DETECTION OF VENTRICULAR ARRHYTHMIAS USING LEARNING VECTOR QUANTIZATION

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ABSTRACT

This paper addresses the problem of automatic discrimination of rhythms in ECG signals. In performing the discrimination, fourth-order AR parameters of successive segments are estimated and the related roots are computed and used as inputs to the learning vector quantization (LVQ) classification algorithm. In discriminating normal (NSR) rhythm from arrhythmias, 98% of normal data and 88% of data with arrhythmia are classified correctly. Also in discriminating VF from VT, 72% of data with VF and 86% of data with VT are determined properly.

I. INTRODUCTION

Cardiac arrhythmia is one of the leading causes of mortality in the world. Most dangerous are those arrhythmias generated in the ventricles, *ventricular tachycardia* (VT), and *ventricular fibrillation* (VF) which may occur after a period of VT. During VF, the chaotic electrical activity in the myocardium (heart muscle) results in diminished cardiac output, which in most cases, if not treated, results in sudden cardiac death. VT may be considered as a period of continuous PVCs (changes in the direction of QRS (most significant wave in ECG) wave from positive to negative and vice versa). If the frequency of VT goes higher, P and T waves diminish and the waveform becomes so similar to a zigzag formed wave. In figure 1, examples of ECG signals for the three rhythm types of interest in the present paper are shown.

The procedures used in discriminating ECG rhythms may be classified in 2 methods of analysis: time domain analysis and frequency domain analysis.

Time domain analysis is usually concentrated on wave shapes, and usually simulates the physician's analytic methods. For example, decreases in R-R intervals (time intervals between successive QRSs), changes in the pitch period, alterations in the amplitude, changes in the overall form of wave, and any similar properties may be considered. But getting inaccurate results of these properties in many different heart rhythms make them less reliable. For example, reduction in R-R intervals may happen in many arrhythmias like VF, VT, PVC and etc. [1]

The second class of analysis, which is more reliable and more acceptable from the engineer's point of view, is frequency based analysis, which tries to extract some features from frequency spectrum. Frequency spectrum of a wave may be estimated using one of these 2 methods: parametric estimation and nonparametric estimation.

In nonparametric estimation, which usually uses Fast Fourier transforms (FFT), a curve is estimated by which some features are extracted. Some examples of these features are dominant frequency, median frequency, spectral edge, and etc. In those methods, a predefined window (with a short duration of around 3 sec) should move over the wave, then useful features of each moment may be extracted and interpreted in order to estimate the occurrence of an arrhythmia or its duration.[4],[5]

In parametric estimations, system modelling is a useful tool. For instance, by using an Auto regressive (AR) model, we can decrease the amount of data to just a few coefficients (depending on model order). In such a way, the feature extraction step has been eliminated and it is only required to find the correlation between coefficients (or roots location) and rhythms.

Previous studies in parametric methods can be classified in two groups:

A- The methods that are only based on the value of AR coefficients and usually have been used in estimation of VF duration. [2],[3]

B- Other methods that use some results of time domain analyses (like pitch period,…) with AR coefficients and then use an intelligent system, to discriminate the correct class of arrhythmia.[1]

In this paper, we present a method to discriminate the ECG rhythms using their roots location in AR model. One of the advantages of this study is that, just 2 seconds of data is enough for the estimation while in previous studies (based on Fourier transform and feature extraction from spectrum) processing of more than 8 seconds of data was necessary to discriminate the rhythms. Additionally in this study AR parameters are used on physiological data of human, while in previous studies it has just been used on animal's data or in order to estimate the VF duration; so its usage in rhythm detection is novel application.

This method can be properly used in a real time system, because its delay time (as described above) is very small. So, getting an error rate near those of previous studies seems to be acceptable, because of its very important advantage of being real time!

II. EXPERIMENTAL

In this study, we used the BIH-MIT arrhythmia database [8-9]. They are digitized in frequency of 250 Hz in 12 bits.

The selected data was recorded for up to 300 seconds in 29 patients and then AR modelling, followed by LVQ neural network were incorporated. From all 29 data sets, 19 sets were used for training and the others were used for testing the algorithm.

In order to prepare a proper dataset, we should separate different parts of signal and make a compatible matrix containing special codes as a target. In this paper, a down sampling method was used on raw ECG data with a rate of 10, to reduce the amount of data and its processing time.

III. MATHEMATICAL ANALYSIS

In an AR process of order p, the signal x[n] at time instant n may be represented as a linear combination of p previous values of the same signal. Specifically, the process is modelled as

$$x[n] = \sum_{i=1}^{p} a[i]x[n-i] + e[n] \qquad (1)$$

Where a[i] is the i'th coefficient of the AR model and e[n] is a white noise with zero mean and variance s^2 .Various methods are currently used to estimate the coefficients of an autoregressive process, a[i]. In this study we used Yule-Walker method. This method works by minimizing the estimation error power ρ, defined as

$$\rho = \frac{1}{N}\sum_{n=\infty}^{-\infty}\left|x[n] - \sum_{i=1}^{p} a[i]x[n-i]\ \right|^2 \qquad (2)$$

The minimization is achieved by the solution of the autocorrelation matrix

$$\begin{bmatrix} r_{xx}[0] & r_{xx}[-1] & \cdots & r_{xx}[-(-p-1)] \\ r_{xx}[1] & r_{xx}[0] & \cdots & r_{xx}[-(-p-2)] \\ \vdots & \vdots & \ddots & \vdots \\ r_{xx}[p-1] & r_{xx}[p-2] & \cdots & r_{xx}[0] \end{bmatrix} \cdot \begin{bmatrix} a[1] \\ a[2] \\ \vdots \\ a[p] \end{bmatrix} = \begin{bmatrix} r_{xx}[1] \\ r_{xx}[2] \\ \vdots \\ r_{xx}[p] \end{bmatrix} \qquad (3)$$

where

$$r_{xx}[i] = \begin{cases} \frac{1}{N}\sum_{n=0}^{N-1-i} x^*[n]x[n+i] & i = 0, 1, \cdots, p \\ r^*_{xx}[-i] & i = -(p-1), -(p-2), \cdots, -1 \end{cases} \qquad (4)$$

In this step, the data is swept with a window of predefined shape and length (rectangular window with a length of 2 sec in this study).The value of Overlap is selected as 1 sec. It is obvious that a shorter window, gives a better time resolution but the analysis needs more time and this makes the procedure unreliable in real time applications. It is acceptable to have at most 1 second of error (from the physician's point of view), so selecting the window length equal to 2 sec seems to be suitable.

While the window sweeps along the signal, its contents are analysed with AR model. The selection of model order in the AR process is of critical importance. Very low order results in smoothed estimate, while very large order causes spurious peaks. In other similar studies, the order is selected as 4 for fix models [2] and 12 for adaptive ones [3]. In this paper, we used the selected order for fix analysis (based on the results of [2] that are computed using Akaike Information Criterion (AIC)). Because of getting acceptable results, it is not required to increase the model order.

After solving the equations with Yule-Walker method, we obtain 5 coefficients (with model order of 4), and 4 roots of model are found after solving the final equation. In order to extract special features of this information, the plot of roots on real/imaginary plane can be used. In every step of window, 4 roots are extracted and plotted on plane.

It is obvious in a glance that different arrhythmias, occupy different regions on the plane. (See figure 2)

Classification with LVQ

Wide usage of intelligent systems, especially neural networks, and their powerful abilities makes them proper to be used in most applications. But the important point is the selection of proper type, which gives the best results. This needs an exact study in properties of our case. For this special instance, we should classify our data in 3 different classes, which can be done with most of neural networks. But what makes the LVQ (learning vector quantization) more suitable for this purpose, is its special power of combining subclasses. This network has two separated layers (figure 3). The first layer works just like simple competitive network, and the second layer works as a linear net. In the first layer, each of output neurons is classified as one of subclasses (depending on its relative distance from each prototype (subclass)). Then in second layer, the linear part combines the subclasses to produce proper classes.

In this case, because of having many separated subclasses (see figure 2), this networks seems to be the best choice. It is obvious that if we choose the number of subclasses (number of output neurons of competitive layer) same as our real subclasses (in figure2), the network gives the best results.

Training and testing the NN

The MATLAB neural network toolbox is used to simulate the LVQ network, in two different modes:

A- To discriminate normal (NSR) rhythm from arrhythmias. So the input data consists of all 3 mentioned above kinds of arrhythmias and results will show if that part of signal is NSR (normal) or VT and VF (abnormal).

B- To discriminate VF from VT. So the input data consists of VT and VF and results will show if that part of signal is VT or VF.

In the first mode, we used a network with 5 neurons in hidden layer, with training error limit of 0.1 and epoch limit of 150.But in the second mode, number of neurons in hidden layer is selected as 15 (equal to the number of subclasses), with training error limit of 0.1 and epoch limit of 300.

There is a very important point in testing this network. In fact, we train the NN (neural network) with inputs, equal to the imaginary and real parts of AR model roots. So, when we start testing the network, we sweep the signal with a moving window and extract the values of roots at each step. Now, we have 4 roots to detect the type of rhythms in this frame. But our network is just trained to detect the state of each root, one by one. So we should combine the results of network for 4 roots and decide on the type of rhythm in this frame.

The combination algorithm presented in this paper obtains the result of network for every 4 roots in each frame, and selects the state with more repetition as the final state of that frame.

In mathematical method, we can take an average of 4 decisions of network (which are in the form of codes, indicating each rhythm), and round it to find the proper code of arrhythmia with more repetitions.

IV. RESULTS AND DISCUSSION

We found the results which are gathered in table 1 and 2. It can be seen that in discriminating normal (NSR) rhythm from arrhythmias, 98% of normal data and 88% of data with arrhythmia are classified correctly. Also in discriminating VF from VT, 72% of data with VF and 86% of data with VT are determined properly.

The novel method presented in this paper has some advantages and disadvantages. One of the advantages of this study is that just two seconds of data is enough for the estimation while in previous studies processing of more than eight seconds of data was necessary to discriminate the rhythms. Additionally in this study AR parameters are used on physiological data of human, while in previous studies, it just has been used on animal data or in order to estimate the VF duration, so it’s usage in rhythm detection is a new application.

If we compare the results of this method with previous studies, it can be said the ability of this method in determining normal (NSR) rhythm from arrhythmias is high and also its output in discriminating VF from VT is comparable with previous ones. In fact, the most important preference of this method is very small delay time that makes it proper for real time systems.

As mentioned before, we would like to emphasize that there are considerable difficulties in justifying these results and comparing them to those obtained by others. So, we have found 2 recent papers attempting to perform similar classification as we have been doing here [1-11].

Compared with [11], which its classification method is more similar to the one addressed in this paper, the classification results for detection of NSR, VT and VF are 94%, 82% and 78%, i.e. somewhat lower classification accuracy than what is reported in the present paper.

Comparing to [1], the classification results for detection of NSR, VT and VF are 91%, 91% and 73% in the first method, 94%, 30% and 84% in second method and 97%, 91% and 73% in third method respectively. Our comparable results are 98%, 89% and 73% respectively.

These are, unfortunately not reliable comparisons since the test and training sets are not the same in two studies, and just all the cases are derived from MIT-BIH database. Finally, it should be pointed out, that visual discrimination of data (can be seen in figure 2), makes us expectant to get better results, using more powerful neural networks in combination with other features in future studies.
Finally it should be mentioned that there are other types of arrhythmias such as arterial fibrillation, PVC runs and etc. This method will be tested on these types of arrhythmias in future work.

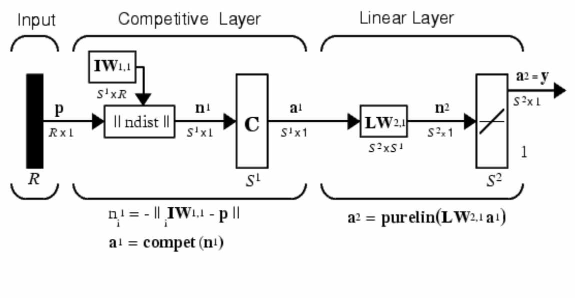

Figure 3. Block diagram for LVQ networks

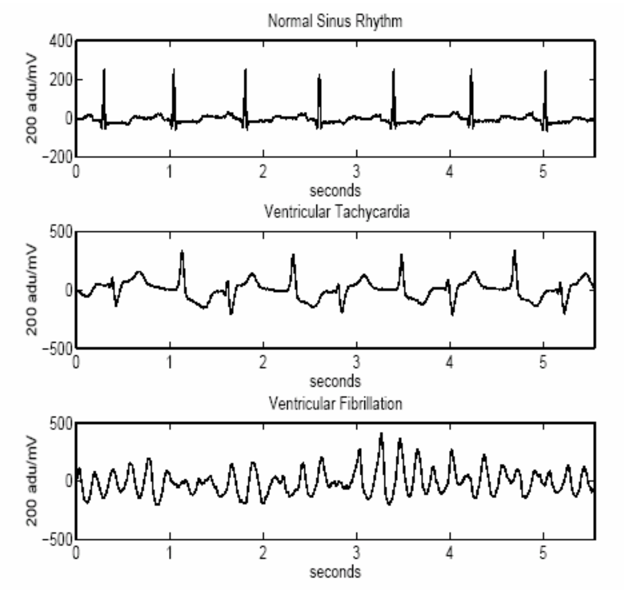

Figure 1. Examples of normal sinus rhythm, ventricular tachycardia and ventricular fibrillation

Table 1. Classification results in mode A

	Classified as	
	Abnormal	Normal
100 Normal Input	2	98
100 Abnormal Input	88	12

Table 2. Classification results in mode B

	Classified as	
	VT	VF
100 VF Input	27	73
100VT Input	89	11

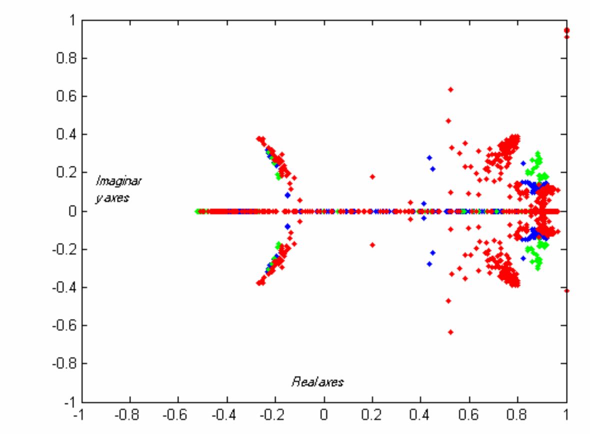

Figure 2. Autoregressive model roots location for training and test dataset. (Blue: normal, Green: VT and Red: VF)

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