EEG index for control operators' mental fatigue monitoring using interactions between brain regions

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A R T I C L E I N F O

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A B S T R A C T

Mental fatigue is a gradual and cumulative phenomenon induced by the time spent on a tedious but mentally demanding task, which is associated with a decrease in vigilance. It may be dangerous for operators controlling air traffic or monitoring plants. An index that estimates this state on-line from EEG signals recorded in 6 brain regions is proposed. It makes use of the Frobenius distance between the EEG spatial covariance matrices of each of the 6 regions calculated on 20 s epochs to a mean covariance matrix learned during an initial reference state. The index is automatically tuned from the learning set for each subject. Its performance is analyzed on data from a group of 15 subjects who performed for 90 min an experiment that modulates mental workload. It is shown that the index based on the alpha band is well correlated with an ocular index that measures external signs of mental fatigue and can accurately assess mental fatigue over long periods of time.

1. Introduction

Monitoring mental states using physiological signals has received more and more attention from researchers during the last years. Lots of articles were published on systems that detect drowsiness in drivers and, to a lesser extent, on systems that detect mental fatigue in operators. Drowsiness is defined as a state of impaired awareness associated with a desire or inclination to sleep whereas mental fatigue is a physiological state that arises when someone spends a long time on a tedious task or on a task requiring sustained attention, such as air traffic control or monitoring of nuclear plant. The consequence of mental fatigue is a difficulty to process incoming information in a fast and efficient way, which makes it a dangerous state for process operators. It was shown that the persons that spent a long time on a task were more prone to make errors and their reaction time was increased (Paus et al., 1997).

Physiological modifications can be observed when mental fatigue increases. The ocular activity is modulated. Blinks are more frequent and their duration is longer (Akerstedt & Gillberg, 1990). Several ocular recorded via (near) infra-red eye-tracking systems, high frame rate cameras or electro-oculography (EOG) were proposed in the literature and used as features to classify mental fatigue (Hu & Zheng, 2008; Hu & Zheng, 2009). One of the most efficient ocular features for estimating the mental fatigue is the perclos (percentage of eyelid closure), which increases with fatigue (Knipling, 1998). This feature was defined by Wierwille and Ellsworth, 1994. It measures the percentage of eyelid closure over the time. Mental fatigue is also known to alter the cerebral activity. 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]. An increase of activity in the alpha and theta bands predominantly in the parietal and central regions of the brain is generally observed when the subject is fatigued or tired, in association with a decrease in higher frequency bands (Akerstedt & Gillberg, 1990; Klimesch, 1999; Lal & Craig, 2002; Tanaka et al., 2012; Trejo, Kubitz, Roispal, Kochavi, & Montgomery, 2015).

Many research works were conducted recently to develop automatic systems to detect drowsiness or mental fatigue from EEG signals. Most often, spectral features are extracted from the EEG signals (or from linear combinations of the signals obtained by principal component analysis (Cao, Sun, Zhu, & Yan, 2010; Jung, Stensmo, & Sejnowski, 1997),

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independent component analysis (Lin et al., 2005) or sparse representation (Yu, Lu, Ouyang, Liu, & Lu, 2010), recorded with 1–32 electrodes, using either a Short Time Fast Fourier transform (Shi & Lu, 2013), a wavelet transform (Subasi, 2005; Khushaba, Kodagoda, Lal, & Dissanayake, 2011; Yu et al., 2010) or auto regressive models (Zhao, Zheng, Zhao, Tu, & Liu, 2011). Then, the features are merged into two to five levels of fatigue by a classifier. The most popular classifiers are Gaussian linear or quadratic classifiers (Ji, Li, Cao, & Wang, 2012; Rosipal, Peters, Kecklund, Akerstedt, Gruber, & Woertz, 2007), neural networks (Jung et al., 1997, Subasi, 2005) or kernel-based classifiers such as SVM (Cao et al., 2010; Shen, Li, Ong, Shi-Yun, & Wilder-Smith, 2008; Zhang et al., 2009; Zhang, Zheng, & Yu, 2009; Zhao et al., 2011). More recently, Roy, Charbonnier, & Bonnet, 2014 used a common spatial filter associated with a Fisher Linear Discriminant Analysis classifier. Some authors use a regression model to merge the features, which provides a continuous index of mental fatigue (Lin et al., 2005; Lin et al., 2008a, 2008b). Trejo et al., 2015 used a kernel partial least square decomposition combined with a linear regression classifier. The major drawback of these methods is the necessity to learn the models. Because of the large inter-subject variability, learning an inter-subject model that can fit any new individual is very difficult. The model must be learnt for each subject to be accurate. This requires a training session to be planned for any new individual before using the system, which is hardly practical for an everyday use. Indeed, the subject should reach advanced states of mental fatigue during the training session to allow the classifier to be trained on these classes.

To avoid learning a model, some papers propose indices calculated from EEG signals to estimate mental fatigue (Dasari, Shou, & Ding, 2013; Jap, Lal, Fischer, & Bekiaris, 2009), such as the ratio of slow waves to fast waves computed as the sum of the average power in α and θ divided by the average power in β, or the frequency of occurrence of alpha bursts (Borghini et al., 2012). But they do not quantitatively relate these indices to levels of mental fatigue. Lin et al. (2008a, 2008b) and Picot, Charbonnier, and Caplier, 2012 propose to analyze the driver's drowsiness by comparing the EEG signals measured on line to an initial state estimated at the beginning of a driving session. They both use the EEG power spectrum in the alpha and theta bands recorded with one electrode (Oz or P3). The first ones propose to calculate the Mahalanobis distance between a feature vector formed of the spectral power in 1 Hz bins of frequency in the alpha (4 bins) or theta band (5 bins) during an epoch to the same mean vector calculated during the initial state and show that this distance is correlated with fatigue. The second ones convert the proposed index into a classification in 2 classes: alert/drowsy.

In the same idea, this paper presents an indicator to monitor operators' mental fatigue. In this work, mental fatigue is defined as the gradual and cumulative process induced by the time spent on a tedious but mentally demanding task, which is associated with a decrease in vigilance. The indicator compares the EEG spectral content recorded on line with 32 electrodes to the EEG spectral content recorded in an initial state, when the subject is not fatigued. The EEG signals are averaged in 6 regions of interest (ROIs) and then filtered in a frequency band of interest. The mean spatial covariance of the filtered signals is computed from a short period at the beginning of the session, which forms the initial state. For the rest of the session, the Frobenius distance between the initial state mean covariance and the covariance calculated on 20 s sliding epochs is transformed into a mental fatigue index that varies between 0 and 1. The index performance is analyzed by comparison with an ocular index using the Perclos on a data set formed of EEG and EOG signals that were recorded from 15 subjects who underwent an experiment manipulating mental workload. During the experiment, the subjects had to keep their attention focused on a screen and perform a boring but mentally demanding task during one hour and a half. The EEG index is also compared to the participants' answers to a questionnaire evaluating their level of fatigue.

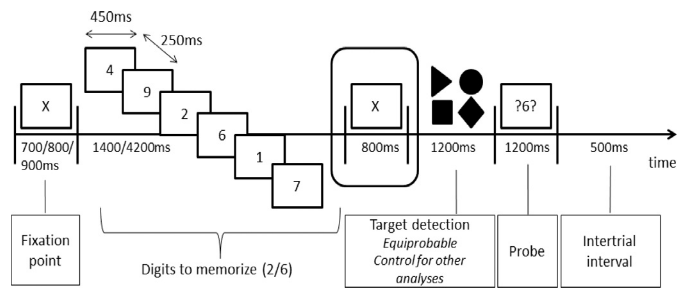

Fig. 1. Trial structure. Participants memorize a list of 2 or 6 digits, and answer whether the probe item was in the list.

The method is a self-tuned one, which can provide a mental fatigue index from a very short training period, recorded when the subject begins his/her task and is thus not mentally tired. The training is straight forward. It does not require any trial and errors to set tuning parameters. This is a major advantage compared to methods that use supervised classification methods such as neural networks, SVM or regression kernels. Those methods need to be trained on a learning set formed of examples of all the classes to recognize, which includes data gathered during a high mental fatigue state. The index that is provided is continuous and has a value between 0 and 1. It has a clear meaning, which allows its direct use to assess the subject's mental fatigue state, contrary to methods that provide a ratio of averaged powers or a distance that still have to be related to the subject's mental fatigue.

The paper is organized as follows. The experimental design and the data used to evaluate the performances of the index are described in Section 2. The method to produce the index is detailed in Section 3. Results are presented in Section 4 and discussed in Section 5.

2. Material

2.1. Ethic statement

This research was promoted by Grenoble's clinical research direction (France) and was approved by the French ethics committee (ID number: 2012-A00826-37) and the French health safety agency (B120921-30). It was conducted according to the principles expressed in the Helsinki Declaration.

2.2. Participants

Fifteen healthy volunteers performed the experiment (25 years old $\pm$ 3.5 years; 9 females). They were right handed, had normal or corrected-to-normal vision, had no neurological or psychiatric disorders, nor were they under any medication. They signed a written consent and received an 80-euro compensation. They were asked to have a normal amount of sleep the day before the experiment to avoid sleep deprivation.

2.3. Experiment

The experiment consisted of 750 consecutive trials. A trial lasted 7.3 s in average. For each trial, the participant 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 participant had to answer as quickly and as accurately as possible whether the probe was present or not in

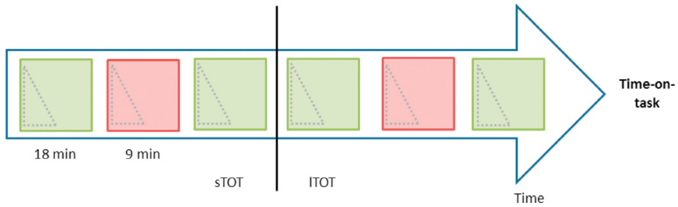

Fig. 2. Time course of the experiment.

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-min. blocks and four 18-min. blocks were performed, for a total of 90 min. of recording (Fig. 2). The participants were allowed short breaks of 5 min between blocks. At the end of the session, each participant had achieved 750 trials, 375 in low and 375 under high workload conditions, presented in a random order. Given that the task was repetitive, boring but mentally engaging, mental fatigue was supposed to increase with time-on-task. This was confirmed thanks to behavioral and subjective measures. The participants had to assess their mental fatigue using Karolinska Sleepiness Scale (Akerstedt & Gillbert, 1990) before, in the middle and at the end of the experiment. Their subjective answers, as well as an increase in reaction times and a decrease in accuracy, showed that the participants felt increasingly tired.

2.4. Data acquisition and pre-processing

Participants' EEG activity was recorded using a BrainAmp™ 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 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.

3. Method

3.1. Preprocessing

Let $\mathbf{X} \in \mathbb{R}^{32\times 10{,}000}$ be a 20-s EEG epoch. First, ocular artefacts are removed by applying the blind source separation algorithm SOBI (Belouchrani, Abed-Meraim, Cardoso, & Moulines, 1997). The EEG signal is written as the instantaneous linear combination of source signals: $\mathbf{X} = \mathbf{AS}$ with $\mathbf{S} \in \mathbb{R}^{32\times 10{,}000}$, the matrix of source signals.

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

$$\mathbf{S} = \mathbf{W}^{\mathbf{T}}\mathbf{X} \text{ with } \mathbf{W}^{\mathbf{T}}\mathbf{A} \approx \mathbf{I}_{32} \tag{1}$$

where $\mathbf{W}$ 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 then selected as ocular sources and set to 0 prior to reconstructing the EEG signal.

$$\tilde{\boldsymbol{X}} = \mathbf{W}^{-\mathbf{T}}\mathbf{DS} \tag{2}$$

where $\mathbf{D}$ 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 theta, alpha, and beta bands using a 5th order Butterworth filter. The EEG signals are further averaged in six regions of interest (ROIs), which are displayed Fig. 3:

Thus, each epoch $\breve{\mathbf{X}}$ is transformed into a $6 \times 10{,}000$ epoch formed of 6 signals filtered in the b band. For implementation purposes, each epoch is further split into 2-second epochs $\mathbf{X}_{bi}$ (6×1000) where b stands for θ, α or β.

3.2. Creation of the initial reference state

Let T be a period of time when the subject is not tired. It forms the learning period and it is composed of N_L 2 s epochs $\mathbf{X}_{bi}$ which contain 6 zero mean signals.

The covariance of the signals in each epoch is calculated by:

$$\Sigma_i = \frac{1}{1000}\mathbf{X}_{bi}\mathbf{X}_{bi}{}^{T} \tag{3}$$

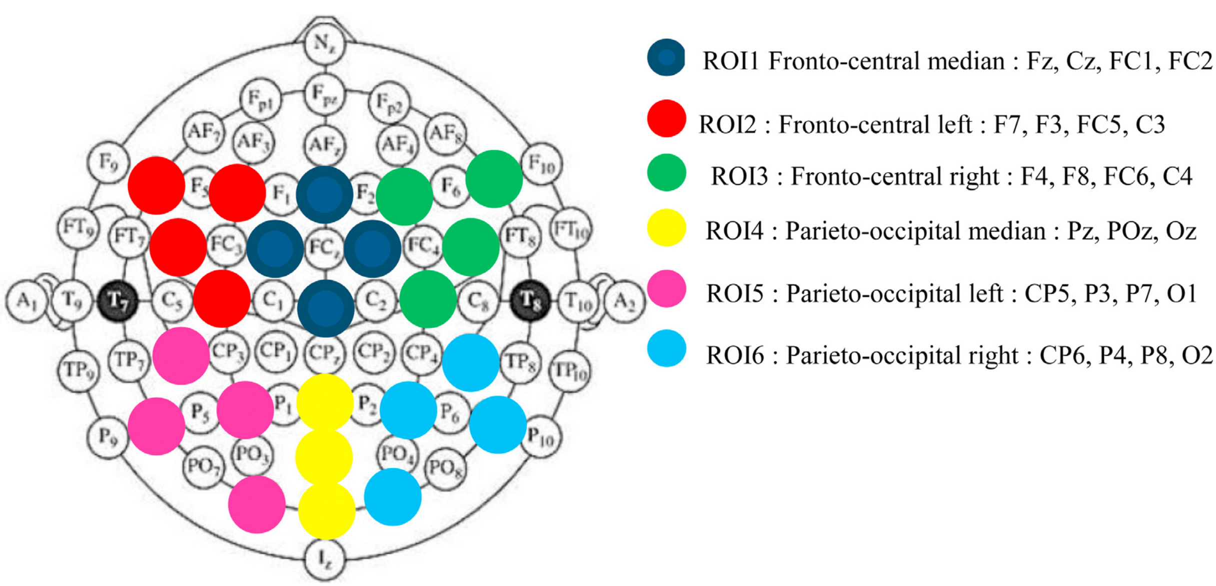

Fig. 3. Regions of interest (ROIs).

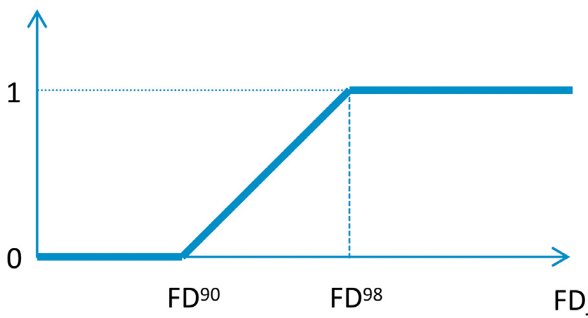

Fig. 4. Transformation of FDj into a fatigue index.

The mean covariance during the learning period is:

$$\Sigma^L = \frac{1}{N_L}\sum_{k=1}^{N_L}\Sigma_k \tag{4}$$

And the covariance of the signals during a 20 s epochs is:

$$\Sigma l_j = \frac{1}{10}\sum_{k=j-9}^{j}\Sigma_k \tag{5}$$

The Frobenius distance between $\Sigma^L$and Σl_j is calculated as:

$$FD_{\mathrm{j}} = \left\|\Sigma^L - \Sigma l_j\right\|_F = (trace\left[(\Sigma^L - \Sigma l_j)(\Sigma^L - \Sigma l_j)^T\right])^{\frac{1}{2}} \tag{6}$$

$N = \frac{N_L}{10}$ Frobenius distances can be computed from 20 snon-overlapping epochs during the learning period. The empirical distribution of these N values FD_{j} is computed. Let us note FD^{90} the 90th percentile and FD^{98} the 98th percentile of the distribution.

3.3. Mental fatigue index

The mental fatigue index makes use of the Frobenius distance between Σ^L and the covariance Σl_j calculated during a 20 s epoch. The distance FD_{j} is compared to the empirical distribution estimated during the learning period using the function presented in Fig. 4.

If FD_{j} is below the 90th percentile, the index is equal to 0. Its meaning is that the distance calculated is in the same range as the distances measured during the learning set. If FD_{j} is above the 98th percentile, the index is 1, which means that the distance is significantly higher (and thus the covariance matrix is significantly different) than what was measured during the learning set. For a gradual change of the fatigue index, any value of FD_{j}between FD^{90} and FD^{98} gets a value between 0 and 1. The 98th percentile is chosen because it is an estimate of the highest value reached by the distance during the learning state, more robust to outliers than the maximum. The 90th percentile is chosen because it gives a fair assessment of the distance highest values without being too close to the 98th percentile. It thus limits the index switches between 0 and 1 and allows the index to change gradually.

For an on-line implementation, the mental fatigue index is computed on a sliding window with an overlap of 2 s. A current epoch X of 20 s is recorded, preprocessed as in 3.1 and split in 2 s epochs. The index is calculated backward, every 2 s, from 2 s after the beginning of X until the current time, using the 2 s epochs calculated on the previous epoch X and on the current one.

4. Results

As explained in 2.3, each experiment lasts for 90 min and is split into 6 different blocks of 9 or 18 min separated by a short break. The learning set is formed of the last 15 min of block 1. The first 3 min are removed to avoid transitory effects due to the participant's getting used to the task. Therefore, a total of 45 epochs is available to learn the empirical distribution ofFD_{j}. The 98th percentile is close to the second highest value of FD_{j}.

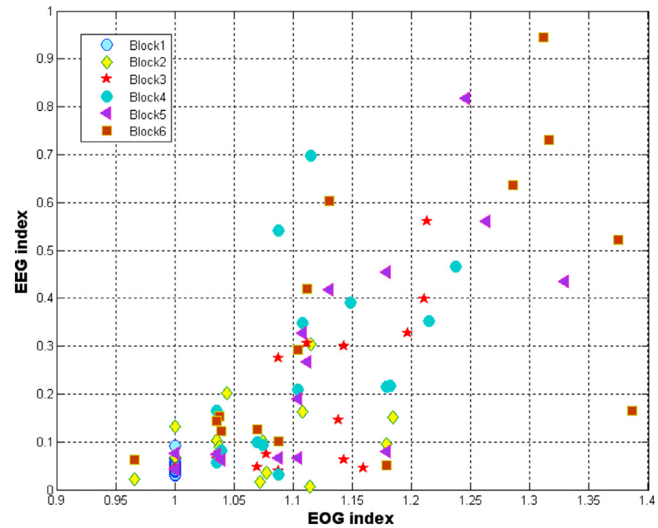

Fig. 5. Mean value per block of the EEG index using signals filtered in the alpha band in function of the mean value of the EOG index, for the 15 subjects.

4.1. Comparison with an EOG index

The EEG index is compared to an EOG index calculated per subject and per block. For each subject, blinks are extracted from the vertical EOG signal and the percentage of closure (Perclos) is calculated for each blink (Wierwille, 1994). The mean value of the Perclos is calculated for each of the 6 blocks. The ratio between the mean value in each block on the mean value in the first block is calculated. This ratio is calculated so as to have comparable measures between subjects. It measures the evolution of the Perclos compared to the first block, in percentage.

The mean value of the EEG index is calculated for each subject and each block. The correlation between the EEG index and the EOG index is calculated using the 90 values obtained (6 blocks, 15 subjects). Fig. 5 displays the EOG index in function of the EEG index using signals filtered in the alpha band.

The EOG index is higher than 1 from block 2 to blocks 6 for all the blocks of the 15 subjects except for 2 blocks where it decreased below 1. This confirms the fact that mental fatigue globally increased during the experiment, since the Perclos increases. Fig. 5 shows that an increase in the EOG index is associated with an increase in the EEG index and that the increase is higher in blocks 4–6.

The correlation reaches 0.71 when the signals are filtered in the alpha band. However, it decreases to 0.47 when the signals are filtered in the theta band and to 0.35 when the signals are filtered in the beta band. This is consistent with the results reported in the literature where changes in the alpha band, and in a lesser extent in the theta band, were observed when mental fatigue increased. Various combinations of the theta and alpha indices were tried : the mean, the maximal or the minimal value of the two indices. The highest performance was obtained using the mean. The correlation with the EOG index reached 0.69, which is slightly lower than the correlation value obtained with the alpha index.

Fig. 6 displays the EEG index in the 3 bands for one subject. The green marks show the beginning and end of each block. One can see the increase of the alpha EEG index in function of the time spent on the task. An increase in the theta band can also be seen

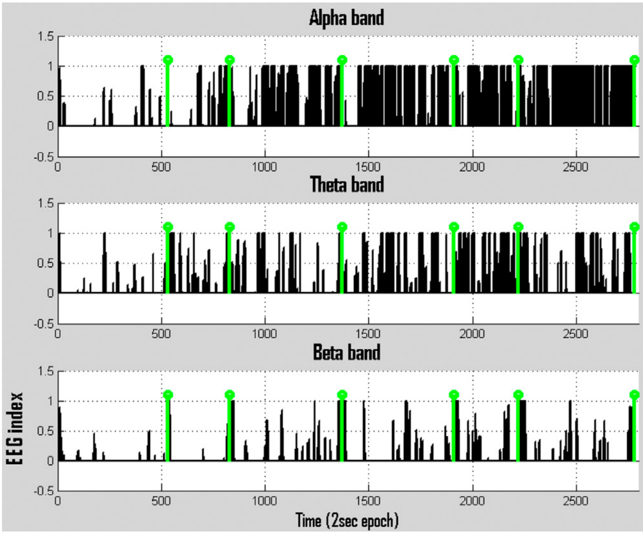

Fig. 6. Time evolution of the EEG index in the alpha, theta and beta bands, for one subject.

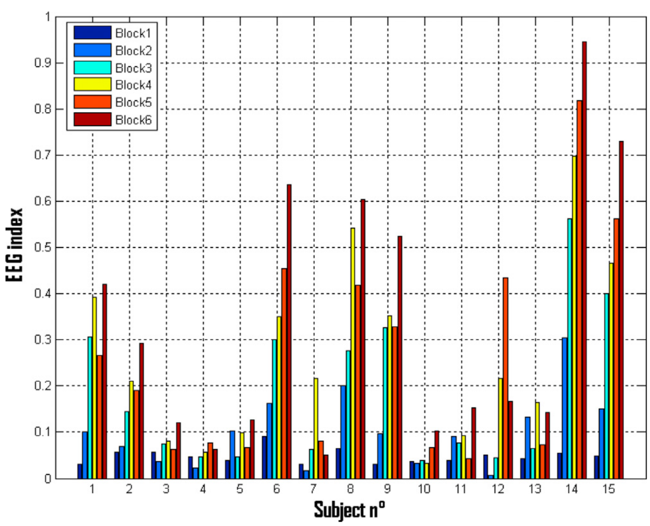

Fig. 7. Mean value EEG index per block, for the 15 subjects.

when the time on task increases but in a lesser extent than in the alpha band. On the other hand, no gradual increase nor decrease is observed in the beta band.

4.2. Analysis of the index in the alpha band

Results in the alpha band are now further analyzed. Fig. 7 displays the averaged value of the EEG index in each block, for each subject. One can see that a group of 7 subjects seems to get increasingly tired, with an EEG index higher than 0.4 (which means that more than 40% of the epochs forming the block are different from the learning set), while the rest seems to be unaffected by the time spent on the task.

The subjects are now separated in two groups: the group with an index higher than 0.4 in the last block (6 subjects) and the others (9 subjects). For these two groups, the value of the EOG index in the last block as well as the difference between the KSS score at the end and at the beginning of the experiment are displayed in a boxplot in Fig. 8. The variation of the KSS score and the value of the EOG index are higher in the group with an index above 0.4. This shows that the group with a higher EEG index does exhibit

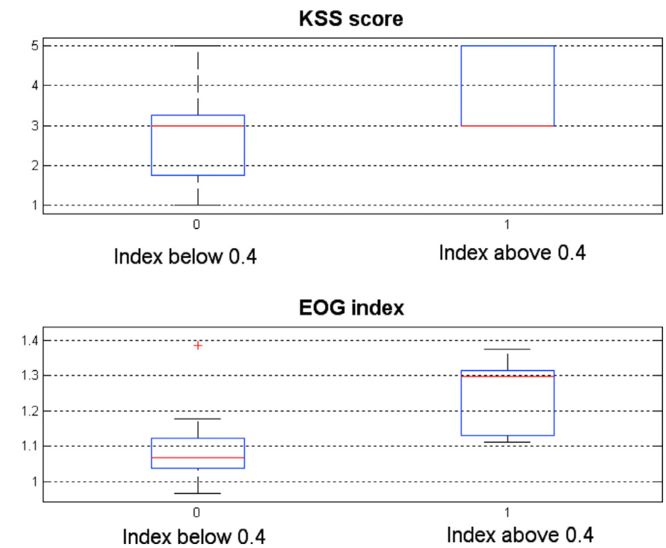

Fig. 8. Boxplot of the EOG index and the variation of the KSS score for the 2 groups of subjects.

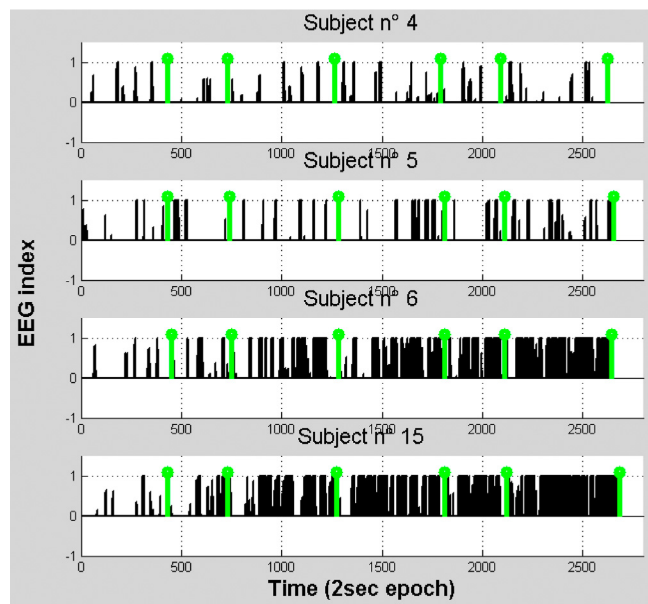

Fig. 9. Time evolution of the EEG index in the alpha band for subjects no. 4, 5, 6 and 15.

external signs of mental fatigue associated with a subjective perception of fatigue.

4.3. Analysis of 4 subjects representative of the two groups

In what follows, the EEG indices of 4 subjects representative of their group (2 from the first group - n°4 and 5, 2 from the second group - n°6 and 15) are further analyzed. Their evolutions in time are displayed in Fig. 9. The 4 subjects exhibit two very distinct behaviors. The EEG indices of the first 2 subjects do not increase in time. They remain equal to 0 except for brief periods of times. On the other hand, the indices of the last two increase with the time spent on the task. Once the index has reached a high value, it remains globally high except when the subject stops for a short break. The index gets shortly back to 0 just after the break before increasing again. Moreover, the longer the time spent on the task, the shorter the effect of the break. The variation of the KSS score

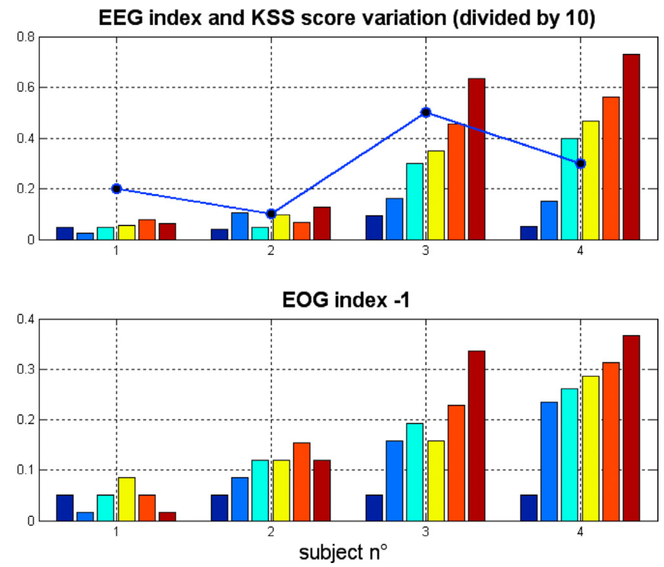

Fig. 10. EEG index per block, KSS variation (divided by 10; blue line) and EOG index minus 1 per block for subjects 4, 5, 6 and 15. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

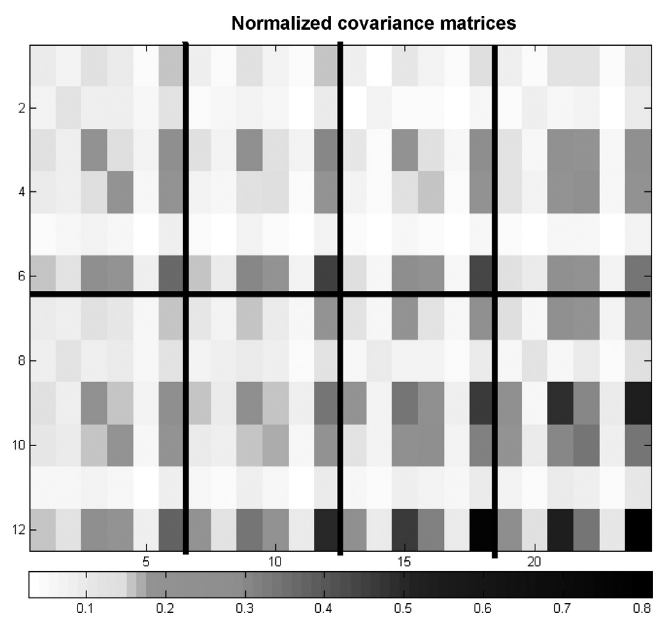

Fig. 11. Normalized mean covariance matrices in block 1 and block 6 for subjects no. 4, 5, 6 and 15.

and the EOG index displayed in Fig. 10 confirms the evolution towards a fatigue state for the last two subjects.

To analyze the changes that occurred in the EEG signals for these 4 subjects, the mean covariance matrices in block 1 and in block 6 are analyzed. The trace of the covariance matrix divided by the number of ROIs provides information on the global energy of the EEG signals. It is equal to 5.7, 3, 0.86 and 10.4 μV^2 for subjects 4, 5, 6 and 15 in block 1 and to 6, 3.5, 1.4, and 20.1 μV^2 in block 6. One can see that they are very different from one subject to another and cannot be directly compared. An inter-subject classifier able to detect mental fatigue for any subject will get poor results on these subjects. It shows the necessity to learn a classifier for any new subject or, as proposed in this paper, to analyze the evolution of the EEG signals from an initial state. Fig. 11 displays the covariance matrices for these 4 subjects as a unique image. The lines from 1 to 6 correspond to the matrices in block 1, the lines from 7 to 12 to the matrices in block 6. Subjects 4, 5, 6 and 15 are displayed in columns. The columns from 1 to 6 are the matrices of subject 4, then columns 7 to 12 are the matrices of subject 5 and so on. All the matrices are normalized by dividing each matrix of one subject by the trace of the covariance in block 1 of the same subject.

One can see almost no changes between block1 and block 6 for subjects 4 and 5. For subjects 6 and 15, the changes can be seen mostly in ROIs 3 (Fronto-central right), 4 and 6 (Parieto-occipital median and right). The variance in the alpha band increases in the 3 ROIS, as well as their covariance. The covariance with ROI 1 (Fronto-central median) also increases. On the other hand, ROIs 2 (Fronto-central left) and 5 (Parieto-occipital left) seem unaltered.

5. Discussion

A method to monitor operators' mental fatigue is proposed. The method analyzes the evolution of the current covariance matrix, calculated using a 20 s epoch and 6 different ROIs, from the mean covariance learned at the beginning of the session, when the subject is assumed not to be fatigued. The statistical distribution of the distance between the mean covariance of the learning set and the covariance calculated from 20 s epochs is learned and used to transform the distance into a binary index. For this index, 1 means that the distance currently measured is significantly different (higher than the 98th percentile) from what was observed during the learning set while 0 means that it is similar. The analysis of the mean covariance matrices in block 1 for 4 subjects shows that the covariance matrix in the initial state is very different for each individual. However, the computation of a deviation from an original state makes it possible to overcome this inter-individual variability issue. All the information required to calculate the fatigue index is gathered at the beginning of the session: the mean spatial covariance matrix, which provides information on the energy of the signals in each ROI as well as their interaction, and the variations of the covariance matrix during the initial state. The parameters that convert the distance into a fatigue index (the 90th and 98th percentiles of the distance) are tuned for each subject in an automatic way, without any assumption on the distance distribution function.

The on-line implementation of the index is rather easy. EEG is recorded during 20 s, de-noised and filtered, then split in 2 s epochs. The mean covariance can be calculated at the end of the learning period as well as the distance distribution function and the 2 percentiles that tune the conversion of the distance into an index. Then, the covariance on the next 20 s epochs can be calculated every 2 s using two consecutive 20 s epochs when the sliding window overlaps two epochs. Thus, the index is calculated every 2 s but updated every 20 s.

Epochs of 20 s were chosen in concordance with the literature. Moreover, considering the experiment's design, in which mental workload varies a lot over short periods of time, 20 s ensure that the EEG variations due to changes in workload are smoothed out.

In this paper, the EEG indicator was compared to an external sign of mental fatigue, the Perclos, calculated using the EOG, to evaluate its performance. The Perclos is known to be well correlated with fatigue (Wierwille & Ellsworth, 1994). The KSS score variation was also used to analyze the performances of the EEG indicator. Another common way to evaluate a subject's fatigue state is to use the behavior parameters. In this study, both the accuracy and the reaction time were measured. However, though some significant differences were observed at the group level between reaction times and accuracies in the block 2 and the block 5, no correlation was obtained between changes in Perclos and changes in accuracies or reaction times per block, for the different subjects. No correlation between the EEG indicator and the behavior parameters was observed either. This may be because the task was rather simple and could still be achieved with acceptable performances, even when the subjects were tired. The same observation was made by Trejo et al., 2015 who conducted a rather similar experiment.

The results showed that the EEG index based on the alpha band was significantly correlated with changes in Perclos. Also, 6 subjects out of 15 seemed to be increasingly tired, with an index gradually changing from 0 to 1 with increasing time-on-task. The other subjects' index remained globally close to 0, with only very short periods when the index reached 1. Using KSS questionnaires, these subjects reported to feel globally less tired than the other 6. The proposed index is not meant to be used as an instant indicator of fatigue that would raise an alarm whenever it gets higher than 1. Indeed, sudden changes in the covariance matrix can be observed even in the initial state though they are not related to increased fatigue. Mental fatigue is seen as a gradual and cumulative process induced by time on task. A high index can be seen as fatigue only if it remains high for some time. Therefore, the index mean value computed over a period of time can give an overall assessment of fatigue. In the case of these experiments, it can inform us on which participant is still fit to perform the task at the end of each block. In the same idea, its mean value during periods of, say, 10–15 min could be used to assess the global fatigue state of an operator who has to concentrate on information displayed on a screen and to decide if it is time for him/her to have a break. In the same idea as Trejo et al., 2015, the evolution of the subjects toward the fatigued state can be observed over time. However, contrary to Trejo et al., the index is not a regression index learnt from data gathered at the beginning and at the end of the session but it measures a statistical deviation from the initial not fatigued state. The refreshing effect of the breaks can be observed on the time evolution of the index. Indeed, for subjects who feel tired at the end of the session (reported by KSS questionnaire), the index gets back to 0 during the period following the break. It was also observed that the freshening effect of the break diminished over time with the subject becoming tired more quickly.

The fact that the index makes use of the covariance matrix of EEG signals recorded at 6 different locations on the scalp is quite innovative as it makes it rather sensitive to changes in interactions in brain regions. Indeed, covariance can be seen as a simple connectivity measure. The index is not only sensitive to changes in the EEG energy in the alpha band (the diagonal terms of the covariance matrix) but also to the changes in the interrelationship between the signals measured in the ROIs. The ROIs were selected to cover all the areas of the scalp. For the 4 subjects that were further analyzed, the main changes are observed in ROI1 (Fronto-central median), ROI3 (Fronto-central right), ROI4 (Parieto-occipital median) and ROI6 (Parieto-occipital right). The variance of EEG in ROI3, ROI4 and ROI6 globally increases as well as their covariance. The variance of ROI1 (Fronto-central median) does not increase much but its covariance with ROI3, ROI4 and ROI6 increases. Globally, this means that, as expected from the literature, alpha activity from fronto-central and parieto-occipital sites is a good indicator of one's mental fatigue state in a general manner. Yet here only median and right electrode sites seem really relevant. But most importantly, this study shows that not only is alpha activity relevant at the electrode site level, it is also a good marker for mental state estimation based on inter-electrode connectivity.

This paper showed that it is possible to assess mental fatigue using EEG signals. Ocular indices are another efficient way to assess fatigue. They are well correlated with fatigue (Hu & Zheng, 2009) and are used as a reference in this paper. The extraction of ocular indices can be done through EOG signals. However, this requires for the operator to wear EOG electrodes near his eyes, which can be very uncomfortable and can impair her/his performance. Ocular signals can be also extracted using high frame cameras Picot, Charbonnier, Caplier, and Vu, 2012. However, with a frame rate of 30 fpm, standard cameras record about 5 frames during a standard blink (duration about 15 ms) and may provide only a very inaccurate estimation of the blink duration. In addition, high frame rate cameras are expensive, which makes this solution less competitive. The advantage of using EEG signals is that an accurate fatigue indicator can be calculated at a low cost. The new technology that is now emerging to record EEG in a friendly way, such as EEG headsets (like the Emotiv headset for instance) or caps, makes it possible to imagine a system that would monitor operators' mental fatigue using EEG analysis during long periods of operation. Moreover, the wealth of information provided by EEG signals makes it possible to combine the indicator proposed with indicators estimating other mental states, such as workload levels (Roy, Bonnet, Charbonnier, Campagne, & Jallon, 2015) to have a global assessment of the operator's ability to fulfill her/his mission.

6. Conclusion

In this paper, an on-line innovative EEG index is proposed to assess operators' mental fatigue over long periods of time. It uses the EEG signals recorded from 24 electrodes merged into 6 regions of interest. The index measures the deviation of the spatial covariance matrix calculated on 20 s from a mean spatial covariance matrix learned during an initial state. It is automatically tuned using the 90th and 98th percentiles of the distance distribution calculated during the initial state. The index performance was analyzed on a group of 15 subjects who performed a tedious but mentally demanding task on a computer during 90 min. The index was compared with an ocular index measuring the external signs of mental fatigue as well as with the subject's fatigue evaluation using the Karolinska Sleepiness Scale. It was shown that it can be used based on the alpha activity to make an efficient assessment of an operator's mental fatigue state. The correlation with the ocular index was as high as 0.7.

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