Removal methods of EMG Artifacts from EEG Signals

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Abstract. Electromyography (EMG) is the superposition of motor unit action potential (MUAP) in many muscle fibers in time and space. In real measurement, EMG signals will contaminate Electromyography signals, therefore they bring great difficulties to the qualified analysis and interpretation of EEG signals, and it is a momentous step to remove EMG artifacts from EEG signals. In the recent years, new methods were developed for EEG artifacts removal such as Multivariate Empirical Mode Decomposition and Singular Spectrum Analysis. In particular, some researchers combined the two methods and used their respective advantages to remove artifacts more thoroughly without affecting the EEG signal, such as the combination of Independent Component Analysis and Wavelet Method. In this paper, new methods for muscular artifacts removal from EEG above are discussed. Moreover, traditional methods including signal transform, filtering methods and Blind source separation (BSS) are also reviewed.

1. Introduction
Electroencephalography (EEG) records not only the brain activity but also the electrical signals generated by other activities outside the brain, which are not generated by the brain activity. Common artifacts include electrooculography (EOG), electromyography (EMG), electrocardiography (ECG) and power-line interference. The existence of artifacts has a great impact on subsequent EEG analysis, which may lead to the loss of important information. Therefore, artifact removal is one of the most important preprocessing steps in the application of neural information processing, which is of great significance to neuroscience research and clinical diagnosis.

Figure 1. EMG artifact produced by subjects turning their heads with a swift movement.[1]
One of the most traditional methods of artifacts removal from EEG signal is the regression method. In 1970, Hillyard et al. firstly proposed a regression method based on time domain to remove EEG artifacts [2]. Then Whitton ameliorated the regression method based on frequency domain and combined this method with EEG detection software respectively [3]. P He et al. used adaptive filtering to remove ocular artifacts from EEG, achieving easy, stable and fast convergence [4].

The appearance of BSS is an important achievement in the development of artifact removal methods such as Principal Component Analysis, Independent Component Analysis and Canonical Correlation Analysis. Berg and Scherg firstly introduced PCA to remove eye component artifacts, which proved superior to regression and dipole method [5]. After that Makieg et al. firstly applied ICA for routine EEG and EPR analysis in 1996 [6]. Then CCA was firstly proposed by Clercq, W.D. et al. to remove EMG artifacts from EEG in 2006 [7].

Moreover, signal decomposition methods eliminating EEG artifacts emerged to meliorate the removal of EEG artifacts such as Kumar, S.P used Wavelet Transform to remove ocular artifacts from EEG signal in 2008 [8]. And signal decomposition methods were also combined with BSS to remove artifacts from EEG data. Kevric and Subasi presented wavelet combined with PCA together for artifacts removal and Chen, X. et al. introduced Ensemble Empirical Mode Decomposition-Canonical Correlation Analysis approach to remove muscular artifacts for pervasive EEG [9, 10].

In this review, signal transforms like wavelet, Empirical Mode Decomposition and Multivariate Empirical Mode Decomposition are firstly introduced. Secondly, two types of filter, Butterworth analog filter and adaptive filter, are discussed in details including development and merit. In addition, the advantages and limitations of blind source separation including PCA, ICA and CCA are also introduced. Finally, the new methods such as singular spectrum analysis and method of combining ICA and wavelet that have been put forward in recent years are reviewed.

2. Methods

2.1. Signal Transform

2.1.1. Wavelet

Wavelet transform is a development of Fourier transform which provides a "time-frequency" window changing with frequency [8]. Wavelet transform can refine the signal step by step, and finally achieve time subdivision at high frequency and frequency subdivision at low frequency. It can automatically adapt to the requirements of time-frequency signal analysis, thus being capable to focus on any detail of the signal.

Wavelet transform requires non-intersecting frequency bands of EEG signal and artifacts, however, the frequency bands of EEG, ECG artifact and EOG artifact are overlapped. Therefore, the recent preprocessing techniques tend to combine the classical wavelet transform with the existing denoising methods.

2.1.2. Empirical Mode Decomposition

Different from wavelet transform, EMD decomposes the signal according to the time scale characteristics of the data itself without setting any primary function in advance [11]. Therefore, it is suitable for analyzing non-linear and non-stationary signal sequence and has high signal-to-noise ratio [12]. The essence of EMD is to identify all Intrinsic Oscillatory Mode contained in the signal through the characteristic time scale. In this process, the characteristic time scale and the definition of IMF have certain experience and approximation. The limitation of EMD algorithm, however, is its sensitivity to noise which causes the complexity of mode mixing [13].

MEMD is a modified method based on EMD which analyzes intrinsic modes in multiple channels at the same time. Hence MEMD can remove artifacts (especially broadband muscle artifacts) more effectively and accurately [14]. An EMG artifact removal method based on MEMD developed by
Chaolin Teng et al. decomposed the EEG signal into multiple multivariable eigenmode functions (MIMFs) of different frequency bands [15]. Then remove the MIMFs with EMG artifacts and the rest of the MIMFs were used to reconstruct the clean EEG signal. The experimental results showed that the signal-to-noise ratio of EEG signal was significantly improved, and the mean square error was also markedly reduced.

2.2. Filtering method

2.2.1. Butterworth analog filter
Butterworth filter is a type of electronic filter, which was first designed by British engineer Stephen Butterworth (1930). The characteristic of Butterworth filter is that the frequency response curve in the pass band is flat to the maximum extent. John S. Barlow (1984) proposed a 4-pole Butterworth analog filter to eliminate EMG artifacts in clinical EEG recordings [16]. Prototype filters was assembled with 4-pole Butterworth filtering implemented with an older variable electronic filter. Then a 20-channel unit was assembled in such a way that cut-off frequency varied by changing components for each channel on the assembly board. When considering the removal of EMG artifact while minimizing the distortion of EEG signal, the results showed that with 12.5 Hz cut-off frequency, the filter reached relatively satisfied EMG artifact elimination.

One of advantages of Butterworth analog filter is continuous on-line operation which is indispensable for routine EEG usage. The overlap of the frequency ranges of the EEG and EMG, however, limited its utilization.

2.2.2. Adaptive filter
Adaptive filter uses adaptive algorithm to change the parameters and structure of filter according to the change of environment.

In recent years, a very promising technology is ANFIS (Adaptive Network-based Fuzzy Inference System) proposed by Jyh-Shing Roger Jang. It consists a hybrid algorithm of back propagation algorithm and least square method which is used to adjust the premise parameters and conclusion parameters [17]. C. Kezi Selva Vijilal et. al. applied this technique to the removal of EEG artifacts like EOG, EMG and ECG [18]. Although ANFIS has the ability of fast response and dealing with fuzzy and uncertain problems, its filtering results can be further improved.

Jing Hu et. al.(2013) designed an adaptive FL-BPNN (Functional Link- Back Propagation Neural Network) filter to adjust the parameters of fuzzy rules [19]. The experimental results show that the performance of this filter is better than that of ANFIS filter (mean squared error is selected as the performance evaluation index). A year later they advanced their method by developing a new adaptive filter that combines FLNN (Functional Link Neural Network) with ANFIS [20]. They also compared their method with the filters described above based on mean squared error and signal-to-noise ratio. The superiority of FLNN-ANFIS is distinct according to the experimental results.

![Figure 2. General structure of an adaptive filter system.[21]](image)
2.3. Blind source separation

2.3.1. Principal component analysis
PCA transforms a group of variables that possibly have correlation into a group of linearly uncorrelated variables through orthogonal transformation. The transformed variables are called principal components. PCA was firstly introduced to eye component artifacts removal by Berg and Scherg [5], avoiding the distortion to the topography. The central components of eye movement and blink artifacts were extracted from EEG signal. The results of Berg and Casarotto’s [22] work indicated that PCA outperforms regression method and dipole method.

One of the defects of PCA is that it is difficult to satisfy the requirement that artifacts are unrelated to EEG data. In addition, when the drift potential resembles the EEG data, PCA fails to effectively separate the interference[21].

2.3.2. Independent Component Analysis
ICA is one of extensively used BSS techniques which algorithm is used to separate multiple signals into additive components by assuming that the sub components are non-gaussian signals and are statistically independent of each other. ICA removes undesired artifacts (ICs) and reconstructs clean EEG signal to achieve the purpose of noise reduction.

Makieg et al. firstly applied ICA for routine EEG and EPR analysis in 1996 [6] and then Vigaro et al. removed artifacts from EEG and determined whether it was artifact by observing ICA independent components and their mapping on electroencephalogram [23, 24]. In 2000, Jung et al. upgraded the same method to denoise three groups of experimental data, and compared the results with PCA and regression algorithm [25]. Romero et al. evaluated the effect of ICA in removing artifacts at different sleep states, and found that the bidirectional performance of EEG and EOG had minute effect on ICA denoising in 2003 [26]. A method introduced by Joyce et al. in 2004 automatically extract and remove eye movement artifacts after ICA analysis, and the result was equivalent to that of manual removal [27]. In recent years, hybrid methods based on ICA for automatic artifact removal have developed rapidly. Raofen Wang et al. combined ICA and fuzzy C-Means clustering techniques to automatically suppress ocular artifacts [28]. The experimental results demonstrated that the correct rates of all features (wavelet entropy, 0-5 Hz energy, kurtosis, mutual information and correlation) used to classify the artifacts and EEG components respectively were above 99%. Frølich and Dowding [29] compared five widely used ICA-based methods to contrast the ability of extracting oscillatory activity. It is concluded that adequately high-pass filtering counts for much.

The advantage of ICA is that it can effectively and flexibly estimate the non-Gaussian original signal, however, the signal source is usually ambiguous about whether it is Gaussian or non-Gaussian. Moreover, biomedical signal acquisition is not linear instantaneous in many cases. How to deal with nonlinear convolution signal and how to automatically use ICA to remove artifacts are promising research directions of ICA [30].

2.3.3. Canonical Correlation Analysis
CCA extracts two representative comprehensive variables from the two groups of variables, uses the correlation between the two comprehensive variables to reflect the overall correlation between the two groups of indicators, and separates the components from the uncorrelated sources.

Clercq, W.D. et al. used this technique for the first time to remove EMG artifacts from EEG [7]. A Vergult et al. published the results of this technology in clinical practice to improve the interpretation of ictal scalp EEG [30]. It is a remarkable improvement that BSS-CCA increased the sensitivity of seizure localization from 62% to 81% and eliminated most muscle artifact contamination in ictal EEGs.

Compared with ICA, CCA uses second-order statistics which requests shorter calculation time. In addition, ICA technique is sufficient to remove ocular artifacts, but brain and muscle activities will interfere with each other during the separation and result in inhibiting real brain activity when EMG artifacts are cleared up. Thus, CCA algorithm outstrips ICA algorithm in removing muscle artifacts.
2.4. New methods

2.4.1. Singular spectrum analysis
Singular spectrum analysis, an efficient subspace based technique, was proposed by AK Maddirala and RA Shaik [31] to eliminate muscular artifacts from the single channel EEG data [31].

The single channel signal was mapped into a multi-channel signal, and then the orthogonal eigenvectors were estimated from the covariance matrix of multi-channel data by singular value decomposition. An arbitrary threshold (0.275) was set to find these eigenvectors, which were used to establish the corresponding subspace of EEG signals. After the subspace was identified, the multi-channel data was simply projected into the subspace, and back embedded to extract the EEG signal.

According to the results, it is evident that the EMG artifacts can be efficiently decimated without damaging ictal activity.

Figure 3. 10 seconds of 21-channel EEG recordings (left) and 10 sec of 21 channel EEG signals after the application of the proposed method (right). [31]

Figure 3. 10 seconds of 21-channel EEG recordings (left) and 10 sec of 21 channel EEG signals after the application of the proposed method (right). [31]
2.4.2. ICA and Wavelet Method

In order to eliminate the defects of ICA and wavelet transform, a new technique based on the combination of ICA and wavelet for noise reduction is proposed.

Akhtar et al. developed a framework based on ICA and wavelet denoising (WD) to automatically remove artifacts from multichannel EEG signal. ICA was used to extract artifact-only independent components (ICs) from the given EEG data, then remove any cerebral activity from the extracted artifacts ICs using wavelet denoising. The major advantage of this method is the shorter computing time because it is unnecessary to identify all ICs.

In 2020, R Kashid and KP Paradeshi focused on EMG artifacts removal from 16-channel EEG data using this technique. Symlet wavelet and Hard thresholding were used for fulfilling SWT Wavelet decomposition. This approach performed well for EMG artifacts removal including Teeth squeeze, Jaw clench and Forehead movement.

3. Conclusions

Methods of EMG removal from EEG signals such as signal transform, filtering, BSS and new methods developed in recent years are discussed above.

Compared with ECG, EOG and other artifacts, the interference of EMG signal to EEG is more difficult to eliminate. The main reason is that EMG artifact has the characteristics of high amplitude, wide spectrum and physiological distribution, which leads to the failure of some simple artifact removal methods. The existence of artifacts has a great impact on the subsequent EEG analysis, which may lead to the loss of important information, therefore, the removal of EMG artifacts is a momentous step.

Among these removal method, singular spectrum analysis has prominent superiority, which efficiently eliminates the muscular artifacts and persists the ictal activity. ICA and wavelet Method also perform well in removing various EMG artifacts from raw EEG signal, particularly in teeth squeeze, jaw clench, forehead movement removal.

Using a single method to remove artifacts usually cannot remove perfectly. Only by combining various methods and giving full play to the advantages of each part can a satisfactory removal effect be achieved.

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