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Entropy Criterion Based Delineation of QRS-Boundaries using PNN in Single-Lead Electrocardiogram

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Abstract

This paper is an attempt for the delineation of QRS-boundaries in electrocardiogram using Probabilistic Neural Network (PNN) and entropy criterion. Delineation is helpful for the analysis of ECG signal. For the determination of QRS-boundaries, delineation process is applied to the ECG signal. Delineation process is applicable only when detection of QRS-complex is completed first. Probabilistic Neural Network and Entropy criteria is applied for the detection of QRS-complexes. The results of detection rate of QRS-complexes are obtained is quite encouraging i.e. 99.34%. The delineation performance of the proposed algorithm is validated using referees annotations and the combined program median provided in the CSE multi-lead measurement library. The results of delineation are presented using BA- plots and they are found to be well within tolerance limits as specified by CSE working group.

Keywords: BA-Plot, Delineation, Probabilistic Neural Network (PNN), QRS-boundaries, Refree's Annotation.

1. INTRODUCTION

The Electrocardiogram of the human is an interesting research area for the medical doctors, scientist and engineers of the prime importance. ECG is the representation of working of the heart. The analysis of the ECG is widely used for diagnosing many cardiac diseases. Since most of the clinically useful information in the ECG is found in the intervals and amplitudes defined by its significant points such as characteristic wave peaks as well as boundaries, the development of accurate and robust methods for automatic ECG delineation is a subject of major importance, especially for the analysis of long recordings. The most prominent waveform within the electrocardiogram (ECG) is QRS-complexes. Since it reflects the electrical activity within the heart during the ventricular contraction, the time of its occurrence as well as its shape provide much information about the current state of the heart. Fig-1 shows typical ECG signal wave which is recurrent in nature. Due to its characteristic shape, it serves as the basis for the automated ECG analysis. QRS-detection is necessary to determine the heart rate and as reference for beat alignment. ECG wave delineation provides fundamental features (amplitudes and intervals) to be used in subsequent automatic analysis. The delineation results of the algorithms and the established medical diagnostic rules can be used for ECG signal interpretation and diagnosis.
The QRS-complex in the ECG signal has high amplitude and quick variations within it makes. QRS-detection is easier as compared to the other waves. Thus, it is generally used as a reference within the cardiac cycle. A wide diversity of algorithms has been proposed in the literature for QRS-detection. The application of Probabilistic Neural Network (PNN) as a classifier has been developed in the present work for detection and delineation of QRS-complexes in the ECG signal. The literature review of the various methods developed for the delineation and detection of QRS-complexes as reported in references [1]-[4]. Few other QRS-detectors have been reported recently using PCA-ICA based algorithm [7], Adaptive quantized threshold [14], Hybrid Complex Wavelet [5], transformative approach [6], continuous wavelet transform [8], multiscale filtering based on mathematical morphology [9], Support Vector Machine [10]-[13] etc. have been proposed. Most of the QRS-detectors consist of two main stages: a 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. So in this way filtered ECG signal is developed and that is very much useful for present work.

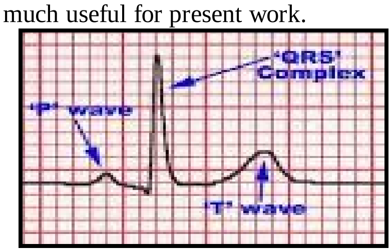

Figure 1 ECG Waveform

Detection of QRS-complexes is the primary task for the delineation. Delineation is the process to determine the onset and offset of the QRS-complexes of the electrocardiogram. In this algorithm, PNN has been used as a classifier to delineate 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 not only detects the QRS complexes but also delineates them simultaneously. The onsets and offsets of the detected QRS complexes are well within the tolerance limits specified by the expert cardiologists in the CSE study and are available in the CSE library. Before delineation, QRS-complexes must be identified. The following section describes the detection of QRS-complexes in ECG with the help of Probabilistic Neural Network.

2. QRS-COMPLEXES DETECTION METHOD

2.1 Probabilistic Neural Network

Specht's [15] claim that a PNN trains 100,000 times faster than back-propagation (BPA) is at best misleading. While they are not iterative in the same sense as back-propagation, kernel methods require that you estimate the kernel bandwidth, and this requires accessing the data many times. Furthermore, computing a single output value with kernel methods requires either accessing the entire training data or clever programming, and either way is much slower than computing an output with a feed-forward network and there are a variety of methods for training feed-forward nets that are much faster than standard back-propagation. So the distinguishing feature of PNN as compared to the back-propagation neural network is that the computational load in the training phase is transferred to the evaluation phase. However, the speed of computation is noticeably more than the BPA feed forward.

The Probabilistic Neural Network (PNN) belongs to the Neural Network family which provides a general solution to pattern classification problems. The basic idea behind PNN is the Baye's 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 symbols and notations used in the MATLAB Neural Network Toolbox have been 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.

2.2 Pre-processing of ECG Signal

Before attempting the detection of QRS-complexes, it is necessary to pre-process the ECG signal. When an ECG recording of the subject is done and it 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 subject is acquired. The finite impulse response (FIR) notch filter proposed by Alste and Schilder [16] has been used to remove baseline wander. The adaptive filter used 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 50 Hz power line interference. The idea behind the per-processing of ECG signal is to pre-process the signal in order to make it convenient for detection and delineation purpose.

2.3 Generation of Feature Signal

The input vector $\mathbf{x}_i$ to the PNN classifier is a set of entropy values. Detection of QRS using entropy as feature has explained in this section. As explained earlier 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.

As discussed in the earlier, 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.

2.4 Detection of QRS-complexes

QRS-detection algorithm consist several steps as reported in the literature [37], Pre-processing of ECG signal, Training of Probabilistic Neural Network (PNN), Testing of PNN and finally Post-processing is done. The algorithm has been tested on dataset-3 of CSE multi-lead measurement library [19]. The detection consist wide varieties of QRS-morphologies and a detection rate of 99.34%, the percentage of false positive detection is 0.83% and false negative detection is 0.66% has been achieved. The following cases demonstrate the strength of the PNN based algorithm for the detection of QRS-complexes.

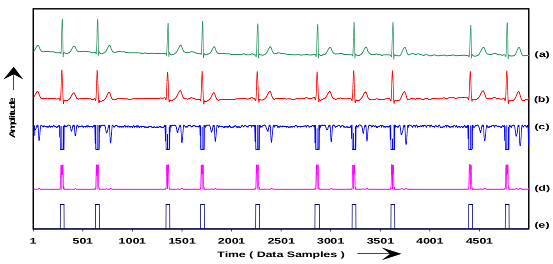

Figure 2 Detection of QRS-complexes using Entropy as feature in Lead-V4 of record MO1_057
(a) Raw ECG (b) Filtered ECG (c) Entropy QRS (d) Entropy Non-QRS (e) QRS-detection by PNN

Fig. 2 displays results obtained at the preprocessing stage and QRS-detection in lead-V4 of record MO1_057. As depicted in Fig. 4.2(a) raw ECG signal has some baseline wander and it has been removed in the filtered ECG as shown in Fig. 4.2(b). The QRS-complexes are prominent in this case. In this case, T-waves are some what peaky in nature, therefore entropy belonging to QRS-complex in the region of T-wave is also low indicating higher certainty of T-wave region belonging to QRS-complex, but due to low value of non-QRS entropy, these T-waves have not been detected as QRS-complexes by the PNN thereby eliminating the chances of T-wave being identified as QRS-complex. Hence all the QRS-complexes in this case are correctly identified.

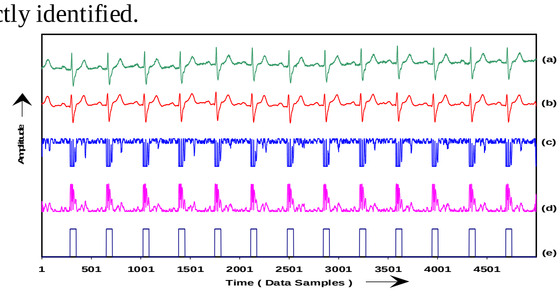

Figure 3 Detection of QRS-complexes using Entropy as feature in Lead-V6 of record MO1_076
(a) Raw ECG (b) Filtered ECG (c) Entropy QRS (d) Entropy Non-QRS (e) QRS-detection by PNN

Fig. 3 shows QRS-detection in lead-V6 of record MO1_076. As shown in the Fig. 3(a) raw ECG signal has some noise and baseline wander and it has been removed in the filtered ECG as shown in the Fig. 3(b). The QRS-complexes are prominent in this case as shown in Fig. 3(b). In this case, T-waves are peaky in nature. Therefore, these T-waves are not detected as QRS-complexes by the PNN. In spite of that the entropies of T-waves are not comparable with that of QRS-complexes.. Hence all the QRS-complexes in this case are correctly identified.

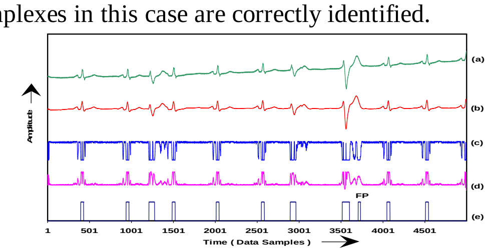

Figure 4 Detection of QRS-complexes using Entropy as feature in Lead-I of record MO1_028
(a) Raw ECG (b) Filtered ECG (c) Entropy QRS (d) Entropy Non-QRS (e) QRS-detection by PNN

Fig. 4 shows QRS-detection in lead-I of record MO1_028. As shown in the Fig. 4(a) raw ECG signal has some noise and baselines wander and it has been removed in the filtered ECG as shown in the Fig. 4(b). The amplitude of the third T-wave is slightly high and the 8^{th} T-wave is extremely high in this case having low QRS-entropies and high non-QRS-entropies in the region of the third and 8^{th} T-wave. The amplitude and slope of the 8^{th} T-wave is extremely high in this case. The 8^{th} T-wave has very low QRS-entropies and very high non-QRS-entropies in its region as compared to other T-waves. Therefore, the 8^{th} T-wave has been correctly detected as a QRS-complex by the algorithm indicating false positive detection.

3. CSE DATABASE OF ECG SIGNAL

This library has been developed to standardize and evaluate the performance of computer measurement programs. The dataset-3 of CSE multi-lead measurement library [19] has been used in the present study to validate the detection and delineation results of the proposed algorithm. It consists of 125, original 12-lead simultaneously recorded ECG covering a wide variety of cardiac abnormalities such as incomplete right bundle branch block, complete right bundle branch block, left anterior fascicular block, complete left bundle branch block, acute myocardial infraction, anterior myocardial infraction, postero-diafragmatic myocardial infraction, lateral or high-lateral myocardial infraction, apical myocardial infraction, myocardial infraction + intraventricular, conduction defect, left ventricular hypertrophy, right ventricular hypertrophy, pulmonary emphysema, ischemic ST-T changes, bigeminy, trigeminy, multiple PVC's, multiple APC's, supraventricular tachycardia, atrial flutter, atrial fibrillation, 1^{st} AV-block, 2^{nd} AV-block, Wolf-Parkinson-white syndrome, pacemaker, etc. Every record picked from CSE ECG database is of 10 sec duration sampled at 500 samples per second thus giving 5000 samples. These ECGs were analyzed by a group of five referee cardiologists and eleven different computer programs. Attention was focused on the exact determination of the onsets and offsets of P, QRS and T-waves. Median results of the referee's coincided best with the medians derived from all the programs studied in the CSE library and therefore combined program median can be used as a robust reference.

4. DELINEATION OF QRS-BOUNDARIES

In Electrocardiograms (ECGs), most of the clinically useful information lies in the wave intervals, amplitudes, or morphology. Therefore, efficient and robust methods for automated ECG delineation are of great importance. The QRS complex is relatively easier to detect and is thus generally used as a reference within the cardiac cycle. The analysis of electrocardiograms (ECGs) has received increasing attention because of its vital role in many cardiac disease diagnoses. Therefore, the development of efficient and robust methods for automatic ECG delineation is a subject of major importance. Delineation of QRS-complexes are reported in the literature, using K-means algorithm [32], wavelet bases and adaptive threshold technique [33], first-derivative, Hilbert and Wavelet Transforms [35].

The fundamental requirement of the ECG delineation is the identification of component waves of the ECG signal. ECG delineation is an important stage in automatic disease diagnosis as it is used to identify a particular disease. After detecting the fundamental ECG components using PNN, the ECG parameters namely P-on, P-peak, P-off, QRS-on, Q-peak, R-peak, S-peak, QRS-off, T-peak and T-end are extracted. From these fundamental measurements, the parameters of diagnostic significance, namely, the heart rate, P-amplitude, PR-interval, QRS-interval, QT-interval, QRS-peak-to-peak amplitude, ventricular activation time (VAT) and frontal plane axis (FPA) are obtained and extracted. The algorithm is validated by extensive testing using data-set 3 of the CSE multi-lead measurement library. To validate the delineation results, the mean and standard deviation of the differences between automatic and manual annotations by the referee cardiologists as well as the combined program median available in the CSE library, are calculated. The performance of the proposed delineation algorithm is compared with the other delineation algorithms tested on the standard database.

The Bland-Altman analysis is not a statistical test measured with a *p*-value. Instead, it is a process used to assess agreement between two methods of measurement. An important requirement of the Bland-Altman method [39] for measuring agreement is that the two methods for measuring the same characteristic use the same scale of measurement. This implies that when plotted, the points should line up along the *line* $y = x$ *(line of identity)*. It is possible for two measures to have strong linear agreement using a Pearson's correlation (r) when they are not measuring the same quantity because a correlation analysis does not require that the two measurements be on the same scale or to even be measurements of the same characteristic. The analysis is based on examination of two plots.

The delineation performance of the proposed algorithm is validated using referees annotations and the combined program median provided in the CSE multi-lead measurement library [40]. Out of the 125 records in the data-set 3, referees have analyzed selected beat of every fifth record and marked onsets and offsets of QRS-complex considering all the twelve leads simultaneously. Thus, out of 125 records onsets and offsets of QRS-complex are available for 25 records. The median results of the combined programs studied in the CSE data-set 3 are available for all 123 records. In the present work, onsets and offsets of QRS-complex are compared with the referee's annotations as well as the combined program median and the BA- plots are plotted.

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5. DELINEATION RESULTS

The mean (*m*) is calculated as the average of the errors, taken as the time difference between the automatic (proposed algorithm) and the referee cardiologist annotations/ combined program median. Standard deviation (*s*) in milliseconds (*ms*) is also calculated. The mean and standard deviation of errors between automatic (proposed PNN based algorithm) and manual annotations/combined program median are displayed in Table 1. It is observed that the mean and standard deviation of errors of the QRS-onsets as detected by the proposed algorithm is very low where as the mean and standard deviation of errors of the QRS-offsets as detected by the proposed algorithm is large due to large error in offsets of some of the QRS-complexes. This is because the QRS-offset and T-ends are usually over lapping and sometimes it is difficult to demark.

Table 1 : Mean and standard deviation of errors using PNN and Entropy as feature

Parameter	Mean Error (ms)	Standard Deviation (ms)
QRS-onset (CSE Referee's annotation and proposed PNN based algorithm)	2.84	13.79
QRS-offset (CSE Referee's annotation and proposed PNN based algorithm)	12.41	6.13
QRS-duration (CSE Referee's annotation and proposed PNN based algorithm)	9.57	14.66
QRS-onset (CSE combined program median and proposed PNN based algorithm)	5.53	12.04
QRS-offset (CSE combined program median and proposed PNN based algorithm)	16.03	7.73
QRS-duration (CSE combined program median and proposed PNN based algorithm)	15.50	13.38

Fig 5-10 displays Bland-Altman plots showing the amount of disagreement between automatic (proposed PNN based algorithm) and manual annotations/combined program median using the difference and disagreement related to the magnitude of measurement. Out of the 25 manual annotations by the referee's cardiologists 96% of the QRS-onsets and 95% of the QRS-offsets are within the tolerance limits. Similarly, out of 123 CSE combined program medians 96% of the QRS-onsets and 97% offsets are within the tolerance limits. These figures show the effectiveness of the PNN based algorithm for the delineation of the QRS-complexes. The algorithm not only detects but delineates all kinds of morphologies of the QRS-complexes.

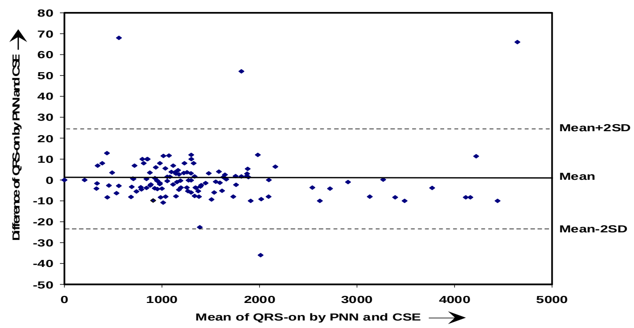

Figure 5 BA Plot for QRS-onset of single Lead QRS-detection by PNN and Entropy as a feature using combined program median

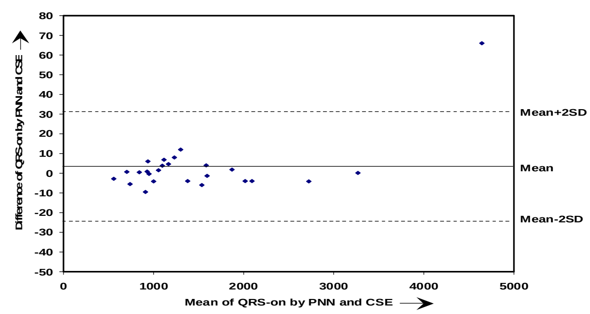

Figure 6 BA Plot for QRS-onset of single Lead QRS-detection by PNN and Entropy as a feature using referee's annotations

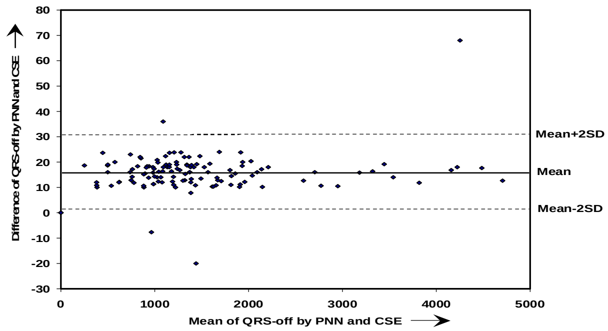

Figure 7 BA Plot for QRS-offset of single Lead QRS-detection by PNN and Entropy as a feature using combined program median

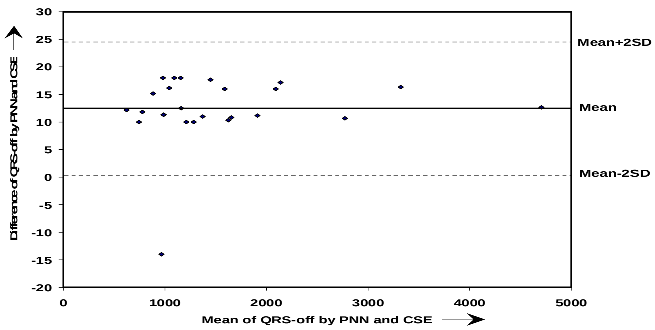

Figure 8 BA Plot for QRS-offset of single Lead QRS-detection by PNN and Entropy as a feature using referee's annotations

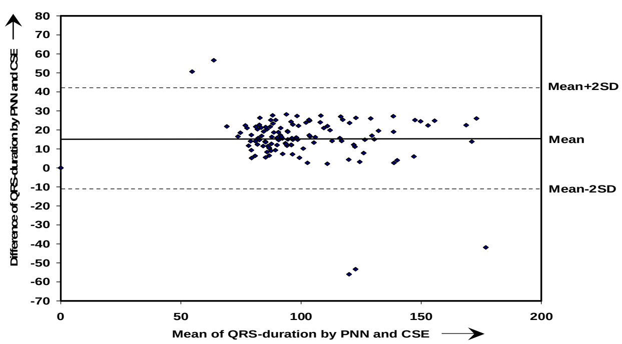

Figure 9 BA Plot for QRS-duration of single Lead QRS-detection by PNN and Entropy as a feature using combined program median

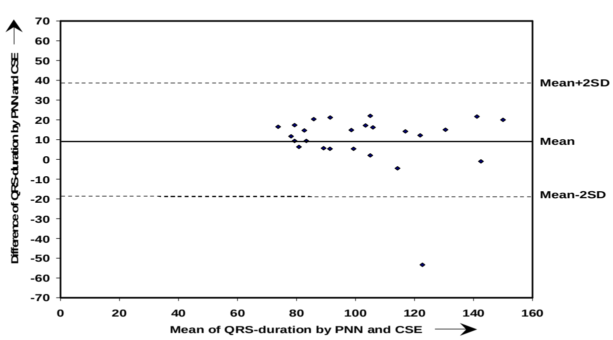

Figure 10 BA Plot for QRS-duration of single Lead QRS-detection by PNN and Entropy as a feature using referee's annotations

6. CONCLUSION

The algorithm has been developed for the delineation of QRS-complex in simultaneously recorded ECG signal. It has been done using PNN as classifier and entropy as feature is presented in this paper. The proposed algorithm is trained and tested. The method has been exhaustively tested using the data-set 3 of CSE multi-lead measurement library covering a wide variety of QRS-complexes consists of wide variety of morphologies. The PNN based algorithm not only successfully detects the component waves of the ECG, but also delineate them accurately. The delineation results shows that the standard deviations of the errors are within the tolerances as suggested by the CSE working group. The information obtained by this method is very useful for the automated ECG interpretation. Much work has been carried out in the field of QRS-detection. Though the performance is good.. 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 proposed PNN based algorithm using entropy as feature, not only detects the QRS-complexes but also delineates them precisely. This paper will be helpful for interpretation of ECG signal.

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