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A Measurement of Heart Rate in 12 lead ECG by an Entropic Method Using Artificial Neural Network

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Abstract: ***Application of Artificial Neural Network is used for measurement of heart rate in 12 lead ECG (Electrocardiogram) using combined entropic methods. The ECG signal is filtered using Digital filtering techniques to remove power line interference and base line wander. The K-means algorithm is used as a classifier for detection of QRS and non-QRS complexes in ECG. Both algorithms performed highly effectively with using standard CSE ECG database. The Artificial Neural Network is used for detection of QRS complexes. The effectiveness of the method has been demonstrated by its accuracy rate of 99.79%. The method has certain limitations as well thus giving FP and FN of 0.068% and 0.002% respectively. Over all this method is found to be most effective one.***

Keywords: ANN: Artificial neural network, FN: False negative, FP: False positive, EBPANN: Error Back Propagation ANN

1. Introduction

ECG is a process which records electrical activity of heart over a period of time using electrodes which are placed on body's surface and connecting them to a recording apparatus called Electrocardiograph. Therefore any abnormality of the heart can be found out by monitoring the various features and parameters of the ECG. The heart is unique among the muscles of the body. It possesses the properties of the automatic impulse formation and rhythmic contraction. At every heart beat, heart will have orderly progression of depolarization that starts with pacemaker cells in the sinus node, spreads out through the atrium, passes through the atrioventricular node down into the Bundle of His branches and into the Purkinje fibers system spreading down and to the left throughout the both ventricles.

The excitation of the muscles fibers throughout the myocardium results in the cardiac contraction. ECG is used not only to access the state of heart in critical cases, but it is being used as a routine medical check-ups. Hence there arises a need for the automatic analysis of ECG. This helps in providing quality treatment and quick disposal of medical cases. Among the various features of ECG, QRS complex is the most important feature because other features; like P-wave, T-wave, ST-segment etc. are identified in context with it. The detection is said to be false positive (FP) if non-QRS wave is detected as QRS complex, and is said to be false negative (FN) if detector fails to detect QRS complex.

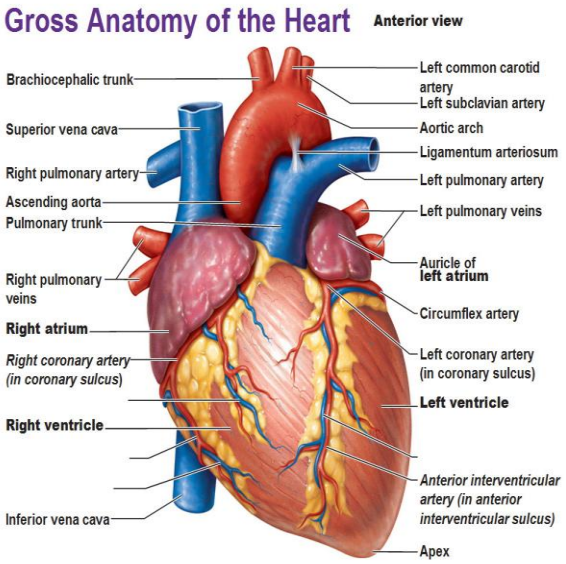


Figure 1: Anatomy of heart

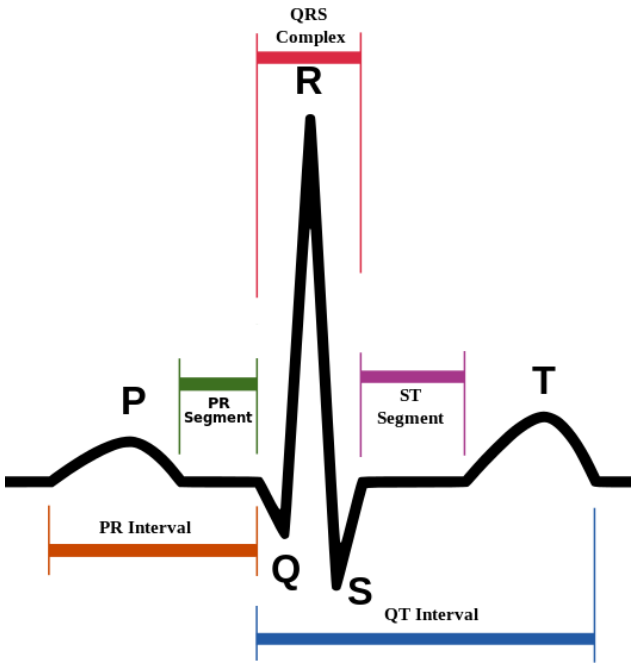


Figure 2: ECG cycle

The Entropy is a statistical measure of uncertainty. The entropy concept can be used as a suitable criterion in the design of optimum feature selection. Features that reduce the uncertainty of a given situation are considered more informative than those that have the opposite effect. Thus, a meaningful feature selection criterion is to choose the features that minimize the entropy of the pattern class under consideration. An accurate detection of QRS complex is very important and it forms the basis of reliable ECG interpretation and diagnosis system. In present work a combined entropy technique for detection of QRS-complexes in 12-lead ECG using Artificial Neural Network (ANN) has been presented

2. Method

A 12 lead digitized ECG of a patient is acquired. It is filtered to remove 50 Hz power line interference and base line wander using adaptive nose canceller [2] shown in fig.1. A lead of ECG is taken and slope is calculated at every sampling instant of the filtered ECG signal. The slope is taken as a prominent feature because slopes in the QRS regions are higher than that in the non-QRS regions. Fig.2 depicts the fact. The various slopes obtained at different sampling instant are then divided into two classes namely, QRS-class and non-QRS class, using K-means of clustering algorithm. The means and standard deviations of both the classes are calculated and the probability of each sample belonging to QRS as well as non-QRS class is calculated for all 12-leads using relation:

$$p_i(x) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left[-\frac{1}{2}\left(\frac{x - m_i}{\sigma_i} \right)^2 \right];$$

i = 1, 2; x = 1, 2... 5000 (1)

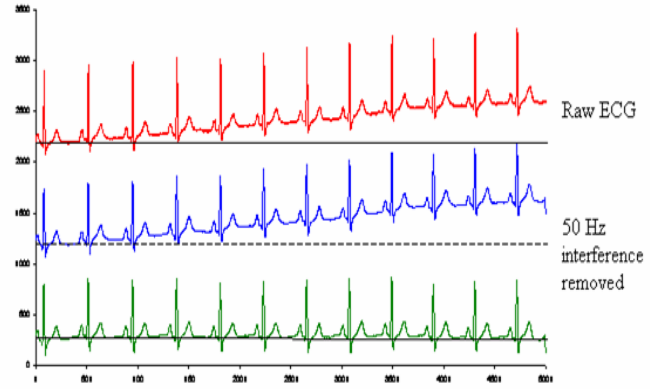


Figure 3: Raw ECG and ECG after removal of power line interference and base line wonder

The ECG signals have been picked from CSE (Common Standard Electrograph) ECG library. Each lead is sampled at 500 Hz and recorded for 10 sec duration. The probability calculated above, therefore, is for sampling instants x = 1, 2 … 5000.

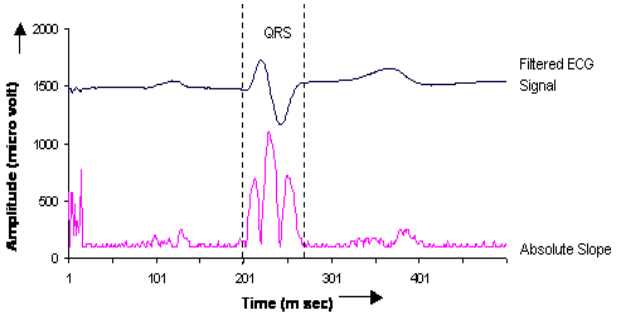


Figure 4 Filtered ECG signal and corresponding absolute slope

After calculating probability their Shannon's entropy for belonging to QRS as well as non-QRS region is calculated. Similarly entropies of each sampling instants is calculated for both the classes using the relation:

$h_i(x) = -p_i(x) \log_e p_i(x)$; i=1,2;x=1,2,.5000 (2)

Similarly both the entropies are calculated for all 12 leads. The average entropy of all 12 leads, at the same sampling instant, is calculated, to nullify any spurious signal, for both QRS and non-QRS class respectively using the relation:

$$H_i(x) = \frac{1}{12} \sum_{j=1}^{12} p_{ij}(x) \log_e p_{ij}(x);$$

i = 1, 2; x =1, 2. . . 5000 (3)

Now maximum and minimum for both entropies lead are calculated to normalize both the entropies using the relation:

$$H_{in}(x) = \frac{H_i(x) - H_{i\min}}{H_{i\max} - H_{i\min}};$$

i=1,2; x=1,2,...5000 (4)

where:

$H_{in}(x)$ is normalized i^{th} entropy of x^{th} sampling instant.

$H_i(x)$ is i^{th} average entropy of x^{th} sampling instant.

H_{imin}, H_{imax} are the minimum & maximum values of i^{th} entropy.

The combined normalized entropy (Hcn) is calculated from entropy of QRS (H1n) and entropy of Non-QRS (H2n) by using the following relationship.

$H_{cn} = (1 - H_{2n}) H_{1n}$ (5)

Where

$H_{cn}(x)$ is combined normalized i^{th} entropy of x^{th} sampling instant.

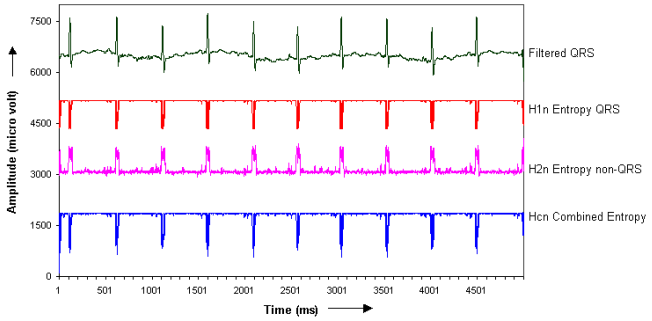


Figure 5 Filtered ECG, entropy QRS, entropy non-QRS and combined entropy curves

Fig. 5 shows filtered ECG, QRS entropy curve, non-QRS entropy curve and combined entropy curve. It is observed that QRS entropy curve having lower value of entropy in QRS region as compared to non-QRS region indicating lower uncertainty of its belonging to QRS region or higher certainty of this region belonging to QRS. The combined entropy curve obtained by using the equation (5) confirms the belonging of this region to the QRS region. In the same QRS region; the QRS entropy and combined entropy curve show lower values i.e. higher certainty QRS region. Thus, in gross indicates the presence of QRS complex.

Similarly, in non-QRS region, the non-QRS entropy curve shows higher values i.e. lower certainty or higher certainty of occurrence of non-QRS region. In the present work combined normalized entropy has been taken as the features for the identification of QRS complex.

3. Artificial Neural Networks

The theme of Artificial Neural Network resembles with networks of cells in human brain called biological Neurons. Artificial neural network is basically biologically motivated networks. ANN consists of components which function almost similar to the fundamental biological neuron. ANN is based on Biological Neuron Model that is a mathematical description of the properties of nerve cells. The artificial neuron is designed to mimic the first order characteristics of the biological neuron. When a set of inputs 'x' is applied, then each input is multiplied by corresponding weight 'w'. The weighted input is analogous to a synaptic strength in biological neuron. All the weighted inputs are then summed to determine the activation level of the neuron. Each input signal is multiplied by associated an weight, $w_1, w_2, \ldots w_n$ before it is applied to the summation block, labeled $\sum$. The summation block corresponds roughly to the biological cell body. It adds all the weighted inputs algebraically and produces an output called "*NET*".

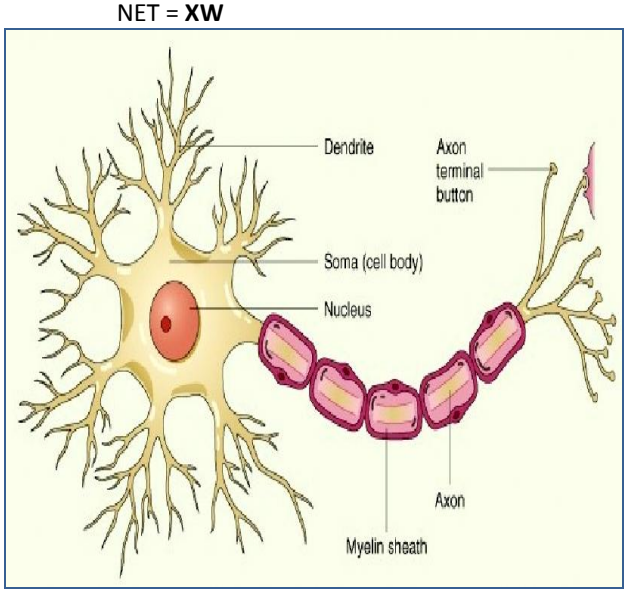
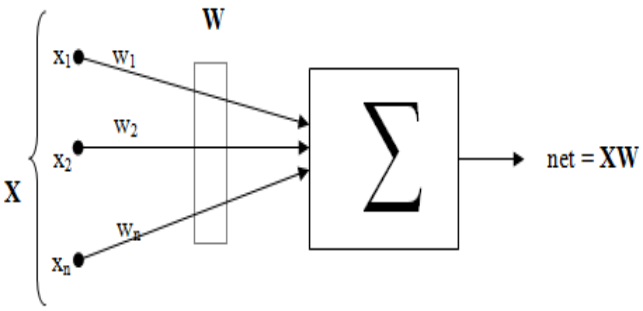


Figure 6: Biological Neuron



$$net = x_1w_1 + x_2w_2 + \ldots\ldots + x_nw_n$$

Figure 7: Model of Neuron

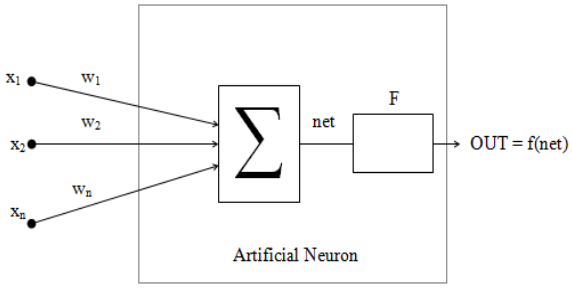


Figure 8: Artificial Neuron with Activation Function

4. Training of ANN

A sliding window of size 10 sampling instants is moved over combined normalized entropy. Ten values of combined normalized entropy at a sampling instant are taken to form input-vector for the ANN. During training of EBP ANN, the window is moved over the combined normalized entropy curves and the input vectors, of 10 values each, formed at each sampling instant is fed to the ANN. When the window is lying completely within the QRS region during their cruise, the desired output of the ANN is set equal to '1'. Similarly, when the sliding window is lying completely within non-QRS region, the output of ANN is set to '0'. The regions when the window is lying partially in QRS region as well as in non-QRS-regions are not considered for training of ANN. A set of ECGs covering wide range of variation is used as training set to train the ANN using MATLAB.

5. Testing of ANN

During testing of an ECG, the sliding window is moved over the combined normalized entropy curves of the ECG and the input vector of 10 values each, as explained above, is fed to trained ANN and the output is obtained. It is observed that when the window is moving through QRS region, the output of the ANN is high near 1. Similarly, when the window is moving through non-QRS region, the output of the ANN is low, near 0. Thus a train of high values '1' is obtained at the output when the window is moving through QRS region. Similarly, a train of low values (near 0) is obtained in non-QRS region. The output of the ANN is smoothed by moving a averaging-windows which takes 10 continuous sampling instants and the average is obtained using the relation:

$$O_i = \frac{1}{10}\sum_{i=1}^{10} A_i \; ; i = 1, 2. .. 4980 \quad (5)$$

Where: **A_i = Neural Net output**

O_i = Averaged Neural Net output

On this averaged ANN output a threshold is set. If the averaged ANN output is higher than the threshold value then the output is set to equal to 1, otherwise it is set to '0'. After thresholding, a train of 1's is obtained in QRS region and a train of 0's in non-QRS region. However, in QRS region when the slope is changing its sign i.e. near peak extreme the slope is very low. As such within a train of 1's a few 0's may also appear. To remove this difficulty, an over rider rule was applied i.e. whenever a train of four continuous 0's is obtained within a train of 1's, the 0's are also set equal to 1's.

Thus when the sliding window is moved during testing, a pattern of train of 1's and 0's is obtained in the QRS & non-QRS regions respectively. Fig. 7 shows the detection of QRS complexes by ANN.

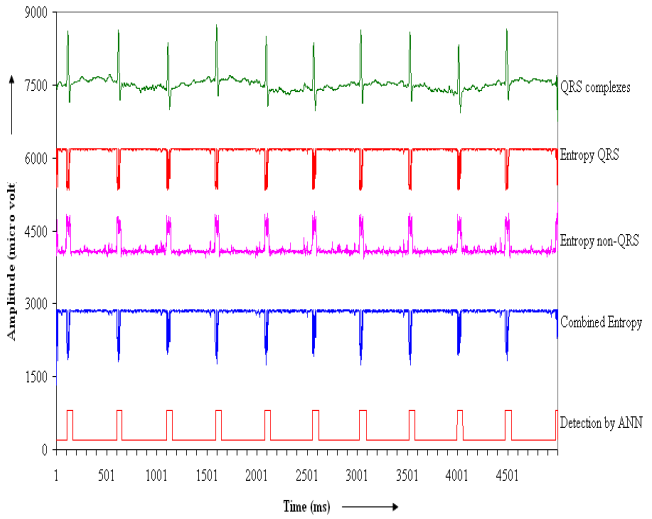


Figure 9: Filtered ECG, Entropy curves of QRS, non-QRS, Combined Entropy and QRS detection

5.1 Algorithm for Detection of QRS Complex:

Step 1 Acquire a digital sample of 12-lead ECG signal of a patient. Then, Filter the raw ECG signal to remove 50-Hz power line interference and baseline wander.

Step 2 Pickup one lead out of 12-leads ECG and calculate the slope at every sampling instant of the filtered ECG signal.

Step 3 These slopes are clustered into two classes using K-means of clustering algorithm into slopes belonging to QRS and slopes belonging to non-QRS region.

Step 4 Calculate the means m_1 and m_2 and standard deviation σ_1 and σ_2 for each class.

Step 5 Calculate probability of each sample 'x' belonging to QRS as well as Non-QRS region using the equation

Step 6 For a particular lead, calculate entropies h_1 and h_2 at each sampling instant for both classes (QRS and non-QRS). Calculate both the entropies for remaining 11 leads in a similar way.

Step 7 At every sampling instant; find the average entropy of all 12 leads (to nullify any spurious signal) for both QRS and non-QRS class respectively using equation (3).

Step 8 Calculate the maximum and minimum for both entropy. Then, normalize both the entropies using the equation (4).

Step 9 Calculate the combined normalized entropy by using the equation (5)

Step 10 A sliding windows of size 10 sampling instants is moved over the combined normalized entropy. Ten values of combined normalized entropies are picked up at a time to form input-vector for the artificial neural network. Then the windows are moved forward by a step of one sampling instant and a set of 10 values is picked up to form input-vector for every new sampling instant.

Step 11 During the training of EBP ANN, the window is moved over the combined entropy curve. When the window is lying completely within the QRS region during their cruise, the desired output of the ANN is set to '1'. Otherwise output of ANN is set to '0'. The regions when the window is lying partially in QRS region as well as non-QRS-regions are not considered during training of the ANN. Hence not included in the training set.

Step 12 A set of ECGs covering wide range of variation, from normal as well as abnormal cases are picked up from CSE ECG database. The combined entropy of these cases is used as training set to train the EBP ANN using MATLAB.

Step 13 During testing of an ECG, the sliding window is moved and the input vector of 10 values each, as explained above, is fed to the ANN and the ANN output is obtained.

Step 14 A sliding averaging-window is moved which averages the neural net output..

Step 15 Threshold is set on this averaged neural net output. The values which are more than the threshold, output is set to '1' and for the values which are less than the threshold, outputs is set to '0'. Thus, a train of 1's and 0's are generated.

Step 16 Now an over rider is applied, such that whenever a train of four continuous 0's is obtained within a train of 1's, the 0's are also set equal to 1's.a clear view of QRS region by a pulse, and non QRS by no pulse is created as shown by red color in the figure 4.

Step 17 The train of 1's is picked up and using their duration, an average pulse width of 1's is evaluated.

Step 18 Those trains of 1's whose duration turns out to be more than the average pulse width are detected as QRS regions and the other ones are detected as non-QRS regions.

6. Training Pattern

A set of ten 12-lead ECGs of selected cardiac cycle covering a wide variety of variation, is used as training pattern and the desired output of the ANN is set to '1' for QRS region and '0' for non-QRS region. These patterns were used to train 10-8-2-1 EBP ANN using MATLAB. It was implemented on Pentium 4 processor with 1.7 GHz clock. The artificial neural network was trained for 0.000001 mean square error (MSE) after 6 epochs in 2.5 minutes as shown in figure 9.

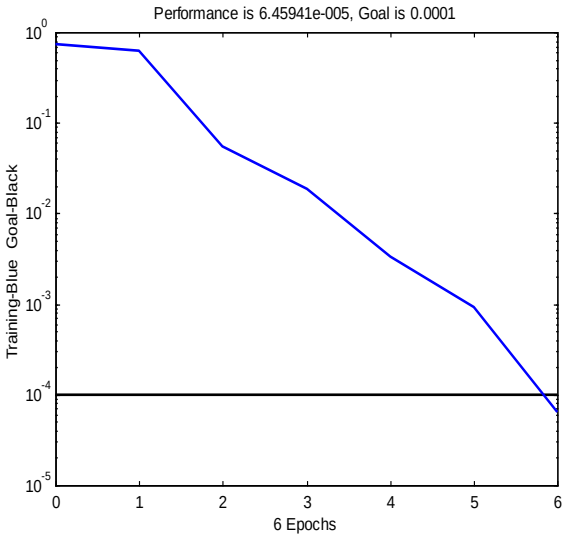


Figure 10 Training of Neural Network using MATLAB

7. Test Results

The algorithm for QRS detection was tested on 40 cases of 12-leads ECGs sampled at 500 Hz picked from CSE ECG database. There were 480 QRS-complexes in all. The numbers of false positive (FP) and false negative (FN) were 13 and 1 respectively. Thus gives the detection rate of 97.08 %. Mostly the error due to FP detection was confined to that signal where P and T waves were peaky in nature having their slopes comparable with that of QRS complexes. Similarly, the errors due to FN detection were confined to those signal having wider QRS complexes where the slopes in QRS regions were small. Table 1 summarized the test results.

Table 1: Test Results

S No.	Patient	Total Qrs	Correct Detection	Not Detected (FN)	False Positive (FP)	% Detection
1.	MO1_001	17	17			100
2.	MO1_002	19	19			100
3.	MO1_003	17	17			100
4.	MO1_004	12	12			100
5.	MO1_006	9	9			100
6.	MO1_007	17	17			100
7.	MO1_008	10	10			100
8.	MO1_009	12	12			100
9.	MO1_010	7	7			100
10.	MO1_011	15	15			100
11.	MO1_012	13	13			100
12.	MO1_013	12	12			100
13.	MO1_014	8	8			100
14.	MO1_015	6	6			100
15.	MO1_016	16	16			100
16.	MO1_017	10	10			100
17.	MO1_018	15	15			100
18.	MO1_019	13	13			100
19.	MO1_020	22	22			100
20.	MO1_021	7	7			100
21.	MO1_022	12	12		10	100
22.	MO1_023	8	8			100
23.	MO1_024	9	9			100
24.	MO1_025	10	10			100
25.	MO1_026	13	13			100
26.	MO1_027	14	14			100
27.	MO1_028	10	10		3	100
28.	MO1_029	10	10			100
29.	MO1_030	12	12			100
30.	MO1_031	11	11			100
31.	MO1_032	14	14			100
32.	MO1_033	9	9			100
33.	MO1_034	9	9			100
34.	MO1_035	11	11			100
35.	MO1_036	12	12			100
36.	MO1_037	13	13			100
37.	MO1_038	11	11			100
38.	MO1_039	9	9			100
39.	MO1_040	12	11	1		100
40.	MO1_041	11	11			100

8. Discussion

Some of the test results discussion as follows:

Case 1: MO1_009

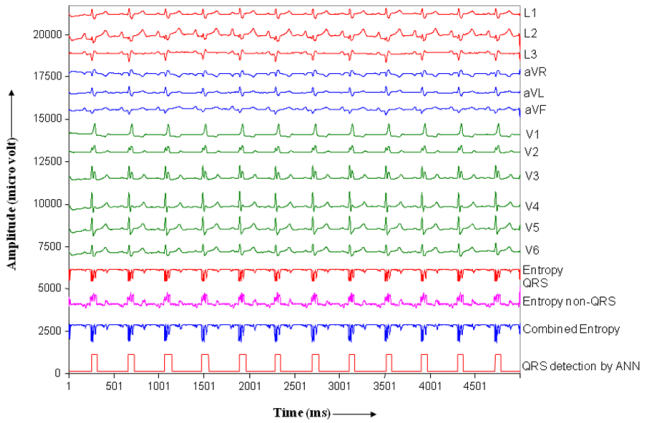


Figure 11: 12 lead ECG Mo1_009, Entropy curves of QRS, non-QRS, Combined Entropy and QRS detection by ANN

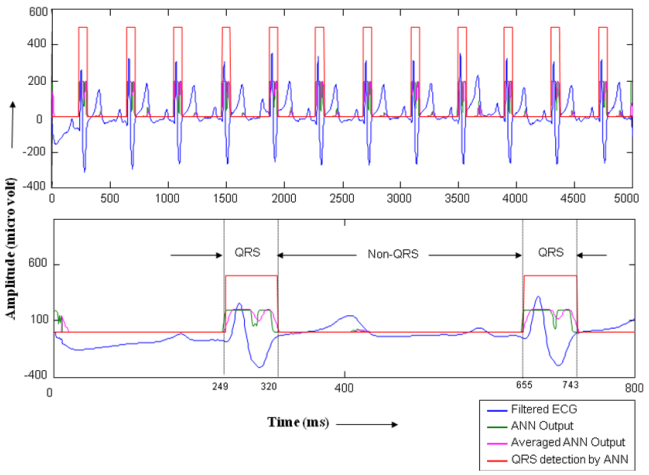


Figure 12: QRS detection of ECG MO1_009 by ANN

Figure 11, Shows the 12 lead ECG of patient MO1_009 with Entropy curves of QRS, non-QRS, Combined Entropy and QRS detection by ANN. Figure 12 explains the correct detection of QRS complexes

Case 4: MO1_040:

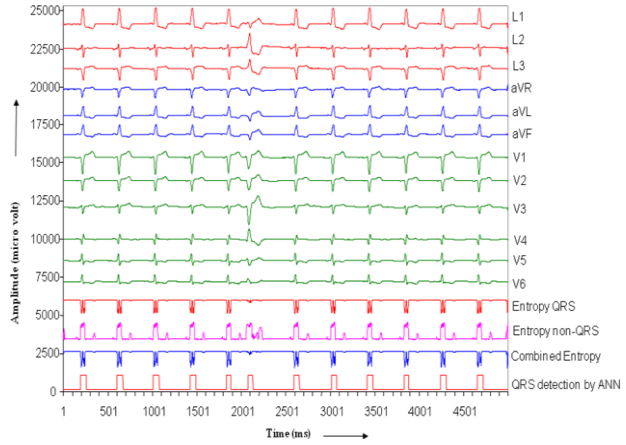


Figure 13: 12 lead ECG Mo1_040, Entropy curves of QRS, non-QRS, Combined Entropy and QRS detection by ANN

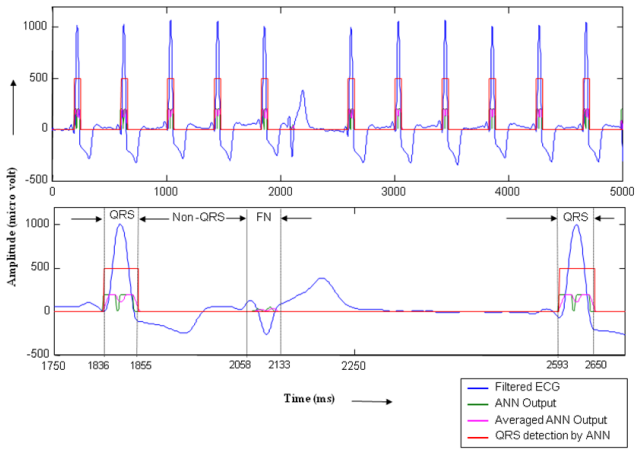


Figure 14: QRS detection of ECG MO1_040 by ANN

Figure 13, Shows the 12 lead ECG of patient MO1_040 with Entropy curves of QRS, non-QRS, Combined Entropy and QRS detection by ANN. In this case of the total 12 number of QRS only 11 QRS are detected correctly. One of the QRSs is not detected because its combined entropy was very less Figure 14 explains the correct detection of 11 QRS complexes out of 12 QRS.

9. Conclusions

This paper presents a derivative based on new approach for QRS detection in ECG signals. A combined entropic method for the detection of QRS complexes in 12-lead ECG using EBP ANN is used. This method is useful for ECG classification and cardiac diagnosis. The effectiveness of the method has been demonstrated by its accuracy rate of 97.08%.The method has certain limitations as well thus giving FP and FN of 2.70% and 0.02% respectively. Over all this method is found to be most effective one.

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