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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.

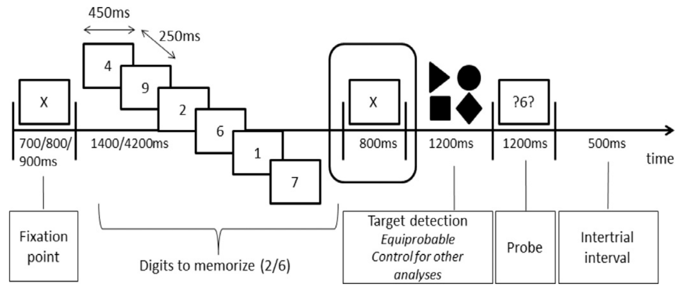

Fig. 1. Trial structure. Participants memorize a list of 2 or 6 digits, and answer whether the probe item was in the list.

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