

BRAIN CONNECTIVITY: A COMPARISON BETWEEN PARALYSIS AND PRE- PARALYSIS

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ABSTRACT

Electroencephalogram (EEG) is a method of recording the electrical activity of the brain. This technique has been widely used to understand the behaviour of the brain or as a tool for diagnosis to certain neurological conditions. However, the EEG signal was always found contaminated with muscle activity. Having muscle activity in the EEG signal can be a major drawback when studying the causal interactions of different areas of the brain also termed as the effective connectivity of the brain. A comparison between the effective connectivity paralysed state and pre-paralysed state shows that the brain behaves quite differently when the muscles are paralysed. As a consequence, outstanding results are obtained. It was seen that the brain tends to be more synchronised when the muscles are in a paralysed state and that the frontal lobe, motor control and the auditory cortex are the areas with highest information flow. On the other hand, in the pre-paralysis state, a considerable amount of disturbances was found and concluded to be muscle activity. To obtain those results, two sets of tests were done, namely, the head muscle task and the oddball task. The connectivity calculation of the head muscle task had the aim of triggering the masseter muscle, frontalis muscle and the paraspinal muscle whereas the oddball task is a simple auditory task. The oddball task provides a good comparison to whether muscle activity has an influence on the effective brain connectivity. This study confirms that brain connectivity should be calculated from EEG data that had noise removed or should be measured directly from the brain, not the scalp.

DECLARATION OF ORIGINALITY

I certify that this work does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any university, and that to the best of my knowledge and belief it does not contain any material previously published or written by another person except where due reference is made in the text.

PRATISHTAH SOBRUN

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1 INTRODUCTION

The electroencephalogram is also known as the EEG is a method of recording the electrical activity of the brain and, generally falls between the frequency range of 0 to 100 Hz (Bakhshayesh, Fitzgibbon et al. 2014). The recordings are by placing electrodes over the scalp in an organised way (10-20 system), hence covering a large area. The EEG has been used as a method to understand and analyse neurological disorders. However, the EEG signal gets contaminated by noise and other artefacts as it is being recorded from electrodes these artefacts can be classified as biological artefact and external artefact. Biological artefacts caused by the human body, include the muscle activity (electromyogram -EMG), eye movements (Electrooculogram- EOG) and cardiac activities (electrocardiogram – ECG). On the other hand, external artefact occurs because of interference in the line, placement of leads and electrodes. The external artefacts can be reduced by ensuring proper placement of electrodes and performing the experiment in a Faraday cage to avoid interference. For long, studies about how to alleviate the effects of those artefacts have been undertaken so that a much better EEG signal is obtained. As a consequence, more accurate results when studying a neurological disorder. Most algorithms developed, tend to help then reduction of the biological artefact (Jafarifarmand and Badamchizadeh 2013). One way of reducing the effect of EMG from an EEG signals, blocking the muscle activity in the body. A study has been made at Flinders University (South Australia) with the approval of Clinical Research Ethics Committee of Flinders University and Flinders Medical Centre, to intravenously inject a paralyzant in the subject to eliminate muscle activity (Whitham, Pope et al. 2007). The dominant arm was paralysed leaving the non-dominant arm for communication. The subjects were asked to tap their fingers when a response was needed. The recordings were collected from six subjects, but only five subjects are being used due to some loose channels in the sixth subject. A total of 115 EEG channel recordings were taken and the patients were asked to perform a set of tasks before and after paralysis (Whitham, Pope et al. 2007). The aim of that experiment was to identify the presence of EMG when the brain has to work on mental tasks. There are three types of test done, namely the baseline state, photic stimulation and oddball paradigm (Whitham, Pope et al. 2007). The baseline state includes closing the eyes and then opening the left eye, and this process is repeated between tests. Photic stimulation involves a 16 Hz light flashed for 10 s when the eyes are closed and left eye open (Whitham, Pope et al. 2007). The oddball paradigm involves playing tones of low and high pitch; that is 500 Hz and 1000Hz, and the subjects were asked to press the key when a high tone was heard. After considerable analysis, mapping and comparing the results before and after the neuromuscular blockade, it was found that the EEG signals above 20 Hz were contaminated by EMG signal (Whitham, Pope et al. 2007).

In this current research, the understanding how different areas of the brain are connected is proposed. From the paralysis and pre-paralysis data collected, brain connectivity calculation is performed. A comparison of effective connectivity is achieved, and the aim of this research is to compare the connectivity in the paralysed and pre-paralysed state. The importance of this investigation lies along the lines of understanding whether the connectivity is affected by muscle activity and also how the brain behaves when all the muscle activity has been suppressed. So far, scalp EEG has been the simplest and cheapest modality used to understand what is happening in the brain compared to MRI and or more invasive techniques. However, impressive results were obtained at the end of this study. It was found that the pre-paralysed data was contaminated by muscle activity, which could also be referred as noise. Hence, the application of the connectivity algorithm on scalp EEG returns noise. The presence of noise in the result is an important discovery proves that connectivity should be done on cleaned data. During this study, fascinating outcomes were seen in the paralysed state. Firstly, there is an increased connectivity to the centre of the brain. Activity in the frontal area of the brain has been detected in the paralysis state, and it was seen that the information flow is more synchronised. This study is bound to be very helpful for researchers who are looking at brain connectivity in neurological disorders.

2 LITERATURE REVIEW

Multiple research has been done to understand brain connectivity which is the interaction of different areas or points on the brain. In this current study, the aim is to look at brain connectivity from scalp EEG. However, to do so, there is a need to understand what exactly is brain connectivity and why has it been so popular. This literature review will give an overview of the background information required to appreciate the result and discussion chapters. This section projects the background of the study and develops into the direction where the current research is going.

2.1 Brain connectivity

Brain connectivity can be calculated from the mapping of EEG/MEG, diffusion MRI or functional MRI. There has been a numerous amount of research involved in finding meaningful conclusions from the brain connectivity. There are three types of brain connectivity, namely, structural/anatomical connectivity, functional connectivity and effective connectivity. The importance of brain connectivity lies in the fact that it can be useful to draw meaningful conclusions about the neurobiology of the brain and hence getting more information about the neurological abnormalities and disorders (Rubinov and Sporns 2010). One of the most crucial aspects of brain connectivity is to understand the pattern, and therefore a good knowledge of the anatomy of the brain is required. An overview of the brain anatomy is given at a later stage in this chapter.

The brain networks are made up of nodes, also referred to vertices and links referred as edges. In general, the nodes are representative of the brain regions and the links represent the anatomical, functional or effective connectivity (Rubinov and Sporns 2010). The term anatomical connectivity is defined as "the white matter tracts between pairs of brain region" (Rubinov and Sporns 2010), and functional connectivity refers to "the magnitudes of temporal correlations in activity and may occur between pairs anatomically unconnected regions" (Rubinov and Sporns 2010). The functional connectivity will depend on the measure being used and will show linear, nonlinear and interaction with different time scales accordingly. The one that we are more concerned with in this project is the effective connectivity, which is defined as "direct or indirect causal influences of one region on another and may be estimated from observed perturbation" (Rubinov and Sporns 2010).

The anatomical connections characterise the connection pathways between the cortical areas and the functional and effective connectivity related to the time series of the brain dynamics of the anatomical analysis. The difference between the functional and effective connectivity is that the functional connectivity refers to the patterns of cross-correlation between the stronger signals, and effective connectivity relates to the patterns of the causal interactions (Rubinov and Sporns 2010).

The brain mapping consists of nodes and links, and generally, nodes determine a particular region in the brain with important patterns that determine the anatomical and functional connections. Links, however, is a representation of whether a connection is present or not. They general carry weight, direction and they give information on the strength of the connection (Rubinov and Sporns 2010).

Weights can be defined as the size density or coherence, however when analysing anatomical connection and for functional and effective connections, they are associated with the magnitude of the connections as well as the causal interactions (Rubinov and Sporns 2010). It is said that the weaker links can be a cause of spurious connections and appears in functional and effective connections mainly. As a consequence, these links tend to hide the effects of stronger and more valuable connections. Therefore, these spurious signal are often discarded by applying an appropriate threshold. Those threshold values are arbitrary, and it is crucial to ensure that the network is well characterised, that is, studying all the values before setting a threshold. Connections with negative values are removed from the networks because they have no significant meanings (Rubinov and Sporns 2010).

To calculate brain connectivity, a network measure is used. Measures are sets of mathematical concepts that illustrate the patterns in the brain connectivity by analysing the strength of the links. As a consequence, the dependence of one node to another (Rubinov and Sporns 2010).

2.2 Connectivity measures

The techniques used to understand the relationships of connections in a dynamic system and that give an insight into their spatiotemporal organisation, is referred as a connectivity measure (Bakhshayesh, Fitzgibbon et al. 2014).

A measure is used to identify the causal and hidden dependencies in a dynamical system that is based on a time series. Understanding the patterns and the interactions of various regions in the brain shows its importance when identifying the functional aspect of a normal or pathological brain (Bakhshayesh, Fitzgibbon et al. 2014).

As a consequence, it becomes essential to define the dynamical links within this network, and this is referred to as the effective connectivity. As mentioned above, the effective connectivity is characterised by how neural systems influence one another (Bakhshayesh, Fitzgibbon et al. 2014).

There are many methods that have been used to understand the brain connectivity. Most of them include mathematical modelling, independent component analysis or simulation.

There has been a tremendous amount of research to try to study the relationship between real time series, for example, the Electroencephalography (EEG) (Bakhshayesh, Fitzgibbon et al. 2014). There

are a few standard measures, classified as linear and non-linear measures. Some example of the linear measures include cross-correlation and coherence, and non-linear measures depend on information like the phase index or information theory. The information theory includes correntropy or mutual information. Phase index detects the difference between two signal and mutual information related to the amount of information being shared (Lachaux, Rodriguez et al. 1999). Correntropy is an extension of the correlation in the non-linear space (Gunduz and Principe 2009). However, Bakhshayesh and her team found that no measure performed better than the other and they all have their set of advantages and disadvantages (Bakhshayesh, Fitzgibbon et al. 2014).

One very popular measure is the transfer entropy which calculates the average information about say $x(t)$ which was obtained from the past of $y(t)$, which is not already present in the past of $x(t)$ (Bakhshayesh, Fitzgibbon et al. 2014). Transfer entropy is classified as mutual information and can be interpreted as the diversity of state transitions in the destination and subtract the noise associated with those state transition and the state of the source (Bakhshayesh, Fitzgibbon et al. 2014). Transfer entropy is considered to be a model-free measure (Vicente, Wibral et al. 2011) and has multiple advantages. Some of the benefits are that it can handle a large amount of data, it is robust and efficient when setting thresholds during effective connectivity calculation (Vicente, Wibral et al. 2011).

To test the statistical significance of a connectivity value, phase randomised surrogate data was generated to give data with the same statistical properties as the original data, but with the dependencies between signals destroyed by the phase randomisation (Bakhshayesh, Fitzgibbon et al. 2014). The connectivity measures were computed for 100 surrogate realisations, and the fifth largest was selected as a threshold for 5% significance level (Bakhshayesh, Fitzgibbon et al. 2014). Of the connectivity measure calculated on the original data exceeds the threshold. Then it is regarded as significant, and a directed link is placed in the model (Bakhshayesh, Fitzgibbon et al. 2014)

2.3 Methods

2.3.1 Component analysis

Other methods of analysing brain connectivity are through a component analysis to improve data analysis by using mathematical modelling. This method accommodates the nested structure of time series data to investigate its effectiveness by applying it to a multi-subject functional neuroimaging data for the brain (Jung, Takane et al. 2016). It was found that the method can be implemented to capture an important aspect of neural interaction (Jung, Takane et al. 2016). Independent component analysis also referred as ICA is a method of removing noise from a signal based on

statistical analysis. It involves the recovery of independent sources from a mixture. Most of the time specific knowledge about the source is not known (Castella, Moreau et al. 2004, Zhao, Shen et al. 2015).

2.3.2 Inverse source reconstruction

It is not easy to study the information flow between different areas of the brain because of noise and volume conduction. A simulation study was done to test the measures of effective connectivity to understanding the neural interaction in an EEG signal (Haufe, Nikulin et al. 2013). The technique used is an inverse source reconstruction to get a better understanding of the connectivity. The effect of volume conduction has been found to conflict with the results, but it depends on the measure used and the statistical testing approach used. The measure that was best suited for this study was Granger-Causal (CG) methods (Haufe, Nikulin et al. 2013). It has been seen that Phase-Slope Index (PSI) performs well on simulated data and the authors have devised a theoretical framework to understand and reduce the effects of volume conduction. However, at the same time making sure that the time-lagged brain interactions are kept intact for better connectivity estimates (Haufe, Nikulin et al. 2013). The latter is achieved by using time reversed data as surrogates for statistical testing. Hence, it was possible to prove that the CG is a robust measure to understand the brain connectivity and similar result was obtained using the PSI (Haufe, Nikulin et al. 2013). The authors performed four experiments which involved the interaction of sources of connections. Two dipole models involving linear dynamics and a time delayed linear influence (Haufe, Nikulin et al. 2013). The four experiments were as follows:

1. Measures like the Granger causality, Phase-Slope Index and partial directed coherence were used to study the effective connectivity on two interacting sources (Haufe, Nikulin et al. 2013).
2. Considering a simulated EEG with both noise and volume conduction and applying the same measures (Haufe, Nikulin et al. 2013).
3. Evaluation of the effects of a reference electrode and signal to noise ratio and a simulated EEG (Haufe, Nikulin et al. 2013).
4. Evaluation of inverse source reconstruction as a method of preprocessing for analysis (Haufe, Nikulin et al. 2013).

As a general comment, all the three measures showed that it 's hard to draw conclusions from the simulated data using these three measures. Volume conduction and the noise were difficult to estimate. However, this situation can be improved by inverse statistical testing (Haufe, Nikulin et al. 2013).

2.4 Current research on brain connectivity (functional)

There have been studies that suggest that some of the brain regions are more active when they are at rest when compared to cognitive tasks (Hampson, Driesen et al. 2006). It might be an acceptable hypothesis but however, Hampson et al., suggested that there might be other reasons behind those hypotheses. One possibility is that, with the decrease in metabolic activity, there might be an increase in the different regions of the brain. It has been found that there is an inverse relationship that exists between the activation of the brain region and how it engages on the other side of the brain. Therefore, the reactivation is accompanied by an increase in activity rather than a decrease in some regions of the brain. On the other hand, functional connectivity existing gives more details about the interactions between different areas (Hampson, Driesen et al. 2006).

The reason for the reverse relationship is due to the neural synchronisation rather than the rate of neural firing in the brain. It is important to note that the theta rhythm becomes more prominent than before. It is generally in the 4 to 7 Hz range (Tesche and Karhu 2000), and this shows the synchronisation of the neural activity. This shows the presence of the cognitive function which indicates a reduction in the metabolism (Hampson, Driesen et al. 2006). The deactivation of the brain causes an increase in its engagement. Therefore, the engagement will define the functional connectivity of the brain, and particularly useful in Default Mode Network (DMN) (Gevins, Smith et al. 1997). DMN refers to the dependence of regions of the brain that has been activated during a particular memory-based task (Hampson, Driesen et al. 2006). The subjects were scanned using an MRI, and the brain scans were taken while then patients were performing a memory task. Two scans were baseline where the subject had to press a button when the letter A appears on the screen. Once the scans were obtained the data was analysed using some statistical methods namely t- test and ROI to understand the functional connectivity and their location. The r- and z- transforms were used with a p-value of 0.005%. From the scans, some areas of the brain were activated namely dorsolateral prefrontal cortex bilaterally, left ventrolateral prefrontal cortex, left premotor cortex, right frontal pole, bilateral inferior parietal lobule, a region at the junction of dorsal anterior cingulate cortex and medial frontal gyrus, right insula, right temporal gyrus, and a subcortical region at the intersection of the left thalamus, caudate, and lenticular nucleus (Owen, McMillan et al. 2005).

2.5 Anatomy of the brain

In the representation shown in Figure 2.1, a basic overview of the brain regions is given. The brain consists of 6 lobes, namely the frontal lobe, the parietal lobe, the temporal lobe, the occipital lobe, limbic lobe and the insular lobe. Each area of the brain has specific functions.

The frontal lobe is the centre for memory. It includes human reasoning and decision making, emotional responses and working memory (Dharani 2015).

The parietal lobe consists of the motor control where the movement is registered and the sensory cortex where all the sensations are controlled (Dharani 2015).

Temporal lobe consists of the auditory cortex which processes sound signal and it is also the centre of which language is understood and processed (Dharani 2015).

The occipital lobe has one primary function which is the processing of vision in the visual cortex (Dharani 2015).

The insular lobe is involved with the appreciation of taste and spoke the language (Dharani 2015). It is located deep inside the lateral fissure of the brain (Dharani 2015).

The limbic lobe is located between the frontal and the temporal lobe and it is responsible for instinctual behaviours and emotions (Dharani 2015).

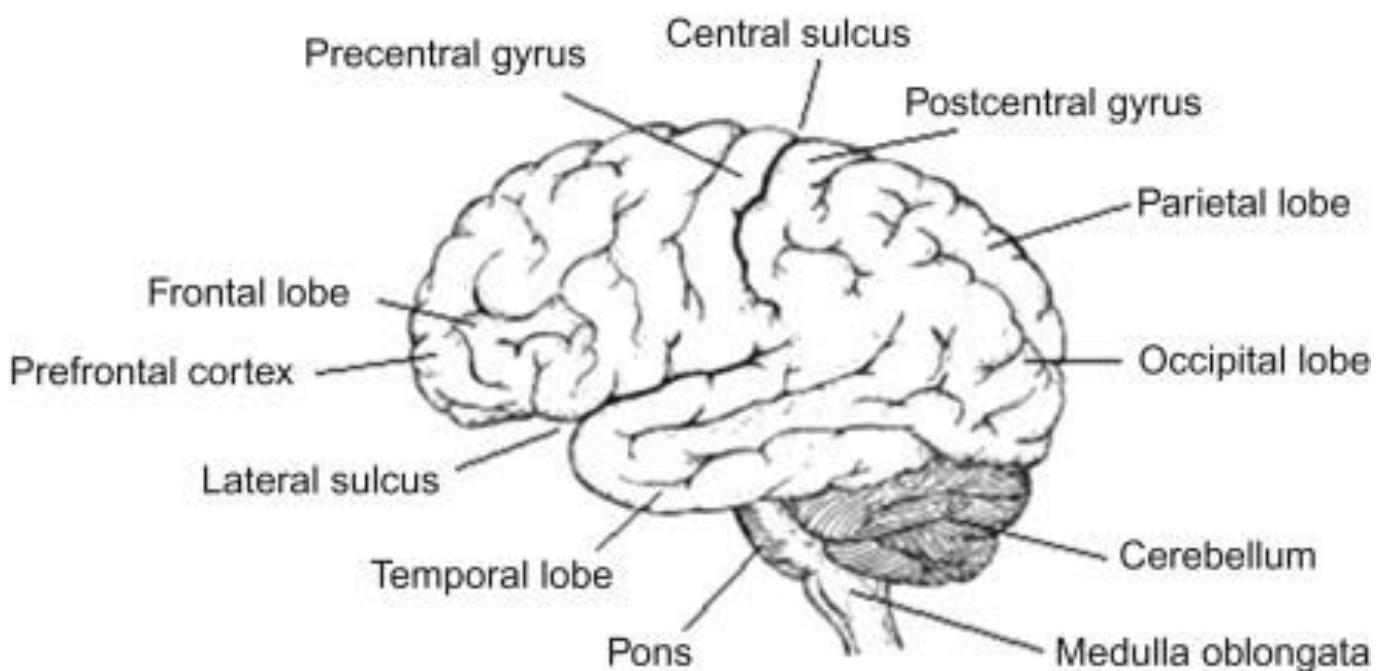


Figure 2.1 An overview of the important regions of the brain (Dharani 2015)

2.6 Muscles of the head

In Figure 2.2 and Figure 2.3, the major head muscles are presented. The tasks chosen in this study are head muscles tasks and the oddball task. The head muscle tasks include triggering the muscles for biting, frowning and moving the neck by pressing it on the pillow.

For the bite movement, the muscles that are related to mastication are the masseter muscle, the temporalis muscles and the pterygoid muscles ("General Articles Archives - Am-Medicine", 2016). Frowning involves the frontalis muscles and the orbicularis muscle ("General Articles Archives - Am-Medicine", 2016). The neck movement includes the paraspinal muscle which is located at the back of the head. It was found that there is a possibility that the sternomastoid are also participating in the neck movement ("General Articles Archives - Am-Medicine", 2016).

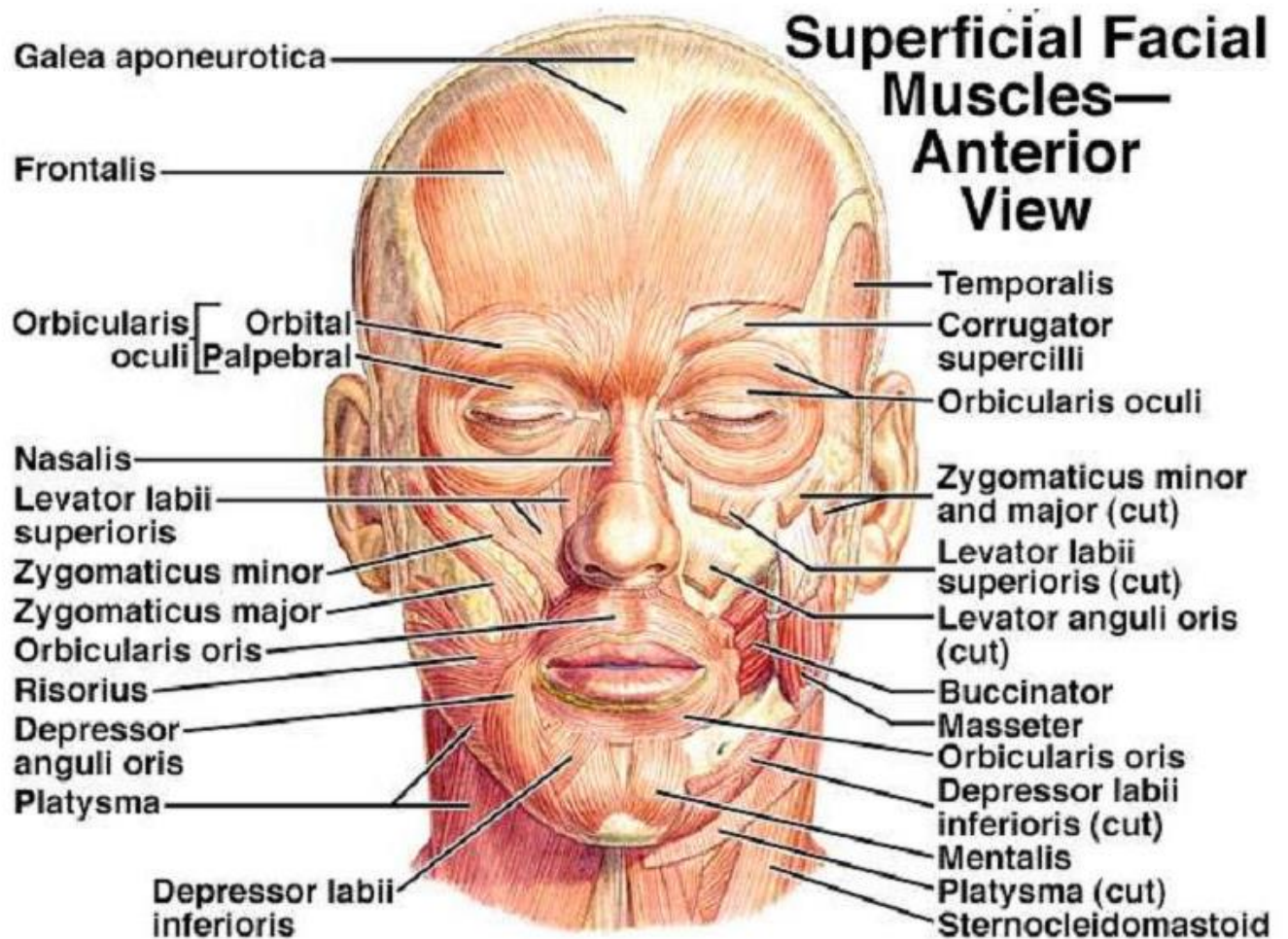


Figure 2.2 The head muscles in anterior view ("General Articles Archives - Am-Medicine", 2016)

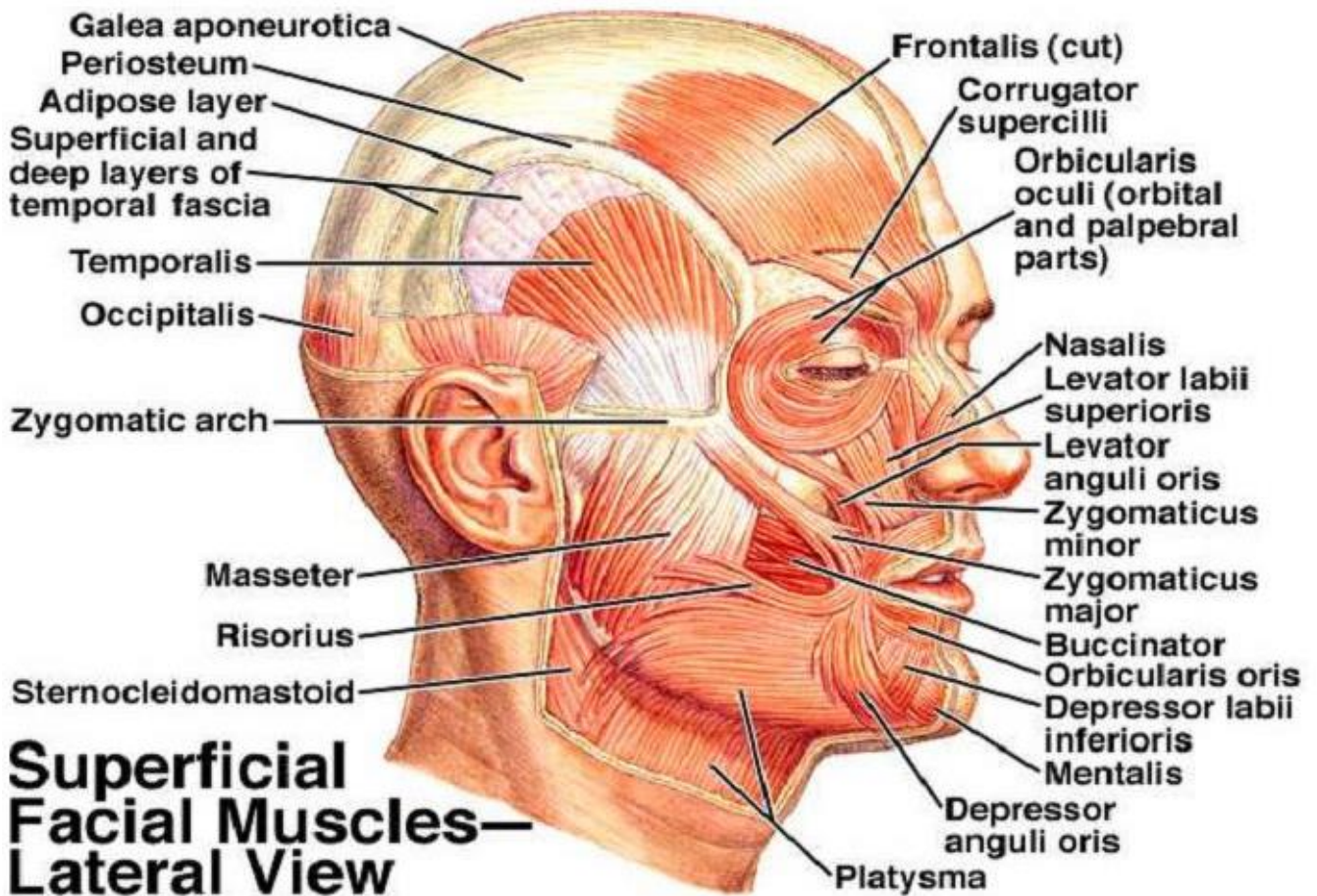


Figure 2.3 the head muscles in deep lateral view ("General Articles Archives - Am-Medicine", 2016)

2.7 Proposal

In this research, we are using the paralysis and pre-paralysis data from Whitham et al. (Whitham, Pope et al. 2007), to investigate the effective connectivity networks of the brain. The reason for using the paralysis data is that the EMG signals will be eliminated and therefore no biological artefact will be present. This research will be a novel as there hasn't been any research done to analyse the connectivity on a paralysed subject yet. Furthermore, the mental tasks are useful because it enables us to understand which region experiences a strong connection and under what task. The procedure involves finding out appropriate measures for the analysis and apply them to the existing dataset. MATLAB is the computing tool used in this project and the statistic threshold for the connection was taken as $p=0.05$. However, a Bonferroni correction was done to ensure that more valuable results are obtained, and no meaningful connections are ignored during the process. The Bonferroni method is used when there are multiple comparisons. It was suggested to one of the methods to be exploited in our project to ensure that a better comparison is made. The result from this research will be a brain mapping of different tasks and an evaluation of which region of the brain has the strongest

connection based on the statistics. Moreover, it was found that the scalp EEG before paralysis is contaminated by muscle activity and hence cannot be used for connectivity calculations unless it is cleaned. Researchers and neurologists long assumed that connectivity could not be calculated from scalp EEG. However, the result of this study provides proof of what was simply taken as a fact.

3 MATERIALS AND METHODS

3.1 Experiment set-up

During the paralysis experiment, EEG was recorded from 6 subjects. The subjects in this experiment were identified by their initials, namely 'jow', 'am', 'als', 'jow', 'ddla' and 'rw'. It should be noted that the paralysis test was approved by the Clinical Research Ethics Committee of Flinders University and Flinders Medical Centre. All the subjects had a clear idea and knew what the experiment was about. The experiment was conducted in a Faraday cage to avoid the external noise while recording. Their legs were supported in an elevated position during the investigation and were not changed during paralysis. The injection of a paralyzant into the body was done by an anaesthetist who remained in the Faraday cage all throughout the experiment along with a neurologist. All other equipment that is, the monitoring equipment and the ventilator was kept outside the Faraday cage and was connected through ports found inside the Faraday cage. The monitoring equipment was being supervised by another anaesthetist who was outside the Faraday cage. Communication with the subjects involved a finger tapping response for yes/no (Whitham, Pope et al. 2007).

The EEG recording was done using 128 channels electrode cap placed on the head to obtain an optimum and uniform coverage. The electrodes used were Ag/AgCl electrodes (Easy Cap Falk Minnow, Germany) and both a 10/20 and a 10/05 arrangement. The electrode impedance was kept below 15 KOhms. It is important to note that some of the electrodes were taken out of the cap placed at different sites on the body so as to obtain the respiration rate, EOG, ECG, the EMG on the (1) left force arms (extensor indicis), (2) the left and right masseter and (3) the left and right cervical paraspinal muscle. During the whole process, the left ear was taken as the reference. The sampling was at a rate of 5000 samples per second, and a 16 bit analogue to digital conversion was used (Whitham, Pope et al. 2007).

During the paralysis and pre-paralysis tests, the subjects were given mental tasks to perform. These tasks were mainly focused on proving that EEG frequencies above 20 Hz are contaminated by EMG. However, some of the tasks were relevant to the study of connectivity on paralysed and pre-paralysed subjects. The Table 3.1 below shows the tasks that were performed. The tasks were categorised into 3 groups, namely the baseline state, photic stimulation and the oddball paradigm. The baseline state involves eyes closed and left eye open for 10 seconds. The photic stimulation occurs when a 16 Hz light is presented on closed eyes of left eye open for 10 seconds. Lastly, the oddball paradigm where high (1000Hz) and low tones (500 Hz) were presented to the subjects, and they were asked to press the appropriate keys only when the high pitch tones were heard. The high

pitched tones counted for approximately 25% over a period of 3 minutes. The tones were randomly presented for 50 milliseconds after every second.

To understand the differences between the paralysis state and the pre-paralysis state, the head muscle tasks play an important role where the presence and absence of muscle activity can be easily detected. This experiment was categorised as head muscle contractions mainly the masseter, frontalis and paraspinal muscles. Masseter involves a biting movement, frontalis involves a frowning movement, and finally paraspinal involves neck movement.

Table 3.1 The procedure and the tasks (Whitham, Pope et al. 2007)

Pre-paralysis study	Paralysis study
Finger tapping left and right	Sphygmomanometer cuff inflation, non-dominant arm
Sphygmomanometer cuff inflation, non-dominant arm	Paralyse (cisatracurium)
Deflate sphygmomanometer	Adjust ventilation
Rest 1 min	Check paralysis (measure motor action potential in extensor digitorum brevis)
Eyes closed	Eyes closed
Left eye held open	Left eye held open
Eyes closed – strobe	Eyes closed – strobe
Left eye held open – strobe	Left eye held open – strobe
Oddball paradigm	Oddball paradigm
Subtraction	Subtraction
AVLT	AVLT
Auditory discrimination	Auditory discrimination
Finger tapping non-dominant (actual) and dominant (fictive)	Finger tapping non-dominant (actual) and dominant (fictive)
	Deflate sphygmomanometer
	Rest 5 min
Head muscle contraction (masseter, frontalis, paraspinal)	Head muscle contraction (masseter, frontalis, paraspinal)
Eyes closed	Eyes closed
Left eye held open	Left eye held open
	Finger tapping left and right (actual attempted)
	Undertake experiential tests
	Sedate (propofol and fentanyl)

MATLAB has been used to do all the relevant analysis of the EEG signal, and all the recordings were recalculated to ensure that the linked ear referencing was applied to all the analysis to maintain consistency in the results. The EEG signals from the tasks performed for both the paralysed and unparalysed subjects were stored in the Flinders University tool EEG toolbox, known as the 'eeg3' and 'eeglocal'. These are a set of functions written by a team at the Bio-signals lab at Flinders University.

The 'eeglocal' toolbox contains the EEG tests that were conducted at Flinders University and functions that allow the loading of the subject data. Some examples of the data that can be loaded based on the research that has been done are, +diurnal, +gamma, +io (meta study and neuro scans), +meditation, +peak study, +rat, +paralysis and +util. These folders allow the users to load the EEG data for those different categories. The type of data used in this research involved loading the subjects along with their paralysis and pre-paralysis data. It also contains the various types of mental tasks and tests they were asked to perform during those states. The tests are represented in Table 3.1. The eeg3 toolbox contains functions that can be called in the MATLAB toolbox.

3.2 Setting the paths

The connectivity analysis starts by loading the data from the 'eeglocal' source, and a 'start-up' program has been created to access those EEG data depending on the categories that need to be loaded. It becomes helpful when obtaining the required information. The 'start-up' code was written by the Associate Professor Kenneth J. Pope at Flinders University. A sample of the 'start-up' code is given in the appendix.

The 'start-up' code works out where the most important files are, and eventually sets the appropriate path to the directory that is needed. The next section is to establish the path for 'eeg3', as it is better to have the path loaded beforehand. The paths include extracting the paralysis/ gamma/ meditation data from 'eeglocal'. To make this possible, a set of function have been created to support this action.

3.3 Loading the subjects

A simple command is used to load the subjects, and it can be seen that only six subjects have performed the paralysis. However, later during the analysis of the EEG signals from the subjects, it was observed that one electrode was not correctly placed on the scalp of the subject "als". Hence, to maintain uniformity, the data from the subject named "als' was discarded. An example of the code used to load the data Figure 3.1. Loading the subject involved accessing the 'eeglocal' toolbox and loading the paralysis and the pre-paralysis data based on their name initials.

```
d_pre_am = eeglocal.paralysis.load( 'am', [ 'study.preparalysis.' task]);
```

Figure 3.1 Loading the data

3.4 Loading the tasks

The tasks can be loaded using a certain set of keys. These keys are a set of command that allows the specific tasks to be loaded. In this case, all the tasks will be related to paralysis and pre-paralysis can be loaded. There were instances where data was not available for a certain subject and the reason being, that the test was not successful with that particular subject. An example of the keys is given the appendix in section 9.2. From the list of keys, it becomes easier to access the data of the related tasks.

For the code to work properly, the subject and the relevant task was loaded simultaneously.

3.5 Loading the channels and 10-20 labelling

The channels are loaded using the functions written by the experts at Flinders University, and the 10-20 labelling system was used done.

The ten-twenty electrode system was first introduced by Jasper in 1947 in an international EEG Congress that was held in London (Oostenveld and Praamstra 2001, Milnik 2009). He emphasised on an accurate placement of electrode as shown in Figure 3.2. Since then, Jasper's work became the standard way to place electrodes on the scalp for both clinical and non-clinical setting. But as the technology is advanced, topographic methods became more popular, and there was a need for better and more channels, also referred as electrodes. Hence in 1985 the 10-20 system evolved from being a 21 electrodes system (Jasper 1958, Klem, Luders et al. 1999) to a 74 electrodes system (Chatrian, Lettich et al. 1985), also known as the 10-10 system shown in Figure 3.3. The 10-20 system is a subset of the 10-10 system and gives a better resolution of the EEG. Modern EEG recordings involve 128 channels (electrodes), and it is referred as the 10-05 system (Oostenveld and Praamstra 2001). In this experiment, a 128 channel cap was used and there 115 channels were successfully recorded. Therefore, the 10-05 system was used, but however, the number of channels were reduced to an extended version of the 10-20 system. The evolution of the placement of electrodes is shown in Figure 3.2, Figure 3.3 and Figure 3.4. This increase in the number of electrodes or rather channels have played a major role in improving the resolution over the years (Oostenveld and Praamstra 2001).

3.5.1 The 10-20 system

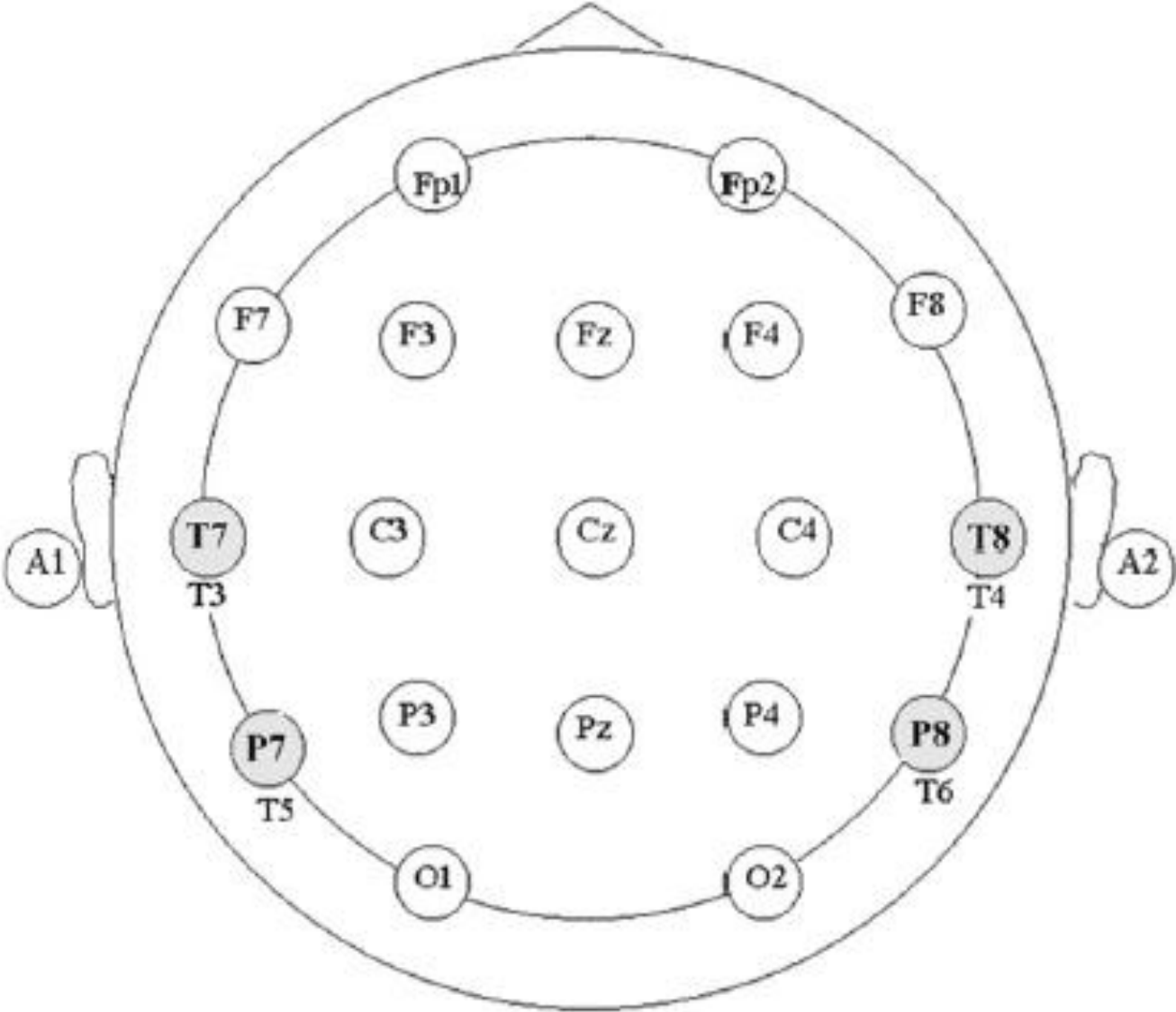


Figure 3.2 The International placement of electrodes (10-20 system) (Jasper 1958, Milnik 2009)

3.5.2 10-10 system

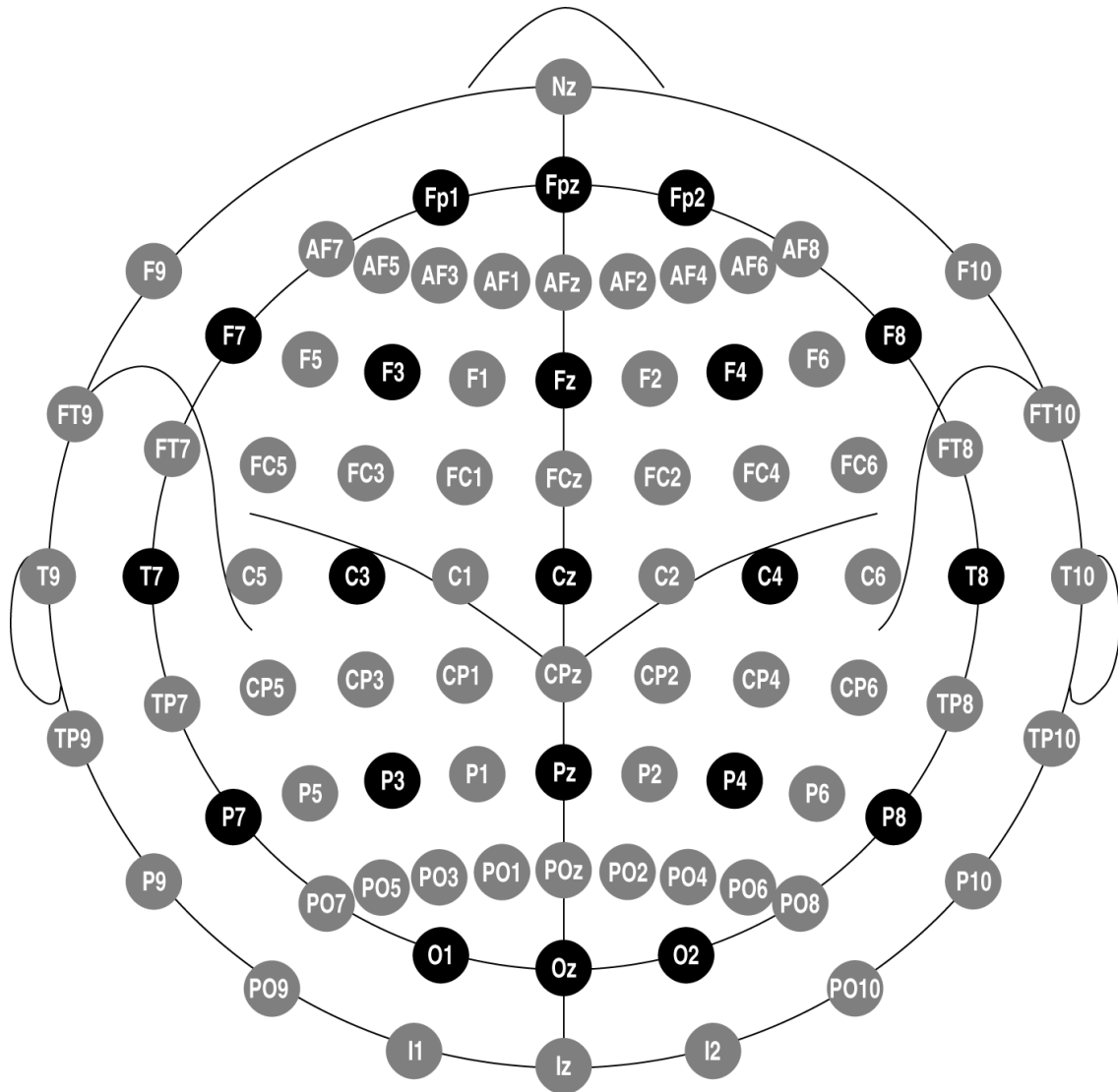


Figure 3.3 The 10-10 system is an extension of the 10-20 system (Oostenveld and Praamstra 2001)

3.5.3 10-05 system

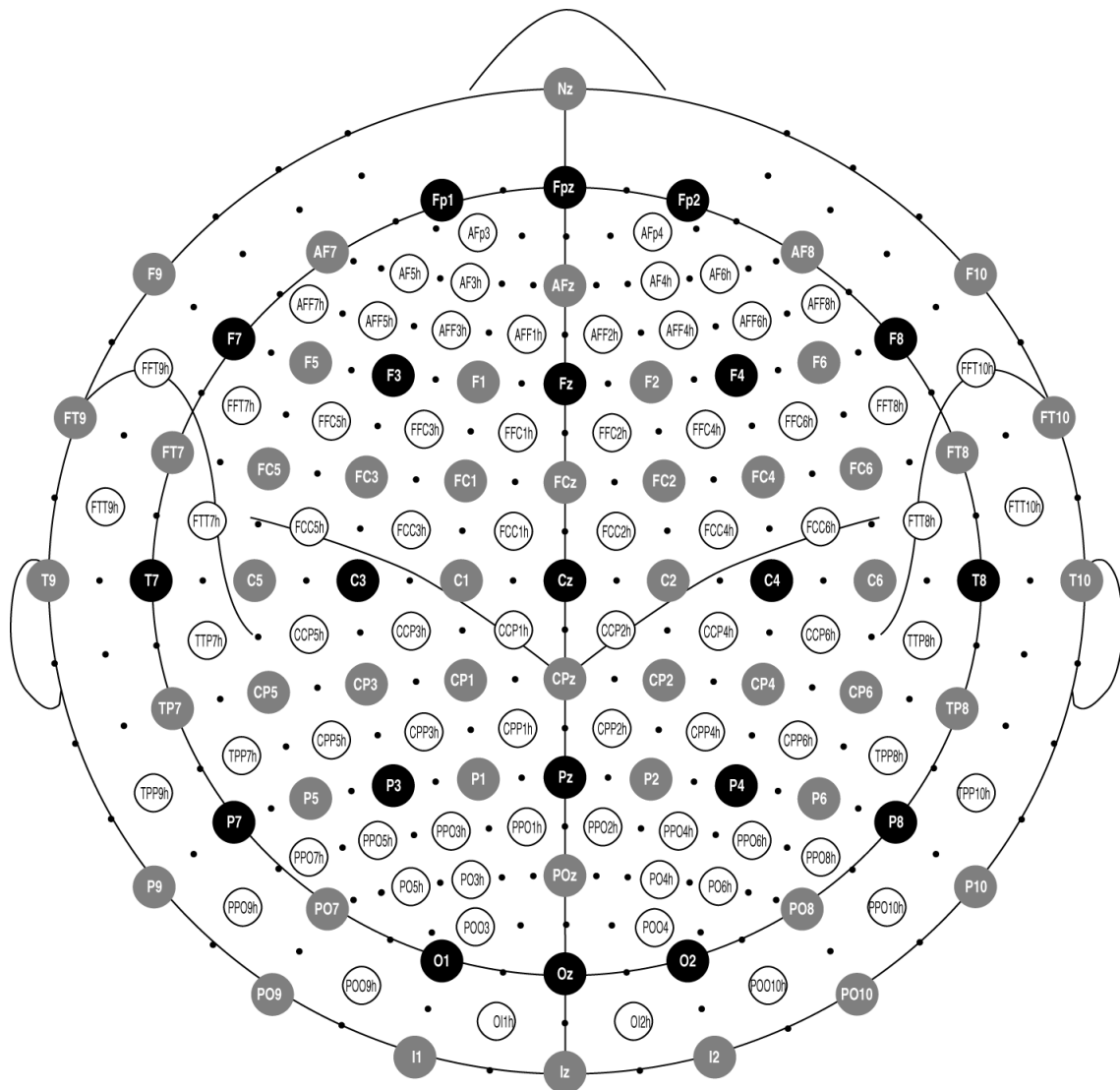


Figure 3.4 10 05 system (128 channels) is an extension of the 10 20 and 10 10

3.6 Connectivity calculation

The connectivity is calculated between channels, and this is done by calling the function written in the 'eeg3' toolbox. This connectivity function was written by Associate Professor Kenneth J. Pope and Hanieh Bakhshayesh at Flinders University. It was updated during this research, making the code more efficient while reducing the number of steps. When using the connectivity function, a measure is used, and an adjacency matrix is obtained by applying statistics principles like null hypothesis and Bonferroni correction method. In the old connectivity function, the adjacency matrix

was calculated separately by applying the connectivity function along with the measure to be used shown in Figure 3.5.

```
AM = connectivity( d, @transferentropy);
```

Figure 3.5 Original connectivity function

The updated version of the connectivity function was written by Associate Professor Kenneth Pope at Flinders University as shown in Figure 3.6.

```
function [ avAM, chans, AM, AMs, pt_pval, avAMt, pt_teststat, pt_thr, pt_dist] = ...  
connectivity( d, measure, varargin)
```

Figure 3.6 Updated connectivity function

The description of the function regarding the input and the outputs is given in Figure 3.7.

As a note, it is important to understand the concept of the adjacency matrix. According to graph theory, if there is n number of nodes in a network, the adjacency matrix will result in an nxn square matrix (Liu and zhao 2012). In this current research, the adjacency matrix is a 66x66 matrix which represents the number of channels arranged in rows and columns. When the channels were arranged with themselves, a value of zero was seen along the diagonal of the matrix.

To prevent those values from affecting the statistic tests, a small code was written to remove the diagonal along with the channel labelling.

```
% [ avAM, chans, AM, AMs, pt_pval, avAMt, pt_teststat, pt_thr, pt_dist] = connectivity( d, measure, varargin)  
%  
% Calculates the connectivity between channels of eeg3.eeg object(s), and  
% the calculates permutation tests to determine the significance of the
```

Figure 3.7 The role of the connectivity function

The updated connectivity function returns set channels and p-values for whether the values of transfer entropy are significant. As a note, if the elements of the do not have the same channel, then it automatically reduces all elements of d to the largest common set of channels.

The inputs to the function are given in the Figure 3.8 Inputs to the connectivity function and the outputs in Figure 3.9.

```

% Inputs (required):
% d          matrix of eeg3.eeg objects
% measure    handle to the measure calculating function
%
% Inputs (optional parameter pairs):
% 'verbose'  (true) controls the extent of text written out
% 'AM'       ([]) allows pre-calculated adjacency matrices to be input
% 's'        ([]) allows pre-calculated surrogates to be input
% 'AMs'      ([]) allows pre-calculated surrogate adjacency matrices to be input
% 'surrogate_type' ('trial shuffling') surrogate calculation method
% 'Nperm'     (10000) number of permutations in the permutation test
% 'permstatype' ('independent') type of permutation test
% 'alpha'    (0.05) alpha for statistical tests
% 'permloops' ('fastandbig') vs 'slowandsmall' for looping channel pairs vs permutations

```

Figure 3.8 Inputs to the connectivity function

```

% Outputs:
% avAM       averaged adjacency matrix
% chans      set of channels for the rows and columns of avAM
% AM         unaveraged adjacency matrices
% AMs        unaveraged adjacency matrices for surrogates
% pt_pval    p-values for the significance of the elements of avAM
% avAMt      thresholds for significance for avAM
% pt_teststat test statistics for the significance of the elements of avAM
% pt_thr     thresholds for the test statistics
% pt_dist    full distributions of the surrogates
%
% be careful, the last output can be very large. 128 channels and 10000
% permutations mean pt_dist requires 1.5 GB. It is only collected together
% if you ask for it, or choose the fastandbig looping of the permutation
-% tests.

```

Figure 3.9 Outputs to the connectivity function

The effective connectivity was found in both pre-paralysed and paralysed subjects and adjacency matrices for each subject was found. The mean of the adjacency matrices are calculated, and the difference between of the pre- paralysis is found. The measure used is normalised transfer entropy and using a given set of related equations; the connectivity is obtained.

3.7 Normalised transfer entropy

There are a set of different measures that can be used on effective connectivity. Some examples are Multivariate Granger Causality, Kullback- Leibler divergence, directed coherence and phase synchrony.

The transfer entropy measure was selected for this research as it has multiple advantages. This measure has been proven to work well with effective connectivity by Vicente et al. More details

about the methods they used has been discussed in Chapter 2 (Vicente, Wibral et al. 2011). Some of the advantages that they suggested are given below.

Transfer entropy better than Granger causality which showed some complications when there was a need for detecting non-linear interactions (Vicente, Wibral et al. 2011). Granger causality is based on a stochastic model that works mainly for linear data models (Vicente, Wibral et al. 2011). They were able to show that transfer entropy can be detected effective connectivity when two signals are combined using a non-linear function. Transfer entropy has shown a good response to the thresholds that were set during the calculation of effective connectivity (Vicente, Wibral et al. 2011).

They also noticed that the transfer entropy can handle multiple signals that have large time delays (Vicente, Wibral et al. 2011).

The effectiveness of transfer entropy was also seen when it showed robustness when dealing with the problem of volume conductivity only when a linear function is used.

Transfer entropy combines with a time shifted data test helps to reject noisy signals which can be applied to EEG and MEG sensor level signals where linear mixing of signals are essential (Vicente, Wibral et al. 2011). It is important to note that the time is shifting test, the transfer entropy tends to return false positive that cannot be neglected. This false positive is due to the fact the causality is not present, and the transfer entropy is zero (Vicente, Wibral et al. 2011).

Finally, Vicente et al. suggested that transfer entropy is a model-free measure, and therefore computation is easier compared to other methods that require models (Vicente, Wibral et al. 2011).

The normalised transfer entropy is used because it gives more reliable results especially because of noisy data.

3.8 Statistical testing

After applying the normalised transfer entropy, and the adjacency matrix is obtained, it becomes easier to apply the statistical tests. One of the tests is the null hypothesis test. α , alpha (p-value) refers to a 5% chance that the experimental results could have been obtained by random chance alone and therefore, the confidence level when analysing the result is at 95%. Multiple tests were performed on the data and this reduces the statistical significance of the results. Therefore, the p-values had to be corrected to reflect the actual significance of the result. As a consequence, we decided to do a modified Bonferroni correction, not the original Bonferroni correction. In Bonferroni, alpha is divided by the number of tests performed. This does making it harder to find significant result. The Bonferroni correction concept involves multiplying all the p-values by the number of tests. It is known that Bonferroni is regarded as too conservative, fewer significant results is obtained.

Modified Bonferroni is generally accepted as more appropriate than no correction or Bonferroni correction. In modified Bonferroni, p-values from smallest to largest is arranged. The smallest is then compared to alpha, the second smallest is compared to alpha/2, the third smallest is compared to alpha/3, so on. Alternatively, after ordering the p-values from smallest to largest, we multiply them by their rank order, that is, the first (smallest) is multiplied by one, the second is multiplied by two, and so on. Essentially, the result most likely (smallest p-value) to be significant is tested like it would as a single test, and every subsequent test is made progressively more difficult to get a significant result.

The permutation test is done to compare the connectivity among the channels selected hence we get a better resolution of the result. The more the number of permutations the better. However, the higher the number of permutations the longer the computation time. A number of 10000 permutations was selected because the connectivity difference between the pre-paralysis and paralysis is a statistically small difference. The role of the permutation test is to randomly swap the data between the mean adjacency matrix of the pre-paralysis state and the mean the adjacency matrix of paralysis state. The difference between the two matrices or rather vectors is computed. The values obtained from the difference is compared to the original vector, and if it falls above the 97.5 percentile or the 2.5 percentile, the transfer entropy value is considered to be significant with an alpha of 0.05 in a two-sided test. The function used is given in Figure 3.10.

```
[~, pvals] = permutationtest_multi( AM_pre_mean, AM_para_mean, ...  
    2, 'Nperm', 10000, 'type', 'independent', 'alpha', 0.05, 'multiple_tests_correction', 'Bonferroni');
```

Figure 3.10 The function used for statistical analysis

However, if the number of permutations goes higher, it becomes harder to draw valuable conclusions because of the increase in the number of arrows inside the brain mapping as seen in Figure 3.11 and Figure 3.12. It is something quite unexpected, and we found that it is not necessary to have more than 10000 permutations.

Mean oddball. alltones preparalysis vs paralysis connectivity (1020)

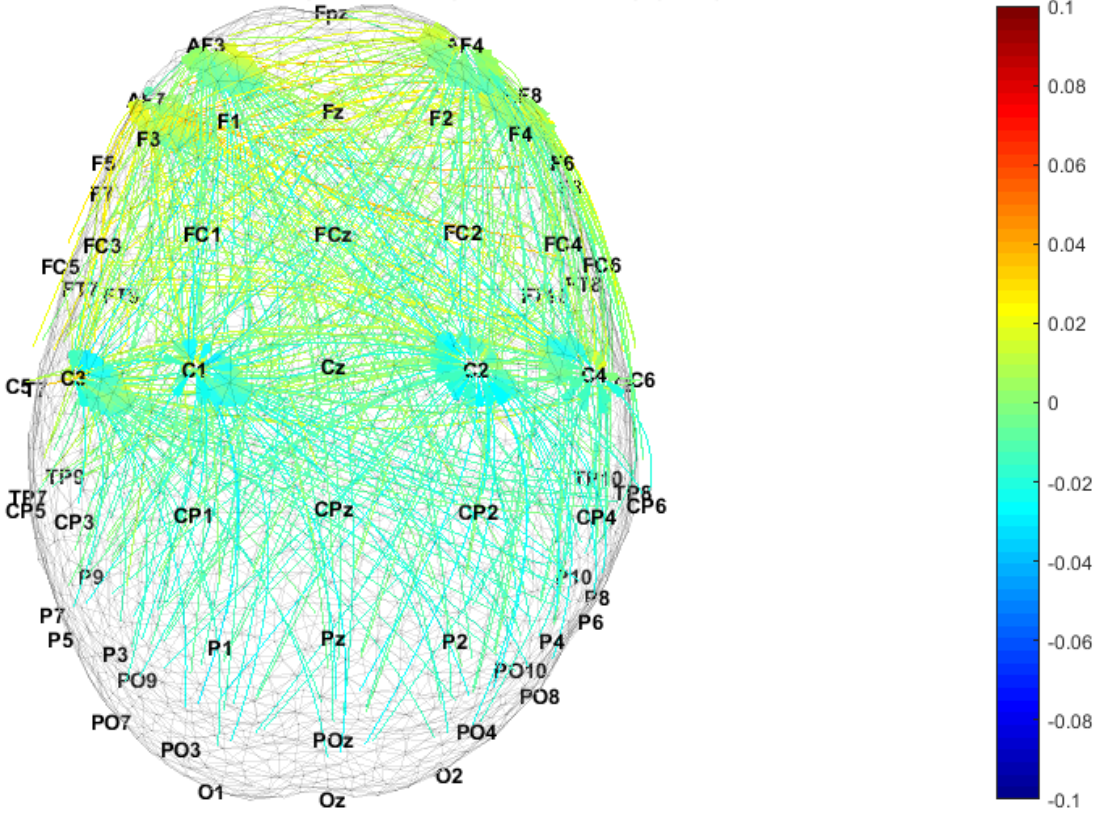


Figure 3.11 A plot with 10000 permutations

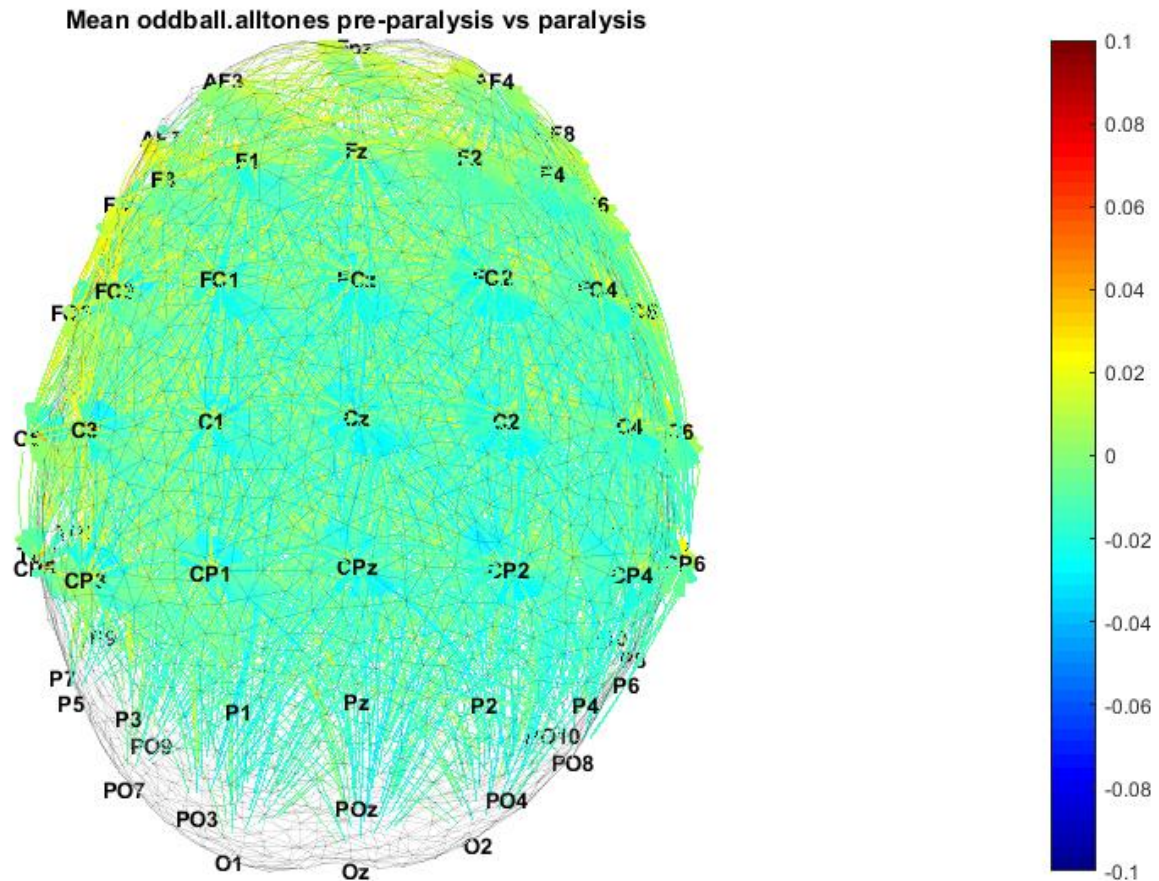


Figure 3.12 A plot with 50000 permutations

3.9 Plot connections

The function `plot_connections3d_v3` was written by Associate Professor Kenneth J. Pope at Flinders University. It was updated from the `plot_connections3d_v2` and the latter was updated from `plot_connection3d` which was one of the first versions. The v2 and v3 part of the name of the function refer to the version 2 and version 3. The function takes an adjacency matrix, the channel pair labels and the p values as inputs. The term 'conlims' sets the scale for the colour gradient for understanding the brain mapping better.

The version 3 was adapted from the version 2 to ensure that it works efficiently with the updated version of the connectivity function as well as the permutation test function that is, `permutationtest_multi`. An example is given in Figure 3.13.

```
% plot the results
plot_connections3d_v3( AM_pre_mean - AM_para_mean, cpl_shaped, pvals, 'conlims', [-1 1] * 0.1);
set(gcf, 'Name', [ 'Mean' ' ' task ' preparalysis vs paralysis connectivity(1020)']);
```

Figure 3.13 The updated plot connections function

3.9.1 An overview of the plot connection function

The `plot_connection3d_v3` function ensures that the labels and adjacency matrix have the same number of elements. The labels represent the electrodes names based on their locations on the scalp. It is important because if there is a mismatch the figure will return a blank picture. The different ways of matching these two matrices. The first method is to match the adjacency matrix and the labels. A variable 'cpl' is created to store the labels. The second method is to check if the adjacency matrix is a square matrix by checking the size in one dimension and in two dimensions (that is the rows and the columns). Both should match. Hence, check if the labels or channel names matches the size of the adjacency matrix in one dimension (rows). A variable 'cpl' is created to store the channel pair labels. An example is given in Figure 3.14.

```
% select out the required
if isvector( AM)
    assert( numel( AM) == numel( labels), 'Labels and adjacency matrix must have the same number of elements if vectors');
    cpl = labels;
elseif ismatrix( AM)
    assert( size( AM, 1) == size( AM, 2), 'Adjacency matrix must be square if a matrix');
    assert( size( AM, 1) == numel( labels), 'Labels must be channel names, matching size of square adjacency matrix');
    cpl = chan_pair_labels( labels);
end
```

Figure 3.14 Ensuring that the size of the adjacency matrix and the labels are the same

The next stage, multiple test correction is applied to the result. It occurs only if the user requests for a multiple test correction, the options are 'none', 'modified Bonferroni' and 'Bonferroni'. If there is an error when stating which tests needs to be performed, the code returns 'don't know what multiple tests correction has been requested'. The formula of how those multiple correction tests are done are as shown in the section of code in Figure 3.15. This code had to be updated to match the aim of this study.

```

% do the multiple tests corrections
switch p.Results.multiple_tests_correction
    case 'none'
    case 'modified Bonferroni'
        [ ~, si] = sort( pvals( :));
        pvals( si) = pvals( si) .* ( 1:numel( pvals));
    case 'Bonferroni'
        pvals = pvals * numel( pvals);
    otherwise
        error( 'Don''t know what multiple tests correction has been requested');
end
inds = pvals < p.Results.alpha;

```

Figure 3.15 Multiple tests correction

After doing these tasks, the code of the function 'plot_connection3d_v3' continues as the function plot_connections3d_v2. A section of the code is seen in Figure 3.16.

```

% do the job through the old version of the code
fig = plot_connections3d_v2( AM( inds), cpl( inds), ...
    p.Results.h, p.Unmatched);

```

Figure 3.16 Switching to the old version of plot connections

The function 'plot_connection3d_v2' ensures a clear and precise display of the brain connectivity. That involves:

- Creating a brain in 3 dimensions using a mesh
- Getting the position of the labels
- Using arrows to see the direction of the connectivity inside the brain.

Step 1

Load the head mesh which is stored as a .mat file as seen in Figure 3.17

```

% load head mesh
if exist( 'vol.mat', 'file')
    load( 'vol.mat');
    head_pnts = vol.bnd( 1);
else
    fprintf( 'Warning:: can''t find vol.mat to provide a head mesh\n');
end

```

Figure 3.17 Loading the head mesh

Check whether the labels are channels and channel pairs is done, and that involves confirming the size of the adjacency matrix and the labels. These two should match. The next step to do is to identify the channels along with getting the name of the channels. Figure 3.18 shows how the matching was done.

```

% are the labels channels or channel pairs
if all( size( AM) == size( labels))
    fprintf( 'Assuming input labels are channel pairs\n');
    Np = N1;

    % identify channels
    ch_name = {};
]   for i = 1:Np
        ind = strfind( labels{ i}, '-');
        %         ind = ind{ 1};
        ch_name{ i, 1} = labels{ i}; %#ok<*AGROW>
        ch_name{ i, 1} = strtrim( ch_name{ i, 1}( 1:( ind - 1)));
        ch_name{ i, 2} = labels{ i};
        ch_name{ i, 2} = strtrim( ch_name{ i, 2}( ( ind + 1):end));
    end
    Nc = size( ch_name, 1);

```

Figure 3.18 Verifying the channels and the adjacency matrix

Step 2

The location of the electrode and channel names are arranged based on their x, y and z-direction. As a note, the brain mapping returns a 3-dimensional image and the direction in the x, y and z planes are given in terms of angles in degrees. The function 'getmontage' is used. This function was written by the Bio-signals Lab team at Flinders University. A section of the 'getmontage' code is given in Figure 3.19.

```

% get channel positions
mont = get3dmontage( ch_name( :));
x = zeros( Nc, 1);
y = zeros( Nc, 1);
z = zeros( Nc, 1);
for i = 1:Nc,
    ind = find( strcmp( ch_name{ i}, { mont.label}));
    x( i) = mont( ind).x;
    y( i) = mont( ind).y;
    z( i) = mont( ind).z;
end

```

Figure 3.19 Plotting the x, y and z coordinates

The function `get3dmontage` positions the channel names on the head mesh and plots the x, y and z coordinates.

Step 3

The next step is to prepare the display of the results. It includes the brain mesh, the type arrows, the colour gradient for the scale and most important the arrangement of all on the brain. The axes and the position of the brain map need to be set beforehand to ensure that it fits the MATLAB 'figure' option as shown in Figure 3.20.

```

% prepare figure
if ~exist( 'h', 'var') || isempty( h),
    figure( 'Position', [ 100, 100, 1000, 1000]);
    ha = subplot( 1, 1, 1);
elseif strcmp( get( h, 'Type'), 'axes')
    ha = h;
elseif strcmp( get( h, 'Type'), 'figure')
    figure( h);
    ha = subplot( 1, 1, 1);
else
    error( 'Don't know what h is');
end

```

Figure 3.20 Preparing the figure

The codes mentioned above were written by the team at the Bio-signals Lab at Flinders University. These codes were used and put together to match the aim of this project and updated as progress was made.

3.10 Tasks

The tasks were carefully selected for this study. This project compares connectivity between pre-paralysis and paralysis. Therefore, the task selected should ensure that a clear difference between the two is seen. The first set of tasks is referred as the head muscle tasks, involving

'headmuscle.bite', 'headmuscle.frown' and 'headmuscle.neck'. The second set of the tasks is the oddball task, and it accesses the EEG data by using 'alltones.oddball'. This part of the code will extract the respective EEG file for both paralysis and pre-paralysis. An example of loading the task is given in Figure 3.21

```
task = 'oddball.alltones';
```

Figure 3.21 Loading the tasks

3.11 Epochs

In this study, epochs are used to divide the time duration of each task by a set amount. It is done only to the head muscle task because the duration is too small and the statistical analysis for calculating the connectivity is not possible. The statistical testing requires a large amount of data to be fed. However, the head muscle tasks last for 10 seconds each. Hence dividing the time into small 'fake epochs,' it becomes possible to input more information to ensure a reliable result. The 'fake epoch' function was written with the help of Associate Professor Kenneth J. Pope to ensure that the final code works efficiently. The epochs function and the application of the epochs is given in Figure 3.22 and Figure 3.23 respectively.

```
function x = fake_epochs( d, block_length)

    tb = d.timebase;
    Nblock = floor( diff( tb) / block_length);
    x = eeg3.eeg.alloc( 1, Nblock);

    for ctr = 1:Nblock
        end_block = tb( 1) + ctr * block_length;
        x( ctr) = d.selecttime( end_block - block_length, end_block);
        x( ctr).time.start = 0;
    end
```

Figure 3.22 Epoch function

```

% Epoch
D_pre_am_x = fake_epochs( D_pre_am, 2);
D_pre_rw_x = fake_epochs( D_pre_rw, 2);
D_pre_jow_x = fake_epochs( D_pre_jow, 2);
D_pre_ddla_x = fake_epochs( D_pre_ddla, 2);
D_pre_jbw_x = fake_epochs( D_pre_jbw, 2);

D_para_am_x=fake_epochs( D_para_am, 2);
D_para_rw_x=fake_epochs( D_para_rw, 2);
D_para_jow_x=fake_epochs( D_para_jow, 2);
D_para_ddla_x=fake_epochs( D_para_ddla, 2);
D_para_jbw_x=fake_epochs( D_para_jbw, 2);

```

Figure 3.23 Application of the Epochs

3.12 Averaging over subjects

Five subjects were selected out of the six who participated in the previous research. One possible reason being that there were some loose channels and it was harder to get the connectivity from the results will not be accurate. Analysing subjects individually do not give reliable conclusions, however, by taking the mean, the matching patterns will be retained, and the anomalies will be discarded. Hence, the result obtained can be trusted. The averaging was done over the adjacency matrices of each subject for both the pre-paralysis and paralysis task. This is seen in the Figure 3.24.

The difference between the adjacency matrices of pre-paralysis and paralysis was plotted to see the difference in connectivity.

```

AM_pre_mean = mean([ AM_pre_am_shaped,AM_pre_rw_shaped,AM_pre_jow_shaped,AM_pre_ddla_shaped,AM_pre_jbw_shaped],2);

```

Figure 3.24 Mean of the adjacency matrices

4 RESULTS

4.1 Problems involved when acquiring of the results

One of the most common problems was to ensure that the paths were set correctly as multiple functions were called during the coding part of this research. It was important to ensure that all the paths are set properly before running the code, as pieces of code were kept in the respective author's folders.

The oddball task required a considerable computation time because the EEG file for this task was bigger than the others. It can be explained by the fact the oddball task lasted for 3 minutes. It took approximately 60 minutes per subject. It is due to the loading of the EEG file, calculating the connectivity and running the permutation test 10000 times.

As a consequence, when an average was done on the subjects, the experiment took approximately 5 hours, as each step had to be repeated for all five subjects. For this code to run an interrupted internet and power supply is required because once stopped, it had to be restarted.

Another problem faced during this research is the fact that the Bio-signals Lab team at Flinders University wrote most of the functions and if there is any issue, it was hard to understand where the problem was. The reason being most of the functions were linked with one another and debugging was tedious work.

Moreover, the most of the functions were lengthy and it was tedious work to understand and apply those functions efficiently for better result and efficient computation times.

In addition to this, there were only six subjects out of which one set of data was discarded. All the conclusions were based on the results obtained from those five subjects.

4.2 Understanding the brain mapping

When the average on subjects was done on adjacency matrices for both pre- paralysis and paralysis, the difference between the two was plotted. It is essential to understand the scale so that it becomes easier to draw valid conclusions.

The scale ranges from -0.1 to 0.1 and the colour ranges from dark blue to dark red as it increases. The mean adjacency matrix of paralysis was subtracted from the mean adjacency matrix of the pre-paralysis data. Therefore, dark blue to light blue represent that the connections are stronger in the paralysis and yellow to dark red represents that the connection is stronger in pre-paralysis. However,

when the signal is same in both, it signifies that the connections between both pre-paralysis and paralysis are the same. The distribution of connection strength is seen in Figure 4.1.

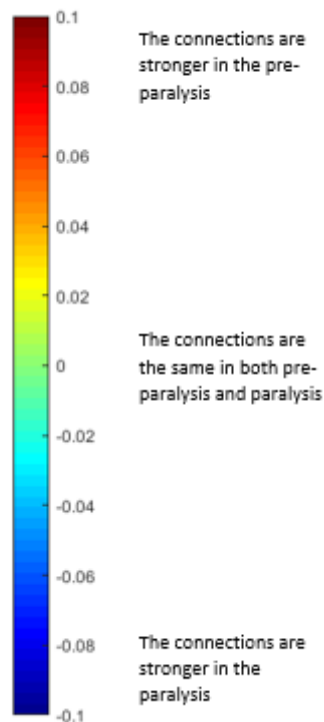


Figure 4.1 Understanding the scale

4.3 Head muscle task

The head muscle task consists of 3 tasks namely bite movement, frown movement and neck movement. The brain mapping is in 3-dimensions, and the mapping has been rotated to ensure that the discussion becomes clear.

4.3.1 Bite movement

Biting can also be referred as mastication and involves the movement of the jaw muscles that is the temporalis muscle, masseter muscle and the pterygoid muscle. These muscles cause the temporomandibular joint to move which causes the chewing process. The figures below show the difference between pre-paralysis and paralysis at different angles. Parts (a) to (h) in Figure 4.2 and Figure 4.3 point to the important areas that will be analysed in the Discussion chapter.

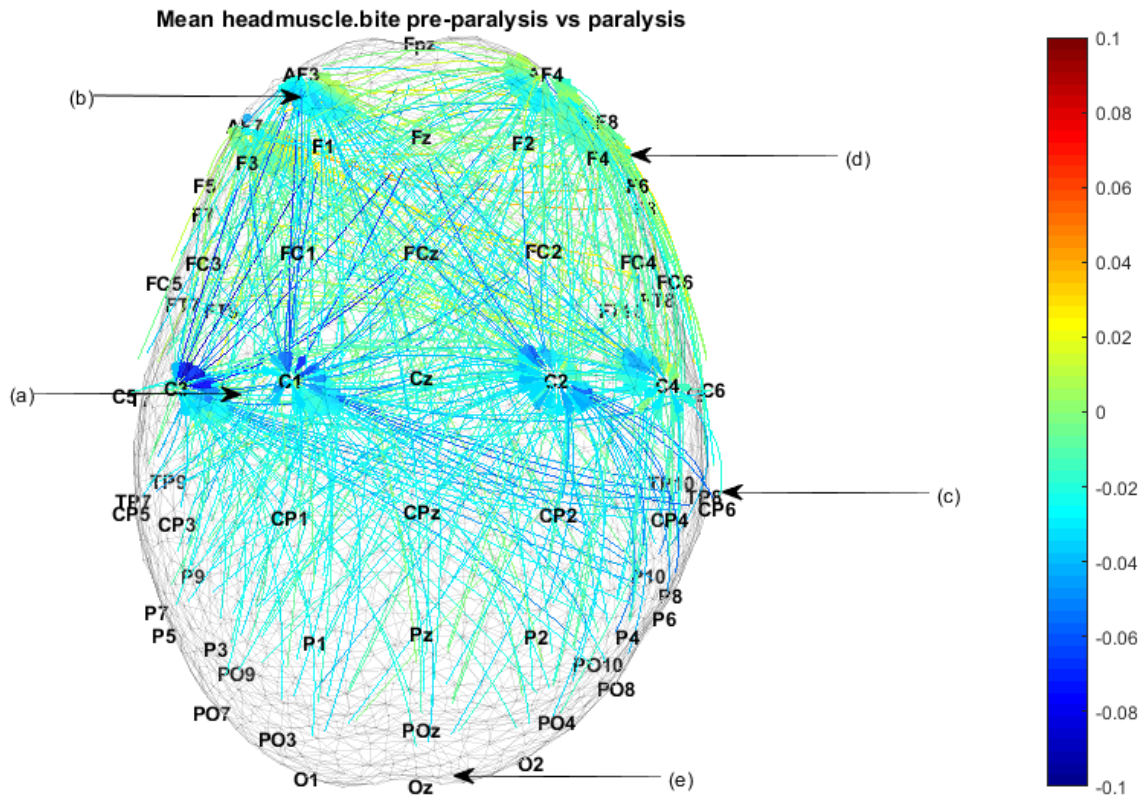


Figure 4.2 Mean head muscle (bite) X-Y view

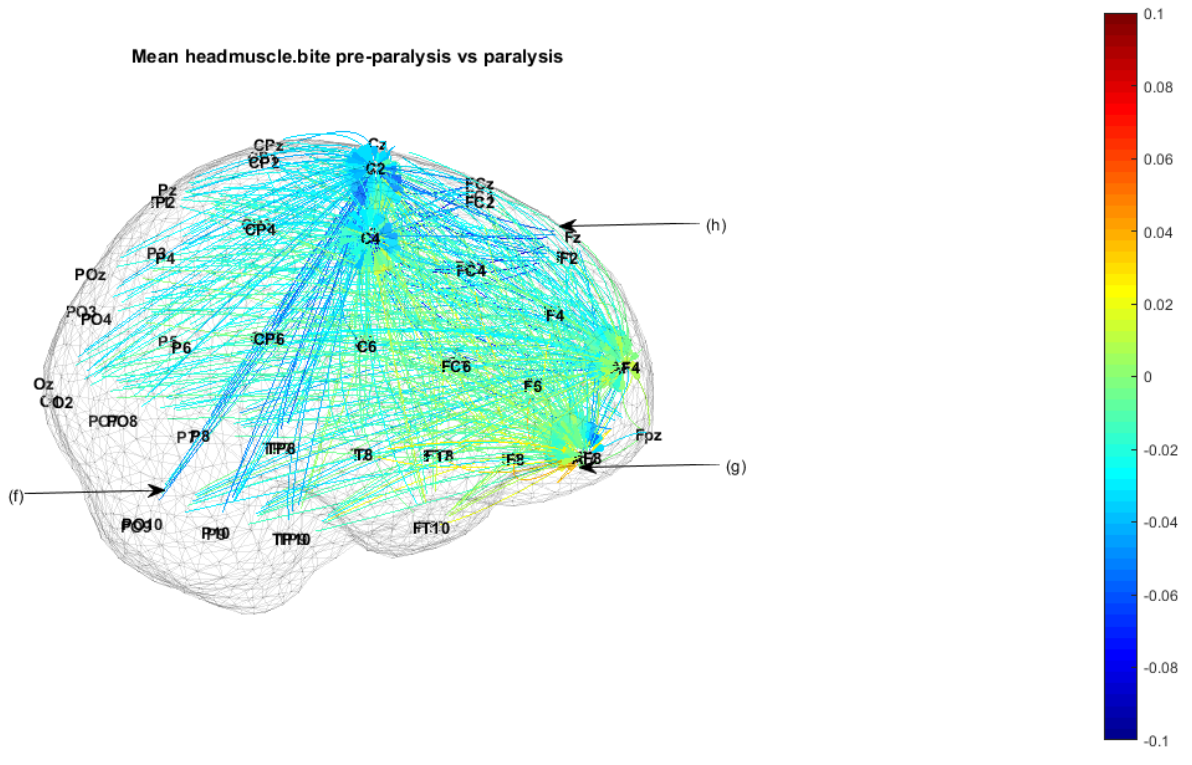


Figure 4.3 Mean head muscle (bite) X-Z view

From Figure 4.2 and Figure 4.3 above, the arrow at (a) points to the light blue band formed by the arrows converging on the parietal area to the motor control are. The arrow at point (b) a high concentration of blue arrows to the frontal area. The arrow at point (c) shows information flow from the parietal to the centre of the brain in paralysis. The arrow at point (d) shows a high concentration of green arrows toward the frontal region of the brain. The arrow (e) pointing at the occipital lobe show no connections in that area. Information flow is away from the occipital lobe. The arrow at (f) shows strong connections in paralysis (blue) from parietal lobe to the centre of the brain and (g) shows strong connections in the pre-paralysis (orange) at the frontal region. Finally, point (h) points to the flow of information from the frontal region to the centre of the brain.

4.3.2 Frown movement

The muscles involved during frowning is referred as the frontalis muscles. The frontalis muscle is located at the front of the skull that is starting from the forehead and spreads till the bridge of the nose. The Figure 4.4 and Figure 4.5 below show the difference between pre-paralysis and paralysis at different angles. Parts (a) to (l) points to the important areas that will be analysed in Chapter 5 Discussion.

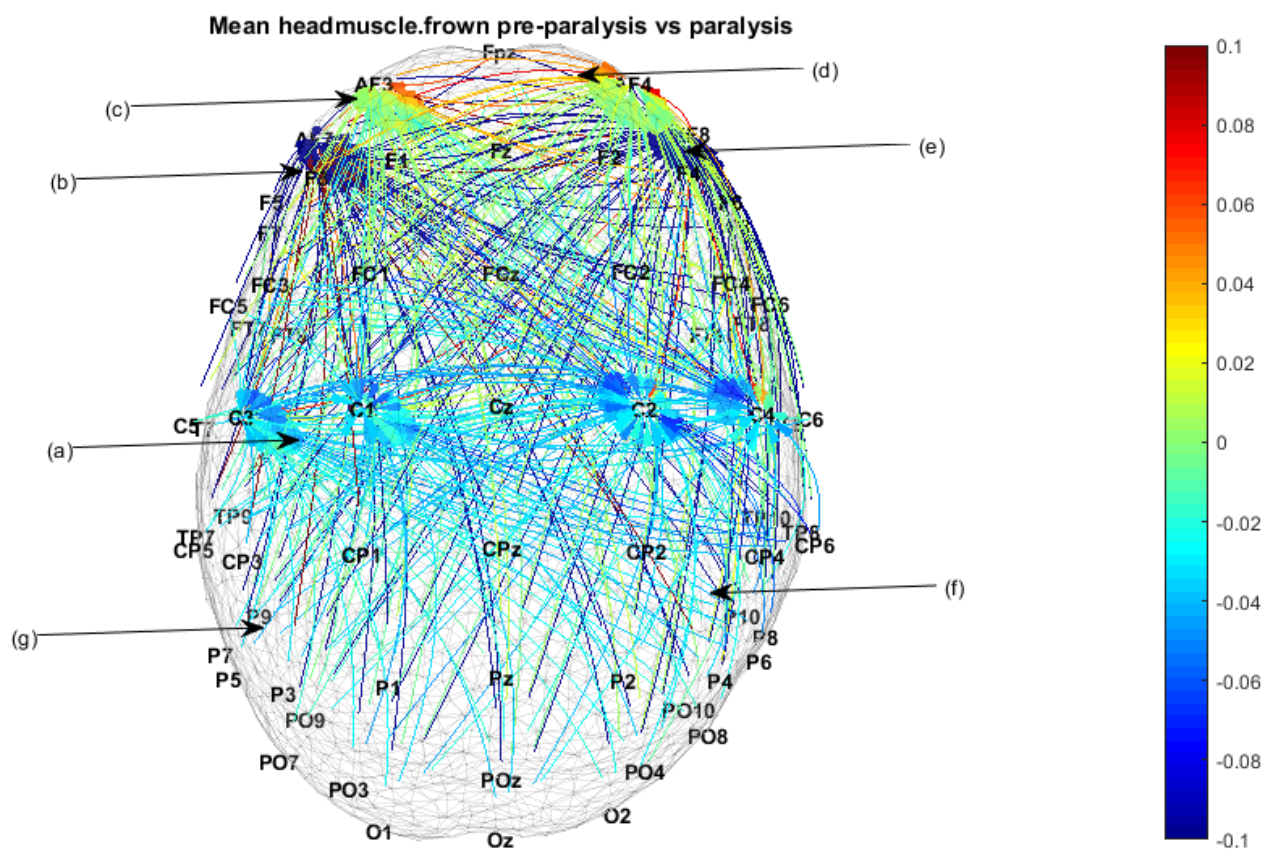


Figure 4.4 Mean head muscle (frown) X-Y view

From the above representations, Figure 4.6 and Figure 4.7, the arrow that points to (a) shows a band of blue arrows converging to the centre of the brain. The arrow at point (b) and (i) show the convergence of dark blue lines to the frontal region that shows strong connections in paralysis. At point (d) green arrows converge to the frontal region showing similarities between pre-paralysis and paralysis. The arrow pointing at (c), (e), (h) and (i) indicates that there is strong information flow in pre-paralysis in the frontal section which is shown by the orange lines. At point (f) the movement of light blue arrows flowing from the temporal/ parietal lobe to the centre of the brain. There is not information flow to the occipital lobe being located by the arrow at (g).

4.4 Oddball

The oddball task was the only task that didn't involve any muscle activity. Like all the other tests it was done with the eyes closed. The oddball involved counting the number of high tones from a set of high and low tones. This task lasted for 3 minutes.

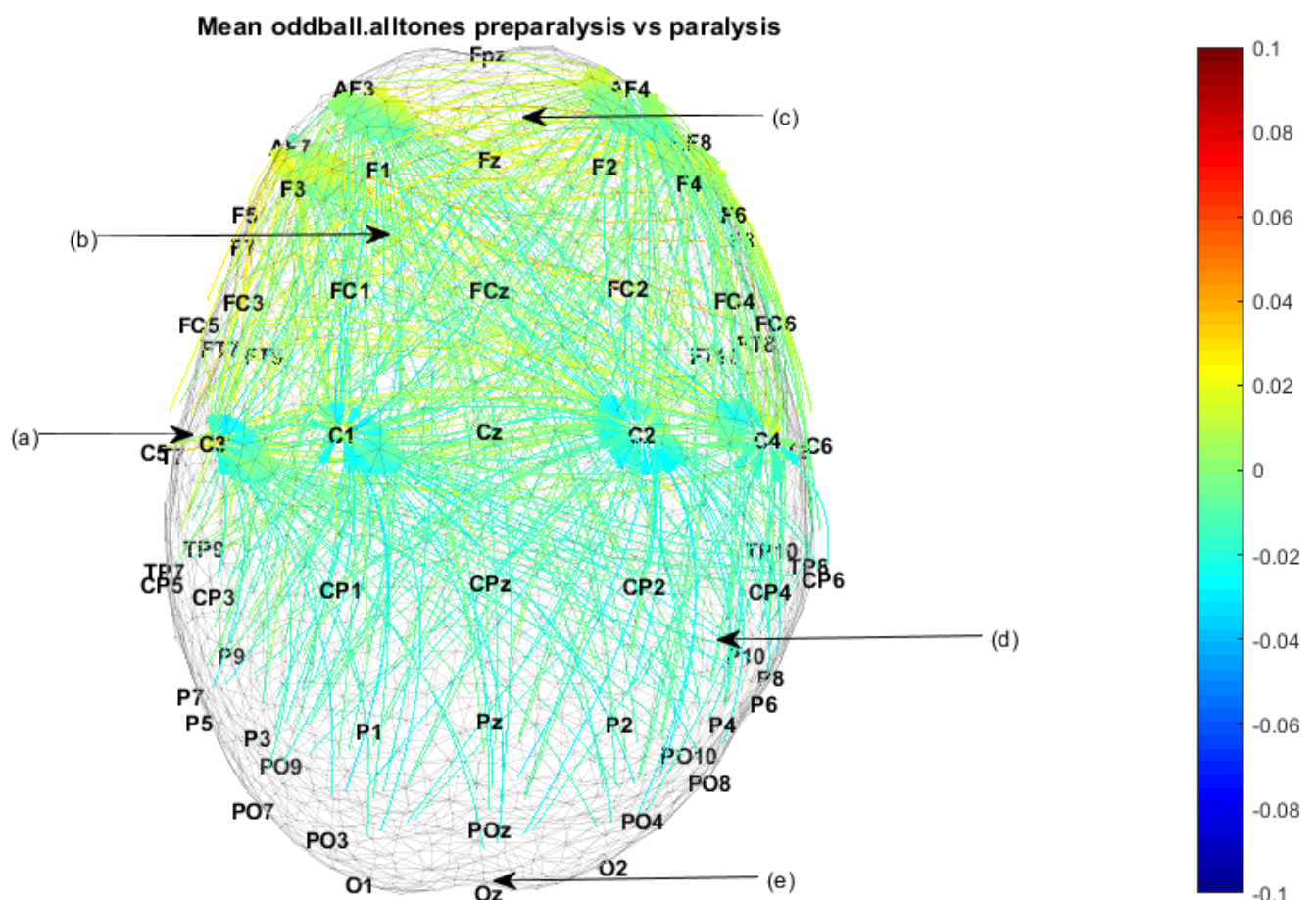


Figure 4.8 Mean oddball X-Y view

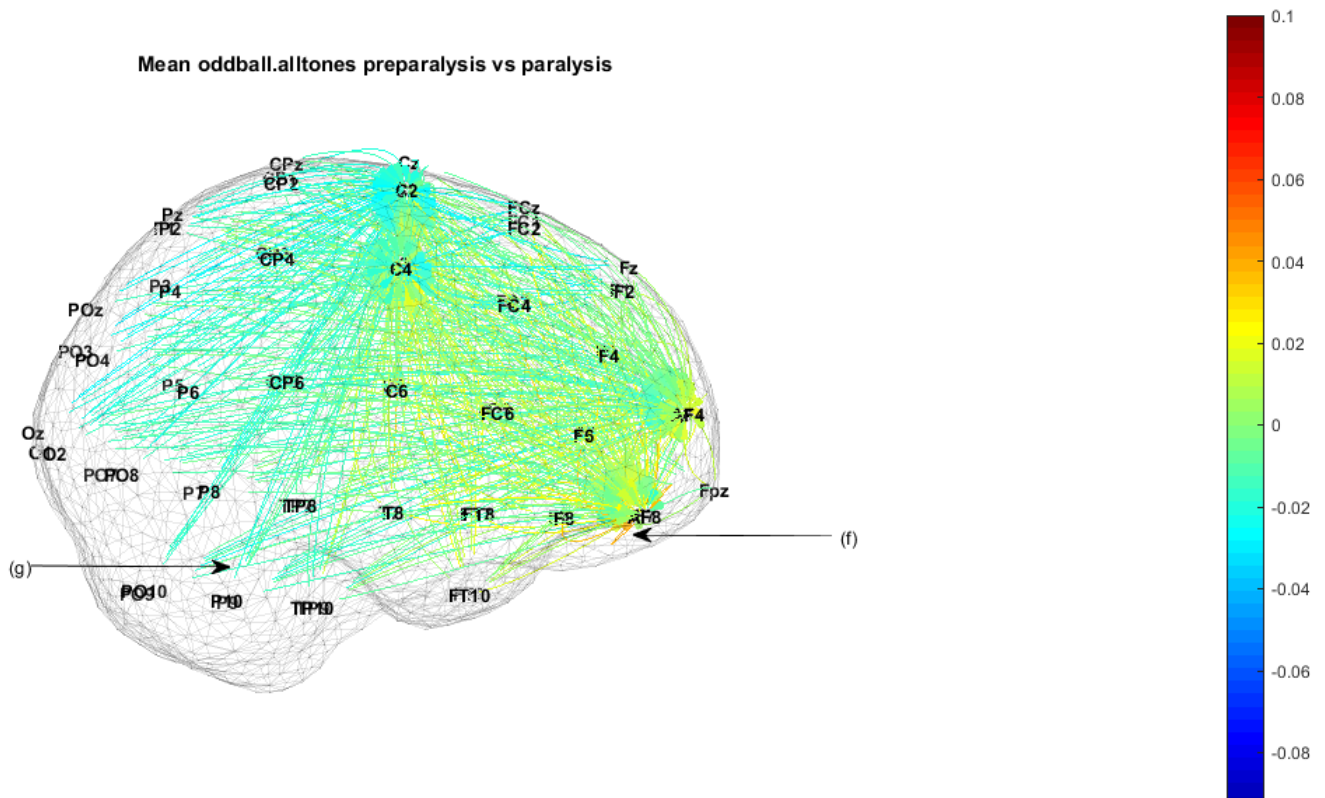


Figure 4.9 Mean oddball X-Z view

From Figure 4.8 and Figure 4.9, there is a blue band of arrows around the central area of the brain pointed at (a). At (b) and (d) flow of information in paralysis is slightly stronger in paralysis. The important part to notice is the direction of the information flow in both situations. Point(c) indicates that there are a few yellow lines at the frontal area of the brain. The arrow at point (e) shows no information flow at the back of the brain. The arrow at (f) shows that there is no information flow at the back of the head. Point (g) show strong connections moving the parietal/ temporal lobe in paralysis.

5 DISCUSSION

The reason behind conducting connectivity tests on head muscle tasks was to see whether there is a difference in connectivity between paralysis and pre-paralysis. On analysing the images obtained, it became clear that there is a big difference.

The difference in the adjacency matrices is analysed, and if there is a positive difference, that means that the connections are stronger in the pre-paralysis case, and if the difference is negative, there is a stronger connection in the paralysis.

5.1 Discussion for the bite task

Considering the first case where the masseter muscle and temporalis muscle were contracted that is the bite movement. From the Figure 4.2 and Figure 4.3 at point (a) the blue band which shows a negative difference, therefore, stronger connections in paralysis. This concentration of arrows along C3, C1, C2 and C4 shows that the motor control region is experiencing a high connectivity in paralysis and compared to pre-paralysis. The activation of the motor cortex is because the biting movement is controlled by that region of the brain. Another possible conclusion that can be drawn from the existence of this blue band across the motor cortex is proprioception. Proprioception is a concept that refers to "the cumulative neural input to the central nervous system (CNS) from specialised nerve endings, called mechanoreceptors, located in the joints, capsules, ligaments, muscles, tendons and skin" (Fortier and Basset 2012). However, there is no information flow to the centre of the brain that is the longitudinal fissure. One possible reason could be that the longitudinal fissure does not have any converging arrows. Referring to the Figure 4.2, the channels Fz, FCz, Cz, Cpz, Pz, POz, and Oz fall on the longitudinal fissure. At (b) and (h) there are two cases to consider, firstly, information flow from the back of the brain to AF3 (light blue) and secondly flow of information from AF3, F3, F1, Fz, F2 and F4 to C3, C1, C2 and C4 (dark blue). Keeping in mind that these are consequences of stronger signals in the paralysis state, in the first case, one possible deduction could be 'thinking', that is the activation of the frontal lobe because the subjects are thinking. It could be explained by the fact that they were given a task and that triggers the thought process. As a note, the frontal lobe is the region of the brain that's responsible for the 'thinking' and 'decision making'. The second case shows that there is a strong connection from the frontal area to the central area, which is the motor control region. The same kind of information flow is seen at points (c) and (f), where dark blue lines appear from the parietal lobe to the centre of the brain. It seems that there is an information flow from the parietal lobe to the motor control region. This scenario is more prominent in the paralysis state than the pre-paralysis state. However, at point (d) there are some green lines which show similarity in the connectivity in both paralysis and pre-paralysis state.

One conclusion can be that there is some activity in the frontal area in both states, which could be due to 'thinking'. The green arrows could mean there is muscle contamination in the pre-paralysis state. As a note, the mapping is based on statistically small differences between the paralysis and the pre-paralysis. At point (g) however, yellow and orange arrows show that there the difference between paralysis and pre-paralysis is positive, therefore stronger connections are due to the pre-paralysis state. This result is slightly ambiguous as it was difficult to conclude what exactly is happening in that region of the brain. However, if a closer look is taken, it shows that these orange arrows could be a consequence of muscle activity. In this case, muscle activity could be arising from the head muscles and eye movement. As a conclusion to this result, muscle activity is interfering with brain connectivity. At point (f), the only noticeable thing would be that there is no information flow to the back of the head that is to the visual cortex. It confirms that the results could be correct as the experiments were performed when the eyes are closed.

5.2 Discussion for the frown task

The second case involves the movement of the frontalis muscle that is the muscle responsible during frowning as shown in Figure 4.4 and Figure 4.5. Considering (a), again there is a blue band which is the activation of the motor control area of the brain, this can be seen across C3, C1, C2 and C4 which is located exactly above the motor cortex. The motor control region is the region responsible for muscle movement, but even in the paralysis state, the movement information is sent despite the fact that the muscles are not moving. It can also be a case of proprioception (Fortier and Basset 2012) where the subjects are still maintaining their balance even though there are not moving any muscle. Once again, there is no information flow along the longitudinal fissure. At point (b), (e) and (j) dark blue lines converge to the AF3 and AF8 channels. These dark blue arrows suggest that stronger connections are present in the paralysis state. This region corresponds to the frontal lobe which allows 'thinking', concentration and 'decision making'. Therefore, one possible conclusion can be that the subjects are concentrating on the task given to them. However, at point (k) the same kind of pattern as in Figure 4.2 Mean head muscle (bite) X-Y view, whereby there is an information flow from the parietal lobe or rather the auditory cortex to the motor cortex. At point (c) and (h) there is some similarity between pre-paralysis and paralysis shown as the green arrow. The fact the green arrows points to the frontal regions it confirms that thinking processes might be happening or concentration. They also show muscle contamination from the pre-paralysed state and green arrows are seen because of the statistically small difference between the two states. However, that the fact that at point(d) and (i) show some uncontrolled orange and red arrows state that the string connections due to the pre-paralysis state can be related to noise. This noise is a consequence of muscle activity. The muscle activity detected in the pre-paralysis could be due to the orbicularis and corrugator EMG across the left and right lateral frontal area which is where the muscles are located.

It gives another proof the EEG is contaminated with muscle activity, and the connectivity is not obtained on raw data. Finally, at point (l), it can be seen that there is no information flow to the occipital lobe, more precisely the visual cortex. It makes sense because all the subjects had both eyes closed during this experiment.

In this test, despite the fact that, there is a convergence of information flow to the frontal area of the brain, as seen at point (b), (e), (j) can be due to thinking or memory related activities, this result is quite unusual. Deducing what exactly is happening inside the brain can quite challenging. In this case, we see that we see a more synchronised movement of arrows in the paralysis state compared to the pre-paralysis state. One possible reason for this synchrony is the absence of muscle activity.

5.3 Discussion for the neck task

The next task performed was neck movement which involved the paraspinal muscle. In Figure 4.6 and Figure 4.7 at point (a), similar to the bite and frown movement, there is a blue band of arrows across the motor cortex. It represents the flow of information towards the motor cortex; that suggest that movement is occurring in the in the paralysis state. It is important to note the nervous stimulation is sent to the brain despite the fact the subjects cannot move their muscles. As mentioned earlier, another, reason for the blue band could be due to proprioception. It means the subjects are aware of what happens to the limbs as an example and cannot move them due to being paralysed. Light blue arrows coming from AF3 to C3, C1, C2 and C4, at point (j) show that there is a signal flow from the frontal lobe to the motor control area. One possible suggestion can be because of the thinking process, or the subjects are in a concentration phase and hence involving the activation of the motor cortex which sends the stimulus. The same occurs at the parietal lobe, more precisely at the auditory cortex at point (f) there is the existence of the flow of information towards the motor control region. It is another dominant feature to consider. This pattern is seen in all the other tasks as well. Another similarity that can be seen from the previous cases is that there is no information flow along the longitudinal fissure. At point (b) and (i) dark blue arrows converge to the channel AF7 which is quite unusual, and this can be due to the thinking or concentration processes as explained earlier. However, there are some yellow lines at point (e), (h) and a few green lines at point (d). At (d) the green arrows converging to the frontal lobe, show that this information is present in both paralysis and pre-paralysis. As a note, these plots were based on statistically significant differences and blue lines could be appearing yellow because of muscle activity. Due to the unsynchronised information flow from pre- paralysis it becomes difficult to understand what is happening during that state. One possible interpretation could be due to the position of the neck and the effects it has on the sternomastoid which are located not too far from the electrodes. At point (c) and (e) a deep red colour is seen, and the only deduction that can be made is the presence

of muscle activity. An explanation of this situation is that moving the neck also means moving the occipital muscle which is located above the occipital lobe. At point (g), there is no convergence at the back of the head which states that no signal is coming to the visual cortex. It is because the eyes were closed during the tasks for both paralysis and pre-paralysis.

The way the information flow is more synchronised in the paralysis state is noted. As mentioned before, this could be due to the absence of muscle activity.

5.4 Discussion for the oddball task

The tasks mentioned above were conducted by triggering the head muscles, therefore putting forward a way to differentiate between pre-paralysis and paralysis states. To confirm some of the results mentioned above, the connectivity test was conducted on the oddball task. This task involved counting the number of high tone in a set of low tones and high tones. It did not involve any muscle movement but involves and decision making. Referring to Figure 4.8 and Figure 4.9 This is seen at point (d) (or (g)) and (b) where information is flowing from the auditory cortex and the frontal region respectively. However, the major concern is that there is a blue band across the motor cortex is still present without any induced muscle activity. The deduction that seems to be more logical is the existence of proprioception, which was defined earlier as the nervous reaction due to the receptors found in the joints, muscles or even tendons (Fortier and Basset 2012). Therefore, there subjects have a tendency of moving their legs in the paralysis state, but however, the muscles can move even though the signal are transmitted. At point (c) and (f) yellow and orange arrows can be seen and most of it are located in the frontal part of the brain, which shows a level of higher activity. It demonstrates that connectivity cannot be measured from scalp EEG because it is contaminated with noise which arises from muscle activity.

To validate this research, the results have demonstrated that the brain is more synchronised when in a paralysed state and the fact that no one has explored this aspect of connectivity it is hard to confirm the results. Moreover, one conclusion that can be drawn is that muscle contamination affects the brain connectivity. Hence studies involving calculating the connectivity from raw data should involve an additional step that is removing the noise. Proprioception is an important aspect to consider when considering connectivity in the paralysis state. It shows that the subjects can still be aware of the position and state of their limbs. The fact that there is no information flow to the back of the brain that is the visual cortex suggests that the code works and gives reliable results. The more active regions of the brain are mainly the frontal lobe, motor control and the parietal lobe. No convergence was seen along the longitudinal fissure which suggests that there is no information flow to that area of the brain.

The consequence to the real world is that researchers have tried to understand the brain connectivity on raw data for a long time whether it is through scalp electrode or other modalities. However, based on the results obtained, this proved that EEG from scalp electrodes is contaminated by muscle activity.

6 FUTURE WORK

As a plan for this, more evidence on the concept of proprioception needs to be found. It can be done by conducting other paralysis and pre-paralysis tasks to see whether the same pattern is seen.

The first task to compare is the subtraction tasks that was done in both paralysed and pre- paralysed state. It will enable a better what happens when the person is doing the mental calculation and doing the memory-related task. The expected result would show the convergence of blue arrows to the frontal area which is the centre of all mental tasks, for example, thinking, concentrating, decision making and memory. The blue arrows will be due to the stronger connections in the paralysis state. However, the pre-paralysis state is expected to give results similar to the one in the oddball task. It is because the subtraction task is not any triggering any muscle. The blue band across the motor cortex is expected to be seen due to proprioception.

The second task to be done would be the auditory discrimination. It is expected to give results similar to the oddball task as it involved listening to a set of similar sounding words and reacting to a specific word. The only difference that could be expected when compared to an oddball task is the fact that the oddball task lasts for 3 minutes whereas the auditory task was shorter. The expected results will be slightly different that is a better range of colours should be seen.

The next task involves running a test involving the visual cortex, where information flow is from the front of the brain to the back. In this situation, noise will be prominent in the pre-paralysis state, and there will be connections from the frontal area to the occipital are. It will confirm that the results are correct. These connections are expected to be present in the paralysis state mainly considering that the noisy connections are not reliable from the pre-paralysis state. The convergence toward the motor control area is expected to be present if proprioception occurs.

Another aspect that needs to be looked at is whether the 50 Hz peak due to the power supply has an on the effective brain connectivity. The 50 Hz frequency can affect both the pre-paralysis data as well as the paralysis.

The other improvement to this situation is to use clean pre-paralysis data and then compare it to the paralysis state. This comparison can be made in a similar way, which is finding the adjacency matrices of both the cleaned and the paralysed data, and looking at the difference between the two after a set number of permutations. Removing the noise due to muscle activity can be done using independent component analysis. This technique consists of extracting clean EEG from signals that contains both EEG and muscle activity. Deciding of the right algorithm can be a tedious task as none of them can remove 100% of the noise. Therefore, the results obtained could still have some noise

in it. A considerable amount of research is being done at Flinders University to find the best algorithm, and it might take a few more years to find the best-suited algorithm.

However, if the results obtained is close to the paralysed state results, it confirms that when measuring connectivity from the scalp of a non-paralysed person, the consequence will be noise. This result can guide other researchers studying brain connectivity in the future.

7 CONCLUSION

EEG has been a popular method of measuring the brain activity, especially when studying neurological disorders. The biggest problem faced when taking the measurement is the amount of noise or rather artefacts present in the signal. These artefacts can be both biological and technical. Biological artefacts refer to those that are caused by muscle activity inside the body, and the technical artefacts are due to external issues like the 50 Hz interference peak due to the mains or the placement of the electrode. The muscle activity can be caused by the eye movement, facial muscle or even the cardiac muscle movements. There is a considerable amount of research being done as well as development in this field to alleviate the effects of the biological artefact. The reason being that noise affects the quality of the information and it becomes harder to draw valuable conclusions on the EEG signals.

In this study, the aim was to the difference in connectivity between pre-paralysis and paralysis. In this case, effective connectivity has been used. Effective connectivity related to the causal interaction between a pair of nodes. Nodes refer to a different region of the brain. The reason for comparing paralysis data with pre-paralysis data was to show the difference between the two and the effects of noise.

The EEG data for both paralysis and pre- paralysis was obtained during an experiment at Flinders University with the approval of ethics committee of Clinical Research Ethics Committee of Flinders University and Flinders Medical Centre. The muscle activity was eliminated by injecting a paralyzant into the patient. As a note, the whole body was paralysed, but communication was maintained by a simple finger-tapping exercise (Whitham, Pope et al. 2007).

The subjects were asked to perform certain tasks to understand if there is any difference in the EEG collected from the paralysed and pre-paralysed. Some of the tasks involved a baseline state, photic stimulation and oddball paradigm. The baseline state includes closing the eyes and then opening the left eye, and this process is repeated between tests (Whitham, Pope et al. 2007). Photic stimulation involves a 16 Hz light flashed for 10 s when the eyes are closed and left eye open (Whitham, Pope et al. 2007). The oddball paradigm involves playing tones of low and high pitch; that is 500 Hz and 1000Hz, and the subjects were asked to press the key when a high tone was heard (Whitham, Pope et al. 2007). The reason for this experiment was to evaluate the presence of noise in a signal that's above 20 Hz. By using this existing data set, the evaluation of brain connectivity was done. The main aim of the project was to test whether scalp EEG can be used to understand brain connectivity. By following the methodology stepwise, that is starting from loading five subjects, calculating the connectivity by applying normalised transfer entropy, conducting a permutation test and plotting the connectivity, some unexpected results were found.

The muscle activity was very prominent in the pre-paralysis and could be seen along the frontal lobe. Those connections representing the muscle activity were very conspicuous when the head muscle tasks were performed but however, it was slightly less in the oddball task. Moreover, significant connections were spotted in the head muscle task which showed that the brain connectivity is similar in both paralysis state and pre-paralysis state. This could be due to the small difference, however, this difference is statistically significant due to the permutations and Bonferroni correction. In this case, the muscle activity is as significant as the connectivity in the paralysed state.

Interesting connections were found in the paralysis data. It is the first time that such results are seen, and the difficulty lies in understanding what is happening inside the brain during paralysis. The main question remains that whether or not the brain behaves differently when it is paralysed compared to when it is not. Information flow is mostly toward the frontal lobe, motor control and the parietal lobe. This pattern is seen in all cases. The fact that there is no information flow towards the occipital lobe states that the code can be trusted as the eyes were closed during all the experiments. Therefore, an inactive visual cortex was expected.

We were able to suggest some reasons for the existence of the connections, for example the convergence of the arrows toward the motor cortex could be due to proprioception which is the awareness of the limbs even though they cannot move. The concentration of connection in the frontal region which is also the 'thought processing' region of the brain. One suggestion was that the subjects are thinking.

As a conclusion, it seems that these results can be helpful to all those studying brain connectivity as there was no proof that studying effective connectivity from scalp EEG could be contaminated. Proving whether cleaned EEG signals could be used for brain connectivity will require more research to be done. However, for the time being we know that scalp EEG cannot be directly used for studies on brain connectivity, at this stage, the raw EEG data cannot be used for understanding brain connectivity.

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9 APPENDIX

9.1 'Start-up' code

```
% welcome message
disp( 'Hello Pratishtah');

% work out where important folders are
sharedEEGrootpath = 'V:\EEG\';
if ~exist( sharedEEGrootpath, 'dir'),
    sharedEEGrootpath = 'V:\';
end
mymatlabrootpath = [ sharedEEGrootpath 'People\Pratishtah\MATLAB'];

% save paths into my preference
% setpref( 'kjp', 'mymatlabrootpath', mymatlabrootpath);
% setpref( 'kjp', 'sharedrootpath', sharedEEGrootpath);
% setpref( 'kjp', 'myrootpath', myunirootpath);

% I have stuff I always want available to matlab in Matlab, Matlab\bin and
% Matlab\contrib in Documents, so get them in the path and javapath
if exist( mymatlabrootpath, 'dir')
    addpath( mymatlabrootpath);
%     addpath( genpath( fullfile( mymatlabrootpath, 'bin')));
%     addpath( genpath( fullfile( mymatlabrootpath, 'contrib')));
end

% I always want eeg3 to be available, so set up its paths and preferences
if exist( fullfile( sharedEEGrootpath, 'Matlab'), 'file')
    addpath( fullfile( sharedEEGrootpath, 'Matlab'));
    eeg3.util.setuppaths( fullfile( sharedEEGrootpath, 'Matlab'));
    setpref( 'eegunit_toolbox', 'basepath_meditation', ...
        fullfile( sharedEEGrootpath, 'Projects', 'Meditation'));
    setpref( 'eeglocal', 'paralysispath', ...
        fullfile( sharedEEGrootpath, 'Projects', 'Paralysis', 'Data'));
    setpref( 'eeglocal', 'gammapath', ...
        fullfile( sharedEEGrootpath, 'Projects', 'Gamma', 'Data'));
    setpref( 'eeglocal', 'meditationpath', ...
        fullfile( sharedEEGrootpath, 'Projects', 'Meditation', 'Data'));

% I have eeg3 stuff I always want available and that others might also want
% to see, so its kept in my shared People folder. Set up paths to
% People\Kenneth\Matlab\bin and contrib in my part of shared EEG drive, but
% take out a dodgy folder in contrib
addpath( genpath( fullfile( sharedEEGrootpath, ...
    'People', 'Kenneth', 'Matlab', 'bin')));
addpath( genpath( fullfile( sharedEEGrootpath, ...
    'People', 'Kenneth', 'Matlab', 'contrib')));
% except for the legacy code in MVGC which breaks things badly
rmpath( genpath( fullfile( sharedEEGrootpath, ...
    'People', 'Kenneth', 'Matlab', 'contrib', 'MVGC', 'utils', 'legacy')));

end

% Ask where I want to work today and change directory etc as appropriate
% done = false;
% while ~done,
%     folder = input( 'Which project do you want to work on? ', 's');
%     done = project( folder);
```

```

%     if ~done,
%         disp('Sorry, can't find that project');
%     end
% end

% go to the directory where evreythng happens
cd( mymatlabrootpath);

% tidy up and done
clear all

```

9.2 Keys

```
function keys = local_getDefaultKeys
```

```

keys = { ...
    'study.preparalysis.baseline.eyesclosed', ...
    'study.preparalysis.baseline.lefteyeopen', ...
    'study.preparalysis.baselinefinal.eyesclosed', ...
    'study.preparalysis.baselinefinal.lefteyeopen', ...
    'study.preparalysis.baselinecuff.eyesclosed', ...
    'study.preparalysis.baselinecuff.lefteyeopen', ...
    'study.preparalysis.baselinecombined.eyesclosed', ...
    'study.preparalysis.baselinecombined.lefteyeopen', ...
    'study.preparalysis.strobe.eyesclosed', ...
    'study.preparalysis.strobe.lefteyeopen', ...
    'study.preparalysis.strobe.Hz16', ...
    'study.preparalysis.strobe.Hz40', ...
    'study.preparalysis.strobe.Hz60', ...
    'study.preparalysis.oddball.alltones', ...
    'study.preparalysis.subtraction.trial', ...
    'study.preparalysis.avlt.learn', ...
    'study.preparalysis.avlt.recall', ...
    'study.preparalysis.fingertapping.both', ...
    'study.preparalysis.auditorydisc.both', ...
    'study.preparalysis.headmuscle.bite', ...
    'study.preparalysis.headmuscle.frown', ...
    'study.preparalysis.headmuscle.neck', ...
    'study.preparalysis.headmuscle.climbing', ...
    'study.preparalysis.motor.rhythmic', ...
    'study.preparalysis.motor.squeeze', ...
    'study.paralysis.baseline.eyesclosed', ...
    'study.paralysis.baseline.lefteyeopen', ...
    'study.paralysis.baselinefinal.eyesclosed', ...
    'study.paralysis.baselinefinal.lefteyeopen', ...
    'study.paralysis.baselinecombined.eyesclosed', ...
    'study.paralysis.baselinecombined.lefteyeopen', ...
    'study.paralysis.strobe.eyesclosed', ...
    'study.paralysis.strobe.lefteyeopen', ...
    'study.paralysis.strobe.Hz16', ...
    'study.paralysis.strobe.Hz40', ...
    'study.paralysis.strobe.Hz60', ...
    'study.paralysis.oddball.alltones', ...
    'study.paralysis.subtraction.trial', ...
    'study.paralysis.avlt.learn', ...
    'study.paralysis.avlt.recall', ...
    'study.paralysis.fingertapping.both', ...
    'study.paralysis.auditorydisc.both', ...
    'study.paralysis.headmuscle.bite', ...
    'study.paralysis.headmuscle.frown', ...
    'study.paralysis.headmuscle.neck', ...

```

```

    'study.paralysis.joke.punchline', ...
    'study.paralysis.saccade.trial', ...
    'study.paralysis.botheyesopen.trial', ...
    'study.paralysis.sedated.trial', ...
    'study.paralysis.motor.rhythmic', ...
    'study.paralysis.motor.squeeze', ...
    'study.paralysis.headmuscle.climbing', ...
};

```

9.3 Calculation of the connectivity for the oddball task

```

task = 'oddball.alltones';

% load and prepare pre- and post- oddball data
d_pre_am = eeglocal.paralysis.load( 'am', [ 'study.preparalysis.' task]);
d_pre_rw= eeglocal.paralysis.load( 'rw', [ 'study.preparalysis.' task]);
d_pre_jow= eeglocal.paralysis.load( 'jow', [ 'study.preparalysis.' task]);
d_pre_ddla = eeglocal.paralysis.load( 'ddla', [ 'study.preparalysis.' task]);
d_pre_jbw = eeglocal.paralysis.load( 'jbw', [ 'study.preparalysis.' task]);

d_para_am = eeglocal.paralysis.load( 'am', [ 'study.paralysis.' task]);
d_para_rw= eeglocal.paralysis.load( 'rw', [ 'study.paralysis.' task]);
d_para_jow= eeglocal.paralysis.load( 'jow', [ 'study.paralysis.' task]);
d_para_ddla = eeglocal.paralysis.load( 'ddla', [ 'study.paralysis.' task]);
d_para_jbw = eeglocal.paralysis.load( 'jbw', [ 'study.paralysis.' task]);

% D_pre = eeglocal.util.tenfive( d_pre);
% D_para = eeglocal.util.tenfive( d_para);
% D_pre = D_pre.selectchan( eeg3.util.labels1005);
% D_para = D_para.selectchan( eeg3.util.labels1005);

D_pre_am =eeglocal.util.tenfive( d_pre_am);
D_pre_rw= eeglocal.util.tenfive( d_pre_rw);
D_pre_jow= eeglocal.util.tenfive( d_pre_jow);
D_pre_ddla = eeglocal.util.tenfive( d_pre_ddla);
D_pre_jbw = eeglocal.util.tenfive( d_pre_jbw);

D_pre_am =D_pre_am.selectchan( eeg3.util.labels1020);
D_pre_rw= D_pre_rw.selectchan( eeg3.util.labels1020);
D_pre_jow= D_pre_jow.selectchan( eeg3.util.labels1020);
D_pre_ddla =D_pre_ddla.selectchan( eeg3.util.labels1020);
D_pre_jbw = D_pre_jbw.selectchan( eeg3.util.labels1020);

D_para_am = eeglocal.util.tenfive( d_para_am);
D_para_rw= eeglocal.util.tenfive( d_para_rw);
D_para_jow= eeglocal.util.tenfive( d_para_jow);
D_para_ddla = eeglocal.util.tenfive( d_para_ddla);
D_para_jbw = eeglocal.util.tenfive( d_para_jbw);

D_para_am = D_para_am.selectchan( eeg3.util.labels1020);
D_para_rw= D_para_rw.selectchan( eeg3.util.labels1020);
D_para_jow= D_para_jow.selectchan( eeg3.util.labels1020);

```

```

D_para_ddla = D_para_ddla.selectchan( eeg3.util.labels1020);
D_para_jbw = D_para_jbw.selectchan( eeg3.util.labels1020);

% check channels are the same pre- and post-
chans = eeg3.util.labels1020;
for i = 1:numel( d_pre_am)
    chans = intersect( chans, D_pre_am( i).chan.getlabels);
    chans = intersect( chans, D_pre_rw( i).chan.getlabels);
    chans = intersect( chans, D_pre_jow( i).chan.getlabels);
    chans = intersect( chans, D_pre_ddla( i).chan.getlabels);
    chans = intersect( chans, D_pre_jbw( i).chan.getlabels);

    chans = intersect( chans, D_para_am( i).chan.getlabels);
    chans = intersect( chans, D_para_rw( i).chan.getlabels);
    chans = intersect( chans, D_para_jow( i).chan.getlabels);
    chans = intersect( chans, D_para_ddla( i).chan.getlabels);
    chans = intersect( chans, D_para_jbw( i).chan.getlabels);

end
D_pre_am = D_pre_am.selectchan( chans);
D_pre_rw = D_pre_rw.selectchan( chans);
D_pre_jow = D_pre_jow.selectchan( chans);
D_pre_ddla = D_pre_ddla.selectchan( chans);
D_pre_jbw = D_pre_jbw.selectchan( chans);

D_para_am = D_para_am.selectchan( chans);
D_para_rw = D_para_rw.selectchan( chans);
D_para_jow = D_para_jow.selectchan( chans);
D_para_ddla = D_para_ddla.selectchan( chans);
D_para_jbw = D_para_jbw.selectchan( chans);

% % Epoch
% D_pre_am_x = fake_epochs( D_pre_am, 2);
% D_pre_rw_x = fake_epochs( D_pre_rw, 2);
% D_pre_jow_x = fake_epochs( D_pre_jow, 2);
% D_pre_ddla_x = fake_epochs( D_pre_ddla, 2);
% D_pre_jbw_x = fake_epochs( D_pre_jbw, 2);
%
% D_para_am_x=fake_epochs( D_para_am, 2);
% D_para_rw_x=fake_epochs( D_para_rw, 2);
% D_para_jow_x=fake_epochs( D_para_jow, 2);
% D_para_ddla_x=fake_epochs( D_para_ddla, 2);
% D_para_jbw_x=fake_epochs( D_para_jbw, 2);
%

% calculate connectivity for pre- and post-
tic
[ ~, chans_pre_am, AM_pre_am] = connectivity( D_pre_am,
@normalisedtransferentropy);
[ ~, chans_pre_rw, AM_pre_rw] = connectivity( D_pre_rw,
@normalisedtransferentropy);
[ ~, chans_pre_jow, AM_pre_jow] = connectivity( D_pre_jow,
@normalisedtransferentropy);
[ ~, chans_pre_ddla, AM_pre_ddla] = connectivity( D_pre_ddla,
@normalisedtransferentropy);

```



```

AM_para_mean = mean(
[AM_para_am_shaped,AM_para_rw_shaped,AM_para_jow_shaped,AM_para_ddla_shaped,AM_p
ara_jbw_shaped],2);

tic
[~, pvals] = permutationstest_multi( AM_pre_mean, AM_para_mean, ...
    2, 'Nperm', 10000, 'type', 'independent', 'alpha', 0.05,
'multiple_tests_correction', 'Bonferroni');
toc
% plot the results
plot_connections3d_v3( AM_pre_mean - AM_para_mean, cpl_shaped, pvals,'conlims',
[-1 1] * 0.1);
set( gcf, 'Name', [ 'Mean' ' ' task ' preparalysis vs paralysis
connectivity(1020)'] );
plot_connections3d_v3( AM_para_mean, cpl_shaped, pvals,'conlims', [-1 1] *
0.1)
set( gcf, 'Name', [ 'Mean' ' ' task ' paralysis connectivity(1020)'] )
plot_connections3d_v3( AM_pre_mean, cpl_shaped, pvals,'conlims', [-1 1] * 0.1)
set( gcf, 'Name', [ 'Mean' ' ' task ' preparalysis connectivity(1020)'] )

```

9.4 The calculation of the connectivity for the bite task

```

task = 'headmuscle.bite';

% load and prepare pre- and post- oddball data
d_pre_am = eeglocal.paralysis.load( 'am', [ 'study.preparalysis.' task]);
d_pre_rw= eeglocal.paralysis.load( 'rw', [ 'study.preparalysis.' task]);
d_pre_jow= eeglocal.paralysis.load( 'jow', [ 'study.preparalysis.' task]);
d_pre_ddla = eeglocal.paralysis.load( 'ddla', [ 'study.preparalysis.' task]);
d_pre_jbw = eeglocal.paralysis.load( 'jbw', [ 'study.preparalysis.' task]);

d_para_am = eeglocal.paralysis.load( 'am', [ 'study.paralysis.' task]);
d_para_rw= eeglocal.paralysis.load( 'rw', [ 'study.paralysis.' task]);
d_para_jow= eeglocal.paralysis.load( 'jow', [ 'study.paralysis.' task]);
d_para_ddla = eeglocal.paralysis.load( 'ddla', [ 'study.paralysis.' task]);
d_para_jbw = eeglocal.paralysis.load( 'jbw', [ 'study.paralysis.' task]);

D_pre_am =eeglocal.util.tenfiver( d_pre_am);
D_pre_rw= eeglocal.util.tenfiver( d_pre_rw);
D_pre_jow= eeglocal.util.tenfiver( d_pre_jow);
D_pre_ddla = eeglocal.util.tenfiver( d_pre_ddla);
D_pre_jbw = eeglocal.util.tenfiver( d_pre_jbw);

D_pre_am =D_pre_am.selectchan( eeg3.util.labels1020);
D_pre_rw= D_pre_rw.selectchan( eeg3.util.labels1020);
D_pre_jow= D_pre_jow.selectchan( eeg3.util.labels1020);
D_pre_ddla =D_pre_ddla.selectchan( eeg3.util.labels1020);
D_pre_jbw = D_pre_jbw.selectchan( eeg3.util.labels1020);

D_para_am = eeglocal.util.tenfiver( d_para_am);
D_para_rw= eeglocal.util.tenfiver( d_para_rw);
D_para_jow= eeglocal.util.tenfiver( d_para_jow);
D_para_ddla = eeglocal.util.tenfiver( d_para_ddla);
D_para_jbw = eeglocal.util.tenfiver( d_para_jbw);

```

```

D_para_am = D_para_am.selectchan( eeg3.util.labels1020);
D_para_rw= D_para_rw.selectchan( eeg3.util.labels1020);
D_para_jow= D_para_jow.selectchan( eeg3.util.labels1020);
D_para_ddla = D_para_ddla.selectchan( eeg3.util.labels1020);
D_para_jbw = D_para_jbw.selectchan( eeg3.util.labels1020);

% check channels are the same pre- and post-
chans = eeg3.util.labels1020;
for i = 1:numel( d_pre_am)
    chans = intersect( chans, D_pre_am( i).chan.getlabels);
    chans = intersect( chans, D_pre_rw( i).chan.getlabels);
    chans = intersect( chans, D_pre_jow( i).chan.getlabels);
    chans = intersect( chans, D_pre_ddla( i).chan.getlabels);
    chans = intersect( chans, D_pre_jbw( i).chan.getlabels);

    chans = intersect( chans, D_para_am( i).chan.getlabels);
    chans = intersect( chans, D_para_rw( i).chan.getlabels);
    chans = intersect( chans, D_para_jow( i).chan.getlabels);
    chans = intersect( chans, D_para_ddla( i).chan.getlabels);
    chans = intersect( chans, D_para_jbw( i).chan.getlabels);
end
D_pre_am = D_pre_am.selectchan( chans);
D_pre_rw = D_pre_rw.selectchan( chans);
D_pre_jow = D_pre_jow.selectchan( chans);
D_pre_ddla = D_pre_ddla.selectchan( chans);
D_pre_jbw = D_pre_jbw.selectchan( chans);

D_para_am = D_para_am.selectchan( chans);
D_para_rw = D_para_rw.selectchan( chans);
D_para_jow = D_para_jow.selectchan( chans);
D_para_ddla = D_para_ddla.selectchan( chans);
D_para_jbw = D_para_jbw.selectchan( chans);

% Epoch
D_pre_am_x = fake_epochs( D_pre_am, 2); % for statistics, needs to be fed with
moe data that is why we epoch the EEG signal
D_pre_rw_x = fake_epochs( D_pre_rw, 2);
D_pre_jow_x = fake_epochs( D_pre_jow, 2);
D_pre_ddla_x = fake_epochs( D_pre_ddla, 2);
D_pre_jbw_x = fake_epochs( D_pre_jbw, 2);

D_para_am_x=fake_epochs( D_para_am, 2);
D_para_rw_x=fake_epochs( D_para_rw, 2);
D_para_jow_x=fake_epochs( D_para_jow, 2);
D_para_ddla_x=fake_epochs( D_para_ddla, 2);
D_para_jbw_x=fake_epochs( D_para_jbw, 2);

% calculate connectivity for pre- and post-
tic
[ ~, chans_pre_am, AM_pre_am] = connectivity( D_pre_am_x,
@normalisedtransferentropy);
[ ~, chans_pre_rw, AM_pre_rw] = connectivity( D_pre_rw_x,
@normalisedtransferentropy);

```



```

[~, chans_pre_jow, AM_pre_jow] = connectivity( D_pre_jow_x,
@normalisedtransferentropy);
[~, chans_pre_ddla, AM_pre_ddla] = connectivity( D_pre_ddla_x,
@normalisedtransferentropy);
[~, chans_pre, AM_pre_jbw] = connectivity( D_pre_jbw_x,
@normalisedtransferentropy);

[~, chans_para_am, AM_para_am] = connectivity( D_para_am_x,
@normalisedtransferentropy);
[~, chans_para_rw, AM_para_rw] = connectivity( D_para_rw_x,
@normalisedtransferentropy);
[~, chans_para_jow, AM_para_jow] = connectivity( D_para_jow_x,
@normalisedtransferentropy);
[~, chans_para_ddla, AM_para_ddla] = connectivity( D_para_ddla_x,
@normalisedtransferentropy);
[~, chans_para_jbw, AM_para_jbw] = connectivity( D_para_jbw_x,
@normalisedtransferentropy);
toc

save mean_bite.mat AM_pre_am AM_pre_rw AM_pre_jow AM_pre_ddla AM_pre_jbw

load mean_bite.mat

% do the statistical comparison between pre- and post-
Nch=numel( chans);
cpl = chan_pair_labels( chans);
cpl_shaped = cpl( :);
cpl_shaped( 1:( Nch + 1):( Nch * Nch)) = [];



```

%pre paralysis
AM_pre_am_shaped = reshape(AM_pre_am, Nch *Nch, []);
AM_pre_rw_shaped = reshape(AM_pre_rw, Nch *Nch, []);
AM_pre_jow_shaped = reshape(AM_pre_jow, Nch *Nch, []);
AM_pre_ddla_shaped = reshape(AM_pre_ddla, Nch *Nch, []);
AM_pre_jbw_shaped = reshape(AM_pre_jbw, Nch *Nch, []);

AM_pre_am_shaped(1:(Nch + 1):(Nch * Nch), :) = [];
AM_pre_rw_shaped(1:(Nch + 1):(Nch * Nch), :) = [];
AM_pre_jow_shaped(1:(Nch + 1):(Nch * Nch), :) = [];
AM_pre_ddla_shaped(1:(Nch + 1):(Nch * Nch), :) = [];
AM_pre_jbw_shaped(1:(Nch + 1):(Nch * Nch), :) = [];

AM_pre_mean = mean([
AM_pre_am_shaped,AM_pre_rw_shaped,AM_pre_jow_shaped,AM_pre_ddla_shaped,AM_pre_jb
w_shaped],2);


```

%paralysis

AM_para_am_shaped = reshape( AM_para_am, Nch *Nch, []);
AM_para_rw_shaped = reshape( AM_para_rw, Nch *Nch, []);
AM_para_jow_shaped = reshape( AM_para_jow, Nch *Nch, []);
AM_para_ddla_shaped = reshape( AM_para_ddla, Nch *Nch, []);
AM_para_jbw_shaped = reshape( AM_para_jbw, Nch *Nch, []);

AM_para_am_shaped( 1:( Nch + 1):( Nch * Nch), :) = [];
AM_para_rw_shaped( 1:( Nch + 1):( Nch * Nch), :) = [];
AM_para_jow_shaped( 1:( Nch + 1):( Nch * Nch), :) = [];
AM_para_ddla_shaped( 1:( Nch + 1):( Nch * Nch), :) = [];
AM_para_jbw_shaped( 1:( Nch + 1):( Nch * Nch), :) = [];

```


```


```

```

AM_para_mean = mean(
[AM_para_am_shaped,AM_para_rw_shaped,AM_para_jow_shaped,AM_para_ddla_shaped,AM_p
ara_jbw_shaped],2);

tic
[~, pvals] = permutationtest_multi( AM_pre_mean, AM_para_mean, ...
    2, 'Nperm', 10000, 'type', 'independent', 'alpha', 0.05);
toc
% plot the results
plot_connections3d_v3( AM_pre_mean - AM_para_mean, cpl_shaped, pvals,'conlims',
[-1 1] * 0.1);
set(gcf, 'Name', [ 'Mean' ' ' task ' preparalysis vs paralysis
connectivity(1020)']);
plot_connections3d_v3( AM_para_mean, cpl_shaped, pvals,'conlims', [-1 1] * 0.1)
set(gcf, 'Name', [ 'Mean' ' ' task ' paralysis connectivity(1020)'])
plot_connections3d_v3( AM_pre_mean, cpl_shaped, pvals,'conlims', [-1 1] * 0.1)
set(gcf, 'Name', [ 'Mean' ' ' task ' preparalysis connectivity(1020)'])

```

9.5 The calculation of the connectivity for the frown task

```
task = 'headmuscle.frown';
```

```
% load and prepare pre- and post- oddball data
d_pre_am = eeglocal.paralysis.load( 'am', [ 'study.preparalysis.' task]);
d_pre_rw= eeglocal.paralysis.load( 'rw', [ 'study.preparalysis.' task]);
d_pre_jow= eeglocal.paralysis.load( 'jow', [ 'study.preparalysis.' task]);
d_pre_ddla = eeglocal.paralysis.load( 'ddla', [ 'study.preparalysis.' task]);
d_pre_jbw = eeglocal.paralysis.load( 'jbw', [ 'study.preparalysis.' task]);

```

```

d_para_am = eeglocal.paralysis.load( 'am', [ 'study.paralysis.' task]);
d_para_rw= eeglocal.paralysis.load( 'rw', [ 'study.paralysis.' task]);
d_para_jow= eeglocal.paralysis.load( 'jow', [ 'study.paralysis.' task]);
d_para_ddla = eeglocal.paralysis.load( 'ddla', [ 'study.paralysis.' task]);
d_para_jbw = eeglocal.paralysis.load( 'jbw', [ 'study.paralysis.' task]);

```

```

D_pre_am =eeglocal.util.tenfive( d_pre_am);
D_pre_rw= eeglocal.util.tenfive( d_pre_rw);
D_pre_jow= eeglocal.util.tenfive( d_pre_jow);
D_pre_ddla = eeglocal.util.tenfive( d_pre_ddla);
D_pre_jbw = eeglocal.util.tenfive( d_pre_jbw);

```

```

D_pre_am =D_pre_am.selectchan( eeg3.util.labels1020);
D_pre_rw= D_pre_rw.selectchan( eeg3.util.labels1020);
D_pre_jow= D_pre_jow.selectchan( eeg3.util.labels1020);
D_pre_ddla =D_pre_ddla.selectchan( eeg3.util.labels1020);
D_pre_jbw = D_pre_jbw.selectchan( eeg3.util.labels1020);

```

```

D_para_am = eeglocal.util.tenfive( d_para_am);
D_para_rw= eeglocal.util.tenfive( d_para_rw);
D_para_jow= eeglocal.util.tenfive( d_para_jow);
D_para_ddla = eeglocal.util.tenfive( d_para_ddla);
D_para_jbw = eeglocal.util.tenfive( d_para_jbw);

```

```
D_para_am = D_para_am.selectchan( eeg3.util.labels1020);
```

```

D_para_rw= D_para_rw.selectchan( eeg3.util.labels1020);
D_para_jow= D_para_jow.selectchan( eeg3.util.labels1020);
D_para_ddla = D_para_ddla.selectchan( eeg3.util.labels1020);
D_para_jbw = D_para_jbw.selectchan( eeg3.util.labels1020);

% check channels are the same pre- and post-
chans = eeg3.util.labels1020;
for i = 1:numel( d_pre_am)
    chans = intersect( chans, D_pre_am( i).chan.getlabels);
    chans = intersect( chans, D_pre_rw( i).chan.getlabels);
    chans = intersect( chans, D_pre_jow( i).chan.getlabels);
    chans = intersect( chans, D_pre_ddla( i).chan.getlabels);
    chans = intersect( chans, D_pre_jbw( i).chan.getlabels);

    chans = intersect( chans, D_para_am( i).chan.getlabels);
    chans = intersect( chans, D_para_rw( i).chan.getlabels);
    chans = intersect( chans, D_para_jow( i).chan.getlabels);
    chans = intersect( chans, D_para_ddla( i).chan.getlabels);
    chans = intersect( chans, D_para_jbw( i).chan.getlabels);

end
D_pre_am = D_pre_am.selectchan( chans);
D_pre_rw = D_pre_rw.selectchan( chans);
D_pre_jow = D_pre_jow.selectchan( chans);
D_pre_ddla = D_pre_ddla.selectchan( chans);
D_pre_jbw = D_pre_jbw.selectchan( chans);

D_para_am = D_para_am.selectchan( chans);
D_para_rw = D_para_rw.selectchan( chans);
D_para_jow = D_para_jow.selectchan( chans);
D_para_ddla = D_para_ddla.selectchan( chans);
D_para_jbw = D_para_jbw.selectchan( chans);

% Epoch
D_pre_am_x = fake_epochs( D_pre_am, 2); % for statistics, needs to be fed with
moe data that is why we epoch the EEG signal
D_pre_rw_x = fake_epochs( D_pre_rw, 2);
D_pre_jow_x = fake_epochs( D_pre_jow, 2);
D_pre_ddla_x = fake_epochs( D_pre_ddla, 2);
D_pre_jbw_x = fake_epochs( D_pre_jbw, 2);

D_para_am_x=fake_epochs( D_para_am, 2);
D_para_rw_x=fake_epochs( D_para_rw, 2);
D_para_jow_x=fake_epochs( D_para_jow, 2);
D_para_ddla_x=fake_epochs( D_para_ddla, 2);
D_para_jbw_x=fake_epochs( D_para_jbw, 2);

% calculate connectivity for pre- and post-
tic
[ ~, chans_pre_am, AM_pre_am] = connectivity( D_pre_am_x,
@normalisedtransferentropy);
[ ~, chans_pre_rw, AM_pre_rw] = connectivity( D_pre_rw_x,
@normalisedtransferentropy);
[ ~, chans_pre_jow, AM_pre_jow] = connectivity( D_pre_jow_x,
@normalisedtransferentropy);

```



```

AM_para_mean = mean(
[AM_para_am_shaped,AM_para_rw_shaped,AM_para_jow_shaped,AM_para_ddla_shaped,AM_p
ara_jbw_shaped],2);

[~, pvals] = permutationtest_multi( AM_pre_mean, AM_para_mean, ...
    2, 'Nperm', 10000, 'type', 'independent', 'alpha', 0.05);

% plot the results
plot_connections3d_v3( AM_pre_mean - AM_para_mean, cpl_shaped, pvals,'conlims',
[-1 1] * 0.1);
set( gcf, 'Name', [ 'Mean' ' ' task ' preparalysis vs paralysis
connectivity(1020)']);
plot_connections3d_v3( AM_para_mean, cpl_shaped, pvals,'conlims', [-1 1] *
0.1)
set( gcf, 'Name', [ 'Mean' ' ' task ' paralysis connectivity(1020)'])
plot_connections3d_v3( AM_pre_mean, cpl_shaped, pvals,'conlims', [-1 1] * 0.1)
set( gcf, 'Name', [ 'Mean' ' ' task ' preparalysis connectivity(1020)'])

```

9.6 The calculation of the connectivity for the neck task

```

task = 'headmuscle.neck';

% load and prepare pre- and post- oddball data
d_pre_am = eeglocal.paralysis.load( 'am', [ 'study.preparalysis.' task]);
d_pre_rw= eeglocal.paralysis.load( 'rw', [ 'study.preparalysis.' task]);
d_pre_jow= eeglocal.paralysis.load( 'jow', [ 'study.preparalysis.' task]);
d_pre_ddla = eeglocal.paralysis.load( 'ddla', [ 'study.preparalysis.' task]);
d_pre_jbw = eeglocal.paralysis.load( 'jbw', [ 'study.preparalysis.' task]);

d_para_am = eeglocal.paralysis.load( 'am', [ 'study.paralysis.' task]);
d_para_rw= eeglocal.paralysis.load( 'rw', [ 'study.paralysis.' task]);
d_para_jow= eeglocal.paralysis.load( 'jow', [ 'study.paralysis.' task]);
d_para_ddla = eeglocal.paralysis.load( 'ddla', [ 'study.paralysis.' task]);
d_para_jbw = eeglocal.paralysis.load( 'jbw', [ 'study.paralysis.' task]);

D_pre_am =eeglocal.util.tenfive( d_pre_am);
D_pre_rw= eeglocal.util.tenfive( d_pre_rw);
D_pre_jow= eeglocal.util.tenfive( d_pre_jow);
D_pre_ddla = eeglocal.util.tenfive( d_pre_ddla);
D_pre_jbw = eeglocal.util.tenfive( d_pre_jbw);

D_pre_am =D_pre_am.selectchan( eeg3.util.labels1020);
D_pre_rw= D_pre_rw.selectchan( eeg3.util.labels1020);
D_pre_jow= D_pre_jow.selectchan( eeg3.util.labels1020);
D_pre_ddla =D_pre_ddla.selectchan( eeg3.util.labels1020);
D_pre_jbw = D_pre_jbw.selectchan( eeg3.util.labels1020);

D_para_am = eeglocal.util.tenfive( d_para_am);
D_para_rw= eeglocal.util.tenfive( d_para_rw);
D_para_jow= eeglocal.util.tenfive( d_para_jow);
D_para_ddla = eeglocal.util.tenfive( d_para_ddla);
D_para_jbw = eeglocal.util.tenfive( d_para_jbw);

D_para_am = D_para_am.selectchan( eeg3.util.labels1020);

```

```

D_para_rw= D_para_rw.selectchan( eeg3.util.labels1020);
D_para_jow= D_para_jow.selectchan( eeg3.util.labels1020);
D_para_ddla = D_para_ddla.selectchan( eeg3.util.labels1020);
D_para_jbw = D_para_jbw.selectchan( eeg3.util.labels1020);

% check channels are the same pre- and post-
chans = eeg3.util.labels1020;
for i = 1:numel( d_pre_am)
    chans = intersect( chans, D_pre_am( i).chan.getlabels);
    chans = intersect( chans, D_pre_rw( i).chan.getlabels);
    chans = intersect( chans, D_pre_jow( i).chan.getlabels);
    chans = intersect( chans, D_pre_ddla( i).chan.getlabels);
    chans = intersect( chans, D_pre_jbw( i).chan.getlabels);

    chans = intersect( chans, D_para_am( i).chan.getlabels);
    chans = intersect( chans, D_para_rw( i).chan.getlabels);
    chans = intersect( chans, D_para_jow( i).chan.getlabels);
    chans = intersect( chans, D_para_ddla( i).chan.getlabels);
    chans = intersect( chans, D_para_jbw( i).chan.getlabels);

end
D_pre_am = D_pre_am.selectchan( chans);
D_pre_rw = D_pre_rw.selectchan( chans);
D_pre_jow = D_pre_jow.selectchan( chans);
D_pre_ddla = D_pre_ddla.selectchan( chans);
D_pre_jbw = D_pre_jbw.selectchan( chans);

D_para_am = D_para_am.selectchan( chans);
D_para_rw = D_para_rw.selectchan( chans);
D_para_jow = D_para_jow.selectchan( chans);
D_para_ddla = D_para_ddla.selectchan( chans);
D_para_jbw = D_para_jbw.selectchan( chans);

% Epoch
D_pre_am_x = fake_epochs( D_pre_am, 2); % for statistics, needs to be fed with
moe data that is why we epoch the EEG signal
D_pre_rw_x = fake_epochs( D_pre_rw, 2);
D_pre_jow_x = fake_epochs( D_pre_jow, 2);
D_pre_ddla_x = fake_epochs( D_pre_ddla, 2);
D_pre_jbw_x = fake_epochs( D_pre_jbw, 2);

D_para_am_x=fake_epochs( D_para_am, 2);
D_para_rw_x=fake_epochs( D_para_rw, 2);
D_para_jow_x=fake_epochs( D_para_jow, 2);
D_para_ddla_x=fake_epochs( D_para_ddla, 2);
D_para_jbw_x=fake_epochs( D_para_jbw, 2);

% calculate connectivity for pre- and post-
tic
[ ~, chans_pre_am, AM_pre_am] = connectivity( D_pre_am_x,
@normalisedtransferentropy);
[ ~, chans_pre_rw, AM_pre_rw] = connectivity( D_pre_rw_x,
@normalisedtransferentropy);
[ ~, chans_pre_jow, AM_pre_jow] = connectivity( D_pre_jow_x,
@normalisedtransferentropy);

```



```

AM_para_mean = mean(
[AM_para_am_shaped,AM_para_rw_shaped,AM_para_jow_shaped,AM_para_ddla_shaped,AM_p
ara_jbw_shaped],2);

[~, pvals] = permutationtest_multi( AM_pre_mean, AM_para_mean, ...
    2, 'Nperm', 10000, 'type', 'independent', 'alpha', 0.05);

% plot the results
plot_connections3d_v3( AM_pre_mean - AM_para_mean, cpl_shaped, pvals,'conlims',
[-1 1] * 0.1);
set( gcf, 'Name', [ 'Mean' ' ' task ' preparalysis vs paralysis
connectivity(1020)']);
plot_connections3d_v3( AM_para_mean, cpl_shaped, pvals,'conlims', [-1 1] *
0.1)
set( gcf, 'Name', [ 'Mean' ' ' task ' paralysis connectivity(1020)'])
plot_connections3d_v3( AM_pre_mean, cpl_shaped, pvals,'conlims', [-1 1] * 0.1)
set( gcf, 'Name', [ 'Mean' ' ' task ' preparalysis connectivity(1020)'])

```