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Detection of ECG Characteristic Features Using Slope Thresholding and Relative Magnitude Comparison

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***Abstract*— The paper proposes a simple and efficient algorithm for automatic detection of the characteristic points (Q, R, S, T, P peaks and onset and offset points) from a single lead digital ECG data. The squared double difference signal of the ECG data is used to localize the QRS regions and the significant peak in the QRS regions are detected by relative magnitude comparison and peak intervals are processed according to some criteria to ensure accuracy of detection. Next the other peaks in the QRS region are detected with respect to the significant peak to make the algorithm adaptive to different QRS morphologies. The T wave features are then detected by magnitude and slope threshold based search on selected windows. The performance of the algorithm is tested on 12-lead ECG data from the PTB diagnostic ECG database, and a high detection sensitivity of 99.8% is detected.**

Keywords- ECG characteristic points; squared double difference; slope thresholding; relative magnitude comparison;

I. INTRODUCTION

The electrocardiogram (ECG) is the recording of the electrical activity of the myocardium during one cardiac cycle and is characterized by a recurrent sequence of P, QRS, T and a conditional U wave. ECG is recorded by placing electrodes on the body surface and a standard 12 lead system is used to get an overall view of the hearts activity [1]. ECG is used as an important diagnostic tool for various cardiac diseases due to the ability to correlate the different ECG wave signatures with the actual operation of the heart and its ease of recording in a non-invasive manner. Automated ECG analysis has presently become an important area of biomedical research due to its rapid, accurate and reliable diagnostic ability and its wide application in the field of telemedicine. The key step for automated ECG analysis tool is the detection of the different characteristic points in the ECG of which QRS detection is of prime importance. Different QRS detection algorithms available in literature are broadly classified as amplitude and derivative based, digital filter based, template matching based, non linear transformation based and wavelet based [2]. The derivative based approaches [3-5] are based on the high frequency content of the ECG signal which yields higher

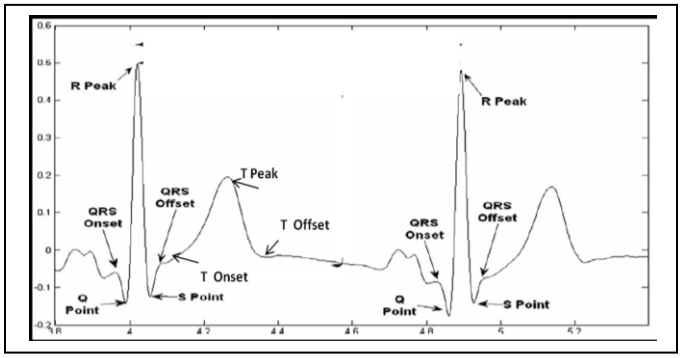

Fig. 1. ECG characteristic points

magnitudes of the derivatives and use first, second and other modified derivative operators. Due to ease of implementation and low computation cost, these methods are widely used but have relatively high noise susceptibility. Template matching based approach [6] relies on cross correlation based comparing of standard QRS template with several ECG segments, though have low noise sensitivity but are computationally complex and needs manual segmentation of ECG data. Non-linear transform based methods [7] use Hilbert transform to enhance the QRS signature and increase its detection probability. The use of digital filters [8] to extract the QRS complex based on its frequency content is also computationally complex. Wavelet based techniques [9] depend on the availability of suitable mother wavelet and scale values. A new and effective approach was implemented using a histogram and improved genetic algorithm to search and detect the QRS regions [10]. Artificial Neural Network or Support Vector Machine is also used as a classifier to detect the QRS complex [11-12]. An advanced algorithm to pre-process the RR intervals was proposed to increase the accuracy of detection [13]. Difficulties in accurate QRS detections rise because of the physiological variability of the QRS complex and presence of different noises in the ECG signal. The noise sensitivities of 9 different algorithms were tested [14] to infer that the derivative based approaches had higher performance index for

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low frequency noises, while algorithms based on digital filtering performed well for high frequency noise.

In this paper a simple algorithm has been proposed for detection of ECG characteristic points based on amplitude differencing, relative magnitude comparison and slope thresholds. The squared double difference signal of the ECG data is used to localize the QRS regions and the peaks in the region are detected by relatively magnitude comparison. The algorithm has been made adaptive to different types of QRS morphologies and also ensures accuracy of detection by processing the peak intervals. The onset and the offset points are detected by empirically selected slope based criteria. Some of the time plane features R-R interval, QRS width, QT were also extracted to evaluate the efficiency of the algorithm. The algorithm is validated on 1 min ECG records from the PTB-diagnostic ECG database for all 12 leads of both healthy and diseased data. The algorithm yielded an overall detection accuracy of more than 90% and is also computationally undemanding as it does not require any correlation operation, data segmentation, and complex training algorithms.

II. METHODOLOGY

The proposed algorithm operates on digitized ECG data from a single lead. The digital ECG data from a single lead is read as a 2-d array of the time instants and the sample points. After initial denoising of the data, the QRS regions are identified by processing the squared double difference signal of the ECG data array. Then the characteristic points in QRS regions are identified by relative magnitude and slope comparison. Next the T wave features are identified by relative magnitude and slope threshold based search on selected window.

A. Initial smoothing and filtering

The derivative based approach amplifies the high frequency noises, which leads to high difference signals due to noise. So, initial smoothing and filtering of the ECG data is done to eliminate power frequencies and high frequency noise by using wavelet co-efficient thresholding as shown in Fig 2 (a).

B. Identification of the QRS regions

The higher slope of the QRS regions yields high amplitude of derivatives in these regions. As the sampling instants of digital ECG data remains constant the amplitude differences are proportional to the derivatives. Double differencing and squaring intensifies the magnitudes of the difference signal in the QRS regions which aids in the localization of the QRS regions. From the squared double difference signal the QRS regions are identified using the following steps- The process involves the following steps:-

1) Formation of double difference array: From the ECG data array e(n) the squared double differences are calculated at all points to yield the difference array.

$$d1(i) = e(i+1) - e(i),\ i = 1 \ldots . n-1 \quad (1)$$

$$d2(j) = d1(j+1) - d1(j),\ j = 1 \ldots . n-2 \quad (2)$$

$$d(j) = |d2(j)|^2 \quad (3)$$

where e(n) is the ECG data array, n is the total no. of points in the data, and d(j) is the squared double difference array as shown in Fig 2(b).

2) Magnitude thresholding: The array elements above a constant threshold value of 3% (empirically determined) of the maximum are selected.[Fig 2(c)].

3) Sorting and elimination: Since the maximum duration of the QRS regions can be 150ms-160ms, to eliminate possibility of detection of several elements in the same QRS region all the difference elements within an interval of 75ms on both sides of each thresholded difference element are eliminated. For this all elements are first sorted in descending order of magnitude then each array element from the start are taken and all elements with location index within a interval of 75ms of each element are eliminated to select one element corresponding to each QRS region. The final selected difference peaks corresponding to each QRS region are shown in Fig 2 (d).

4) Selection of QRS regions: Since The QRS regions are identified to be within a window of ±75ms on both sides of the index locations of the selected difference element locations on the original ECG data array. Figure 2 illustrates the processing steps for the detection of QRS window.

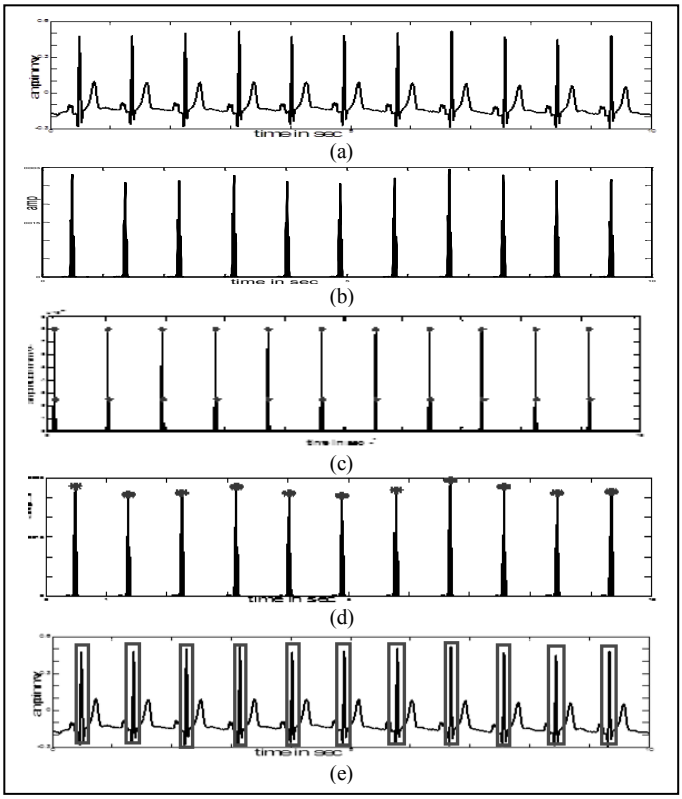

Fig. 2. QRS window selection a) filtered ECG data b) double difference signal c) selected difference peaks after magnitude thresholding d) selected difference peaks after elimination and interval processing e) detected QRS windows

C. Detection of Q,R and S peaks and QRS onset and offset

The QRS morphology varies from person to person and also for different leads or for different diseases. So the algorithm has to be made adaptive to the different morphologies. We consider cases without ectopic beats so that the QRS morphology remains the same for all the beats. It first detects the most significant peak (Q, R or S) in each QRS window by relative magnitude comparison. The interval between two peaks is then processed according to certain criteria to ensure accuracy of detection. After identifying the significant peak to be Q R or S, the other fiducial points in the QRS region are detected by search for slope inversion points.

1) Detection of significant peak - For each QRS window average of the maximum and minimum values for each window are calculated and subtracted from all data points of the window to get the relative magnitudes. The position of the absolute maximum of the relative magnitudes in the corresponding QRS window is the location of significant peak. This detected significant peak can be a Q, R or S depending on the QRS morphology.

2) Processing the peak intervals:- The peak detections may not be accurate. False detections occur mostly due to noise which causes spurious peak detections. On the other hand, undetected peaks always result in the loss of information. To ensure accurate detection, the interval between two selected peaks (which is equivalent to the RR interval) are processed according to pre-defined criteria which include limiting the interval to eliminate false detection and back searching to eliminate missed peaks. It is considered that the minimum difference between two successive R peaks (or Q or S) can be 200ms.

3) Identification of the significant peaks: - Next the detected peaks are identified to be Q, R or S.

- If the magnitude of the detected peak is greater than the average of the maximum and minimum amplitude of that window, then the detected peak is a positive R peak.
- If the detected peak amplitude is less than the average, it is a Q or S peak. If the location of the peak is in the left side of the QRS window it is a Q peak. Else it is a significant S peak.

4) Detection of other peaks in QRS regions: - After detection of the significant peak, the other point in the QRS window are detected by searching for slope inversion points i.e points where the amplitude difference of the data changes sign and remains so for atleast thirty data points.

- If the detected significant peak is a Q peak, then a search for slope inversion points is carried on towards the end of the ECG data array starting from the detected peak within the QRS window. The index of the first slope inversion point after the Q is a R peak, the next is S.
- If the detected significant peak is a R peak then search for slope inversion points is carried on both sides of the R peak within the QRS window to detect the Q and S points. Index of slope inversion point towards the start of the array from of the R peak is a Q, and that towards the end of the array is a S.
- If the detected peak is a S peak, then search for slope inversion points is done towards the start of the data array to detect the R and Q points respectively.

5) Detection of QRS onset and offset - Ordinarily, the Q and S waves are high frequency components. The corresponding onset and offset values are the points having nearly zero or minimum slope region before the Q and after the S wave.

- The QRS onset point is detected as the minimum slope point within a window of 40 ms starting from the Q peak index ~~along~~ the start of the ECG data array.
- The QRS offset point is detected as the minimum slope point within a window of 40 ms starting from S point index towards the end of the ECG data array.

Fig. 3 shows the different steps for detection of the QRS wave features.

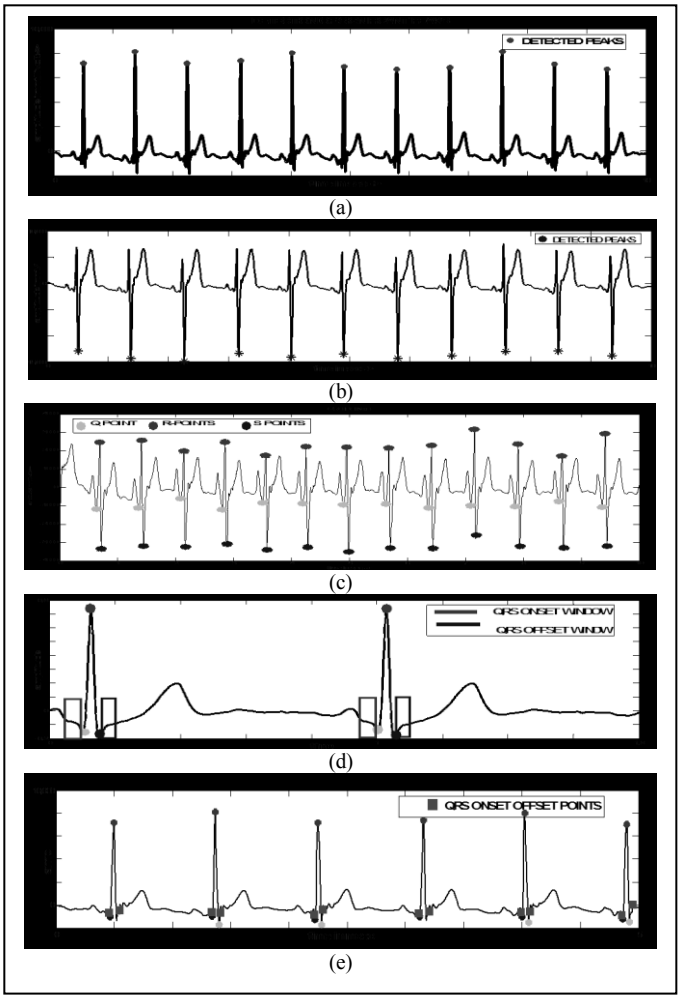

Fig. 3. Detection of QRS peaks and QRS onset and offset a) detection of R peaks as significant peaks b) detection of S peaks as significant peaks c) detection of all QRS peaks d) selection of search window for detection of QRS onset and offset e) detection of QRS onset and offset points

D. Detection of T wave features

The T peaks lie on the downside of the QRS regions and can be upright or inverted. To detect the T peak first a search window is selected after every QRS region according to the possible location of the T wave. Then the T peak is detected and then the onset and offset points are detected by slope threshold based search.

1) Selection of T wave search window: - The interval between the QRS offset point index and next successive QRS onset point is measured. The search window for detection of T wave is selected starting from the QRS offset point to a distance equal to two third of the interval measured.

2) Detection of T peak: - The T peak is detected as the absolute maxima point (positive or negative) within the window

3) Detection of the T onset and offset: - The average slope for the T wave search window is calculated and a slope threshold of 5% of the average value (emprically determined) is selected. A slope threshold based search is initiated starting from the T peak on its either side.The point where the slope first falls below the threshold value on the upside of the T peak is the T onset. The same point on the downside of the T peak is the T offset point.

Fig 3 shows the detection of the T wave features.

The P wave features can also be detected by similar steps on the window to the downside of the T wave window till the succeeding QRS onset point. But for detection of the P onset and offset points a relaxation on the slope threshold criteria was allowed.

E. Extraction of some time plane features

After correct detection of the different fiducial points, some time plane features of the ECG which are important clinical parameters are also extracted.

R-R Interval = Delay between two successive R peaks.

QT Interval= T Offset – Q Onset

QRS Interval = QRS Offset - Q Onset

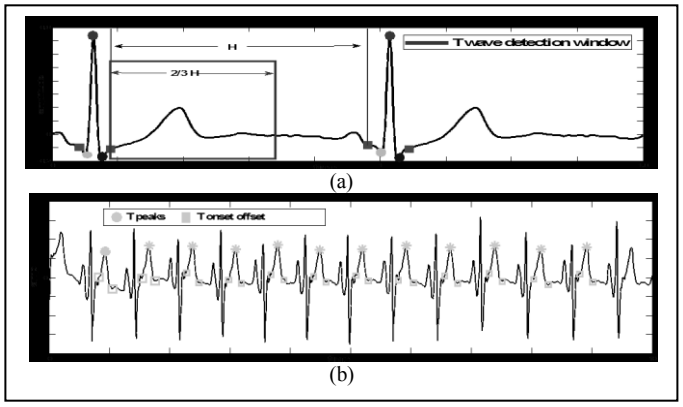

Fig. 4. Detection of T wave features a) search window selection b) detection of T wave features

III. RESULTS

A. Used database

The algorithm is validated with arbitrarily chosen ECG data from Physikalisch-Technische Bundesanstalt diagnostic ECG database (ptb-db) available under the Physionet website. The algorithm is tested on 10 seconds ECG data for all 12 leads of both healthy patients and patients affected with different diseases. Since PTB-db database contains 12-lead signal, it corresponds to 12 different patterns, each having different characteristic features.

B. Parameters evaluated

Quality figure of QRS detection algorithm is given by Detection Sensitivity (S_e) and Positive Predicitivity (P+).

$$Detection\ Sensitivity(S_e) = \frac{TP}{TP + FN} \times 100\% \qquad (4)$$

$$Positive\ Predictivity\ (P+) = \frac{TP}{TP + FP} \times 100\% \qquad (5)$$

where TP -stands for True Positives which is the total no of peaks correctly detected by the detector. FP-denotes False Positive i.e. false peak detection .FN- denotes False Negative i.e. failure to detect.

Since the PTB databases have different R–R Intervals, a measure of correct feature extraction is represented by coefficient of variation.

The feature extraction performance analysis metric which is used for the validation of the test results is the coefficient of variation. Here, xi = i th feature interval, n = number of beats.

$$\text{Mean} = \frac{1}{n}\sum x_i \qquad (6)$$

$$\text{Standard Deviation (S.D.)} = \sqrt{\frac{\sum(x_i - mean)^2}{n}} \qquad (7)$$

$$\text{Co-efficient of variation (COV)} = \frac{S.D}{mean} \times 100 \qquad (8)$$

The standard deviation (S.D) and Coefficient of variation (COV) is measured for the extracted features. SD measures the absolute dispersion or variability of a distribution. It facilitates the comparison of the whole data set with the mean. COV is a dimension less number which also gives the measure of dispersion within a series of data. The percentage value shows the dispersion as a percentage of mean.

C. Test results

The algorithm is tested on 60 seconds ECG data for all 12 leads of both healthy patients and patients affected with different diseases for more than 50 records. Cases of ectopic beats and premature ventricular contractions were not considered. Table 1 tabulates the test results for peak detection algorithms for both normal and diseased patients for all 12 leads and also calculates the detection sensitivity and positive predictivity for each.

TABLE I. TEST RESULTS FOR PEAK DETECTION ALGORITHM

Lead nos	Total peak	Detected peak	TP	FN	S_e (%)	P+ (%)
I	510	509	1	0	99.8	100
II	510	510	0	0	100	100
III	510	509	1	0	99.8	100
aVr	510	510	0	0	100	100
aVl	510	510	0	0	100	100
aVf	510	510	0	0	100	100
V1	510	510	0	0	100	100
V2	510	509	2	1	99.6	99.8
V3	510	510	1	1	99.8	99.8
V4	510	510	0	0	100	100
V5	510	510	0	0	100	100
V6	510	510	0	0	100	100

An overall detection sensitivity of 99.88% and a positive predictivity of 99.96 % were obtained for testing on more than 50 records each 60 sec.

Next the different ECG time plane features were calculated from the characteristic point indices. Table II shows the coefficient of variation for the different extracted time plane features for some 1 min patient records for leads I and II. For other leads also the algorithm performed equally well.

TABLE II. TEST RESULTS FOR TIME PLANE FEATURE EXTRACTION

PID/ Record no Category	LEAD	RR INTEVAL(in ms)		QRS WIDTH(in ms)		QT WIDTH(in ms)	
		Mean	*COV(%)*	*MEAN*	*COV(%)*	*Mean*	*COV(%)*
121/ s0311lre normal	I	909.0	.75	96.0	6.81	399.1	4.94
	II	910	.73	98.5	6.59	381.9	6.06
105/ s0303lre normal	I	833.3	.50	101.3	5.89	391.1	7.89
	II	830.8	.49	89.1	6.07	378.2	5.99
043/ s0144lre (MI)	I	670.8	.10	83.2	4.19	291.5	11.67
	II	666.6	.15	79.0	4.87	295.8	8.96
002/ s0015lre (MI)	I	770.2	.46	93.5	5.19	332.5	7.69
	II	769.8	.52	89.4	4.37	341.9	7.81
055/ s0194lre (MI)	I	714.6	.68	107.5	6.90	310.9	6.26
	II	720.5	.72	106.9	7.60	315.7	6.9

For the different time plane features an average coefficient of variation of 4.5% is obtained.

IV. CONCLUSION

The proposed algorithm is simple, easy to implement, and has low execution time. It has relatively low computational complexity compared to the other works available in literature which are based on digital filters, wavelets etc as it involves only differencing and slope and magnitude based search. Fairly high detection sensitivity for detection of peaks and a low coefficient of variation of the different time plane features extracted was obtained both for normal and infarction data. Though conventional derivative based methods are very sensitive to high frequency noise which leads to false detections, in these method some false peak detections could be eliminated by processing the intervals between the peaks. The algorithm is made adaptive to the different kinds of QRS morphologies. But for the proposed algorithm the effect of ectopic beats has not been investigated. Moreover, due to the choice of empirically selected slope thresholds is not fully efficient for all types of data.

Due to the low computational overhead for the proposed algorithm, it can be easily implemented on an embedded platform for wireless telemedicine applications.

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