

Comparative Analysis of Different Wavelets for EEG Signal Denoising

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ABSTRACT: The purpose of the study was to investigate the feasibility of using wavelet transform for processing of EEG signals. In this paper we introduce five wavelets along with ICA for processing of EEG and determine the best wavelet for processing. The five wavelets are symmlet, coiflet, haar, daubechies and bi-orthogonal, among these five wavelets the Daubechies is proved as the best for the EEG signal reconstruction. The experimental results shows that the proposed method gives better results than the existing methods.

KEYWORDS: EEG, ICA, Symmlet, Coiflet, Haar, Daubechies

I. INTRODUCTION

The EEG signal contains among the useful information, which allow scientists to view the cerebral activity, redundant or noise information. In order to conclude that something is wrong or that the patients have a disease further processing is necessary. EEG obtained from scalp electrodes is a sum of the large number of neurons potentials. The interest is in studying the potentials in the sources inside the brain and not only the potentials on the scalp, which globally describe the brain activity. Direct measurements from the different centers in the brain require placing electrodes inside the head, which means surgery. This is not acceptable because of the risk for the subject. Another possibility is to calculate the signals of interest from the EEG obtained on the scalp. These signals are weighed sums of the neurons activity, the weights depending on the signal path from the brain cell to the electrodes. Because the same potential is recorded from more than one electrode, the signals from the electrodes are supposed to be highly correlated. If the weights were known, the potentials in the sources could be computed from a sufficient number of electrode signals. Independent component analysis (ICA)

For brain signal acquisition various methods used such as electroencephalography (EEG), Functional Magnetic Resonance Imaging (fMRI), Near Infra-Red Spectroscopy (NIRS) and Magneto encephalography (MEG). From this method EEG is widely used signal acquisition method because of high temporal resolution and safe for use [1]. EEG used in medical purpose and also for brain computer interfacing (BCI). That EEG signal processing important for proper analysis disease. Signal processing of EEG is fundamental for analysis of brain activity and diagnosis of normality or abnormality of signal that is important for analysis of any disease.

A. SIGNAL DE-NOISING

During EEG recording many of other influence introduce noise which called as artifact. These artifacts come from patient body or instrument, as an example eyes movement, the heart, muscles and line power. Before processing EEG, removal of this artifact is primary task and it form fundamental step for EEG signal processing.

EEG signal de-noising can be done by wavelet. Here we used different wavelets for de-noising. Most of time EEG signal contain neural information below 100 Hz so it's beneficial to use wavelets.

The rest of this paper is organized as follows. Section II first reviews existing method. Our proposed method is described in Section III. Then experimental results are reported in Section IV to demonstrate the superior performance of our framework. Finally, conclusions are presented in Section V.

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Website: www.ijirset.com

Vol. 6, Issue 1, January 2017

II. EXISTING METHOD

In the existing method neural information processing architecture inspired by quantum mechanics and incorporating the well known Schrodinger wave equation is implemented. The existing architecture referred to as recurrent quantum neural network (RQNN) can characterize a nonstationary stochastic signal as time-varying wave packets. An unsupervised learning algorithm enables the RQNN to effectively capture the statistical behavior of the input signal and facilitates the estimation of signal embedded in noise with unknown characteristics.

The results from a number of benchmark tests show that simple signals such as dc, staircase dc, and sinusoidal signals embedded within high noise can be accurately filtered and particle swarm optimization can be employed to select model parameters.

The RQNN filtering procedure is applied in a two-class motor Imagery-based brain-computer interface where the objective was to filter electroencephalogram (EEG) signals before feature extraction and classification to increase signal separability. A two-step inner-outer fivefold cross-validation approach is utilized to select the algorithm parameters subject-specifically for nine Subjects.

This MI is translated into a control signal by classifying the specific EEG pattern that is characteristic of the subject's imagined task, e.g., movement of hands and/or foot. These raw EEG signals have a very low signal-to-noise (SNR) ratio because of the interference from the electrical power line, motion artifacts, electromyogram (EMG)/ electrooculogram interference. Preprocessing is carried out to remove such unwanted components embedded within the EEG signal and good preprocessing results in increase in signal quality resulting in better feature separability and classification performance.

III. PROPOSED METHOD

In the proposed system the independent component analysis (ICA) is implemented. If the weights were known, the potentials in the sources could be computed from a sufficient number of electrode signals. Independent component analysis (ICA) sometimes referred to as blind signal separation or blind source separation, is a mathematical tool that can help solving the problem. Along with the ICA the five wavelets are implemented in order to find the best wavelet for the reconstruction of the signal.

A. INDEPENDENT COMPONENT ANALYSIS PROCEDURE

We assume that we observe n linear mixtures s_1, \dots, s_2 of n independent components:

$$s_j = a_{j1}x_1 + a_{j2}s_2 + \dots + a_{jn}s_n, \quad j=1, \dots, n$$

In this equation the time has been ignored. Instead, it was assumed that each mixture x_j as well as each independent component s_i are random variables and

$s_j(t)$ and $x_i(t)$ are samples of these random variables. It is also assumed that both the mixture variables and the independent components have zero mean. If not subtracting the sample mean can always center the observable variables x_i . This procedure reduces the problem to the model zero-mean:

$$\hat{s} = x - E(s)$$

Let s be the random vectors whose elements are the mixtures s_1, \dots, s_n and let x be the random vector with the components x_1, \dots, x_n . Let A be the matrix containing the elements. The model can now be written:

$$s = Ax \text{ or } x = \sum_{i=1}^n a_i s_i$$

The above equation is called independent component analysis or ICA.

This ICA procedure is used along with all the five wavelets and we compare the results to know the best wavelet. The Wavelets used here are symmlet, daubachies, coiflet, haar and bi-orthogonal.

Wavelet families are mainly distinguished into two categories: Orthogonal and Biorthogonal. Orthogonal wavelet families are, Daubechies, Coiflet and Symlet. The performance of wavelet based coding depends on the wavelet decomposition structure. Before employing a computationally intensive procedure for finding the optimal basis, it will be helpful to know, a priori, if appreciable gain can be achieved by using the optimal basis over known good wavelets.

International Journal of Innovative Research in Science, Engineering and Technology

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Vol. 6, Issue 1, January 2017

To remove noise from the EEG signal, dwt based symlet wavelet function is used. The major sources of noise like color noise, real muscle artifact; electrode motion and baseline wander noises. This methodology involves four steps. They are decomposition, thresholding, denoising for EEG signals. Symlet wavelet function is used to decompose and denoising the ECG signal. After decomposing, thresholding technique is applied to detailed coefficient, to obtain threshold signal. Denoised signal is obtained from threshold signal. The same procedure is repeated for all the remaining four wavelets. Haar wavelet is a sequence of rescaled "square-shaped" functions which together form a wavelet family or basis.

The Daubechies D4 transform has four wavelet and scaling function coefficients. Each step of the wavelet transform applies the scaling function to the data input. If the original data set has N values, the scaling function will be applied in the wavelet transform step to calculate N/2 smoothed values. In the ordered wavelet transform the smoothed values are stored in the lower half of the N element input vector.

The coiflet wavelet function has 2N moments equal to 0 and the scaling function has 2N-1 moments equal to 0. The two functions have a support of length 6N-1. General characteristics: Compactly supported wavelets with highest number of vanishing moments for both phi and psi for a given support width.

In order to gain greater flexibility in the construction of wavelet bases, the orthogonality condition is relaxed allowing semi-orthogonal, biorthogonal or non-orthogonal wavelet bases. Biorthogonal Wavelets are families of compactly supported symmetric wavelets. The symmetry of the filter coefficients is often desirable since it results in linear phase of the transfer function.

B. DENOISING PROCEDURE

The general de-noising procedure involves three steps. The basic version of the procedure follows the steps described below.

1. Decompose - Choose a wavelet, choose a level N. Compute the wavelet decomposition of the signal s at level N.
2. Thresholding: Threshold detail coefficients - For each level from 1 to N, select a threshold and apply soft or hard thresholding method to the detail coefficients.
3. Reconstruct - Compute wavelet reconstruction using the original approximation coefficients of level N and the modified detail coefficients of levels from 1 to N.

Among the above five wavelets daubachies is the best wavelet. This is proved in terms of PSNR. The daubachies wavelet gives better PSNR when compared to other four wavelets.

IV. RESULTS

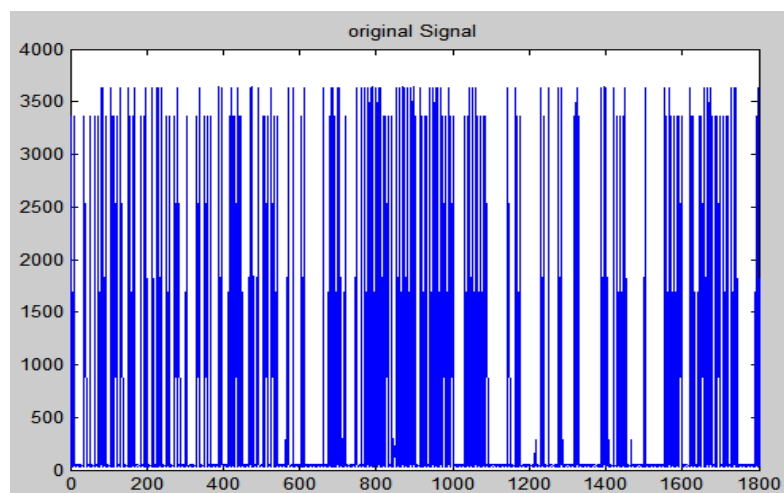


Fig.1. Original input signal

International Journal of Innovative Research in Science, Engineering and Technology

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Vol. 6, Issue 1, January 2017

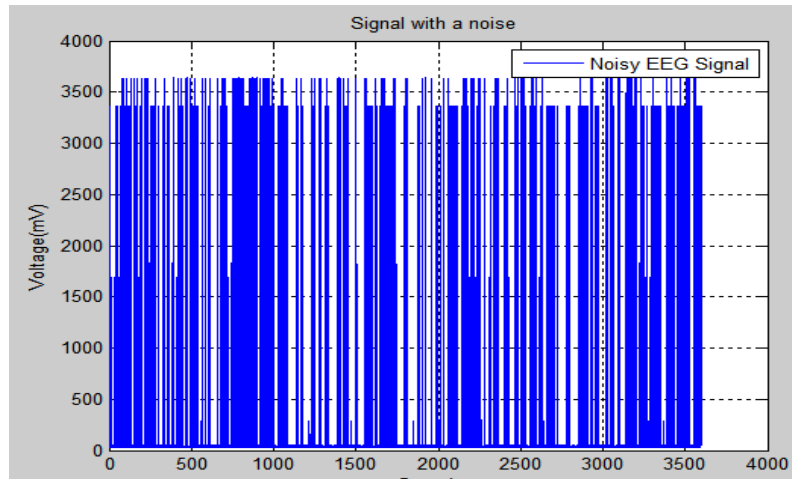


Fig.2. Input signal with noise

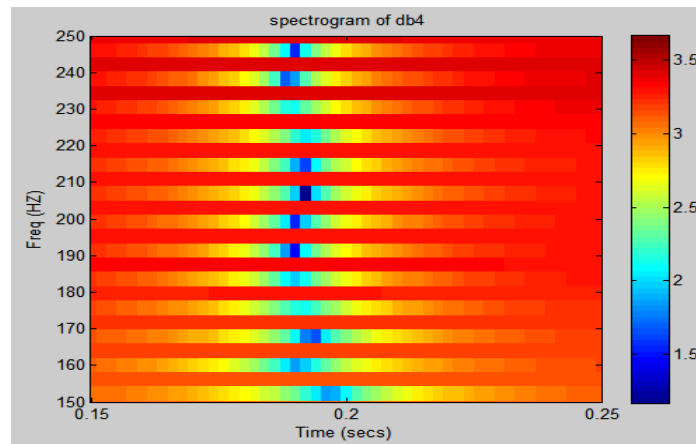


Fig.3. Spectrogram of db4

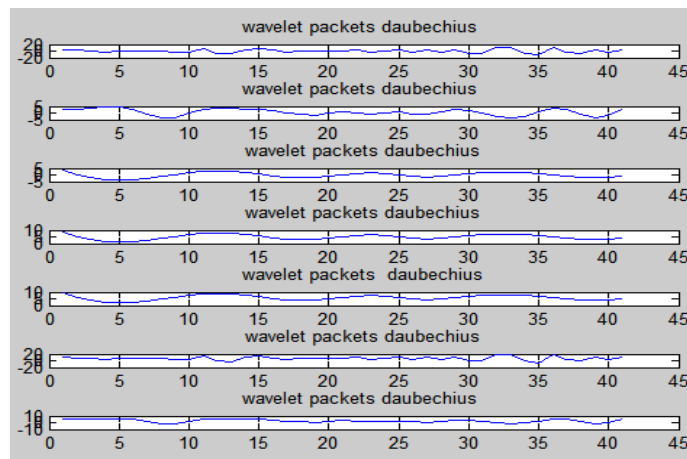


Fig.4. Wavelet packets using daubechius

International Journal of Innovative Research in Science, Engineering and Technology

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Website: www.ijirset.com

Vol. 6, Issue 1, January 2017

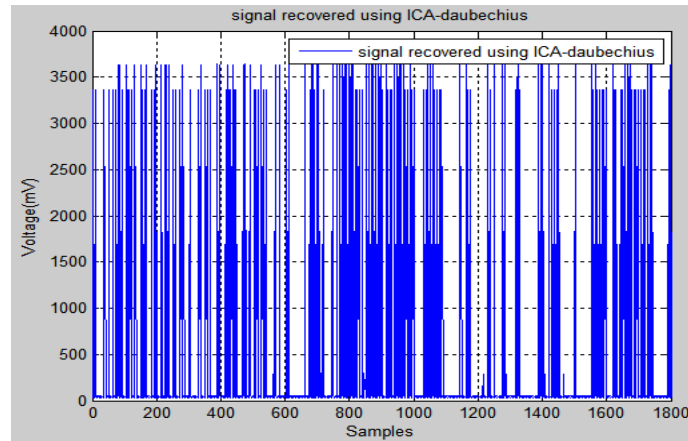


Fig.5. Signal recovered using db4

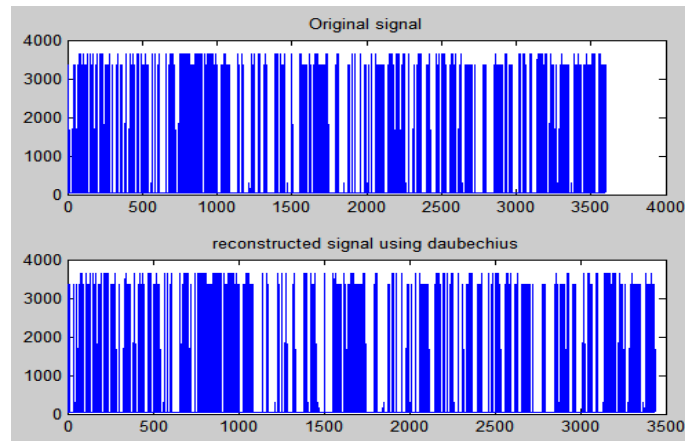


Fig.6. Original signal and its reconstructed signal

I. Comparison Table

Table1: comparison of proposed an existing methods

	PSNR	TIME (sec)
Proposed method	12.9709	15.206
Existing method	11.2484	110.32

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Vol. 6, Issue 1, January 2017

V.CONCLUSIONS

This study presents an analysis and comparison of the wavelet families for EEG signal processing considering PSNR and time in seconds. The effects of Biorthogonl, Haar, Daubechies, Coiflet and Symlet wavelet families on EEG signal are examined. We analyzed the results for a wide range of wavelet families and found that the wavelet Daubachies(db4) provides best performance for denoising the signal i.e. reconstruction of the signal. The computational time required for the proposed method family is less in comparison to other existing methods. As far as the quality is concerned we got a fair signal quality with wavelet db4.

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