Research Article

Performance Improvement in Electroencephalogram Signal by Using DWT

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Abstract: The nature of the electroencephalogram (EEG) signal is very fluid and spontaneous. Because of its lower amplitude, it is polluted by certain artifacts such as power line noise and baseline noise. Similarly, power line and baseline sounds have polluted electromyogram (EMG) and electrocardiogram (ECG) signals. These objects taint the initial signal's properties. Owing to the existence of objects, these signals cannot be accurately analyzed; hence, these sounds must be removed before analyzing the raw signal. The two important artifacts that corrupt a patient's EEG record are power line interference and baseline interference. This paper focuses on extracting power line and baseline artifacts from EEG signals using an effective de-noising algorithm called DWT (Discrete Wavelet Transform) to improve the signal's efficiency by increasing fidelity parameters including MSE, MAE, SNR, and PSNR. The MATLAB simulation is to be used for the implementation.

Keywords: Discrete Wavelet Transform, electromyogram, electrocardiogram, Electroculogram and Independent Component Analysis.

1. Introduction

One of the most important instruments for observing brain function is electroencephalography (EEG). If it lacks the accuracy and resolution of many other brain imaging technologies in terms of spatial localization of brain function, its key benefits are low costs, relative ease of usage, and outstanding time resolution. The EEG is commonly used in many fields of clinical work and study for these purposes. The very low signal-to-noise ratio of the brain impulses are attempting to observe, along with the vast range of noise sources, is one of the most difficult problems of utilizing EEG. While there are many other techniques for measuring brain function that include precise spatial localization of brain activity with high accuracy and resolution, EEG is commonly utilized in clinical study and work due to its lower prices, relative ease of usage, and superior time resolution. The majority of waves are between 0.5 and 500Hz, although most therapeutic EEGs are between 20 and 40Hz [1]-[6].

Signal anomaly reports are caused by a variety of causes such as line interruption, EOG (Electro-oculo-gram), and ECG (Electro-cardio-gram). These noise sources heighten the need to analyze the EEG and obtain clinical knowledge. As a result, complex filter architecture is needed to reduce such artifacts in EEG recordings. By conducting m^{th} order FIR filtering on adaptive RLS algorithm and the research work predicted an adaptive filtering approach for eradicating ocular objects from EEG data. The accuracy is calculated quantitatively using simulated data and compared to the precision of the time-domain regression approach. The findings indicate that EEG channels are frequency based for ocular signal transmission. Clinicians and physicians will use the EEG to analyze the function of the brain in a non-invasive way. It's been used for a long time, and it's been used to diagnose brain injury, sleep cycles, and multiple central nervous system diseases including seizures and epilepsy. However, the EEG source signals are combined with other signals such as EOG and Electro-myo-gram (EMG), making analyzing the pure EEG and collecting therapeutic knowledge more complex. A new approach for de-noising objects in mixed EEG signals is presented in this article. The knowledge theoretic principle of shared information measured using B-Spline is used in developing an approach for independent component analysis (ICA) to eradicate these objects. The author of this paper introduces a B-Spline estimator for reciprocal knowledge that can be used to find individual components in EEG signals. In related simulations, tests revealed that B-Spline mutual information independent component analysis (BMICA) outperforms the traditional independent component analysis algorithms of Quick ICA, JADE, SOBI, and EFICA. In addition to generating purer EEG signals for study, BMICA has been found to be more accurate than the well-known Quick ICA [7]-[14].

Several sources of noise contaminate EEG from preterm baby detection devices, which must be eliminated in order to properly detect signals and conduct automated research accurately. Band-pass and adaptive filters (AF) are also used, but the performance of these filters may be harmed by preterm EEG patterns like the trace alternant and sluggish delta-waves [15]-[18]. The author of this paper suggested that EEG decomposition be combined with AF to increase the overall de-noising operation. They compare the output of filtered signals using artificially polluted signals from actual EEGs and three decomposition techniques: the discrete wavelet transform, empirical mode decomposition (EMD), and a recently developed edition, the full ensemble EMD with adaptive noise. Simulations show that using EMD-based techniques before AF will minimize root mean squared errors in de-noised EEGs by up to 30% and the introduces technique for separating objects from Electroencephalograms (EEG) signals. Line disturbance, EOG, and ECG are all factors that affect EEG signals. The removal of artifact from scalp EEGs is extremely important for both automatic and visual examinations of underlying brainwave behaviour.

These noise sources make studying the EEG and collecting scientific knowledge about pathology more complex. As a result, it's critical to devise a method for reducing certain objects in EEG recordings. To distinguish the independent components (ICs) from the original EEG signal, this paper uses spatially-constrained independent component analysis (SCICA). The next move is to use wavelet de-noising (WD) to remove the brain function from the purged objects, and then the artifacts are projected back and subtracted from EEG signals to obtain clean EEG results. Thresh-holding is used to demarcate the objects in this case, and a stronger thresh-holding method named "Otsu" thresh-holding is used.

2. Related Work

Signal processing's area of non-integer order filters is increasingly expanding. Theoretical foundations for such filters are well known. However, several issues around filter tuning and execution remain unsolved. Trauma that is not adequately detected or diagnosed too late will result in irreversible brain injury. As a result, a safe instrument that can be utilized by emergency responders to achieve a prompt diagnosis of TBI at the site of injury is needed. Seizures, which are irregular changes in brain electrical activity that last for a long time, may disrupt the functions of different organs, resulting in brain damage. Delta (4Hz), theta (4-8Hz), alpha (8-13Hz), beta (13-30Hz), and gamma (38-42Hz) are typical EEG levels that each reflect different neuronal states in the brain, with the gamma scale thought to lead to local processing of particular areas. Since today's state-of-the-art EEG systems can use up to 256 electrodes and sample at a pace of up to 16kHz.

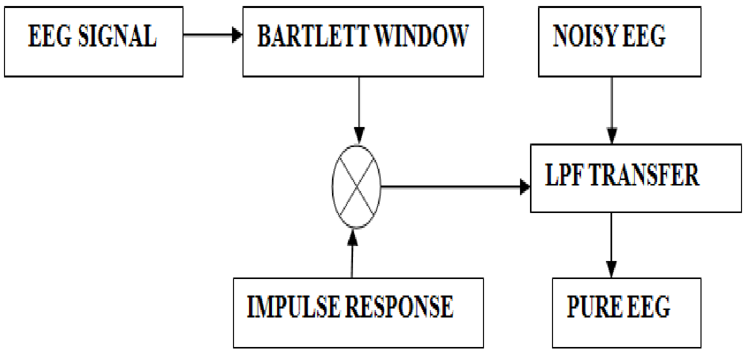

Figure.1. Block Diagram of Existing Method

Figure 1 depicts the block diagram of the current system. With N=50 tests, the EEG signal is added to the Bartlett frame. FrFT is added to the display of the Bartlett pane. The improved EEG signal is obtained by passing the resulting signal via a low pass filter. The fidelity parameters such as signal to noise ratio (SNR), MSE, MAE, and sensitivity are measured and evaluated in the MATLAB setting using the FrFT parameter, which is varied from 0 to 1 in steps of 0.1.

3. Proposed System of EEG

The EEG is a bioelectric brain activity that doctors use to research the working state of the brain and diagnose certain neurophysiologic conditions and disorders. It's often used in neurophysiology as a non-invasive process. Physiological signals in EEG recordings, such as eye blinks, muscle agitation, and heart pulses, distort the fundamental mechanisms and render interpretation difficult. The EOG (electrical activity produced by eye movement) is powerful enough to be noticeable in the EEG. The EOG is a measurement of the possible disparity between the cornea and the retina when it varies with eye movement. Eyelid action, such as eye blinks, is another typical artifact that affects the corneal-retinal potential differential. Since the blinking artifact creates a more abruptly shifting waveform than eye action, the blinking artifact has more high-frequency components. Ocular Artifacts (OA) are electrical signals generated by the blinking of the eyes and the contraction of the eyeballs.

Another typical artifact is electrical activity of contracting muscles, which is determined by the EMG on the body surface. When the patient is conscious, this sort of artifact appears while eating, grimacing, jaw clenching, frowning, chewing, laughing, sucking, and hiccupping. Muscular objects are a common name for these artifacts (MA). They are on the mill volt scale, and they contaminate the EEG signals, which are on the microvolt scale. The frequency spectrum of an EEG signal is 0 to 64Hz, with OA occurring between 0 and 16Hz and MA occurring between 50 and 500Hz. When a correction algorithm is applied to wavelet-based EOG and EMG signals over the entire duration of the signal, it results in the thresh-hold of both low and high frequency components also in non-OA regions. There is a significant lack of useful source EEG interaction due to the overlapping of these objects over the desired signals.

The aim of signal analysis is to translate a signal and derive relative knowledge from it. Fourier transform analysis, which breaks down a signal into constituent sinusoids of various frequencies, is perhaps the most well-known method for transforming. Many non-stationary or transitory traits, such as drift, patterns, sudden transitions, and event beginnings and ends, are present in the most interesting signals. Fourier analysis is not designed to distinguish these properties, which are also the most critical aspect of a signal. The standard method is to add time dependence while maintaining linearity in the Fourier analysis. The concept is to use a "absolute frequency" parameter (local in time) to make the "local" Fourier transform look at the signal from a window where it is roughly stationary. Another option is to change the Fourier transform's sine wave base function to simple functions that are more concentrated in time (but less concentrated in frequency).The wavelet transform of a sigmoid x(t) is defined as,

$$WTX(T,a) = \left(1/\sqrt{a}\,\right)\int_{-\infty}^{+\infty} x(t)h(t-T/a)\,e^{-j2\pi ft}\,dt \qquad (1)$$

$$WTZ(T,a) = \left(1/\sqrt{a}\,\right)\int_{-\infty}^{+\infty} x(at)h(t-T/a)\,e^{-j2\pi ft}\,dt \qquad (2)$$

In WT, signal analysis is done with the aid of a special feature named the mother wavelet, h(t). This function is time-transformed to select the portion of the signal to be evaluated. A scale parameter, which is equivalent to frequency, is then used to enlarge or contract the portion of the signal that has been chosen. The wavelet is a narrow function of the initial function for small values of a, which approximately correlates to higher frequencies. The wavelets are extended and correspond to low frequency for very high values of a. The WT analyzes high frequency components at a higher time resolution than low frequency components. This is particularly useful when studying short transient waveforms like EEG bursts. WTX (T, a) is the signal's projection onto a wavelet moved by T and scaled by a, and therefore shows the wavelet's contribution to the signal. As a result, rather than a time-frequency representation, such a transition leads to a time-scale decomposition in which dimensions are proportional to frequency. A "Wavelet" is a tiny waveform with condensed energy in time. A signal is converted into a sequence of wavelets using Wavelet Transforms. For EEG signal processing, the wavelet transform is a useful method. The wavelet transform has the advantage of being localized in both time and frequency, while other classical approaches, such as the Fourier transform, are just localized in frequency.

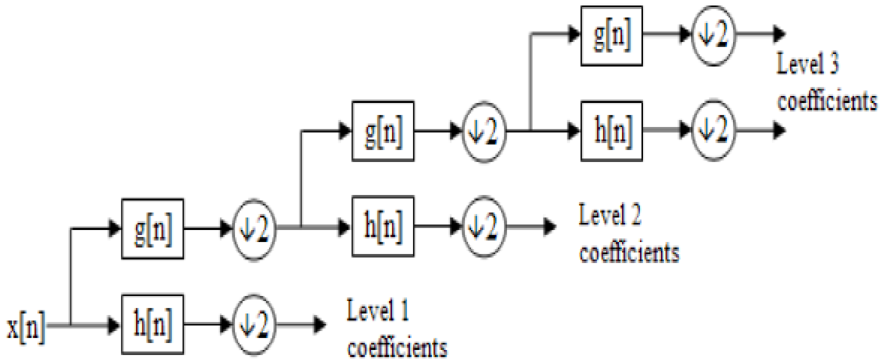

Figure.2. Signal Decomposition Using DWT

The Figure.2 shows Signal Decomposition Using DWT. Furthermore, the wavelet transform provides reasonable time resolution for low-frequency components of the signal being studied as well as good frequency resolution for high-frequency components. It overcomes the limitations of other related approaches, such as the short-time Fourier transform, which has continuous time-frequency localization across both frequencies. As a consequence, a wavelet transform may be used to track complex signal transformations that are time and frequency localized. The continuous wavelet transform (CoWT) is an effective tool for detecting singularities. The basic DWT is a discrete and easy implementation of CoWT (generally with real valued basis) (Discrete Wavelet Transform). Normal DWT has the same data size in the transition domain as the signal, making it a non-redundant transform. A basic filter bank arrangement of recursive FIR filters may be used to enforce standard DWT. Multi-resolution Analysis (MRA) helps DWT to display and process different signals at multiple resolution resolutions, which is a very important feature. The information of the signal can be obtained at several scales by correlating the initial signal with wavelet functions of various sizes. These wavelet feature correlations may be organized in a hierarchical system known as multi-resolution decomposition. The multi-resolution decomposition algorithm divides the signal into "information" at various scales and "approximation," a coarser representation of the signal.

4. Results And Discussion

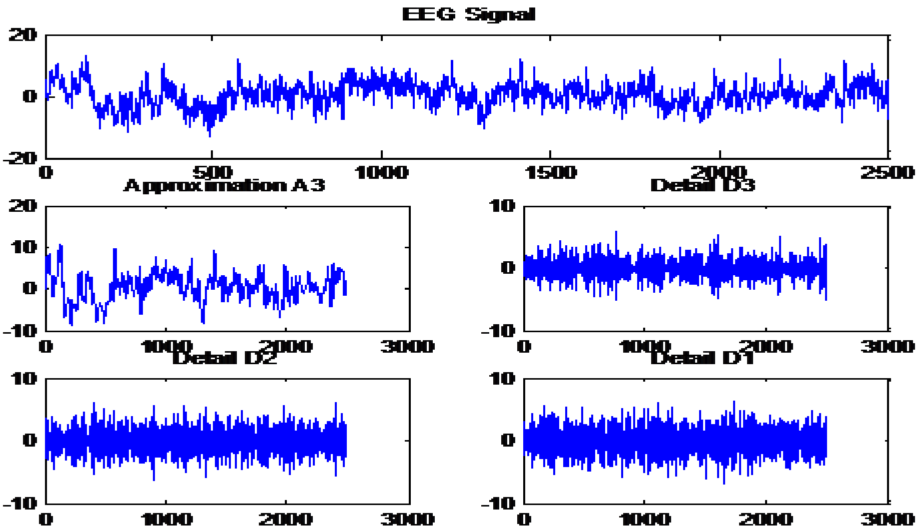

Figure.3. Input EEG Signal

The calculation of the SWT of a signal x (k) is seen in Figure 2 and Figure.3 shows Input EEG Signal, where Wj,k and Vj,k are the detail and approximation coefficients of the SWT, respectively. The low pass and high pass wavelet filters Hj and Gj are the normal low and high pass wavelet filters, respectively. The filters H1 and G1 are obtained in the first step by up sampling the filters in the previous step (i.e. Hj-1 and Gj-1). The detail coefficients Wj,k are equal to the high pass filter output, and the approximation coefficients Vj,k are equal to the low pass filter output. Hj and Gj are a bank of ideal narrowband filters based on the wavelet transform's time frequency properties. EOG and EMG signals contaminate the EEG recordings. Non-cortical activities are the EOG and EMG cues. Since the retina, facial muscles, and brain all have physiologically distinct origins, the reported EEG is a superposition of the true EEG, a portion of the EOG signal, and certain EMG signals. It can be expressed in the following way:

$EEG_{rec}(t) = EEG_{true}(t)+s.EOG(K)+t.EMG(K)$ (3)

where,

$EEG_{rec}(t)$ – Recorded EEG which is contaminated signal and holds artifacts,

$EEG_{true}(t)$ – EEG due to the cortical activity (i.e., Brain activity),

s.EOG(K) – Propagated ocular artifact due to eye blinks and movements, and having impact over the recording site,

t.EMG(K) – Propagated muscular artifact due to eye blinks, jaw clenching, swallowing spit which again reflects over the recording site,

$EEG_{true}(t)$ is to be estimated from by efficiently removing unwanted artifacts s.EOG(k) and t.EMG(K) and at the same time retaining the EEG activity.

Figure.4 shows Gamma, Beta, Alpha, Theta and Delta Components of the EEG signal, Figure.5 shows DWT Coefficients for De-noised EEG Signal, Figure.6 shows the De-noising of EEG Signal and Figure.7 shows Spectrum Representation of Input EEG, Noisy EEG and De-noised EEG Signal

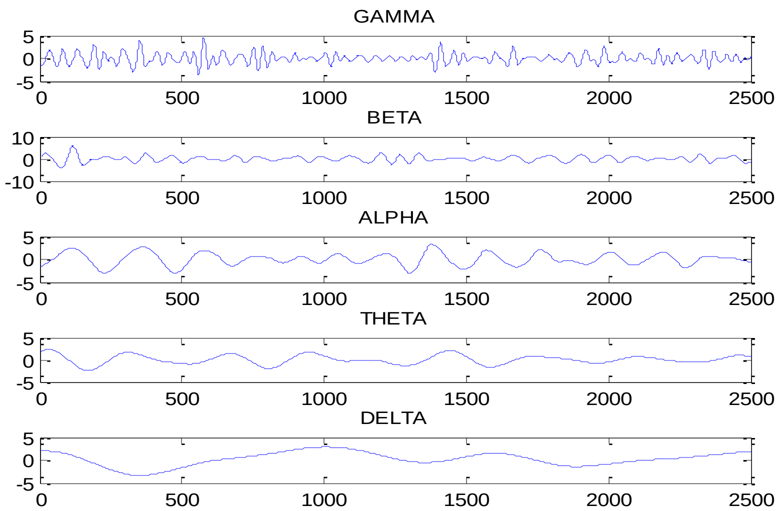

Figure.4. Gamma, Beta, Alpha, Theta and Delta Components of EEG signal

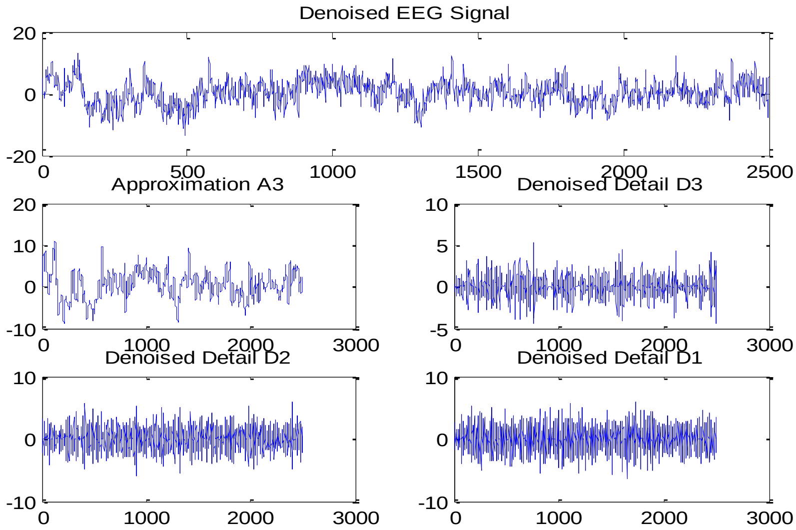

Figure.5. DWT Coefficients for De-noised EEG Signal

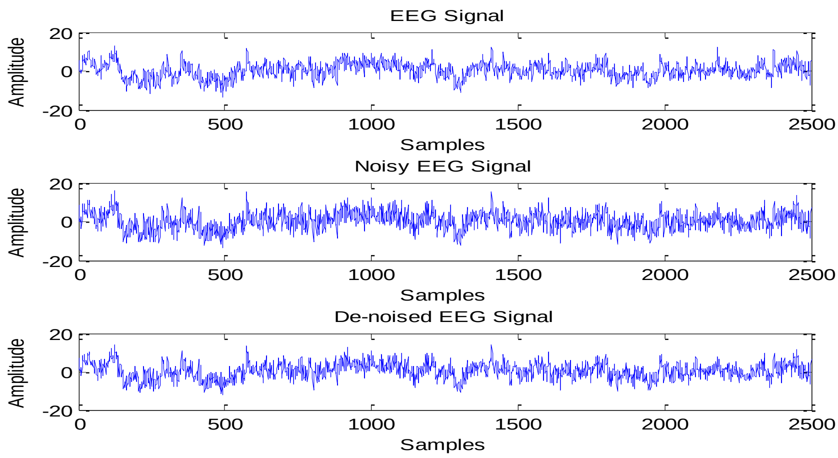

Figure.6. De-noising of EEG Signal

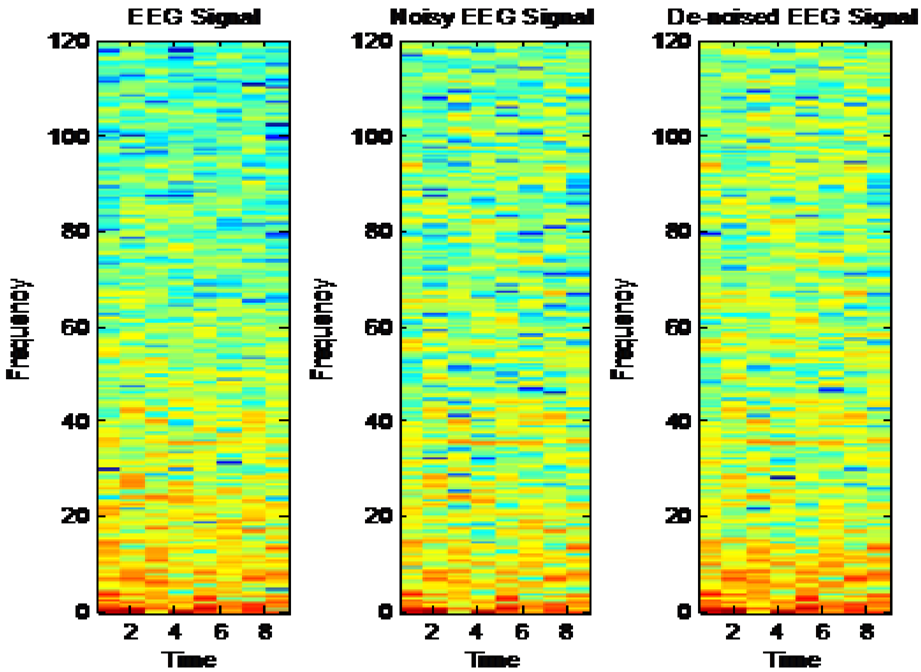

Figure.7. Spectrum Representation of Input EEG, Noisy EEG and De-noised EEG Signal

5. Conclusion

EEG signals, wavelet-based de-noising methods are investigated. Signals with higher PSNR and SNR, as well as a low MSE, are considered to be less distracting. Using various fidelity parameters such as MSE, MAE, SNR, and PSNR, it was determined that the wavelet approach generated the strongest de-noising results due to its multi-resolution capabilities. Through choosing the right wavelet to decompose the signal, the wavelet transform analyzes the signals in both the time and frequency domains and eliminates signals with low noise amplitudes. Just the low pass components of the signals are decomposed in the wavelet transform. EEG de-noising dependent on DWT is used, which results in improved noise cancellation. For non-stationary waves, the DWT design is the best computational instrument.

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