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International Journal Of Engineering And Computer Science ISSN:2319-7242
Volume 2 Issue 7 (July 2013), Page No. 2155-2161

PNN Based Detection of QRS-complexes in Electrocardiogram using Entropy

***M. K. Bhaskar*[1], *S. S. Mehta*[2], *N. S. Lingayat*[3], *Guneet Singh Mehta*[4]**

[1, 2] Department of Electrical Engg., MBM Engineering College, JNV University, Jodhpur, Rajasthan-India

[3] Department of Electrical Engg., Dr. B. A. T. University's, I.O.P.E, Lonere-402103, Maharashtra-India

[4]Department of Electrical Engg., Indian Institute of Technology, Jodhpur, Rajasthan-India

Abstract: ***This paper deals with the PNN based detection of QRS-complexes in Electrocardiogram (ECG) using entropy criteria. Recorded Raw ECG signal consist of baseline wander and power line interference. This is known as noise and that can be separated by using digital filtering techniques and this signal is known as filtered signal of ECG. In this entropy criteria is used generate the feature signal and this feature signal is applied to pattern classifier. The QRS-complexes are detected using Probabilistic Neural Networks as pattern classifier. The proposed algorithm is implemented using MATLAB. The performance evaluation of the algorithm is validated using each lead of the 12-lead simultaneously recorded ECGs from the dataset-3 of the CSE multi-lead measurement library. The detection rate of QRS-complexes is 99.34% by using proposed algorithm. The percentage of false negative is 0.66% and false positive is 0.83%. The results obtained by the proposed algorithm in terms of performance, based on the detection rate of QRS-detection that is compared with the other methods as reported in the literature. The algorithm that is proposed in this paper, demonstrate the strength for the QRS-detection field***

Keywords: ***Detection Rate, Electrocardiogram (ECG), Entropy, Morphologies of QRS-complexes, Probabilistic Neural Networks (PNN), QRS-complexes.***

1. Introduction

The QRS-complex is the most characteristic waveform within the ECG signal. Its high amplitude makes QRS-detection easier than the other waves. The recorded ECG signal has contains the various information about the working of the heart. ECG signal consists of different wave components like P-wave, QRS-complex and T-wave in each beat of ECG signal as shown in Fig. 1.

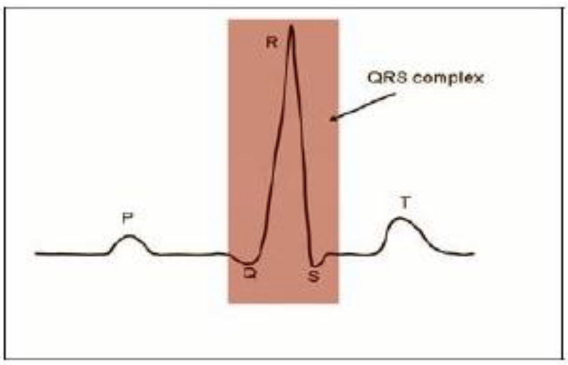

Fig.1 QRS-complexes in ECG signal

An electrocardiogram (ECG) is the representation of the electrical activity of the heart (*cardiac*) muscle as it is recorded from the body surface. The muscle cells (*myocardial cells*) of the heart are linked so closely to one another that electrical impulses can easily spread from one cell to the next. The *myocardial cells* have a negative electric resting potential. In the resting state, *myocardial cells* are *polarized*, with the inside of cells being negatively charged with respect to the outside. This charge is created by having a greater concentration of certain charged particles (ions) on one side of the cell membrane as compared with the other side. In response to stimulation, movement of these ions occurs. This causes a rapid loss of internal negative potential and thus generates electricity. This process is known as *depolarization* as illustrated in Fig. 2.

An increase in ventricular muscle mass (hypertrophy) usually results that increased in amplitudes of QRS-complex. Some diseases which cause death of heart muscle and replacement by scar tissue (such as myocardial infractions) will be reflected in characteristic changes in morphology of the QRS-complex. Therefore, QRS-detection is an important step in almost all automated ECG analysis systems. These kinds of detection strategies are very important to detect QRS-complexes.

The literature survey of the various methods developed for the detection of QRS-complexes is taken in consideration [1-4]. Few other QRS-detectors are reported recently using transformative approach [6], Hybrid Complex Wavelet [5], continuous wavelet transform [8], PCA-ICA based algorithm [7], multiscale filtering based on mathematical morphology [9], Support Vector Machine [10-13] Adaptive quantized threshold [14] etc. Most of the QRS-detectors consist of two main stages such as preprocessing stage, including linear filtering followed by nonlinear transformation and the decision rule [2]. Digital filtering techniques are used in the present work to remove power line interference and baseline wander present in the ECG signal during preprocessing stage. Therefore these digital filtering techniques are important to process the ECG signal.

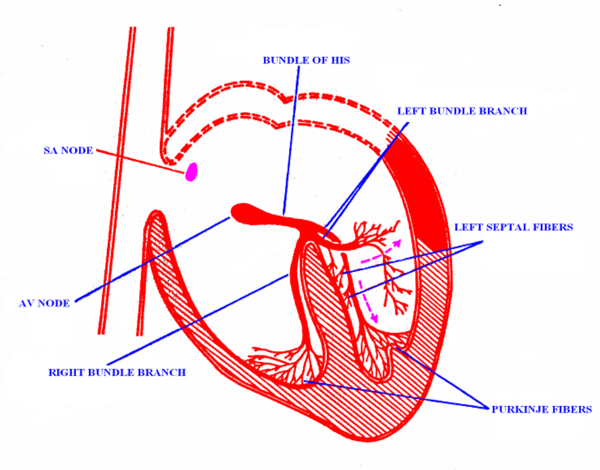

Fig. 2 : Electrical conduction system of heart

Probabilistic Neural Network is applied as a classifier to detect QRS and non-QRS regions. Most of the QRS detection algorithms reported in literature detects R-peak locations and separate rules are applied for the delineation of QRS i.e. to locate the onsets and offsets of the QRS complexes. The proposed PNN based algorithm successfully detects the QRS complexes. Among many types of neural networks, the multilayer feed-forward neural network, also known as back propagation network, has become the main architecture of choice. One problem with this method is that back propagation is a stochastic searching algorithm to find the point with a minimum error in the error space. If the searching space is large, the training time becomes prohibitively long, without guaranteed global minimum. Another drawback of such architecture is that it is difficult to decide not only how many layers are needed but also how many neural nodes are required in each layer. All these parameters have to be tried experimentally, which is very time consuming. Furthermore, if the architecture of the neural network is decided after these trials and then architecture is once fixed, the network will have difficulty to adapt itself to a new environment. To overcome these shortcomings, Probabilistic Neural Networks (PNN) was proposed by Specht in 1988 [16] because time is the important parameter for any QRS-detection algorithm. PNN may require more neurons than a standard feed-forward back propagation network, but they require less set-up time and training time. PNN's works best when an adequate number of samples are available to train with and those samples possess good class distinctions.

The PNN has been chosen as the network model to use in the present problem of QRS-detection. This paper is structured as follows. A brief architecture of the PNN is described in section 2. In section 3, preprocessing of the ECG signal is explained. Feature signal generation is discussed in section 4. An algorithm for the detection of the QRS-complexes is explained in section 5. The detection results of the proposed algorithm are reported in section 6 with the aid of computer simulations.

2. Architecture of PNN

The PNN provides a general solution to pattern classification problems. The basic idea behind PNN is the Bayes classification rule and Parzen's method of density estimation. The architecture and computation units of PNN implement these approaches. The most important advantage of PNN is that training is easy and instantaneous. Weights are not trained but assigned. Existing weights will never be altered but only new vectors are inserted into weight matrices during training. The PNN model of Mathwork's Matlab Neural Network Toolbox has been used in the present work for the detection of QRS-complexes.

The architecture of the PNN is shown in Fig. 3. The symbols and notations used in the Matlab Neural Network Toolbox are adopted in this section to describe the architecture of PNN. It has three layers: the input layer, the Radial Basis Layer and the competitive layer. Radial basis layer evaluates vector distances between input vector and row weight vectors in the weight matrix. These distances are scaled by Radial Basis Function non-linearly. Then the competitive layer finds the shortest distance among them, and thus finds the training pattern closest to the input pattern based on their distance.

The $R\times1$ dimensional input vector $\mathbf{p}$ is presented as a black vertical bar as shown in Fig. 3. In Radial Basis Layer, the vector distances between input vector $\mathbf{p}$ and the weight vector made of each row of the weight matrix $\mathbf{W}$ are calculated. The vector distance is defined as the dot product between the two vectors. Assuming the dimension of $\mathbf{W}$ as $Q\times R$, the dot product between $\mathbf{p}$ and the i^{th} row of $\mathbf{W}$ produces the i^{th} element of the distance vector $\| \mathbf{W} - \mathbf{p} \|$, whose dimension is $Q\times1$ as shown in Fig. 2. Then, the bias vector $\mathbf{b}$ is combined with $\| \mathbf{W} - \mathbf{p} \|$ by an element by element multiplication, represented as '.*' in Fig. 3 and the result is denoted as

$$\mathbf{n} = \| \mathbf{W} - \mathbf{p} \| .* \mathbf{b}.$$

The transfer function in PNN has built into a distance criterion with respect to a center. It is defined as

$$radbas(n) = e^{-n^2} \tag{1}$$

Each element of $\mathbf{n}$ is substituted in Eq. (1) and produces corresponding element of $\mathbf{a}$, the output vector of Radial Basis Layer. The i^{th} element of $\mathbf{a}$ can be represented as

$$a_i = radbas(\|\mathbf{W}_i - \mathbf{p}\| .* \mathbf{b}_i) \tag{2}$$

where $\mathbf{W}_i$ is the vector made of the i^{th} row of $\mathbf{W}$ and $\mathbf{b}_i$ is the i^{th} element of bias vector $\mathbf{b}$.

The i^{th} element of $\mathbf{a}$ equals to 1 if the input $\mathbf{p}$ is identical to the i^{th} row of input weight matrix $\mathbf{W}$. Radial basis neurons with a weight vector close to the input vector $\mathbf{p}$ produces a value near

1 and then its output weights in the competitive layer will pass their values to the competitive function. It is also possible that several elements of **a** are close to 1 since the input pattern is close to several training patterns.

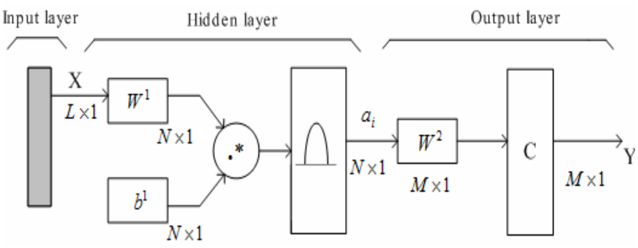

Fig. 3 : Architecture of the PNN

***Q*=** number of input/target pairs = number of neurons in layer 1 and ***K*=** number of classes of input data = number of neurons in layer 2.

There is no bias in a competitive layer. In this layer, the vector **a** is first multiplied with layer weight matrix **M**, producing an output vector **d**. The competitive function c, produces 1's corresponding to the largest element of **d** and 0's corresponding to the other elements. The output vector of the competitive function is denoted as **c**.

3. Pre-Processing of ECG Signals

The recorded ECG signal is acquired and this signal may contain noise from various sources. Therefore, before any kind of processing these noises should be minimized. This section describes the techniques used for the removal of power line interference, baseline wander and enhancement of the ECG signal. A raw ECG signal of a patient is acquired. The finite impulse response (FIR) notch filter proposed by Alste and Schilder [15] has been used to remove baseline wander. The adaptive filter to remove baseline wander is a special case of notch filter, with notch at zero frequency (or dc). This filter has a "zero" at dc and consequently creates a notch with a bandwidth of $(\mu/\pi)*f_s$, where f_s is the sampling frequency of the signal and μ is the convergence parameter. Frequencies in the range 0-0.5 Hz are removed to reduce the baseline drift. The convergence parameter used is 0.0025. The filter proposed by Furno and Tompkins [17] has been used to remove 50Hz power line interference. This noise removal from raw ECG signal will help to increase in detection rate.

4. Generation of Feature Signal

Slope is used as an important discriminating feature because slope of the ECG signal is greater in the QRS-region than in the non-QRS-region. The slope at every sampling instant is calculated and then squared to enhance the QRS-complexes. This is then smoothened using moving window integrator. Various window sizes ranging from 10 samples to 40 samples were tried in the present work. The window size of 20 samples was found optimum. Too large window size affects the onsets and offsets of the detected QRS-complexes where as too small size leads to more number of false negatives. By using this technique the feature signal in which QRS-complexes has been enhanced while other components are suppressed.

The input vector $\mathbf{x}_i$ to the PNN classifier is a set of two entropy values. Detection of QRS using two entropies curves, one for QRS-region and another for non-QRS-region are obtained. During the training of PNN, two synchronizing sliding windows of size of ten sampling instants each are moved over both the entropy curves. Thus ten values each from both entropy curves, in all twenty values are picked to form an input vector $\mathbf{x}_i$ to the PNN classifier. When the window lies completely in the QRS-region, the desired output of the PNN is set to 1 and when it lies completely in the non-QRS-region, the desired output is set to zero. The ECG portions, when the window lies partially in QRS as well as non-QRS-regions are not included in the training set. The PNN is trained on a set of training data covering wide variety of ECG signals, picked from CSE ECG data-set 3.

A set of twenty calculated normalized entropy values (ten belonging to QRS and ten belonging to non-QRS) are used at an instant to form the input vector for the PNN. During testing, a train of 1's is obtained when the window traverse through the QRS-region and zero's for the non-QRS-region. The train of 1's is picked and using their duration, an average pulse width of 1's is evaluated. 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. In some cases, when the P or T-waves are peaky in nature, the PNN gives a train of 1's but of smaller duration as compare to that of the QRS-complex. In order to differentiate between trains of 1's for QRS-complex and that for peaky P or T-waves, an average width or duration of all the trains of 1's is calculated. Those trains whose duration is greater than average pulse width are picked up as QRS-complexes by the algorithm and those whose duration is smaller than the average pulse width are discarded. This reduces the number of false positive detection of QRS-complexes to a great extent.

5. Algorithm for QRS-detection

The PNN model of Mathwork's Matlab (7.5) Neural Network Toolbox is used for the detection of QRS-complexes. In this section a formal QRS detection algorithm is presented.

Step 1: Preprocessing

1.1 Acquire raw ECG signal of a patient.
1.2 Use digital filtering techniques to remove baseline wander and power line interference.
1.3 Calculate the slope at every sampling instant of the filtered ECG signal.
1.4 Classify the slope values into two classes, namely QRS and non-QRS class using K-means of clustering algorithm.
1.5 Calculate the probability, $P_i(x)$ of slope at each sampling instant belonging to each of the two classes.
1.6 Calculate the entropy $h_i(x)$ at each sampling instant for QRS and non-QRS class to get two entropy curves.
1.7 Normalize these entropies.

Step 2: Training of PNN

2.1 Select certain portions of ECGs covering a wide variety of QRS and Non-QRS morphologies from the CSE data set 3 to train PNN.

2.2 Transform the data to the format of PNN. Training instance matrix is an R by Q matrix of Q training instances. Where R = No. of elements in the input vector. In this case, the number of training instances is equal to the number of samples of the selected of ECGs covering a wide variety of QRS and Non-QRS morphologies.

2.3 Select the value of spread factor SF. The value of SF cannot be selected arbitrarily. A too small SF value can result in a solution that does not generalize from the input/ target vectors used in the design. In contrast, if the spread factor is large enough, the radial basis neurons will output large values for all the inputs used to design a network. The optimum value of SF has obtained in the present work is 0.1.

Step 3: Testing of PNN

3.1 Begin with the first record of the CSE ECG data set 3.

3.2 Each record from CSE ECG data set 3 is of 10 second duration sampled at 500Hz, giving 5000 samples, i.e. 5000 testing instances.

3.3 For each testing instance, testing label of “1” is obtained if it belongs to the QRS region and a label of “0” is obtained if it belongs to the non-QRS region.

Step 4: Post processing phase

4.1 Club the continuous train of labels of 1’s from the predicted labels to form a pulse of unit amplitude. Pick up the trains of labels of 1’s and using their duration, calculate average pulse duration of 1’s. Those trains of 1’s, whose duration turns out to be more than the average pulse duration, can be marked as QRS regions and the other ones as non-QRS regions.

4.2 In some cases, when the P or T waves are peaky in nature, the PNN gives trains of labels of 1’s but of smaller duration as compare to that of QRS complex. In order to differentiate between trains of labels of 1’s for QRS complex and peaky P or T waves, calculate an average duration of all the trains of labels of 1’s. Those trains of labels of 1’s whose duration is greater than average pulse duration can be picked up as QRS complexes and those whose duration is smaller than the average pulse width can be discarded. Thus, average pulse duration criterion reduces the number of false positive detections.
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6. Performance Results

Table-1 displays the lead-wise test results of the QRS-detection algorithm using entropy as a feature. Detection rate (DR) of 99.34% is achieved when entropy is used as a feature. The percentage of false positive detection is 0.83% and false negative detection is 0.66%.

TABLE-1 : Lead-wise detection results of the QRS-complexes using entropy

Lead	Total QRS	Correct Detection	False Positive	False Negative	% Detection
I	1488	1474	6	14	99.06
II	1488	1480	9	8	98.46
III	1488	1483	18	5	99.66
aVR	1488	1479	12	9	99.40
aVL	1488	1481	16	7	99.53
aVF	1488	1476	24	12	98.19
V1	1488	1479	7	9	99.40
V2	1488	1476	16	12	99.19
V3	1488	1475	10	13	98.13
V4	1488	1477	8	11	99.26
V5	1488	1480	7	8	99.46
V6	1488	1479	15	9	99.40
Total	**17856**	**17739**	**148 (0.83%)**	**117 (0.66%)**	**99.34**

Table-2 : Comparison of proposed PNN based algorithm with other QRS-detection algorithms validated using CSE database

Sr. No.	**Reference**	**Method**	**Number of Cases/beats used for testing**	**Detection rate**
1	Proposed Algorithm (Entropy as feature)	Probabilistic Neural Network	125 cases, 17856 beats	99.34%
2	Mehta and Lingayat [12]	Support vector machine	125 cases, 17856 beats	99.30%
3	Chouhan and Mehta [14]	Adaptive quantized threshold	125 cases, 17856 beats	98.56%
4	Kyrkos et al. [23]	Time recursive prediction technique	1181beat	99%
5	Gritzali[22]	Length and energy transformation	14292 beats	99.60%
6	Trahanias, and Skordalalkis [24]	Bottom up approach	14292 beats	98.49%
7	Mehta et al. [20]	Pattern Recognition	100 cases	99.83%
8	Vijaya et al. [26]	Neural network	3657beats	98.96%
9	Saxena et al. [21]	Wavelet transform	125 cases	99.86%
10	Trahanias[25]	Mathematical morphology	14292 beats	99.38%

The false positive detections are relatively more. This is mainly due to the peaky P and T-waves in some records. Highest detection rate is obtained in lead-III and the lowest detection rate is obtained in lead-V3. False positive detections are more in lead III, aVL, aVF, V2 and V6. False negative detections are more in lead I, aVF, V2 and V3 compared to other leads. Table-2 shows the comparison with other referred methods is that the proposed method quite encouraging and good detection rate.

The following cases illustrate the effectiveness of the PNN based algorithm for a given problem of QRS-detection.

Fig. 4 showing the various steps for QRS-detection algorithm using PNN and entropy as feature of lead-III of record MO1_064. A raw ECG signal is acquired as shown in Fig. 4(a). It is then filtered using filtering techniques to obtain a filtered ECG as shown in Fig. 4(b). The entropy of QRS-region of the filtered ECG shown in Fig. 4(c). Fig. 4(d) shows the QRS-complexes using entropy of the QRS-region, because the entropy belonging to QRS-class is low i.e. uncertainty of the occurrence of QRS is low or in other words certainty of the occurrence of QRS-region is high. Fig. 4(e) shows entropy of the non-QRS-region and Fig. 4(f) shows detection of QRS-complexes using entropy of non-QRS-region. It can be seen that entropy belonging to non-QRS is high i.e. uncertainty of the occurrence of non-QRS is high or in other words certainty of non-QRS is low. Fig. 4(g) shows QRS-detection by compare the results of QRS-detection using the best output by taken into consideration of entropies of QRS-region and Non-QRS-region. The Fig. 4(h) shows the QRS-detection by PNN after post-processing.

Some of the ECG signal has peaky P and T-Waves, inverted peaky P and T-Waves, some noisy signals look like a QRS region, P and T-Waves. Therefore, due to presence of this kind of signal mentioned above, the algorithm wrongly detects as false positive case. So, post-processing phase is developed and applied in the algorithm. In this post-processing phase, the average width of the candidate QRS-Complexes is calculated. If the width of a candidate QRS-complex is less then the average width then those QRS-detection is discarded & if it is more, it is identified as QRS-complex. Thus, post-processing reduces the false positive cases and improves the accuracy of the algorithm.

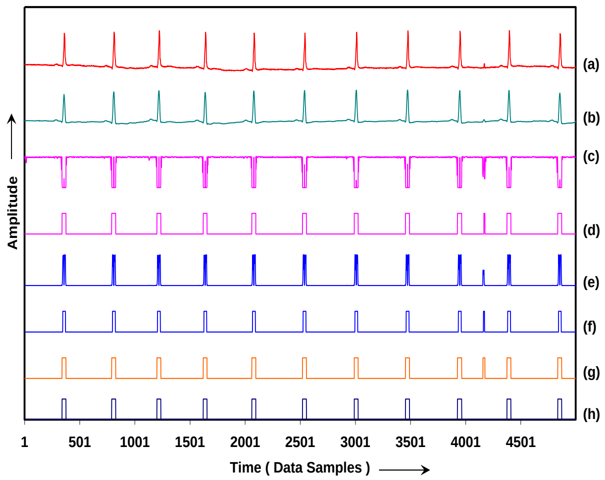

Fig. 4 : Steps for QRS-detection algorithm using PNN and Entropy as feature in Lead-III of record MO1_064 (a) Raw ECG (b) Filtered ECG (c) Entropy QRS (d) Detection using entropy QRS (e) Entropy Non-QRS (f) Detection using entropy Non-QRS (g) Detection QRS-complexes by taking best of Entropy QRS and Entropy Non-QRS (h) Final QRS-detection by PNN after post-processing

Some of the ECG signal has peaky P and T-Waves, inverted peaky P and T-Waves, some noisy signals look like a QRS region, P and T-Waves. Therefore, due to presence of this kind of signal mentioned above, the algorithm wrongly detects as false positive case. So, post-processing phase is developed and applied in the algorithm. In this post-processing phase, the average width of the candidate QRS-Complexes is calculated. If the width of a candidate QRS-complex is less then the average width then those QRS-detection is discarded & if it is more, it is identified as QRS-complex. Thus, post-processing reduces the false positive cases and improves the accuracy of the algorithm.

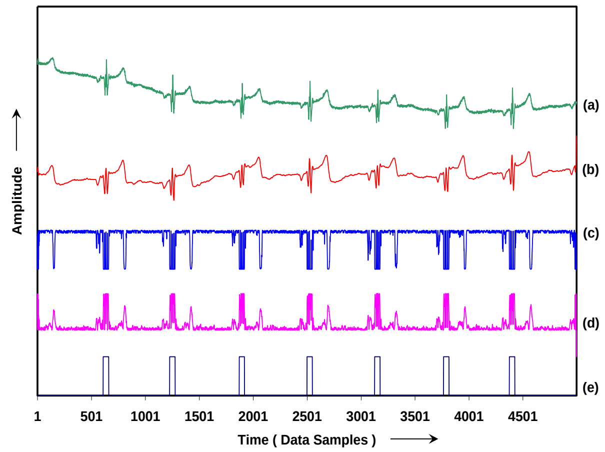

Fig. 5 : Detection of QRS-complexes using Entropy as feature in Lead-aVL of record MO1_021 (a) Raw ECG (b) Filtered ECG (c) Entropy QRS (d) Entropy Non-QRS (e) QRS-detection by PNN

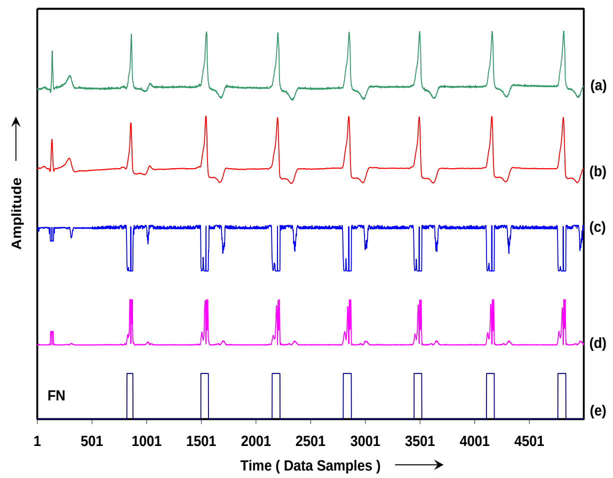

Fig. 6 : Detection of QRS-complexes using Entropy as feature in Lead-II of record MO1_050 (a) Raw ECG (b) Filtered ECG (c) Entropy QRS (d) Entropy Non-QRS (e) QRS-detection by PNN

Fig. 5 shows results obtained at the preprocessing stage and QRS-detection in lead-aVL of record MO1_021. As depicted in Fig. 5(b), the preprocessor removes noise and baseline wander present in the signal. The P-waves are not prominent in this case. It can be seen from Fig. 5(c) and (d) that in the QRS-region, the entropy belonging to QRS-class is low i.e. uncertainty of the occurrence of QRS is low or in other words certainty of the occurrence of QRS-region is high. Similarly, in this region entropy belonging to non-QRS is high i.e. uncertainty of the occurrence of non-QRS is high or in other words certainty of non-QRS is low. The T-Waves are prominent and their entropies are comparable with that of QRS-complexes as shown in Fig. 5(c) and (d). Still they are not detected as false positive case. This is because their pulse width duration is smaller than the average pulse width. Hence all the seven QRS-complexes are correctly identified by the PNN as shown in Fig. 5(d).

QRS-detection in lead-II of record MO1_050 is displayed in Fig. 6. As shown in Fig. 6(e), PNN fails to detect the first QRS-complex because of low amplitude, the higher value of QRS-entropy and lower value of non-QRS-entropies in the region of this QRS-complex. Whereas all other QRS-complexes having lower QRS-entropies and higher non-QRS-entropies, have been successfully identified by the PNN.

7. Conclusion

The detection of QRS-complexes using PNN and generation of feature signal is done by using entropy criteria. Two kinds of entropies are using; one is the entropy of QRS-region and second is the entropy of non-QRS-region. PNN is trained for the both entropies and then testing is done. Therefore, in this way detection of QRS-complexes is completed for each lead of 12-lead simultaneously recorded data.

Table-1 displays the lead-wise test results of the QRS-detection algorithm using entropy as a feature. Detection rate (DR) of 99.34% is achieved when entropy is used as a feature. The percentage of false positive detection is 0.83% and false negative detection is 0.66%.

The false positive detections are relatively more. This is mainly due to the peaky P and T-waves in some records. Highest detection rate is obtained in lead-III and the lowest detection rate is obtained in lead-V3. False positive detections are more in lead III, aVL, aVF, V2 and V6. False negative detections are more in lead I, aVF, V2 and V3 compared to other leads. Table-2 shows the comparison with other referred methods is that the proposed method quite encouraging and good detection rate. Heart related diseases which results in changes in the myocardial muscle mass will changes the ECG. For example, an increase in ventricular muscle mass (hypertrophy) usually results that increased in amplitudes of QRS-complex. Some diseases which cause death of heart muscle and replacement by scar tissue (such as myocardial infractions) will be reflected in characteristic changes in morphology of the QRS-complex. Therefore, QRS-detection is an important step in almost all automated ECG analysis systems and that is the demand in the field of biomedical engineering.

Much work has been carried out in the field of QRS-detection. Though the performance is good, each method has situations where it fails. Using the CSE database, the algorithm performed effectively with accurate QRS-detection over 99.34% of the total beats, even in the presence of peaky P and T-waves and wide variety of QRS-morphologies. The algorithm can be implemented by using PNN architecture of MATLAB to reproduce the results. The PNN model of Mathwork's Matlab Neural Network Toolbox has been used in the present work for the detection of QRS-complexes.

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