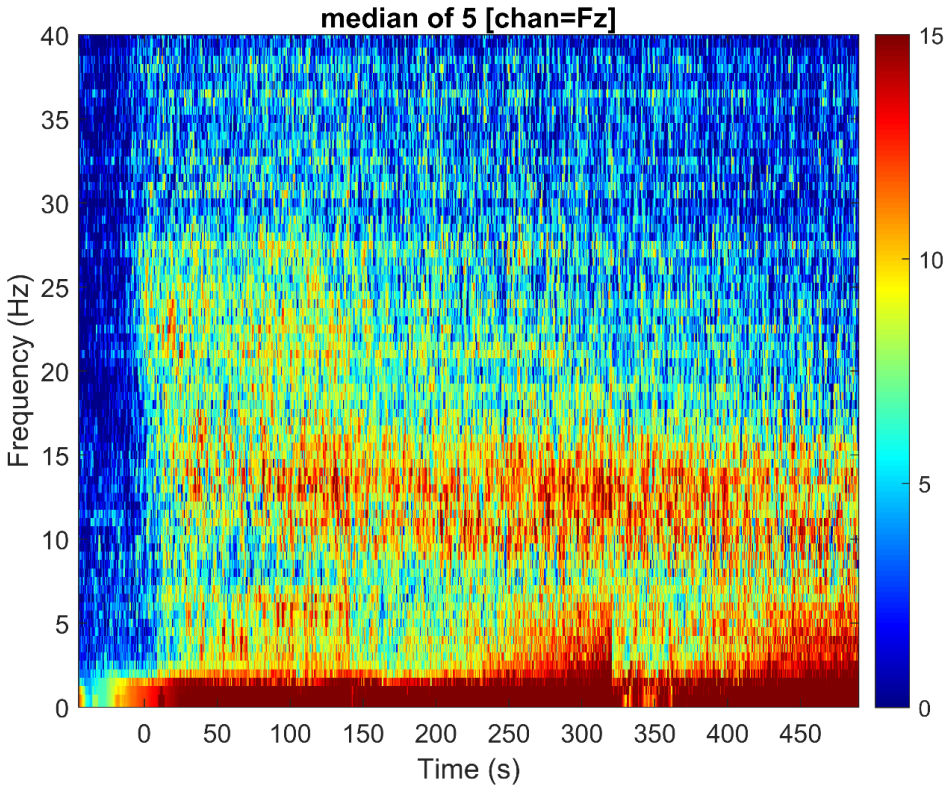

Figure 13: Median of all 5 participants on the EEG channel 'Fz'. This spectrogram was taken using a paralysis baseline and shows a high amount of delta activity, with some power in the high beta / gamma frequency bands.

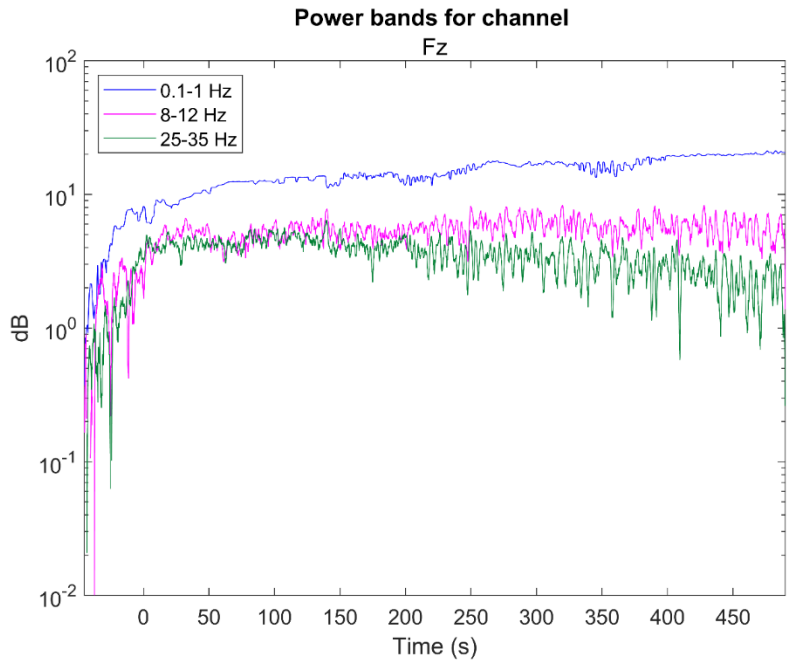

Figure 14: The power bands of the spectrographs taken of all 5 participants using a paralysis baseline. The power bands are Delta (blue), Alpha (pink), and Gamma (green). t=0 marks LOC and all bands show a significant increase in power post LOC

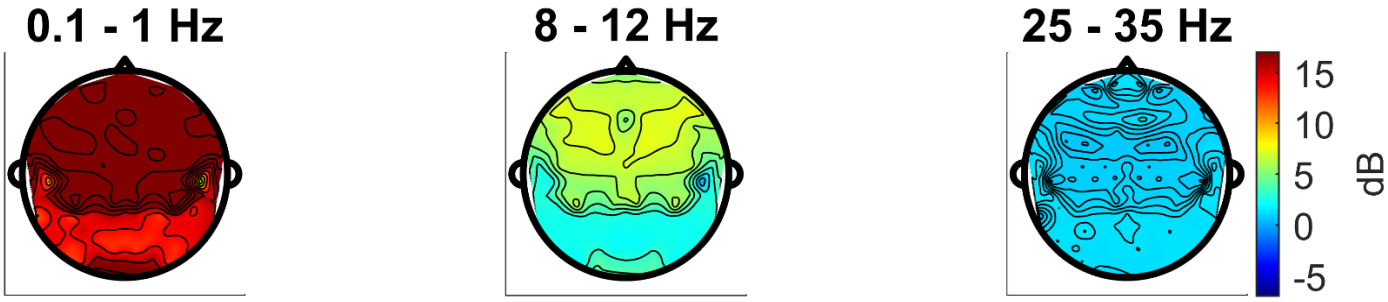

Figure 15: The spatial distribution of power at low delta (left), alpha (middle), and gamma (right) frequencies. The powers of the signal are relative to paralysis, and show that there is a decrease in power of the occipital region of the brain. There is also a localized decrease in power in the temporal region for both low delta and alpha frequencies.

Relative to Pre-Paralysis

The following section contains the produced median figures of all 5 participants, although these figures instead used a pre-paralysis baseline in their generation. Figure 16 contains the median spectrogram with respect to paralysis, 17 contains the average powerbands from the spectrogram as they vary over time, and figure 18 demonstrates the topography of the EEG cap well after LOC.

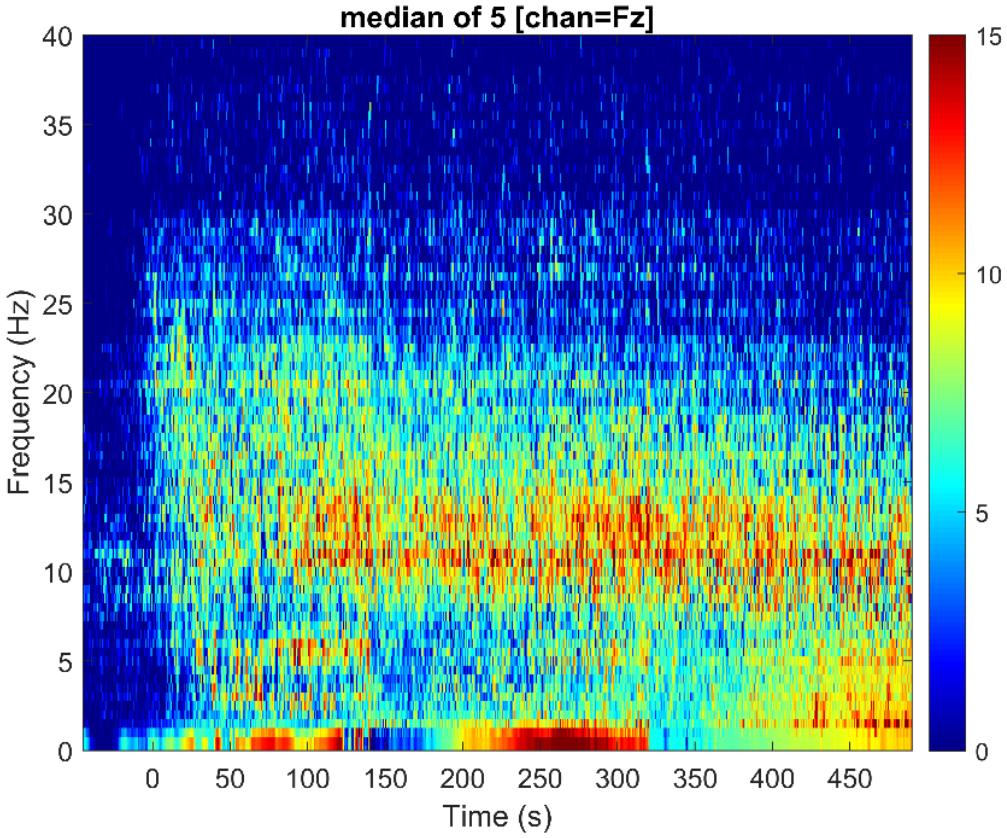

Figure 16: Median of all 5 participants on the EEG channel 'Fz'. This spectrogram was taken using a pre-paralysis baseline and shows intermittent delta activity, with some power in the low beta / high alpha bands and a reduction in power in the gamma band.

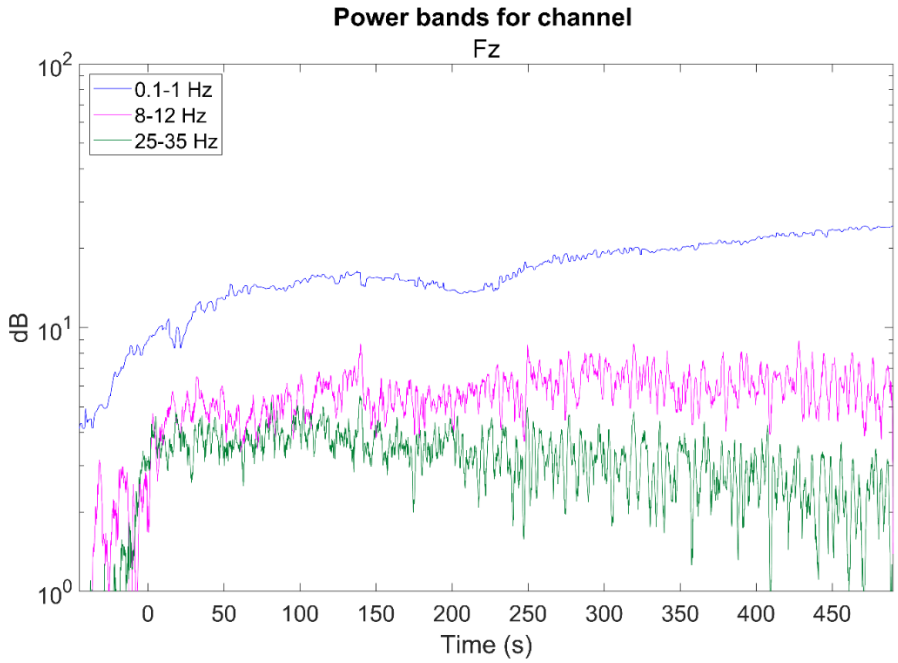

Figure 17: The power bands of the spectrographs taken of all 5 participants when using a pre-paralysis baseline. The power bands are Delta (blue), Alpha (pink), and Gamma (green). t=0 marks LOC and all bands show a small increase in power post LOC

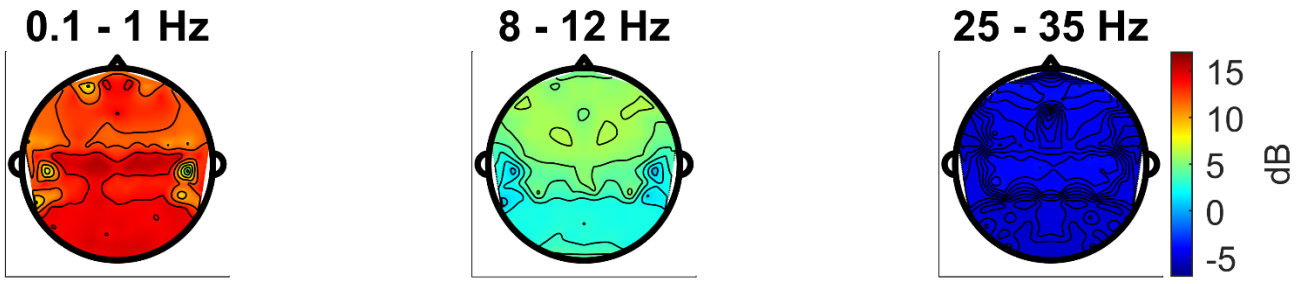

Figure 18: The spatial distribution of power at low delta (left), alpha (middle), and gamma (right) frequencies. The powers of the signal are relative to paralysis and show that there is a decrease in power of the occipital region of the brain, and a localised decrease in the temporal region.

Connectivity Analysis

Shown in figures 19 through 22 is the results of the connectivity analysis performed using both transfer entropy (TE) and a normalised TE algorithm. As discussed in the methodology, symbolic TE was also tested as a variant, but didn't display any connections between channels, see Appendix F for details.

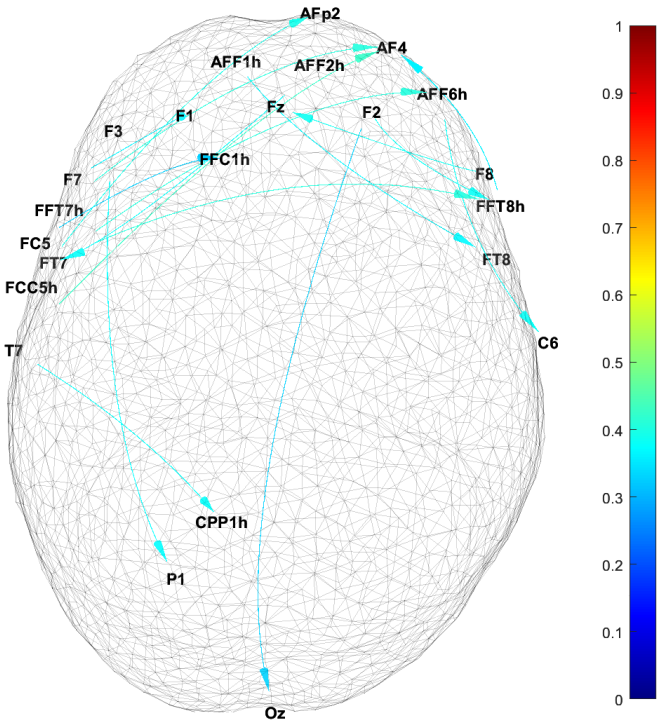

Figure 19: A top-down view of the brain, with the top of the figure representing the frontal region of the brain and the bottom representing the occipital region. A transfer entropy (TE) connectivity measure was taken of all 5 participants, and the brains connectivity between channels prior to LOC is shown.

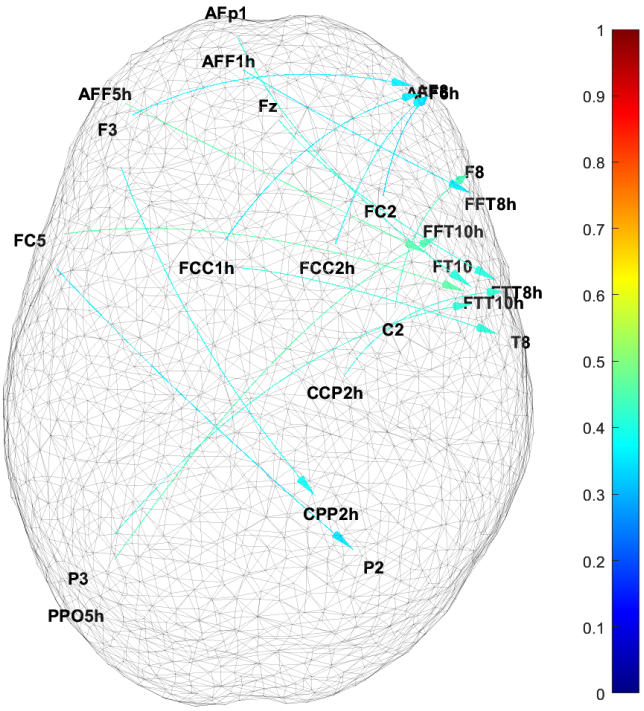

Figure 20: A top-down view of the brain, with the top of the figure representing the frontal region of the brain and the bottom representing the occipital region. A transfer entropy (TE) connectivity measure was taken of all 5 participants and averaged, the brains connectivity between channels after LOC is shown.

Across the results, it is noted that the algorithms chosen calculates the p-values for each found connection. Each connection between channels displayed on the model of the brain are hence considered statistically significant ($p<0.05$). Using the TE algorithm, conscious activity revealed some connections toward the frontal region of the brain, with the remainder travelling towards the temporal lobes or (in one case) the occipital lobe. Unconscious TE revealed heavy activity heading towards the right temporal lobe of the brain.

Normalised TE revealed a lot more connections between channels. In the chosen conscious data set, not only are there more connections directed at the frontal cortex, but additionally more travelling to both temporal lobes. The unconscious data set also had an increase in channel connections, with some pointed at the frontal and occipital regions of the brain, but the majority of connections directed at the temporal lobes.

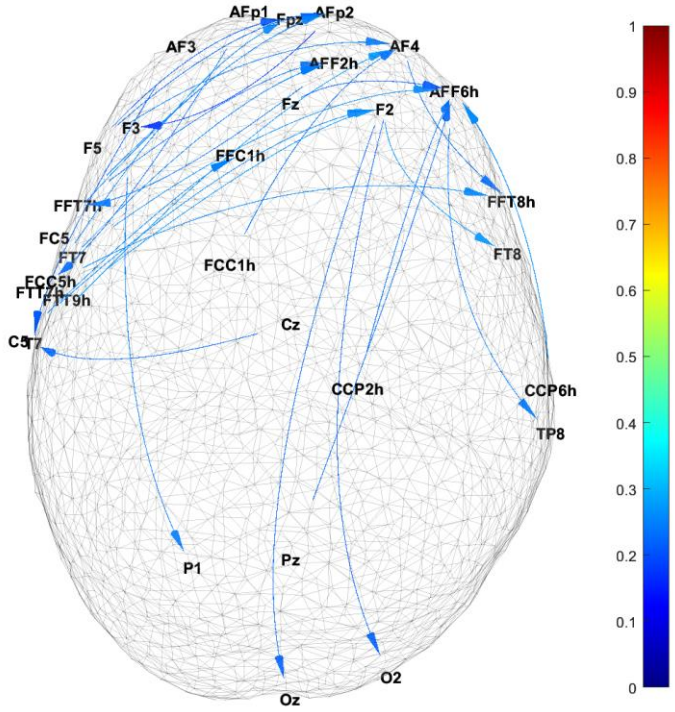

Figure 21: Connectivity analysis of the conscious brain, averaged between 5 participants. This was made using a normalised transfer entropy algorithm. Most of the connections lead toward left temporal and frontal regions of the brain.

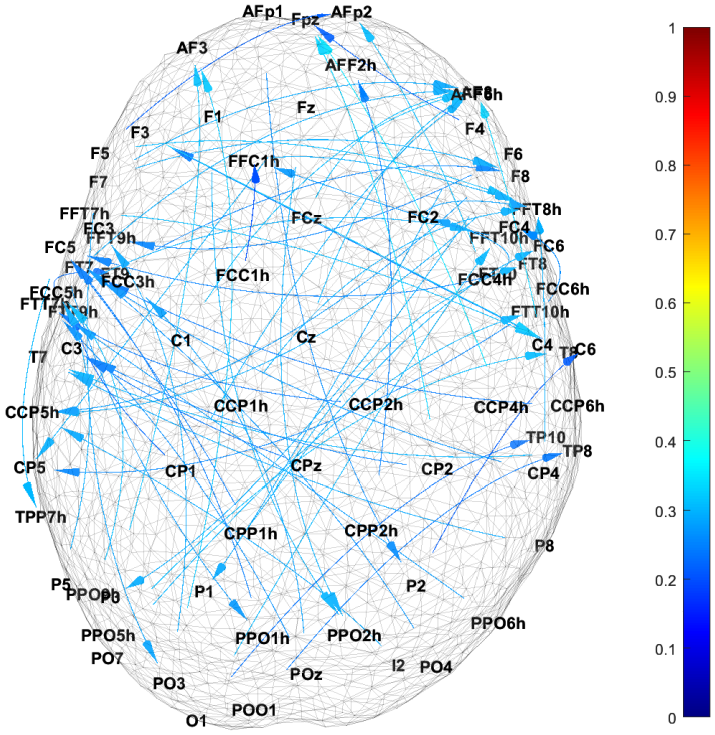

Figure 22: Normalised transfer entropy analysis of the unconscious brain, averaged between 5 participants. Whilst some connections are moving towards the frontal and occipital regions, most connections are travelling towards the temporal regions of the brain.

DISCUSSION

Comments on pre-paralysis baseline findings

The first objective of the project was to create a new method for generating spectrograms within the BSL. This objective was fuelled by the lack of ‘smoothness’ in the spectrograms being generated by the BSL as compared to other academic papers and their results generation. Hence, as can be observed in Figure 23, there is a significant increase in both resolution that adds additional clarity to the shape of the spectrogram, in addition to smoother transitions between values on the figure. The frequency domain had a twofold resolution increase, whilst the time domain had a fivefold increase. This is a significant outcome as it increases the clarity at which the data can be viewed, allowing for smaller details to become observable. One currently unexplained element of the data is the bursts of delta energy around 50 and 250 seconds. Whilst not confirmed to be as such, it is hypothesised that the multitaper-method struggles with low frequencies due to the unconvincing appearance of the bursts.

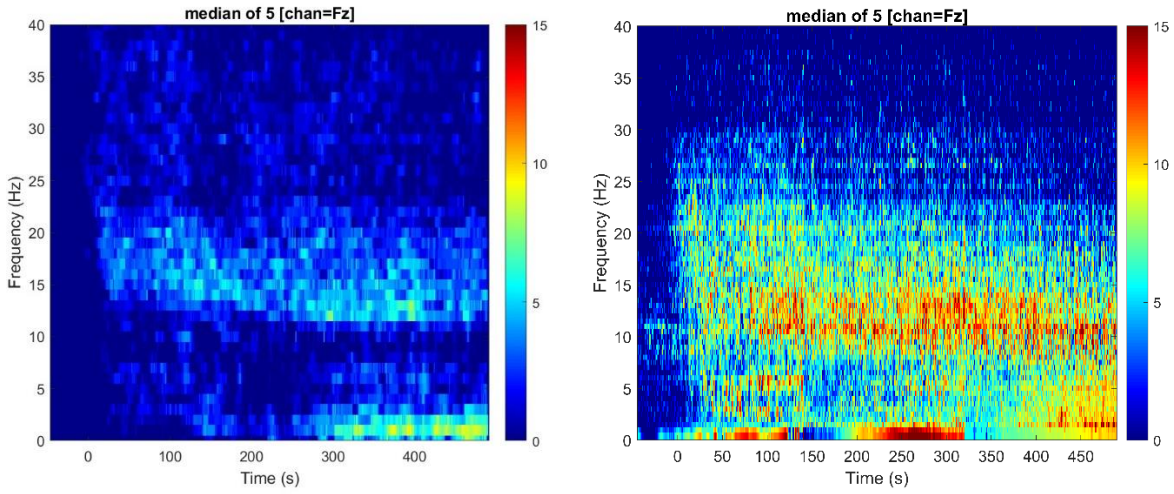

Figure 23: A comparison between the spectrograms generated using one of many available toolboxes (left) and the multitaper-method (right). The powers vary between results due to changes in baseline used. The high alpha / low beta landmark can still be seen on the graph, but the delta landmark is harder to locate on the right figure due to sudden bursts of delta power. There is an improvement in both frequency and time resolution as a result of the multitaper-method for increased detail.

Comparing the outcomes of the new BSL spectrograms to similar research in Figure 24, the time resolution of the spectrograms are similar, although this project's spectrograms has a lower resolution in the frequency domain. The spectrogram on the left also features a much smoother transition between powers across the time domain. One key difference in methodology between the two spectrograms is that smoothing priors are implemented as well (Purdon et al., 2013). Implementing this could potentially account for the difference in resolution and additional smoothness in the figure. Hence, implementing smoothing priors would be the appropriate next step in attempting to improve the spectrogram estimates that can be created in the BSL.

Figure 24 has been partially removed due to Copyright restrictions.

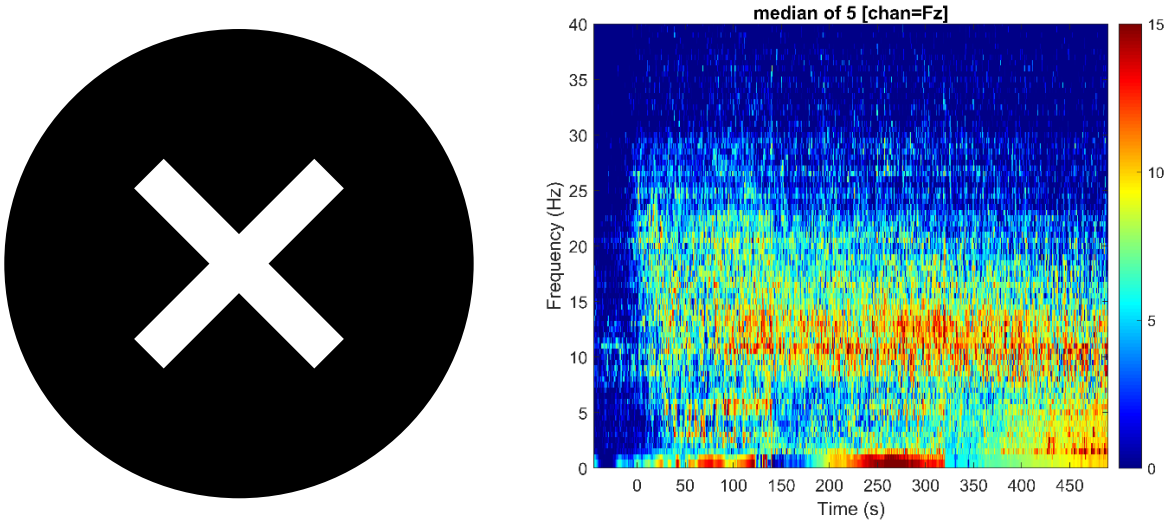

Figure 24: A comparison between the spectrograms generated in a similar paper (left) (Purdon et al., 2013) and the multitaper-method (right). The multitaper method still has a better frequency resolution as opposed to the other paper. The high alpha / low beta landmark can be seen on both spectrograms, but the delta landmark is incredibly clearer and distinguishable on the left. Additionally, the spectrogram made using the BSL data appears to be much noisier than the left spectrogram, although this may be due to the lack of smoothing priors implemented in the BSL's data.

The second goal of the project was to either support or challenge the existence of landmarks within a spectrogram that correlates to consciousness. From these spectrograms, support is shown for the existence of a landmark appearing at high alpha / low beta frequencies upon loss of consciousness. This is significant as this means there is a recurring signature that could be measured in clinical settings that could help measure depth of anaesthesia. However, due to the artifacts found at very low frequencies using multitaper estimation, the existence of the delta landmark is neither supported nor challenged.

The spectrograms created using a pre-paralysis baseline were then expanded into different views to be able to further reveal differences between consciousness and unconsciousness. As discussed earlier, there is support for the existence of a high alpha / low beta landmark appearing upon LOC. The power bands analysis in Figure 25 demonstrates that there is a clear increase in alpha band power upon onset of LOC. This holds true for low delta frequencies here too, yet it is noted that neither low delta nor alpha powers reach that of the referenced paper on the left. It is also observed that the use of a pre-paralysis baseline has significantly reduced the power in the gamma region (as skeletal muscle contains significant power at those frequencies).

Figure 25 has been partially removed due to Copyright restrictions.

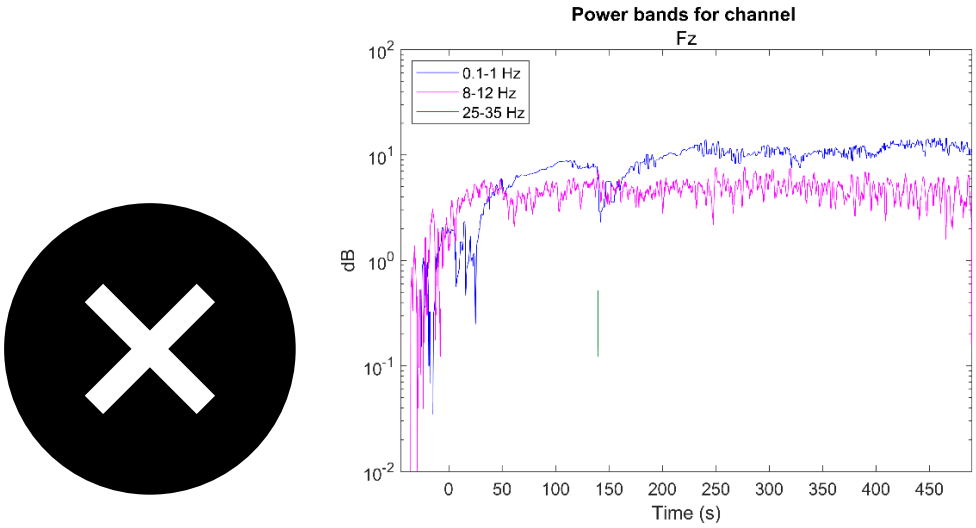

Figure 25: The power bands of a similar experiment (left) (Purdon et al., 2013) and the bands generated using the multitaper method with the BSL data (right). All bands are matched in colour and frequency range. Upon loss of consciousness (t = 0), there is a rise in power common between both the low delta and alpha frequency bands. In the BSL data, there is a missing response from the gamma band of frequencies due to the suspension of skeletal muscle artifact by the paralysant.

The topology analysis made using the BSL dataset is compared against a paper that had the same research goals in Figure 26, where a pre-paralysis baseline was used. Like all other visualisations of the BSL data set, the power is noticeably lower across all channels and frequencies as opposed to the literature. The delta band topology does share the high powers found at almost all channels, but unlike the paper referenced does not feature the decrease in power around the frontal and occipital regions of the brain. Given that noise from smooth muscle (gut, heart, etc.) is present at low frequencies, it is unknown how to interpret these high powers.

For alpha frequencies, the same general shape can be observed as to the literature, where the main increase in power post LOC is in the frontal cortex, and there is a decrease in power around the occipital region. The topology of gamma frequencies show a small decrease in the occipital region of the brain, whilst the alpha topology shows an increase in power in the frontal region of the brain in addition to a decrease in the occipital region. The gamma topology, unlike the literature, does not show an increase in power in the medial-frontal region of the brain, although this is expected as when using a baseline that features a lot of gamma activity (pre-paralysis skeletal muscle artifact), there is expected to be heavy attenuation in the gamma band. One feature of the BSL's dataset that was not observed within other papers is the decrease in power around the temporal lobes in both the delta and alpha bands of frequencies. While this may seem significant, before any hypothesis is made, additional review of individual participants and outliers within channels need to be checked prior.

Figure 26 has been partially removed due to Copyright restrictions.

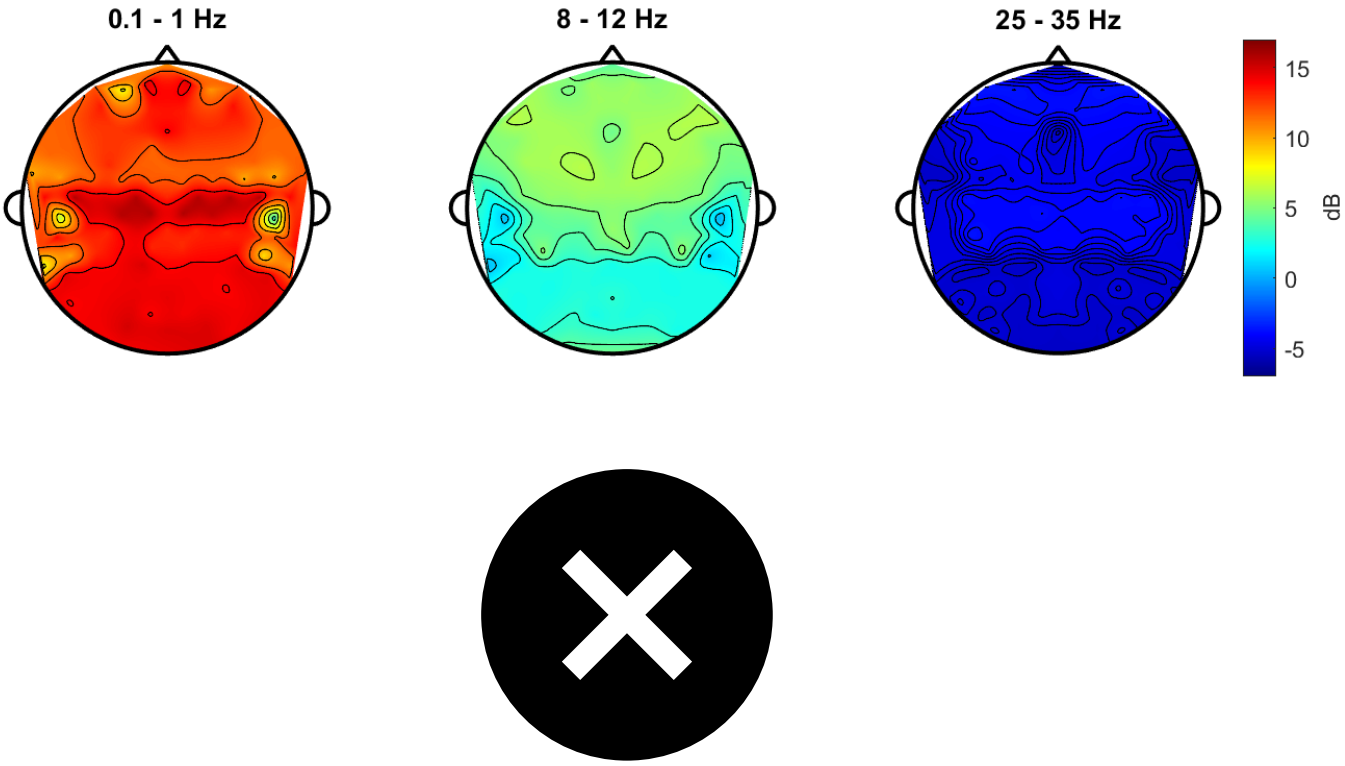

Figure 26: The spatial distribution of power using the BSL data set (top) and from a similar paper (bottom) (Purdon et al., 2013). The topologies are viewed using 3 different frequency bands, and the time of the recording that is used for both sets of topologies is several minutes post LOC.

Addressing the peak of the topology power in the alpha range, it's clear that the majority of activity in the brain during unconsciousness is in the frontal cortex. As that's where abstract thinking and conscious thought occurs (El-Baba Rami and Schury, 2023), it shows some level of thought is still active within the brain during unconsciousness. This is a well-documented phenomena where patients can recall certain memories from when they are under anaesthesia (Guerra, 1986).

There is also decrease in alpha power around the central-parietal band of the head. This makes sense considering that's the approximate location of the somatosensory cortex, where humans perceive tactile stimulus. In a clinical setting where unconsciousness is induced for reducing patient sensation during surgery, this is ideal.

Regarding the connectivity analysis that used the normalised transfer entropy algorithm (Figure 21 and Figure 22), it was unexpected for that many channels to be found to show statistically significant connections during unconsciousness. It was hypothesised that there would a significant decrease in connectivity once the brain is unconscious, which was not supported by the data. The main notable feature of the connectivity post LOC is that many of the connections are pointed towards the temporal lobes of the brain. This may correlate to the decrease in power in the temporal lobes in Figure 26. It appears, given the decrease in power in those regions, it could be that the brain is sending an inhibitory signal to the auditory processing region of the brain (temporal lobes). It is hypothesised that the purpose of this behaviour is to supress a function within the brain that 'wakes up' the patient due to auditory stimulation. However, there is no further evidence to support this theory, and hence further investigation is required.

To further investigate this feature of the connectivity analysis, the code was run again multiple times, with each iteration using data that had been bandpass filtered to a brain rhythm band. The bands tested to further explore this occurrence was theta, alpha, beta and gamma frequencies, the full results of this testing can be found in Appendix G.2 – Band Passed Connectivity For a Pre-Paralysis Baseline. The outcomes of this exploration shows that the temporal signals start at beta frequencies which can be seen in Figure 27, but the majority of them are found in the gamma band of frequencies, as seen in Figure 28. This is a significant finding of the report that suggests that gamma frequency brain waves inhibits signals in the brain during unconsciousness but again, further investigation is required.

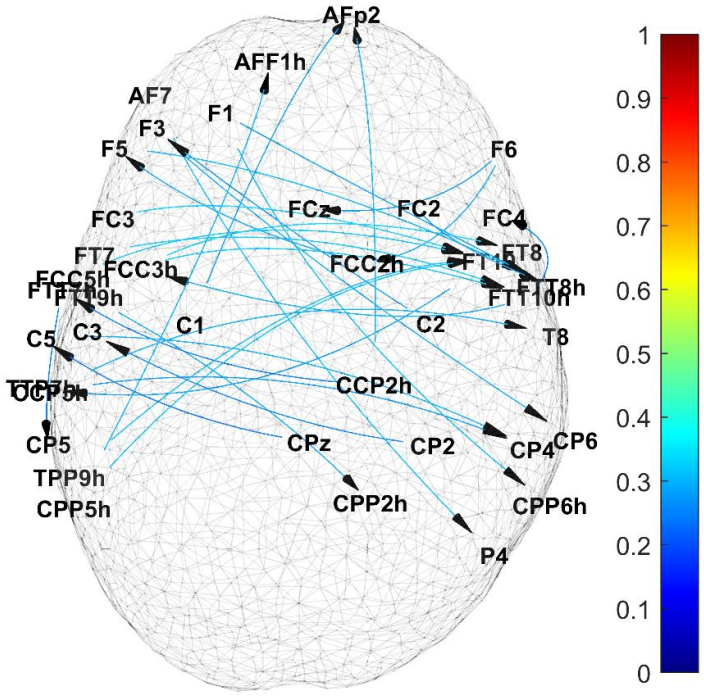

Figure 27: Unconscious connectivity analysis, bandpass filtered to include beta frequencies and attenuate all others.

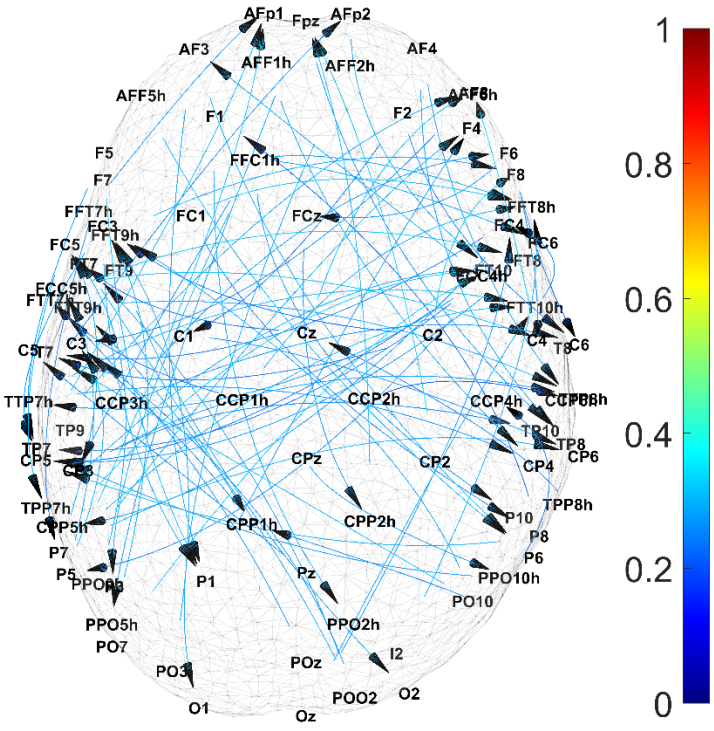

Figure 28: Unconscious connectivity analysis, bandpass filtered to include beta frequencies and attenuate all others.

Comments on Paralysis Baseline Findings

One of the more intriguing outcomes of the project were the findings made from the paralysis baseline. As the use of paralysant has removed skeletal muscle artifact from the EEG recording, any signals found at that frequency range are significant as it is typically hard to find brain activity in that range due to muscle artifact. As can be seen in Figure 14, there is an increase in the gamma frequency band by about 6 decibels. This is a significant finding as it implies that the brain has some unknown high frequency signals that occurs upon loss of consciousness. This potentially ties into the hypothesis that high frequency signals within the brain are the root cause of inhibitory signals that reduce perception of stimulation during unconsciousness, but another study is required to explore this further. As discussed in the results section, additional figures, including topography charts, connectivity analysis, and power band graphs can be found in appendices. This is due to many of the figures with the paralysis baseline mirror the findings of the pre-paralysis baseline with the exception of gamma frequencies.

CONCLUSION

With the research of this paper complete, it has been reaffirmed and validated, some of the findings of previous research regarding spectrogram observations between the conscious and unconscious brain. Within the EEG recordings used for analysis, noise-smoothened spectrograms revealed an increase in power for frequencies in the alpha bands. This matched findings from past papers that explored the unconscious brain, where similar increases of power were found in those bands. However, there was a lack of activity found in the delta frequency band.

Regarding how the power of different frequency bands varies across the topology of the head, it was affirmed that in the alpha band, the highest power of those frequencies are found in the frontal part of the head. Additionally, it was shown that with the removal of skeletal muscle noise, there is significant activity happening the gamma band of frequencies.

Final findings of the report had shown that there is a difference in channel connectivity between the conscious and unconscious brain. The unconscious brain was found to have significant connections to the temporal lobes, and it is hypothesised that this may have an inhibitory effect on the senses.

Through the findings of this study, both affirmations to existing research and new conjectures to how the unconscious brain were made. However, the new conjectures made regarding connectivity between the unconscious brain need further research. As this study comprised of only 5 participants, a new study that focuses on brain connectivity with a wider set of participants is proposed. It is hoped that these findings will push forth new research opportunities and expand current works into creating tools for clinical use.

FUTURE RESEARCH

By the end of this project, there are questions posed by the results discussion that have not been achieved yet. Firstly, the methods used to generate spectrograms within the project are not perfect, featuring artifacts around very low frequencies (0.1-2Hz). Being able to refine the methods used to generate a multi-taper spectrum is the next required step in the project. The most likely way to achieve this is to implement smoothing priors into the code, as one paper has used them in tandem with multi-taper estimates to produce very clean spectrograms (Purdon et al., 2013).

Secondly, one of the major limitations of this report was that there was the limited number of participants within the BSL's data set, that being 5 participants. This reduces the statistical power of the findings, reducing the certainty that the hypothesised meanings of the results are true. Hence, recording more data that includes LOC in addition to ROC (return of consciousness) would be beneficial to increase the statistical power of the findings and get more insight into arousal from unconsciousness. However, the ability to be able to record additional participants using the methods from the BSL in 2006 would be incredibly unlikely in today's world given the costs and ethics approval needed. A good alternative to recording data may be to reproduce the experiment with the removal of pharmaceutical paralysis as to make it easier to pass by an ethics board.

This, however, comes with the issue of not providing suitable data to validate the increase in power seen in the gamma band upon LOC, as it is hypothesised to be connected to inhibition of sensory signals within the brain. This specific finding requires a recreation of the data collection *specifically* with the paralysis of the participants in order to find support for, as it is unlikely that current noise removal techniques would not be able to adequately remove skeletal muscle noise without also removing the low power, high frequency signals found during unconsciousness. Otherwise, additional data collection would be able to validate that the findings of the connectivity analysis performed within the report. As one of the major findings of the connectivity analysis was the connections found directed at the temporal lobes in the brain. As this paper is the only one that demonstrates this connection in propofol-induced unconsciousness, support for the findings shown is necessary.

Additionally, one aspect of the gap which has not been filled in this project is the effect of other anaesthetics. As discussed in the introduction, different anaesthetics are used clinically, and there are differences in patient reaction to them. Whilst useful to have an exploration into the effect of propofol on the brain as it goes unconscious, as this paper does, the gap question introduced still applies to other clinically used anaesthetics. As one of the overarching goals of the paper details, there is a need to be able to predict a patient's risk of arousing from unconsciousness, and this need cannot be filled with an understanding of propofol alone.

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APPENDICES

Appendix A – All Spectrogram Figures and Data Loading Code

```
% script for reproducing the Boston paper figures

% use pretty_print:
% pretty_print( 'target', 'slide', 'filename', 'myFig2B.png')

% Guide to variable names:

% d  = All loaded subjects from the experiment
% dr = All loaded subjects with a resampled sampling rate

%% Declare all definitions and variables

% Variable definitions
fs0 = 5000;
fs = 500;

frequencyRange = [ 0 40];

median_filter_order = 19;

% Baseline choice %
% 1 for no baseline
% 2 for baseline.eyesclosed recording
% 3 for baseline from sedation recording
% 4 for baseline.preparalysis recording
baselineChoice = 2;


% Title definitions
figure2B_name = 'Fig. 2.B';
figure2C_name = 'Fig. 2.C';
figure2D_name = 'Fig. 2.D';

% Timing info for unconscious data
times = [ ...
    1 803; ...                  % JOW  data
    0.0002, 600.0002; ...       % RW   data
    79, 679; ...                % JBW  data
    0.0002, 1275; ...           % DDLA data
    0.0002, 712; ...            % AM   data
    ];

% Loss of consciousness (LOC) time values for
% JOW, RW, JBW, DDLA, AM respectively
LOC = [ 285 108 45 703 120];
% possibly JOW 185 seconds later?
% old values:
% LOC = [ 100 108 125 690 120];

% same for the background segments
relaxed_background_times = ...
    [ 20 70; 30 80; 10 40; 50 400; 30 80];
% these are definitely dodgy
% old_relaxed_background_times = ...
%     [ 40 355; 9 29; 99 119; 19 39; 125 320];
```

```
% what to study this run?
participants = { 'jow', 'rw', 'jbw', 'ddla', 'am'};
partiNo = numel(participants);

chans = {'Fz'};

% chans = {'F7', 'F3', 'Fz', 'F4', 'F8'; ...
%          'T7', 'C3', 'Cz', 'C4', 'T8'; ...
%          'P7', 'P3', 'Pz', 'P4', 'P8'};

chanNo = numel(chans);

nonEEG = { 'ECGII' 'HEOG_R' 'LJAW' 'REAR' 'RNECK' 'VEOG_D' ...
    'VEOG_U' 'ECGIII' 'HEOG_L' 'LNECK' 'RJAW' 'RESP' 'HEMG'};

% if ifempty(chans) == 1
%     warning('No desired channels selected. Assuming all channels needed');
%     chans = eeglocal.util.tenfive;
% end

% Paths to data
data_paths = { ...
    'Real_JOW_13_April_06', '7_after_post_7.cnt'; ...
    'Real_RW_23_Nov_06', 'par_6.cnt'; ...
    'Real_JBW_28_March_07', 'jbw_2007-03-28_sedation_1.cnt'; ...
    'Real_DDLA_29_Jun_07', '5.para.car.filt.cnt'; ...
    'Real_AM_27_Nov_07', '9.cnt'; ...
    };

% Frequency bands we care about
powerBandFreqs = {[0.1 1], [8 12], [25 35]};
bandNo = size( powerBandFreqs, 2);

line_colours = [ 0 0 1; 1 0 1; 0 0.5 0.2];



%% Load in data (should need to do this once per session only)

% Selectable channels;
% Use these comments as a guide to what channels can be selected for
% analysis. Fill in the array variable below with desired channels to
% analyse so that the data for all desired channels can be stored in
% a cell array.
%

% Load this in for easy access in functions
local_path = getpref( 'eeglocal','paralysispath');

partiData = eeg3.eeg.alloc( 1, partiNo);
partiBaseline = eeg3.eeg.alloc( 1, partiNo);
partiPreBaseline = eeg3.eeg.alloc( 1, partiNo);

for parti = 1:partiNo
    % load sedation data for one subject, one channel, specified times
    tic
    d = eeg3.eeg.load( fullfile( local_path, data_paths{ parti, 1}, ...
        data_paths{ parti, 2}), 'range', times( parti, :) * fs0);
```

```
    b1 = eeglocal.paralysis.load( participants{parti}, ...
        'study.paralysis.baseline.eyesclosed');
    b2 = eeglocal.paralysis.load( participants{parti}, ...
        'study.preparalysis.baseline.eyesclosed');
    toc

    % convert cap to extended 10-20
    d = eeglocal.util.tenfive( d);
    d.subject = participants{parti};

    partiData(parti) = d;

    b1 = eeglocal.util.tenfive( b1);
    b1.subject = participants{parti};
    partiBaseline(parti) = b1;

    b2 = eeglocal.util.tenfive( b2);
    b2.subject = participants{parti};
    partiPreBaseline(parti) = b2;

end


%% Save loaded data to save time in future
save("allPartiRawData.mat", ...
        "partiData", "partiBaseline", "partiPreBaseline", "-v7.3");
%% Generate spectrum estimations for all selected data

% Check users choice on data
switch baselineChoice
    case 1
        useParalysisBaseline = false;
        usePreParalysisBaseline = false;
        useSelfBaseline = false;
    case 2
        useParalysisBaseline = true;
        usePreParalysisBaseline = false;
        useSelfBaseline = false;
    case 3
        useParalysisBaseline = false;
        usePreParalysisBaseline = false;
        useSelfBaseline = true;
    case 4
        useParalysisBaseline = false;
        usePreParalysisBaseline = true;
        useSelfBaseline = false;
    otherwise
        error('Please use an acceptable choice for baseline');
end


% Allocate space for data
subjectSpect = eeg3.timefreq.alloc(1, partiNo);
timebases = zeros( partiNo, 2);

% reduce number of channels
preppedData = partiData;%.selectchan(chans);
preppedData = preppedData.discardchans( nonEEG);
if useParalysisBaseline == true
    preppedBase = partiBaseline;%.selectchan(chans);
```

```
    preppedBase = preppedBase.discardchans( nonEEG);
elseif usePreParalysisBaseline == true
    preppedBase = partiPreBaseline;%.selectchan(chans);
    preppedBase = preppedBase.discardchans( nonEEG);
end

% loop over participants
tic
for parti = 1:partiNo
    %resample to a manageable sample rate for analysis
    d = preppedData(parti);
    dr = d.resample(fs);


    % Create spectrogram of selected data
    ds = spect_eeg3(dr, frequencyRange);

    % Create baseline if selected
    if useParalysisBaseline || usePreParalysisBaseline == true
        b = preppedBase(parti);
        br = b.resample(fs);
        bs = spect_eeg3(br, frequencyRange);

        for i = 1:size(bs.chan)
            testChans{i} = bs.chan(i).label;
        end
        ds = ds.selectchan(testChans);
        ds = relbaseline2(ds, bs);

    elseif useSelfBaseline == true
        ds = relbaseline2( ds, ds.selecttime( ...
            relaxed_background_times( parti, 1), ...
            relaxed_background_times( parti, 2)));
    end


    % Time align loss of consciousness
    ds.time.start = ds.time.start - LOC(parti);

    % We get the timebase of the recording for later use
    timebases( parti, :) = ds.timebase;

    % collect final results together
    subjectSpect(parti) = ds;
end
toc

% find times for which all participants have data
timebase = [ max( timebases( :, 1)), min( timebases( :, 2))];
subjectSpect = subjectSpect.selecttime( timebase( 1), timebase( 2));

save("allPartiChanSpect_paralysisBaseline.mat", "subjectSpect");

%% View individual spectrograms

% set up figure
tiledlayout( 2, 3);
set( gcf, 'Name', 'Individual spectrograms');
clims = [ 0 15];
cmap = jet( 128);
```

```
% loop over participants
for parti = 1:partiNo
    nexttile
    data = subjectSpect(parti);
    data.label = append('Participant ', num2str(parti));

    % display individual spectrogram
    data.plot( 'Clim', clims, 'YLim', frequencyRange, 'scale', 'linear');
    colormap( cmap);
end

% and show the average
nexttile
data = simple_timefreq_median( subjectSpect);
data.label = sprintf( 'median of %d', partiNo);
data.plot( 'Clim', clims, 'YLim', frequencyRange, 'scale', 'linear');
colormap( cmap);


% print to file?
% pretty_print( 'filename', 'JOW_relative_far.png', 'target', 'ppt');

%% Show average of single channel

singleChanData = subjectSpect.selectchan( 'Fz');
clims = [ 0 15];

data = simple_timefreq_median( singleChanData);
data.label = sprintf( 'median of %d', partiNo);
data.plot( 'Clim', clims, 'YLim', frequencyRange, 'scale', 'linear');
set( gcf, 'Name', 'Individual spectrograms');
cmap = jet( 128);
colormap( cmap);
% Make background transparent if desired
% set(gcf, 'color', 'none');
% set(gca, 'color', 'none');



%% Power band estimation for all selected data

chanPower = cell(1, chanNo);

for chan = 1:chanNo
    % now calculate power in the various bands of interest
    tempm = simple_timefreq_median(subjectSpect);
    tempm.data = medfilt1( tempm.data, median_filter_order, [], 2);
    dp = eeg3.eeg.alloc( 1, bandNo);
    legend_strings = cell( 1, bandNo);
    for bandi = 1:bandNo
        % median filter on the band power to make it look better
        temp = medianfreq( tempm.selectfreq( ...
            powerBandFreqs{bandi}(1), powerBandFreqs{bandi}(2)));
        dp( bandi).data = medfilt1( temp.data, median_filter_order);
        dp( bandi).label = sprintf( 'median power from %d to %d Hz', ...
            powerBandFreqs{ bandi}(1), powerBandFreqs{ bandi}(2));
        % should worry about the units and history
        dp( bandi).units = tempm.units;
        dp( bandi).history = tempm.history;
```

```
        dp( bandi).time = tempm.time;
        dp( bandi).chan = tempm.chan;
        legend_strings{ bandi} = sprintf( '%d-%d Hz', ...
        powerBandFreqs{ bandi}(1), powerBandFreqs{ bandi}(2));
    end
    chanPower{chan} = dp;
end


%% 2B Graph generation

y = size(chans, 1);
x = size(chans, 2);
tiledlayout(y, x);

set( gcf, 'Name', figure2B_name);

medianSpect = simple_timefreq_median(subjectSpect);

for chan = 1:chanNo
    nexttile

    % Make average of all loaded spectrograms for plotting
    data = medianSpect.selectchan(chans{...
        ceil(chan/x), ...
        rem(chan + (x-1), x) + 1});

    % Set variables for plotting
    clims = [ 0 15];

    % display averaged normalised spectrogram
    data.plot( 'Clim', clims, 'YLim', frequencyRange, 'scale', 'linear');
    colormap( jet( 128));
end


%% 2C Graph generation

p = tiledlayout(1, 1);

legend_strings{1} = '0.1-1 Hz';

for chan = 1:numel(chanPower)
    nexttile
    set( gcf, 'Name', figure2C_name);

    dp = chanPower{chan}.selectchan('Fz');

    % display averaged band power
    hl = dp.plot;
    for linei = 1:numel( hl)
        set( hl( linei), 'Color', line_colours( linei, :));
    end

    title('Power bands for channel ', dp(1).chan.label);
    legend( legend_strings, 'Location', 'northwest');
end

set( gca, 'YLim', [ 0.01 100], 'YScale', 'log');
```

```
%% MY topologies, calculate chanpower first

chanTop = chanPower{1};
endTime = chanTop(1).timebase;
endTime = endTime(2) - 30;
stepTime = chanTop(1).time.step;

chanTop = chanTop.discardchans( nonEEG);

chanTop = chanTop.selecttime( endTime - stepTime / 2, endTime);
titles = {'0.1 - 1 Hz', '8 - 12 Hz', '25 - 35 Hz'};


% prepare to display averaged normalised spectrogram
hf = findobj( 0, 'Name', figure2D_name);
if isempty( hf)
    figure
    set( gcf, 'Name', figure2D_name);
end
clf
originalSize = cell(3);
clims = [-7 17];

% chanTop( 2).plottopography( 'Clim', clims,'log', false);

% display topographies
for bandi = 1:bandNo
    subplot( 1, 3, bandi)
    chanTop( bandi).plottopography( 'Clim', clims,'log', false);
    title(titles{bandi})
    originalSize{bandi} = get(gca, 'Position');
    if bandi ~= 3
        colorbar('off')
    end
    set(gca, 'Position', originalSize{bandi});
    set(gcf, 'color', 'none');
end


%% INCLUDE THETA, BETA FREQ BANDS

% Frequency bands we care about
altPowerBandFreqs = {[4 8], [12 25]};
bandNo = size( altPowerBandFreqs, 2);

alt_line_colours = [ 1 0.5 0; 0.5 0.7 1];

chanPower = cell(1, chanNo);

for chan = 1:chanNo
    % now calculate power in the various bands of interest
    tempm = simple_timefreq_median(subjectSpect);
    tempm.data = medfilt1( tempm.data, median_filter_order, [], 2);
    dp = eeg3.eeg.alloc( 1, bandNo);
    legend_strings = cell( 1, bandNo);
    for bandi = 1:bandNo
        % median filter on the band power to make it look better
        temp = medianfreq( tempm.selectfreq( ...
            altPowerBandFreqs{bandi}(1), altPowerBandFreqs{bandi}(2)));
```

```
        dp( bandi).data = medfilt1( temp.data, median_filter_order);
        dp( bandi).label = sprintf( 'median power from %d to %d Hz', ...
            altPowerBandFreqs{ bandi}(1), altPowerBandFreqs{ bandi}(2));
        % should worry about the units and history
        dp( bandi).units = tempm.units;
        dp( bandi).history = tempm.history;
        dp( bandi).time = tempm.time;
        dp( bandi).chan = tempm.chan;
        legend_strings{ bandi} = sprintf( '%d-%d Hz', ...
        altPowerBandFreqs{ bandi}(1), altPowerBandFreqs{ bandi}(2));
    end
    chanPower{chan} = dp;
end



% 2C Graph generation

p = tiledlayout(1, 1);


for chan = 1:numel(chanPower)
    set( gcf, 'Name', figure2C_name);

    dp = chanPower{chan}.selectchan('Fz');

    % display averaged band power
    hl = dp.plot;
    for linei = 1:numel( hl)
        set( hl( linei), 'Color', alt_line_colours( linei, :));
    end

    title('Power bands for channel ', dp(1).chan.label);
    legend( legend_strings, 'Location', 'northwest');
end

set( gca, 'YLim', [ 0.01 100], 'YScale', 'log');

% TOPOLOGIES WITH NEW FREQS

chanTop = chanPower{1};
endTime = chanTop(1).timebase;
endTime = endTime(2) - 30;
stepTime = chanTop(1).time.step;

chanTop = chanTop.discardchans( nonEEG);

chanTop = chanTop.selecttime( endTime - stepTime / 2, endTime);
titles = {'4 - 8 Hz', '12 - 25 Hz'};


% prepare to display averaged normalised spectrogram
hf = findobj( 0, 'Name', figure2D_name);
if isempty( hf)
    figure
    set( gcf, 'Name', figure2D_name);
end
clf
originalSize = cell(3);
```

```
clims = [-7 17];

% chanTop( 2).plottopography( 'Clim', clims,'log', false);

% display topographies
for bandi = 1:bandNo
    subplot( 1, 2, bandi)
    chanTop( bandi).plottopography( 'Clim', clims,'log', false);
    title(titles{bandi})
    originalSize{bandi} = get(gca, 'Position');
    if bandi ~= 2
        colorbar('off')
    end
    set(gca, 'Position', originalSize{bandi});
    set(gcf, 'color', 'none');
end
```

Appendix B – EEG Wrapper Function for Handling Data

```
function [bt] = spect_eeg3( d, band)
%        bt = spect_eeg3( d, band)
% Calculate power in a specified band in the channels of an eeg3 object


% handle multiple inputs
if numel( d) > 1
    bt = d;
    for i = 1:numel( d)
        bt( i) = spect_eeg3( d( i), band);
    end
    return
end

% operating on a single object

% definitions
band_information = { ...
    'delta', [ 1 4]; ...
    'theta', [ 4 8]; ...
    'alpha', [ 8 13]; ...
    'beta', [ 13 25]; ...
    'low gamma', [ 25 48]; ...
    'high gamma', [ 52 98]; ...
    'mu', [ 8 12]; ...
    };

% parse the first input
assert( isa( d, 'eeg3.eeg'), 'First input must be an eeg3 object');

% ensure the second input is meaningful and convert to a useful format
switch class( band)
    case 'double'
        assert( all( size( band) == [ 1 2]), sprintf( ...
            '%s:: If numerical, band must be a 1x2 vector specifiying the frequency
range', mfilename));
    case 'char'
        ind = find( strcmp( band, band_information( :, 1)));
        if isempty( ind)
```

```
            error( '%s:: Unknown band name', mfilename);
        else
            band = band_information{ ind, 2};
        end
        % do something fancy to convert a band name to frequency limits
    otherwise
        error( '%s:: Don''t know how to interpret the second argument', ...
            mfilename);
end

% Create the output object
bt = eeg3.timefreq.alloc(1);
% Create the spectrogram data and select the frequency range
[ spectData, newSR] = estimation_generation( d, band( 2));


% Push the spectrogram data into the output object
bt.data = spectData;
bt.label = sprintf( 'Spectrum estimation from %s to %d Hz',...
    num2str(band( 1)), band( 2));
bt.freq.step = 0.5;
bt.chan = d.chan;
bt.subject = d.subject;
% Should worry about the samplerate
bt.time.samplerate = newSR;
bt.time.step = 1 / newSR;
% Ensure units are correct
bt.units.name = 'decibel';
bt.units.symbol = 'dB';
bt.units.tex = 'dB';
```

Appendix C – Multitaper Method Loop for Spectrum Estimation

```
%Takes in an eeg file and extrapolates the needed analysis
function [ spect, newSR] = estimation_generation( eegObject, maxFreq)

% parse input arguments
assert( isa( eegObject, 'eeg3.eeg'), 'First input must be an eeg3 object');

% definitions
blockLength = 2; % seconds
newSR = 10; % Hz
chanNo = eegObject.nchan;

% pull out useful information
fs = eegObject.time.samplerate;
eegDataLength = eegObject.ntime;

% derived
frs = 0:( 1 / blockLength):maxFreq;
Nfreq = maxFreq * blockLength + 1;
assert( Nfreq == numel( frs), 'Got frequencies wrong :<');
blockSlide = fs / newSR;
Nblocks = floor(( eegDataLength - blockLength * fs)/blockSlide);

% Make the overall spectrogram for all channels for the subject
spect = zeros(chanNo, Nblocks, Nfreq);
```

```
for chani = 1:chanNo

    % make space for the output channel spectrogram
    chanData = zeros( Nfreq, Nblocks);

    % Retrieve the appropriate data needed for the specific channel
    eegData = eegObject.data(chani, :);

    % Working on subject whatever, channel something something
    fprintf('Starting estimation generation for subject %s, channel %s...', ...
             eegObject.subject, eegObject.chan(chani).label);

    % Loop over blocks of the channel of data
    for blockNo = 1:Nblocks
        blockStart = ( blockNo - 1) * blockSlide + 1;
        blockEnd = blockStart + blockLength * fs - 1;
        [spectBlock, f] = pmtm(eegData(blockStart:blockEnd), blockLength, ...
            blockLength * fs, fs);
        chanData(:,blockNo) = spectBlock( 1:Nfreq);

    end

    % Transforming data into dB
    chanData = 10 * log10(chanData);
    % Transforming data into format useable by timefreq object
    chanData = chanData.';
    chanData = reshape(chanData, 1, size(chanData, 1), size(chanData, 2));

    % Place into output spectrogram
    spect(chani, :, :) = chanData;
    fprintf(' Complete!\r')

end
```

Appendix D - Connectivity Code for Testing Connectivity at Multiple Frequency Bands

```
%% Unconscious connectivity analysis
%  Code is intended to load in data from unconscious participants
%  (set of 5) and generate a connectivity plot of the baseline recording
%  and the before / after of the participant being brought unconscious.



%% Declare all definitions and variables

% Variable definitions
fs0 = 5000;
fs = 500;

% Timing info for unconscious data
times = [ ...
    1 803; ...                  % JOW  data
    0.0002, 600.0002; ...       % RW   data
    79, 679; ...                % JBW  data
    0.0002, 1275; ...           % DDLA data
    0.0002, 712; ...            % AM   data
```

```
    ];

% Loss of consciousness (LOC) time values for
% JOW, RW, JBW, DDLA, AM respectively
LOC = [ 285 108 45 703 120];

% what to study this run?
participants = { 'jow', 'rw', 'jbw', 'ddla', 'am'};
partiNo = numel(participants);

% Which baseline to use? Choose either before or after paralysis
% 'study.paralysis.baseline.eyesclosed'
% Or
% 'study.preparalysis.baseline.eyesclosed'
baselineRecordingName = 'study.paralysis.baseline.eyesclosed';

chans = eeg3.util.labels1005;

% chans = {'F7', 'F3', 'Fz', 'F4', 'F8'; ...
%          'T7', 'C3', 'Cz', 'C4', 'T8'; ...
%          'P7', 'P3', 'Pz', 'P4', 'P8'};

chanNo = numel(chans);

baselineSegment = [4, 6];

% Paths to unconsciousness data
data_paths = { ...
    'Real_JOW_13_April_06', '7_after_post_7.cnt'; ...
    'Real_RW_23_Nov_06', 'par_6.cnt'; ...
    'Real_JBW_28_March_07', 'jbw_2007-03-28_sedation_1.cnt'; ...
    'Real_DDLA_29_Jun_07', '5.para.car.filt.cnt'; ...
    'Real_AM_27_Nov_07', '9.cnt'; ...
    };

%% Load in data (run once per session only)

% Load this in for easy access in functions
local_path = getpref( 'eeglocal','paralysispath');

partiData   = eeg3.eeg.alloc( 1, partiNo);
partiBaseline = eeg3.eeg.alloc( 1, partiNo);

for parti = 1:partiNo
    % load sedation and basline data for one subject

    tic
    partiData(parti) = eeg3.eeg.load( fullfile( local_path, data_paths{ parti, 1}, ...
        data_paths{ parti, 2}), 'range', times( parti, :) * fs0);

    partiBaseline(parti) = eeglocal.paralysis.load( participants{parti}, ...
        baselineRecordingName);
    toc

end

%% Reformat data for connectivity

%  Requires that partiData and partiBaseline to be loaded prior
```

```
% which channels to drop and/or which to keep
nonEEG = { 'ECGII' 'HEOG_R' 'LJAW' 'REAR' 'RNECK' 'VEOG_D' ...
    'VEOG_U' 'ECGIII' 'HEOG_L' 'LNECK' 'RJAW' 'RESP' 'HEMG'};
chans = eeg3.util.labels1005;
timebases = zeros( partiNo, 2);

% Resample recordings to a reasonable rate
partiConnectivity = arrayfun(@(x) x.resample(fs), partiData);
connectivityBaseline = arrayfun(@(x) x.resample(fs), partiBaseline);

% convert sedation data to 10-20 and add participant names
for parti = 1 : partiNo
    % convert cap to extended 10-20
    partiConnectivity( parti) = eeglocal.util.tenfive( partiConnectivity(parti));
    partiConnectivity( parti).subject = participants{ parti};
end

% Ensure baseline starts and time zero and are the same size within task
for i = 1:partiNo
    partiConnectivity(i).time.start = 0;
    connectivityBaseline(i).time.start = 0;
end

% time align sedation data
for parti = 1:partiNo
    partiConnectivity(parti).time.start = ...
        partiConnectivity(parti).time.start - LOC(parti);
    % We get the timebase of the recording for later use
    timebases( parti, :) = partiConnectivity(parti).timebase;
end

% find times for which all participants have data
timebase = [ max( timebases( :, 1)), min( timebases( :, 2))];
partiConnectivity = partiConnectivity.selecttime( timebase( 1), timebase( 2));

% partiConnectivity = partiConnectivity.selecttime( 0, ...
%     ( min( partiConnectivity.ntime) - 1) / partiConnectivity( 1).time.samplerate);
connectivityBaseline = connectivityBaseline.selecttime( 0, ...
    ( min( connectivityBaseline.ntime) - 1) / connectivityBaseline(
1).time.samplerate);

% Removes channels that don't work with connectivity analysis
% Select desired channels
partiConnectivity = partiConnectivity.selectchan( chans);
partiConnectivity = partiConnectivity.discardchans( nonEEG);
connectivityBaseline = connectivityBaseline.selectchan(chans);
connectivityBaseline = connectivityBaseline.discardchans( nonEEG);

%     % convert cap to extended 10-20
%     partiData(subject) = eeglocal.util.tenfive( partiData(subject));
%     partiData(subject).subject = subjects{subject};

%% If desired, perform bandpass filter
fs = partiConnectivity(1).time.samplerate;

consciousTimes = [-45, -5];
unconsciousTimes = [432, 492];
bandnames = { 'theta', 'alpha', 'beta', 'gamma', 'allFreqs'};
bands = [ 4, 8; 8, 12; 12, 25; 25, 48];
Nbands = size( bandnames, 2);
```

```
for bandi = 1:Nbands
    baseEEG = connectivityBaseline;
    consciousEEG   = partiConnectivity.selecttime( ...
        consciousTimes(1), consciousTimes(2));
    unconsciousEEG = partiConnectivity.selecttime( ...
        unconsciousTimes(1), unconsciousTimes(2));

    % Never write a for loop in matlab, unless you are running out of memory
    if bandi ~= 5
    baseEEG = baseEEG.lowpass( bands( bandi, 2)).highpass( bands( bandi, 1));
    consciousEEG = consciousEEG.lowpass( bands( bandi, 2)).highpass( bands( bandi, 1));
    unconsciousEEG = unconsciousEEG.lowpass( bands( bandi, 2)).highpass( bands( bandi,
1));
    end

    % Connectivity analysis

    connectivityFunction = @normalisedtransferentropy;
    functionName = "normalisedTE_paralysisBase_";
    tic
    % Do connectivity on bits of the data
    [ ~, connectivityChans, AM0] = connectivity( ...
        baseEEG, ...
        connectivityFunction, 'permloops', 'slowandsmall');
    [ ~, ~, AMbefore] = connectivity( ...
        partiConnectivity.selecttime( consciousTimes( 1), consciousTimes( 2)), ...
        connectivityFunction, 'permloops', 'slowandsmall');
    [ ~, ~, AMafter] = connectivity( ...
        partiConnectivity.selecttime( unconsciousTimes( 1), unconsciousTimes( 2)), ...
        connectivityFunction, 'permloops', 'slowandsmall');
    toc
    % now do a permutationtest - either through connectivity function or
    % directly through the permutationtest function
    tic
    [ ~, ~, ~, ~, ptPvalBefore] = ...
        connectivity( partiConnectivity, connectivityFunction, ...
        'AM', AMbefore, 'AMs', AM0, 'permloops', 'slowandsmall');
    toc
    tic
    [ ~, ~, ~, ~, ptPvalAfter] = ...
        connectivity( partiConnectivity, connectivityFunction, ...
        'AM', AMafter, 'AMs', AM0, 'permloops', 'slowandsmall');
    toc

    fileName = append(functionName, bandnames{bandi}, ".mat");
    save(fileName, ...
        "ptPvalAfter", "ptPvalBefore", "AMbefore", "AMafter")
end

%% Get all chans from available data and create av AM's
chanIndex = size(ptPvalAfter, 1);

chans = cell(1,chanIndex);

for i = 1:chanIndex
chans{i} = connectivityBaseline(1).chan(i).label;
end

avAMbefore = mean(squeeze(AMbefore), 3);
```

```
avAMafter  = mean(squeeze(AMafter) , 3);


%% Plot connectivity analysis onto a 3D plot

baselinePlot = plot_connections3d_v3( avAMbefore, chans, ptPvalBefore);
set( gcf, 'Name', 'Conscious Connectivity');

connectivityPlot = plot_connections3d_v3( avAMafter, chans, ptPvalAfter);
set( gcf, 'Name', 'Unconscious Connectivity');
```

Appendix E – An EEG Montage Mapped onto the Positions of Channels on an EEG Cap

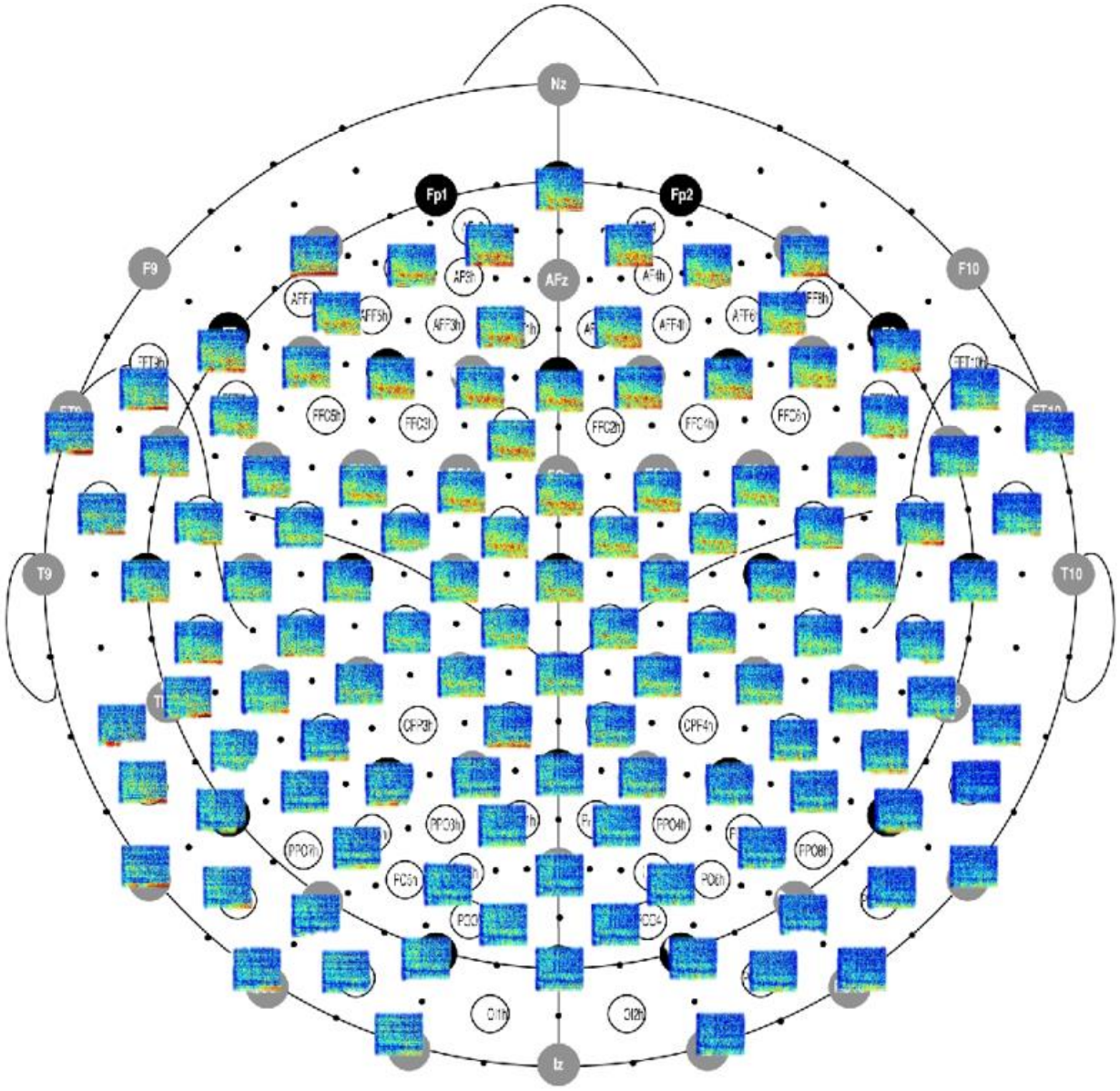

Figure 29: An EEG montage, featuring all channels from the BSL recordings in 2006, oriented onto an EEG topography, with a nose at the top for orientation.

Appendix F – Results of Symbolic Transfer Entropy Analysis

Unfortunately, using ranks instead of amplitudes resulted in a connectivity analysis with no connections. It is not entirely known if there's an error with the code or not, so it's left as an open issue for another student to peek at and try to get working in a continuation of this project.

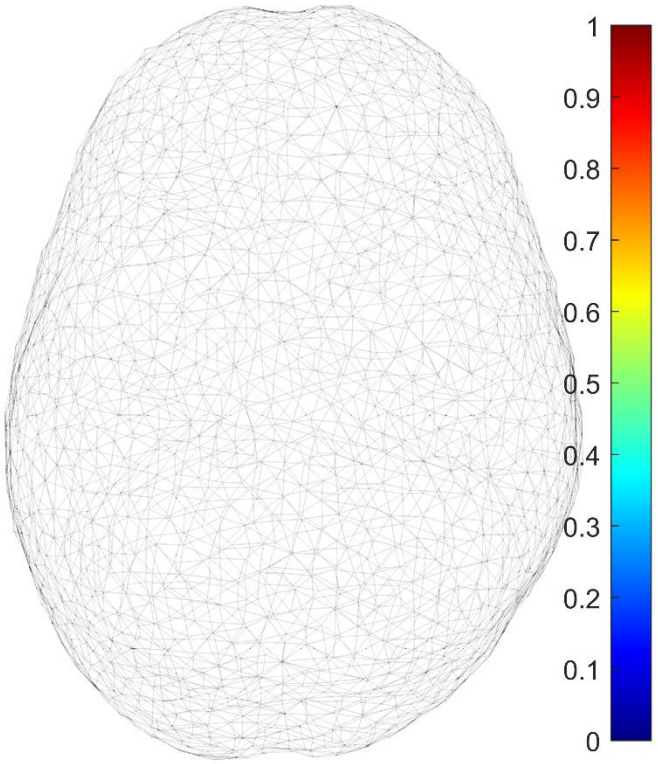

Figure 30: The 'results' of the symbolic TE connectivity analysis

Appendix G.1 – Band Passed Connectivity for a Paralysis Baseline

This section contains the findings of performing a bandpass filter to perform a connectivity analysis using frequency bands typically found in brain analysis. The first section goes over the conscious segments of connectivity and the second section goes over unconscious connectivity. All data shown here was using a paralysis baseline.

Conscious Connectivity

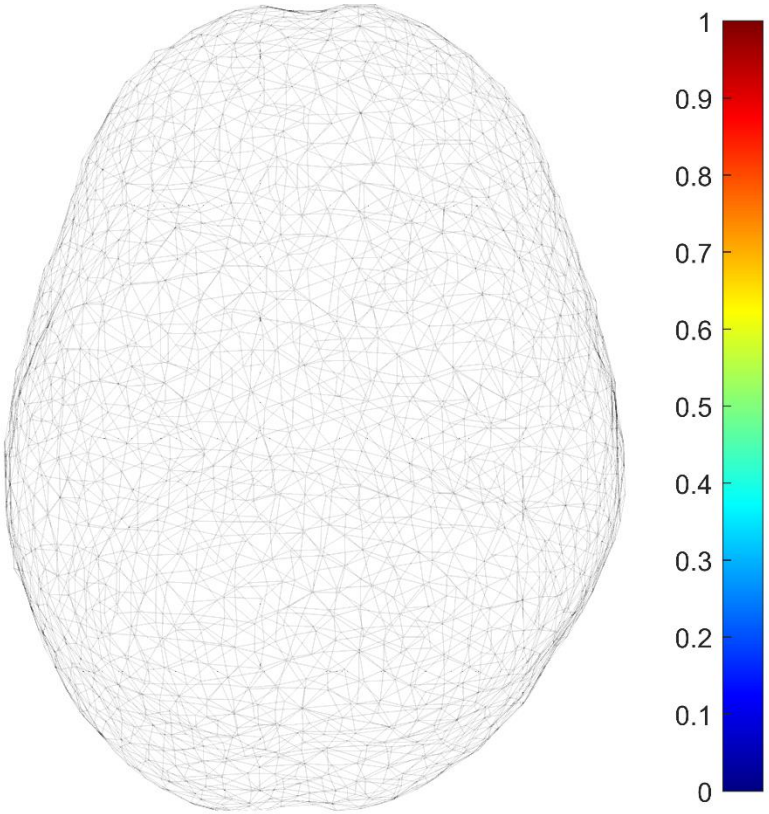

Figure 31: Theta band passed connectivity. Analysis was done on conscious participant data with a paralysis baseline used.

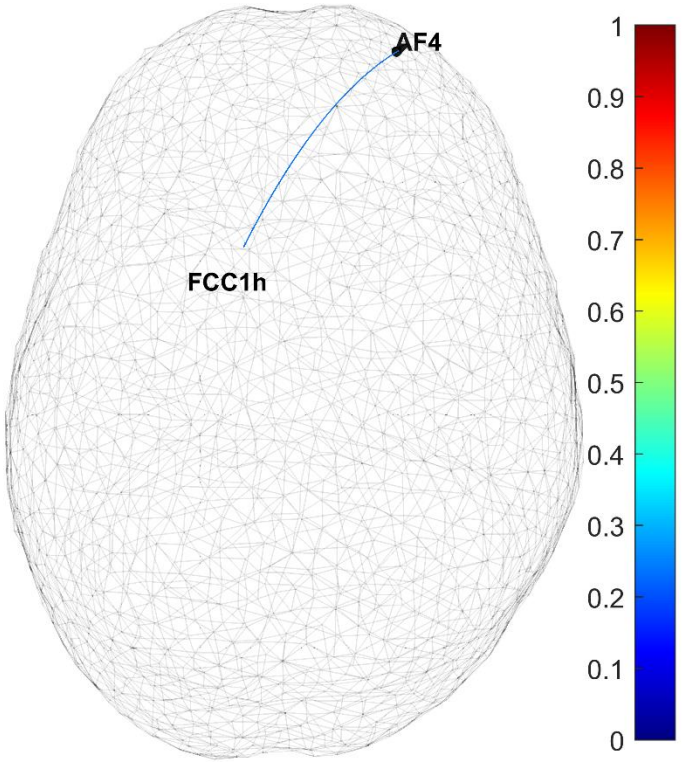

Figure 32: Alpha band passed connectivity. Analysis was done on conscious participant data with a paralysis baseline used.

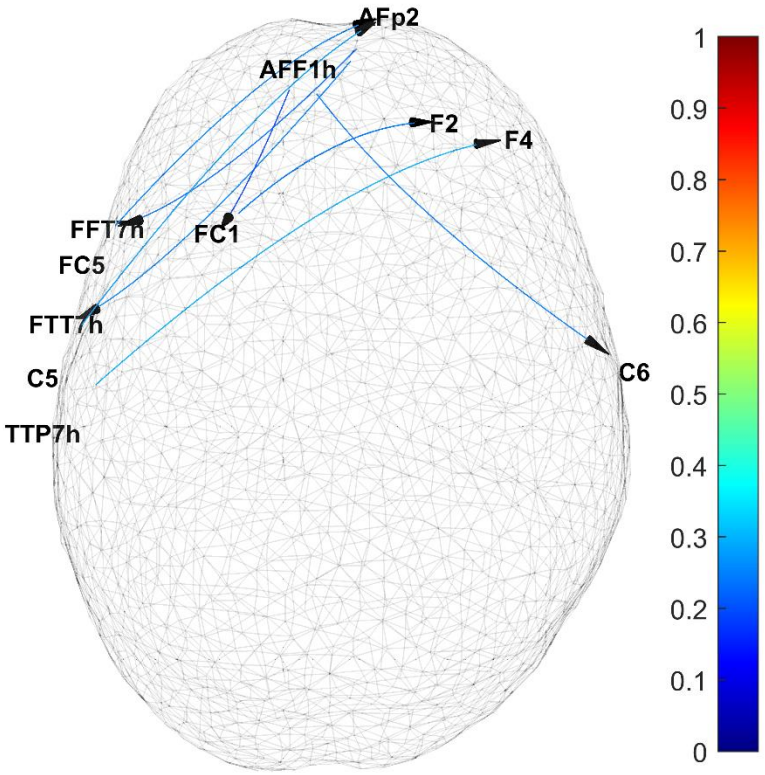

Figure 33: Beta band passed connectivity. Analysis was done on conscious participant data with a paralysis baseline used.

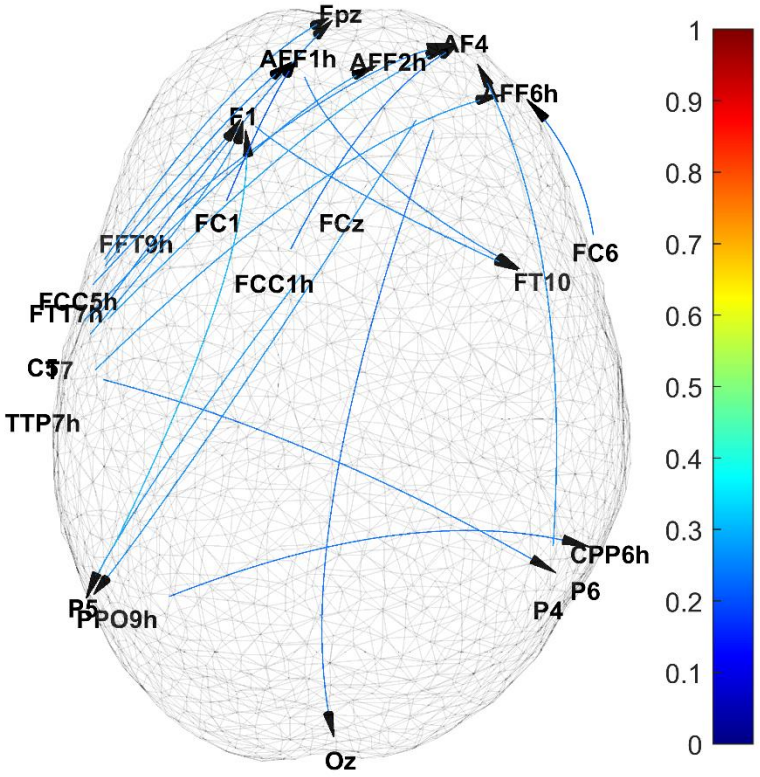

Figure 34: Gamma band passed connectivity. Analysis was done on conscious participant data with a paralysis baseline used.

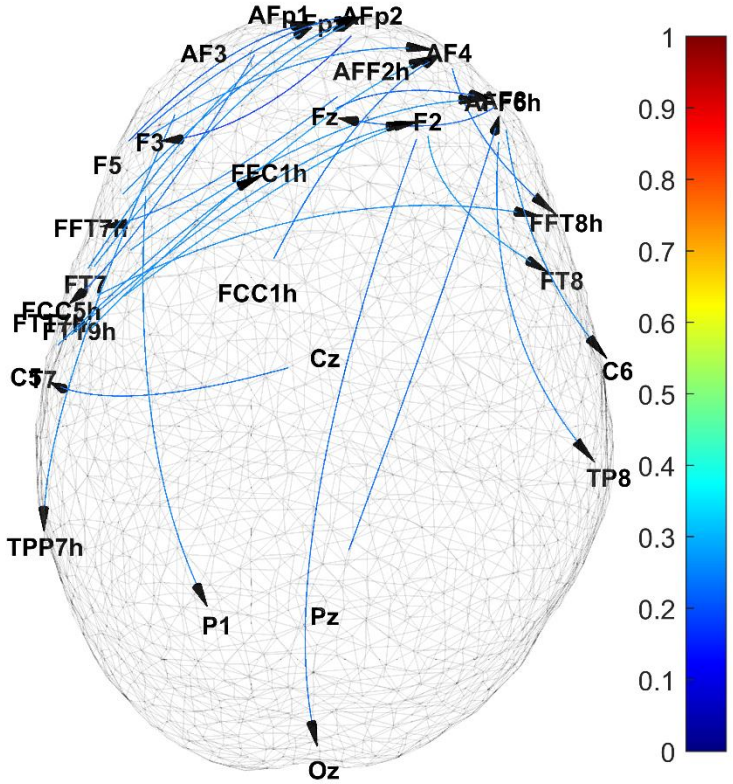

Figure 35: All frequencies connectivity analysis. Analysis was done on conscious participant data with a paralysis baseline used.

Unconscious connectivity

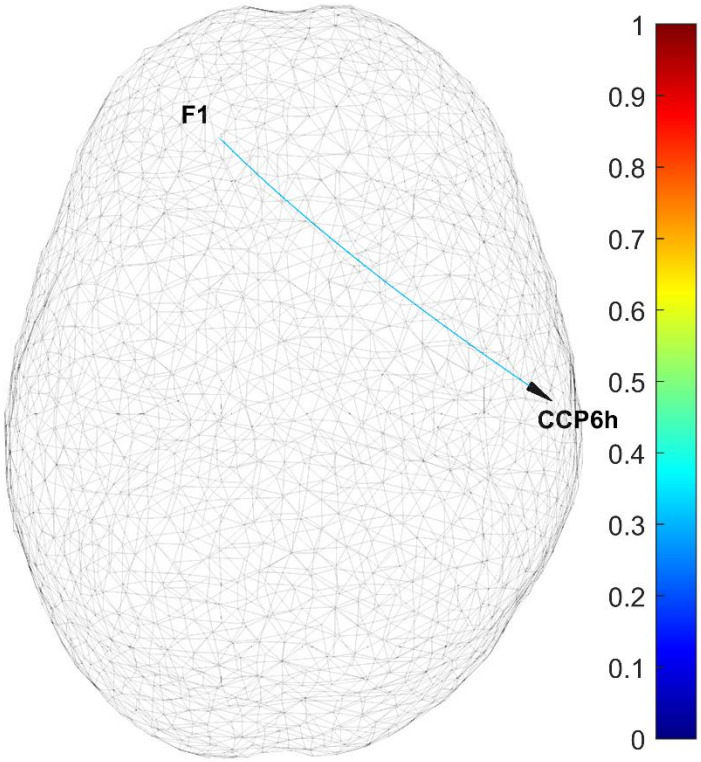

Figure 36: Theta band passed connectivity. Analysis was done on unconscious participant data with a paralysis baseline used.

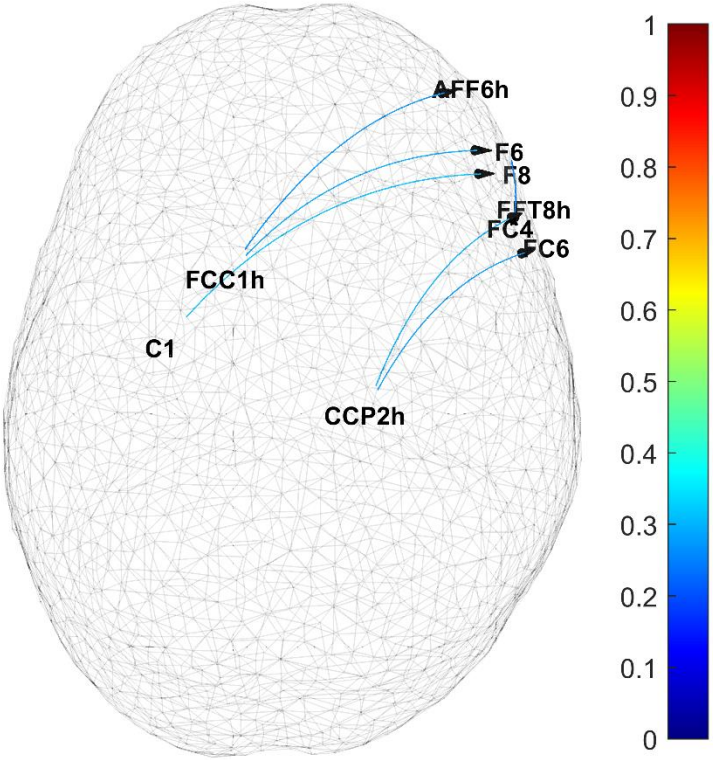

Figure 37: Alpha band passed connectivity. Analysis was done on unconscious participant data with a paralysis baseline used.

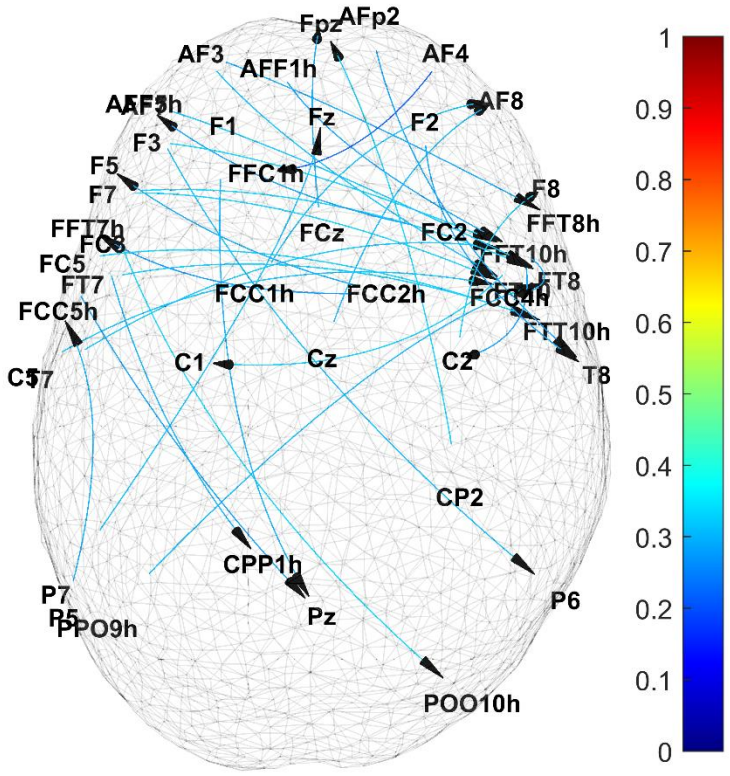

Figure 38: Beta band passed connectivity. Analysis was done on unconscious participant data with a paralysis baseline used.

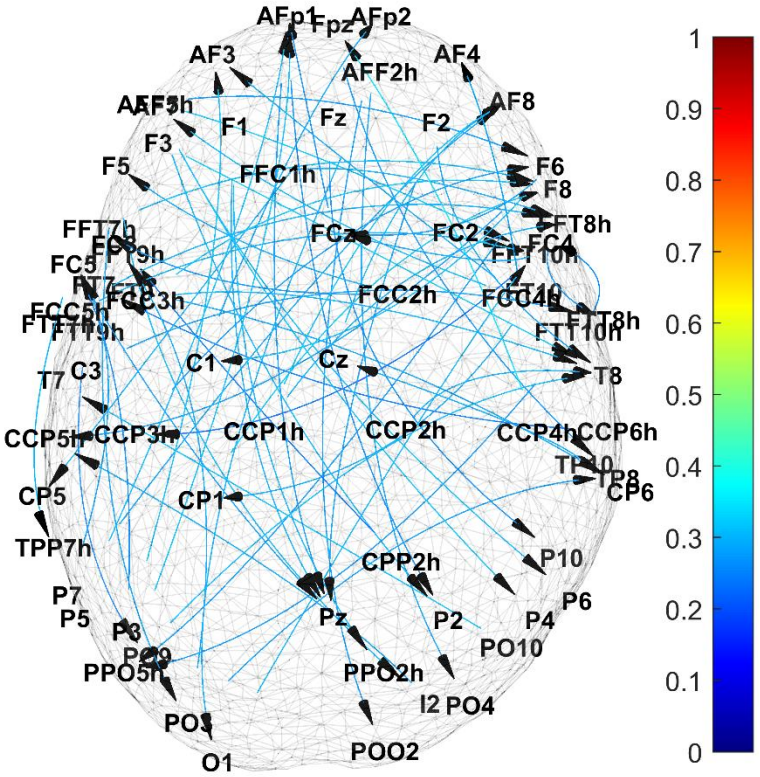

Figure 39: Gamma band passed connectivity. Analysis was done on unconscious participant data with a paralysis baseline used.

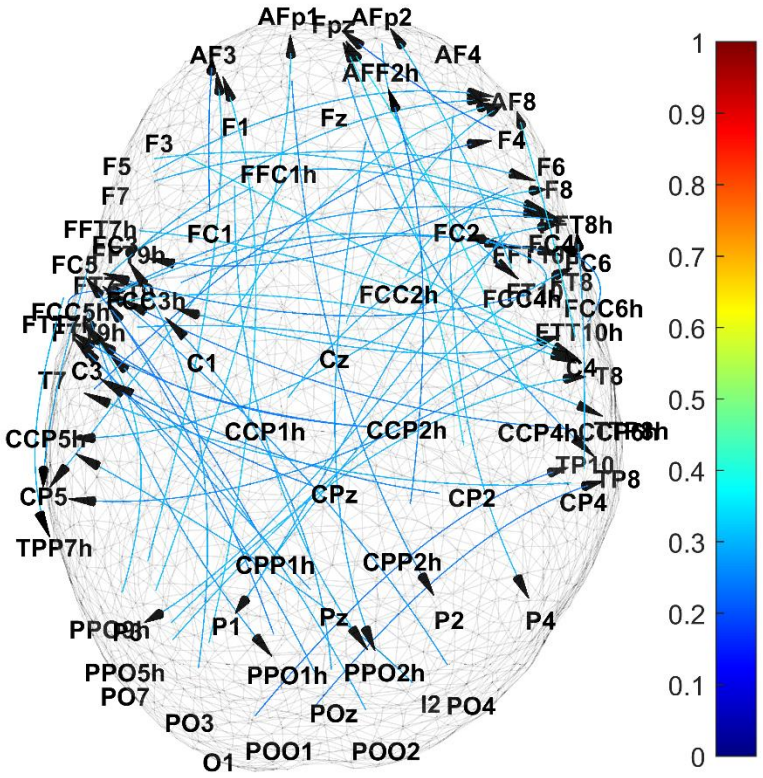

Figure 40: All frequencies connectivity analysis. Analysis was done on unconscious participant data with a paralysis baseline used.

Appendix G.2 – Band Passed Connectivity For a Pre-Paralysis Baseline

This section contains the findings of performing a bandpass filter to perform a connectivity analysis using frequency bands typically found in brain analysis. The first section goes over the conscious segments of connectivity and the second section goes over unconscious connectivity. All data shown here was using a pre-paralysis baseline.

Conscious Connectivity

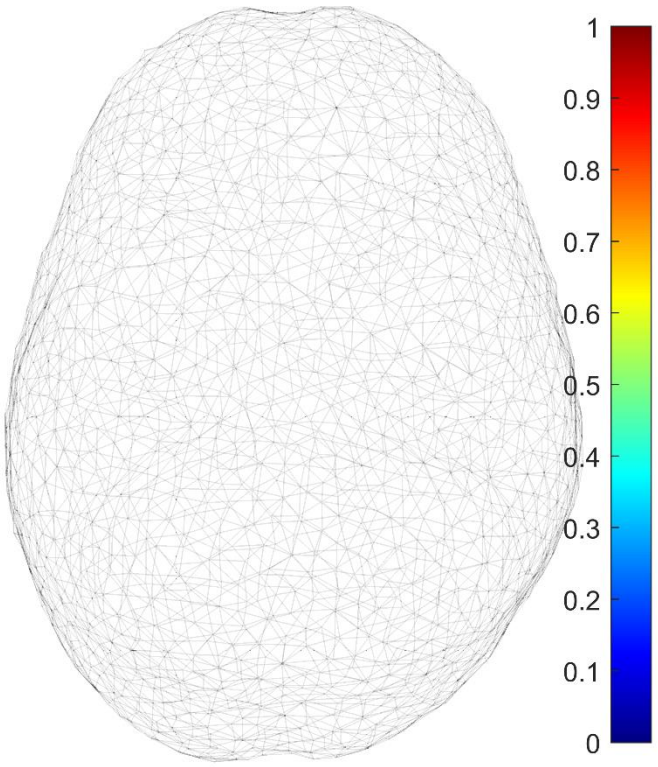

Figure 41: Theta band passed connectivity. Analysis was done on conscious participant data with a pre-paralysis baseline used.

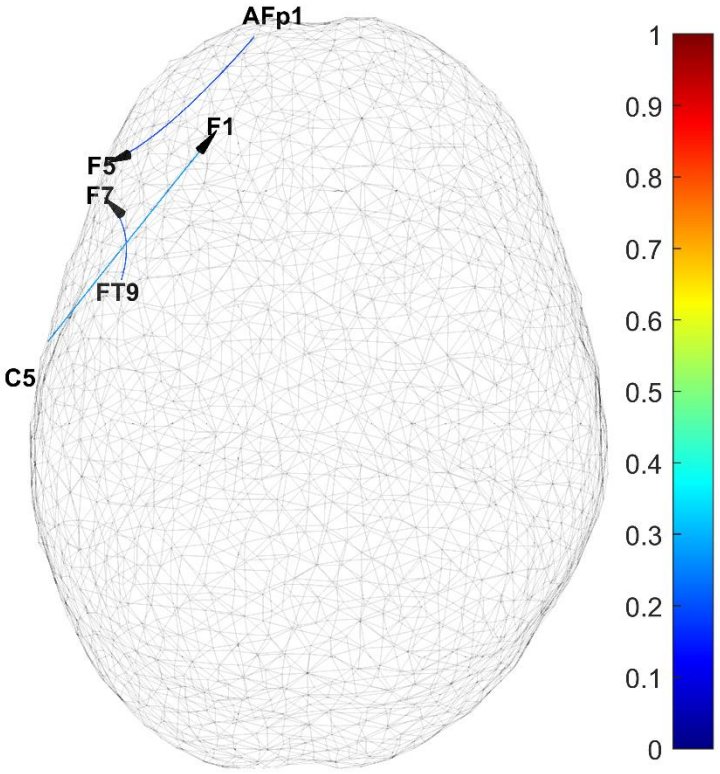

Figure 42: Alpha band passed connectivity. Analysis was done on conscious participant data with a pre-paralysis baseline used.

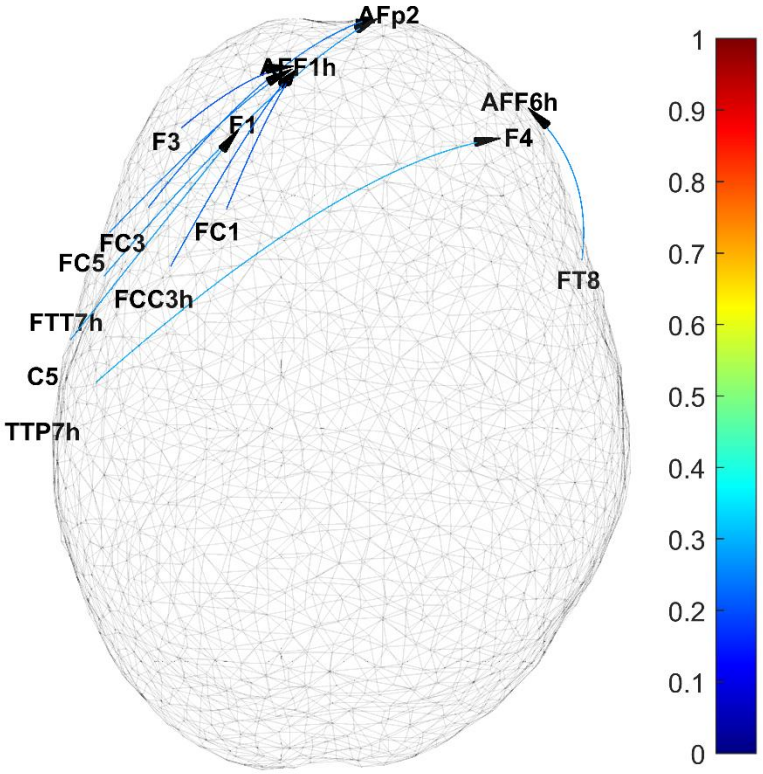

Figure 43: Beta band passed connectivity. Analysis was done on conscious participant data with a pre-paralysis baseline used.

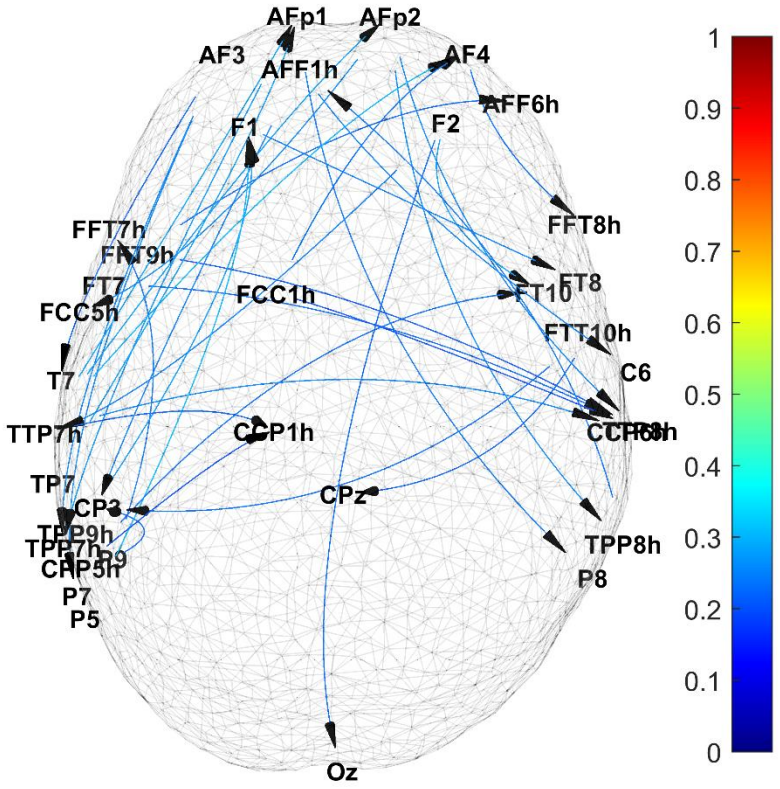

Figure 44: Gamma band passed connectivity. Analysis was done on conscious participant data with a pre-paralysis baseline used.

Unconscious Connectivity

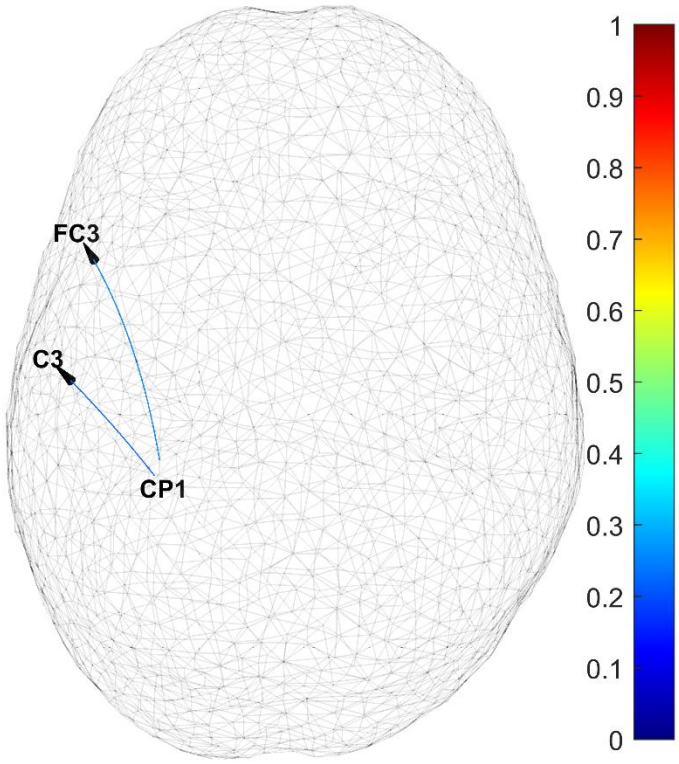

Figure 45: Theta band passed connectivity. Analysis was done on unconscious participant data with a pre-paralysis baseline used.

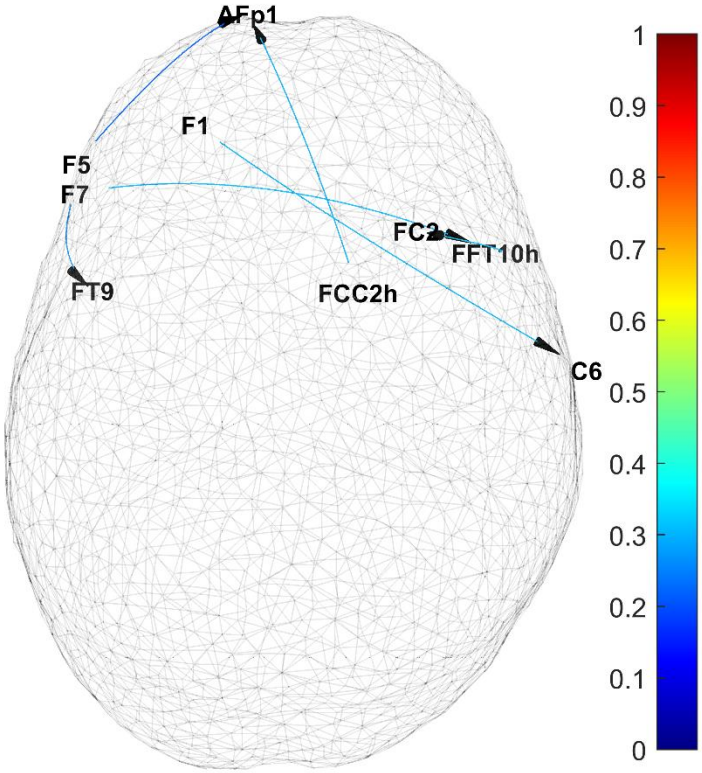

Figure 46: Alpha band passed connectivity. Analysis was done on unconscious participant data with a pre-paralysis baseline used.

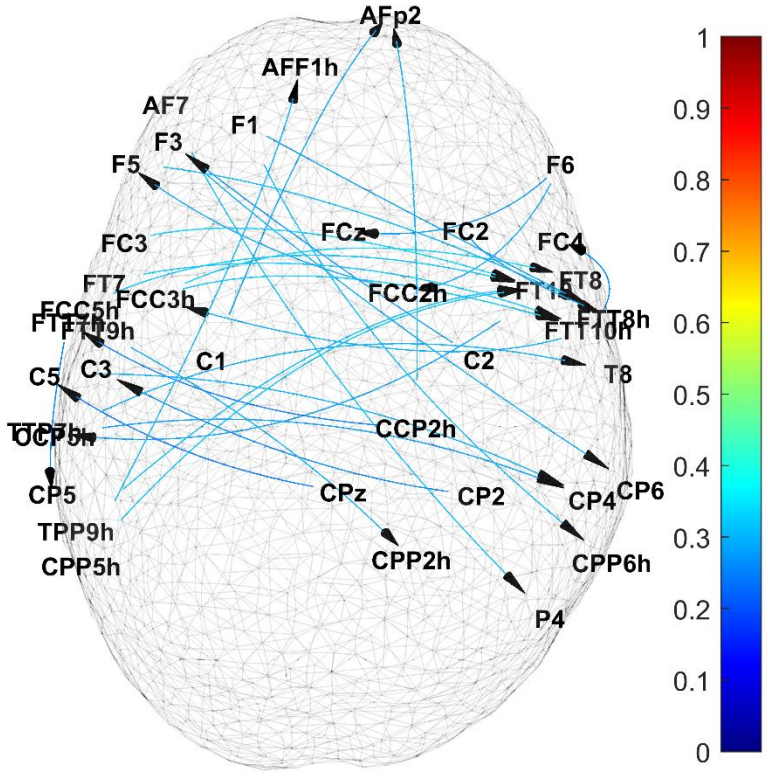

Figure 47: Beta band passed connectivity. Analysis was done on unconscious participant data with a pre-paralysis baseline used.

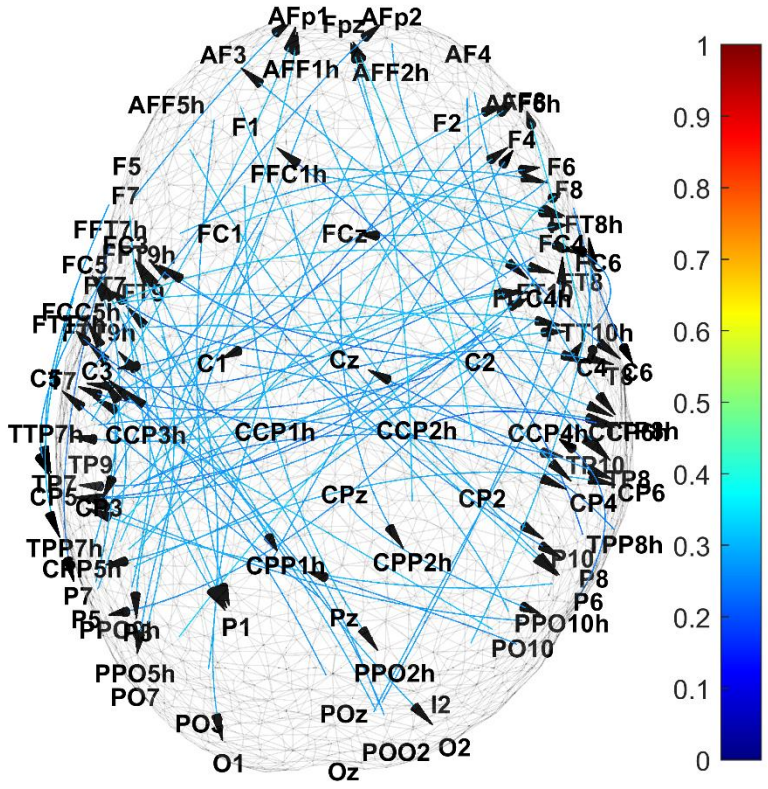

Figure 48: Gamma band passed connectivity. Analysis was done on unconscious participant data with a pre-paralysis baseline used.

Appendix H – Additional Frequencies in Power Band and Topography Analysis

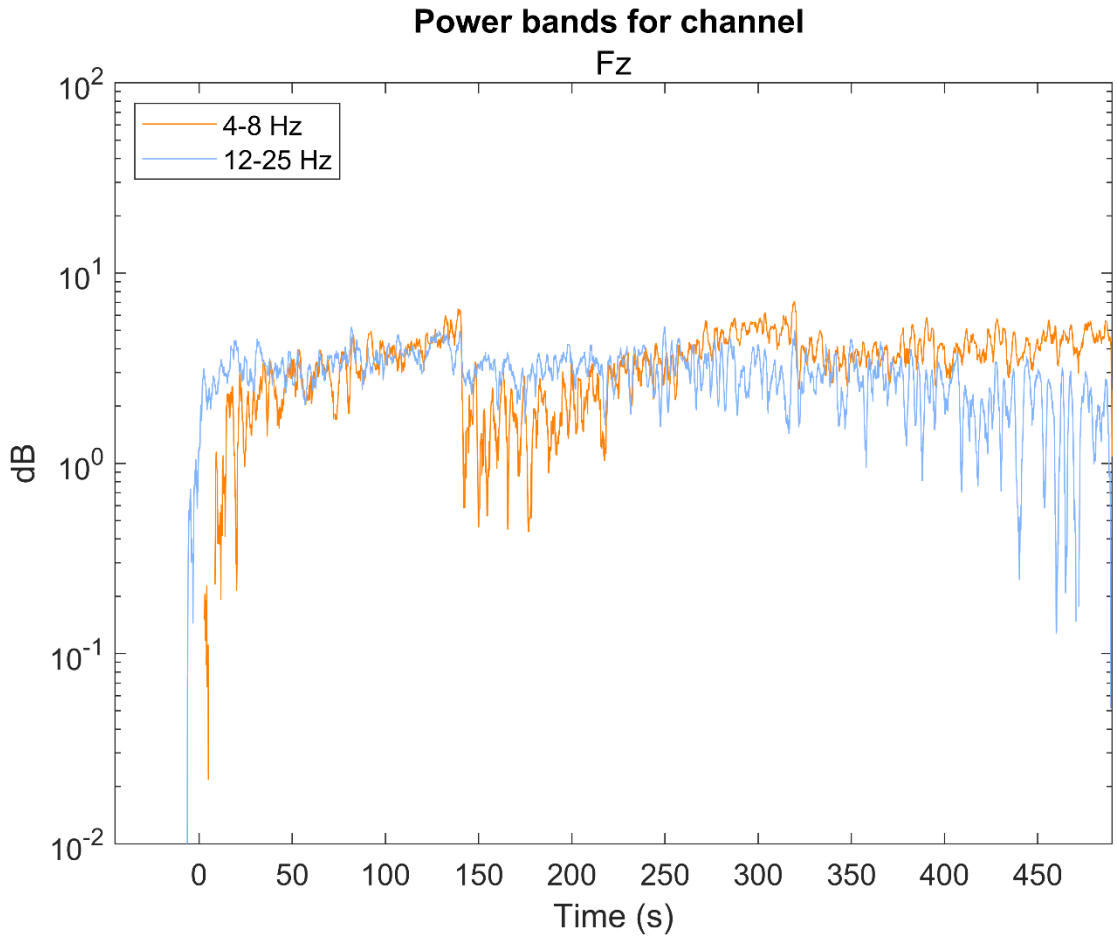

Figure 49: Band power estimates for the theta (orange) and beta (blue) frequency ranges, done for a pre-paralysis baseline.

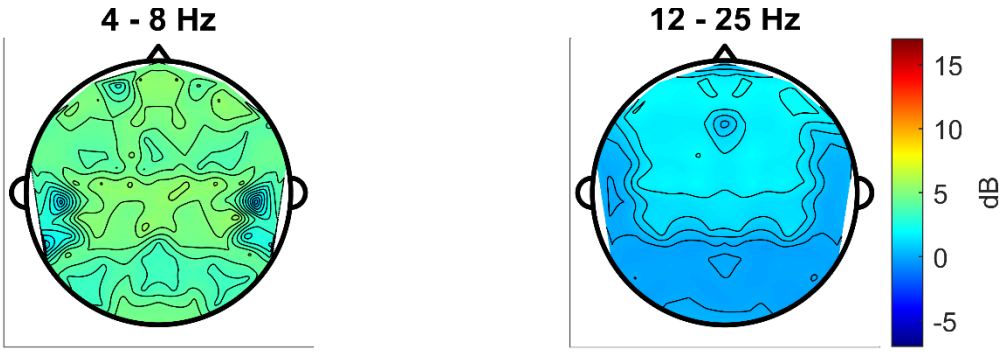

Figure 50: An EEG topology done for a pre-paralysis baseline, one for the theta frequency range (left) and the other for the beta frequency range (right).

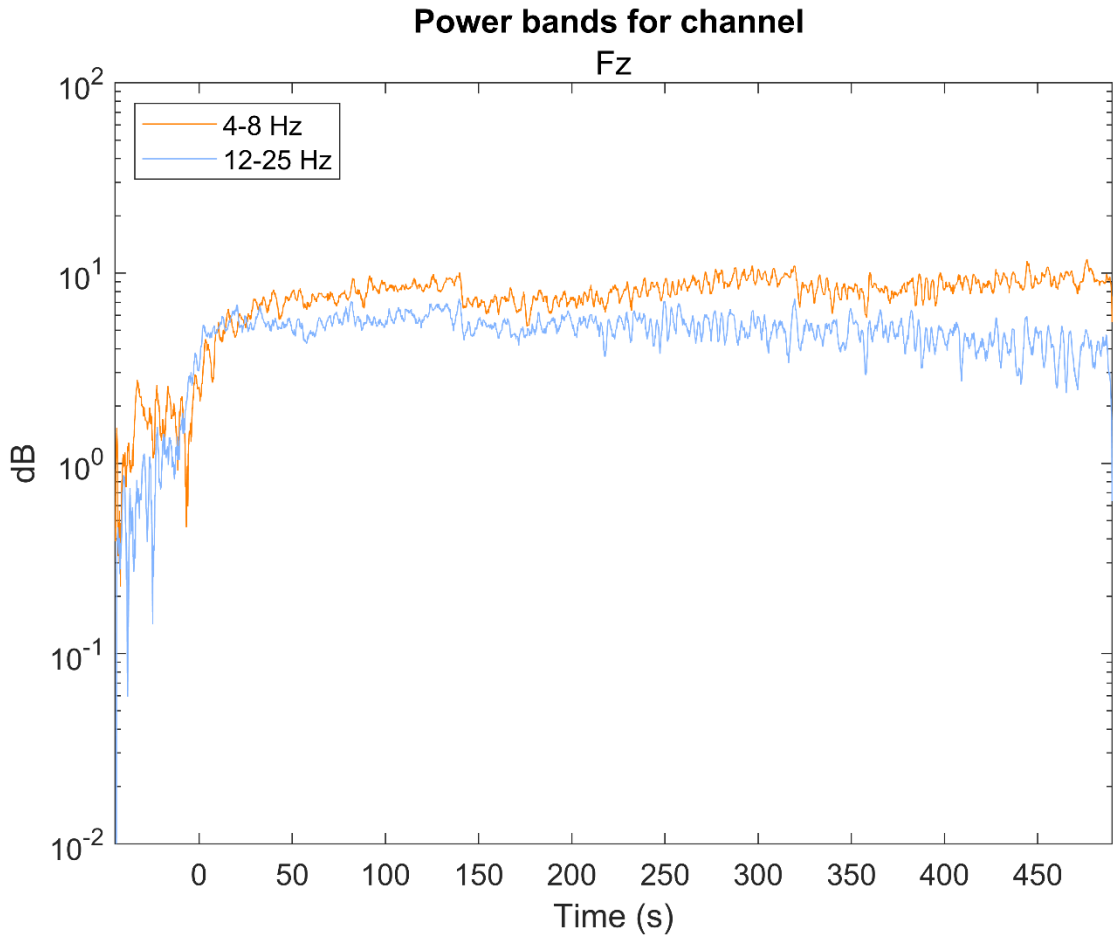

Figure 51: Band power estimates for the theta (orange) and beta (blue) frequency ranges, done for a paralysis baseline.

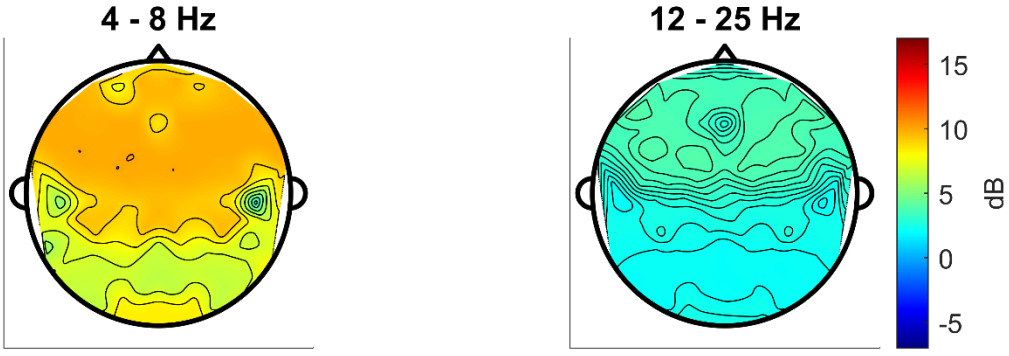

Figure 52: An EEG topology done for a paralysis baseline, one for the theta frequency range (left) and the other for the beta frequency range (right).