A Novel Approach for Different Morphological Characterization of ECG Signal

R. Harikumar and S. N. Shivappriya

Abstract The earlier detection of Cardiac arrhythmia of ECG waves is important to prevent cardiac disorders. A good system depends heavily upon the precise and consistent estimate of ECG signal morphology i.e. QRS complex, T and P wave. From the benchmark data bases: MIT-BIH Arrhythmia, QT and European ST-T database the ECG is fetched then the noise is removed from the digitized ECG signal. To analyze various power spectrum of ECG signal Stationary Wavelet Transform (SWT) is applied to the de-noised signal. Based upon the spectrum QRS complex T and P waves are detected and also delineated using different amplitude threshold values. This gives simple and reliable method for the detection and delineation of the constituent waves from a given ECG signal has been the fundamental goal of automatic cardiac arrhythmia detection. This algorithm allows delineation of different morphologies of QRS complex P and T wave.

Keywords ECG · Wavelet transform · Cardiac arrhythmia

1 Introduction

1.1 Electrical Cardio Gram

In recent years, ECG signal plays an important role in the primary diagnosis, prognosis and survival analysis of heart diseases. Electrocardiography has a

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profound influence on the practice of medicine. This paper deals with the detection of QRS complexes of ECG signals using derivative based/Pan-Tompkins/wavelet transform based algorithms. The electrocardiogram signal contains an important amount of information that can be exploited in different manners. The Electrogram is composed of the wave and complexes. Waves and complexes in the normal sinus rhythm are the P-wave, PR-interval, PR segment, QRS complex, ST segment, QT interval and T wave.

The P-wave is caused by atrial depolarization. In normal sinus rhythm, the SA node acts as the pacemaker. The P-wave is usually smooth and positive. The P-wave duration is normally less than 0.12 s. The PR interval is the portion of the ECG wave from the beginning of the P wave (onset of the atrial depolarization) to the beginning of the QRS complex (onset of the ventricular depolarization).The PR segment is the portion on the ECG wave from the end of the P-wave to the beginning of the QRS complex. The PR segment is corresponds to the time between the end of atrial depolarization to the onset of the ventricular depolarization.

The QRS complex represents the time it takes for the ventricles in normal sinus rhythm, each P wave is followed by a QRS complex. The QRS complex proceeds ventricular contraction. ST segment represents the period of the ventricular muscle contraction before repolarization. The ST segment is normally iso-electric (no electrical activity is recorded). However, the ventricles are contracting. The QT interval begins at the onset of the QRS complex and to the end of the T wave. It represents the time of the ventricular depolarization until ventricular repolarization. T wave occurs due to ventricular repolarization.

In electrocardiograms (ECGs), most of the clinically useful information can be found in the wave intervals, amplitudes, or morphology. Therefore, efficient and robust methods for automated ECG delineation are of great importance. The QRS complex is relatively easy to detect and is thus generally used as a reference within the cardiac cycle. For P and T wave detection and delineation (i.e., determination of peaks and boundaries of the P and T waves), most existing methods perform QRS detection first. They then define temporal search windows before and after the detected QRS location to search for the P and T waves using filtering [1], basis expansions [2], or thresholding. Because of the low slope and magnitude of the P and T waves, as well as the presence of noise, interference, and baseline fluctuation, P and T wave delineation remains a difficult task.

Furthermore, in addition to delineation, accurate estimation of the waveform itself may be important, e.g. for T wave different pathological detection [4]. Wavelets are new promising approach to analyze and characterize the non-stationary signals such as ECG, EEG, and EMG etc. Wavelet transform (WT) decomposing signals into elementary building blocks that are well localized both in time and frequency, wavelet transform can characterize the local regularity of signals. This feature can be used to distinguish ECG waves from serious noise, artifacts and baseline drift.

1.2 Cardiac Arrhythmias

Any disturbances in the heart's normal rhythmic contraction are called an arrhythmia. Normal sinus rhythm is characterized by a regular rhythm and PR interval duration range of 0.12–0.20 s. Arrhythmias can be recognized by evaluating the systematic manner. Some arrhythmias are atrial fibrillation, atrial flutter, ventricular fibrillation and ventricular flutter. Among these we see the causes of the one of the arrhythmia: atrial fibrillation.

Atrial fibrillation (AF): This arrhythmia [3] will occur due to fast beating rate (300–500 beats/min) of the atrium. Here no P wave is observable. Here ventricle beats very slowly. This atrial fibrillation is very frequent arrhythmia which going to effect elderly people: 2–5 % of people over 60 years old and 10 % over 70 years old. It results in partial disorganization of atrial electrical activity, due to two electrophysiological properties. Due to AF upper heart chambers (atria) quiver instead of pumping blood effectively. Blood in the atria may pool and clot. If a clot breaks loose and advances to the brain, a stroke can result.

Atrial refers to the heart's two upper chambers, the left and right atria. The two lower chambers are called the ventricles. Fibrillating means quivering, or rapid beating. Irregular, rapid beating of the atrial chambers characterizes Atrial Fibrillation. This happens when the normal system that conducts electricity in the atria malfunctions. A storm of electrical activity across both atria causes them to fibrillate 300–600 Times/min.

The ventricles pick up only a small number of these impulses, but the ventricular rate can approach 180 or higher. Whether Atrial Fibrillation happens at high or low heart rates, its irregular rhythm means the ventricles can't pump blood efficiently to the rest of the body. Instead, blood pools in the heart and the body doesn't get enough. This can result in varying symptoms [5] from relatively mild ones, such as fatigue and cough, to serious ones, such as angina and stroke.

1.3 ECG Databases

Different ECG Databases are used for the present work such as Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) Arrhythmia databases, European Society of cardiology database and QT Database. The QT Database includes ECGs which were chosen to represent a wide variety of QRS and ST-T morphologies, in order to challenge QT detection algorithms with real-world variability. The records were chosen primarily from among existing ECG databases, including the MIT-BIH Arrhythmia Database, the European Society of Cardiology ST-T Database, and several other ECG databases collected at Boston's Beth Israel Deaconess Medical Center.

2 Materials and Methods

The Automatic Detection of ECG wave is important to cardiac disease diagnosis. The new pre-processing approach can remove the low-frequency components without introducing distortions in the ECG waveform.

2.1 Pan-Tompkins Algorithm

The QRS detection provides the fundamentals for almost all automated ECG analysis algorithms. Pan-Tompkins proposed a real-time QRS detection algorithm based on analysis of the slope, amplitude, and width of the QRS complexes [8] of typical cardiac signal as shown in Fig. 1. The algorithm includes a series of filters and operators that perform derivative, squaring, integration, adaptive thresholding operations and search procedures.

Band pass Filtering: The band pass filter for the QRS detection algorithm reduces noise in the ECG signal by matching the spectrum of the average QRS complex. This attenuates noise due to muscle noise, power line interference, baseline wander, T wave interference. The pass band that maximizes the QRS energy is in the 5–35 Hz range. The filter implemented in this algorithm is composed of cascaded high pass and low pass Butterworth IIR filters.

Derivative Operator: The next processing step is differentiation, standard technique for finding the high slopes that normally distinguish the QRS complexes from other ECG waves. The derivative procedure suppresses the low frequency components of P and T waves, and provides a large gain to the high-frequency components arising from the high slopes of the QRS Complex.

Squaring: The squaring operation makes the result positive and emphasizes large differences resulting from QRS complexes; the small differences arising from P and T waves are suppressed. The high frequency components in the signal related to the QRS complex are further enhanced. This is a nonlinear transformation that consists of point by point squaring of the signal samples.

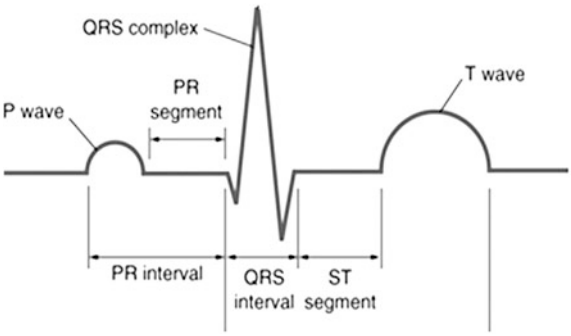

Fig. 1 Morphology of a mean PQRST-complex of an ECG recorded from a normal person

Integration: The squared waveform passes through a moving window integrator. This integrator sums the area under the squared waveform over a suitable interval, advances one sample interval, and integrates the new predefined interval window. The half-width of window has been chosen as 27 to include the time duration of extended abnormal QRS complexes, but short enough that it does not overlap both a QRS complex and a T-wave. MA (moving average) filter extracts features in addition to the slope of the R wave.

2.2 Wavelet Based Delineation

Time–frequency wavelet theory [7] is used for the detection of life threatening electrocardiography (ECG) arrhythmias. This is achieved through the use of the raised cosine wavelet transform (RCWT). The RCWT is found to be useful in differentiating between ventricular fibrillation, ventricular tachycardia and atrial fibrillation. Ventricular fibrillation is characterized by continuous bands in the range of 2–10 Hz; ventricular tachycardia is characterized by two distinct bands: the first band in the range of 2–5 Hz and the second in the range of 6–8 Hz; and atrial fibrillation is determined by a low frequency band in the range of 0–5 Hz.

A classification algorithm is developed to classify ECG records on the basis of the computation of three parameters defined in the time–frequency plane of the wavelet transform. Furthermore, the advantage of localizing and separating ECG signals from high as well as intermediate frequencies is demonstrated. The above capabilities of the wavelet technique [6, 9] are supported by results obtained from ECG signals obtained from normal and abnormal subjects.

Wavelet based morphological Detection and Delineation of ECG consists of following stages:

Pre-processing: This stage utilizes a filtering unit to remove the artifact signals from the ECG signal. These signals include baseline wandering, power line interferences, and a high frequency noise. After the preprocessing stage [10, 11], the Stationary Wavelet Transform is applied to the De-noised signal. Most of the energy of the ECG signal lies between 2^1 and 2^4 of the scales.

QRS complex Detection: First the noise is removed from the digitized ECG signal. Then SWT is applied. In the ECG signal R wave is having maximum amplitude, which is detected at larger scale (2^3). Fixing the R peak is simple in comparison to the location of the P and T wave boundaries. The level-3 SWT Low pass filter coefficients are given to the differentiator, squaring circuit and moving window average process from which the R peak is detected.

Setting the search window (100 ms) before and after the R-peak, two minima points are detected, they are respectively known as minima-1 and minima-2. Fixing the same search window before and after the minima-1 and minima-2, the QRS onset and offset (zero crossing) points are detected. Normally the onset and offset of the QRS complex have high frequency and low amplitude signal, which

are detected at finer scale (2^1). The reason for detecting the onset and offset points at scale (2^1), rather than the original signal are to avoid the effect of baseline drift.

QRS Delineation (onset, offset and individual waves): One of the novelties with respect to [7] is the detection and identification of QRS individual waves. The algorithm departs from the position given by the detector, in this delineation process WT based algorithm departs from the position given by the detector, n_{qrs}, which must be flanked by a pair of maximum moduli with opposite signs at scale 2^2 namely at n_{pre} and n_{post}. The delineator looks before n_{pre} and after n_{post} for significant maxima of accounting for other adjacent slopes within the QRS complex. To consider a maximum modulus as significant, it must exceed the threshold, γ_{QRSpre} or $\gamma_{QRS_{post}}$ respectively for previous or subsequent waves. The morphology of QRS complex depends of the number of significant maxima moduli within the corresponding search window.

The onset (offset) of the QRS is before (after) the first (last) significant slope of the QRS, which is associated with a maximum of $|w_{2^2} x[n]|$. So first identify the samples of the first and last peaks associated within the QRS $w_{2^2} x[n]$ say n_{first} and $n_{last.}$

Onset and offset are determined by applying two criteria:

1. searching for the sample where is $|w_{2^2} x[n]|$ below a threshold (ξ_{QRSon} or ξ_{QRSend}) relative to the amplitude of the maximum modulus ($|w_{2^2} x[n_{first}]|$ or $|w_{2^2} x[n_{last}]|$);
2. searching for a local minimum of $|w_{2^2} x[n]|$ before n_{first} or after n_{last}.

T wave Detection: Fixing the search window (200 ms) after the offset of the QRS complex, the T wave is detected. Finding maxima of $|w_{2^4} x[n]|$ in that window; that maxima value which are exceeding this threshold value $\in_T$ are considered to be the T wave peak. Fixing the same search window before and after the T wave peak the onset and offset (zero crossing) points are detected. In order to avoid errors in detecting the onset and offset of these P and T waves due to baseline drift and motion artifacts, the scale 2^4 is selected.

T wave Delineation: Maximum of $|w_{2^4} x[n]|$ with amplitude greater than this threshold γ_T are considered as significant slope of the wave or T wave peak. Depending upon number and polarity of the found maximum, one out of six possible T wave morphologies: positive (+), negative (−), biphasic (+/− or −/+), only upwards, and only down wards. If the T wave is not found in scale 2^4 , repeat the above process over $|w_{2^4} x[n]|$. To identify the wave limits of T wave the same criteria as for QRS onset and offset with thresholds and applied to scale 2^k.

P wave Detection: Fixing the search window (200 ms) before the offset of the QRS complex, the T wave is detected. Finding maxima of $|w_{2^4} x[n]|$ in that window; that maxima value which are exceeding this threshold value $\in_p$ are considered to be the P wave peak. As like the T wave the onset and offset points of P wave also detected.

P wave Delineation: As like the T wave delineation process P wave Delineation also done.

2.3 Different Morphological Detection

Once the QRS complex has been detected, the T wave can be analyzed because ventricular repolarization always follows depolarization. Conversely, the P wave does not lend itself as easily to analysis because atrial and ventricular rhythms may be independent of each other. In the vast majority of cases, however, atrial and ventricular rhythms are associated so that P wave detection may be based on a backward search in time, beginning at the QRS complex and ending at the end of the preceding T wave. A method of wave delineation determines the boundaries of each wave within the PQRST complex so that, with the resulting time instants, different wave durations can be computed.

Once a wave has been delineated, [9] other measures characterizing the wave, such as amplitude and morphology, can be easily computed. Instead, many methods for wave delineation exploit the change in slope that occurs at a boundary to avoid the problems because of low-frequency noise. This type of delineation is to find the end of the S wave; the other wave boundaries of the PQRST complex can be found in a similar way. In this example, the search for the endpoint starts when the steepest upslope of the S wave occurs and continues until the derivative of the signal falls below a certain threshold value.

This wavelet based Delineation system gives more accurate detection peaks and fiducial points of QRS complex, P and T wave (positive (+), negative (−), biphasic (+/- or -/+) absence of wave, signal with low SNR only upwards, and only down wards) compare with the Pan-Tompkins Algorithm. With these different Morphological features mostly all of the arrhythmias are detected.

3 Validation Using Different Databases

As there is no golden rule to determine the peak, onset and end of the ECG waves, the validation of the delineator must be done using manually annotated databases. For these purposes, some easily-available or standard databases are used, namely the MIT-BIH Arrhythmia database (MITDB), the QT database (QTDB) and the European ST-T database (EDB). In this paper totally 151 different ECG signals (consists of normal, arrhythmic signals) are used for the detection and delineation of time and amplitude of QRS complex, P and T waves is done in more precise manner (Table 1).

The MITDB includes specially selected Holter recordings with anomalous but clinically important phenomena. The EDB files present ischemic episodes extracted from Holter recordings. These databases include annotations of QRS positions: R marks (MITDB) or QRS onsets (EDB). The QTDB includes some records from EDB and MITDB and also from several other MIT-BIH databases (ST Change, Supraventricular Arrhythmia, Normal Sinus Rhythm, Sudden Death, and Long Term).

Table 1 Characteristic of the validation databases

Databases	Files	Leads	*fs (Hz)*	Record duration
MITDB	25	2	360	30 min
QTDB	92	2	250	1 min
EDB	34	2	250	30 min

To assess the QRS detector [12, 13] calculate the sensitivity Se = TP/(TP + FN) and positive predictivity PP = TP/(TP + FP), where TP is the number of true positive (correct) detections, FN stands for the number of false negative(missed) detections, and FP stands for the number of false positive(wrong) detections. Error beats E = FN + FP.

4 Results and Discussion

The pre-processed ECG signal is given to SWT process after this detection and delineation of QRS complex T and P waves were done. The WT-based detector, in contrast to most QRS detectors found in the literature, allows to take advantage of the same wavelet analysis stage for ECG wave delineation, due to the particularly appropriate characteristics of time-scale analysis.Detection and Delineation ECG signal is done for 151 annotations of MITDB, QTDB and EDB of above mentioned record time. Detection and Delineation of P, QRS, T wave comparison table with their performance metrics and different Morphological features of individual ECG signal components are shown in Tables 2, 3 and 4.

Table 2 Validation of P wave

Database	P Wave					
	Detection			Delineation		
	Se (%)	PP (%)	E	Se (%)	PP (%)	E
MITDB	99.24	89.84	4,889	99.23	89.42	5095
QTDB	99.45	89.02	542	99.45	88.51	565
EDB	99.86	89.51	2,263	99.86	89.39	2,286

Table 3 Validation of QRS complex

Database	QRS complex					
	Detection			Delineation		
	Se (%)	PP (%)	E	Se (%)	PP (%)	E
MITDB	99.31	99.78	498	99.30	99.39	675
QTDB	99.45	99.77	24	99.45	99.76	25
EDB	99.89	99.81	65	99.89	99.32	176

Table 4 Validation of T wave

Database	T Wave					
	Detection			Delineation		
	Se(%)	PP(%)	E	Se(%)	PP(%)	E
MITDB	99.28	96.21	2080	99.28	96.02	2167
QTDB	99.45	98.85	63	99.45	98.64	73
EDB	99.89	98.44	416	99.89	98.16	489

Table 5 Various abnormalities and their characteristic

S. No.	Name of abnormality	Characteristic features
1	Atrial fibrillation	Absence of P wave
2	Dextrocardia	Inverted P-wave
3	Tachycardia	R–R interval <0.6 s
4	Bradycardia	R–R interval >1 s
5	Hyperkalemia	Tall T-wave and absence of P-wave
6	Myocardial Ischaemia	Inverted T-wave
7	Hypercalcaemia	QRS interval <0.1 s
8	Sinoatrial block	Complete drop out of a cardiac cycle
9	Sudden cardiac Death	Irregular ECG
10	Ventricular Fibrillation	Highly oscillated ECG

The wavelet analysis of ECG signal using different scales based on their power spectrum gives high performance on detection of different morphological features and also solves many technically computing problems. This performance improvement is, according to the multiscale approach, which permits to attenuate noise at rough scale, and then to refine the precision of the positions with the help of the finer scale. Table 5 shows different rhythmic changes of ECG signal component and their corresponding abnormalities.

5 Conclusion

The Wavelet Transform is a new promising technique in non invasive electro cardiology for providing improved methods for denoising, detection and delineation of cardiac arrhythmia signal. This work shows that the important features can be extracted both from the morphological and statistical characteristics of the ECG signal. Different morphological features were detected with Stationary Wavelet Transform. Mathematical approach fixes different amplitude threshold levels for the detection and delineation of QRS complex, P and T waves. A computer based ECG signal classifier can be developed by employing the extracted features—pathological features and statistical features for detection of all of the Cardiac arrhythmias and Cardiac Vascular Diseases.

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A.1 6 APPENDIX

The amplitude thresholds in the presented algorithms can be grouped into three types. First, the thresholds used to decide if a pair of maximum moduli with opposite sign can account for a wave: $\in^1_{QRS}$,$\in^2_{QRS}$, $\in^3_{QRS}$, $\in^4_{QRS}$ (for QRS detection), $\in_T$ and $\in_P$. (in the T/P wave delineation). These thresholds are proportional to the RMS value of the WT at the corresponding scales. For QRS detection, in each expert of 2^{16} samples.

$\in^1_{QRS}$ = RMS ($W_{2^i}x[n]$), i = 1, 2, 3

$\in^4_{QRS}$ = 0.5RMS ($W_{2^4}x[n]$).

For T and P waves

$\in_T$ = 0.25 RMS ($W_{2^4}x[n]$) where the RMS is measured in each interval between

$\in_P$ = 0.02 RMS ($W_{2^4}x[n]$) two consecutive QRS. The morphology of QRS complexes and the type of T/P wave depend of number of significant maximum moduli. The thresholds to determine if they are significant, $\gamma_{QRS_{pre}}$, $\gamma_{QRS_{post}}$, γ_T and γ_P are related to the amplitude of the global maximum modulus within the corresponding search window (sw).

$\gamma_{QRS_{pre}}$ = 0.06 max($|W_{2^2}x[n]|$), $n \in SW_{QRS}$ A third group of thresholds are used to $\gamma_{QRS_{post}}$ = 0.09 max($|W_{2^2}x[n]|$), $n \in SW_{QRS}$ determine the onset/offset of QRS complex. They are proportional to the amplitude of the WT at the first/last maximum modulus of the complex or wave.

$$\xi_{QRSon} = \begin{cases} 0.05W_{2^2}x[n_{first}], \text{if } W_{2^2}x[n_{first}] > 0 \\ 0.07W_{2^2}x[n_{first}], \text{if } W_{2^2}x[n_{first}] < 0 \end{cases}$$

$$\xi_{QRSend} = \begin{cases} 0.125W_{2^2}x[n_{last}], \text{if } W_{2^2}x[n_{last}] > 0 \\ 0.71W_{2^2}x[n_{last}], \text{if } W_{2^2}x[n_{last}] < 0 \end{cases}$$

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