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A Robust Approach to Wavelet Transform Feature Extraction of ECG Signal

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Abstract: *This proposed paper discusses various techniques and transformations proposed earlier in literature for extracting feature from an ECG signal. In addition this paper also provides a comparative study of various methods proposed by researchers in extracting the feature from ECG signal. We also propose an improved algorithm for feature extraction through wavelet transform. Eighty four original input features were extracted from pre-processed signals by wavelet transform per 12 lead ECG signal.*

Keywords: *wavelet transform, feature extraction, ECG signal.*

1. INTRODUCTION

1.1 ECG

The ECG (electrocardiogram) is a time-varying signal which reflects the ionic current flow causing the cardiac fibers to contract and subsequently relax. To obtain surface ECG the potential difference between two electrodes is recorded such that they are placed on the skin surface. In one normal cycle of the ECG we have successive a trial depolarisation or repolarisation and ventricular depolarisation or repolarisation. This occurs with every heartbeat. Simply, the ECG is an instrument that measures and records the electrical activity within the heart through electrodes placed in specific locations on the skin.

1.2 Standard 12 Lead ECG

The standard 12 lead ECG signal has been used by us for analysis. For many years, the 12-lead ECGs have offered the most cost-effective, efficacious, and non-invasive diagnosis of cardiac ailments. The 12 lead ECG signal is created by obtaining 12 different electrical views of the heart. There are 10 electrodes are used for this purpose. An electrode is placed on each arm and leg and six are positioned across the chest wall. The signals recorded from the 10 electrodes are combined together to form a 12-lead ECG. The 12 lead's signals are combined into a single waveform which is used by us throughout this analysis.

1.3 Waves and Intervals

P wave: formed when the right and left atria are sequentially activated (depolarized). The right and left atria are depolarized when signal is sent from the SA node.

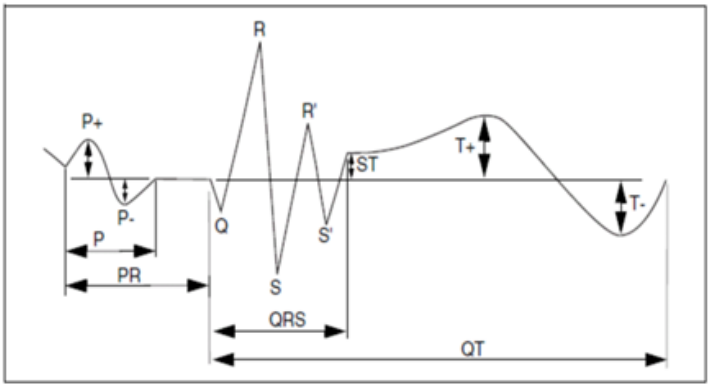


Figure.1
(A Sample ECG Signal showing P-QRS-T Wave)

1.4 Waves and Intervals

P wave: formed when the right and left atria are sequentially activated (depolarized). The right and left atria are depolarized when signal is sent from the SA node.

QRS complex: ventricular depolarization (normally both the right and left ventricles are simultaneously activated). The ventricles are depolarized when signal is sent from NA.

ST-T wave: ventricular repolarization. Signal has been passed on to the wall and re-polarization is induced due to that signal.

U wave: this wave's origin is not fully clear - but it probably represents "after de-polarizations" of the Ventricles. Noiseless U wave has very low amplitude, and sometimes it is completely absent.

PR interval: The PR interval is measured as the duration from the starting point of the P wave (p onset) to the starting point of the QRS complex (q onset)

QRS duration: represents the ventricular muscle depolarization duration

QT interval: The QT interval measured as the duration from the onset of the QRS complex to the offset of the T wave. Its duration represents ventricular depolarization and re-polarization

RR interval: it represents the breathe rate if sampling frequency or time period is present. It is duration of ventricular cardiac cycle (an indicator of ventricular rate)

PP interval: its length (duration) is same as that of RR interval. It is represents duration of atrial cycle (which is an indicator of atrial rate)
Figure 1 shows a sample ECG signal depicting the different waves and intervals.

1.5 Literature Review

Computerized electrocardiography is currently a well-established practice, supporting human diagnosis. Many algorithms have been proposed over previous years for developing the automated systems to accurately classify the electrocardiographic signals in real-time[6-11].The investigation of the ECG has been extensively used for diagnosing many cardiac diseases. The majority of the clinically useful information in the ECG is stored in the amplitudes and intervals defined by its features (peaks and time durations of characterstic waves).

The ECG feature extraction system provides these fundamental features (intervals and amplitude) which are used in further analysis. In recent times, a number of techniques have been proposed to detect these features [2] [3] [4]. ECG is basically responsible for monitoring patients and their diagnosis. The features extracted from the ECG signals play an impportant role in the diagnosis of any cardiac disease. Thus developing accurate and quick methods for ECG feature extraction is vital. So it is necessary that the feature extraction algorithm performs accurately. The main purpose of the feature extraction scheme is to find minimum number of properties of the ECG signal which can successfully detect abnormalities and result in efficient prognosis. Some of the features extraction methods implemented in previous research includes Hermitian Basis, Karhunen-Loeve Transform, Discrete Wavelet Transform and other methods.

Every method has its own advantages and limitations [1][13-27].

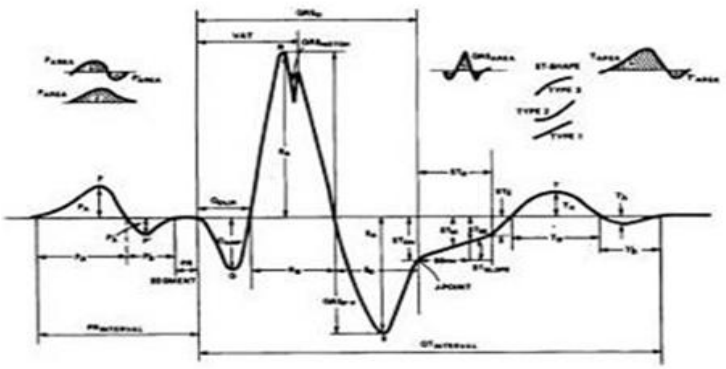


Figure.2 The numerous ECG measurements that can be made with computer-based algorithms.

In recent year, several research and algorithm have also been developed for the exertion of analyzing and classifying the ECG signal. The numerous classifying algorithms which have been used during the last decade include Hidden Markov Model, Fuzzy Logic methods, Genetic Algorithm, Self-Organizing Map, Bayesian, Artificial Neural Network, digital signal analysis, Support Vector Machines and other method with each approach exhibiting its own advantages and disadvantages.

II. Methodology

2.1 Overview

The proposed algorithm can be demarcated into following steps:

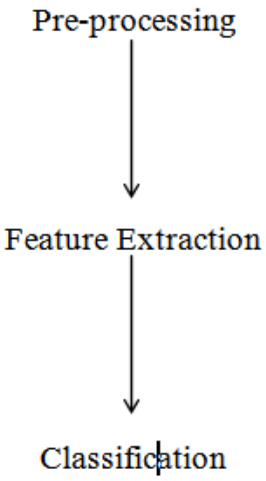


Figure 3 shows a block diagram elucidating the various sub processes within the proposed algorithm.

In this paper the normal ECG data has effectively

been differentiated from abnormal ECG data by the
successful implementation of the above mentioned steps.

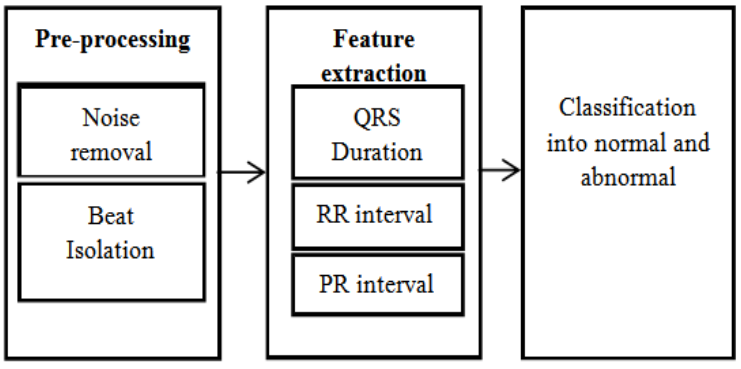


Figure.3 Block diagram of the proposed algorithm.

For abnormal ECG data we have considered the ECG data from the MIT/BIH Arrhythmia Database which is digitized at a sampling rate of 360Hz. The database contained ECG of 48 patients. In addition, due to the lack of normal data there, Physikalisch Technische Bundesanstalt (PTB) Diagnostic ECG Data base was also used, which had been sampled at 1000 Hz, were resampled at 360Hz and then used. The database consists of 549 records from 290 subjects. It also includes detailed clinical summary, which entails age, gender and diagnosis. Wherever applicable, data on medical history, medication and interventions is also included. Details like coronary artery pathology, ventriculography, echocardiography, and hemodynamics is provided for 268 subjects. The diagnostic classes of these subjects are summarized below:

Diagnostic Class	Number of Subjects
Myocardial infarction	148
Cardiomyopathy/Heart failure	18
Bundle branch block	15
Dysrhythmia	14
Myocardial hypertrophy	7
Valvular heart disease	6
Myocarditis	4
Miscellaneous	4
Healthy controls	52

Table.1 Distribution of subjects having various heart ailments.

2.2 Pre-processing

Pre-processing entails noise reduction, QRS complex detection and isolation and beat segmentation for feature extraction and it is designed for ECG signals sampled at 360Hz. The noise cancellation unit involves 3 steps. The first step involves appending 100 zeros at the starting and end of the raw ECG signal. This removes the possibility of window crossing the signal boundaries while looking for peak locations. After this Zero Crossing removal is done wherein the signal is base adjusted so that its base coincides with the zero level of the graph. We choose the first value in the signal matrix as the base value. All other values of the signal matrix is calculated as follows,

$$Y[n] = X[n] - zc, \quad (zc = X[1]) \qquad (1)$$

Where Y[n] represents base line corrected signal values, X[n] represents signal not adjusted to base line and zc is equal to Y[n].

The wavelet transform (WT) has been verified as a good tool for pre-processing and QRS complex detection [29]. For a signal *s* of length *N*, the maximum number of stages that the DWT can contain is given by $\log_2 N$. In the first step two sets of coefficients, starting from, are produced: approximation coefficients CA_1, and detail coefficients CD_1. To obtain the approximation vectors is convolved with a low-pass filter Lo_D and for obtaining detail vector it is convolved with the high-pass filter Hi_D. This is followed by dyadic decimation (down sampling). So for signal Y(n),

$$Y(n) = CA_j [Y(n)] + CD_j [Y(n)], \qquad (2)$$

where $CD_j[x(n)]$ represents the detail signal at j level and $CA_j[x(n)]$ represents the approximate signal at j level. Here, j level signifies the decomposition at scale 2j. During wavelet decomposition the signal is down sampled. This essentially means plotting the samples at a lower sampling frequency than the sampling frequency of the original signal. This reduces details, noise, while at the same time preserves the QRS complex. This leads to separation of frequency bands and smoother and cleaner signals.

For the purpose of removal of Power Line Interference we discard the detail signal as these noises are high frequency noises (50-60 Hz),

$$D(n) = CA_4 [Y(n)] : CD_4 : CD_3 : CD_3 : CD_1, \qquad (3)$$

Where D(n) is the decomposed signal. Figure 4 (b) shows the decomposed signal. Here the db4 decomposition has been used. Figure 4 (c) shows all

the reconstructions of this decomposed signal. The first level reconstruction of this signal is used for further processing as it is relatively free of noise. Higher level reconstructions have lesser noise but also higher information loss.

$$y(i) = CA_1[Y(i)] \quad (4)$$

The smoothed signal is shown in Figure 4 (d) .For the detection of the QRS complex we first detect the R peaks in the first level reconstructed signal Y[n] and then corresponding to those R peaks we define QRS complex regions in the original signal X[n].

After this Baseline Wander is removed from the signal using a new BAWAL (Baseline Wander removal Algorithm) which involves baseline wander removal through QRS complex isolation. The maximum value of the signal is first calculated and then a threshold is applied for detection of R peaks in the ECG signal. Any point in the signal above the threshold is then considered for R peak detection. The threshold we found most appropriate for distinguishing normal ECG signal from abnormal ECG signal was 0.6*max, where max is the maximum value of the signal. The points will thus be given as,

$$y1(j) = y(x>(0.6*max)) \quad (5)$$

These points are depicted in Figure 4 (d). Once these sample points have been detected in the first level reconstruction they are mapped onto the original signal through interpolation. In order to obtain only 1 value for every R peak we search for local maximum in the vicinity of each point. If the point itself is local maximum then it is taken as a R peak otherwise the local maximum is taken as a tentative R peak and the point is discarded. If this tentative R peak coincides with one of the sample points taken after interpolation then that point is taken as R peak.

This method works well for low to moderate baseline wander and for no ST elevation. But in the case of ST elevation or high baseline wander two or more R peaks may be detected for every real R peak. To remove the baseline wander we calculate the J point (J(j)) and the onset of the QRS complex (QRS(j)) for all the detected R peak values. The RR intervals are now calculated,

$$RR(j) = R(j+1) - R(j), \quad (6)$$

where R(j) is the t coordinate of the jth R peak. These intervals are divided by two to get the middle point of the intervals which is then used to segment the signal into beats cantered around the detected R peaks,

$$RR'(j) = RR(j) / 2 \quad (7)$$

So now the j^{th} beat is defined as sample points from RR'(j-1) to RR'(j), the first beat starting at x=0. For every beat we define the zero value (ZV) of the beat as,

$$ZV(j) = (J(j) + QRS(j)) / 2 \quad (8)$$

The baseline wander is now removed by adjusting each value in a particular beat by its ZV,

$$(Y(i))j = Y(i) - ZV(j), \quad (9)$$

where $(Y(i))_j$ is the baseline wander adjusted signal values in the j^{th} beat. But the number of R peaks and beats calculated will still be more than the real number of R peaks due to ST segment elevation in abnormal signal and initial base line wander. To make the algorithm for detection of R peaks baseline wander and ST elevation proof we calculate the ratio of difference in amplitudes of successive R peaks to the distance between them(RAT(j)),

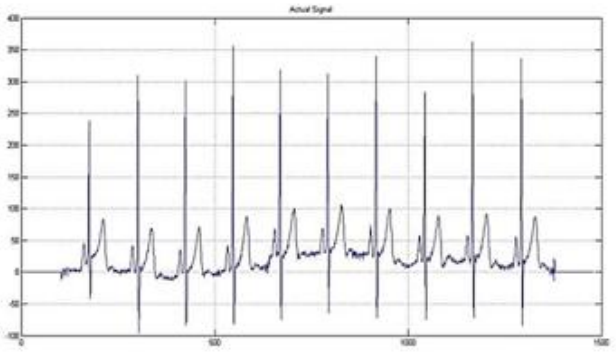
$$RAT(j) = (Y(R(j+1)) - Y(R(j)) / (R(j+1) - R(j)) \quad (10)$$

A threshold is applied to RAT(j) values. We choose the threshold as 1. For values greater than 1 we compare the R peak values and discard the lower values,

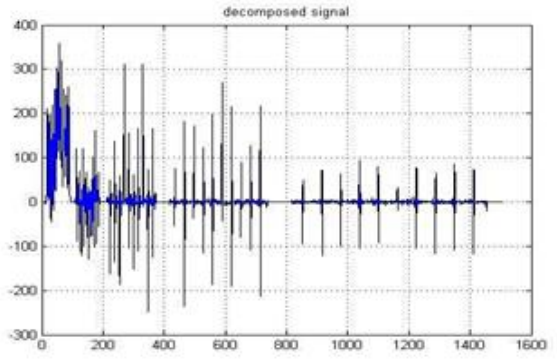
$$R(j) = (\max(R(j), R(j+1), \ldots R(j+n)) |_{RAT(j) \geq 1}, \quad (11)$$

where n is the number of values above threshold in one cluster or corresponding to one R peak. These give the real R peak values. Corresponding to these peak values we segment the signal into beats to get the real beats in the original signal,

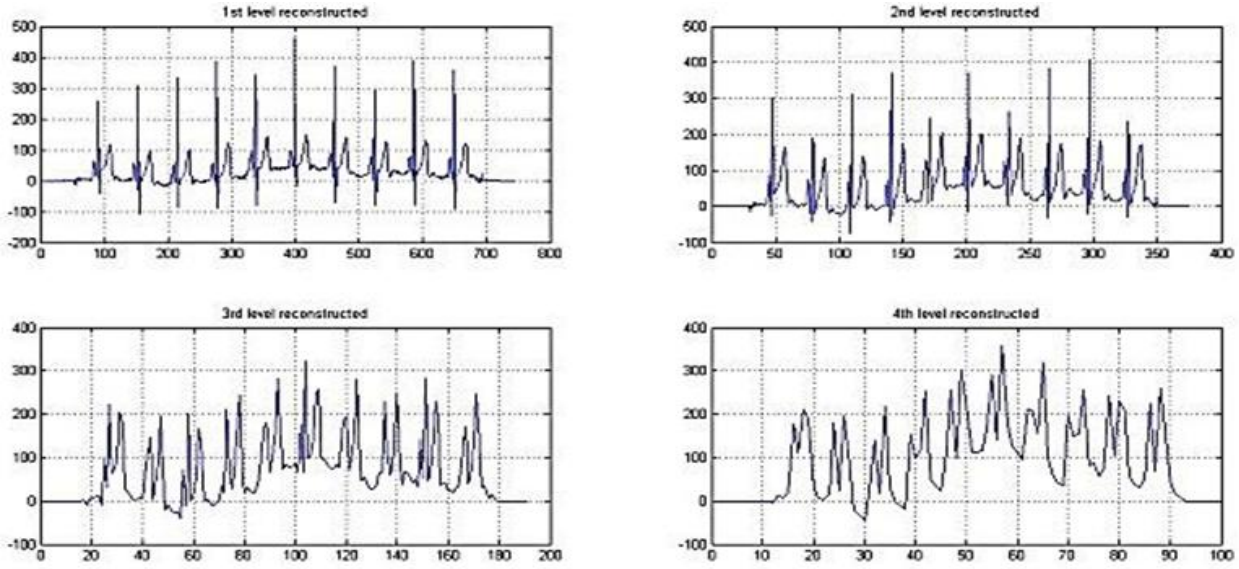
$$RR(j) = R(j+1) - R(j) \quad (12)$$



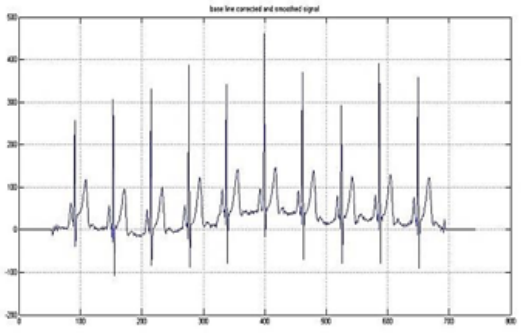
(a) Actual ECG signal



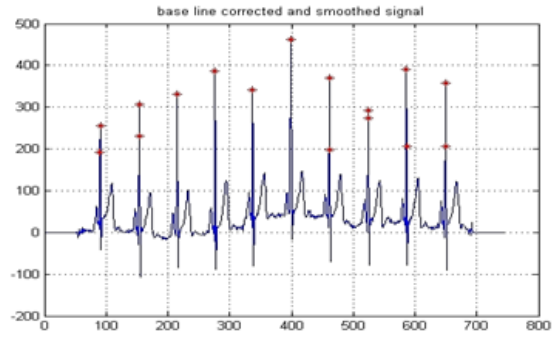
(b) 'db4' decomposed signal



(c) Different level reconstructions



(d) Smoothed signal



(e) Signal values above threshold value

Figure.4 Pre-processing of ECG signal

$$RR'(j) = RR(j) / 2 \quad (13)$$

$$ZV(j) = (J(j) + QRS(j)) \quad / 2 \qquad (14)$$

$$(Y(i))j = Y(i) - ZV(j), \qquad (15)$$

where, (Y(i))j gives the signal values adjusted to baseline wander and free from effects of ST elevation, R(j) gives the real R peaks and the real jth beat can now be isolated as sample points from RR'(j-1) to RR'(j), the first beat starting at x=0.

2.3 Feature Extraction

The classification of ECG signal into normal and abnormal ECG signal requires the knowledge of three parameters. These are the RR interval (Heart Rate), the PR interval and the QRS duration. For determining these parameters a first set of features is obtained from the original ECG signal. This set consists of the R peaks, the onset of P wave, the onset of QRS complex and j point.

The R peaks have been obtained previously and have been used to segment the ECG into different beats. After segmentation into beats each beat is analysed
separately to extract the features contained in it. We search the segment behind the R peaks in every beat to obtain the Q peak as the point where the slope changes from positive to negative as we move away from the R peak.

$$Q(j) = (R(j)-i+1)|_{y(R(j)-i)>=(y(R(j)-i+1))}, \qquad (16)$$

where, Q(j) is the Q peak in the jth beat segment and i is the distance from the R peak. From this, the onset of the QRS complex is calculated as the first inflexion point as we move away from the Q point towards the left.

$$QRS(j) = (Q(j)-i+1)|_{y(Q(j)-i)<=(y(Q(j)-i+1))}, \qquad (17)$$

where, QRS(j) is the onset of the QRS complex in the jth beat segment and i is its distance from the Q peak. For the onset of P waves we first calculate the P peaks by searching the area to the left of the Q peaks for a maximum. This is the P peak.

$$P(j) = (R(j) -i)|_{y(i)=max}, \qquad (18)$$

where, P(j) is P peak of the jth beat segment, i is an index and max is the maximum value of the signal to

the left of the R peak. The P wave onset can now be calculated as,

$$PON(j) = (P(j)-i+1) |_{y(P(j)-i)>=(y(P(j)-i+1)}, \qquad (19)$$

where, PON(j) is the P onset of the jth beat segment and i is distance from P peak. The J point is hard to extract as the ST-T segment rises very sharply and hence the ST segment may not be easily separable. In order to find J point the S peak is first found out as follows,

$$S(j) = (R(j)+i)|_{(y(R(j)+i)<=(y(R(j)+i+1)}, \qquad (20)$$

where, S(j) is the S peak of the jth beat segment and i is the distance from R peak. Hence, it is calculated as the point after the R peak where slope changes from negative to positive. The T peak is now calculated as the point of maximum in the region after the R peak in the beat segment.

$$T(j) = (R(j) +i)|_{y(i) = max2}, \qquad (21)$$

where, T(j) gives the T peak of the jth beat segment, I is an index and max2 is the maximum value of the signal in the beat to the right of the R peak. The region between the S peak and T peak is now analysed for any slope change. First we analyse if the slope changes from positive to negative,

$$J(j)=(S(j)+i)|_{(y(S(j)+i)>((y(S(j)+i+1))-k))}, \qquad (22)$$

where, J(j) is the J point in the j^{th} beat segment, I is its distance from the S peak and k is a constant equal to 0. If the J point and T point coincide we analyse the area between the S and T peaks again for the first inflexion point as we move

away from S peak and towards T peak. For this case k = 1. If J point and T peak still coincide then we look for the point where slope decreases. For this purpose the value of variable k is increased till we find a J point not coinciding with T peak. All the extracted features are shown in Figure 5.

The primary basis for classification of the ECG signal by a physician is through the analysis of the rhythm of the ECG signal. The feature extraction scheme used in this paper, therefore, takes into account three ECG durations, namely,

- The RR interval or Heartbeat of the patient is measured as the distance between two successive R peaks.
- The PR interval is measured as the length from the onset of the P wave to the onset of the QRS complex.
- The QRS complex width measured from the onset of the QRS complex to the j point.

Now the reduced feature set consists of these three features. These features are calculated as follows,

RR(i) = R(i+1) - R(i) (23)

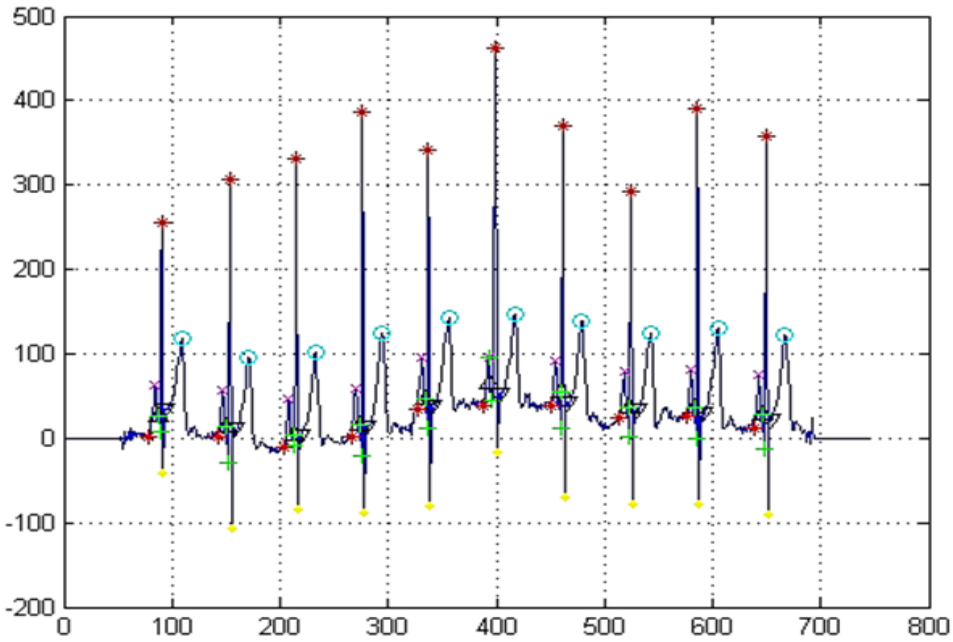


Figure.5 All the extracted features

PR(i) = Q(i) - P(i) (24)

QRS(i) = J(i) - Q(i) (25)

here, i represents the index of the beat, R(i) represents the R peak in the i^{th} beat, Q(i) represents the onset of the QRS complex in the i^{th} beat, P(i) represents the onset of the P wave in the ith beat, J(i) represents the j point of the i^{th} beat. Constant K is designated the value of the RR interval that a normal person is expected to have. Constant L is similarly the value of the PR interval of a normal person and M is the QRS complex width of a normal person. The feature set is modified using these three constants to produce features A, B and C, where,

$$\text{Feature A} = \frac{RR(i)}{K} \quad (26)$$

$$\text{Feature B} = \frac{PR(i)}{L} \quad (27)$$

$$Feature\ C = \frac{QRS(i)}{M} \quad (28)$$

In this paper the values of the three factors K, L

and M are chosen to be 0.8 seconds, 0.16 seconds and 0.08 seconds. The values of these factors depend upon the

sampling frequency of the data.

2.4 Classification

The classification of the ECG signal as one belonging to a healthy or not healthy person is done on the basis of the three features extracted. The ECG signal is classified as normal if the following conditions are met,

- The mean feature A lies between 0.6 and 1.0.
- The mean feature B lies between 0.75 to 1.25.
- The mean feature C lies between 0.5 to 1.5.

When a signal does not satisfy all the above three conditions simultaneously it is classified as abnormal.

IV. Conclusions

The proposed algorithm in this paper can be used for accurate and fast feature extraction from any ECG signal and for further classification into normal and abnormal signal. The ECG signal has been properly analyzed an errors have been effectively minimized. The baseline wander removal algorithm and subsequent segmentation into beats is very effective and lead to highly accurate feature extraction. The techniques used for feature extraction too are very efficient and show 100% accuracy. The original feature set was reduced to three features that were used for classification. The features and hence the classification is purely rhythm based. We have used a simple classifier but the features extracted are so distinct that they lead to highly accurate distinction between normal and abnormal ECG data.

The interpretive statements that are designed are to aid the clinician—not be the sole factor for diagnosing or making transport decisions. They help clinicians make a more comprehensive diagnosis of a patient's cardiac condition.

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