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EOG artifact removal using a wavelet neural network

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ABSTRACT

In this paper, we developed a wavelet neural network (WNN) algorithm for electroencephalogram (EEG) artifact. The algorithm combines the universal approximation characteristics of neural networks and the time/frequency property of wavelet transform, where the neural network was trained on a simulated dataset with known ground truths. The contribution of this paper is two-fold. First, many EEG artifact removal algorithms, including regression based methods, require reference EOG signals, which are not always available. The WNN algorithm tries to learn the characteristics of EOG from training data and once trained, the algorithm does not need EOG recordings for artifact removal. Second, the proposed method is computationally efficient, making it a reliable real time algorithm. We compared the proposed algorithm to the independent component analysis (ICA) technique and an adaptive wavelet thresholding method on both simulated and real EEG datasets. Experimental results show that the WNN algorithm can remove EEG artifacts effectively without diminishing useful EEG information even for very noisy datasets.

1. Introduction

An EEG signal is the recording of neural electrical activities caused by nerve firings. Typically, EEG signals, carrying information about rhythmic activities at different frequency bandwidths of δ—delta (0.5–4 Hz), θ—theta (4–8 Hz), α—alpha (8–13 Hz), β—beta(13–30 Hz) and γ—gamma (30–50 Hz) [1–3], are recorded using electrodes placed across the scalp. EEG waveforms are characterized by three components, including shape, frequency, and amplitude. Based on those components, useful signatures/features in brain signals can be extracted by various techniques. However, EEG recordings are usually contaminated by physiological artifacts from various sources, such as eye blinking/movement, heart beating and movement of other muscle groups [4]. Such types of artifacts are mixed together with brain signals, making interpretation of EEG signals difficult [5].

Eye movement or blinks usually produce large electrical potentials, generating significant electrooculographic (EOG) artifacts in recorded EEG signals. Removal of EOG artifacts is nontrivial because those artifacts overlap in frequency and time domains with EEG signals. Fortunately, the effect of EOG artifacts on EEG signals is found most significantly in low frequency bands such as δ, θ and α [6]. Eye blinking generates spike-like shaped signal waveforms with their peaks reaching up to 800 μV and occurs in a very short period of 200–400 ms [7]. Meanwhile, artifacts generated by eye movement are square-shaped, smaller in amplitude but last longer in time and concentrate in lower frequency bands [8].

In recent years, there has been an increasing interest in applying various techniques to remove ocular artifacts from EEG signals [4,5,8–13,16–22,44]. The methods for removing EOG artifacts based on regression have been widely studied [4,9,11,12,39,44]. Regression methods often assume that the scalp potential is a linear combination of brain and ocular potentials. By subtracting propagated EOG from EEG recordings, EEG signals can be recovered [11]. Regression can also be done in frequency domain based on the concept that subtraction in the frequency domain is equivalent to filtering in the time domain. By eliminating spectral estimates of EOG from EEG recordings, it is possible to recover the non-contaminated EEG [11]. Both types of regression methods are off-line and rely on EOG recordings, which are however, not always available [4,9,17].

Berg and Scherg [13,38] proposed a principle component analysis (PCA) based technique for removing eye movement artifacts. This method assumes that each EEG channel recording is simultaneously generated by multiple sources across the scalp. By decomposing multiple channel EEG data into principle components using PCA, the artifactual sources can be identified and

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removed. Their experiments showed that the PCA based method outperformed regression based models. However, PCA methods usually failed to completely separate artifacts from cerebral activities [14], and the orthogonal assumption for data components, which is always required while using PCA, is hardly satisfied [8]. Independent component analysis (ICA), which was originally developed for blind source separation (BSS) problems, has been used as an alternative method for EEG artifact removal [4,15–17]. ICA usually requires a large amount of data and visual inspection to eliminate noisy independent components, making the method time-consuming and not suitable for real-time applications.

Recently, wavelet analysis has been used as an effective tool for measuring and manipulating non-stationary signals such as EEG. Wavelet-based methods, especially the wavelet thresholding techniques, have received significant attentions for EEG artifact removal [17–22]. For this class of methods, wavelet coefficients at low-frequency sub-bands are corrected by some thresholding functions before signal reconstruction. As an online artifact removal method, the most important advantage of using this method for EEG correction is that it does not rely on either the reference EOG signal or visual inspection. However, its performance is not consistent because the method is sensitive to the selections of wavelet basis and thresholding functions. Thus, an online method which can remove EOG artifact effectively is still desirable.

This paper proposes a novel, robust, and efficient Wavelet Neural Network (WNN) technique to remove EOG artifacts by combining the approximation capabilities of both wavelet and neural network methods. In WNN, EOG recordings are not required once the NN being trained and the WNN algorithm can perform artifact correction in a single channel data. The method (1) decomposes the contaminated EEG signals to a set of wavelet coefficients, (2) passes the coefficients located in low frequency wavelet sub-bands through a trained artificial neural network (ANN) for correction and (3) reconstructs a clean version of EEG signals based the corrected coefficients. We applied the method to EEG data contaminated by EOG artifacts and compared the results with those obtained by other state-of-the-art methods including ICA and a wavelet thresholding method.

The rest of the paper is organized as follows. Section 2 reviews the related work and the motivation of this paper. Section 3 details the proposed technique. Section 4 describes the datasets used in this paper and the experiment design. Experimental results are presented in Section 5. We provide discussions in Section 6 and conclude this paper in Section 7.

2. Related work

2.1. EEG model

Cerebral signals, recorded by an EEG recording system, result from neural firing activities. On the other hand, EOG artifacts are non-cerebral activities spreading over the entire recording scalp and contaminating the EEG electrode recordings. For that reason, an EEG recording can be represented as a superposition of a true EEG signal and some portions of the artifacts. When an EOG artifact presents, it is assumed that the model for the contaminated EEG signal is in the following form [17],

$$\mathrm{EEG}_{rec}(t) = \mathrm{EEG}_{true}(t) + k{*}\mathrm{EOG}(t) \tag{1}$$

where $\mathrm{EEG}_{rec}(t)$ is the recorded contaminated EEG, $\mathrm{EEG}_{true}(t)$ denotes the true EEG signal, $\mathrm{EOG}(t)$ represents the original potential changes caused by ocular activities and k symbolizes the propagated factor and varies between 0 and 1 depending on the location of the recording electrode. Hence, $k{*}\mathrm{EOG}(t)$ represents the propagated ocular artifact from the eye to the recording site, which directly adulterates the brain signals. Estimating $\mathrm{EEG}_{true}(t)$ from observed $\mathrm{EEG}_{rec}(t)$ is non-trivial and is equivalent to minimizing the effect of ocular artifacts. Similar to other artifact removal techniques, the goal of the proposed wavelet neural network technique is to recover $\mathrm{EEG}_{true}(t)$ from $\mathrm{EEG}_{rec}(t)$.

As a random signal, a true EEG signal owns the noise-like (flat) power spectrum. In some cases when a subject performs specific tasks, the biological neural system introduces activities at particular frequencies making the power spectrum deflated. As a major artifactual type, once mixed with $\mathrm{EEG}_{true}(t)$, the ocular artifact $k{*}\mathrm{EOG}(t)$ causes proliferation in low frequencies and generates spike-like shape data segments across time domain. These properties are utilized by both wavelet thresholding [17] and the proposed WNN technique for artifact removal.

2.2. Wavelet transform and its application to EOG Artifact removal

2.2.1. Wavelet transform

The wavelet transform [23–26] is a transform in which a set of basis functions, known as wavelets, are well localized both in time and frequency domains. Wavelets can be constructed from a single function $\psi(t)$, named mother wavelet or analyzing wavelet, by means of translation and dilation,

$$\psi_{a,\tau}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-\tau}{a}\right) \tag{2}$$

Continuous wavelet transform (CWT) of a signal $x(t)$, defined as the correlation between the wavelet and the signal itself, can be implemented by the following formula,

$$W(a,\tau) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} x(t)\psi^{*}_{a,\tau}(t)dt \tag{3}$$

where $\psi^{*}(t)$ denotes the complex conjugate of $\psi(t)$. The above Eq. (3) indicates that the wavelet is passed through the analyzed signal and yields a set of coefficients representing the image of the analyzed signal at different scales in time and frequency domains. The scale parameter a plays a crucial role in wavelet transform. While value of a changes from high to low, the wavelet is expanded and becomes less sharper in frequency domain. Accordingly, the low frequency terms can be analyzed with a less sharper time resolution, which is a useful property especially in analyzing transient waveforms such as EEG corrupted with ocular artifacts, where transients occur at low frequency.

Wavelet transform results in a time-scale decomposition in which scales are basically related to frequency [27]. The highest scale corresponds to the sharpnest frequencies represented in the signal (less or equal to half of the sampling rate), and bandwidth of this scale ranges from a half to a quarter of the sampling rate. While that bandwith is reduced by two, the number of coefficients at lower resolution decreases aproximately by a factor of two compared to that of the higher resolution next to it. A proper selection of coefficients from different scales may be used to compress or represent original/corrected signals by using the inverse formula of Eq. (3). Discrete wavelet transform (DWT) is the discretized version of wavelet transform applied to discrete time series, in which parameters a and τ in Eqs. (2) and (3) can be represented as $a_i = 2^{-i}$ and $\tau_{i,j} = 2^{-i}j$, where i and j are positive integers. Selection of i and j determines properties of mother wavelet function $\psi(t) = 2^{-i}\psi(2^{-i}t-j)$, which constitues an orthonormal basis of Hilbert space, consisting of finite–energy signals [28]. DWT can be implemented with a simple recursive filtering scheme providing a highly efficient wavelet representation of the