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Probabilistic Neural Network Based Delineation of QRS-complexes in Single-Lead ECG using Slope Criterion

M. K. Bhaskar, S. S. Mehta, N. S. Lingayat, Guneet Singh Mehta, D. A. Shete

Abstract— This paper presents the delineation of QRS-complexes in electrocardiogram using Probabilistic Neural Network (PNN) and Slope criteria. Before going to the step of delineation of QRS-complexes, first follow the step of detection of QRS-complexes. The results of detection rate of QRS-complexes are obtained is quite encouraging i.e. 99.23% using slope criteria and PNN. The delineation is process to determine the onset and offset of QRS-region. 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.

Index Terms— BA-Plot, Combined Program Median, Delineation, Probabilistic Neural Network (PNN), QRS-complexes, Refree's Annotation.

I. INTRODUCTION

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 (characteristic wave peaks and 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 QRS-complex is the most striking waveform within the electrocardiogram (ECG). 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 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 is the most characteristic waveform within the ECG signal. Its high amplitude and quick variations within it makes QRS-detection 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 is given in [1-4]. Few other QRS-detectors have been reported recently using Hybrid Complex Wavelet [5], transformative approach [6], PCA-ICA based algorithm [7], continuous wavelet transform [8], multiscale filtering based on mathematical morphology [9], Support Vector Machine [10-13] Adaptive quantized threshold [14] 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.

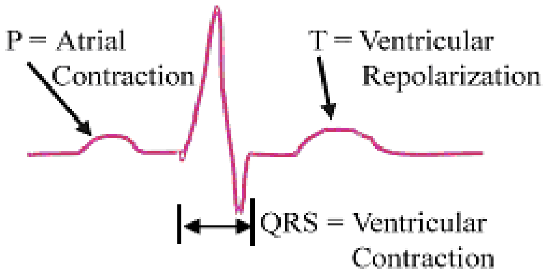

Fig-1 : Wave Contractions

Delineation is the process to determine the onset and offset of the QRS-complexes of the electrocardiogram. 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.

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* Correspondence Author
M. K. Bhaskar, Department of Electrical Engineering, M.B.M. Engineering College, J.N.V. University, Jodhpur, Rajasthan, India.
S. S. Mehta, Department of Electrical Engineering, M.B.M. Engineering College, J.N.V. University, Jodhpur, Rajasthan, India.
N. S. Lingayat, Department of Electrical Engineering, Dr. B.A.T. University, I.O.P.E. Lonere-402103, Maharashtra, India.
Guneet Singh Mehta, Department of Electrical Engineering, Indian Institute of Technology, Jodhpur, Rajasthan, India.
D. A. Shete, Department of Electrical Engineering, Government Polytechnic College, Latur, Maharashtra, India.

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.

II. DETECTION OF QRS-COMPLEXES

A. Probabilistic Neural Network

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 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 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.

B. Pre-Processing of 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.

C. Generation of Feature Signal

Slope of the ECG signal 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 are enhanced while other components are suppressed.

D. Detection of QRS-Complexes

QRS-detection algorithm consist several steps as reported in the literature [38], 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 99.23%, the percentage of false positive detection is 1.03% and false negative detection is 0.77% has been achieved.

The following cases illustrate the effectiveness of the PNN based algorithm for the detection of QRS-complexes.

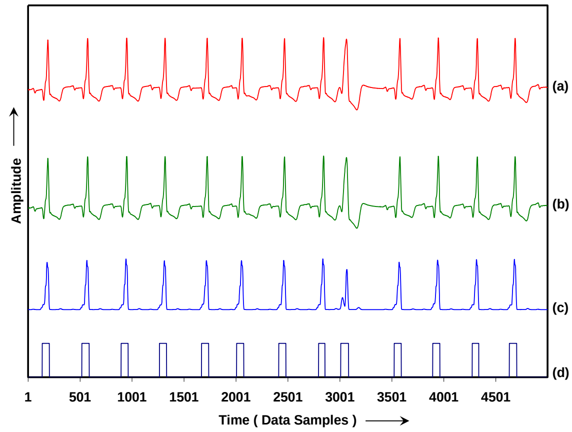

Fig. 2 : Detection of QRS-complexes using slope as feature in Lead-V1 of record MO1_026 (a) Raw ECG (b) Filtered ECG (c) Feature signal (d) QRS-detection by PNN

Fig. 2 displays QRS-detection in lead V1 of record MO1_026. As depicted in Fig. 2(b), the preprocessor removes noise and baseline wander present in the signal.

The P and T-waves are not prominent in this case. Therefore, The algorithm has correctly identified all the QRS-complexes as shown in Fig. 2(d).

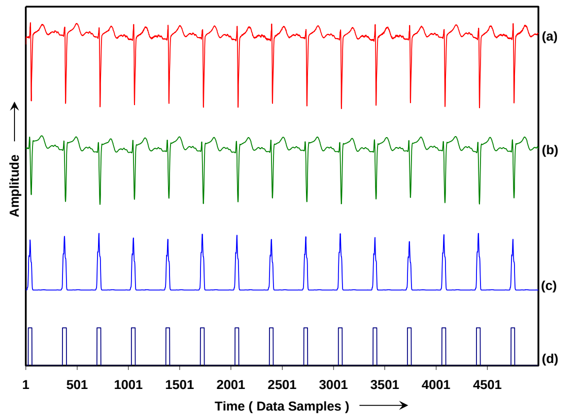

Fig. 3 : Detection of QRS-complexes using slope as feature in Lead-V2 of record MO1_083 (a) Raw ECG (b) Filtered ECG (c) Feature signal (d) QRS-detection by PNN

Fig. 3 demonstrates QRS-detection in lead V2 of record MO1_083. All the QRS-complexes are prominent in nature. The P-Waves have very low amplitude whereas T-wave has slightly more amplitude as compared to P-Waves in this case.

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Since the slope in the QRS-region are higher in QRS-region as shown by the curve in Fig. 3(c), PNN successfully detects all the QRS-complexes without any false detection.

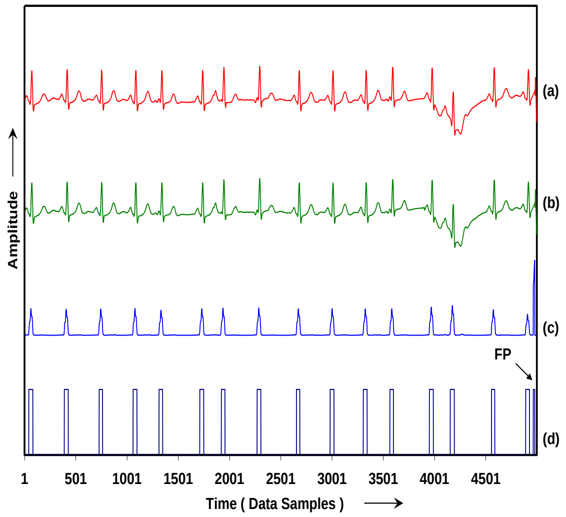

Fig. 4 : Detection of QRS-complexes using Slope as feature in Lead-V6 of record MO1_006 (a) Raw ECG (b) Filtered ECG (c) Feature signal (d) QRS-detection by PNN

As another example, detection of QRS-complexes in lead-V6 of record MO1_006 has been explained in Fig. 4. It can be seen that the baseline drift is so abrupt that it could not be completely removed by the pre-processor. Moreover, a sharp noisy peak is present after the last QRS-complex. It can be seen that all the QRS-complexes have been successfully detected by PNN even in the presence of abrupt baseline wander. However, the noisy peak present after the last QRS-complex has been falsely picked up as QRS-complex – a case of false-positive (FP). This due to the fact the slope of the noisy peak is comparable with QRS-complexes.

III. CSE DATABASE OF ECG SIGNAL

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. This library has been developed to standardize and evaluate the performance of computer measurement programs. It consists of 125, original 12-lead simultaneously recorded ECGs 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, 1st AV-block, 2nd 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.

IV. DELINEATION OF QRS-COMPLEXES

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.

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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.

V. 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 3. 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 precisely.

TABLE-1: MEAN AND STANDARD DEVIATION OF ERRORS USING PNN AND SLOPE AS FEATURE

Parameter	Mean Error (ms)	Standard Deviation (ms)
QRS-onset (CSE Referee's annotation and proposed PNN based algorithm)	12.96	8.16
QRS-offset (CSE Referee's annotation and proposed PNN based algorithm)	38.00	14.40
QRS-duration (CSE Referee's annotation and proposed PNN based algorithm)	38.00	14.40
QRS-onset (CSE combined program median and proposed PNN based algorithm)	13.25	7.30
QRS-offset (CSE combined program median and proposed PNN based algorithm)	36.67	13.82
QRS-duration (CSE combined program median and proposed PNN based algorithm)	36.67	13.82

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.

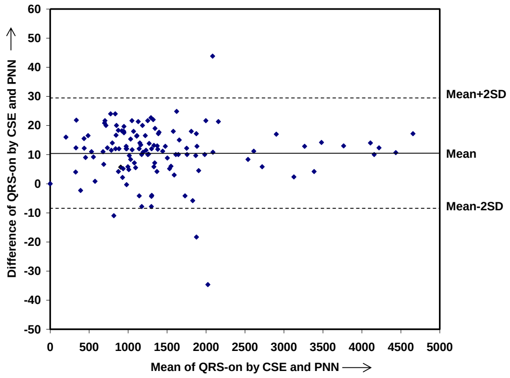

Fig. 5 : BA Plot for QRS-onset of single Lead QRS-detection by PNN and slope as a feature using combined program median

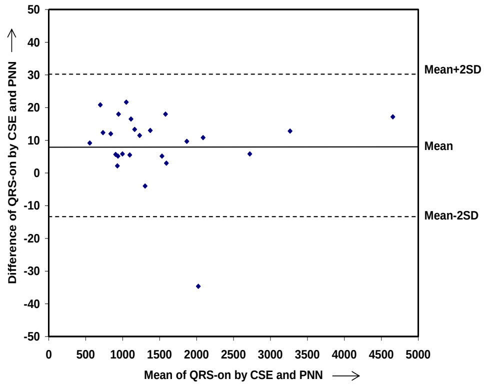

Fig. 6 : BA Plot for QRS-onset of single Lead QRS-detection by PNN and slope as a feature using referee's annotations

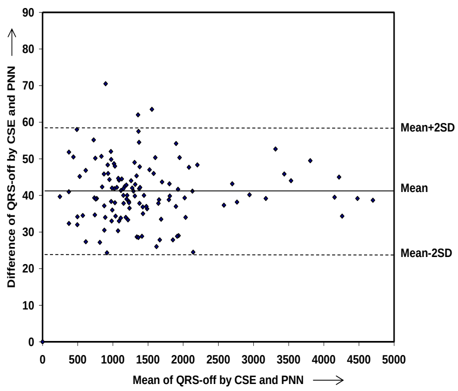

Fig.7 : BA Plot for QRS-offset of single Lead QRS-detection by PNN and slope as a feature using combined program median

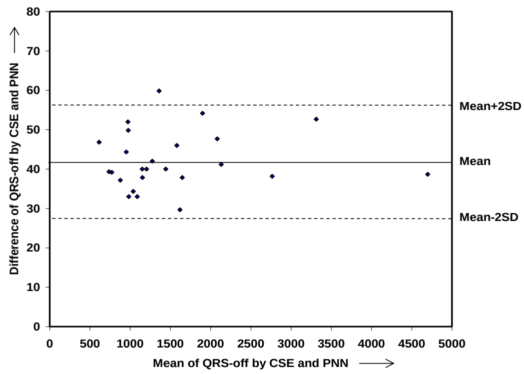

Fig. 8 : BA Plot for QRS-offset of single Lead QRS-detection by PNN and slope as a feature using referee's annotations

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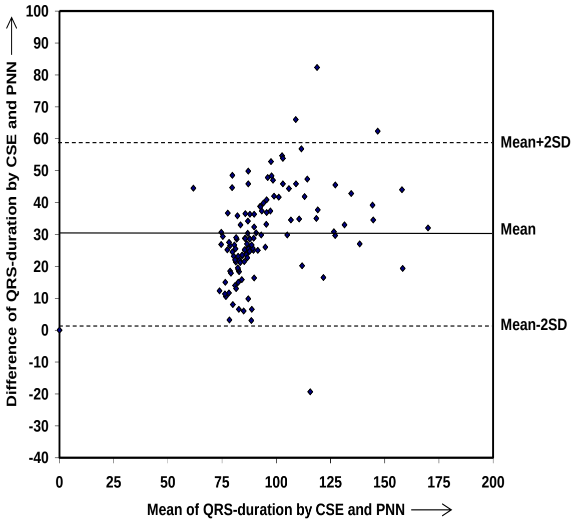

Fig. 9 : BA Plot for QRS-duration of single Lead QRS-detection by PNN and slope as a feature using combined program median

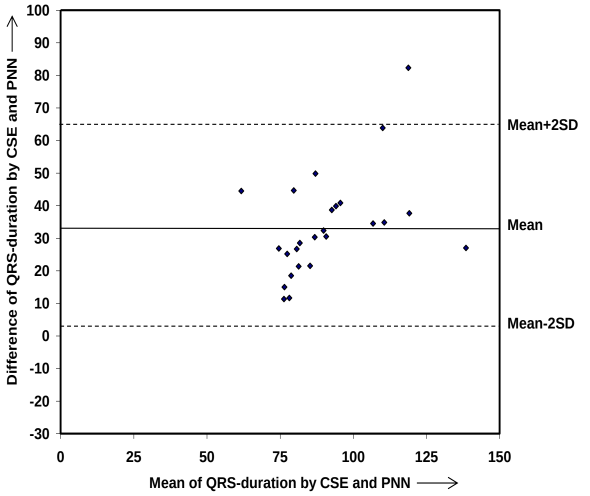

Fig. 10 : BA Plot for QRS-duration of single Lead QRS-detection by PNN and slope as a feature using referee's annotations

VI. CONCLUSION

An algorithm for QRS-complex delineation in simultaneously recorded ECG signal using PNN as classifier has been presented in this paper. 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 show that the standard deviations of the errors are within the tolerances suggested by the CSE working party. 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, each method has situations where it fails. Using the CSE database, the algorithm performed effectively with accurate QRS-detection over 99.23% 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 not only detects the QRS-complexes but also delineates them precisely.

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