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A global approach for automatic artifact removal for standard EEG record

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Abstract— **The EEG signal is a record of the brain activity using multiple electrodes placed on the scalp. Unfortunately, it can be hardly contaminated by a lot of noises called artifacts. These latter can be generated by various actions such as eye blinks, eye movements or the skeletal muscle activities (jaw, forehead, ...).**

This study will focus on a global artifact removal method using Independent component Analysis (ICA) on signals cut in frequency bands. The interest of this method resides in automatizing the artifactual source identification and enables a global filtering of records using constant bases. A brief overview of the project will be made in order to introduce the method used. Next, the results will be presented and their validation will be discussed in the conclusion.

I. INTRODUCTION

The statistical analysis of electrical recordings of the brain activity by an Electroencephalogram (EEG) is a major problem in Neuroscience. Cerebral signals have several origins thus leads us to the complexity of their identification. Therefore, the noise removal is of the prime necessity to make easier data interpretation and representation, and to recover the signal that matches perfectly a brain functioning [1].

The authors have been working on a standard examination with a 19 electrodes (10/20) system. During the standard examination, some elements must be kept. It can be notified especially:

- Paroxysms (epilepsy indicators). They are graphical elements that can be seen under various forms. The most common on is called peak wave. The paroxysms belongs to a very large frequency band (1-30 Hz) which makes the numerical filtering difficult to use.
- Reactivity to eye closure. This will be characterized by a alpha rhythm apparition (8-13 Hz) mainly located in the occipital region.
- Slow waves (< 4 Hz). These waves can be seen as pathological for the adult.

The main purpose of the filtering process will be to keep as its best these signals and erase the ones with artifactual origins. The artifact types can be broken down as follows:

- Eye blink. It is represented by a low frequency signal (< 4 Hz) that can be important in amplitude. It is a symmetrical activity mainly located on the front electrodes (FP1, FP2) with a low propagation.
- Eye movement. It is also represented by a low frequency signal (< 4 Hz) but with a higher propagation. It is caused by the fact that eyes represent dipoles and their movement leads to an alteration of the electrical field. It is characterized by a dissymmetry between the 2 hemispheres.
- Forehead movement. It is mainly a high frequency activity ($>$ 13Hz) due to its muscular origin. However, slight electrodes displacement can be observed on low frequencies ($<$ 4Hz).
- Jaw clenching. It is also a high frequency ($>$ 13Hz) and muscular activity and may also cause some low frequencies.

II. METHODOLOGY

A. Independent component analysis (ICA)

1) Principals: The ICA problem was introduced by Herault and Jutten [2]. It was originally proposed to solve the blind source separation problem to recover n independent sources $S(t) = [S_1(t), S_2(t), ..., S_n(t)]^T$ which are linearly mixed by an unknown matrix A. The sources are distributed in a precise way along m different channels $X(t) = [X_1(t), X_2(t), ..., X_m(t)]^T$. It is assumed that the number of electrodes is more important than the number of sources ($m > n$).

After using several forms of separation, based especially on independency, an estimated version of sources can be investigated $U(t) = [U_1(t), U_2(t), ..., U_n(t)]^T$ using $U(t) = WX(t)$. The matrix W is called the separating matrix which aims to invert the mixing process (The mixing matrix will be $M = W^{-1}$). The separation criterion of sources used to determine W is an independency measure optimization. It can be shown that maximizing independency means maximizing the component non-gaussianity.

2) ICA Algorithms: It exists several ICA algorithms using various measurements. Most of them aims to maximizing the non-gaussianity of the components distribution. It exists different ways to measure the non-gaussianity namely: neguentropy and the Kurtosis.

First of all, the neguentropy is defined as $J(p_x) = \int p_x(u) \log \frac{p_x(u)}{\Phi_x(u)} du$ where $\Phi_x(u)$ is the distribution function of the Gaussian law. It is a positive value and equals to 0 for a Gaussian law. There is, for example, InfoMax algorithm that maximizes the neguentropy [3].

The Kurtosis is defined as $Kurt(x) = E(x^4) - 3(E(x^2))^2$ where $E(x)$ is the expected value of x. It is equal to:

- 0 for a Gaussian law
- -1.2 for a uniform law
- 3 for Laplace's law

FastICA algorithm are designed to maximize this measure [4], [5].

3) Filtering with ICA: The filtering method can be divided into 3 steps :

1) *Source detection by ICA*
2) *Artifact source identification and cancellation*
3) *Signal reconstruction by inverse transformation*

The cancellation of one source is equivalent to put a zero in the corresponding line of the separation matrix (W') or in the corresponding column in the mixing matrix (M'). The filtering matrix is then :

$$F = M'W' \tag{1}$$

Once the filtering matrix determined, it can be applied to the whole record using the equation:

$$X'(t) = FX(t) \tag{2}$$

$X'(t)$ is the filtered signal.

One of the major problem of the ICA method resides in the manual identification of the nature of the source (artifactual or cerebral).

4) Sources in the real case: In reality, the number of sources is highly greater than the number of channels. Indeed each neurone can be considered as an electrical emitting source different from his neighbor. However, signals of these neurones are not independent and a resulting signal of the activity of identical action can be measured. It has to be reminded that ICA do not allow to determine every sources but only a resulting activity signal from a group of neurones. The signal can be approximately considered as independent of the remaining cerebral activity.

Therefore, only most important sources can be detected. On the other hand, the hypothesis giving that the number of main sources is lower than the number of channels can be verified by carrying out a principal component analysis (PCA) on the resting signal. Indeed, it can be noticed that 99% of the signal is carried by the 10 first components and then only 10 sources will be required to rebuild almost completely the signal.

It is not possible to find a real independency between cerebral sources. However, the set of cerebral signals can be considered as independent from artifactual sources. This is the reason why that sources separation can be supposed as efficient even if cerebral sources can not be entirely identified.

B. Automatic source identification

Several methods have been tried in order to identify automatically the sources [6], e.g, with the use of the Hurst's indicator to characterize the components carrying the artifacts [7]. An other method is to use temporally constrained ICA [8].

The authors of this article would like to present here a global method for sources identification. This method is based on a training step during which artifactual sources will be identified from the cerebral ones. A filtering matrix will be obtained using Eq. 1. This method requires to ask the patients to carry out several times 5 ordered artifacts:

- eye blinks
- eye movements
- jaw clenching
- forehead movements
- head movements

This procedure has to be followed for the source identification:

1) *Take a resting moment and a moment including all types of artifacts in the EEG.*
2) *Calculate ICA on the build record. The separation matrix W is obtained as well as the mixing matrix $M = W^{-1}$.*
3) *For each ICA component i,*
   a) *Computation of $R_i = \frac{\sigma^i_{repos}}{\sigma^i_{artifact}}$ where (σ^i_t is standard deviation at time t)*
   b) *If $R_i > threshold$ then i will be considered as an artifact source. The line i of W will be put to 0.*
   c) *Else i will be considered as a cerebral source and i will be saved.*
4) *Obtain the filtering matrix F (Eq. 1).*

Once the training step is over, the complete record can be filtered by multiplying the signals by the filtering matrix F (Eq. 2).

Various parameters and settings have been fixed empirically:

- The threshold can be fixed to a value of 1.6.
- The training step on these 5 artifacts enables also to filter the speaking, swallowing, coughing and nearly other facial movement. Therefore, the training step should contained at least 3 repetitions of each of the 5 artifacts.
- This method can operate even if there are a few artifacts during the resting time used in learning.
- These artifacts can be learnt with eyes closed or opened but the resting time should contain eyes closed EEG .
- The method was tested with RunICA [10] and FastICA algorithms. The results seems to be similar. One can

notice that FastICA algorithm is quicker but the drawback is that the convergence with FastIca is not ensured under special cases.

The results of this methods can be seen on figure 3b.

C. Segmentation in frequencies bands

In general case, ICA allows to spatially characterize the artifact. However, artifacts can be defined as well by their frequencies. This is reason why ICA on a segmented signal in frequency bands will be carried out.

The aim of this study is to combine ICA filtering with numerical filtering. Another advantage of this method is that it enables to increase the number of sources.

Here is a description for using ICA on frequency band decomposition:

1) *Cut each of the channel in frequency bands.*
2) *Make the ICA on each frequency band and erase artifactual sources (a filtering matrix will be then obtained for each frequency band).*
3) *Rebuild the signal by summing signals of each frequency band.*

The detection process describe in section II-B was used with this principle of frequency bands decomposition. The figure 1 sums up the learning process and the figure 2 the filtering process.

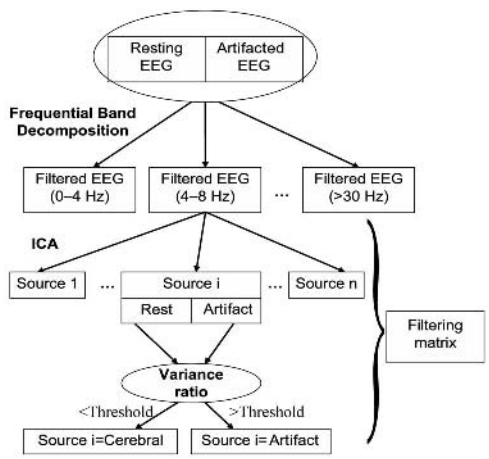


Fig. 1: Learning artifacts process

Various tests were carried out to determine the best choice for these frequency bands. First the common segmentation used by neurologists was chosen namely:

1) The band Δ $(0-4$ Hz): Corresponds to a slow rhythm often pathological and corresponds as well to the speed of a human motor movement (blinks or eye movements or electrode displacement)
2) The band θ $(4-8$ Hz): Generally in low quantity, with a bitemporal localization. It may reveal some abnormalities.
3) The band α $(8-13$ Hz): Generally poor in artifacts. The signal is located mainly in the occipital regions when eyes are closed.

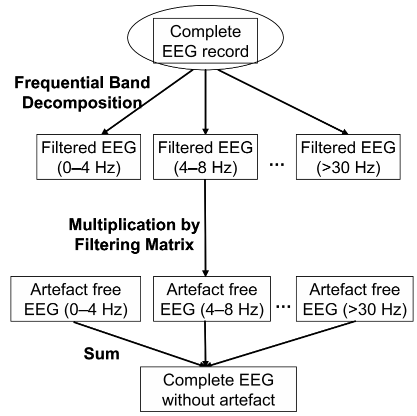


Fig. 2: Filtering process on complete EEG

4) The band β $(> 13$ Hz) : Generally characterized by muscular activity. Taking account of its width, a more precise segmentation was carried out for the followed frequency bands (13 - 20 Hz), (20 - 30 Hz) and $(> 30$ Hz).

It can be noticed that only a few of cerebral sources are saved in the last frequency band $(> 30$ Hz). This is due to the fact that noise appears in a non synchronized way in this band. Thus showing the limitation of the method.

The results of this method are shown on the figure 3c.

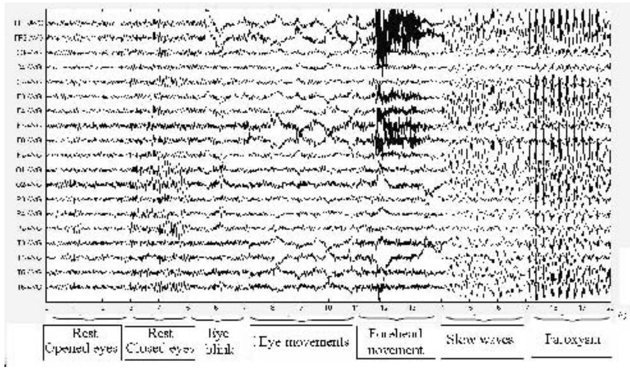
III. RESULTS AND COMMENTS

Standard examinations of 20 minutes are applied to the method. The experiments are computed with Matlab using a EEGlab interface [11]. Since the computation time are short, this method can be easily implemented in real time once the learning step is over. Indeed, it takes approximately 5 minutes for the learning process and about 2 minutes for the filtering process.

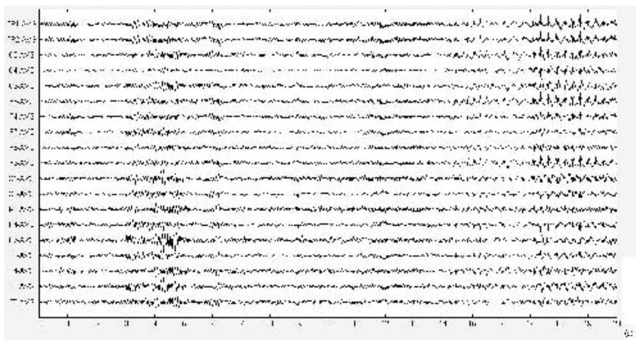
The first results (figure 3) seem very interesting. The method using frequency band decomposition seems to be better so as to filter artifacts and to conserve the cerebral activity. Indeed, residuals of artifact can remain using only ICA. The α activity is conserved with both methods but the first one reduce much more slow waves and paroxysms. It can be noticed also that the shape is well conserved.

In order to complete visual analysis of EEG, two ratios are computed on the filtered EEG with frequency band decomposition. These ratios aims to quantify filtering quality on various frequency bands $(\delta, \theta, \alpha, \beta)$.

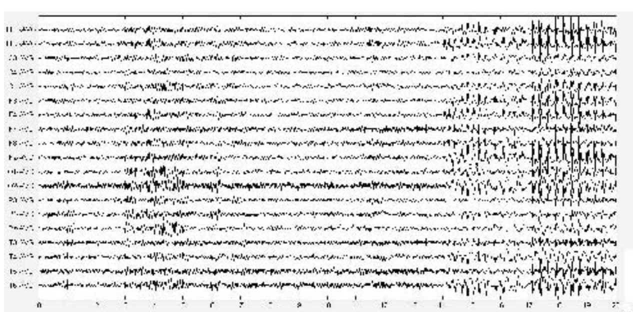
The first table (Table I) represents the proportion of conserved cerebral signals. it can be seen as the ratio of standard deviation between filtered signals and unfiltered signals. This ratio are calculated at various times with grapho-elements. A ratio close to 1 means that the signal is well conserved, and a ratio close to 0 means the signal is removed. This table shows that the α activity is conserved at 99% , but slow waves and paroxysms are a little bit reduce (65% and 62% in low frequency). This can be explained by the fact that learning is not fully adapted to these particular signals.



(a) Original EEG



(b) Filtered EEG with ICA



(c) Filtered EEG with ICA on frequency band decomposition

Fig. 3: Results of Filtering on various particular instant

TABLE I: $\sigma_{Filtered\ instant}/\sigma_{Unfiltered\ instant}$

Frequency band	Δ	θ	α	β
Rest (opened eyes)	0.79	0.89	0.99	0.88
Rest (closed eyes)	0.80	0.94	**0.99**	0.94
Cerebral slow waves	**0.65**	0.79	0.94	0.81
Paroxysms	**0.62**	0.66	0.95	**0.83**

The second table (Table II) represents the proportion of remaining artifacts after and before filtering. it can be interpreted as the ratio of standard deviation between various artifact time and the rest time. The ratio value which is calculated before and after the filtering proves that all artifacts are greatly reduced. It only remains few residuals in low frequency during muscular activity which is mainly due to electrode movement and are too random to be perfectly filtered.

IV. CONCLUSIONS AND FUTURE WORKS

First results obtained seems to be very promising even if more clinical test could be carried out. The combination of

TABLE II: $\sigma_{Artefact}/\sigma_{Rest\ (eyes\ closed)}$ *(After filtering / Before filtering)*

Frequency band	Δ	θ	α	β
Eye blink	**1.14/2.60**	0.73/0.85	0.55/0.56	0.84/0.94
Eye movement	**1.07/3.24**	0.75/0.84	0.46/0.47	0.83/0.96
Fronthead	**1.58/3.31**	0.88/0.94	0.90/0.91	**1.02/2.55**
Jaw	**1.44/2.06**	0.94/0.99	1.08/1.09	**1.18/4.65**

ICA and band frequency decomposition seems to be more efficient than all method we have studied [9]. In addition, the learning process described here enables to automate the filtering process. Indeed, it solves one of the major problem of ICA which is the identification of artifactual components. Another advantage of this method resides in the creation of a global filter thus enabling to filter all type of artifacts (muscular and ocular) and reducing computation time since learned matrix can be applied to the entire record.

Nevertheless, this method is limited to frequencies under 30 Hz. Indeed, high frequencies can not be linearly separated because of their non synchronization. Another drawback is the reduction of amplitude during slow waves and paroxysms. It should be interested to detect the changing time of cerebral activity (slow waves, paroxysms) and then adapt the filtering process to these particular moments.

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