SOCIETY FOR SCIENCE AND EDUCATION
UNITED KINGDOM

JBEMi JOURNAL OF BIOMEDICAL ENGINEERING AND MEDICAL IMAGING

ISSN: 2055-1266
VOLUME 4 NO. 3

99.9% Accurate R Wave Extraction from ECG Signal using Wavelet Transform

Syed Hassaan Ahmed, Syed Kashif Abbas, Tahir Zaidi
College of E&ME, National University of Sciences and Technology, Islamabad, Pakistan
syed.ahmedbukhari83@ee.ceme.edu.pk; skanshah@gmail.com; tahirzaidi@ceme.nust.edu.pk

ABSTRACT

ElectroCardiogram(ECG) is used to measure and diagnose electrical activity of heart. R peak detection from ECG signal is our main concern. It is the basic mark for the identification of different arrhythmias. In this paper, R wave extraction is performed by using Wavelet Transform. The wavelet transform has risen over late years as an effective time– frequency analysis and it is efficiently analyze complex non stationary signals. In this research, R wave is extracted accurately then heart beat is analyzed by the detection of RR intervals. R wave extraction is performed and implemented in the most familiar multipurpose tool, MATLAB .In this research,99.9% accurate R peak is detected by this type of approach. By accurate detection of R peak, cardiac diseases can easily be identified such as Sinus tachycardia, Sinus bradycardia, Supraventricular tachycardia (SVT), Atrial fibrillation (AF), Ventricular tachycardia and Heart block.

Keywords—ECG signal, R-wave, QRS complex-R interval, wavelet transform, Peak detection

1 Introduction

Electrocardiogram (ECG) represents the electrical movement of the heart demonstrating the contraction and Relaxation of heart muscle.ECG is the diagnostic tool for the identification of electrical activities of heart. R peak detection form ECG signal is responsible for its identification. If arrhythmias are not treated properly then it cause sudden cardiac death[1]-[2].

In the previous couple of decades a few methods and techniques are evolved for ECG analysis and arrhythmia detection to enhance its accuracy and sensitivity. These methods include Wavelet coefficient [3], Autoregressive Modeling [4], RBF Neural Networks [5], selforganizing map [6], and fuzzy c-means clustering techniques [7]. Figure1 shows the typical ECG waveform with R-R interval and basic waves such as P,Q,R,S,T and U[8]

DOI: 10.14738/jbemi.43.2898
Publication Date: 13th May 2017
URL: http://dx.doi.org/10.14738/jbemi. 43.2898

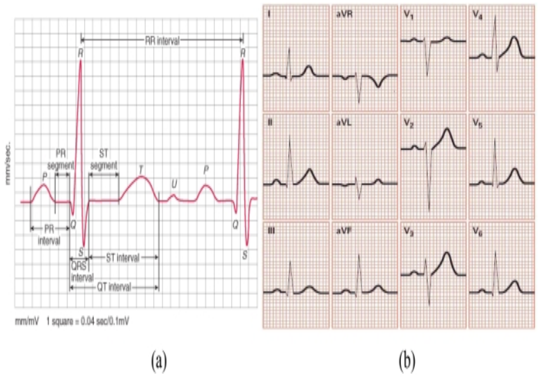

Figure 1: ECG signal generation using MATLAB and its Real image

In the literature, ECG signal processors operate at different frequency ranging from 0.25 Hz to 400 kHz [9]–[12]. ECG Signal detection includes elimination of different noises like baseline drift [10]-[14], waveform detection [15]-[17],feature extraction [18],and heart rate classification[19]-[28].

Among the several techniques investigated in the literature are included time domain analysis [29]–[32], statistical approach [33]–[35], hybrid features [36], [37], frequency-based analysis [38], and time–frequency analysis [39]–[41] for feature extraction of ECG signals. These feature extraction tools are combined with classification algorithms such as linear discriminants [29], [30], [42], neural networks [35], [39], [41], neurofuzzy approach [43], and support vector machines (SVMs) [33], [34], [36], [44]-[48] to provide efficient detection and analysis of cardiac abnormalities.

Heart Rate classification techniques were also used by several researchers, some of them have used waveform features extraction techniques [19]-[26] and some have used wavelet transform [23]-[24] method for its extraction.

Wavelet analysis is used to eliminate noise from ECG signal and it also used to identify possible cardiovascular abnormalities. It is used for stationary as well as non stationary signals. it gives both frequency and time domain information of signal during its processing. In fact, it covers quite a large area as it also deals with continuous and discrete domain signals.

2 Wavelet Transform

2.1 The Continuous Wavelet Transform

A wavelet is simply a small wave has energy concentration in time for the analysis of transient, non stationary or time-varying phenomena as shown in figure 2.

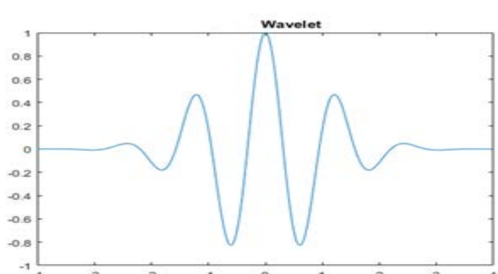

Figure 1: Mother Wavelet

Equation (1) highlights the continuous wavelet transform[49].

$$W(\alpha,\beta)=\int_{-\infty}^{\infty}x(t)\frac{1}{\sqrt{|\alpha|}}\Psi^{*}(\frac{t-\beta}{\alpha})dt \tag{1}$$

Where β acts to translate the function across $x(t)$ and variable α acts to vary the time scale of probing function Ψ .

(i) If α >1 then the wavelet function , Ψ , is stretched along time axis
(ii) If 0< α <1 then it contacts the wavelet function , Ψ .
(iii) If α <0 then the wavelet function , Ψ , flipped along time axis.

If β =0 and α =1 then wavelet is in its natural form,which is termed as mother wavelet as shown in figure(2) and its expression is shown in equation (2).

$$\Psi_{(1,0)}\equiv\Psi(t) \tag{2}$$

The wavelet shown below ,in figure(3) , is the popular Morlet wavelet which is defined by equation(3) and it is implemented using MATLAB.

$$\Psi(t)=e^{-t^{2}}\cos(\pi\sqrt{\frac{2}{\ln 2}}t) \tag{3}$$

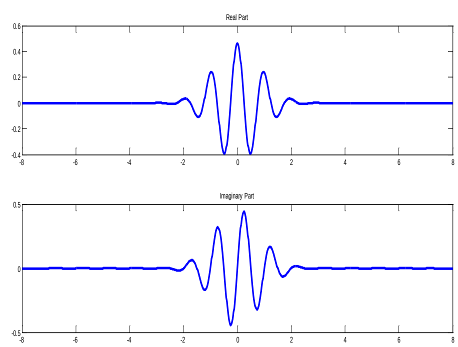

Figure 2: Morlet Wavelet using MATLAB

Maxican hat wavelet is defined by equation (4).Figure 4 shows its implementation using MATLAB.

$$x(t)=\sum(Analysis+Syntheis) \tag{4}$$

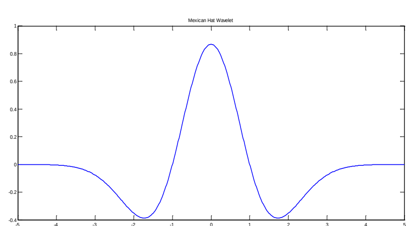

Figure 3: Maxican Hat Wavelet using MATLAB

Figure 5 shown below describe the Haar wavelet using MATLAB.

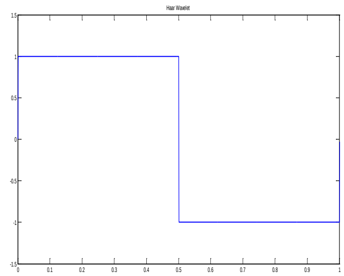

Figure 4: Haar Wavelet using MATLAB

2.2 The Discrete Wavelet Transform

The Continuous Wavelet Transform is highly redundant.The basic analytical expression for the Discrete Time Wavelet Transform(DWT) is expressed in equation(5).

$$x(t) = \sum_{i=-\infty}^{\infty} \sum_{j=-\infty}^{\infty} d(i, j) 2^{-i/2} \Psi(2^i t - j) \tag{5}$$

Here scaling function is used to compute the DWT.Scaling function is defined by equation (6).

$$\varphi(t) = \sum_{n=-\infty}^{\infty} \sqrt{2} c(n) \varphi(2t - n) \tag{6}$$

In the DWT, the wavelet can be defined from the scaling function as defined in equation (7).

$$\Psi(t) = \sum_{n=-\infty}^{\infty} \sqrt{2} d(n) \varphi(2t - n) \tag{7}$$

Where d(n) is a series of scalers that are related to equation(5)

In most cases Discrete time wavelet transform based analysis is best described by filter banks. Figure 6 highlights the analysis part of DWT filter bank and Figure 7 describes the synthesis part of filter bank by using Discrete time wavelet transform.

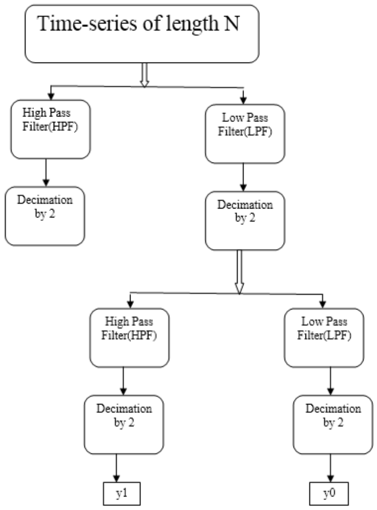

Figure 6: Analysis part of DWT filter bank

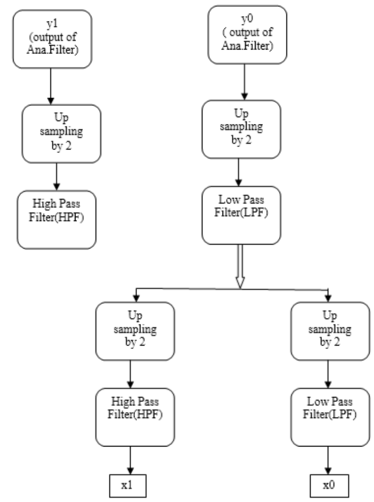

Figure 5: Synthesis Part of Filter bank using DWT

Designing the filter in a wavelet filter bank is quite challenging. A main concern is to reconstruct the original signal after passing through the analysis and synthesis part by using Low pass and high pass filters. Here first Signal is analyzed and it is passes through synthesis part and then it is added using summation block and original signal is recovered as defined by equation 8.

$$x(t) = \sum (Analysis + Syntheis) \tag{8}$$

3 Methodology

Wavelet Transform Method:

Flow Chart for R-wave detection using Wavelet Transform is demonstrated in Figure 8.

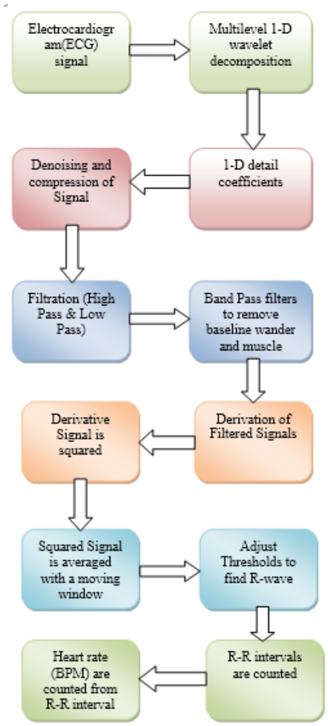

Figure 8: Block Diagram to Detect R-wave using Wavelet Transform

4 Results

By Applying Wavelet Transform Method

Figures[9-16] show the implementation of Wavelet Transform algorithm for R-wave detection .Figure 9 shows the original Real Time ECG signal generation using MATLAB.. Here Low pass and High Pass filter is designed to remove to get rid of the baseline wander and muscle noise and then Filtered signal is passed through Band Pass Filter. Derivative filter is applied on Filtered signal to highlight the QRS complex for the detection of R-wave. Derivative signal is passed through moving Average filter after taking its square to further removes the remaining noise.And Then Threshold Filter is applied to find Peaks of R-wave from ECG signal [13] and R-R interval is determined.Figure 16 describes the R-wave detection from ECG signal using Wavelet Transform algorithm.

and Figure 10 describes the R-wave detection using MATLAB and then Heart rate is calculated from R-R interval as by following Equation (9)as shown in Figure 17.

$$Heart\ Rate(BPM) = \frac{60*Sampling\ Rate}{R-R\ interval} \tag{9}$$

Figure 9 shows the Real time ECG signal generation using MATLAB.

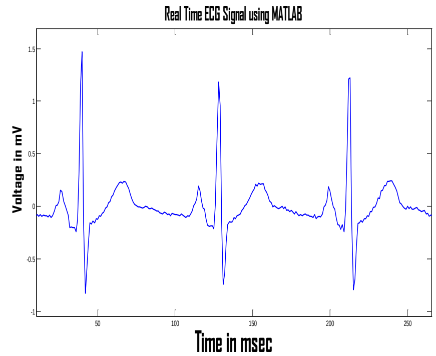

Figure 6: Real Time ECG signal Generation

Figure 10 shows the Smooth ECG signal generation using MATLAB.

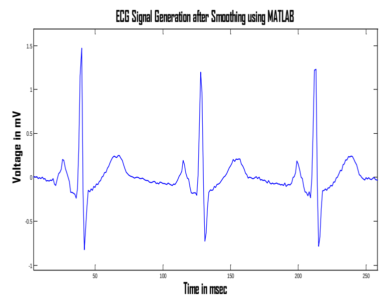

Figure 7:Smooth ECG signal Generation using Wavelet Transform

Figures 11 describes the Clean ECG generation after passing through Wavelet and denoise it by wavelet decimation operation.

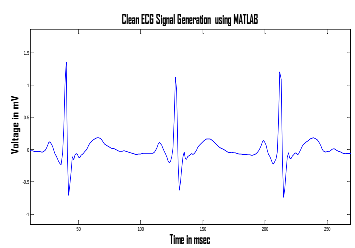

Figure 8: Clean ECG signal using Wavelet by MATLAB

Figure 12 shows the behavior of Clean ECG signal after passing through the low filter[50].Here pan-Tompkins techniques are used for filteration to get rid of baseline wander and muscle noise.

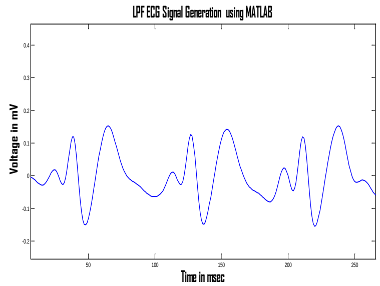

Figure 9: Low Pass Filtered ECG Signal

Figure 13 shows ECG behavior after high pass filtration to discard high frequency noise.

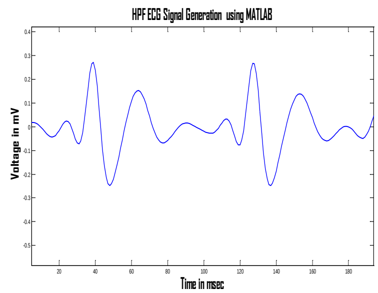

Figure 10: High pass filtered ECG Signal

Figure 14 shows that Filtered ECG signal is derivated using derivative filter to highlight the QRS complex

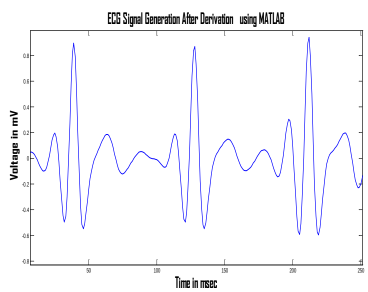

Figure 11: ECG Signal after passing through Derivative Filter

Figure 15 explains that derivative ECG signal is squared to highlight the dominant peaks form QRS complex for accurate detection of R peaks.

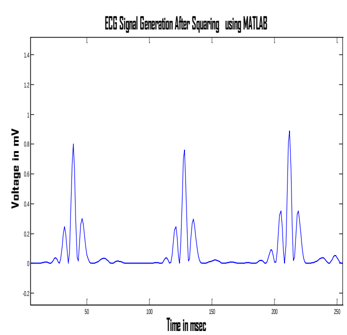

Figure 12: Squared ECG Signal

Now R peak is detected when squared ECG signal is passed through moving average filter as shown in figure 16.Here R peaks are detected accurately by applying algorithm developed by Pan-Tompkins[50] .

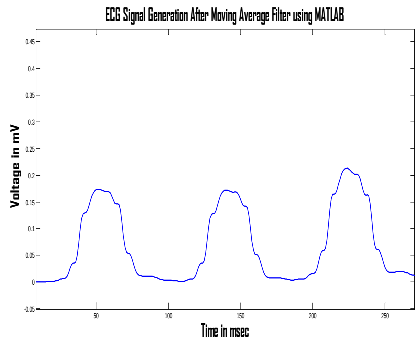

Figure 13: R peak detection after moving Average filter

Figure 17 shows the heart rate (BPM) calculated from R-R interval by pre-processing of ECG signal.

Figure 17: Heart Rate detection using MATLAB

Table I highlights the behavior of R-wave detection using MATLAB by the implementation of WAVLET TRANSFORM accurately. Here R peak location, its amplitude and R-R interval is calculated and analyzed.

Table 1: R peak detection using Wavelet Transform

Sr #	R Peak Location	R Peak Amplitude	R-R Interval
1	40	0.1733	88
2	128	0.1720	84
3	212	0.2128	83
4	295	0.2188	83
5	378	0.2293	88
6	466	0.2303	93
7	559	0.1994	49
8	608	0.0031	49
9	657	0.1815	93
10	750	0.1890	50
11	800	0.0048	43
12	843	0.2244	50
13	893	0.0101	45
14	938	0.2154	50
15	988	0.0088	49
16	1037	0.1935	60
17	1097	0.0005	42
18	1139	0.1995	61
19	1200	0.0018	41
20	1241	0.1716	51
21	1292	0.0058	47
22	1339	0.2036	51
23	1390	0.0083	46
24	1436	0.2216	51
25	1487	0.0088	44
26	1531	0.1981	51
27	1582	0.0096	47
28	1629	0.1980	101
29	1730	0.1894	51
30	1781	0.0073	44
31	1825	0.1964	49
32	1874	0.0037	41
33	1915	0.2169	72

5 Discussion

After implemented Wavelet transformation method using MATLAB,we can easily detect R wave.R-R interval and heart rate can also be analyzed by finding R wave. And it is easily concluded that R-Wave detection using WAVLET TRANSFORM gives us more accurate and efficient result as it is proved by the visualization of ECG signal as shown in Figure 1.

6 Identification of Arrhythmias

Table 2 highlights the classification of Arrhythmias based on BPM .We can easily identified cardiac diseases after finding heart rate from ECG signal by above mentioned Equation(9)

Table 2: Arrhythmias classification on the basis of BPM

Name of Arrhythmia	Heart Rate(BPM)
Sinus tachycardia	>100
Sinus bradycardia	< 60
Supraventricular tachycardia (SVT)	140-240
Atrial fibrillation (AF)	160-180
Ventricular tachycardia	120-200
Heart block	20-40

7 Conclusion

R-wave is detected from ECG signal which are obtained from Wavelet Transform. It is concluded that Wavelet Transformation provide us accurate and efficient result regarding R-peak detection and its results are 99.9% accurate.R-R interval is also calculated form R-Peak detection using MATLAB . With this algorithm, abnormalities of the ECG are obtained from the extracted feature.Heart rate is also calculated from R-R intervals and several arrhythmias are also identified from the Heart rate,including Sinus tachycardia, Sinus bradycardia, Supraventricular tachycardia (SVT), Atrial fibrillation (AF), Ventricular tachycardia and Heart block.

Hence Wavelet Transform is the best method for the detection of R-Peak from Real time ECG signal generated from MATLAB as it is less time consuming and more efficient.

ACKNOWLEDGMENT

The author would like to thank Prof. Dr J.Tompkins, Dr David Dorran, Mr. Hooman Sedghamiz and Mr. Ehsan Mirrahimi for interesting discussion.

BIBLIOGRAPHY

[1] S. Da, Clinical Electrocardiography. St. Louis, MO, USA: Mosby, 1977.

[2] S. Da, Primary Cardiology, G. K. Parisianos, Ed. Belmont, MA, USA:Athena Scientific, 1991.

[3] P. de Chazal, B. G. Celler, R. B. Rei, "Using Wavelet Coefficients for the Classification of the Electrocardiogram", Proceedings of the 22nd Annual EMBS International Conference, July 23-28, 2000, Chicago IL.

[4] [4] N. Srinivasan, D. F. Ge, S. M. Krishnan, "Autoregressive Modeling and Classification of Cardiac Arrhythmias", Proceedings of the Second Joint Conference Houston. TX. USA - October 23-26,2W2

[5] Hafizah Hussain, Lai Len Fatt , "Efficient ECG Signal Classification Using Sparsely Connected Radial Basis Function Neural Network", Proceeding of the 6th WSEAS International Conference on Circuits, Systems, Electronics, Control and Signal Processing, December 2007, pp. 412-416.

[6] Marcel0 R. Risk, Jamil F. Sobh, J. Philip Saul, "Beat Detection and Classification of ECG Using Self Organizing Maps", Proceedings - 19th International Conference – IEEEIEMBS, Chicago, IL. USA Oct. 30 - Nov. 2, 1997

[7] Yuksel Ozbay, Rahime Ceylan, Bekir Karlik, "Integration of type 2 fuzzy clustering and wavelet transform in a neural network based ECG classifier", Expert Systems with Applications, vol. 38, pp. 1004–1010, 2011.

[8] N. Maglaveras, T. Stamkapoulos, K. Diamantaras, C. Pappas, M. Strintzis, "ECG pattern recognition and classification using nonlinear transformations and neural networks: A review", Int. J. Med. Inform, vol 52, pp. 191–208, 1998.

[9] X. Liu, Y. J. Zheng, M.W. Phyu, B. Zhao,M. Je, and X. J. Yuan, "A miniature on-chip multi-functional ECG signal processor with 30 μW ultralow power consumption," in Proc. Annu. Int. Conf. IEEE Engineering in Medicine and Biology, Buenos Aires, Argentina, pp. 2577–2580, 2010.

[10] S. Y. Hsu et al., "A sub-100 μW multi-functional cardiac signal processor for mobile healthcare applications," in Proc. Symp. VLSI Circuits, Honolulu, HI, USA, pp. 156–157 2012.

[11] L. F. Cheng, T. C. Chen, and L. G. Chen, "Architecture design of the multifunctional wavelet-based ECG microprocessor for realtime detection of abnormal cardiac events," in Proc. Annu. Int. Conf. IEEE Engineering in Medicine and Biology Soc., San Diego, CA, USA, pp. 4466–44692012.

[12] S. Ari, "ECG signal enhancement using S-Transform," Comput. Biol. Med., vol. 43, no. 6, pp. 649–660, Jul. 2013.

[13] M. Zivanovic and M. Gonz´alez-Izal, "Simultaneous powerline interference and baseline wander removal from ECG and EMG signals by sinusoidal modeling," Med. Eng. Phys., vol. 35, no. 10, pp. 1431–1441,Oct. 2013.

[14] A. Fasano and V. Villani, "Baseline wander removal for bioelectrical signals by quadratic variation reduction," Signal Process., vol. 99, pp. 48 57, Jun. 2014.

[15] M. Merino, "Envelopment filter and K-means for the detection of QRS waveforms in electrocardiogram," Med. Eng. Phys., vol. 37, no. 6, pp. 605– 609, Jun. 2015.

[16] C.Ye, "Heartbeat classification using morphological and dynamic features of ECG signals," IEEE Trans. Biomed. Eng., vol. 59, no. 10, pp. 2930–2941, Oct. 2012.

[17] C. A. Bustamante, “ECG delineation and ischemic ST-segment detection based in wavelet transform and support vector machines,” in Proc. Pan Amer. Health Care Exchanges, pp. 1–7, 2013.

[18] Y.-C. Yeh, “Feature selection algorithm for ECG signals using range overlaps method,” Expert Syst. With Appl., vol. 37, no. 4, pp. 3499–3512, 2010.

[19] L. Mariano and M. J. Pablo, “Heartbeat classification using feature selection driven by database generalization criteria,” IEEE Trans Biomed. Eng., vol. 58, no. 3, pp. 616–625, Mar. 2011.

[20] J. Oster et al., “Semi-supervised ECG ventricular beat classification with novelty detection based on switchingKalman filters,” IEEE Trans.Biomed. Eng., vol. 62, no. 9, pp. 2125–2134, Sep. 2015.

[21] L. de Oliveira, “Premature ventricular beat classification using a dynamic Bayesian network,” in Proc. IEEE Int. Conf. Eng. Med. Biol. Soc., pp. 4984–4987, Aug./Sep. 2011.

[22] G. de Lannoy, “Weighted conditional random fields for supervised interpatient heartbeat classification,” IEEE Trans. Biomed. Eng., vol. 59, no. 1, pp. 241–247, Jan. 2012.

[23] X. Jiang, “ECG arrhythmias recognition system based on independent component analysis feature extraction,” in Proc. IEEE Region 10 Conf., pp. 1–4,Nov. 2006.

[24] T. Ince, “A generic and robust system for automated patient-specific classification of ECG signals,” IEEE Trans. Biomed. Eng., vol. 56, no. 5, pp. 1415–1426, May 2009.

[25] M. Lagerholm, “Clustering ECG complexes using Hermite functions and self-organizing maps,” IEEE Trans. Biomed. Eng., vol. 47, no. 7, pp. 838– 848, Jul. 2000.

[26] V. S. R.Kumari and P. R.Kumar, “Cardiac arrhythmia prediction using improved multilayer perceptron neural network,” Int. J. Electron., Commun., Instrum. Eng. Res. Develop., vol. 3, no. 4, pp. 73–80, 2013.

[27] C. V. Banupriya and S. Karpagavalli, “Electrocardiogram beat classification using probabilistic neural network,” Int. J. Comput. Appl. (IJCA), vol. 1, no. 7, pp. 31–37, 2014.

[28] L. S. de Oliveira, “Premature ventricular beat classification using a dynamicBayesian network,” in Proc IEEE Eng. Med. Biol Soc. Conf., pp. 4984–4987,2011.

[29] P. de Chazal, M. O’Dwyer, and R. B. Reilly, “Automatic classification of heartbeats using ECG morphology and heartbeat interval features,” IEEE Trans. Biomed. Eng., vol. 51, no. 7, pp. 1196–1206, Jul. 2004.

[30] P. de Chazal and R. B. Reilly, “A patient-adapting heartbeat classifier using ECG morphology and heartbeat interval features,” IEEE Trans. Biomed. Eng., vol. 53, no. 12, pp. 2535–2543, Dec. 2006.

[31] S. Mitra, M. Mitra, and B. B. Chaudhuri, “A rough-set-based inference engine for ECG classification,” IEEE Trans. Instrum. Meas., vol. 55, n o. 6, pp. 2198–2206, Dec. 2006.

[32] S. Raj, K. Maurya, and K. C. Ray, “A knowledge-based real time embedded platform for arrhythmia beat classification,” Biomed. Eng. Lett., vol. 5, no. 4, pp. 271–280, Dec. 2015.

[33] F. Melgani and Y. Bazi, “Classification of electrocardiogram signals with support vector machines and particle swarm optimization,” IEEE Trans. Inf. Technol. Biomed., vol. 12, no. 5, pp. 667–677, Sep. 2008.

[34] S. Osowski, L. T. Hoai, and T. Markiewicz, “Support vector machinebased expert system for reliable heartbeat recognition,” IEEE Trans. Biomed. Eng., vol. 51, no. 4, pp. 582–589, Apr. 2004.

[35] S. Raj, S. Luthra, and K. C. Ray, “Development of handheld cardiac event monitoring system,” IFAC-PapersOnLine, vol. 48, no. 4, pp. 71–76, 2015.

[36] C. Ye, B. V. K. V. Kumar, and M. T. Coimbra, “Heartbeat classification using morphological and dynamic features of ECG signals,” IEEE Trans. Biomed. Eng., vol. 59, no. 10, pp. 2930–2941, Oct. 2012.

[37] S. Raj, K. C. Ray, and O. Shankar, “Cardiac arrhythmia beat classification using DOST and PSO tuned SVM,” Comput. Methods Programs Biomed., vol. 136, pp. 163–177, Nov. 2016.

[38] K. Minami, H. Nakajima, and T. Toyoshima, “Real-time discrimination of ventricular tachyarrhythmia with Fourier-transform neural network,” IEEE Trans. Biomed. Eng., vol. 46, no. 2, pp. 179–185, Feb. 1999.

[39] T. Ince, S. Kiranyaz, and M. Gabbouj, “A generic and robust system for automated patient-specific classification of ECG signals,” IEEE Trans. Biomed. Eng., vol. 56, no. 5, pp. 1415–1426, May 2009.

[40] S. Banerjee and M. Mitra, “Application of cross wavelet transform for ECG pattern analysis and classification,”IEEE Trans. Instrum. Meas., vol. 63, no. 2, pp. 326–333, Feb. 2014.

[41] S. Raj, G. S. S. P. Chand, and K. C. Ray, “Arm-based arrhythmia beat monitoring system,” Microprocess. Microsyst., vol. 39, no. 7, pp. 504–511, 2015.

[42] M. Llamedo and J. P. Martinez, “Heartbeat classification using feature selection driven by database generalization criteria,” IEEE Trans. Biomed. Eng., vol. 58, no. 3, pp. 616–625, Mar. 2011.

[43] T. H. Linh, S. Osowski, and M. Stodolski, “On-line heart beat recognition using Hermite polynomials and neuro-fuzzy network,” IEEE Trans. Instrum. Meas., vol. 52, no. 4, pp. 1224–1231, Aug. 2003.

[44] G. D. Fraser, A. D. C. Chan, J. R. Green, and D. T. Macisaac, “Automated biosignal quality analysis for electromyography using a oneclass support vector machine,” IEEE Trans. Instrum. Meas., vol. 63, no. 12, pp. 2919–2930, Dec. 2014.

[45] S. Raj and K. C. Ray, “A comparative study of multivariate approach with neural networks and support vector machines for arrhythmia classification,” in Proc. Int. Conf. Energy, Power Environ., Towards Sustain. Growth (ICEPE), pp. 1–6,Jun. 2015.

[46] X. Liu, J. Zhou, Y. Yang, B. Wang, J. Lan, C. Wang, J. Luo, W. L. Goh, T. T. H. Kim, and M. Je, “A 457 nW near-threshold cognitive multifunctional ECG processor for long-term cardiac monitoring,” IEEE J. Solid-State Circuits, vol. 49, no. 11, pp. 2422–2434, 2014

[47] M. Milanesi, “Independent component analysis applied to the removal of motion artifacts from electrocardiographic signals,” Med. Biol. Eng. Comput., vol. 46, no. 3, pp. 251–261, Mar. 2008.

[48] O. Sayadi and M. B. Shamsollahi, "Model-based fiducial points extractionfor baseline wandered electrocardiograms," IEEE Trans. Biomed. Eng., vol. 55, no. 1, pp. 347–351, Jan. 2008.

[49] Akansu,A.N. and Haddad,R.A.,Multiresolution Signal Decomposition: Transforms, subbands, wavelets. Academic Press , San Diego CA,1992.

[50] Patrick S. Hamilton, Willis J. Tompkins, ―Quantitative Investigation of QRS Detection rules using the MIT/BIH Arrhythmia Database‖, IEEE Transactions on Biomedical Engineering, Vol. BME-33, N0.12, December 1986, PP No. 1157-1165.