Removal of Power Line Interference from EEG using Wavelet-ICA

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ABSTRACT
Electroencephalogram (EEG) signals are of having very small amplitudes and so these can be easily contaminated by different Artifacts. Due to the presence of various artifacts in EEG, its analysis becomes difficult for the clinical evaluation. 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 and eye movements related are most prominent. To deal with these artifacts, there are various methods evolved by different researchers. In this paper, to remove power line noise of 50 Hz frequency, a new Wavelet analysis and Independent Component Analysis (ICA) based technique is presented, which is applied to a single channel EEG Signal. The signal is first decomposed into spectrally non-overlapping components using Stationary Wavelet Transform (SWT). The SWT decomposes single channel EEG signal into components based upon different frequency levels. The ICA algorithm is then applied to derive the independent components. The wavelet-ICA components associated with artifact related event is selected and cancelled out. The artifact free wavelet components are reconstructed to form artifact free EEG. The performance analysis of the algorithm is done using Signal to Noise Ratio (SNR).

Keywords
EEG, SWT, ICA, SNR, CWT, DWT

1. INTRODUCTION
The electrical activity of active nerve cells produces currents spreading through the head which can be recorded as the electroencephalogram (EEG), which are complex in nature. EEG signals ranges from 0.5 to 100 μV in amplitude (peak to peak), which is about 100 times lower than ECG signals [1]. EEG waveforms can be categorized into four basic groups: delta (0.4-4 Hz), theta (4-8 Hz), alpha (8-13 Hz) and beta (13-30 Hz)[1]. 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. Critical point in EEG signal processing is the need for careful treatment and reduction of these artifacts which contaminate the EEG signals and thus can lead to wrong results and conclusions. 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 it results in unacceptable data loss when there is high degree of contamination in the raw data. Alternative to this method is to remove the artifact/noise from the data which includes different methods such as filtering, 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 [7]. Wavelet Transform is used to decompose the signal. Then ICA is applied and then Wavelet-ICA components are reconstructed back to form de-noised signal.

2. EASE OF USE
2.1 Wavelet Transform
The wavelet transform (WT) [3, 4 &5] is one of the leading techniques for processing non-stationary signals. The WT is thus well suited for EEG signals, since these are non-stationary. The major feature of the WT is its capacity of decomposing a signal into components that are well localized in scale (which is essentially the inverse of frequency) and time [6]. The continuous WT (CWT) uses a family of wavelets by "continuously" scaling and translating a localized function called the mother wavelet. The discrete WT (DWT) is obtained by discretising the scale and translation variables "dyadically", i.e. by using powers of two. This allows implementing the CWT on a computer. The DWT is not translation invariant [5]. However, such invariance is required in some applications like change detection and de-noising [5]. The transform obtained by removing the down- samplers and up-samplers from the CWT is translation invariant, and naturally called the stationary WT (SWT) [5]. 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).

$$\psi(a,b)(t) = 2^{a/2}\,(2^{a}t-b) \qquad (1)$$

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 [8]. To preserve the translation invariance property, a new approach has been defined as *stationary wavelet transform* (SWT) which is close to the DWT one [9].

2.2 ICA
Independent Component Analysis (ICA) [2] involves the task of computing the matrix projection of a set of components onto another set of so called independent component. Here, the objective is to maximize the statistical independence of the outputs. If the inputs to the ICA are known to be linear instantaneous mixture of a set of sources, the ICA process provides an estimate of the original sources. The original source vector S is of size M x N and the mixing matrix **A** is of

size M x M, where M is the number of statistical independent sources and N is the number of samples in each source.

The result of the separation process is the de-mixing matrix **W** which can be used to obtain the estimated statistical independent sources, $\hat{S}$ from the mixtures.

In the EEG signal processing, if the number of channels (mixed signals) are more than or equal to the sources, ICA algorithm is suitable. A group of algorithms i.e. ICA can recover these sources. The modeling of ICA can be done by following equation stated as

$$x = A.s \tag{2}$$

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.

$$s^* = W.x \tag{3}$$

$$W = A\text{-}1 \tag{4}$$

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 [2,5]. In this paper FastICA algorithm is applied. It estimates the independent components from given multi-dimensional signals.

2.3 Wavelet-ICA

In ICA model, the input must be a matrix and not a vector [6]. This means we can't apply ICA directly to the single channel signal. So, 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.

First of all baseline wandering is removed by taking average of the signal. Then SWT is used for wavelet decomposition with mother wavelet S*ymlet* and decomposition level 8. This 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 un-mixing matrix (A and W respectively) along with the matrix of independent components. After this, selection of desired sources of interest is done, i.e. here we remove the components related to artifacts. To obtain the appearance of signal in the form of wavelet components, the source of interest is multiplied with the mixing matrix A. and to recover the signal in the form of original signal; wavelet reconstruction is done using inverse stationary wavelet transform (ISWT).

3. RESULTS AND DISCUSSION

Procedure described above is applied on 20 different epochs of 4 patients. Data was taken from CSIO Chandigarh. The time period of signals was 4 seconds with 1024 number of samples and sampling frequency 256 samples per second. Figure 1 shows the raw EEG signal, and signal after removing baseline wandering. FFT of raw signal and filtered signal with proposed algorithm are plotted and shown in figure 2 and 3 respectively.

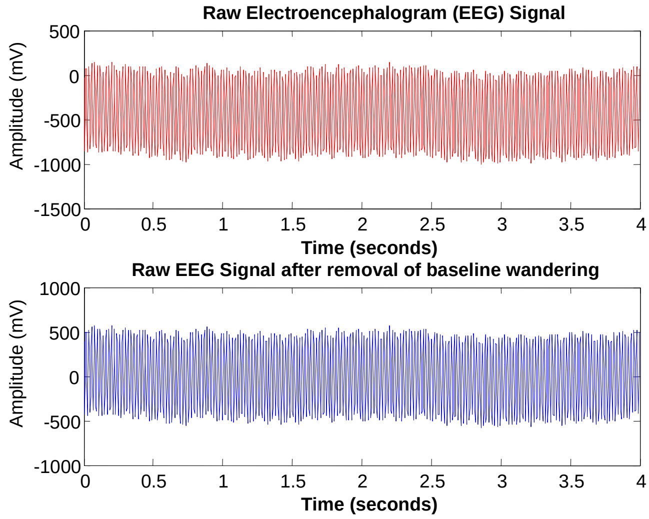

Figure1. EEG Signal in original form are shown, with raw signal (red), Raw EEG after removing baseline wandering (blue)

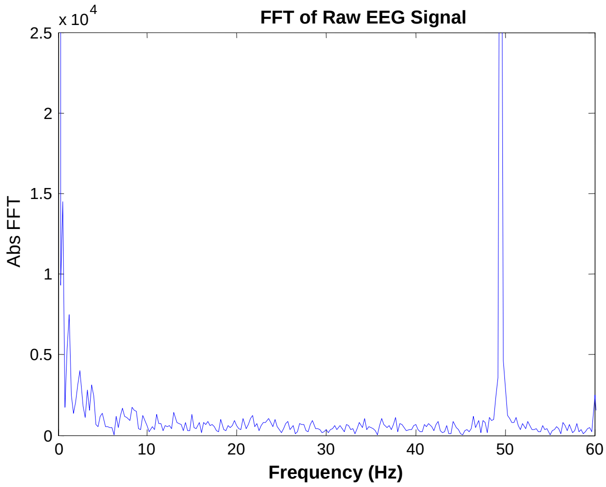

Figure2. FFT of Original Signal

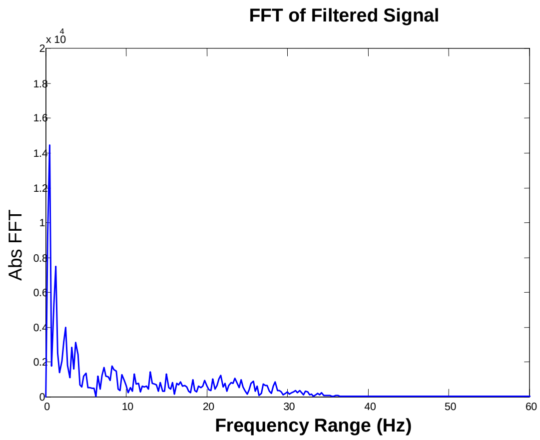

Figure3. FFT of Filtered signal with proposed algorithm

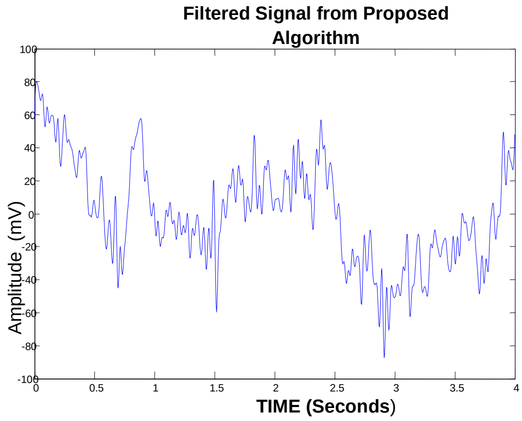

Figure4. Filtered EEG Signal using Proposed Algorithm

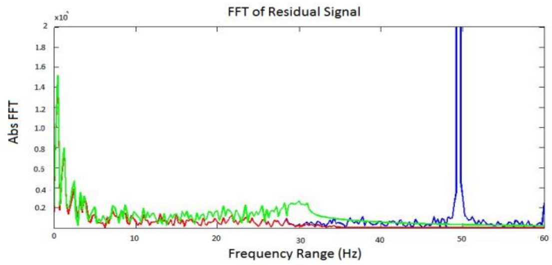

Figure5. Signals in frequency domain are shown, with raw signal (blue line), result from LPF (green line) and using the Wavelet-ICA proposed Algorithm (red line)

The performance analysis of the algorithm was done using *signal to noise ratio* (SNR). The results of the proposed algorithm are compared with that of low pass filter, and are shown in table 1. The present method shows better results with higher SNR as compared to the low pass filter, and it is consistent for all the signals. The frequency correlation graph of the present method and low pass filter is shown in figure 5 with the original signal. The SNR value of proposed method is better as compared to that of a low pass filter (table 1). The average values of SNR using Low pass Filter comes 42.44 and for proposed method it is 46.13. Filtered signal using the proposed algorithm in time domain is shown in figure 4.

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.

Table1. Comparison of SNR of Low Pass Filter and Proposed Method

Subject	SNR of Low Pass Filter	SNR of Proposed Method
1	43.10	47.28
2	41.86	45.12
3	43.06	46.86
4	41.76	45.27

4. CONCLUSION AND FUTURE SCOPE

In this paper, a method is proposed for the removal of power-line interference from a Single channel EEG signal on the basis of joint use of wavelet analysis and FastICA technique. Stationary 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 power line noise. From the FFT plots shown in figure 5, it is clear that power line interference in EEG signals can be removed in a better way by the joint use of Wavelet analysis and FastICA technique. When compared with low pass filter, this method shows better SNR results with negligible information loss. Wavelet based de-noising gives better results. As Wavelet Transformation is multi-resolution technique, so the signal can be analyzed in both time domain as well as in frequency domain. Artifacts that have spectral overlap with underlying EEG signals cannot be removed using conventional filtering.

Future scope of this work is that we will implement the proposed algorithm to remove the other artifacts like ocular artifacts and muscle artifacts from EEG signals and will try to develop a new algorithm to improve the results for removing ocular artifacts from EEG signals.

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