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An efficient new method for the detection of QRS in electrocardiogram ☆

Ashok Kumar Dohare [a,*], Vinod Kumar [a], Ritesh Kumar [b]

[a] Electrical Engineering Department, Indian Institute of Technology, Roorkee 247667, Uttrakhand, India
[b] Cardiology Department, Rajendra Institute of Medical Science, Ranchi 834001, Jharkhand, India

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ABSTRACT

A simple and efficient new method for QRS detection in Electrocardiogram (ECG) is proposed in this paper. Initially data is preprocessed using two stage median filter for removing baseline drift. The second stage enhances the peaks of ECG wave components by using sixth power of signal. The next stage identifies the QRS complex by taking a variable window size. The detection sensitivity (Se) and positive predictivity (+P) of CSE (Common Standards for Quantitative Electrocardiography) measurement database, MIT/BIH (Massachusetts Institute of Technology/Beth Israel Hospital) Arrhythmia database, European ST-T database and QT database are Se 99.51 & +P 99.69%, Se 99.21 & +P 99.34%, Se 99.53 & +P 99.72% and Se 99.87 & +P 99.95% respectively. These four standard databases used to perform QRS detection considered 368 cases, tested 1,006,168 beats and achieved overall average sensitivity 99.52% and positive predictivity 99.69%. The MIT/BIH Noise Stress Test Database also tested by proposed method.

1. Introduction

The electrocardiogram is the most suitable technology for recording of electrical activity generated by myocardial contraction. The pattern of electrical propagation is not random, but spreads over the structure of the heart in a coordinated manner. This results in a measurable change in potential difference on the body surface of the subject. Fig. 1 shows the characteristic shape, segments and time intervals of ECG signal.

The QRS complex is the most important waveform known as reference waveform for analysis of ECG signals. Cardiologist or Clinician diagnoses cardiac abnormalities by observing ECG. The performance of an automatic ECG analyzing system depends mostly upon the accurate and reliable detection of the QRS complex. Once the location of QRS complex is determined, then other wave components of ECG signal such as P & T waves, PR interval, QRS interval, QT interval and PQ & ST segments are determined with respect to the position of QRS complex. Therefore detection of accurate QRS complex is the most important objective in automatic ECG signal analysis.

In QRS detection major problems are arising due to morphological variations of P–QRS–T waveforms, position of waveforms and change in cyclic intervals of the ECG waveforms of different patients and noises occurrence at acquiring data [1,2]. Therefore, most of QRS detectors described in the literature [3] can be divided into two parts: the preprocessor and decision rules. There are many QRS detection methods developed by researchers in the last three decades based on above criteria using different approaches. These are derivatives [4,5], digital filters [6–8], wavelet-transform [9–15], neural networks

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* Corresponding author. Tel.: +91 1332 284331, mobile: +91 9456381742; fax: +91 1332 286351.
E-mail address: dohareashok@gmail.com (A.K. Dohare).

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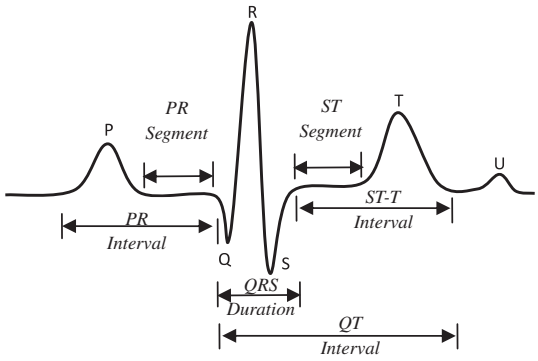

Fig. 1. ECG segments and time intervals.

[16], support vector machine (SVM) [17], k-means [18], mathematical morphology [19], combined threshold method [20], moving averaging method [21], phase space method [22], Hilbert Transform method [23] and Body sensor network based [24].

These existing derivative and digital filter based algorithms determine QRS complex assuming a noise free ECG and without P & T waves removed by using low pass filter, high pass filter or band pass filter. Similarly in wavelet transform a preselected frequency band is assumed in which QRS complex energies exist using a combination of low and high pass filter. In wavelet transform method QRS complex energies decrease, if the scale is larger than 2^4 and the energies of artifacts increase for scales greater than 2^5 [9]. In wavelet based methods there are no general rules for selecting a wavelet for a particular application. Selection criteria of wavelet for a particular application depend on trial method. In wavelet methods, fringing effects occurs at both the ends of the signal and phase shift problems also occur. So in order to overcome these effects some operations are needed. Methods based on ANN and SVM require exhaustive training, settings and estimation of model parameters. Most of these techniques for QRS detection are computationally complex because of using more preprocessing steps.

In this paper we propose a simple new method for QRS detection using minimum preprocessing steps and simple decision rules, so there is no requirement of derivative, digital, band pass filter and no search back. This method is based on sixth power of ECG signal that intensifies the signal strength more as compared to noise and artifacts including P and T-waves. In this proposed method the signal is preprocessed by two stage median filter for removing wander baseline drift using sampling frequency f_s. This method does not need any training, settings and estimation of model parameters. There is no requirement of filter to remove P and T-waves. This method is based on vertically differential change in slope rate by taking higher order of ECG signal. Average value of higher power signal is changed and attained some threshold level to discriminate amplitude of QRS complex from artifacts and, P & T-wave. In this method, the increase in the energy of QRS complex is much more as compared to noise artifacts or P and T waves. Now decision rules are applied to find high peak in QRS region which is R or S location. This method is simple in computation, efficient and detects QRS in normal and abnormal ECGs and does not require any arrangement for phase shifting and fringing effects reduction. The proposed QRS detection method has been tested on large scale using many standard ECG databases such as CSE, MIT/BIH Arrhythmia, European ST-T and QT database and also tested noise performance on MIT/BIH Noise Stress Database. So this method is useful for ST segment analysis, arrhythmia analysis and different heart diseases analysis.

This paper is organized as follows. Section 2 describes various types of standard data bases. In Section 3 concept of new method and detailed steps of implementation are given. Experimental results and discussions for evaluation of the method with various standard data bases such as CSE, MIT/BIH arrhythmia, European ST-T, QT and MIT/BIH Noise Stress database are given in Section 4. Section 5 describes conclusion.

2. ECG databases

The CSE database sampled at 500 Hz for 8–10 s duration. The CSE multilead measurement database is composed of original 250 and 250 so-called artificial ECG recordings (artificial data means one good real data beat repeated up to full length of data). This data has been split into two equal sets i.e. data set-3 and data set-4. The data set 3 & 4 consist of 125 original (MO1_001 to MO1_125) and 125 artificial (MA1_001 to MA1_125) cases of standard CSE multilead data set-3 and 125 original (MO2_001 to MO2_125) and 125 artificial (MA2_001 to MA2_125) cases of standard CSE multilead data set-4.

The MIT/BIH Arrhythmia database consists of 48 records. Each recording consists of two leads, the modified limb lead II and one of the modified chest leads V1, V2, V3, V4, V5 or V6. The duration of each record is 30 min and sampled at 360 Hz. The database contains approximately 109,000 beat labels.

The European ST-T Database contains nearly three hundred hours' worth of ambulatory ECG recordings, annotated beat-by-beat. This database consists of 90 annotated excerpts of ambulatory ECG recordings. The duration of each record is 120 min and sampled at 250 Hz. This database contains approximately 790,559 beat labels.

The QT Database consists of 105 records. Each recording consists of a wide variety of ECG morphologies. Each record was sampled at 250 Hz.

The MIT/BIH Noise Stress Database contains 12 half-hour recordings data-set at different SNR labels (24, 18, 12 00 and −6 dB). This database is created by using MIT/BIH Arrhythmia Database (118 & 119) with different typical noises.

3. Methodology

In general, the QRS detection is mainly divided in two parts: first part is noise removal, and second is QRS detection. Recorded ECG signal has noises such as 50/60 Hz power line interference due to power line, electromyogram noise due to muscle tremor which belongs to high frequency noise, wander baseline drift due to sudden patient movement or breathing and motion artifact due to bad electrode. Wander baseline drift and motion artifact belong to low frequency in which the wander baseline drift frequency is lower than 1 Hz. In this study, we considered only wander baseline drift as removable and QRS is detected in the presence of other noises. Various methods used for this purpose in the literature are band-pass filter [6], wavelet based [21] and median filter [25]. In this study for removing wander baseline drift, we considered two stage median filter using window widths $f_s/2$ and f_s. Median filter is a nonlinear filter which is simple to operate with high speed. The proposed QRS detection method employs a simple two stage median filter for removing baseline drift by using two window widths related to sampling frequency of recorded data. After that, baseline drift free signal is further enhanced by point to point six time data multiplication where the sharp peaks such as Q, R, S are more enhanced than artifacts and P & T waves. Detail steps of preprocessing are explained in the next section.

3.1. Detection of QRS

In the ECG signals, Q, R and S waves are high frequency, sharp waves whereas P and T waves are low frequency and less sharp waves. The data of Q, R and S waves are having linear slope variation. If squaring or higher power of signal is done then

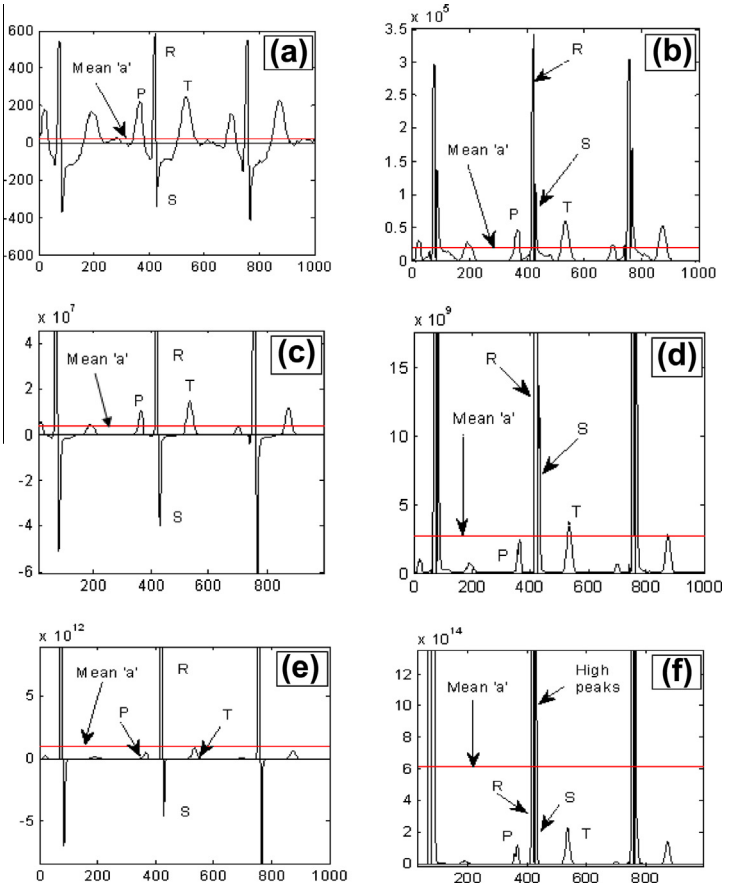

Fig. 2. Mean value position variation with higher power: (a) Original data. (b) Second power. (c) Third power. (d) Fourth power. (e) Fifth power. (f) Sixth power.

data becomes nonlinear. In this case ratio of slope rate of sharp waves with respect to less sharp or slow waves will increase and will discriminate the QRS complex with respect to P & T waves.

For automatic QRS detection, a threshold value is required to distinguish between QRS complex and other ECG wave components such as P and T waves. This threshold value is related to amplitude of peak value of QRS complex. In this proposed method, mean value of enhanced signal works as threshold for separation of QRS from other waves, as shown in Fig. 2. In the first step, when signal is without multiplication, the mean value of signal crosses all peaks, as shown in Fig. 2(a). In the second step when signal is squared, the mean value of signal crosses all peaks but with an upward shift which is more than that in the first step as shown in Fig. 2(b). Similarly mean of third and fourth steps is shifted upwards which is clearly higher than artifacts and some waves as shown in Fig. 2(c) and (d). Now in the fifth step when power of signal is fifth, the mean value '**a**' of signal becomes higher than all artifacts and P and T- waves with a possibility of touching T-wave as shown in Fig. 2(e). In the sixth step when power of signal is sixth, the mean value '**a**' of signal is clearly above all waves except QRS complex waves as shown in Fig. 2(f). In this step, 'R' or 'S' wave peaks are clearly distinguished from peaks of P & T waves. So sixth power of signal and mean value '**a**' has been used to detect 'R' peaks in this paper.

A variable window width has been selected by choosing mean value '**a**' of sixth power of signal as a threshold to determine exact location of either 'R' or 'S' peak (on mapping of time window in enhanced signal or filtered signal or original signal) which is higher than threshold value in magnitude. After that other waves are determined such as 'Q' & 'S' or 'Q' & 'R'. A schematic block diagram of the proposed method for QRS detecting system is as shown in Fig. 3 and detailed steps with results are described in the next section.

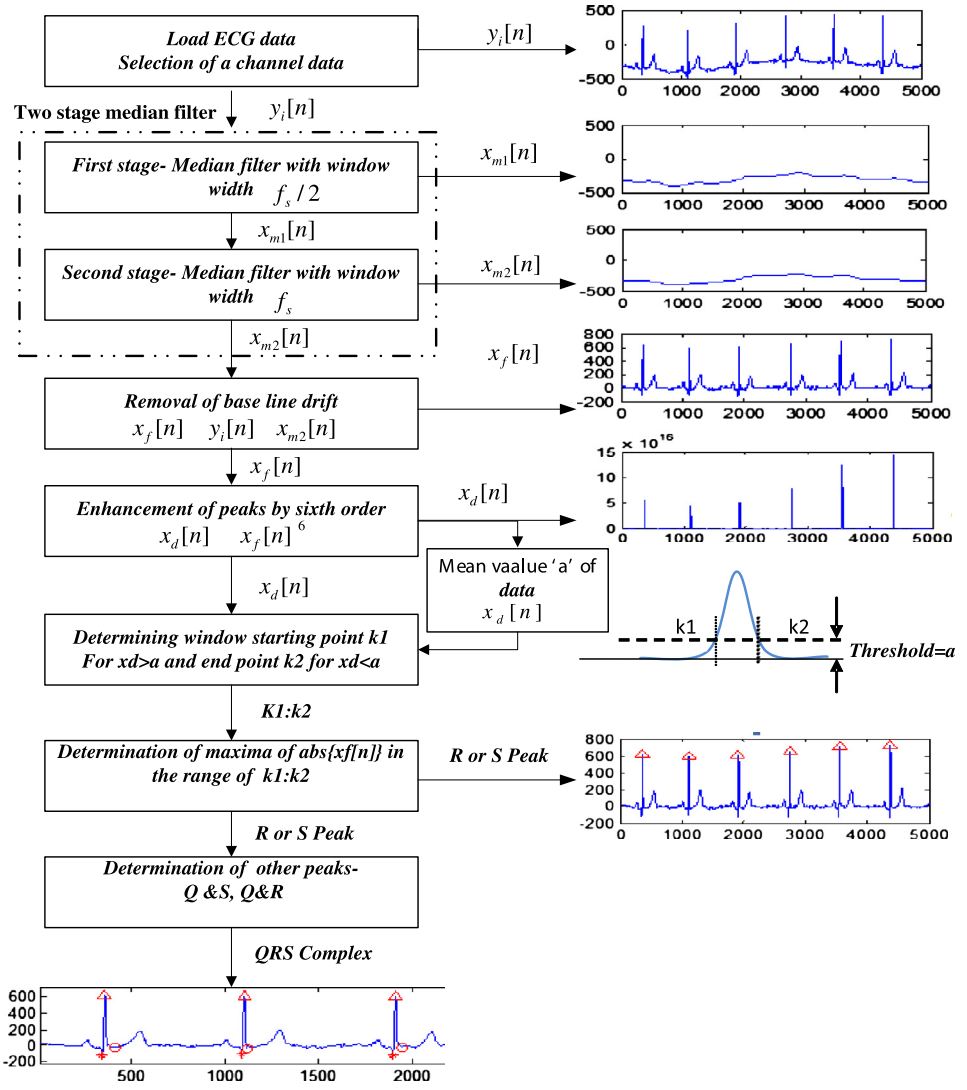

Fig. 3. Schematic diagram of QRS detection method.

3.2. Method steps with results

1. Load ECG data (single or multi channel) having sampling frequency f_s, given by

$$\begin{bmatrix} y_1[n] \\ - \\ y_i[n] \\ - \\ y_p[n] \end{bmatrix} = \begin{bmatrix} x_{11}[n] & x_{12}[n] & x_{1m}[n] \\ - & - & - \\ x_{i1} & x_{i2} & x_{im} \\ - & - & - \\ x_{p1}[n] & x_{p2}[n] & x_{pm}[n] \end{bmatrix} \quad (1)$$

where $y_1[n],\ldots,y_p[n]$ represent channel data for 'p' number of channels and $x_{11}[n],\ldots,x_{1m}[n]$ represent data values of respective channel.

2. Select any one channel of ECG data say $y_i[n]$ having total samples N, as shown in Fig. 4(a) for $N = 5000$.
3. Removing baseline drift, apply two stage median filter.

(A) First stage median filter: – using window width $f_s/2$.

(a) Input data $y_i[n]$ having total samples 'N' and sampling frequency f_s.

(b) In this stage median value of input data $y_i[n]$ to be determined and stored in an array $x_{m1}[n]$ from 1 to $f_s/4$ points, using a variable window size of $f_s/4$ to $f_s/2$.

(c) In next stage median values of input data $y_i[n]$ to be determined and stored in an array $x_{m1}[n]$ from $f_s/4 + 1$ to $N - f_s/4$ points, using a moving window size $f_s/2$.

(d) In last stage median values of input data $y_i[n]$ to be determined and stored in an array $x_{m1}[n]$ from $N - f_s/4 + 1$ to N points, using a variable window size of $f_s/2$ to $f_s/4$. Fig. 4(b) shows the plot of median values $x_{m1}[n]$.

(B) Second stage median filter: – using window width f_s.

(a) Take first stage data $x_{m1}[n]$ having total samples 'N'.

(b) In this stage median values of data $x_{m1}[n]$ to be determined and stored an array $x_{m2}[n]$ from 1 to $f_s/2$ points, using a variable window size of $f_s/2$ to f_s.

(c) In next stage median values of data $x_{m1}[n]$ to be determined and stored an array $x_{m2}[n]$ from $f_s/2 + 1$ to $N - f_s/2$ points, using a moving window size f_s.

(d) In last stage median values of input data $x_{m1}[n]$ to be determined and stored an array $x_{m2}[n]$ from $N - f_s/2 + 1$ to N points, using a variable window size of f_s to $f_s/2$. Fig. 4(c) shows the plot of median values $x_{m2}[n]$.

(e) To remove baseline drift from signal $x_f[n]$, subtract second stage median filter output $x_{m2}[n]$ from input data $y_i[n]$, as shown in Fig. 4(d).

$$x_f[n] = y_i[n] - x_{m2}[n] \quad (2)$$

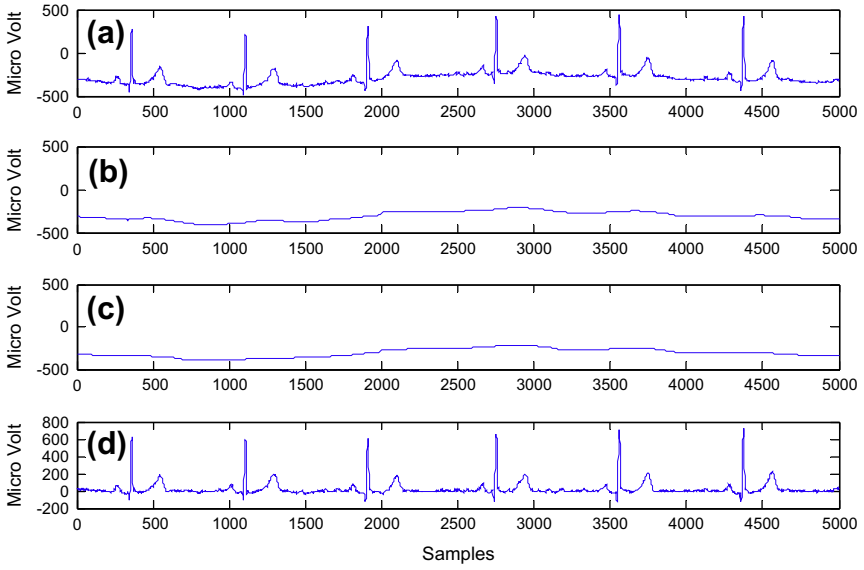

Fig. 4. Outputs of median filter: (a) Original signal (MO1_015, Lead I) $y_i[n]$, (b) First stage median filter output $x_{m1}[n]$, (c) Second stage median filter output $x_{m2}[n]$ and (d) Baseline drift free signal $x_f[n]$.

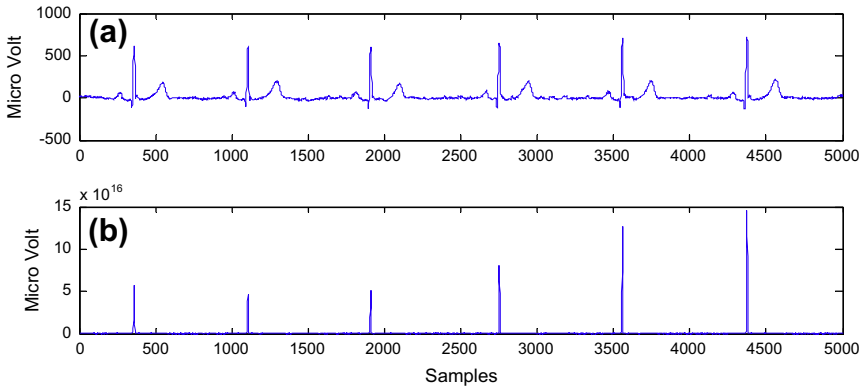

Fig. 5. Enhanced peaks in signal (MO1_015, Lead I): (a) Baseline drift free signal $x_f[n]$ and (b) Data with enhanced peaks $x_d[n]$.

4. Enhancement of various peaks such as P, QRS, T waves is done by using sixth power of filtered data $x_f[n]$ and is shown in Fig. 5(b). Data $x_d[n]$; with enhanced peaks are

$$x_d[n] = \{x_f[n]\}^6. \tag{3}$$

5. Mean value of peaks enhanced data $x_d[n]$ of length 1 to $2f_s$ is taken as threshold value '**a**' for starting peak.
6. Steps to determine variable window width $(k_2 - k_1)$:
   (A) To determine starting point k_1 of first peak: For the first peak, compare $x_d[n]$ to threshold value '**a**', if it is greater than threshold value, then mark point k_1, as shown in Fig. 6(a).
   (B) To determine ending point k_2 of first peak: For first peak, compare $x_d[n]$ from k_1 onwards to threshold value '**a**', if this value is less, and then mark point k_2, as shown in Fig. 6(a).
7. Determine end point 'K' of current ECG cycle: Select window $(k_2{:}(k_2 + f_s/2))$ in enhanced data, determine the standard deviation of enhanced data as following:
   (a) First 8 samples of standard deviation of input data are determined using a variable window of size 8 to 16. Similarly the last 8 samples are determined using window size of 16 to 8.
   (b) The remaining in between samples are obtained by standard deviation of input data with fixed size of 16. All standard deviation samples are stored in an array, and then the minima of this standard deviation is found, which is the end point k of current cycle or starting point of next cycle of ECG wave as shown in Fig. 6(b).
8. Detection of QRS:
   (A) detection of QRS high peak:
   The window $(k_1{:}k_2)$ when mapped in original or filtered data has absolute maxima or high peaks marked by symbol (^) as shown in Fig. 7. If detected peak is positive then it is 'R' otherwise 'S' wave.
   (B) If 'R' wave peak is detected, then find other waves such as 'Q' and 'S':
      (a) To determine 'Q' wave – search left side from 'R' wave up to 60 ms to find first minima.
      (b) To determine 'S' wave – search right side from 'R' wave up to 60 ms to find first minima.

   (C) If detected peak is 'S' wave, then find other waves such as 'R' and 'Q':
      (a) To determine 'R' wave – search left side from 'S' wave up to 80 ms to find first maxima.
      (b) To determine 'Q' wave – search left side from 'S' wave up to 80 ms to find first minima. The marking of 'Q', 'R', and 'S' waves are by symbol '*', '^' and 'o' as shown in Fig. 8.

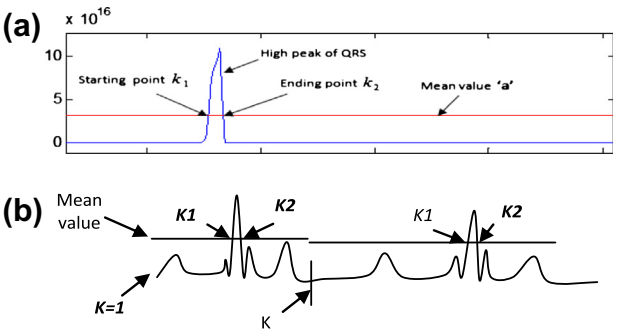

Fig. 6. (a) Detection of variable window point k_1 & k_2 and (b) detection of end point 'k' or starting point 'k' of next cycle in the enhanced signal $x_d[n]$.

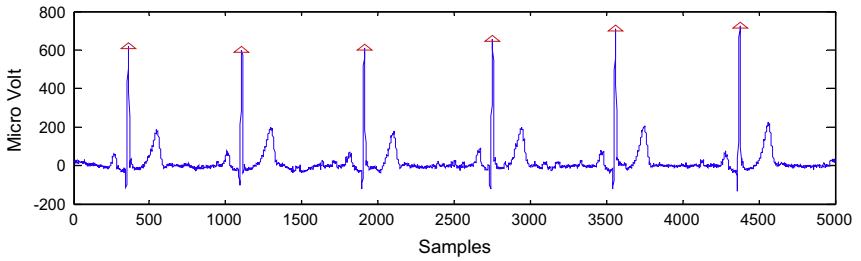

Fig. 7. Detection of peak in the filtered signal (MO1_015, Lead I), here R-wave peak is marked as (^).

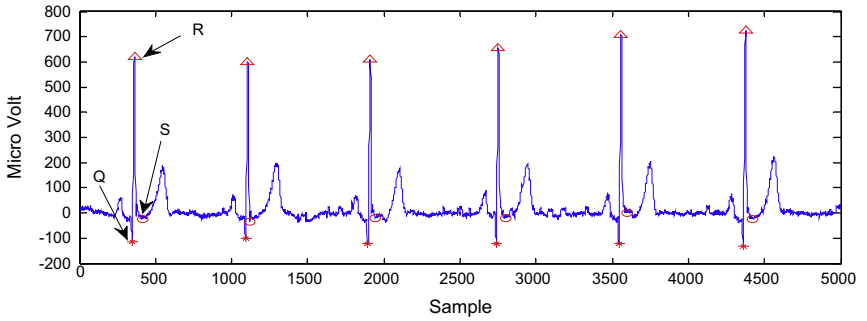

Fig. 8. Detection of QRS peaks in the filtered signal (MO1_015, Lead I), here Q,R,S peaks are marked as '*', '^' and 'o' respectively.

9. **Adaptive threshold**: After first peak detection using threshold '**a**' (a = mean (1:2 times f_s)), determine adaptive threshold '**a**' (a = mean (enhanced data (end point of current cycle: end point of current cycle + 1.5 times f_s))).
10. For next peak to last peak find starting point k_1 using adaptive threshold '**a**', starting from end point of previous cycle and following step 6 (A) and for ending point k_2, follow step 6 (B). Skip period (automatically determined) is used to eliminating false peak detection due to abnormal 'T' wave.

4. Experimental results and discussion

The evaluation of this proposed new method was done with various standard ECG database, such as CSE Database (CSEDB) data set-3 (MO1_001 to MO1_125), MIT/BIH Arrhythmia Database (MIT/BIH AD), European ST-T Database (EDB) and QT Database (QTDB). In order to evaluate the performance of the proposed method, in terms of Sensitivity (Se) and Positive predictivity (+P) [3] given in Eqs. (4) and (5).

$$\text{Sensitivty (Se)} = \text{TP}/(\text{TP} + \text{FN}) \tag{4}$$

$$\text{Positive Predictivity (+P)} = \text{TP}/(\text{TP} + \text{FP}) \tag{5}$$

where TP-True Positive, is being identified as correctly detected QRS, FN-False Negative identified when QRS is present and detector is not detected, FP-False Positive, means QRS is not present, but detector detects QRS location. In this section five experiments perform our algorithm with different types of standard database. Kohler et al. [3] suggested computational load as low, medium and high according to generation of the feature signals and complexity of techniques used, so we consider computational load and compare performance of detectors with proposed method.

4.1. Experiment 1

In this experiment, CSE data set-3 original 125 cases (MO1_001 – MO1_125) considered, and perform 12 standard lead ECG QRS detection. This database contains normal, abnormal and many heart diseases. Fig. 9 shows QRS detection in CSE data base record MO1_016 (Lead I). In this record variation in baseline drift is large and the proposed method is able to correctly detect all QRS locations. A summary of all 125 original cases is presented in Table 1. In this table, for all 12 lead ECG used to evaluate QRS detection, it is observed that the proposed new method detected total 55 false positives and 88 false negative resulting in overall QRS detection sensitivity (Se) and positive predictivity (+*P*) of MO1 series as 99.51% and 99.69%, respectively. The false positive detection was found mainly in the ECG signals where 'P' and 'T' waves were peakier than QRS complexes. In this case, Lead I and II show more false positive and false negative than other leads due to more peaky 'P' waves and heavy noisy signals. In literature for QRS detection, some researcher [10,16] used CSE database data set -3 using

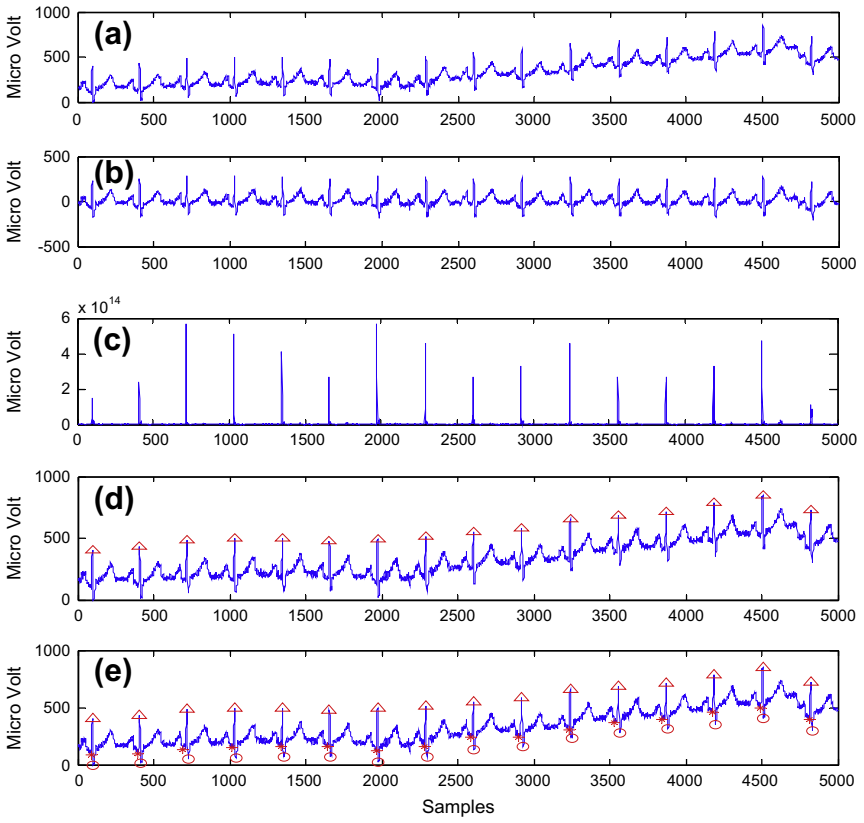

Fig. 9. MO1_016 Lead-I (a) Original data, (b) Baseline drift free signal (c) Enhanced peaks (d) Detection of maxima value of R wave (e) Marking of QRS waves as ('*', '^' and 'o').

Table 1
Results of the QRS detection Algorithm for the CSE database data set-3 (125 original cases full length).

Lead name	Total QRS	TP	FP	FN	Se%	+P%	Lead name	Total QRS	TP	FP	FN	Se%	+P%
I	1497	1478	13	19	98.73	99.13	V1	1497	1494	3	3	99.80	99.80
II	1497	1476	22	21	98.60	98.53	V2	1497	1489	0	8	99.47	100.00
III	1497	1493	0	4	99.73	100.00	V3	1497	1492	0	5	99.67	100.00
aVR	1497	1493	2	4	99.73	99.87	V4	1497	1495	0	2	99.87	100.00
aVL	1497	1489	15	8	99.47	99.00	V5	1497	1492	0	5	99.67	100.00
aVF	1497	1491	0	6	99.60	100.00	V6	1497	1494	0	3	99.80	100.00
							Total	17,964	17,876	55	88	99.51	99.69

Table 2
Comparison of QRS detection with other algorithm using CSE database data set-3 (MO1_001-MO1_125).

S. no.	QRS detector	Data	Cases	Using beats	TP	FP	FN	Se%	+P%	Computational load [3]
1	Mehta et al. [18]	DS3	125	17,856	17,616	204	240	98.66	98.86	High
2	Proposed algorithm	DS3	125	17,964	17,876	55	88	99.51	99.69	Low

artificial data, which is a single good, beat of original signal, and repeated for ten seconds. Researcher [17,18] performs QRS detection of original CSE database data set-3, so our algorithm comparison shown in Table 2 with original data set-3, performance of proposed method is comparable and higher.

4.2. Experiment 2

In this experiment, MIT/BIH arrhythmia data was considered, which mostly contains normal, RBBB, LBBB, APC, PVC with wander baseline drift and artifacts. In this study our algorithm performs QRS detection with 48 records in full length,

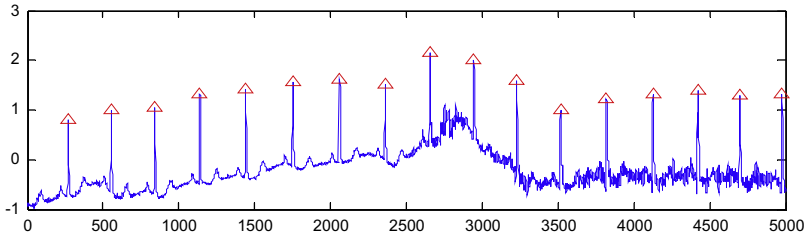

Fig. 10. QRS detection in MIT/BIH 103 first lead (ML-II).

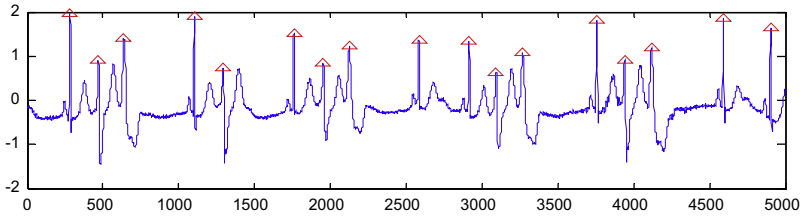

Fig. 11. QRS detection in MIT/BIH 106 first lead (ML-II).

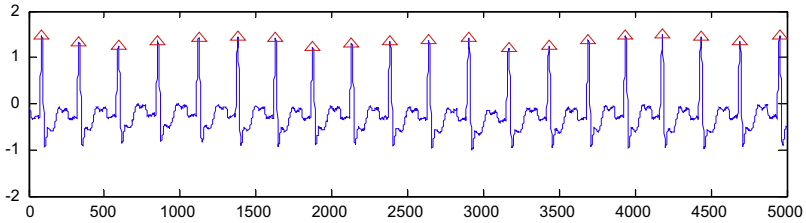

Fig. 12. QRS detection in MIT/BIH 109 LBBB first lead (ML-II).

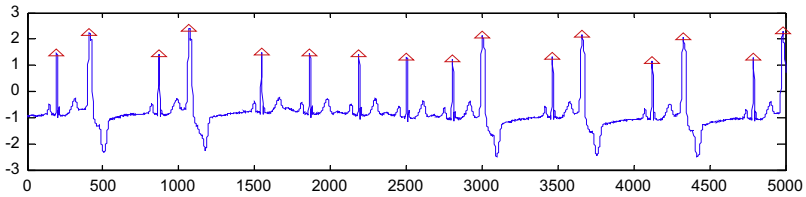

Fig. 13. QRS detection in MIT/BIH 119 first lead (ML-II).

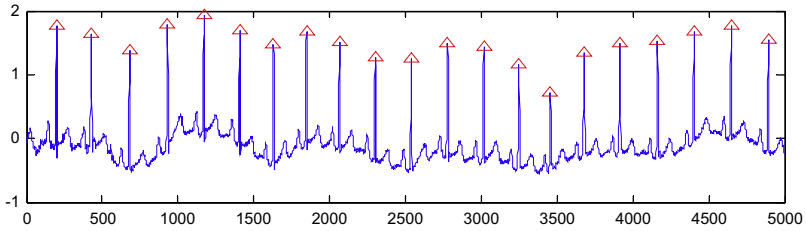

Fig. 14. QRS detection in MIT/BIH 212RBBB first lead (ML-II).

without power noise and artifacts removing, only wander baseline drift removed. Some records having different diseases shown in Figs. 10–14. MIT/BIH arrhythmia data record 103 highly baseline drifts, with noises, which is clearly detected as shown in Fig. 10. Fig. 11 depicts QRS detection performance for record 106 MIT/BIH arrhythmia data. In this data, variation

Table 3
Comparison of QRS detection with other algorithm using MIT/BIH AD database.

S. no.	QRS detector	Cases	Using beats	TP	FP	FN	Se%	+P%	Computational load [3]
1	Yeh et al. [4]	48	109,809[a]	109,643	58	166	99.85	99.95	Low
2	Pan and Tompkins [6]	48	109,809[a]	109,208	507	277	99.75	99.54	High
3	Hamilton and Tompkins [7]	48	109,267	108,927	248	340	99.69	99.77	Medium
4	Adnane et al. [8]	48	109,494	109,241	393	253	99.77	99.64	Low
5	Saxena et al. [10]	48	103,763	103,664	102	99	99.90	99.90	Medium
6	Martnez et al. [11]	48	109,428	109,208	153	220	98.80	99.86	High
7	Ghaffari et al. [12]	48	110,159	109,837	322	120	99.89	99.71	High
8	Ghaffari et al. [13]	48	109,428	109,327	129	101	99.91	99.88	High
9	Choouakri et al.[15]	48	109,488	108,043	3068	1446	98.68	97.24	High
10	Zhang et al. [19]	48	109,510	109,297	204	213	99.81	99.81	Medium
11	Christov [20] Alg-I	48	110,050	109,548	215	294	99.69	99.69	Medium
12	Christov [20] Alg-II	48	110,050	109,615	239	240	99.74	99.65	Medium
13	Chen et al. [21]	48	110,050	109,615	239	24	99.78	99.78	Medium
14	Proposed method	48	109,966	109,096	728	870	99.21	99.34	Low

[a] Values computed according to the record–record tables in the referred works since there is a discrepancy between total values and the sum of the individual ones.

of morphology, highly PVC, change in amplitude and sudden change in RR interval are correctly detected. Fig. 12 shows record 109 where LBBB beats are clearly detected. Fig. 13 describes the QRS detection in record 119 MIT/BIH arrhythmia data, which has wide PVCs and variation in RR interval. Fig. 14 represents the QRS detection in record 212 MIT/BIH arrhythmia data, which has RBBB beats clearly detected.

In the given literature many researchers developed QSR detector where they mostly evaluated the performance of method by using MIT/BIH arrhythmia database. In literature almost all researchers used single first annotated lead evaluated for QRS detection. In Table 3 we observe that performance of all 48 records of first lead is good and within limit of required QRS detection. The proposed new method detected total 728 false positives and 870 false negative resulting in overall QRS detection sensitivity (Se%) and positive predictivity (+P) of MIT/BIH arrhythmia database as 99.21% and 99.34%, respectively, which is higher and comparable to other methods.

4.3. Experiment 3

In this experiment, European ST-T database was used and QRS detection was performed on 90 ECG records. This database contains normal, abnormal and variation in ST-T interval and T wave morphology. Fig. 15 shows QRS detection in record e0105 (MLIII), in which variation in T wave is larger than R peak. In this experiment proposed method is able to correctly detect QRS locations. Summary of all 90 cases represented in Table 4. In this table, all cases used first lead to evaluate QRS detection and we observe that the proposed new method detected total 2190 false positives and 3679 false negatives resulting in overall QRS detection sensitivity (Se) and positive predictivity (+P) of European ST-T database as 99.53% and 99.72% respectively, which is comparable and higher than other methods.

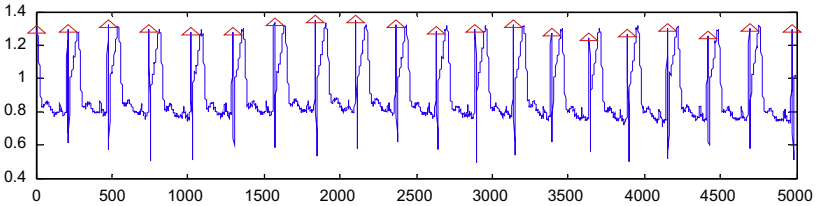

Fig. 15. QRS detection in data e0105 (MLIII).

Table 4
Comparison of QRS detection with other algorithm using European ST-T database (EDB).

S. no.	QRS detector	Data	Cases	Using beats	TP	FP	FN	Se%	+P%	Computational load [3]
1	Martnez et al. [11]	EDB	90	787,103	784,059	4077	3044	99.61	99.48	High
2	Ghaffari et al. [13]	EDB	90	787,103	784,210	3554	2893	99.63	99.55	High
3	Proposed method	EDB	90	790,559	774,180	2190	3679	99.53	99.72	Low

4.4. Experiment 4

In this experiment, QT database was used and QRS detection was performed on 105 ECG records. This database contains normal, abnormal and variation in QRS, ST-T interval and T wave morphology. Table 5 depicts the overall performance of the proposed method which detected total 41 false positives and 107 false negative resulting in overall QRS detection sensitivity (Se) and positive predictivity (+P) of QT database as 99.87% and 99.95%, respectively, which is higher and comparable to other methods.

The comparison of QRS detection performance of proposed method with other methods using standard database of CSE, MIT/BIH Arrhythmia, European ST-T and QT database is shown in Tables 2–5 respectively. Table 6 represents overall performance of proposed method, using four different standard databases, with 368 cases and total **1,006,168** beats analysis. The overall average sensitivity of 99.52% and positive predictivity of 99.69% was achieved considering all four standard databases.

The new method was implemented by using MATLAB 7.8.0 (2009a) Software in a PC with Intel Core 2 Duo 2.67 GHz processor. The average computational times for CSE, MIT/BIH Arrhythmia, European ST-T and QT database (full length) are 0.5–0.8 s, 80–85 s, 230–250 s and 22–26 s respectively.

4.5. Experiment 5

In this section two example performances related to noise handling problems are presented, in order to understand how the SNR affects the performance of the QRS detector. Example one was performed using zero mean, white Gaussian noise with variance, to find QRS detection rate [21] by selecting the varying SNR values from 0 to 15 dB. Table 7 depicts the experimental performance of proposed algorithm with varying SNR of record 119 of MIT/BIH arrhythmia database. Comparison of

Table 5
Comparison of QRS detection with other algorithm using QT database.

S. no.	QRS detector	Data	Cases	Using beats	TP	FP	FN	Se%	+P%	Computational load [3]
1	Martnez et al. [11]	QT	105	86,892	86,824	107	68	99.92	99.88	High
2	Ghaffari et al. [13]	QT	105	86,892	86,845	79	47	99.94	99.91	High
3	Proposed method	QT	105	87,679	87,572	41	107	99.87	99.95	Low

Table 6
QRS detection summary of CSE, MIT/BIH Arrhythmia, European ST-T and QT database.

S. no.	Data	Cases	Using beats	TP	FP	FN	Se%	+P%
1	CSE DS-3	125	17,964	17,876	55	88	99.51	99.69
2	MIT/BIH AD	48	109,966	109,096	728	870	99.21	99.34
3	European ST-T	90	790,559	774,180	2190	3679	99.53	99.72
4	QT	105	87,679	87,572	41	107	99.87	99.95
Total		368	1,006,168	988,724	3935	4892	99.52	99.69

Table 7
SNR versus QRS detection rate Algorithm for the record 119 MIT/BIH AD.

SNR (dB)	Total QRS	TP	FP	FN	Se (%)	+P (%)	Min (Se + P) [21]
0	22	3	41	19	13.64	6.82	6.82
1	22	5	38	17	22.73	11.63	11.63
2	22	5	37	17	22.73	11.90	11.90
3	22	6	32	16	27.27	15.79	15.79
4	22	9	28	13	40.91	24.32	24.32
5	22	10	22	12	45.45	31.25	31.25
6	22	13	20	9	59.09	39.39	39.39
7	22	13	19	9	59.09	40.63	40.63
8	22	15	13	7	68.18	53.57	53.57
9	22	19	5	3	86.36	79.17	79.17
10	22	19	5	3	86.36	79.17	79.17
11	22	22	0	0	100.00	100.00	100.00
12	22	22	0	0	100.00	100.00	100.00
13	22	22	0	0	100.00	100.00	100.00
14	22	22	0	0	100.00	100.00	100.00
15	22	22	0	0	100.00	100.00	100.00

Table 8
Comparison of QRS detection rate with other algorithm using varying SNR for the record 119 MIT/BIH AD.

SNR (dB)	Proposed algorithm			Chen et al. [21]		
	Se (%)	+P (%)	Min (Se + P) [21]	Se (%)	+P (%)	Min (Se + P) [21]
0	13.64	6.82	6.82	93.85	92.82	92.82
1	22.73	11.63	11.63	97.21	95.87	95.87
2	22.73	11.90	11.90	97.77	99.15	97.77
3	27.27	15.79	15.79	99.16	99.16	99.16
4	40.91	24.32	24.32	99.72	99.17	99.17
5	45.45	31.25	31.25	100.00	98.9	98.9
6	59.09	39.39	39.39	100.00	99.44	99.44
7	59.09	40.63	40.63	100.00	99.44	99.44
8	68.18	53.57	53.57	100.00	99.72	99.72
9	86.36	79.17	79.17	100.00	99.72	99.72
10	86.36	79.17	79.17	100.00	99.72	99.72
11	100.00	100.00	100.00	100.00	99.72	99.72
12	100.00	100.00	100.00	100.00	99.72	99.72
13	100.00	100.00	100.00	100.00	99.72	99.72
14	100.00	100.00	100.00	100.00	99.72	99.72
15	100.00	100.00	100.00	100.00	100.00	100.00

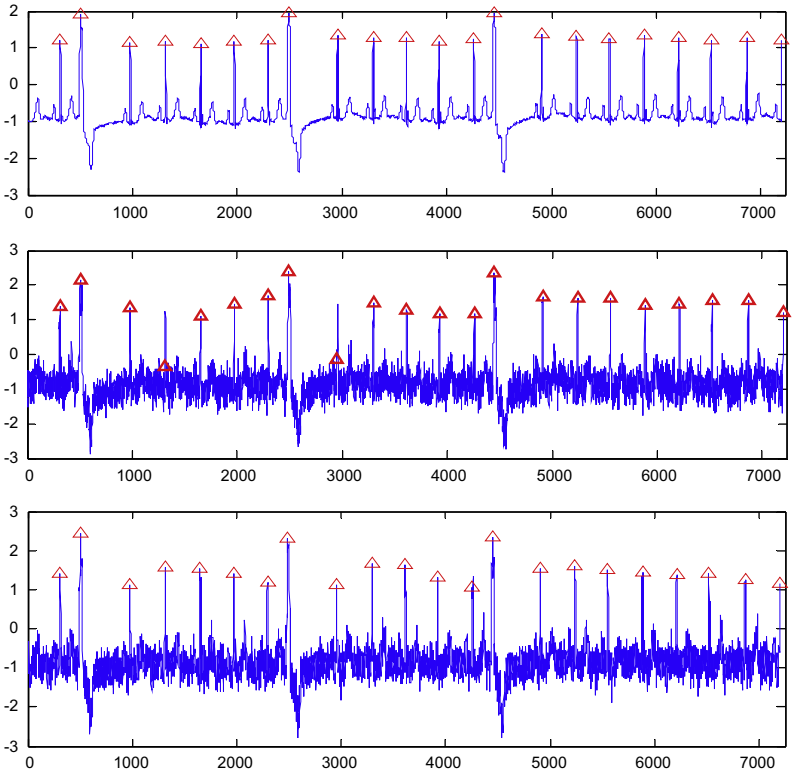

Fig. 16. QRS detection of record 119 (MLIII) MIT/BIH arrhythmia database at different level of SNR: (Top) QRS detection of original data without adding noise, (Middle) QRS detection at SNR 11 dB, and (Bottom) QRS detection at SNR 12 dB.

QRS detection rate performance with other algorithm is represented in Table 8. Observing results in Tables 7 and 8, we find that a QRS detection rate of 100% could be achieved at SNR 11 dB by proposed algorithm which is comparable to other algorithms [21]. Fig. 16 shows QRS detection algorithm for a data record 119 at different level of SNR.

In this section another example of QRS detection was performed on 12 data-set noisy full lengths (118e24 to 118e_06 and 119e24 to 119_06) from MIT–BIH Noise Stress Test Database. Experimental results of QRS detection performance of proposed algorithm are depicted in Table 9, in which sensitivity and positive predictivity of data record 118 and 119 varied from 99.96 to 72.62 for SNR 24 dB to −6 dB. This performance is higher [22] and comparable [23,24] to other algorithms shown in Table 10.

Table 9
Algorithm performance for the record MIT/BIH Noise stress database 118 and 119.

Data name	Total QRS	TP	FP	FN	Se%	+P%	Data name	Total QRS	TP	FP	FN	Se%	+P%
118e24	2278	2271	7	7	99.69	99.69	119e24	1987	1987	1	0	100.00	99.95
118e18	2278	2216	66	62	97.28	97.11	119e18	1987	1980	7	7	99.65	99.65
118e12	2278	2149	138	129	94.33	93.96	119e12	1987	1907	95	80	95.97	99.25
118e06	2278	1941	278	337	85.21	87.47	119e06	1987	1952	268	253	88.17	86.73
118e00	2278	1732	440	546	76.03	79.74	119e00	1987	1531	453	456	77.05	77.73
118e_6	2278	1650	508	628	72.43	76.45	119e_6	1987	1443	545	544	72.62	72.56

Table 10
Comparison of QRS detection performance with other algorithms using MIT/BIH Noise stress database.

Data name	Total QRS	Proposed method		Plesnik et al. [22]		Benitez et al. [23]		Li and Tan [24]			
								Algorithm-I		Algorithm-II	
		Se%	+P%	Se%	+P%	Se%	+P%	Se%	+P%	Se%	+P%
118e24	2278	99.69	99.69	98.46	100.00	100	100	99.32	99.79	100.00	99.64
118e18	2278	97.28	97.11	97.76	99.96	99.96	99.82	98.49	99.00	100.00	99.46
118e12	2278	94.33	93.96	88.98	96.99	98.81	97.28	96.66	97.78	99.90	89.32
118e06	2278	85.21	87.47	68.70	84.96	94.69	91.13	91.23	81.11	99.63	73.34
118e00	2278	76.03	79.74	43.59	61.56	84.15	82.66	77.30	71.34	99.53	57.68
118e_6	2278	72.43	76.45	25.37	54.37	78.45	77.16	63.47	72.04	89.93	52.01
119e24	1987	100.00	99.95	99.85	99.95	100.00	99.95	100.00	98.17	100.00	99.58
119e18	1987	99.65	99.65	99.80	99.95	99.95	99.80	99.28	98.04	99.88	98.99
119e12	1987	95.97	99.25	96.28	99.07	99.14	95.12	98.25	97.37	99.28	88.52
119e06	1987	88.17	86.73	81.03	89.54	95.87	88.85	96.33	89.99	99.63	70.24
119e00	1987	77.05	77.73	41.92	58.74	89.73	81.34	89.58	75.38	99.28	53.38
119e_6	1987	72.62	72.56	23.65	44.76	81.08	74.17	78.09	66.27	98.01	49.14

5. Conclusion

An effective and reliable QRS detection method based on peak enhancements by sixth power and variable window width has been presented here. This proposed new method was tested on various standard databases such as CSE, MIT/BIH Arrhythmia, European ST-T and QT database and obtained good results & statistical indices are higher or comparable to those cited in the scientific literature. The proposed method is very simple, fast and reliable to determine QRS at different sampling frequency rates without any denoising. In this study we used only wander baseline drift by using two stage median filters, and signal enhanced by sixth power of signal. In case of noisy signal QRS detection was clear which was verified at different SNR values. Different SNR values with 12 data of MIT–BIH Noise Stress Test Database were tested. The QRS detection performance achieved was higher and comparable to developed algorithms. This method is useful for QRS detection in multilead ECG system using some composite lead system such as spatial velocity concepts and easy to use in real time QRS peak detection. In this method we observed that QRS detector work accurately at different sampling frequency without down sampling of signal. This method is applicable for designing composite heart diseases analyzer, such as ST segment and arrhythmia monitoring.

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Ashok Kumar Dohare received the B.E. degree in Electronics and Instrumentation from the Samrat Ashok Technological Institute Vidisha (India) in 1991 and M.E. degree from SGSITS Indore (India) in 2004. He is working as Associate Professor in the Govt. Engineering College Rewa Madhya Pradesh (India). Presently he is a research scholar in the Electrical Engineering Department, Indian Institute of Technology, Roorkee, under QIP.

Vinod Kumar received his B.Sc. (Electrical Engineering) degree from Punjab University (India) in 1973, ME and Ph.D. degree from University of Roorkee (India) in 1975 and 1984 respectively. He is presently Professor in Electrical Engineering Department of Indian Institute of Technology Roorkee. His areas of interest are Measurement and Instrumentation, Medical Instrumentation, Medical Image Processing, Digital Signal Processing and Telemedicine.

Ritesh Kumar received the M.B.B.S. degree from Patna Medical College, Patna (India) in 1995 and the M.D. degree from Institute of Medical Science, Varanasi (India) and D.M. (Cardiology) L.P.S. Institute of Cardiology, Kanpur (India) in 2004. Presently he is working as Associate Professor in Department of Cardiology, Rajendra Institute of Medical Sciences Ranchi (India).