Automatic Diagnostic System for Long-Term ECG Data from Holter Monitor

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ABSTRACT
An Electrocardiogram (ECG) gives significant information for the cardiologist to detect cardiac diseases. Automation algorithm is essential to analyse long ECG data. In this paper, we have proposed fully automated, high efficiency, accurate and fast algorithm to detect abnormalities in ECG based on wavelet transform. The algorithm consists of pre-processing, feature extraction and diagnosis. Number of heart beats and Premature Ventricular Contraction (PVC), Premature Atrial Contractions (PACs), Supraventricular tachyarrhythmia and Bradycardia are diagnosed accurately and result matches with doctors opinion. The average sensitivity of algorithm is 99.70%.

Keywords:
Abnormality detection, ECG signal, wavelet transform, noise, baseline drift.

1. INTRODUCTION
An electrocardiogram (ECG) records the electrical activity of the heart that is generated by depolarization and repolarization of the atria and ventricles. The analysis of the ECG has been widely used for diagnosing many cardiac diseases. The importance of the Electrocardiography is remarkable since heart diseases constitute one of the major causes of mortality in the world. According to WHO (World Health Organization) by 2030, almost 23.6 million people will die from CVDs (Cardio Vascular Diseases), mainly from heart disease and stroke. In many cases patients have to be monitored continuously for a long period of time. A Holter monitor is a portable device used for continuously monitoring heart activity for at least 24 hours (often for two weeks at a time) during normal activity. The Analysis of this huge ECG data takes a substantial time and is practically impossible to analyze manually. Therefore an automatic algorithm and software is needed to analyze this huge amount of Holter ECG signals.

Several such automated algorithms are suggested in literature [1]-[10]. S. Z. Mahmoodabadi et al. [9] proposed algorithms to extract features of the ECG signal using Daubechies (db6). Zhao et al. [12] proposed a feature extraction method using wavelet transform and support vector machines obtaining the quadratic spline mother wavelet, for the detection of QRS complex and T and P waves. A.K.M. Fazlul Haque et al. [6] used FFT (Fast Fourier Transform) for the extraction of small variations of the ECG signal.

In this paper, we are proposing an automated algorithm for ECG abnormality detection. The paper is divided into five sections. In section 2 characteristic features and abnormalities of ECG are explained. Development of Automatic ECG Abnormality Diagnostic System (AEADS) is discussed in section 3. Result and discussion is in section 4 and section 5 concludes the paper.

2. CHARACTERISTIC FEATURE AND ABNORMALITIES OF ECG
The ECG signal of a normal heartbeat is characterized by recurrent wave sequence of P, Q, R, S, T and U wave. But small U wave is visible in 50 to 75% of ECG's. Each beat is characterized by these characteristic points. A typical ECG signal for one cardiac cycle is shown in fig1. Most of the clinically useful information in ECG signal is encapsulated in the wave and intervals of ECG defined by its features. The amplitude and interval value for a normal ECG signal are listed below.

Amplitude P-wave — 0.25 mV
R-wave — 1.60 mV
Q-wave — 25% R wave
T-wave — 0.1 to 0.5 mV

Duration P-R interval: 0.12 to 0.20 s
Q-T interval: 0.35 to 0.44 s
S-T interval: 0.05 to 0.15 s
P-wave interval: 0.11 s
QRS interval: 0.09s

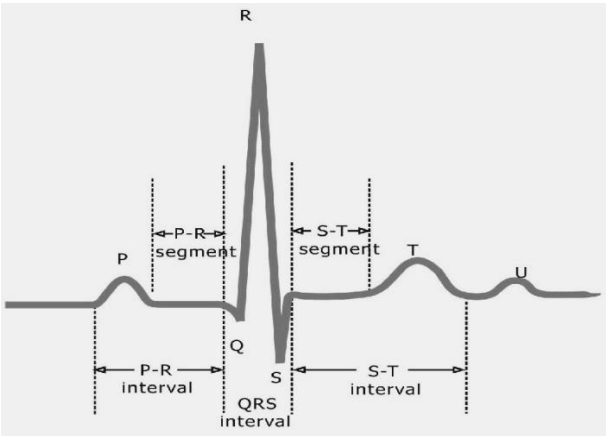

Fig 1: Typical one-cycle ECG tracing [1]

Table 1. Various abnormalities and their characteristic

Name Of Abnormality	**Characteristic Features**
Dextrocardia	Inverted P-wave
Tachycardia	R-R interval <0.6 s
Bradycardia	R-R interval >1 s
PVCs	QRS complex>0.11 s
PACs	Narrow QRS complex
Hyperkalemia	Tall T-wave and absence of P-wave
Myocardial ischaemia	Inverted T-wave
Sudden cardiac death	Irregular ECG

The variation from these standard values of the normal ECG signal leads to various abnormalities. Table 1 outlines various abnormalities and their characteristic.The normal value of heart beat lies in the range of 60 to 100 beats/minute. A slower rate than this is called bradycardia (Slow heart) and a higher rate are called tachycardia (Fast heart). If the cycles are not evenly spaced, an arrhythmia may be indicated.

3. AUTOMATIC ECG ABNORMALITY DIAGNOSTIC SYSTEM (AEADS)

Automation of ECG signal is required to analyze a large amount of data from Holter monitor. Fig 2 shows the Holter monitor. When used for the heart, much like standard electrocardiography the Holter monitor records electrical signals from the heart via a series of electrodes attached to the chest. Fig 3 shows the block diagram of automatic ECG abnormality diagnostic system. The input to the system is raw ECG signal which may contain noise, hence preprocessing is required to get correct result. The preprocessing stage removes noise and baseline drift from the raw ECG signal. Feature extraction is carried out on the preprocessed signal and based on the feature extration output, the abnormalities are detected. Wavelet transform technique is used for preprocessing and Feature extraction of the ECG signal.

The Wavelet Transform is a time-scale representation that has been used successfully in a broad range of applications. One of the advantages of the Wavelet Transform is that it is able to decompose signals at various resolutions, which allows accurate feature extraction from non-stationary signals like ECG.

For wavelet analysis the input sequence x (n) is passed through several levels of low pass h (n) and high pass g (n) analysis filters. At each level, detail information is produced by the high pass filter while the coarse approximation is produced by the low pass filter. Fig 4 shows two level decomposition. The same can be carried out for more levels. In our application we have used seven level decomposition. The reconstruction process is the reverse of decomposition, where the approximation and detail coefficients at every level are up-sampled by 2 and passed through low-pass h (n) and high pass g(n) synthesis filters and finally added as shown in fig 5.

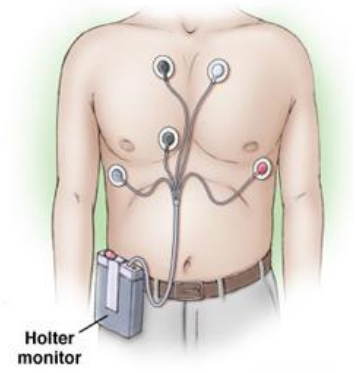

Fig 2: Holter Monitor

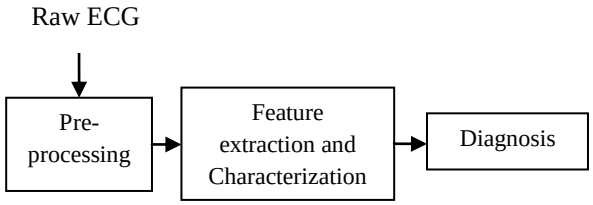

Fig 3: Automatic ECG Abnormality Diagnostic System (AEADS)

Wavelet families include Biorthogonal, Coiflet, Harr, Symmlet, Daubechies (Db) wavelets etc. Selecting a wavelet function which closely matches the signal to be processed is of utmost importance in wavelet applications. Daubechies Wavelet shows similarity with ECG signal. Therefore, we have chosen Daubechies (Db6) Wavelet for preprocessing and extracting features of ECG signal in our application.

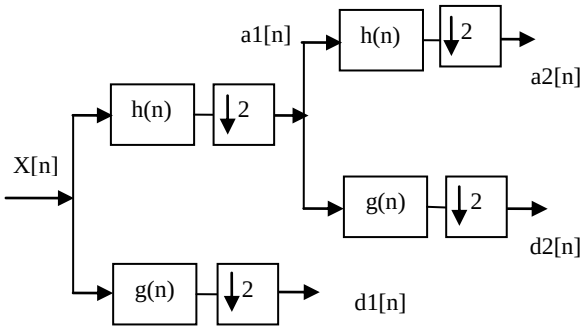

Fig 4: Two level wavelet decomposition

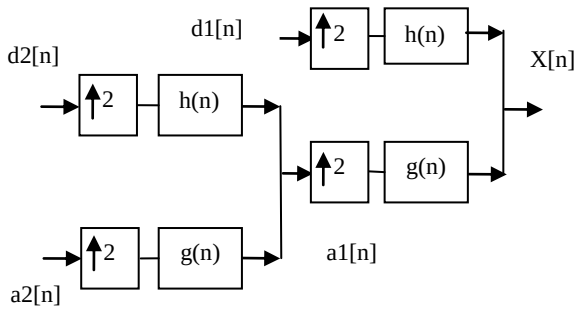

Fig 5: Two level wavelet reconstruction

3.1 Preprocessing

Preprocessing is an important step as noise in an automated detection may lead to wrong diagnosis. One of the common problems in ECG signal processing is baseline drift removal and noise suppression. ECG signal contains noises due to frequency interference, baseline drift, electrode contact noise, polarization noise, muscle noise, the internal amplifier noise and motor artifacts. In most of the ECG recordings the respiration, electrode impedance change and increase body movements are the main causes of the baseline drift. This baseline drift can be eliminated without changing or disturbing the characteristics of the waveform. The algorithms presented in this section are applied directly at one run over the whole digitized ECG signal which are saved as data files provided by Physionet [11]. This algorithm is applied to the MLII lead.

The noise cancellation procedure includes four steps as shown in fig 6: Wavelet decomposition, setting approximation equaled to zero, detail coefficients thresholding and Wavelet reconstruction.

1. *Wavelet Decomposition*: The input ECG signal x(t) is decomposed using Daubechies db6. As a result of this transformation so-called approximations a(n) and details d(n) are obtained. Here 7 level of decomposition is chosen.

2. *Setting approximation co-efficients to zero*: Baseline drift is reduced by setting the approximation co-efficients to zero and detail co-efficients of s scale greater than 5 are also equaled zero.

3. *Detail coefficients thresholding*: High frequency noise is cancelled by applying level based thresholding to detail co-efficients before reconstruction. A threshold value δ [12] is calculated by the following equation.

$$\delta = \sigma \sqrt{2 log L} \qquad 1$$

Where the noise is Gaussian with standard deviation σ of the DWT coefficients and L is the number of samples of the processed signal. A soft thresholding method is used for noise removal.

4. *Wavelet Reconstruction*: After modification of wavelet co-efficient, the signal is reconstructed back. The ECG baseline drift and its high frequency noise are reduced from the reconstructed signal.

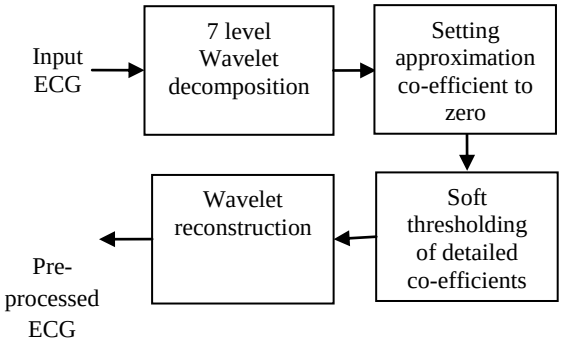

Fig 6: ECG pre-processing algorithm

3.2 Feature extraction

Extraction stage extracts diagnostic information from the ECG signal. The description of the ECG features is there in section 2. Fig 7 is the block diagram for ECG feature extraction.

First, the peak of the QRS complex with its high dominated amplitude in the signal is detected. Then Q and S waves are detected. The Zero crossing of the signal is found next. P and T waves are the last things to be found.

1. *R Detection:*

In order to detect the peaks, specific details of the signal are selected. The detection of R peak is the first step of feature extraction. The R peak in the signal from the Modified Lead II (MLII) lead has the largest amplitude among all the waves compared to other leads. Seven level wavelet decomposition is done on the pre-processed ECG signal using db6. The details d3-d7 is kept and all other details are removed. This procedure removes low frequency and high frequency content of the signal. The reconstructed signal is then squared. Thresholding is done on the squared signal to detect the R peak. Because of noise or higher amplitude T waves can be falsely detected as R wave. In order to avoid this, minimum interval is choosen for subsequent R wave occurrence below which spurious R wave is eliminated.

2. *Q and S Detection:*

A Q and S peak occurs about the R peak. In order to make the peaks noticeable, all the details of the signal are removed up to detail d5. The approximation signal remained, is searched for minimum points about the R peaks formerly detected. The left point denotes the Q peak and the right one denotes the S peak.

3. *Zero Crossing Detection:*

Many zero reference level is present in the ECG signal. To find the zero crossing details d3-d7 are kept and all other details are removed. The two zero crossing of the signal before the Q wave and after the S wave are registered.

4. *P and T Detection:*

These waves are more noticeable when keeping details d3-d6. At these levels, low frequency and high frequency ripples of the signal are removed. The extermums of the signal before and after the zero crossings about each R peak which are formerly detected denotes P and T peaks. Zero crossings of the signal about the P and T peaks which were detected are the onset and offset points of the waves, respectively.

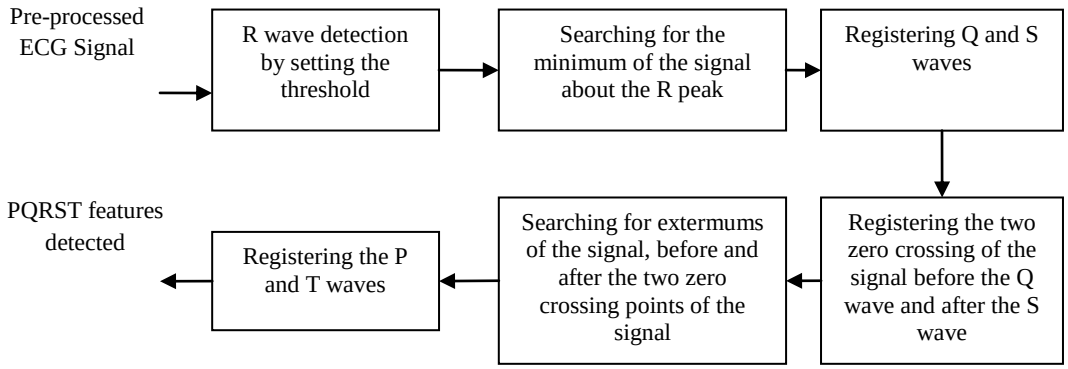

Fig 7: ECG feature extraction algorithm

3.3 Diagnoses

The output of feature extration block is QRS complex and T and P waves. The diagnoses is done on these features to calculate heart beat rate, the ST segment, PR and QT intervals, QRS duration, the heart rhythm etc. Further, this information is used to detect diseases like Premature Ventricular Contraction (PVC), Premature Atrial Contractions (PACs), Supraventricular tachyarrhythmia and Bradycardia. The PVC's are diagnosed by finding QRS interval. If the QRS interval is greater than 0.11s, then it is diagnosed as PVC. PAC's are characterized by an abnormally shaped P wave which appears early and upright, different from normal sinus rhythm. Supraventricular tachyarrhythmia is characterized by heart rate greater than 150 beats per minute and P wave is usually not visible. If the R-R interval is greater than 1s, it is diagnosed as Bradycardia.

4. RESULTS AND DISCUSSION

The proposed algorithm is implemented in Matlab on Intel Pentium dual core processor at a speed of 2.30 GHz on 64bit operating system. In the first phase, the algorithm is tested on synthetic ECG signal generated using Matlab. Using the proposed algorithm, features detection and characterisation is done on synthetic data with 100 % accuracy. The real ECG data required for analysis is collected from Physionet MIT-BIH arrhythmia database [11].

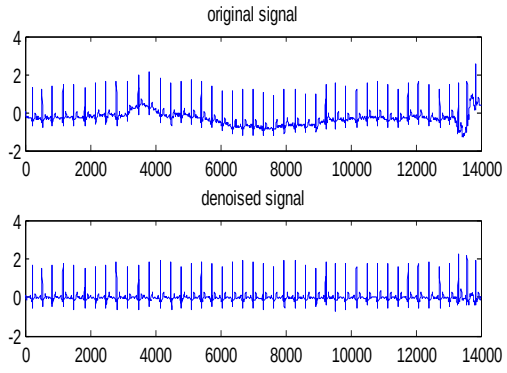

Fig 8: Original and Pre-processed ECG signal

The source of the ECGs included in the MIT-BIH Arrhythmia Database is a set long-term Holter recording that were obtained by the Beth Israel Hospital Arrhythmia Laboratory.

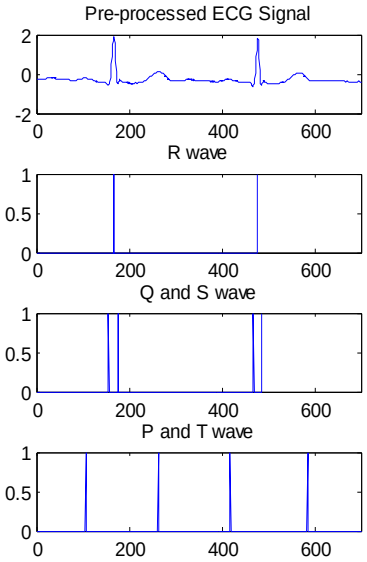

Fig 9: PQRST characteristic features

Each record has notes on the important features and also it has tables of rhythms and annotations, which summarize the contents of the database. These tables are helpful in finding a record with a specific set of characteristics.

The original ECG signal is pre-processed to remove baseline drift and high frequency noise. The fig 8 shows the ECG signal before and after Pre-processing. The original signal in the fig 8 drifts below the zero base line and more drift is observed in the middle and at the end of the signal. In pre-processed signal these baseline drifts and noise are removed using wavelet transform.

The pre-processed ECG signal is then decomposed at seven levels for feature extraction. As a result of this decomposition approximation and detail co-efficients are obtained. These detailed co-efficients are used to find the PQRST characteristic features. The R peak is detected by keeping details d3-d7 and all other details are made zero. Detection of R peaks is very important because they define the cardiac beats and the exactness of all forthcoming detections depends on R peak. The Q and S detection is done by keeping details greater than d5 and all other details are made zero. The details

d3-d6 is kept for P and T detection and all other details are made zero. Detected PQRST characteristic features is shown in fig 9 (Record "103" of MIT-BIH arrhythmia database is used for the fig 9). For the purpose of clear visibility of PQRST characteristic features only two beats are shown in fig9.

These detected features are used to find the number of heart beat in various records of the data base. The numbers of heart beats are detected by counting the R peak. Table 2 lists the total number of beats in each record and the sensitivity obtained by proposed algorithm. Sensitivity is calculated by the number of Beats detected by AEADS to the total number of beats in the record. The average sensitivity for 10 records using Db6 wavelet is 99.70%. This algorithm is also tested for different wavelets Haar, Db4, Coif1, Sym2, Bior2.6 and their results are shown in Table 2. The best result is obtained for Db6 wavelet. The algorithm also finds abnormalities in the ECG signal. Table 3 shows the abnormalities detected by AEADS. As it is clear from the table that the result perfectly matches with the doctor's prediction available in physionet website [11].

Table 3: Abnormalities detected by AEADS

Rec.	Disease detected	Doctor's prediction [11]
100	PVCs, APCs	PVCs, APCs
101	APCs	APCs
103	APCs	APCs
105	PVCs	PVCs
106	Ventricular tachycardia, PVCs	Ventricular tachycardia, PVCs
114	Supraventricular tachyarrhythmia, PVCs	Supraventricular tachyarrhythmia, PVCs
200	Ventricular tachycardia, PVCs, APCs	Ventricular tachycardia, PVCs, APCs
232	Sinus bradycardia, Supraventricular tachyarrhythmia	Sinus bradycardia, Supraventricular tachyarrhythmia

Table2: Sensitivity of signal records (Rec.) obtained by proposed AEADS for different wavelets.

Rec.	Total Number of Beats	Sensitivity (in Percentage)					
		Haar	DB4	DB6	Coif1	Sym2	Bior2.6
100	2273	99.65	99.96	99.96	99.91	99.82	99.91
101	1865	99.57	99.73	100	99.57	97.26	99.46
103	2084	99.90	99.81	99.81	98.72	99.90	99.76
111	2124	99.15	99.81	99.91	99.57	99.71	99.58
119	1987	81.78	100	100	99.89	99.89	99.95
121	1863	99.73	99.24	99.40	98.60	99.83	99.36
123	1518	99.80	99.80	99.80	99.80	99.80	99.80
213	3251	99.26	99.38	99.26	99.26	99.20	99.29
220	2048	99.21	99.31	99.32	99.60	99.16	96.16
233	3079	87.82	91.68	99.55	99.51	99.41	99.61
Average Sensitivity in Percentage		96.59	98.87	99.70	99.44	99.39	99.29

5. CONCLUSION

In this paper we have proposed fully automated, high accuracy and fast AEADS. The algorithm uses wavelets for pre-processing and feature extraction. The number of heart beat is detected based on the occurrence of R wave. The average sensitivity of the algorithm is 99.70%. The comparison made between the proposed algorithm and literature is listed in Table 4. Hence this algorithm comparable gives best results. This proposed detector also able to detect Premature Ventricular Contraction (PVC), Premature Atrial Contractions (PACs), Supraventricular tachyarrhythmia and Bradycardia. The algorithm can be extended to detect many other abnormalities like Dextrocardia, Hyperkalemia, Myocardial ischaemia, sudden cardiac death.

Table4: comparison between the proposed algorithm and literature

Methods	Sensitivity
Proposed detector AEADS	99.70%
S.Z. Mahmoodabadi et.al [8]	99.18% ± 2.75
Sonia Rezk et.al [20]	99.38%
Awadhesh Pachauri et.al [23]	96.65%
C. Li, C. Zheng et.al [21]	99.50%
I. Christov. [22]	99.92%

6. REFERENCES

[1] Naregalkar Akshay et al. 2010. ECG Noise Removal and QRS Complex Detection Using UWT. International Conference on Electronics and Information Engineering (ICEIE).

[2] P. Sasikala et al. 2010. Robust R Peak and QRS detection in Electrocardiogram using Wavelet Transform. International Journal of Advanced Computer Science and Applications (IJACSA), Vol. 1, No.6.

[3] MujeebRahman et al. 2011. An Algorithm for Detection of Arrhythmia. IEEE Ajman University of Science & Technology.

[4] S. Karpagachelvi et al. 2010. ECG Feature Extraction Techniques - A Survey Approach. International Journal of Computer Science and Information Security (IJCSIS), Vol. 8, No. 1.

[5] A. K. M. FazlulHaque et al. 2009. Detection Of Small Variations Of ECG Features Using Wavelet. ARPN Journal of Engineering and Applied Sciences, Vol. 4, No. 6.

[6] BachirBoucheham. 2011. Abnormality Detection in Electrocardiograms by Time Series Alignment. Communications in Information Science and Management Engineering (CISME), Vol.1 No.3.

[7] Mohammad Niknazar et al. 2009. Detection of Characteristic Points of ECG using Quadratic Spline Wavelet Transfrom. International Conference on Signals, Circuits and Systems.

[8] S. Z. Mahmoodabadi et al. 2005. ECG Feature Extraction Using Daubechies Wavelets. Proceedings of the Fifth IASTED International Conference ,Benidorm, Spain.

[9] C. Saritha et al. 2008. ECG Signal Analysis Using WaveletTransforms. Department of Physics and Electronics, S.S.B.N. College Anantapur, Andhrapradesh, India,16.

[10] Qibin Zhao, and Liqing Zhan. 2005. ECG Feature Extraction and Classification Using Wavelet Transform and Support Vector Machines. International Conference on Neural Networks and Brain, ICNN&B '05, vol. 2, pp. 1089-1092.

[11] Massachusetts Institute of Technology.1997. Cambrige. MITBIH, database distribution.

[12] M. Kania et al. 2007. Wavelet Denoising for Multi-lead High Resolution ECG Signals. Measurement Science Review, Volume 7, Section 2, No. 4,

[13] E. Hostalkova et al. Wavelet Signal And Image Denoising. Institute of Chemical Technology Department of Computing and Control Engineering

[14] Digvijay Ghosh. 2005. Wavelet Aided SVM Analysis of ECG Signals for Cardiac Abnormality Detection. IEEE Indicon Conference, Chennai, India.

[15] K. V. L. Narayana et al. 2011. Wavelet based QRS detection in ECG using Matlab. Innovative Systems Design and Engineering, Vol 2, No7.

[16] Gordan Cornelia et al, "ECG Signals Processing Using Wavelets" University of Oradea , Electronics Department, Faculty of Electrical Engineering and Information Technology Oradea, Romania.

[17] Veena N. Hegde et al. 2011. Comparison of Characterizing and Data Analysis Methods for Detecting Abnormalities in ECG. IEEE.

[18] R. Sudirman et.al. 2010. Modeling Of EEG Signal Sound Frequency Characteristic Using Time Frequency Analysis", Fourth Asia International Conference on Mathematical/Analytical Modelling and Computer Simulation

[19] Md. Abdullah Arafat et al. 2009. Automatic Detection Of ECG wave Boundaries Using Empirical Mode Decomposition. IEEE

[20] Sonia Rezk et.al. 2011. An Algebraic Derivative-Based Method For R Wave Detection. 19th European Signal Processing Conference (EUSIPCO)

[21] C. Li, C. Zheng, and C. Tai. 1995. Detection of ECG characteristic points using wavelet transforms. IEEE Trans. Biomed. Eng, 42:21–28

[22] I. Christov. 2004. Real time electrocardiogram QRS detection using combined adaptive threshold. Biomed. Eng. Online, 3(1):p28

[23] Awadhesh Pachauri et.al. 2009. Robust Detection of R-Wave Using Wavelet Technique. World Academy of Science, Engineering and Technology 56.