Biomedical Signal Processing and Control 14 (2014) 256–264

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Eye blink characterization from frontal EEG electrodes using source separation and pattern recognition algorithms

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ARTICLE INFO

Article history:
Received 17 February 2014
Received in revised form 2 July 2014
Accepted 11 August 2014
Available online 6 September 2014

Keywords:
Blink detection
Blink characterization
EEG
Source separation
Maximum likelihood classifier
Mental fatigue

ABSTRACT

Due to its major safety applications, including safe driving, mental fatigue estimation is a rapidly growing research topic in the engineering field. Most current mental fatigue monitoring systems analyze brain activity through electro-encephalography (EEG). Yet eye blink analysis can also be added to help characterize fatigue states. It usually requires the use of additional devices, such as EOG electrodes, uncomfortable to wear, or more expensive eye trackers. However, in this article, a method is proposed to evaluate eye blink parameters using frontal EEG electrodes only. EEG signals, which are generally corrupted by ocular artifacts, are decomposed into sources by means of a source separation algorithm. Sources are then automatically classified into ocular or non-ocular sources using temporal, spatial and frequency features. The selected ocular source is back propagated in the signal space and used to localize blinks by means of an adaptive threshold, and then to characterize detected blinks. The method, validated on 11 different subjects, does not require any prior tuning when applied to a new subject, which makes it subject-independent. The vertical EOG signal was recorded during an experiment lasting 90 min in which the participants' mental fatigue increased. The blinks extracted from this signal were compared to those extracted using frontal EEG electrodes. Very good performances were obtained with a true detection rate of 89% and a false alarm rate of 3%. The correlation between the blink parameters extracted from both recording modalities was 0.81 in average.

1. Introduction

During the realization of monotonous and repetitive tasks, mental fatigue, or reduced alertness, arises with growing time-on-task (TOT). This is a gradual and cumulative process that leads to shallow or even impaired information processing and can therefore result in a significant decrease in performance [13]. It can even produce major, life-threatening accidents when operators are driving, dealing with heavy machinery or carrying out security procedures.

Several fatigue level physiological markers have been used by monitoring systems. Amongst them are indices of cerebral activity, such as band power features recorded via electro-encephalography (EEG), which are early indicators of fatigue. Indices of ocular activity, such as spontaneous eye blink parameters, recorded via (near) infra-red eye-tracking systems or electro-oculography (EOG) are also useful for characterizing mental fatigue or drowsiness states [17]. Especially, eye blinks are well known indicators of arousal and cognitive state [19,13,2,6]. Indeed, their frequency, duration, amplitude, closing or opening duration and speed parameters are subject to fluctuations depending on the operator's mental fatigue level [9,20]. All those measures of eye blink characteristics can be performed using EOG, a technique that records variations in electric potential that arise from eye movements [5,8]. In order to record vertical eye movements, such as eye blinks, two electrodes can be placed, respectively, above and below one eye. Although very efficient, this technique raises some difficulties for the subjects. Indeed, the use of sensors placed over the face can reduce the operators' visual field, which can therefore lead to poorer performances. Moreover, EOG electrodes can be uncomfortable to wear, and it seems unreasonable to expect people to wear them on a daily basis. Another solution to monitor eye blink activity is the use of an eye tracker. However this requires purchasing the device. This can be a costly solution if several operators were to be equipped with a mental fatigue monitoring device.

The solution that is proposed in this paper is the use of scalp electrodes, namely EEG electrodes, to record at once both cerebral and ocular activities, without the need for any other device. A new method for eye blink detection and characterization that

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http://dx.doi.org/10.1016/j.bspc.2014.08.007
1746-8094/

could be applied for mental fatigue monitoring is proposed. This method is based on signal recorded from frontal and fronto-central EEG electrodes, and includes signal processing steps such as source separation, source classification, reconstruction of the ocular signal in the sensor space, and extraction of several eye blink parameters.

Since most EEG studies only concentrate on cerebral activity, they usually consider EEG-recorded ocular activity as noise. In consequence, a huge proportion of the EEG literature focuses on how to rid EEG data of those artifacts [12,14]. The earliest publications concerned off-line analyses, but there is an increasing number of published works relating to online denoising systems [15], and even dedicated chips [22]. Several authors perform source separation in order to denoise their EEG data. Thus, [23] carry out their source separation step using the Second-Order Blind Identification algorithm (SOBI; [3]), and then extract four features on 10-s time segments to classify sources into cerebral and artifactual ones using Support Vector Machines (SVMs). However, some of their features are computed with the use of a reference EOG signal. Therefore, they propose a method which is not completely EEG-based. As for [11], they perform their source separation using an independent component analysis (ICA). Then, they decide for each 3-s time segment whether a source is artifactual or not using the number of maxima and thresholds. Their method includes normalization before the segmentation step, which seems unrealistic in a real-time application. Lastly, [25,26] also perform an ICA. However they use only one feature on 5-s time segments, namely entropy, to perform their identification of artifactual sources.

On top of their specific limitations, all those methods are focused on an EEG denoising application. However, in this paper's application, removing ocular activity from the EEG data is considered a loss of information. A few authors have published work related to actually using this information. Hence, [21] detect the presence of eye blinks in the EEG data using SVM in order to allow subjects to control a wheelchair. Here, the blinks are just detected, but not characterized. Along the same lines, [16] detect horizontal eye movements from electrodes placed on the forehead in order to pilot a robot. Ref. [24] estimate glance from EEG to allow cursor control by avoiding high-pass frequency filtering which is usually performed on the EOG signal to remove the long-term drift. Therefore, they also use generally removed ocular information present in the EEG signal. Thus, those articles introduce work aimed at using EEG-recorded ocular activity for motor-control applications.

The ocular activity can also be used to monitor an operator's mental state, such as its mental fatigue level. Still, to the best of our knowledge, only two research teams have studied the use of ocular activity recorded on the scalp for mental state monitoring. Ref. [7] have recently published work that includes measuring the eye blink rate computed from EEG via an ICA, in order to estimate several mental states. However, they do not provide the reader with their method, and they only perform a basic blink rate extraction and do not characterize the blinks. Ref. [1] propose a system placed on the forehead that allows for both cerebral and ocular activities' measurement. This system is intended to monitor one's drowsiness by detecting eye blinks along with power spectral measures. However, they do not detail their method as for blink characterization and parameters exploitation, and their system includes a driven right leg (DRL) circuit, which is not realistic for a daily living application.

In this paper, a new method to extract and characterize blink activity from EEG signals usually used to monitor cerebral activity is first detailed. The validation process used to evaluate the performances is then presented. And finally, the results obtained on data from 11 different subjects undergoing an experiment where mental fatigue increases are analyzed and discussed.

2. Blink detection and characterization method

In order to detect and characterize the eye blinks using only the EEG signal, several processing steps are performed. First, the signal is split into epochs, from which a source separation step is performed and a supervised classifier is used to identify ocular sources. Then, the data are back projected in the sensor space in order to execute blink segmentation. Lastly, blink characterization is executed. The operational mode for blink detection is illustrated in Fig. 1.

2.1. Source separation

The EEG signal at time instant t is often written as the instantaneous linear combination of source signals:

$$\mathbf{x}(t) = \sum_{i=1}^{N_s} \mathbf{a}_i s_i(t) + \mathbf{n}(t) = \mathbf{A}\mathbf{s}(t) + \mathbf{n}(t) \tag{1}$$

where N_s is the number of sources, that coincides usually with the number of electrodes $N_s = N_e$, so the unknown mixing matrix $\mathbf{A}$ is square. $\mathbf{n}$ is some additive noise. By considering an epoch of time, (1) can be written in matrix form using $\mathbf{X} = \mathbf{AS} + \mathbf{N}$ where $\mathbf{X} = [\mathbf{x}_1 \ldots \mathbf{x}_{N_e}]^T$ is a $N_e \times N_t$ EEG data matrix and $\mathbf{S} = [\mathbf{s}_1 \ldots \mathbf{s}_{N_e}]^T$ is a $N_e \times N_t$ source data matrix. The ith column of $\mathbf{A}$, denoted $\mathbf{a}_i$, is the spatial pattern of the ith source. The sources are estimated using the relation:

$$\mathbf{s}(t) = \mathbf{W}^T \mathbf{x}(t) \tag{2}$$

where $\mathbf{W}^T \mathbf{A} \approx \mathbf{I}_{N_e}$.

The ith column of $\mathbf{W}$, denoted $\mathbf{w}_i$, is called a spatial filter: the ith source waveform is then extracted as a linear combination of electrode channels.

In order to perform the source separation step, we selected a common second-order statistic algorithm, the SOBI algorithm, for its robustness to outliers and its efficiency on short time intervals [10]. It is applied on 20-s epochs of EEG signal recorded from 11 frontal electrodes, with a sampling period T_e. The signals are initially filtered in the (0.5–40 Hz) band using a fifth order Butterworth filter. The SOBI algorithm assumes stationary and uncorrelated sources for any time lag. It is solved by approximate joint diagonalization. In this work, it is computed using 10 time lags [4].

2.2. Ocular source identification

A source is supposed to originate from ocular activity (OA) or not (NOA). Each source is classified into OA or NOA using a maximum likelihood classifier. Six features are extracted on each source.

The NOA sources (i.e., EEG sources) are supposed to be Gaussian, to affect all electrodes in a quite homogenous manner and to have a small variance, whereas the OA ones are assumed to be non-Gaussian, to greatly affect frontal electrodes and to present a high variance. Thus, for each source, $\mathbf{s}_i$ with epochs that last for 20 s, the following set of $N_f = 6$ temporal, spatial and frequency features is computed:

(1) *Kurtosis*:

$$f_i[1] = \frac{k_4(\mathbf{s}_i)}{[k_2(\mathbf{s}_i)]^2} \tag{3}$$

$$k_\alpha(\mathbf{y}) = \frac{1}{N_t} \sum_{n=1}^{N_t} (y[n] - m(\mathbf{y}))^\alpha$$

where $m(\mathbf{y})$ designates the temporal sample mean.