Evaluation of Functional Brain Connectivity correlated with Power Spectrum Density during Mental Fatigue.

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Abstract.

The progressive and gradual escalation of mental fatigue implies specific alterations in both power spectral values and brain connectivity. Detect these variations can improve the understanding of mental fatigue, and lead to identifying sensitive channels to mental state changes and also to identify brain connectivity profiles. This article aims to identify pairs of electrodes that could be used as indicators of mental fatigue based on highly correlated connectivity variations with power spectral values, and also high significance through both normal and fatigue states. In an effort to validate the selected pairs of channels, labeled and unlabeled datasets were subjected to statistical analysis. Our results indicate the concentration of channels in the anterior and posterior brain regions in the left hemisphere, and attenuation of brain connectivity.

Categories and Subject Descriptors: J.2.8 [**Applied Computing**]: Computing industry

Keywords: Time Series Analysis, Brain Connectivity ,Mental Fatigue

1. INTRODUCTION

The natural decay of attention, concentration, and performance in a prolonged task, as much as the demonstration of tiredness or exhaustion can be interpreted as the manifestation of mental fatigue. [Dasari et al. 2017].

In terms of Electroencephalography (EEG) signal, mental fatigue is detected by specific electrodes and frequencies, that reflect distinct patterns of physiological states [Strimbu and Tavel 2011]. Considering the individuality of brain behavior and the type of task performed, the identification of these sensitive electrodes (Mental fatigue biomarkers), is based on the values of Power Spectral Density(PSD), that shows disturbances of magnitude through brain regions. [Wascher et al. 2014; Cajochen et al. 1995; Dimitrakopoulos et al. 2018]

Methodologies to describe the occurrence of mental fatigue using electroencephalographic (EEG) signals have been implemented in several environments, especially in long-term driving task [Dimitrakopoulos et al. 2018]. Changes in EEG power spectral density (PSD) in theta (θ - 4-8Hz), alpha (α - 8-15Hz) and beta (β- 15-30Hz) bands, mostly in the frontal and parietal sites, are often associated with the occurrence this mental condition [Holm et al. 2009; Eoh et al. 2005; Schier 2000]. Case of Studies such as [Charbonnier et al. 2016] observed increment of the alpha and theta power during the task.

This work aims to identify brain connectivity biomarkers of mental fatigue, based on alterations in the PSD values. The next sections describe the implemented methodology in three stages 1) correlation analysis of brain connectivity and PSD values, 2) significance verification of correlated channels, and 3) variation of connectivity between mental states.

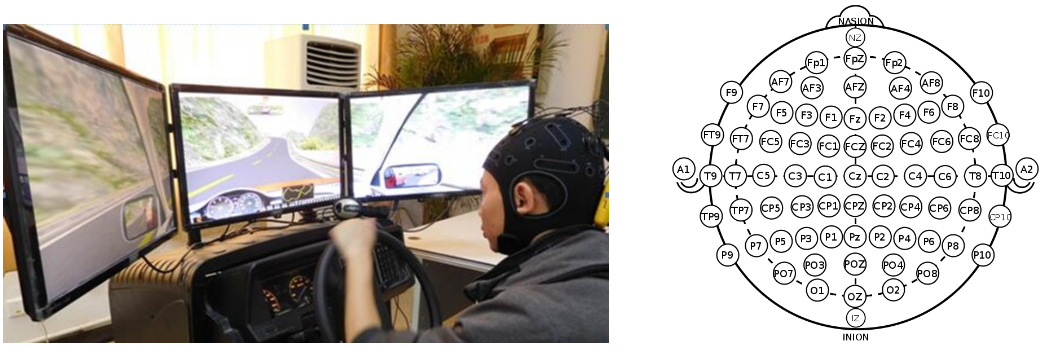
2. DATA ACQUISITION AND DATASETS

Two datasets were considered, the first (Dataset I) is in public domain, provided by [Min et al. 2017], which refers to a two-class driver fatigue study. The second (Dataset II), is a private dataset of two-class excavator fatigue study, obtained from a mining company in Brazil. Even though the age influence in the capacity of the subjects to deal with mental fatigue, this gap between both datasets was not considered relevant for the study, once it aims to implement the analysis in labeled and unlabeled datasets.

2.1 Driver Dataset

The Driver dataset, referred as Dataset I, consists of EEG data collected from 12 healthy male subjects with an average age of $19 - 24$ years old, at a sample rate of 1 kHz from 30-channel electrode cap, referenced to two electrically linked mastoids at A1 and A2, based on the international extended 10-20 system (Figure 1(b)). Prior to the experiment, a session comprised 5 minutes of practicing to adapt participants to the experimental procedures. After this period, each subject performs the simulated driving task during 1-2 hours. Figure 1(a) illustrates the setup used in the experiment.

The collected data are heterogeneous since the stop criteria are based on the experiment reaching 2 hours or the subject self-reporting exhaustion. Fatigue questionnaires were applied, the Chalder Fatigue Scale and Li′s Subjective Fatigue Scale [Lee et al. 1991; Borg 1990]. The first and last 5 minutes of the experiment were labeled as normal and fatigue states.



(a) Snapshot of the experiment setup performed on a static driving simulator (ZY-31D car driving simulator.

(b) Extended 30 channels EEG 10-20 Electrode Topology System

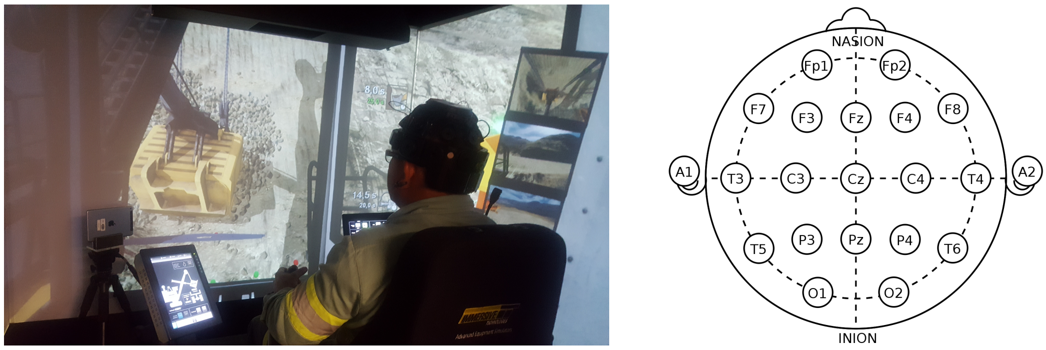
Fig. 1: Configuration of the Sustained-attention driving task experiment.

2.2 Excavator Dataset

The Excavator dataset (Dataset II) provides the recorded EEG data of 24 healthy male subjects with an average age of 36.7 ± 6.8 years old. The subjects were experienced operators performing controlled experimental sessions in a virtual reality excavator simulator in the *Complexo Eliezer Batista* S11D mining at VALE. Figure 2(a) shows the VR environment, which consisted of three projection screens and two joysticks for controlling the excavator. Experiments sessions had productive focus and were carried out during the work shift of the operators in the course of the two weeks.

A session comprised 15 min adaptation operating the VR simulator, no EEG was recorded during the adaptation phase. After this period, each subject performed a 60 min operation simulating a standard mining task. The first and the last 3 min represent the fatigue and non-fatigue analyzed data.

The EEG data were recorded with the BrainMaster systems at a sampling rate of $300Hz$ from 19 active electrodes according to the 10-20 system 2(b) and the reference was set at the Pz electrode and re-referenced to the average of auricular electrodes (A1 and A2) [Odom et al. 2010]. The EEG equipment operates with Bluetooth, which allowed the subject to perform their tasks without movement restrictions.



(a) Snapshot of the experiment setup performed on a excavator simulator (Immersive Technologies)

(b) EEG 10-20 Electrode Topology System

Fig. 2: Configuration of the Sustained-attention driving task experiment.

3. DATA PRE-PROCESSING

The raw data were preprocessed in two stages; filtering and Independent Component Analysis (ICA) calculation. The database was double filtered for anti-aliasing purposes, first with a fourth-order band-pass Butterworth, ranged from 1 to 100 Hz to delimitate the frequencies of interest until gamma rhythm ($100Hz$), and a $60Hz$ notch filter, to attenuate noises such as electrical disturbances and interference from the environment.

The filtered data is then submitted to the Independent Component Analysis (ICA) to be decomposed into independent sources linearly mixed in several sensors [Jung et al. 2000]. ICA is used as a technique for removing so-called artifacts, defined as sources of signal corruption such as blinking, eye movements, and electrode impedance. Other signals beside the EEG that are also identified and removed by ICA are Electrocardiography (ECG), Electromyography (EMG), Electrooculography (EOG) and many others, which can distort EEG signal recording.

In most cases, the analysis of data in relation to a stimulus or condition (events) is done by segmentation, where fragments of the data are analyzed separately to evidence any particular behavior that may be related to the stimulus or event. In the dataset used, there is no formally determined event, however, the detailed analysis of the signal can provide greater resolution in the detection of discrete changes caused by the mental condition of the entire time series. Thus, following the ICA calculation, the continuous filtered data were divided into $1s$ segments (trials). All these pre-processing steps were performed off-line using the FieldTrip toolbox for EEG/MEG-analysis [Oostenveld et al. 2011].

4. SPECTRAL ANALYSIS

The Power Spectral Density (PSD) emphasizes power magnitude alterations over a range of frequencies, per unit of time [Cohen 2014]. The analyzed time series are converted into a complex-valued function of frequency (frequency domain), and its energy is measured by the similarity of the signal convoluted with a delayed version of itself [Stoica et al. 2005].Thus, considering a signal of finite duration, the mathematical definition of PSD $S_{xx}(\omega)$ is the Fourier Transform of the signal's autocorrelation, given by the equation 1:

$$\begin{aligned} S_{xx}(\omega) = F\left\{r(t)\right\} = F\left\{\int_{\infty}^{-\infty} x(t)x(-t)dt\right\} &= F\left\{x(t) * x(-t)\right\} \\ &= X(\omega)X^*(\omega)) = \left|X(\omega)\right|^2 \end{aligned} \tag{1}$$

where ω is the angular frequency, $r(t)$ is the autocorrelation of the signal x(t), $\Im$ is the Fourier transform, and $X^*(\omega)$ is its complex conjugate of $X(\omega)$.

In an attempt to maintain a reasonable resolution of the signal at the frequencies, the multitaper windowing method calculates the Fourier coefficients. It also circumvents the effects of the Heisenberg uncertainty principle, which deals with the troubled relationship of the resolution of the same signal in time and frequency.

5. CONNECTIVITY ANALYSIS

The brain activity is observed according to connections between electrodes through cortical regions. These brain networks can describe anatomic connections, statistical dependencies, and causal relations among channels [Sporns 2012]. The EEG connectivity based on statistical parameters (functional connectivity) is the most commonly used to analyze physiological disorders, neurological diseases and also mental states. Hence, the accurate analysis of functional connectivity (FC) can indicate sensitive channels or pairs of channels to brain dynamic changes (biomarkers).

Three main sources of EEG signal distortion need to be considered: volume conduction, common reference, and sample size [Bastos and Schoffelen 2016].The first concerns to the interference through the electrical potential of a population of neurons, head tissue, and electrodes. The second, to spurious connectivity produced by the usage of a common reference channel of two or more electrodes. The last problem occurs when connectivity is calculated in datasets in which the sample size varies due to the different sampling rate, overestimating connectivity values.

Some metrics are exempted to one or all of these trade-offs. The implemented connectivity metric of debiased weighted Phase Lag Index (dwPLI) is a scalp-level connectivity measure, robust in relation to all the three distortion sources [Vinck et al. 2011]. It is represented by symmetric matrices with the phase relationships between channels through the frequencies.

Differently to PSD, the spectral analysis for connectivity calculation is based on the Fourier Transform of the cross-correlation between two different signals (Cross Spectral Density, CSD), that organizes the information of connections in an adjacency matrix. Thus, the dWPLI is based on the magnitude of the imaginary component of the CSD. Multitaper windowing of the EEG signal's Fourier Tranform [Mitra 2007] is also used. The dWPLI mathematical representation Ω, is given by the equation 2 :

$$\Omega = \left(\frac{\left|E\left\{\Im\left\{CSD_{x,y}^{n}\right\}\right\}\right|}{E\left\{\left|\Im\left\{CSD_{x,y}^{n}\right\}\right|\right\}}\right)^2 \tag{2}$$

where $\Im\left\{CSD_{x,y}^{n}\right\}$ is the Fourier transform of the cross-correlation between signal X and the complex conjugate of Y, $E\left\{\right\}$ is the expected value, that refers to the value calculated by the sum of all trials n, multiplied by its probability of occurrence.

dwPLI is given by a number between -1 and 1 indexing the extent to which the phases of the oscillations in each channel have a consistent phase relationship with respect to each other. Phase differences near 0° and 180° usually represent volume conduction effect rather than true occurrences [Chennu et al. 2017]. The mean dwPLI values at frequencies across all channels were used to represent the connectivity between channel pairs. Since the EEG capture equipment contains 19 useful channels, each dwPLI is given by a 19×19 matrix.

6. STATISTICAL ANALYSIS

To emphasize particular behaviors of brain connectivity, and analyze its relationship with the PSD, the correlation, the significance test and the analysis of variation were sequentially implemented in the data. The correlation, as an indicator of linear associations within two variables [Cohen et al. 2014], selects channels that follow the linear increase or decrease of the PSD in both mental states, which can be considered as possible biomarkers of mental fatigue. The significance test is then implemented, aiming to identify channels that are not only correlated with PSD but also presents significant differences between normal and fatigue states. Finally, the simple analysis of variation indicates pairs of electrodes, from the group of significantly correlated channels, that presents a higher variation of connectivity.

Positive and negative Pearson correlation was calculated based on the values of PSD and connectivity, both organized by the number of subjects, mental states, and frequencies (12 x 2 x 7), of (30 channels x 5 minutes) and (30 channels x 30 channels x 5 minutes) respectively. The bandwidths followed the order of α (8-15Hz), β (15-30Hz), θ (4-8Hz), $\alpha 1$ (8-10Hz), $\alpha 2$ (10-15Hz), $\beta 1$ (15-19Hz) and $\beta 2$ (19-30Hz). The symbol for Pearson's correlation is ρ, measured according to the parameter r, a -1-to-1 range variable that indicates a perfect negative and positive linear relationship [Cohen et al. 2014]. The considered values of r are -0.7 and 0.7, to calculate de negative and positive correlation.

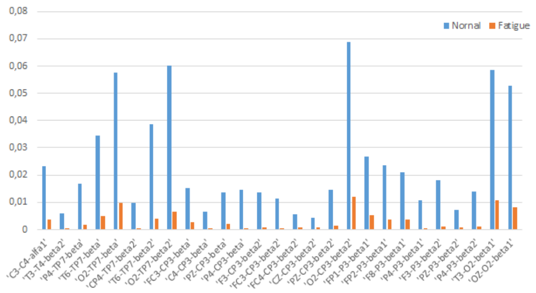
To verify significant differences between pairs of values of the same channels, but from different data(normal and fatigue states), the Wilcoxon signed-rank test was preferred than ANOVA and T-test, because normal distribution was not required. Right and left tailed test were calculated, considering the hypothesis of the values from normal and fatigue states were higher or lower than other, this distinction of significance direction is important to obtain the connectivity behavior through mental states. Two hypotheses were considered, 1) normal values greater than fatigue values (NF), and 2) fatigue values greater than normal values (FN).

Finally, the variation of connectivity in the selected channels were calculated by each pair combination per channel, aiming to identify the precise pair and specific frequency that are sensible to the fatigue state. The variation was calculated in relation to the normal values, thus as higher the variation, lower the fatigue connectivity value. In order to obtain the most sensitive pairs of channels, only those with a variation greater than 5 were selected.

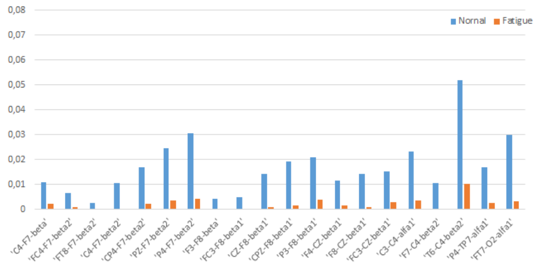
7. RESULTS AND DISCUSSION

The distribution of pairs from the positive and negative correlation in the scalp and its predominance of connections in the left hemisphere confirms the relationship between mental fatigue and the dynamic of long-range connectivity from anterior to posterior cortical regions, the left lateralization and the decay of connectivity magnitude [Xu et al. 2018; Liu et al. 2010].

In the driver dataset, the significant difference between values of both mental states reinforces the hypothesis of the connectivity attenuation with the increase of mental fatigue. However, on the contrary of expected, the unlabeled data of excavator dataset indicated the opposite behavior, with



(a) Channels with positive correlation and significance from the Normal to Fatigue state.



(b) Channels with negative correlation and significance from the normal to fatigue state.

Fig. 3: Selected channels according to its correlation. In (a) 27 channels were selected by positive Pearson correlation. In (b), 20 channels were selected by the negative Pearson correlation.

	PcorrNF	NcorrNF
$\alpha 1$	C3 - C4	P4 - TP7
$\alpha 2$	–	FT7 - O2
β	TP7-O2; TP7-P4;TP7-T6; CP3-P4;CP3-PZ;CP3-C4; CP3-FC3	C4 - F7; F3 - F8
$\beta 1$	P3-Fp1; P3-Fp2; P3-F8; P3-P4; P3-T3; O2-T3	F8-FC3;F8-Cz;F8-CPz; F8-P3; CZ-F4;CZ-FC3
$\beta 2$	T3-T4; TP7-CP4;TP7-T6; TP7-O2;P3-F3;P3-PZ;P3-P4 CP3-F3;CP3-FC3;CP3-FC4; CP3-CZ;CP3-PZ;CP3-O2	F7-FC4;F7-FT8;F7-C4; F7-PZ;F7-P4

Table I: Selected Channels from dataset I based on positive correlation and significance.

greater values in the last three minutes of the experiments, suggesting that maybe the subjects were fatigated in the beginning of the recording, and rested through the experiment. This may indicate that long work hours workers require prolonged experiments to detect fatigue.

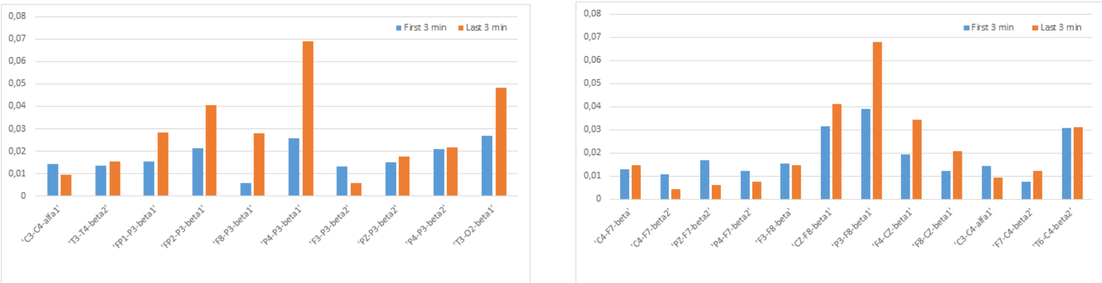
7.1 Driver Dataset

The channel selection by correlation and significance indicates higher occurrence of channels when the tailed Wilcoxon Test consider values of normal state greater than the fatigue state (NF). The positive correlation returned 27 channels to the NF scenario, and no channel selected to the hypothesis of fatigue state higher than the normal state (FN). The negative correlation returned 20 channels NF and just one channel to FN. The analysis continued, considering NF channels only. The figure 3 shows the connectivity values of selected channels for the positive correlation 3(a) and negative correlation 3(b).

Channels from the positive correlation (PcorrNF) have greater amplitude than those selected by the negative correlation(NcorrNF), and tends to concentrate connections around TP7, CP3 and P3 in β, $\beta 1$ and $\beta 2$ frequencies. For these same frequencies in the NcorrNF scenario, pairs of channels were linked around F8 and F7. Just one pair in $\alpha 1$ were selected (C3 - C4) in the PcorrNF, most of pairs in alpha were selected by the negative correlation. The table I shows the pairs of selected channels in both PcorrNF and NcorrNF.

7.2 Excavator Dataset

Shared channels from both datasets were considered to evaluate the connectivity in the excavator dataset. It was expected that the last 3 minutes of recording would present the fatigue state characteristics of



(a) Channels of dataset I with at least three connections from selected pairs.

(b) Channels with negative correlation and significance from the normal to fatigue state.

Fig. 4: Selected channels according to its correlation. In (a) 27 channels were selected by positive Pearson correlation. In (b), 20 channels were selected by the negative Pearson correlation.

greater magnitude concerning to the first 3 minutes of experiments. However, as shown by the figure 4, the connectivity values showed the opposite behavior, indicating the assumption that the subject started the experiment already in the state of mental fatigue, and the comfortable environment of data recording enables its rests.

The figure 5 shows the channels that present at least three connections from selected pairs, named here as hubs. The PcorrNF hubs were concentrated in the left posterior region of the scalp, in β, $\beta2$ and $\beta2$ frequencies, which can be related to alertness levels and attention. In 5(b), shared hubs in both datasets were analyzed in dataset II.

a) Channels of dataset I with at least three connections from selected pairs.

b) Shared channels of both datasets that presents at least three connections of selected pairs.

Fig. 5: Distribution of hubs according to PcorrNF(orange colors) and corrNegNF(green colors) in both datasets.

8. CONCLUSION

In spite of differences related to the number of channels, type of experiment and sampling rate, in both datasets, the distinction between mental states are noted by the positive and negative correlations in its respective concentration in the posterior and anterior regions. It is also noticed higher values of connectivity in the normal states, enforcing the behavior of attenuation of connectivity due to mental fatigue, interpreted as the decrease of the brain's capability to continue a task. It is suggested for future works, the graph analysis of selected channels, or even include graph parameters as criteria for biomarkers detection.

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