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Detection of mental fatigue using an active BCI inspired signal processing chain

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Abstract: This paper presents a novel electro-encephalography (EEG) signal processing chain designed to classify two levels of mental fatigue that appears after having spent a long time on a tedious task. The decrease in vigilance associated with mental fatigue makes it a dangerous state for operators in charge of complex systems. The processing chain, inspired from active brain computer interface computing, is implemented as follows: the EEG signal is initially filtered in a given frequency band and 15 electrodes out of 32 are then selected using a method based on Riemannian geometry. Next, a spatial filtering step is carried out using 6 common spatial pattern (CSP) filters. Lastly, a binary classification is performed using Fisher's linear discriminant analysis (FLDA). The features used are the log variance of the 6 CSP filtered signals. The results obtained on 20 healthy volunteers are excellent with 100% of accuracy when the beta band is used. These performances drop to 84% and 68% when the same data are processed with a traditional signal processing chain where fatigue is classified by means of a FLDA classifier fed by the averaged power, or relative power, in the beta band extracted from 15 selected electrodes.

1. INTRODUCTION

Mental fatigue, which arises from growing time-on-task, can be a serious problem for tasks that need a sustained attention since information processing becomes less efficient in this state. Detecting mental fatigue on operators in charge of the control of complex systems, such as air-traffic operators, could help prevent accidents.

Physiological modifications occur when subjects are mentally tired, which results in behavioral consequences. Both of them are described in the literature, to propose detection systems of that dangerous state. In particular, changes in ocular and cerebral activities can be monitored by the means of electro-oculography (EOG) and electro-encephalography (EEG). Even though changes in ocular activity such as an increase in the blink frequency and duration can be accurate indicators of fatigue, they generally appear later than changes in brain activity, which is why EEG-based indicators have received a lot of attention.

The EEG signal is traditionally analyzed in five frequency bands, namely delta [< 4 Hz], theta [4-8 Hz], alpha [8-13 Hz], beta [13-30 Hz] and gamma [> 30 Hz]. Mental fatigue alters the EEG spectrum. An increase of activity in the alpha and theta bands predominantly in the parietal and central regions of the brain is generally observed, in association with a decrease in higher frequency bands (Lal et al, 2002, Paus et al, 1997, Klimesch, 1999, Tanaka et al, 1990, Tanaka et al, 2012).

Different systems based on these EEG changes were proposed to detect mental fatigue. The traditional signal processing chain consists in the elimination of ocular artifacts, the extraction of features from EEG epochs of various sizes (most often the absolute or relative averaged power in the alpha, theta and beta bands), and then the classification into different levels of fatigue by means of diverse classifiers (e.g. bayesian classifiers, SVM and neural networks), possibly after a principal component analysis (PCA) transformation. The number of electrodes used may vary from 1 to 32 (Zang et al, 2008, Shen et al, 2008, Rosipal et al, 2007, Jung et al, 1997).

In this paper, an original 32 EEG channel signal processing chain, inspired by active brain computer interfaces computing, is proposed to classify two levels of mental fatigue (low vs. high). A high level of mental fatigue is supposed to be reached after a long time spent on a repetitive task. The EEG signal is filtered in a given frequency band prior to being processed as follows. First, specific electrodes are selected. Next, a spatial filtering step is carried out. Lastly, a binary classification is performed using Fisher's linear discriminant analysis (FLDA). The classification accuracy is used to analyze the discriminative power of each frequency band. The detection performances of the method are compared with more traditional signal processing chains in which mental fatigue is classified using the absolute or relative averaged power in one band, extracted from several electrodes.

The experimental design and the data used to evaluate the performances of the signal processing chain are described in section 2. The signal processing chain is detailed in section 3. Results are presented and discussed in section 4.

2. MATERIAL

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 volunteers (9 females; age: M = 25 years, S.D. = 3.5) participated in the experiment. Its goal was to submit the participants to different levels of cognitive workload during a long time, to induce mental fatigue. The experiment was composed of successive trials. For each trial, 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). The participants 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 were considered, i.e. 2 and 6 digits to memorize (low and high workload respectively). Two 9-minute blocks and four 18-minute blocks were performed, for a total of 90 minutes of recording (Fig. 2). The participants were allowed short breaks between blocks. Given that the task was repetitive and stimulus poor, the length of the experiment allowed us to presuppose 2 levels of mental fatigue depending on time-on-task (short/long).

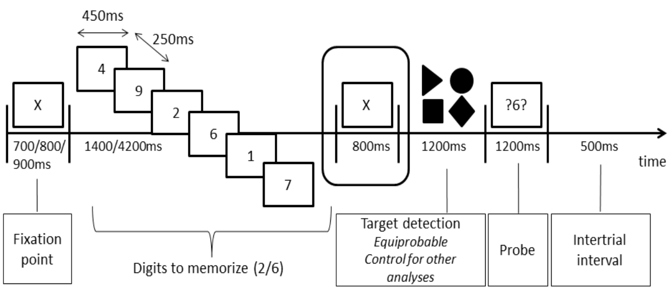

Fig. 1. Trial structure. Participants memorize a list of 2 or 6 digits, and answer whether the probe item was in the list. The circled segment is used for analyses.

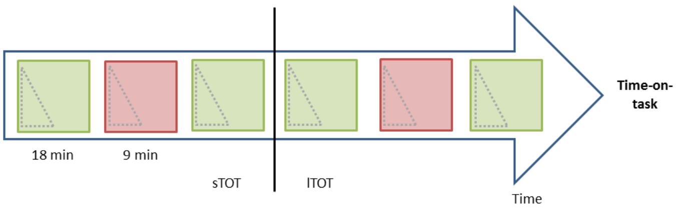

Fig. 2. Time course of the experiment. The red blocks are the ones used for analyses.

2.2. Data acquisition and pre-processing

Mental fatigue manipulation was confirmed thanks to behavioral and subjective measures. Participants' reaction times (RTs) and accuracy were recorded, as well as their answers to a mental fatigue questionnaire (Karolinska Sleepiness Scale) before, in the middle and at the end of the experiment. In addition, we recorded participants' EEG activity using a BrainAmpTM system (Brain Products, Inc.) and an Acticap® equipped with 32 Ag-AgCl active electrodes that were positioned according to the 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 and re-referenced to a common average reference.

Time segments of 800 ms of signal were then selected at a specific time during the trial (circled on Fig. 1). This epoching step was performed to only analyze time segments in which participants were loaded and had not yet performed the recognition task. This way, we avoided analyzing neural correlates associated with memory-encoding and memory-scanning processes. A total of 160 epochs was selected for each subject, 80 from the beginning of the experiment (figure 2, block n°2). They were labeled sTOT for short time-on-task. The remaining 80 were selected from the end of the experiment (figure 2, block n°5). They were labeled lTOT for long time-on-task.

3. METHOD

Each epoch, named *X*, is a 32 channels x 400 samples EEG data matrix. First, X is EOG de-noised by applying the blind source separation algorithm SOBI as detailed below (Belouchrani et al., 1997). The EEG signal is written as the instantaneous linear combination of source signals: $X=AS$ with *S*, the 32 x 400 matrix of source signals.

The 32 EEG signals are at first transformed into 32 sources:

$$S = W^T X \text{ with } W^T A \approx I_{32} \quad (1)$$

where *W* is the demixing matrix calculated with SOBI. This algorithm assumes stationary and uncorrelated sources for any time lag.

The 10 sources the most correlated with the EOG signal are selected as ocular sources and set to 0 prior to reconstructing the EEG signal.

$$X = (W^{-1})^T DS \quad (2)$$

where *D* is a diagonal matrix with binary diagonal elements where the corresponding index of the sources selected as ocular sources are set to 0 and the other sources set to 1.

After this denoising step, each epoch is filtered in the $\delta, \theta, \alpha,$, α_{low} , α_{high}, and β bands using a 5^{th} order

Butterworth filter. An epoch is therefore characterized by 6 matrices X_b, with b=δ, θ, α, β, α_{low} and α_{high}.

The classification chain is applied on epochs filtered in a given frequency band, X_b.

A learning set, S_L, is used to tune the signal processing chain:
Fifteen electrodes out of 32 are selected using the method proposed by Barachant and Bonnet, 2011. The electrodes are selected so as to maximize the discriminability between the two levels of mental fatigue, using the Riemanian distance between the covariance matrices of the two classes, estimated on S_L.

$$X_{b15} = T_{15} X_b \tag{3}$$

with T_{15}, a 15 x 32 matrix, composed of 0s and only one element equal to 1 in each row, localized on the column corresponding to the selected electrode.

Then, a common spatial pattern filter (CSP) is calculated using the filtered signals from the 15 selected electrodes (Blankertz et al, 2008).

$$Z_b = W_{CSP}{}^T X_{b15} \tag{4}$$

CSP filters are frequently used in BCI applications. The filtered signals Z_b are linear combinations of the original signals X_{b15} where specific weights are applied on the electrodes, to increase the discriminability of the signals in the two classes. The weighting matrix W_{CSP} is calculated so as to maximize the variance of the filtered signals in one class and minimize the variance in the other class.

$$W_{CSP} = \arg\max_W \frac{W^T \Sigma_s W}{W^T \Sigma_l W} \tag{5}$$

under the constraint:

$$W^T (\Sigma_l + \Sigma_s) W = I_{15} \tag{6}$$

Σ_s is the covariance matrix of the filtered signals in sTOT and Σ_l, the covariance of the filtered signals in lTOT. The solutions satisfy the equation:

$$\Sigma_1 W_{CSP} = \lambda^* \Sigma_2 W_{CSP} \tag{7}$$

which is solved by a General Eigenvalue Decomposition (GEVD). The eigenvectors form the columns of W_{CSP}.

3 pairs of filters (6 filters) corresponding to the 3 highest and the 3 lowest eigenvalues are selected.

$$Z_{bCSP} = [z_{b1} \quad \ldots \quad z_{b6}]^T = T_6\, W_{CSP}{}^T X_{b15} \tag{8}$$

with T_6, a 6 x 15 matrix, composed of zeros and only one element equal to 1 in each row, localized on the column corresponding to a selected filter.

The log variance of each of these signals is then computed and used as the feature vector:

$$F_b = [\log(\mathrm{var}(z_{b1})) \quad \ldots \quad \log(\mathrm{var}(z_{b6}))]^T \tag{9}$$

An FLDA classifier has been applied. The learning set is used to compute the coefficients (W_0, ω_0) of the separating hyper-plane:

$$W_o{}^T F_b - \omega_o = 0\,. \tag{10}$$

The coefficients are estimated so as to maximize the ratio of the variance between classes (inter-class variance) on the variance within classes (intra-class variance).

At the end of the learning phase, the following parameters are thus learned: T_{15}, W_{CSP}, T_6 W_o, ω_o

Each epoch, X_{bi}, from the validation set $\mathbf{S}_V$, is thus classified into the decision $D(X_{bi}) \in \{-1,1\}$, with -1 being the class lTOT, and +1 being the class sTOT, using the signal processing chain:

$$Z_{bCSPi} = T_6 W_{CSP}{}^T T_{15} X_{bi} \tag{11}$$

$$D(X_{bi}) = sign(W_o{}^T F_{bi} - \omega_o)$$

Classification is implemented in a subject-dependent way. For each subject, the 160 epochs are randomly split into 10 subsets of 16 epochs, formed of 8 epochs labeled sTOT and 8 epochs labeled lTOT. A random ten-fold cross validation process is applied. 9 subsets are grouped to form the learning set $\mathbf{S}_L$, and the remaining set forms the validation set $\mathbf{S}_V$, which is used to compute the classification accuracy. The global accuracy, obtained on the 10 subsets and averaged across participants, is the performance index.

4. RESULTS

Classification results with the BCI inspired signal processing chain

The results obtained by the signal processing chain are analyzed in the frequency bands: δ [< 4 Hz], θ[4-8 Hz], α[8-13 Hz] and β [13-30 Hz]. Additionally, as some authors report changes in the EEG activity in the lower α band when mental fatigue increases, α was also split in two bands: α low [8-10Hz] and α high [11-13 Hz].

The classification accuracy reached in average for the 20 subjects is presented in Table I. The numbers in coma express the standard deviation.

Frequency band	Mean (sd)
δ	0.61 (0.07)
θ	0.95 (0.05)
α	0.96 (0.03)
α low	0.81 (0.06)
α high	0.80 (0.05)
β	**1.00 (0.01)**

TABLE I Classification accuracy per frequency band obtained using our processing chain (average across participants).

The best performances are obtained with the β, α and θ bands, as was expected from the litterature. The performances are as high as 95% of correct classification for the θ and α bands and reach 100% for the β band. The discriminative capacity of the delta band is much lower with only 61% of accuracy, which shows that fatigue cannot be correctly detected using this band. Let us note that the very poor performances using the δ band could also be due to the length of 800ms chosen for the epochs, which is rather short for an accurate estimation of the δ waves. Splitting the α band in two bands results in a loss of performance of about 15% compared to the performances in the whole band. This can be explained by the fact that the two bands are too narrow and relevant information on fatigue may be distributed in the two bands or either one depending on the subject. On the contrary, the performances reached with the β band are optimal. The sole analysis of the changes in this band are sufficient to accurately detect mental fatigue. The standard deviation of 0.01, the lowest in all the bands, shows that optimal results of 100% are obtained for almost all of the subjects. The worst performance reached is 97% for one subject. The results obtained are much better than those reported in the litterature when fatigue is analysed on short segments (85% when the EEG is analysed on 1 second, King et al., 2006).

Classification results with a traditional signal processing chain

Results with absolute powers. In order to evaluate the improvement brought by our signal processing chain, we also analyzed the results obtained by a more traditional classification chain.

In this case, no CSP filter is applied on the band pass filtered data. Therefore, for a given frequency band, we used the same electrode selection as before (15 electrodes are selected using the method proposed by Barachant and Bonnet, 2011) on the training set $\mathbf{S}_L$. Then, for each electrode, the averaged power in the band is computed using the Welch periodogram. The relative power is also computed as the ratio of the average power in the band of interest divided by the average power in the [1-40Hz] band. Then, an FLDA classifier is trained on the $\mathbf{S}_L$. The feature vector is now composed of 15 features: the average power (or the relative power) of the 15 electrodes.

For each subject, the classification accuracy is computed as described in section 3, using a ten-fold cross validation.

The mean accuracy using the average power in each band, as well as the standard deviation obtained on the 20 subjects, are presented in Table II.

Frequency band	Mean (sd)
δ	0.74 (0.07)
θ	0.78 (0.09)
α	0.75 (0.08)
α low	0.73 (0.08)
α high	0.73 (0.07)
β	**0.84 (0.08)**

TABLE II Classification accuracy per frequency band obtained using a common processing chain with the average absolute power (average across participants).

The accuracy drops by about 15% for all the bands, except for the δ band. Indeed, the results for this band were very poor with the method proposed earlier in the paper. However, the length of the segments is too short to extract reliable information in this band, and no conclusion can be drawn from the results.

Let us note that not only is the accuracy decreased with the α, θ and β bands, but the standard deviation is also increased. This means that, contrary to the processing chain we proposed, the performances vary significantly from one subject to another.

The decrease in accuracy in the θ to β bands clearly shows the interest to introduce the CSP filter in the processing chain. It enhances information from various electrodes prior to extracting the frequency features. To our knowledge, it is the first time that a chain including both electrode selection and a CSP filter is used to detect mental fatigue.

When analyzing the discriminative power of each band, similar results are obtained: the β band gets the best results. In average, it enables 84% of the epochs to be correctly classified, while the use of the θ and α bands allows us to reach only 78% and 75%.

Results with relative powers. The results obtained using ratios of averaged powers, or what is usually called relative power, are presented in Table III.

The performances are significantly decreased compared to absolute power. The best performances are still reached with the beta band, but only 68% of the epochs are correctly classified, with an increased standard deviation of 0.09. This tends to show that the information on the signal energy, which is lost here when relative power is used, is informative to detect growing mental fatigue.

These results also show that mental fatigue is rather difficult to detect when traditional signal processing chains and features are used, even in a subject-dependent way (the chain is tuned and validated on the same subject). Performances with the beta band vary from 68% with relative power to 84% with averaged power. They increase to 100% with the signal processing chain that includes the CSP filter.

Frequency band	Mean (sd)
Ratio θ/α	0.58 (0.05)
δ relative	0.58 (0.05)
θ relative	0.65 (0.09)
α relative	0.63 (0.06)
β relative	**0.68 (0.09)**

TABLE III Classification accuracy per frequency band obtained using a common processing chain with the average relative power (average across participants).

Lastly, a multi-band classifier was tested. The processing chain proposed in section 3 was tuned for each frequency band. Then, the feature vectors $\mathbf{f}_i$ were merged to form an enlarged feature vector that feeds the FLDA classifier. Two band combinations were tried: merging of the alpha, theta and beta bands and merging of the delta, alpha low, alpha high, theta and beta bands.

The classification accuracy reached when 3 bands were used reached 99% (standard deviation 0.01) and 95% when 5 bands were used (standard deviation of 0.05). For every subject, the accuracy was lower when 5 bands were used compared to 3 bands. It even dropped to 85% for three subjects. Merging several bands thus decreased the classification accuracy, compared to using only the β band. The two classes are already perfectly well separated when only beta is used. Adding new features, and more especially features from the δ, α low and α high bands, whose discriminative power is lower, increases the representational space dimension, adds noise in the data and then spreads the classes.

5. CONCLUSION

A novel signal processing chain inspired from BCI computing was proposed to detect mental fatigue. The main innovation compared to more traditional signal processing chains is the introduction of a CSP filter that produces signals with improved discriminability between the two classes. Classification is carried out using the log variance of the filtered signals.

Optimal classification performances of 100% were obtained when the EEG signals filtered in the beta band were used. Performances in the θ and α bands were slightly lower, with 95% and 96% respectively. These results were compared with traditional signal processing chains, where the features used are either the averaged power or the relative power in given frequency bands, calculated on the same 15 selected electrodes. The performances computed on the same data set, using the same kind of classifier (FLDA), dropped by 15% for all frequency bands when the absolute power was used, and by 30% when the relative power was used.

Though the results obtained on 20 different subjects are excellent, the use of such a detector to monitor mental fatigue is impaired by its requiring a long training period. The results were obtained in a subject-dependent way. A training set that includes data recorded during short and long time-on-task is required for any new subject. The system ability to classify mental fatigue on the same subject using data recorded another day was not evaluated. Since CSP filters are known to be occasionally over fitting, one can expect the performances to decrease when the processing chain is applied on the same subject on another day.

Thus, the perspectives of this research are to adapt the method to a subject-independent use, in which classifiers learnt on a pool of subjects could be applied on a new one, for instance by means of regularized CSP filters (Lotte and Ghan, 2011). Furthermore, those processing chains should be compared for other mental states' assessment. Indeed, recent work demonstrates that workload could be evaluated by applying the same methodology, although interaction effects between mental fatigue and workload may appear (Roy et al., 2013)

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