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Qualitative Analysis of Brain and Heart Signals using DWT

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Abstract: ***Bio-signal processing is a widely carried out by the researchers for better understating of complex biological processes. Instead of studying complete biosignal; a decomposed biosignals gives better and more accurate information about the various dynamics involved in the process. Wavelet is one of the powerful transform which is applicable to time and frequency domain. While dealing with various types of physiological signals it is a tedious task to choose the correct or accurate wavelet for the given biosignal analysis. Electrical brain and heart signal along with peripheral pressure signal for 120 subjects is studied by the authors. Authors have checked various quality metrics decide suitability of various Wavelets for EEG, ECG, PP and PPG signal decomposition and reconstruction. The methodology was applied to normal as well as diseased subjects. Our results based on performance parameters like Mean Square Error, Mean Approximate Error, Signal to Error Ratio, PRMSD shows that orthogonal and biorthogonal wavelets are more suitable for bio-signal decomposition and reconstruction. This shows that selection of wavelet should not always be based on similarity between the mother wavelet and the nature of bio-signal.***

Key Words: ***Decomposition, Reconstruction, Electroencephalogram, Pressure Pulse, Electrocardiogram, Photoplethysmogram, Wavelet, Performance Parameters.***

I. INTRODUCTION

Health monitoring during daily life is the field with fast growing interest for researchers all over the world, which leads to various phyiological/biological signal measurements like photoplethysmogram (PPG), pressure pulse (PP), electrocardiogram (ECG). PP and PPG are the biological signals captured at the peripheral site.

PP signal is mechanical in nature where as PPG is an optical signal. These two signals are generated because of change in blood volume with every heart beat. In PPG, electro-optical method is used to determine hemodynamic parameters. PPG acquired from different body sites and monitoring is widely used in the healthcare domain as it provides physiological information non-invasively such as cardiac output, oxygen saturation, heart rate, blood pressure (continuous and cuff less) and respiration rate. Electrocardiogram (ECG or EKG) is an electrical heart signal.

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Very commonly used signal in cardiovascular studies. Electroencephalogram (EEG) is the brain signals captured from scalp or forehead. It is electrical brain signal generated because of neuronal activity. EEG is widely studied in epileptic patients. All these biosignals are captured non-invasively for shorter or longer duration depending upon the requirement. Instead of studying complete biosignals, a decomposed signal reveals more information and in an accurate form. So, decomposition and reconstruction of all the above mentioned biosignals is carried out and quality metrics are studied for the same. [1-5]

II. ANALYSIS &SYNTHESIS OF BIOSIGNALS

Study of complete biosignal do not revel all the necessary information of that biosignals. So it is desireable to study any biosignals in various bands (freqency bands). Such kind of study gives us improtant information related to a biosignals at a specific time and frequency.

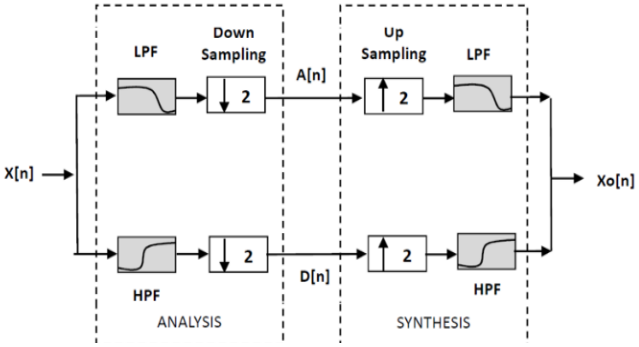


Fig 1: Decomposition & Reconstruction of Biosignal[5]

To carry out such study various transforms are available. In this paper, we are applying WT to divide the biosignals into various components and bring it back to original signal [5,6]. This work was carriedout to check how to decice which wavelet is suitabel from the complete available wavelet bank. Figure 1 shows the block diagram representation of anaysis and synthesis of a signal.

A. Analysis & Synthesis

Biosignals decomposition/analysis is carried out by multi-resolution analysis using complementary high pass (CD) and low pass (CA) filters to get much finer signal details progressively. Discrete wavelet transform (DWT) with various types of wavelets are used for the decompositionanalysis. It is a filter that divide the biosignal into bands at each level known as detailed component and approximate component [7,8].

'Detailed component' is the output obtained in CD and 'Approximate component' is the putput obtained in CA. After each level of decomposition of a biosignal, CA and CD components are obtained. Again CA component is further decomposed to obtain next level CD (High Component) and CA (Low Component) components. In this paper 6 level decomposition is carried out for 5 different types of wavelets. Reconstruction of a decomposed signal is carried out to obtain the original signal again and that is carried out by using 'Inverse Discrete Wavelet Transform' (IDWT). IDWT was applied by the authors for five different wavelets to get the original signal from the previously decomposed biosignal. By modifying the wavelet coffeficients between decompostion and reconstruction. It having a wide application in the area of denoisign and compression of biosignals. Methodology followed by the authors is shown in Figure 2.

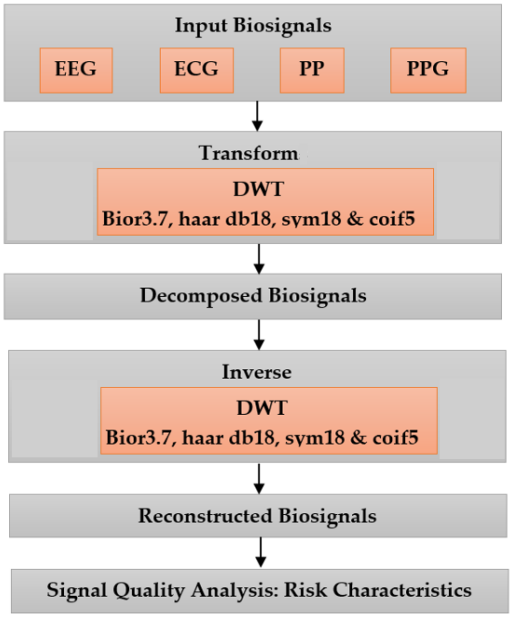


Fig 2: Flowchart of Methodology

III. DISCERTE WAVELET TRANSFORM (DWT)

A.Wavelet Family

Various types of wavelets are studied by the researchers for various biosignals based on various properties of the wavelet, such as orthogonality, biorthogonality, symmetry etc. Haar, Daubechies, Coiflet and Symlet are the orthogonal wavelets which are capable of almost perfect reconstruction of a signal. Bior is a bi-orthogonal wavelet. [9,10] Fourier Transform (FT) is widely used for biosignal feature extraction. But the drawback of FT is, it gives good results for the complete time series of a stationary signal [10-15]. Whereas, WT with variable window size can be applied over a length of a signal. That's why WT is popular among the researchers as a feature extraction technique for non-stationary signals [16,17]. WT is divided into 2 types: 1. Continuous Wavelet Transform (CWT) and 2. Discrete Wavelet Transform (DWT). [18, 19]

B. CWT: Continuous Wavelet Transform

$$X(x,y) = \frac{1}{\sqrt{y}} \int_{-\infty}^{\infty} X(t)\varphi\left(\frac{t-x}{y}\right) dt \qquad (1)$$

Where, 'ψ' is the mother wavelet, 'x' is a time shift and 'y' modulates the width.

C. DWT: Discrete Wavelet Transform

$$\Psi_{(x,y)}(t) = 2^{x/2}\,\psi\,(2^{-x/2}(t-y)) \qquad (2)$$

The DWT means selecting a subset of scales 'x' and positions 'y' of the mother wavelet 'ψ (t)'. [20,21].

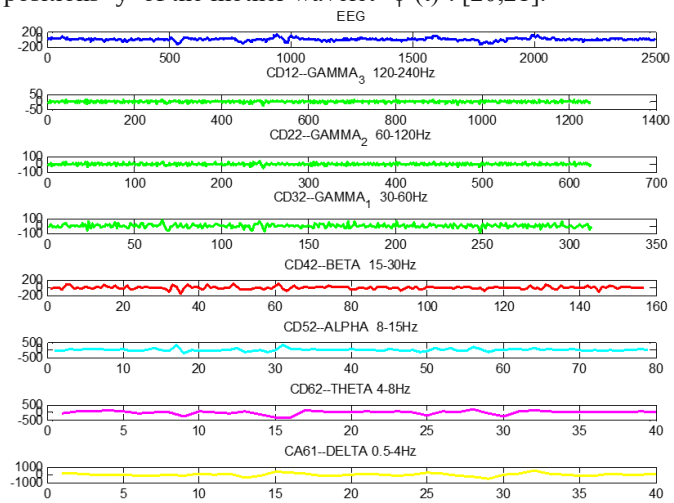


Fig 3: Decomposed of Normal EEG Signal (Haar Wavelet)

Decomposition and reconstruction of biosignals EEG, ECG, PP and PPG was carried out using five wavelets such as haar, db18, sym18, coif5 and bior3.7. Figure 3 shows the normal EEG signal decomposition by haar wavelet and Figure 4 shows the normal EEG signal reconstruction using haar wavelet. By observing the oroginal signal and the reconstructed signals, it is difficult to make out the difference between the two signals by naked eye. So various statistical parameters were applied on original and reconstruced sigal to findout the variations between the two. These varations were interpreted in terms of risk charateristics.

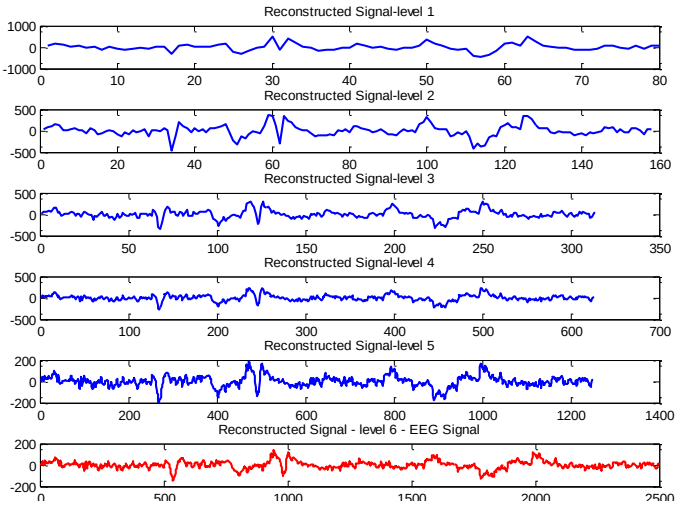


Fig 4: Reconstrcted Normal EEG (Haar Wavelet)

IV. QUALITY METRICS

Five wavelets were applied on the four types of biosignals for analysis/decomposition and synthesis/reconstruction.

It is important to decide which wavelet is best suited when number of varied wavelets are available.

As a quality metric, four risk charactertics are studied to check the suitability of a perticular wavelet in decomposition and reconstruction, based on which the one more accurate transfrom/wavelet can be further used for various applications such as Water Marking or Stegnography. Risk functions MSE and MAE are calculated from the original and reconstructed biosignal.

$$MSE = \sum_{n=1}^{n}[x(n) - y(n)]^2 / N \qquad (3)$$

x(n) is original signal; y(n) is reconstructed signal and N are the number of samples

$$MAE = \sum_{n=i}^{j}|x(n) - y(n)| / (j - i) \qquad (4)$$

Four biosignals (with and without disease) such as EEG, ECG, PP ad PPG are used to evaluate the performance of a three transfroms and five wavelets. SER is estimated as a ratio of power of original signal to the power of error signal. Later on by applyign log scale SER is converted into dB. Percent root mean square error (PRMSD) is the most commonly used distortion measure.

$$SER = 10 \log_{10} (\text{ANY BIOSIGNAL}_{\text{signal}}/\text{ERROR}_{\text{signal}})^2 \qquad (5)$$

$\text{ANY BIOSIGNAL}_{\text{signal}}$: Root mean square amplitude of original BIOSIGNAL

$\text{ERROR}_{\text{signal}}$: Root mean square amplitude of error signal.

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

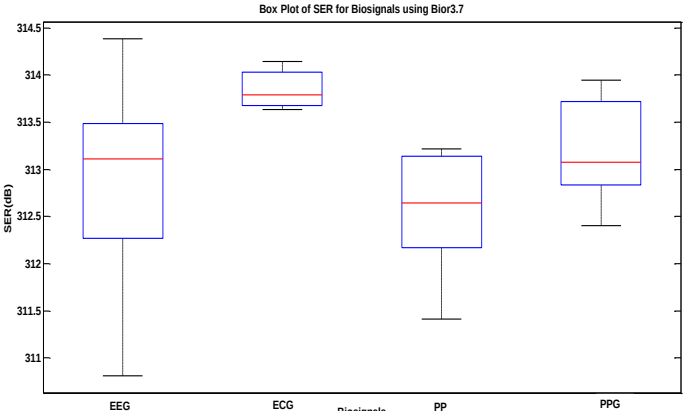
Lot of other risk charateristics from statistical domain are studied by various resesrchers during the last decade. Depending upon the application and accuracy required after the retrival of data, one can choose the number of statiscal parameters needs to be studied.

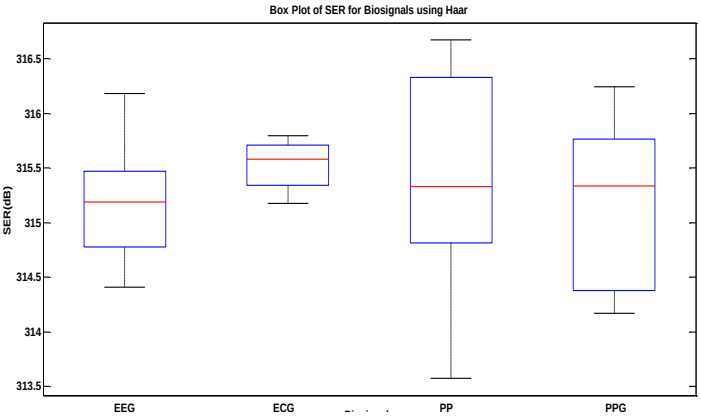
V. DETAILS OF DATABASE

Authors have used web based freely available ECG database published by Massachusetts Institute of Technology (Cambridge, MA, USA) and Boston's Beth Israel Hospital developed the MIT-BIH Arrhythmia Database of 30 subjects [29]. Database used for EEG signals is published by Karunya University, Coimbatore, India. Database consists real EEG signals of normal, focal and generalised epileptic seizures captured from patients of age group between 1 - 107 year[30]. PP and PPG database was collected at Cummins College of Engineering for Women by using PowerLab. ADInstruments had developed PowerLab hardware and when it is combined with ADInstruments software a multichannel real time acquisition with variable sampling rate and analysis of various bio signals can be carried out. MLE1010 is the piezo electric pulse transducer used to record the changes in the peripheral pressure pulse by converting from the finger BP into an electrical signal like voltage. For PPG acquisition, optical sensor developed by the authors is used. It uses IR LED with wavelength of 860 nm as a source and silicon bury brown diode in OPT 101 as a detector. Database of total 120 subjects aged between 1-89 years was studied by the authors.

VI. RESULTANALYSIS

Statistical parameters like MSE, MAE, SER and PRMSD were calculated using wavelets like haar, db18, coif5, sym18, bior3.7. SER was calculated from reconstructed and decomposed 1D signal. Figure 5, Figure 5 shows the boxplot of SER obtained for EEG, ECG, PP, PPG by using DWT. Table 1, 2, 3 and 4 shows risk chatracteristics in the form of MSE, MAE, SER and PRMSD for variouswavelets applied to EEG, ECG, PP and PPG signals respectively. Maximum error between the original EEG and reconstructed EEG by using coiflet wavelet is 6.00E-14 ± 5.43E-14. For ECG signal it is 1.44E-11 ± 2.79E-11 by using coiflet. For PP signal it is 4.61E-12 ± 4.22E-12 using coiflet and for PPG signal it is 3.79E-15 ± 4.65E-15 using coiflet. Good SER is achieved for all the biosignals by using haar wavelet and bior3.7 wavelet. PRMSD is also lower for all the biosignals when decomposition and analysis was carriedout by using haar and bior3.7 wavelets. It can be seen from the box plots shown below that SER for all the biosignals is better when decompostion and recostruction was carried out by haar and bior wavelet, whereas it was worst for coiflet wavelet.





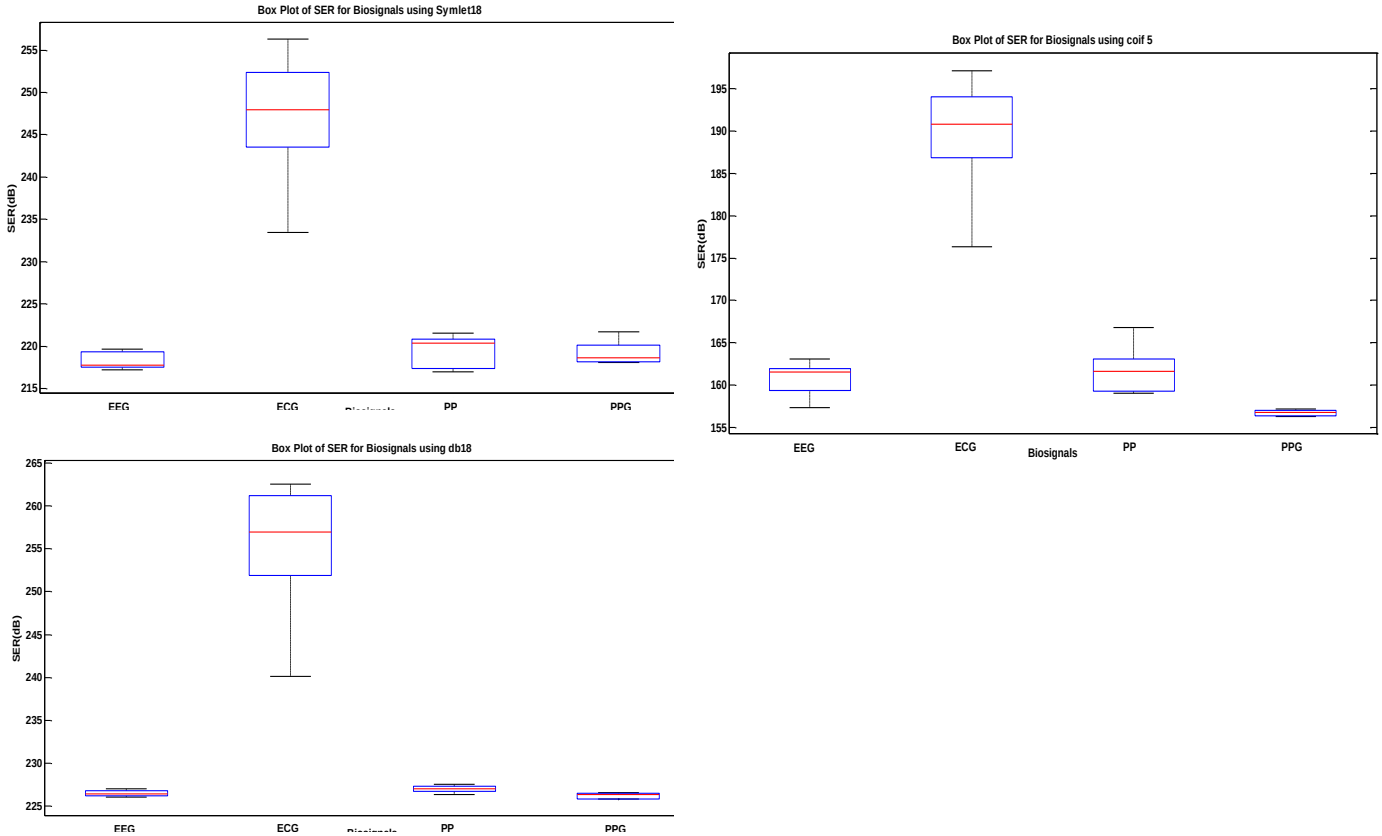


Fig 5: Boxplot of SER for EEG, ECG, PP & PPG signal using DWT (bior3.7, haar, sym18, db18 and coif18)

Table 1: Risk Characteristics for EEG Signal using DWT

FOR EEG SIGNAL: Mean ± Standard Deviation				
WT	MSE	MAE	SER	PRMSD
bior 3.7	7.13E-29 ± 4.50E-29	5.99E-15 ± 1.95E-15	312.84 ± 1.2983	2.30E-14 ± 3.57E-15
haar	2.34E-29 ± 6.61E-30	2.77E-15 ± 1.81E-15	315.18 ± 0.6487	1.75E-14 ± 1.28E-15
sym18	7.57E-20 ± 6.31E-20	1.84E-10 ± 7.35E-11	218.31 ± 1.0716	1.22E-09 ± 1.47E-10
db18	1.26E-20 ± 1.15E-20	8.02E-11 ± 3.22E-11	226.47 ± 0.3962	4.75E-10 ± 2.15E-11
coif5	6.00E-14 ± 5.43E-14	1.80E-07 ± 9.12E-08	160.71 ± 2.1659	9.45E-07 ± 2.52E-07

Table 2: Risk Characteristics for ECG Signal using DWT

FOR ECG SIGNAL: Mean ± Standard Deviation				
WT	MSE	MAE	SER	PRMSD
bior 3.7	7.97E-26 ± 7.53E-27	2.40E-13 ± 1.25E-14	313.84 ± 0.2148	2.03E-14 ± 4.99E-16
haar	1.09E-25 ± 1.29E-26	2.71E-13 ± 1.36E-14	315.52 ± 0.2444	1.67E-14 ± 4.73E-16
sym18	2.82E-17 ± 5.48E-17	2.54E-09 ± 3.21E-09	247.14 ± 8.483	6.82E-11 ± 8.15E-11
db18	5.66E-18 ± 1.16E-17	1.25E-09 ± 1.63E-09	255.24 ± 8.8782	2.91E-11 ± 3.89E-11
coif5	1.44E-11 ± 2.79E-11	2.19E-06 ± 2.60E-06	189.53 ± 7.8694	4.96E-08 ± 5.81E-08

Table 3: Risk Characteristics for PP Signal using DWT

FOR PP SIGNAL: Mean ± Standard Deviation				
WT	MSE	MAE	SER	PRMSD
bior 3.7	7.14E-27 ± 4.27E-27	5.58E-14 ± 2.15E-14	312.56 ± 0.7211	2.36E-14 ± 2.01E-15
haar	8.53E-28 ± 4.59E-28	1.76E-14 ± 6.47E-15	315.40 ± 1.1880	1.71E-14 ± 2.42E-15
sym18	8.38E-18 ± 5.65E-18	1.99E-09 ± 7.83E-10	219.42 ± 2.0049	1.09E-09 ± 2.56E-10
db18	1.04E-18 ± 6.74E-19	7.53E-10 ± 3.19E-10	226.99 ± 0.4444	4.47E-10 ± 2.29E-11
coif5	4.61E-12 ± 4.22E-12	1.62E-06 ± 7.7E-07	161.72 ± 3.1150	8.59E-07 ± 2.64E-07

Table 4: Risk Characteristics for PPG Signal using DWT

FOR PPG SIGNAL: Mean ± Standard Deviation				
WT	MSE	MAE	SER	PRMSD
bior 3.7	1.25E-31 ± 1.09E-31	1.98E-16 ± 1.20E-16	313.20 ± 0.6047	2.19E-14 ± 1.52E-15
haar	2.36E-31 ± 2.16E-31	2.57E-16 ± 1.71E-16	315.16 ± 0.8506	1.75E-14 ± 1.71E-15
sym18	9.49E-22 ± 7.66E-22	1.79E-11 ± 1.05E-11	219.25 ± 1.4776	1.10E-09 ± 1.73E-10
db18	3.99E-22 ± 4.47E-22	1.29E-11 ± 9.38E-12	226.20 ± 0.3629	4.90E-10 ± 2.05E-11
coif5	3.79E-15 ± 4.65E-15	4.33E-08 ± 3.23E-08	156.69 ± 0.3750	1.46E-06 ± 6.32E-08

Table 5: Risk Characteristics for Noisy PPG Signal using DWT

FOR NOISY PPG SIGNAL: Mean ± Standard Deviation				
WT	MSE	MAE	SER	PRMSD
bior 3.7	1.16E-30 ± 5.39E-31	6.97E-16 ± 2.50E-16	312.80 ± 0.6525	2.30E-14 ± 1.66E-15
haar	2.62E-31 ± 8.74E-32	2.82E-16 ± 6.21E-17	315.67 ± 0.3454	1.64E-14 ± 6.39E-16
sym18	2.46E-21 ± 1.22E-21	3.50E-11 ± 1.48E-11	215.47 ± 5.6383	1.69E-09 ± 6.09E-10
db18	2.03E-22 ± 5.17E-23	9.14E-12 ± 1.03E-12	226.34 ± 0.9148	4.83E-10 ± 5.53E-11
coif5	2.24E-15 ± 1.17E-15	3.92E-08 ± 1.84E-08	156.05 ± 9.47	1.58E-06 ± 6.94E-07

VII. CONCLUSION

Various mother wavelets were applied to various biosignals such as EEG, ECG, PP and PPG collected from 120 normal and diseased subjects to check the suitable mother wavelet for signal analysis and synthesis. Sharp spikes is the peculaity of many biosignals, 'db' and 'Haar' wavelet will not be able to completely revel such sharp spikes.It was observed that Haar and Bior3.7 wavelet shows the better results of synthesis of four types of normal and diseased biosignals. It was observed that for the biosignal analysis symmetric or near symmetric wavelets give better results. MSE, MAE, SER and PRMSD were calculated and compared from original and reconstructed EEG, ECG, PP and PPG. Better results of decomposition /analysis and reconstruction/synthesis were obtained by using Haar, Bior3.7 wavelets. Knowledge of risk charateristics and statistical features can be applied on the decompositon/recosntruction results before slecting any specfic wavelet. PSD, SNR, NRMSE can also be applied to the data as a quality metric. This work will be very useful in the field of water marking and stegnography were data hiding in the decmposed signal and reconstuction and retrival of data plays important role.

REFERENCES

1. Shriram R, Sundhararajan M. Coherence Analysis of Pressure Pulse and Photoplethysmogram at various sites. 2015. International Journal of Applied Engineering Research (IJAER), Vol 10, No 6, pp. 14959-14968.
2. Shriram R, Sundhararajan M, Daimiwal N. Statistical Analysis of Pulse Acquired from various Body sites using Piezoelectric and Optical Transducer. 2015. International Journal of Control Theory and Applications (IJCTA), Serial Publications, Vol 8, No. 3, pp. 831-838.
3. Shriram R, Sundhararajan M, Daimiwal N. Wave Transit Time based Cuffless Continuous Blood Pressure Measurement. Elsevier International Conference on Resent Trends in Engineering Sciences (ICRTES), Nasik, 23rd–24th November 2013, pp. 170-174.
4. Shriram R, Sundhararajan M, Shete S, Daimiwal N. Statistical features based comparison 1 of analysis and synthesis of normal and epileptic electroencephalogram for various wavelets. Turkish Journal of Electrical Engineering and Computer Sciences 2017; 25: 1795-1806.
5. Ting W, Guo-Zheng Y, Bang-Hua Y, Hong S. EEG feature extraction based on wavelet packet decomposition for brain computer interface. Measurement 2008; 41: 618–625.
6. Iqbal M, Zabihi M, Rafsanjani H B, Touyama H. Study of EEG Signals during working memory task using wavelet coefficients. IEEE conference on E-Health and Bioengineering; 24-26 November 2011; Lasi: IEEE. pp. 1-4.
7. Malina T, Folkers A, Hofmann U G. Real-time EEG processing based on Wavelet Transformation. 12th Nordic Baltic Conference on Biomedical Engineering and Medical Physics; June 2002: Reykjavik.
8. Aydemir O, Kayikcioglu T. Wavelet Transform Based Classification of Invasive Brain Computer Interface Data. Radio Eng 2011; 20: 31-38.
9. Rafiee J, Rafiee M A, Prause N, Schoen M P. Wavelet basis functions in biomedical signal processing. Expert Syst Appl2011; 38: 6190–6201.
10. Adeli H, Ghosh-Dastidar S, Dadmehr N. A Wavelet-Chaos Methodology for Analysis of EEGs and EEG Sub-bands to Detect Seizure and Epilepsy. IEEE Bio-Med Eng 2007; 54: 205-211.
11. Shedeed H. A new Method for Person Identification in a Biometric Security System based on Brain EEG Signal Processing. World Congress on Information and Communication Technologies; 11-14 December 2011; Mumbai, India: IEEE. pp. 1205-1210.
12. Sanei S, Chambers J. EEG Signal Processing. 1st ed, Cardiffy, UK: Wiley 2007.
13. Subasi A. EEG signal classification using wavelet feature extraction and a mixture of expert model. Expert Sys Appl 2007; 32: 1084 –1093.
14. Subasi A, Ercelebi E. Classification of EEG signals using neural network and logistic regression. Comp Meth Prog Bio2005; 78: 87-99.
15. Wang D, Miao D, Xie C. Best basis-based wavelet packet entropy feature extraction and hierarchical EEG classification for epileptic detection. Expert Syst Appl 2011; 38: 4314–14320.
16. Chang K, Lo P. Meditation EEG Interpretation Based on Novel Fuzzy-Merging Strategies and Wavelet Features. Biomed Eng-App Bas C 2005; 17: 167-175.
17. Garces Correa A, Leber E. An Automatic Detector of Drowsiness based on Spectral Analysis and Wavelet Decomposition of EEG Records. 32nd Annual International IEEE EMBS Conference; 31 August – 4 September 2010, Buenos Aires, Argentina: IEEE. pp. 1405-1408.
18. Olkkonen H. Discrete Wavelet Transforms - Biomedical Applications. US: InTech, 2011.
19. Shaker M. EEG Waves Classifier using Wavelet Transform and Fourier Transform. INT J Biomed Sci 2006; 1: 85-90.
20. Shaker M. EEG Waves Classifier using Wavelet Transform and Fourier Transform. World Academy of Science, Engineering & Technology, Int J Med Health Pharm Biomed Eng 2007; 1: 169-174.
21. Fracastoro G, Fosson S M, Magli E. Steerable Discrete Cosine Transform. IEEE Transactions on Image Processing, Jan 2017, vol. 26, no. 1, pp 303–314.
22. Haweel R T, El-Kilani W S, Ramadan H H. A Fast Modified Signed Discrete Cosine Transform for Image Compression. 9th International Conference on Computer Engineering Systems (ICCES), Dec 2014, pp 56–61.

23. Chadha A R, Vaidya P P,Roja M M . Face Recognition using Discrete Cosine Transform for Global and Local Features. International Conference on Recent Advancements in Electrical, Electronics and Control Engineering, Dec 2011, pp 502–505.
24. Isa M R M, Aljareh S. Biometric Image protection based on Discrete Cosine Transform Watermarking Technique. International Conference on Engineering and Technology (ICET), Oct 2012, pp 1–5.
25. Yuan-Yuan L, He-Xin C, Yan Z, Hong-Yan S. Discrete Cosine Transform Optimization in Image Compression based on Genetic Algorithm. 8th International Congress on Image and Signal Processing (CISP), Oct 2015, pp 199–203.
26. Kumar S, Muttoo S K. Distortionless Data Hiding based on Slantlet Transform. International Conference on Multimedia Information Networking and Security, Nov 2009, vol. 1, pp 48–52.
27. Mohammed R T, Khoo B E. Image Watermarking using Slantlet Transform. IEEE Symposium on Industrial Electronics and Applications, Sep 2012, pp 281–286.
28. Selesnick I W. The Slantlet Transform. IEEE Transactions on Signal Processing, May 1999, vol. 47, no. 5, pp 1304–1313.
29. Moody G B, Mark R G. The MIT-BIH Arrhythmia Database on CD-ROM and software for use with it. Computers in Cardiology, Sep 1990, pp 185–188.
30. Selvaraj T, Ramsamy B, Jeyaraj S, Suviseshamuthu E. EEG Database of Seizure Disorders for Experts & Application Developers. Clin EEG Neurosci 2014; 45: 304-309.

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