AUTOMATIC REMOVAL OF OCULAR ARTIFACTS FROM EEG DATA USING ADAPTIVE FILTERING AND INDEPENDENT COMPONENT ANALYSIS

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ABSTRACT

A method to eliminate eye movement artifacts based on Independent Component Analysis (ICA) and Recursive Least Squares (RLS) is presented. The proposed algorithm combines the effective ICA capacity of separating artifacts from brain waves, together with the online interference cancellation achieved by adaptive filtering. The method uses separate electrodes localized close to the eyes (Fp1, Fp2, F7 and F8), that register vertical and horizontal eye movements, to extract a reference signal. Each reference input is first projected into ICA domain and then the interference is estimated using the RLS algorithm. This interference estimation is subtracted from the EEG components in the ICA domain. Results from experimental data demonstrate that this approach is suitable for eliminating artifacts caused by eye movements, and the principles of this method can be extended to certain other sources of artifacts as well. The method is easy to implement, stable, and presents a low computational cost.

1. INTRODUCTION

The electroencephalogram (EEG), the record of the neuronal electrical activity, is a good indicator of abnormality in the nervous central system. The occurrence of electrical artifacts generated by eye movements and blink contamination produce a signal known as Electrooculogram (EOG). This well recognized 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 artifacts and brain waves without altering important information of EEG activity.

On the other hand, many applications such as brain computer interface (BCI) require online and real-time processing of EEG signal. The potential of optimal filtering based on adaptive methodologies that search very efficiently the optimal solution could be used in EEG signal to optimally perform in real time tasks [2, 11, 12].

Taking these requirements into account, several papers have published different methods about automatic removal of EEG artifacts using independent component analysis (ICA) [7]. ICA allows to separate components in complex signals with the possibility of discriminating between artifacts and brain waves. This method is widely used as a tool to eliminate artifacts [1, 3, 4] with the possibility of combining it with other methods such as Bayesian classifier or high-order statistics [8, 9].

The method proposed describes an adaptive filtering applied to EEG data components obtained by ICA for eliminating EOG contamination. The principal difference with other methods for ocular artifacts removal is the use of ICA components as reference inputs corresponding to noise that we want to eliminate. The adaptive filtering works under ICA domain using the EEG reference electrodes localized close to the eyes. We test the correspondence of these electrodes with ocular artifacts using the scalp topographic map [5].

This paper is organized as follows: Section II explains the approach for removing EOG artifacts based on ICA and adaptive filtering and describes the procedure by means of pseudo code. Section III shows the results of the EOG noise canceller applied to real EEG data. In Section IV the main results are discussed and in Section V the conclusions of the paper are given.

2. METHODS

2.1 Independent Component Analysis (ICA) of EEGs

The ICA technique appears ideally suited for performing source separation in domains where, (i) the sources are independent, (ii) the propagation delays of the 'mixing medium' are negligible, (iii) the sources have p.d.f's not too different from the gradient of the logistic sigmoid, and (iv) the number of independent signal sources is the same as the number of sensors, meaning that if we employ M sensors, using the ICA algorithm we can separate M sources.

In EEG source analysis, just the assumption (iv) is questionable [14], since we do not know the effective number of statistically independent brain signals contributing to the EEG recorded from the scalp, and this is the foremost problem in interpreting the output of ICA. However ICA still proves to be useful in this domain [1, 3, 4, 8, 9, 12].

We assume that at time "n" we build a vector of measurements from M sensors $\mathbf{x}(n) = [x_1(n), x_2(n), ..., x_M(n)]^T$ and that we store N such vectors as columns in matrix $\mathbf{X} = [\mathbf{x}(1), \mathbf{x}(2), ..., \mathbf{x}(N)]$. In ICA, the observed signal $\mathbf{X}$ is assumed to be a linear combination of M unknown and statistically independent sources (assuming that the number of unknown sources is equal to the number of observations). The objective of the ICA algorithm is to find a separating or demixing matrix $\mathbf{W}$ such that we estimate the sources as $\mathbf{S}' = \mathbf{W}\mathbf{X}$.

There are many well known procedures for solving de ICA problem, for instance those based on Fast-ICA or kernel-ICA [10]. Without loss of generality we will use here the Joint Approximate Diagonalization of Eigen-matrices (JADE) that is based on the diagonalization of cumulant matrices [1]. This algorithm has been successfully applied to processing of real data sets and EEGs and the JADE Matlab code is available in [13]. For EEG, the value of M depends on the montage used by the electrodes. It is possible then to estimate a signal $\mathbf{S}' = \mathbf{W}\mathbf{X}$; where $\mathbf{W} = [\mathbf{w}_1, \mathbf{w}_2, ..., \mathbf{w}_M]^T$ is the

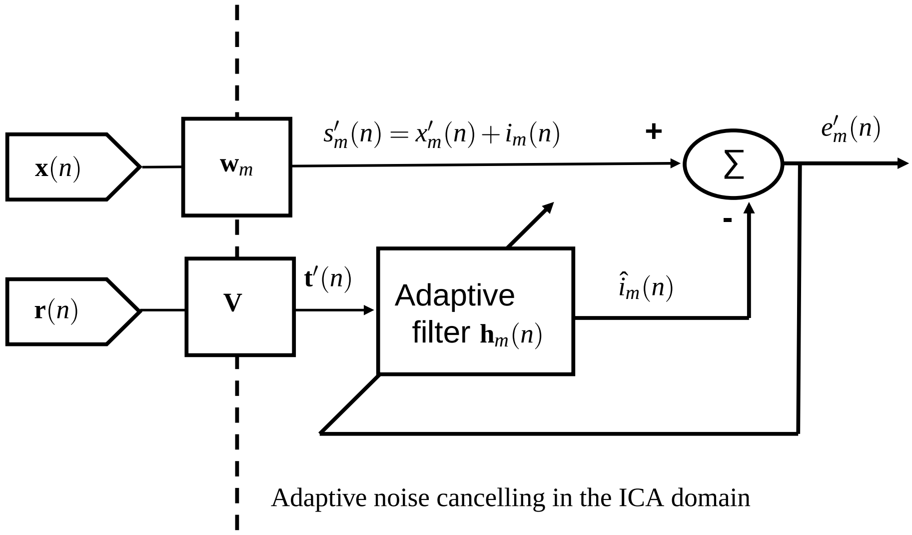

Figure 1: General scheme of automatic EOG noise cancellation using adaptive filtering and ICA. Processing of signal from sensor "*m*" is shown, this scheme has to be run *M* times in parallel to process all EEG data.

mixing matrix obtained by ICA and $\mathbf{S}^{'}$ is the linear combination of the used channels. The columns of the inverse matrix $\mathbf{W}^{-1}$ give the projection strengths of the respective components onto the scalp sensors. These weights give the scalp topographic of each component, and provide evidence about the physiological origin of the components [5, 6].
"Filtered" EEG can be derived as $\mathbf{X}' = \mathbf{W}^{-1}\mathbf{S}''$, where $\mathbf{S}''$ is the matrix of activations waveforms, with the rows in $\mathbf{S}'$ representing artifact sources set to 0. The rank of "filtered" EEG data is less than that of the original data.
It is important to know that the spatial order in $\mathbf{S}'$ does not correspond to spatial order in $\mathbf{X}$, nevertheless, we can use the scalp topographies of the components as an indicator of the biologic origin of the sources [15].

2.2 Removing EOG artifact by adaptive filtering and ICA

In conventional adaptive noise cancellation systems, the primary input signal is a combined signal $x(n)+i(n)$ where $x(n)$ represents the "clean" (unavailable) signal and $i(n)$ is the interference. We assume the availability of a reference signal $r(n)$ assumed to be correlated with $i(n)$. The goal is to obtain an output signal $e(n)$ that is the residual after substracting from $x(n)+i(n)$ the best least squares estimation of $i(n)$, $\hat{i}(n)$.
The proposed artifact removal method comprises two steps. First, ICA projections are obtained for EEG data ($\mathbf{W}$ matrix in $\mathbf{S}^{'} = \mathbf{W}\mathbf{X}$) and for reference data ($\mathbf{V}$ matrix in $\mathbf{T}' = \mathbf{V}\mathbf{R}$), where $\mathbf{R} = [\mathbf{r}(1), \mathbf{r}(2), ..., \mathbf{r}(N)]$ and $\mathbf{r}(n) = [r_1(n), r_2(n), r_3(n), r_4(n)]^T$, $r_j(n)$ being signals obtained from electrodes localized close to eyes as Fp1, Fp2, F7 and F8, which register vertical and horizontal eye movements [16].
The second step is the use of every ICA projection data in an adaptive filter scheme, to be run *M* times (possibly in parallel). The adaptive filter with weigths $\mathbf{h}_m(n)$ aims at estimating the interfering component $\hat{i}_m(n)$ present in the *m*-th ICA channel in a Least Squares sense, from the reference signal $\mathbf{t}'(n)$. The filter operates in ICA domain, and the residual signal is:

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

where

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

The equation (2) represents a transversal filter with four tap weights. We need to estimate the clean EEG ICA components $x'_m(n)$ adjusting the coefficients of the filter by solving:

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

We expect that $x'_m(n)$ and $\mathbf{t}'(n)$ are incorrelated, and hence the filter only estimates the interference $\hat{i}_m(n)$. The solution of Eq.(3) is given by the well known Recursive Least Square (RLS) algorithm. The use of the forgetting factor λ, where $0 < \lambda \leq 1$, allows to use the algorithm in non-stationary situations [17]. Finally, in this section we present the pseudo code of EEG adaptive filtering using RLS and ICA (See Table 1).

3. EXPERIMENTS AND RESULTS

The EEG records of 3 patients using the 10-20 International System of Electrode Placement with additional anterotemporal electrodes T1/T2 were recorded at Hospital Universitario de Navarra, Deparment of Neurophisiology (Pamplona, Spain). Raw EEG data were digitized at a sample rate of 200 Hz using "DAD-32" equipment (La Mont Medical) and segmented into pieces every 5 secs. Using the 10-20 International System, the electrodes with major information of eyes movements are Fp1, Fp2, F7 and F8. 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 eye. 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 [16]. These electrodes will be our

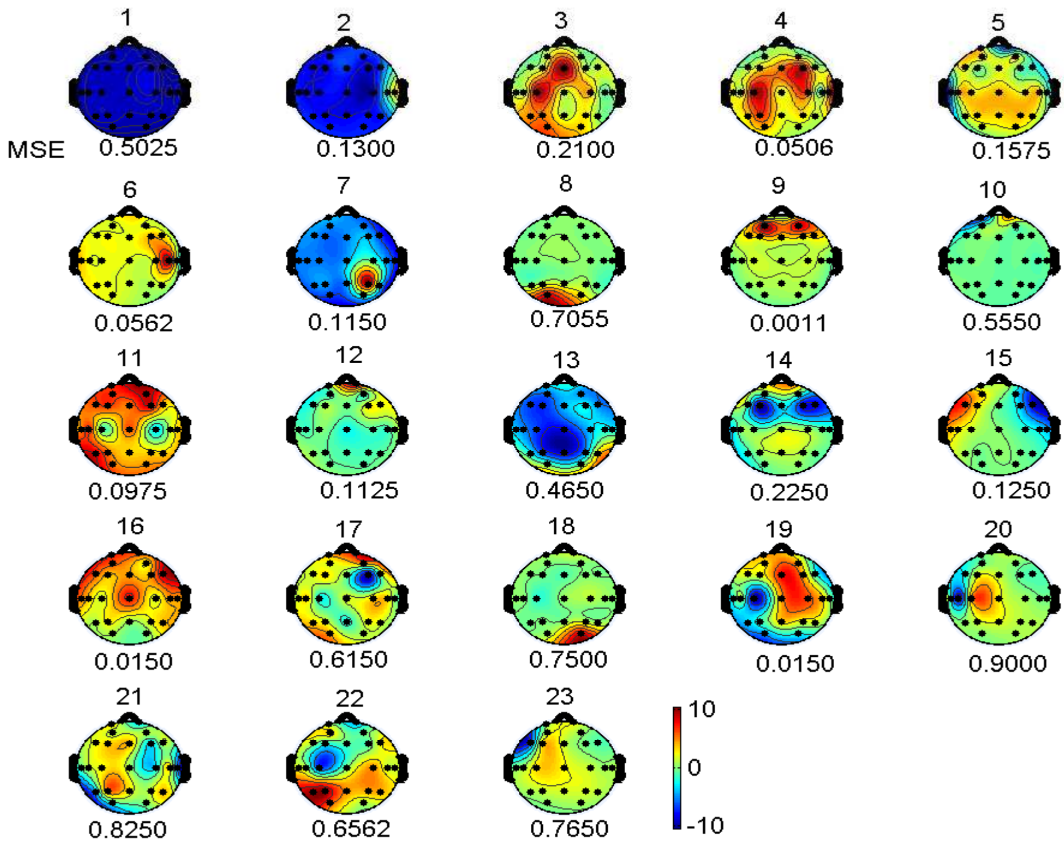

Figure 2: Topographic map of the components with their MSE values. Each figure represents the component activity for each projection. Note that the component number 9, with a maximum in the frontopolar region, also presents a minimum MSE.

Table 1: RLS-ICA Algorithm

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

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$\mathbf{W} = jade(\mathbf{X})$
$\mathbf{V} = jade(\mathbf{R})$
$\mathbf{S}'' = \mathbf{W}\mathbf{X}$
$\mathbf{T}' = \mathbf{V}\mathbf{R}$

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

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

$$\textbf{do} \begin{cases} \pi(n) = \mathbf{t}'^T(n)\mathbf{P}(n-1) \\ \mathbf{k}(n) = \pi^T(n)/(\lambda + \pi(n)\mathbf{t}'(n)) \\ \lambda(n) = s'_m(n) - \mathbf{h}_m^T(n-1)\mathbf{t}'(n) \\ h_m(n) = h_m(n-1) + \alpha(n)\mathbf{k}(n) \\ P(n) = (P(n-1) - \mathbf{k}(n)\pi(n))/\lambda \end{cases}$$

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

reference signals to build **R**.
A Pentium III with Matlab was used for the implementation of the algorithm in Table 1. By means of cross-validation we explored different values to λ and we observed that this parameter is not critical for the performance of the algorithm. We use the value $\lambda = 0.9$. The cancellation with the RLS algorithm was fast compared with ICA computing, the method is simple and its amount of computation is not expensive. Although it is an adaptive method oriented to real-time applications, in this work we just present off-line results, since to fully extend these results to a time varying scenario, an adaptive ICA algorithm should be used.
To further validate the results, we analyze using the topographic scalp map the projections corresponding with the minimum values in MSE. Fig.2 shows the topographical projection for each component and its correspond MSE value. Observe that the component number 9 presents the minimum MSE and its projection presents a maximum activity in the frontopolar region.
Fig.3 represents the ICA projections of the EEG data, and it is possible to observe that ICA has been able to separate the Electrooculogram (EOG) contribution, mainly represented in this case by the component number 9.
Fig.4 presents the results of artifact elimination caused by eyes movements when we are using the reference signals close to the eyes. We compare results with and without ICA preprocessing. We highlight two EEG segments with presence (dotted box B) and absence of artifacts (dotted box A). Note in this figure how the proposed algorithm rejects the

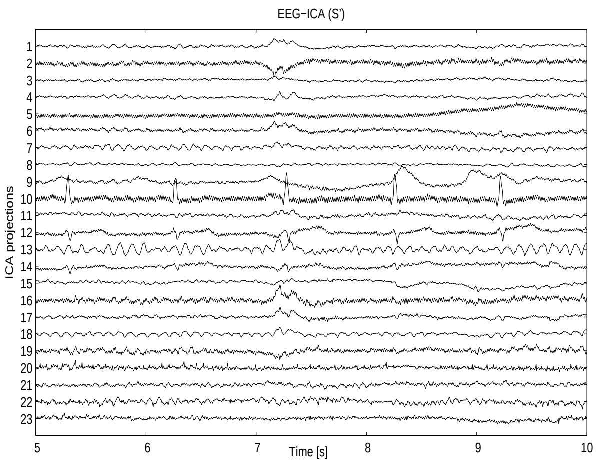

Figure 3: Filtered ICA projections using RLS. Observe that the waveform of the component number 9 corresponds to eye movements and its localization is in frontopolar region showing the minimum MSE (See Fig2).

negatives and positives peaks corresponding to vertical eyes movements (in both figures the dotted box B). In fact, ICA has demonstrated minimal distortion using measures such as minimal correlation analysis or average waveform similarity [1, 5]. On the other hand, the results without ICA preprocessing are not satisfactory, since the EOG interference is still present, which proves the usefullness 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).

4. DISCUSSION

ICA appears to be a generally applicable and effective method for removing artifacts and independent noise, providing considerable performance improvements [18]. It is commonly supposed that the introduction of a new block in a preprocessing system is not suitable, but the proposed approach gives us a new alternative method for eliminating noise without calibration. Furthermore, it is easy to implement, very stable and presents a fast convergence.

As we discussed before, the ICA potential is the availability of removing real noise components without modifying others in standard EEG. Even though there are some other electrical activities in abnormal EEG that could be modified or eliminated, several studies present good results using ICA in a pre-processing stage [19] and other experiments as adaptive on-line ICA [20] perform good effective components separation using gradient adaptive step size.

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

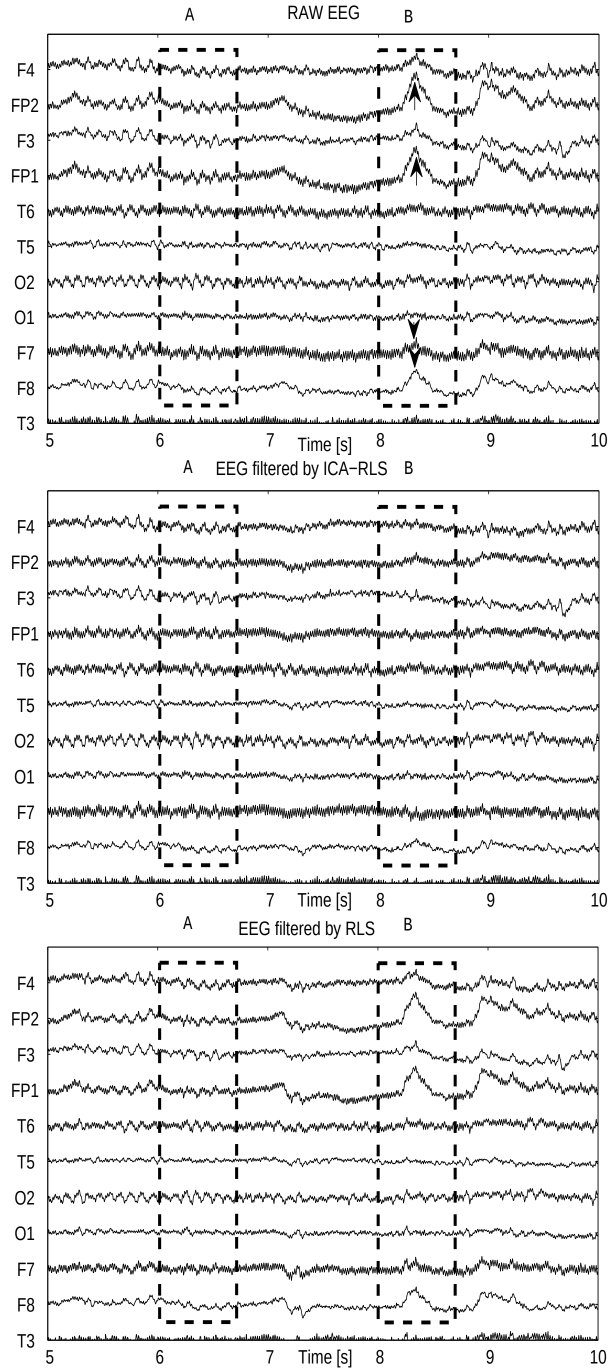

Figure 4: An example of EOG artifact rejection using RLS-ICA and RLS. We show the EOG peaks (marked with arrows in the dotted box B) caused by eye movements on the electrodes Fp1, Fp2, F7 and F8. The result from RLS-ICA algorithm shows how the algorithm rejects the positive pulse corresponding to eye opening and the negative deflection close to peak since it corresponds to eye closing (dotted box B). Note also the poor performance of RLS algorithm (bottom) and how our method does not introduce significant changes in the absence of ocular artifacts (dotted box A).

5. CONCLUSIONS

An automatic artifact cancellation using EEG data is presented. This method efficiently rejects artifacts produced by eyes movements and it relies on independent component analysis (ICA) and Recursive Least Squares (RLS) adaptive filtering. Our preliminary results show that this method is able to eliminate eye movement artifacts, and we consider that it may be a relevant technique for e.g. Somatosensory Evoked Potential (SEPs) and event related potentials (or fields (magnetoencephalography) due to the limited number of responses in a run.

Futher 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.

6. ACKOWLEDGEMENTS

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