Detection of Ventricular Arrhythmia from ECG

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(Received on 28th April, 2016 Accepted on 8th August, 2016)

Abstract

The Ventricular Arrhythmias particularly Ventricular Tachycardia (VT) and Ventricular Flutter (VF) are life threatening arrhythmias and can lead to heart attacks if not detected and treated timely. In this paper, a method has been proposed that can differentiate between normal Electrocardiograms (ECGs) and two abnormal ECGs of VT and VF. The classification is performed by means of Artificial Neural Networks (ANN). Reflection coefficients of the Auto-Regressive Models of extractions from the ECG recordings are computed and used as features for input to the ANN. The ANN is trained using ECG samples that are characteristic of Non-diseased (normal), VT and VF. After suitable training and validation, the proposed algorithm has been found to have an accuracy of 100%, 97% and 94% for classification of Normal ECG, VF and VT respectively.

Keywords: Ventricular Arrhythmia detection and classification, Electrocardiogram, AR Modeling, Artificial Neural Networks

INTRODUCTION

The number of people dying from heart diseases is increasing day by day [1]. One of the main causes of heart related deaths is Ventricular Arrhythmia. Arrhythmia can be defined as the irregular rhythm of heart, that is, the heart beats may be either too fast or too slow. Four chambers make up the human heart, with the upper two chambers called the Atria and the lower two called Ventricles. The arrhythmia which originates from the lower chambers of the heart is known as Ventricular Arrhythmia [2]. The two main types of Ventricular Arrhythmia are Ventricular Tachycardia (VT) and Ventricular Flutter (VF). Ventricular Tachycardia is characterized by faster than normal heartbeats and

Ventricular Flutter is characterized by the cardiac muscles contracting without coordination [3]. These arrhythmias can lead to inevitable death if left untreated. Therefore, it is of utmost importance that these arrhythmias are detected timely and action taken timely in order to save lives.

The paper is organized into different sections. After introduction, the previous work carried out to detect abnormality from ECG signals is described and the proposed algorithm is explained thereafter. Subsequently, the results are presented and discussed. Finally, the conclusion is drawn on the basis of results and discussion.

Previous Work

Cardiac Arrhythmias can be detected by ECG signal analysis. Therefore, the topic of cardiac arrhythmia detection and classification has been of focus in Computer Aided Diagnosis area. A literature survey indicates various methods through which these detections have been performed. Lee *et al* [4] proposes an algorithm for the detection of different types of Cardiac Arrhythmias using Support Vector Machines[5] based on Morphological Features. He extracted three morphological features of an ECG based on the QRS complex which are RR interval, QRS slope, and QRS shape similarity. Their method has been shown to work for a number of cases. However, not all morphological features are always present in abnormal ECGs. T. Conde *et al.* [6] suggests an algorithm for detecting cardiac arrhythmia by finding a vector representation of the ECG signal and classifying QRS complex through the use of neural networks [7, 8]. Vuksanovic and M. Alhamdi [9] developed an algorithm to classify three types of ECG's. The three types ECGs were Normal, Arrhythmia and Ventricular Arrhythmia. In the proposed method signals were classified using K-nn [10] rule with classification being performed using Linear Discriminant Analysis (LDA) [11] and Quadratic Discriminant Analysis (QDA). Noh *et al.* [12] proposes an algorithm in which abnormal ECG detection is carried out with the help of template matching where a normal ECG is first generated and then the real time ECG input is compared with the generated ECG to determine abnormality. An algorithm based upon bi-spectral analysis techniques, obtained using autoregressive model [3] estimation, is proposed by Khadra *et al* [13] to classify arrhythmia types. The extracted features are frequency support of the bi-spectrum that serves as the quantitative measure for classification. In an algorithm proposed by Jung and Tompkins [14], wavelet decomposition [15] is used for the detection and classification of Ventricular Tachycardia, Ventricular Fibrillation, Ventricular Flutter and Supraventricular tachycardia in ECGs.

It is clear from the above discussion that different methods have been proposed to detect and classify ventricular arrhythmia. However, most of them include lengthy computations or do not provide reasonable detection rates. It is therefore necessary to develop methods that may perform this detection more accurately and are less computationally intensive. This paper proposes a novel method that improves upon the shortcomings of previous work that has been discussed.

Detection of Ventricular Arrhythmia from ECG

The proposed method follows a five step procedure to detect ventricular arrhythmia from ECG as shown in Figure 1. The first three processes form the preprocessing phase of the signal which is followed by feature extraction. Lastly, the extracted features are passed on to the trained Neural Network for classification of the ECG.

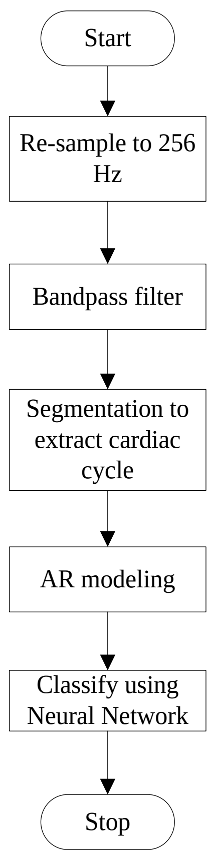

Figure 1: Methodology

The database of PhysioNet, specifically Massachusetts Institute of Technology - Beth Israel Hospital (MIT BIH) Normal Sinus Rhythm Database, Creighton University (CU) Ventricular Tachyarrhythmia Database and Malignant Ventricular Ectopy database [16], is used as the source of ECG signals.

A. *Resampling*

The sampling frequencies of signals used from the PhysioNet database for the considered arrhythmias were different and shown in Table 1.

Table 1: Sampling Frequencies of Signals in the PhysioNet Database

Parameter	**Normal Sinus Rhythm**	**Ventricular Tachycardia**	**Ventricular Flutter**
Sampling Frequency	128 Hz	250 Hz	250 Hz

By default, the ECG recordings of MIT-BIH NSR, MIT-BIH CU Ventricular Tachyarrhythmia and MIT-BIH Malignant Ventricular Ectopy were sampled at 128 Hz, 250 Hz and 250 Hz respectively. Since all three recordings needed to be processed by the same system, it was necessary to resample them at the sample frequency. Therefore, all these recordings were resampled at 256 Hz. A Linear interpolation kernel is used for this purpose.

B. *Filtering*

After resampling process, all three recordings have the same sampling frequency but contain baseline drift [9] and motion artifacts which are a common artifact in practical ECG recording. In order to minimize this, a Bandpass filter was applied on the ECG recordings. The normalized upper and lower cut-off frequency of the Bandpass filter was chosen to be 0.0062 and 0.7591.

C. *Segmentation*

Since the ECG recording are of non-uniform duration and also since the conditions to be detected are characterized by specific parts of the ECG signal, segmentation has been performed to extract the parts of the signal which characterize the desired conditions. To do so, all ECG recordings was divided into 200 segments with each segment containing 300 samples. Each segment is of 1.2 seconds as it is sufficient to capture information of a single cardiac cycle. It is necessary to extract each cardiac cycle as every cycle forms the basis for feature extraction individually.

D. *AR Modeling*

The extraction of discriminative features is one of the most important steps for detection and classification of signals either one dimensional or multidimensional. In this paper, features are extracted through Auto Regressive Modeling. An Auto Regressive (AR) model is a linear prediction formula that predicts an output y_t of a system based on its previous inputs. An AR Model of order ‘m’ can be written mathematically as given in Equation:

$$y(t) = \sum_{i=1}^{m} a(i).\, y(t-i) + \varepsilon\,(t) \qquad (1)$$

where a(i) represent coefficients of AR model, y(t-i) is series under investigation, ε(t) is output of uncorrelated errors and ‘m’ is the order of model and it indicates the number of past samples which have been used to estimate the present value of signal. When performing AR modeling, it is important to determine a suitable order of AR model so that estimated signal is modeled accurately.

In this method, an AR model was estimated for one segment of an ECG signal. Each segment contained 300 samples and had time duration of 1.2 seconds. Since single ECG recording is divided into 200 segments with every segment being estimated using 4 coefficients, the total number of coefficients for a single ECG recording becomes 800. Reflection Coefficients of the AR model were calculated using the Burg’s method [17].

In order to determine that the AR model has suitable accuracy in estimating the signal, the Periodogram Power Spectral Density [18] was used a metric. The Periodogram PSD is defined as the modulus squared of the Discrete Fourier Transform of the signal. It can be expressed mathematically as given in Equation:

$$S(f) = \frac{\Delta t}{N}\left|\sum_{n=0}^{N-1} x_n\, e^{-i2\pi nf}\right|^2 - \frac{1}{2\Delta t} < f \leq \frac{1}{2\Delta t} \qquad (2)$$

The Periodogram PSD was computed for AR mode estimations of order 4 and 5 and the comparison of the PPSD of the original ECG and the signal estimated by AR models has been shown in Figure 2 and Figure 3.

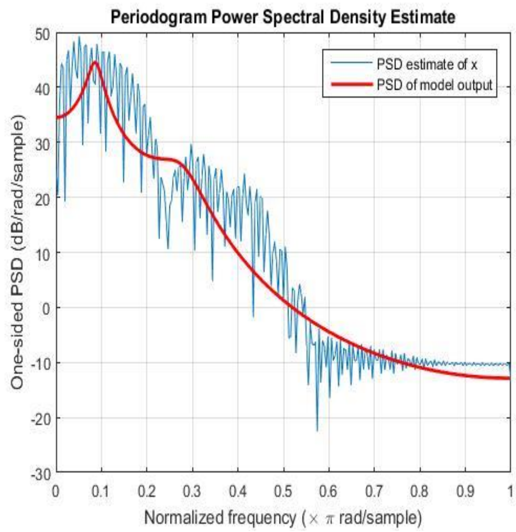

Figure 2: Periodogram PSD of order 4 AR Model

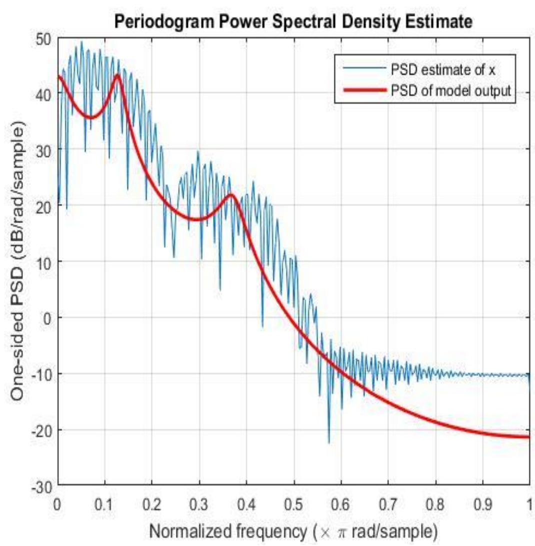

Figure 3: Periodogram PSD of order 5 AR Model

It can be seen in Figure 2 and Figure 3, the AR model estimate of 4 coefficients is more accurate in estimating the ECG signal as compared to signal estimate using 5 coefficients of the AR model.

E. Classification

Once the ECG signals have been preprocessed and feature extraction has been performed, the next step is to perform classification of the signals. To perform classification, a two layer feed forward Neural Network is used that is shown in Figure 4.

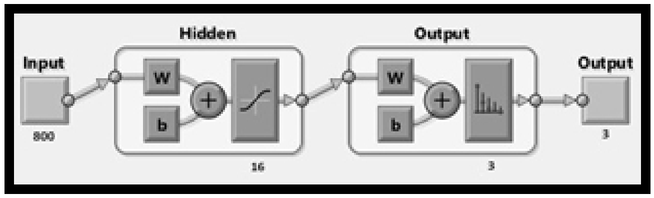

Figure 4: Feed Forward Network

The Hidden layer of the network comprises a Log-Sigmoid [19] transfer function whose output is given by Equation:

$$a = \frac{1}{1 + e^{-n}} \tag{3}$$

Where 'a' is the output and 'n' is the input matrix. The output layer consists of a Softmax [20] transfer function whose behavior is described by Equation 4.

$$\mu_k = \frac{e^{(\eta_k)}}{1 + \sum_j e^{(\eta_k)}} \tag{4}$$

Where η_k is a vector of k values, μ_k is a vector of k values between the range of 0 and 1 which sum up to 1. For training purposes, the AR model reflection coefficients of samples of each category of ECG (Normal, VT and VF) were used. As mentioned earlier, the order of AR Model is selected as 4 which mean a single segment of signal will be represented by four reflection coefficients and there are 200 segments of an ECG. Therefore, a single ECG recording will have 800 (200x4) inputs. The details of feed forward neural network are shown in Table 2. Table 3 shows the numbers of samples used for training of the network for NSR, VF and VT respectively.

Table 2: Details of Neural Network

Input Layer	Hidden (Log Sigmoid)	Output (Softmax)
800 I/p Lines	16 Neurons	3 Neurons

RESULTS AND DISCUSSION

The proposed method uses reflection coefficients, obtained from AR Model, which serve as distinct features. The ECG signals to be classified are provided as input to the ANN after suitable preprocessing and computation of the AR model reflection coefficients of order 4 for each signal.

The total number of samples and trained number of samples are shown in Table 3. An ECG recording has 200 segments and each segment is considered separate sample for training.

Table 3: Total and trained number of samples

	Total Number of Samples	Trained Number of Samples
NSR	3600	2600
VF	7000	1000
VT	4400	1000

The number of correctly and incorrectly classified ECGs is shown in Table 4.

Table 4: Number of Correctly and Incorrectly Classified ECGs

Number of trained samples	NSR	VF	VT
NSR	1000	18	4
VF	X	5820	3400
VT	X	162	200

The percentage of correctly and incorrectly classified ECGs is shown in Table 5.

Table 5: Percentage of Correct and Incorrect Detections

Classes	NSR	VF	VT
Correctly Classified ECGs	100%	97%	94%
Incorrectly Classified ECGs	00%	03%	06%

It can be observed from Table 5 that the proposed algorithm is able to detect normal ECGs with very high accuracy (100%), ECGs which are characteristics of VF are classified with a correctness percentage of 97% whereas these are incorrectly detected as VT 3%. For VT, the correctly detected percentage is 94%. Table 6 shows the comparison of our classification with results by other authors who have used same dataset i.e. PhysioNet (specifically Massachusetts Institute of Technology - Beth Israel Hospital (MIT BIH) Normal Sinus Rhythm Database, Creighton University (CU) Ventricular Tachyarrhythmia Database and Malignant Ventricular Ectopy database).

Table 6: Sensitivity (Se %) comparison with the methods cited in the Literature

Algorithms	Se (%) of NSR	Se (%) of VF	Se (%) of VT
SVM based Morphological Features, Lee *et al*. [4]	100	92	74.07
Quantitative Analysis, Khadra *et al*. [13]	100	91.7	81.8
Wavelet Decomposition, Jung *et al*. [14]	X	86.7	93.9
PNN Neural Network, Darouei *et al*. [21]	98.15	93.3	90
Algorithm proposed in this paper	100	97	94

It can be observed from Table 6 that the method described in this paper outperforms previous approaches proposed for the task of classification of the three types of ECGs; Normal, VT and VF. This is especially true for the case of VF where an improvement of three percent can be observed. In the case of VT, similar accuracy is achieved by [14].

The feature extraction process used in the proposed method has been found to perform reasonably better for differentiating among the three types of ECGs. The classification process in the proposed method is relatively cheap to implement two layer feed forward Neural Network which provides satisfactory performance.

CONCLUSION

In this paper, three cardiac arrhythmias Normal Sinus Rhythm (NSR), Ventricular Tachycardia (VT) and Ventricular Flutter (VF) are classified using Artificial Neural Networks (ANN). The features used are reflection coefficients of AR model which serve as the inputs to the Feed Forward Neural Network. The features have been shown to be robust enough to allow classification with a two layer network. Recommendation for future work in this direction is to look at the classification of arrhythmias of both upper and lower chambers of the heart using similar techniques. Furthermore, instead of detecting VT and VF individually, more complicated ECGs could be classified which may exhibit multiple defects in one recording.

ACKNOWLEDGMENT

This research was supported by Mehran University of Engineering and Technology, Jamshoro.

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