Official URL: http://dx.doi.org/10.5220/0005638201220128

Charbonnier, Sylvie and Roy, Raphaëlle N. and Doležalová, Radka and Campagne, Aurélie and Bonnet, Stéphane Estimation of Working Memory Load using EEG Connectivity Measures. (2016) In: International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2016), 21 February 2016 - 23 February 2016 (Rome, Italy).

Estimation of Working Memory Load using EEG Connectivity Measures

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Keywords: Workload, EEG, Connectivity.

Abstract: Working memory load can be estimated using features extracted from the electroencephalogram (EEG). Connectivity measures, that evaluate the interaction between signals, can be used to extract such features and therefore provide information about the interconnection of brain areas and electrode sites. To our knowledge, there is no literature regarding a direct comparison of the relevance of several connectivity measures for working memory load estimation. This study intends to overcome this lack of literature by proposing a direct comparison of four connectivity measures on data extracted from a working memory load experiment performed by 20 participants. These features are extracted using pattern-based or vector-based methods, and classified using an FLDA classifier and a 10-fold cross-validation procedure. The relevance of the connectivity measures was assessed by statistically comparing the obtained classification accuracy. Additional investigations were performed regarding the best set of electrodes and the best frequency band. The main results are that covariance seems to be the best connectivity measure to estimate working memory load from EEG signals, even more so with signals filtered in the beta band. point.

1 INTRODUCTION

Monitoring mental states using physiological signals, and more specifically EEG (electro-encephalogram) signals, has received more and more attention from researchers these last years. Indeed, it possesses numerous human factors applications, ranging from safety (e.g. driving, nuclear plant monitoring), to smart technology development (Fairclough, 2009; Parasuraman et al., 2012). Several mental states are currently under research focus, such as mental fatigue, attention, and affective states. Amongst them is working memory load, which reflects task difficulty and the associated mental effort (Gevins and Smith, 2007). This difficulty can be characterized in terms of quantity of engaged cognitive resources. Monitoring working memory load is particularly relevant for implementing user adaptive interfaces and user monitoring devices for safe transportation.

Working memory load modulates the EEG signals recorded on the scalp. Several studies showed that the band power in the theta (4-8 Hz) and delta (2-4 Hz) frequency bands at frontal sites increases with workload, while the band power in the alpha band (8-12 Hz) at parietal sites decreases (Holm et al. 2009; Antonenko et al., 2010; Roy et al, 2013).

Working memory load estimation can be performed thanks to tools that have been developed for active Brain Computer Interfaces (BCIs). Thus, most of the processing chains dedicated to workload estimation that are reported in the literature include a feature extraction step (e.g. frequency filtering) and a translation step (e.g. classification). Additionally, spatial filtering techniques commonly used for active BCI applications have recently been applied to enhance working memory load estimation. The most commonly used features are power band values or their log variance after spatial filtering (Roy et al., 2013). Connectivity measures have also, yet less often, been applied to workload estimation, such as coherence, phase coherence and functional connectivity estimated by directed transform function (resp. Belyavin et al., 2007; Grimes et al., 2008; Zhang et al., 2015). These measures estimate interactions between brain regions from EEG signals. To our knowledge, there is no literature regarding a direct comparison of the relevance of several connectivity measures for working memory load estimation, nor any assessment of the relevance of pattern-based versus vector-based methods.

The main goal of this article is therefore to propose a comparison of several connectivity measures to determine which one enables the more accurate estimate of working memory load. This study proposes a traditional signal processing chain using EEG signals recorded at different locations on the scalp. It is formed of a pre-processing step, a feature extraction step, and a classification step using FLDA (Fisher Linear Discriminant Analysis). The originality of the method comes from the features that are used, i.e. connectivity measures, which are either vector-based or pattern-based features. Several methods such as cross-correlation, spatial covariance, spectral coherence and phase locking value are implemented. Their performance, measured by the classification accuracy reached, is compared. The accuracy is computed from a database extracted from an experiment in which workload was manipulated by varying the number of items in working memory load. Additional investigations were performed regarding the best set of electrodes and the best frequency band.

The paper is organized as follows. The experimental design and the data used to evaluate the performance of the method are described in section 2, the processing chain and the connectivity measures are presented in section 3, the results are detailed and discussed in section 4.

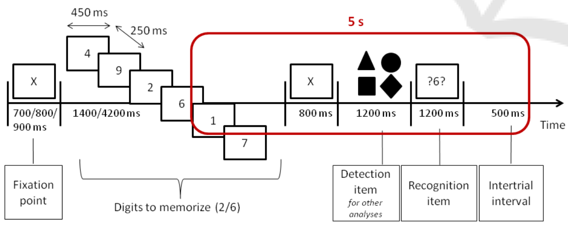

Figure 1: Trial structure. Participants memorize a list of 2 or 6 digits, and answer whether the probe item was in the list. The circled window was used for analysis.

2 MATERIALS

This research was promoted by Grenoble's hospital (France) and was approved by the French ethics committee (ID number: 2012-A00826-37).

2.1 Experimental Design

Twenty healthy right-handed volunteers (9 females; age: M = 25 years, S.D. = 3.5) participated in the experiment. The experiment lasted for 10 minutes and consisted of 80 trials. For each trial, the participants had to memorize a list of sequential digits visually presented on a computer screen. Then, a probe item flanked with question marks was displayed (Fig. 1). They had to answer as quickly and as accurately as possible whether the probe was present or not in the memorized list using a response box. Two levels of workload (WKL) were considered, i.e. 2 and 6 digits to memorize (low and high WKL respectively). Trials of low and high WKL were pseudo-randomly presented.

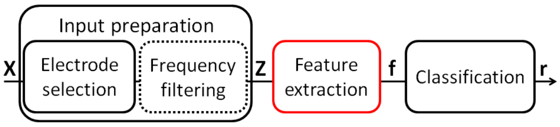

Figure 2: Global structure of the processing chain.

2.2 Data Acquisition and Preprocessing

Participants' EEG activity was recorded using a BrainAmpTM system (Brain Products, Inc.) and an Acticap® equipped with 32 Ag-AgCl active electrodes that were positioned according to the extended 10-20 system. The reference and ground electrodes used for acquisition were those of the Acticap, i.e. FCz and AFz respectively. The data were sampled at 500 Hz. The EOG activity was also recorded using two electrodes positioned at the eyes outer canthi, and two respectively above and below the left eye. Moreover, the EEG signal was band-pass filtered between 1 and 40 Hz, re-referenced to a common average reference and corrected for ocular artifacts using the signal recorded from the EOG electrodes and the SOBI algorithm. Time segments of 5 s were then selected (circled on Figure 1). Thus, for each participant, the database consisted of 80 5 s epochs, 40 in the low WKL condition, and 40 in the high WKL condition.

3 METHODS

3.1 Processing Chain

Let **X** be the 5 s epoch. It is a 32 by 2500 matrix. The processing chain is a traditional one, formed of a pre-processing step, a feature extraction step and a classification step (Figure 2).

In the pre-processing step, specific EEG channels are selected and filtered in a frequency band of interest using a 5th order Butterworth filter. The bands are either the theta (4-8 Hz), alpha (8-12 Hz), beta (13-30 Hz) or gamma band (>30 Hz). In this step, **X** is transformed into a l by 2500 matrix **Y**, with l the number of selected channels. Then, in the feature extraction step, the feature vector **f** is computed from **Y** using connectivity measures, as detailed in section 3.2. The length of **f** depends on the used connectivity measure. Next, **f** is transformed into one of two WKL levels, low or high, in the classification step.

3.2 EEG Channel Selection

Five different sets of electrodes were used. The selected channels and thus the brain regions used to measure interactions between the EEG signals were different for each set. They were selected according to the literature as detailed below.

Set 1: In order to analyze the interactions between frontal and parietal sites, 4 regions of interest (ROIs) are created: frontal right area (F4, F8, FC2, FC6), frontal left area (F7, F3, FC5, FC1), parietal right area (P4, P8, PO4, PO8) and parietal left area (P3, P7, PO3, PO7). These 4 regions were reported as regions where EEG is altered when workload changes (Roy et al, 2013). The EEG signals of each ROI are averaged to form 4 virtual electrodes, circled in blue in Figure 3. Here, l is equal to 4.

Set 2: Only 1 channel is selected from each ROI, namely FC5, FC6, P3 and P4, circled in green in Figure 3. This selection is performed so as to check that no relevant information is lost by merging the signals into ROIs. Here, l is equal to 4.

Set 3: In order to analyze the interactions between central and parietal sites in the middle of the scalp, 2 major electrode sites are selected, namely Fz, and Pz (Gevins and Smith, 2007), circled in orange in Figure 3. Here, l is equal to 2.

Set 4: Since connectivity measures of frontal areas were reported to be particularly sensitive to workload modulations (Zhang and Tian, 2015), in order to analyze the interactions between the signals from only this particular site, 4 electrodes located at the frontal right site are selected, namely F4, F8, FC2 and FC6, circled in red in Figure 3. Here, l is equal to 4.

Set 5: In the same manner, in order to analyze the interactions between the signals from only this particular site, 4 electrodes located at the frontal left site are selected, namely F7, F3, FC5 and FC1, circled in red in Figure 3. Here, l is equal to 4.

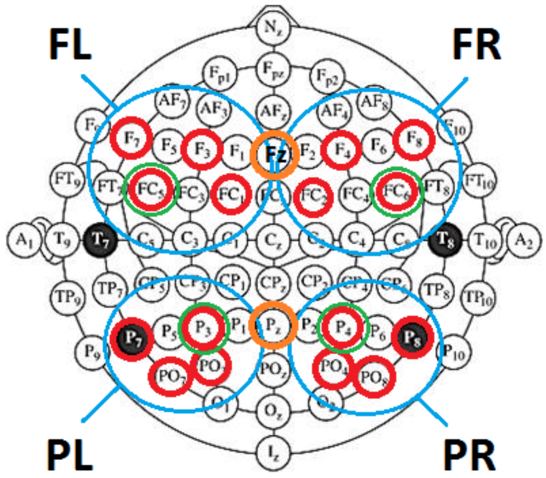

Figure 3: Illustration of the 5 different electrode sets.

3.3 Classification

For each participant, a training set is used to learn the classification function and a validation set is used to evaluate the performances. Two different classification method types are investigated – pattern-based methods and vector-based methods.

Pattern-based methods are used when the connectivity measure represents a function in time, such as cross-correlation or PLV. A pattern of high WKL (respect. low) is computed by averaging all the functions extracted from the epochs of the learning set labelled high WKL (respect. low). The Euclidian distances between the function extracted from the candidate epoch of the validation set and the two patterns are computed and the candidate epoch is assigned to the label whose pattern is the closest.

As for vector-based methods, a feature vector is built from the connectivity measures by selecting specific values in the measures, such as the mean or maximal values. The classification method used is the Fisher's Linear Discriminant Analysis (FLDA), which is very popular in BCI (Lotte et al., 2007).

3.4 Performance Evaluation

The performance of each processing chain is assessed based on its intra-subject binary classification accuracy with a ten-fold random cross validation procedure. The 80 epochs of each participant are randomly split into 10 subsets, which are used one after the other as a validation set while the 9 others are grouped to form the training set while the 9 others are grouped to form the training set. The performance of the different processing chains is compared using statistical tests. Hence, repeated-measures ANOVAs were used to detect significant differences amongst group means and Tukey post-hoc tests were used to find means that were significantly different from each other. The first ANOVA had 2 factors –electrode set and pattern-based classification method (respectively 5 and 2 levels). The second one also had 2 factors – electrode set and vector-based classification method (respectively 5 and 7 levels). A single ANOVA could not be performed to directly compare those methods as the same number of levels could not be reached for both. Lastly, an additional ANOVA was performed for the two best classification methods of each type and their best electrode set as previously determined. These had only one factor, namely the frequency band (5 levels). The significance level used was $\alpha = 0.05$.

3.5 Connectivity Measures

Interactions between brain regions were estimated with 4 connectivity measures: cross-correlation, covariance, coherence and PLV (for a review on connectivity measures see Greenblatt et al., 2012). Cross-correlation, covariance and coherence were computed using the signals filtered in the [1-40 Hz] band as well as in the theta (4-8 Hz), alpha (8-12 Hz), beta (13-30 Hz) or gamma band (>30 Hz). PLV was computed using the signals filtered in the [1-40 Hz] band only.

Let us note l, the number of EEG signals and N the number of samples in an epoch **Y**, y_i, the signal n°i and y_{ik} the value at time k of signal n°i.

3.5.1 Cross-correlation

The cross-correlation is a measure of similarity of two time series as a function of the lag of one relative to the other. It varies between -1 (negative linear relationship) to 1 (positive relationship). 0 means that there is no linear relationship. It is computed as follows:

$$c_{y_i y_j}(\tau) = \frac{1}{N-\tau} \sum_{k=1}^{N-\tau} \left(\frac{y_{i_k} - \bar{y}_i}{\sigma_{y_i}} \right) \left(\frac{y_{j_{k+\tau}} - \bar{y}_j}{\sigma_{y_j}} \right) \quad (1)$$

where $\bar{y}$ and σ_y denote mean and variance. The cross-correlation is a function of length $2N-1$.

$l(l-1)/2$ combinations of signals, and thus $l(l-1)/2$ cross-correlation functions, can be computed from **Y**. For the pattern-based methods, the features used are the $l(l-1)/2$ functions formed of $2N-1$ samples. Whereas for the vector-based methods, the feature vector is built by extracting the mean, maximal or minimal value of each of the $l(l-1)/2$ functions. Its length is thus $l(l-1)/2$.

3.5.2 Covariance

The spatial covariance between y_i, *and* y_j, is calculated as follows:

$$s_{y_i y_j} = \frac{1}{N} \sum_{k=1}^{N} \left(y_{i_k} - \bar{y}_i \right) \left(y_{j_k} - \bar{y}_j \right) \quad (2)$$

The covariance is the non-normalized correlation at $\tau=0$.

$l(l+1)/2$ spatial covariances can be calculated from **Y** and stored in the feature vector **f**.

3.5.3 Spectral Coherence

The spectral coherence, also called magnitude squared coherence, is a measure of the degree of relationship, as a function of frequency, between two signals. It is a real-valued function varying between 0 and 1. It is expressed as:

$$\left| \rho_{y_i y_j(f)} \right|^2 = \frac{\left| S_{y_i y_j(f)} \right|^2}{S_{y_i y_i(f)} \, S_{y_j y_j(f)}} \quad (3)$$

with f, the frequency in Hz, S_{yiyi}, the spectral density of y_i and S_{yiyj} the cross power spectral density of y_i and y_j. In this work, the spectral density is computed using Welch's averaged modified periodogram with a Hamming window of 512 samples and 50% overlap.

$l(l-1)/2$ coherence functions can be computed from **Y**. For the vector-based methods, the feature vector is built by extracting the mean or maximal value of each of the $l(l-1)/2$ functions.

3.5.4 PLV

The phase locking value (PLV) measures the stability of the phase difference between two signals y_i and y_j. It is expressed as:

$$PLV = \frac{1}{M} \sum_{i=1}^{M} e^{j|\varphi^1(i) - \varphi^2(i)|} \quad (4)$$

$$zi_k = yi_k + jHT(yi_k) \quad (5)$$

where M denotes the number of samples in the time window, φ_1 and φ_2 are instantaneous phases from analytic signals z_i, z_j (5), which can be obtained with Hilbert transform HT from y_i, y_j.

The PLV has values between 0 and 1, where 0 means total randomness and no phase synchronization between the signals and 1 means complete phase synchronization. It was computed on a sliding window of 512 samples with a 75% overlap, which provided 15 values per epoch. And *l(l-1)/2* PLV functions were obtained per epoch.

For the pattern-based method, the features used are the *l(l-1)/2* functions formed of the 15 samples. Whereas for the vector-based method, the feature vector is built by extracting the mean or the maximal value of each of the *l(l-1)/2* functions.

4 RESULTS

Two different types of classification methods were investigated - pattern based methods (using cross-correlation or PLV functions) and vector based methods (using the maximal cross-correlation amplitude, the covariance, the coherence mean or maximal value, the PLV mean or maximum value). The classification accuracy for each participant (using a ten-fold cross validation method) was computed for each classification method, each connectivity measure, each frequency band and each electrode subset. As detailed earlier, the results were analyzed using ANOVAs and Tukey's tests.

4.1 Electrode Sets

The first 2 ANOVAs showed that there was no statistical difference in the results when different electrode subsets were used, regardless of the classification method (pattern-based methods: $p=0.36$; vector-based methods: $p=0.84$).

4.2 Classification Methods

When using the pattern-based classification methods, the cross-correlation function gave better results than the PLV function regardless of the electrode set ($p<0.05$). When using the vector-based classification methods, the best method was covariance ($p<0.001$). It gave the best results regardless of the electrode set. The classification accuracies for the vector-based methods are displayed in Figure 4.

4.3 Frequency Bands

We investigated the chain performance deeper by assessing the impact of the considered frequency band. As regards the pattern-based methods,

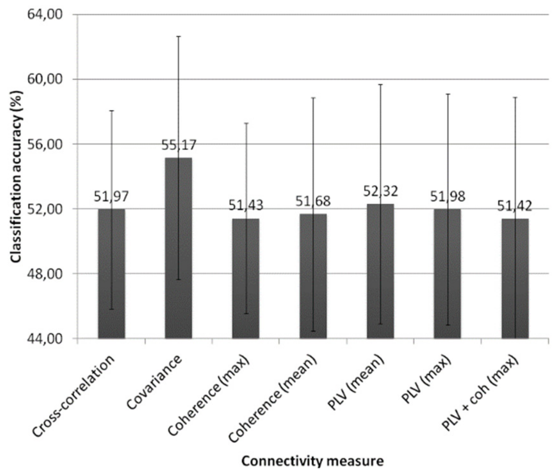

Figure 4: Mean classification accuracy reached using signals filtered in the [1-40 Hz] band for each vector-based method.

cross-correlation gave better results when the signals were filtered in the [1-40 Hz] band than when the signals were filtered in the theta or gamma bands ($p<0.05$). However, the results were not significantly different when the signals were filtered in the alpha or beta band. Regarding the vector-based classification methods, the best results were obtained with covariance using the signals filtered in the beta band ($p<0.001$). Covariance gave results that were significantly better in the beta band than in the [1-40 Hz], theta or gamma bands ($p<0.001$) (Figure 5).

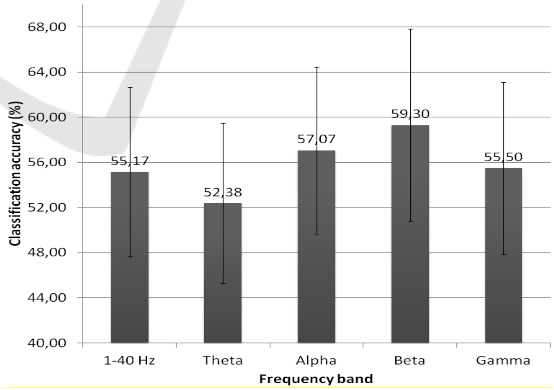

Figure 5: Mean classification accuracy obtained using covariance for each frequency band. 1: [1-40 Hz]; 2: theta; 3: alpha; 4: beta; 5: gamma band.

4.4 Best Results

Amongst all investigated methods, electrode sets and frequency bands, the best results were obtained with the covariance when the signals were filtered in the beta band. The highest mean accuracy, computed with the 20 participants was 60.64%. It was reached with the electrode subset #2, with 4 channels selected from frontal right, frontal left, parietal right and parietal left areas. It was proved to be significantly different from random. Figure 6 presents the obtained accuracy in this configuration for each participant. It can be seen that the performance reaches at least 70% for 5 participants out of 20.

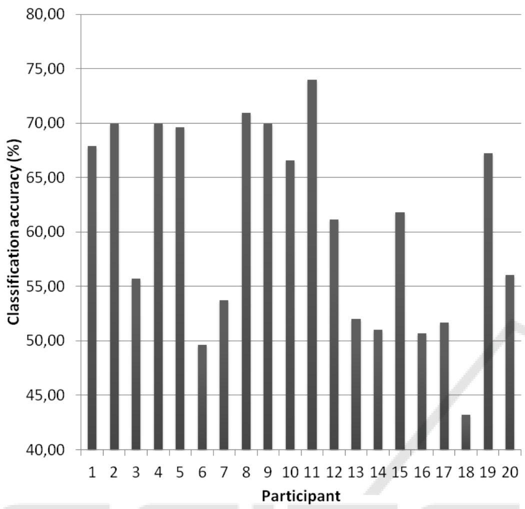

Figure 6: Obtained accuracy with the chain based on covariance in the beta band with the electrode set #2 for each participant.

The highest accuracy reached with pattern-based cross-correlation was 57% and was proved to be significantly different from random. This accuracy was obtained in the [1-40 Hz] band using electrodes from the frontal right scalp region (electrode subset #4).

5 DISCUSSION

This article presents a direct comparison of several connectivity measures in order to better estimate working memory load. The best results are reached using covariance in the beta band with as high as 61% using 4 electrodes evenly distributed on the scalp.

The global accuracy may seem rather low. Yet, they are in the same range than the accuracy reached by Roy and collaborators (2013) on the same data set, who obtained 63% of mean accuracy. The processing chain designed by Roy et al. made use of the 32 electrodes. It consisted of a Common Spatial Pattern filter able to enhance the signal differences in the two classes and an FLDA classifier. The best results were also obtained when the signals were filtered in the beta band. Therefore here using covariance, we can reach the same performance using only 4 electrodes which is a nice improvement for future real-life implementations. Moreover, contrary to most of the literature, here we estimate workload between two states of engagement in a task. Indeed, several authors obtain very high classification accuracies, however they only estimate workload between a state of engagement and a state of relaxation (e.g. Heger et la., 2010). It should be better to say that they evaluate task engagement. Thus, the results have better be compared to that of Grimes and collaborators (2008) who obtained 65% of correct classifications. Hence, the results of this study are in line with the literature and provide information as to which combination of method, band and electrode set are the more relevant for workload estimation.

Regarding the comparison between connectivity measures, the covariance performed significantly better than all the other methods. One explanation could be that the energy of the filtered signals is kept when the covariance is used while the cross-correlation, the coherence and the PLV are normalized values where the information on the energy of the signal is lost. Energy could be a discrimant feature to detect workload levels.

Finally, no significant difference could be found when the different electrodes subsets were used. This could be explained by the fact that the electrodes subsets were selected according to the literature and defined areas that are all known to be affected by a change in the workload level.

This work shoul be pursued by evaluating the relevance of covariance for other mental states such as loss of control for driving applications.

6 CONCLUSIONS

This article presents a direct comparison of several bivariate connectivity measures in order to better assess working memory load. Covariance in the beta band seems to enable a better classification of this mental state. Only multivariate connectivity measures were tested. Multivariate measures could also be tried in the future. This is a promising preliminary work towards better user state estimation.

ACKNOWLEDGEMENTS

Grenoble Neurophysiology facility IRMaGe was partly funded by the French program "Investissement d'Avenir" run by the "Agence Nationale pour la Recherche": Grant "Infrastructure d'Avenir en Biologie Santé " (ANR-11-INBS-0006).

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