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Article

RADIAL BASIS FUNCTION NEURAL NETWORK IN THE ANALYSIS OF SEGMENTED ELECTROCARDIOSIGNALS

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Abstract

Artificial neural networks (ANN) are used to model the information processing capabilities of nervous systems. Research in the field of analysis and interpretation of the cardiovascular diseases with ANN has been attracting more attention in recent years. This paper proposes the use of segmentation of electrocardiograms in time relative to R-wave. The ECG parameter is chosen as an approach based on ECG segmentation on 3 key areas that are responsible for the atria, ventricles depolarization and repolarization of the ventricles. Radial basis function neural network (RBFNN) is chosen for the recognition of abnormality in each segment.

Results show that in the analysis of atria, ventricles depolarization and repolarization of the ventricles segments, the best spread values for each RBFNN are 1, 2.5 and 1.5 respectively. By selecting the optimal spread values for each segment the average sensitivity for all segments is 82.4 and the average specificity is 93.7.

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Introduction:

In the latest years, diseases and death associated with cardiovascular diseases increased significantly in most countries of the world. Therefore, cardiovascular diseases may become the biggest cause of death in all continents [1].

One of the methods that are mostly noted by specialists, for assessing the heart activity, is electrocardiogram (ECG). ECG is the measure of how the electrical activity of the heart changes over time as action potentials propagate throughout the heart, during each cardiac cycle [2].

The electrocardiogram is used to measure the electrical activity of the heart rhythm. It provides information about chamber size and is the main test used to assess myocardial ischemia and infarction. The basis of a single ECG recording is that the electrical depolarization of myocardial tissue produces a small dipole current which can be detected by electrode pairs on the body surface. To produce an ECG, these signals are amplified and either printed or displayed on a monitor [1].

The normal ECG waveform (Fig. 1) has similarities in shape regardless of its orientation. The first deflection 'known as a P wave' is caused by atrial depolarization and it is a slow deflection with a low-amplitude. A shaper that is larger than the P wave; which reflects ventricular activation is known as QRS complex. Initial downward and upward deflections are called the Q wave and R wave respectively. The S wave is the last part of ventricular activation. The T wave is another slow and low-amplitude deflection that results from ventricular repolarization [3].

Today, it is more common to use automated methods for analyzing and interpreting ECGs. As a recognition system, a core neural network method was chosen. The use of neural network analysis in clinical practice improves the accuracy of the cardiovascular diseases diagnosis. ANNs are connections of simple artificial neurons operating in a parallel manner. These artificial neurons are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between neurons. Neural networks are trained to perform a particular function by modifying the values of the connections between neurons [4].

ANNs have been trained to perform complex functions in various fields of application including pattern recognition, identification, classification and control systems [4].

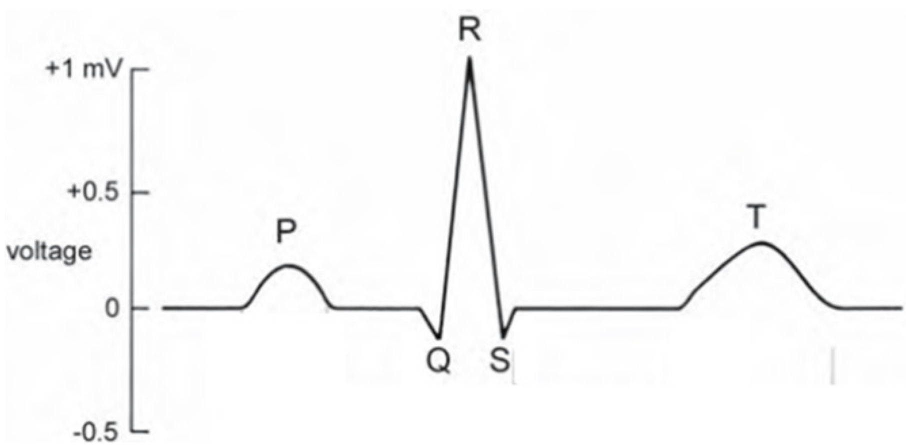


Fig 1. A Typical ECG Waveform for One Cardiac Cycle

Artificial Neural Networks (ANNs), increasingly, in the field of medicine, especially, in the analysis of heart by using ECG waveform are used [5,6,7,8,9].

Classification of heartbeats is one of the most developed applications to the ECG waveform [10,11].

Other studies emphasize on classification, based on the overall behavior of the ECG [12,13].

In this paper, the ECG is chosen as an approach based on ECG segmentation on 3 key areas that are responsible for the atria, ventricles depolarization and repolarization of the ventricles.

The principle of the separation of ECG waveform into segments is to refine the localization of pathological changes in the ECG signal.

Abnormalities in the ECG in each segment are determined by using a RBFNN.

The construction of a RBFNN, consist of three layers. The input layer: and it consists of the normalized segments of the ECG waveform. The second layer: a hidden layer that applies a nonlinear activation function. The output layer: it applies a linear activation function. It consists of one neuron and indicates the presence or absence of abnormality in ECG waveform segments.

Determining a spread parameter is the most important part in training RBFNNs. In this work, the way that the optimum number of this parameter was found by investigating different RBFNNs with various values of spread parameter.

2. Material and Methods

2.1 Database and Processing Data

In this work, the ECG archive published in www.PhysioNet.org was used to train and test the RBFNN.

From selected data we created a database, which is divided into training and testing database. Radial basis function neural networks are trained by the normalized segments of the ECG. It learns to recognize the presence or absence of abnormality in these segments with a sufficiently low error rate. Testing the neural networks is used to test the performance of the RBFNNs.

Algorithm pre-processing signal in creating experimental database segmented ECG is shown in Figure 2.

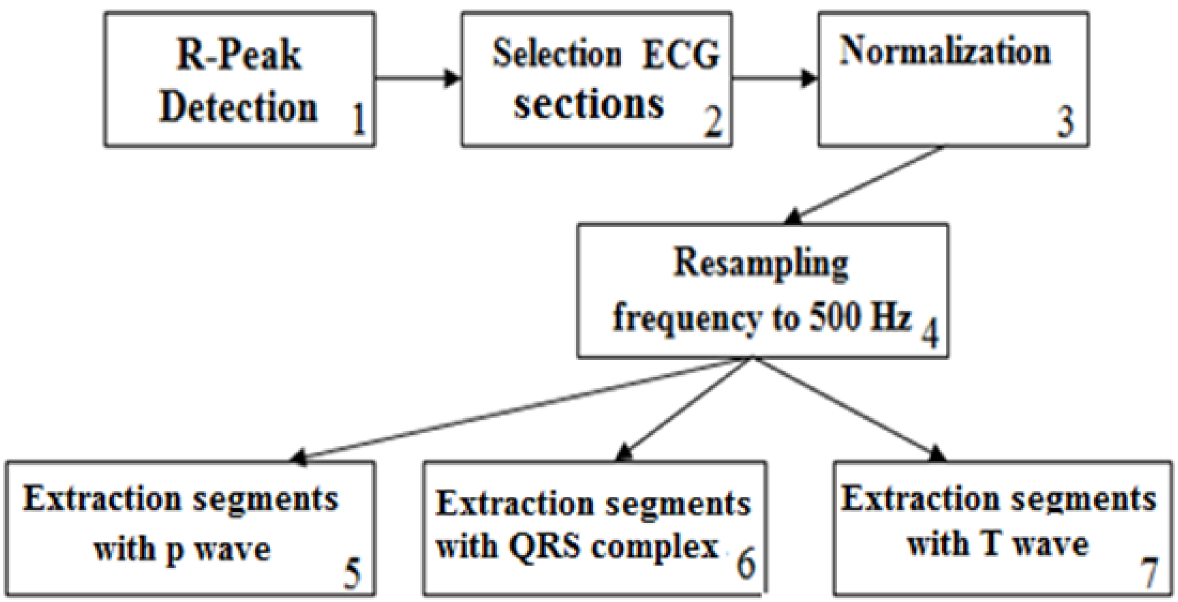


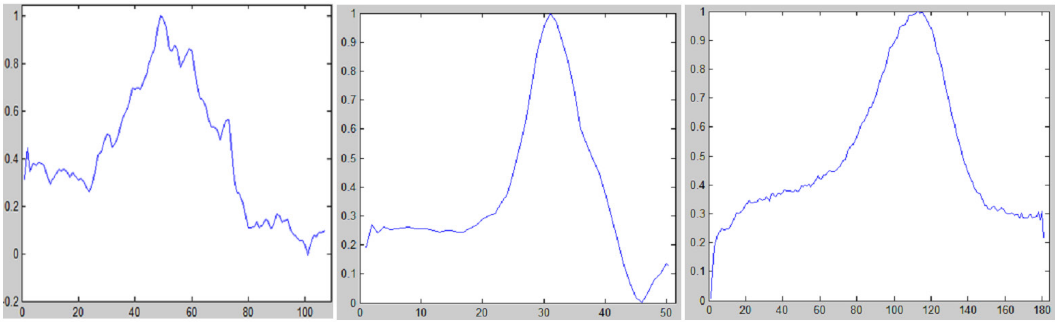
Fig.2 Algorithm Pre-processing Signal in Creating Experimental Database Segmented ECG.

The main stages of processing ECG are the detection of R- peak in the ECG; ECG sections containing P-QRS-T complexes; changing sampling frequency to 500 Hz, and finally normalization and segmentation of ECG.

Normalization is the process of organizing the ECG signals by minimizing its amplitude without losing information.

At the stage of pre-processing, segmentation of ECG on the time zones corresponding to the different departments of the heart is performed (atria, ventricles depolarization and repolarization of the ventricles).

Figure 3 shows examples of normalized ECG segments: the atria segment (Figure 3.a), ventricles depolarization segment (Figure 3.b) and repolarization of the ventricles segment (Figure 3.c).



A B C

Fig.3 Normalized Atria Segment (Fig.3.A), Ventricles Depolarization Segment (Fig.3.B) and Repolarization of the Ventricles Segment (Fig.3.C).

2.2 Radial Basis Function Neural Network (RBFNN)

The type of ANN that was used in this work was the radial basis function neural network; it is one of the most important classes of ANNs. In this neural network, the activation function of the hidden layer is determined by the distance between the input vector and a prototype vector. A significant property of RBFNNs is that they form a unifying link between a number of disparate concepts [14].

As mentioned in the introduction, RBFNN involves three layers with entirely different roles. The input layer is made up of source nodes. The second layer is a single hidden layer that applies a nonlinear transformation (Gaussian Activation Functions) from the input space to the hidden space. The last layer is the output layer which is a set of linear units that can be thought of as computing a weighted sum of evidence from each of the feature template RBF units (Figure 4).

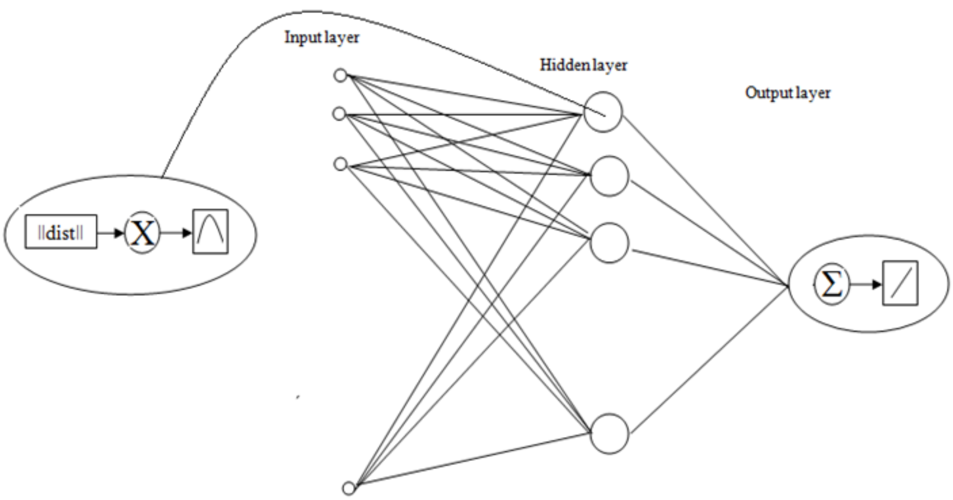


Fig.4 Topic RBFNN Structure.

The radial basis activation function (Gaussian Activation Functions) has two parameters, the center and the spread parameter (Figure 5).

If the spread parameter is inappropriate, too large or too small, values of spread parameter could cause under-fitting or over-fitting problems. The way that the optimum number of this parameter was found was by investigating different RBFNNs with various values of spread parameter. Then we selected the spread parameter value that gave the best sensitivity and specificity.

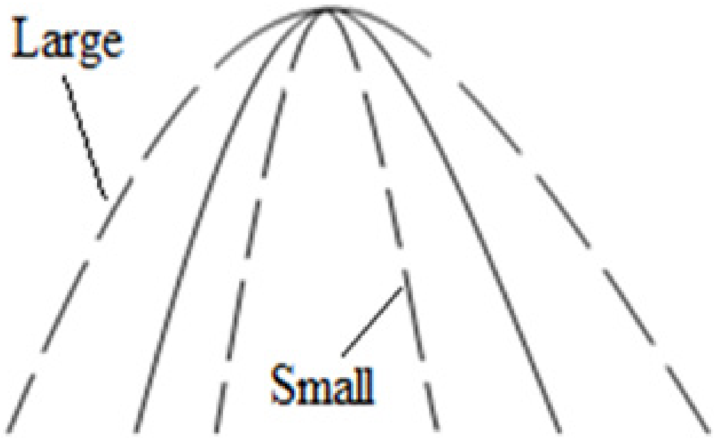


Fig. 5, Gaussian Activation Functions with Varying the Values of Spread Parameter.

3.Results and discussion

The research results presented in this paper are intended to solve the problem of constructing cardiovascular system early in diagnosis complexes. The basis of recognition core is proposed to use radial basis function as neural network (RBFNN).

In this paper, to measure performance of diagnosis, the presence or absence of abnormality for each segment of ECG with artificial neural network; we use the terms of its sensitivity and its specificity.

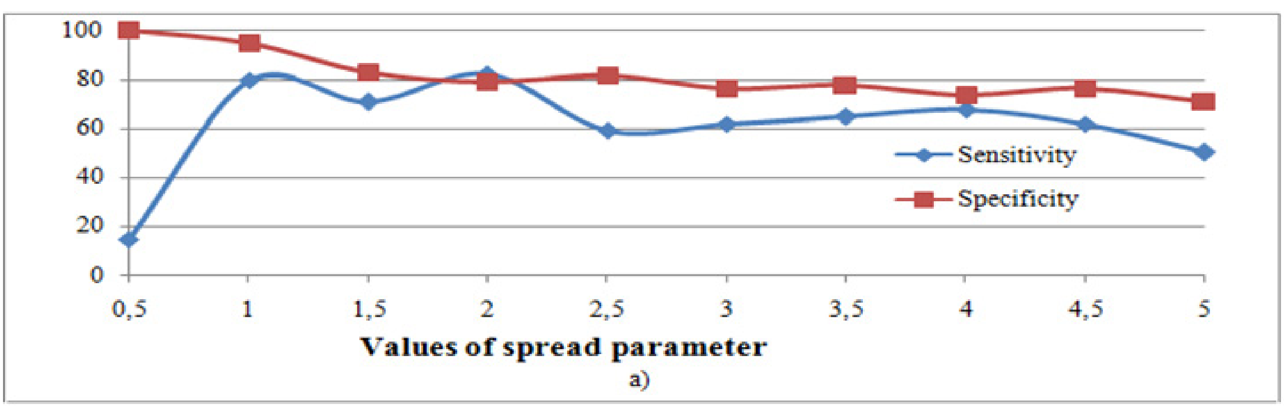
Sensitivity and specificity can be calculated by the formulas shown below;

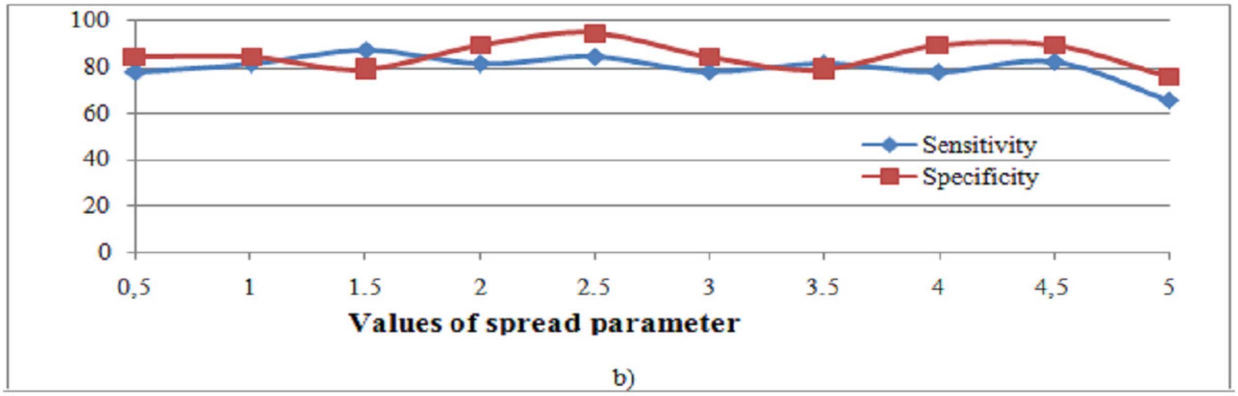
Sensitivity = TP/(TP + FN) % = (Number of true positive assessment)/(Number of all positive assessment).

Specificity = TN/(TN + FP) % = (Number of true negative assessment)/(Number of all negative assessment).

As previously mentioned, determining a spread parameter is the most important part in training RBFNN. The way the optimum number of this parameter was found, was by investigating different RBFNN with various values of spread parameter. Then we did compute the sensitivity and specificity to measure the performances of these RBFNNs for recognizing the presence or absence of abnormality in each segment of ECG (fig 6, tab1).

Next we selected the best spread values by taking the combination of sensitivity and specificity values, for which the increase of one parameter does not cause the fall of another.





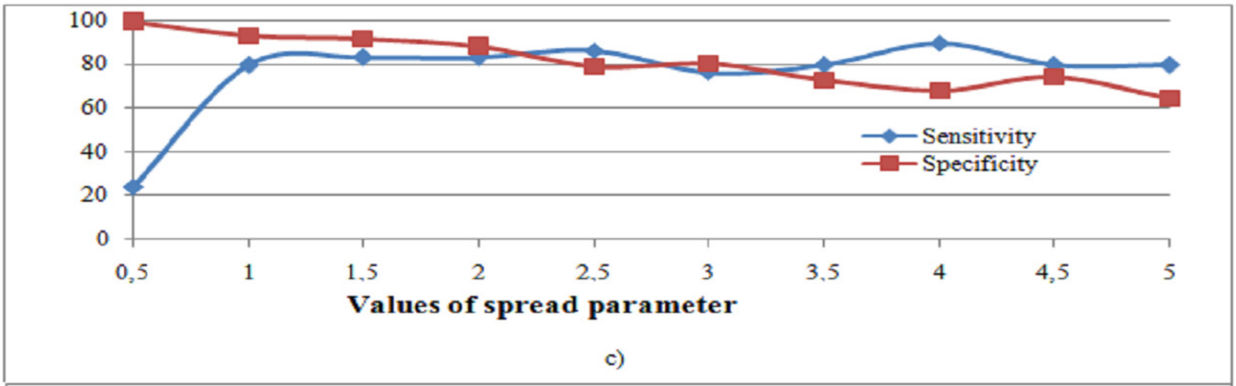


Fig. 6, Rrelationship between Values of Spread Parameter and Sensitivity and Specificity a) Atria Segment b) Ventricles Depolarization Segment c) Repolarization of the Ventricles Segment.

Results show that for analysis of atria, ventricles depolarization and repolarization of the ventricles segments, the best spread values for each RBFNN are 1, 2.5 and 1.5 respectively.

As shown in table 1, by selecting the optimal spread value for each segment, the average sensitivity and specificity for all segments are 82.4 and 93.7 respectively.

Table 1, Results Obtained by Using RBF to Recognizing the Presence or Absence of Abnormality for the Three Segments of ECG.

Segment of ECG	Sensitivity	Specificity	Spread
Atria	80	94.7	1
Ventricles Depolarization	84.3	94.9	2.5
Repolarization of the Ventricles.	82.8	91.4	1.5
Average	82.4	93.7	

4.Conclusion

In this paper, for the ECG parameter, an approach was chosen based on ECG segmentation on 3 key areas that are responsible for depolarization of the atria, ventricles depolarization and repolarization of the ventricles. Abnormalities in the ECG in each segment are determined by using a RBFNN with Gaussian activation functions.

In this work we used three RBFNNs for the recognition of abnormality in each segment.

Results show that for the analysis of atria, ventricles depolarization and repolarization of the ventricles segments; the best spread values for each RBFNN was 1, 2.5 and 1.5 respectively. By selecting the optimal spread values for each segment the average sensitivity and specificity for all segments was 82.4 and 93.7 respectively.

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