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Statistical features-based comparison of analysis and synthesis of normal and epileptic electroencephalograms for various wavelets

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Abstract: An electroencephalogram (EEG) is an electrical signal in microvolts captured noninvasively from the brain, which provides important and unique information about the brain. The frequency of an EEG signal lies between 0 and 100 Hz. Decomposition of an EEG signal into various bands such as alpha, beta, delta, theta, and gamma is essential in seizure-related studies. EEGs play a key role in the diagnosis of epileptic seizures and neurological disorders. In this paper, multiple wavelet families for decomposition and reconstruction are explored and are compared based on risk functions and reconstruction measures. While dealing with the wavelets it is a difficult task to choose the correct/accurate wavelet for the given biosignal analysis. Various statistical properties were studied by the authors to check the suitability of various wavelets for normal and diseased EEG signal decomposition and reconstruction. The methodology was applied to 3 groups (63 subjects) consisting of both sexes and aged between 1 and 80 years: 1) normal healthy subjects, 2) patients with focal seizures, and 3) patients with generalized seizures. Our result shows that the Haar and Bior3.7 wavelets are more suitable for normal as well as diseased EEG signals, as the mean square error, mean approximate error, and percent root mean square difference of these wavelets are much smaller than in other wavelets. The signal-to-error ratio for Haar and Bior3.7 was much higher than in any other wavelet studied.

Key words: Decomposition, wavelet, reconstruction, electroencephalogram, epilepsy, statistical features

1. Introduction

An electroencephalogram (EEG) represents the entire brain dynamics in the form of an electrical signal captured from the surface of the head. It is the superimposition of various processes related to the brain. The amplitude of the EEG signal is in microvolts (200 μV). The amplitude, frequency, and characteristics of an EEG signal change from one state to the other, and with age. An EEG is decomposed mainly into 5 subbands: delta (0–4 Hz), occurring during deep sleep, during childhood, and in serious organic brain diseases; theta (4–8 Hz), occurring in childhood, during emotional stress; alpha (8–13 Hz), occurring in a normal person in an awake state; beta (13–30 Hz), affected by mental activity; and gamma (above 30 Hz) [1,2]. Instead of studying the complete EEG, EEG subband-related information yields more accurate information about the underlying neuronal activities [3].

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2. Materials and methods

Traditional Fourier transform can be used for the feature extraction of EEG, but it works well for the whole-time series of a stationary signal [4,5]. In this paper a wavelet filter is used for the subband decomposition as it has various advantages such as time-frequency localization, scale-space analysis, flexibility, and multirate filtering. Over the length of a signal, variable window size can be applied in the wavelet transform (WT). Depending on the signal specifications, this allows the wavelet to get stretched or compressed [6,7]. This makes WT a very popularly used feature extraction technique for nonstationary signals, such as EEGs [8,9]. There are two types of WT: continuous wavelet transform (CWT) and discrete wavelet transform (DWT) [10,11].

CWT: Continuous wavelet transform

$$X\left(a,b\right)=\frac{1}{\sqrt{b}}\int_{-\infty}^{\infty}X\left(t\right)\varphi\left(\frac{t-a}{b}\right)dt \tag{1}$$

Here 'ψ' is the mother wavelet, 'a' is a time shift, and 'b' modulates the width.

DWT: Discrete wavelet transform

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

The DWT means selecting a subset of scales 'a' and positions 'b' of the mother wavelet 'ψ (t)' [12,13]. While dealing with the wavelets the most important concern is how to choose the correct/accurate wavelet for the analysis of a given signal or image. All wavelets can be applied to a given signal/image for its analysis, but the results obtained from each wavelet would differ a bit and might or might not be acceptable depending on the application requirement. The authors have applied various wavelets for analysis and synthesis of an EEG signal to study various risk characteristics.

2.1. Wavelet family

Haar is the simplest and oldest of the wavelet family. The most widely used wavelet in signal processing is the Daubechies; it is also called the modified Haar wavelet. Haar, Daubechies, Coiflet, and Symlet are the orthogonal wavelets capable of almost perfect reconstruction of a signal. Generally, a wavelet is selected based on the shape of the mother wavelet and its ability to analyze the signal [14,15]. Specifications of the wavelet family are as shown in Table 1.

Table 1. Specifications of the wavelet family [16].

Property	Haar	db	Coiflet	Symlet	Bior
Discrete wavelet transform	√	√	√	√	√
Continuous wavelet transform	√	√	√	√	√
Orthogonal analysis	√	√	√	√	
Biorthogonal analysis	√	√	√	√	√
Near symmetry			√	√	√
Asymmetry	√	√			

2.2. Analysis and synthesis

Decomposition of a signal known as analysis and reconstruction of a signal is called synthesis [16]. Figure 1 shows the diagrammatic representation of decomposition and reconstruction of a signal.

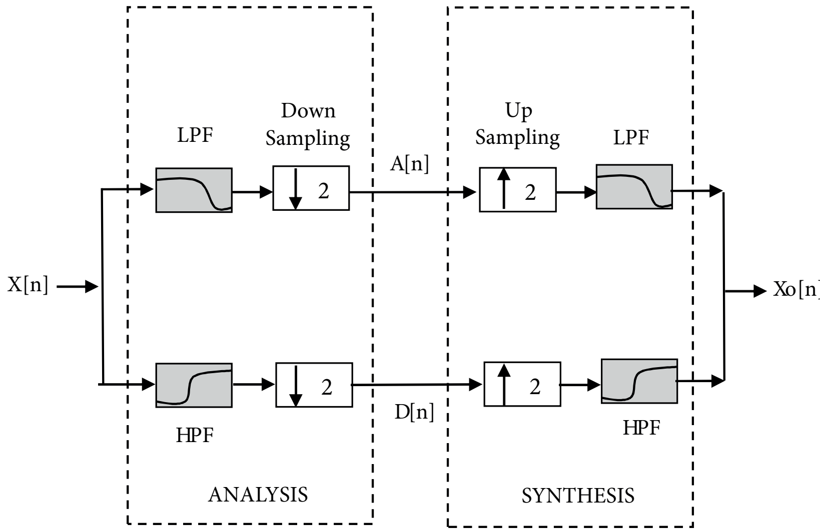

Figure 1. Representation of analysis and synthesis.

2.2.1. Analysis

EEG signal decomposition is carried out by employing multiresolution analysis using complementary low pass (CA) and high pass (CD) filters to obtain progressively finer signal details. Table 2 shows the EEG subband decomposition and corresponding frequency for each subband.

Table 2. EEG subband decomposition and corresponding frequency.

Level of decomposition	CA/CD	LPF/HPF	Frequency band
1st level	CA11	LPF	0–125 Hz: for further level
	CD12	HPF	125–250 Hz: Gamma_3
2nd level	CA21	LPF	0–62.5 Hz: Ignore
	CD22	HPF	125–62.5 Hz: Gamma_2
3rd level	CA31	LPF	0–31.25 Hz: Ignore
	CD32	HPF	31.25–62.5 Hz: Gamma_1
4th level	CA41	LPF	0–15.62 Hz: Ignore
	CD42	HPF	15.62–31.25 Hz: Beta wave
5th level	CA51	LPF	0–7.81 Hz: Ignore
	CD52	HPF	7.81–15.62 Hz: Alpha wave
6th level	CA61	LPF	0–3.90 Hz: Delta wave
	CD62	HPF	3.90–7.81 Hz: Theta wave

DWT is used for the decomposition. It works as a filter to divide the signal into bands at each specific level known as detailed and approximate components [17,18]. The output CD is known as the detailed component and output CA is known as the approximate component. After the 1st level of decomposition HIGH and LOW level components of the EEG signal are obtained. The LOW level component is further decomposed to obtain HIGH and LOW level components. In this paper a 6-level decomposition is explained for 6 different wavelets. The number of decomposition levels depends on sampling frequency of the signal and bandwidth. Six-level EEG signal decomposition is shown in Figure 2.

2.2.2. Synthesis

Reconstruction of a decomposed signal is known as synthesis. It is the reverse of decomposition, and is achieved by inverse discrete wavelet transform (IDWT). IDWT reconstructs the EEG signal from the given coefficients by performing 6 levels of inverse discrete wavelet transform. Figure 3 shows the reconstructed EEG signal.

3. Database collection

The authors have used the web-based freely available EEG database published by Karunya University, Coimbatore, India. The database consists of real EEG signals of normal subjects and focal and generalized epileptic seizures captured from patients of the age group between 1 and 107 years. It is a 16-channel EEG recording with 250 Hz of sampling frequency [19]. The study was carried out by the authors on 63 subjects aged between 1 and 80 years.

4. Results

Decomposition and reconstruction of an EEG signal (normal, focal epilepsy, and generalized epilepsy) using Haar, Symlet, Coiflet, db18, Bior3.7, and Rbio 6.8 is shown below. Six levels of decomposition are carried out to extract all the required EEG subbands. Figures 4–6 show the EEG signal (normal EEG, EEG with focal seizures, and EEG with generalized seizures) decomposition by Haar and other wavelets. Six levels of reconstruction were carried out to compose the original EEG signal from the decomposition levels. Figure 7 and Figure 8 show the reconstruction of an EEG signal.

4.1. Statistical features: MSE, MAE, SER, and PRMSD

Six wavelets were applied to the EEG data for analysis and synthesis. When more than one wavelet is applied to the data, a situation arises where it becomes important to decide which one is the best suited. Risk function or mean square error (MSE) is the property of data that measures the average squared difference between the actual signal and the reconstructed signal. Mean absolute error (MAE) is also a measure to know how much deviation is present in the reconstructed signal from the original signal.

$$MSE = \sum_{n=1}^{n} \left[a\ (n) - b\ (n)\right]^2 / N \tag{3}$$

a (n): original signal

b (n): reconstructed signal

N: no. of samples

$$MAE = \sum n = i^j\ \left| a\,(n) - b\,(n) \right| / \,(j - i) \tag{4}$$

Normal EEGs and epileptic EEGs (focal or generalized) are used to evaluate the performance of a wavelet. Table 3 shows the performance analysis of various wavelets. The calculations of mean square error and mean absolute error are shown for normal and epileptic EEGs. The maximum error between the original EEG and reconstructed EEG using Haar wavelet is 1.2294e-013, while error by using Bior3.7 wavelet is 1.5101e-013. It shows that the maximum error introduced during reconstruction by both wavelets is almost the same, which is lower than the rest of the wavelets studied in this paper. The error, MSE, and MAE for various wavelets are shown in Table 3.

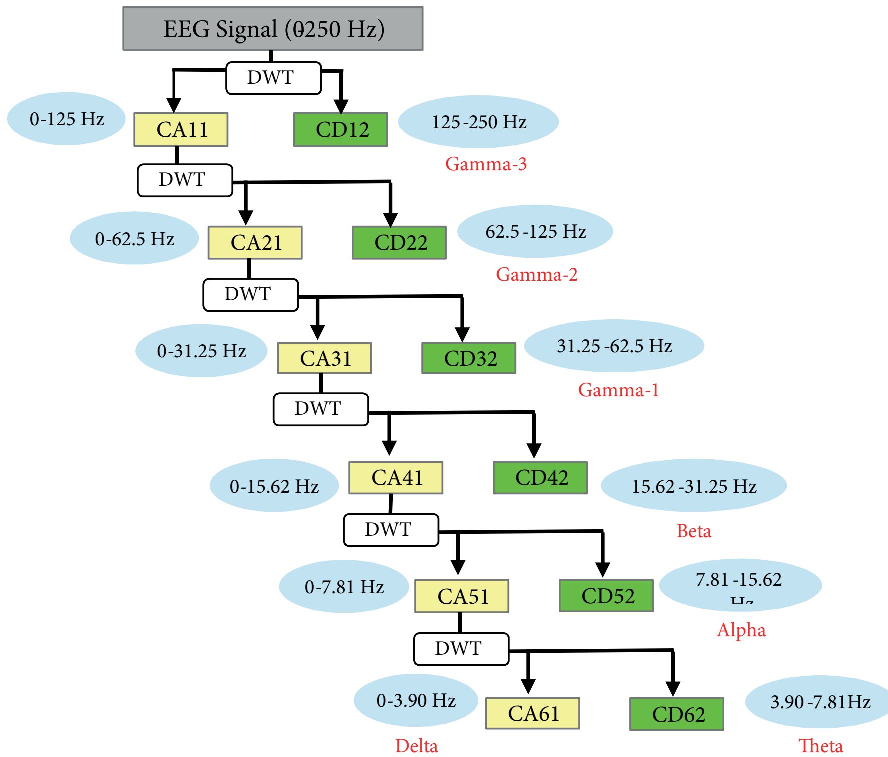

Figure 2. Six-level EEG signal decomposition.

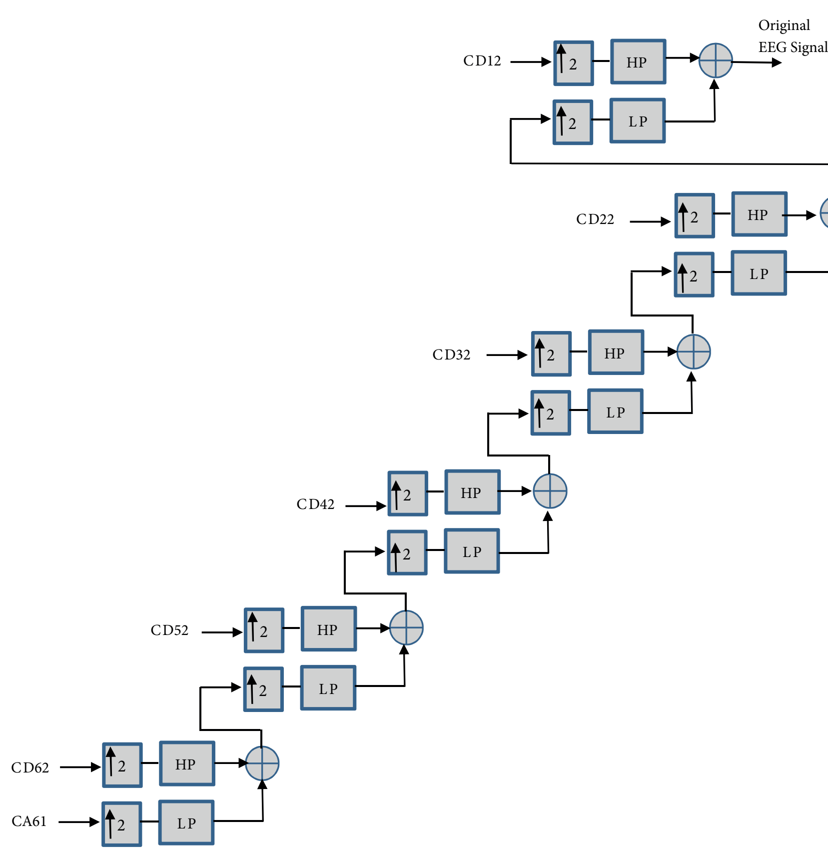

Figure 3. EEG signal reconstruction.

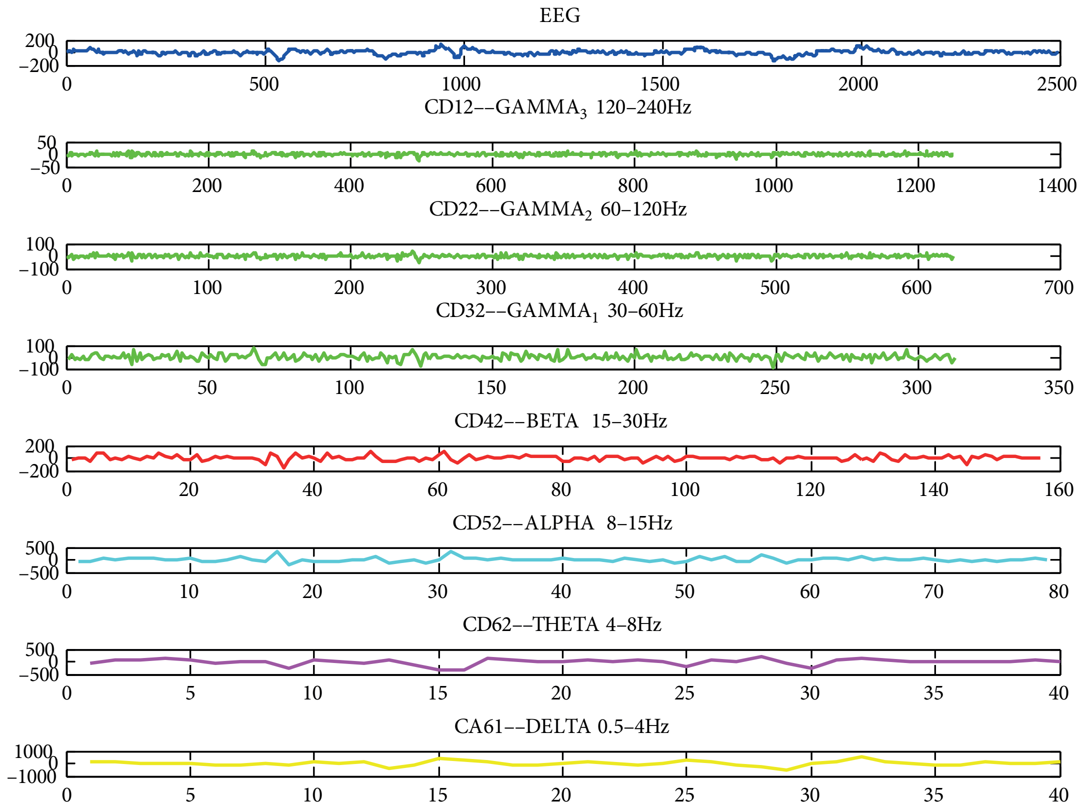

Figure 4. Decomposition of a normal EEG signal using Haar wavelet.

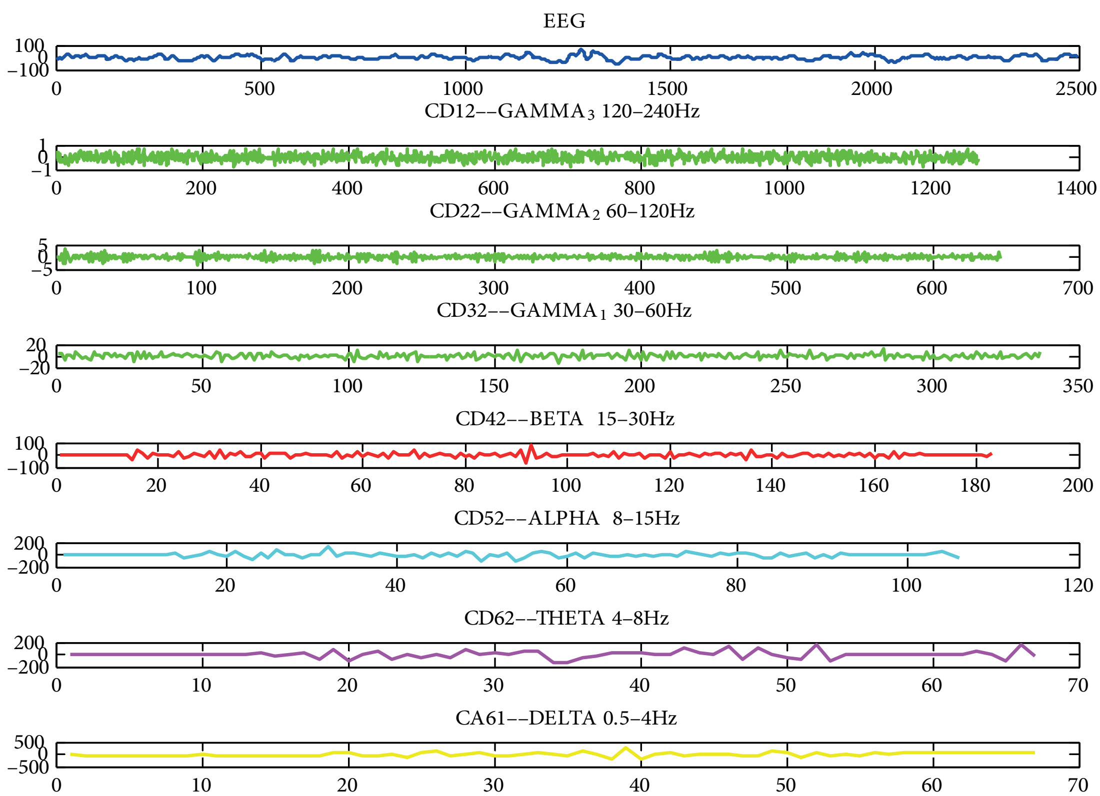

Figure 5. Decomposition of an EEG signal with focal seizures using Coiflet5 wavelet.

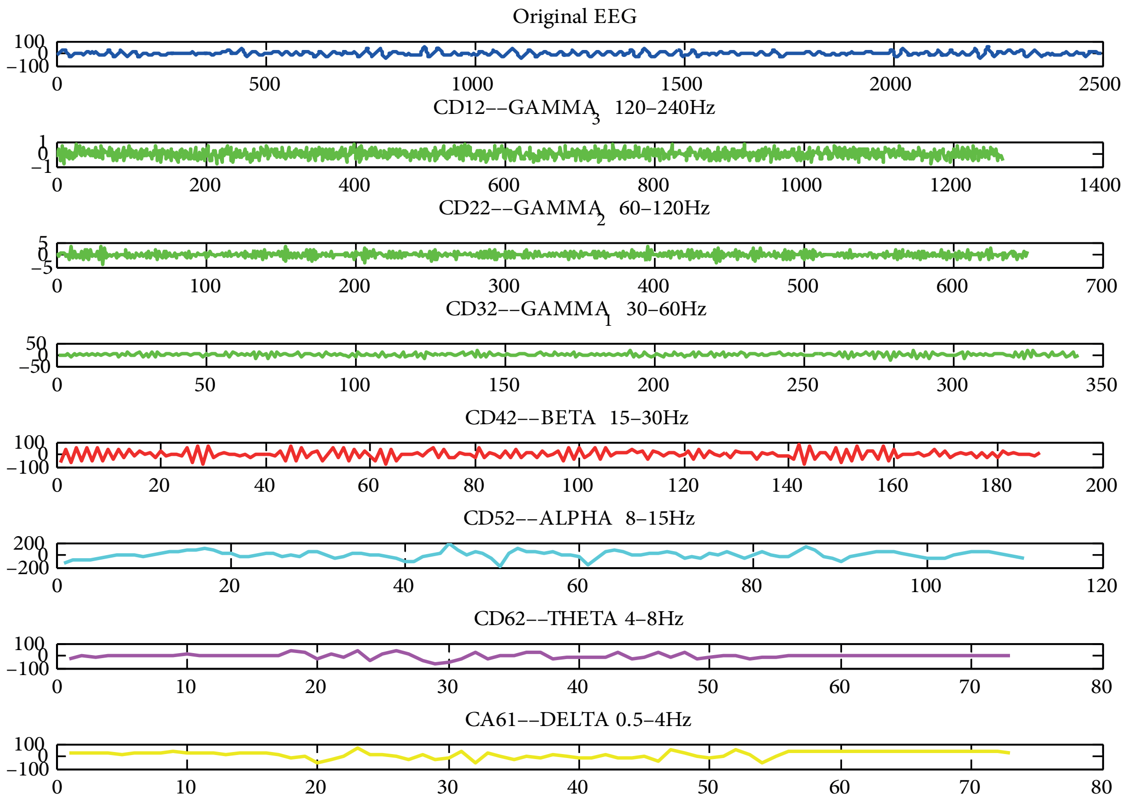

Figure 6. Decomposition of an EEG signal with generalized seizures using Symlet18 wavelet.

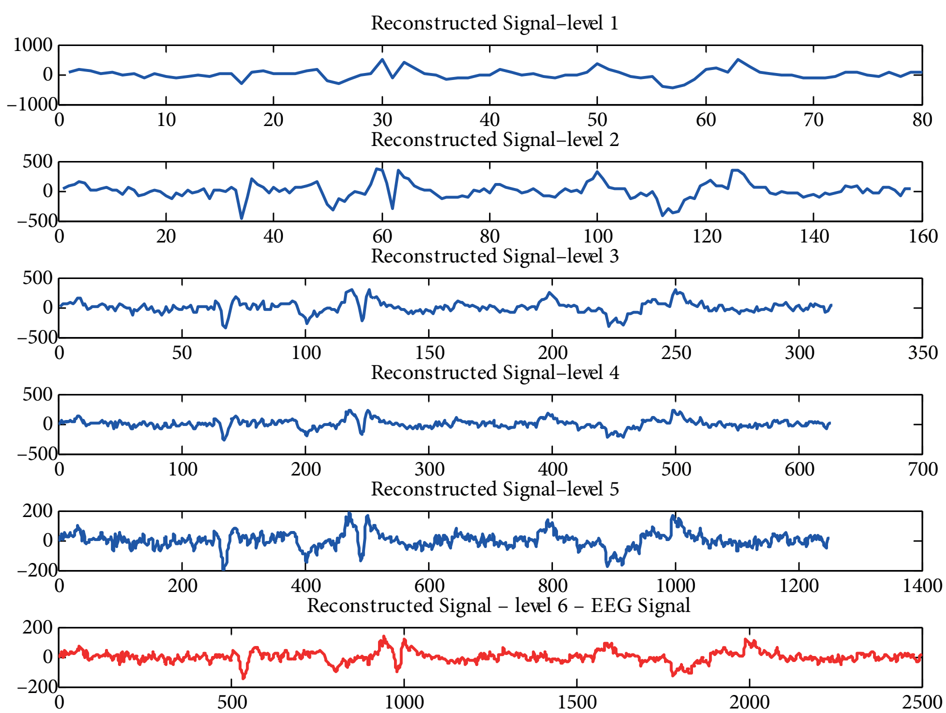

Figure 7. Normal EEG signal reconstruction using Haar wavelet.

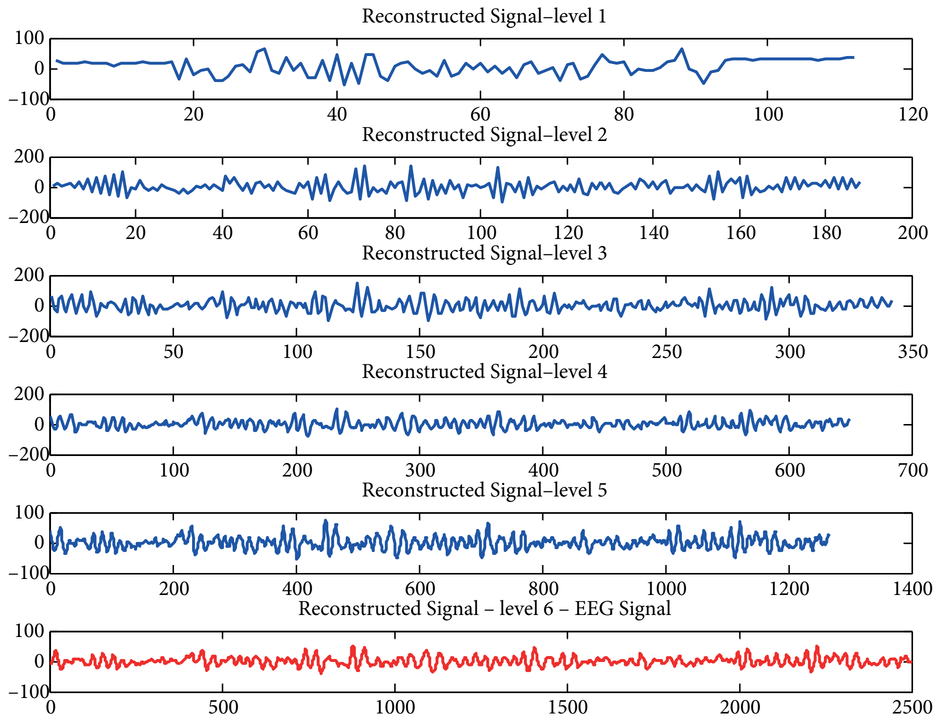

Figure 8. Reconstruction of an EEG signal with generalized seizures using Symlet18 wavelet.

Table 3. MSE and MAE of EEG signals for various wavelets.

EEG Type	Wavelet	MSE (μV^2)	MAE (μV)
Normal EEG	Haar	2.4571e-029	3.0360e-015
	db18	8.8805e-021	7.5233e-011
	Symlet18	3.9468e-019	5.0506e-010
	Coif5	2.6378e-016	1.2907e-008
	Bior3.7	1.2045e-028	6.9175e-015
	rBio6.8	2.4512e-024	1.2484e-012
Focal epileptic EEG	Haar	6.2740e-030	1.6898e-015
	db18	4.8132e-023	5.4889e-012
	Symlet18	3.9532e-022	1.5620e-011
	Coif5	1.6111e-017	3.1912e-009
	Bior3.7	1.1062e-029	2.0429e-015
	rBio6.8	7.0952e-026	2.0956e-013
Generalized epileptic EEG	Haar	6.0507e-030	1.6566e-015
	db18	1.9171e-022	1.0905e-011
	Symlet18	1.1972e-021	2.7176e-011
	Coif5	4.0830e-017	5.0639e-009
	Bior3.7	9.1290e-030	1.9568e-015
	rBio6.8	1.9558e-025	3.4709e-013

Signal-to-error ratio (SER) is estimated as the power of the original signal divided by the power of the error signal and then it is converted into dB by applying a logarithmic scale. Percent root mean square difference (PRMSD) without considering the mean is estimated for normal and epileptic EEGs using 6 wavelets. It is one of the most commonly used distortion measures. PRMSD can also be calculated by considering the mean value of the signal. Reconstruction fidelity by pointwise comparison of original data and the reconstructed data is given by the PRMSD. Numerical measure of the residual root mean square error (RMS) is provided by the PRMSD.

$$SER = 10log_{10}\left(EEG_{signal}/ERROR_{signal}\right)^2 \tag{5}$$

EEG_{signal}: Root mean square amplitude of original EEG signal.

$ERROR_{signal}$: Root mean square amplitude of error signal.

$$PRMSD = \sqrt{\frac{\sum_{n=1}^{N}\left[a\left(n\right)-b(n)\right]^2}{\sum_{n=1}^{N}\left[a(n)\right]^2}} \times 100 \tag{6}$$

SER and PRMSD by 6 wavelets is shown in Table 4. MSE, MAE, SER, and PRMSD for each level of EEG reconstruction using Haar wavelet and Bior3.7 wavelet are shown in Table 5 and Table 6 respectively. Good SER is achieved using Haar and Bior3.7 wavelets, and PRMSD is also lower for these two wavelets.

Table 4. SER and PRMSD of EEG signals using various wavelets.

EEG Type	Wavelet	SER (dB)	PRMSD
Normal EEG	Haar	314.7563	1.8289e-014
	db18	242.3277	7.6492e-011
	Symlet18	233.8044	2.0407e-010
	Coif5	190.8965	2.8522e-008
	Bior3.7	313.6632	2.0742e-014
	rBio6.8	270.9358	2.8393e-012
Focal epileptic EEG	Haar	315.5031	1.6782e-014
	db18	246.5277	4.7165e-011
	Symlet18	237.3258	1.3605e-010
	Coif5	191.4642	2.6717e-008
	Bior3.7	313.1457	2.2015e-014
	rBio6.8	274.9361	1.7914e-012
Generalized epileptic EEG	Haar	315.2575	1.7263e-014
	db18	240.2491	9.7173e-011
	Symlet18	232.2939	2.4283e-010
	Coif5	186.9657	4.4845e-008
	Bior3.7	313.4713	2.1205e-014
	rBio6.8	270.1624	3.1037e-012

5. Discussion

An EEG signal can be categorized into symmetric, orthogonal, nonstationary, and compact [20]. Many advantages of wavelet transform over the other transforms such as Fourier and autoregressive models made us apply the wavelet to an EEG signal for analysis and synthesis [21]. Wavelet transform provides a multiresolution description of a nonstationary EEG signal. At low frequencies it represents good frequency resolution and at high frequencies it gives better time resolution. Selection of the correct mother wavelet plays a very important

Table 5. MSE, MAE, SER, and PRMSD for subbands of EEGs using Haar wavelet.

EEG signal with focal epilepsy				
EEG subbands	MSE (μV^2)	MAE (μV)	SER (dB)	PRMSD
EEG signal 250 Hz	8.8678e-030	2.0021e-015	315.3630	1.7055e-014
64–128 Hz	1.5722e-029	2.5164e-015	315.8465	1.6125e-014
32–64 Hz	3.1111e-029	3.6472e-015	315.7569	1.6299e-014
16–32 Hz	5.8405e-029	5.0382e-015	315.5090	1.6771e-014
8–16 Hz	5.1260e-029	4.7209e-015	316.9843	1.4309e-014
0–8 Hz	8.6847e-029	6.7963e-015	314.5719	1.8681e-014
EEG signal with generalized epilepsy				
EEG subbands	MSE (μV^2)	MAE (μV)	SER (dB)	PRMSD
EEG signal 250 Hz	1.2929e-030	8.2916e-016	314.7764	1.8246e-014
64–128 Hz	2.4209e-030	1.0325e-015	314.9730	1.7831e-014
32–64 Hz	3.8787e-030	1.3474e-015	315.6312	1.6536e-014
16–32 Hz	6.4807e-030	1.7725e-015	315.3259	1.7128e-014
8–16 Hz	6.7606e-030	1.6491e-015	315.1442	1.7494e-014
0–8 Hz	2.5182e-030	1.0540e-015	314.0301	1.9884e-014
Normal EEG signal				
EEG subbands	MSE (μV^2)	MAE (μV)	SER (dB)	PRMSD
EEG signal 250 Hz	1.0579e-028	4.8218e-015	315.6833	1.6437e-014
64–128 Hz	1.8285e-028	6.3807e-015	316.2935	1.5316e-014
32–64 Hz	4.2896e-028	9.2733e-015	315.5289	1.6732e-014
16–32 Hz	7.3487e-028	1.3686e-014	315.9641	1.5914e-014
8–16 Hz	2.1723e-027	1.9178e-014	313.3515	2.1499e-014
0–8 Hz	4.2945e-027	3.0153e-014	313.0514	2.2255e-014

Table 6. MSE, MAE, SER, and PRMSD for subbands of EEG using Bior3.7 wavelet.

EEG signal with focal epilepsy				
EEG subbands	MSE (μV^2)	MAE (μV)	SER (dB)	PRMSD
EEG signal 250 Hz	1.3369e-029	2.2645e-015	313.5802	2.0941e-014
64–128 Hz	2.6094e-029	3.3785e-015	313.7972	2.0424e-014
32–64 Hz	7.7740e-029	5.8480e-015	312.5531	2.3569e-014
16–32 Hz	2.6728e-028	1.1050e-014	311.7838	2.5752e-014
8–16 Hz	7.2196e-028	1.6606e-014	312.3462	2.4137e-014
0–8 Hz	4.9710e-028	1.4351e-014	312.9830	2.2431e-014
EEG signal with generalized epilepsy				
EEG subbands	MSE (μV^2)	MAE (μV)	SER (dB)	PRMSD
EEG signal 250 Hz	1.8331e-030	8.9285e-016	313.2601	2.1727e-014
64–128 Hz	3.6012e-030	1.2898e-015	313.5803	2.0940e-014
32–64 Hz	1.1370e-029	2.3142e-015	312.4807	2.3767e-014
16–32 Hz	3.3370e-029	4.2886e-015	312.4783	2.3773e-014
8–16 Hz	6.5750e-029	5.3862e-015	312.4098	2.3961e-014
0–8 Hz	9.5534e-030	2.2806e-015	312.9774	2.2446e-014
Normal EEG signal				
EEG subbands	MSE (μV^2)	MAE (μV)	SER (dB)	PRMSD
EEG signal 250 Hz	1.4019e-028	5.6864e-015	314.4605	1.8922e-014
64–128 Hz	2.1632e-028	7.5470e-015	315.6355	1.6528e-014
32–64 Hz	8.1694e-028	1.4575e-014	313.1093	2.2107e-014
16–32 Hz	1.0803e-027	2.0905e-014	315.3927	1.6997e-014
8–16 Hz	2.7908e-027	2.8785e-014	315.8641	1.6099e-014
0–8 Hz	1.4737e-026	4.9627e-014	311.5963	2.6314e-014

and crucial role [22]. Six wavelets were selected based on various properties such as symmetry, near symmetry, orthogonality, biorthogonality, and possibility of CWT/DWT. The importance of maintaining the similarity between the biosignal and the mother wavelet is verified as the work is carried out. Daubechies is a modified Haar wavelet, which is highly asymmetric. The Symlet and Coiflet family is also designed by the Daubechies to be a symmetrical wavelet with compact support. Bior and Rbio are symmetric wavelets with very compact support [23]. The nature of the Haar wavelet resembles a step function, which does not match with the nature of EEG signals, while the nature of Bior3.7 matches the EEG signal's nature. Mean and standard deviation in the performance parameters like MSE, MAE, PRMSD, and SER are shown in Table 7.

Table 7. Mean and standard deviation in MSE, MAE, PRMSD, and SER for 3 categories of EEG.

Mean ± standard deviation using Haar wavelet				
EEG type	MSE (μV^2)	MAE (μV)	SER (dB)	PRMSD
Normal	4.636e-028 ± 1.1e-028	7.79e-15 ± 3.854-015	315.6 ± 0.4081	8.43e-014 ± 2.44e-13
Focal epilepsy	2.427e-030 ± 2.31e-030	9.47e-30 ± 4.28e-030	315 ± 0.2459	1.77e-014 ± 4.98e-16
Generalized epilepsy	2.837e-030 ± 2.77e-030	1.06e-15 ± 4.61e-016	315.2 ± 0.2802	1.75e-014 ± 5.69e-16
Mean ± standard deviation using Bior3.7 wavelet				
EEG type	MSE (μV^2)	MAE (μV)	SER (dB)	PRMSD
Normal	8.89e-028 ± 1.2e-027	9.66e-15 ± 5.05e-015	313.2 ± 0.8516	2.21e-014 ± 2.17e-15
Focal epilepsy	3.467e-030 ± 3.58e-030	1.05e-15 ± 4.95e-016	313.2 ± 0.2695	2.19e-014 ± 6.84e-16
Generalized epilepsy	4.57e-030 ± 4.718e030	1.21e-15 ± 5.77e-016	313.1 ± 0.3599	2.19e-14 ± 7.99e-16

6. Conclusion

To check the suitability of various mother wavelets based on statistical properties, they were applied to a total of 63 normal and epileptic real EEG signals for analysis and synthesis. The EEG signal contains sharp spikes, and db and Haar wavelets cannot completely reveal the characteristics of impulsive components. The result shows that Haar and Bior3.7 wavelets show better reconstruction of an EEG signal (normal as well as diseased) as compared to any other wavelet. This shows that near symmetric or symmetric wavelets are more suitable for EEG signal analysis. Statistical features like MSE and MAE improvements or SER and PRMSD are measured and compared during analysis and synthesis of normal EEGs and EEGs with generalized and focal seizures. Better results of analysis and synthesis for normal and diseased EEGs were obtained using Haar and Bior3.7 wavelets. This shows that the similarity between the nature of the mother wavelet and the biosignal should not always be the only important criterion for signal processing, but that optimization of various statistical parameters and the knowledge about the features need to be studied, and will help the user in selecting the suitable wavelet. It is always recommended to check the suitability of more than one wavelet for the given data. Other statistical features like PSD and SNR can also be applied to subbands of EEG signals to classify normal and epileptic EEGs.

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