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A ECG signal PQRS detection and comprehensive estimation of signal noise

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***Abstract*---**Automated bioelectric signal analysis has an important application in the wisdom medical care. In this work, we focus on ECG-signal and address a novel approach for cardiac arrhythmia diseases classification. We designed a novel analysis framework which extract different feature transformations from ECG signals. And we trained the ANN model for multi-feature to obtain the prediction. Finally, we tested our approach on the public database of MIT-BIH arrhythmia. And the results of experiments on the database demonstrate our model has better classification performance than other approaches.

***Keywords*---**ECG signals, ECG denoising, Hilbert transform, synchronous detection, intrinsic mode function, instantaneous frequency, local oscillation.

Introduction

An electrocardiogram (ECG) as a cardiac activity record provides important information about the state of the heart [1]. ECG arrhythmia detection is necessary for early diagnosis of heart disease patients. On the one hand, it is very difficult for a doctor to analyze an electrocardiogram with a long recording time for a limited time [1]. On the other hand, people are also almost unable to recognize the morphological changes of ECG signals without tool support. Therefore, an effective computer-aided diagnosis system is needed to solve this problem. Most ECG classification methods are mainly based on one-dimensional ECG data. These methods usually need to extract the waveform's characteristics, the interval of adjacent wave, and the amplitude and period of each wave as input. The main difference between them is the selection of the classifier [2,3].

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ECG Signal

Data from the MIT-BIH arrhythmia database, which was provided by the Massachusetts Institute of Technology (MIT) and the Boston Hospital (BIH) in 1987 (http://www.physionet.org/physiobank/database/mitdb/), was utilised in most of the research studies. The database is taken for one of the mainstream databases in discovering and clustering arrhythmias and has been utilised in great number for algorithm verification. An annotation file with each recording is presented by the MIT-BIH arrhythmia database, preparing the reference for each heartbeat e.g., the category and the heartbeat locations. The category annotation is utilised as the criterion for the classified results [6,7,8,9].

Research Motivation

Previously, numerous automatic ECG data classification approaches using techniques such as hidden Markov models [4], wavelet transforms [5], support vector machine [6], Artificial Neural Network [7] etc. were developed. Feature extraction as well as signal pre-processing was a crucial requirement for these techniques to be applied. Extracting the features required the involvement of a medical expert and was done using hand-crafted methods. Therefore, these techniques became time-consuming, expensive and susceptible to the loss of data in the feature extraction phase. Additionally, these techniques faced a lot of significant challenges due to the morphological features of the signal having the nature of being highly individual and variable i.e. same symptoms of arrhythmia may display different morphologies of the signal in varying circumstances. Hence, a good classification performance could not be achieved when exposed to new ECG data [10, 11].

QRS Detection

The presence of a heartbeat and its occurrence time is basic information required in all types of ECG signal processing. As the QRS complex is that waveform that is most easily discerned from the ECG, beat detection is synonymous to the detection of QRS complexes [12, 13]. The design of a QRS detector is of crucial importance because poor detection performance may propagate to subsequent processing steps and, consequently, limit the overall performance of the system. Beats that remain undetected constitute a more severe error than do false detections; the former type of error can be difficult to correct at a later stage in the chain of processing algorithms, whereas, hopefully, false detections can be eliminated by, for example, performing classification of QRS morphologies [14,15,16].

Proposed Methodology- Material And Methods

Signal filtering Methods - Hilbert transform

Instantaneous frequency is defined mainly the Hilbert Transformation (HT), and time-frequency techniques. The IMFs have a vertically symmetric and narrow band form, that allow the second step of the HHT to be applied the Hilbert transform of each IMF [17,18,19]. As explained below, the Hilbert Transform obtains the best fit of a sinusoid to each IMF at every point in time, identifying an instantaneous frequency (IF), along with its associated instantaneous amplitude (IA). The IF and IA provide a time-frequency decomposition of the data. The transform is defined as the convolution of a signal [20,21,22].

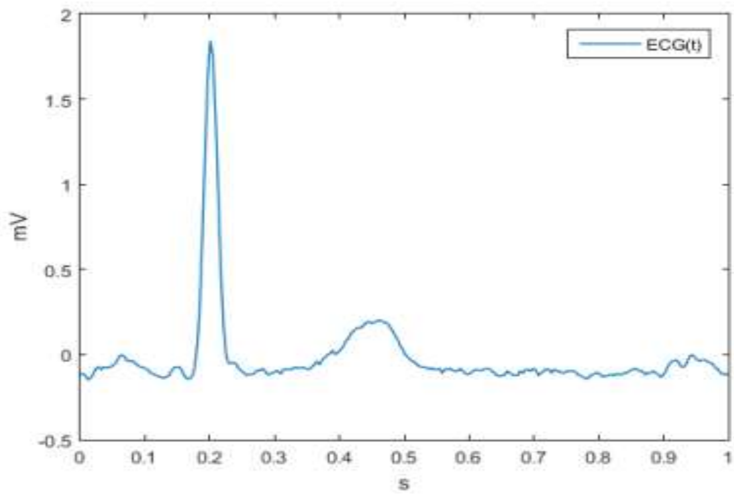

Fig. 1 A plot of ECG(t), representing a part of an ECG-signal.

$$Z\,(t) = ECG(t) + i \cdot H(ECG(t))$$

A parametric plot of $z(t)$, that is, a plot of ECG(t) against H(ECG(t)) reveals interesting things about the ECG(t). In the work, we have shown that if the QRS complex is high enough, it will always produce a closed loop around the origin in the complex plane, distinguishable from the rest of the graph. Also, we have justified this using the fact that the QRS complex resembles a deformed sine wave. By looking at analytic sine waves and deformed sine waves we have established that all type of sine waves, if expanded to analytic signals, form loops enclosing the origin in the complex plane. Thus, the QRS complex, which is a deformed sine wave, also produces enclosed loops in the complex plane [23, 24].
Mathematical modelling of discrete level function for ECG signal Using HT
ECGDTFT=U(ω). (-i.sgn(ω)).

$$\mathbf{ECG(t)} = \begin{cases} \frac{N-2J}{N}\phi_0(t,\sigma) + \frac{2J}{N}\phi_1(t,\sigma) & 0<=j<10 \\ \frac{N-J}{N}\phi_0(t,\sigma)+\frac{2N-2J}{N}\phi_1(t,\sigma) & 10<=j<20 \\ \frac{N-2J}{N}\phi_0(t,\sigma)+\frac{2J}{N}\phi_1(t,\sigma)+\frac{J}{N}\phi_2(t,\sigma)+\frac{1.2(N-J)}{N}\phi_3(t,\sigma)+\frac{0.4(N-J)}{N}\phi_4(t,\sigma) & 20<=j<30 \\ \frac{N-2J}{N}\phi_0(t,\sigma)+\frac{2J}{N}\phi_1(t,\sigma)+\frac{J}{N}\phi_2(t,\sigma)+\frac{0.4(N-J)}{N}\phi_3(t,\sigma)+\frac{1.2(N-J)}{N}\phi_4(t,\sigma) & 30<=j<40 \end{cases}$$

Where,
ϕ_0, ϕ_1, ϕ_2, ϕ_3 and ϕ_4

ECG(t) Hilbert Transformation five level Function in terms of time, N number of number of linear shapes, discrete-time Fourier transform (DTFT) U(ω) and j Transformation filtration level.

Signal classification method- layered architecture (ANN)

Neural Network Algorithms – Artificial Neural Networks arguably works close enough to the human brain. Conceptually artificial neural networks are inspired by neural networks in the brain but the actual implementation in machine learning is way far from reality. ANN take in multiple inputs and produce a single output. Point to note ANN's are inspired by the animal brain, but nowhere close to biological neural networks.

Proposed Algorithm

Computation ANN Input: ECG signals, Classification rate, Hidden layers networks.
Computation ANN Output: ECG trained artificial neural network.
Step 1. Data collection
Define the data sets class per second ECG signal collected. Its numerical approach assign training weight factor with respect to define samples.

$$H = {J_k}^T J_k$$
$$g = {J_k}^T e$$

Where,
H and g is ECG signal data collection variable and J_k is a define ECG data based Jacobian matrix.

Step 2. Data Preprocessing and Feature selection
To determine weight parameters of inputs with each input ECG sample generate different number of neural network in hidden layers. Also these ECG signal network multiplied by different number of like as +1 and -1.
Step 3. ECG signals some of all of each ANN weighted inputs.
In these forward propagation steps gives a total summation of all types of ECG signal class weight inputs, now gives some mathematical equation given blow as-

$$W_{k+1} = W_k - \left[{J_K}^T J_k + \mu I\right]^{-1} {J_K}^T e$$

Where,
W_k= ECG signal current weight
W_{k+1} = Next weight
I = the identity matrix
e_k = Last error
And μ = Combination coefficient

Step 4. Generate Computation outputs.
The computation of evaluation output establishment best selection of Neural network generate by passing that the total some of activation function class.
Step 5. Error Occurrence

The classification system modelling observation of first order derivative error define different performance function of neural network now shows some mathematical MAE (Mean absolute error) and mean square error.

$$MAE = \frac{1}{N}\sum_{t=1}^{N} |A_t - \hat{A}_t|$$

$$MSE = \frac{1}{N}\sum_{t=1}^{N} {e_t}^2$$

Where,
N = number of test samples
A_t = actual value
and $\hat{A}_t$ = forecasted value

Fig. 2. Flow chart of proposed Methodology

Result and Analysis

The proposed Hilbert transform with adaptive thresholding technique is tested on nineteen recorded ECG signals from database according to the method presented. The performance of the proposed method is evaluated with sensitivity (Se), Positive predictivity (P+) and detection error rate (DER). The proposed method detected 44325 beats (DB) from a total of 44329 annotation true beats (TB). It detected true positive of 44207, false-negative beats of 122 and 118 false-positive beats.

Signal Denoising

a) Traditional signal Denoising using DWT (Discrete wavelet transform)

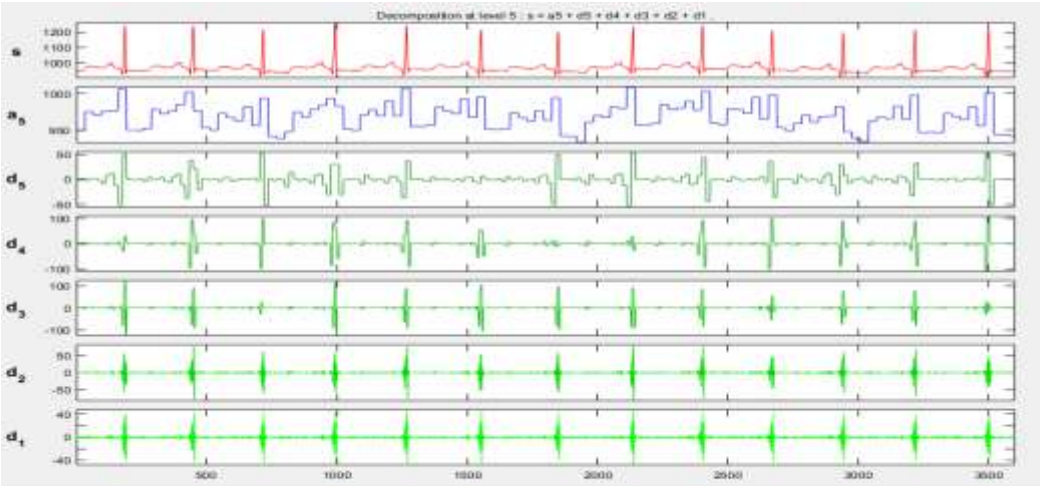

Fig. 3. Normal Signal Decomposition dwt different level signal coefficient like d_1, d_2, d_3, d_4, d_5 and a_5.

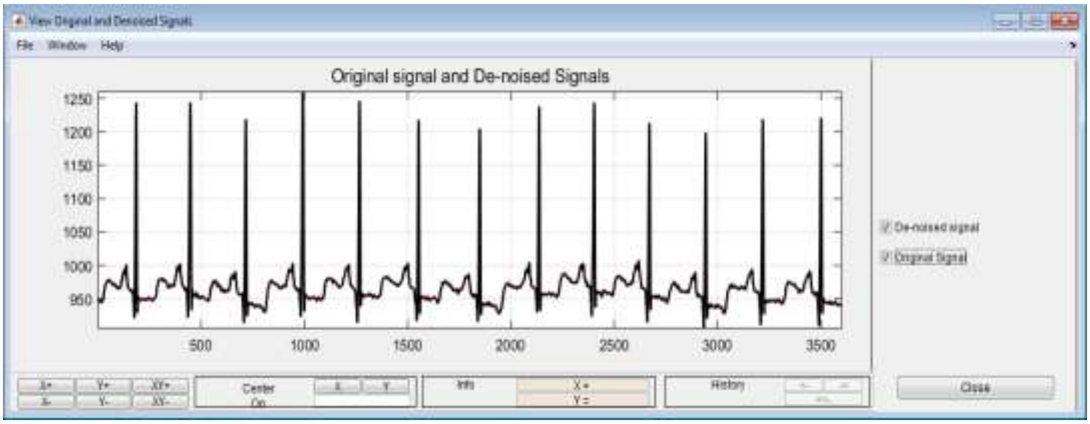

Fig. 4. Normal Signal Denoised signal Thresholding

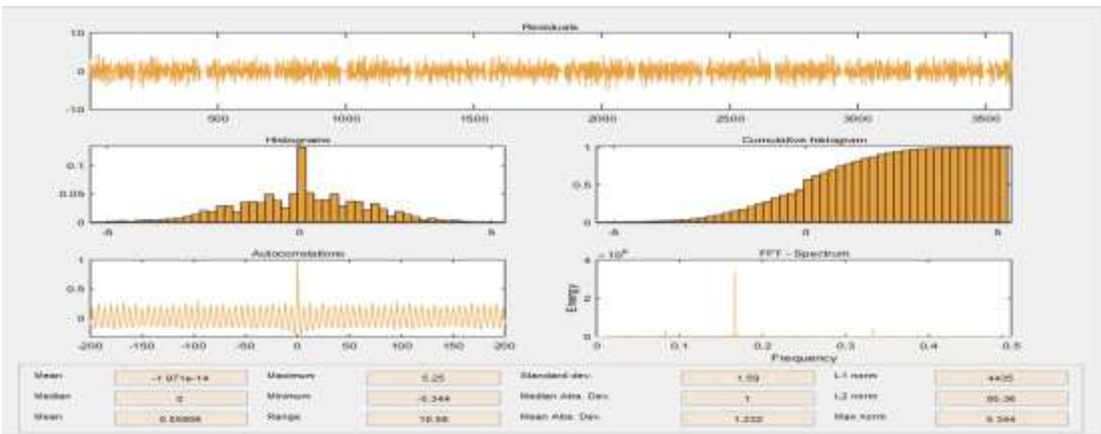

Fig. 5. Normal Signal Energy loss estimation

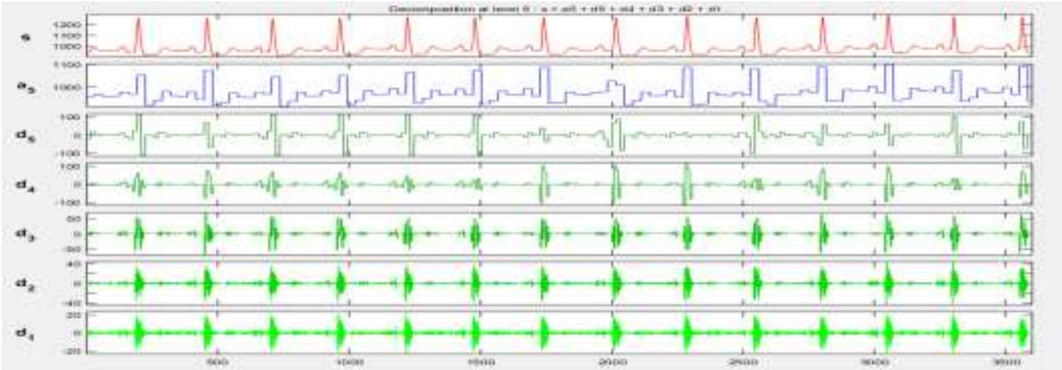

Fig. 6. Bradycardia signal Decomposition dwt different level signal coefficient like d_1, d_2, d_3, d_4, d_5 and a_5

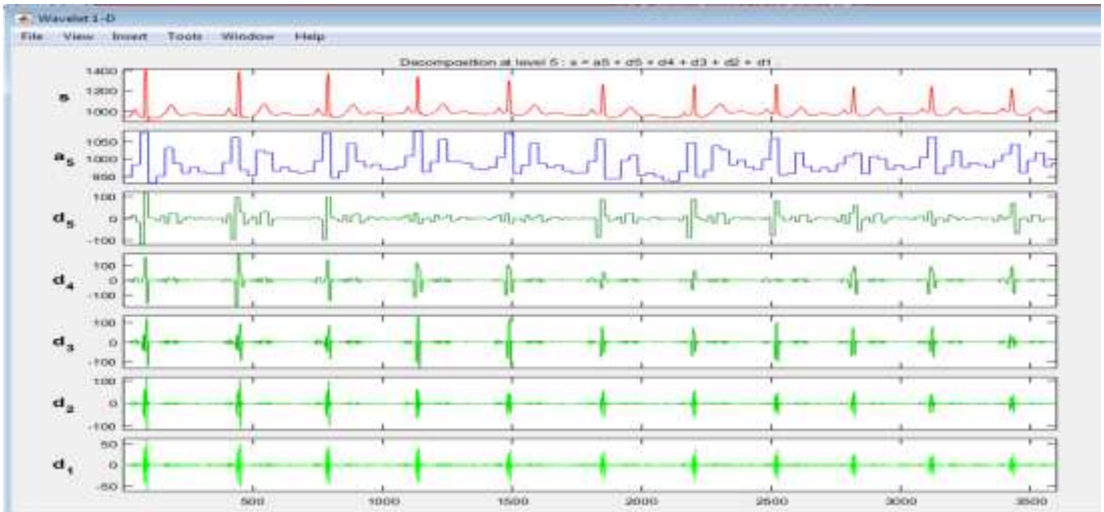

Fig. 7. Tradycardia signal Decomposition dwt different level signal coefficient like d_1, d_2, d_3, d_4, d_5 and a_5

b) Proposed signal Estimation using HT

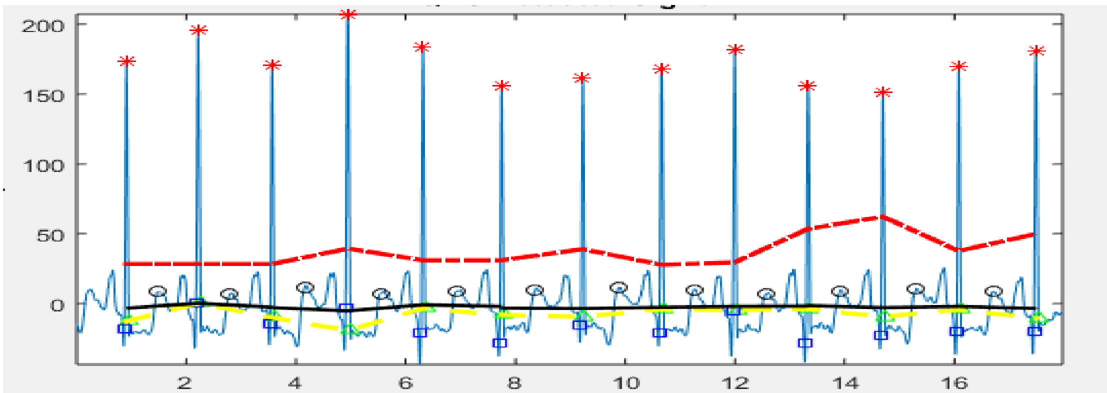

Fig. 8. Normal Signal PQRS detection and filtration without signal energy loss

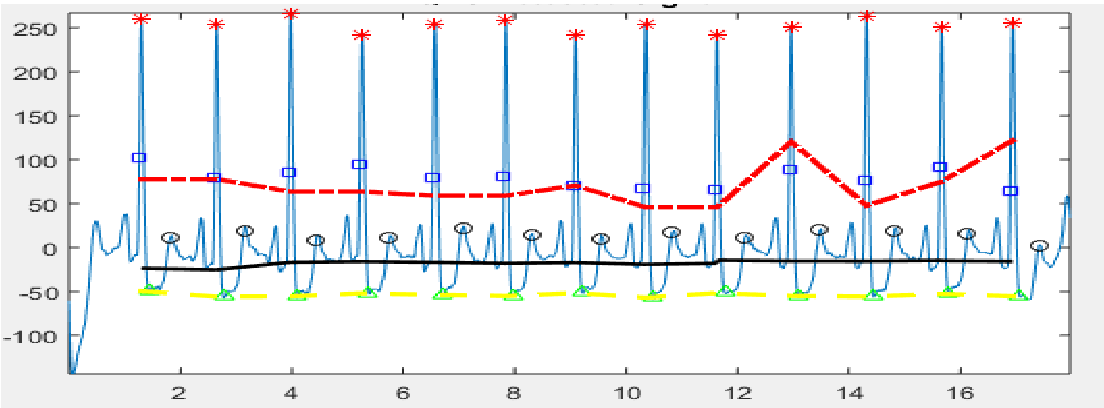

Fig. 9. Bradycardia signal PQRS detection and filtration without signal energy loss

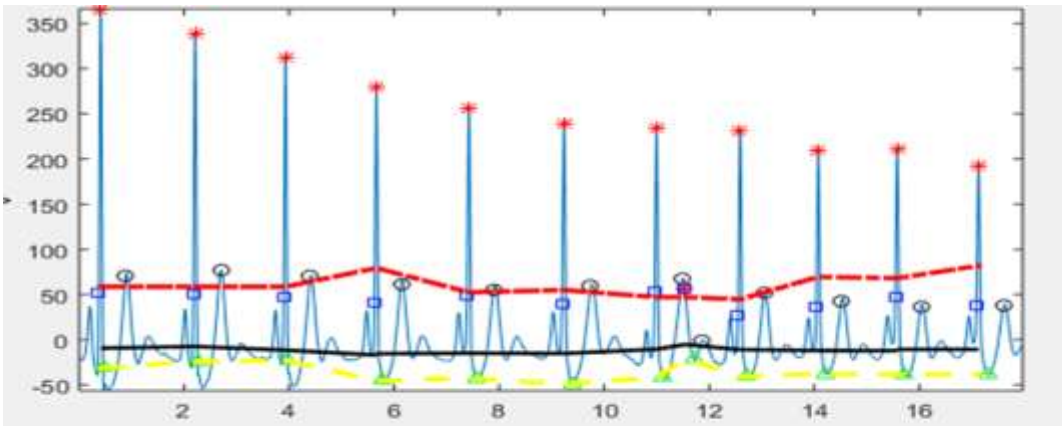

Fig. 10. Tradycardia signal PQRS detection and filtration without signal energy loss

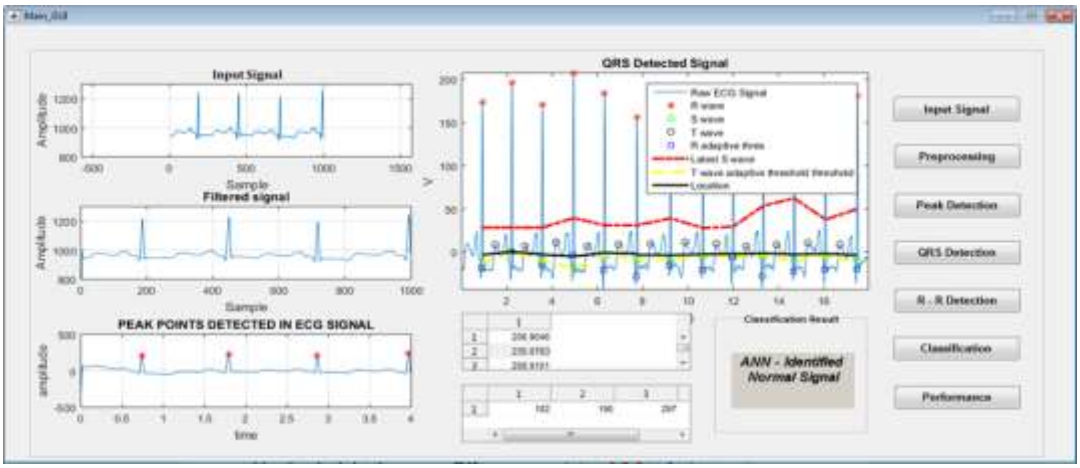

Fig. 11. QRS detection and classification window MATLAB 2015a software, 8Gb RAM (intel Processor) in normal signal

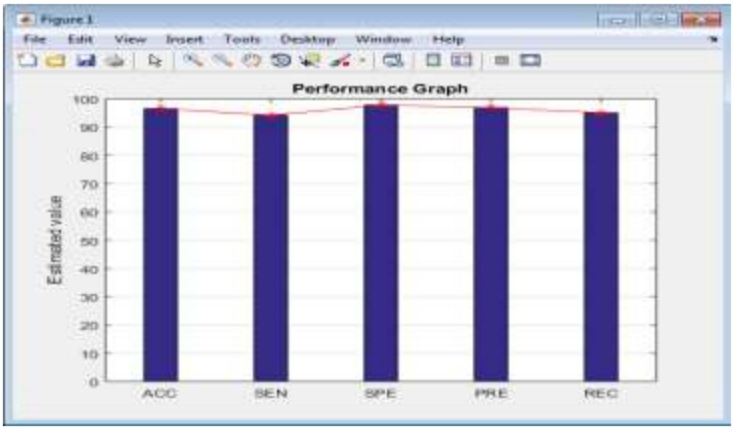

Fig. 12. Performance evaluation parameters in normal signal

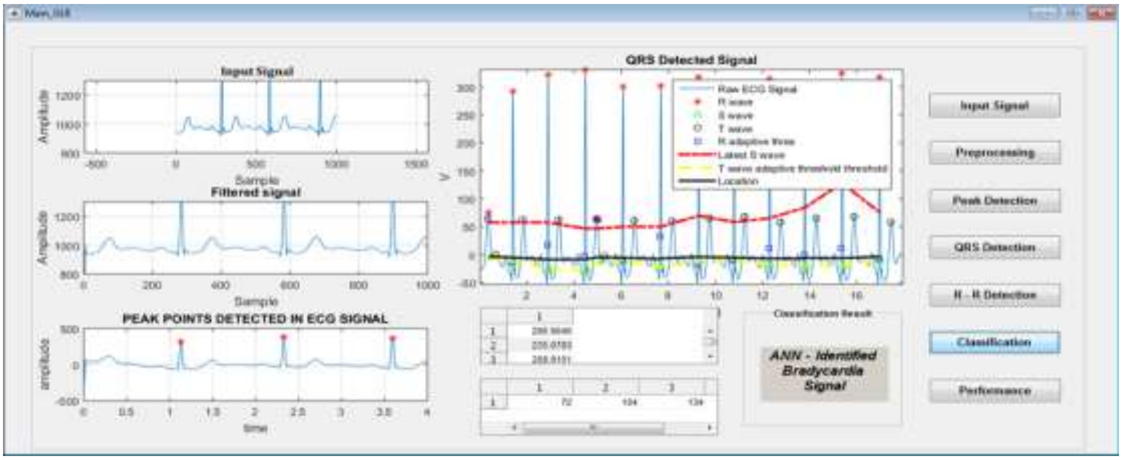

Fig. 13. QRS detection and classification window MATLAB 2015a software, 8Gb RAM (intel Processor) in bradycardia signal

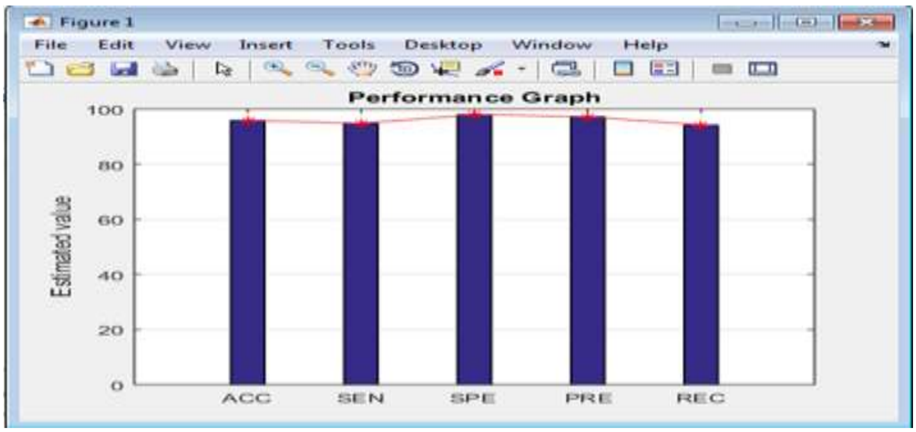

Fig. 14. Performance evaluation parameters in bradycardia signal

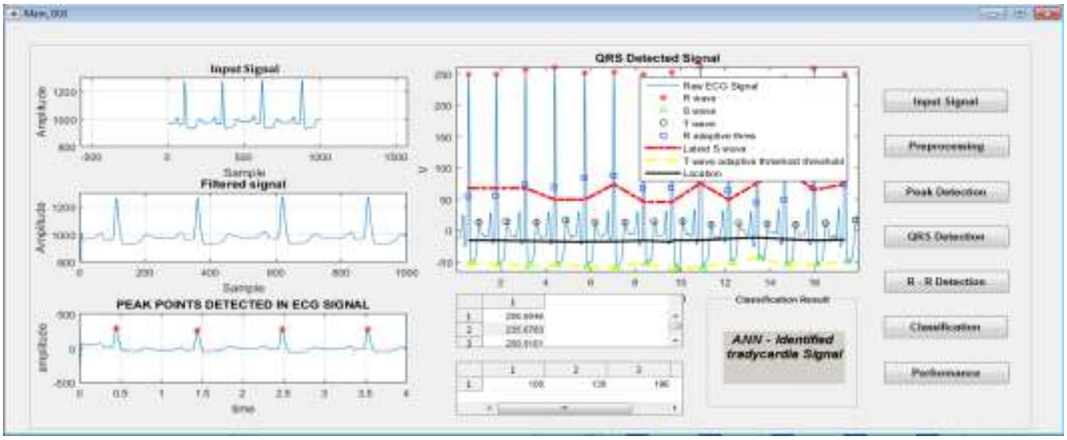

Fig. 15. QRS detection and classification window MATLAB 2015a software, 8Gb RAM (intel Processor) in tradycardia signal

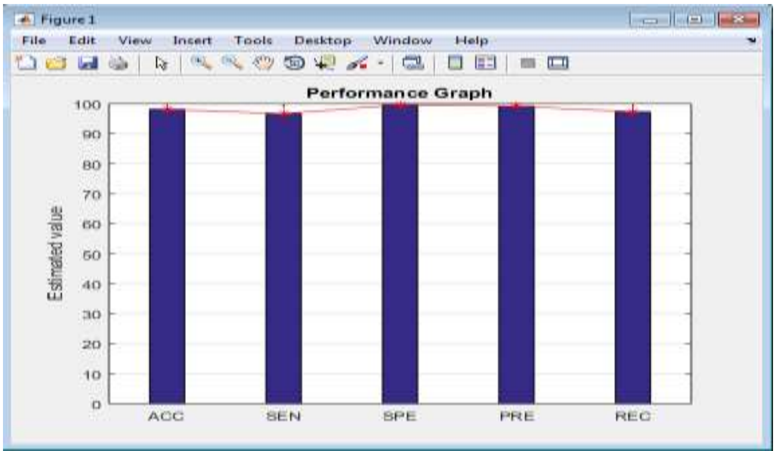

Fig. 16. Performance evaluation parameters in tradycardia signal

PARAMETERS	Normal signal	Bradycardia signal	Tradycardia signal
ACC	96.5091	95.8715	98.1387
SEN	94.1644	94.7404	96.6317
SPE	97.7693	97.9687	99.6500
PRE	96.8676	97.1829	99.1593
REC	95.0244	94.1717	97.3067

Table 1.1 Performance Evaluation Parameters Comparison

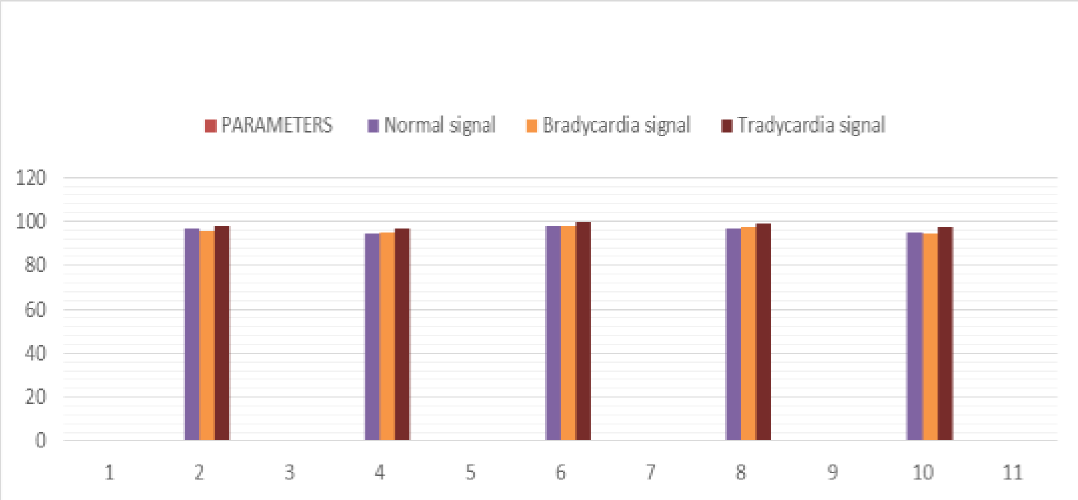

Fig. 17. Performance evaluation parameters comparison

Conclusion

In this paper a Layer -based ECG classification algorithm was proposed which achieves superior classification performance compared to previous works. In addition, as opposed to many previous deep-learning based algorithms, it has low computational costs and meets timing requirements for continuous execution on wearable devices with limited processing power. Future directions include exploring other techniques to further increase the classification performance, studying other features in addition to wavelet, and improvements on single-lead ECG processing.

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