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# Classification of Arrhythmias Using Linear Predictive Coefficients and Probabilistic Neural Network

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## Abstract

Cardiac arrhythmia, which means abnormality of heart rhythm, in fact refers to disorder in electrical conduction system of the heart. The aim of this paper is to present a classifier system based on Probabilistic Neural Networks in order to detect and classify abnormal heart rates, where besides its simplicity, has high resolution capability. The proposed algorithm has three stages. At first, the electrocardiogram signals impose into preprocessing block. After preprocessing and noise elimination, the exact position of R peak is detected by multi resolution wavelet analysis. In the next step, the extracted linear predictive coefficients (LPC) of QRS complex will enter in to the classification block as an input. A Support Vector Machine classifier is developed in parallel to verify and measure the PNN classifier's success. The experiments were conducted on the ECG data from the MIT-BIH database to classify four kinds of abnormal waveforms and normal beats such as Normal sinus rhythm, Atrial premature contraction (APC), Right bundle branch block (RBBB) and Left bundle branch block (LBBB). The results show 92.9% accuracy and 93.17% sensitivity.

**Keywords:** Arrhythmia; Linear Predictive Coefficient; Multi resolution Wavelet Analysis; Probabilistic Neural Networks.

## Introduction

Heart diseases have been one of the leading causes of death in many countries. Due to the complex nature and various treatment methods, early diagnoses and treatment of such diseases have attracted great interest among researchers. One of the most common heart diseases is Cardiac Arrhythmia which is caused by disorders in electrical conduction system of the heart. The arrhythmias are identified according to their occurrence area within heart (atrial or ventricle) and their effects on heartbeat [1]. We call arrhythmias started at the atrial, atrial arrhythmia and those originated from ventricle, ventricle arrhythmia [1].

According to the importance of early diagnosis and considering this fact that the shape of electrocardiogram signal represents heart state and its internal reactions at each moment, one can come to this conclusion that this disease will result in abnormal changes in the shape of electrocardiogram signal by disturbing the cardiac conduction system. Since the biosignals are non-stationary signals, such changes might appear randomly and over time in the signal. In other words, the possibility of observing illness indexes in indefinite intervals during day is high which makes the simultaneous monitoring of signal a time consuming and complex phenomenon. In this case, using computer based methods to diagnose and classify data will become more important. Various methods have been proposed to classify arrhythmias which evaluate such changes by using different algorithms and a variety of features.

 

Varieties of systems are used as the classifier. These are mostly based on artificial neural networks (ANNs) [2], fuzzy logic [3], support vector machine [4-5], Ant colony optimization [6], k-nearest neighbor [8]. Moreover, features have been based on wavelet transform [2, 4-6], morphological features [6], nonlinear dynamic parameters [3] and statistical features like AR coefficients [7].

The proposed method in [2] has used wavelet coefficients and multi layer neural networks to classify 3 different types of arrhythmias. Several high-performance training algorithms such as Variable Learning Rate, Resilient Back propagation, and Reduced Memory Levenberg-Marquardt algorithms are used for training of network. In [3], by applying 4 dynamic, nonlinear parameters of electrocardiogram signal and fuzzy system, the classification of 8 arrhythmia types has been done. Through statistical analysis of the calculated features it has been shown that they differ significantly between normal heart rhythm and the different arrhythmia types.

In [4], the better performance of Support Vector Machines (SVM) has been shown in comparison with methods such as RBF [1]neural networks and the K-nearest neighbor algorithm. For improving the generalization performance of the SVM, Particle Swarm Optimization (PSO) has been used. The proposed algorithm in [5] also has used support vector machines while the performance of this classifier has been improved by using ELM[2] method. Since the generalization performance of the SVM classifier is not satisfactory for the correct classification, the ELM classifier is used which search for the best value of the parameters that tune its discriminate function. In [6] by combining the time and frequency domain features and applying Ant Colony Optimization (ACO), the classification of 6 different types of arrhythmias has been performed. Both time domain and discrete wavelet transform (DWT) based frequency domain features are used in this research. The obtained sensitivity of the classification scheme reveals the better classification using mix feature set. AR Modeling for Automatic Cardiac Arrhythmia Diagnosis is proposed in [7] which explore the ability of autoregressive models (AR) to extract relevant features from ECG in order to classify cardiac arrhythmias. In this research, after extraction of autoregressive model coefficients, a Quadratic Discriminant function (QDF) based algorithm is used for classification. The evaluation results proof an improvement in classification accuracies.

One of the recent researches based on clustering algorithms has been proposed in [8] which describe a multi stage classification system based on combination of diverse features along with K-Nearest Neighbor methodology. A diverse set of features include higher order statistics, morphological features, Fourier transform coefficients, and higher order statistics of the wavelet package coefficients extracted for each different type of ECG beat. The results show that the multi-stage classifier for discriminating a wide range of heartbeats presents an optimal system with relatively good performance.

## Material and Method

### A. *The Proposed Algorithm*

The aim of this research is to present a classifier system in which the classification of normal and abnormal beats is done. As a classifier probabilistic neural network is preferred because of its high performance and for characterizing the ECG signal to detect or predict abnormalities Linear Predictive Coefficients is used. The structure of proposed algorithm has been shown in figure (1). This algorithm consists of three steps: signal preprocessing, feature extraction, classification. At the first step, the signal must be preprocessed and its noises must be eliminated. The exact detection of waves and their time intervals is one of the on hand problems in most feature extraction algorithms. In this research the feature extraction method based on multi resolution wavelet analysis has been used to extract R wave and consequently QRS complex [9]. In the second step,

[1] Radial Basis Function
[2] Extreme Learning Machine

the Linear Predictive Coefficients of QRS complex has been extracted and 20 coefficients are taken as an input to the probabilistic neural network in order to classify the beats.

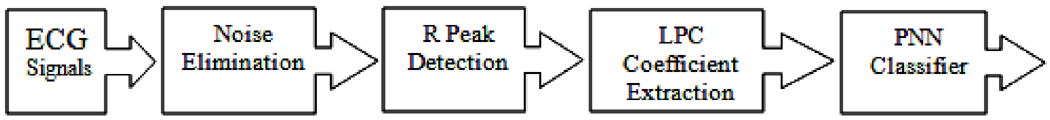


**Figure 1**. The block diagram of proposed algorithm

B. *Dataset*

The MIT-BIH Arrhythmia Database has been used in order to evaluate the algorithm. The records were obtained by the Beth Israel Hospital Arrhythmia Laboratory. This database contains 48 two channel 30 minute signals with different types of Arrhythmias, which 23 cases of these signals have been collected randomly among 4000, 24-hour signals. The signals have been sampled with 360Hz frequency and 11 bit resolution and labeled by two cardiac specialists [10].

C. *Signal Preprocessing*

In fact, the aim of this step is to improve the signal to noise ratio of ECG in order to more accurate analysis. Unfortunately, The ECG is often contaminated by noise and artifacts (e.g. baseline wandering, A/C interference and electromyography Contamination) that can be within the frequency band of interest and can manifest with similar morphologies as the ECG itself. Therefore, noise elimination is the most important stage introduced at each preprocessing methods. This step starts with detection of R peak as the most prominent peak in the signal with the aid of multi resolution wavelet analysis. The wavelet transform is considered as a powerful tool in the field of decomposing signal into different set of frequency bands. This decomposition allows one to selectively examine the content of a signal within the chosen bands for the purpose of compression, filtering, or signal classification and feature extraction [9]-[11]. The wavelet transform of x (t) is defined as equation (1):

$$W_a \cdot x(b) = \frac{1}{\sqrt{a}} \int x(t) \cdot \Psi\left(\frac{t-b}{a}\right) dt, \quad a > 0 \tag{1}$$

where a, b and $\psi(t)$ represent dilation, translation factor and mother wavelet, respectively. Selection of appropriate type of mother wavelet cast an important role in signal processing .The Daubechies wavelet picks up more details which is missed by other wavelet algorithms. Therefore, in this research we prefer to use the Daubechies (6) mother wavelet which is similar in shape to QRS complex and its energy spectrum is concentrated around low frequencies. After decomposing the signal in to 8 levels, the information of levels 3, 4 and 5 which have more likeness and similarity with the shape of QRS complex are used to detect R peak. So the obtained signal from the summation of these three states is given to a peak detection algorithm after squaring and the exact position of peaks is obtained. In this method, unlike Pan-Tompkins classic method, R peaks have no time delay, because in this method, filter is not used to differentiate R peak [12]. In order to eliminate A/C interference and electromyographic contamination a 20ms averaging filter is applied [13]. Baseline wandering is removed by subtracting from the recorded signal the first-order polynomial that best fits the signal and crosses the initial iso-electric points [14].

*D. Linear Predictive Coefficients Analysis*

Linear Predictive Coefficients (LPC) analysis is one of the most powerful tools in signal processing, especially speach signals which is able to extract the dominant features of speech signal. The capability of precise estimation of signal parameters and high speed computations is considered as an advantage of this technique which has become a base to use these coefficients in evaluation of electrocardiogram signal changes [15].

The general idea of this analysis is that each sample of signal could be written as a linear equation in terms of previous inputs and outputs [15]:

$$S(n) = \sum_{k=1}^{P} a_k s(n-k) + Gu(n) \tag{2}$$

In this case, we can represent the frequency effect of different parameters of speech signal as a digital filter:

$$H(z) = \frac{S(z)}{U(z)} = \frac{G}{1 - \sum_{k=1}^{P} a_k z^{-k}} \tag{3}$$

By considering a linear approximation, one can estimate each sample of signal from p previous samples of it:

$$\hat{S} = \sum_{k=1}^{P} a_k s(n-k) \tag{4}$$

The basic approach is to find a set of predictor coefficients that will minimize the mean square prediction error [15]:

$$e(n) = S(n) - \hat{S}(n) = S(n) - \sum_{k=1}^{P} a_k s(n-k) \tag{5}$$

As previously mentioned, linear predictive coefficients are used to directly estimate the parameters of speech signal, so we could refer to speaker's recognition, speech recognition, speech classification and signal dereverberation as important applications of this analysis. It is noteworthy to know that because of time varying nature of the signal, coefficients must be calculated from short segments. Consequently, in order to extract these coefficients in an interval including 100 samples of QRS complex, we determine 20 LPC coefficients and use these coefficients as inputs of classification block.

*E. Support Vector Machine*

Support vector machines originally proposed by Vladimir N. Vapnik are supervised learning models which analyze data and recognize patterns specifically in data classification problems.

The applications of SVMs cover several fields such as object recognition, speech and speaker recognition and verification, face detection and gender determination from facial images and spam mail identification[16]. Unlike other classification methods such as neural networks that is based on structural risk minimization and attempt to minimize the misclassification errors SVMs minimize the probability of misclassifying a previously unseen sample drawn randomly from a fixed but unknown probability distribution [17]. Consider a training data set with finite number of elements ($x_i$, $y_i$) which $x_i$ $x_i$ are the input vectors and $y_i \in \{-1, +1\}$ is the class labels. Using a (non)linear function $\varrho(.)$, SVM maps the input vector x from the input space to the high dimensional feature space. Therefore, a hyper plane with maximal distance should match the equation (6):

$$\begin{aligned} &W^T\varphi(x) + b \geq 1,\ \forall x \in c_1 \\ &W^T\varphi(x) + b \leq -1\ ,\ \forall x \in c_2 \end{aligned} \tag{6}$$

Therefore the optimization problem is defined as:

$$\text{Minimize} \quad J(W) = \frac{1}{2}\|W\|^2$$
$$\text{Subject to} \quad d_i(W^T\varphi(x_i) + b) \geq 1 \tag{7}$$

The lagrangian function proposed for solving the above maximization problem with respect to constraints is [16]:

$$\min_{w,\xi,b} J_1(W,\xi) = \frac{1}{2}W^TW + C\sum_{i=1}^{N}\xi_i) \tag{8}$$

Such that

$$d_i(W^T\varphi(x_i) + b) \geq 1 - \xi_i,\ i = 1,\ldots,N$$
$$\xi_i \geq 0,\ i = 1,\ldots,N \tag{9}$$

where C is a positive constant for regularization that provide a tradeoff between misclassification error and large margin.

*F. Probabilistic Neural Network*

The Probabilistic Neural Networks first proposed by especht[18] have more applications in fields of pattern recognition and estimating data probability of each class. PNN create a new space by applying non-linear mapping operations into input space where the possibility of linear decomposition of samples would be superior. One of the advantages of PNN training is that this training method only requires one step and in decision making levels there is such guarantee that by increasing the number of training samples, we could approach more to the optimal Bayes' decision boundaries [18]-[19]. The architecture of typical probabilistic neural network has been shown in figure (3). In this structure, four layers have been specified including: input layer, pattern layer, summation layer and decision layer. The input layer does not perform any computation and simply distributes the input to the neurons in the pattern layer. Consider the input, X = ($x_1$, $x_2$, ..., $x_n$) which is applied to the pattern layer. The neurons of pattern layer are divided into k groups where each of them relates to a single class.

The output of ith neuron of pattern in kth group is obtained by equation (10):

$$F_{k,i}(x) = \frac{1}{(2\pi\sigma)^{n/2}}\exp(-\frac{\|X - X_{k,i}\|^2}{2\sigma^2} \tag{10}$$

In the above equation, $X_{k,i}$ is the core center and σ is introduced as smoothing parameter. The summation layer neurons compute the maximum likelihood of pattern being classified into $C_i$ by summarizing the output of all neurons that belong to the same class by a weight factor:

$$P_k(x) = \sum_i^{M_k} W_{ki}F_{k,i}(x) \tag{11}$$

where $M_k$ represents the number of neurons of k's class and $W_{ki}$ are positive constants which consider as a weight parameter for which the following equation is satisfied:

$$\sum_i^{M_k} W_{ki} = 1 \tag{12}$$

Finally, according to equation (13), the input vector X is belonged to a class which has highest value of $P_k(x)$.

$$C(X) = \arg\max_{1\leq k\leq K}(P_k) \tag{13}$$

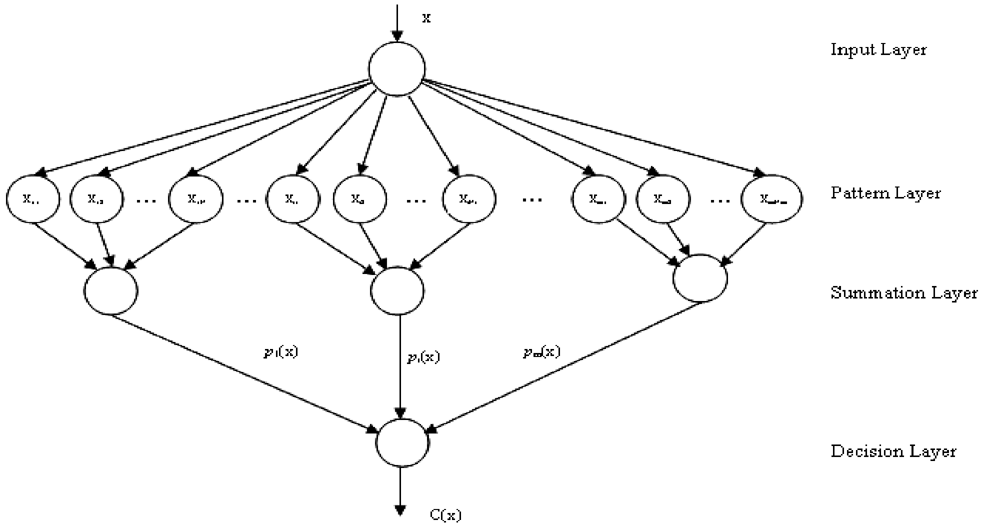


**Figure 3.** Structure of PNNs

## Results and Discussion

In order to evaluate the algorithm, the electrocardiogram signals of MIT-BIH database is used to detect 4 types of Beats. These Beats include normal beat, Right Bundle Branch Block, Left Bundle Branch Block and Atrial Premature Contraction beats. The first criterion to evaluate the performance of a classifier is the accuracy of classifier in classification of classes which is equal to the percent of the number of data classified correctly to whole number of data. Since in medical diagnoses, the mistake of diagnosing a patient as a healthy person or conversely diagnosing a healthy person as a patient would have irrecoverable consequences, confining to evaluate based on only accuracy percent does not seem appropriate .

In the field of medical diagnoses, the new criterion of sensitivity is also defined which is a criterion on capability of classifier to correctly diagnose of disease and is determined by equation (14):

Sensitivity criterion:

$$\mathrm{Se}(\%) = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} * 100 \tag{14}$$

where, the true positive (TP) is the number of abnormal beats truly classified and False negative (FN) is the number of healthy beats categorized as an abnormal incorrectly. The results of proposed algorithm on 4 different types of Arrhythmias have been shown in table (1). Also, Table I shows the classification result for SVM classifier. PNN System's wide comparison results indicate PNN combined with LPC features gives better sensitivity and accuracy for the classification than SVM algorithm.

As indicated in table (1) the overall sensitivity of this method is 91.3%, 85.7%, 98.4% and 97.3% in normal data, Atrial Premature Contraction (APC), Right Bundle Branch Block beats (RBBB) decomposition and Left Bundle Branch Block beats decomposition, respectively.

Performance comparison of this method with previous methods has been represented in Table (2). It reveals that the proposed classifier provides satisfiable results according to the different number of data used in these methods (the number of studied signals is different in each method). Specifically the simplicity and less computation are among the valuable features of this algorithm.

**Table 1**. The classification result of proposed algorithm for categorizing four different type arrhythmias

| Total | LBBB | RBBB | APC | Normal | | Method |
|---|---|---|---|---|---|---|
| 93.17 | 97.3 | 98.4 | 85.7 | 91.3 | **Sensitivity** | **PNN** |
| 92.9 | | | | | **Accuracy** | |
| 91 | 98 | 88 | 88 | 90.7 | **Sensitivity** | **SVM** |
| 90.25 | | | | | **Accuracy** | |

**Table 2**. Performance compression of several methods for arrhythmia detection

| Sensitivity | Accuracy | Classifier | Feature | Reference |
|---|---|---|---|---|
| **--** | **96.5** | MLP | Wavelet Coefficients | Kiani Sarkaleh et all [2] |
| **93.13** | **--** | Fuzzy | Nonlinear Dynamic Features | Anuradha et all [3] |
| **--** | **89.72** | SVM-PSO | Wavelet Coefficients | Melgani et all [4] |
| **--** | **89.67** | SVM-EML | Wavelet Coefficients | S. Karpagachelvi et all [5] |
| **90** | **--** | Antcoloni | Wavelet Coefficients & morphologic features | Korürek et all [6] |
| **93.17** | **92.9** | PNN | LPC | The proposed algorithm |

Using the advantage of Multi resolution wavelet analysis in order to detect the exact location of R peaks is one of the important aspects of this research which makes the results more reasonable and reliable. As mentioned above, several factors have been used in the researches for classification of arrhythmias. Plenty of golden hours might be allocated for extraction of these features which in online diagnosis could force some limitations in studies. In this work, Linear Predictive Coefficients has been preferred as the features for discrimination of these classes from each other that would bring about more real time and online results.

## Conclusions

The classification of arrhythmic beats is one of the most important applicable fields of computer science in the medicine scope. In this field, so many algorithms have tried to classify and detect such arrhythmias by adopting different features and classifiers [2-10]. In this article, the classification of different types of arrhythmias has been presented by using linear predictive features and probability neural networks. The multi resolution wavelet analysis has been applied to detect the exact position of R peak in order to have better performance and present more desirable results. The obtained results confirm the high decomposition capability of this method with 93.17% sensitivity and 92.9% accuracy. The results obtained from its comparison with other methods confirm using LPC coefficients as an index feature of arrhythmia besides presenting desirable results.

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