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Wavelet-ICA based Denoising of Electroencephalogram Signal

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Abstract

Electroencephalogram (EEG) signals are having very small amplitudes and because of that they can be easily contaminated by different Artifacts. The presence of artifacts makes the analysis of EEG difficult for clinical evaluation. The major types of artifacts that affect the EEG are Power Line noise, eye movements, Electromyogram (EMG), and Electrocardiogram (ECG). Out of these artifacts Power Line noise is most prominent. To deal with these artifacts, there are numerous methods and techniques have been evolved by different researchers. In this paper, a new Independent Component Analysis (ICA) and Wavelet analysis based technique is presented based on joint use. This Wavelet-ICA combination is targeted to Single Channel EEG Signal. In the Algorithm, signal is decomposed into spectrally non-overlapping components using wavelet decomposition. The ICA algorithm is then applied to derive the independent components. The wavelet-ICA components associated with artifactual event is selected and cancelled out. The artifact free wavelet components are reconstructed to form artifact free EEG. ICA is a multichannel technique. So it cannot be applied directly to Single channel EEG signal. Thus it needs a technique which can represent the single channel signal into virtual multichannel Signal. Stationary Wavelet Transform (SWT) is used to decompose the signal. The SWT decomposes single channel EEG signal into components based upon different frequency levels. The performance analysis of the algorithm is done using Signal to Noise Ratio (SNR).

Keywords: EEG, ICA, Wavelet, SWT, SNR

1. Introduction:

The electrical activity of active nerve cells produces currents spreading through the head which can be recorded as the electroencephalogram (EEG). EEG signals are very complex in nature. Usually, EEG signals are measured from peak to peak and normally range from 0.5 to 100 µV in amplitude, which is about 100 times lower than ECG signals [1]. Electroencephalography waveforms can be categorized into four basic groups: delta (0.4-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz). Sometimes one more wave may appear named as Gamma (above 30 Hz).

Due to very low in amplitude, EEG signals are prone to artifacts and noise. The noise can be electrode noise or can be generated from the body itself. These various types of noises that can contaminate the signals during recordings are the electrode noise, baseline movement, EMG disturbance, eye movements, eye blinks and sometimes ECG disturbance. The noises in the EEG signals are called the artifacts and these artifacts are needed to be removed from the original signal as noise/artifacts makes analysis and further processing of the EEG signals difficult.

There are many approaches to deal with these artifacts. Simply rejecting contaminated EEG epochs is one of the common methods. But this method involves manually reviewing the data, identifying contaminated segments, and then subsequently rejecting those segments. This process is laborious and results in unacceptable data loss when there is a high degree of contamination. Alternative to this method is to remove the artifact/noise from the data which includes different methods such as Wavelet Transform, Independent component Analysis (ICA).

This paper represents a new algorithm based on joint use of ICA and Wavelet Analysis. ICA is a multichannel technique [2]. Thus, ICA cannot be applied directly to Single channel EEG signal. Thus it needs a technique which can represent the single channel signal into virtual multichannel Signal. Wavelet Transform is used to decompose the signal. Then ICA is applied and then W-ICA components are reconstructed back to form de-noised signal.

2. ICA for Single Channel Signal:

In the EEG signal processing, if the number of channels (mixed signals) are more than or equal to the sources, ICA algorithm is suitable but when the number of sources are higher than the number of channels, a group of algorithms called underdetermined (over-complete) [3] ICA can recover these sources. Single Channel ICA is extreme case of underdetermined ICA (one sensor) [4]. The modeling of ICA can be done by following equation stated as

$$x = A.s \tag{1}$$

where, x is the mixed signal, s is the number of sources determined and A is the mixing matrix. The main aim of ICA is to find out the un-mixing matrix W to acquire the independent components under the conditions of independent criterions.

$$s^{*} = W.x \tag{2}$$

$$W = A^{-1} \tag{3}$$

If the coefficients s^{*} are treated as independent random variables then we have a generative linear statistical model. Furthermore if we assume that A is square and invertible we have the classic ICA model [4]. In this paper we have applied FastICA algorithm [2, 3].

3. Wavelet Decomposition:

Wavelet analysis is a time-frequency analysis [5] and has the capacity of representing local characteristics in the time and scale (frequency) domains. Its capability in transforming a time domain signal into time and frequency localization helps to understand more the behavior of a signal. In low frequency, it has lower time resolution and in high frequency, it has higher time resolution and lower frequency resolution [6].

The discrete wavelet transform (DWT) decomposes the signal into two phases: detail and approximation data on different scales. The approximation domain is sequentially decomposed into further detail and approximation data. These decompositions of the signal act as the input matrix for ICA technique. The DWT means choosing subsets of the scales 'a' and positions 'b' of the mother wavelet ψ (t).

$$\psi_{(a,b)}(t) = 2^{a/2}\,\psi(2^{a}t-b) \qquad (4)$$

Here, the mother wavelet functions are dilated by powers of two and translated by integers. Scales and positions chosen based on power of two are named as dyadic scales and positions. The discrete wavelet transform does not preserve the translation invariance [7]. To preserve the translation invariance property, a new approach has been defined as *stationary wavelet transform* (SWT) which is close to the DWT one [8]. The SWT can be explained as in the figure 1

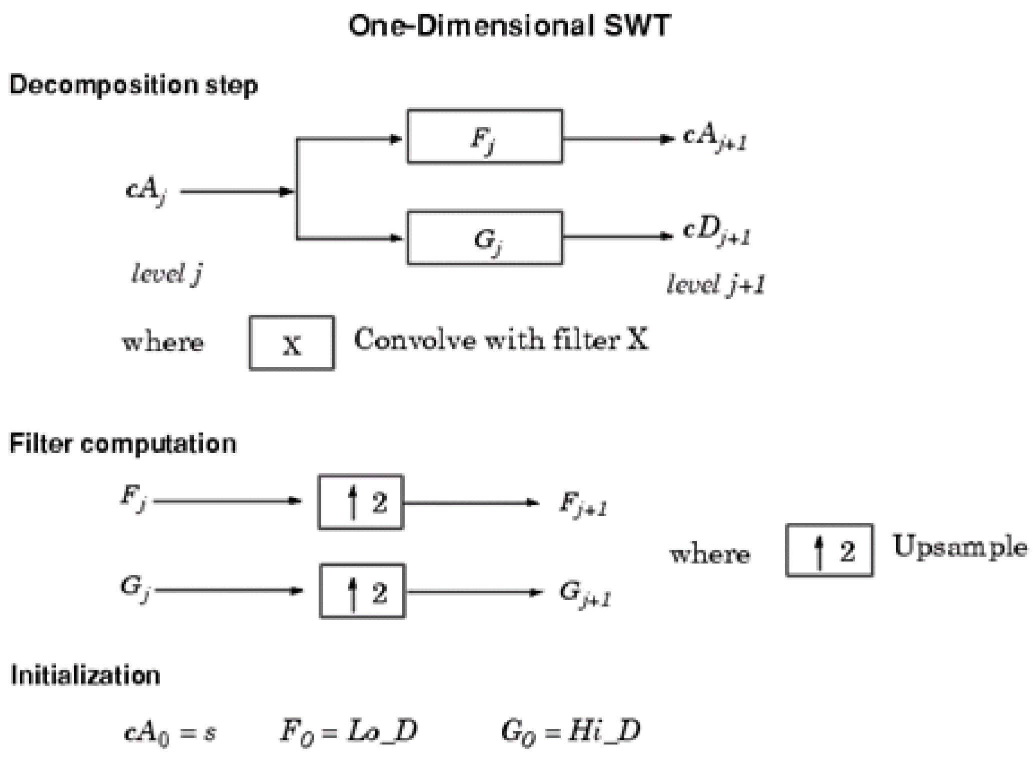

Figure 1. Stationary Wavelet Decomposition of Signal [8]

4. Wavelet-ICA Methodology

In ICA model, the input must be a matrix instead of a vector [9]. So, ICA cannot be applied directly to the single channel signal. Therefore, it is necessary to construct the input matrix if single channel data is available. Wavelet decomposition is used to form the input matrix in the method of Wavelet-ICA technique.

SWT is used for wavelet decomposition with mother wavelet *symlet* and decomposition level 10. Then the decomposed signal acts as input for the ICA in the form of matrix. The FastICA is applied to the decomposed signal to find out the mixing and unmixing matrix (A and W respectively) along with the matrix of independent components. After this, selection of desired sources of interest is done. To obtain the appearance of signal in the form of wavelet components, the source of interest is multiplied with the mixing matrix A. now, to recover the signal in the form of original signal; wavelet reconstruction is done using inverse SWT. Before applying the algorithm, some preprocessing is done so as to remove the baseline wandering by taking the mean of the signal.

5. Results and Discussion

The above discussed method was applied on 40 different EEG epochs of 5 patients. The time period of signals was 4 seconds with 1024 number of samples and sampling frequency 256 samples per second. The figure 2 shows the raw EEG signal, denoised signal and residual 50 Hz noise.

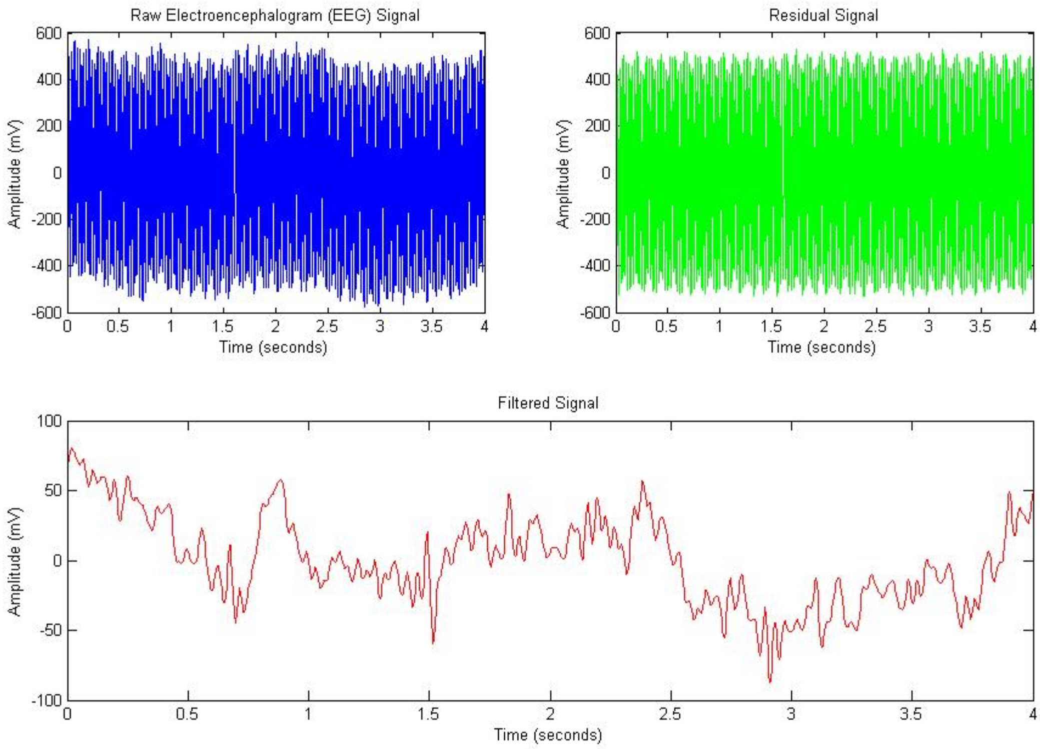

Figure 2. EEG Signal in original form are shown, with raw signal (blue), residual signal (green) and filtered signal (red)

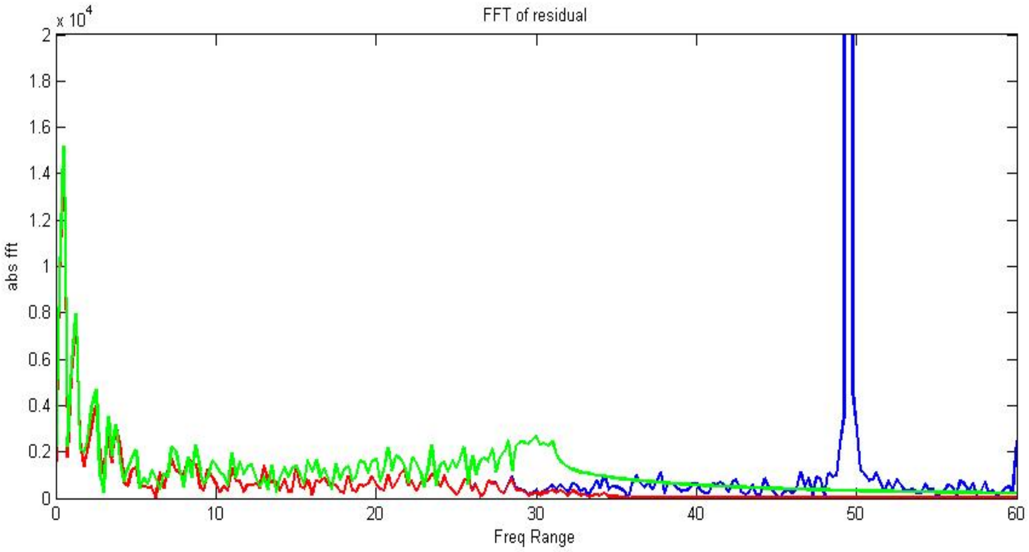

Figure 3. Signals in frequency domain are shown, with raw signal (blue line), result from LPF (green line) and from present method (red line)

The performance analysis of the algorithm was done using *signal to noise ratio* (SNR). The signal to noise can be explained as

$$\mathrm{SNR} = 20\log\frac{\mathrm{rms(filtered\ signal)}}{\mathrm{rms(noise)}}$$

The result of the proposed algorithm is compared with that of low pass filter (elliptic). The present method shows better results with higher SNR than low pass filter. The result was consistent for all the signals. The frequency correlation graph of the present method and low pass filter is shown in figure 3 with the original signal. The SNR value of proposed method and the low pass filter is shown in table 1. The low pass signal also generates some distortion in the filtered signal which can lead to information loss. The present method preserves the signal and chances of information loss are minimal.

Table 1. Comparison of SNR of Low Pass Filter and Proposed Method

Subject	SNR of Low Pass Filter	SNR of Proposed Method
1	43.15	47.85
2	43.06	47.26
3	44.55	48.88
4	41.06	45.04
5	41.17	43.75

5. Conclusion:

In this paper, a method is proposed for the denoising of Single channel EEG signal on the basis of joint use of wavelet analysis and FastICA technique. The wavelet analysis is done to de--compose the signal vector into input matrix for the ICA technique. In this paper, the target noise was 50 Hz powerline noise. When compared with low pass filter, this method shows better results with negligible information loss.

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