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Principal component analysis for reduction of ocular artefacts in event-related potentials of normal and dyslexic children

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Abstract

Objective: The aim of this study was to reduce ocular artefacts in single trial event-related potentials (ERPs) recorded in normal and in dyslexic children.

Methods: ERPs were recorded during passive and active reading of centrally presented alphabetic letters and non alphabetic symbols. EEG was recorded from 10 EEG locations using the 10–20 system. Diagonal EOG from the right eye was also recorded. Principal component analysis (PCA) was applied in order to reduce ocular artefacts: the first or the second principal component (PC) was subtracted when the correlation coefficient between the component and EOG was greater or equal to 0.9 or 0.95, respectively. Performance of the method was tested on simulated and real data, on both single and averaged trials, varying EOG amplitude and artefact transmission characteristics.

Results: Applying the method to real recordings from normal and dyslexic children, we obtained a significant increase in the number of useful trials. In normal children we retrieved 41.0% of the rejected trials in passive and 39.1% in active reading. In dyslexic children 36.7 and 32.2% of the rejected trials in passive and active reading could be included in the respective averages.

Conclusions: The method allows an increase in the number of trials suitable for averaging, a great improvement in ERP quality and a reduction in the recording time.

Keywords: Principal component analysis; Ocular artefacts; Blinking; Dyslexia; Event related potential; Single sweep analysis

1. Introduction

Event-related potentials (ERPs) are often affected by the presence of different kinds of artefacts, such as oscillations of the reference potential, gross body movements of the subject being examined, muscular and ocular activities. Among these sources of noise, the most critical is probably the one deriving from ocular movements and blinking: in fact, it is always physiologically present, larger in amplitude than EEG and frequently superimposed on event-related responses.

Usually, experimenters visually or automatically reject on-line the artefact-contaminated trials before averaging the recorded sweeps, thus increasing the time duration of the test. Time duration of the test is critical in children, because the cerebral activity related to cognitive processes is likely to change with time and because children cannot maintain a good level of attention or remain still for a long period. Moreover, when dealing with children affected by neuro-behavioural problems, attention disorders, autism, or dyslexia, the incidence of ocular artefacts heavily increases. Furthermore, avoiding blinking is a task superimposed on the experimental condition and requires a division of resources between the experimental task and self-monitoring of ocular activity: this condition may elicit morphological modifications of the cerebral responses (Weerts and Lang, 1973; Verleger, 1991; Ochoa and Polich, 2000).

As a consequence, several computerized approaches have been proposed for reducing ocular artefacts in raw EEG. They include: linear regression, in the time or in frequency domain (Verleger et al., 1982; Gratton et al., 1983; Gasser et al., 1986; Semlitsch et al., 1986; Kenemans et al., 1991; Croft, 2000; Croft and Barry, 2000; Picton et al.,

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2000a,b; Verleger, 2000), topographic approaches (Berg and Scherg, 1991, 1994; Koles et al., 1995; Koles and Soong, 1998), spatial component approaches (principal component analysis (PCA) and independent component analysis (ICA); Lagerlund et al., 1997; Vigario, 1997; Kobayashi and Kuriki, 1999; Jung et al., 2000; Picton et al., 2000a,b) and autoregressive models (Cerutti et al., 1988).

The linear regression-based methods reduce ocular artefacts by subtracting from EEG the EOG scaled by appropriate attenuation factors. This approach sometimes overestimates the attenuation factors for the presence of EEG components in EOG and assumes that the propagation system is linear (Iacono and Lykken, 1981; Gratton et al., 1983; Gasser et al., 1985; Berg and Scherg, 1994).

In the topographic approaches, both EEG and EOG activities are estimated by applying empirical measurements to a priori models. The spatial component approach builds dipole models of blinks, saccades and brain activity using decomposition techniques, such as PCA and ICA. Both these approaches have a great computational cost relative to the modelling of the cerebral and ocular sources of activity; furthermore, they require a great number of recording channels in order to make the source estimation and the artefact correction process reliable and accurate. One exception is the method proposed by Ille et al. (1997), where PCA is applied without modelling the ocular and cerebral sources of activity.

Although the advantage of autoregressive models with exogenous inputs is that they allow us to simultaneously extract an individual ERP trial from the background EEG and to reduce the EOG artefact, they are computationally heavy and need the input of a previously computed ERP average of good quality.

The aim of the present work is to reduce ocular artefacts from single trials, through the subtraction of the principal component containing the EOG.

2. Methods

2.1. Analytic description of the method

The approach proposed in the present paper for the reduction of ocular artefacts stems from a previous study devoted to the improvement of the SNR in evoked neuromagnetic fields (Kobayashi and Kuriki, 1999).

We model the EEG as a linear combination of independent activities generated by different sources located in or outside the brain, expressed in the following equation

$$\mathrm{EEG}_n(t) = \sum_{m=1}^{M} \mathrm{a}_{n,m}\mathrm{PC}_m(t) \tag{1}$$

where $\mathrm{PC}_m(t)$ is the activity of the mth source or *principal component*, that affects the nth EEG trace with a weight $\mathrm{a}_{n,m}$.

We assume that the number of components is equal to the number of EEG traces and that the most relevant contributions to the EEG traces are the ones deriving from cerebral and ocular activities. In particular, it is possible to assume that ocular artefacts are transmitted in the EEG channels with the same morphology recorded in EOG, scaled in amplitude without time delay (Gasser et al., 1986): they can therefore be identified for their high spatial correlation across the recording sites.

From a mathematical point of view, PCA identifies the sources that are maximally independent and at the same time account for the maximal amount of spatial variance of original data in the least square sense: thus the components extracted by means of the PCA technique can be used to remove coherent activities spread over the data.

PCA was applied to every single trial, that was organized in a matrix **D**, of dimensions T (number of samples in each trace) and 11 (1 EOG and 10 EEG channels), containing EOG and all EEG recordings, according to the following equation:

$$\begin{aligned}\underset{(T,11)}{\mathbf{D}} &= [\mathbf{EOG}\ \ \mathbf{EEG_1}\ \ \mathbf{EEG_2}\ \ \ldots\ \ \mathbf{EEG_{10}}] \\ &= [\mathbf{EOG}\ \ \mathbf{Fz}\ \ \mathbf{Cz}\ \ \mathbf{Pz}\ \ \mathbf{Oz}\ \ \mathbf{C4}\ \ \mathbf{C3}\ \ \mathbf{T4}\ \ \mathbf{T3}\ \ \mathbf{P4}\ \ \mathbf{P3}]\end{aligned} \tag{2}$$

The presence of EOG in matrix **D** forces PCA to isolate the ocular artefact in a single principal component (PC) representing a large percentage of spatial variance of data, because EOG is independent from EEG sources and completely describes the ocular artefact.

PCA (Donchin and Heffley, 1978; Koles, 1991; Kobayashi and Kuriki, 1999) is based on the computation of the estimate of the spatial correlation matrix $\hat{\mathbf{R}}$ of the original data.

When $\mathbf{a_n}$ and λ_n are respectively the nth eigenvector and the nth eigenvalue of $\hat{\mathbf{R}}$; the eigenvectors are organized in column order in a matrix **A**, with the constraint (the symbol $*$ denotes transpose):

$$\mathbf{a}_j^*\mathbf{a}_j = a_{1,j}^2 + a_{2,j}^2 + \ldots + a_{11,j}^2 = \sum_{i=1}^{11} a_{i,j}^2 = 1 \tag{3}$$

The product of the eigenvectors and the original data matrix

$$\mathbf{a}_n^*\mathbf{D}^* = \mathbf{PC_n} \tag{4}$$

is defined as the nth principal component, while

$$\frac{\lambda_n}{\sum_{j=1}^{11}\lambda_j} \times 100 = \mathrm{PC}(\%) \tag{5}$$

is the spatial variance expressed in percentage value, associated to the nth PC and calculated in function of the corresponding eigenvalue.

Since the identity matrix is

$$\mathbf{I} = \mathbf{A}^*\mathbf{A} = \mathbf{A}\mathbf{A}^* \tag{6}$$

we can expand **D** as follows

$$\mathbf{D} = \mathbf{DI} = \mathbf{DAA}^* = \mathbf{D}\left(\mathbf{a_1}\mathbf{a_1^*} + \mathbf{a_2}\mathbf{a_2^*} + \ldots + \mathbf{a_{11}}\mathbf{a_{11}^*}\right) \tag{7}$$

Therefore, the subtraction of a generic PC from the original data matrix **D** can be realized as follows

$$\mathbf{D_{new}} = \mathbf{D} - \mathbf{D}\mathbf{a_n}\mathbf{a_n^*} = \mathbf{D} - (\mathbf{D}^*)^*\mathbf{a_n}\mathbf{a_n^*} = \mathbf{D} - (\mathbf{a_n^*}\mathbf{D}^*)^*\mathbf{a_n^*}$$

$$= \mathbf{D} - \mathbf{PC_n^*}\mathbf{a_n^*} = \mathbf{D} - \left(\mathbf{a_n}\mathbf{PC_n}\right)^* \tag{8}$$

The subtraction of the *n*th component from the *j*th EEG trace is weighted on the basis of the *j*th element of the *n*th eigenvector as indicated by the following expression

$$\mathbf{EEG_{j}}_{new} = \mathbf{EEG_j} - a_{j,n}\mathbf{PC_n^*} \tag{9}$$

$\mathbf{EEG_{j}}_{new}$ represents the *j*th EEG trace in which the artefact has been reduced by subtracting a PC weighted with $a_{j,n}$ related to the distortion entity present in the recorded signal.

The analytic structure of the method and the values of its parameters were set after careful examination of the results obtained by its application to both real and simulated data. In particular, we noticed that ocular artefacts were mainly contained in the first two PCs: therefore, we subtracted from each trial the first or the second PC only when the correlation coefficients between these PCs and EOG (respectively called c1 and c2) were over a certain value. When c1 was greater or equal to 0.9 then the first PC was subtracted from the original data matrix; otherwise, the second PC was subtracted if c2 was greater or equal to 0.95. In all other cases, we considered that the EOG did not affect the EEG and the original data matrix was not modified by the method. The subtraction of a PC was based both on its spatial and temporal characteristics: in fact we focused only on the two PCs with the higher spatial variance and we verified their similarity with EOG in time through the calculation of c1 and c2.

Since PCA also detects the coherent activity over data, the portion of raw EEG that was greatly spatially correlated over the scalp was also removed, increasing in this way the SNR of the ERP.

2.2. Simulations

In order to evaluate the capability of the method in reducing ocular artefacts, several simulations were

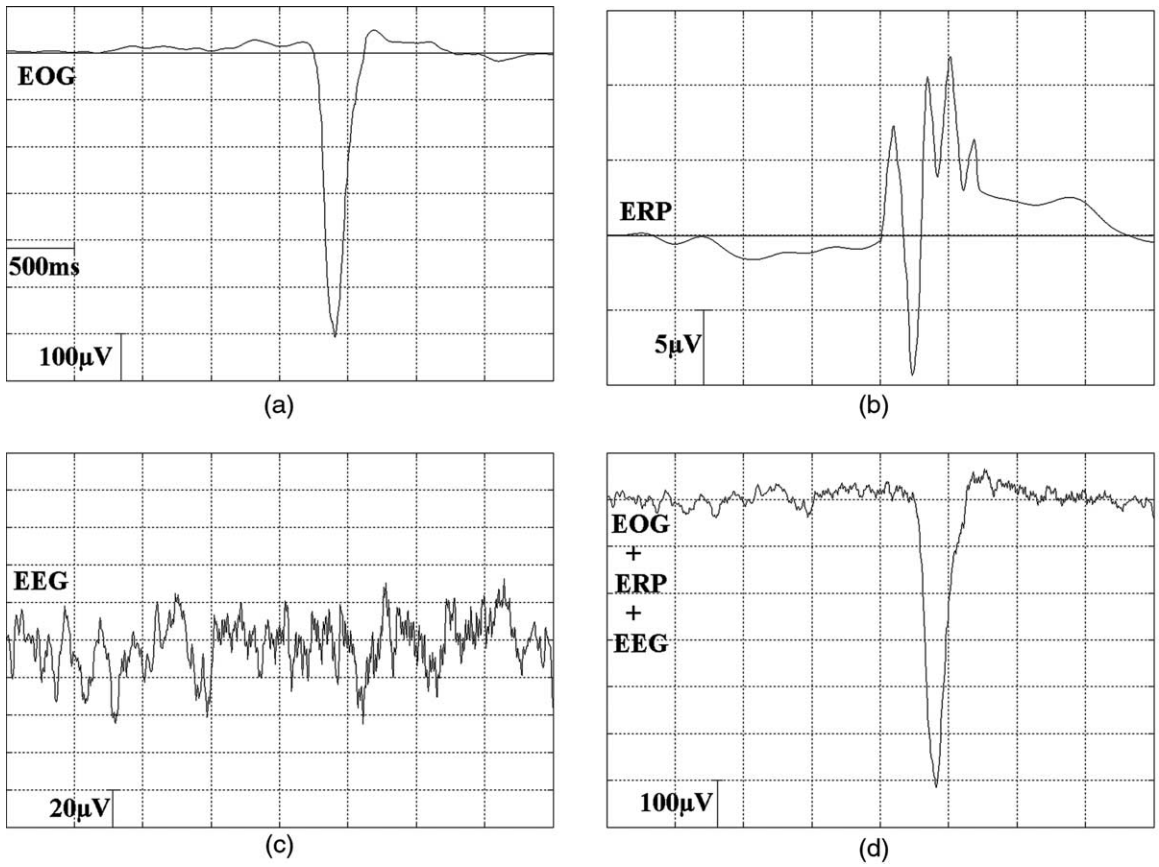

Fig. 1. (a) Simulated EOG and (b) simulated ERP. (c) Simulated raw EEG, obtained by filtering a Gaussian white noise (mean 0 μV and variance 1.70 μV^2) with an autoregressive model. (d) Addition of EOG, raw EEG and ERP: it appears as a real artefact-contaminated recording. The measure of amplitude is different in each panel, while the time unit is the same therefore is indicated only in panel (a).

performed in different conditions. In all these simulations, when dealing with the concept of SNR, the term 'noise' will be addressed to the simulated ocular artefacts only and the term 'signal' to the addition of simulated raw EEG and ERP. In order to avoid any ambiguity relative to symbology, in the simulations the SNR will be indicated as SÑR. The EEG was obtained as the output of an AR(16) model fed with a white Gaussian noise (0, 1.70). For each channel and each trial a different realization of simulated EEG was computed and the same simulated ERP was added to all the EEG channels (Fig. 1). The following conditions were included in the simulations. Condition 1: the artefact latency was maintained fixed and the EOG amplitude was varied with different values of the SÑR in the EEG channels. Condition 2: the absence of distortions in the average after the application of the artefact reduction was verified.

2.2.1. Simulation 1: influence of the EOG amplitude and of the SÑR in the EEG

We simulated EEG recordings affected by an ocular artefact transmitted on the scalp with decreasing amplitude, without delay, with different polarities. The values of SÑR in the different EEG channels are indicated in Fig. 2b. EOG amplitude was varied in 17 steps between 91 and 606 μV.

After the application of the method to the simulated trials, the correlation coefficient between EOG and the first PC was computed for different EOG amplitudes and plotted

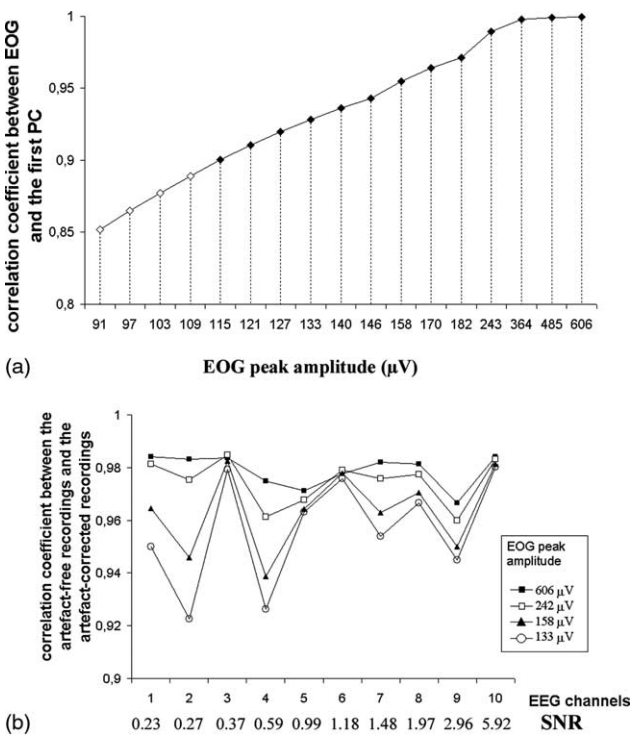

Fig. 2. Simulation 1. (a) Correlation coefficient between EOG and the first PC vs. EOG peak amplitude. (b) Correlation coefficient between the artefact-free recordings and the artefact-corrected recordings vs. SÑR in the different EEG channels, computed for different EOG peak amplitudes.

(Fig. 2a). Decreasing EOG amplitude, the correlation between EOG and the first PC decreases, i.e. the ocular artefact is not completely isolated in a single component. For EOG amplitudes < 115 μV, correlation coefficient between EOG and the first PC is below 0.9: this result suggests this value be used as a threshold for subtraction of the PC for artefact reduction.

For some values of correlation > 0.9 (thus for EOG amplitude > 115 μV), the artefact reduction efficacy was tested by comparing the artefact-free EEG recordings and the artefact-corrected EEG recordings. Fig. 2b shows that maximum correlation coefficients between the artefact-free EEG recordings and the artefact-corrected EEG recordings are obtained for high values of EOG amplitude, when the artefact is better identified. In addition, for lower values of EOG peak amplitude, the correlation coefficient slightly increases in correspondence to high values of SÑR: this indicates an improvement of correction quality.

2.2.2. Simulation 2: influence on averaged ERPs

This simulation was performed to verify that the subtraction of PCs does not cause distortions of the ERP morphology. Ninety single trials were simulated by adding the same ERP_0 to different raw EEG for each channel. An ocular artefact was added to 30 of these trials: *SÑRs* are the same as in Simulation 1. Different ERP_n were evaluated averaging n single trials and the correlation coefficients between ERP_0 and ERP_n were computed. The results are shown in Fig. 3. The ERP'_{60} obtained by averaging the 60 artefact-free trials is the most similar to ERP_0: the corresponding correlation coefficient across the EEG channels is taken as reference. The quality of the ERP''_{60} obtained by averaging 30 artefact-contaminated and 30 artefact-free trials is strongly dependent on the SÑR of

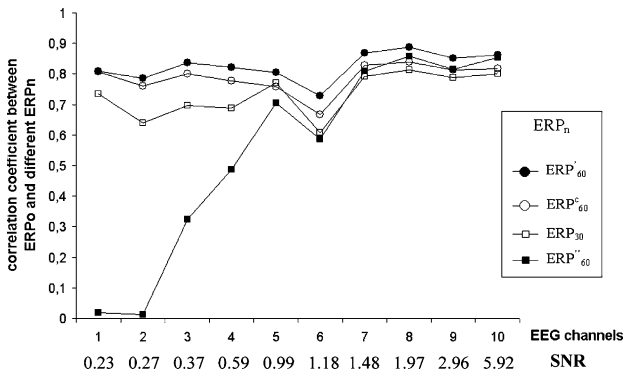

Fig. 3. Simulation 2. Correlation coefficient between ERP_0 and different ERP_n obtained by averaging n single trials vs. the different EEG channels. The line with black circles at the top of the graphic is the correlation between ERP_0 and the ERP'_{60} obtained averaging 60 artefact-free trials. The line with black squares represents the correlation between ERP_0 and the ERP''_{60} obtained averaging 30 artefact-contaminated and 30 artefact-free trials. The line with white squares represents the correlation between ERP_0 and the ERP_{30} obtained averaging 30 artefact-free trials. The line with white circles represents the correlation between ERP_0 and the ERP^c_{60} extracted by averaging 30 corrected and 30 artefact-free trials.

the EEG recordings. In the channels in which the ocular artefact influence is high ($\tilde{SNR} < 0.99$), the similarity with ERP_0 is low (correlation coefficient < 0.7). Without a method for reducing ocular artefacts, the usual approach consists in rejection of artefact-contaminated trials, which leads to an average ERP_{30}: the quality of the outcome is not excellent (correlation coefficient < 0.8) for the reduced number of sweeps in the average. Applying the method described, it is possible to include the corrected trials in the averaging, thus obtaining ERP^c_{60}: the correlation coefficient between ERP_0 and ERP^c_{60} is independent from the $\tilde{SNR}$ of the artefact-contaminated trials and is very close to the one obtained with ERP'_{60}. These results lead us to state that the PCA method correctly reduces the ocular artefacts without altering ERP morphology and makes it possible to retrieve a greater number of trials suitable for averaging.

In addition, in the simulated artefact-contaminated trials, the artefact was supposed to always occur at the same latency: this condition is the worst possible because it amplifies the eventual introduction of distortions, which rarely happens during the experimental procedure. Having tested this very unfavourable condition, the method guarantees that, after artefact reduction, the ERP morphology is unchanged.

3. Experimental protocol

3.1. Subjects

Twenty-four normal children (18 males and 6 females) ranging in age from 8 to 10 years (mean age 9.27 ± 0.23 years) and 15 children with developmental dyslexia (12 males and 3 females) ranging in age from 8 to 10 years (mean age 8.9 ± 0.38 years) participated in the experiment. The children with developmental dyslexia were diagnosed according to DSM IV-R criteria (American Psychiatric Association, 1994) and the discrepancy between chronological age and reading age was obtained using the Direct Test of Reading and Spelling (TDLS), the Italian adaptation of the Boder test (Boder, 1973; Chiarenza and Bindelli, 2001). All children were previously informed of the experimental procedure and written consent was obtained from parents and children. The entire experimental procedure was approved by the hospital's ethical committee.

3.2. Experimental setting

The stimuli consisted in the central presentation of 21 Italian alphabetic capital and small letters and non-alphabetic symbols (such as /, *,], %) produced by a vacuum fluorescent display (brilliance: 175 fLumen). Each stimulus was 8 or 6 mm high for capital and small letters, respectively, and 3.5 mm wide, and its persistence on the screen was 25 ms. A minimum of 4 sets of stimuli were presented in the same random order for all subjects. When cooperation was poor, in the case of some of the dyslexic children, it was necessary to increase the number of stimuli. The distance between the examined subject and the display was 70 cm and the angle of reading was 0.29°.

Reading-related potentials were recorded during both *passive* and *active* conditions. *Passive* conditions consisted in the simple observation of letters (first task) and non-alphabetic symbols (second task). The subjects were instructed to look at letters passively without making any effort to read or articulate them silently. The first and the second tasks were respectively called *letter presentation* and *symbol presentation*. *Active* conditions consisted in the letters being read aloud either in an externally paced (3rd task) or in a self paced manner (4th task) performed by pressing a button placed on the right-hand side: these two other tasks were respectively called *externally paced letter recognition* and *self-paced letter recognition*. It was decided to use single isolated letters rather than words to avoid the influence of semantic inferences from the context to reading process.

Subjects sat in a dimly illuminated, electrically and acoustically shielded room. Resting periods were offered when required. The whole procedure lasted about 2 h, including the EEG montage.

3.3. EEG recording

Ag-AgCl electrodes were applied to the scalp with collodion. Resistance was less than 10 kΩ. EEG was recorded from Fz, Cz, Pz, Oz, C4, C3, T4, T3, P4, P3 referred to linked mastoids. The EOG was bipolarly recorded using two electrodes diagonally placed above and below the right eye: this montage is most frequently used in recording ERPs in children, because it makes it possible to record both blinks and vertical and horizontal eye movements with few electrodes. Lip movements were bipolarly recorded by two electrodes placed on the superior and inferior orbicularis oris muscles. A microphone was used to record subjects' voices. Movements of the subject's right thumb were measured by bipolarly recording the electrical activity from the right forearm flexor muscles. Furthermore, ECG and pneumogram were also recorded.

Physiological preamplifiers (Marazza) were used with the following bandpass filters: 0.02–30 Hz for EEG and EOG; 160–3000 Hz for EMG, and 0.005–3000 Hz for ECG and pneumogram. The EEG and EOG signals were sampled at 250 Hz, with 4 s analysis time, 2 s pre- and 2 s post-stimulus.

3.4. Analysis protocol

Original recordings were visually inspected so that trials affected by artefacts generated by sources different from ocular movements (gross body movements, muscular activity, etc.) could be rejected.

The method for reducing ocular artefacts was applied to all the single trials recorded from both normal and dyslexic subjects: the first or the second PC, extracted by means of PCA (without rotation), was subtracted from each trial if its correlation with the corresponding EOG trace was respectively over 0.9 or 0.95.

We computed the mean number of recorded trials and the mean number of trials suitable for averaging, both before and after applying the method, for each task separately and for each group of children. A two-sided *t* test analysis was performed to evaluate the significance of the increase in the number of useful trials after PCA application.

4. Results

4.1. Example of application in a single trial

Fig. 4 shows 10 EEG traces and the EOG recorded in a 9-year-old dyslexic child during the letter presentation stimulus. The trial is affected by the presence of a great ocular artefact, more evident in channels Fz, Cz, C3, C4 (thin lines). In the present case the first PC (dotted lines) represented 85.28% of the data spatial variance and had a correlation with EOG of 0.99: therefore, according to the method criteria, it was subtracted. The thick lines in Fig. 4 represent the EEG signals after artefact reduction. The maximum subtraction occurs in the temporal window containing the EOG artefact, without modifying the other parts of the original EEG traces. The channels less affected by the artefact are practically unchanged after the application of the method.

4.2. Example of application on an entire test

In Fig. 5 the ERP average of a 9-year-old normal subject during the letter presentation task is plotted. In this subject the massive presence of ocular artefacts obliged the experimenter to reject 96 trials out of 136. The average of

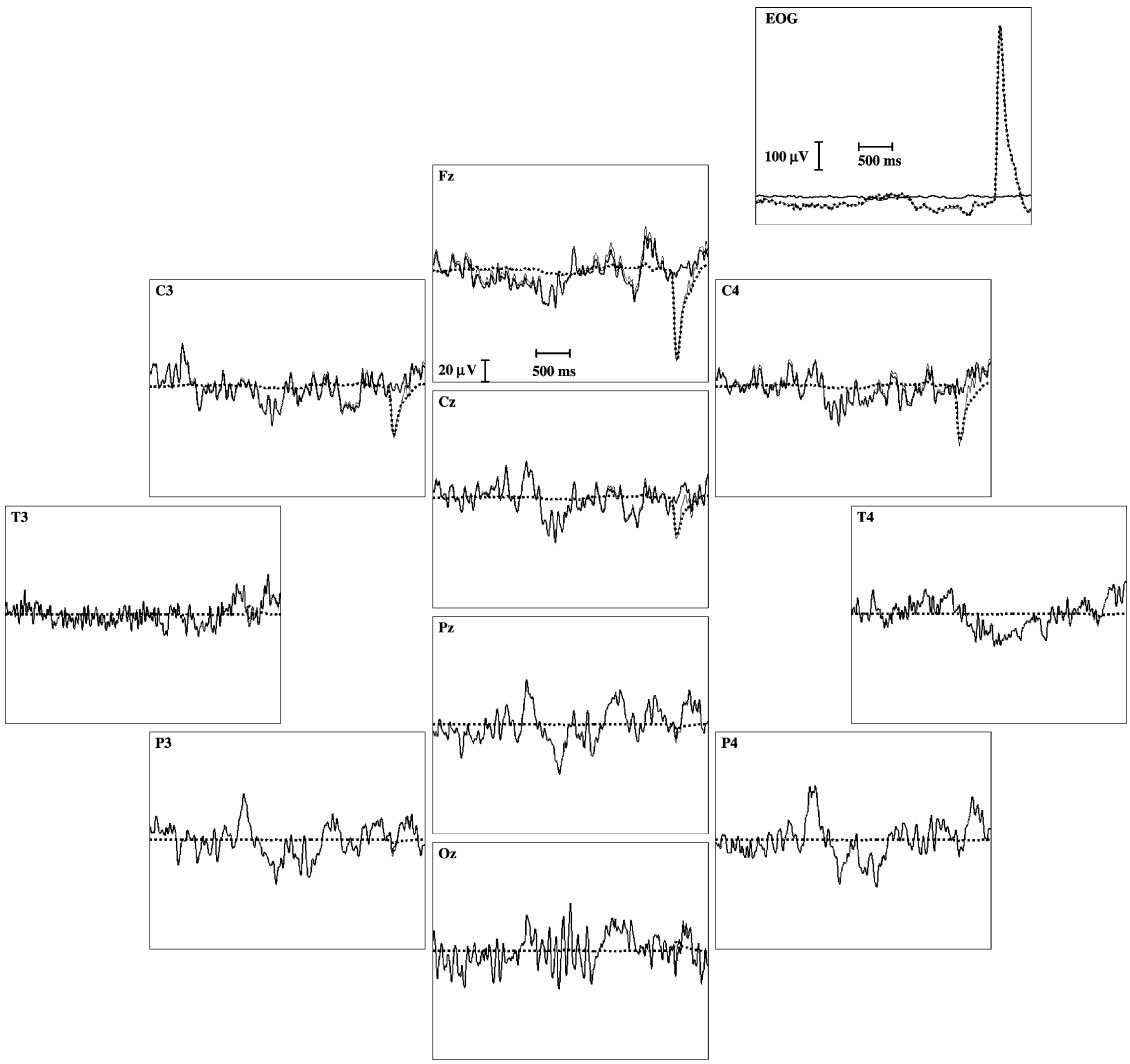

Fig. 4. Single trial recorded from a 9-year-old dyslexic child during the letter presentation task. Solid thinner lines represent the original recorded trial. Dotted lines represent the waveforms to be subtracted after the application of the method. Solid thicker lines represent the corrected trial.

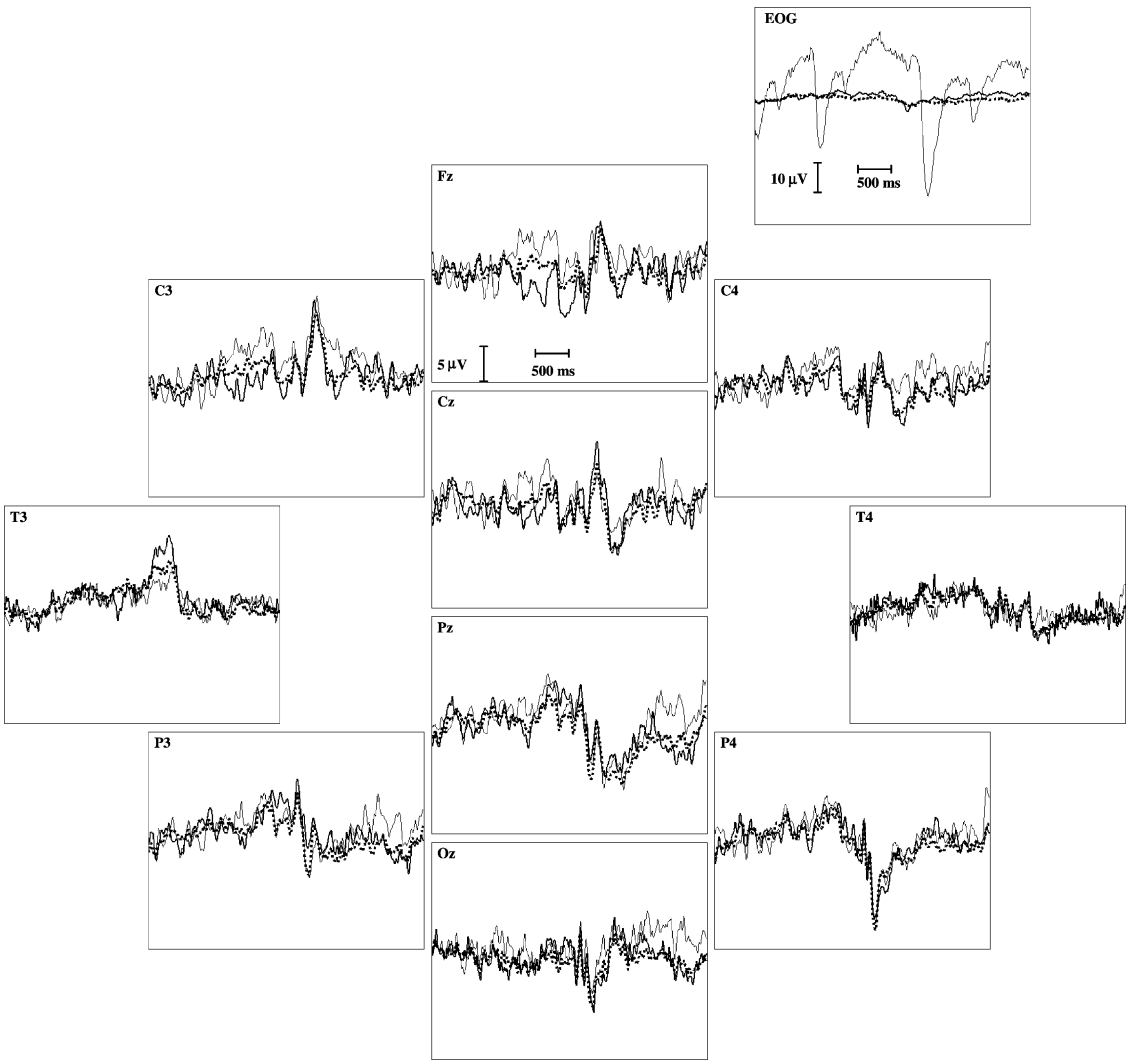

Fig. 5. Solid thinner lines represent ERP_{40a} obtained averaging 40 trials out of 136 without applying the method (i.e. having rejected all trials contaminated by EOG artefacts). Dotted lines represent ERP_{117} obtained averaging 117 trials out of 136 after the application of the method. Solid thicker lines represent ERP_{40b} obtained averaging the first 40 corrected trials.

the remaining 40 trials (ERP_{40a}) is represented in the figure in thin solid lines.

After PCA application, it was possible to average 117 trials out of 136 and the resulting ERP_{117} is plotted in dotted lines. For a more uniform comparison ERP_{40b} was also calculated, averaging the first 40 artefact-free trials after the application of the method, and plotted in thick lines. ERP_{40b} seems more similar to ERP_{117} than to ERP_{40a}.

In order to quantify the similarity among traces, the correlation coefficients were evaluated between ERP_{117} and ERP_{40a} and between ERP_{117} and ERP_{40b} across the EEG channels. Fig. 6 shows that the correlation coefficient for ERP_{40b} was generally higher, except for C3, than for ERP_{40a}, indicating an improvement in the SNR.

Thus the application of PCA produces a double effect on the signal: (i) it increases the number of trials suitable for

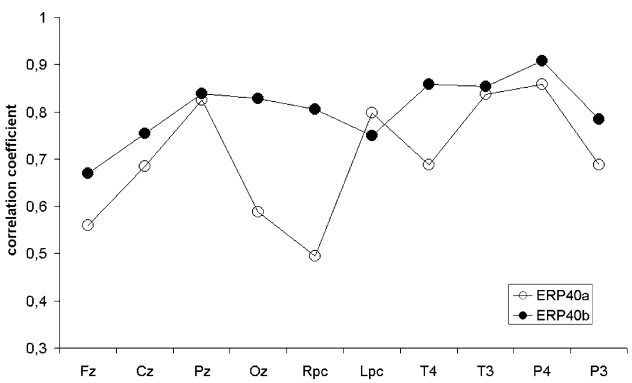

Fig. 6. The line with white circles represents the correlation in all the EEG channels between ERP_{117} and ERP_{40a}. The line with black circles represents the correlation in all the EEG channels between ERP_{117} and ERP_{40b}.

averaging; (ii) it increases the SNR of single recordings subtracting spatially correlated raw EEG activity. Both effects contribute to reducing the required number of sweeps and shortening the recording time.

4.3. Group results: normal and dyslexic subjects

The SNR of ERPs is influenced by the number of averaged trials. Mean and standard deviations of recorded trials and of the percentage of artefact-free trials before and after ocular artefact reduction are shown in Fig. 7 for normal and dyslexic children in passive and active conditions.

The group and task conditions greatly influence the SNR of EEG. In dyslexic children the percentage of artefact-contaminated trials was significantly higher (df 133, $t = 2.697$, $P < 0.01$) than in normal ones. In active conditions, there was a significantly higher percentage of artefact-contaminated trials than in passive ones (df 149, $t = 5.074$, $P < 0.0001$). Thus, it was necessary to record more trials from dyslexic children (df 96, $t = 4.304$, $P < 0.0001$) than from normal ones and more during active conditions (df 140, $t = 2.959$, $P < 0.005$) than during passive ones.

For both groups and tasks, the application of the method significantly increased the number of trials that could be used. Considering normal children, ocular artefact reduction allowed us to retrieve for averaging 41.0% of the rejected trials in passive conditions (df 92, $t = 6.651$, $P < 0.0001$) and 39.1% in active ones (df 94, $t = 9.169$, $P < 0.0001$). Similar results were obtained from dyslexic children: in fact it was possible to average 36.7% (df 58, $t = 5.453$, $P < 0.0001$) and 32.2% (df 54, $t = 7.401$, $P < 0.0001$) of the rejected trials in passive and active conditions, respectively.

5. Discussion

Ecological approach to the study of reading processes requires observation of the related phenomena in a natural environment, and investigation of all aspects of reading including reading aloud. EEG recorded in these conditions will be subject to many different types of artefact from other physiological signals, such as eye movements, blinks and speech articulation. Ocular artefacts (EOG) are naturally present during reading and cannot be voluntarily suppressed without introducing distracting instructions superimposed on the actual task being performed. Speech artefacts are particularly critical because they can sometimes mimic the EOG, and this problem becomes worse when dealing with non-cooperative subjects. The application of an automatic algorithm for artefact reduction is crucial to the reliability of the morphological characteristics of ERPs and for the subsequent statistical analysis and interpretation. In the present work we focused on reduction of ocular artefacts during reading.

Transmission of ocular artefacts varies across the EEG channels, due to the morphological and structural characteristics of the scalp; it is also influenced by interindividual variability and by the different subtypes of ocular activities. Task and group conditions greatly influence the incidence of artefacts in EEG recordings.

In order to avoid loss of event-related potentials components, it is desirable to reduce ocular artefacts only when they are largely spread over the scalp and when EOG

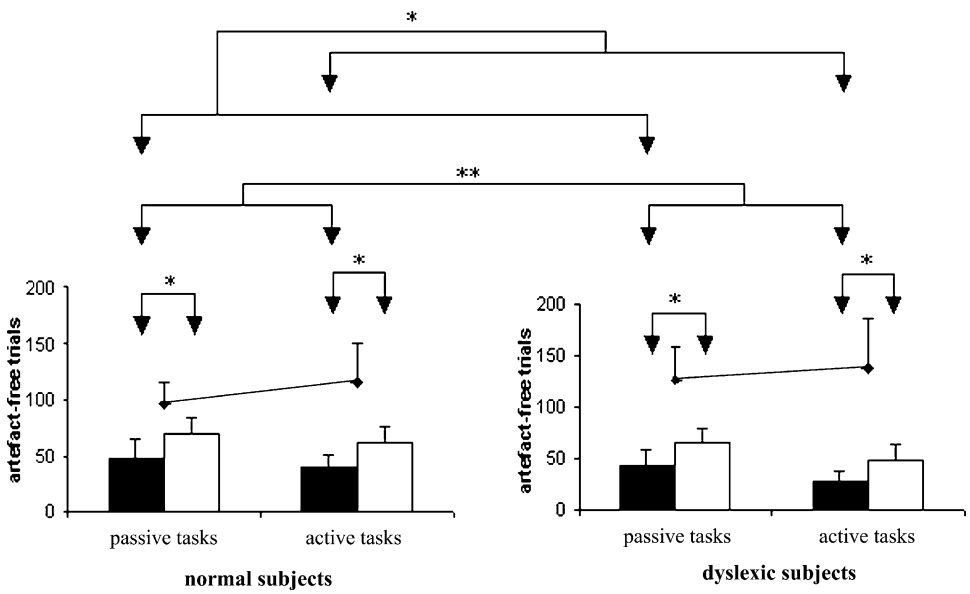

Fig. 7. The lines upon the columns indicate the number of recorded trials. Black columns indicate the mean percentage of originally artefact-free trials. White columns indicate the mean percentage of artefact-free trials after artefact reduction. Bars indicate the standard deviation values. *$P < 0.0001$; **$P < 0.01$.

amplitude is higher than 100 μV. In the present work a methodology for artefact reduction, based on PCA, was proposed. PCA was previously used in a topographic approach for reducing ocular artefacts (Lagerlund et al., 1997; Picton et al., 2000a). Using this approach, repeated voluntary eye movements and blinks were recorded during calibration sessions and averaged; PCA was applied to extract the ocular components and their spatial distribution; the cerebral activity was modelled using dipole sources, thus increasing the computational load. The contribution of ocular artefacts to the different scalp recordings was subtracted, obtaining a 'corrected' EEG. This approach produces good results in terms of reduction of ocular artefacts and makes it possible to precisely identify the scalp topographies of the different subtypes of ocular activity. The outcomes are sufficiently reliable when the cerebral activity is recorded from a great number of scalp sites and when the different ocular artefacts are separately modelled. This method requires performing a calibration session. Some researchers (Records, 1979) claim that voluntary eye movements and blinks are different from the ones that are spontaneously executed. Furthermore, the recording of calibration data leads to an inconvenient lengthening of test duration when dealing with non-collaborative subjects or with children affected by cognitive disorders.

The PCA method proposed in this work for reducing ocular artefacts is based on a conceptual linear model similar to that of the linear regression methods. In fact, both these approaches assume that the electrical activity recorded on the scalp can be expressed as the summation of 'true' brain activity unaffected by ocular artefacts and the electrical activity due to ocular artefacts transmitted over the scalp.

In linear regression methods, the artefact can be approximated to EOG and can be reduced by subtracting from the recorded EEG a certain fraction of the EOG amplitude accounting for the topographic distribution of ocular activity over the scalp. Linear regression can be performed in either the time or in the frequency domain. Researchers applying linear regression in the time domain claim that constant regression coefficients are sufficient to represent the ocular artefact transmission over the scalp. Researchers applying linear regression in the frequency domain claim that frequency dependent transfer functions have to be considered because transmission of ocular activity varies with frequency.

Estimation of the regression coefficients can be performed according to different criteria, which lead to different artefact reduction performances. A simple way to estimate the regression coefficients is to compute the amplitude ratio of the artefact in the different EEG channels vs. the EOG channel (Hillyard and Galambos, 1970; Corby and Kopell, 1972). Another approach consists in estimating the regression coefficients by trial and error until the EOG average shape is no longer present in the EEG average (Roth et al., 1980). This intuitive procedure can be mathematically expressed as the minimization of the absolute value of the covariance of EOG and 'true' EEG (Verleger et al., 1982; Gratton et al., 1983): this assumes that EOG and 'true' EEG have to be independent.

In all cases, the estimation of the regression coefficients requires a manual selection of the trials containing the artefacts and an average of the single trial estimates. Because of great inter- and intra-individual variability of artefact transmission there is no agreement among researchers if it would be better to repeat the regression coefficient estimation for each subject and session or to average the estimates (Verleger et al., 1982; Semlitsch et al., 1986).

Even though researchers generally acknowledge that blinks and eye movements have different scalp topographies, often only one correlation coefficient for blink correction is estimated, thus decreasing the computational load (Kenemans et al., 1991; Verleger, 2000). This simplification is quite acceptable when ocular movements are reduced by a fixation point on the screen for presenting the visual stimuli.

One controversial point related to the reliability of linear regression methods is the assessment of the presence of cerebral activity in EOG. There is no agreement about the actual ERP distortions due to forward propagation of EEG. The possible sources of distortion arise from the following procedures: coefficient estimation and EOG subtraction (Croft and Barry, 2002). The distortion produced during the coefficient estimation is limited because estimation is performed in correspondence to segments whose variance is mainly due to EOG activity and for only a minor part to EEG and because correlation coefficients are averaged. The effects of forward propagation of EEG on the EOG subtraction procedure are currently being debated.

Summing up, linear regression methods are easy to apply, have lower computational costs compared to topographic approaches and perform well in reducing ocular artefacts. However, the eventual presence of cerebral components in EEG recordings can potentially introduce distortions into averaged ERPs. Furthermore, correction of all the subtypes of ocular artefacts involves estimating different regression coefficients for each of them. In addition, artefact-contaminated trials have to be manually selected and classified and this is a time consuming task.

Using the PCA method presented in this paper, the artefact contained in the EOG is well represented by one of the two PCs with maximum spatial variance. The other components contain both the raw EEG and the event-related responses. The artefact is reduced by subtracting from the recorded EEG one PC weighted with the corresponding eigenvector of the correlation matrix. Subtraction of one PC occurs only when the correlation coefficient between the PC and EOG is over a certain threshold. The method does not reduce the ocular artefacts that are distributed out of the first two PCs. We noticed, however, that this restriction was sufficient for reducing the artefacts with great amplitude,

independent of polarity and largely transmitted over the scalp. Thresholds depend only on the type of recorded ERPs and are independent from subjects or sessions. The values of the parameters of the method are the result of empirical work, based on systematic, precise observation of raw data and of partial results obtained in the various steps of signal processing for artefact reduction. Manual selection and categorization of the different subtypes of artefact-contaminated trials is not required because the fraction of ocular activity present in the different scalp recordings is automatically quantified by the eigenvectors of the correlation matrix of data.

The problem of forward propagation of cerebral activity in EOG recording does not affect the PCA method because the PCs being subtracted, which are strongly correlated with EOG, are by nature independent from the EEG. Applying the PCA method it is not necessary to use different coefficients for the different subtypes of EOG artefacts, as it occurs applying linear regression methods.

PCA decomposition was not used in the present work to identify ERP components or to find a precise relationship between PCs and cerebral sources of activity. For these reasons, in the present study the number of recording channels is not critical for correction performances because it does not affect the precision of artefact estimation.

This method allowed us to retrieve a percentage of artefact-contaminated trials varying between 32.2 and 41.0%, considering all tasks performed by normal and dyslexic children. Implementation of this method during data acquisition would therefore significantly reduce recording time.

In conclusion, the PCA method made possible an efficient reduction of ocular artefacts without introducing distortions on event-related potentials. In respect to topographic approaches, it is computationally efficient even when applied to fairly large EEG data sets. It requires neither recording of calibration data nor modelling of ocular and cerebral electrical sources. In comparison to linear regression methods, it is equally simple and fast to apply and is based on the same linear model of ocular artefacts transmission over the scalp. Furthermore, there is no need to identify and separate blink artefacts from those deriving from vertical and horizontal eye movements and its performance is not influenced by the presence of EEG in the EOG recordings. Certainly, the method would improve if more than two electrodes were used to measure the different components of eye activity. On the other hand, adding more electrodes to children with neurocognitive problems surely would cause much more discomfort and consequently would increase blinks and artefacts. The fact that diagonal EOG recording picks up most of the artefact is an honourable compromise. We applied PCA to reduce ocular artefacts in ERPs recorded from normal and dyslexic children during passive and active reading of letters and symbols. Active tasks, such as reading aloud and button pressing, are more demanding than passive ones in terms of control of non-requested movements. It is very difficult for dyslexic children to maintain attention and concentration for long periods and the ones in our tests showed more difficulties in motor control than normal ones (Chiarenza et al., 1982). Consequently, the availability of a simple and efficient method for ocular artefact reduction is an indispensable means for studying ERPs in normal children and especially in children with different pathologies.

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