Interpretation of Normal and Pathological Beats using Multiresolution Wavelet Analysis

Shubhada Ardhapurkar[1], Ramchandra Manthalkar[2], Suhas Gajre[2]

[1]International Center of Excellence in Engineering and Management, Aurangabad, India
[2]S.G.G.S. Institute of Engineering and Technology, Nanded, Maharashtra, India

Abstract

The discrete wavelet transform has great capability to analyze the temporal and spectral properties of non stationary signal like electrocardiogram (ECG). In this paper, we developed and evaluated a robust algorithm using multiresolution analysis based on the discrete wavelet transform (DWT) for twelve-lead ECG temporal feature extraction. The study, with support of physiological knowledge, attempted interpretation of ECG beats with different patterns. Selection of appropriate group of wavelet coefficients along with decision rules is used to determine P, Q, R, S and T wave locations, amplitudes, onsets and offsets We evaluated the algorithm on normal and abnormal beats from various manually annotated databases from physiobank with different sampling frequency. An appropriate value of threshold at QRS detector offered sensitivity of 99.5% and positive predictivity of 98.9% over the first lead of the MIT-BIH Arrhythmia Database.

1. Introduction

The electrocardiogram, ECG, provides useful information about functioning of heart required for cardiovascular assessment. Muscular contraction (systole) is associated with electrical changes known as depolarization. The contraction of atria manifests itself as 'P' wave, contraction of ventricles produces the 'QRS' complex and repolarisation of ventricular mass produces the 'T' wave. ECG interpretation consists of detection of wave components P, QRS and T along with positions, magnitudes. Cardiac disorders can be correctly and timely identified on the basis of accuracy of detection.

Several approaches for ECG interpretation are found in literature having sensitivity above 99%. The worldwide popular, first of its kind, real time QRS detection based on slope amplitude and width was introduced by Pan and Tompkins [1]. Wavelet is a powerful tool for analysing ECG. Shubha Kadambe et al. compared the performance of dyadic wavelet transform based QRS detector with detectors based on Okada, Hamilton–Tompkins, and multiplication of the backward difference algorithms [4]. A review of all above seven types of algorithms along with the advantages was explained in [5]. A precise approach was developed and evaluated by Martinez et al. using stationary wavelet transform [7]. Zhao et al. [8] proposed a feature extraction method combined wavelet transform and support vector machines to provide accuracy of 99.68%. Saurabh Pal and Mahmoodabadi et al. described approaches for ECG feature extraction by selection of discrete wavelet coefficients [9]-[10]. In the algorithm presented by Szi-wen Chen et al, filtering procedure based on moving averages provides smooth spike-free ECG signal [12]. A simple and reliable method termed as Difference Operation Method (DOM) to detect the QRS complex of an ECG signal was proposed [15].

The paper describes steps for ECG characteristic points detection by multiresolution wavelet analysis. The results of experimentation on various ECG signals with different sampling frequency are explained.

1.1. Multiresolution analysis

The DWT analyses the signal at different resolution. (hence, multiresolution) through the decomposition of the signal into several successive frequency bands. The DWT utilizes two set of functions $\phi(t)$ and $\psi(t)$, each associated with the low pass and the high pass filters respectively. These functions have a property that they can be obtained as the weighted sum of the scaled (dilated) and shifted version of the scaling function itself:

$$\phi(t) = \sum_n h(n)\sqrt{2}\phi(2t-n) \tag{1}$$

$$\psi(t) = \sum_n g(n)\sqrt{2}\phi(2t-n) \tag{2}$$

h[n] and g[n] are the half band low pass filter and high pass filter respectively. Conversely, a scaling function $\phi_{j,k}(t)$ or wavelet function $\psi_{j,k}(t)$ that is discretized at scale j and translation k can be obtained from the original (prototype) function $\phi(t) = \phi_{0,0}(t)$ or $\psi(t) = \psi_{0,0}(t)$.

$$\psi_{j,k}(t) = 2^{(-j/2)}\phi(2^{-j}t - k) \tag{3}$$

$$\phi_{j.k}(t) = 2^{(-j/2)}\phi(2^{-j}t - k) \quad (4)$$

Decomposition of the signal into different frequency bands is therefore accomplished by successive low pass and high pass filtering of the time domain signal. Filtering followed by sub-sampling constitutes one level of decomposition, and it can be expressed as follows:

$$D_1(k) = y_{high}[k] = \sum_n x(n) * g(2k - n) \quad (5)$$

$$A_1(k) = y_{low}[k] = \sum_n x(n) * h(2k - n)) \quad (6)$$

1.2. Normal and pathological ECG

Abnormal heart conditions causes deviation in P,Q, R,S and T wave parameters from normal values [10]. Table 1 shows list of variations in morphology.

Table 1. Characteristics of Pathological beats

Beat type	Change in Morphology
RBBB Right Bundle Branch Block	A terminal R wave in lead V1 QRS >0.10 sec QRS normal or deviated to the right , Slurred S wave in leads I and V6,RSR' pattern in lead V1 with R' taller than R
LBBB Left Bundle Branch Block	QRS >0.10 sec ,QRS negative (QS or rS complex) in V1 and V2 QRS positive in V5 and V6 and often notched (RsR' wave) Absence of small, normal Q waves in I, aVL, V5, and V6 Wide monophasic R waves in I, aVL, V1, V5, and V6
PVC Premature Ventricular Contraction	Irregular rhythm whenever PVC occurs. P Waves: and PR Interval not associated with PVC. QRS: Wide (>0.10 sec), bizarre appearance
PAC Premature Atrial Contraction	Irregular rhythm whenever a PAC occursP Waves: Present; may have a different shapePR Interval varies ; otherwise normal QRS: Normal
Fusion of normal with paced beats	TP segment is absent.
Left Ventricular Hypertrophy	R in lead I and S in lead III > 25mm R in AVL > 12 mm,S> 25 mm in V1, R> 25 mm in V5
Mayocardial Infarction	ST elevation or ST depression Pathological Q wave
Hypertrophy	Notch and enlarged P wave (Atrial Hypertrophy)Wide QRS complex (Ventricular Hypertrophy)

2. Algorithm implementation

Step1: R Detection:

- In order to detect R peaks, the reconstructed signal is obtained from detail coefficients of 3-5 scales (cD_3-cD_5) and setting rest of coefficients to zero. The reconstructed signal is thresholded (Threshold T_R =RMS (cD_4)). Differentiation of thresholded signal gives locations of positive and negative transitions and absolute maximum within these locations and denoted as R peaks (Figure 1). Table 2 details selection of coefficients and thresholds for different sampling frequency. The rules to detect various configurations of QRS complex (QRS, QS, rSr', RsR', RS, rS, rSR',QR, R).
- R wave is always directed upward and has positive value. The magnitude of peak will declare 'r' or 'R'.
- Peak with amplitude greater than 0.25 mV declare R otherwise 'r'.
- If R has succeeding R at a distance greater than 0.2 ms (0.2 ms is refractory period of heart) then it can belong to QRS, RsR', RS, QR or R pattern.
- Q and S, S or Q is searched If next immediate peak after R (or r) is observed with an intermediate opposite magnitude indicates RSR'(or rSr') pattern. The comparable middle value denotes a notch and R' must be discarded.
- Premature ventricular contraction (PVC) beats may contain r peaks. Figure 2 and 3 shows detection of various configurations.

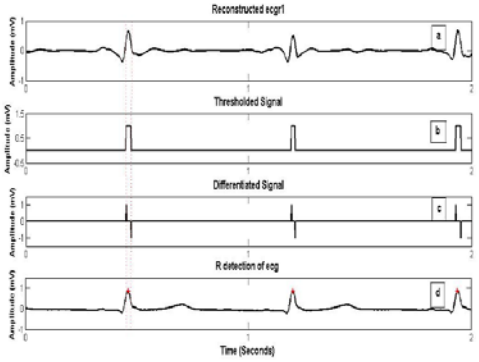

Figure 1. (a) Reconstructed signal ecgr1 of 11AL.dat (b) Thresholded signal (c) Differentiation of thresholded signal (d) Detected R peaks

Table 2. Selection of coefficients and threshold.

For R detection	Detail coefficients	Threshold
Fs=128	cD_1, cD_2, cD_3	RMS(cD_2)
Fs=250	cD_2, cD_3, cD_4	RMS(cD_3)
Fs=360	cD_3, cD_4, cD_5	RMS(cD_4)
Fs=500	cD_3, cD_4, cD_5	RMS(cD_4)
Fs=1000	cD_4,cD_5, cD_6	RMS(cD_5)

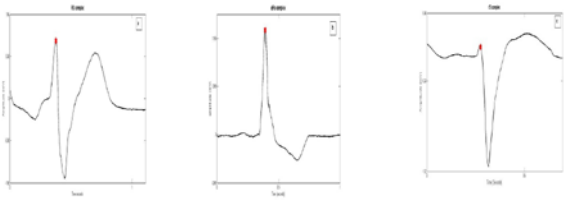

Figure 2. (a)RS (b) R (c)rS complex

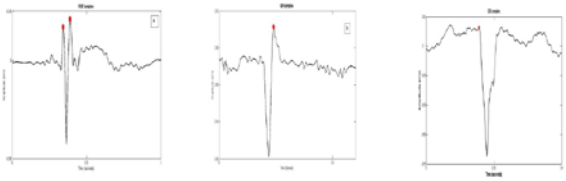

Figure 3. (a)rSr' (b) QR (c)QScomplex

Step 2: Q and S peak Detection:

Detail coefficients cD_2–cD_6 are used for reconstructing signal. QRS interval can vary from 0.04 sec to 0.12 seconds. However the local minima Q and S peaks are searched around R peaks within 0.16 seconds window considering pathological conditions. The locations and corresponding magnitudes are noted (figure 4). If magnitudes are less than 10% of R –peak then absence of Q or S peaks is declared.

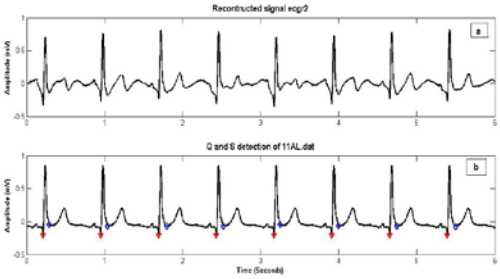

Figure 4. (a) Reconstructed signal (b) Detection of Q and S peaks in 11AL.dat

Step 3: P and T Wave Detection

P and T waves are high-flying when only cD_4-cD_7 coefficients are kept for reconstruction (figure 5). P peak is obtained by finding absolute maximum from first zero crossing point immediately before Q (within 100 samples as PR interval 0.12-0.20seconds). T peak is searched after S (170 samples as QT interval 0.34-0.44seconds).By keeping only cD_5, the signal ecgr4 is reconstructed. The appropriate zero crossings on both sides of QRS complex of ecgr4 gives onset and offset points of P and T waves (figure 6).

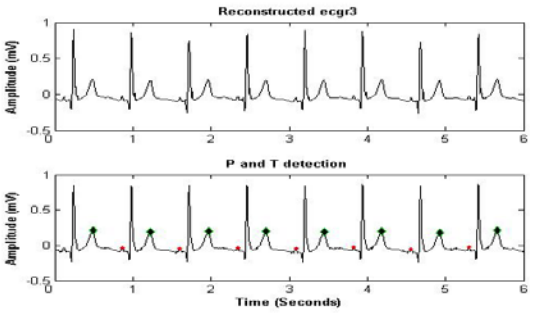

Figure 5. (a) Reconstructed signal (b) Detection of P and T peaks in 11AL .dat

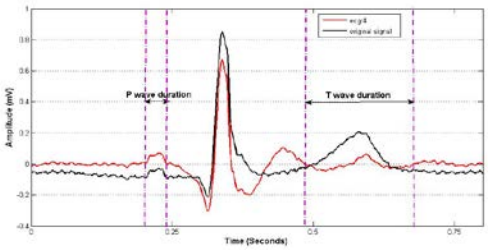

Figure 6. Onset and Offset detection of P and T wave

3. Results

The algorithm was evaluated on records from physionet ECG databank and on records from Glasgow Institute of Cardiovascular and Medical sciences. The algorithm correctly identifies (1) S peaks even in case of QRS followed by inverted T wave (2) Three different morphologies of T wave positive, biphasic (+/-) and negative (in leads aVR, V1 may be in lead III) (3) The P wave morphologies considered are: absence of P wave (PVC beats), positive, negative, biphasic P wave (mostly observed in lead V1) and P wave fused with T wave. (figure 7 and 8). Table 3 shows performance of proposed algorithm on various databases. Table 4 indicates mean values of important features of LBBB, RBBB, Premature Ventricular Contraction (PVC), Atrial premature beats (APC), Myocardial Infarction (MI) and Hypertrophy .

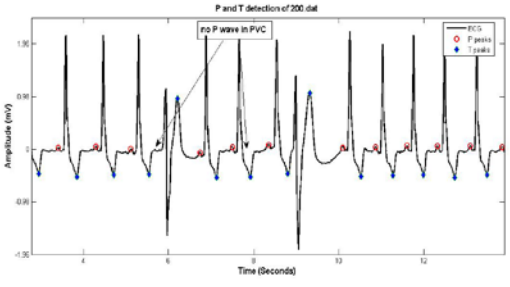

Figure 7. Detection of positive P wave for normal beat and absence of P wave for PVC beats of 200.dat

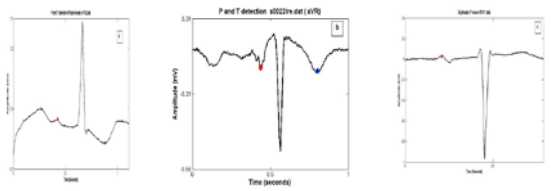

Figure 8. (a) Fusion of paced and normal beat in 102.dat (b) Negative P in s0022lre.dat (c) Biphasic P in 61V1.da

Table 3. Performance on various databases

Database	Specifications	Detected Beats	Se (%)	PP (%)
Arrythmia database*	360Hz, 2channel,11 bit resolution over 10 mV	50838	99.5	99
Normal Sinus Rhythm Database*	128Hz, 2channel,11 bit resolution over 10 mV	27123	99.8	100
PTB Diagnostic Database*	1kHz, 15channel, 16 bit resolution over 32 mV	9061	99.5	99.8
Glasgow database	500Hz, 15channel,12 bit over 2 mV	4200	100	100

(*= MIT BIH database from physiobank)

Table 4. Mean values of features for pathological beats

Patient ID	Beats category	Lead Number	QRS duration	QT interval	R-R interval
111	LBBB	ML II	0.12	0.43	0.84
118	RBBB	ML II	0.10	0.59	1.2
214	PVC	ML II	0.15	0.50	0.54
200	APC	ML II	0.10	0.44	0.52
s0080lre	MI	V1	0.09	0.20	0.72
S0432 Re	Hyper trophy	Lead I	0.08	0.5	0.88
11AL	Normal	aVL	0.09	0.36	0.74

4. Conclusion

Choice of proper coefficients in multiresolution wavelet analysis changes with different sampling frequency. The study has proposed additional decision rules to detect different pathological conditions. Denoising is prerequisite for accurate detection of ECG signals. To detect of atrial and ventricular flutter beats energy content of subbands should be monitored. Accuracy can be enhanced at the cost of computational burden.

Acknowledgements

The work was supported by funds from All India Council for Technical Education (AICTE), New Delhi under Research Promotion Scheme Grant Number 8023/RID/RPS-86/2011-12. We thank Prof. Peter W. MacFarlane of University of Glasgow, Scotland for providing ECG database for our research work.

References

[1] Jiapu Pan, Wiilis, Tompkins, A Real Time QRS Detection . IEEE Transactions On Biomedical Engineering, 1985:230-238.

[2] Shubha Kadambe, Robin Murray, G. Faye Boudreaux-Bartels, Wavelet Transform-Based QRS Complex Detector. IEEE Transactions On Biomedical Engineering, 1999, 46.

[3] Bert-Uwe Köhler, Carsten Hennig,Reinhold Orglmeister, The Principles of Software QRS Detection Reviewing and Comparing Algorithms for Detecting ECG Waveform . IEEE Engineering In Medicine And Biology, 2002 :42-57.

[4] Juan Pablo Martínez, Rute Almeida, Salvador Olmos, Ana Paula Rocha, Pablo Laguna, A Wavelet-Based ECG Delineator: Evaluation on Standard Databases. IEEE Transactions on Biomedical Engineering,2004,51:570-581.

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

[6] S. Z. Mahmoodabadi, A. Ahmadian, M. D. Abolhasani, ECG Feature Extraction using Daubechies Wavelets . Proceedings of the fifth IASTED International conference on Visualization, Imaging and Image Processing, 2005: 343-348,

[7] Saurabh Pal, Madhuchhanda Mitra, Detection of ECG characteristic points using Multiresolution Wavelet Analysis based Selective Coefficient Method. Measurement, 2010, 43: 255-261.

[8] Szi-Wen Chen, Hsiao-Chen Chen, Hsiao-Lung Chan, A real-time QRS detection method based on Moving-Averaging Incorporating With Wavelet Denoising . Computer Methods And Programs In Biomedicine,2006, 82:187–195.

[9] Yun-Chi Yeh, Wen-June Wang, QRS complexes detection for ECG signal: The Difference Operation Method. Computer Methods And Programs In Biomedicine,2008 , 91 :245–254.

[10] Barbara Aehlert ,RN, ECGs Made Easy, Elsevier prints, Second Edition, 2004.

Address for corresponadance
Shubhada S. Ardhapurkar,
International Center of Excellence in Engineering and Management, Waluj, Aurangabad, Maharashtra, INDIA
Phone: +91-240-2558128 Email: vaidyashubha21@gmail.com