EEG Ocular Artefacts and Noise Removal

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***Abstract*— The goal of this paper is to apply and compare different noise and artefacts removal methods for electroencephalographic (EEG) signal processing. More precisely, we present several combinations of wavelet denoising (WD) and independent components analyses (ICA) algorithms. These methods are tested on simulated EEG, using different evaluation criteria.**

I.INTRODUCTION

One of the most common brain disorders is epilepsy. Most epilepsies are characterized by repeated seizures, caused by bursts of excessive electrical activity in the brain. In clinical practice this electrical activity is measured by the electroencephalogram (EEG), which records the potential changes caused by brain activity. In EEG recordings, the sensors are placed on the scalp according to predefined rules (10-20 system in our case). Therefore, the sensors record brain activity transmitted by volume conduction from different dynamic neocortical processes. An example of a normal EEG (5 channels in average reference montage during 8 seconds) is shown in figure 1.

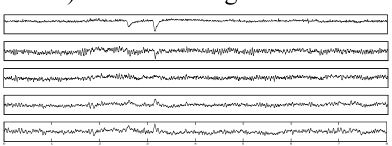

Fig 1. Example of EEG

EEG channels also record other signals, such as noise or artefacts, supposed independent from brain processes. These perturbations overlap with the brain neural activity and may be present in all sensors, increasing the difficulty of EEG interpretation. Therefore, a useful tool would be a method able to remove noise and external artefacts like eye or muscle activities. A current hypothesis is that these artefacts are independent from brain activity, either normal or pathologic. Under this hypothesis a frequently used method is the blind source separation (BSS) by independent component analysis (ICA) [1], [2]. Moreover, as EEG's are non-stationary signals with low SNR ratios, it seems that wavelet denoising (WD) can be appropriate to tackle the noise problem. In this communication, we explore different ways for combining several ICA and WD methods. These methods are tested and compared on simulated EEG signals, using different evaluation criteria.

This communication is organized as follows. In the second section, we describe the test signals we have used to simulate EEG recordings, we present the evaluated ICA and WD algorithms and their interaction and we introduce the evaluation criteria. The third section presents the obtained results and it is followed by a fourth section that concludes and presents the perspectives of this work.

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II.METHOD

A. Simulated signals

The EEG recordings are the result of mixing independent neuronal sources, artefacts and noise. All these components, as well as the mixing system, are unknown. In order to choose the most appropriate algorithms for our applications, we decided to generate simulated sources and mixing matrices. In this way, we can compare the results of ICA and WD algorithms with known reference signals.

In order to simulate real EEG's we mixed independent sources simulating normal or pathologic brain activity with different types of noise and artefacts sources (eye blinking). Two groups of sources were used: the first one contains 5 sources: 4 simulated sources having frequencies close to the real brain signals and one ocular blinking artefact source, figure 3(a). The second group includes 7 sources: the signals from the first group plus two more signals simulated using the time–frequency signal processing technique developed by Rankine *et al* [3]: a background EEG signal, and a seizure signal. The resulting simulated sources are presented figure 4(a).

Using these sources, simulated EEGs were created by two techniques:

1) The 5 (respectively 7) sources were mixed using 20 different random matrices, in order to obtain the same number of simulated EEG channels. Next, independent white noise with different distributions (uniform, Gaussian and Lapacian) and different signal to noise ratios (SNR= 0, 5, 10, 15, 20 dB) was added. This method is schematised figure 2. In figures 3(b) and 4(b) are shown the mixed noisy signals (simulated EEG1 and EEG2). The model of this instantaneous noise mixture can be written as:

$$\mathbf{x}(k) = \mathbf{A}\mathbf{s}(k) + \mathbf{n}(k) \tag{1}$$

where

$\mathbf{x}$ is a N-dimensional vector with the mixed signals (sensors),
$\mathbf{A} \in \mathbf{R}^{\mathbf{N}x\mathbf{N}}$ is the unknown nonsingular mixing matrix,
$\mathbf{s}$ is a N-dimensional vector of independent source signals,
$\mathbf{n}$ is an additive vector noise,
k being the time index after sampling.

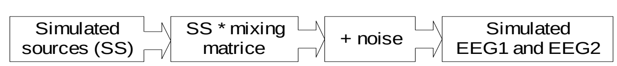
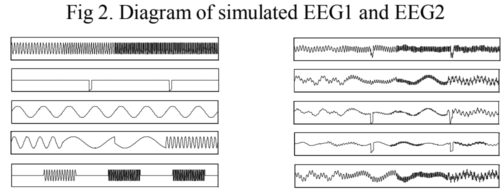
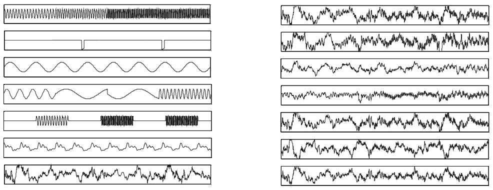


Fig 2. Diagram of simulated EEG1 and EEG2



(a) (b)

Fig 3. (a) Simulated sources, (b) Simulated EEG1



(a) (b)

Fig 4. (a) Simulated sources, (b) Simulated EEG2

2) Along with the 5 (7) simulated sources, we considered three sources of noise (one for each type of noise, normalised to σ=1). The random mixing matrices were generated accordingly, i.e. 8x8 (the 5 sources figure 3(a) and 3 noise sources) respectively 10x10 (the 7 sources figure 4(a) and 3 noise sources). The simulation diagram is presented figure 5. In figures 6(a) and 7(a) are shown the considered signal and noise sources. Figures 6(b) and 7(b) show the resulting mixed noisy signals (simulated EEG3 and EEG4).

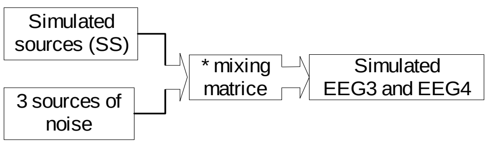
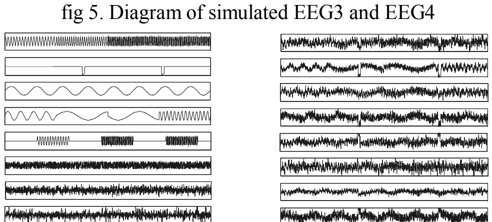
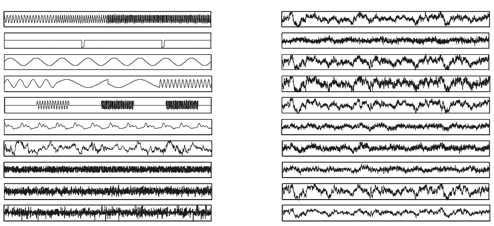


fig 5. Diagram of simulated EEG3 and EEG4



(a) (b)

Fig 6. (a) Simulated and noise sources (b) simulated EEG3



(a) (b)

Fig 7. (a) Simulated and noise sources (b) simulated EEG4

B. Independent Component Analysis

The goal of blind source separation is to recover independent sources given only sensor observations. These sensor observations are modelled as linear mixtures of independent source signals. The term blind indicates that both the source signals and the way in which they are mixed are unknown. Several algorithms for BSS were developed in the last 15 years. Some of the most important are described in [2] and implemented in ICALAB [4] toolbox under MATLAB. ICA is a method for solving the blind source separation problem by finding a linear transformation of the signals measured by sensors such as the estimated source signals are as statistically independent from each other as possible. The mixing ICA model (without noise) is given by:

$$\mathbf{c}(k) = \mathbf{A}\mathbf{s}(k) \tag{2}$$

The idea of ICA is to find a linear transformation **B** of the dependent sensor signals **c** that makes the outputs as independent as possible:

$$\hat{\mathbf{s}}(k) = \mathbf{B}\mathbf{c}(k) = \mathbf{B}\mathbf{A}\mathbf{s}(k) \tag{3}$$

where

c is the mixed signals,

$\hat{\mathbf{s}}$ is an estimate of the sources,

B is the separation matrix.

The sources are exactly recovered when **B** is the inverse of **A**. As it was pointed out by different authors ([1],[2]), obtaining the exact inverse of the **A** matrix is, in most of the cases, impossible. Therefore source separation algorithms search to find a **B** matrix such as the product **BA** is a permuted diagonal and scaled matrix. Consequently, sources can be recovered up to their order (permutation) and their amplitude (scale).

Different types of algorithms were proposed. Most of them are based explicitly or implicitly on high order statistics (HOS) computation [1],[2]. Another type of algorithms uses the non stationary structure of the signals (i.e. their time or frequency structure) to separate them [9],[10]. These methods use only second order statistics (SOS). As EEG signals are highly non stationary, this type of algorithms is the most widely used.

C. Wavelet denoising

Besides ocular or muscular artefacts, real EEG recordings are contaminated with noise. Nowadays a classical solution for noise removal from non-stationary signals is WD, which we considered for improving the separation results.

The basic idea is: decomposing the signal on a wavelet basis (discrete wavelet transform, DWT), we obtain a representation of the signal that concentrates most of its energy in few wavelet coefficients having large absolute values. On the contrary, noise energy distribution does not change (for noises modelled as random uncorrelated processes), which means that its energy will not be retained by large value coefficients. Therefore, denoising can be achieved by thresholding the wavelet coefficients.

Consider the *i-th* noisy mixture observation from (1),

$$\mathbf{x}(k) = \mathbf{A}\mathbf{s}(k) + \mathbf{n}(k) = \mathbf{c}(k) + \mathbf{n}(k) \tag{4}$$

where $\mathbf{c}(k)$ is the noise free mixture.

Being W and W^{-1} the forward and inverse DWT operators, then the WD will be performed, for a given sensor signal $\mathbf{x}_i$, in the following process [5]:

$$\mathbf{w}_i = W(\mathbf{x}_i) \tag{5}$$

$$\hat{\mathbf{w}}_i = T(w_i, \lambda) \tag{6}$$

$$\hat{\mathbf{c}}_i = W^{-1}(\hat{\mathbf{w}}_i) \tag{7}$$

where

w is the wavelet coefficients vector

T(λ) thresholding operator, λ threshold

$\hat{\mathbf{w}}$ is the wavelet coefficients after tresholding

$\hat{\mathbf{c}}$ is the denoised signal.

The main problem is to compute the threshold, which means responding to the question: where to fix the frontier between small and large wavelet coefficients? Several algorithms have been proposed in the last years, the most well known being Donoho's universal thresholding [6]. This algorithm computes a threshold which, asymptotically, ensures that any gaussian noise will be left in the denoised signal. The first consequence is an apparently noise-free signal, visually very satisfactory. The main drawback is the high value of the threshold, which can lead to information lost by signal distortion.

In EEG case, it is of great importance not to loose information potentially useful to medical diagnosis. Moreover, EEG informative signals often have small amplitudes, and their wavelet coefficients can have rather low values. Therefore, others algorithms tend to be more appropriate. We have tested here the SURE thresholding and the minimal denoising [6],[7].

WD and ICA were implemented in two ways, as shown in figure 8:

1) WD after ICA, on the estimated noisy sources ($\mathbf{y}$).
2) WD before ICA, on the noisy mixture signals ($\mathbf{x}$).

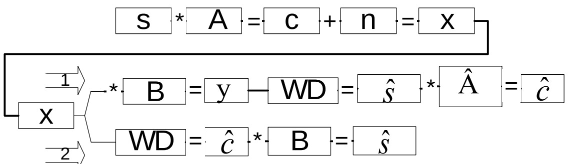


Fig 8. Denoising and separation methods

In first method denoising was made after ICA. In this way, we have obtained $\hat{\mathbf{c}}$ as the denoised mixture. In second method, we have separated before denoising. In this case to find $\hat{\mathbf{c}}$ it is necessary to remix the separated denoised estimated sources ($\hat{\mathbf{s}}$) using the estimated mixing matrix ($\hat{\mathbf{A}}=\mathbf{B}^{-1}$). Both methods were compared using the evaluation criteria detailed hereafter.

D. Evaluation criteria

For denoising algorithms evaluation, we have used the classical criterion of the mean squared error (*MSE*) between the original signals and their denoised versions. For the $\mathbf{c}_i$ component of the vector $\mathbf{c}$ (i^{th} sensor, i=1…N), we have :

$$MSE_i = \frac{1}{M}\sum_{k=1}^{M}\left(\mathbf{c}_i(k)-\hat{\mathbf{c}}_i(k)\right)^2 \tag{8}$$

where M is the length of the signal and $\hat{\mathbf{c}}_i$ is the denoised version of the signal. As we are in a multi-channel set-up (multiple simulated sources mixed to obtain the same number of recordings), the denoising quality criterion was the average *MSE* for the N signals (MSE_{avg}).

To validate the separation method, we have chosen the index of separability *IS* [2]. The index is computed from the $N\times N$ transfer matrix $\mathbf{G}$ between the original sources and the estimated ones after separation:

$$\mathbf{G} = \mathbf{BA} \tag{9}$$

In order to obtain the *IS* is necessary to take the absolute value of elements of $\mathbf{G}$ and to normalize the lines $\mathbf{g}_i$ by dividing each element by the maximum absolute value of the line. The lines of the resulting matrix $\mathbf{G'}$ will be:

$$\mathbf{g}_i' = \frac{|\mathbf{g}_i|}{\max|\mathbf{g}_i|} \tag{10}$$

The separability index is obtained on the new $\mathbf{G'}$ matrix by :

$$IS = \frac{\sum_{j=1}^{N}\left(\sum_{i=1}^{N}\left(\mathbf{G}'(i,j)\right)-1\right)}{\left[N(N-\mathbf{1})\right]} \tag{11}$$

For the evaluation of both separability and denoising methods, we have chosen the correlation (ρ) between the simulates sources ($\mathbf{s_i}$, $i=1…N$) and the estimate independent components ($\hat{\mathbf{s}}_\mathbf{j}$).

$$\rho = \frac{\mathrm{cov}\left(\mathbf{s_i}, \hat{\mathbf{s}}_\mathbf{j}\right)}{\sigma_{s_i}\sigma_{\hat{s}_j}} \tag{12}$$

To avoid taking into account small values of correlation and estimated sources correlated with more than one original source, we have chosen to discard correlation values smaller than 0.5:

$$r_{ij}\begin{cases}\rho, & \text{if } \rho \geq 0.5\\ 0, & \text{if } \rho < 0.5\end{cases} \tag{13}$$

For each original source $\mathbf{s_i}$ we retain only one estimated source $\hat{\mathbf{s}}_\mathbf{j}$, for which the correlation is maximal.

$$r_i = \max_j(r_{ij}) \tag{14}$$

Finally, we compute our r_{avg} criterion as:

$$r_{avg} = \frac{1}{N}\sum_j r_i \tag{15}$$

For perfect source recovering, the three criteria should have the values r_{avg}=1, MSE_{avg} =0 and *IS*=0.

III.RESULTS

Several test were performed on the simulated signals shown in figures 3, 4, 5 and 6. All algorithms were compared using 20 random matrices and three types of noise having 5 different SNR ratios. The mean results over all simulations are presented hereafter.

1. The first test aims to choose a source separation algorithm both in ideal conditions (without noise) and on noisy signals. Twenty ICA algorithms were tested. The best 4 results (considering the previously defined separation criteria) are presented table I, see also [8].

	SOBI	**AMUSE**	**EVD**	**SOBIRO**
	$\mathbf{r_{avg}}$			
Mixed signals	0.9898	0.9960	0.9938	**0.9983**
Noisy mixed signals	0.7480	0.5866	0.6379	**0.7319**
	$\mathbf{IS_{avg}}$			
Mixed signals	0.0700	0.0600	0.0700	**0.0098**
Noisy mixed signals	0.1293	0.4419	0.4173	**0.0810**

Table I. Comparison of algorithms on simulated signals

From the results of the table I, we decided to use the SOBI-RO [9], [10] algorithm to remove the ocular artefacts. This result confirms our bibliographical research, which indicate that second order statistics ICA algorithms perform well on non-stationary EEG signals [11],[12],[13].

2. Next, we introduced a WD step. The tresholding of the wavelet coefficients can be done either before source separation (on the noisy mixture) or after the separation (on estimated noisy sources). We present the results of the two methods. Ten denoising methods were tested on the simulated EEG1 and EEG2, the results of the three best algorithms (SURE, universal and iterative minimal denoising [6],[7]) are shown in table II, III, IV and V and

compared with results obtained without denoising. In figure 9 we show an example of separated denoised signals.

Algorithm	No denoising	Sure	Universal	Minimal
r_{avg}	0.6500	**0.7673**	0.7259	0.7278
MSE_{avg}	0.1815	**0.0512**	0.0800	0.0784
IS_{avg}	**0.1013**	0.1285	0.1529	0.1588

Table II. Results in EEG1, denoising before ICA.

Algorithm	No denoising	Sure	Universal	Minimal
r_{avg}	0.4754	**0.6689**	0.6252	0.6077
MSE_{avg}	1.2869	**0.3334**	0.5206	0.5637
IS_{avg}	**0.1598**	0.1751	0.1888	0.2011

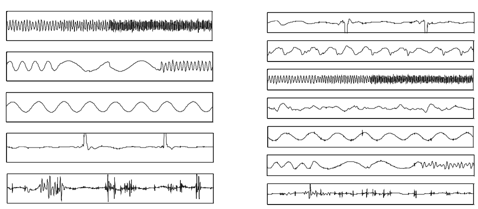
Table III. Results in EEG2, denoising before ICA.

Algorithm	No denoising	Sure	Universal	Minimal
r_{avg}	0.7012	0.8384	0.8300	**0.8455**
MSE_{avg}	0.1570	**0.0403**	0.0551	0.0636
IS_{avg}	0.0629	**0.0629**	0.0629	0.0629

Table IV. Results in EEG1, denoising after ICA.

Algorithm	No denoising	Sure	Universal	Minimal
r_{avg}	0.5104	**0.7076**	0.6638	0.6656
MSE_{avg}	0.9596	**0.3040**	0.4535	0.5544
IS_{avg}	0.1465	**0.1465**	0.1465	0.1465

Table V. Results in EEG2, denoising after ICA.



(a) (b)

Fig 9. Separated denoised signals from simulated EEG1(a) simulated EEG2(b)

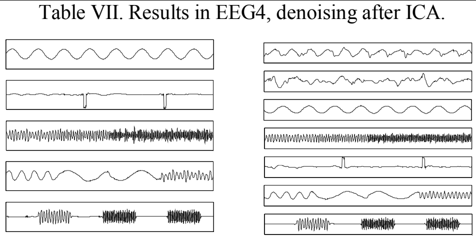
3. Finally we present the results of denoising after ICA on the simulated EEG3 and EEG4. In this case we evaluated using only the correlation criterion computed on the informative sources, without considering the three noise sources. The IS was discarded, because in the estimated mixing matrix the elements corresponding to the noise sources have no signification. The MSE can not be directly computed neither, as we do not know the "clean" mixture **c**. Results are presented in tables VI and VII. In figure 10 we show an example of the separated denoised signals.

Algorithm	No denoising	Sure	Universal	Minimal
r_{avg}	0.9240	**0.9702**	0.9633	0.9676

Table VI. Results in EEG3, denoising after ICA.

Algorithm	No denoising	Sure	Universal	Minimal
r_{avg}	0.9069	**0.9479**	0.9253	0.9391

Table VII. Results in EEG4, denoising after ICA.



(a) (b)

Fig 10. Separated denoised signals from simulated EEG3(a) simulated EEG4(b)

IV. CONCLUSION AND PERSEPECTIVES

We may conclude that the SOBI-RO algorithm works well in EEG source separation and particularly for identifying eye artefacts. This conclusion is supported by the bibliography.

Concerning the denoising step, we concluded that it improves overall performances comparing with simple ICA. The results are better if we apply WD after ICA than if the denoising is performed directly on the noisy mixture.

This conclusion is valid for both kinds of simulated EEG, as presented in figures 3(b) and 4(b) (informative mixture plus independent noise) and in figures 6(b) and 7(b) (independent sources mixed with noise). By comparing denoising algorithms, we concluded that SURE and minimal algorithms perform better for our application.

This work has several perspectives. First of all, coloured noise will be considered. Next separation on wavelet coefficients directly will be tested. We will also adapt SOBI algorithm for simultaneous utilisation in both temporal and wavelet domains. Finally, we will test our methods on real EEGs and ask for medical validation.

REFERENCES

[1] Te-Won Lee, Independent component Analysis Theory and Applications, Kluwer Academic Publisher, Boston, 1998.

[2] A. Cichocki, Shun-ichi Amari, Adaptative blind Signal and Image Processing Learning Algorithms and Applications, John Wiley & Sons, ltd, 2002.

[3] N. Stevenson, L. Ranking, M. Mesbah and B. Boashash "Newborn EEG seizure simulation using time – frequency signal synthesis" APRS Workshop on Digital Image Computing, 2005

[4] A. Cichocki, S. Amari, K. Siwek, T. Tanaka et al., ICALAB Toolboxes, http://www.bsp.brain.riken.jp/ICALAB.

[5]A. Paraschiv-Ionescu, C. Jutten, K. Aminian, B. Najafi, Ph. Robert, "Wavelet de-noising for highly noisy source separation" Circuits and Systems, 2002. ISCAS 2002. IEEE International Symposium**.**

[6] D. Donoho and I. Johnstone, "Adapting to unknown smoothness via wavelet shrinkage," J. Amer. Statist. Assoc., vol. 90, pp. 1200-1224, Dec. 1995.

[7] R. Ranta, V. Louis-Dorr, Christian Heinrich, D. Wolf, "Iterative wavelet-based denoising methods and robust outlier detection" IEEE Signal Processing Letters pages 557-560 vol. 12 num. 8 - august 2005.

[8] Rebeca Romo-Vazquez, Radu Ranta, Valerie Louis-Dorr, Didier Maquin, "Ocular artifacts removal in scalp EEG: combining ICA and wavelet denoising." PSIP, 2007, Mulhouse, France.

[9] A. Belouchrani, K. Abed-Meraim, J.F. Cardoso, E. Moulines, "A blind source separation technique using second order statistics", IEEE Transactions on signal processing, vol. 45, No. 2, February, 1997.

[10] A. Belouchrani, A. Cichocki, "Robust whitening procedure in blind source separation context" Electronics Letters, vol. 36, No. 24, 2000, pp. 2050-2053.

[11] Joep J. M. Kierkels, Geert J. M. Van Botel, and Leo L. M. Vogten. 'A Model-Based Objective Evaluation of Eye Movement Correction in EEG Recordings'IEEE, Transactions on biomedical engineering, vol, 53, No. 2, February 2006.

[12] C.W. Hesse and C.J. James, "Seizure tracking and detection in ictal EEG using time-structure based blind source separation methods and prior spatial topographical information" Proceedings of the IFMBE, EMBEC'05, Prague, Czech Republic, November 20-25, 2005.

[13] Sutherland, M.T., and Tang A.C. " Blind source separation can recover systematically distributed neuronal sources from "resting" EEG", Proceedings of the Second International Symposium on Communications, Control, and Signal Processing (ISCCSP 2006), Marrakech, Morocco, March 13-15.