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Performance Evaluation of a Modified ECG De-noising Technique Using Wavelet Decomposition and Threshold Method

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Abstract: According to recent survey due to drastically changing weather and unhealthy lifestyle, irrespective of age people are suffer from different health issues, among them heart related diseases are very common. So to prevent some emergency health hazards due to such kind of diseases distant and continuous health monitoring is very useful, but due to lack of expert intervention both processes are very sensitive to noise. So our aim is to get a noise free medical data through above said processes to treat a patient properly. In this work experimental signal data is chosen from a 12 lead noisy ECG database which is formed using a MATLAB coded program by taking noisy and clear data from MIT-BIH noise stress test database and CSE clear ECG database respectively. Generated noisy ECG signals are decomposed using wavelet decomposition. Distorted coefficients generated during the process are recovered using threshold technique and the de-noised signal is achieved using changed coefficients. After de-noising process amplitude and duration of different segments and intervals of de-noised ECG signals for several SNR values and also for clear ECG signals are obtained by running an ECG feature extraction program developed in MATLAB. Compare both parameters to study the performance of the whole de-noising procedure, Again sensitivity, predictivity and detection accuracy are checked for each de-noised data for different SNR values and represent them graphically to detect the accuracy of the process.

Keywords: De-noising, Wavelet, Decomposition, Threshold, Reconstruction

1. Introduction

All of us aware about the importance of online medical facilities due to Pandemic situation. During such a period when people facing difficulties to get in touch with any doctors for their regular health checkup or could not went to hospitals for their medical necessities, then online medical facilities are only hope. Telemonitoring is such a medical facility which uses information technology to monitor patients at a distance. Using such an advance application, real time monitoring of patients in ambulance can be possible which reduces the time to initiate treatment and allows the emergency crew to be better prepared, telemonitoring also allow reduction of chronic disease complications thanks to better followup for which one get better healthcare service without using hospital beds [9].

Though telemonitoring has huge application and great advantage but it faces certain drawbacks also. One of the most important drawbacks of it is effect of noise in long distant data.

For proper evaluation of any patient health condition the most necessary requirement is noise less medical data, so to improve the feature of telemonitoring system noise elimination is one of the important condition. Among all kind of medical data, in this paper we concentrate only on noise elimination from ECG data.

1.1. Electrocardiogram

Electrocardiogram or ECG is a most important medical data for a distant monitoring system which gives a complete picture of the electrical condition of human heart. Figure 1 gives a typical picture of ECG waveform.

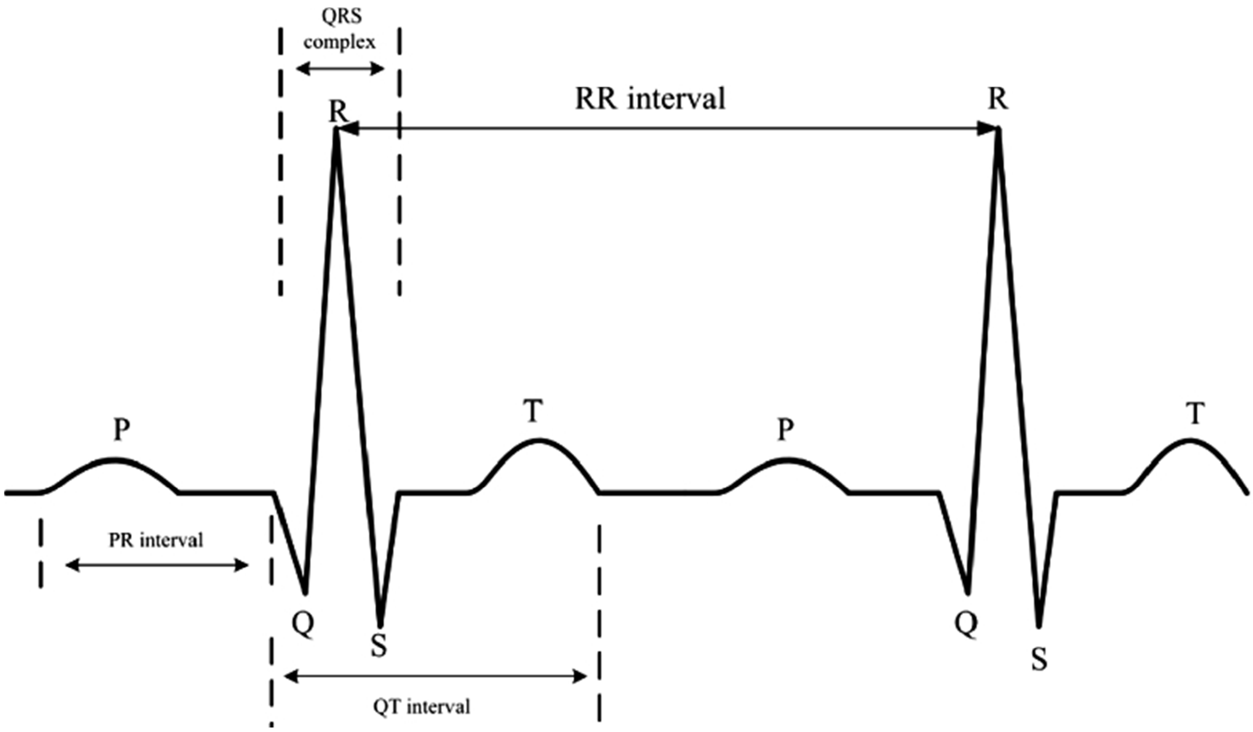


Figure 1. *Typical picture of an ECG waveform.*

An ECG shows a voltage vs. time representation of hearts electrical activity in a form of signal, which is normally displayed as millivolts (mV) and seconds. It shows a series of peaks and waves that corresponds to ventricular or atrial depolarization and repolarization [14], each segment of the signal representing a different event associated with the cardiac cycle. An ECG signal contains P wave, QRS complex and a T wave. These units of electrical activity can be further broken down into the PR interval, the ST segment, and the QT interval [10, 11]. Such ECG wave segments and intervals have certain standard values which are as follows:

P Wave: 60-80ms.

QRS Complex: 80-120ms.

Twave: 60-120ms.

PR Interval: 120-200ms.

QT Interval: 360-440ms.

ST Interval: 100-120ms.

1.2. Noise in ECG

Noise is an unwanted signal which appears almost randomly and degrade total feature of any kind of signal. ECG signal also contaminate with various kind of noises through its acquisition process [2, 3] which reduces its application value. The noise database which used in this paper contains three types of such noises related to ECG measurement, whichare:

I) *baseline wander (bw)*: It is a low frequency noise causes due to offset voltages in the electrodes, respiration, and body movement. As an effect of this noise the isoelectric line changes its position due to lead or cables movement, patient movement or lose electrode or wire contact etc.

II) *Electrode motion artifact (em)*: It is a kind of noise which can closely mimic elements of the ECG signal, it causes due to motion of the electrode. More specifically, movement of the electrode or lead wire produces deformations of the skin around the electrode site. The deformations of the skin change the impedance and capacitance of the skin around the sensing electrode. The impedance and capacitance changes are sensed by the ECG electrode and result in artifacts that are manifest as large amplitude signals on the ECG.

III) *Muscle noise (ma)*: This kind of noise has a spectrum which overlaps with the ECG signal; this noise is generally causes due to muscle contraction and generated potential at millivolt level. [2, 3]

Though here we consider only noises occur during measurement process but ECG can be contaminated during distant transmission also which does not discuss in this paper kept for our future study.

The level of distortion of any noisy signal can be verified using different values of signal to noise ratio or SNR; it is defined as the ratio of signal power to the noise power. SNR basically compare the level of desired signal to the level of imposed noise and helps to identify the degradation level of any kind of experimental signal. Here in this paper we basically try to de-noise a noisy ECG signal which is created by us using a clear and noisy ECG database. Being a non-stationary signal de-noising of such signal is very difficult. A proficient technique for such a non-stationary signal processing is the wavelet transform. The wavelet transform can be used for decomposition of a signal in the time frequency scale plane.

1.3. Discrete Wavelet Transform

Wavelet analysis is a branch of applied mathematics that has produced a collection of tools for signal and image processing. It can be used to extract information from a variety of data types. Unlike the Fourier transform, wavelet analysis gives a multi-resolution analysis of signals. It could focus on any signal′s details and is an efficient method in signal processing. Wavelet transform can decompose a signal into several scales that represent different frequency bands, and at each scale, the positions of the signal′s instantaneous structures can be determined approximately. Different decomposition scales can be selected for different processing targets. Moreover, the time and the frequency domains can be simultaneously located. For non-stationary signal analysis, it has great advantages. Discrete wavelet transform is realized by passing the signal through a series of low-pass and high-pass filters [15]. Wavelet transform decomposes the signal into detailed components and approximates components of different scales. Figure 2 is a schematic diagram of discrete wavelet transform, where x[n] is the discrete input signal with length n; g[n] is a low-pass filter, which can filter out the high-frequency part of the input signal and output the low-frequency part. h[n] is a high-pass filter. Contrary to the low-pass filter, it filters out the low-frequency part and outputs the high-frequency part. ↓is a down-sampling filter. [1]

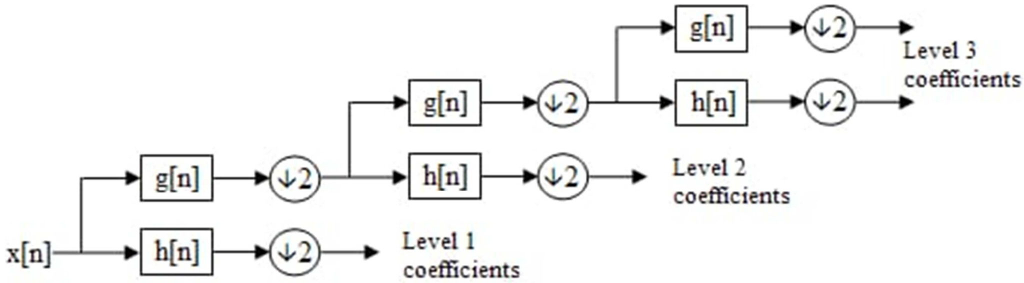


Figure 2. *Block diagram of decomposition process of discrete wavelet transform.*

At present, many wavelet bases have been developed, such as Haar, Daubechies (Db), Symlet and so on, for the analysis and synthesis of signals. In our previous work we generate a noisy signal and try to analyze its various features [16]. Here in our present experiment we use Daubechies2 or db2 as wavelet base, using this wavelet generated noisy ECG signals were decomposed in several levels by giving detailed and approximation coefficients, signals are de-noised by restoring distorted coefficients using threshold technique again different parameters of clear, noisy and de-noised signals were compare to get better result.

2. Methodology

2.1. Generation of Noisy ECG Signal Database

For performing de-noising process a noisy signal must be generated. In this work to generate noisy signal noise samples were taken from MIT- BIH PhysioNet noise stress test database (NSTDB) [6, 7] which contains three type of noise, each noise samples of this database were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range. The required clear ECG samples were taken from CSE multi-lead ECG database. Each record of the database includes 15 simultaneously measured signals:

the conventional 12 leads (i, ii, iii, avr, avl, avf, v1, v2, v3, v4, v5, v6) together with the 3 Frank lead ECGs (vx, vy, vz) and digitized at 500 samples per second with 16 bit resolution, each sample were measured in micro-volt range. [16]

SNR level have been maintained for above said process were -6db, 0db, 6db, 18db, 12db and 24db. Since the sampling rates were different for noise and clean database a re-sampling has been done to make the number of samples equal. Noise samples (bw, em or ma) which are used contains only two lead of noise data, so to generate third orthogonal lead of NSTDB, Principal Component analysis (PCA) has been used, This method was described by Clifford et al [5]. In Principal component analysis process data transformed into an orthogonal basis set, For this a set of values of 2^{nd} order linearly uncorrelated variables called principal components can be obtained by converting a set of observations of possibly correlated variables. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the largest possible variance, and each succeeding component in turn has the highest variance possible under the constraint that it be orthogonal to the preceding components. In PCA the directions in the data with the most variation, i.e. the eigenvectors corresponding to the largest eigenvalues of the covariance matrix usually been found, and the data onto these directions are projected. A MATLAB function developed by [5] is used to generate principal components of the NSTDB two lead ECG data and the 1^{st} column of the transposed orthogonal matrix gives the third orthogonal lead’s data. Assuming the resultant leads form an orthogonal lead set with arbitrary orientation, the Dower transformation [8] was then used to create realistic correlated 12-lead sets of noise. The purpose of this step was to generate 12-lead noise records with realistically correlated, but not identical noise on the different leads and these noises are then titrated with clear samples of CSE multi-lead Database. To generate noisy signal 12 lead clear data samples of 10s were selected randomly and added with 10s calibrated 12 lead noise samples. In present experiment we use 125 clear ECG data and three type of noise to generate noisy ECG database. To control the signal to noise ratio (SNR) a coefficient η has been computed which can be expressed as

$$\eta = \sqrt{\exp\left(\frac{-\ln(10)*s}{10}\right)\frac{P_C}{P_v}} \quad (1)$$

Noisy ECG signal was generated using the following expression:

$$N_{ecg} = C_{ecg} + \eta * v \quad (2)$$

Where,

N_{ecg}= the output noisy signal

C_{ecg}= Initial 10 s clear ECG signal

v = 10s randomly selected noisy sample

η= Amount of the noisy sample which added with clear signal

P_C= Power of the clean signal

P_v= power of noisy signal.

Our aim is to de-noise this generated noisy signal.

2.2. Shift the Signal by Detecting R Peaks

Before de-noising process each generated noisy signal is compared with its clear ECG signal and observed that each QRS peak of noisy data is shifted by a constant value, so at the beginning of de-noising process, using MATLAB code each peak is try to bring into their desired position, for which at first we try to detect the positional value of each R peak [4] using following steps:

Step 1: In this step an ECG signal (D) is selected as an input signal and normalization have been performed on selected signal to bring the integer sample values by using the following equation:

$$y[n] = \mathrm{fix}((D/\max(D))*100) \quad (3)$$

Step 2: In this step histogram is generated for which total normalized sampled data was divided into a series of intervals on purely trial and error basis, each interval act as a window. The number of intervals is obtained by using the following equation.

$$w_n = \mathrm{round}((y[n]/\mathrm{window}) \quad (4)$$

Step 3: This step count how many sample values differs in each w_n interval of ECG signal and stored them in z[n] array, where n= 1 to w_n.

Step 4: Frequency of samples can be shown in successive intervals of equal size by histogram generated in step 2. Total number of intervals can be calculated using expression written bellow

$$n = \sum_{i=1}^{k} m_i \quad (5)$$

where,

n= total number of intervals

k= total number of bins

m_i=histogram

Step 5: Threshold value is assigned to *tsd* which is obtained by using the following equation.

$$tsd = \mathrm{integer}\,(\max(w_n)/2)+4 \quad (6)$$

the above threshold value (tsd) is a function of w_n which is chosen completely in trial and error basis, all the R peak regions are detected accurately after computing this threshold value.

Step 6: The condition based on which the largest bin marked as the R peak region is,

$$\text{If} z[n-1] < z[n] > z[n+1] \quad (7)$$

and

z[n]>tsd.

Step 7: Now the R peaks location is found from the entire marked histogram bin by computation of maximum value within the histogram bin from y[n] array. So R peaks

$$R(i) = y[j] \quad (8)$$

Where,

i= number of R peaks

y = noise removal ECG signal

and

j= 1 to length of ECG signal.

Now the above whole process of R peak detection is done for both clear and noisy ECG signal by which location of R peak is detected and by taking difference between those positional value of Rpeak for noisy and clear ECG signal, amount of shift can be calculated for each signal, now by adding or subtracting that value the drift in position can be fixed.

2.3. Wavelet Decomposition of Noisy ECG Signal

After shifting process multilevel wavelet decomposition is performed on the noisy ECG signal. A proper value of decomposition layer play an important role in this process, so its value should be calculated properly, generally in order to eliminate high frequency noise and extract low frequency components the number of decomposition layer will be increased to some extent [15]. But if the number of layer is too high the error become very large and if the number is too small the de-noising effect will be unsatisfactory. So obtaining more wavelet coefficients the number of decomposition layers should be approximately increased. In our present work we calculate the value of decomposition layer using MATLAB code, whose value is 11. After decomposition detailed and approximation coefficient of each layer are calculated using MATLAB code.

2.4. Application of Threshold

Now calculated coefficients are de-noised using threshold method. The value of threshold for de-noising is calculated using the formula [1].

$$\lambda = \sigma\sqrt{2\log N} \quad (9)$$

Where,
λ = value of threshold,
N = the number of samples,
and
σ= the standard deviation.

Here in this paper both hard and soft threshold are used. In hard threshold processing when absolute value of wavelet coefficients are less than the given threshold, it will be zero. When the wavelet coefficients are larger than the given threshold it will remain unchanged [1] that is as follows –

$$\omega = \omega, \quad \text{for } |\omega| \geq \lambda \qquad (10)$$
$$= 0, \quad \text{for} |\omega| < \lambda$$

Where,
ω = certain wavelet coefficient, and
λ= given threshold.

In soft threshold processing when absolute value of the wavelet coefficient is less than the given threshold value, set it as zero. If it is larger than the given threshold value, let the wavelet coefficient subtract the threshold value [1] that is as follows -

$$\omega = [\mathrm{sgn}(\omega)](|\omega| - \lambda), \text{ for } |\omega| \geq \lambda \qquad (11)$$
$$=0, \text{ for} |\omega| < \lambda$$

Though hard threshold process is superior to soft threshold in mean square but it impose additional oscillation and jump point to de-noised signal which does not have the smoothness of the clear signal. The wavelet coefficients obtained by soft threshold have good continuity and the tested signal will not produce additional oscillation. However due to compression of the signal there will be certain deviation which directly affects the approximation level between the reconstructed signal and clear signal. The total comparison process of threshold technique to get de-noised signal is done using MATLABcode. In this process coefficients which are responsible for distortion changed and get new values.

2.5. Reconstruction of ECG Signal After De-noising

After completion of threshold process using those changed value of coefficients and other unchanged coefficients we reconstruct the new de-noised signal. Whole reconstruction process is done using MATLAB code. After reconstruction using algorithm of detection and identification of ECG waves by histogram approach [4] we compare the feature and different parametric values of reconstructed ECG signal with the clear ECG signal.

3. Result

In this present work we try to de-noised the noisy ECG signal which is generated using 125 clear ECG data from CSE multi-lead database and sample noises of three type (ma, em, bw) from MIT- BIH PhysioNet noise stress test database (NSTDB) for different values of SNR. Here using 'db2'wavelet 11 level decomposition upon noisy ECG signal is performed.

Figure 3 shows all 11 level decomposition layers.

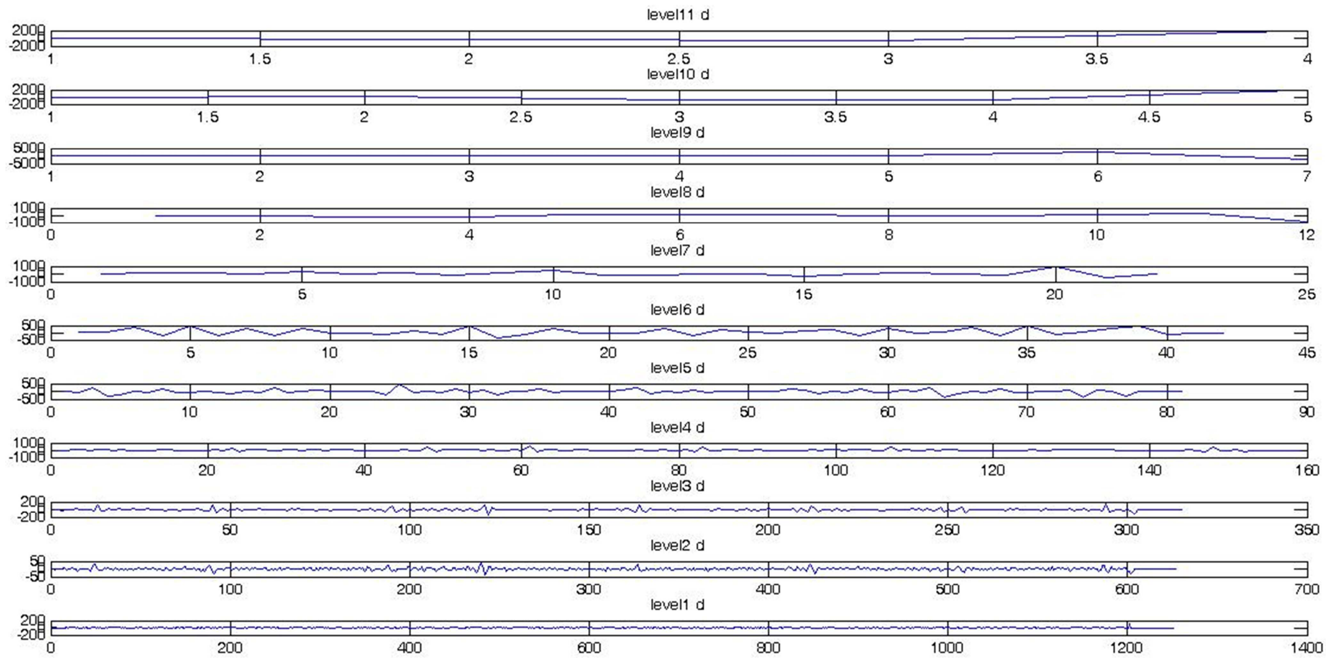


Figure 3. *11 level wavelet decomposition layers of Noisy ECG signal MO1-024.*

After decomposition using threshold method noisy signals are de-noised. Figure 4 shows noisy signal and de-noised signal after threshold.

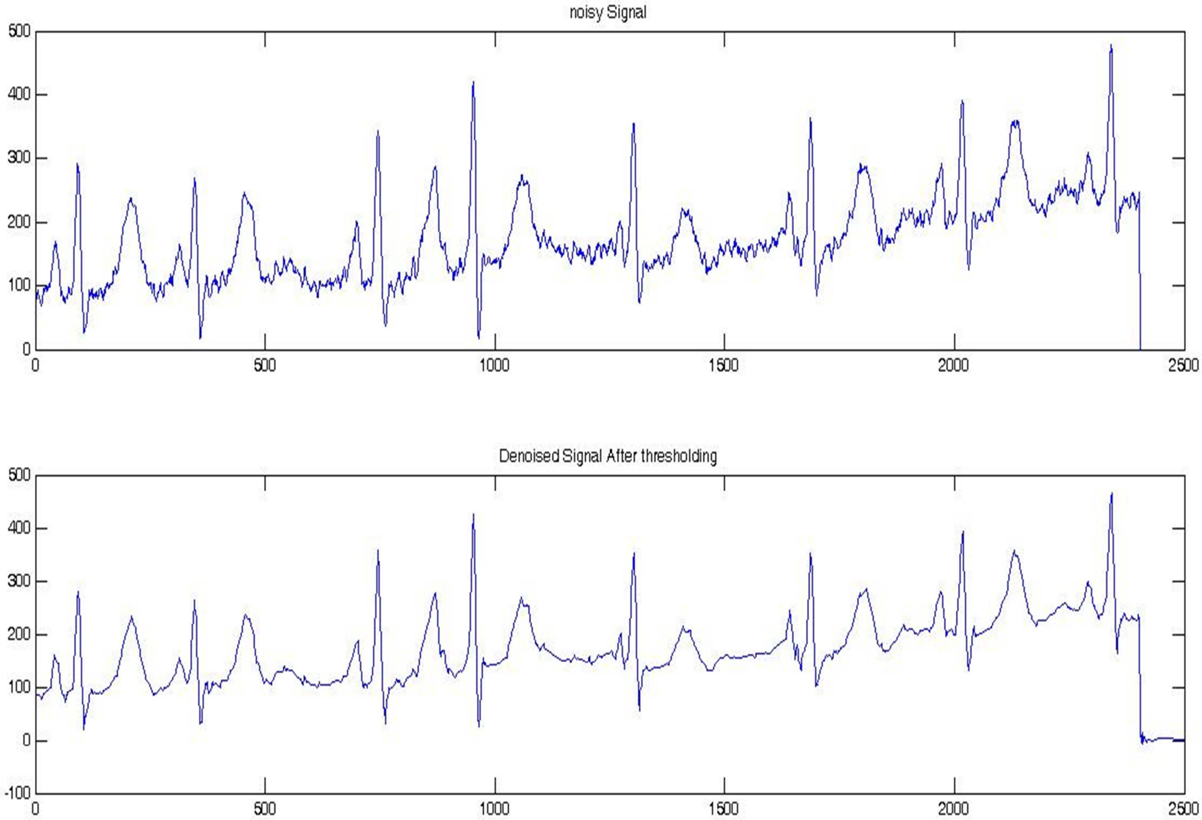
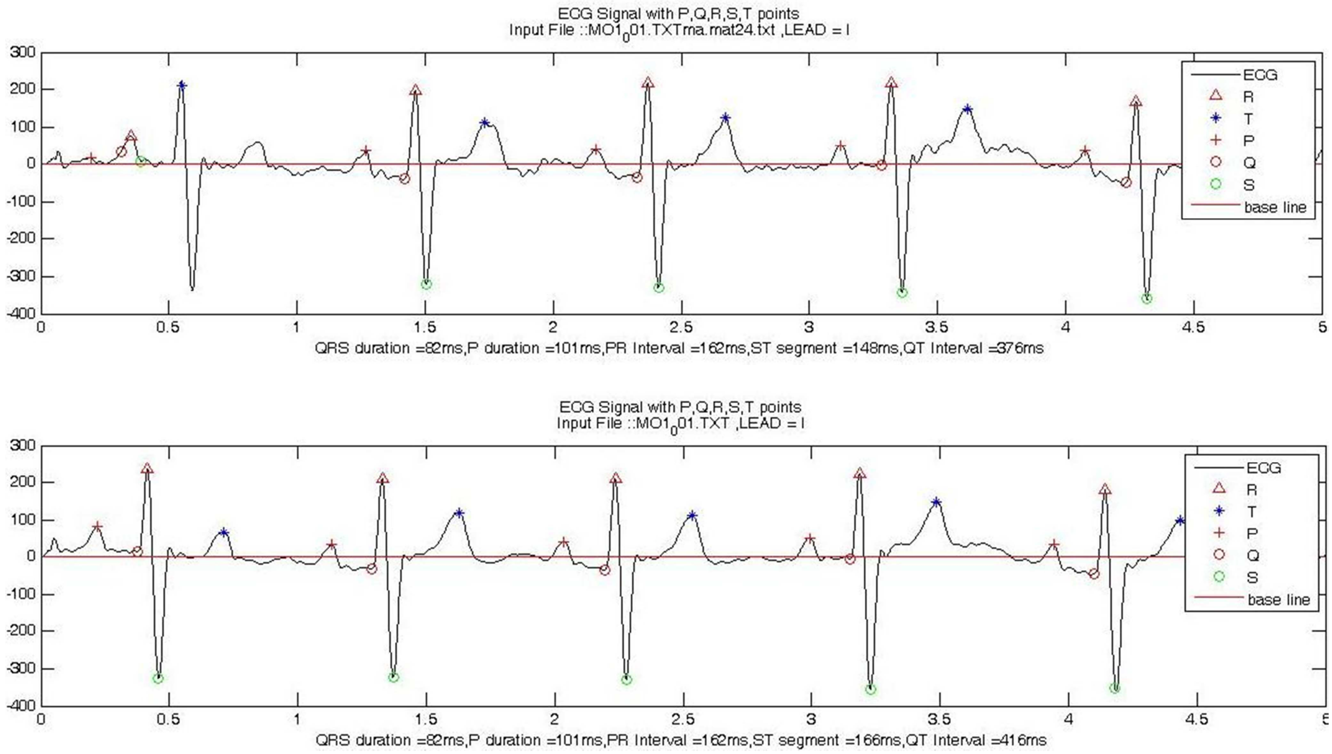


Figure 4. *Noisy and de-noised signal of MO1-024.*

After de-noising we generate a database of reconstructed signals, then using algorithm of histogram approach [4] we verified the amplitude and duration of different segments of clear, noisy and reconstructed ECG signals simultaneously. Figures 5 and 6 shows the features of clear, noisy and reconstructed signal of different data.



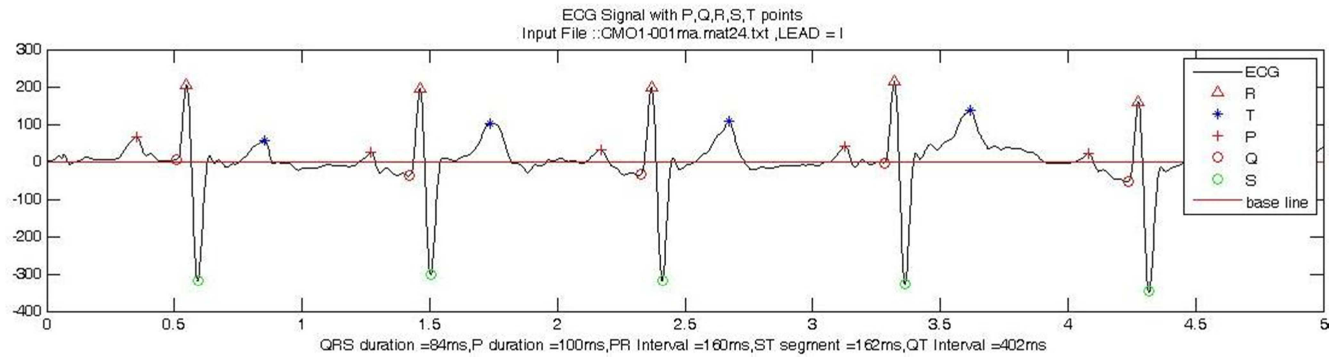


Figure 5. Feature of clear, noisy and reconstructed ECG signal MO1-001.

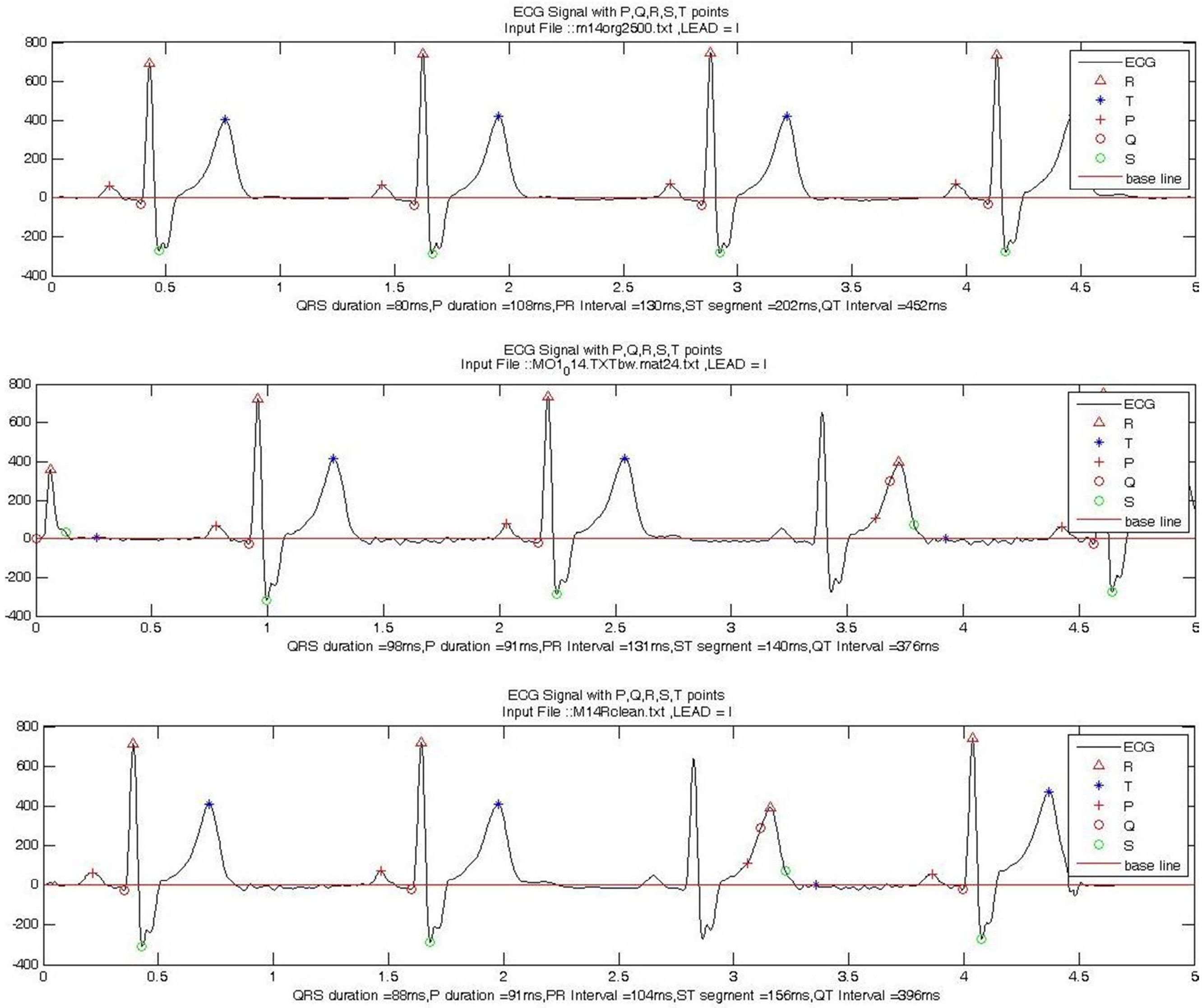


Figure 6. Feature of clear, noisy and reconstructed ECG signal MO1-014.

After extracting the values of the amplitude and duration of various segments of ECG signals for clear, noisy and reconstructed data, we compare those values [12, 13] for each signal data. Tables 1, 2, 3 and 4 shows the comparison values of different parameters of ECG signal.

Table 1. *QT interval.*

Data	Original	Noisy	Clean	Error in noisy signal	Error in de-noised signal
MO1-014	452	376	452	16.8	0
MO1-028	416	414	416	0.4	0
MO1-034	366	342	370	6.5	1.09
MO1-057	366	360	360	1.6	1.6
MO1-066	384	388	388	1.04	1
MO1-073	386	384	386	0.5	0
MO1-075	404	402	402	0.4	0.4
MO1-082	354	368	360	3.95	1.6
MO1-097	384	382	388	0.5	1
MO1-098	406	408	406	0.4	0
MO1-116	370	374	370	1.08	0
MO1-119	432	400	434	7.4	0.4
MO1-120	408	408	408	0	0
MO1-006	384	388	388	1.04	1
MO1-055	428	392	428	8.4	0

Table 2. *Value of QRS.*

Data	Original	Noisy	Clean	Error in noisy signal	Error in de-noised signal
MO1-014	80	98	80	22.5	0
MO1-056	72	72	72	0	0
MO1-057	80	80	80	0	0
MO1-066	78	76	76	2.6	2.6
MO1-067	100	100	100	0	0
MO1-073	114	112	114	1.3	0
MO1-074	104	106	106	1.9	1.9
MO1-075	108	112	112	3.7	3.7
MO1-083	138	136	138	1.4	0
MO1-101	114	112	114	1.7	0
MO1-102	116	116	116	0	0
MO1-116	104	106	106	1.9	1.9
MO1-121	74	74	74	0	0
MO1-006	78	76	76	2.5	2.5
MO1-057	80	86	80	2.8	0

Table 3. *PR interval.*

Data	Original	Noisy	Clean	Error in noisy signal	Error in de-noised signal
MO1-001	194	158	170	18.55	12.3
MO1-002	126	124	108	1.58	14.2
MO1-006	126	126	114	9.5	9.5
MO1-007	142	126	126	11.2	11.2
MO1-008	140	104	118	25.7	15.7
MO1-012	160	154	128	3.75	20
MO1-013	180	148	156	17.7	13.3
MO1-014	168	131	128	22	23.8
MO1-027	110	96	112	12.7	1.8
MO1-028	122	120	118	1.6	3.2
MO1-029	166	156	122	6	26.5
MO1-057	128	114	118	10.9	7.8
MO1-066	142	124	124	12.6	12.6
MO1-067	158	130	128	17.7	18.9
MO1-073	138	122	124	11.59	10.1

Table 4. *ST interval.*

Data	Original	Noisy	Clean	Error in noisy signal	Error in de-noised signal
MO1-013	198	186	192	6	3
MO1-029	148	146	144	1.3	2.7
MO1-056	180	178	178	1.1	1.1
MO1-057	120	128	120	6.6	0
MO1-073	104	104	104	0	0
MO1-074	168	164	166	2.3	1.1
MO1-098	142	142	144	0	1.4
MO1-120	154	156	156	1.2	1.2
MO1-006	142	144	144	1.4	1.4

Data	Original	Noisy	Clean	Error in noisy signal	Error in de-noised signal
MO1-043	160	134	162	16.25	1.2
MO1-055	188	140	186	25.5	1
MO1-073	104	106	104	1.9	0
MO1-098	142	140	140	1.4	1.4
MO1-007	80	74	80	7.5	0
MO1-014	202	186	202	7.9	0

To study the performance of the of the used process or to detect its accuracy three statistical measurements Selectivity, Predictivity and Detection accuracy, which are commonly used for ECG peak detection are calculated for different SNR and shown in table 5. These measuring quantities can be defined as follows:

Selectivity: The ratio of the number of correctly detected events TP to the total number of events.

It can be expressed as

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

Where FN is false negative or number of missed events.

Predictivity: The ratio of the number of correctly detected events TP to the total number of events detected by the analyzer.

It can be expressed as

$$PP(\%)=\frac{TP}{TP+FP}\%$$

Where FP is the number of falsely detected events.

Detection accuracy: The ratio of percentage of detected peaks to the total number of peaks. It can be expressed as

$$DA(\%)=\frac{Detectedpeak}{Totalpeak}\%$$

Calculated Selectivity, Predictivity and Detection accuracy, for several SNR represented graphically which shows accuracy falls for lower value of SNR respectively in following figures.

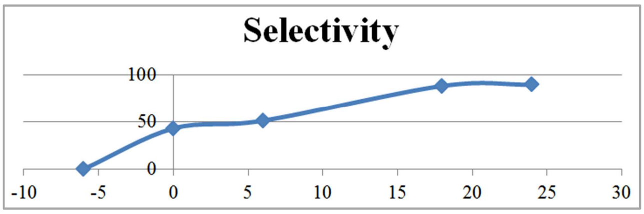


Figure 7. *Graphical representation of selectivity.*

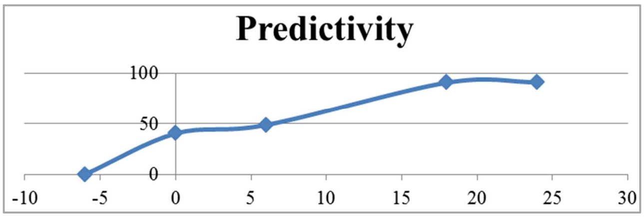


Figure 8. *Graphical representation of predictivity.*

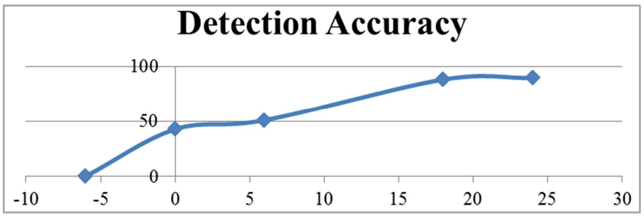


Figure 9. *Graphical representation of detection accuracy.*

Table 5. *Calculated values of Se, PP, DA for different ECG data.*

Original signal	SNR	TP	FP	FN	Se	PP	DA
MO1-003	24	7	0	0	100	100	100
MO1-004	24	6	0	0	100	100	100
MO1-007	24	6	0	0	100	100	100
MO1-008	24	5	0	0	100	100	100
MO1-009	24	5	0	0	100	100	100
MO1-017	24	5	0	0	100	100	100
MO1-018	24	6	0	0	100	100	100
MO1-019	24	5	0	0	100	100	100
MO1-001	18	5	0	0	100	100	100
MO1-002	18	6	0	2	75	100	75
MO1-003	18	7	0	0	100	100	100
MO1-004	18	6	1	1	85.7	85.7	85.7
MO1-008	18	5	0	0	100	100	100
MO1-009	18	6	0	0	100	100	100
MO1-010	18	4	0	0	100	100	100
MO1-016	18	5	1	1	83.3	83.3	83.3
MO1-017	18	5	0	0	100	100	100
MO1-002	6	7	0	3	70	100	70
MO1-010	6	2	2	1	66.6	50	66.6
MO1-011	6	2	2	1	66.6	50	66.6
MO1-015	6	3	1	0	100	75	100
MO1-001	0	2	3	0	100	40	100

Original signal	SNR	TP	FP	FN	Se	PP	DA
MO1-002	0	6	0	2	75	100	75
MO1-009	0	4	2	1	80	66.6	80
MO1-010	0	2	2	1	66.6	50	66.6
MO1-011	0	6	1	0	100	85.7	100

4. Conclusion

After performing the whole experiment it can be seen that the used algorithm of this paper can minimize noise from ECG signal, which is clear from figure 2. In this experiment we also observe features of clear, noisy and de-noised ECG signals and verify different parametric values of those signals like QRS complex, QT, PR and ST intervals, after comparing those values we observed that though we get nearly 100% accuracy for de-noised data of QRS complex and QT intervals but the detection accuracy for PR and ST interval are more or less distorted in de-noised dataset. Statistical Analysis of thosede-noised data are also been done to detect the accuracy of the process, which shows its accuracy degraded with lower SNR values. So in our further work we try to overcome such limitations.

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