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A quick survey of EEG signal noise removal methods

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Abstract

An Electroencephalogram (EEG) is produced as a consequence of the electrical voltage of neurons in the brain. The EEG signal is crucial for detecting brain activity and attitude. Because this signal has very low amplitude, it is easily corrupted by different artefacts. The study and analysis of brain signals in the presence of these artifacts is a challenging task. ECG, EOG, EMG, and motion are the popular artifacts that induce disturbance to the EEG signal. This survey paper emphasizes the artifact elimination methods with their substantial parameters that must be considered during the study of published research on this trend.

Keywords: Electroencephalogram; EEG Artifact Removal Method; Discrete Wavelet Transform; Principle Component Analysis; Mean Squared Error

1. Introduction

Electroencephalography (EEG) is a record of an electro-gram of the electrical potentials on the scalp generated by the neurons of the brain. Due to its advantages of high temporal resolution, relative noninvasiveness, and lower cost of equipment, it is widely used in research such as cognitive science, neuroscience, and neural engineering [1-3]. EEG recordings provide a complete knowledge about overall activity of the millions of neurons in the brain. Brain is one of the most important organs of humans, for controlling the coordination of human muscles and nerves [4-6]. The human brain is divided into five different lobes named as the frontal lobe, parietal lobe, occipital lobe, temporal lobe, and cerebellum. These lobes are the origins of the various electrical potential that are generated based on human activities. As the electrical field produced by the neural activation travels, its voltage decreases and with every barrier (Dura mater, skull, skin) between the cortex and scalp, which are recorded as electroencephalogram and shortly known as EEG (Fig. 1). EEG is one commonly used non-invasive facility to investigate the intricacy of human brain. The EEG is used in the evaluation of brain disorders. It is also used to evaluate people who are having problems associated with brain. An EEG is also used to determine brain death. EEG works on a very low frequency range. These waves are categorized as follows: [7]

- Delta waves: These waves range from 0-3.5 Hz frequency. These are generally broad, diffused shaped and may be bilateral with widespread. The subject's states are deep, trance, non-REM sleep and dreamless sleep.
- Theta waves: These waves range from 4-7 Hz frequency. These are generally regional can have many lobes and may be lateralized or diffuse. The subject's states are instinctive, innovative, recall, drowsy and imaginary.
- Alpha waves: These waves range from 8-13 Hz frequency. These are generally regional, involves full lobe. The subject's states are wakeful and resting.

Beta waves: These waves range from 14-40 Hz frequency. These are generally recorded from the parietal and frontal region of brain. These are further divided into various sub regions.

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- Low beta
- Mid-range beta
- High range beta

- Gamma waves: These waves range above 40 Hz frequency. These are much localized in nature. The subject's state is thinking. These waves show the state of the person. We can use these waves as study and analysis of the brain activity and related problems with the help of different frequency components. Different frequency of brain waves is shown in Fig. 2.

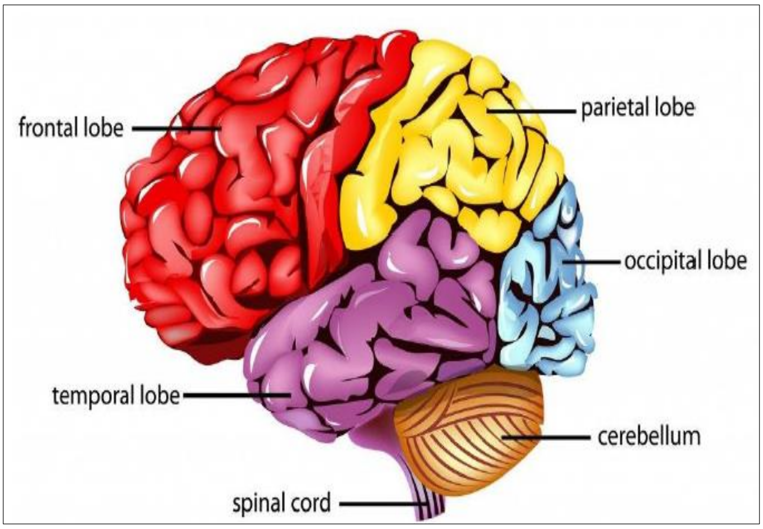

Figure 1 Elements of Human Brain [8]

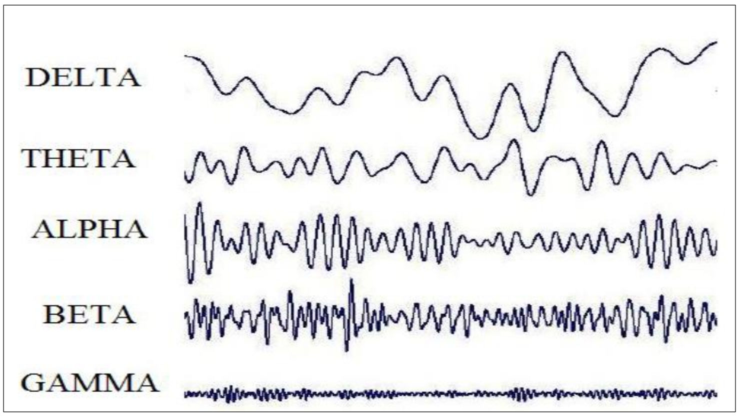

Figure 2 Different Brain Waves [7]

2. Types of Noises in EEG Signals

In pre-processing of EEG data identifying the artifacts has the highest priority. The artifacts corrupt the originality of EEG data. In this regard, the artifacts are requisite to get rid of actively. The electroencephalogram is often contaminated with the noise. These noises may be physiological or non-physiological reason. In this review paper, we consider only physiological signal. These are [8]:

2.1. Ocular Artifacts

Ocular artifacts generate significant artifacts in the EEG recordings. The origin of ocular artifacts is eye movement and blinks which can propagate over the scalp and be recorded by EEG activity [9]. More specifically, eye movement artifacts produce by changes in orientation of the retina and cornea dipole, and blink artifacts caused by ocular conductance due to the alterations of contact of the cornea with eyelid. In addition, because of volume conduction effect, both ocular artifact and EEG activity propagated to head surface and record by the electrodes. Such ocular signals can be recorded using electrooculogram (EOG). The amplitude of EOG is generally many times greater than EEG and its frequency are similar with the frequency of EEG signals. Worthy to note that not only EEG data can be contaminated by the EOG, but in turn, EOG can also be contaminated by EEG. Consequently, bidirectional interference will introduce removal error when we remove EOG artifacts [9].

2.2. Muscle Artifacts

EMG has a broad classification from 0Hz to >200Hz. EMG is the muscle activity potential that contaminates the original EEG signal [10]. Moreover, EMG has an effect on both temporally and spatially [10].

2.3. Glossokinetic artifact

This artifact is caused due to the tongue. Tongue act as a dipole and movement of the tongue creates potential which spreads from frontal to occipital areas [11].

2.4. Cardiac Artifacts

The pulsating human heart generates the electric potentials known electrocardiogram. These electric potentials of the heart (ECG signals) are conducted to the scalp, which is intermingled with the EEG signals, thereby creates the potential change in the measured signal of EEG Cardiac artifacts are of two types Mechanical and Electrical. Every contraction and irregular interval of cardiac arrhythmia can be considered as mechanical artifacts. The electrical artifacts may be due to the heart electrodes. ECG artifacts may disrupt the EEG background activity that which is the replica of epileptiform discharges. Moreover, it usually is diphonic or triphonic with an active component that has duration within the spike range. Cardiac artifacts are of two types Mechanical and Electrical. Every contraction and irregular interval of cardiac arrhythmia can be considered as mechanical artifacts. The electrical artifacts may be due to the heart electrodes [12].

2.5. Respiration artifact

This artifact occurs when the movement of the body is due to the respiration. This causes the change in impedance of the electrodes which causes disturbance. This also happens when the patient is lying on electrode and continuously inhaling and exhaling [13].

2.6. Skin artifact

These artifacts occur when the impedance between the skin and the electrode change due to natural phenomena of the body [13].

3. Artifact Removal Approaches

During the recording of EEG the patient is asked to stay calm with no movement of any part. But it is impossible to stay stable during the recording. These artifacts combine with the EEG signal which may give a wrong interpretation while analysing. So, the removal of these artifacts is necessary in order to get the correct information. There are several artifact removal techniques. These techniques are applied to the raw EEG signal. Some of these techniques are given below [14].

3.1. Blind Source Separation (BSS)

The BSS method includes a variety of unsupervised learning algorithms without prior information and extra reference channels. The general methodology of BSS can be described as follows. Let X be observed signals obtained from scalp electrodes. Also, let S be the source signals which includes original signals and artifacts. These source signals are linear mixed by an unknown matrix A [9]:

$$X = AS \quad (1)$$

To get the observed signals. The BSS algorithm is a reversed version:

$$\mathrm{U} = \mathrm{WX} \quad (2)$$

Where U is the estimation of sources and the W is the reverse mixing of X. Then components representing the artifacts are removed and the remaining components reconstruct EEG data to achieve the purpose of denoising. In that following, we describe some representative works that have adopted the BSS algorithms [9].

3.1.1. Principal Component Analysis (PCA)

PCA is one of the simplest and widely used BSS techniques, which algorithm is based on Eigen values of covariance matrix. In this method, it firstly converts correlated variables into uncorrelated variables using orthogonal transformation. Such uncorrelated variables are called principal components (PCs). These PCs of EEG signals will be implemented using Single Value Decomposition (SVD). Berg and Scherg firstly introduced principal component analysis to remove ocular artifacts [9].

3.1.2. Independent Component Analysis (ICA)

ICA is a multivariate analysis which is one of the widely used BSS techniques that attempts to decompose the original signals into a brand-new set of linear signals called independent components (ICs) along with the artifacts detection in the given signal. ICA generally detects artifacts in the given signal by using the following steps: initially, the ICs are formed from the given signal using decomposition method. Secondly, the ICs which are varying from each other are identified and removed from the set of signals. Lastly, the artifact free signal can be formed by concatenating the remaining ICs [15].

3.1.3. Canonical Correlation Analysis (CCA)

Canonical correlation analysis (CCA) is another commonly employed BSS technique. Unlike ICA method that use higher order statistics, CCA use second order statistics which bring shorter computational time. CCA also differ from ICA in its conditions to separate components. The CCA separate components from uncorrelated sources whereas ICA from statistical independent sources. CCA find the linear relation between two multi-dimensional random variables by maximize the pairwise correlations across the two data sets. In contrast to ICA that only takes statistical distribution of the same sample values into account, CCA consider the autocorrelation in the source signals and demonstrated that have similar qualitative results, but consume a little computational complexity [16].

3.2. Empirical Mode Decomposition (EMD)

EMD is an empirical and data-driven method developed to perform on non-stationary, non-linear, stochastic processes and therefore it is ideally suitable for EEG signal analysis and processing. However, the computational complexity of EMD is quite heavy, so may not be suitable for online applications. Moreover, the theory behind EMD is still not complete and so far used in empirical studies, therefore it is difficult to predict its robustness in all EEG recordings. EMD algorithm decomposes a signal; s[n] into a sum of the band-limited components/functions, c[n] called intrinsic mode functions (IMF) with well-defined instantaneous frequencies [17]. There are two basic conditions to be an IMF:

- The number of extrema must be equal (or at most may differ by one) to the number of zero crossings
- Any point, the mean value of the two envelopes defined by the local maxima and the local minima has to be zero [17].

3.3. Filtering Methods

Numerous filtering methods was employed in the cancelation of artifacts from the EEG, for instance, adaptive filtering, wiener filtering and Bayes filtering, in which different methods implemented with different principle of optimization. Nevertheless, for the intention to minimize the mean square error between the predicted EEG and primary EEG, a weighting coefficient W will be adapted. Following article briefly illustrates two commonly used filtering approaches accordingly [18].

3.3.1. Adaptive Filtering

An adaptive filter is a system with a linear filter that has transfer function controlled by variable parameters and a means to adjust those parameters according to an optimization algorithm [19]. The filter weights can adapt based on the feedback from output of the system and it requires a reference input to compare the desired output with the output. An improved adaptive filtering by optimal projection which is based on common spatial pattern for artifact removal is mentioned in [20, 21], especially for epilepsy patient's EEG. Let s[n] denote the observed which is combination of the original EEG, x[n] and additive artifact r[n]. Then, if the artifact source v[n] is available from a dedicated channel (e.g.

EOG or ECG); an algorithm (e.g. LMS, RLS, etc.) can be used to an artifact-free EEG, $x'[n]$ given that the desired EEG artifact signal are independent (or at least uncorrelated). An illustration of the use of adaptive filter for EOG removal is shown in Fig. 3 [19].

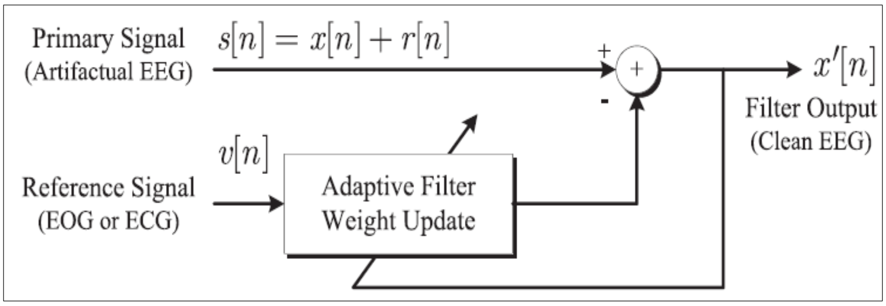

Figure 3 Typical use of adaptive filtering in canceling physiological artifacts with available artifact source channel as reference [19]

3.3.2. Wiener Filtering

In signal processing, the wiener filter solves the signal estimation problem. It is capable of estimating the target process by time-invariant filtering of an observed noisy signal process of presumptuous stationery and noise spectra. However, it is a statistical filtering method to examine and inspect the true EEG data, employs a linear invariant filter to minimize the mean square error between the pure EEG signal and estimated signal. However, the limitation of extra reference channels overcomes by wiener filter but a bit complex in computation [8].

3.4. Sparse Decomposition Methods

Sparse component analysis (SCA) is another effect signal processing method to decompose signals sparsely in over-completer dictionary [9]. The over-complete dictionary can be calculate from complete dictionary by over-sampling. A dictionary can be constructed by waveforms or atoms, such as wavelet, Fourier and Dirac basis. After over-sampling, the orthogonality may not be true whereas the basis in the complete dictionary is orthogonal to each other. Signal sparsity can be measured with $l_p(0 \leq p \leq 1)$ as follows [9]:

$$\| x \|_p = \left(\sum_{j=1}^{n} |x_j|^p\right)^{\frac{1}{p}} \tag{3}$$

Where X represents the signal, and n is the dimension of X [9].

4. Performance Evaluation

The performance of the denoising approaches can be evaluated five criteria which are MSE, RMSE, SNR, SNR improvement, and PRD, while the formula of these criteria as follows [22, 23]:

$$MSE = \frac{1}{N}\sum_{n=1}^{N} [x(n) - \hat{x}(n)]^2 \tag{4}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N} [x(n) - \hat{x}(n)]^2} \tag{5}$$

$$SNR\ Out = 10\log_{10}\left\{\frac{\sum_{n=1}^{N} [x(n)]^2}{\sum_{n=1}^{N} [x(n)-\hat{x}(n)]^2}\right\} \tag{6}$$

$$SNR\text{imp} = 10\log_{10}\left\{\frac{\sum_{n=1}^{N} [\delta(n)-x(n)]^2}{\sum_{n=1}^{N} [x(n)-\hat{x}(n)]^2}\right\} \tag{7}$$

$$PRD = 100 * \sqrt{\left\{\frac{\sum_{n=1}^{N} [x(n)-\hat{x}(n)]^2}{\sum_{n=1}^{N} [x(n)]^2}\right\}} \tag{8}$$

Where x (n) denotes the original EEG signal, $x^{\wedge}(n)$ is the denoised EEG signal and N is the sampling number.

5. Conclusion

EEG signals are produced from the cerebral cortex, which are detected by scalp electrodes. However, EEG signals are always contaminated with undesired signals. In reality, a broad range of approaches have been suggested to eliminate the artifacts, and these artifact elimination techniques still necessitate improvement in efficiency and accuracy. This survey research summarizes the basic methods and outcomes of the recent published papers. There is no single best strategy for reducing all types of artifacts. As a consequence, the fundamental focused future task is to carry out a specific approach for adequate minimization of noise with excellent accuracy and computational efficiency. Furthermore, there is a future room where machine learning and conventional techniques may be integrated to improve a novel approach to attain a powerful algorithm to reduce artifacts in EEG signals.

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