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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 causing 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. Here, 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.

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 biomedical data are compressed and stored in storage elements and processed and analyzed later by experts to detect abnormalities if any. Persons having critical and multiple abnormalities require simultaneous analysis of different physiological signals. Computer based automatic procedure helps a lot in this application as an assistive diagnosis and monitoring tool.

Electrocardiogram (ECG) is one of the major physiological signals generated from heart's rhythmic polarization and depolarization. ECG is characterized by a number of waves as P, QRS, T related to the heart activity. It is recorded, studied, analyzed and interpreted for diagnosis of cardiac abnormalities. Automation in the entire process may lead to better clinical evaluation and resulting medication. Automatic analysis consists of the steps shown in Fig. 1. In this paper an adaptive QRS detection method in presence of high and low frequency noise is discussed.

The first problem faced by an automatic ECG signal processing technique is the unwanted frequency components present in it as noise generated due to non-cardiac reasons. The low frequency noise is originated from respiration or body movement of the subject during recording. It shifts the ECG signal from zero potential baseline in a nonconventional way and thus makes it very difficult to estimate certain low frequency phenomena like ST segment morphology. Moreover, larger baseline drift may cause clipping of the peaks of ECG by saturation of ECG amplifier. A high frequency noise called power line interference appears due to interference of supply frequency with the recorded ECG signal. Cables carrying the ECG signal from patient to monitoring system are susceptible to electromagnetic interference of power frequency of 50 Hz (or 60 Hz) and thus act as the source of the noise. It also appears due to poor transmission channel conditions. Some other sources of high frequency noise in ECG are electromyographic noise during recording, noises from the signal conditioning circuit etc. So it is very difficult to eliminate it during recording or transmission.

The second step of ECG signal processing is QRS detection. The QRS complex is the most prominent waveform of the signal and hence detection of QRS complex becomes the entry point of almost all ECG analysis algorithms. The temporal and spatial information of QRS complex and its texture are used for heart rate measurement and diagnosis of several abnormalities like myocardial infarction, cardiac arrhythmias, conduction abnormalities, ventricular hypertrophy, etc.

Several methods are proposed for ECG enhancement by eliminating noise. Most of the methods are based on designing a digital filter [1,2], which passes the required high frequency parts of ECG suppressing the baseline wander and a low pass filter

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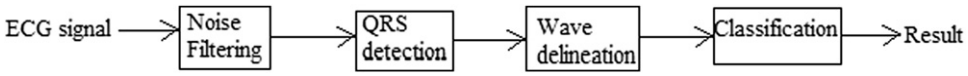

Fig. 1. Steps for automatic ECG analysis.

[2–4] for removing power frequency interference. The main problem of low pass or band pass filtering is that ECG frequency spectra is quite overlapping with that of the 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 shortcoming 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 reported. In many nonsyntactic 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 multiresolution 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 cardiological 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 pre-filtering 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_1 of upper and low envelope is calculated and the difference d_1 between the signal $x(t)$ and m_1 is computed as $d_1(t)$, i.e.
$$x(t)-m_1 = d_1(t) \quad (1)$$
5. If $d_1(t)$ satisfies the conditions of IMF, then d_1 is the first frequency and amplitude modulated oscillatory mode of $x(t)$.
6. If d_1 is not an IMF, then the shifting process described in steps (1), (2) and (3) are repeated on d_1. Thus d_{11} is calculated as
$$d_1-m_{11} = d_{11}(t) \quad (2)$$
in which m_{11} is the mean of upper and low envelope value of d_1.
7. Let after k cycles of operation, d_{1k} become an IMF, that is
$$d_{1(k-1)}-m_{1k} = d_{1k} \quad (3)$$
8. Then, it is designated as $c_1 = d_{1k}$, the first IMF component from the original data.
9. Subtracting c_1 from $x(t)$, r_1 is calculated as
$$r_1 = x(t)-c_1 \quad (4)$$
which is treated as the original data for next cycle.
10. 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
$$NSD = \sum_{k=1}^{T} \frac{|d_{k-1}(t)-d_k(t)|^2}{d_k^2(t)} \quad (5)$$

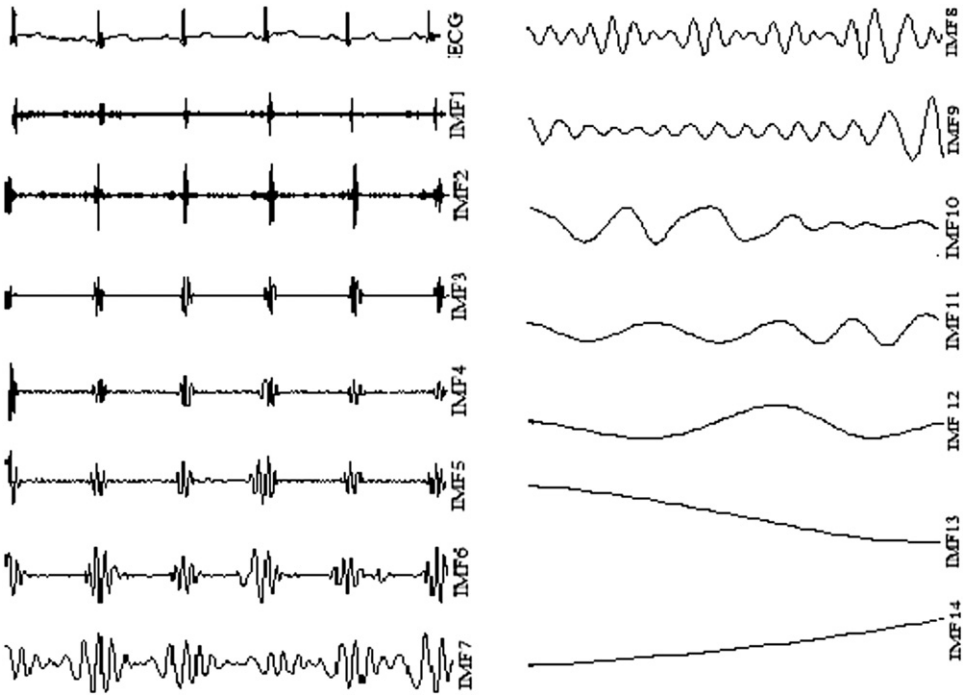

Fig. 2. ECG and resulting IMFs after Empirical Mode Decomposition.

By summing up, we finally obtain

$$x(t) = \sum_{n=1}^{N} c_n(t) + r_n(t) \tag{6}$$

Residue r_n is the mean trend of $x(t)$. The IMFs c_1, c_2, …, 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

3.1.1. Baseline wander correction

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 upto a certain IMF (Fig. 3B, 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 (Bradycardia) 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.

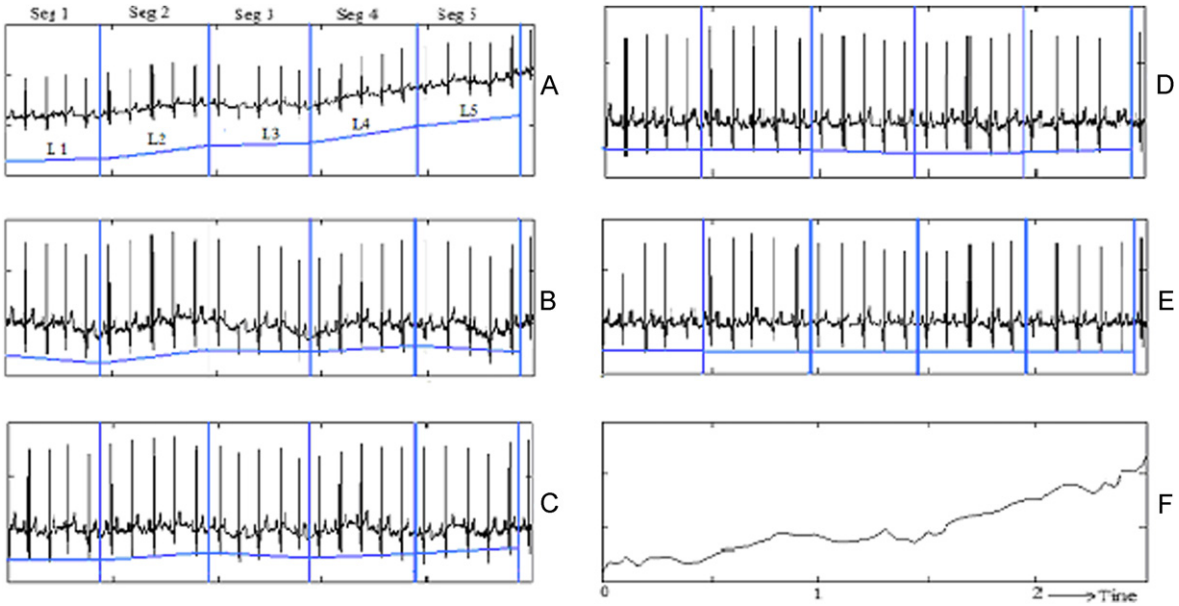

Fig. 3. A—Original ECG wave showing segments and slopes; B, C, D—Stepwise representation of baseline correction method; E—Reconstructed baseline corrected signal; F—Extracted baseline.

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 noise 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.

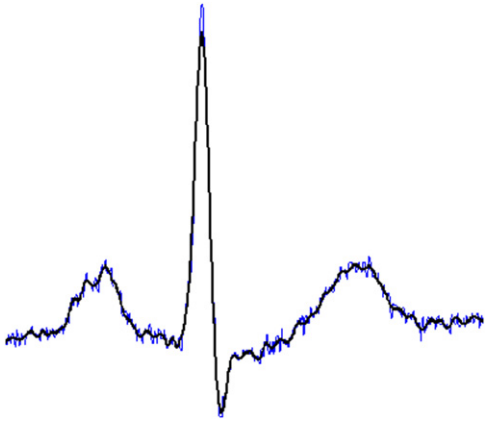

Fig. 4. Peak distortion due to direct IMF removal.

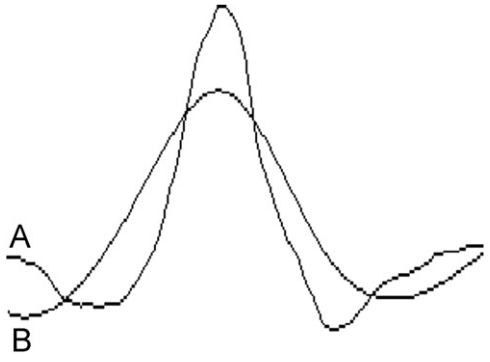

Fig. 5. A—Original QRS complex; B—Distorted QRS complex.

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

signal mean is calculated in each reconstruction as

$$A_K = \text{Mean}\left[\sum_{i=1}^{K} c(i)\right] \quad (7)$$

where k varies from 1 to N.

As high frequency noise is approximately of zero mean, it is expected that a zero or very low value of signal mean should correspond to noise. In almost all cases the 1st IMF represents noise and some useful high frequency component also. Hence a threshold signal mean level is determined upto which the cumulative mean should be considered as noise signal mean. The set of IMFs having a cumulative mean above that threshold value are considered to have useful information of ECG. Mean values correspond to IMF no. are shown in Fig. 6. This method fails to identify the noisy IMFs in some cases specially when the signal has a nearly zero mean. It occurs if the ECG has sharp large R peak and large S wave in opposite direction. Inverse T wave also contributes in this difficulty. Thus an IMF power based test better performs to identify noisy IMFs as described below.

(2) A confirmative test is made by calculating signal power of each IMF. It is a common observation that the presence of power frequency noise in ECG results in small amplitude and high frequency oscillation around the actual ECG trace. Because of small amplitude, the signal power corresponding to noise must be small. Here the power of each IMF is calculated as

$$P_K = 10 \times \log_{10} \sum |c_k(i)|^2 \quad (8)$$

where k is IMF number.

The corresponding plot of IMF energy vs. IMF no. is shown in Fig. 7.

It is seen that there is a moderate band of power in all IMFs except some lower order (i.e. high frequency) IMFs in which the power is drastically small. It is seen that the set of IMFs with sufficiently lower power and that of extremely smaller value of signal mean are same. Hence there is a possibility to have mostly noise in those IMFs and they can be disregarded during reconstruction. In case if number of noisy IMFs calculated from signal mean and signal energy are different, the lower of the two is selected for removal to minimize the distortion of the reconstructed wave. So the denoised signal X_d is obtained as

$$X_d = \sum_{j=P+1}^{N} c(i) \quad (9)$$

where P is the noise order of IMF.

Because of this lower order IMFs removal, some important high frequency contents may be lost. They are retrieved back by a peak correction method as explained in the next section.

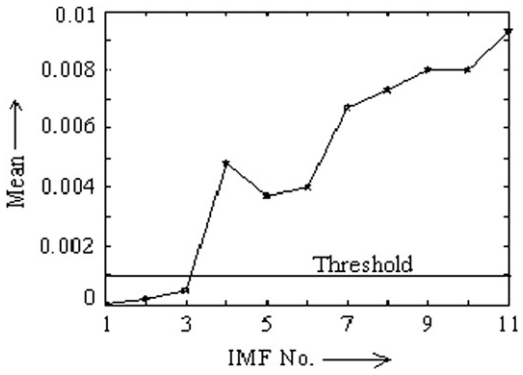

Fig. 6. Plot of signal Mean vs. IMF no.

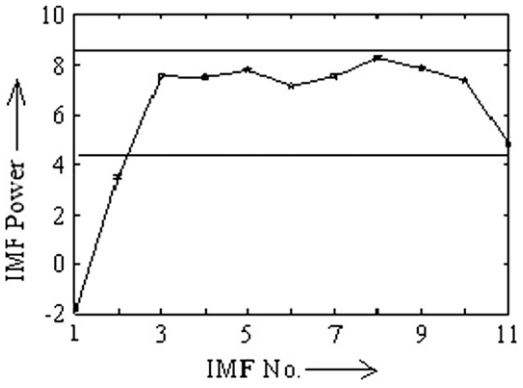

Fig. 7. Plot of IMF power vs. IMF no.

3.1.3. 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 signal peak 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,

$$M_x = \sum_{i=1}^{L} c(i) - K \times \left[Max\left\{\sum_{i=1}^{L} c(i)\right\}\right] \quad (10)$$

where M_x is magnitude information; L is the order of IMF upto which it contains noise level, $c(i)$ is ith 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_x is added to the earlier reconstructed signal to get ECG signal free from power frequency noise as

$$x_d = X_d + M_x \quad (11)$$

The peak information M_x 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

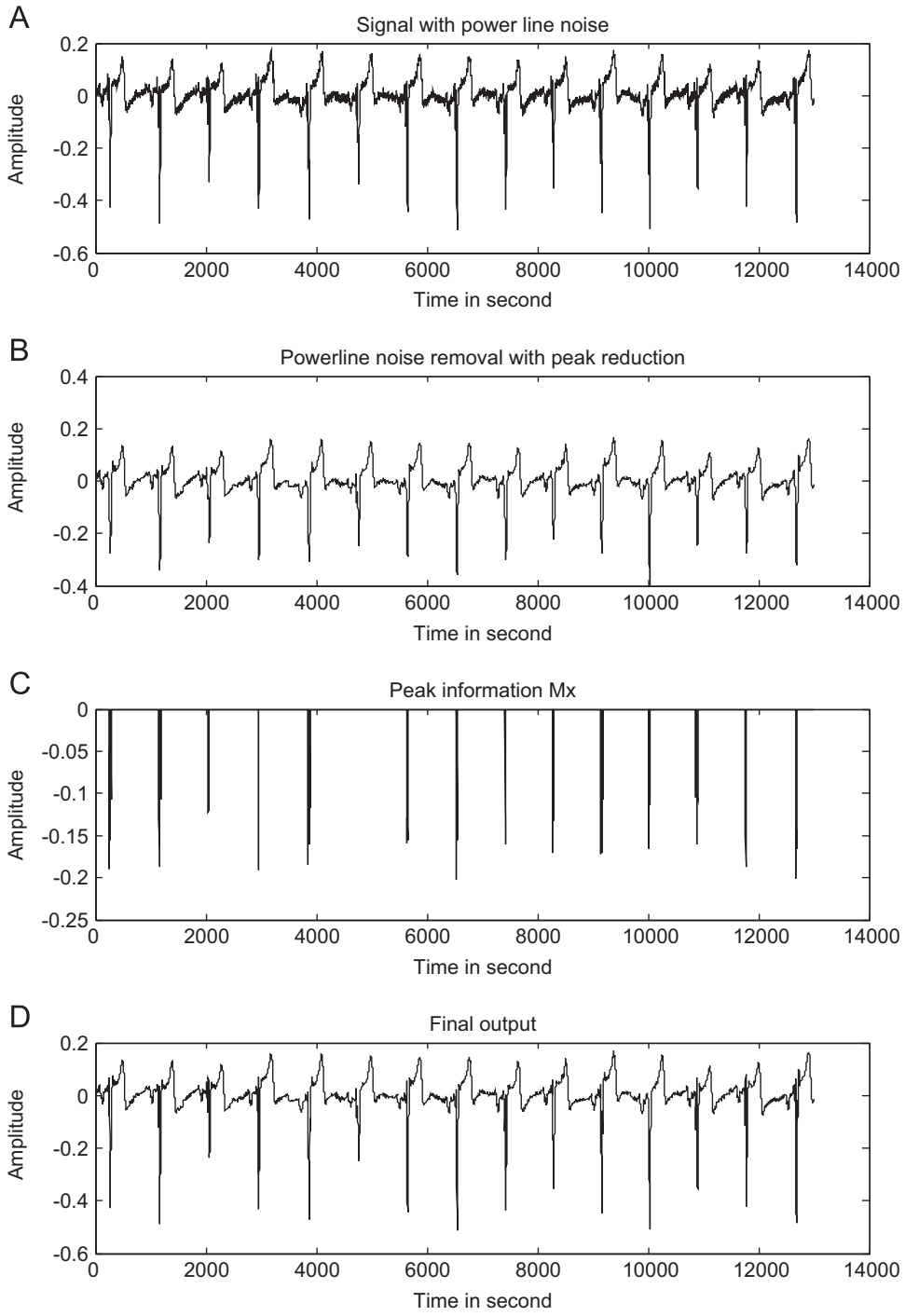

Fig. 8. A—Original Signal with power line noise; B—Peak reduction due to direct elimination of noisy IMFs; C—Peak information as stored in M_x; D—Final denoised output.

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

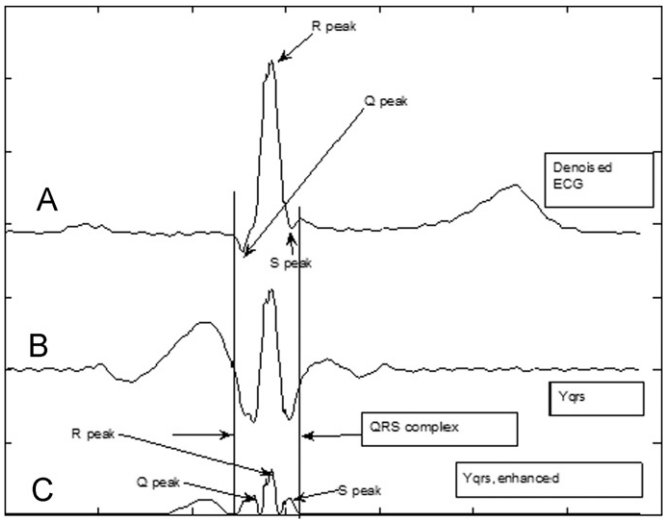

Fig. 9. A—Denoised ECG; B—Plot of Y_{QRS}; C—Plot of $Y_{QRS,enhanced}$.

earlier. So the QRS complex is expected to present in the signal given by

$$Y_{QRS} = \sum_{L+1}^{L+2} C(i) + M_x \tag{12}$$

where M_x 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 given by the minimum amplitude points of $Y_{QRS,enhanced}$ before the Q peak and after the S peak point respectively as shown in Fig. 9C. In some cases Q or S or both may be very small in magnitude or absent. In that case the $Y_{QRS,enhanced}$ morphology will vary accordingly and QRS complexes are denoted by the onset and offset of central large peak of $Y_{QRS,enhanced}$.

4. Result and analysis

The proposed method is tested against a set of arbitrarily 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 ECG enhancement algorithm is performed and then QRS detection is done on denoised ECG in a single run.

4.1. ECG 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 wanders 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

$$P = 10 \times \log_{10} \sum_{n=1}^{L_n} |x(n)|^2 \tag{13}$$

where L_n is the length of database.

Then Percentage Noise Retention (PNR) is calculated as

$$PNR = \frac{P_{ds} - P_{cs}}{P_{cs}} \times 100\% \tag{14}$$

where P_{ds} is power of denoised signal and P_{cs} 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

$$\rho_{1,2} = \frac{\sum_{n=0}^{L} x_{cs}(n) x_{s1,2}(n)}{[\sum_{n=0}^{L} x_{cs}^2(n) \sum_{n=0}^{L} x_{s1,2}^2(n)]^{1/2}} \tag{15}$$

where ρ_1 is the cross-correlation coefficient between the clean signal $x_{cs}(n)$ and noisy signal $x_{s1}(n)$ and ρ_2 is the same between clean signal $x_{cs}(n)$ and denoised signal $x_{s2}(n)$. The proposed method for ECG enhancement is tested with baseline wanders 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

$$x_{bw}(t) = x_{cs}(t) + K_1 \sum_m C_m (BW)_m \tag{16}$$

where $x_{bw}(t)$ 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
Signal power and cross correlation coefficient comparison table for clean signal with BW noise and filtered signal.

Database	Input clean signal power (dB)	Added BW noise power (dB)	Output filtered signal power (dB)	PNR (%)	ρ_1	ρ_2
P247s479[a]	31.7037	26.3965	31.6937	−0.0315	0.8769	0.9892
P174s300[a]	30.9433	43.5672	31.4679	1.6954	0.3739	0.7097
P219s441[a]	34.4752	11.7453	34.4716	-0.0104	0.9295	0.9901
P150s287[a]	33.3768	31.2573	33.3821	0.0159	0.7483	0.984
P107s199[a]	32.5739	18.5630	32.5866	0.0390	0.9077	0.9824
105[b]	33.0761	21.4149	33.086	0.0299	0.8931	0.9874

[a] Stands for Physionet PTB diagnostic database.
[b] 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

$$x_{pl}(t) = x_{cs}(t) + K_2 \sum_p C_p (PL)_p \quad (17)$$

where $x_{pl}(t)$ is signal with power line noise and (PL) represents each power line noise, C_p is the pth 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

$$x_{bw,pl}(t) = x_{cs}(t) + K_1 \sum_m C_m (BW)_m + K_2 \sum_p C_p (PL)_p \quad (18)$$

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

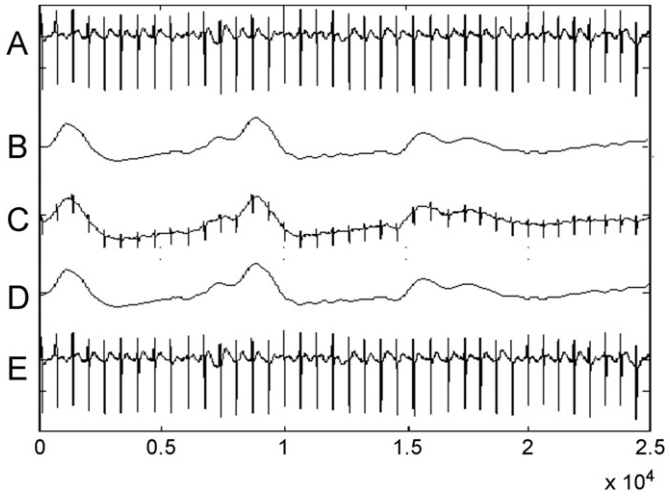

Fig. 10. A—Clean ECG; B—Added baseline drift; C—Resulting noisy signal; D—Extracted baseline; E—Denoised signal.

Table 2
Signal power and cross correlation coefficient comparison table for clean signal with PL noise and filtered signal.

Database	Input clean signal power (dB)	Added PL noise power (dB)	Output filtered signal power (dB)	*PNR* (%)	ρ_1	ρ_2
P247s479	31.7037	12.6062	31.733	.0924	0.9219	0.9577
P174s300	30.9433	14.13	30.9266	−0.054	0.9145	0.98
P219s441	34.4752	18.4717	34.3965	−0.2283	0.9172	0.9489
P150s287	33.3768	19.6642	33.3636	−0.0395	0.9074	0.9824
P107s199	32.5739	8.248	32.5746	0.0021	0.9455	0.9925
105	33.0761	21.7785	33.0798	0.0112	0.9011	0.9837

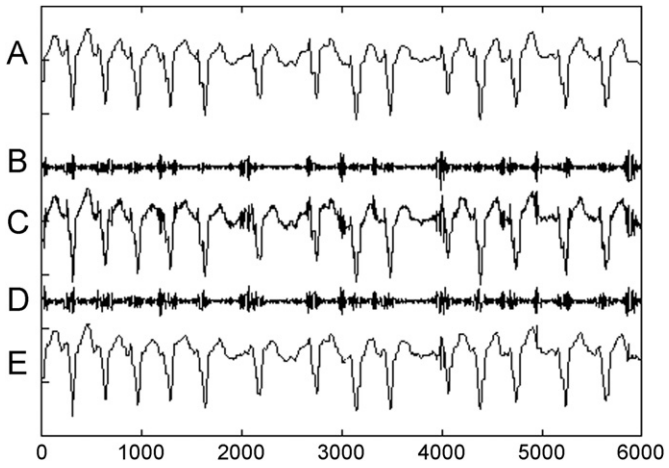

Fig. 11. A—Clean ECG; B—Added power line interference; C—Resulting noisy signal; D—Extracted power line; E—Denoised signal.

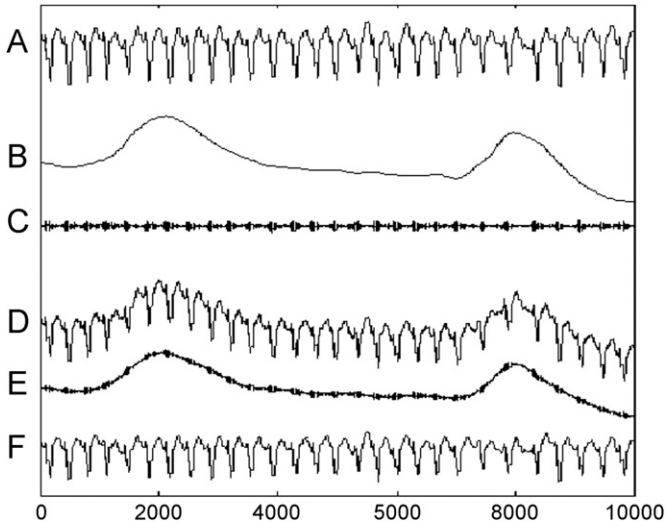

Fig. 12. A—Clean ECG; B—Added baseline drift; C—Added power line noise; D—Resulting noisy signal; E—Extracted total noise; F—Denoised signal.

Table 3
Signal power and cross correlation coefficient comparison table for clean signal with PL and BW noise and filtered signal.

Database	Input clean signal power (dB)	Added noise power (dB)	Output filtered signal power (dB)	*PNR* (%)	ρ_1	ρ_2
P247s479	31.7037	19.3539	31.7275	0.0751	0.9723	0.9878
P174s300	30.9433	29.1417	30.9901	0.1512	0.7946	0.9708
P219s441	34.4752	43.5338	34.514	0.1125	0.5223	0.9877
P150s287	33.3768	25.6588	33.3897	0.0386	0.8962	0.9902
P107s199	32.5739	30.3211	32.6744	0.3085	0.8078	0.9846
105	33.0761	41.1613	33.0635	−0.0381	0.8057	0.9924

coefficients ρ_1 and ρ_2 indicates the structural difference of noisy and filtered signals due to elimination of noise. Value of ρ_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 30 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 3. *PNR* and cross correlation coefficient ρ_2 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

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

$$\text{Specificity } (Sp\%) = \frac{TN}{TN+FP} \times 100\%$$

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 $\rho_2$values for Butterworth filtering of same signals.

Database	*PNR* (%)	ρ_2
P247s479	0.349	0.986
P174s300	0.8255	0.82
P219s441	1.9739	0.8942
P150s287	0.5889	0.9126
P107s199	−0.1593	0.8357
105	1.0994	0.875

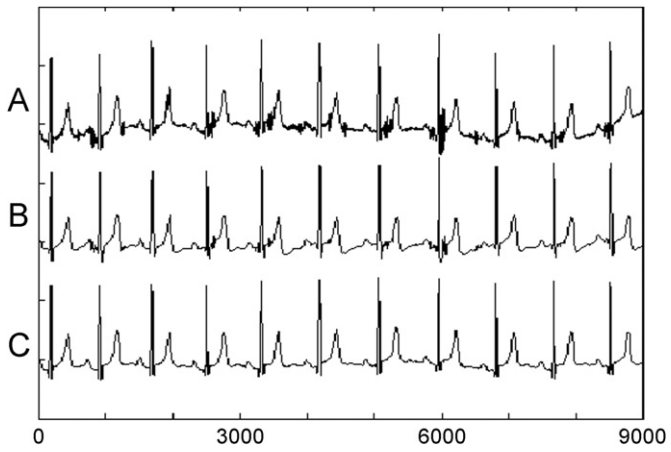

Fig. 13. A—Noisy signal; B—Output of Butterworth bandpass filter; C—Output of EMD based filter (proposed method).

Table 5a
Results obtained for QRS detection for PTB Diagnostic Database.

Type of data	No. of beats	FP	FN	*Se* (%)	*Sp* (%)
Normal	30,342	21	32	99.89	99.93
MI	22,800	22	31	99.86	99.90
Hypertrophy	634	12	17	97.27	98.06
Dysrhythmia	757	8	15	98.00	98.92

Table 5b
Results obtained for QRS detection for MIT-BIH Arrhythmia Database.

Total no. of beats	Normal	Others	FP	FN	*Se* (%)	*Sp* (%)
45,936	34,066	11,870	17	54	99.88	99.96

Table 6
Comparison of QRS detection performance with some standard methods.

Sl. no.	Method	Database used	*Se* (%)	*Sp* (%)
1	Z.E.H.Slimane et al. [21]	MIT-BIH	99.84	99.92
2	Ghaffari et al. [27]	MIT-BIH	99.91	99.72
3	Christov (Algo. 2) [26]	MIT-BIH	99.74	99.65
4	C.Li et al. [15]	MIT-BIH	99.89	99.94
5	Present work	PTB Diagnostic database	98.75*	99.20*
6	Present work	MIT-BIH	99.88	99.96

* 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 ECG 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 cardiological conditions with a good 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.

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