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The Classification of the Heart Rate Variability Using Radon Transform with Back-Propagation Neural Networks

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Abstract:- This paper will present an algorithm for Heart Rate Variability HRV signals classifications. In this algorithm we used Radon transform of binary matrix of scatter-gram of heart rate HRV signals to extract features of binary matrix. Artificial neural network (ANN) technique with back-propagation networks (BPN) was used for binary matrix features classifications. Radon transform with 90 projections was selected because it presented the best inverse Radon transform that gave a closer image of the original scatter-gram. The optimum numbers of neurons in the hidden layer of BPN is 145 was obtained. Two databases were formed, one for training and the second for testing the accuracy of the BPN to recognize on types of heart rate variability. The two database consist of HRV signal pathologies, sympathetic activity, normal cardiac, parasympathetic activity, arrhythmia, availability problem with breath, existence of stress and the composition of these pathologies. This algorithm present the accuracy of diagnosis for sympathetic activity, normal cardiac, parasympathetic activity, arrhythmia, availability problem with breath and existence of stress were 97,396%, 98,438%, 100%, 94,792%, 87,3265% and 91,146% respectively.

Keywords:- *Artificial Neural Network; Heart Rate Variability; Scatter-Gram; Radon Transform; Inverse Radon Transform; Back-Propagation Networks.*

I. INTRODUCTION

Heart diseases are a major cause of mortality in the developed countries. The electrocardiogram (ECG) remains the simplest non-invasive diagnostic method for determining various heart pathologies. One of the methods which are mostly noted by specialists, for assessing the heart activity and discrimination of cardiac abnormalities, is called Heart Rate Variability (HRV) signal. HRV signal is generated from electrocardiogram (ECG) by calculating the R—R time intervals of the (ECG).This is a more robust method since the R—R time intervals are less affected by the noise. Different HRV signal analysis methods for detecting types of HRV such as time domain analysis, geometric (creating histogram), nonlinear analysis (creating scattergram) and frequency-domain methods. Many algorithms have been proposed over previous years for automatic cardiac arrhythmia detection and classification, for examples of the techniques used include: artificial neural networks, wavelet transforms, rule-based algorithms, support vector machines and fuzzy inference system [1-8].

Neural networks are being used increasingly in the field of medicine especially in the analysis of heart, which is configured for data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. The ANNs are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. We can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. It have been trained to perform complex functions in various fields of application including pattern recognition, identification, classification, and control systems [9].

Back propagation networks is one of the most important models in the artificial neural network, it's kind of supervised feed-forward training method with back error propagation.

In this paper, we proposed an algorithm BPN (three layers) for classification HRV which is associated with crating feature with using Radon transform from binary matrix of scattergram. Back-propagation or error back propagation is a form of supervised training. When using a supervised training method, the network must be provided with both sample inputs and anticipated outputs. The anticipated outputs are compared against the actual outputs for given input. Using the anticipated outputs, the backpropagation training algorithm then takes a calculated error and adjusts the weights of the various layers backwards from the output layer to the input layer [10].

The content of this paper is organized as follows: in section 2 includes the Data Analysis, in section 3 presents the results, Discussion and conclusions is given in section 4.

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II. DATA ANALYSIS

A. Database and processing data

The system analysis is an important part of our research paper because it provides detail information to make clarity of our study and explain the stages we passed through in details to achieve the goal of our research which is making recognition of HRV. The proposed algorithm includes preprocessing, feature extraction with Radon transform and recognition of types of HRV by ANN (BPN). Block diagram of the proposed algorithm is shown in Figure 1.

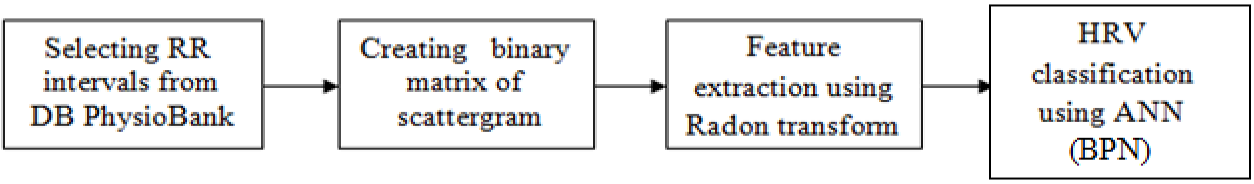
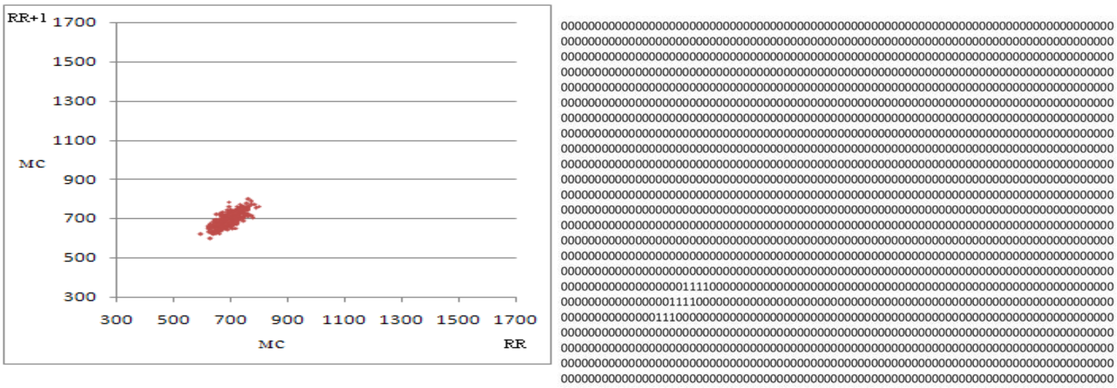


Fig 1:- Block diagram of the classification algorithm of types of HRV with ANN (BPN)

The HRV data used in this work is generated from the ECG signals provided at the PhysioNet web site in the PhysioBank. PhysioBank is a large and growing archive of well-characterized digital recordings of physiologic signals, time series, and related data for use by the biomedical research community; it contains over 70 databases that may be freely downloaded [12].

From selected date of HVR signal we created scattergrams. The scattergram is a nonlinear heart rate variability method where constructed by plotting each current cycle against the previous beat (RR vs. RR(n-1)). After that from obtained scattergrams we created binary matrices of scattergrams. The scattergram of HRV signal and the binary matrix of scattergram are shown in figure 2.



a b

Fig 2:- Scattergram of HRV signal : a) Scattergram b) Binary matrix scattergram.

B. Feature Extraction

After creating binary matrix of scattergram we used Radon transform for binary image of scattergram. Applying the Radon transform on a binary image of scattergram f(x,y) for a given set of angles can be thought of as computing the projection of the image along the given angles. The resulting projection is the sum of the intensities of the pixels in each direction, i.e. a line integral. The result is a new image R(ρ,θ). The Radon transform is a mapping from the Cartesian rectangular coordinates (x,y) to a distance and an angel (ρ,θ), also known as polar coordinates [13]. The scattergram of heart rate and the transform Radon for a set of angels of binary image of scattergram is shown in Figure 3.

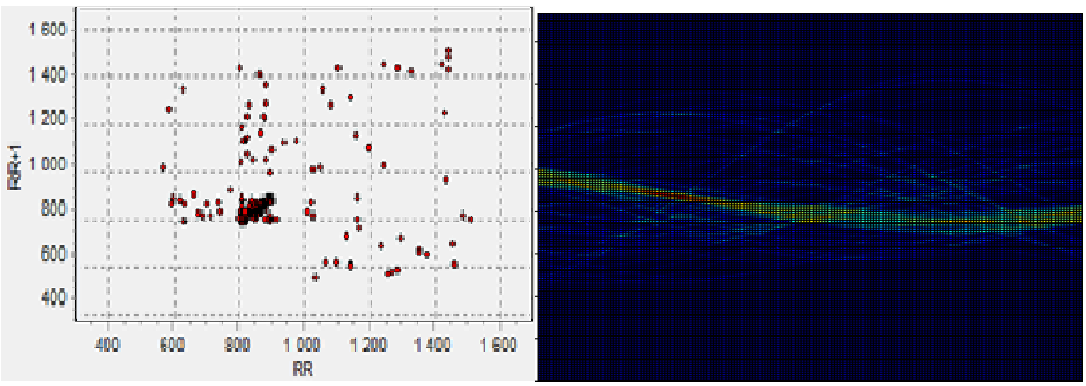


Fig 3:- Radon transform for Scattergram.

Using the Inverse Radon transform can be used to reconstruct images. The following figure 4. shows the results of four reconstructions of the binary image of scattergram. In (figure 4.a) shows the binary image of scattergram, which was reconstructed from only 18 projections, is the least accurate reconstruction. Binary image of scattergram in figures 4.b and 4.c which were reconstructed from 36 and 45 projections respectively, they are a little bit better than the image in figure 4.a. , but they still not clear enough. Reconstructing binary image of scattergram using 90 projections is most close to the original scattergram that is shown in figure 4.d. In this research we used Radon transform with 90 projections for binary image of scattergram.

We created the database from the features that where obtained from the Radon transform for binary image of scattergram.

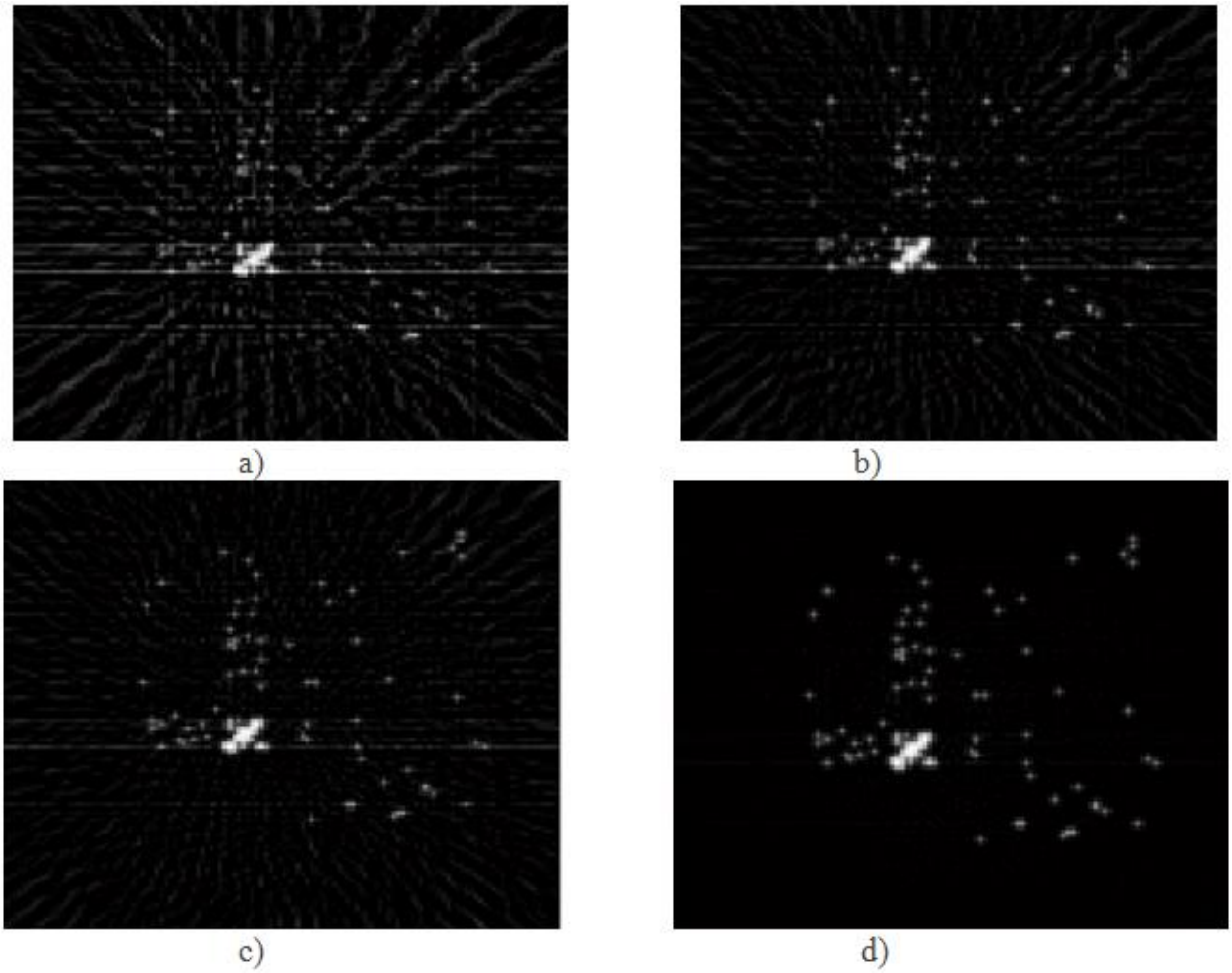


Fig 4:- Inverse Radon transform: a) 18 projections b) 36 projections c) 45 projections d) 90 projections

Database consists of the following pathologies: sympathetic activity, normal cardiac, parasympathetic activity and existence of stress, arrhythmia and availability problem with breath and the composition of these pathologies. The database was divided in to training and testing database.

C. Data Classification

This step is the classification of the HRV by considering their features that where created by using Radon transform for binary image of scattergram. In this paper the ANN is used for classification. As previously mentioned that the most important and commonly used in classification in ANN is the BPN. This neural known as backpropagration or the generalized delta rule .it is simply method to minimize the total error of the output computed by the net ,which consists of input layer, hidden layers and output layer. The inputs of the neural network in this paper are the features that where obtained using Radon transform for binary image of scattergram and outputs where coded in to 6 output as shown in table 1.

The hidden layer is the collection of neurons which has activation function applied on it as well as provides an intermediate layer between the input layer and the output layer [14]. Many researchers have been made in evaluating the number of neurons in the hidden layer but still none was accurate.

In this paper optimum number of neurons in the hidden layer is found by is by varying the number of neurons in the hidden layer and computes the performances of these NNs and selects the number of neurons that gives the best performance. Searching optimum number of neurons in a range between the number of output neurons and half of the number of input nods.

As shown in table 1 types of HRV were divided in to three main groups: sympathetic activity, normal cardiac, parasympathetic activity. Each group was divided in to sub groups: existence of stress, arrhythmia, availability problem with breath and the composition of these pathologies. So the total types of HRV in this work are 18 classes and the outputs of these classes were coding in to 6 outputs for the ANN.

Inputs of ANN		Outputs of ANN					
Features using Radon transform for binary image of scattergram.		Y1	Y2	Y3	Y4	Y5	Y6
Sympathetic type	Sympathetic activity	1	0	0	0	0	0
	arrhythmia	1	0	0	1	0	0
	breath	1	0	0	0	1	0
	arrhythmia & breath	1	0	0	1	1	0
	Stress	1	0	0	0	0	1
	Stress& arrhythmia	1	0	0	1	0	1
Normal Cardiac Standards	Normal Cardiac	0	1	0	0	0	0
	arrhythmia	0	1	0	1	0	0
	breath	0	1	0	0	1	0
	arrhythmia & breath	0	1	0	1	1	0
	Stress	0	1	0	0	0	1
	Stress & arrhythmia	0	1	0	1	0	1
Parasympathetic type	Parasympathetic activity	0	0	1	0	0	0
	arrhythmia	0	0	1	1	0	0
	breath	0	0	1	0	1	0
	arrhythmia & breath	0	0	1	1	1	0
	Stress	0	0	1	0	0	1
	Stress & arrhythmia	0	0	1	1	0	1

Table 1:- Coding outputs of ANN in to 6 outputs

III. RESULTS

To evaluate the performance of the classification of heart rate variability with BPN, three craterous are used : Sensitivity Specificity and Accuracy, the respective definitions are as follows:

Sensitivity = T_P /(T_P + F_N) =(Number of true positive assessment)/(Number of all positive assessment). (3.1)

Where T_P stands for true positive and F_N for false negative.

Specificity = T_N/(T_N+ F_P) =(Number of true negative assessment)/(Number of all negative assessment). (3.2) Where T_N for true negative and F_P for false positive.

Accuracy = (T_N+ T_P)/(T_N+T_P+F_N+F_P) =(Number of correct assessments)/(Number of all assessments). (3.3)

As previously mentioned optimum number of neurons in this hidden layer has to be found and it has to have the highest average of sensitivity specificity and accuracy for types of HRV.

Result obtained by using BPN to classify the HVR with using the Radon transform with 90 projections for binary image of scattergram shows that optimum numbers of neurons in the hidden layer is 145 neurons (table 2).

Inputs	Sensitivity	Specificity	Accurse	Number of neurons in the hidden layer
Y1	98%	97,183%	97,396%	145
Y2	92,593%	99,394%	98,438%	
Y3	100%	100%	100%	
Y4	81,481%	96,97%	94,792%	
Y5	80,3165%	88,98383%	87,3265%	
Y6	93,913%	87,013%	91,146%	
Average				

Table 2:- Result classify the HVR with 90 projections for binary image of scattergram.

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The BPN classifier with 145 neurons in the hidden layer can discriminate sympathetic activity with accuracy of 97,396%, normal cardiac with accuracy of 98,438%, parasympathetic activity with accuracy of 100%, arrhythmia with accuracy of 94,792%, availability problem with breath with accuracy of 87,3265% and existence of stress with accuracy of 91,146%.

IV. DISCUSSION AND CONCLUSIONS

In this paper we have presented a new approach classification algorithm for types of HRV, which is associated with Radon transform for feature extraction from binary matrix of scattergram by BP/MLP neural network.

Radon transform with 90 projections gives the best inverse Radon transform and have the most closer image to the original scattergram.

In this paper optimum number of neurons in the hidden layer is found by is by varying the number of neurons in the hidden layer and computes the performances of these NNs and selects the number of neurons that gives the best performance. BPN with 145 numbers of neurons in the hidden layer has the best performance, with accuracy of discrimination sympathetic activity, normal cardiac, parasympathetic activity, arrhythmia, availability problem with breath and , existence of stress were 97,396%, 98,438%, 100%, 94,792%, 87,3265% and 91,146% respectively.

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