Discrete Cosine Transform based ECG Signal Analysis and Processing

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Abstract

Cardiovascular disease (CADs) is considered the primary leading cause of death. Irregular activity of heart, these disease can be detected and classified by Electrocardiogram (ECG), which is constructed from using electrodes placed on human skin to record the electrical activity of the heart. Because QRS complex represents the basic part of the ECG signal, these components should be recognized in order to analysis the other characteristics of the signal. Different methods and algorithms are proposed to analysis and processing the ECG signal. In this paper, a new QRS complex recognition method are proposed based on discrete cosine transform (DCT) with variable adaptive threshold method, which is used to determine threshold based on characteristic of each ECG signal to detect upper and lower levels of threshold to detect the peak of the signal. At first, the DCT is applied to the ECG signal to isolate it into different coefficients and eliminate or reduce the noises of the signal based on processing of high frequency components of DCT coefficients, which have less information, then the ECG is reconstructed by cropping the most important coefficients to be used in threshold determination. The basic idea is that the reconstructed signal have high differences between the components of the signal, and this facilitates the process of calculating the threshold value, which is used later to find peaks of ECG signal. The proposed method is tested and its performance are determined based on three different datasets, which are MITBIH Arrhythmia dataset, (LTSTDB) and (EDB) and the performance are evaluated using different metrics, which are Detection rate, accuracy, specificity and sensitivity. The experimental results show that the proposed method is performed or outperformed other works, therefore it can be used in peak detection applications.

Keywords

ECG, DC, QRS and DR.

Introduction

Cardiovascular disease (CADs) is considered the primary leading cause of death. Irregular activity of heart, which is named as arrythmia beat or rate may lead to sudden death. Electrocardiogram (ECG) is discovered more than 100 years ago, which is a series of electrical waves and deflections record activity of the heart from a certain view. It can be considered as promising tool for examining cardiac tissues and structures diagnosis heart problems because it reflects activity of the heart as electrical wave. ECG signal is constructed from using electrodes placed on human skin to record the electrical activity each a period of time and represent it by different waveforms. These extracted signals contains details description about the heart and its functional activities, therefore, it is used for diagnosis of heart diseases, heartbeat classification, etc. ECG often is used in fields of disease classification, detection of up normality of heartbeat, also it may be used in recognition or biometric identification, therefore it is very important indicator and low cost tool in diagnosis of heart problems and examining structure of tissue (P. Xiang, H. et al.; (2016), O. El Bcharri et al. 2017)). ECG can be characterized by sequence waves of P, QRS and T-wave for each beat. The QRS complex is the most important components of ECG waveform, thus it reflects hearts activity during the ventricular contraction, its time and shape provide current state information of the heart (Gaurav J. et al. (2012); Rachid H. Et al. (2014)).

R peak represents the most important part of QRS complex, therefore it is used to represents and define the shape of the signal overall, and thus distinguish this part is very necessary to determine the other characteristics of the signal, since location of R-peak can be used to determine components of ECG signal, therefore R peak must determined accurately. After determined R location, other ECG components like P and T waves are evaluated based on R peak according to their locations with respect to QRS complex. There are different methods and approaches are introduced to recognize peaks of ECG signal, some of then can be described in the following section (Gargasas, et al. (2004).; Aqeel M. Hamad Alhussainy (2020); Antonio E. et al. (2018)).

Literature Survey

Seon et al. (2017) proposed a new algorithm for QRS complex recognition based on DWT, this method is used first by removing or reducing noise and by creating Shannon envelope by first applying derivative function, which is accomplished by using first order (HPF), then normalization is applied to extract peak of energy, later it is used to recognize R peak based on determining R-R interval, different filters types are used for smoothing the signal.

Xuanyu et.al. (2018) used threshold method to determine QRS peak of the ECG signal. The basic stages in this method are signal processing, detection of peak and design threshold method to detect QRS complex. Good rate of detection, sensitivity and the specificity are achieved. The experiments are tested on MIT-BIH dataset. The results are compared with other algorithms, then the RR time is evaluated based on the location of R peak.

Aiyun et. al. (2020) introduced a simple method for QRS complex detection. At first, the original signal is enhanced by using filters like a band pass filter and first-order derivative, then extreme points are determined by using moving window, then QRS complex is detected by using a threshold. The proposed method is Tested by using MIT BIH Dataset and the results are showed that the proposed method is achieved high accuracy.

Trio et. al. [2019] introduced peak detection of QRS complex by using average filter with thresholding method. The signal is detrended to reduce baseline noise of the signal. Then band pass filter is applied, this filter have low pass and high pass filter to eliminate the noises in the QRS complex location of the signal, also squaring process are used to convert all points of the signal to positive, then moving average and thresholding method are used.

Daizong et. al. [2018] presented efficient QRS complex detection algorithm. At first, it is used a differentiator with different frequency center to derive frequency band of ECG signal, then Hilbert transform is applied to create first derivative envelop of the signal. Later threshold method is used to reduce FP and FN. The method is tested by MIT-BIH dataset and the results show that proposed method was achieved good Sensitivity and error rate with low execution time.

Hung et. al. [2019] introduced an improved method to detected QRS complex based on using a bi-orthogonal spline of wavelet with four level used to reduce noises and to get best level detail of wavelet filter in order to reduce or remove more details information from high frequency sub band. QRS peaks detected based on selection of extremum pairs of details coefficients of wavelet transform by using set of rules to make decision. The obtained results are proved that the proposed method is achieved good accuracy with low rate of error, positive prediction and sensitivity value. The algorithm tested on MIT-BIT dataset.

Billal et. al. [2019] suggested an approach for QRS complex recognition for (ECG) signal. This method is reconstructed two type of signals in order to detect QRS. The QRS complex point is determined at first, P wave is determined by using method. This method extracted P waves without other details information from original signal. It is applied and tested by using MIT BIH dataset.

Aqeel M Hamad [2020] proposed a new algorithm for QRS complex detection based on DWT. At first, the signal applied to DWT with adaptive threshold to remove the noises, then DWT applied to extract approximation coefficients, later, statistical information is determined from approximation coefficients, which represent the significant information of the, later, threshold is computed, it is determined based on statistics information of original and the reconstructed signal by low components only. Then two thresholds are determined, which will be updated based on number of detected peaks. This process continues until the same values of the peaks are obtained until by the two thresholds. The proposed method is tested by (LTSTDB) and (EDB) dataset.

Research Methodology

In this paper, a new QRS complex detection method are proposed based on discrete cosine transform (DCT) with threshold method, which is used to determine threshold based on characteristic of each ECG signal to detects upper and lower level of threshold to detect the peak of the signal. The block diagram of the proposed method is shown in Figure 1. The basic idea of the proposed method is that the most important information, which give the general shape of the signal can be determined from the basic coefficients of DC, then this coefficient can be processed to be used to determine the effected thresholds levels based on reconstructing the signal from these most significant information only which can recognize the important segment of the signal.

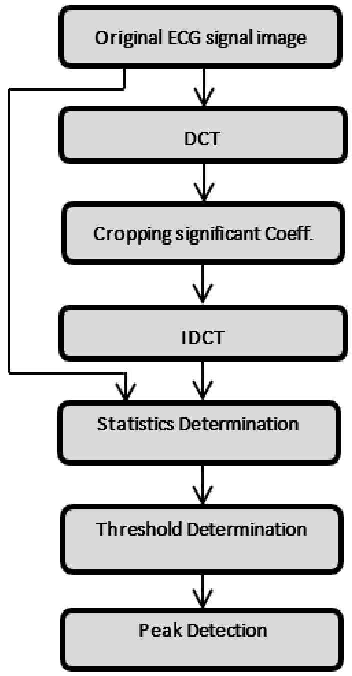

Figure 1 Block diagram of the Proposed QRS detection method

Discrete Cosine Transform (DCT)

Discrete Cosine Transform (DCT) is used to separate the signals into different frequencies parts, therefore, the information's of the signals are separated according to their important. The most important information is treated separately, while the details are processed in lossy manner as required in some application such as compression and enhancement, thus DCT can be used in signal processing application, it is used cosine function to determine the different frequencies by eq. (1): (Wan Azani M. et al. (2019); Tsai S. and Yang S. (2017); Arthita G. and Rama C (2016)).

$$\mathrm{D(i,j)} = \frac{1}{2\sqrt{N}} C(i)C(j) \sum_{x=0}^{N-1} \sum_{x=0}^{N-1} (P(x,y)) \cos[\frac{(2x+1)\, i\pi}{2N}] \cos[\frac{(2y+1)\, i\pi}{2N}] \quad (1)$$

Where C(i) is determined by eq.(2):

$$\mathrm{C(i)} = \begin{cases} \frac{1}{\sqrt{2}} \; if\ i = 0 \\ 1\ if\ i > 0 \end{cases} \quad (2)$$

N is the size of the block [Matej U.& Rozenn D(2017)].

Proposed Algorithms

A new QRS detection algorithm are proposed based on DCT, which are used to select most significant coefficients of the original signal, by extract most significant frequencies from the coefficient of DCT, Which represents the general structure of the signal, then IDCT were applied to reconstruct the signal. Then deterministic statistics are determined to be combined with the statistics of the original signal to calculate the upper and lower thresholds. These two threshold values are used to determine the range of values that have the value of R peak of ECG signal, then the values of thresholds are updated based on number of detected peaks. The proposed algorithms is shown in Figure 2 and Figure 3.

Algorithm I

Input = $\boldsymbol{ECG\ signal}$;
Output=Peaks of the signal

Step 1 Preprocessing (Enhancement and arrangement).
Step 2 Determine statistics of the signal mean, maximum and standard deviation.
Step 3 Applying DCT.
Step 4 crop the most significant coefficients of DCT (DC coefficients).
Step5 Applying invers (IDCT) to reconstruct the signal.
then determine $mean_{DCT}, max_{DCT}$ *and* std_{DCT}
Step 6 Calculate threshold parameters as following:

$$T_1 = \lambda_{max} * max_{DCT} + (1 - \lambda_{max}) * max_{ori} \quad (3)$$

$$Where\ \lambda_{max} = \frac{max_{DCT}}{max_{DCT} + max_{ori}} \quad (4)$$

$$T_2 = \lambda_{mean} * mean_{DCT} + (1 - \lambda_{max}) * mean_{ori} \quad (5)$$

$$Where\ \lambda_{mean} = \frac{mean_{DCT}}{mean_{DCT} + mean_{ori}} \quad (6)$$

$$T_3 = \lambda_{std} * std_{DCT} + (1 - \lambda_{std}) * std_{ori} \quad (7)$$

$$Where\ \lambda_{std} = \frac{std_{DCT}}{std_{DCT} + std_{ori}} \quad (8)$$

Where max_{ori}, $mean_{ori}$ *and* std_{ori} *are maximum, mean and standard deviation of the original signal while* $mean_{DCT}, max_{DCT}$ *and* std_{DCT} *are maximum, mean and standard deviation of the reconstructed signal after DCT respectively.*
Step 7 Compute the lower and upper threshold as in equation (9 and 10):

$$Th_L = (0.05 * T_1) + (0.5 * T_2) + (0.1 * T_3) \quad (9)$$

$$Th_U = (0.7 * T_1) + (0.5 * T_2) + (0.1 * T_3) \quad (10)$$

Step 8 Determine the peaks for upper and lower thresholds by applying ***(Algorithm II)*** *and determine:*
N1 peak number of peaks by applying upper threshold
N2 peak number of peaks by applying upper threshold.
Step 9 while (N1peak!= N2peak)
$Th_L = Th_L + \Delta * \beta$ *% update lower threshold* (3.14)
$Th_U = Th_U - (\Delta * \beta)$*% update upper threshold* (3.15)
Where $\Delta = Th_U - Th_L$ *and* β *is constant selected empirically, we used* $\beta = 0.25$.
Step 10 update peak detection based on:
If (no peak detected after 1.5 time of RR)
*Th=th*0.75*
Else
If (there is peak in less than 0.8 time of RR)
*Th=th*1.5*
Step 11 Compute R-R time and HR by

$$RR\ time = samples\ number\ *\ time\ of\ sample \quad (11)$$

$$Heart\ Rate\ (HR) = \frac{60}{RR\ time} \quad (12)$$

Figure 2 The proposed Algorithm for peak recognition

Algorithm II

Input =signal, Th ;
Output=Peaks of the signal

```
Step 1 initialization   Input ECG signal, th, variables initialization and detection
       window size
Step 2 determine max=max. of signal
Step 3 while (I < size of signal)
                {if (th<max) Do
                    Th =th*0.9;
                  End
                    if (signal > th) %Update Peaks and Peaks coordinates
                      {
                        Peak(p)=signal(i);
                        Peak coordinate(p)=I;}
                     End
                  I=i+1; p=p+1;
         End
Step4 Correction of detected peaks
       while (I < size of Peak)
                while {Peak(i+1)-Peak(i)==1)
                        sample_No= sample_No+1;i=i+1;
                end
              p.p_sample(s)= sample_No;
             sample_No=1;s=s+1;
         end
Step 5 Determine number of samples between successive peaks
         while (i < size of  p.p_sample )
             Maxpeak(i)=signal (Peak coordinate(k));
            Maxcoordinate(i)= Peak coordinate(k);
            K=k+ p.p_sample(i);i=i+1;
        End
Step 6 Upate final peaks and its coordinate
      while (I < size of Peak )
          Max= Maxpeak(y);
          Maxcor= Maxcoordinate(y);
         For j=1: p.p_sample(i)
            If (signal(Peak coordinate(j))>max)
                Max= signal (Peak coordinate(j));
               Maxcor= Peak coordinate(j));
            End
     End
```

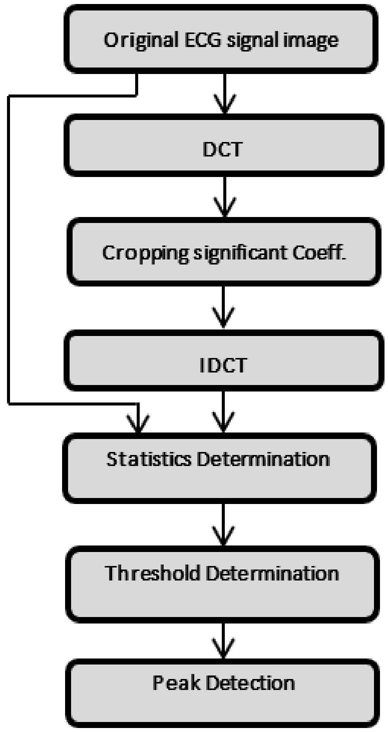

Figure 3 Peak Determination Algorithm

Performance Measures

Different measures were used to determine the efficiency of the proposed algorithms, which are applied to the three dataset EDB, LSTDB and MIT-BIH. These metrics can by described as following:

1. Accuracy: It is the ratio of (TP) to total number of detected peaks.

$$ACC(\%) = \frac{TP}{TP + \mathrm{FN} + FP} \quad (13)$$

2. Sensitivity: It is the ratio of the true detected peaks to total detected peaks.

$$Sen(\%) = \frac{TP}{FN + TN} \quad (14)$$

3. Detection Rate: It is the ratio of the difference between actual detected peaks and failed detected peak to actual detected peaks.

$$DR(\%) = \frac{TP}{(TP + FN)} \quad (15)$$

4. Specificity: It is the ratio of true peaks to true peaks and false positive.

$$Spe(\%) = \frac{TP}{TP + FP} \quad (16)$$

Where, (TP) is true detection, FN shows the failure of the algorithm to detect the peak, If the algorithm detects non-peak as QRS complex, it is named as false positive (FP).

Results and Discussions

The proposed method is used to recognize peaks of ECG. It is tested and are evaluated by using three different databases, which are (LTSTDB) (F. Jager, A. et al. (2003)), (EDB) (A. Taddei et al. (1992).) and MITBIH Arrhythmia database (B. George and R. Mark. (2001)). MITBIH is sampled at rate 360, while other datasets sampled at 250 samples per second. These data sets are the standard data, which can be used to test ECG signal processing application. The algorithm is implemented by using matlab (2019a) CPU 2.9GH intel with cori7 with 16 GB of RAM, operating system windows ten. The results of preprocessing stage for two different signals are shown in Figure 4 and Figure 5.

The noisy signal is enhanced based on DCT as shown in Figure 4, where the details information, which have noise is preprocessed. As shown in Figure 5, there is no fixed level for drawing samples of ECG signal, thus, in order to process the signal and determine its peaks, arrangement steps is required. For ECG signal in Figure 6, it is clear that the signal have less problem and it is processed correctly, and this proved that the preprocessing can be applied for any quality of signal, which may have different characteristics.

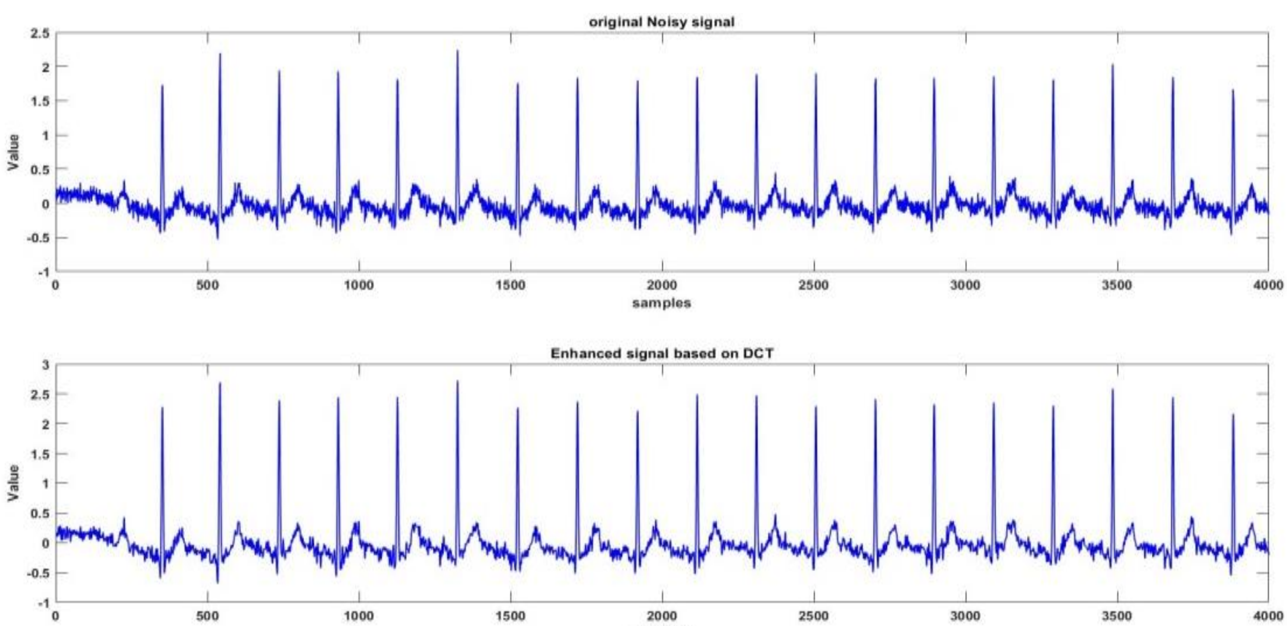

Figure 4 Noisy and Enhance ECG signal based on DCT

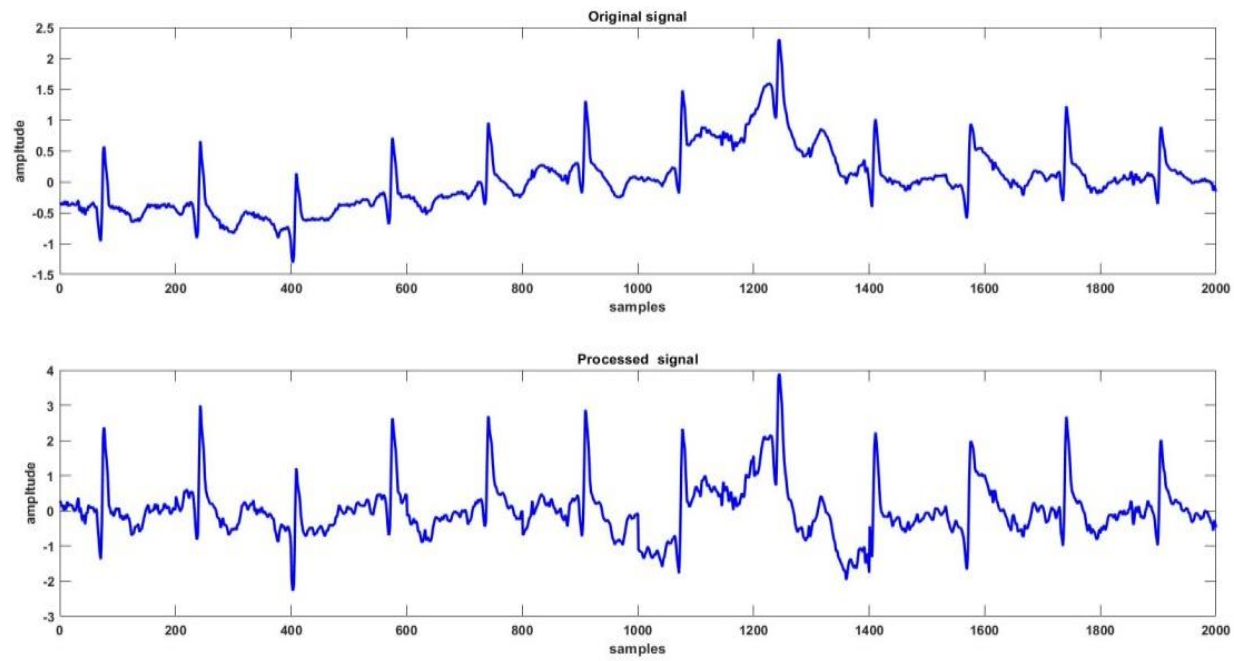

Figure 5 Level enhancement of ECG signal

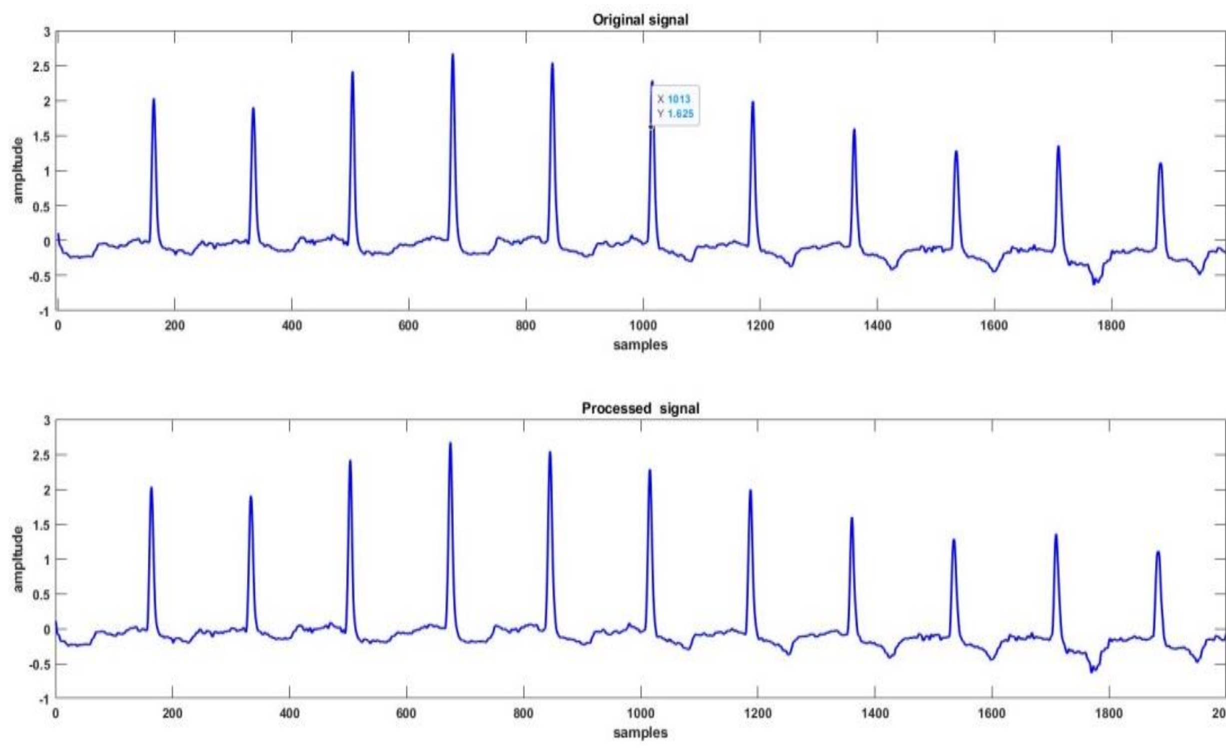

Figure 6 Level enhancement for ECG signal

The ECG signal may be extracted in inverted form due to extraction problem, therefore, in order to detect the R peaks, the signal should be inverted and this can be accomplished by determining the absolute value of maximum and minimum value of the signal then comparing between them and correct the signal according to the result of this comparison. It is clear from Figure 7 that, this method is perfect for all ECG signals.

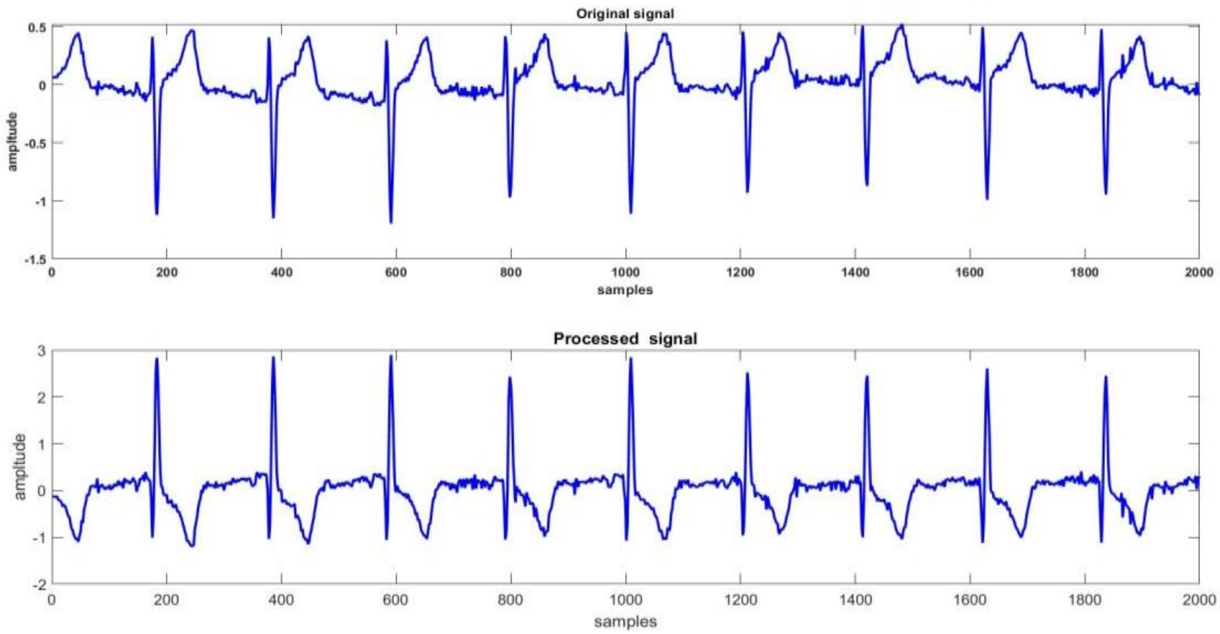

Figure 7 preprocessing and arrangement of ECG signal

Figure 8 and Figure 9 show the differences between values of samples of original and the reconstructed ECG signal after applying (DCT, Cropping and processing, and IDCT) for (20081m and e108m) signals, respectively. The shape of the signal can be modified to isolate the peaks to facilate its recognition by using the modified coefficients. For instance, in Figure 9, It is clear that, peaks points are amplified greater than other points based on this fact, the differences between peak of the signal and highest point in the signal is explained in red lines, which is approximately (1.02), for original signal, while it is (2.47) for the processed signal, this increasing in the difference can facility peak recognition by obtaining appropriate value of threshold. This improvement of signal is accomplished by applying DCT and cropping of most significant coefficient to be used later in threshold computation. Figures 10 and 11 show the reconstruction of the signal by one quarter and one half coefficients only, respectively.

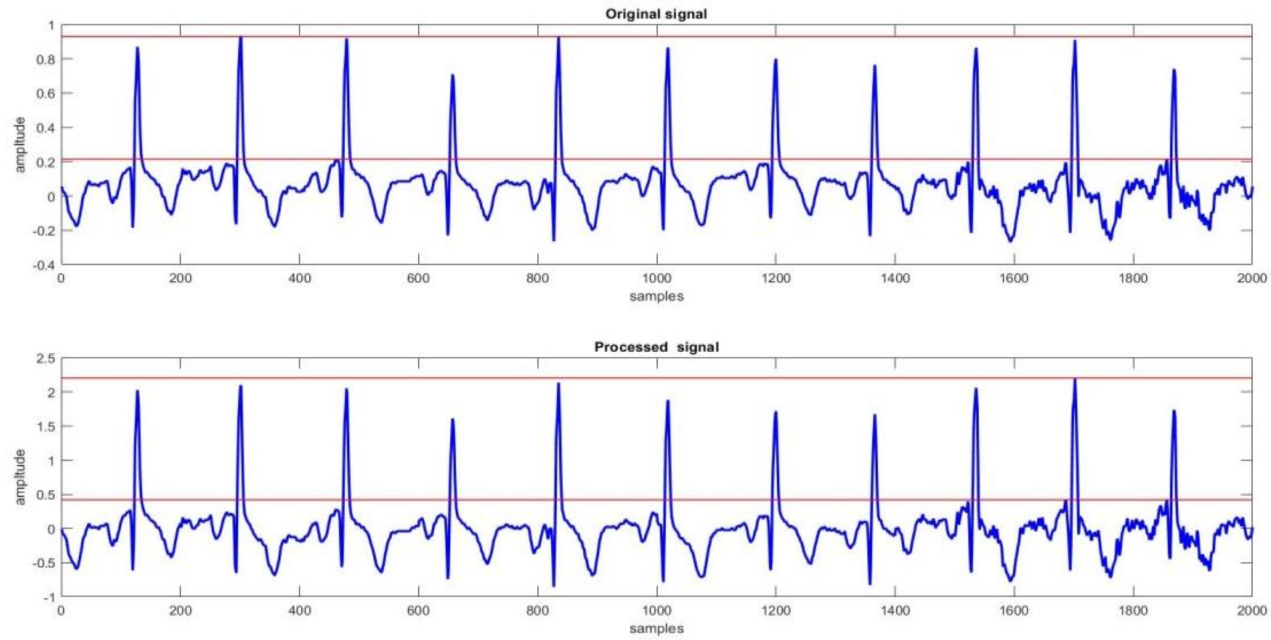

Figure 8 Differences between the values of ECG samples

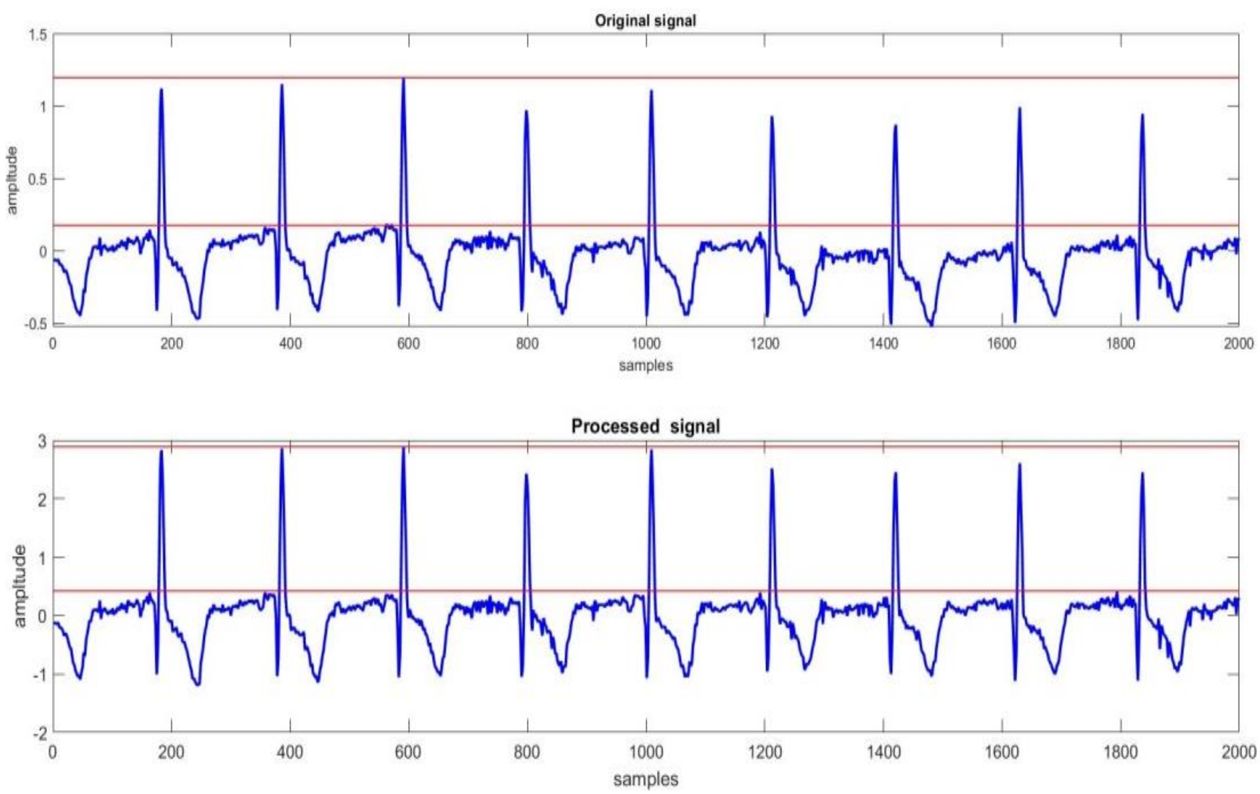

Figure 9 Differences between the values of ECG samples

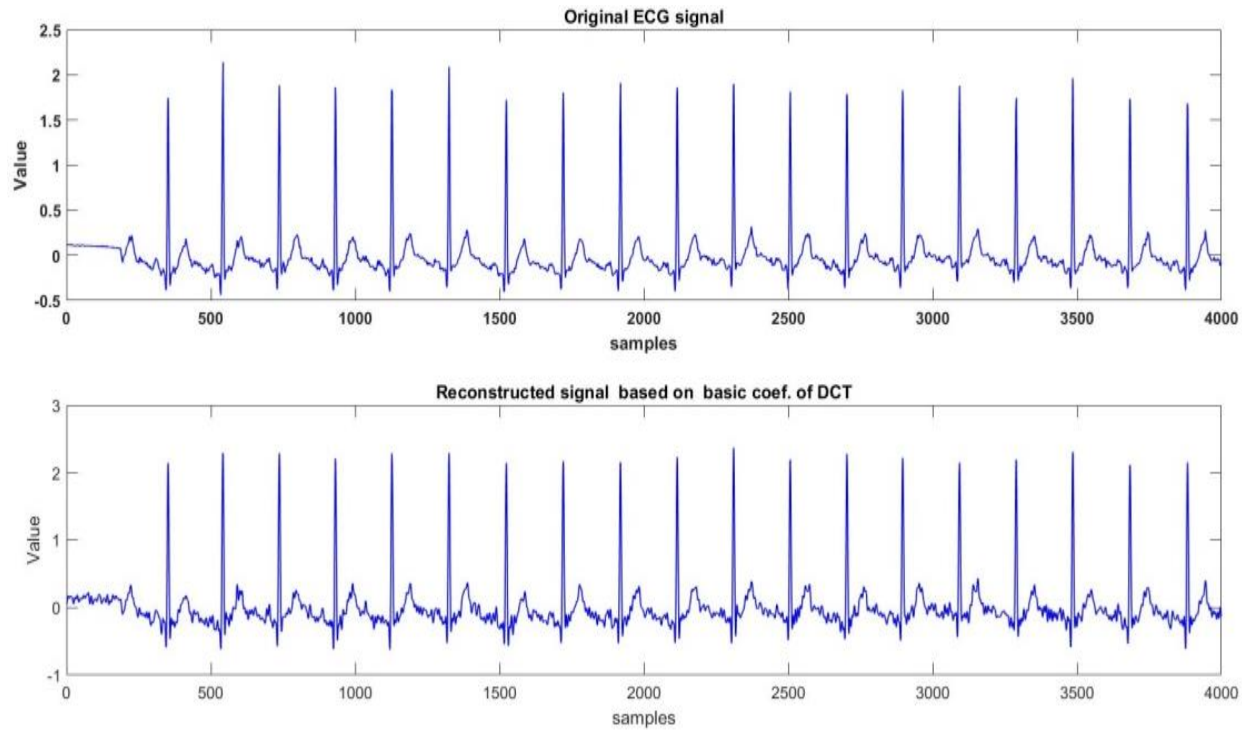

Figure 10 Original and Reconstructed ECG signal based on one quarter coefficients of DCT

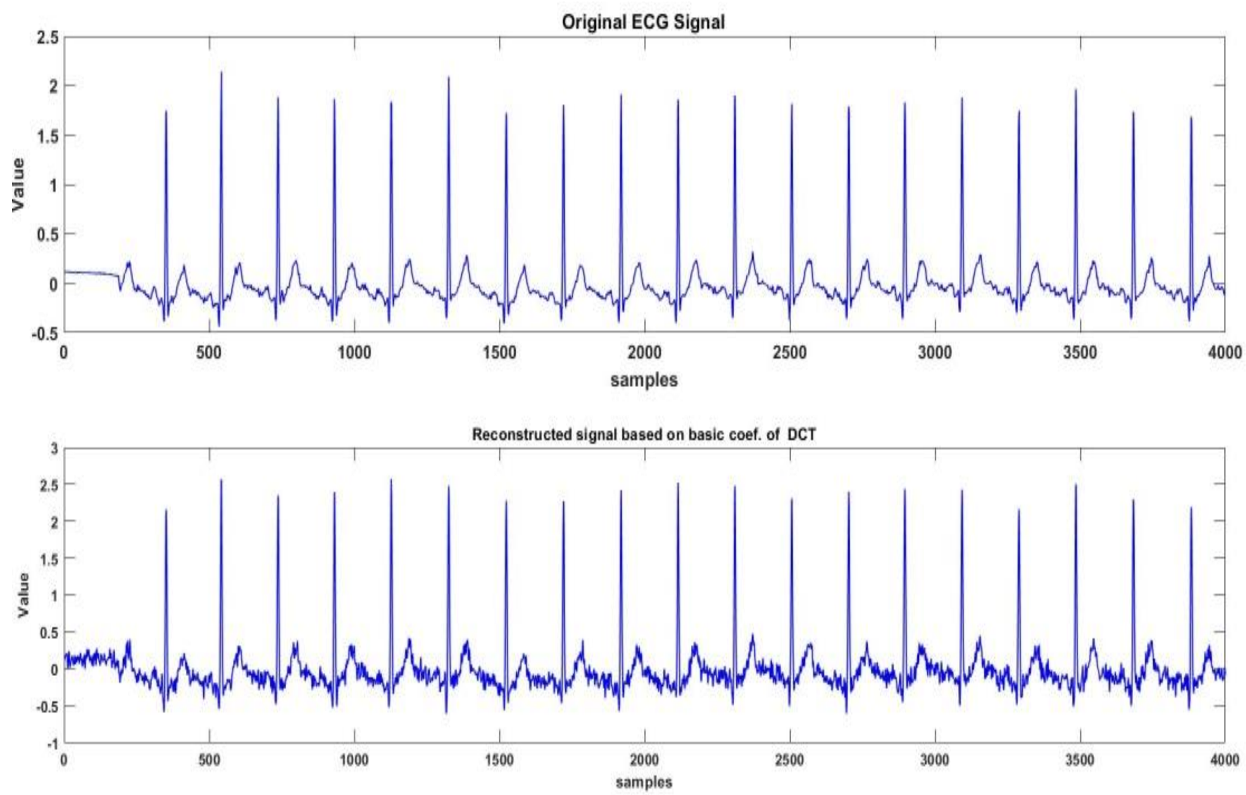

Figure 11 Original and Reconstructed ECG signal based on one half coefficients of DCT

The proposed method are applied to determine the peaks of ECG signal by computing variable threshold values as shown in Figure 12. It is clear that, there are different values for threshold according to the samples value for each samples window and this can provide adequate flexibility to deal with variable values signals like ECG. The proposed method was tested and evaluated based on three different dataset (MIT-BIH, EDB and LTSTDB).

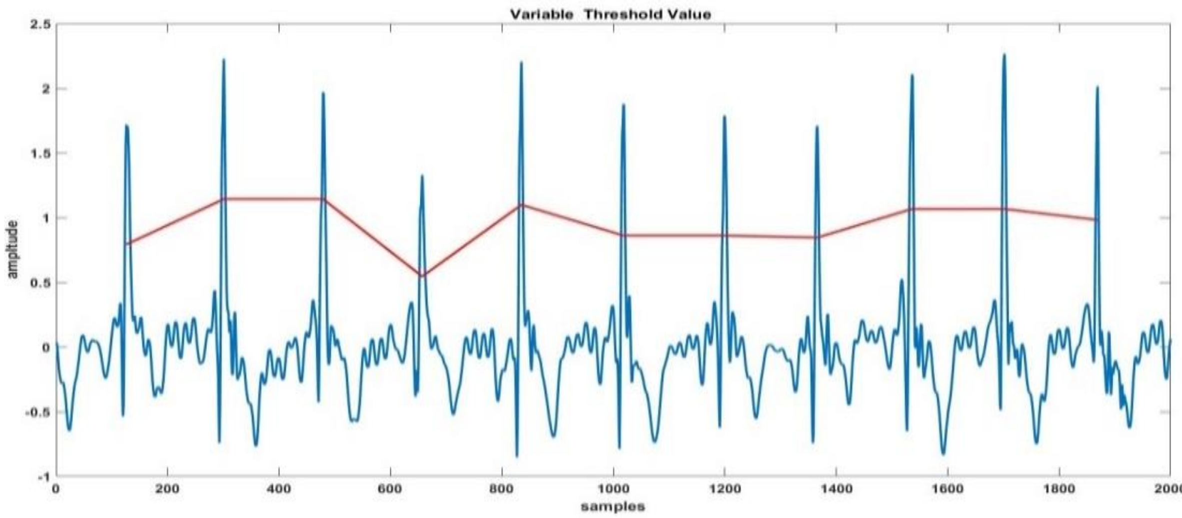

Figure 12 Variable threshold value based on signals value

EDB Dataset Results

The proposed system performance is tested based on EDB dataset for some signals with one minute and the results are compared with [Park J. et al. (2017)], as shown in Table 1, there is high development in term of accuracy (99.25%), specivity (99.6153%) and Detection rate (99.6153%), where all the signal are achieved perfect performance except record e0108m, which achieved (96.1538 %), (92.5925%) and (**96.1538**%) for Spe, Acc and DR respectively, where all the metrics are perfect for most of signals. Based on the determined peaks, R–R interval is computed by using samples number between detected peaks according to eq. (11), the heart rate (HR) is evaluated by using R–R time according to eq. (12). Average of R–R interval and HR are calculated. The values of R-R time were changed according to each signal, for instance, R–R time is 0.80 for (e0103m) signal and 1.009 for (e0121m) signal, therefore, the value of HR is changed based on these values, which were 74 and 59 for first and second signal respectively. Figure 13 shows performance of the results in term of accuracy, specificity, sensitivity and detection rate as compared with [Park J. et al. (2017)] for different signal, while different stages of proposed method is shown in Figure 14 for description of (**e0182m**) signal.

Table 1 Performance of the proposed Method compared with (ParkJ. Et al. (2017))

signal	SPE [proposed]	SPE [Park J. et al. (2017)]	ACC [proposed]	ACC [Park J. et al. (2017)]	SEN [proposed]	SEN [Park J. et al. (2017)]	DR [proposed]	DR [Park J. et al. (2017)]	R–R proposed	HR proposed
e0103m	100	100	100	96.6666	100	96.77	100	100	0.80	74.63
e0104m	100	97.1830	100	95.8333	100	98.59	100	97.1830	0.802	74.74
e0105m	100	100	100	96.2962	100	96.43	100	100	0.803	74.63
e0106m	100	96.4285	100	94.7368	100	98.21	100	96.4285	0.82	73.115
e0107m	100	94	100	90.3846	100	96.08	100	94	1.015	59.113
e0108m	96.1538	100	92.5925	94.4444	96.29	94.74	96.1538	100	1.018	59.44
e0121m	100	98.6111	100	94.6666	100	96.1	100	98.6111	1.009	59.47
e0166m	100	98.0392	100	98.0392	100	100	100	98.0392	1.01	59.40
e0202m	100	98.7951	100	96.4705	100	97.67	100	98.7951	1.0094	59.442
e0818m	100	98.5294	100	95.7142	100	97.14	100	98.5294	1.0081	59.515

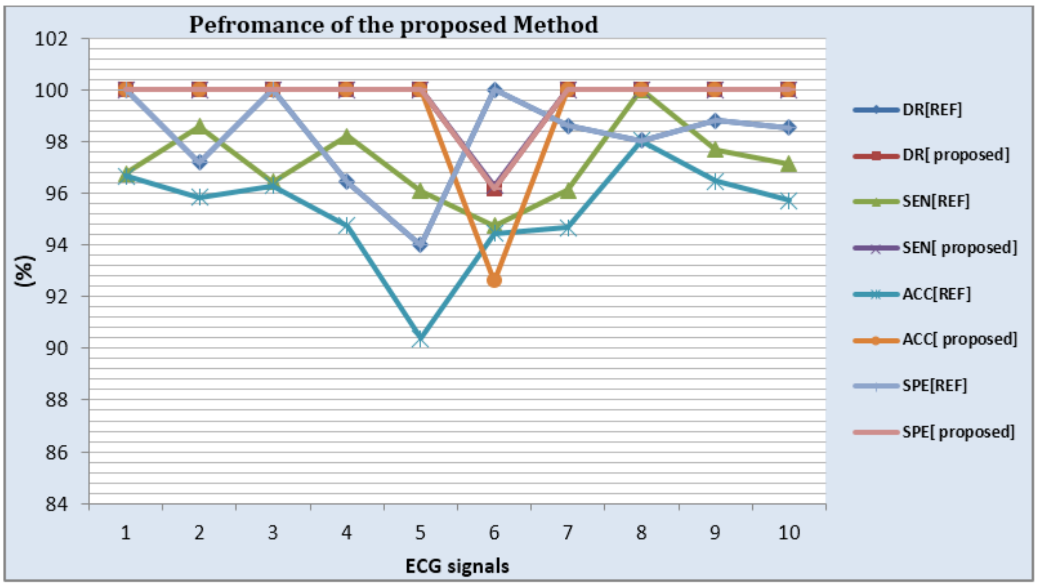

Figure 13 Performance of the proposed method for EDB dataset

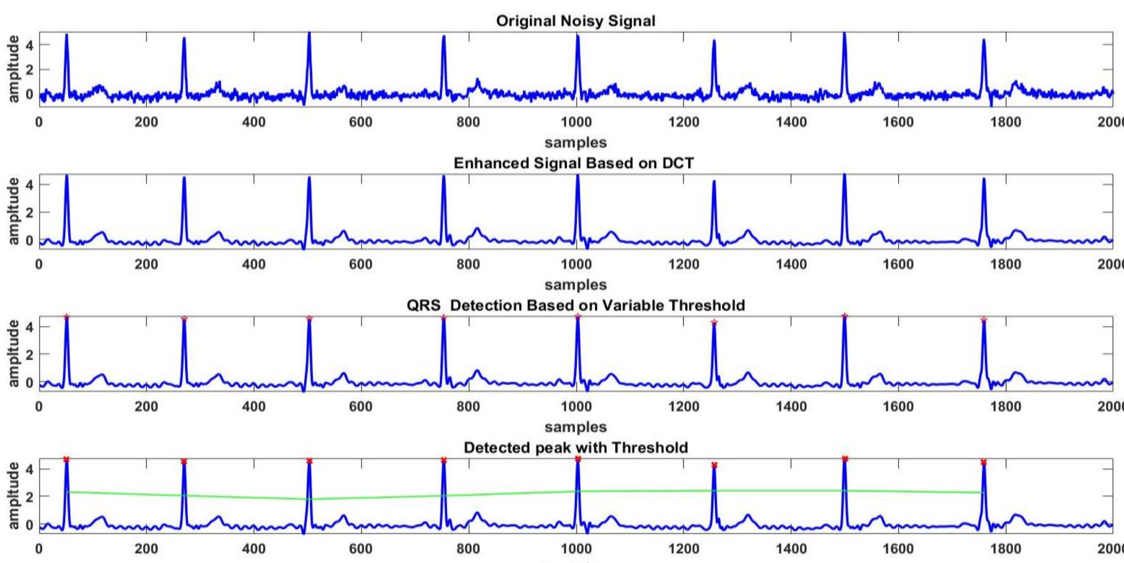

Figure 14 Noisy, Enhanced, threshold and peak detection for (e0818m) ECG signal

LTSTDB Dataset Results

The system is tested by using the second type of ECG database, which is LTSTDB database. It represents ten records of ECG samples for one minute. The performance is shown in Table 2, it is clear that high development in all metrics are achieved (Spe = 99.2933%), (Acc = 98.3286%) and DR (98.935%), respectively verse (Spe = **97.75280**%), (Acc = 95.60439%) and DR (98.863%), where most signals are detected perfectly (100%) in all metrics, beyond some signals, also the R–R interval and (HR) for this dataset is listed in this Table. The compaction between the different performance metrics of the proposed method with (ParkJ. et al. (2017)) method is shown in Figure 15, which shows the improvement of all metrics. The description results for (S20091m) signal is shown in Figure 16.

Table 2 Performance of the proposed Method compared with (ParkJ. et al. (2017)) for LSTDB dataset

signal	SPE [proposed]	SPE [ParkJ. et al. (2017)]	ACC [proposed]	ACC [ParkJ. et al. (2017)]	SEN [proposed]	SEN [ParkJ. et al. (2017)]	DR [proposed]	DR [ParkJ. et al. (2017)]	R–R proposed	HR proposed
S20011m	100	98.5507	98.59154	97.1428	100	98.57	100	98.550	1.0075	59.55
S20021m	100	98.6111	100	97.2602	100	98.61	100	98.611	1.0094	59.44
S20031m	100	98.6486	98.70129	96.0526	100	97.4	100	98.648	1.0094	59.44
S20061m	100	100	100	97.8260	100	97.87	100	100	1.01	59.40
S20081m	100	98.6666	96.34146	93.6708	100	95.12	100	98.666	1.008	59.51
S20091m	100	99.0566	100	99.0566	100	100	100	99.056	1.0056	59.66
S20111m	95.18072	100	94.04761	94.0476	98.76	94.38	95.18072	100	1.055	56.872
S20121m	100	98.2758	100	93.4426	100	95.24	100	98.275	1.046	57.38
S20131m	100	98.6842	100	96.1538	100	97.47	100	98.684	1.0094	59.44
S20571m	97.75280	98.8636	95.60439	95.6043	97.8	96.77	97.75280	98.863	1.0094	59.44

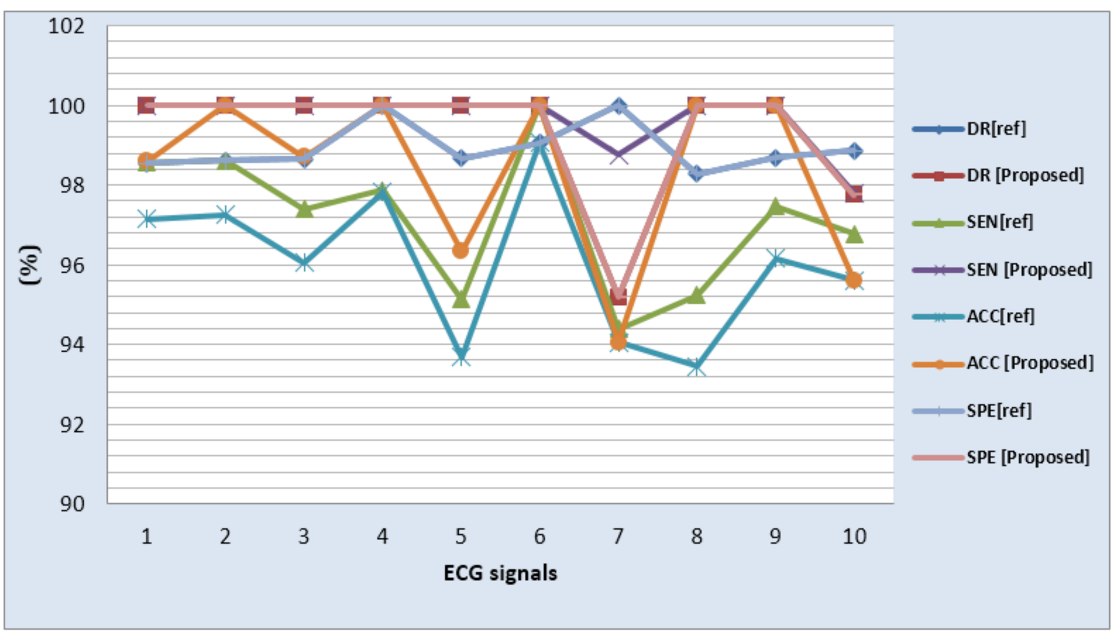

Figure 15 Performance of the results of proposed method for LSTDB dataset

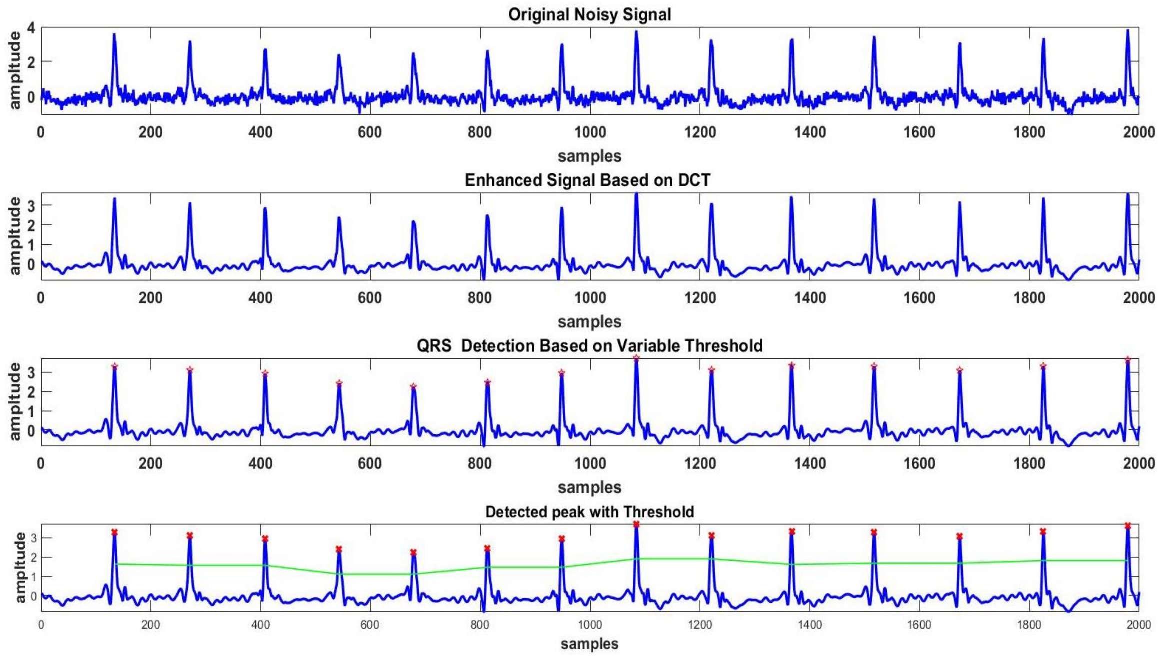

Figure 16 Noisy, enhanced, threshold and peak detection for (e0818m) ECG signal

MITBIH Arrhythmia Database Results

This classic database commonly used for testing QRS complex detection methods. It is contains 48 half hour records. The sampling frequency of this database is 360 Hz. The proposed algorithm used MIT-BIH database to determine the performance of the proposed method. As shown in Table 3, the proposed method performed or outperformed the results of (Xuanyu L. et al. 2018)) method, where it achieved average of (99.92756%), (99.4569471%) and (99.547%) for DR, ACC and SPE, respectively, against (99.92756%), (99.4079785%) and (99.4988498%) for (Xuanyu L. et al. 2018)). The different stages of peak detection for (record100) is shown in Figure 17, which shows perfect detection based on variable threshold values, while the comparison of different metrics between the proposed method and (Xuanyu L. et al. 2018) method are shown in Figure 18.

Table 3 Performance of the proposed Method compared with (Xuanyu L. et al. 2018) for MIT-BIH dataset

Signal	DR (Xuanyu L. et al. 2018)	DR [Proposed]	ACC (Xuanyu L. et al. 2018)	ACC [Proposed]	SPE (Xuanyu L. et al. 2018)	SPE [Proposed]
Record 100	99.9560052	99.95598592	99.9120492	99.9120105	100	100
Record 101	100	100	99.8394004	99.8928762	99.8394004	99.8928762
Record102	100	100	100	100	100	100
Record103	99.9520383	99.95203837	99.8562529	99.8562529	99.9520383	99.9520383
Record104	100	100	99.2873051	99.4645247	99.2873051	99.464524
Record105	100	100	98.3180428	98.4686064	98.3180428	98.4686064
Record106	99.7048696	99.70486965	99.6558505	99.6558505	99.9506903	99.9506903
Record107	99.8598130	99.85981308	99.7200186	99.7200186	99.9532273	99.9532273
Record108	100	100	97.7272727	97.8357380	97.7272727	97.8357380
Record109	99.8029168	99.80291683	99.7635933	99.7635933	99.9605211	99.9605211
Average	99.9275643	99.92756239	99.4079785	99.4569471	99.4988498	99.5478222

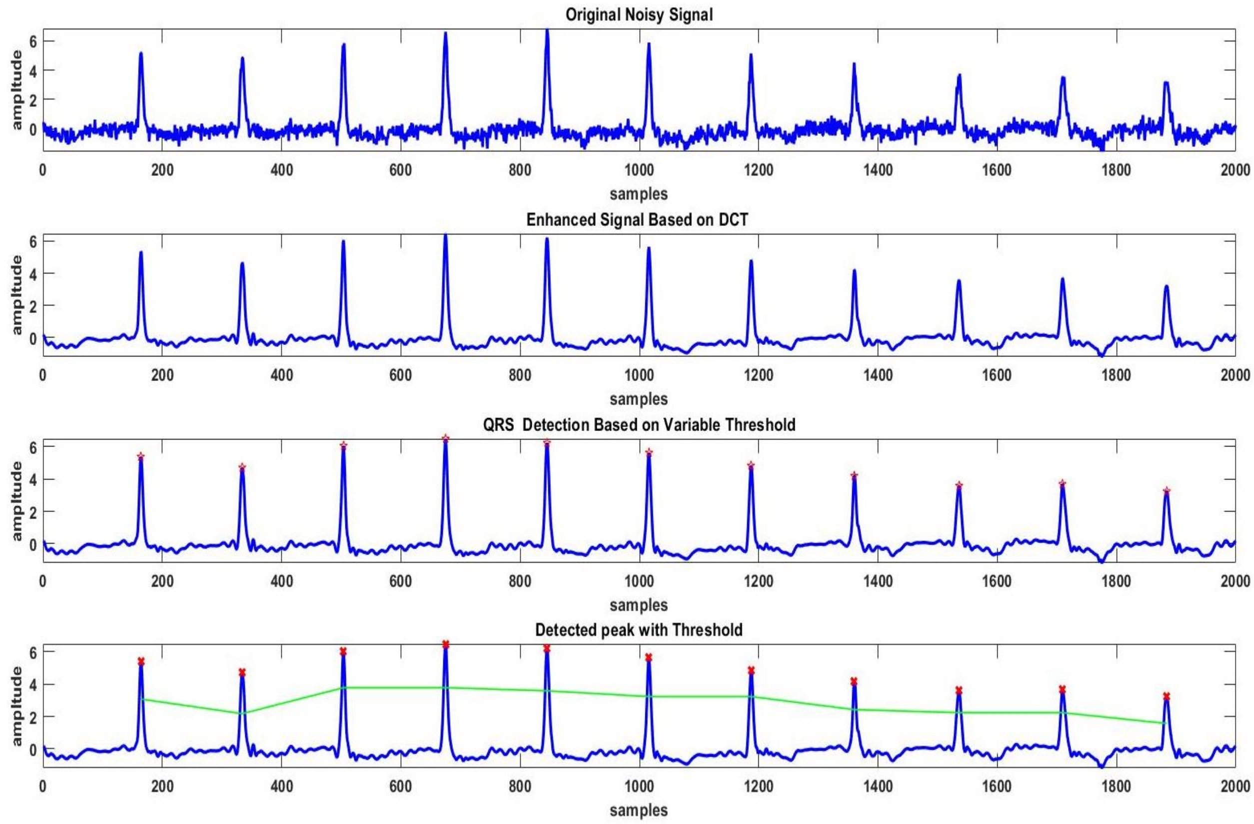

Figure 17 Noisy, enhanced, threshold and peak detection for (recoed100) ECG signal

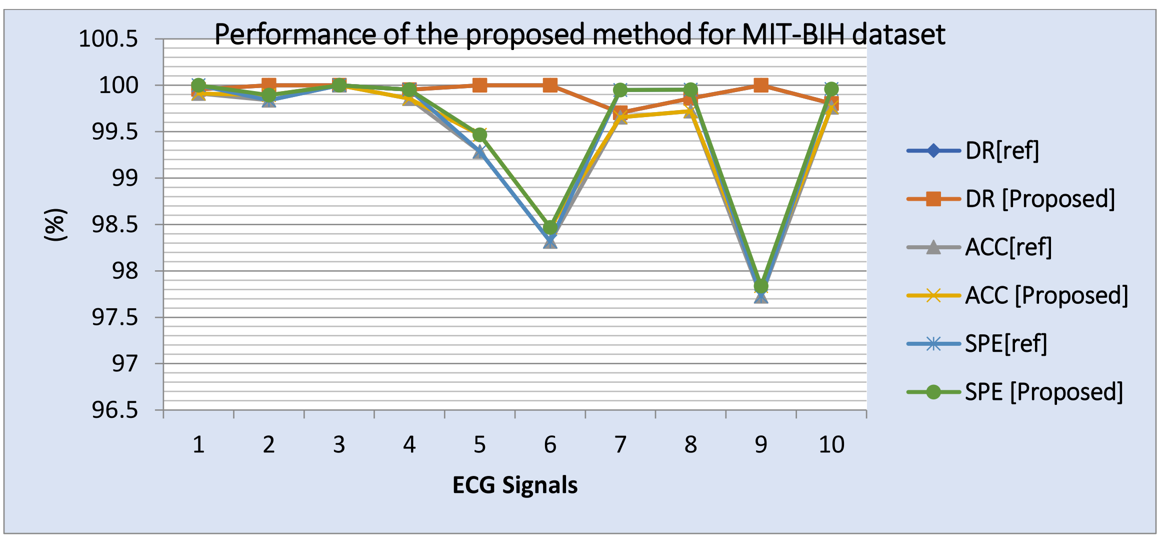

Figure 18 performance of the results of proposed method for MIT-BIH dataset

Conclusion

ECG often is used in fields of disease classification, detection of up normality of heartbeat, also it may be used in recognition or biometric identification, therefore it is very important indicator and low cost tool in diagnosis of heart problems and examining structure of tissue. R peak represents the most important part of QRS complex, therefore it define the overall shape of the signal, and thus distinguish this part is very necessary to determine the other characteristics of the signal. Since the location of R-peak can be used to determine components of ECG signal, therefore R peak must determined accurately. After determined R location, other ECG components like P and T waves are evaluated based on R locations with respect to other coordinates of QRS complex.

In this paper, a new QRS complex detection method are proposed based on discrete cosine transform (DCT) with variable adaptive threshold method, which is used to determine threshold based on characteristic of each ECG signal to detects upper and lower level of threshold to detect the R peaks. The proposed method was tested, its performance are evaluated based on three different datasets, which are MITBIH Arrhythmia dataset, (LTSTDB) and (EDB).

The experimental results proved that DCT can achieve high description for the signal by isolate its components, therefore, clearer details can be obtained through the reconstructed signal based on important coefficients of DCT, which give great details about the features of the signal. Also, using variable adaptive threshold according to samples values of each window can provide adequate flexibility to deal with variable values signal like ECG signal, Thus, the results of the proposed method exceeded the results of the other methods. For (LTSTDB), the proposed method is achieved (Spe=99.29%), (Acc=98.32%) and DR (98.93%), respectively verse (Spe=97.75%), (Acc=95.60%) and DR (98.86%), while for EDB, it is satisfied (Spe=99.29%), (Acc=98.32%) and DR (98.93%), respectively verse (Spe=97.75%), (Acc=95.60%) and DR (98.86%)for Ref.[]. Also the method is tested in MIT-BIH dataset and it achieved average of (99.927%),(99.456%) and (99.54%) against (99.92%), (99.40%) and (99.499%) for DR, ACC and SPE, respectively.

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