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MULTIRESOLUTION ANALYSIS OF READING RELATED POTENTIALS TO CALCULATE ACTIVATION MAPS IN DYSLEXIA

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Abstract: The problem of obtaining a reference signal for ERP during reading tasks is here addressed. The classical procedure based on the calculation of grand-averages on a group of subjects, is strongly affected by the high inter-subject variability, that becomes especially relevant when dealing with long-latency waves related to the cognitive functions. A dynamic time warping procedure is applied to the signals after a time-scale decomposition through wavelet transform. The multi-scale decomposition of the signal permits to optimise the time warping procedure to the different temporal dynamics of the analysed components and then the reconstruction of a more reliable template. The procedure is applied for the mapping of the cognitive functions in the study of normal and dyslexic children.

Introduction

Developmental dyslexia is a neurological disorder characterized primarily by reading difficulties despite average intelligence, adequate education and normal sensory acuity. The aetiology of this condition is still unknown: the most recent theories hypothesize a genetic disruption of the cerebral structure, that would produce compromised phonological awareness and visual/auditory perception [1]. In order to investigate the reading processes, event-related potentials (ERPs) are recorded in normal children and in children with developmental dyslexia. Comparing ERPs from different subjects is difficult for the high inter-individual variability of the morphology: dealing with children performing cognitive tasks this variability greatly increases. As a consequence, it is difficult to define a normal "pattern". Usually, a grand-average is evaluated from a group of normal subjects, but this is heavily affected by inter-individual variability producing jitter in alignment of the relevant peaks. Previous works [2, 3] proposed an approach based on Dynamic Time Warping (DTW) technique for the automatic alignment of the waves and quantification of the morphological characteristics of ERPs. However the performances of the method depend on the setting of some parameters and on the time spreading of the different waves.

The wavelet decomposition allows the alignment of the signal at different scales. After proper reconstruction of the aligned details, the method leads to the calculation of a reliable template for normal subjects, which can constitute a reference pattern for evaluating pathological subjects.

Materials and Methods

Acquisition protocol: 16 normal and 4 dyslexic children aged 9, underwent the study. The clinical protocol was designed including different tasks, which are supposed to elicit, in the child, different level of responses, discriminating among prevalent visual, attentive, cognitive and phonetic functions. The children underwent four different trials of reading-related activity, according to the following order: *letter presentation* (*lp,* the alphabetic letter was presented on a screen, and the child had only to watch at it)*, symbol presentation* (*sp,* symbols without any semantic meaning were presented on the screen)*, letter recognition externally paced* (*lre,* the child had to pronounce the letter presented on the screen by an external operator)*, letter recognition self paced* (*lrs* the child had to pronounce the letter presented on the screen by himself pushing a button. The EEG was recorded through 10 different leads located according the modified 10-20 international system. In order to better quantify the stimulus related activity the following signals were also recorded: EOG for the evaluation of the ocular movements and blinks; lip EMG and phonogram (PHN), through a microphone, for the characterization of the speaking activity; ECG; pneumogram (PNG); arm EMG for the detection of the onset of the self paced presentation.

Each stimulation was repeated until the number of artifact-free responses was large enough for a reliable calculation of the average, at least 80-100 responses after artifact removal (see below).

Signal analysis The first step of the analysis was the ocular and blinking artifact removal according to the methodology presented in [4]. The obtained sweeps were then averaged according the traditional procedure, for each EEG channel and for each trial. The further step is usually the calculation of the grand-averages on the normal population in order to obtain reference patterns for the evaluation of the pathological signals. However the inter-subject variability, especially in the long latency components, related to cognitive and reading functions, may produces a jitter among the signals and a misalignment of the ERPs. For such a reason the Dynamic Time Warping procedure was proposed in [2, 3] in order to obtain an optimized template.

The Dynamic Time Warping (DTW) is a technique of nonlinear alignment for locally contracting or dilating the time axis of two signals, in order to reduce distortions due to normal morphological differences in the waveforms. The procedure is introduced for minimizing latency differences by means of a function *w(k)* called *warping function,* defined as in the following:

$$w(k) = w(i(k), j(k))$$

The warping function is obtained through the minimization of the *dissimilarity function D(x,y),* where

$$D(x, y) = \sum d(k)$$

and

$$d(k) = d(w(k)) = d(i, j) = \|x(i) - y(j)\|$$

$\|x(i) - y(j)\|$ is a measure of the distance between the waveforms and can be defined differently. In the current application it is evaluated as:

$$d(i, j) = |x(i) - y(j)| + |\dot{x}(i) - \dot{y}(j)| + |\ddot{x}(i) - \ddot{y}(j)|$$

.

The warping procedure produces important results and applications: 1) the possibility of a more realistic averaging of the sweeps, by summing samples with a morphological, instead of temporal, correspondence; 2) automatic tracking of fiduciary points on the sweeps; 3) creation of a template of the ERP. Some bounds are given to the algorithm, for example the *r* value that represents the maximum time shift allowed between two waves to be aligned. The same *r* can not be used for mid-latency or long-latency waves that are, at the same time, present in the same response. In addition the DTW algorithm has an heavy computational cost which increases with the number of samples in the signals. The above considerations led to the solution of applying the DTW procedure to the signals after wavelet decomposition.

Wavelet Transform performs the analysis of a signal *x(t)* according to wavelet functions that can be defined as:

$$h_{a,\tau} = \left(1/\sqrt{a}\right)h\left((t-\tau)/a\right).$$

Each wavelet is obtained by scaling (contracting or dilating) and shifting in time a wavelet prototype (or *mother wavelet*) *h(t).*

In the discrete time case the dilation factor *a* and the shifting factor τ vary according to the following dyadic rule:

$$a = a_0^j \qquad \tau = k a_0^j T$$

where $a_0 = 2$, *j* and *k* are integers and *T* is the sampling interval of the digital signal.

The analysis results in a set of wavelet coefficients, which indicate how close the signal is to a particular basis function in different time intervals *k* and in different frequency scales *j*.

$$c_{k,j} = \int x(t) h^*_{j,k}(t) dt$$

The resulting analysis has the fundamental characteristic of being multi-scale. In fact, for large values of *j,* we can look at very small details in the signal (high time resolution and low frequency resolution), and for small values of *j* we look at the signal through a larger scale (low time resolution and high frequency resolution).

Signal analysis. Fig.1 shows the ERP's recorded from two different subjects at channel Fz during the *sp* task. The wavelet coefficients for details (D1-D7) and approximation A7 are also displayed. The mother wavelet used for the decomposition is the Coiflet 2.

From a first visual inspection of the figures we can derive a few observations:

1. the waveforms of the ERP's in the two subjects are quite different, even if the same characteristic peaks can be detected;
2. details D1-D3 do not actually contain relevant information, but are mainly noise added to the signal;
3. short latency waves are characterized by high frequencies, while long latency waves are characterized by low frequencies and are then separated into different wavelet details, as represent the ERP viewed at different scales;
4. As the decomposition level increases the number of wavelet coefficient decreases.

The above observations suggested the following procedure for the averaging procedure and the calculation of a template:

1. ERP's decomposition through discrete wavelet transform up to level 7;
2. alignment through DTW of the approximation coefficients for the complete post-stimulus time;
3. alignment through DTW of the D7 coefficients for the complete post-stimulus time;
4. alignment through DTW of the D6 coefficients for the post-stimulus time up to 1.3 sec
5. alignment through DTW of the D5 coefficients for the post-stimulus time up to 0.85 sec;
6. alignment through DTW of the D4 coefficients for the post-stimulus time up to 0.47 sec;
7. reconstruction of the average starting from the aligned coefficients.

Fig. 2 shows an example of the coefficients al level D4 for two different subjects. The dotted lines link the coefficient pairs with a morphological correspondence in the two sequences, while the dark line in the middle is the calculated double mean. The procedure is iterated according a binary tree on the whole set of 16 subjects and for the coefficients of interest (D4, D5, D6, D7, A7). A reference template is obtained by the wavelet reconstruction procedure on the aligned details and A7 approximation. Fig.3 shows an example of the template (bold line) superimposed to the traditional grand-average (thin line). The template results in a more readable and interpretable pattern than the grandaverage.

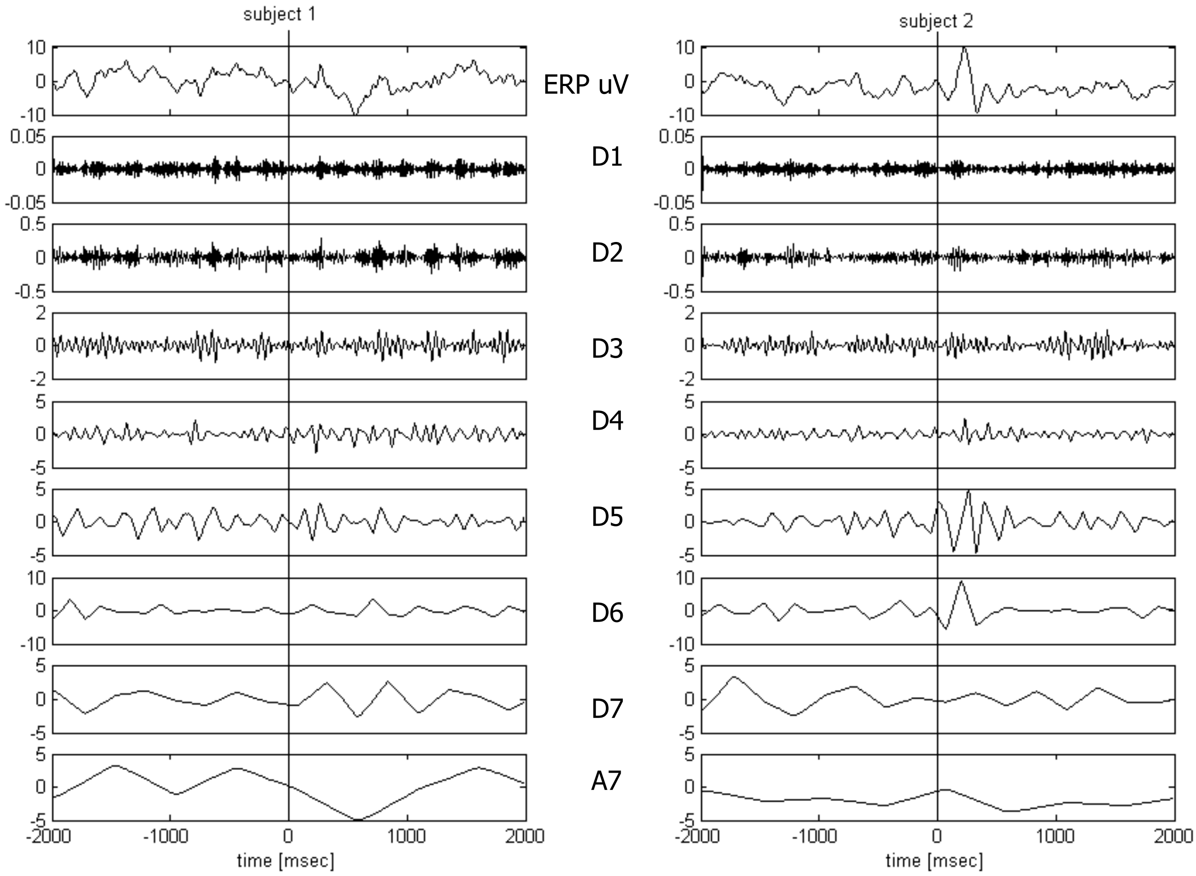

Figure 1 The upper panels show the example of two ERPs obtained at channel Fz from two different subjects during the *sp* task. The middle panels show the detail D1-D7 of the wavelet decomposition, while the lower panels shows the last approximation A7. The line at time t = 0 represents the stimulus time.

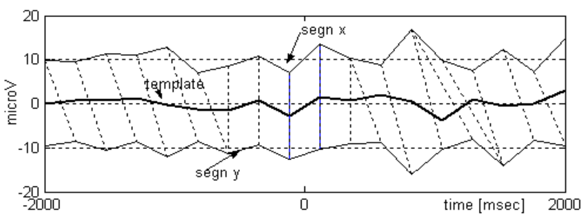

Figure 2 Alignment of the coefficients al level D4 (Fz, sp) for the subjects shown in Fig.1. The dotted lines link the coefficient pairs with a morphological correspondence in the two sequences, while the dark line in the middle is the calculated double mean.

Results

A few peaks, shown in Fig.4, were measured on the template, because have been related to to different cognitive functions and are enhanced during the different tasks: Nminor, around 150 ms, is related to attention; Pmajor, around 300 ms, is traditionally linked to cognitive processes; Nmajor, between 400 and 500 Hz, seems related to the association graphema-phonema during reading [5].

Their latencies were recognized on the whole set of recorded EEG channels, in order to put into evidence the sequence of activation of the different cortical areas during the mentioned functions.

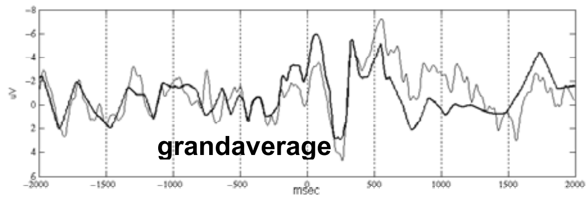

Figure3 Template (bold line) superimposed to the traditional grand-average (thin line) (Fz., *sp*)

The relation between the Nmajor wave and the association graphema-phonema seems confirmed in Fig.5 where the ERP templates are shown, corresponding to three different tasks *sp* (bold line), *lp* (dotted line) and *lre* (dashed line). As the task demands more effort in the interpretation of the stimulus and in the association between the presented symbol and the production of a sound, the amplitude of the Nmajor peak increases.

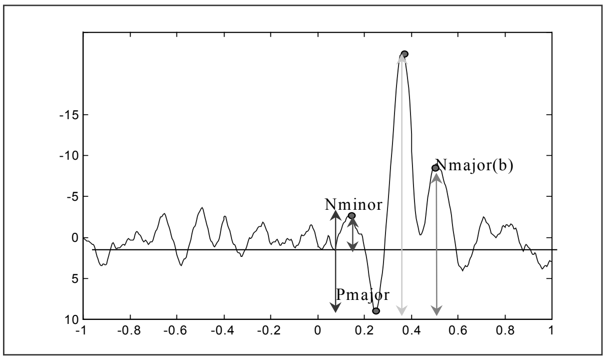

Figure 4 Characteristic peaks of event-related response to an externally paced stimulus (Fz during *lpe* task). The marked peaks have been related to different cognitive tasks (see text for details) (time in sec, and amplitude in uV).

A second relevant observation is noteworthing: the presence of very-long-latency wave during the *lre* task. Such wave di not appear in the grandaverage (not shown in the paper), becaose they are occasionally present in single subjects with a large inter-subject variability. Their origin is not yet completely clear, but are probably related to phonetic feedbacks or to motor activity. Other waves were investigated and measured on the whole set of electrodes and the latencies were considered for obtaining *activation maps* for the different functions.

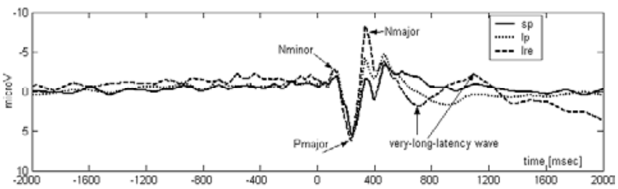

Figure 5 Superimposition of templates obtained during different tasks at channel Fz: bold line=*sp*; dotted line= *lp*; dashed line = *lre.*

The maps are shown in Fig.6. All the considered waves implies different levels of attention and are charactetrized by a fronto-occipital propagation, as expected. Further the waves mainly connected to cognitive processes, and to the association graphema-phonema, involve also the the left hemisphere, where the language areas are located.

Discussion and Conclusion

The presented method is proposed to calculate reliable templates of ERP and constitutes a good alternative to the classically used grand averages. The application of the Dynamic Time Warping procedure allows to overcome some pitfalls of te grandaverage, and in particular the jitter always present when different subjects are considered and mainly affecting long-latency waves with high inter-subject variability. The DTW procedure was also optimized introducing the wavelet decomposition: in fact the algorithm parameters can be optimally tuned for the different signal details.

The method was applied in the study of the reading related potentials and allowed to highlight some mechanisms involved in the reading process. The better comprehension of the underlying mechanisms, will allow a better diagnosis and classification of dislexia in children , the planning of an individual therapy and the follow-up of the rehabilitation.

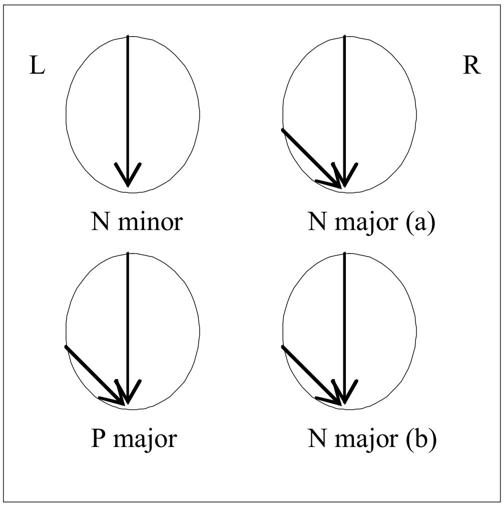

Figure 6 Activation maps in Lre task for characteristic peaks showed in Fig.4.

References

[1] E. L. Grigorenko, “Developmental dyslexia: an update on genes, brains and environments,” *J. Child. Psychol. Psychiat.*, vol. 42, no. 1, pp. 91–125, 2001.

[2] H. Sakoe, S. Chiba, “Dynamic Programming algorithm optimisation for spoken word recognition,” *IEEE Trans. Acoust., Speech, Signal Processing*, vol. 26, no. 1, pp. 43–49, Feb. 1978.

[3] A. M. Bianchi, G. A. Chiarenza, S. Cerutti, “Study of single sweep event related brain potentials in dyslexia,” in *IFMBE Proc. IX , MEDICON 2001,* Pula*,* Croatia*,Jun. 2001 Part I, pp. 376-379.*

[4] S. Casarotto, A. M. Bianchi, S. Cerutti, G. A. Chiarenza, “Principal Component Analysis for reduction of ocular artefacts in event-related potentials of normal and dyslexic children. Clin. Neuroph., 115: 609-619, 2004.

[5] E. Courchesne, “Neurophysiological correlates of cognitive development: changes in long-latency event-related potentials from childhood to adoulthood,” *Electr. Clin. Neurophysiol.*, vol. 45, pp. 468–482, 1978.

REDUCTION OF OCULAR ARTEFACTS WITH PCA AND ANALYSIS OF READING FUNCTION WITH ERPs

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Abstract: Aim of this work is to reduce ocular artefacts superimposed to EEG recordings for improving the investigation of cognitive functions in children. ERPs were recorded in normal children during the execution of *active* and *passive* reading tasks. Principal Component Analysis was applied to isolate in a single component the ocular artefacts: the first or the second principal component was subtracted when the correlation coefficient between the component and EOG was over a certain threshold. Simulated data were employed to assess that the method did not alter ERPs morphology. Application of the method to real recordings allowed a great increase of the number of trials useful for averaging. A comparison among the ERPs recorded in different conditions highlighted interesting neurophysiological correlates of reading processes. Reading non-alphabetic symbols requires less cognitive resources than reading letters. Active reading during an externally-paced condition produces ERPs of greater amplitude than passive reading. Active reading during a self-paced condition further increases ERPs amplitude, decreases the latency of pre-lexical components and increases that of post-lexical components.

Introduction

Learning to read is a very important skill for the social and working life of each individual. Intact intellective functions, normal sensory acuity and adequate education are necessary prerequisites for reading. Reading processes are very complex and involve perceptive systems, both visual and auditory, verbal-motor coordination, attention mechanisms, phonological analysis skills, memory and feedback processes.

In order to investigate the cerebral functions engaged in the reading processes, event-related potentials (ERPs) were recorded: this approach is simple and low-cost, allows an high temporal resolution analysis and is non-invasive. ERPs were computed by averaging several EEG traces synchronized with specific repetitive events. They were analysed through a quantification of certain parameters, latency and amplitude of the most relevant components. The SNR of ERPs depends on the number of averaged trials: as this number increases, the cancellation of raw EEG improves together with ERPs quality. EEG recordings are usually affected by artefacts of different origins, such as muscular activity, gross body movements, etc. that constrain to reject a consistent amount of trials from averaging. The artefacts deriving from ocular movements and blinks are particularly important because they are physiological and larger in amplitude than the cerebral responses. The usual approach to these artefacts consists in rejecting the artefact-contaminated trials, thus lengthening the tests duration. Some analytical approaches have been proposed to reduce ocular artefact: linear regression, in the time or frequency domain (1,2,3,4), autoregressive models (5) and topographic approaches (6,7).

In the present work we developed a method based on Principal Component Analysis (PCA) for reducing ocular artefacts in event-related potentials (8). Then, we applied the method to real ERPs for extracting components related to reading functions.

Materials and Methods

Principal Component Analysis (PCA) is a procedure for decomposing a set of signals into an equal number of components, called Principal Components (PCs), that combine linearly to reconstruct the original signals. The PCs are orthogonal, represent the maximum amount of spatial variance contained in the original data and minimize the reconstruction mean squared error. Therefore, PCA is able to pick up the coherent activity spread over the data.

We assume that cerebral activity derives from a linear combination of independent activities generated by different sources, the most relevant being the cerebral and ocular ones. Furthermore, ocular activity practically transmits on the scalp with the same morphology recorded by EOG, scaled in amplitude according to the distance from the eyes and without significant delays. Therefore, ocular artefacts transmitting on several scalp locations are strongly correlated.

We organized EEG and EOG recordings into a matrix **D** in column order:

$$\underset{(\#samples,\#channels)}{\mathbf{D}} = \left[\mathbf{EOG} \quad \mathbf{EEG_1} \quad \cdots \quad \mathbf{EEG_{10}}\right] \tag{1}$$

Applying PCA to matrix **D** the generic EEG recording can be expressed by:

$$\mathrm{EEG}_n(t) = \sum_{m=1}^{M} a_{n,m} \mathrm{PC}_m(t) \tag{2}$$

where $a_{n,m}$ is the weight of the *m*th PC on the *n*th EEG trace. Including EOG recording in matrix **D** makes easier to isolate in a single PC the ocular activity characterized by a great spatial variance because EOG is independent from EEG signals and completely represents the artefact.

PCA technique is based on the estimate of the spatial correlation matrix $\hat{\mathbf{R}}$ of the original data. PCs can be computed by the following equation:

$$\mathbf{PC_n} = \mathbf{a_n^*} \mathbf{D}^* \tag{3}$$

where $\mathbf{a_n}$ is the *n*th eigenvector of $\hat{\mathbf{R}}$ and * denotes transpose. The spatial variance associated to the *n*th PC is obtained as:

$$\mathbf{PC}\,(\%) = \lambda_n \Big/ \sum_j \lambda_j \times 100 \tag{4}$$

where λ_n is the *n*th eigenvalue of $\hat{\mathbf{R}}$. If it is possible to demonstrate that one PC entirely contains only the ocular artefact, the subtraction of the considered PC produces the artefact reduction, as shown by the following equation:

$$\mathbf{EEG_{jnew}} = \mathbf{EEG_j} - a_{j,n} \mathbf{PC_n^*} \tag{5}$$

The weight $a_{j,n}$ is related to the distortion entity present in *j*th EEG trace due to artefact transmission.

Applying this method to real recordings we empirically noticed that ocular artefacts were mainly contained in the first 2 PCs representing the greatest part of data spatial variance. Therefore, the first PC was subtracted if its correlation with EOG was ≥ 0.9; otherwise, the second PC was subtracted if its correlation with EOG was ≥ 0.95. In all other cases, we considered that EEG recordings were not affected by ocular artefacts and consequently we did not modify the original data. Since the first 2 PCs contain the coherent activity present in the data, the method also partially reduces raw EEG activity.

Some simulations were executed to test the method's performances varying EOG amplitude and artefacts transmission characteristics. See (8) for details. In particular, we verified that PCs subtraction does not alter averaged ERPs morphology: we used simulated EOG, raw EEG and ERP to build a set of trials. As an index of averaged ERPs quality we considered the correlation coefficient with the originally simulated ERP. The quality of an ERP computed from 60 artefact-free trials is high and depends only on the finite number of averaged trials that prevents a complete cancellation of raw EEG. The quality of an ERP computed using 30 artefact-free and 30 artefact-contaminated trials is low and strongly dependent on artefact transmission in the EEG channels. After the rejection of the artefact-contaminated recordings, only 30 trials can be averaged: the corresponding ERP has a better quality but it greatly suffers from the low number of averaged trials. Applying the method, an ERP is obtained from 30 artefact-free and 30 artefact-corrected trials: its quality is close to that of the ERP computed using 60 artefact-free trials and is independent from artefact transmission in the original recordings. These results confirm that the method increases the number of useful trials while leaving unaltered the cerebral responses.

The method was applied to ERPs recorded from 24 normal children of age between 8 and 9 yrs. Each subject performed four reading tasks. The stimuli consisted in Italian alphabetic capital and small letters and non-alphabetic symbols visually presented. In the first two tasks (*symbol presentation* SPR and *letter presentation* LPR) subjects passively watched at symbols and letters respectively without making any effort in reading or articulating silently them. In the other two tasks (*externally-paced letter recognition* LRE and *self-paced letter recognition* LRS) subjects read aloud the letters that appeared on the screen after the technician or the subjects themselves respectively pressed a button. These tasks were specifically designed to progressively elicit several mechanisms involved in reading. We employed simple stimuli, i.e. single letters and symbols, to prevent the subjects resort to high-level functions for reading, such as inferences from the context. Furthermore, we considered that reading is an active process where the individual intentionally activates specific perception, attention and motor processes for task execution. For this reason, we also let the subjects voluntary decide when to begin reading by pressing a button (LRS). EEG was recorded from *Fz, Cz, Pz, Oz, C4', C3' T4, T3, P4, P3* referred to linked mastoid. EOG was bipolarly recorded using 2 electrodes placed over and below the right eye. EEG and EOG recordings were bandpass filtered between 0.02-30 Hz. EMG from the lips and the forearm flexor muscles were recorded and bandpass filtered between 160-3000 Hz. Each trial lasted 4 s, 2 s pre- and 2 s post-stimulus. The sample rate was 250 Hz.

The latency and amplitude of the most relevant components were manually measured. A two-sided paired t-test analysis was performed on 8 normal children of mean age 8.75 ± 0.26 yrs to compare the latency and amplitude of the ERP components in the four reading tasks. We report in the Results paragraph the statistically significant latency and amplitude differences at the level of $p<0.05$.

Results

Figure 1 shows the EOG and some EEG recordings of a single real trial: the ocular activity recorded by EOG transmits in the EEG channels with different amplitudes. The first PC computed by means of PCA represents the 85% of the data spatial variance and its correlation with EOG is 0.99. Subtracting this PC allows to reduce the most evident distortions of the EEG recordings caused by ocular artefact transmission. The modification of the original data is mainly limited to the temporal window containing the artefact and to the most affected EEG channels.

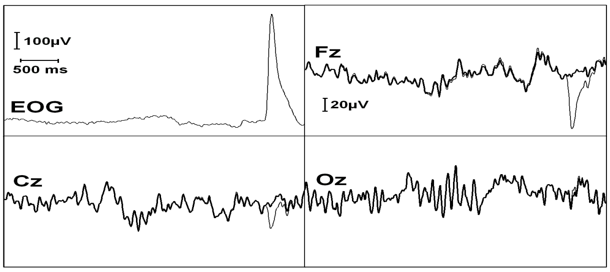

Figure 1: Solid thin lines represent the original recording. Solid thicker lines represent the same recording after ocular artefact reduction.

Applying the method to different sets of ERPs, we noticed that the recovery of trials depends on task condition: in fact, for increasing effort and attention demand the occurrence of artefacts increases. The mean percentage of trials useful for averaging in our original data was 47.1±17.1% and 37.9±13.4% for passive and active conditions respectively. The percentage of useful trials is significantly reduced in active tasks compared to passive ones ($p<0.01$) because active tasks elicit more artefacts, both of ocular and non-ocular origin. After PCA application, the number of useful trials significantly increases in all tasks ($p<0.001$). In particular, 41.0% and 39.1% of the originally rejected trials was retrieved in passive and active conditions respectively.

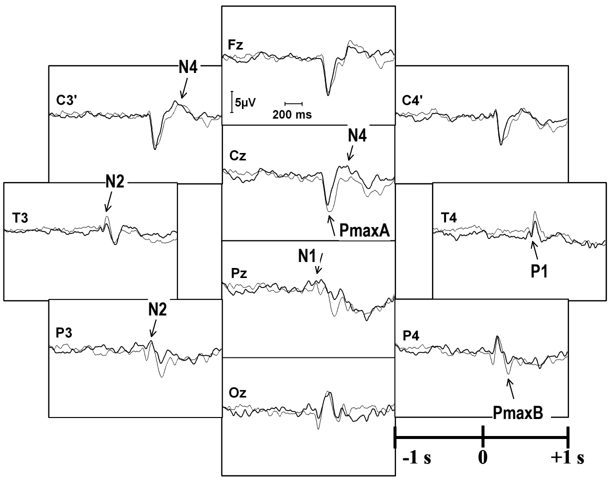

Figure 2: Superimposition of grand averages of ERPs recorded in LPR (thinner lines) and SPR (thicker lines).

On the basis of the EMG activity of the forearm flexor muscles and of the lips, the ERP components can be divided into four periods. The components N0, P0, N1, P1 (<160 ms) belong to the pre-lexical period and correspond to the first stages of visual information processing; the components N2, PmaxA, PmaxB, N3 (160-420 ms) belong to the lexical period and are likely related to stimuli categorization and control mechanisms; the long-latency components P4, N4, P600a, P600b (420-800 ms) are characteristic of the post-lexical period and are associated with long-term memory and feedback processes.

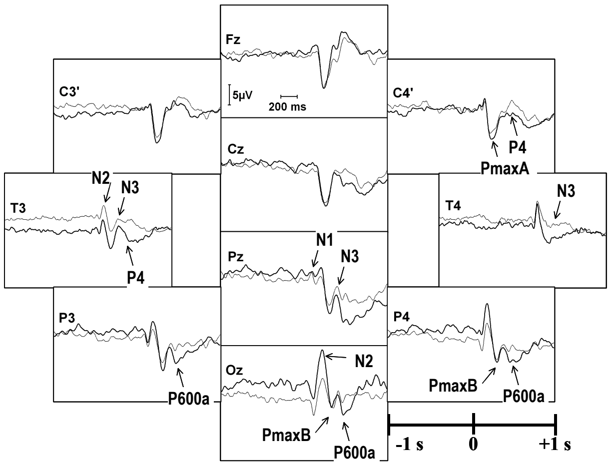

Figure 3: Superimposition of grand averages of ERPs recorded in LPR (thinner lines) and LRE (thicker lines).

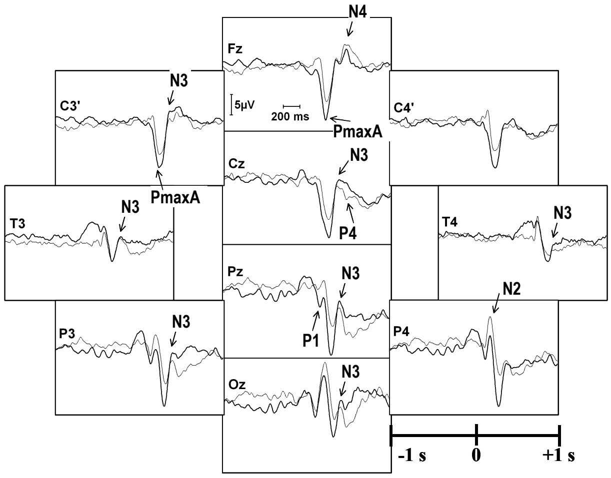

Figure 4: Superimposition of grand averages of ERPs recorded in LRE (thinner lines) and LRS (thicker lines).

Figure 2 shows the superimposition of grand averages of ERPs recorded in the letter presentation (LPR) and symbol presentation (SPR) tasks. The latency of N1 in *Pz* was significantly increased (Δl=41 ms) in SPR compared to LPR, while that of N4 in *Cz* and *C3'* was reduced (Δl=50 ms). The following potentials were statistically reduced in amplitude in SPR compared to LPR: N1 in *Pz*, P1 in *T4*, N2 in *T3* and *P3*, PmaxA in *Cz* and PmaxB in *P4* (Δa between 1.39 and 5.16 µV).

Figure 3 shows the superimposition of grand averages of ERPs recorded in the letter presentation (LPR) and externally-paced letter recognition (LRE) tasks. The latency of N2 in *T3* significantly decreased (Δl=14 ms) passing from LPR to LRE, while that of N1 in *Pz*, PmaxB in *P4* and N3 in *Pz* increased (Δl between 10 and 23 ms), as well as the latency of P4 in *T3* and P600a in *P3* (Δl between 26 and 68 ms). The following potentials had an higher amplitude in LRE than in LPR: N2 in *Oz*, PmaxA in *C4'*, PmaxB in *Oz* and *P4*, N3 in *T4* and *T3* (Δa between 1.84 and 5.37 μV), P4 in *T3* and of P600a in *Oz* and *P4* (Δa between 2.69 and 4.28 μV).

Figure 4 shows the superimposition of grand averages of ERPs recorded in the externally-paced (LRE) and self-paced (LRS) letter recognition tasks. The latency of N2 in *P4* and PmaxA in *Fz* and *C3'* decreased (Δl=15 ms) in LRS compared to LRE while that of N3 in *T4* and *T3* decreased (Δl=35 ms), as well as the latency of P4 in *Cz* and N4 in *Fz* (Δl=18 and 67 ms respectively). The following potentials had an higher amplitude in LRS than in LRE: P1 in *Pz* (Δa=4.7 μV) and N3 in *Cz*, *Pz*, *Oz*, *C3* and *P3* (Δa between 4.61 and 7.73 μV).

Discussion & Conclusions

The method for reducing ocular artefacts is based on a hypothesis of linear transmission of ocular artefacts over the scalp. With respect to linear regression, it does not require a manual selection of artefact-contaminated trials according to the subtype of ocular activity nor the computation of correspondingly different subtraction weights. Furthermore, the cerebral activity picked up by EOG does not influence the artefact reduction process because the subtracting PC is uncorrelated with both raw EEG and event-related responses. The method has a low computational cost and can be applied to compute a better average to be used as input of autoregressive models for improving single-trial response extraction. The threshold values applied to the correlation between EOG and the subtracting PCs are independent from subject and session and were empirically set according to the EEG montage and the ERP category. Artefact reduction realized by the method is effective even when EOG is recorded using only 1 bipolar channel: this characteristic allows to reduce both the complexity of the experimental set up and the discomfort for patients. The application of the method to real data reveals a significant increase of the number of trials for averaging: therefore the duration of tests is reduced and the quality of ERPs is improved. The method is computationally efficient and theoretically simple. It can be easily integrated in every tool for signal processing and its application does not require specific mathematical expertise.

The main differences between LPR and SPR were noticed during the pre-lexical period: an overall reduction of both latency and amplitude of the ERP components in SPR compared to LPR suggests that processing non-alphabetic symbols requires less cognitive resources than processing letters (9). During the LRE task, there was a general increase of ERPs amplitude compared to LPR. This effect, localized in the temporal-parietal and posterior regions, could be explained with the activation of attention processes of these areas involved in reading (10). The self-paced letter recognition task produced a further increase of amplitude with respect to the externally-paced one: this increase could be explained as a recruitment of preparation and volitional processes. The involvement of these processes is also manifested in the increase of ERPs duration during the self-paced tasks in comparison to the externally-paced condition. These physiological evidences can be used in understanding the lack of acquisition of reading skills in different pathological conditions, as developmental dyslexia.

References

[1] VERLEGER R., GASSER T. and MÖCKS J. (1982): 'Correction of EOG artifacts in event-related potentials of the EEG: aspects of reliability and validity', *Psychophysiology,* **19**(4), pp. 472-480

[2] GASSER T., SROKA L. AND MÖCKS J. (1986): 'The correction of EOG artifacts by frequency dependent and frequency independent methods', *Psychophysiology*, **23**(6), pp. 704-712

[3] CROFT R.J. and BARRY R.J. (2000): 'EOG correction of blinks with saccade coefficients: a test and revision of the aligned-artefact average solution', *Clin. Neurophysiol.*, **11**, pp. 444-451

[4] PICTON T.W., VAN ROON P., ARMILIO M.L., BERG P., ILLE N. and SCHERG M. (2000): 'The correction of ocular artefacts: a topographic perspective', *Clin. Neurophysiol.*, **11**, pp. 53-65

[5] CERUTTI S., CHIARENZA G.A., LIBERATI D., MASCELLANI P. and PAVESI G. (1988): 'A parametric method of identification of single-trial event-related potentials in the brain', *IEEE Trans. Biomed. Eng.*, **35**(9), pp. 701-711

[6] BERG P. and SCHERG M. (1994): 'A multiple source approach to the correction of eye artifacts', *Electroencephalogr. clin. Neurophysiol.*, **90**, pp. 229-241

[7] KOLES Z.J. and SOONG A.C.K. (1998): 'EEG source localization: implementing the spatio-temporal decomposition approach', *Electroencephalogr. clin. Neurophysiol.*, **107**, pp. 343-352

[8] CASAROTTO S., BIANCHI A.M., CERUTTI S. and CHIARENZA G.A. (2004): 'Principal component analysis for reduction of ocular artefacts in event-related potentials of normal and dyslexic children', *Clin. Neurophysiol.*, **115**(3), pp. 609-619

[9] SHAYWITZ S.E., SHAYWITZ B.A., PUGH K.R., FULBRIGHT R.K., CONSTABLE R.T. et al., (1998): 'Functional disruption in the organization of the brain for reading in dyslexia', *Proc. Natl Acad. Sci USA*, **95**, pp. 2636-2641

[10] MCDERMOTT KB., PETERSEN S.E., WATSON J.M. AND OJEMANN J.G. (2003): 'A procedure for identifying regions preferentially activated by attention to semantic and phonological relations using functional magnetic resonance imaging', *Neuropsychologia*, **41**, pp. 293-303