International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-7 Issue-5, January 2019

An overview on Biomedical Signal Analysis

Jagdeep Rahul, Marpe Sora, Lakhan Dev Sharma

Abstract: The signal processing is widely used tool in biomedical field for extracting the information of physiological activities for diagnosis purpose. Aim of this paper is to give an overview on various transforms used for biomedical signal analysis, Fast Fourier Transform (FFT), Laplace Transform (LT), Hilbert Transform, Wavelet Transform (WT) and Hadamard Transform are discussed for ECG and EEG. The finally some advanced algorithms and methods for automatic detection of abnormalities in cardiovascular system and neuroscience have been considered in this study. Wavelet transform gives highest accuracy in feature identification of both ECG and EEG. The variety of transform techniques are explored in this study and found that wavelet transform is very good tool for both stationary (ST) and non-stationary(non-ST) biomedical signal analysis. The CWT and DWT are suitable for ECG and EEG signal analysis respectively

Keywords: Biomedical signals, ECG, EEG, Wavelet Transform, Hilbert Transform, Hadamard Transform.

I. INTRODUCTION

The most of the physiological process generate the signal that reflects their nature and activities. The generated signal could be in any form that includes biochemical activity as of hormones, neurotransmitter and electrical activity as of voltage or current signal, physical activity as of pressure and temperature signals. If there is any alteration in its normal biological process causes change in the normal biological signal, shows disease in biological system, which leads to the pathological process. A pathological process determines the condition of disease by observing the corresponding signal of the system. Biomedical signals are the bioelectric potentials, generated when human system performs the nerve conduction, brain activity, heartbeat, muscle activity and so on. The majority of biomedical signals are divided into two categories such as event related potential and action potential [1]. An action potential signal is an electrical signal and generated by physiological activities at a single cell.

Revised Manuscript Received on 30 January 2019.
***** Correspondence Author

Jagdeep Rahul, Department of Electronics and Communication Engineering, Rajiv Gandhi University,(A.P.) India.

Marpe Sora, Department of Computer Science and Engineering, Rajiv Gandhi University,(A.P.) India.

Lakhan Dev Sharma, Department of Electronics and Communication Engineering, MLV Textile & Engineering College, Bhilwara, (Raj.) India.

Event related potentials are more general and termed as evoked potential. Electroencephalogram (EEG), Electromyogram (EMG), Electroneurogram (ENG) and Electrocardiogram (ECG) are at present action potential signals. The potentials related to event or evoked potentials are phonocardiogram (PCG), electrogastrogram (EGG), vibroarthrogram (VAG), carotid pulse (CP), Speech signal, vibromyogram (VMG), signals from the catheter-tip sensors and oto-acoustic emission signal [2].

1.1 Action potential related biomedical signals

The ENG is recorded for study of nerve conduction velocity. It is an electrical signal and used to measure the velocity of propagation of a stimulus (action potential) in a nerve. Any deceasing in the velocity of conduction in nerve may cause neural disease [3]. The EMG is associated with the action potential generated by the skeletal muscle fiber, neuron fiber when excited by motor neuron. The mechanical output of a muscles produced by simulation and contraction activity of several of its motor units. The measurement of these potentials can be done at the surface of the body or directly from the muscle of interest. The EMG signal is the summation of individual action potential of all fibers constituting the muscle not a single fiber [4]. The ECG is an electrical representation of contractile behavior of the heart, which can be recorded by using the surface electrode and leads on the chest and limbs. The ECG generates the P wave, QRS complex and T wave, which reflects the rhythm of electrical depolarization and repolarization of the myocardium (Outer Layer of heart), connected with the activity of the atrium and ventricles. The ECG is most commonly known and recognized biomedical signal [5, 6, 7]. The EEG is the recorded manifestation of bioelectric potentials generated by the electrical activity of the brain. The EEG pattern is very complex, difficult to recognize as compare to the ECG. The EEG potential represents a summation of all action potentials of neurons in the brain. The EEG measurements are acquired from the electrode placed on the surface of the scalp. The EEG waveform varies with the location of electrode on the scalp surface. The EEG wave is popularly known as brain wave. The EEG signals are used to study the nervous system, monitoring of sleep, biofeedback and control, and diagnosis of disease like epilepsy, Alzheimer [8, 9]. Biomedical signal processing techniques[27,28] includes several methods namely signal acquisition done by sensors, removal of artifacts using various filters, detection of events and waves, feature extraction, pattern classification and diagnosis, which determine the status of health using normal and abnormal signal samples. Aim of this review is to give the attention towards the various biomedical signals, those are very important in medical field for identification and diagnosis of various diseases.

II. METHODOLOGY

The basic transform techniques and algorithms mostly used in the field of cardiology and neuroscience for biomedical signal processing are described in this section. The transform techniques such as Fast Fourier transform, Discrete Wavelet transform, Hilbert transform, Laplace transform and Hadamard transform.

2.1 Outline of transform techniques for biomedical signal analysis

2.1.1 ECG signal analysis using transform based techniques

The Fast Fourier transform is well known method, which is used for converting time domain signal in to frequency domain to obtain frequency coefficients. The FFT is used to identifying QRS complex peak (R) in ECG signal and further arrhythmia classification was done by using neural network [10]

$$X_k = \sum_{n=0}^{N-1} xne^{\frac{-2\pi i}{N}nk} \quad \text{Where } k = 0,\dots, N\text{-}1 \qquad (1)$$

The wavelet transform allows the user to analyze the data in two dimensions, time and frequency domain simultaneously. The wavelet transform provide the different scale with different resolutions of ECG signal in both frequency and time representation. The discrete wavelet transform (DWT) is used for detection of QRS complex and arrhythmia [11]. This transform is use to detect heart rate with better accuracy as compare with the other transform techniques. The arrhythmia, disorder and other abnormalities of heart can be detected on the basis of ECG morphology [12]. The wavelet transform equation for signal *x(t)* is defined by eq. (2)[11]:

$$W_a x(b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\Psi\left(\frac{t-b}{a}\right) dt \qquad (2)$$

Where ɑ is the scaling, b= translation parameter.

The DWT is widely used transform technique on ECG signal, due to its good time and frequency localization ability. The DWT gives good frequency resolution at low frequency range and also good time resolution at high frequency range. The DWT allows decomposition of signal into different scale due to its multi-scale features [13].

DWT is expressed by eq. (3) [14].

$$W(j,k) = \sum_j \sum_k x(k) e^{\frac{-j}{2}} \Psi(2^{-j}\, n - k) \qquad (3)$$

Where Ψ(t) represents the mother wavelet.

The electrical axis of heart is shifted due to changes in body position causes false ischemia alarm. The body position change (BPC) detector using laplacian noise model is used to differentiate the body position change (BPC) and ischemia event [15]. The BPC using Karhunen-Loève transform (KLT) and coefficient pattern in their KTL domain are able extract the both ST segment and QRS complex features. The BPC detector tested for fixed data set and found that probability of detection (Pd) is increased by 12% without compromising with the probability of failure (Pf). In KLT domain based laplacian noise model produces better noise characteristics than Gaussian noise model. Furthermore performance achieved by this model also superior to the Gaussian noise model both in respect to false alarm rate and sensitivity. The BPC detector significantly improves the detection accuracy of ischemia event in ECG signal [16].

The first Hilbert transform for ECG signal analysis was described by Bolton and Westphal [17]. One of the suitable combinations of Hilbert transform with moving average filter is used for R- peak detection of ECG signal. The noises like muscular noise, motion artifacts and electrode contact noise, presented in the signal were removed by band pass chebyshev filter for the bandwidth of [6-18] Hz[18]. The Hilbert transform is expressed in equation (4) [18]:

$$\hat{x}(t) = H[x(t)] = \frac{1}{\pi}\int_{-\infty}^{\infty} x(t)\frac{1}{t-\tau}\, d\tau \qquad (4)$$

Where $x(\tau)$ represents time function

Hilbert transform works as a linear filter with the properties of an odd function. It does not change the spectral component of amplitude but changes the phase value. The Hilbert transform with moving average filter significantly increases the detection accuracy with low amplitude of QRS complex of ECG signal [18].The fast conjugate symmetric sequence ordered complex Hadamard transform (CS-SCHT) is used to detect the atrial fibrillation (AF) in ECG signal [19]. The proposed algorithm was used to calculate the CS-SCHT using sparse- matrix factorization method is expressed using given below matrix equation.

$$H_M = \begin{bmatrix} H_{M/2} & H_{M/2} \\ H_{M/2}S_{M/2} & -H_{M/2}S_{M/2} \end{bmatrix} . P_m$$

Where $M = 2^m$ and P_m is the permutation matrix

$$S_{2^{m-1}} = \begin{bmatrix} I_{2^{m-2}} & 0 \\ 0 & jI_{2^{m-2}} \end{bmatrix}$$

Where I^{m-2} is an identity matrix of order $2^{m-2} \times 2^{m-2}$

For real time application and fast computation, CS-SCHT can be used. It could also be applied for both real and complex value signal. The CS-SCHT is having advantages over conventional Hadamard transform are less memory requirement and low computational complexity of an order $\log_2$ (M) for M data sample [19].

2.1.2 EEG signal analysis using transform based techniques

The continuous wavelet transform method has been used by M. akin [20]. For the purpose of spectral analysis tool for both Fast Fourier and wavelet transform techniques, applied to the EEG signal and found that WT offers better spectral characteristics in the case of diagnosis [20]. The Continuous Wavelet Transform (CWT) and Short Term Fourier Transform (STFT) methods are used for detecting epileptic seizure activities in EEG signal for real time applications. Particularly, WT is used for analyzing the non-stationary signal because it provides an alternative of STFT for EEG. The STFT have only advantage over WT takes less time. The CWT takes more time but gives good resolution and better performance for detecting the epilepsy activities. [21].

2.1.3 An overview on ECG signal analysis algorithm.

Qin. et.al [22] proposed an adaptive and time efficient automatic R- peak detection algorithm for ECG signal processing. The time domain signal directly applied to the wavelet multiresolution analysis (WMRA), followed by signal mirroring, local maximum detection, amplitude and time interval thresholding. This algorithm shows better performance, high detection accuracy and less time consuming as compare to the traditional Pan-Tompkins method [22].

Acharya et.al [23] proposed a method of automatic detection of arrhythmias using different interval of tachycardiac ECG segments with convolution neural network. The proposed method consist of eleven layer deep convolution neural network (CNN) along with output layer with four neurons, representation of each neurons were Normal (N_{sr}), ventricle fibrillation (V_{fib}), Atrial flutter (A_{fl}) and Atrial fibrillation (A_{fib}) of ECG class.
The classification of normal and tachycardiac arrhythmia ECG segment were done in this method. The MIT-BIH (A_f,A_{fl},A_{fib}), MIT-BIH Arrhythmia (A_{fl},N_{sr}) and CUDB (V_{fib}) database were used for computation. Two and five seconds ECG segment were considered as an input and no QRS detection was performed in this method. The use of CNN in ECG segment for detection of arrhythmia achieved accuracy of 92.5% for two second and 94.5% for five second input data [23].

2.1.4 An overview on EEG signal analysis algorithm.

The Electroencephalography (EEG) basically recorded for localization of seizures and identification of epileptic dysfunction. Ali. et. al [25] proposed a method for recording of weak signals of normal and epileptic EEG signal. The EEG signal applied to Hilbert Vibration Decomposition (HVD) for extracting the monocomponent of the input signal. The HVD method, illustrated in fig.1, works on the repeated signal shifting process. It uses Hilbert Transform to obtain analytic signal and estimate the instantaneous frequency for decomposition of signal and has three iterative steps for the extraction of the monocomponents. In the first step, it estimates the largest energy monocomponent of instantaneous frequencies. In next step, detection of energy envelops using synchronous detection. Finally the estimated monocomponent is substracted from the initial value of the input signal. The classifier using HVD has reduced computational complexity and produced better accuracy as compare with EMD based HHT and STFT [24].

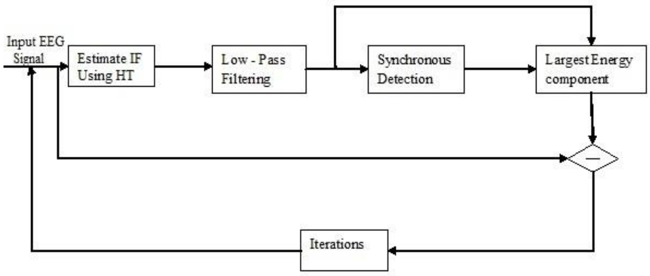

Fig.1. Block diagram of Hilbert Vibration Decomposition [24]

III. DISCUSSION

In this review, an overview on biomedical signal processing has been presented. The comparative study of various transform techniques for biomedical signal gives an idea about the advancement in biomedical field. The transform techniques like FFT, WT, Laplace Transform, Hilbert Transform and Hadamard Transform were used in biomedical signal analysis. The WT has become one of the emerging tool for time and feature analysis of ECG and EEG data. The WT has ability to extract the related component of the signal using variety of wavelet based techniques as far better than the traditional Fourier transform methods. The laplace transform basically used to detect the ischemia event in ECG signal. The advantage of Hilbert Transform is that it changes the phase value without changing the spectral component of the amplitude. The Hadamard Transform is well known for low memory requirement and less computational complexity.The EEG is a non-stationary and nonlinear signal, which doesn't fallow any fix pattern. The continuous wavelet transform (CWT) has ability to perform efficient analysis of non-stationary signal over a wide range of applications. The CWT allows arbitrary high resolution of signal in time frequency domain. Normally CWT based algorithms used for identification of epileptic seizure in EEG data.

Table 1
Transforms used in the study of biomedical signal processing

Transform	Purpose of Study	Accuracy	Limitations	Reference
Fast Fourier Transform	• R-Peak detection in ECG signal • S Peak detection in ECG • Heart rate computation	98.48% (Feature Identification)	Artificial neural network data set required for training	Gothwal et al.[10]
Wavelet Transform	• Arrhythmia classification of ECG signal • QRS- complex detection • Motion artifacts removal of ECG signal	99.92 % (Beat Detection)	Not quantified	Kaur et al[11], Nagai et al.[25]
Laplacian based-Karhunen-Loeve transform	• Ischemic event detection	Improved accuracy	Single investigation	Ana M.[15]
Hilbert Transform	• QRS Detection • Weak ECG signal Detection	Average detection accuracy of 99.80	Not Quantified	Manikandan[18] Jihong [26]
Hadamard Transform	• Atrial Fibrillation detection	99.3% (With LMNN classifier)	Not Quantified	P. Kora[19]

The above table mainly shows the utility of transform for the analysis of ECG signal using various transform techniques but few transform techniques among them are also suitable for EEG signal analysis like continuous WT, Hilbert transform, Hadamard transform. The average accuracy in feature identification of ECG signal is found highest in wavelet transform. The Hilbert transform and Hadamard transform give good accuracy in feature identification and also capable of detecting atrial fibrillation, QRS complex in weak ECG signal.

IV. CONCLUSION

Biomedical signal processing play very important role in educational and research area of biomedical engineering. With wide knowledge of physiological signal and use of advanced clinical methods make diagnosis process easy. The variety of transform techniques have been explored in this study and found that wavelet transform is very good tool for both stationary and non-stationary biomedical signal analysis. The CWT and DWT are suitable for ECG and EEG signal analysis respectively. Further advanced algorithms investigated in ECG and EEG signal for features extraction of data and identification of heart and brain abnormalities.

Most of the automatic detection algorithms in biomedical signal processing require latest data set for better accuracy.

REFERENCES

1. Rangayyan RM. Biomedical signal analysis: a case study approach. New York: Wiley-IEEE Press; (2001).
2. Kacar S, Sakoglu Ü. Design of a novel biomedical signal processing and analysis tool or functional neuroimaging. Comput Methods Programs Biomed (2016):46–57.
3. Jasjeet Kaur, Amanpreet Kaur. A Review on Analysis of EEG Signals, International Conference on Advances in Computer Engineering and Applications (ICACEA). (2015), pp 957-960.
4. Raez MBI, Hussain MS, Mohd-Yasin F. Techniques of EMG signal analysis: detection, processing, classification and applications. Biological Procedures Online. (2006);8:11-35. doi:10.1251/bpo115.
5. M. K. Islam, A. M. Haque, G. Tangim, et al. Study and Analysis of ECG Signal Using MATLAB & LABVIEW as Effective Tools. International Journal of Computer and Electrical Engineering, Vol. 4, No. 3, June 2012, pp 404-408.
6. Gacek A. An Introduction to ECG Signal Processing and Analysis. In: Gacek A., Pedrycz W. (eds) ECG Signal Processing, Classification and Interpretation. Springer, London, (2012). https://doi.org/10.1007/978-0-85729-868-3_2.
7. Goutham, Swapna & Ghista, Dhanjoo & Martis, Roshan & Peng Chuan Alvin, et. al. ECG signal generation and heart rate variability signal extraction: Signal processing, features detection, and their correlation with cardiac diseases. Journal of Mechanics in Medicine and Biology. 12(4), (2012): 1240012. DOI: 10.1142/S021951941240012X.
8. F. Lopes da Silva (2012). EEG: Origin and Measurement. DOI: 10.1007/978-3-540-87919-0_2.
9. U.R. Acharya et al. Automated EEG analysis of epilepsy: A review. Knowledge-Based Systems 45 (2013) pp. 147–165. DOI: http://dx.doi.org/10.1016/j.knosys.2013.02.014.
10. Himanshu G., Silky K., Rajesh K. (2011) Cardiac arrhythmias detection in an ECG beat signal using fast fourier transform and artificial neural network. J. Biomedical Science and Engineering, 4, (2011) pp. 289-296.
11. Inderbir K., Rajni R., Anupma M., (2016) ECG Signal Analysis and Arrhythmia Detection using Wavelet Transform. Journal of the Institute of Engineering (India), 97(4), (2016) pp. 499–507: DOI 10.1007/s40031-016-0247-3.
12. M. Llamedo, J.P. Martinez, Heartbeat classification using feature selection driven by database generalization criteria. IEEE Trans. Biomed. Eng. 58(3), (2011) pp. 616–625.
13. Y. Sung-Nien, C. Ying-Hsiang, Electrocardiogram beat classification based on wavelet transformation and probabilistic neural network, Elsevier. Pattern Recognit. Lett. 28(10), (2007) pp. 1142–1150.
14. Rajni, I. Kaur. Electrocardiogram signal analysis-an overview. Int. J. Comput. Appl. 84(7), (2013) pp. 22–25.
15. Ana M., Leif S., Pablo L. Detection of body position changes from the ECG using a Laplacian noise model. Biomedical Signal Processing and Control 14 (2014) 189–196.
16. F. Jager, R.G. Mark, G.B. Moody, S. Divjak. Analysis of transient ST segment changes during ambulatory monitoring using the Karhunen–Loève transform,in: Proceeding of Computers in Cardiology, IEEE Computer Society Press, (1992),pp. 691–694.
17. R.J. Bolton, L.C. Westphal. Hilbert transform processing of ECG's, 1981 IREECON International Convention Digest, IREE, Melbourne, (1981), pp. 281–283.
18. M. S. Manikandan, Soman, . A novel method for detecting R-peaks in electrocardiogram (ECG) signal, Biomedical Signal Processing and Control 7 (2012) pp.118– 128.
19. P. Kora et al., ECG based Atrial Fibrillation detection using Sequency Ordered Complex Hadamard Transform and Hybrid Firefly Algorithm, Eng. Sci. Tech., Int. J. (2017), DOI: http://dx.doi.org/10.1016/j.jestch.2017.02.002.
20. M . akin,. Comparison of Wavelet Transform and FFT Methods in the Analysis of EEG Signals, Journal of Medical Systems, Vol. 26, No. 3, (2002) pp.241-247.
21. M. K. Kiymik, I.Guler, et al. Comparison of STFT and wavelet transform methods in determining epileptic seizure activity in EEG signals for real-time application, Computers in Biology and Medicine 35 (2005) 603–616.
22. Qin Qin, Jianqing Li, Yinggao Yue, and Chengyu Liu. An Adaptive and Time-Efficient ECG R-Peak Detection Algorithm, Journal of Healthcare Engineering, Volume 2017, Article ID 5980541, 14 pages. DOI: https://doi.org/10.1155/2017/5980541.
23. U. Rajendra Acharya, Hamido Fujita, Oh Shu Lih, Yuki Hagiwara, Jen Hong Tan, Muhammad Adam. Automated detection of arrhythmias using different intervals of tachycardia ECG segments with convolutional neural network. Information Sciences 405 (2017) 81–90.
24. Ali Yener Mutlu. Detection of epileptic dysfunctions in EEG signals using Hilbert vibration decomposition. Biomedical Signal Processing and Control 40 (2018) 33–40.
25. S. Nagai, D. Anzai, et al. Motion artefact removals for wearable ECG using stationary wavelet transform. Healthcare Technology Letters, Vol. 4, Iss. 4, (2017) pp. 138–141. DOI: 10.1049/htl.2016.0100.
26. Jihong Yan, LeiLu. Improved Hilbert–Huang transform based weak signal detection methodology and its application on incipient fault diagnosis and ECG signal analysis. Signal Processing 98(2014) pp. 74–87.
27. Nang Anija Manlong, Jagdeep Rahul, Marpe Sora "ST Segment Analysis for Early Detection of Myocardial Infarction." International Journal of Computer Sciences and Engineering 6.6 (2018): 1500-1504.
28. CM Khamhoo, J Rahul, M Sora." Algorithm for QRS Complex Detection using Discrete Wavelet Transformed" International Journal of Electronics Engineering. Volume 10, Issue 2 (2018).pp. 352-357.

AUTHORS PROFILE

Jagdeep Rahul has received the undergraduate degree in Electronics & Communication from Bundelkhand University, India in 2009. He has completed his Master of Technology from ABV-IIITM, India in 2012. He is currently pursuing Ph.D. in Biomedical Signal Processing from Rajiv Gandhi University. He is also working as Assistant Professor at Rajiv Gandhi University.

Marpe Sora is working as Assistant Professor at Rajiv Gandhi University, Doimukh, Arunachal Pradesh. He has completed his Master of Technology from Tezpur University and Ph.D. from Guwahati University, India.

Lakhan Dev Sharma is assistant professor at M L V Textile and Engineering College, Bhilwara, Rajasthan, India. He has completed his Ph.D. from Electronics and Communication Engineering department of Dr B. R. Ambedkar National Institute of Technology, Jalandhar in year 2018. In year 2012 he has completed his Masters of Technology from ABV- Indian Institute of Information Technology, Gwalior, India. He has teaching experience at various technical institute and university level. His research interests include biomedical signal and image processing.