



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

Raphaëlle N. Roy<sup>a</sup>, Sylvie Charbonnier<sup>b,\*</sup>, Stéphane Bonnet<sup>a</sup>

<sup>a</sup> CEA/LETI/DTBS/LE2S, MINATEC Campus, Grenoble, France

<sup>b</sup> Gipsa-lab, UMR 5216, Gipsa-Lab, Université Grenoble Alpes & CNRS, Grenoble, France

## ARTICLE INFO

### Article history:

Received 17 February 2014

Received in revised form 2 July 2014

Accepted 11 August 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.

© 2014 Elsevier Ltd. All rights reserved.

## 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

\* Corresponding author. Tel.: +33 476826415.

E-mail address: [Sylvie.Charbonnier@gipsa-lab.grenoble-inp.fr](mailto:Sylvie.Charbonnier@gipsa-lab.grenoble-inp.fr) (S. Charbonnier).

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:

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

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  $\mathbf{X} = \mathbf{A}\mathbf{S} + \mathbf{N}$  where  $\mathbf{X} = [\mathbf{x}_1 \dots \mathbf{x}_{N_e}]^T$  is a  $N_e \times N_t$  EEG data matrix and  $\mathbf{S} = [\mathbf{s}_1 \dots \mathbf{s}_{N_e}]^T$  is a  $N_e \times N_t$  source data matrix. The  $i$ th column of  $\mathbf{A}$ , denoted  $\mathbf{a}_i$ , is the spatial pattern of the  $i$ th source. The sources are estimated using the relation:

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

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

The  $i$ th column of  $\mathbf{W}$ , denoted  $\mathbf{w}_i$ , is called a spatial filter: the  $i$ th 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:

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

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

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

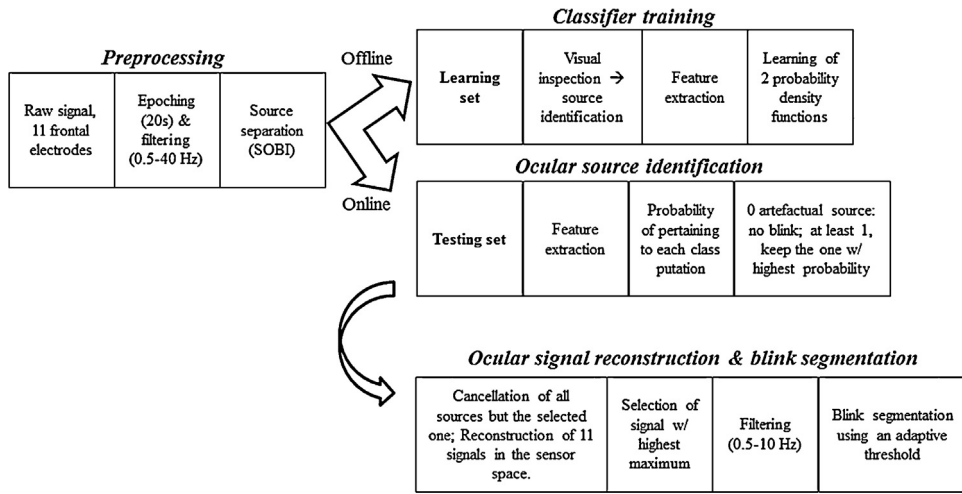


Fig. 1. Blink detection method: operational mode.

(2) Absolute skewness:

$$f_i[2] = \left| \frac{k_3(\mathbf{s}_i)}{[k_2(\mathbf{s}_i)]^{3/2}} \right| \quad (4)$$

(3) Dispersion:

$$f_i[3] = \|\hat{\mathbf{a}}_i\|_1 \quad (5)$$

where  $\hat{\mathbf{a}}_i$  denotes the  $N_e \times 1$  estimated spatial pattern for the  $i$ th source, that is also equal to the  $i$ th column of  $\mathbf{W}^{-T}$ .

(4) Propagation:

$$f_i[4] = \frac{(1/N_e - 1) \sum_{e=1}^{N_e} (\|\hat{\mathbf{a}}_i\|_1 - \|\hat{\mathbf{a}}_e\|_1)^2}{\|\hat{\mathbf{a}}_i\|_1} \quad (6)$$

(5) Frequency ratio:

$$f_i[5] = \frac{\int_{0.5}^5 \hat{P}_{s_i}(f) df}{\int_{0.5}^{40} \hat{P}_{s_i}(f) df} \quad (7)$$

where  $\hat{P}_{s_i}(f)$  is an estimate of the power spectrum of  $s_i(t)$  computed using the Welch periodogram method (2-s window length, 50% overlap).

(6) Percentile ratio:

$$f_i[6] = \frac{\text{Per}_{99}(s_i)}{\text{Per}_{50}(s_i)} \quad (8)$$

where  $\text{Per}_\alpha(x)$  denotes the  $\alpha$  percentile of the absolute value of  $x$ .

All features are chosen in order to be insensitive to the source absolute amplitude and sign. It is assumed that each feature vector  $\mathbf{f}$  is drawn from a multivariate Gaussian distribution conditionally to its class:

$$\varphi(\mathbf{f}|\omega = \omega_k) = \frac{1}{(2\pi)^{N_f/2} \sqrt{|\Sigma_k|}} e^{-1/2(\mathbf{f}-\mathbf{m}_k)^T \Sigma_k^{-1} (\mathbf{f}-\mathbf{m}_k)} \quad (9)$$

The model parameters, the sample mean ( $\mathbf{m}_k$ ) and the sample covariance matrix ( $\Sigma_k$ ), of both classes OA and NOA were estimated from a learning set. During the learning phase, an expert was required to visually annotate each source epoch  $\mathbf{s}_i$  as originating from OA or NOA.

Since equal priors  $P(\omega_k)$  are assumed, the class attributed to each source signal is simply given by  $\max_{\omega_k} \varphi(\mathbf{f}_i|\omega = \omega_k)$ .

Once the  $N_e$  sources are classified, if several sources are classified as originating from OA, the source with the highest probability of belonging to the OA class is selected:  $i^* = \max_{i \in \mathcal{J}} \varphi(\mathbf{f}_i|\omega = \omega_{OA})$ .

If no source is selected as an ocular source, then it is assumed that no blink occurred during the epoch.

### 2.3. Blink segmentation

If an ocular source has been identified, its ocular activity is back-projected to the sensor space using the relation:

$$\mathbf{X}_{eye} = \mathbf{W}^{-T} \mathbf{D}(\mathbf{e}_{i^*}) \mathbf{W}^T \mathbf{X} \quad (10)$$

$\mathbf{D}(\mathbf{e}_{i^*})$  is a diagonal matrix with binary diagonal elements given by the vector  $\mathbf{e}_{i^*}$ .  $\mathbf{e}_{i^*}$  is a vector formed of  $N_e$  zeros except element  $i^*$  which is equal to 1.

$\mathbf{X}_{eye}$  expresses the impact of the ocular activity on the EEG electrodes, cleaned from the EEG activity. This back projection is done to obtain a signal whose amplitude is comparable from one epoch to the next one. Indeed, in the source space, the information on the source amplitude is not available. Furthermore, the demixing matrix  $\mathbf{W}$  is recomputed for each epoch.

When back projected in the signal space, the channel with the highest magnitude in  $\mathbf{X}_{eye}$  is considered to be the most relevant signal for blink characterization: this signal is denoted  $x_{eye}(t)$ . Then,  $x_{eye}(t)$  is band-pass filtered between 0.5 and 10 Hz using a 5th-order Butterworth filter. A threshold is set to the value:

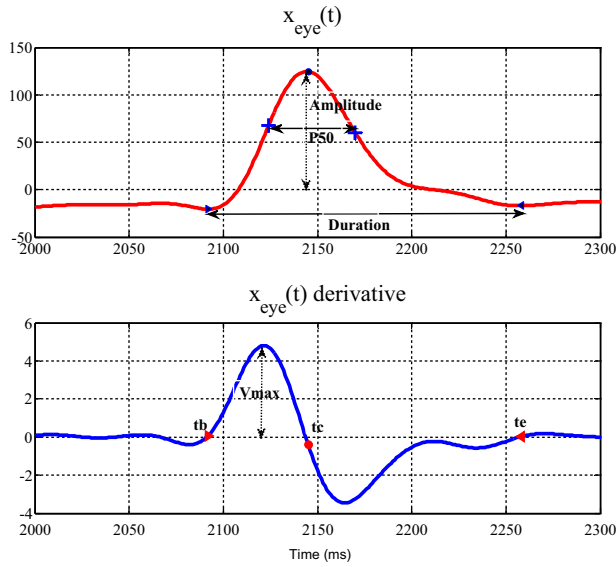
$$m + \kappa \text{median}(|x_{eye} - m|) \quad (11)$$

where  $m = \text{median}(x_{eye})$  is the median amplitude value of the signal during the epoch. This thresholding allows the blinks to be segmented by producing a set of time intervals  $[\alpha_i, \beta_i]$  whenever the signal exceeds the threshold. Since the ocular activity does not produce a Gaussian signal, the use of the median (instead of the mean and standard deviation) in the detection threshold enables the background noise level to be accurately estimated.

Let us note that the complete blink detection method, from source separation to blink identification, requires only one parameter to tune,  $\kappa$ , that sets the level of the detection threshold. This parameter expresses the relative amplitude of an expected blink compared to the signal background noise. It is not subject dependent. The same value for  $\kappa$  can be used for any subject.

### 2.4. Blink characterization

For each blink interval  $[\alpha_i, \beta_i]$ , the beginning time of the blink  $tb_i$  can be located by identifying the last zero-crossing of  $\dot{x}_{eye}$  in the time interval  $[\alpha_i - 0.5 \text{ s}, \alpha_i]$  using the numerical derivative of  $x_{eye}(t)$  (Fig. 2). Identically, its ending time  $te_i$  can be located by finding the first zero-crossing of  $\dot{x}_{eye}$  in the time interval  $[\beta_i, \beta_i + 0.5 \text{ s}]$ . The closure time of the eyelid  $tc_i$  is chosen as the first zero-crossing of  $\dot{x}_{eye}$  in the time interval  $[tb_i, te_i]$ .



**Fig. 2.** Reconstructed signal used for eye blink characterization, its derivative and timing parameters.

The parameters listed and defined in Table 1 can be derived from these time instants [9,17,20].

### 3. Validation method

The proposed method was applied on a dataset and the results were compared with the ones obtained using a vertical EOG (EOGV) reference signal. The method was tested in a subject-independent fashion, without any prior calibration. Indeed, it was thought robust enough to test its generalization capability.

#### 3.1. Data

The method was applied on 90 min of signal recorded from 11 volunteers who underwent a working memory experiment

**Table 1**  
Blink parameters, definition and computation.

Blink parameter	Definition	Computation
Amplitude (A)	Max. btw beg & end	$\max_{t \in [tb_i, te_i]} x_{eye}(t)$
Duration (D)	Time elapsed btw beg & end	$te_i - tb_i$
Duration 50 (D50)	Time elapsed btw beg & end of 50% of the blink's amplitude	$t_{50e_i} - t_{50b_i}$
Duration 80 (D80)	Time elapsed btw beg & end of 80% of the blink's amplitude	$t_{80e_i} - t_{80b_i}$
Closure duration (CD)	Time elapsed btw beg & max	$tc_i - tb_i$
Opening duration (OD)	Time elapsed btw max & end	$te_i - tc_i$
Mean closure velocity (CV)	SE	$\frac{\int_{tb_i}^{tc_i} dt \dot{x}_{eye}(t)}{tc_i - tb_i}$
Mean opening velocity (OV)	SE	$\frac{\int_{tc_i}^{te_i} dt \dot{x}_{eye}(t)}{te_i - tc_i}$
Max. closing velocity (CVmax)	Highest instantaneous CV	$\max_{t \in [tc_i, te_i]} \dot{x}_{eye}(t)$
A/CVmax	SE	A/CVmax

Btw, between; beg, beginning; SE, self-explanatory.  $t_{\alpha}b_i$  (resp.  $t_{\alpha}e_i$ ) is the time at which the signal  $x_{eye}(t)$  starts to exceed  $\alpha\%$  of the blink amplitude (resp. the time at which the signal  $x_{eye}(t)$  starts to fall below  $\alpha\%$  of the blink amplitude).

authorized by the local ethics committee (Grenoble Hospital, authorization number: 2012-A00826-37). They performed 736 trials in which they had to memorize a list of 2 or 6 sequential digits visually presented on a computer screen. In each trial was inserted a geometrical shape detection task. The total experiment lasted 90 min. Given that the task was repetitive and stimulus poor and that the experiment lasted 90 min, it was presupposed that the level of mental fatigue increased during the experiment. This was confirmed for each participant thanks to behavioral and subjective measures. Participants' reaction times for the detection task increased with growing time-on-task ( $p < .01$ ). Participants were also asked to answer a mental fatigue questionnaire (Karolinska questionnaire) before, in the middle and at the end of the experiment. They all declared to feel increasingly tired ( $p < .01$ ; see [18], for the detailed experimental protocol and results).

The EEG signal was recorded from the 11 following frontal and fronto-central Ag–AgCl unipolar active electrodes positioned according to the extended version of the 10–20 system on an Acticap® (Brain Products Inc.): Fz, Fp1/2, F7/8, F3/4, FC5/6 and FC1/2. In addition, the EOGV signal was recorded using two vertically aligned electrodes placed, respectively, above and below the left eye. The reference and ground electrodes used for acquisition were those of the Acticap, i.e., FCz for the reference electrode, and AFz for the ground electrode, although the raw EEG signal was band-pass filtered between 1 and 40 Hz, and re-referenced to a common average reference. Impedance was kept below 10 k $\Omega$  for all electrodes. The signal was amplified using a BrainAmp™ system (Brain Products, Inc.) and sampled at 500 Hz with a 0.1 Hz high-pass filter and a 0.1  $\mu$ V resolution. Regarding data allocation between training and testing sets, only the 20 min of the first subject were used as the training set. The remaining 70 min of this subject, as well as the 90 min of the four other subjects were used as the testing set. Signals were split into 20-s non-overlapping epochs. The analyses were performed using Matlab (the 2010b version) and its Signal Processing toolbox.

#### 3.2. Method

In order to validate the method, the blink detection and blink characterization steps were executed on both the EEG and the EOGV data and the obtained results were compared. The steps applied on the EEG data were detailed before; the ones applied on the EOGV data are detailed below.

##### 3.2.1. Blink detection evaluation

As for detecting blink sections from the EOGV signal, first the signal was band-pass filtered between 0.5 and 10 Hz using the same IIR filter applied on the EEG data. Then, a 100  $\mu$ V fixed threshold selected by visual inspection was set. This thresholding step performs blink segmentation. Intersections between the temporal segments obtained from the EOG signal and from the EEG signal were then computed. When the intersection between an EOG segment and an EEG segment was empty, the blink was considered a false negative, else it was a true positive. When the intersection between an EEG segment and an EOG one was empty, then the detected blink was considered a false positive. The true positive rate (TPR) is thus the number of true positives divided by the number of EOG blinks. The false positive (FPR) rate is the number of false positives divided by the number of EEG blinks.

##### 3.2.2. Blink characterization evaluation

The characterization step applied on the EOGV signal is the same as the one applied on the EEG signal, i.e., the same parameters were extracted. The parameters extracted from the EEG and from the EOGV signals were compared using their correlation coefficient,



computed on the true positives only. Indeed, some parameters do not have the same values and thus cannot be compared with a mean comparison test. The amplitude of the EEG blinks (and thus of all the features that use the amplitude, such as velocities) are different from the amplitude of the EOG blinks. A high correlation coefficient means that there exists a strong linear relationship between 2 parameters. The computation of correlation coefficients is extremely sensitive to large outliers, whose presence may artificially increase the value of the correlation. Therefore, the data were preprocessed prior to computing the coefficients in order to remove those extreme values that are due to EOG signal disruptions detected as blinks. EOG blinks whose amplitude exceeded  $1500 \mu\text{V}$  were thus excluded.

## 4. Results

### 4.1. Source classification

Fig. 3 displays the distribution of the 6 features from the training set in both classes. One can see that the temporal features (kurtosis, skewness and percentile ratio) provide a very efficient class separation. The frequency ratio is also a good discriminative feature, while dispersion and propagation, although still discriminative, are more overlapped. To evaluate classifier accuracy, sources were extracted from each epoch of subject 1 and subject 2 and visually classified as ocular source or not. The percentage of correctly classified sources is quite high with 97% for both subjects. This shows that the chosen features allow a clear discrimination between ocular and non-ocular classes and that the features are subject-independent. Indeed, although the learning step was achieved using data from subject 1, the results obtained with subject 2 are just as good in this case.

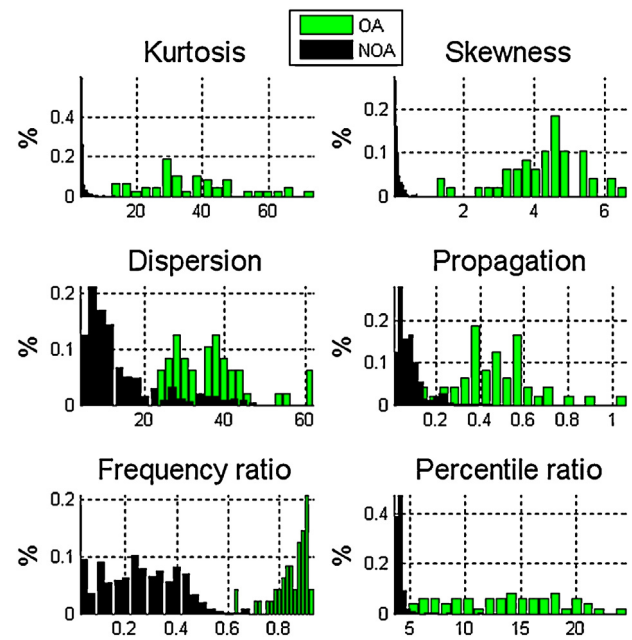


Fig. 3. Distribution of the 6 features used for source classification.

### 4.2. Signal reconstruction & blink detection results

Fig. 4A–C shows the matrix of signals  $\mathbf{X}$  (piled up using an offset), recorded on the 11 electrodes, the extracted sources and the reconstructed signals  $\mathbf{X}_{\text{eye}}$ . A zoom is done on 2 consecutive blinks. In this case, the ocular source was identified as source 1. The signals that are highly impacted by ocular activity are Fp1 and Fp2,

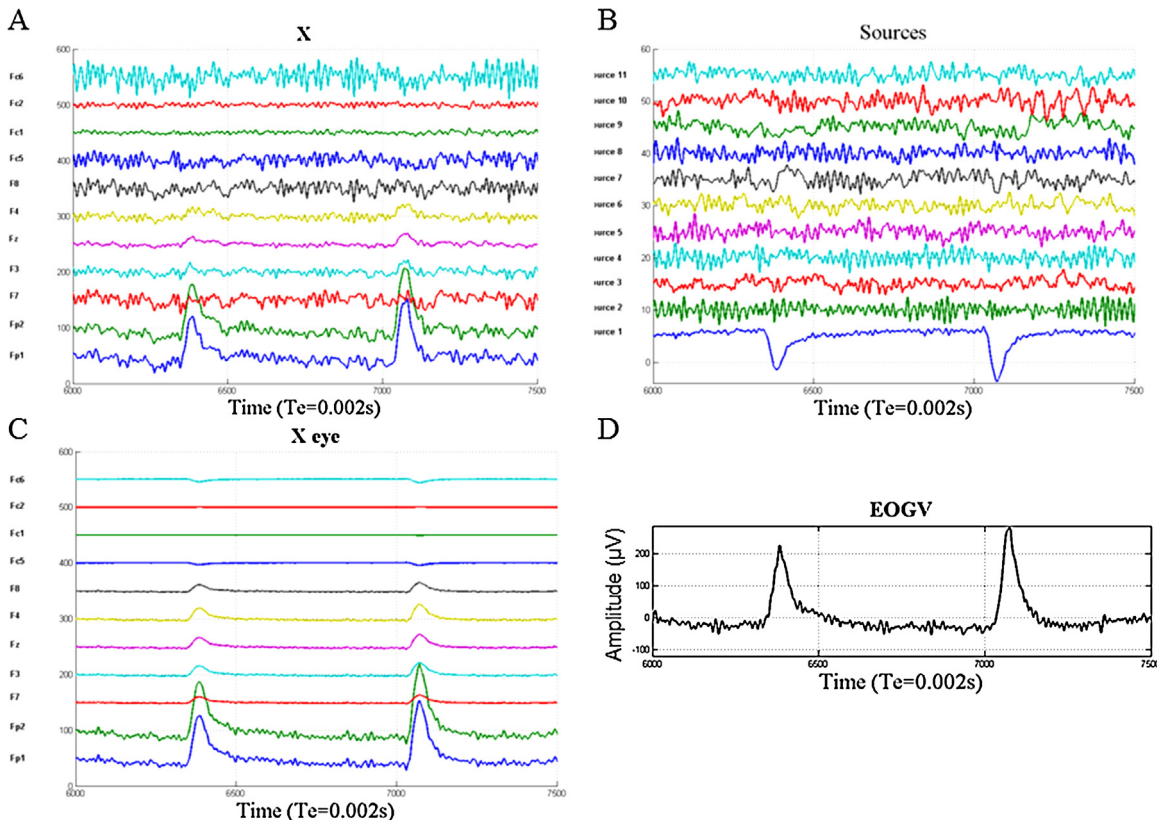
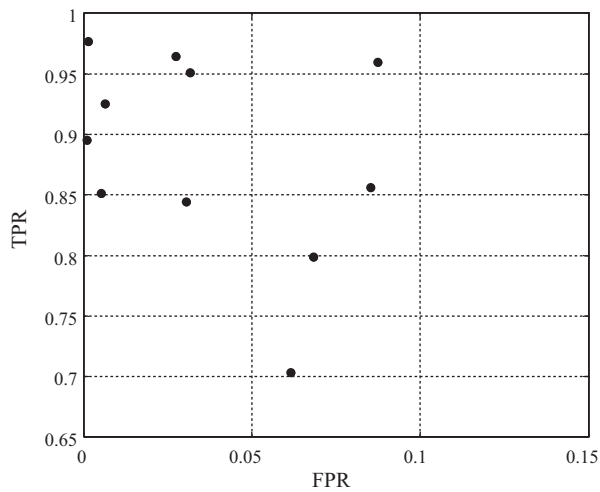


Fig. 4. (A) Example of recorded signal. (B) Sources obtained using the SOBI algorithm on the previous signal. (C) Signal obtained in the sensor space by back projecting the identified ocular source (here source 1 in B). (D) Reference signal (vertical electro-oculogram) for the same recording period.



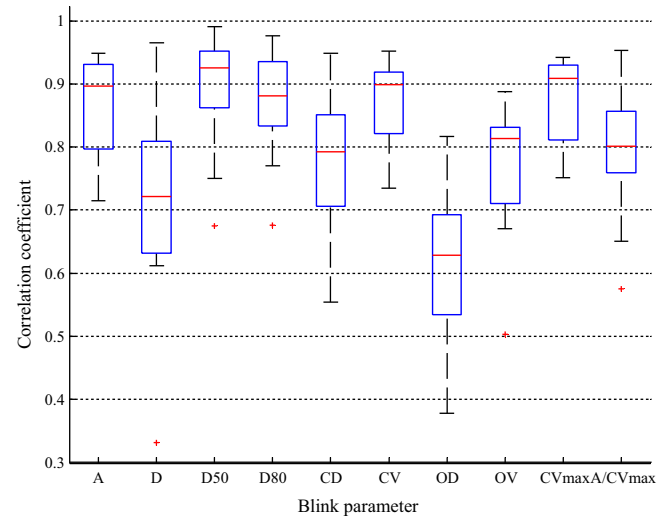
**Fig. 5.** Blink detection: True positive rate (TPR) in function of false positive rate (FPR) for each.

localized above the eyes, as well as Fz, F3, F4, F7 and F8. In contrast, FC1, FC2, FC5 and FC6 are almost not corrupted by the blinks. The reconstructed signals are clearly EEG denoised.  $X_{eye}$  Fp1 and Fp2 exhibit typical blink patterns while, in the original signals, the blink shapes are distorted by EEG waves. The method allows for a very good reconstruction of the ocular activity signal from the EEG signal, as illustrated in Fig. 4C ( $X_{eye}$  Fp1) and D, which displays the vertical EOG. The shapes of the 2 signals are very similar, even though their amplitudes are obviously different.

Blinks were extracted by setting the only tuning parameter,  $\kappa$ , to 10. The same value is used for every subject. Results are presented in Fig. 5, in which each dot represents the TPR as a function of the FPR for one subject. One can see that they are very good with 89% of true detections and 3% of false alarms, in average. The performances are about the same whichever subject is considered, except for subject 5 who obtained poorer results. This shows that the method can be applied without any prior calibration for a large majority of new individuals. Although the impact of the ocular activity on frontal EEG signals may vary from one subject to another, the use of the adaptive threshold enables the parts of the signal that clearly stand out from the background noise, i.e., the blinks, to be automatically selected. Let us note that the different subjects do not exhibit the same blinking characteristics. The number of blinks during the 90-min recording varies from 671 for subject 5 to 2913 for subject 2. The poorest results are obtained for subject 5, with 70% of true detection and 6% of false alarms. Subject 5 seldom blinks and his blinks' amplitude is rather small. An analysis of the blinks missed by the method showed that most of them are blinks for which the EOG amplitude does not exceed  $150 \mu V$ . On the contrary, blinks of large amplitude are very well detected.

#### 4.3. Blink characterization results

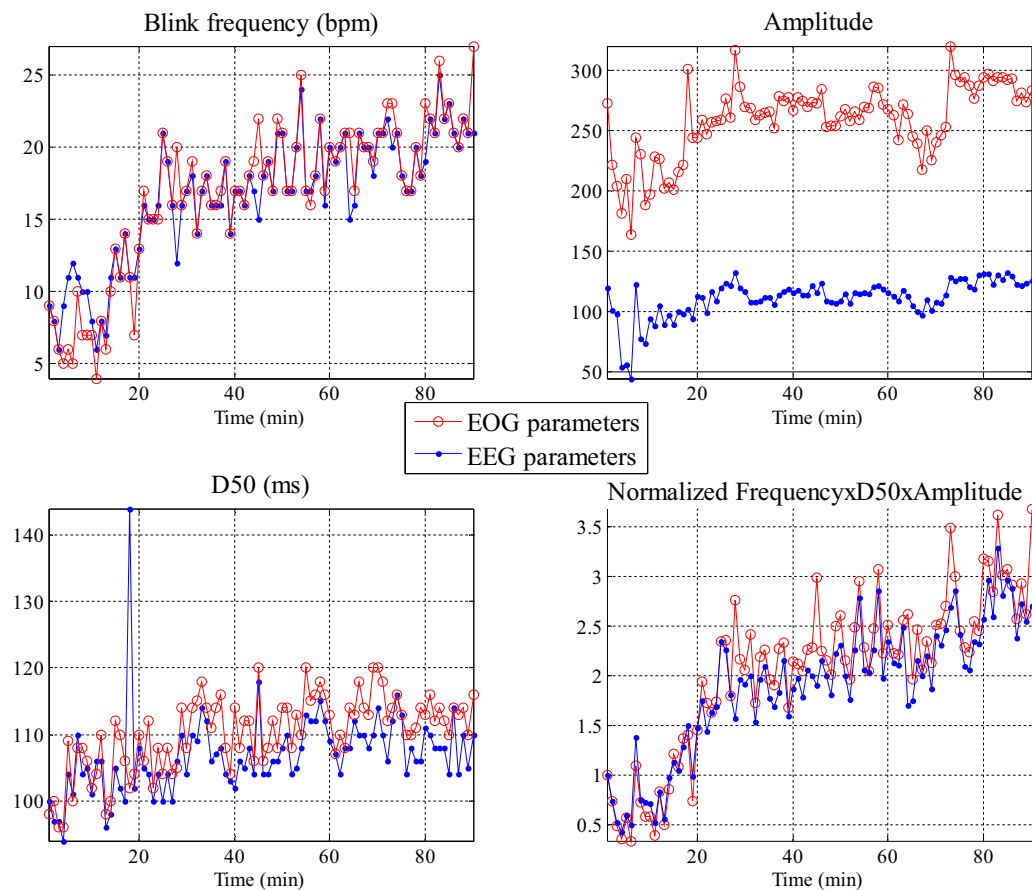
Blink characterization results obtained for the 11 subjects are presented as box and whisker plots in Fig. 6. For each box, the central mark is the median, the edges are the 25th and 75th percentiles and the whiskers extend to the most extreme data points not considered as outliers, whereas outliers are individually plotted with crosses. The boxes summarize the correlation coefficients obtained for each subject between the features extracted from the EEG and EOGV signals. The parameters are presented in the following order: (1) A, (2) D, (3) D, (4) D80, (5) CD, (6) CV, (7) OD, (8) OV, (9) Vmax and (10) A/Ovmax. The results are very promising with correlation coefficients as high as 0.81 in average. More precisely, the



**Fig. 6.** Distribution of the correlation coefficients between the EOG and EEG-extracted parameters.

correlation coefficients of amplitude, duration (D, D50 and D80), mean closure velocity and maximal closure velocity, which are very relevant parameters to detect mental fatigue, are higher than 0.88 in average. Since these parameters are highly correlated, when performing online mental fatigue monitoring, indicators based on these blink parameters extracted from EOG or EEG, are likely to evolve in the same way in time. The fact that the parameters, including amplitude, are well correlated shows the importance of the back projection in the signal space. Indeed, the blink amplitude computed in the source space is only poorly correlated (about 0.60) with the EOG blink amplitude. The poorest results are obtained for subject 5 whose blinks are globally small and short.

An illustration of the temporal evolution of the blink parameters computed on one of the subjects is given in Fig. 7. The following parameters are presented: Blink frequency computed on non-overlapping windows of 1 min (i.e., the concatenation of 3 successive epochs) on the upper left part, mean amplitude on 1 min non-overlapping windows on the upper right part, mean duration at 50% on the lower left part, and the product of the normalized frequency by the normalized amplitude by the normalized D50% on the lower right part. The normalized variable is computed as the value of the variable divided by the value measured during the first minute of the recording. It provides a mental fatigue indicator that gives some clue about the periods during which the eyes are closed. The more frequent or longer or deeper the blinks are, the higher the indicator is. Each variable is divided by its initial value so as to make it count for the same amount in the indicator and to have comparable EEG and EOG indicators. Thus, during the recording's first minute, the indicator is equal to 1. The indicator can be seen as an online indicator that compares the subject's current fatigue state with the fatigue state estimated during the first minute, when the subject has not spent any time on the task so far. One can see on the figure that the parameters estimated from the EOG signal or the EEG signals have the same evolution. Blink frequencies are very similar. The amplitude evolves in the same way but with a different value when extracted from EOG or from EEG. Durations are globally similar except for a very different value at time 19 min, probably due to an error made in the classification of the sources on one epoch. The mental fatigue indicators evolve in the same way. One can see that they rapidly increase after 20 min spent on the task, remain stable, and then increase again at the end of the experiment, which confirms the assumption that subject 5's mental fatigue level increased with time-on-task.



**Fig. 7.** Temporal evolution of the blink parameters extracted on subject 5 using EEG and EOG. Upper left part: blink frequency; upper right part: amplitude; lower left part: duration; lower right part: mental fatigue indicator.

## 5. Discussion

In this article, a new method for detecting and characterizing eye blinks recorded on the scalp through EEG is presented. The main aim of this method is to make use of an otherwise discarded ocular information. This ocular information is of major interest to assess one's mental fatigue state. To the best of our knowledge, no study had yet been conducted on how to characterize ocular activity from EEG recordings.

Since our goal is to characterize blinks and not only to detect them – which could be done using a fronto-polar EEG derivation, the proposed method includes a source separation step, a source classification step through the use of temporal, spatial and frequency features, and an important back projection step in the sensor space in which blink segmentation is performed via an adaptive thresholding process. Next, the blinks are characterized by computing several parameters related to the blinks' temporal features. This processing chain enables us to reconstruct an EEG-derived eyeblink very similar in shape to the EOG blink, since it has been EEG denoised. It is thus possible to compute blink parameters such as closing velocity parameters, which are very useful to detect drowsy states. The strengths of the processing chain are its subject-independent usability, and the absence of calibration period. The data are processed on line: 20 s of signal are recorded and the whole process, from source separation to blink characterization, is applied on this epoch. Information on blinks is then updated every 20 s. However, it could be possible to make this process faster by using overlapping epochs, for instance with 10-s overlaps.

The method was validated against a vertical EOG reference signal. Detection performance was very high with an average good

detection rate of 93.62% and a false alarm rate of 4.2%. The results are particularly satisfying since they were obtained for 11 different subjects, with different blinking characteristics. Moreover, the recordings were done when the subjects underwent a working memory experiment during which mental fatigue increased. Very good characterization performances were also obtained, with a correlation of 0.83 between EOG-extracted and EEG-extracted eye blink parameters. The highest correlations were obtained for the maximum instantaneous closing velocity, lid closing velocity and amplitude. The lowest was obtained for the opening duration. This could be explained by the uncertainty to determine the time parameter  $t_e$ , reflecting the blink end, because of the background noise corrupting the EEG reconstructed signal. In any case, both amplitude and duration characteristics were well estimated by the method.

These good results show that both the source separation and the classification steps performed very well. The proposed features analyze the signal source in the temporal domain using the kurtosis, the skewness and the ratio of percentiles. These features do not consider the signal amplitude but only its distribution shape. EEG (NOA) sources exhibit a Gaussian behavior, while blinks make the OA source distribution asymmetric, with large tails. The ratio of frequency analyzes the source in the frequency domain. Eye blinks elicit power increases in the delta and theta range 0–8 Hz, which makes the ratio of low frequencies on high frequencies much higher for OA sources. Finally, dispersion and propagation are features extracted from the mixing matrix **A**. They analyze the way the signals are reconstructed from the sources. The amplitude of blinks is higher than that of EEG waves. Thus, the coefficients of the OA sources are higher than the ones of the NOA sources.

From the obtained results, the proposed features seem to be subject-independent. Indeed, the learning set was formed with epochs selected from one subject, in the beginning of the experiment. Results from one subject to the other are comparable. Although eye blink parameters vary with mental fatigue, the features chosen to perform ocular source identification remain discriminative even after a long time on task. No degradation in performance was observed at the end of the experiment when the mental fatigue level was proved to be higher by behavioral indices.

Finally, the use of the adaptive threshold, recalculated for each epoch, makes the system self-regulating. The background noise is evaluated using the median of the absolute difference to the median during the epoch. The value for  $\kappa$  is set to 10, which means that blinks are detected as large outliers.

The system is able to detect, for each epoch of 20 s, whether the subject has blinked or not. Indeed, for some subjects with a low blinking rate, it may happen that no blink is present during the epoch. This lack of blink is detected either during the classification step, where no source is detected as OA, or by the adaptive threshold, where no portion of signals exceeds the threshold.

One limitation of the study is the number of subjects used to validate the method. Only 11 subjects were available. Yet, the cumulated recordings lasted 990 min, and mental fatigue increased for each subject, as shown by behavioral indices such as reaction times and accuracy. The obtained results can be regarded as quite sufficient for a proof of concept. One can suppose that the features used to select the ocular sources should remain discriminant in advanced drowsy states, where blink shapes become larger and longer. Kurtosis should remain high because blinks, even long ones, create large variations which result in tails in the signal distribution. Long blinks make the signal asymmetrical, which result in a high skewness. The low on high frequency ratio should also remain high as well as the features extracted from the mixing matrix. Yet, validation on drowsy subjects would be necessary to make sure that the proposed method is still robust in this situation. Therefore, another experimental campaign has to be conducted to answer this issue in the near future.

To conclude, the study was performed on data recorded from subjects that underwent an experiment in which the cognitive load was modulated. They had to concentrate on information displayed on the screen and were not physically active, which avoided the occurrence of recording artifacts. The developed method could be directly applied on operators who monitor complex systems during long periods of time, such as air traffic controllers or nuclear plants operators, who have to concentrate during long periods on information displayed on a screen. The new technology that is now emerging to record EEG in an easy and practical way, such as EEG headsets or caps with dry electrodes, enables us to envision an EEG system that would monitor operators' mental state for long periods. The proposed method makes it possible to assess mental fatigue or drowsiness with an indicator that combines information from both cerebral and ocular activities without using EOG electrodes, which would be difficult to bear for a long period of time and which may impair the operators' performances. In such applications, the source separation and automatic classification steps proposed here could be used in two ways: to detect and monitor ocular activity, but also to EOG denoise the EEG signals, which is an essential step prior to any EEG analysis. This would make the monitoring system completely EOG free.

## 6. Conclusion

This article describes an innovative method for detecting and characterizing eye blinks using electrical activity measured from the scalp through EEG electrodes using a source separation step

and a classification step. Top performances are obtained in the validation phase on different subjects, without any prior subject specific tuning. An online mental fatigue indicator computed from both EEG and EOG signals is proposed. It allows comparison of the subject's current mental fatigue state to a presupposed non-fatigued initial state. Indicators calculated from EEG and EOG signals evolved in a similar manner over time.

This method allows for a more practical mental state monitoring with the use of only one recording modality, namely EEG, since blink activity can be monitored along with cerebral activity, without the need for any other device.

## Acknowledgments

The authors thank Laurent Vercueil, MD, Aurélie Campagne, PhD, Eric Guinet and Sylvain Harquel for their help with data acquisition.

## References

- [1] J. Arnin, D. Anopas, M. Horapong, P. Triponyuwasi, T. Yamsaard, S. Iampetch, Wireless-based portable EEG-EOG monitoring for real-time drowsiness detection, in: *Proceedings of the IEEE Engineering in Medicine and Biology Conference*, Osaka, Japan, 2013, pp. 4977–4980.
- [2] G. Barbato, V. De Padova, A.R. Paolillo, L. Arpaia, E. Russo, G. Ficca, Increased spontaneous eye blink rate following prolonged wakefulness, *Physiol. Behav.* 90 (1) (2007) 151–154.
- [3] A. Belouchrani, A. Cichocki, Robust whitening procedure in blind source separation context, *Electron. Lett.* 36 (24) (2000) 2050.
- [4] A. Belouchrani, K. Abed-Meraim, J.-F. Cardoso, E. Moulines, A blind source separation technique using second-order statistics, *IEEE Trans. Signal Process.* 45 (2) (1997) 434–444.
- [5] P. Berg, M. Scherg, Dipole models of eye movements and blinks, *Electroencephalogr. Clin. Neurophysiol.* 79 (1) (1991) 36–44.
- [6] G. Borghini, L. Astolfi, G. Vecchiato, D. Mattia, F. Babiloni, Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness, *Neurosci. Biobehav. Rev.* 44 (2014) 58–75.
- [7] G. Borghini, G. Vecchiato, J. Toppi, L. Astolfi, A. Maglione, R. Isabella, C. Caltagirone, W. Kong, D. Wei, Z. Zhou, L. Polidori, S. Vitiello, F. Babiloni, Assessment of mental fatigue during car driving by using high resolution EEG activity and neurophysiological indices, in: *Proceedings of the IEEE Engineering in Medicine and Biology Conference*, San Diego, CA, 2012, pp. 6442–6445.
- [8] A. Bulling, J.A. Ward, H. Gellersen, G. Troster, Eye movement analysis for activity recognition using electrooculography, *IEEE Trans. Pattern Anal. Mach. Intell.* 33 (4) (2011) 741–753.
- [9] P.P. Caffer, U. Erdmann, P. Ullsperger, Experimental evaluation of eye-blink parameters as a drowsiness measure, *Eur. J. Appl. Physiol.* 89 (3/4) (2003) 319–325.
- [10] M. Congedo, C. Gouy-Pailler, C. Jutten, On the blind source separation of human electroencephalogram by approximate joint diagonalization of second order statistics, *Clin. Neurophysiol.* 119 (2008) 2677–2686.
- [11] J. Gao, P. Lin, Y. Yang, P. Wang, Automatic removal of eye-blink artifacts based on ICA and peak detection algorithm, in: *2nd International Asia Conference on Informatics in Control, Automation and Robotics*, 1, Wuhan, China, 2010, pp. 22–27.
- [12] T.-P. Jung, S. Makeig, C. Humphries, T.-W. Lee, M.J. McKeown, V. Iragui, T.J. Sejnowski, Removing electroencephalographic artifacts by blind source separation, *Psychophysiology* 37 (2) (2000) 163–178.
- [13] S.K.L. Lal, A. Craig, A critical review of the psychophysiology of driver fatigue, *Biol. Psychiatry* 55 (3) (2001) 173–194.
- [14] T. Liu, D. Yao, Removal of the ocular artifacts from EEG data using a cascaded spatio-temporal processing, *Comput. Methods Prog. Biomed.* 83 (2) (2006) 95–103.
- [15] N. Mammone, F. La Foresta, F.C. Morabito, Automatic artifact rejection from multichannel scalp EEG by wavelet ICA, *IEEE Sens. J.* 12 (3) (2012) 533–542.
- [16] S. Oh, P.S. Kumar, H. Kwon, V.K. Varadan, Wireless brain-machine interface using EEG and EOG: brain wave classification and robot control, in: *Proceedings of the SPIE 8344, Nanosensors, Biosensors, and Info-Tech Sensors and Systems*, San Diego, CA, 2012.
- [17] A. Picot, S. Charbonnier, A. Caplier, On-line detection of drowsiness using brain and visual information, *IEEE Trans. Syst. Man Cybern. A: Syst. Hum.* 42 (3) (2012) 764–775.
- [18] R.N. Roy, S. Bonnet, S. Charbonnier, A. Campagne, Mental fatigue and working memory load estimation: interaction and implications for EEG-based passive BCI, in: *Proceedings of the IEEE Engineering in Medicine and Biology Conference*, Osaka, Japan, 2013, pp. 6607–6610.



- [19] J. Santamaria, K.H. Chiappa, The EEG of drowsiness in normal adults, *J. Clin. Neurophysiol.* 4 (1987) 327–382.
- [20] R. Schleicher, N. Galley, S. Briest, L. Galley, Blinks and saccades as indicators of fatigue in sleepiness warnings: looking tired? *Ergonomics* 51 (7) (2008) 982–1010.
- [21] S. Sen Gupta, S. Soman, P. Govind Raj, R. Prakash, S. Sailaja, R. Borgohain, Detecting eye movements in EEG for controlling devices, in: *Proceedings of the IEEE International Conference on Computational Intelligence and Cybernetics*, Bali, Indonesia, 2012, pp. 69–73.
- [22] W.-Y. Shih, J.-C. Liao, K.-J. Huang, W.-C. Fang, An efficient VLSI implementation of on-line recursive ICA processor for real-time multi-channel EEG signal separation, in: *Proceedings of the IEEE Engineering in Medicine and Biology Conference*, Osaka, Japan, 2013, pp. 6808–6811.
- [23] L. Shoker, S. Sanei, J. Chambers, Artifact removal from electroencephalograms using a Hybrid BSS-SVM algorithm, *IEEE Signal Process. Lett.* 12 (10) (2005) 721–724.
- [24] T. Tan, J.P. Hakenberg, C. Guan, Estimation of glance from EEG for cursor control, in: *Proceedings of the IEEE Engineering in Medicine and Biology Conference*, Osaka, Japan, 2013, pp. 2919–2923.
- [25] Z. Xue, J. Li, S. Li, B. Wan, Using ICA to remove eye blink and power line artifacts in EEG, in: *Proceedings of the 1st International Conference on Innovative Computing, Information and Control*, 3, Beijing, China, 2006, pp. 107–110.
- [26] D.-H. Zhu, J.-J. Tong, Y.-Q. Chen, An ICA-based method for automatic eye blink artifact correction in multi-channel EEG, in: *Proceedings of the 5th International Conference on Information Technology and Applications in Biomedicine*, Shenzhen, China, 2008, pp. 338–341.