Detection of ECG characteristic points using Multiresolution Wavelet Analysis based Selective Coefficient Method

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ABSTRACT

Automatic extraction of time plane features is important for cardiac disease diagnosis. This paper presents a multiresolution wavelet transform based system for detection and evaluation of QRS complex, P and T waves. Selective coefficient method is based on identification of proper and optimum set of wavelet coefficients to reconstruct a wave or complex of interest from the ECG signal. The performance of the system is validated using original 12 lead ECG recording collected from the physionet PTB diagnostic database. The measured values are compared with the manually determined values and measurement accuracy is calculated. The test result shows over 99% true detection rate for R peak and base accuracy over 97%, 96%, 95%, 98% for heart rate, P wave, QRS complex and T wave respectively.

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1. Introduction

The new generation of medical treatment has been supported by computerized processes. Signals recorded from the human body provide valuable information about the activities of its organs. Their characteristic shape, or temporal and spectral properties, can be correlated with a normal or pathological function. In response to dynamic changes in the behaviour of those organs, the signals may exhibit time-varying as well as non-stationary responses. The QRS complex is the most prominent waveform within the electrocardiographic (ECG) signal, with normal duration from 0.08 s to 0.1 s [1]. It reflects the electrical activity within the heart for total ventricular muscle depolarization. Its shape, duration and time of occurrence provide valuable information about the current state of the heart. Because of its specific shape, the QRS complex serves as an entry point for almost all automated ECG analysis algorithms and detection of the QRS complex is the most important task in automatic ECG signal analysis [2]. The QRS detection is not a simple task, due to the varying morphologies of normal and abnormal complexes and because the ECG signal experiences different types of disturbances with complex origin. Once the QRS complex has been identified, a more detailed examination of ECG signal can be performed. The T wave is another important wave in the ECG waveform. It generates due to ventricular repolarization. In some pathological conditions the morphology of the T wave may change from beat to beat, the simplest and most easily recognizable change being an amplitude change and the time duration change of the wave. Since the QRS complex represents ventricular depolarization and the T wave represents ventricular repolarization, the QT interval denotes the total duration of ventricular systole. Hence the above-mentioned features are the most vital in cardiological analysis. Different techniques are introduced in last few decades for identification of characteristic points of ECG. Moreover, the detection should be very fast for several cardiac diseases. Various approaches (for example, in many nonsyntactic methods [3,4] for QRS detection, P and T waves and noises are suppressed...
by bandpass filtering and some nonlinear transformation is, performed for QRS complex enhancement. Then some rule based technique is used to identify QRS region. Main drawbacks of this method is that the method may not be unique, as signal frequency band for QRS complex varies from subject to subject and even for different beats of same subject. Some other approaches like neural network [5], fuzzy hybrid neural networks [6] have been employed to improve the quality of the QRS detectors. In [5], an adaptive matched filtering technique is used based on artificial neural network (ANN). The low frequencies are modelled by an ANN based adaptive filter and the residual signal is passed through a matched linear filter for detection of QRS location. A fuzzy hybrid neural network based approach as presented in [6] is utilised to recognize different types of beats resulting from same or different source. However, in most of the cases the efficiency of the algorithms is accompanied by higher computational time and cost. Instead of ECG, dECG (i.e. the derivative of ECG) may be a useful tool for analysis as it highlights the QRS complex and suppresses P and T waves [7] because it deals with the wave gradient instead of the wave itself, which is higher in case of QRS region than P and T waves. This technique is difficult to implement for the waves subjected to high frequency noise. Moreover, separate algorithms are required for detection of P and T waves after extracting QRS complex by this method. Keeping all these points in mind a discrete wavelet based simple algorithm is proposed in the present work.

In the proposed method multiresolution wavelet decomposition [8] of the ECG wave under test generates elementary well-localized forms in time frequency domain. The signal is characterized by these elementary blocks in time frequency domain. This feature is used to isolate the ECG signal from different noises and to make other interfering waves inactive while identifying one wave or complex. The wavelet reconstruction coefficient variations are assessed in terms of their shape and size to combine a selected set and eliminate the interfering components for better detection of a particular wave boundary. The main idea of present work is that, proper accumulation of selective reconstruction coefficients reproduces different part of ECG wave in time-scale domain suppressing the others. This eliminates the scope of probable interaction between adjacent regions and thus accurate detection of wave boundaries is ensured.

2. Discrete wavelet transform

A wavelet is a waveform of effectively limited duration that has an average value of zero. Similar to Fourier series analysis, where sinusoids are chosen as the basis function, wavelet analysis is also based on a decomposition of a signal using an orthonormal (typically, although not necessarily) family of basis functions. Unlike a sine wave, a wavelet has its energy concentrated in time. Sinusoids are useful in analyzing periodic and time-invariant phenomena, while wavelets are well suited for the analysis of transient, time-varying signals, thus well suited for ECG signals. Basically wavelet transform is the convolution operation of the subject signal $f(t)$ and the wavelet function $\psi(t)$. The discrete wavelet transform is expressed as,

$$X_{jk} = \int_{-\infty}^{\infty} f(t) \psi_{jk}(t) dt \quad (1)$$

The approximation coefficient of the signal $f(t)$ is represented as,

$$a_{jk} = \int_{-\infty}^{\infty} f(t) \phi_{jk}(t) dt \quad (2)$$

where $\phi(t)$ is scaling function, $j$ and $k$ are scale and location respectively. For a range of scale $n$, the original signal $f(t)$ under discrete wavelet transform can be represented as,

$$f(t) = \sum_{j=1}^{n} d_{j}(t) + \sum_{j=1}^{n} a_{j}(t) \quad (3)$$

where $d_{j}(t)$ is detail signal approximation and is given by,

$$d_{j}(t) = A_{jk} \phi_{jk}(t) \quad (4)$$

and $a_{j}(t)$ is detail signal approximation in scale $j$.

Thus given an approximation of a signal using translations of a mother wavelet up to some chosen scale, a better approximation can be achieved by using expansion signals with half the width and half as wide translation steps. The wavelet transform as such decomposes a signal into two sub signals - detail signal and approximation signal. Detail signal contains the upper half of the frequency components and approximation signal contains the lower half. The decomposition can be further repeated on the approximation signal in order to get the second detail and approximation signal. Thus in discrete wavelet domain, multiresolution analysis can be performed.

3. System description and implementation

The proposed multiresolution wavelet based approach for ECG feature extraction is performed with Daubechies 6 (Db6) wavelet. There is no predefined rule to select a wavelet for a particular application, rather the selection is application oriented. It is a common practice to select a wavelet function which is having similar physical properties as the subject signal [9]. Daubechies wavelets have structural similarity with QRS complex and their energy spectrums are concentrated around low frequencies. Thus it is expected that some detail coefficients from multiresolution decomposition will show better resemblance with QRS complex of the ECG wave in time scale domain [10,11]. The proposed algorithm is applied on some arbitrarily chosen ECG data from physionet PIB diagnostic database [12]. Decomposition of the signal is done up to level eight. Level of decomposition is taken to be a high value to ensure the presence of some low frequency components of original signal. Fig. 1 shows the details of the algorithm followed. First a proper selection of the wavelet coefficients is made for R peak detection. After R peak detection, five point differentiation is done on the reconstructed wave generated by suitable choice of coefficients for Q and S points. Then the relevant coefficients are identified for T and P wave peak detection. Once the peak is detected, onset and offset of these waves are captured.
3.1. Detection of R peak

The original signal along with the decomposition result is shown in Figs. 2, 3a and 3b. Figs. 3a and 3b represent the wavelet coefficients for scale 1 to 4 and 5 to 8 respectively. From these figures it is seen that small scales represent the high frequency components and large scales represent the low frequency components of the signals. The first and eighth level reconstruction coefficients represent high frequency and low frequency contents of the ECG waveform respectively which in most of the cases appear to be high and low frequency noises. According to the power spectra of the signal [13], it is clear that most energy of the QRS complex is concentrated at decomposition level 3, 4 and 5. Figs. 3a and 3b show that coefficients at level three, four and five show better resemblance with the QRS complex whereas all others appearing to be noisy with respect to the QRS region having most noises at the upper and lower levels. Thus, d3, d4 and d5 coefficients are identified for the detection of QRS complex. The plot of the reconstructed wave comprising of d3, d4 and d5 is shown in Fig. 4.

\[ e_1 = d_3 + d_4 + d_5 \]  

(5)

From Fig. 4, it is clear that although the QRS region is properly captured but it is difficult to identify R peak due to its oscillatory nature. So, a function \( e_2 \) is defined as,

\[ e_2 = \frac{d_4 \times (d_3 + d_5)}{2^n} \]  

(6)

where \( n \) is the level of decomposition. Then the modulus of \( e_1 \times e_2 \) is taken. The corresponding plot is shown in Fig. 5 along with the original wave. It is seen from Fig. 5 that the QRS complex may have less amplitude, but is much closely spaced in time. Hence the R peaks are identified as the maximum amplitude points. The accuracy of the entire feature extraction work mainly depends upon the identification accuracy of R peak. Main advantage of the selective coefficient based approach is that, by selecting an optimum set of coefficients depending on the power spectra of the wave, the probability of error in R peak detection is minimized in spite of the presence of drastic irregularity in the baseline as shown Fig. 6.
3.2. Detection of Q and S point

Once the R peak is detected, the Q and S points are to be identified to detect the complete QRS complex. Generally the Q and S waves have high frequency and low amplitude and their energies are mainly at small scale. For that, decomposition coefficients from d2 to d5 are kept and the reconstruction wave is given by

\[ C_3 = d_2 + d_3 + d_4 + d_5 \]  (7)

Q and S points are the points of inflexion in either side of the R peak. So the first zero slope points on either side of the R peak will represent the Q and S point. Hence five point differentiation on e3 is done using the following formula:

\[
\frac{f(x + 2h) + 8f(x + h) - 8f(x - h) + f(x - 2h)}{12h}
\]

where \( h \) is time division.

First two zero slope points on either side of R peak (as detected earlier) are identified as Q and S points respectively. At this point of analysis, the differentiation can be done because now the high frequency noise is disregarded as the first level reconstruction coefficient is not taken into account.

3.3. Detection of T and P wave

According to the power spectra of ECG signal [13] the energies of T and P waves are mainly at scale levels 6, 7 and 8. But, baseline drift is serious at scale 8, so reconstruction coefficients d6 and d7 are selected to detect T and P waves. Hence the reconstructed wave is formed as,

\[ e_4 = d_6 + d_7 \]  (9)

Then the T peak is identified as the maxima after the detected S point within a predefined stipulated interval. As the T peak is pointed out, T onset and T offset is found out as the minimum potential crossing points on either side of the T peak. The plot of (9) is shown in Fig. 7. Sometimes a serious problem is encountered in automatic ECG feature extraction technique for the signals with myocardial
diseases. It is the unpredictable shape and slope of T wave, specially, the inverted T waves. This problem is taken into account by identifying the type of the T wave at the beginning of the T peak detection algorithm. The type of the T wave is detected by considering the magnitudes within

```
   2 5 10 15 20 25 30
Identified R peaks (positions are marked by vertical lines)
```

Fig. 6. Detection of R peak for wave having baseline drift (first 14 peaks are shown for better visibility).

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<table>
<thead>
<tr>
<th>TABLE 1 - RESULT FOR R PEAK DETECTION</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total no. of beats</td>
</tr>
<tr>
<td>-------------------</td>
</tr>
<tr>
<td>2550</td>
</tr>
</tbody>
</table>
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Fig. 8. Original wave. P, QRS and non-inverted T wave.
the T wave separated by a predefined interval. Its magnitude and sign change (if any) determine the type of the T wave. Thus the significant points as Q, R, S and T waves are identified by selective coefficient method. P wave is detected by the similar method as T before the Q point.

4. Results and analysis

In the present work, physionet PTB diagnostic database is used to evaluate the algorithm. As discussed in the previous section, simulation and testing has been carried out, the results of which are presented in Figs. 3a, 3b, 4 to 9 and Tables 1 and 2. For validation of the algorithm, more than 80 databases are checked. Present method shows 0.24% false positive (FP) and 0.39% false negative (FN) R peaks with a total detection failure of 0.62% as indicated in Table 1. Fig. 6 shows the ECG wave for 30 seconds and first eighteen annotated R peaks (all the peaks are not considered for better visibility). Fig. 8 shows the detected QRS complex, P and T wave for an ECG waveform with non-inverted T wave. An inverted T wave along with corresponding QRS complex and P wave is shown in Fig. 9.

The result of the proposed method for measurement of durations of P wave, QRS complex, T wave and the heart rate measurement is shown in Table 2. The measured values are compared with the manually measured values and the measurement performance is estimated by a factor called inaccuracy as defined below.

\[
\text{Inaccuracy} = \frac{m - n}{m} \times 100\% \quad (10)
\]

where \(m\) is manually measured duration and \(n\) is the respective duration measured by the algorithm.

The heart rate which is the number of beats per second is calculated by the measurement of the time interval of two consecutive R peaks. Heart rate measurement accuracy depends upon the accuracies of two consecutive R peak measurements. So heart rate measurement accuracy is always less than the individual accuracy of R peak detection.

5. Conclusion

In this paper, an algorithm based on Wavelet Transform is presented for the detection of QRS, T, and P waves of ECG. In multiresolution approach, it is easier to characterize the ECG wave so as to identify the different waves and complex. Wavelet Decomposition of ECG wave up to level 8 using orthogonal Daubechies 6 wavelet generates 8 scales of detail coefficients. Smaller scales correspond to lower frequency components and higher scales correspond to lower frequency components of the signals. Reconstruction scales are selected on the basis of the power spectra of different parts of the signal, which eliminates different noise and artifacts and the interference of other part of the signal while extracting a particular wave or complex. Thus the proposed technique is proved to be accurate especially in presence of different noises. It requires less processing time for parameter calculation. The time scale nature of the proposed algorithm has the advantage of identifying the different waves at the point of occurrence of it without being disturbed by the other waves. Selective coefficient approach eliminates the probability of interaction between the adjacent waves. Due to some pathological reasons, sometimes the T wave may be higher in magnitude than the R wave. In that case there is a probability of wrong identification of R peak in time plane based algorithms. Here this difficulty is eliminated by disregarding the reconstruction coefficients responsible for T peak while detecting the R peak. Thus most of the probable sources of errors in detecting R wave are eliminated here. Once the P wave, QRS complex and T wave is identified and measured, some clinically important regions like PR segment, QT segment, ST segments are easy to measure. Moreover, amplitudes of P, R and T waves can easily be measured by the maximum amplitude in the respective complex or wave. So this feature extraction method can be used as a primary measurement tool for automatic and online disease classification and biometric recognition. But some of the ECG waveforms may show very erratic nature due to electrode contact noise or some complicated cardiac abnormalities. The algorithm is not tested with them because of lack of availability of that special kind of database.

References

Empirical mode decomposition based ECG enhancement and QRS detection

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ABSTRACT

In this paper an Empirical Mode Decomposition (EMD) based ECG signal enhancement and QRS detection algorithm is proposed. Being a non-invasive measurement, ECG is prone to various high and low frequency noises coming from baseline wander and power line interference, which act as a source of error in QRS and other feature extraction. EMD is a fully adaptive signal decomposition technique that generates Intrinsic Mode Functions (IMF) as decomposition output. Hence, first baseline wander is corrected by selective reconstruction based slope minimization technique from IMFs and then high frequency noise is removed by eliminating a noisy set of lower order IMFs with a statistical peak correction as high frequency noise elimination is accompanied by peak deformation of sharp characteristic waves. Then a set of IMFs are selected that represents QRS region and a nonlinear transformation is done for QRS enhancement. This improves detection accuracy, which is represented in the result section. Thus in this method a single fold processing of each signal is required unlike other conventional techniques.

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1. Introduction

Automatic computerized analysis of physiological signals is a major field of interest since last few decades. The purpose of automation is to reduce the human effort and time required for analysis and interpretation. This helps in handling a large number of data, for fast processing and decision making, specially in intensive care services. In some cases the long duration biomedica

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ECG signal → Noise filtering → QRS detection → Wave delineation → Classification → Result

Fig. 1. Steps for automatic ECG analysis.

[2-4] for removing power frequency interference. The main problem of low pass or high pass filtering is that ECG frequency spectra is quite overlapping with that of noise spectra specially due to the presence of QRS complex as high frequency component in ECG. An adaptive filtering method [5] is also proposed for baseline correction. Some modern techniques like Principle Component Analysis [6], Neural Network [7], Wavelet Transform [8] etc are proposed for high frequency noise elimination from ECG wave but all have their inherent shortcomings mainly due to the dependence on ECG frequency whose bandwidth is not constant.

Automatic detection of QRS complex is a well visited problem in biomedical signal processing. As a result a number of detection techniques are proposed. In many non-orthogonal methods like [9,10], for QRS detection, P and T waves and noises are suppressed by bandpass filtering and some nonlinear transformation is performed for QRS complex enhancement. Then some rule based technique is used to identify QRS region. All the filter based approaches suffer from a genuine problem of selecting the signal pass band. It is seen that signal pass band of QRS region may overlap with noise frequency. Moreover, it is different for different persons or even in same person at stressed condition or due to a long interval. Another method [11] uses adaptive matched filtering technique based on artificial neural network (ANN). The low frequencies are modeled by an ANN based adaptive filter and the residual signal is passed through a matched linear filter for the detection of QRS location. A fuzzy hybrid neural network based approach is also proposed to recognize different type of beats resulting from same or different source [12]. However, in most of the cases the efficiency of the algorithms is accompanied by higher computational time and cost. Hidden Markov models [13] and pattern recognition techniques are also used for the detection of QRS complex [14]. Wavelet transform based multi-resolution analysis for signal decomposition technique [15,16] is also used for QRS detection. Wavelet has the advantage that it does not require any predefined cutoff frequency for detection. But it is seen that wavelet functions that support compactness and symmetry with the test signal provide better result.

All the methods including wavelet based approach are non-adaptive and hence not globally applicable. Basically due to dynamic changes in the behavior of heart and related organs, the ECG signals may exhibit time-varying as well as non-stationary behavior. Moreover, the unpredictable nature of high and low frequency noises makes the task of noise elimination and QRS detection a difficult one for conventional filtering technique or other non-adaptive approaches. Hence a fully adaptive approach can perform better in almost all physiological conditions. Recently Huang et al. have proposed the Empirical Mode Decomposition method (EMD) [17] as a new tool for the analysis of nonlinear and non-stationary time domain data. Being a completely data driven approach, it extracts the basis function from the signal itself. Thus, it can be used for any kind of ECG signals. Recently EMD is being used for signal decomposition and analysis in different fields of biomedical domain [18,19]. It is also used for QRS detection [20,21] of ECG signal. But these methods require preprocessing of ECG using standard band pass filters prior to EMD based QRS extraction. Thus it requires two fold operation of each ECG signal—(1) for noise elimination and (2) for QRS detection.

In this paper an EMD based single run approach for noise elimination and QRS detection is proposed. Here noises are estimated by statistical technique from the set of decomposed signals and then the QRS region is reconstructed from the relevant components of decomposed signals.

2. Empirical mode decomposition (EMD)

Empirical Mode Decomposition is relatively new signal processing technique used for nonlinear, nonstationary time series decomposition. It is different from Fourier Transform (FT) or Wavelet Transform (WT) because of the fact that the basis functions are directly derived from the signal under test. In a priori basis analysis like FT or WT, the harmonics are definitely like the basis function in one form or other. According to the principle of EMD, it decomposes a signal into a sum of oscillatory functions, namely intrinsic mode functions (IMFs). IMFs should have two basic features—(1) they have the same number of extrema and zero-crossings or differ at most by one and (2) they are symmetric with respect to local zero mean.

The steps of Empirical Mode Decomposition of any signal x(t) are as follows:

1. At first all the local maxima and minima of the given signal are identified.
2. Cubic spline interpolation is used to connect all the local maxima and thus upper envelope of the mother signal is constructed.
3. The procedure is repeated for the local minima to produce the lower envelope.
4. The mean m_i of upper and lower envelope is calculated and the difference d_i between the signal x(t) and m_i is computed as d_i(t), i.e.,
   \[ x(t) - m_i = d_i(t) \]  
5. If d_i(t) satisfies the conditions of IMF, then d_i is the first frequency and amplitude modulated oscillatory mode of x(t).
6. If d_i is not an IMF, then the shifting process described in steps (1), (2) and (3) are repeated on d_i. Thus d_1 is calculated as
   \[ d_1 = m_1 = d_1(t) \]
   (2)
   in which m_1 is the mean of upper and lower envelope value of d_i.
7. Let after k cycles of operation, d_k be an IMF, that is
   \[ d_{i+1} - m_i = d_k \]
   (3)
    Then, it is designated as c_k = d_k, the first IMF component from the original data.
8. Subtracting c_k from x(t), r_k is calculated as
   \[ r_k = x(t) - c_k \]
   (4)
   which is treated as the original data for next cycle.
9. Repeating the above process for n times, n no. of IMFs are obtained along with the final residue r_n. The decomposition process can be stopped when r_n becomes a monotonic function from which no more IMF can be extracted. A popular stopping criteria is to have the value of normalized standard difference (NSD) within a predefined threshold [22] where
   \[ \text{NSD} = \sum_{t=1}^{T} \frac{|d_{i+1}(t)-d_i(t)|^2}{d_i(t)} \]
   (5)
By summing up, we finally obtain
\[ x(t) = \sum_{n=1}^{N} c_n(t) + r(t) \]  

Residue \( r \) is the mean trend of \( x \). The IMFs \( c_1, c_2, \ldots, c_N \) represent the finally obtained amplitude and frequency modulated output set. Their frequency gradually decreases as the order of the IMFs increases.

A typical ECG signal and the resulting IMFs are shown in Fig. 2. It is seen that the lower order IMFs represent the fast or high frequency oscillations and upper order IMFs correspond to slow or low frequency oscillations. If the ECG is corrupted by baseline wander, it should appear in some higher order IMFs and the power frequency noises must be represented in some lower order IMFs. So the first step of this work involves enhancement of ECG by filtering it out from the noise.

3. Material and method

3.1. ECG enhancement by EMD based denoising

It is known from the previous section that Empirical Mode Decomposition decomposes a signal into IMFs of gradually decreasing frequency and baseline wander is expected to present in some higher order IMFs. The residue of EMD operation may contain some parts of total baseline drift but it is not possible to have the entire baseline problem contained in the residue. This is because baseline wander may contain multiple extrema and zero crossings, which the residue cannot have as per its property. So it is a difficult task to identify the no. of higher order IMFs, which contributes to baseline shift. Moreover, they should not contain any useful information. If the entire ECG signal is piecewise divided into small segments, baseline wander basically generates a slope change from segment to segment. The absolute sum of all the slopes approximately indicates the magnitude of baseline drift. The more the sum, the greater the baseline wander. As the baseline components are present in the low frequency IMFs, partial reconstruction of the last few IMFs including residue may represent baseline drift, but it is difficult to identify the order of IMFs responsible for baseline drift. So here a global slope minimization technique is used where last few IMFs are removed one by one as long as the global slope becomes minimum. The steps are as follows:

- FFT of the original signal (i.e. signal with baseline wander) is done to note the frequency contents in the signal.
- The dataset of \( N \) samples are divided into \( P \) segments each having \( n \) no. of samples. Each segment contains, say, \( M \) no. of ECG waves.
- At the two ends of each segment arbitrarily two points are identified in the same part (preferably in TP segment, though not mandatory) of two extreme ECG signals.
- Then consecutive points are connected to draw \( P \) straight lines (Fig. 3A).
- Slope of each straight line is calculated.
- Absolute values of all the slopes are added to achieve global slope of the wave under discussion.
- The global slope is minimized by eliminating higher order IMFs one by one starting from the highest order one up to a certain IMF (Fig. 3A, C, D, E).
- The FFT of the reconstructed wave is done to check the presence of useful components in the baseline corrected ECG if any. It is a common practice to consider baseline wander frequency below 0.5 Hz. During slow heart rate (Bradyarrhythmia) the lowest frequency content in ECG is 0.67 Hz [23]. As the heart rate is not constant, it is wise to consider the frequency of useful components to be above 0.5 Hz (high frequency noise is not considered).
- If by comparing the FFT of reconstructed wave and that of the original wave it is seen that some useful frequency component is lost in the process, the last eliminated IMF is considered during reconstruction. Then the required feature (mainly P and/or T wave) of the wave is preserved and baseline wander is removed.
The step by step reconstruction is shown in the series of figures below.

3.1.2. Power frequency elimination

The basic idea of power line removal using EMD is to perform selective reconstruction of the ECG from the IMFs. It is seen from the previous sections that lower order IMFs contain high frequency components and higher order IMFs contain low frequency components of ECG signal. The basic principle of denoising via EMD is to select a partial list of IMFs, which are not representative of noises to reconstruct ECG. From Fig. 1 it is clear that the first IMF contains mostly high frequency noise and some QRS information. The next few IMFs contain useful information regarding ECG and high frequency noises. Hence, if these IMFs are removed some important information regarding ECG may be lost, if they are retained; some high frequency noises may present in the ECG information. This is illustrated in Fig. 4. It shows that if only first IMF is removed and all others are retained, the resulting output contains considerable levels of noise and may lack some of the useful high frequency parts. If some more IMFs are straight away removed, the resulting wave will be distorted at the sharp edges specially the R peak. This is because R peak has a sharp and high frequency oscillation mode, which is mostly represented in the higher order IMFs. To deal with this problem a window based QRS preservation method is proposed [24]. In this method, before the rejection of first few IMF QRS region is retained and added with the rest after IMF removal. This method has a problem that any noise in the QRS region is ignored. Some model based approach [25] is also proposed for R peak preservation during EMD based denoising of ECG. But it is very difficult to propose a specific model for ECG as the wave differs for different diseases, from person to person; it also differs in the same person during stressed condition or due to a long interval.

Moreover, in some leads S wave has a sharp and long depression below the baseline. Again some coronary artery diseases like Myocardial Infarction are diagnosed by the presence of a long and sharp Q wave in ECG along with other indicative features. In these cases S peak and Q peak may also be distorted along with R. So there is a possibility of distortion of entire QRS complex if first few IMFs are simply removed for denoising as shown in Fig. 5. As a result QRS complex detection will be erroneous.

To overcome all these difficulties, a simple algorithm to choose required IMFs is proposed. The steps are elaborated below:

1. First the cumulative mean of the IMFs are calculated. In this step, first the mean of 1st IMF is calculated. Then the other IMFs starting from the 2nd one are added to it one by one and
3.13. Peak correction

This partial reconstruction leads to deformation in the sharp peaks of the signal as discussed earlier and shown in Fig. 4. Here a signal correction technique is used to remove this error. It is seen from Fig. 8A and B that, although direct removal of the noisy IMFs generates a denoised signal $X_d$ (Fig. 8B), amplitude of sharp peaks are reduced. Hence a peak signal correction technique is employed. It is noticed that removed peak magnitude is contained in the eliminated noise as sharp spikes with amplitude higher than the rest of the part of the noise. So the actual noise is approximated as some fraction of the spike magnitude and the required peak information is extracted from the noise as,

$$M_s = \frac{1}{M_x} \sum_{i=1}^{N} |c(i)|$$

where $M_s$ is magnitude information; $i$ is the order of IMF up to which it contains noise level, $c(i)$ is $i$th IMF and $K$ is a constant multiplying factor whose value is chosen to be 0.5 by trial and error method. This step is very important for QRS detection using EMD method as it retains the QRS texture as it is.

Finally this magnitude information $M_s$ is added to the earlier reconstructed signal to get ECG signal free from power frequency noise as.

$$X_d = X_d + M_s$$

The peak information $M_s$ and finally obtained denoised signal $X_d$ are shown in Fig. 8C and D respectively.

3.2. QRS detection

QRS complex comprises of Q wave, R wave and S wave generated due to ventricular depolarization. Detection of QRS complex is the entry point of almost all ECG analysis technique. In most of the ECG signals R wave appears as a sharp peak in between Q and S waves, which are of lesser amplitude and duration with respect to R wave. Moreover, Q and S peaks are in opposite phase of that of R. So QRS complex is the region between Q wave onset and S wave offset. The complexity of detecting QRS region is that it is completely non-stationary.

Empirical Mode Decomposition of ECG signal has the advantage that it decomposes the signal into a set of amplitude and frequency modulated functions (IMFs). The frequency of the functions decreases towards the higher order on IMFs. As QRS region is a high frequency phenomena, it is expected to present in lower order IMFs. But it is difficult to identify the IMF(s) that contains the QRS information. As mentioned earlier, previous EMD based QRS detection algorithms basically have two steps—first the raw signal is filtered using digital signal
processing approach and secondly, EMD is performed and some lower order IMFs are selected, which may contain QRS information [21]. Thus the method requires two fold processing of each signal—one for noise elimination and feature extraction as the other. Thus it requires higher processing time. Moreover, digital filtering based noise elimination approach has its inherent limitation in terms of cutoff frequency selection and higher order of the filters limits its application in practice.

In the proposed method the raw ECG signal is passed through an EMD based decomposition process and baseline wander and power frequency noises are eliminated as described in earlier sections. Thus a set of IMFs is achieved, which contains only the useful information including the QRS complex. The steps to identify QRS complex from these set of IMFs are described below:

1. It can be expected that the first few IMFs will have the QRS information as QRS region is a high frequency component than the remaining part of the ECG. The selection of first two IMFs from the denoised set of IMFs has an advantage that it contains only the high frequency parts and most low frequency waves like P and T waves are filtered out from consideration. But as these IMFs are in the mid-band IMFs of the entire set, they must be lacking some high frequency information as shown in Figs. 4 and 5. Hence the peak correction factor is added to it as
earlier. So the QRS complex is expected to present in the signal given by

\[ Y_{QRS} = \sum_{i=1}^{n} C(i) + M_i \]  \hspace{1cm} (12)

where \( M_i \) is given by Eq. (10).

This improves the QRS identification accuracy as most of the interfering waves are eliminated as shown in the Fig. 9B.

2. Next, the signal is squared as, \( Y_{QRS,Enhanced} = Y_{QRS}^2 \). It enhances the QRS region as shown in Fig. 9C. This squared signal may have different shapes for different waves as QRS complex has different morphology. If it comprises of sharp, long upright R with small Q and S waves of opposite polarity (Fig. 9A), then the squared signal results in a signal having three consecutive peaks as shown in Fig. 9C. The central peak is the R wave with Q and S peaks on either of it. Hence the Q onset and S offset are chosen databases taken from Physionet PTB diagnostic database and MIT-BIH arrhythmia database having sampling frequency 1 kHz and 360 Hz, respectively. The algorithm is tested with beats of different cardiac conditions as a cardiac disorder results in a change in beat morphology. Normal cardiac rhythm, Myocardial Infarction (MI), Bundle Branch Block (BBB), Hypertrophy, Dysrhythmia beats are taken from PTB database and Premature Ventricular Contraction (PVC) and some BBB data are taken from MIT-BIH database. First the ECC enhancement algorithm is performed and then QRS detection is done on denoised ECC in a single run.

4.1. ECC enhancement

A noisy database of 25,000 samples is taken for validation. In most of the reported works a clean signal is taken and some artificially generated noises are added with it to get a noisy signal and then the proposed algorithm is used. This method has a problem that it is difficult to get a clean signal and the actual noise may be of different kinds than the artificial one. So here denoised signals are considered as clean signals and the extracted baseline wander and power frequency interference are considered as imposed noise. Linear combination of noises extracted from one or more database is used as a test noise for a clean ECG generated from some other database. Different combinations of baseline wavers and power line interferences are used as input noise that gives the sense of practical noises.

For quantitative evaluation of proposed algorithm, the power \( P \) of clean signal and filtered signal are measured by

\[ P = 10 \times \log_{10} \left( \frac{\sum_{i=1}^{n} |x_i|^2}{n} \right) \]  \hspace{1cm} (13)

where \( n \) is the length of database.

Then Percentage Noise Retention (PNR) is calculated as

\[ \text{PNR} = \frac{P_{Signal}}{P_{Noise}} \times 100 \% \]  \hspace{1cm} (14)

where \( P_{Signal} \) is power of denoised signal and \( P_{Noise} \) is power of clean signal. PNR indicates the change in power of clean signal due to addition and elimination of noise in percentage of initial clean signal power. It can be taken as a measure of noise present with the clean signal after EMD based denoising.

Moreover, the correlation between the clean and noisy signal and the same for clean and denoised signal is calculated as

\[ \rho_{1,2} = \frac{\sum_{i=1}^{n} x_{clean}(i)x_{noisy}(i)}{\sum_{i=1}^{n} x_{clean}(i)\sum_{i=1}^{n} x_{noisy}(i)} \]  \hspace{1cm} (15)

where \( \rho_{1,2} \) is the cross-correlation coefficient between the clean signal \( x_{clean}(n) \) and noisy signal \( x_{noisy}(n) \) and \( \rho_1 \) is the same between clean signal \( x_{clean}(n) \) and denoised signal \( x_{denoised}(n) \). The proposed method for ECC enhancement is tested with baseline wander only, with power line interference only and for both baseline and power line noise combined case. The results are demonstrated in following three sub-sections.

4.1.1. Clean signal with baseline wander (BW)

As mentioned earlier, the baseline shifted signal is obtained as

\[ x_{shifted}(i) = x_{signal}(i) + K_1 \sum_{m} x_{BW} \]  \hspace{1cm} (16)

where \( x_{signal}(i) \) is the signal with baseline error (BW) stands for each baseline drift, \( C_m \) is mth linear coefficient, \( m \) is number of individual baselines added and \( K_1 \) is a multiplying factor to modulate the baseline. Thus different forms of baseline are made and the test results are shown in Table 1.

### Table 1

<table>
<thead>
<tr>
<th>Database</th>
<th>Added BW noise power (dB)</th>
<th>Output filtered signal power (dB)</th>
<th>PNR (%)</th>
<th>( \rho_1 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physionet PTB</td>
<td>26.965</td>
<td>31.097</td>
<td>-0.0315</td>
<td>0.8780</td>
</tr>
<tr>
<td>MIT-BIH</td>
<td>30.939</td>
<td>43.079</td>
<td>1.0864</td>
<td>0.3720</td>
</tr>
<tr>
<td>MIT-BIH</td>
<td>30.472</td>
<td>43.079</td>
<td>-0.0104</td>
<td>0.7205</td>
</tr>
<tr>
<td>MIT-BIH</td>
<td>32.3768</td>
<td>33.3821</td>
<td>0.0159</td>
<td>0.7483</td>
</tr>
<tr>
<td>MIT-BIH</td>
<td>32.5739</td>
<td>33.5866</td>
<td>0.0180</td>
<td>0.3807</td>
</tr>
</tbody>
</table>

* Stands for Physionet PTB diagnostic database.

• Stands for MIT - BIH Arrhythmia database.
A typical baseline wander and corresponding filtered signal is shown in Fig. 10.

### 4.1.2. Clean signal with power line (PL) noise

Similar to the earlier one, a signal with power frequency noise is obtained as

$$X_p(t) = X_n(t) + K_2 \sum_p C_p P(t_p)$$

(17)

where $X_p(t)$ is signal with power line noise and $(PL)$ represents each power line noise, $C_p$ is the $p$th linear coefficient, $p$ is number of individual baselines added and $K_2$ is modulating factor of baseline. The test results are tabulated in Table 2 and Fig. 11 shows the performance of the filtering process.

### 4.1.3. Clean signal with baseline wander and power line noise

In the same way a noisy signal with baseline wander and power line noise is prepared as

$$X_{BW+PL}(t) = X_n(t) + K_1 \sum_m C_m BW(t_m) + K_2 \sum_p C_p P(t_p)$$

(18)

where $X_{BW+PL}(t)$ is the signal having both baseline wander and power line noise. In Fig. 12, the clean signal, baseline noise, power line noise, noisy signal, extracted total noise and finally the filtered signals are shown. Table 3 contains the experimental results for this case.

In all three cases, sufficiently low value of PNR indicates the suitability of the proposed method for denoising. Moreover, a variety of noises are used to make a clean signal noisy with different types and different magnitudes of noise to check the versatility of the method. Again wide difference of cross-correlation coefficients $p_1$ and $p_2$ indicates the structural difference of noisy and filtered signals due to elimination of noise. Value of $p_2$ very close to unity proves the morphological similarity of clean and denoised signals.

### 4.1.4. Performance comparison of proposed ECG enhancement technique with Butterworth filtering method

Present method of EMD based ECG enhancement is compared with the performance of standard Butterworth filter. Some noisy
ECG signals as used earlier are taken as test signal. A Butterworth bandpass filter is designed with lower cutoff frequency 0.5 Hz and upper cutoff frequency 33 Hz. The cutoff frequencies are experimentally determined and also supported in [23] and [24]. The ECG signals and noise levels are similar to that in Table 5. PNR and cross correlation coefficient $p_\alpha$ are calculated for the filtered signals as tabulated in Table 4.

It is clear from the comparison of Tables 3 and 4 that proposed EMD based method performs better for ECG enhancement. Fig. 13 also supports the same result.

### 4.2. QRS Detection

Once the filtered signal is finally obtained, the method described in Section 3.2 is used to detect the QRS region. As different diseases generate different texture of waveform, some commonly faced ECG patterns are considered for verification of the algorithm. The proposed method is quantitatively analyzed by two statistical parameters—measurement sensitivity (Se) and specificity (Sp), which are defined as

Sensitivity (Se$%) = \frac{TP}{TP + FN} \times 100\%$

Specificity (Sp$%) = \frac{TN}{TP + FN} \times 100\%$

where TP stands for true positive that indicates the accurate detection of QRS complex, FP stands for false positive indicating a detection of QRS where it is not present and FN or false negative indicates failure of algorithm to detect a real beat.

Results are separately shown for PTB diagnostic database (Table 5a) and MIT-BIH Arrhythmia database (Table 5b) taken from Physionet data bank.

It is seen in Table 5a that the algorithm runs well for the PTB diagnostic database especially for normal and infracted beats but performance deviates a little for hypertropic and dysrhythmic beats.

### Table 4

PNR and $\alpha$ values for Butterworth filtering of same signals.

<table>
<thead>
<tr>
<th>Database</th>
<th>PNR ($\alpha$)</th>
<th>$\alpha$</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1247679</td>
<td>0.248</td>
<td>0.086</td>
</tr>
<tr>
<td>P1742500</td>
<td>0.825</td>
<td>0.82</td>
</tr>
<tr>
<td>P1794441</td>
<td>1.973</td>
<td>0.8142</td>
</tr>
<tr>
<td>P262227</td>
<td>0.5889</td>
<td>0.0126</td>
</tr>
<tr>
<td>P1075199</td>
<td>-0.1393</td>
<td>0.8357</td>
</tr>
<tr>
<td>tds</td>
<td>1.0994</td>
<td>0.875</td>
</tr>
</tbody>
</table>

### Fig. 13

A—Noisy signal; B—Output of Butterworth bandpass filter; C—Output of EMD based filter (proposed method).

### Table 5a

Results obtained for QRS detection for PTB Diagnostic Database.

<table>
<thead>
<tr>
<th>Type of data</th>
<th>No. of beats</th>
<th>FP</th>
<th>FN</th>
<th>Se (%)</th>
<th>Sp (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>32,942</td>
<td>21</td>
<td>32</td>
<td>99.89</td>
<td>99.93</td>
</tr>
<tr>
<td>MI</td>
<td>22,800</td>
<td>22</td>
<td>31</td>
<td>99.66</td>
<td>99.80</td>
</tr>
<tr>
<td>Hypertrophy</td>
<td>634</td>
<td>12</td>
<td>7</td>
<td>97.27</td>
<td>98.06</td>
</tr>
<tr>
<td>Dysrhythmia</td>
<td>757</td>
<td>8</td>
<td>7</td>
<td>98.10</td>
<td>98.92</td>
</tr>
</tbody>
</table>

### Table 5b

Results obtained for QRS detection for MIT-BIH Arrhythmia Database.

<table>
<thead>
<tr>
<th>Total no. of beats</th>
<th>Normal</th>
<th>Others</th>
<th>FP</th>
<th>FN</th>
<th>Se (%)</th>
<th>Sp (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>49,016</td>
<td>34,606</td>
<td>14,410</td>
<td>17</td>
<td>54</td>
<td>99.88</td>
<td>99.95</td>
</tr>
</tbody>
</table>

### Table 6

Comparison of QRS detection performance with some standard methods.

<table>
<thead>
<tr>
<th>Sl. no.</th>
<th>Method</th>
<th>Database used</th>
<th>Se (%)</th>
<th>Sp (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>Ghaffari et al. [27]</td>
<td>MIT-BIH</td>
<td>99.91</td>
<td>99.72</td>
</tr>
<tr>
<td>3</td>
<td>Christov (Alg. 2) [29]</td>
<td>MIT-BIH</td>
<td>99.74</td>
<td>99.65</td>
</tr>
<tr>
<td>5</td>
<td>Present work</td>
<td>PTB Diagnostic database</td>
<td>98.75*</td>
<td>99.20*</td>
</tr>
<tr>
<td>6</td>
<td>Present work</td>
<td>MIT-BIH</td>
<td>99.88</td>
<td>99.96</td>
</tr>
</tbody>
</table>

* Averaged.

It is seen that most of the reported works are validated with MIT-BIH Arrhythmia database. Hence the proposed method is also tested with 21 arbitrarily chosen files from the same database, which mostly contains normal, BBB, paced, PVC and some fused beats. It is seen that the results are comparable to some of the earlier reported works as indicated in Table 6. Further investigations can be made to extract other temporal features and also in some different cardiac irregularity conditions.

### 5. Conclusion

In this paper, an Empirical Mode Decomposition based ECG enhancement and QRS detection technique is proposed. In almost all methods of QRS detection requires first pre-filtering and then some other signal processing algorithm is used for QRS detection. Thus it involves two fold processing of each signal. In this method a single decomposition operation is required followed by a statistical approach for noise elimination and a QRS enhancement operation for QRS detection. In most of the cases recorded ECG becomes noisy due to the presence of unpredictable high and low frequency components generated from the sources other than heart. Thus it makes the extraction of QRS and other features very difficult. Moreover, ECG itself is a nonlinear and nonstationary phenomena. Hence a completely data driven adaptive approach can serve better in almost all kind of ECC signals. Unlike Fourier or Wavelet transform, EMD extracts its basis function from the signal itself and thus generates a set of IMFs by a signal dependent shifting process as described earlier. For baseline wander correction, the entire database is fragmented and the slope of each section is minimized by adaptively removing the higher order IMFs including residue. Thus the entire database under test becomes baseline corrected by global minimization of absolute slope. Power of each IMF is calculated and high frequency noise components are estimated by considering a lower threshold level of power as the high frequency noise power is smaller than that of the IMFs responsible for actual components.
of the ECG. As direct elimination of those IMFs causes a distortion in QRS complex at their peaks, a statistical approach for peak correction is used to retain the QRS morphology. Thus this EMD based filtering removes only the noisy parts of signal retaining all required information as it is.

Once the ECG enhancement is done, partial reconstruction is performed by a set of IMFs taking from the retained list to identify the QRS region and it is enhanced for better visualization of QRS complex. This minimizes the interference of large T or other waves with QRS complex during detection making the identification accurate. The method is tested with ECGs of different pathological conditions with a high detection sensitivity and specificity as shown in the results.

Conflict of interest

We hereby disclose that there is no financial and personal relationships with any other people or organizations/institutes that could inappropriately influence (bias) our work.

References

IEEE computer Society.
Detection of Premature Ventricular Contraction Beats Using ANN

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Abstract—Detection and classification of ventricular complexities from the electrocardiogram (ECG) is of considerable importance in critical care and patient monitoring for the timely diagnosis of dangerous heart conditions. Accurate detection of premature ventricular contractions (PVCs) is particularly important in relation to life-threatening arrhythmias. Model based approach for detection of PVC is a common one. Here a data based approach is proposed where the wave morphology in terms of Form Factor (FF) and R peak amplitude are calculated. Artificial Neural Network (ANN) is used for classification of PVC beats from normal ones. The obtained sensitivity (Se), specificity (Sp) and accuracy are 94.11% and 97.5% and 96.45 respectively.

Index Terms—ECG, Premature Ventricular Contraction (PVC), Wavelet Decomposition, Form Factor(FF), ANN

I. INTRODUCTION

SA node is the source of cardiac impulse in heart [1]. In case of inactivity of this node, one of the cardiac tissues may take over the role of pacemaker introducing ectopic beats. These abnormal rhythms are called arrhythmias. Among the ventricular arrhythmias, the premature ventricular contraction (PVC) is of great importance since its occurrence is much rarer than normal. It increases the risk of sudden death in patients [2]. The wave shapes of PVCs are usually very different from that of the normal beats of the same subject due to the different conduction paths of the ectopic impulses. Recent studies have shown that the occurrence of PVCs is indicative of increased risk of sudden cardiac death, and linked to mortality when associated with myocardial infarction [3]. The detection of PVCs is thus of major importance, since they are associated with an increased risk of adverse cardiac events. Resulting from an ectopic depolarization on the ventricles (which replace the normal start of the cardiac beat), a wider and abnormally shaped QRS complex occurs. Additionally, typically QRS complexes are not preceded by P waves, and T waves are usually larger and with opposite deflection to the QRS complex. Some typical PVCs are shown in figure 1. The automatic detection of PVC has been an active research during the last years. The fundamental differences lie in the morphology of the ECG.

So, the detection of PVC beat involves basically two steps: to identify suitable features capable to distinguish between PVC and normal beats and to employ a suitable technique for classification. In [4] an algorithm for PVC detection based on QRS complex morphological characteristics is presented. In [5] the mean-square value of QRS was proposed as PVC discriminative features, together with two linear prediction coding coefficients. For PVC classification, numerous algorithms such as decision trees and fuzzy ruled based networks have been proposed. Most of the algorithms involve measurement of different wave durations and amplitudes and design of a feature based classifier. But to identify different wave boundaries is a difficult task as the PVC beats have widely irregular shape. In this work a Form Factor [6] based technique with a requirement of only R to R wave (i.e. a complete wave) duration and R amplitude is suggested. Here R to R wave segment is considered because being a complete wave, it includes all the relevant features for PVC beats. Thus the requirement of detection of all the required features is bypassed making the algorithm a simpler one. Form Factor is a statistical parameter that increases with the complexity of the signal. All the PVC and normal beats are assigned with a form factor (FF) value and R amplitudes of each beat are calculated. These two parameters form the basis of the proposed ANN based technique. The method is tested and validated against MIT-BIH Arrhythmia database [7].
II. MEASUREMENT AND METHODS

A. Wavelet based feature extraction

Feature extraction is the most vital job in accurate pattern classification. Automatic feature extraction is done by the multiresolution wavelet based selective coefficient method as reported by S. Pal et al. in [8]. This method requires proper selection of wavelet reconstruction coefficients for different waves in an ECG signal. Thus for detection of R peak two functions are defined as

e_1 = d_4 + d_5 - \cdots \cdots \cdot (1)

e_2 = d_4 \times (d_3 + d_5) - \cdots \cdots \cdot (2),

and modulus of \( e_1 \times e_2 \) is plotted as shown in figure 2. Here d_1 to d_8 are 8 level detail reconstruction coefficients. First plot of figure 2 is the original signal of a subject taken from physionet database, second plot is the denoised signal and third one is the plot of modulus of \( e_1 \times e_2 \) as mentioned earlier. From the third plot the R peak is detected as the highest point. The plot of the wave between two consecutive R peaks is the RR wave segment.

![Original signal, Denoised signal, Plot of modulus of e1 x e2](image)

Figure 2: Original signal modulus of e1 x e2

B. Form Factor

Form factor is an indication of the variance of signal activity. Activity of a signal x(n) is calculated as the variance \( \sigma^2_x \) of the stipulated segment of the signal. From the activity of the signal, mobility \( M_x \) is calculated as the ratio of square root of the activity of the first derivative of the signal and square root of the original signal. Thus

\[
M_x = \left( \frac{\sigma_x}{\sigma_y} \right) \ \text{where} \ x^\prime \ \text{stands for the first derivative of} \ x.
\]

Complexity or the Form Factor is defined as the ratio of the mobility of the first derivative of the signal to the mobility of the signal itself. That is

\[
FF = \frac{M_x}{M_y} = \frac{\sigma_x}{\sigma_y} \ \text{where} \ y^\prime \ \text{stands for the second derivative of the signal.}
\]

It is noticed that though there are some features in the ECG wave which change due to premature ventricular contraction, R amplitude is identified as one feature of classification. because it is possible to measure it almost all kind of ECG waves. Direct measurement of other features (viz. QRS duration, T wave etc.) is omitted to avoid the complexity of the algorithm as they can widely vary in shape and size. Here amplitude of R peak is measured with respect to wavelet zero reference. An inspection of the FF value of one complete wave and R amplitude reveals that though in most of the cases the PVC and normal beats can be isolated with one simpler classification technique, in some databases they are quite interfering leading to misclassification. Hence Back Propagation based Neural Network is used for classification.

E. ANN based Training

First the input and outputs are normalized with respect to their maximum values as it is observed that the neural networks work better if the input and output lie between 0 and 1. It is assumed that the number of neurons in the hidden layer lie within a particular defined range. The weights connecting the input neurons and hidden neurons and the weights connecting the hidden neurons and output neurons are initialized between 0 and 1. One set of inputs and outputs are used as training data. By using linear activation function, the output of the input layer may be evaluated. The inputs to the hidden layer are calculated by multiplying corresponding weights of synapses. Then the inputs to the output layer by multiplying corresponding weights of synapses. Output layer units evaluate the output using linear activation function. The error and the difference between the network output and the desired output is calculated. Lastly adjustments in the weights are made until the error (MSE) reaches the desired level with allowable tolerance value.

III. RESULT AND ANALYSIS

Table 1 shows a partial list (15 no.s) of FF values of RR intervals and R wave amplitude for some normal and PVC beats. It is evident from the analysis that there is an abrupt rise in R wave amplitude of PVC beats and a noticeable amount of change in FF value of the PVC beats. This forms the foundation of the ANN based classification technique. Here more than 150 beats from 6 arbitrarily chosen databases of MIT-BIH arrhythmia database are tested. 100 beats are used to train the ANN and 57 beats comprising of 17 PVC and 40 normal beats are used for testing. It is seen that only two (one normal and one PVC) are misclassified as shown in figure 3.

![Testing samples](image)

Figure 3: Indication error

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**TABLE 1**

<table>
<thead>
<tr>
<th>Sl. No.</th>
<th>Database no.</th>
<th>Features</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>105</td>
<td>1.301</td>
<td>Normal</td>
</tr>
<tr>
<td>2</td>
<td>105</td>
<td>1.2625</td>
<td>Normal</td>
</tr>
<tr>
<td>3</td>
<td>105</td>
<td>1.3319</td>
<td>Normal</td>
</tr>
<tr>
<td>4</td>
<td>105</td>
<td>1.9085</td>
<td>PVC beat onset</td>
</tr>
<tr>
<td>5</td>
<td>105</td>
<td>1.2338</td>
<td>PVC beat offset</td>
</tr>
<tr>
<td>6</td>
<td>105</td>
<td>1.3984</td>
<td>Normal</td>
</tr>
<tr>
<td>7</td>
<td>105</td>
<td>1.3008</td>
<td>Normal</td>
</tr>
<tr>
<td>8</td>
<td>105</td>
<td>1.2829</td>
<td>PVC beat onset</td>
</tr>
<tr>
<td>9</td>
<td>105</td>
<td>1.1392</td>
<td>PVC beat offset</td>
</tr>
<tr>
<td>10</td>
<td>228</td>
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<tr>
<td>11</td>
<td>228</td>
<td>1.0163</td>
<td>PVC beat offset</td>
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<td>12</td>
<td>228</td>
<td>5.3752</td>
<td>PVC beat onset</td>
</tr>
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<td>228</td>
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<td>PVC beat offset</td>
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<td>14</td>
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<td>1.4405</td>
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</tr>
<tr>
<td>15</td>
<td>228</td>
<td>1.378</td>
<td>Normal</td>
</tr>
</tbody>
</table>

In view of this three performance indexes are used as follows:

**Sensitivity (%)** = \(\frac{TP}{TP + FN}\) × 100

**Specificity (%)** = \(\frac{TN}{TN + FP}\) × 100

**Accuracy (%)** = \(\frac{TP + TN}{TP + FN + TN + FP}\) × 100

where TP stands for true positive, TN for true negative, FP stands for false positive and FN stands for false negative. Table 2 shows the performance values parameter values.

**TABLE 2:**

<table>
<thead>
<tr>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>94.11%</td>
<td>97.5%</td>
<td>96.49%</td>
</tr>
</tbody>
</table>

**CONCLUSIONS**

In this work a Form Factor (FF) index and R peak amplitude based Premature Ventricular Contraction (PVC) classification algorithm is presented. Ventricular Arrhythmias (VA) assume a very important role in critical cardiac monitoring. Moreover, VA evolve from simple premature ventricular contractions (PVC) which are in most situations leads to ventricular tachycardia (VT) and finally to critical ventricular fibrillation episodes which are potentially fatal and the main cause of sudden cardiac death. PVC beats are morphologically different from the normal one in terms of different temporal and spatial features. It is not a very easy task to correctly extract all the features for different leads and find a unique decision function based on a number of features. In this present method, only R to R wave is required with the R peak amplitude which reduces the task of extracting a number of features. Hence there is a less probability of errors that may occur in various duration and amplitude measurements. Moreover, each beat is represented by a numerical factor (FF) having different range of values for PVC and normal beats. This simplifies the decision making process. Furthermore, the proposed algorithm could be expected to offer faster implementation than other feature set based algorithm because of less complexity and less data involvement.

**REFERENCES**


Increasing the accuracy of ECG based biometric analysis by data modelling

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ABSTRACT

Here an effort is made to use human electrocardiogram as a tool of biometric analysis for authentication. The proposed method is based on first accurate extraction of characteristic features from each ECG and then design of a suitable classification methodology to comment on the authenticity. As the feature matrix is a huge one, Principal Component Analysis (PCA) is applied to avoid handling of large amount of data. Next, the reduced features from PCA are fitted into a quadratic polynomial model by the method of least square. Then the fitted values for the allowed set of data is obtained and the range over which they vary, provides the signature matrix of a person. Finally the classification is done by a comparison based on nearest neighbor method. The method is tested on ECG of 20 individuals taken from PTB database. This method has accuracy more than 95% with the best fit modeling which becomes only 80% without data modeling proving the importance of best fit modeling of data before classification. This accuracy is comparable with conventional biometric techniques; moreover, ECG biometric can be used with other authentication scheme, with ECG providing liveliness proof.

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1. Introduction

The electrocardiogram (ECG) is a record of time-varying bioelectric potential generated by electrical activity of the heart. It has become a fundamental tool of diagnosing different cardiac and blood circulation abnormalities [1]. The interpretation of ECG leads to a decision on electrical or functional abnormality of heart. In recent past, different studies have been conducted for the use of ECG in biometrics apart from its conventional usage. Biometric analysis and recognition provides security and restricted access to protected areas by identifying the persons using his/her physiological or behavioral features. Presently human fingerprint, face, iris or voice, anatomical traits and behavioral characteristics like signature characteristics and dynamics, etc. are the features that are being used singly or a fusion of more than one of them in biometric recognition systems. However, these biometrics modalities either cannot provide reliable performance in terms of recognition accuracy (e.g., gait, keystroke) or they are prone to falsification externally. Some examples of falsification are 3D fingerprint and face models or plastic surgery on these features, voice playback from a different source and contact lenses with different iris features printed on. In this regard, ECG has a great opportunity to be used as a non-falsifiable biometric parameter. As ECG is the electrical activity generated due to the auto-rhythm of pacemaker cells of cardiac dipole, it is almost impossible to modulate the signal from the outside world.

Recently some research has made to test the applicability of ECG as a biometric feature [2–4]. The possibility to use ECG as a biometric feature is supported by the fact that there is uniqueness in the individual ECG because of physiological and geometrical differences of the heart of different persons [5–7]. Biel et al. [8] have conducted the biometric experiment on ECG recorded from a group of 20 subjects. Twelve features have been selected from each record for identification of a person in a predefined group. Shen et al. [9] have investigated the feasibility of ECG as a new biometric for identity verification. The experiment has been conducted on 20 individuals on seven features,
extracted from mainly QRS complex. Using the techniques of neural network and template matching the experiment of human identity verification has been performed. Lin et al. [10] proposed a technique based on heart rate variability and some other temporal features with only a group of five subjects. A QRS complex based approach with its fourth order Legendre Polynomial as the signature is also proposed by Khalil et al. [11] with good accuracy. Wang et al. [12] has proposed methods using fiducial points and without fiducial points by AC/DCT technique for two groups with 13 subjects in each. Classification is done based on linear discrimination analysis and neural network based technique. In AC/DCT method similarity between the subjects is measured based on normalized Euclidian distance and a nearest neighbor is used as the classifier. This ECG morphology based approach may fail when appearance of two ECGs are similar. Chan et al. [13] use a wavelet distance measurement technique for classification of 50 subjects with accuracy 89%. In [14] S.C. Fang et al. have proposed a technique for person identification by making the classification based on the similarities and dissimilarities on electrocardiogram phase space. A PCA/LDA based approach is also suggested by Baumbar et al. [15]. A non-fiducial feature based technique is reported by J.L.C Loong in [16] using spectral coefficients computed through linear predictive coding (LPC) and classification is done using neural network based approach. Double fold approach is proposed by Safie et al. in [17] where the parameters of the pulse active ratio (PAR) feature vector are represented by a four digit PIN number. Authentication is made for 20 subjects first by verifying the PIN number and finally by ECG feature vector matching. Most of the reported methods either suffers from lack of good accuracy or requires complicated mathematical procedures for processing and classification. Moreover, some of the previous works use 12 lead ECG for biometric authentication which is impractical to use in real biometric system in spite of good result.

In this paper we investigate the applicability of ECG as a biometric parameter with a requirement of fiducial detection for 20 subjects. Here 16 parameters including amplitude, temporal and angular features are extracted. Almost all works regarding ECG based biometric authentication, some data reduction technique is required to handle this large set of database. Principal Component Analysis (PCA) is a commonly used tool used for this purpose as used in the present work also. Additionally, here it is shown that classification accuracy greatly improves if the resulting data after PCA is modeled by a quadratic polynomial based curve fitting algorithm as then higher half of the reduced feature set is better discriminated. The steps of the proposed algorithm are shown in Fig. 1.

Not only for human identification, the technique of using ECG data in biometry offers some unique advantages. In automatic cardiac care units, it is required to monitor the patients continuously. This technique can provide identity of persons remotely without the requirement of any additional data processing. Thus it is advantageous to verify a patient's identity in medical records or prior to drug administration or other medical procedures from a remotely located control room.

2. Materials and methods

2.1. Signal pre-processing and feature extraction

In most of the cases recorded ECG data are corrupted by various high and low frequency noises arising from power line interference (for high frequency noise) and respiration, body movement, EMG, etc. (for low frequency noise). ECG filtering from any kind of above mentioned noise is mandatory from biometric analysis otherwise wrong estimation of features may lead to misclassification. In this work wavelet transform based filtering and feature extraction is performed. The method is taken from [18]. Wavelet transform is basically a convolution operation between the mother wavelet and the test signal as the mother wavelet translates along the test signal in time axis. Here db6 is chosen as mother wavelet due to its structural resemblance with the QRS complex of the ECG signal and decomposition is made up to level eight. Fig. 2 shows the decomposition of a typical ECG signal with db6 wavelet. The coefficient of level one may be considered as mostly noise with respect to the important frequency parameters of ECG when the sampling frequency of the mother signal is 1000 Hz. According to the power spectra of the signal [19], it is clear that most energy of the QRS complex is concentrated at decomposition level 3, 4 and 5. The reconstructed wave with these coefficients is enhanced and the highest potential point is considered as R peak. Generally the Q and S waves are high frequency and low amplitude waves and their energies are mainly prominent at small scale. For that decomposition coefficients from d2 to d5 are retained and a five point differentiation is made to find out the point of inflections for Q and S points on either side of R peak. The energies of T and P waves are mainly at scale levels 6, 7 and 8. But, low frequency base-

![Fig. 1. Block diagram of the entire procedure.](image-url)
1.1.4 1.16 1.18 1.2

Fig. 3. Detection of fiducial points.

Figs. 4A–4C are the pictorial representation of the features used for biometric authentication which is tabulated in Table 1.

2.2. Data transformation by principal component analysis

Principal Component Analysis (PCA) [20] is one of the oldest and most widely used data transformation techniques for multivariable analysis. The dimension of input dataset is reduced using this technique. PCA is mathematically defined as an orthogonal linear transformation that transforms the data to a new coordinate system such that the greatest variance by any projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on.

Let \( X \) be the \( N \) dimensional dataset of length \( L \) where each column represents a specific parameter extracted during multiple observation. The empirical mean of the dataset is calculated as

\[
\mu = \frac{1}{L} \sum_{i=1}^{L} x_i
\]

The variance of the dataset is calculated as

\[
\sigma^2 = \frac{1}{L} \sum_{i=1}^{L} (x_i - \mu)^2
\]

The covariance matrix of the dataset is calculated as

\[
C = \frac{1}{L} \sum_{i=1}^{L} (x_i - \mu)(x_i - \mu)^T
\]

The eigenvectors of the covariance matrix are calculated as

\[
Cv = \lambda v
\]

Where \( \lambda \) is the eigenvalue and \( v \) is the eigenvector.

The principal components are calculated as

\[
P = Cv
\]

The transformed dataset is calculated as

\[
Y = P^T X
\]

The line drift may appear at scale 8, so reconstruction coefficients \( d_6 \) and \( d_7 \) are selected to detect T and P waves. Then the T peak is identified as the maxima after the detected S point within a predefined interval. As the T peak is pointed out, T onset and T offset is found out as the minimum potential crossing points on either side of the T peak. Fig. 3 shows the detected QRS complex, P and T wave for a typical ECG waveform. As it is not possible to define the features which differ from different persons in a group, maximum possible numbers of features are extracted for better accuracy of the analysis.
which results in less accuracy for classification as indicated in the next sections. Hence the resulting data set is statistically modeled based on explicit mathematical function.

The standard form of the statistical model is denoted by,

$$ y = f(x, d) + k $$

where $y$ is the response or output, $x$ stands for the collection of all the predictor variables and $d$ is the collection of all parameters in short, $k$ is the random error.

Polynomial models are most frequently used for mathematical modeling. A general polynomial model is given by,

$$ y = a_0 + a_1 x + a_2 x^2 $$

where $n$ is a non-negative integer denoting the degree of the polynomial. Besides its simplicity and flexibility, polynomial model have the advantage that the mapping retains the input structure of the data. Observation of the PCA output enables to select the quadratic polynomial model as,

$$ y = a_0 + a_1 x + a_2 x^2 $$

Table 1

<table>
<thead>
<tr>
<th>Feature</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>P amplitude</td>
<td>T amplitude</td>
</tr>
<tr>
<td>Q amplitude</td>
<td>P duration</td>
</tr>
<tr>
<td>R amplitude</td>
<td>QRS duration</td>
</tr>
<tr>
<td>S amplitude</td>
<td>T duration</td>
</tr>
<tr>
<td>PQ interval</td>
<td>PR interval</td>
</tr>
<tr>
<td>QT interval</td>
<td>QT segment</td>
</tr>
</tbody>
</table>

The deviation from the mean is given by

$$ D = X - Eu $$

where $u(n) = 1$ for $n = 1,...,N$. Then the covariance matrix is calculated as

$$ C = \frac{1}{N} \sum D \cdot D^T $$

where $D'$ stands for the transpose matrix of $D$. Next the Eigen vector matrix $G$ is calculated which diagonalizes the covariance matrix. Hence,

$$ C^{-1}CG = V $$

where $V$ is the diagonal matrix of Eigen values of $C$. Next, the diagonal matrix $V$ is arranged in descending order and a specific subset of it is selected as basis vector. A plot of the basis vector for a typical record is shown in Fig. 5.
square estimation. Mathematically the least square criteria is given by,

$$e = \sum_{i=1}^{n}(y_i - f(x_i))$$  \hspace{1cm} (8)

In this technique the unknown values of the parameters are so calculated that the sum of the squared deviations between the input and the functional portion of the model is minimized. The output after best fit is shown in Fig. 6. It is clear from this figure that now it will be easier for any classifier to discriminate the patterns.

3. Comparison for authentication

As per the previous steps, the ECG beat pattern for each person is transformed into a set of six best fit values providing the biometric signature for each person. For a classifying system for authentication, it is required to accept a predetermined set of signatures and reject the others. Here the classification is done using a simple nearest neighbor method. It marks a new entry as the class corresponding to a stored signature that gives the minimum distance for each best fit value. Any test signature matrix element value is considered similar to a stored data if the test value falls within ±2% of the stored one.

4. Result and analysis

The algorithm is tested against 20 databases taken from PTB diagnostic data from Physionet data bank [21]. All beats are normal and having 1 kHz sampling frequency. 16 features are extracted from each wave as stated earlier.
To make the result more convenient, all the features are detected nine times from nine different waves of same recorded data. In some arbitrary intervals thus generating a 16 x 9 feature matrix. Then the use of PCA generates the signature matrix with dimension 1 x 6. The resulting output is shown in Fig. 6. It shows the overlapping nature of the matrix mainly in the last three elements which makes classification less accurate.

Quadratic polynomial based best fit modeling modifies the signature matrix making the higher order attributes more significant as shown in Fig. 7. From Figs. 7 and 8 it is seen that the discrimination of the signature matrix for same element especially in the higher order is better if the data is modeled with the best fit algorithm as discussed earlier. As the spread of the signature is more, it is easier to classify using nearest neighbor method. The comparison of each element of the test signature is made with the stored patterns and the signature with minimum distance with most of the elements is identified as equivalent to the test entry. Without the best fit modeling, the accuracy was 80% whereas it becomes 95% with best fit modeling.

5. Discussion

In this work the applicability of ECG for biometric authentication is studied. ECG has a good potential to be a biometric parameter as the signal source is beyond the scope of falsification.

Moreover, it can be used as a liveliness detector along with the biometric application. There are basically two types of methods used for ECG based biometric analysis - on-line feature detection based and depending on overall texture of the signal is the other. Most of the existing works uses feature extraction followed by a classification algorithm based on ANN or other. In this technique, normally for better accuracy of biometric signature, a number of features are detected and each feature is measured several times from different signals of the same person to make it robust and reliable. Hence the resulting data for each person is a huge one and needs to be dimensionally reduced retaining the essence of parameters. Principal Component Analysis is a well adopted tool for the same. Here the classification is made by the measurement of nearest neighbor from the stored set of data of signature matrix by comparison: with the new entry. It is seen that the accuracy level is 95% for person identification. It is noticed that the higher half of the signature matrix for most of the persons are quite similar leading to misclassification in some cases. Hence a novel quadratic curve fitting algorithm is proposed based on square fit of the modeled data. This best fit data shows greater discrimination at the lower half of the signature matrix for each person and the accuracy level goes up to 95% for person identification. This method is also useful for tracking the identity of the patients remotely without any additional data processing. Thus automatic monitoring or other medical procedures may be done without any human intervention. Other physiological or behavioral biometric parameters may be fused with the ECG based technique to make the authentication more reliable.

References

Detection of cardiac arrhythmic beats by logical classifier using binary coding

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Abstract: Cardiac arrhythmia is a rhythmic disorder in heart generated from problems in impulse formation or conduction. Automatic detection of arrhythmia at the time of its occurrence is very essential for continuous cardiac monitoring. As different kinds of arrhythmias produce different morphology of beats, it is difficult to suggest one typical algorithm to classify all kind of arrhythmic beats. In this work, a binary logical classifier is proposed to identify beats such as premature ventricular contraction, bundle branch block, paced and normal. In most of the arrhythmic beats the wave texture is modified along with a change in temporal information. The proposed logical classification requires binary coding of beats based on temporal and morphological features to form a binary array representing the status or signature of the beat. Next the classification is made by the status of the bits depending upon its position in the binary array. This approach of logical classification reduces the complexity of detection because of its binary nature resulting in fast and ready reference of sensitivity and positive predictivity for all kind of test beats. Moreover, this technique is easily hardware implementable because of its binary nature.

1 Introduction

Sino-atrial (SA) node is the natural pacemaker that generates the electrical impulse. This electrical impulse is propagated throughout the heart muscle to produce the rhythmic beating of heart. The natural rhythm of heart may be altered because of abnormalities in impulse formation or conduction. This disorder in heart rhythm is called cardiac arrhythmias. Cardiac arrhythmias represent a problem with the change of rate of rhythm of heart. It can make heart to beat too fast, too slow or with an irregular rhythm. At arrhythmic condition. pumping of blood may not be sufficient and hence lack of blood flow can damage the brain, heart or other organs. Thus arrhythmia is a serious threat to the patient especially for those recovering from acute myocardial infarction. Computerised automatic analysis of electrocardiogram is a very important tool for remote monitoring of cardiac patients in ICCU and for long-term holter electrocardiogram (ECG) analysis. It also helps to identify the time of occurrence of abnormal beats during continuous monitoring. Arrhythmia changes the morphology of the beats. So classification of arrhythmia may be done in two ways – by identifying arrhythmic events like bradycardia or tachycardia and by detecting the arrhythmic beats like premature ventricular contraction (PVC) beats, bundle branch block (BBB) beat and so on. Here computer-based automatic technique is proposed for arrhythmic beat classification. In this work PVC, BBB and paced beat classification method is proposed with respect to the normal. A brief description of these beats is given below.

PVC beats generate when ventricles fire prematurely or prior to atria and are no way related to the performance of the SA node. It is reported that the occurrence of PVCs may lead to sudden cardiac death especially in the presence of myocardial infarction \(^1\). Occurrence of PVC with higher frequency indicates greater intensity of cardiac abnormality. So immediate detection and treatment of PVC is very essential. It can make heart to beat irregularly or a different rate. An erratic beat morphology with a significant change in heart rate (HR) indicates the presence of PVC beat. The cardiac impulse propagates from the AV node to entire ventricular region through the Bundle of His. It is divided into right and left bundle branches. The right and left ventricles contract almost simultaneously when the right and left bundle branches function normally. When the bundle branch is damaged because of any heart disease or cardiac surgery, it cannot carry the impulse properly resulting in a slow rate of propagation and/or a different pathway for the impulse. Thus BBB alters the normal and directional propagation of electrical impulse in the two ventricles. Right BBB (RBBB) slows or ceases the conduction in right ventricle and LBBB does the same for left ventricle. Although RBBB can be treated as an indication of underlying cardiac abnormalities like coronary artery disease, arterial valve disease, cardiomyopathy and so on. So it is required to detect the BBB as it originates. Longer QRS duration and...
prolonged ventricular activation time or QR interval confirms the presence of BBB.

Paced beats are artificial beats generated by pacemaker. A pacemaker is an external pace setter for hearts with extremely slow HR. Slow HR is mostly because of the blockage in arteries in cardiac conduction system and it may lead to weakness, fainting, breathlessness and death. Typical morphology of normal, PVC, paced and BBB beats are shown in Fig. 1.

Different techniques have been made by different researchers for detection of different cardiac arrhythmias [2-6]. Among all, detection of PVC is the most addressed problem in this area [7-10]. Most of the previous works deal with either extraction of features from the ECG signal or modelling of data to generate enhanced arrhythmic symptoms followed by an artificial neural network (ANN) or fuzzy-based classification algorithm. The greater classification accuracy is often accompanied by higher computational cost and larger processing time.

In this work, a binary coded classifier is designed for classification of some cardiac arrhythmic beats as mentioned earlier. Proposed algorithm first generates a beat status word based on QRST temporal features and signal complexity of a complete wave and classifies the beat by a bit status check procedure. The algorithm is tested using the files taken from MIT_BIH Arrhythmia database [11], which is a referred standard for arrhythmia classification. It is a two-lead database having modified lead II in 45 databases and V1 in 40 databases along with lead II, V2, V4, V5 in some other databases. The database is bandpass filtered in the range 0.1-100 Hz and are sampled with 360 Hz sampling frequency. In this work modified lead II files are mostly used. We have selected 25 files for our classification containing mostly normal (N), PVC (V), RBBB (R), LBBB (L) and paced (P) beats. Apart from that the databases have atrial premature beats, ventricular flutter and escape beats and so on, which are not considered in this work and marked as ‘other’. The entire scheme is represented by block diagram in Fig. 2.

2 Material and method

2.1 Signal pre-processing and feature extraction

Although the test signals are bandpass filtered, still some high- and low-frequency noises may present in the signals (as noted in some files) and thus further filtering is required. A number of techniques are proposed for denoising the ECG signals [12, 13]. At this point it must be noted that the arrhythmias considered in this work mostly changes the QRS pattern of the wave form. Hence, it is of primary interest to extract the QRS complex accurately than to denoise the entire signal for this work. QRS region is the high-frequency component of the ECG wave and least corrupted by noises. Moreover, being a cardiac abnormality classification process, beat detection should be faster and hence the algorithm is to be less complicated. QRS enhancement and extraction is sufficient for the present work.

In this research, a wavelet-based decomposition of the signal is proposed. Wavelet decomposition is basically a convolution operation between the test signal x(t) and the wavelet function $\psi(t)$, while the small wave $\psi(t)$ is translated along the temporal axis of the test signal. It decomposes the signal into a set of detail and approximate coefficients containing upper and lower half of the frequency band, respectively. Further decomposition of the approximate coefficient signal generates higher-order detail and approximate coefficients in the similar way. The frequency division in wavelet transform is shown in Table 1. According to this, each level of coefficient contains the frequency half of its earlier level. Thus this multiresolution analysis separates the test signal into its component frequencies retaining the time of occurrence of that frequency. Normally QRS region has the frequency between 10 and 25 Hz. Thus the level of decomposition using wavelet transform and reconstruction coefficients are to be so selected that this frequency range of QRS complex can be accurately captured. Hence it becomes easier to identify the QRS complex by a suitable window.
Here Daubechies 6 (Db6) wavelet is used for signal decomposition because of its structural similarity with the QRS region of the ECG wave. Decomposition is done up to level eight. The method used here for QRS detection is similar to [14]. It is noted that most energy of the QRS region is concentrated at decomposition coefficient levels $d_3$, $d_4$ and $d_5$. The MIT_BIH Arrhythmia database has the sampling frequency 360 Hz. So these levels are also supported by Table 1 for identifying QRS complex. These three coefficients are combined and reconstructed signal is enhanced using (1).

$$QRS_{\text{enhanced}} = \frac{d_4 (d_3 + d_5)}{2}$$  \hspace{1cm} (1)

This equation is obtained empirically and it is experimentally seen that the equation can efficiently capture the R peak. Actually all the coefficients have higher values in the position of QRS regions than the other positions in time scale. So the element by element addition of $d_3$ and $d_5$ enhances the QRS complex. It is further enhanced by multiplying $(d_3 + d_5)$ element by element with $d_4$. This operation is possible as all the coefficient matrices have same number of elements. A typical ECG and its enhanced QRS complexes are shown in Fig. 3.

As $R$ peak detection is based on maxima in amplitude of enhanced signal and $Q$ and $S$ points are identified using the slope of the reconstructed wave for the $QS$ region, the method is independent to database or pattern of the signal, thus signifying the adaptiveness of the method. In this work, we consider only the triangular region made by $Q$, $S$ and $R$ peak points.

### 2.2 Extracted features

#### 2.2.1 Form factor (FF) [15, 16]:

FF is a measure of complexity of a signal. It increases with the increase of variance present in the signal. It is an indication of the variance of signal activity. Activity of a signal $x(n)$ is calculated as the variance of the stipulated segment of the signal. From the activity of the signal, mobility $M_x$ is calculated as the ratio of square root of the activity of the first derivative of the signal and square root of the original signal. Thus

$$M_x = \frac{\sigma_x^{1/2}}{\sigma_x}$$  \hspace{1cm} (4)

where $x$ stands for the first derivative of $x$.

Complexity or the FF is defined as ratio of the mobility of the first derivative of the signal to the mobility of the signal

$$Q_{\text{signal}} = d_2 + d_3 + d_4 + d_5$$  \hspace{1cm} (2)

Then five point differentiation is made using the formula

$$f'(x) = \frac{f(x+2h) + 8f(x+h) - 8f(x-h) + f(x-2h)}{12h}$$  \hspace{1cm} (3)

where $h$ is the sampling period.

$f'(x)$ gives the slope of the signal $Q_{\text{signal}}$. $Q$ and $S$ points are detected as the point of inflection of the slope on either side of the $R$ peak. Differentiation can be done as the high-frequency regions are eliminated in $d_1$ level coefficients. Any high-frequency noise still present is not expected to appear in $QRS$ region, which is almost clean in raw ECG signal also. A typical QRS complex region is shown in Fig. 4.

As $R$ peak detection is based on maxima in amplitude of enhanced signal and $Q$ and $S$ points are identified using slope of the reconstructed wave for the $QS$ region, the method is independent to database or pattern of the signal, thus signifying the adaptiveness of the method. In this work, we consider only the triangular region made by $Q$, $S$ and $R$ peak points.

![Fig. 3](https://www.ietdl.org)  
**Fig. 3** Typical ECG, filtered signals and its enhanced QRS complexes

- a. Typical ECG signal
- b. Filtered signal
- c. Enhanced QRS complex

![Fig. 4](https://www.ietdl.org)  
**Fig. 4** Typical QRS complex for normal beat

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\[ FF = \frac{M_R}{M_S} = \frac{\sigma_R}{\sigma_S} \]  

where \( \sigma^2 \) stands for the second derivative of the signal.

As normally the feature set is non-stationary and has a wide variation for same type beats and obviously for different type beats also, it is very difficult to deal with the features directly. For example, PVC beats have a completely different pattern and different PVC beats show different morphology too. But fortunately there are some typical values for the features for different categories though they are not fixed. Here a code is generated depending on the probable feature values. The code is formed by five binary bits and stands for the signature of a beat. Each bit or a combination of two bits represents a feature as extracted earlier. Coding makes the classification easier.

The method of assigning a code to a feature is explained below.

1. It is experimentally seen that as signal complexity is high for PVC beats, the value of FF for PVC beats is completely different and larger from the other test beats. So it is a measure of the presence of PVC beat. For confirmation the HR is calculated which is higher than the normal or any other beats. So if FF value is greater by a predetermined value \( M_1 \) than that of its earlier beat and if HR change is more than a predetermined value \( H_2 \) for the same pair of beats, than \( D_4 \) is set to 1, or it is 0.

2. \( D_3 \) beat stands for the \( R' \) feature. The presence of \( R' \) peak corresponds to \( D_3 = 1 \), otherwise it is 0.

3. \( D_2 \) and \( D_1 \) are collective bits. It is related to \( QRS \) duration as follows:

   a. If \( QRS_{\text{duration}} \leq H_1 \) then \( D_1 = 0, D_2 = 0 \)
   
   b. If \( H_1 < QRS_{\text{duration}} \leq H_2 \) then \( D_1 = 1, D_2 = 0 \)
   
   \( H_2 < QRS_{\text{duration}} \leq H_2 \)

   c. If \( QRS_{\text{duration}} > H_2 \) then \( D_1 = 0, D_2 = 1 \)

   It is noted that the \( QRS \) duration for BBB beats and that for paced beats are more than the normal \( QRS \) duration. Hence this coding will be helpful for classification of the test beats other than PVC beats. \( H_1 \) and \( H_2 \) are experimentally determined constants based on the \( QRS \) complex duration.

4. If \( QR/RS \) ratio is greater than a certain value \( M \) or if \( S \) wave height is more than \( L \) then \( D_0 = 1 \), otherwise it is 0. This bit is related to BBB beats.

2.4 Classification

The technique for classification of different arrhythmic beats is illustrated in Fig. 6. Intuitively the arrhythmias are classified based on the values of the features, in turn, depending upon the status of the code bits. The PVC beat is identified first. As mentioned earlier, PVC beat is classified based on FF value and HR. Both of these parameter abruptly changes at the onset of PVC beats and thus it is detected by a simple if-else-based rule. For two consecutive PVC beats, this change is not possible to occur. In that case, individual FF value for each beat should exceed a certain predetermined value. Experimentally it is seen that this value should be 4.2. If any of these conditions occur, \( D_4 \) is set at 1, which indicates the test beat to be a PVC type irrespective of other bits.

If \( D_4 \) bit status is 0 then bit \( D_3 \) is checked. A complete BBB generates a sharp notch like \( R' \) peak in the \( QRS \) section. As bit is assigned with this feature, a 1 in 03 bit is related to the presence of complete BBB. But the presence...
of R' peak is not mandatory in BBB. So further inspection is required for detection incomplete BBB or BBB without R' peak as discussed later in this section.

Next the status of bits D2 and D1 are checked collectively. It deals with the QRS duration feature. Normal beats have the minimum value of QRS duration among all the test beats considered here. It is followed by BBB with paced beat having the largest duration of QRS complex. Depending upon this feature normal and paced beats are separated with lower and higher range of QRS duration for normal and paced beats, respectively, and middle one is for BBB as shown in the Fig. 7. The values of H1 and H2 are also indicated in the figure.

Some BBB beats may not have R' peak but there QRS duration is longer than the normal along with a larger RS section and S height. If any of these features is present, D0 bit status is high indicating a BBB beat without R' peak. For longer S wave, obviously the RS section will be longer than QR section and hence QRS/RS ratio should be less than unity for BBB beats.

The typical values of the parameters used here are listed in Table 2.

![Binary logic classifier flowchart](image)

**Fig. 6** Binary logic classifier flowchart

<table>
<thead>
<tr>
<th>QRS DURATION</th>
<th>NORMAL</th>
<th>BBB</th>
<th>PACED</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.077 sec</td>
<td>0.114 sec</td>
<td>0.114 sec</td>
</tr>
</tbody>
</table>

![Segmentation of QRS duration](image)

**Fig. 7** Segmentation of QRS duration

### Table 2 Parameters used for classification

<table>
<thead>
<tr>
<th>H1</th>
<th>H2</th>
<th>M</th>
<th>L</th>
<th>N1</th>
<th>N2</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.077</td>
<td>0.114</td>
<td>1.1</td>
<td>0.5</td>
<td>1.1</td>
<td>50</td>
</tr>
</tbody>
</table>

### 3 Result and analysis

The proposed method is tested against 39 files of MIT-BIH Arrhythmia database with signals of 5 min duration. Most of the beats of the databases in Table 3 are verified with the proposed algorithm. For each beat the main distinguishing features are extracted for better classification. R-peak detection is the entry point for almost all ECG analysis techniques. R-peak detection and QRS-based feature extraction are the most common problems addressed in ECG analysis. In this work, these time plane features are determined using wavelet-based multisolution analysis and classification is made based on this. To eliminate the complexity of classification some binary bits are set or reset depending upon the range of the value of features. Thus five bits are used to form a beat status word. Each bit has a higher weight than the bits of its right. So a bit by bit scan accurately classifies the test beats.

The performance of the algorithm is checked with some performance parameters such as accuracy, sensitivity and positive predictivity defined as follows

\[
\text{Acc} = \frac{N_C}{N_T} \times 100\% \tag{7}
\]

where \(N_T\) is the number of beats correctly classified and \(N_T\) is the total number of beats.

\[
\text{Se} = \frac{TP}{TP + FN} \% \tag{8}
\]

and

\[
\text{Pp} = \frac{TP}{TP + FP} \% \tag{9}
\]

where TP, FP and FN stand for true positive, false positive and false negative, respectively. True positives are the beats, which are correctly classified as a specific class and false positives are the beats, which are wrongly classified to the same class, a false negative is the beat, which undergone a misclassification and assigned to a different class instead. The values of these parameters are tabulated in Table 4 for the QRS detector and in Table 5 for classifier.

The efficiency of the proposed method depends on the accuracy of feature extraction as the features form the status

### Table 3 Databases used for testing the algorithm


### Table 4 Performance parameter for QRS detector

<table>
<thead>
<tr>
<th>No. of beats</th>
<th>TP</th>
<th>FN</th>
<th>FP</th>
<th>Se, %</th>
<th>Pp, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>11 672</td>
<td>11 660</td>
<td>22</td>
<td>26</td>
<td>99.81</td>
<td>99.77</td>
</tr>
</tbody>
</table>
word. Verification of five bit status word is made bit by bit starting from the left side. As each bit is set to 1 depending upon a specific feature condition, there is no scope of overlapping of decision. For example, when HR and FF value abruptly changes, D4 bit is set which specifically indicates the occurrence of PVC beat. Thus when the next bit is checked for a 1 in D4 bit, there is no possibility of having any PVC beat. In this way, the proposed algorithm reduces the probability of misclassification.

An artificial neural network-based approach can also be proposed using the feature values. In that case the input is to be made with the extracted feature set and a training and testing-based algorithm can be proposed with four standard output neuron for four kinds of arrhythmic beats. Two output neuron can also be proposed. However, the application of neural network may make the classification a time consuming one because of its complicated mathematical approach. For clinical purposes the response time of the method should be such that the arrhythmic beats can be classified as early as possible.

Moreover, Table 6 shows the comparison of proposed method with some standard methods for PVC detection based on the proposed performance parameters. In the PVC beats the change of the wave shape with respect to normal beats is not specified as in PVC the QRS region changes in amplitude and duration, T wave may be inverted or attached to J wave or even may be absent subjected to different persons. So the wave shape change occurs in an unknown manner. Hence an FF-based approach is proved to be promising since it deals with signal complexity.

It shows that the proposed method is comparable with the other reported works.

Instead of FF-based rules formation, ANN-based classification method can also be used. In this case as the inputs are in binary mode, the neural network should be a fixed weighted ANN. Hence it may provide a very fast decision regarding the status of the test beat.

4 Conclusion

A simpler technique for arrhythmic beat classification is proposed in this work. Arrhythmia may be fatal to a person having some critical cardiac conditions. Hence the detection of arrhythmic beats at the instant of its occurrence is very important. Almost all beat or disease classification works are feature extraction based. Extracted features are fed to a pre-developed classifier, which may be based on ANN, support vector machine (SVM) or others. In this work, an intermediate step for coding is proposed. Actually arrhythmic beats have different shape with respect to the normal and different kind of arrhythmias causes different morphology of beats. A specific feature or a set of features are combined together to generate a specific bit representing a particular morphology of beat. Thus a sequential bit identification results in arrhythmic beat classification. As the method does not require any complicated classifier, it can identify the presence of an arrhythmic beat at the time of its onset. This method is highly applicable in case of quick reference (central processing unit (CPU) time requirement is 0.787 s.) of arrhythmic beats in standalone cardiac monitoring system. A fixed weight ANN can also provide fast response with the proposed binary beat status word as input. Since the binary coding depends upon the values of the features, the performance of the proposed method depends upon the accuracy of the feature extraction. In this work the above-mentioned performance parameters are the all patient average values as it differs from person to person in MIT_BIH database files. Comparison of the present method with some reported works (Table 2) for PVC detection shows the effectiveness of the proposed algorithm. Comparison of this method for detection of other arrhythmic beats considered here is not made because of lack of reported works. Anyway, it shows appreciable result for other arrhythmic beats as per the performance parameters are concerned. Moreover, being driven by binary logic, the proposed algorithm has the potential to be implemented in hardware by simple digital logic.

5 References


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Table 5 Performance parameters for classifier

<table>
<thead>
<tr>
<th>Beat type</th>
<th>No. of beats</th>
<th>TP</th>
<th>FN</th>
<th>FP</th>
<th>Acc, %</th>
<th>Se, %</th>
<th>Sp, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>normal</td>
<td>9508</td>
<td>9589</td>
<td>7</td>
<td>9</td>
<td>99.93</td>
<td>99.92</td>
<td>99.90</td>
</tr>
<tr>
<td>PVC</td>
<td>992</td>
<td>966</td>
<td>26</td>
<td>12</td>
<td>97.38</td>
<td>97.37</td>
<td>98.77</td>
</tr>
<tr>
<td>BBB</td>
<td>2488</td>
<td>2967</td>
<td>121</td>
<td>59</td>
<td>95.14</td>
<td>95.13</td>
<td>97.56</td>
</tr>
<tr>
<td>paced</td>
<td>992</td>
<td>988</td>
<td>7</td>
<td>18</td>
<td>99.29</td>
<td>99.29</td>
<td>98.21</td>
</tr>
</tbody>
</table>

Table 6 Comparison of proposed PVC beat detection method with some standard techniques

<table>
<thead>
<tr>
<th>Detection technique</th>
<th>Method</th>
<th>Performance parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN</td>
<td>Ince et al. [17]</td>
<td>-</td>
</tr>
<tr>
<td>ANN</td>
<td>Shyu et al. [10]</td>
<td>97.04</td>
</tr>
<tr>
<td>Gaussian process</td>
<td>Me and Bazi [18]</td>
<td>97.10</td>
</tr>
<tr>
<td>Bayesian filtering</td>
<td>Sayadli et al. [7]</td>
<td>98.10</td>
</tr>
<tr>
<td>binary coding</td>
<td>proposed</td>
<td>97.38</td>
</tr>
</tbody>
</table>


