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APPLICATION OF A PROBABILISTIC NEURAL NETWORK FOR CLASSIFICATION OF CARDIAC ARRHYTHMIAS

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ABSTRACT

The electrocardiogram (ECG) is an important tool for providing information about functional status of the heart. Analysis of ECG is of great importance in the detection of cardiac anomalies.
This paper presents a diagnostic system for cardiac arrhythmias from ECG data, using an artificial neural network classifier. In this article we propose a new method for the detection of ventricular and supra ventricular tachycardia (VT and SVT) using probabilistic neural networks (PNN).
After acquisition and pre-processing of ECG signals, we proceed to determine the relevant necessary parameters for the diagnostic; these are: the RR interval, the heart rate, the QRS duration and the QRS complex. To reduce the number of input data of the classifier we apply the discrete wavelet transform for the compression wave of QRS, therefore the total number of parameters applied to the input of our classifier are 13 parameters. The proposed approach is tested using the MIT-BIH database and the results were obtained with rate of classification of 62.5 % for VT and 85.30 % for SVT. The results provided in this article are promising for the development of an automated method for classifying cardiac arrhythmias.
Keywords: Electrocardiogram, cardiac arrhythmia, ventricular tachycardia (VT), supra ventricular tachycardia (SVT), MIT-BIH database, classification, probabilistic neural network, wavelet transform.

1. INTRODUCTION

The past few decades have witnessed an outstanding pace of clinical, surgical, and technological developments. Since then great efforts have been made to benefit from the technological advances and use of computers in the medical field. Since the electro cardiogram (ECG) is used for analyzing the clinical conditions of the heart, the most vital organ in the human body, it is of great important to cardiologists to perform ECG analysis with maximum accuracy [1].
Much research has been done in the field of ECG analysis, all aiming at performing automatic signal detection with near perfect detection rates. For thirty years now, efforts have been oriented to the modeling of the expertise of cardiologists and specialists through computers. This issue has been tackled by many researchers who have come up with a variety of different ECG recognition and QRS detection algorithms that have become widely known in the literature [2], [3], [4], [5], [6]. Among the numerous studied and evaluated methods, artificial neural network methods have taken special attention because of their properties such as non-linearity, learning ability, and universal approximation witch allow them to solve complicated signal processing problems like QRS detection and VT and SVT diagnosis. In this paper, we will present our approach which consists of designing and implementing enhanced artificial neural networks for VT and SVT detection.

1.1. Cardiac Signals

The electrocardiogram (ECG) is a recording from the body surface of the electrical activity generated by the heart. The ECG was originally observed by Waller in 1899. In 1903, Einthoven introduced electrophysiological concepts still in use today, including the labelling of the waves characterizing the ECG. He assigned the letters P through U to the waves avoiding conflicts with other physiologic waves studied at that time. Figure 1 depicts a typical ECG signal.

ECG signals are typically in the range of ±2 mV and occupy a bandwidth of 0.05–150 Hz. The morphology of the ECG waves depends on the amount of tissue activated per unit of time as well as the relative speed and direction of cardiac activation [7].

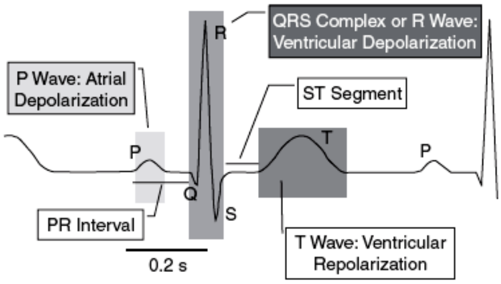

Figure 1. Typical electrocardiogram.

Therefore, the physiological pacemaker potentials, i.e. the SA-nodal potentials, generated by a relative small myocardial mass are not observed on the ECG. The first ECG wave within the cardiac cycle is the P-wave, reflecting atrial depolarization. Conduction of the cardiac impulse proceeds from the atria through a series of specialized cardiac structures (the AV node and the His-Purkinje system) to the ventricles. There is a short relatively isoelectric segment following the P wave, which is the PQ interval, this one is related to the propagation delay (0.2 s) induced by the AV node. Once the large muscle mass of the ventricles is excited, a rapid and large deflection is observed on the ECG surface. Depolarization of the ventricles is represented by the QRS complex or R wave. Following the QRS complex, another isoelectric segment, the ST interval, is observed. The ST interval represents the duration of depolarization after all ventricular cells have been activated, normally between 0.25 s and 0.35 s. After completion of the ST segment, the ventricular cells return to their electrical and mechanical resting state, completing the repolarization phase observed as a low frequency signal known as the T wave. In some individuals, a small peak occurs at the end or after the T wave and is called the U wave. Its origin has never been fully established, but it is believed to be a repolarization potential [7].

1.2. Cardiac diseases (Arrhythmias)

Arrhythmias are due to cardiac problems producing abnormal heart rhythms. In general, arrhythmias reduce hemodynamic performance including situations where the heart's natural pacemaker develops an abnormal rate or rhythm or when normal conduction pathways are interrupted and a different part of the heart takes over control of the rhythm. An arrhythmia can involve an abnormal rhythm increase (tachycardia: >100 bpm) or decrease (bradycardia: <60 bpm) or may be characterized by an irregular cardiac rhythm, e.g., due to asynchrony of the cardiac chambers [7].

2. MATERIALS AND METHOD

The datasets are chosen from the MIT-database which is available at PhysioNet website. Different datasets are selected. Each one represents different types of heart arrhythmias; MIT-BIH Normal Sinus Rhythm Database (NSRDB), CU Ventricular Tachyarrhythmia Database (CUDB) and MIT-BIH Supraventricular Arrhythmia Database (SVDB) [8].

In order to create a database for the classifier implemented in this research, a total of 99 records are analyzed. The records are divided into two groups (learning and testing):

Group I (learning set) contains 53 records; these records are divided into three categories, each category represents one type of heart arrhythmia, the records include 28 cases taken from patients with supraventricular tachycardia (SVT), 14 from ventricular tachycardia (VT) and 11 normal cases. Each

ECG is assigned an annotation indicating its class. This group of data is used for building the classifier.
Group II (test set) contains 46 records; 12 records for normal sinus rhythm (NSR), 22 records for SVT and 12 records for VT. This dataset is used for testing the classification process. The sampling frequency of signals is set at 250 Hz for N and SVT signals and 128 Hz for VT records, cases taken by different frequencies; we proceed by pre-treatment of the signal).
The different parameters considered for cardiac arrhythmia classification using PNN are:
- RR interval
- Heart rate f
- QRS duration
- Shape of the QRS wave

To reduce the number of data used at the entrance of the neural classifier, we applied a discrete wavelet transform [9], [10] to compress the QRS complex, applying the *Debauchies* wavelet, we obtained 10 coefficients at selected scale, therefore the total number of parameters used as input of neural network which is also used for 13 inputs (10 coefficients of the QRS complex, its duration, the RR interval and the heart rate f).

Table 1. MIT-BIH record

Database reference	Victors number	Record link
MIT-BIH Normal Sinus Rhythm Database	23	16265, 16272, 16273, 16420 ,16483, 16935, 16773, 16786, 17052, 17053, 18177, 16539, 16795, 18184
CU Ventricular Tachyarrhythmia Database	26	cu01, cu03, cu06, cu07, cu10, cu11, cu13 ,cu14, cu17, cu18, cu22, cu23, cu24 ,cu28, cu30, cu32, cu33
MIT-BIH Supra ventricular Arrhythmia Database	50	800, 803, 804, 805, 806,808, 809, 811, 820, 821, 824, 826, 829, 840, 841, 844, 846, 849, 852, 853, 856, 864, 871,872, 876, 877, 882, 886, 802, 807, 810, 825, 827,887

3. PROBABILISTIC NEURAL NETWORKS CLASSIFIER

A probabilistic neural network is good for classification problems. When an input is feed into the classifier, the first layer will be able to compute the distance between the input vector and the training input vectors, and produce a vector whose elements show the closeness between the input data points and the training vector points [11].

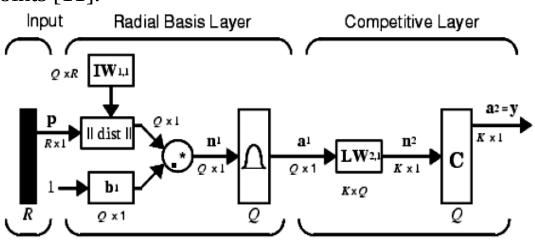

Figure 2. Probabilistic Neural Network architecture [12].

The second layer will sum up "contributions for each class of inputs to produce as its net output a vector of probabilities." As the last step, a transfer function called "compete" will pick the maximum of the probabilities on the second layer, and it will also provide a one for that class and a zero for the other classes [11].

4. RESULTS AND DISCUSSION

The performance of the algorithm [13] was evaluated by computing the percentages of *Sensitivity*, *Specificity*, *Precision* and *classification rate*; the respective definitions are as follows:

1) The sensitivity *(SE)*: $SE=100*TP/ (TP+FN)$ (1)
2) The precision *(PR)*: $PR=100*TP / (TP+FP)$ (2)
3) The specificity *(SP)*: $SP=100*TN/ (TN+FP)$ (3)
4) Classification percentage (CC): $CC=100*(TP+TN)/N$ (4)

Where: *FP = False Positives; FN = False Negatives; TP = True Positives; TN = True Negatives;* and *N= FP + FN +TP +TN.*

The performance of the classification system based PNN is detailed in table 2.

Table2. Results of probabilistic neural network classifier.

Class	% of correct Classification (CC)	Sensitivity (SE)	Specificity (SP)	Precision (PR)
SVT	85.30%	100%	70.58%	77.27%
VT	62.5 %	100%	57.14%	75 %

The proposed NN classifier showed satisfactory performances in discriminating of arrhythmia.

The sensitivity, specificity, precision and classification rate are calculated parameters for each signal to evaluate and compare the results. The testing of the algorithm with the publicly available MIT-BIH database presented a high sensitivity of 100 % for SVT and VT cases.

5. CONCLUSION

Neural Network classifiers are developed as diagnostic tools to aid the physician in the analysis of heart diseases. However, in our cases the PNN classifier does not yield results with 100% accuracy.

The neural network classifier was fed by the combination of different parameters such as; RR interval, heart rate, QRS duration and QRS wave. The accuracy of the tools depend on several factors, such as the size and the quality of the training set, the rigor of the training imparted, and also parameters chosen to represent the input. However, it can be seen from the results that, PNN classifier gives about 85.30% correct classification for SVT and gives about 62.5% correct classification for TV cases with a very high sensitivity of 100% for both cases, the results of classification can be improved.

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