An intelligent classifier for cardiac arrhythmias recognition

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Abstract— **the aim of this article is to propose an intelligent electrocardiogram classifier. The classifier is similar to probabilistic neural networks. In these networks, a user needs to set some parameters optionally. Improper selections may decrease the performance drastically. The proposed method needs no optional parameter settings and all required parameters are extracted from the statistics of the input signals. The proposed classifier has two layers and a database of known signals that has been categorized and labeled to M classes based on their similarities. The first layer calculates the similarities of the input unknown signal to the known signals of each class using Basis Radial functions and outputs Bayesian variables** equal to the number of classes**. The second layer is just a maximum selector of these Bayesian variables as the winner. In fact, it indicates that the input signal most probably belongs to the class in which Bayesian variable is maximum. Five classes of ECG signals from MIT-BIH arrhythmia database are selected to illustrate the good performance of the non-invasive proposed classifier compared to the previous methods. Moreover, acceptable low computational complexity and robustness against high noise are significant features of the proposed classifier.**

Key Words: Electrocardiogram (ECG), Basic Radial Function, Bayesian Variables

I. INTRODUCTION

Bio-signals on the surface of body indicate the status of some internal organs. Therefore, by using non-invasive measurement methods, significant information can be provided. Electrocardiogram (ECG) is the most important signal that cardiologists utilize for diagnostic reasons. In fact, ECG provides the key information about heart function. As a result, continuous monitoring of ECG is valuable and the variations in heart electrical activities can be deployed by physicians. Because of the high mortality rate from heart diseases, faithful detection and classification of ECG arrhythmias are essential for the clinical treatment of patients. In recent years, many algorithms have been developed for the classification of ECG signals.

The QRS complex in ECG signals varies with the origination and the conduction path of the activation pulse in the heartbeat. When the activation pulse does not travel through the normal conduction path, the QRS complex becomes wide, and high-frequency components are attenuated [18]. With the time-domain technique, various features from each heartbeat are extracted to detect arrhythmia waveforms, such as width, height, area of QRS complex, and QRS morphology, etc [1-4]. Moreover, some researches focus on the frequency domain [3, 5]. However, valuable information emerge from both time and frequency domain analysis that can be distinguishable and hence, can be used for classification. Wavelet transformation (WT) opens another category of methods that represent the signal in different translations and scales. Moreover, the discrete wavelet transformation (DWT) decomposes a signal into signals in different coarseness levels. The wavelet transform is very powerful for analyzing time-varying signals. Extracted features from the wavelet analysis can efficiently represent the characteristics of the original signal in different details [10-12]. In [6-8], the wavelet transform is utilized to accurately detect QRS complex, P and T waves in ECG that finally are used to classify ECG. However, the wavelet transform increases the computational complexity significantly since each ECG has to be decomposed by this transformation. In this paper we propose a method to reduce the required computational complexity. In fact, the goal is to find a method that uses the original ECG for classifying and so, there is no need for pre-processing the ECG signals.

As popular classifiers, artificial neural networks (ANNs) have been extensively employed in computer-aided diagnosis (CAD) systems. Among them, the multilayer perceptron (MLP) is probably the most popular [2, 5, 9]. The conventional MLP has demonstrated impressive accuracy in classifying the ECG beats into two (normal and abnormal) categories. However, in order to improve the multi-category classification tasks, hierarchical systems that combine MLP and another ANN are usually indispensable [5, 13-15]. In these systems, the first-level neural networks are responsible for pre-classifying beats into normal and

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abnormal categories, or building a model for the input features. A MLP is then followed to complete the multi-category classification tasks in the second level. Although the MLP-based systems have achieved high accuracy in the classification of multi-category ECG beats, the inherited backpropagation algorithms produce serious computational load. The multi-ANN structure of the hierarchical systems makes the situation worse [17].

On the contrary to the intensive computation in MLP, radial basis-function networks (RBFNs) have been attracting a great deal of interests because of their rapid training, generality, and simple characteristics [11]. Among various paradigms of RBFNs, the probabilistic neural networks (PNNs) inherit many of these characteristics and are particularly suitable for classification tasks [11, 16-19]. One of the popular basis functions used in PNNs is $e^{-n^2/\sigma}$ where n is the function input and σ is an optional parameter. The value of σ has a substantial impact on the performance of the network. In [18] an adaptive neural network is presented that tries to optimize the value of σ. The optimal parameter σ is intended to minimize the object function, which is defined as the squared difference between the real and target outputs. Reference [18] employs the following gradient method to update σ in each iteration (where η is the learning rate, and p is the iteration number):

$$\sigma(p+1) = \sigma(p) + \eta \frac{\partial e}{\partial \sigma} \quad (1)$$

The performance of this method may not be desirable because of some drawbacks of the mentioned adaptive algorithm (e.g. being trapped in a local minimum). In the proposed classifier, σ is set based on the standard deviation of input signal. As a consequence, there is no need for adaptive algorithm. The proposed classifier has two layers and a database of known signals that has been categorized and labeled to M classes based on their similarities. The first layer calculates the similarity of the unknown input signal to known signals of each class using Basis Radial functions and outputs the Bayesian variables equal to the number of the classes. The second layer is just a maximum selector of the Bayesian Variables. The class related to maximum is introduced as the winner. In fact, it indicates that the input signal most probably belongs to the class that its Bayesian variable is maximum. Our simulations on five ECG classes from MIT-BIH Arrhythmia database illustrate a highly acceptable performance, low computational complexity and insensitivity to severe noise of the proposed classifier.

The organization of this paper is as follows: First in section 2, QRS complex and a method to extract it from ECG signal is shortly introduced and then, ECG classes studied here are depicted. In section 3, the proposed method is completely presented and its acceptable performance is illustrated by some simulations in section 4. Finally, some important conclusions are given in section 5.

II. ECG SIGNALS

An ECG signal represents the changes in electrical potential during the heartbeat as recorded with non-invasive electrodes on the limbs and chest; a typical ECG signal consists of the P-wave, QRS complex, and T-waves. The P-wave is the result of slow-moving depolarization of the atria. The rapid depolarization of the ventricles results in the QRS complex of the ECG, which is a sharp wave about 1 mV amplitude and 80–100 ms duration. The plateau part of the action potential after QRS is called the ST segment [18]. In our study, 21 ECG records form MIT-BIH Arrhythmia database are selected to be classified. These records include 5 different classes: Normal (N), Left Bundle Branch Block (LBBB), Right Bundle Branch Block (RBBB), Premature Ventricular Contraction (PVC), Paced Beat (PB). In each class, there are 2400 ECG signals which are divided into two groups (known and unknown). For all, MLII lead is used. The QRS complex of the ECG is important information in heart-rate monitoring and cardiac disease diagnosis. The R-waves are detected by a peak detection algorithm that begins by scanning for local maxima in the absolute value of ECG data. For certain window duration, searching continues to look for a larger value. If this search finishes without finding a larger maximum, the current maximum is assigned as the R peak [5]. Centered on the detected R peak, the QRS complex portion is extracted by applying a window of 280 ms (power spectra of individual QRS complex are at frequencies between 4 Hz and 20 Hz), and P-wave and T-wave are excluded by this window duration. Based on 360 sampling rate used in MIT-BIH Arrhythmia database, 100 samples can be acquired around the R peak (Sampling point n = 100, 50 points before and 50 points after) [18]. For each ECG class, a sample extracted by the above method is depicted in Fig.1.

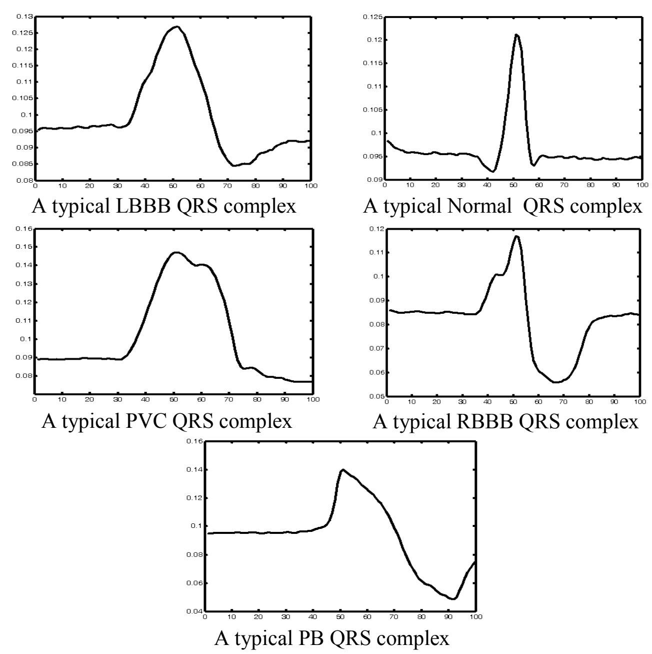

Figure 1. Shapes of QRS complex for each class

III. PROPOSED METHOD

The whole structure of the proposed method is depicted in Fig.2. Let us assume the total number of classes is M and for i^{th} class $n_s^{(i)}$ known QRS complexes are stored in the information bank. The k^{th} input QRS complex is denoted by $r(k)$ and assumed to be unknown. For this input signal, M Baysian variables are made as follows:

$$\eta_i(k)=\sum_{j=1}^{n_s^{(i)}}\exp\left(\frac{-\left\|r(k)-r_j^{(i)}\right\|^2}{2\sigma}\right),\qquad 1\le i\le M \tag{2}$$

Where $r_j^{(i)}$ is j^{th} signal from known signals of i^{th} class in the information bank and σ is the standard deviation of $r(k)$. It means that σ is set based on the standard deviation of the input signal. So, it doesn't need to be selected optionally. This method is based on the technique introduced by Chen that blindly estimates communication channels and data jointly [23]. For $r(k)$, M Bayesian variables are calculated that form the output of the first layer. The second layer is just a maximum selector of its inputs. It introduces the class related to maximum as the winner. In fact, the output of the second layer i.e. $s(k)$ indicates that the input signal belongs to the class in which Baysian variable is maximum with a high probability, and is made as follows (s_i^* means that the input signal is the most similar to signals stored in i^{th} class of the information bank):

$$s(k)=s_i^*\quad if\ \ \eta_i^*(k)=\max\{\eta_i(k),\quad 1\le i\le M\} \tag{3}$$

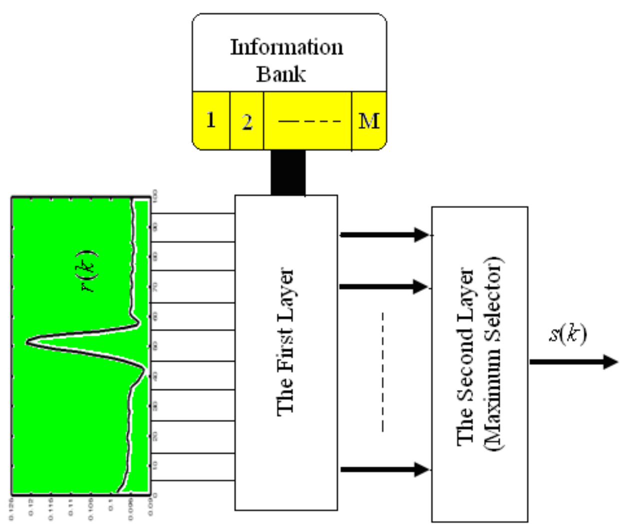

Figure 2. The proposed Classifier

Overally, in the proposed method there is an information bank that stores known QRS complexes of ECG in M separate classes (for each class, $n_s^{(i)}$ known QRS complexes are stored). Based on this information bank, in the first layer M Bayesian variables are made via (2). Since, here five classes are selected to study ($M=5$), five Bayesian variables are made. These variables are the output of the first layer fed to the second layer. The second layer selects its maximum input and shapes its output based on (3). The second layer output s_i^* indicates that signal input most probably belongs to i^{th} class of the information bank. It is worth mentioning that opposite to artificial neural networks, there is no training rule here. The basis of the proposed method is similarity measure of input signal to stored signals in each class of the information bank. For this comparison, distance between input signal and each stored signal in a certain class is measured. Then, it is weighted by exponential function. Finally, the summation of all weighted distances between input signal and all signals in a class is introduced as a Bayesian variable (see (2)). The output of classifier indicates the class having the minimum distance of the input signal corresponding to the maximum Bayesian variable. As it was mentioned before, there are 2400 QRS complexes for each class. First, 1200 complexes of them are considered as known signals and stored in the information bank. Then, it is illustrated that if the number of complexes are reduced significantly, the performance of the proposed classifier decreases slightly. This great reduction causes the information bank to need memory with much less capacity, and moreover, result in much less computational complexity explained in section 4.

IV. SIMULATION

In this section the performance of the proposed method is studied. Five ECG classes are chosen to study. Here, the criterion for measuring noise is the variance of signal to the variance of noise and is noted by SNR (db). In Fig.3 a corrupted ECG with severe noise is shown (noise is considered to be Gaussian). The performance in all following tables is calculated as follows (correct diagnosis means that the unknown input signal is classified to the right category):

$$Performance\,(per\ \%)=\frac{the\ \ total\ \ number\ \ of\ \ correct\ \ diagnoses}{the\ \ total\ \ number\ \ of\ \ trials}$$

In table.1, the performance of the proposed method is summarized for the noiseless state and some states where input signals are corrupted with different powers of noise. Since noise inherently has random values, the performance is the result of averaging over 50 independent experiments for each case. It is essential to notice that in each training process of artificial neural networks different weights may be obtained. As a result, it can be inferred that the response of network may change for the same input when it is trained again. But, in this study there is no training process and the output is unique for the same input. So, in the noiseless state only one experiment is run.

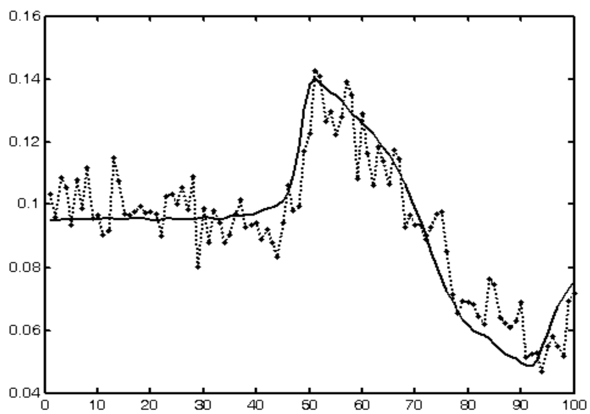

Figure 3: The corrupted QRS complex with noise (SNR= 8.45 db)

Table. 1: The performance of the proposed method with/without considering noise

SNR(db)	N	LBBB	RBBB	PVC	PB	Average (%)
noiseless	99.65	97.66	97.95	100	100	99.05
30	99.65	97.66	97.74	100	100	99.01±0.025
20	99.65	97.89	97.01	100	100	98.91±0.037
10	99.37	97.89	97.26	100	99.84	98.87±0.059
8.45	98.97	97.89	96.92	100	99.68	98.69±0.061

In the next simulation, the impact of the number of known signals in each class is studied. First, 1200 signals are considered and then in each step this number is decreased (the number of signals in each class is noted by Num in the table.2). The result is summarized in the table.2. The very important point is that even with only 40 known signals in each class of the information bank, the performance does not degrade drastically. This great reduction causes the information bank to require less memory and moreover, results in much less computational complexity.

Table .2: The impact of the number of known signals in each class on the performance

Num	N	LBBB	RBBB	PVC	PB	Average (%)
1200	99.65	97.66	97.95	100	100	99.05
320	100	98.83	95.90	98.59	99.61	98.58
160	100	96.49	96.58	98.59	99.61	98.25
80	99.65	96.41	95.90	98.59	99.61	98.03
40	95.22	96.49	96.92	98.59	99.23	97.29

For making each Bayesian variable in the first layer, the computational complexity is as follows:

$n_s^{(i)}$ **subtraction operators** + $n_s^{(i)}$ **absolute operators** + $n_s^{(i)}$ **power of two operators** + $n_s^{(i)}$ **division operators** + $n_s^{(i)}$ **power of exponential operators** + $n_s^{(i)}-1$ **summation operators**

As a result, it can be concluded that the number of stored signals for each class in the information bank is directly related to computational complexity. Of course, if the number is selected too small, the performance may degrade and if it is set very large, on the other hand, the computational complexity may increase drastically, and it needs a large memory. Consequently, there is a trade-off between the desired performance and computational complexity.

Now, we want to compare our method with other ECG beat recognition systems. One of the common methods in the literature is the comparison of the convergence speed of training process for each method. However, since there is no training process here, this comparison is not applicable. In this study, the average classification accuracy is selected for comparison. The methods introduced in references [17] and [18] and some ECG beat recognition systems utilized in [17] are chosen for this comparison: Multiple cardiac arrhythmias recognition using an Adaptive Wavelet Network (AWN) [18], ECG beat classification based on Wavelet Transformation and Probabilistic Neural Network (WT-PNN) [17], ECG recognition using fuzzy hybrid neural network (FHyb-HOSA) [13], a modified mixture of expert network structure for ECG beats classification with diverse features (MME) [21], ECG beat classification using neuro-fuzzy network (Neuro-Fuzzy) [14], ECG beat classification using LVQ and autoregression AR MLP (MLP-LVQ) [22], and Fourier and MLP (MLP-Fourier) [5]. Although because of different circumstances supposed in each method, this comparison is not completely fair. Only the averaged accuracy and the overall performance of the systems are justified. Table.3 compares the accuracy of these systems. Since different numbers of beat types were exploited in different systems, the average classification accuracy was calculated for comparison [17]. The result shows that our proposed method provides relatively high classification accuracy. However, the performance is slightly lower than WT-PNN, but it should be noted that our proposed method works with the original ECG signals and there is no need for pre-processing. Reference [17] first deploys discrete wavelet transformation (two-level wavelet decomposition) to decompose ECG signals. And, then some features are extracted. Finally [17] uses a probabilistic neural network for classification. So prior to classifying, reference [17] needs a pre-processing.

Table .3 : Comparison of the proposed method to other ECG beat classification systems

Method	Number of beat types	Accuracy (%)
The proposed method	5	99.05
AWN	7	96.16
WT-PNN	6	99.65
FHyb-HOSA	7	96.06
MME	5	97.78
Neuro-Fuzzy	4	98.00
MLP-LVQ	2	96.80
MLP-Fourier	3	98.00

V. CONCLUSION

In this study, a novel ECG classifier is proposed. This classifier has two layers and an information bank including a database of known signals that has been categorized in M classes based on their similarities. By means of basis Bayesian functions in the first layer, the similarity measure of the input signal to each class is calculated and the maximum is selected as the winner in the second layer. This indicates the input signal most probably belongs to the class in which Bayesian variable has the maximum value. Four substantial advantages of the proposed method are as follows: 1- The highly acceptable performance even in the presence of severe noises added to ECG signals. 2- The good performance even if the number of known signals is decreased significantly. 3- Using of original ECG signal and no need for pre-processing such as wavelet transformation. 4- User needs to set no parameter optionally and all required parameters can be directly extracted from input signals (As mentioned before, in some cases improper selection leads to decreased performance drastically). The good performance of the proposed classifier is illustrated trough our simulations.

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