Automatic removal of ocular artefacts using adaptive filtering and independent component analysis for electroencephalogram data

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Automatic removal of ocular artefacts using adaptive filtering and independent component analysis for electroencephalogram data

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Abstract: A new method for eye movement artefacts removal based on independent component analysis (ICA) and recursive least squares (RLS) is presented. The proposed algorithm combines the effective ICA capacity of separating artefacts from brain waves, together with the online interference cancellation achieved by adaptive filtering. Eye blink, saccades, eyes opening and closing produce changes of potentials at frontal areas. For this reason, the method uses as a reference the electrodes closest to the eyes Fp1, Fp2, F7 and F8, which register vertical and horizontal eye movements in the electroencephalogram (EEG) caused by these activities as an alternative of using extra dedicated electrooculogram (EOG) electrodes, which could not always be available and could be subject to larger variability. Both reference signals and EEG components are first projected into ICA domain and then the interference is estimated using the RLS algorithm. The component related to EOG artefact is automatically eliminated using channel localisations. Results from experimental data demonstrate that this approach is suitable for eliminating artefacts caused by eye movements, and the principles of this method can be extended to certain other artefacts as well, whenever a correlated reference signal is available.

1 Introduction

The electroencephalogram (EEG) is a record of the neuronal electrical activity that is used as a good indicator of abnormalities in the central nervous system. The occurrence of electrical artefacts generated by eye movements and blink contamination produce a signal known as electrooculogram (EOG). This well-recognised problem that appears in the recorded EEG as an interference causes serious problems in EEG interpretation and analysis. To remove the EOG from the EEG, it is convenient to discriminate between artefacts and brain waves without altering important information of EEG activity.

The standard approach for eliminating interferences in EEG data is digital filters, with typical low cutoff frequency values of 0.1 Hz and high cutoff frequency of 70 Hz. However, linear filtering could distort both amplitude and interchannel phase of signals, overlapping frequency bands of artefacts with the frequency bands of the EEG. The use of filters should always be documented on the EEG recording, so that the specialist can interpret their possible influence. In general, the use of filters should be reduced as much as possible, and even better avoided at all [1].

Taking these requirements into account, several investigators have published different methods alternative to linear filtering for automatic removal of EEG artefacts using independent component analysis (ICA) [2]. ICA allows to separate components in complex signals with the possibility of discriminating between artefacts and brain waves. This method is widely used as a tool to eliminate artefacts [3–5] and could be combined with other methods such as Bayesian classifier or high-order statistics [6, 7].

The method proposed here describes an adaptive filtering approach in ICA space for eliminating EOG contamination using as reference signal the EEG electrodes localised near the eyes because EOG artefacts have an important energy contribution on frontal zone of the brain and this energy is frequently registered at electrodes closely to eyes [5].

The study is organised as follows: Section 2 introduces the ICA and adaptive filtering. This section also explains the approach for removing EOG artefacts based on ICA and adaptive filtering and describes the procedure by means of pseudo code. Section 3 shows the results of the EOG noise canceller applied to real EEG data. In Section 4 the main results are discussed and in Section 5 the conclusions of the study are given.

2 Methods

2.1 Independent component analysis

The ICA technique appears ideally suited for removing artefacts from EEG in domains where (i) the sources are independent, that means, if we use $\boldsymbol{M}$ sensors we can separate at least $\boldsymbol{M}$ independent sources; (ii) the propagation delays from the sources to the electrodes are negligible; and

(iii) the summation of potentials arising from different parts of the brain, scalp and body is linear at the electrodes [8, 9]. In EEG source analysis, just assumption (i) is questionable, as we do not know the effective statistical independence among the sources obtained from EEG data registered from the scalp. Moreover, the nature between ocular artefacts and brain signals is different therefore ICA method can be used to separate the ocular artefacts and EEG brain activity into separate components [3–7, 10].

Let us assume that EEG data $\boldsymbol{X}$ is arranged in a matrix of M sensors or electrodes (rows) by N time points (columns) data values. The value of M depends on the number of electrodes used. The objective of the ICA algorithm is to find a separating or unmixing matrix $\boldsymbol{W}$ such that we estimate the sources as $\boldsymbol{S}' = \boldsymbol{WX}$. The $M \times M$ matrix $\boldsymbol{W}$ obtained by ICA is the linear combination of the used channels. The columns of the inverse matrix $\boldsymbol{W}^{-1}$ contain the relative weights of the respective components at each of the scalp sensors. These weights give the scalp topographic map of each component and could be a good indicator for selecting EOG artefacts [11, 12].

A 'filtered' EEG can be derived as $\boldsymbol{X}' = \boldsymbol{W}^{-1}\boldsymbol{S}''$, where $\boldsymbol{S}''$ is the matrix $\boldsymbol{S}'$ with the row representing artefact source set to 0. We do not know 'a priori' which row must be set to zero, but the linear filtering scheme in Fig. 1 will let us know, as will be shown in what follows. It is important to know that the spatial order in $\boldsymbol{S}'$ does not correspond to the spatial order in $\boldsymbol{X}$.

There are many well-known ICA algorithms that have proven to be capable of isolating both artefacts and brain signals, for instance those based on Fast-ICA or kernel-ICA, Infomax ICA, SOBI, fastICA and Joint Approximate Diagonalization of Eigen-matrices (JADE) [8, 13]. In this study, we used the JADE that is based on the diagonalisation of cumulant matrices [3]. This algorithm has been successfully applied to processing of real data sets and EEGs and JADE Matlab code is available in [14]. An extensive study to identify if other ICA algorithm is more suitable exceeds the scope of this paper and is left as further work.

2.2 Adaptive filtering

In conventional adaptive noise cancellation systems, the primary input signal is a combined signal $x(n) + i(n)$ where $x(n)$ represents the clean signal and $i(n)$ is the interference. This assumes the availability of a reference signal $r(n)$ expected to be correlated with $i(n)$ and uncorrelated with $x(n)$ and the goal is to obtain an output signal $e(n)$ that is the residual after subtracting from $x(n) + i(n)$ the best least squares estimation of $i(n)$, $\hat{i}(n)$.

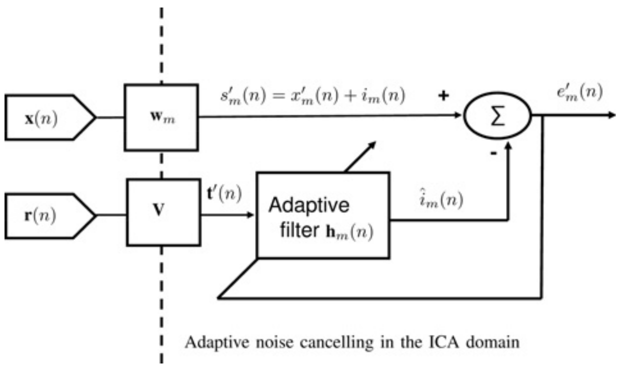

Fig. 1 *General scheme of automatic EOG noise cancellation using adaptive filtering and ICA*

Processing of signal from the mth ICA component is shown, this scheme has to be run M times in parallel to process all EEG data

The method proposed here cannot assume that $x(n)$ and $i(n)$ are completely uncorrelated because we use reference channels that could contain information of the brain. Initially, ICA projections are obtained from both EEG data ($\boldsymbol{W}$ matrix in $\boldsymbol{S}' = \boldsymbol{WX}$) and reference data ($\boldsymbol{V}$ matrix in $\boldsymbol{T}' = \boldsymbol{VR}$), where $\boldsymbol{R}$ is a $P \times N$ matrix that stores measures from the P reference electrodes (Fp1, Fp2, F7 and F8, the ones closest to the eyes) and N time points. These electrodes could register vertical and horizontal eye movements in the EEG caused by eye blink, saccades, eyes opening and closing that produce changes of potentials at frontal areas of the brain [15]. Although EOG-dedicated electrodes could also have been used, the use of the Fp1, Fp2, F7 and F8 electrodes as reference has proved to be a reasonable approach and a more direct method, as dedicated electrodes are not always available.

Next, every ICA projection data are fed into an adaptive filtering scheme in Fig. 1, to be run M times (possibly in parallel), one for every EEG ICA channel to calculate the M filter outputs. In Fig. 1, $\boldsymbol{r}(n)$ is a $P \times 1$ vector storing measures from reference electrodes at time n, $\boldsymbol{h}_m(n)$ is the transversal filter coefficient vector (also $P \times 1$). $\boldsymbol{x}(n)$ is an $M \times 1$ vector storing measures from the EEG electrodes, and $\boldsymbol{W}_m$ is the mth column of the matrix $\boldsymbol{W}$, and also with size $M \times 1$. The adaptive filter with weights $\boldsymbol{h}_m(n)$ aims at estimating the interfering component $\hat{i}_m(n)$ present in the mth ICA channel in a least squares sense, from the reference signal $\boldsymbol{t}'(n)$. The filter operates in ICA domain, and the residual signal is

$$e'_m(n) = s'_m(n) - \hat{i}_m(n) \tag{1}$$

where

$$\hat{i}_m(n) = \boldsymbol{h}_m^T(n)\boldsymbol{t}'(n) \tag{2}$$

Equation (2) represents a transversal spatial filter with four tap weights. We adjust the coefficients of the filter by solving

$$\min_{\boldsymbol{h}_m(n)} \left\{ \sum_{i=1}^{n} \lambda^{n-i} (s'_m(i) - \boldsymbol{h}_m^T(i)\boldsymbol{t}'(i))^2 \right\} \tag{3}$$

The solution of (3) is given by the well-known recursive least squares (RLS) algorithm. The use of the forgetting factor λ, where $0 < \lambda \leq 1$, allows one to use the algorithm in non-stationary situations [16].

Finally, the component selected is expected to concentrate most EOG interference contribution, and must be eliminated by setting to zero the corresponding row in matrix $\boldsymbol{S}'$, to obtain matrix $\boldsymbol{S}''$. It would also be possible to eliminate more than one ICA component, but that study exceeds the scope of this paper and will be proposed as further work.

We have summarised in Table 1 the pseudo code of EEG adaptive filtering using RLS and ICA.

3 Experiments and results

The aim of this section is to evaluate the performance of the proposed method in removing EOG artefacts in

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Table 1 ICA-RLS algorithm

****

Inputs: $\boldsymbol{X}, \boldsymbol{R}, \lambda$
Output: $\boldsymbol{X}'$ (filtered EEG)
Comment: ***** ICA pre-processing using JADE *****

****

$\boldsymbol{W} = jade(\boldsymbol{X})$
$\boldsymbol{V} = jade(\boldsymbol{R})$
$\boldsymbol{S}' = \boldsymbol{WX}$
$\boldsymbol{T}' = \boldsymbol{VR}$

****

Comment: Noise cancellation in every channel $m = 1, \ldots, M$
Comment: ******** RLS Initialisation ********

****

$\boldsymbol{P}(0) = 10^4 \boldsymbol{I}$
$\boldsymbol{h}_m(0) = \boldsymbol{0}$
for $n \rightarrow$ 1 to N

$$\left\{\begin{array}{l} \mathbf{t}'(n) = \boldsymbol{V}\mathbf{r}(n) \text{ ICA projection} \\ \pi(n) = \boldsymbol{t}'^T(n)\boldsymbol{P}(n-1) \\ \boldsymbol{k}(n) = \pi^T(n)/(\lambda + \pi(n)\boldsymbol{t}'(n)) \\ s'_m(n) = \boldsymbol{w}_m^T \boldsymbol{x}(n) \text{ ICA projection} \\ \alpha(n) = s'_m(n) - \boldsymbol{h}_m^T(n-1)\boldsymbol{t}'(n) \\ h_m(n) = h_m(n-1) + \alpha(n)\boldsymbol{k}(n) \\ \boldsymbol{P}(n) = (\boldsymbol{P}(n-1) - \boldsymbol{k}(n)\pi(n))/\lambda \end{array}\right.$$

Comment: *** Recovery of filtered EEG ***
$j = \arg\min_m \left\{\sum_{n=1}^{N} e_m'^2(n)\right\}$
Comment: * Set the jth row in $\boldsymbol{S}'$ to zero to obtain $\boldsymbol{S}''$ *
$\boldsymbol{X}' = \boldsymbol{W}^{-1}\boldsymbol{S}''$

different problems. Several experiments under different signal-to-noise ratios (SNRs), correlation analysis, comparison with other techniques and EEG segment classification have been performed.

3.1 Experiment 1: EOG removal on EEG epochs

3.1.1 Data and setting: An EEG record containing mainly eye movements activity was selected. The data were collected from 23 scalp electrodes placed according to the International 10–20 System. The sampling frequency was 200 Hz and all registers are from adults. This EEG presents a high interference on three channels and artefact ICA component was chosen according to the visual inspection of an experienced neurophysiologist.

Using the 10–20 International System, the electrodes with major information of eyes movements are Fp1, Fp2, F7 and F8, therefore $P = 4$ and $M = 19$ in this experiment. The electrodes that record the largest potential change in the presence of vertical eye movements are Fp1 and Fp2 because they are placed directly above the eyes. The electrodes that record the largest potential change when horizontal (lateral) eye movements are produced are F7 and F8 because they are approximately lateral to the eyes [15]. These electrodes will be our reference signals to build $\boldsymbol{R}$.

A Pentium III with Matlab© (v7) was used for the implementation of the algorithm in Table 1. We explored different values of λ and we observed that this parameter is not critical for the performance of the algorithm (we use the value $\lambda = 0.9$). Although it is an adaptive method oriented to real-time applications, in this study we just present off-line results, as to fully extend these results to a time-varying scenario, an adaptive ICA algorithm with epoch processing should be used, and this has been left as further work.

Table 2 Normalised correlation coefficient between the raw EEG and the EEG filtered by ICA-RLS for each selected segments A and B in Fig. 3

Channel	ICA-RLS		RLS	
	Segment A	Segment B	Segment A	Segment B
F4	0.9978	0.5297	0.8992	0.9562
Fp2	0.9792	**0.2596**	0.9659	0.8633
F3	0.9991	**0.3425**	0.8999	0.8454
Fp1	0.9977	**0.3006**	0.9999	0.8076
T6	0.9986	0.7901	0.9114	0.8399
T5	0.9951	0.9511	0.8999	0.9009
O2	0.9942	0.9834	0.9102	0.9787
O1	0.9991	0.8913	0.9023	0.8888
F7	0.9946	0.5374	0.8699	0.8362
F8	0.9850	**0.3450**	0.9899	0.7963
T3	0.9998	0.9601	0.9974	0.9052

Bold values present the low correlation in the frontal electrodes Fp1, Fp2, F3 and F8 in segment B, which indicates that the EOG has been filtered out

3.1.2 Results: We show in Fig. 2*a* the original EEG with EOG peaks (marked with arrows in the dotted box B) caused by eye movements on the electrodes Fp1, Fp2, F7 and F8. Fig. 2*b* represents the ICA projections of the same EEG data. Note how it is possible to observe that ICA has been able to separate the electrooculogram (EOG) contribution, mainly represented in this case by the component 9.

Fig. 3*a* shows how the ICA-RLS algorithm has been able to eliminate the artefacts with minor modification of the EEG signals. In fact, ICA has demonstrated minimal distortion using measures such as minimal correlation analysis or average waveform similarity [3, 11]. In contrast, the results without ICA pre-processing are not satisfactory, as the EOG interference is still present, as shown in Fig. 3*b* which proves the usefulness of ICA. Furthermore, the proposed ICA-RLS method does not affect those parts of the EEG signals where the EOG is not present (zone A, for instance). To illustrate the performance of the algorithm, we calculate the normalised correlation coefficient between the raw EEG and the EEG filtered by ICA-RLS for each selected segment A and B in Fig. 3. This coefficient informs about the changes in each channel after removing the artefacts. Table 2 shows the correlation between preelimination and postelimination of the eye artefact for segment A (without eye artefact) and segment B (in the presence of eye artefact). Note in this table the high correlation for the segment A for all electrodes, which denotes that ICA-RLS is not modifying the EEG, and the low correlation in the frontal electrodes Fp1, Fp2, F3 and F8 in segment B, which indicates that the EOG has been filtered out [3].

To further validate the results, we analyse using the topographic scalp map, the projections corresponding to every ICA component. In Fig. 4, we have depicted such projections, as well as the mean square error (MSE) value obtained after the ICA-RLS interference cancellation process (MSE $= E\{e_m'^2(n)\}$). Observe that the component 9 presents the minimum MSE and its projection presents a maximum activity in the frontopolar region.

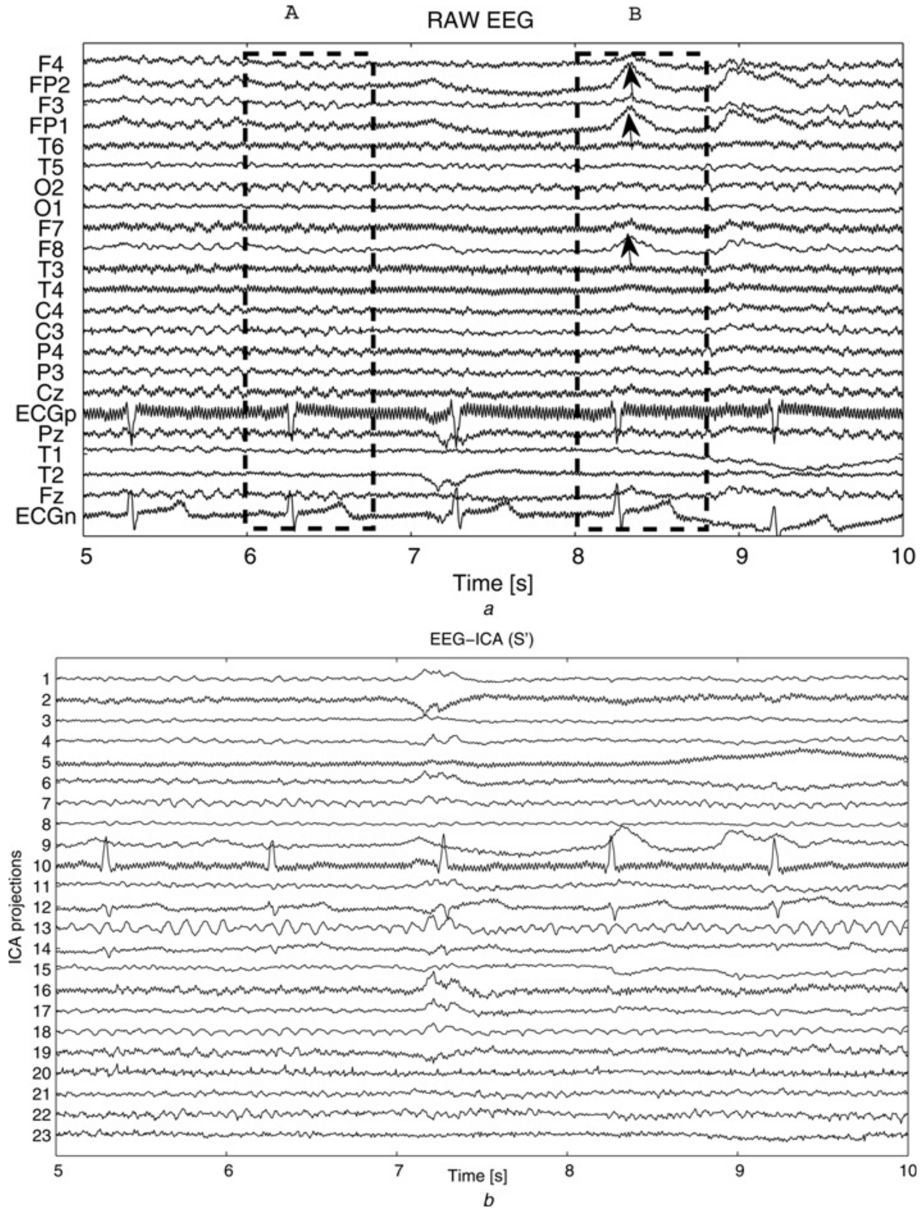

Fig. 2 *Raw EEG data and its ICA decomposition*

a Raw EEG data
b Its ICA decomposition
Note in *a* that the region marked as 'B' is affected by ocular movements, marked with the arrows. In the ICA projections in *b*, the EOG contribution has been mainly concentrated in component 9

3.2 Experiment 2: comparison of the algorithm with other techniques

For further validation of our proposed method, we compare the ICA-RLS algorithm against other techniques. (i) ICA least mean square (LMS) algorithm with step adaptation equal to 10^{-3}. (ii) Visual analysis using topographic maps of the components. (iii) ICA-kurtosis method [5] and (iv) RLS algorithm applied to vertical EOG component as a reference signal [10]. We use the same EEG data described above in experiment 1.

3.2.1 Method: After separating the brain signal B from eye artefact M according to the visual ICA source analysis of an expert, we can express the EEG signal X as follows [17]

$$\boldsymbol{X}(\alpha) = \boldsymbol{B} + \alpha\boldsymbol{A} \tag{4}$$

where α is a factor that permits to increment the contribution of the eye artefact signal $\boldsymbol{A}$. The root mean squared (RMS) value is then

$$\text{RMS}(\boldsymbol{B}) = \sqrt{\frac{1}{KN}\sum_{k=1}^{K}\sum_{n=1}^{N}\boldsymbol{B}^2(k, n)} \tag{5}$$

with N equal to the number of time samples and K equal to the number of EEG channels. The SNR measure is defined as

$$\text{SNR} = \frac{\text{RMS}(\boldsymbol{B})}{\text{RMS}(\alpha\boldsymbol{A})} \tag{6}$$

Modifying the α factor we can find different SNRs and eye artefact estimations $\hat{\boldsymbol{B}}$. The performance of this estimations could be expressed in terms of the relative root mean square

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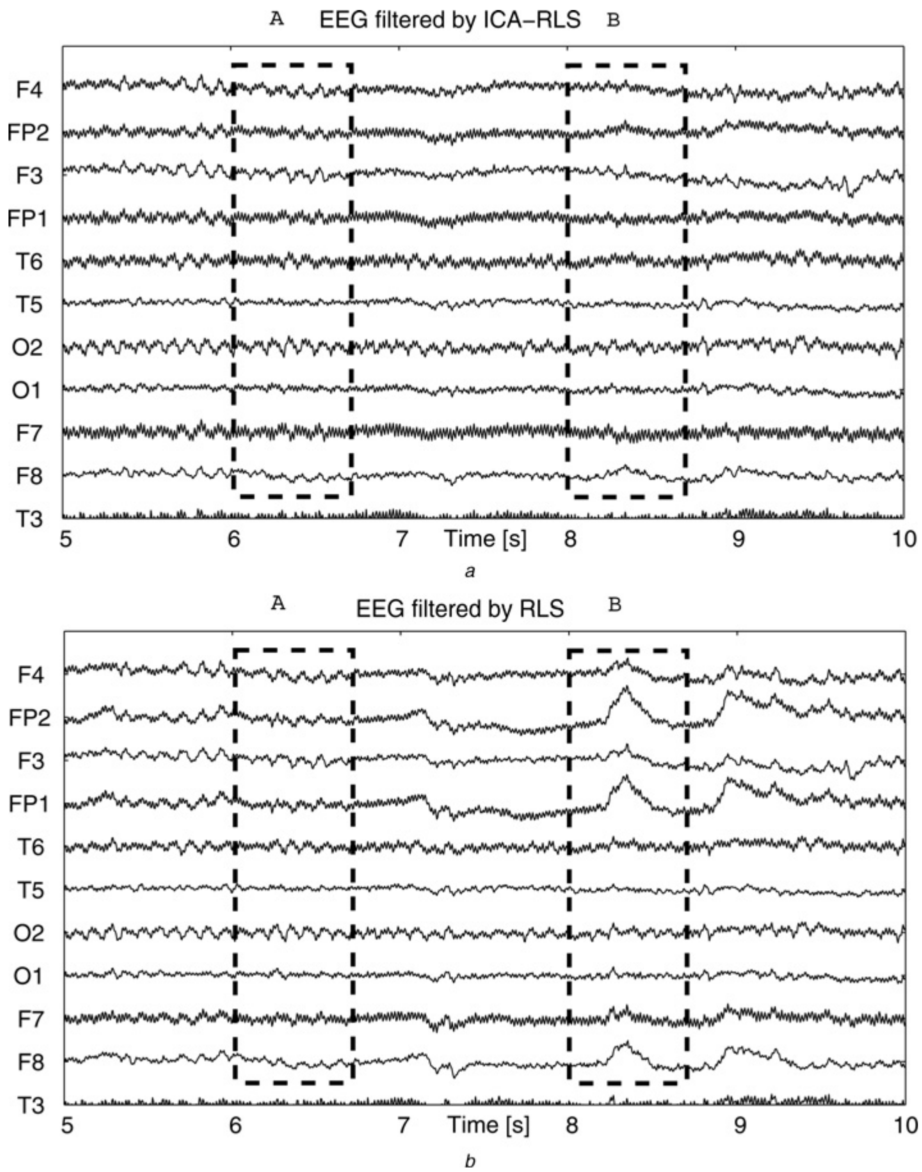

Fig. 3 *Example of EOG artefact rejection using ICA-RLS and RLS*

a Result from ICA-RLS algorithm shows how the algorithm rejects the positive pulse corresponding to eye opening and the negative deflection close to peak as it corresponds to eye closing (dotted box B)
b Note also the poor performance of RLS algorithm when applied without ICA preprocessing and how our method does not introduce significant changes in the absence of ocular artefacts [dotted box A in *a*]

error (RRMSE) defined as follows

$$\text{RRMSE} = \frac{\text{RMS}\,(\boldsymbol{B} - \hat{\boldsymbol{B}})}{\text{RMS}\,(\boldsymbol{B})} \tag{7}$$

3.2.2 Results: Fig. 5 shows the RRMSE as a function of SNR for different EOG removal techniques using α values from 0 to 2. The RRMSE values from visual analysis, ICA-RLS, RLS using vertical EOG [10] and ICA-LMS were 0.06, 0.12, 0.24 and 0.35, respectively. Visual analysis method outperformed all methods for all SNRs but it requires a human expert to operate. The ICA-kurtosis method, when it is exactly implemented as described in [5], does not present a good performance. However, if we change some details in the ICA-kurtosis approach (named as ICA-kurtosis-modified from now on), adapting it to our particular problem, we can obtain the results shown in Fig. 5. ICA-kurtosis-modified shows much closer results to the other methods but still being worse. The changes that we have introduced in the ICA-kurtosis-modified method are:

- Daubechies 8 is used as mother wavelet (original study uses biorthogonal 4.4). This family of wavelets is one of the most commonly used orthogonal wavelets to process non-stationary EEG signals.
- Fp1, Fp2, F3, F4, F7, F8 and C3 are used as EEG channels (original paper uses F3, F4, Fz, Pz, C3, Cz and FP1). Following [15], we think that the proposed subset of electrodes contains more information about eye movement than those proposed in [5].
- Kurtosis has been calculated as $k(x) = E(x - \mu)^4/\sigma^4$ where σ is the standard deviation of x and μ its mean (the kurtosis formula in [5] is $k(x) = E(x^4) - 3[E(x^2)]^2$). We used the equation implemented by Matlab because it is more accurate as it does not ignore the mean of the data.
- We have used the ICA method based on JADE. Although this method presents a high computational cost, it could be

used in real data sets if the extra computation is not a problem (off-line processing, not real time).

The changes mentioned above lead to an improvement in the performance of the algorithm but among all the automated techniques the ICA-RLS method presented the best performance (see Fig. 5).

We have also calculated the computational cost from two points of view: theoretical computational complexity estimation and measured computational time. Computational complexity was estimated taking into account: wavelet analysis corresponds to decomposition series 5, adaptive algorithms use seven reference channels, ICA-RLS and ICA-LMS are based on JADE algorithm, ICA-kurtosis uses Infomax algorithm and the EEG processing does not use epochs, although it implies a large computational cost. The use of epochs is left as a future improvement. RLS method obtained a complexity of the order of $\mathcal{O}(7n^2)$; ICA-LMS of $\mathcal{O}(n^4)+\mathcal{O}(7n)$; ICA-RLS of $\mathcal{O}(n^4)+\mathcal{O}(7n^2)$; and ICA-kurtosis of $\mathcal{O}(n^3)+\mathcal{O}(5N\log_2 n)$, where n is the number of samples.

Execution time was estimated by running the algorithm on a PC computer with Intel(R) Core(TM) 2 processor, 2.66 GHz, 4 Gb-RAM and Matlab© v7.b. The values (in seconds) obtained were RLS: 45; ICA-LMS: 41; ICA-RLS: 76 and ICA-kurtosis: 26. It can be observed that the proposed method is the most computationally demanding method, but it provides the best performance. Therefore if the computational cost is a hard limitation, its use has to be considered. If the extra computation is affordable, then the proposed method should be used.

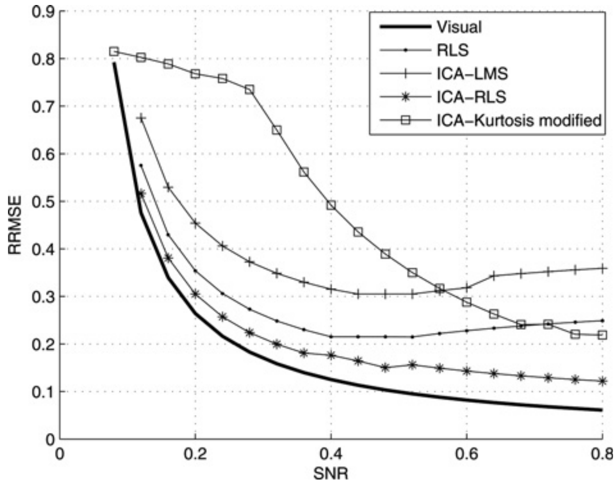

Fig. 5 *Comparison of different EOG artefact removal on the EEG using the RRMSE as a function of SNR*

3.3 Experiment 3: ICA-RLS EOG removal as pre-processing step within a EEG epileptic classifier

Another way of evaluating the performance of an ocular artefact suppression method is to apply the method on a larger data set with others activities such as epileptic seizures. The objective of this experiment is to show how the ICA-RLS approach is suitable as EEG pre-processing step within a classifier. A Support vector machine classifier with radial basis function kernel has been used as an

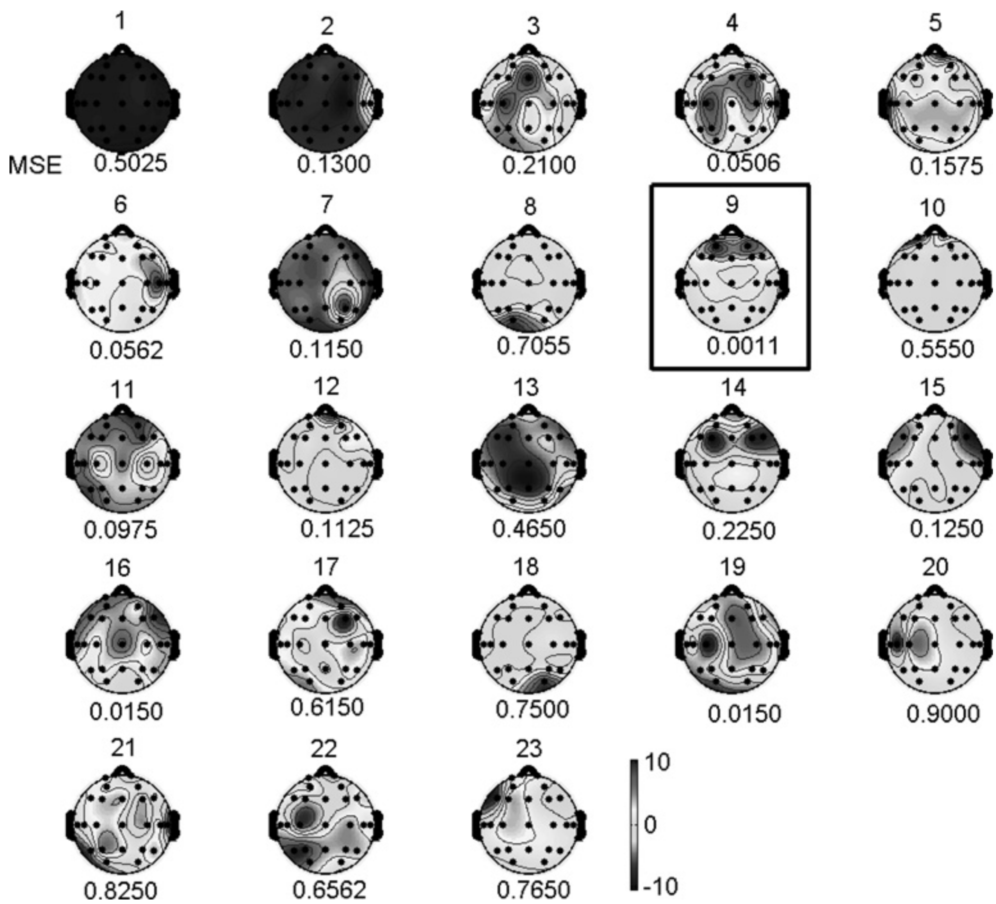

Fig. 4 *Topographic map of the components with their MSE values*

Each figure represents the component activity for each projection. Note that the component 9, with the minimum MSE, presents a maximal activity in the frontopolar region

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Table 3 Comparison between raw EEG and ICA-RLS in a classifier

EEG	ICA-RLS		Raw EEG	
	Sensitivity, %	Specificity, %	Sensitivity, %	Specificity, %
1	90	99	70	86
2	80	89	68	89
3	88	93	82	83
4	90	99	80	40
5	66	100	62	81
6	97	85	70	70
average	85.2	94.2	72	74.8

Performance is based on sensitivity and specifity. More detail of the EEGs records in [19]

epileptic seizure automatic detector and its hyperparameters have been calculated by cross-validation method [18].

3.3.1 Materials: The EEG records of seven adult epileptic patients obtained in a restful wakefulness stage and recorded at the Clinica Universitaria de Navarra, Department of Neurophysiology (Pamplona, Spain). All of them contained focal epileptiform activity, according to experienced neurologists. We used 11 EEG records of 24-min length with 23 channels using the 10–20 International System of Electrode Placement with additional anterotemporal electrodes T1/T2. The seizure duration is around few minutes. In practice, raw EEG data were digitised at a sample rate of 200 Hz using a 'DAD-32' equipment (La Mont Medical) and were filtered by a digital low-pass filter with cutoff frequency of 20 Hz. We also use Fp1, Fp2, F7 and F8 as reference electrodes.

3.3.2 Results: Table 3 shows the comparison between raw EEG and ICA-RLS in a classifier. Note in this table the improvement in classification tasks when we apply the ICA-RLS algorithm. The performance is based on sensitivity and specifity defined as follows:

Sensitivity: Percentage of EEG segments containing seizure activity correctly classified.
Specificity: Percentage of EEG segments not containing seizure activity correctly classified.

Note that, on average, sensitivity improves from 72 to 85.2% and specificity from 74.8 to 94.2%, when we use the proposed ICA-RLS method as a pre-processing stage.

4 Discussion

It is commonly assumed that the introduction of a new block in a pre-processing system is not recommended, but the proposed approach gives us a new alternative method for eliminating noise without calibration. Furthermore, it is easy to implement, very robust and does not need expert supervision.

Equation (3) adjusts the coefficients of the ICA filter based on MSE criteria and helps us to obtain a set of candidate components and then select one of them through source localisations. We could think that the frontal activity could also be subtracted by the algorithm but note in Fig. 1 that all EEG information is contained in the signal $x(n)$. Then, the algorithm does not fail when there are no artefacts (see Table 2) and does not present loss of information from brain signals (see Fig. 5).

Concerning the performance of our method compared with ICA-kurtosis method, we have observed that the latter does not present a good performance when it is implemented as described by the investigators in [5]. We think that the decision rule used in [5] (total number of maxima obtained from nine measures) is not adequate for this application especially when we are eliminating ICA sources.

Adaptive filtering based on ICA would be very helpful in long recordings and online analysis, and although the approach developed in this study is oriented to the elimination of EOG signals, it would be possible to apply it in artefacts more difficult to suppress such as muscle or electrodes artefacts.

5 Conclusions and further work

An automatic artefact cancellation algorithm for EEG data is presented. This method efficiently rejects artefacts produced by eye movements and it relies on ICA and RLS adaptive filtering. Our preliminary results show that this method is able to eliminate eye movement artefacts, and we consider that it may be a relevant technique, for example, somatosensory evoked potential and event-related potentials or fields in magnetoencephalography.

Further analysis in distortion or correlation between corrected EEG and original EEG is necessary for fully demonstrating the effectiveness of our method. Such analysis and the extension of the method to pure on-line scenarios is proposed as further work. In addition, it could be possible to eliminate more than one interfering ICA component, this approach will be studied in the future.

6 Ackowledgment

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