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Comparative Study of Independent Component Analysis and Adaptive Filter for Removal Ocular Artifact from EEG Data

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Abstract

EEG is brain signal process technique that enables gaining the understanding of the complicated inner mechanisms of the brain and abnormal brain waves have shown to be related to specific brain disorders. The analysis of brain waves plays a vital role in identification of various brain disorders. MATLAB provides an interactive graphic computer programme (GUI) permitting users to flexibly and interactively method their high-density encephalogram knowledge set and different brain signal data totally different techniques similar to freelance element analysis (ICA) and reconciling filter. We are going to be showing totally different brain signals by scrutiny, analysing and simulating datasets that is already loaded within the MATLAB package to method the encephalogram signals. Unfortunately, graph knowledge is usually contaminated by ocular artifacts that create the analysis of neural knowledge terribly troublesome. The main focus of this analysis is that the development of a unique technique which will mechanically notice and take away eyeblink artifacts so as to facilitate analysis of graph recordings. During this project, we have a tendency to compare the adaptive filter and freelance part Analysis techniques. For this project we have a tendency to used EEGLAB MATLAB tool chest. By victimisation this tool chest we have done the simulation of our project.

Keywords: *Electro-encephalogram (EEG), Magnetoenc-ephalography (MEG), EEGLAB toolbox, Electro-oculogram (EOG)*

INTRODUCTION

The eye forms an electrical dipole, wherever the tissue layer is positive and also the tissue layer is negative. Once the attention moves (saccade, blink or different movements), the electrical field round the eye changes, manufacturing associate electrical signal referred to as the electro-oculogram (EOG) [1–7]. As this signal propagates over the scalp, it seems within the recorded electro-encephalogram (EEG) as noise or artifacts that gift serious issues in graphical record interpretation and analysis. To correct or take away ocular artifacts from graphical record, several regression-based techniques are projected, together with easy time-domain regression, multiple-leg time-domain regression and regression within the frequency domain. Altogether these regression-based approaches, activity trials are 1st conducted to work out the transfer coefficients between the EOG channels and every of the graphical record channels. These coefficients are then used later within the ‘correction phase’ to estimate the EOG part within the graphical record recording for removal by subtraction. More recently, freelance element analysis (ICA) has been planned to separate the EOG signals from the encephalogram signals. This methodology needs off-line analysis and process of information collected from a sufficiently sizable amount of channels, and its success for the most part depends on correct identification of the noise parts [8–10].

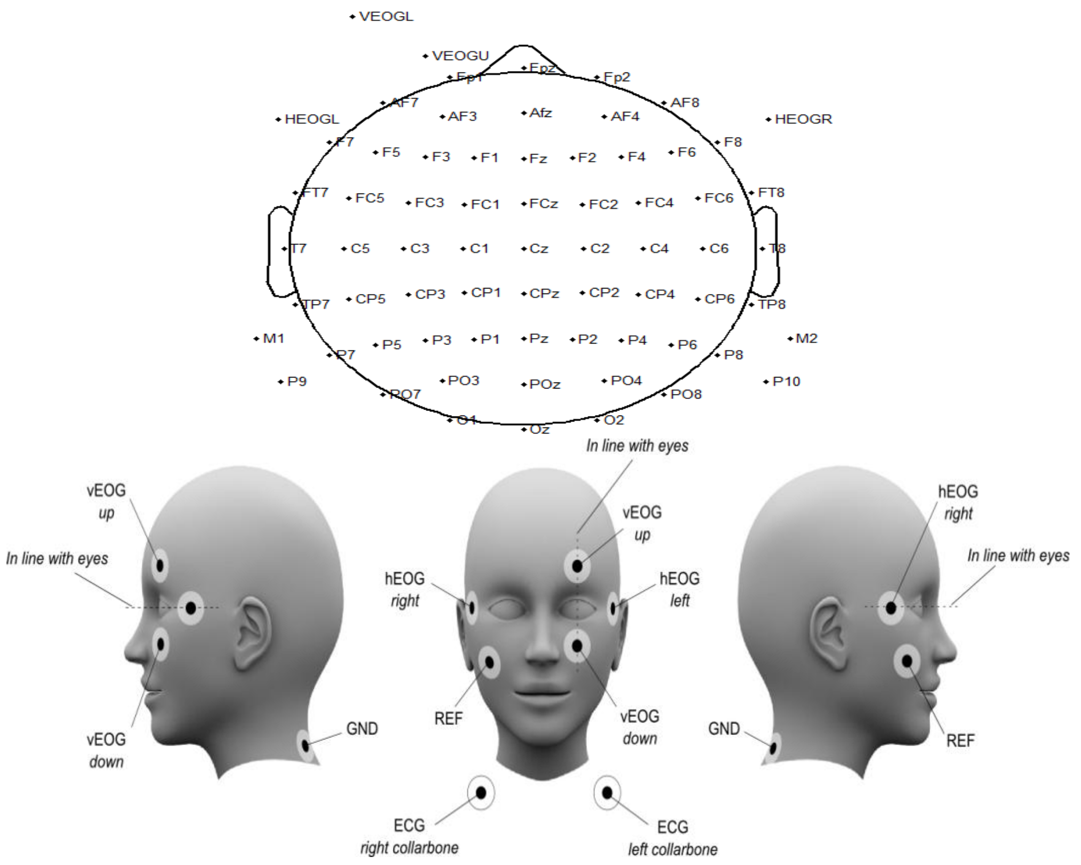

Fig. 1: *EEG Electrodes Placement and EOG (Electro-Oculogram) Electrodes Placement [3, 7].*

When the applications need period removal of ocular artifacts, or once the standardisation trials cannot be conducted thanks to numerous constraints, the ways represented on top of become unsuitable. During this paper, we have a tendency to describe a noise cancellation technique supported adaptive filtering to get rid of ocular artifacts from electroencephalogram [1, 7]. This technique is especially appropriate to our applications as a result of it does not need standardisation trials, and, therefore, the EOG artifacts are often removed on-line. Previous studies have shown that there square measure a minimum of 2 types of EOG artifact to be removed: those made by the vertical eye movement (the corresponding EOG is termed VEOG) and people made by the horizontal eye movement (HEOG). Consequently, a noise canceller with two reference inputs is employed during this application.

SYSTEM AND ARCHITECTURE

In this section, we provide details description about hardware and software of our system. In our system we use different device for sensing, wireless transmission of signal and controlling.

Principle of Removing EOG Artifacts by Adaptive Filtering

Figure 2 shows the block diagram of the noise canceller used in this application. The primary input to the system is the EEG Signal s(n), picked up by a particular electrode (e.g. F7). This signal is modelled as a mixture of a true EEG x(n) and a noise component z(n). rv(n) and rh(n) are the two reference inputs, VEOG and HEOG, respectively. rv(n) and rh(n) are correlated, in some unknown way, with the noise component z(n) in the primary input. hv(m) and hh(m) represent two finite impulse response (FIR) filters of length M (the two filters can have different lengths). The desired output from the noise canceller e(n) is the corrected, or clean, EEG.

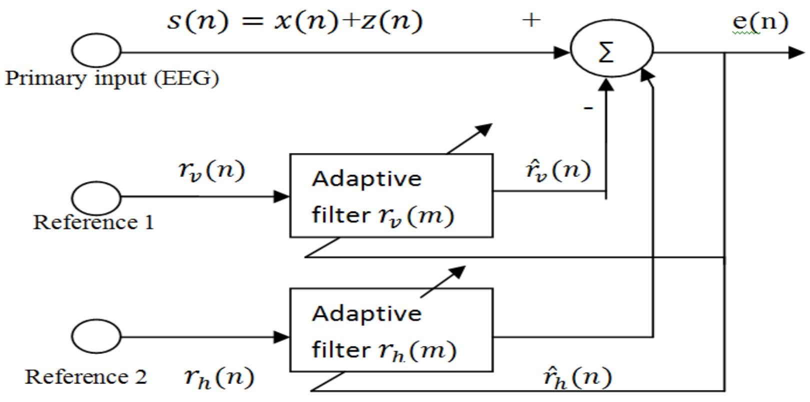

Fig. 2: *Block Diagram of EOG Noise Canceller using Adaptive Filtering with Two Reference Inputs [11].*

$$e(n) = s(n) - \hat{r}_v(n) - \hat{r}_h(n) = x(n) + [z(n) - \hat{r}_v(n) - \hat{r}_h(n)]$$

Where,

$$\hat{r}_v(n) = \sum_{m=1}^{M} h_v(m) r_v(n+1-m)$$

and

$$\hat{r}_h(n) = \sum_{m=1}^{M} h_h(m) r_h(n+1-m)$$

By minimising e(n) instead of E[, we simply use the sample mean to approximate the expected value. In addition, by introducing the forgetting factor l, the algorithm can also be applied to a random process that is not strictly stationary. The filter parameters hv(m), hh(m), m = 1, 2, . . . M, that minimise e(n) can be obtained by solving the following two sets of equations (a total of 2*M equations):

$$\begin{aligned} \varepsilon(n) &= \sum_{i=M}^{n} \lambda^{n-i} e^2(i) \\ &= e^2(n) + \lambda e^2(n-1) + \cdots + \lambda^{n-M} e^2(M) \end{aligned} \qquad (4)$$

are the filtered reference signals. Under the assumption that x is azero-mean stationary random signal that is uncorrelated with *z*, *rv* and *rh*, the expected value (denoted by [ ]) of can be calculated

$$\begin{aligned} E[e^2] &= E[(x + z - \hat{r}_v - \hat{r}_h)^2] \\ &= E[x^2] + E[(z - \hat{r}_v - \hat{r}_h)^2] \end{aligned} \qquad (3)$$

The goal of the noise canceller is to produce an output signal e(n)that is as close to x(n) as possible, by adjusting the filter coefficients *hv(m)* and *hh(m)*. Statistically, this requires a minimization of as E [ ] is not affected by the adjustment of the filter coefficients, minimising is equivalent to minimizing.

Among the varied algorithms of adaptational filtering, we tend to select the algorithmic least-squares (RLS) algorithmic program for our application, attributable to its superior stability and quick convergence. Parallel to the derivation given by VASEGHI (1996) for the case of 1 reference input, we tend to gift here the algorithmic program development for the case of 2 reference inputs. Assuming at time tn we have obtained the following samples:

s(i), rv(i), rh(i) and *e(i)*, for *i=1, 2, . . . n*, we form the following target function e(n) to minimise:

$$\varepsilon(n) = \sum_{i=M}^{n} \lambda^{n-i} e^2(i) = e^2(n) + \lambda e^2(n-1) + \cdots + \lambda^{n-M} e^2(M) \quad (4)$$

where 0 < λ < 1 is called the forgetting factor, and

$$e(i) = s(i) - \sum_{m=1}^{M} h_v(m) r_v(i+1-m) - \sum_{m=1}^{M} h_h(m) r_h(i+1-m) \quad (5)$$

By minimising e(n) instead of, we simply use the sample mean to approximate the expected value. In addition, by introducing the forgetting factor l, the algorithm can also be applied to a random process that is not strictly stationary. The filter parameters hv(m), hh(m), m=1, 2, . . . ,M, that minimize e(n) can be obtained by solving the following two sets of equations (a total of 2*M equations):

$$\frac{\partial \varepsilon(n)}{\partial h_v(m)} = 2\sum_{i=M}^{n} \lambda^{n-i} e(i) \frac{\partial e(i)}{\partial h_v(m)} = -2\sum_{i=M}^{n} \lambda^{n-i} e(i) r_v(i+1-m) = 0 \quad (6)$$

$$\frac{\partial \varepsilon(n)}{\partial h_h(m)} = 2\sum_{i=M}^{n} \lambda^{n-i} e(i) \frac{\partial e(i)}{\partial h_h(m)} = -2\sum_{i=M}^{n} \lambda^{n-i} e(i) r_h(i+1-m) = 0 \quad (7)$$

$$\text{for } m = 1, 2, \ldots, M$$

The above two sets of equations can be represented by the following matrix forms:

$$\boldsymbol{R}_{vv}(n) \cdot \underline{\boldsymbol{H}}_v + \boldsymbol{R}_{vh}(n) \cdot \underline{\boldsymbol{H}}_h = \underline{\boldsymbol{P}}_v(n) \quad (8)$$

$$\boldsymbol{R}_{hv}(n) \cdot \underline{\boldsymbol{H}}_v + \boldsymbol{R}_{hh}(n) \cdot \underline{\boldsymbol{H}}_h = \underline{\boldsymbol{P}}_h(n) \quad (9)$$

where Rvv, Rvh, Rhv and Rhh are each an (M x M) square matrix,

and Hv, Hh, Pv and Ph are each a column vector having a dimension of M

$$\boldsymbol{R}_{vv}(n)(j,k) = \sum_{i=M}^{n} \lambda^{n-i} r_v(i+1-j) r_v(i+1-k) \quad (10)$$

$$\boldsymbol{R}_{vh}(n)(j,k) = \sum_{i=M}^{n} \lambda^{n-i} r_v(i+1-j) r_h(i+1-k) \quad (11)$$

$$\boldsymbol{R}_{hv}(n)(j,k) = \sum_{i=M}^{n} \lambda^{n-i} r_h(i+1-j) r_v(i+1-k) \quad (12)$$

$$\boldsymbol{R}_{hh}(n)(j,k) = \sum_{i=M}^{n} \lambda^{n-i} r_h(i+1-j) r_h(i+1-k) \quad (13)$$

$$\text{for } j, k = 1, 2, \ldots, M$$

$$\underline{\boldsymbol{P}}_v(n)(j) = \sum_{i=M}^{n} \lambda^{n-i} s(i) r_v(i+1-j) \quad (14)$$

$$\underline{\boldsymbol{P}}_h(n)(j) = \sum_{i=M}^{n} \lambda^{n-i} s(i) r_h(i+1-j) \quad (15)$$

$$\text{for } j = 1, 2, \ldots, M$$

$$\underline{\boldsymbol{H}}_v = [h_v(1)\ h_v(2) \cdots h_v(M)]^T$$

$$(T \text{ stands for vector transposition}) \quad (16)$$

$$\underline{\boldsymbol{H}}_h = [h_h(1)\ h_h(2) \cdots h_h(M)]^T \quad (17)$$

Equations (8) and (9) can further be reduced to one matrix

Equation

$$\boldsymbol{R}(n) \cdot \underline{\boldsymbol{H}} = \underline{\boldsymbol{P}}(n) \quad (18)$$

Where,

$$\boldsymbol{R}(n) = \begin{bmatrix} \boldsymbol{R}_{vv} & \boldsymbol{R}_{vh} \\ \boldsymbol{R}_{hv} & \boldsymbol{R}_{hh} \end{bmatrix} \quad \underline{\boldsymbol{H}} = \begin{bmatrix} \underline{\boldsymbol{H}}_v \\ \underline{\boldsymbol{H}}_h \end{bmatrix} \quad \underline{\boldsymbol{P}} = \begin{bmatrix} \underline{\boldsymbol{P}}_v \\ \underline{\boldsymbol{P}}_h \end{bmatrix} \quad (19)$$

From (18), the filter coefficients that minimise e(n) can be solved

$$\underline{\boldsymbol{H}} = [\boldsymbol{R}(n)]^{-1} \cdot \underline{\boldsymbol{P}}(n) \quad (20)$$

Principle of Removing EOG Artifacts by ICA

Fast ICA algorithm was proposed by Finnish scholars Aapo Hyvarinen in 1999 [11]. It is used to decompose the EEG data into multiple independent components in this paper. The ICA model can be represented in Eq. (21) [12–15]. (21)

Where

X(t) = [x1(t),x2(t)…. xn(t)

is the observed signal. A∊ is the mixing matrix. Let n be the number of electrodes, 1 ≤ t ≤ N , N be the number of samples, and m is the number of independent sources respectively. S(t) ∊ is the independent source matrix. Then, S(t) can be obtained by following equation:

$$y(t) = wx(t)$$

(22)

Where X(t) = [y1(t),y2(t)…. ym(t)

Y(t)=[y1(t),... yi(t)... ym(t) ∊ □ is the estimation of S(t) ,y(t) stands for the i-th independent component,1 ≤ i≤ m, w ∊ is the separation matrix [12].

RESULT

Here, this project we compared the results of Adaptive filter and independent component analysis. I have calculated the different parameter of EEG datasets like mean, standard deviation and variance. I have compared the mean, standard deviation and variance of original EEG dataset, ICA Output Dataset in Table 1. In Table 1 if we observed the standard deviation value of all three datasets then we get less standard deviation in ICA method. ICA removes the more ocular artifacts from the EEG dataset as compared to Adaptive filter using RLS algorithm. ICA is latest technology to remove ocular artifacts from EEG datasets. The power spectrum based experiment results indicate that the power spectrums of the Original EEG signals and corrected EEG signals.

Table 1: *Comparison between Original EEG Dataset Parameter, Adaptive Filter Output Dataset Parameter and ICA Output Dataset Parameter.*

Channels	Original EEG Dataset parameter			Adaptive Filter Output Dataset parameter			ICA Output Dataset parameter		
	Mean	Standard deviation	Variance	Mean	Standard deviation	Variance	Mean	Standard deviation	Variance
1	3.4	33.95	1152	1.32	25.66	658.6	1.32	15.42	237.7
2	0.534	23.18	537.2	0.534	23.18	537.2	5.34	12.18	148.4
3	3.58	25.42	646.1	2.01	20.97	439.6	11	18.94	358.7
4	3.55	25.11	630.6	2.33	22.44	503.5	12.5	20.27	411.1
5	4.23	25.18	634.2	3.05	23.1	533.5	8.62	18.04	325.6
6	2.03	21.71	471.3	2.03	21.71	471.3	2.54	10.27	105.6
7	3.26	21.7	471	1.85	17.3	299.4	7.23	15.06	226.9
8	3.49	24.53	601.9	2.36	22.4	501.7	9.73	28.2	408.1
9	2.94	25.9	970.8	2.02	24.6	605.2	12.3	21.73	472.2
10	3.57	18.25	133.2	2.84	17.16	294.4	5.75	13.29	176.6
11	2.41	16.54	273.5	1.47	13.59	184.8	-0.784	10.59	112.2
12	2.87	22.78	519.1	1.75	20.81	433.2	7.93	18.73	358.7
13	2.89	20.87	435.5	2.24	20.12	405	4.02	4.08	288.4
14	2.28	13.94	167.5	2.84	22.79	519.5	6.09	19.94	397.5
15	2.36	18.83	354.6	1.94	12.49	155.9	-1.67	10.24	104.8
16	2.93	23.79	566	1.52	7.26	297.9	-0.607	14.38	81.61
17	2.9	24.03	577.5	2.09	22.69	515	4.33	19.6	384.1
18	2.9	24.03	577.5	2.2	23.31	543.4	2.1	19.13	365.8
19	2.4	16.45	270.5	1.98	15.85	251.2	-1.02	13.1	61.99
20	1.57	6.41	269.9	0.968	15.52	241	-3.75	12.76	70.45
21	2.15	22.1	488.2	1.45	21.23	450.9	2.98	18.23	323.2
22	2.61	25.57	653.7	2.06	24.87	618.5	-0.11	19.61	384.6
23	1.89	21.3	453.6	1.47	20.62	425.3	0.995	16.27	264.7
24	0.655	12.93	167.3	0.48	12.34	152.3	-5.42	10.33	384
25	1.12	18.57	344.9	0.718	18.13	328.7	-5.21	15.94	95.13
26	1.33	23.64	559	0.832	23.05	531.5	-5.52	19.68	387.1
27	0.965	23.44	549.5	542	22.88	523.3	-3.53	17.45	304.5
28	0.768	21.62	467.3	0.542	22.88	523.3	-1.96	15.78	249.1
29	0.383	17.06	290.9	0.176	16.54	273.6	-5.07	13.17	173.5
30	0.297	18	324	-0.06	17.56	308.3	-5.15	15.2	231.1
31	0.286	17.4	302.7	-0.04	16.91	285.9	-6.17	14.22	202.2
32	-0.197	17.8	316.9	-0.44	17.32	299.9	-6.4	14.27	203.6

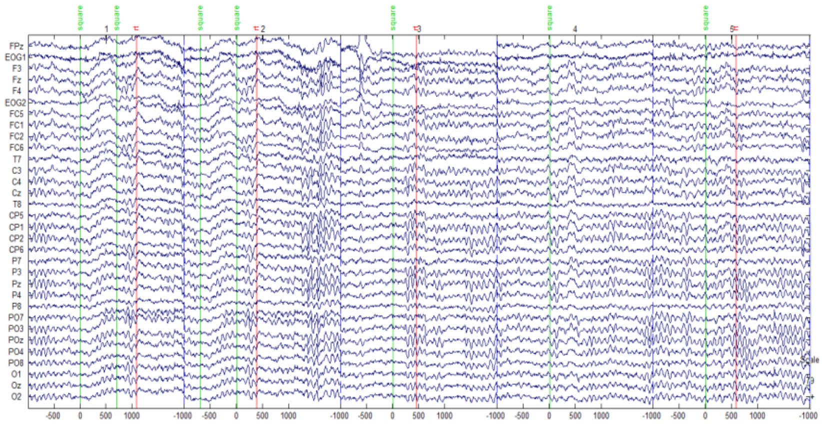

Fig. 3: *Original EEG Dataset.*

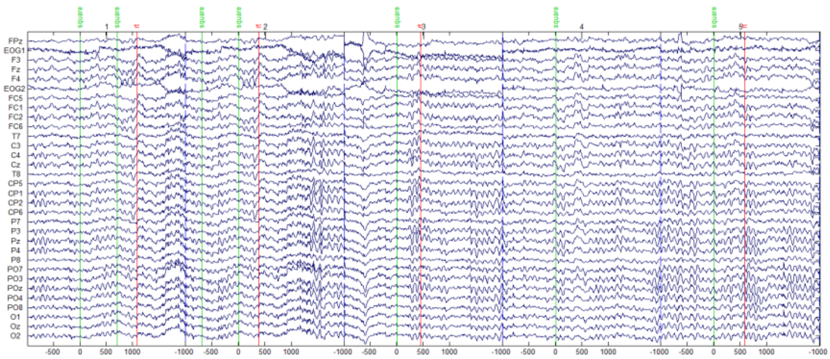

Fig. 4: *Filter EEG Dataset by Adaptive Filter.*

In Figure 3 we show the original EEG datasets. Original datsets has more ocular arifacts. In Figure 4 represent the filter datasets by adaptive filter. Figure 5 represents the clean datasets by ICA method. From this Figure, we conclude that ICA give better result as compared to adaptive filter method. In Figure 5 we draw the channels spectra and map of original signal. In this diagram shows the power vs. frequency graph.

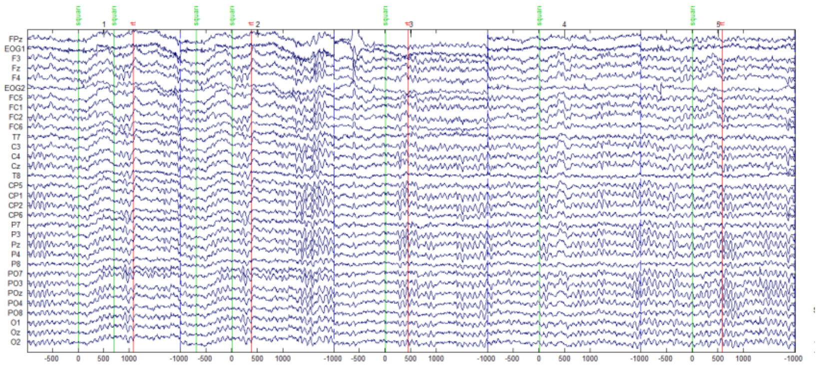

***Fig. 5:** Filter EEG Dataset by ICA.*

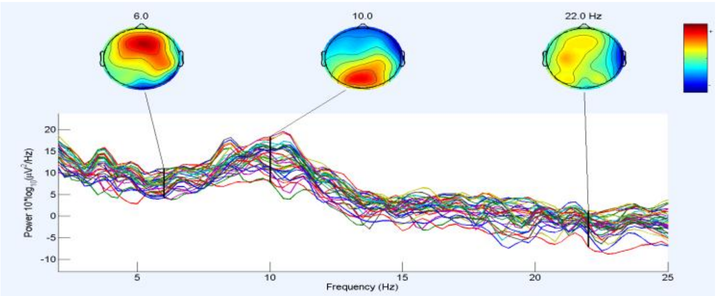

***Fig. 6:** Channel Spectra and Map of Original Datasets.*

CONCLUSION

Automatic artifact cancellation exploitation EEG information is bestowed. This methodology with efficiency rejects artifacts made by eyes movements and it depends on freelance element analysis (ICA) and algorithmic method of least squares (RLS) adaptive filtering. Our preliminary results show that this methodology is ready to eliminate eye movement artifacts, and that we take into account that it should be a relevant technique for e.g. sense modality potential (SEPs) and event connected potentials (or fields (magnetoencephalography) thanks to the restricted variety of responses in an exceedingly 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. ICA appears to be a generally applicable and effective method for removing artifacts and independent noise, providing considerable performance improvements. 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 and other experiments as adaptive on-line ICA 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.

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