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Temporal Predictability Based Blind Source Separation– An Approach For Denoising Eeg Signal

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ABSTRACT

Electroencephalogram (EEG), a biological signal that characterizes the electrical activity of the brain, is essential for brain research, medical diagnosis and treatment.The occurrence of artifacts, such as eye blinks, in EEGsignals complicates the fundamental processes and makes analysis difficult. Large amounts of data must often be rejected because of contamination by eye blinks, muscle activity, line noise, and pulse signals. To avoid this difficulty, signal separation techniques are used to separate artifacts from the EEG data of interest.Analysis of EEG signals is beneficial for diagnosis of many medical specialty diseases like epilepsy, tumors, and varied issues related to trauma. EEG measured by inserting electrodes on scalp sometimes has terribly tiny amplitude, therefore the analysis of EEG signal and the extraction of data from this signal could be a troublesome drawback. In order to diagnosis the disease correctly, perfect analysis of EEG signal is required. The matter of denoising is quite varied owing to type of signals and noise. Blind Source Separation (BSS) using temporal predictability provides effective solution for denoising the EEG due to its shrinkage property. In this paper, temporal predictability is defined and applied to separate linear mixtures of signals. The experiment is carried out with four different source signals, such as, an EEG signal of a sleep recording, a stereo file containing an EEG signal and electrooculogram (EOG) signal, an EEG signal of the recording of an apneic patient and a stereo file containing two EEG signals of a sleep recording. The results show that the temporal predictability property is able to recover supply signals from a group of linear mixtures of these signals by finding an un-mixing matrix that maximizes a measure of temporal predictability for every recovered signal.

KEYWORDS: Blind Source Separation, denoising, EEG signal and Temporal Predictability.

INTRODUCTION

Electroencephalography (EEG) is one of the important way for noticing brain activity. While it cannot match the exactness and resolution of spatial localization of brain activity of many other brain imaging methods, also it has following advantages: low costs, easiness and outstanding time resolution. So, EEG is broadly used in many areas of clinical work and research. One of the main challenges in using EEG is the very small signal-to-noise ratio of the brain signals, attached with noise sources. Normally, four approaches are followed to deal with the issue of noise in EEG recording: elimination of noise sources, signal averaging, rejection of noisy data, and noise removal [1]. Elimination of noise sources is a simplest way to remove the environmental sources of noise, such as AC power lines, lighting and a large array of electronic equipment (from computers, displays and TVs to wireless routers, notebooks and mobile phones). The basic step to avoid electro-magnetic (EM) noise from the recording room is replacing equipment using alternate current with equipment using direct current. An advanced and costly method is to insulate the recording room from EM noise by use of a Faraday cage. Noise signals such as cardiac signal (electrocardiogram, ECG), movement artifacts caused by muscle contraction (electromyogram, EMG) and ocular signal caused by eyeball movement (electrooculogram, EOG) are also traceable with EEG. These noises can be avoided or minimized by asking the participant to be relax and avoid blinking of eyes during the recording EEG. Signal averaging is an efficient method to denoise the EEG signal which has stable occurrences of noises. It cannot be employed when rare events of noises are occurring. Moreover, the symmetric signals only can be denoised. If the noise is not symmetric, its average across time will not be zero but it will rather lead to overall increases or decreases of averaged signal. Signal averaging for noise removal is quite expensive in terms of the number of trials needed to sufficiently increase the signal-to-noise ratio. For these reasons, it is best to rely on signal averaging as a last resort for truly unavoidable noise sources only, and use other strategies to prevent noise before recording and remove it after recording. The most straightforward way for elimination of noisy data is by visual inspection. Most eye-movements, blinks and movement artefacts are somewhat easily identifiable and can be noticed for rejection before averaging and data analysis. When dealing with large datasets, this method might be time consuming. Furthermore, some types of noise can be tough to recognize and find even for the most experienced EEG analyst. Figure 1 shows waveforms of some of the most common EEG artifacts [2].

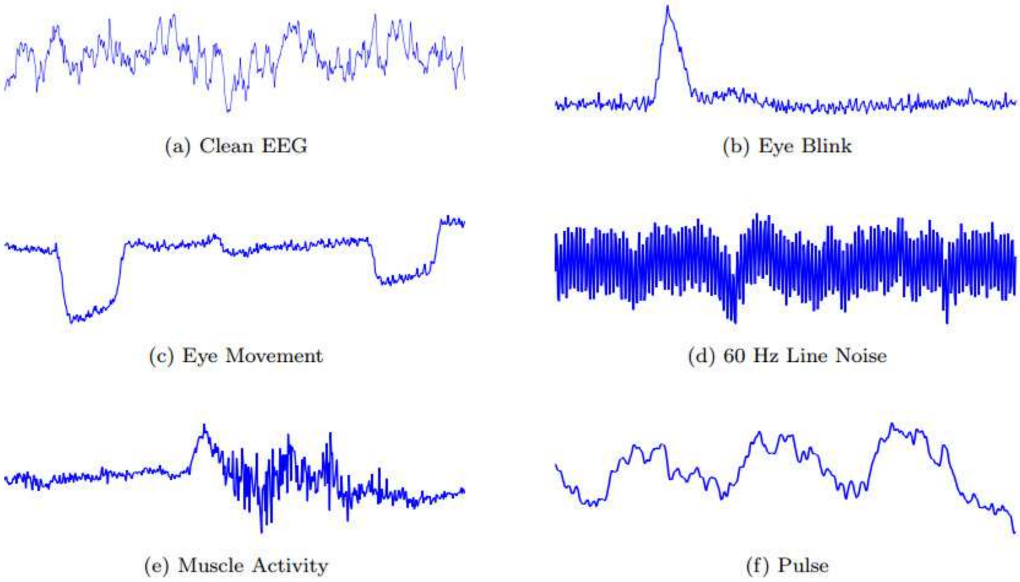

Fig. 1: Waveforms of the most common EEG artifacts

In order to overcome these inabilities and improve the accuracy, systematic approach for denoising is introduced. The exact EEG signal without noise can be obtained only by systematic noise removal methodologies. In this paper, Blind Source Separation (BSS) using temporal predictability approach is proposed to remove the noises from EEG signals.

Literature Review:

EEG was first measured in humans by Hans Berger in 1929. Electrical impulses produced by nerve firings in the brain diffuse through the head and can be measured by electrodes fixed on the scalp. The analysis of EEG data is a challenging task, when noise is mixed with the signal. Many research ideas are proposed to eliminate the noise from the EEG signal.A comparative study of different denoising techniques is presented in [3]. The denoising method eliminates the noise by thresholding in wavelet domain. Discrete Wavelet Transform has the advantage of giving a joint time-frequency representation of the signal and appropriate for both stationary and non-stationary signals. Discrete Wavelet Transform is a multiresolution analysis and provides effective solution.To eliminate the artifacts, the information theoretic model of mutual information assessedby B-Spline is used for making amethod for Independent Component Analysis (ICA) has been presented in [4]. And the results show that B-Spline Mutual Information Independent Component Analysis (BMICA) performs better. In [5], the authorscarried out a comparative study on the performances of two techniques namely, subspace projection and adaptive filtering using two measures, mean square error (MSE) and computational time of each algorithm. ICA methods performs healthy but slowly, so they are used for off-line applications. PCA (principal component analysis) performs quickly but not accurately, so they are used for real-time applications. The performance of adaptive filtering is poor but it is very fast.

Astructure based on ICA and wavelet transform to denoise EEG signal at preprocessing stage is proposedin [6]. And a model of spatially-constrained ICA (SCICA) to extract artifact from EEG recording is also proposed.Thresholding filters are proposed to denoise EEG signals in [7]. Wavelet packets are used and found that they will be effective in denoising of biological signals.Wavelet based image processing methods known as 1-D Double Density and 1-D Double Density Complex for denoising EEG signals at various windows size are implemented in [8]. The performances of these methods were compared and evaluated by calculating the Root Mean Square Error (RMSE). The 1-D Double Density Complex performs better than 1-D Double Density.The possible techniques in biomedical denoising using wavelet transform have been presented in [9]. Wavelet based threshold method and PCA based adaptive threshold method to eliminate the ocular artifacts have been implemented in [10].In comparison to the wavelet threshold method, PCA based adaptive threshold method gives betterPeak Signal to Noise Ratio value and reduces the elapsed time. Combination of ICA and wavelet threshold approach to denoise EEG is presented in [11]. The experiment results show that the EMG and ECG can be removed from EEG signal.The single-channel techniques for muscle artifact removal from multichannel EEG is presented in [12].In [13], the authors have applied some of the commonly used signal processing methods to eliminate eye blink and noise related artifacts from EEG signals recorded using a low cost wireless device from Emotiv.In [14], a new unsupervised, healthy, and computationally fast statistical algorithm that uses modified multiscale sample entropy (mMSE) and Kurtosis to automatically detect the independent eye blink artifactual components, and subsequently denoise these components using biorthogonal wavelet decomposition are proposed.In [15], an automated artifact elimination using linear discriminant analysis (LDA) for grouping of feature vectors extracted from ICA components via image processing algorithms is proposed.

Blind Source Separation Algorithm:

BSS is a temporal predictability based algorithm to separate the mixture. The approximation of BSS is the temporal predictability of any signal mixture is ≤ that of any of its components. This assumption is used to evaluate the weight vector which provides an orthogonal projection of mixtures [16]. Figure 1 shows the BSS model.

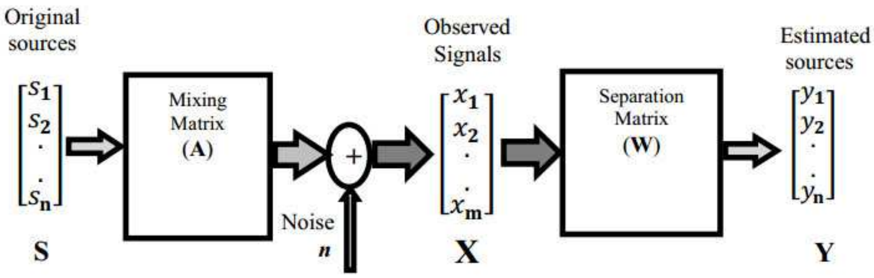

Fig. 1: Schematic Diagram of BSS

The mixing system without noise is:

$$X(k) = A\,S(k) \tag{1}$$

Where $X(k) = [X_1(k),\ldots X_n(k)^T]$ are the mixed signals from sensors (its known), $S(k) = [S_1(k),.S_n(k)^T]$ are the sources (its unknown), superscript T denotes transpose operator, $A \in R^{n\times n}$is a mixing matrix (unknown) and the symbol k is time or sample index. The aim is to recover S from X without knowing A, to solve this problem the separating matrix W should be calculated which it is $W=A^{-1}$ in ideal case. The recovered signals are evaluated by the separating model:

$$Y(k) = WX(k) \tag{2}$$

Where Y is the variation of S up to scaling factor. BSS's measure of temporal predictability of signal y(k) is defined as [16]:

$$F(y) = \log\frac{V_y}{U_y} = \log\frac{\sum_{k=1}^{N}(y_{long}(k)-y(k))^2}{\sum_{k=1}^{N}(y_{short}(k)-y(k))^2} \tag{3}$$

$$y_{short}(k) = \beta_S y_{short}(k-1) + (1-\beta_S)y(k-1):\ 0 \le \beta_S \le 1, \tag{4}$$

$$y_{long}(k) = \beta_L y_{long}(k-1) + (1-\beta_L)y(k-1):\ 0 \le \beta_L \le 1, \tag{5}$$

Where N is the number of samples of y(k), $\beta_s=2^{-1/h}{}_{short}$, $\beta s=2^{-1/h}{}_{long}$and h_{short},h_{long} are half-life parameters (according to the BSS [16] the half-life h_{long} ofβ_L is 100 timeslonger than corresponding half-life h_{short} of β_s). Assume $y(k) = W_i^T X(k)$, $W= [w_1, w_2,\ldots w_n]$, then (3) can rewritten as:

$$F(y_i) = \log\frac{W_i C_{xx}^{long} W_i^T}{W_i C_{xx}^{short} W_i^T} \tag{6}$$

Where $C_{xx}^{long}$is a long-term covariance matrix (N×N) between signal mixtures; C_{xx}^{short} is a short-term covariance matrix (N×N) between signal mixtures; C_{XiXj}^{long} and C_{XiXj}^{short} between i_{th} and j_{th} mixtures defied as:

$$C_{x_ix_j}^{short} = \sum_\tau (X_{i\tau} - X_{i\tau}^{short})(X_{j\tau} - X_{j\tau}^{short}) \quad (7)$$
$$C_{x_ix_j}^{long} = \sum_\tau (X_{i\tau} - X_{i\tau}^{long})(X_{j\tau} - X_{j\tau}^{long}) \quad (8)$$

The main purposeof BSS is to maximize Rayleigh's quotient to get un-mixing vectors; thereby generalized eigenvectors of $C_{xx}^{long}[C_{xx}^{short}]^{-1}$are considered to solve this problem [16, 17, 18]; to find the eigenvectors (w_1, w_2,…w_m) of matrix ($C^{1/short}\,C^{long}$) which are orthogonal in the covariance matrices:

$$W_i C^{short} W_j^t = 0 \quad (9)$$
$$W_i C^{long} W_j^t = 0 \quad (10)$$
$$W_i C^{short} W_j^t = \sum_\tau (y_{i\tau} - y_{i\tau}^{short})(y_{j\tau} - y_{j\tau}^{short}) \quad (11)$$
$$W_i C^{long} W_j^t = \sum_\tau (y_{i\tau} - y_{i\tau}^{long})(y_{j\tau} - y_{j\tau}^{long}) \quad (12)$$

When the short-term half-life parameter h_{short} toward zero value ($h_{short} \rightarrow 0$) then the short-term mean is:

$$y_\tau^{short} \approx y_{\tau-1} \quad (13)$$
$$(y_\tau - y_\tau^{short}) \approx {}^{d y_\tau}\!/_{d\tau} = Y'_\tau \quad (14)$$

Also when the long-term half-life parameter h_{long} toward the infinity ($h_{long} \rightarrow 0$) and y has zero mean then the long-term mean is:

$$y_\tau^{long} \approx 0 \quad (15)$$
$$\left(y_\tau - y_\tau^{long}\right) = y_\tau \quad (16)$$

Now under these situations the probability value for y_i and y_j are equal to zeros:

$$E\left[y_i y_j\right] = 0 \quad (17)$$

Therefore; this show that each recovered signal y_i which can be calculated by $y_i = W_i\,x$;is uncorrelated with every other signal y_j which also calculated by $y_j = W_jx$; as well as ify_i and $y_j$are independent then the expectation value is also zero. This method is effective for any linear mixture with statistically independent signals and it's assured to separate the independent components. The temporal derivative of each recovered signal is uncorrelated with every one and the expectation value equal zero:

$$E\left[y'_i y'_j\right] = 0 \quad (18)$$

Finally, the separating matrix W calculated by Matlab eigenvalue function as:

$$W = eig(C^{long} C^{short}) \quad (19)$$

This is one of the advantages of the BSS to simplify the problem into generalized eigenproblem [19].

RESULTS AND DISCUSSION

The BSS algorithm is applied to the EEG sample under four different cases such as an EEG signal of a sleep recording, a stereo file containing an EEG signal and EOG signal, an EEG signal of the recording of an apneic patient and a stereo file containing two EEG signals of a sleep recording. Previously, the EEG signals are recorded and processed by temporal filter and then by spatial filter.To demonstrate the BSS experiment, the process is classified into three steps:

- EEG signal acquisition
- Filtering using temporal filter: Mostly, the first step for EEG signal processing is a filtering process to eliminatesubguassian interference (line noise), DC and reduce superguassian artifacts (eye blinks).

- Processing the EEG data by BSS: Eliminatingdirty trials causes substantial data loss and controlling eye blinks limits the experimental designs possible and may influence the cognitive processes under investigation.

Case 1: Denoisingan EEG signal of a sleep recording:

An EEG signal of a sleep recording (Signal "EEG Pz-Oz" accelerated at x200) is taken for denoising.The signal mixture of Case 1 is shown in Figure 1. Source signal and the recovered signal are shown in Figure 2. And the correlation magnitudes between source signals and signals recovered from mixtures of source signals for Case 1 are shown in Table 1.

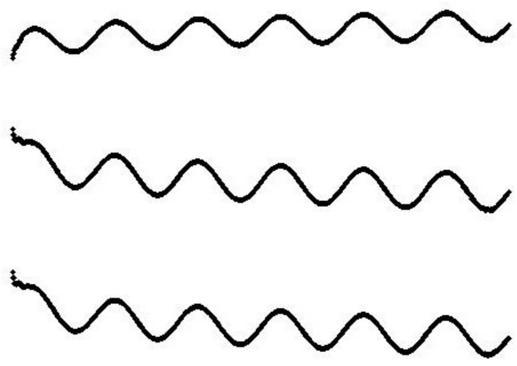

Fig. 1: Signal mixture of a sleep recording EEG signal

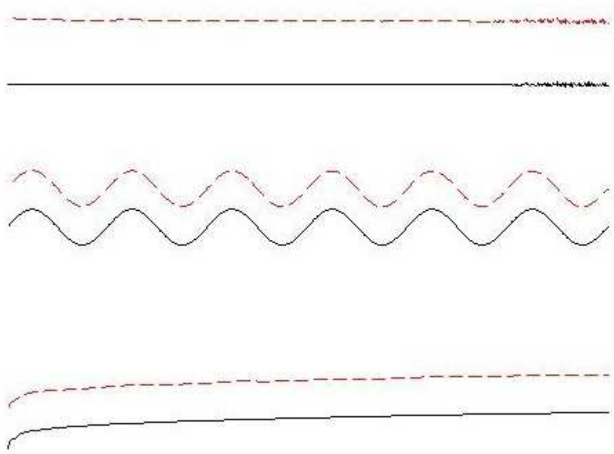

Fig. 2: Source signal (Bottom trace) and recovered signal (Top trace) of a sleep recording EEG signal

Table 1: The correlation magnitudes between source signals and signals recovered from mixtures of source signals for Case 1

Signals recovered	Source signals		
	s_1	s_2	s_3
y_1	0.9984	0.4336	0.0424
y_2	0.0125	0.0129	0.9993
y_3	0.3823	0.9996	0.0777

Case 2: Denoisingan EEG combined with EOG:

A file containing an EEG signal (Signal "EEG Pz-Oz" accelerated at x200) and an EOG signal (Signal "EEG horizontal" accelerated at x200) are taken for denoising.The signal mixture of Case 2is shown in Figure 3. Source signal and the recovered signal are shown in Figure 4. And the correlation magnitudes between source signals and signals recovered from mixtures of source signals for Case 2 are shown in Table 1.

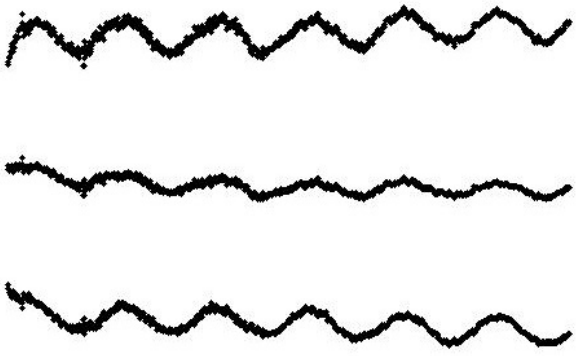

Fig. 3: Signal mixture of EOG combined EEG signal

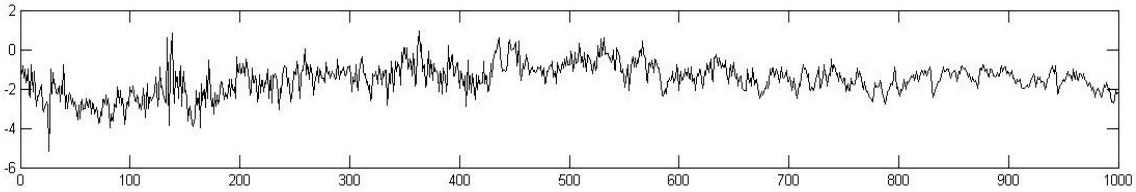

Fig. 4: Source signal (Bottom trace) and recovered signal (Top trace) of EOG combined EEG signal

Table 2: The correlation magnitudes between source signals and signals recovered from mixtures of source signals for Case 2

Signals recovered	Source signals		
	s_1	s_2	s_3
y_1	0.8771	0.5590	0.0014
y_2	0.0039	0.0128	0.9993
y_3	0.0773	0.9995	0.0778

Case 3: Denoisingan EEG signal of an apneic patient:

An EEG signal of the recording of an apneic patient (Signal "EEG C3-M2 accelerated at x200) is taken for denoising. The signal mixture of Case 3 is shown in Figure 5. Source signal and the recovered signal are shown in Figure 6. And the correlation magnitudes between source signals and signals recovered from mixtures of source signals for Case 3 are shown in Table 1.

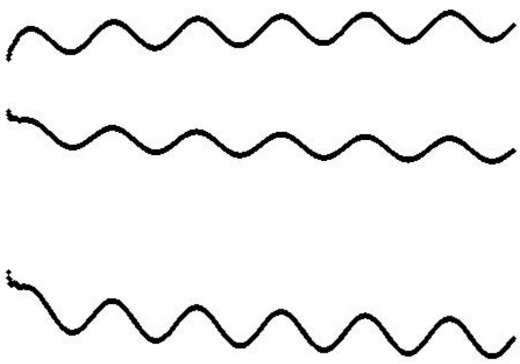

Fig. 5: Signal mixture of an apneic patient’s EEG signal

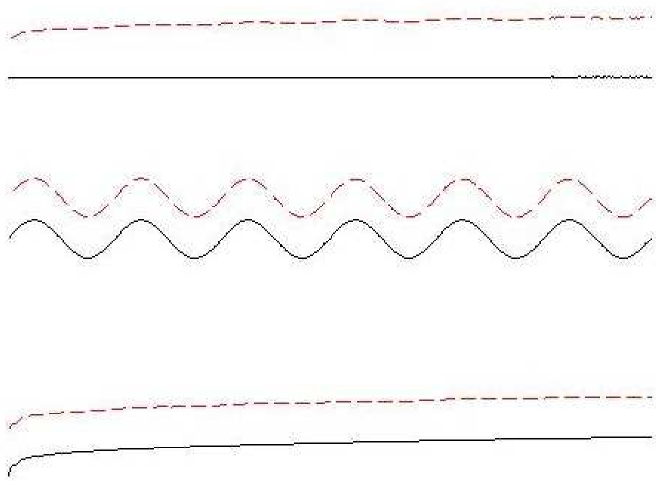

Fig. 6: Source signal (Bottom trace) and recovered signal (Top trace) of an apneic patient's EEG signal

Table 3: The correlation magnitudes between source signals and signals recovered from mixtures of source signals for Case 3

Signals recovered	Source signals		
	s_1	s_2	s_3
y_1	0.9372	0.6057	0.0259
y_2	0.0186	0.0136	0.9994
y_3	0.2527	0.9988	0.0770

Case 4: Denoising a file containing two EEG signals of a sleep recording

A file containing two EEG signals of a sleep recording (Signals "EEG Fpz-Cz" and "EEG Pz-Oz" accelerated at x200) are taken for denoising. The signal mixture of Case 4 is shown in Figure 7. Source signal and the recovered signal are shown in Figure 8. And the correlation magnitudes between source signals and signals recovered from mixtures of source signals for Case 4 are shown in Table 1.

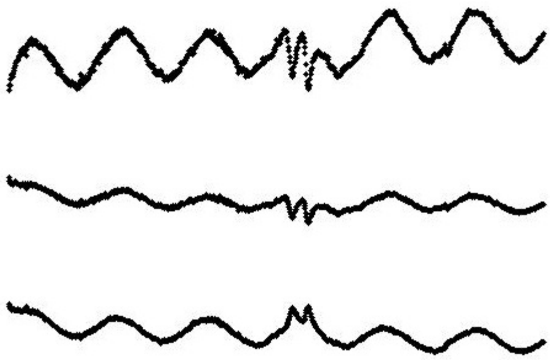

Fig. 5: Signal mixture of a file containing two EEG signals of a sleep recording

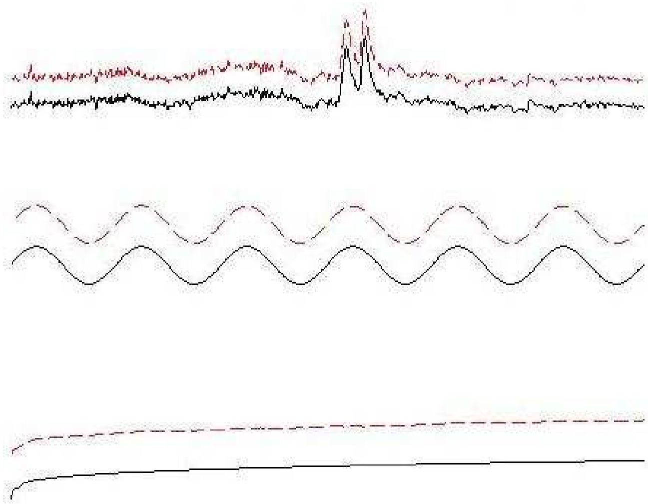

Fig. 8: Source signal (Bottom trace) and recovered signal (Top trace) ofa file containing two EEG signals of a sleep recording

Table 4: The correlation magnitudes between source signals and signals recovered from mixtures of source signals for Case 4

Signals recovered	Source signals		
	s_1	s_2	s_3
y_1	0.9998	0.0616	0.0124
y_2	0.0002	0.0129	0.9993
y_3	0.0666	0.9995	0.0779

Conclusion:

The difficulty in the brain signal analysis is for non-invasively measure the physiological variations occur in various parts of the brain. To get the relevant information (data) for diagnosis, expert knowledge not only in medicine but also in statistical signal processing analysis is required. In brain signal processing, one important assignment is how to automatically detect, extract and eliminate noise and artifacts, then how to improve the extracted signals and classify the brain sources. This paper introduces, a method to separate the noise based on blind source separation method for four different conditions.It is shown that, the BSS method is an efficient method to eliminate the noises completely from EEG signal without removing important and beneficial information (data). It is concluded that thetemporal predictability based BSS method provides less difficulty, easy to separate the noises and is an efficient method for enhancing the quality of EEG signals in biomedical analysis.

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