Comparison of MLP and RBF neural networks for Prediction of ECG Signals

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Summary
In this paper, we investigate the performance of MLP and RBF neural networks in terms of ECG signal prediction. In spite of quasi-periodic ECG signal from a healthy person, there are distortions in electrocardiographic data for a patient. Therefore, there is no precise mathematical model for prediction. Here, we have exploited neural networks that are capable of complicated nonlinear mapping. In this way, 2 second of a recorded ECG signal is employed to predict duration of 20 second in advance. Our simulations show that RBF neural network reconstructs ECG signals with 94% accuracy which is 2% better than MLP architecture.

Key words:
electrocardiogram, artificial neural network, predict, accuracy .

1. Introduction

Electrocardiogram is an important tool for providing information about heart activity [1]. The first electrocardiographic (ECG) signal was obtained in 1895 by Willem Einthoven. Though the basic principles of those systems are still applied, many advances have been made over the years. The schematic of a single heartbeat in ECG signal is indicated in Figure 1 [2]. Since the normal kind of signal belonged to a healthy person is according to a known structure, changing and disturbing in any important parameters represent a heart disease. As a result, physicians try to diagnose different heart disorders by analyzing ECG signals. For example, Gilberto Sierra in 1997 performed a frequency analysis for the purpose of cardiac death forecasting [3] and M. Arvaneh in 2009 predicted paroxysmal atrial fibrillation by dynamic modeling of the PR interval [4].

On the other hand, neural networks are strongly capable in learning and prediction which makes them an efficient tool to deal with nonlinear problems. For example Lean Yu used multistage RBF neural networks for exchange rates forecasting and H. Tonekabonpour in 2011 predicted ischemia via MLP and RBF predictors [5].

In this study, we apply Multilayer Perceptron (MLP) and Radial Basis Function (RBF) for ECG signal. The database consists of 50 signals taken from 50 persons in the intensive care unit (ICU) that 10% of them were healthy and 90% of them were patient. The rest of this paper is organized as follows. The next section briefly describes the architecture of the applied networks. In section 3, the performed process for ECG signal prediction is presented. Finally in section 4 and 5, we have results and conclusion.

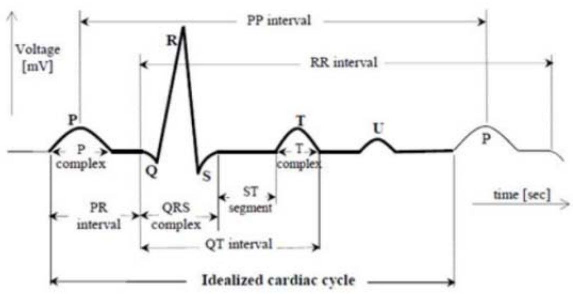

Fig. 1 Schematic of ECG signal [2]

2. Method

Neural network models are extensively applied in various fields such as medicine, mathematical modeling and engineering. In this paper, two different architectures of neural networks have been compared to predict ECG signals. These architectures are multi layer perceptron and radial basis function networks that are explained bellow.

2.1 Multi layer perceptron (MLP) network

One of the most popular neural networks is feed forward MLP network by back propagation training algorithm which is shown in figure 2. Although, the number of neurons in the input and output layers is determined by the user requirements, the number of layers and also the number of neurons in each hidden layer are optimized by trial and error procedure.

Where w_{ij}^{1} is the connection weight from i-th input to the j-th hidden node, w_{jk}^{2} represents the connection weight between hidden and output layer, v_i^{0} is i-th data of the

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input vector, b_j^1 denotes the bias in j-th hidden node and φ(•) is the activation function [7]. The activation function of neurons in hidden layers is normally selected of Sigmoidal type with the following equation:

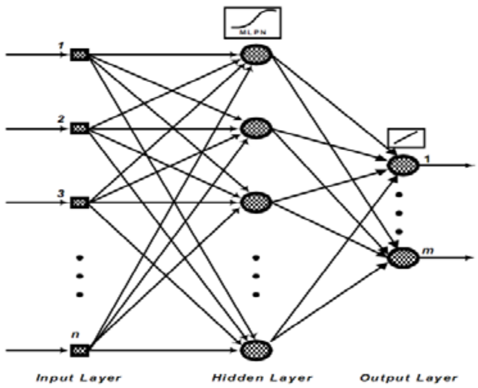

Fig. 2 The three layers of a feed forward neural network which illustrates a MLPN [6]

It can be seen from figure 2 that the output is expressed by:

$$y_o(t) = \sum_{j=1}^{n_j} w_{jk}^2 \phi\left[\sum_{i=1}^{n} w_{ij}^1 v_i^p(t) + b_j^1\right]; \qquad (1)$$

$$1 \le k \le m$$

$$\phi(x) = \frac{1}{1+\exp(-x)} \qquad (2)$$

2.2 Radial basis function (RBF) network

A special type of neural network with different characteristic topology is radial basis function (RBF) network. The RBF network consists of three layers: input layer, hidden layer and output layer. A general structure of the mentioned network has been illustrated in figure 3.
According to figure 3, RBF network computes the output value by the following formula:

$$y_o(t) = \left(\sum_{i=1}^{n_i} w_{ik}^2 \phi[D_i]\right) + b_k^2; \qquad (3)$$

$$1 \le k \le m$$

Where w_{ik}^2 is the connection weight from hidden to the output layer, b_k^2 denotes the bias in k-th output node and φ(•) is a radial activation function. If the activation function is set to be of Gaussian type, then:

$$\phi(D_i) = \exp\left(\frac{-D_i^2}{\sigma^2}\right) \qquad (4)$$

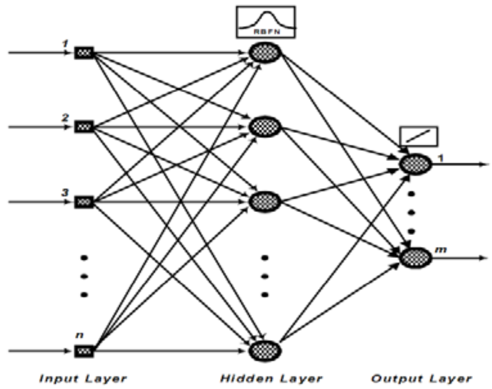

Fig. 3 The three layers of a feed forward neural network which illustrates a RBFN [6]

σ is the radius of each hidden node and D_i is the distance between the input vector X and the center of radial function. For calculation of distance parameter, the Euclidean norm is commonly used which is given by:

$$D_i = \sqrt{\sum_{j=1}^{n} (x_j - C_{ji})^2} \qquad (5)$$

C_{ji} in the above equation is the center for i-th node in hidden layer [8].

3. Prediction of ECG signals

In this work different artificial neural networks have been exploited to estimate [(n+1)th, (n+2)th,…, (n+m)th] samples from n previous ones. Then the estimated samples are returned back to the input layer for prediction of m next samples started from n+m+1.

In the applied networks, input layer consists of 50 neurons which are equal to the number of samples in 2 second of the original signals. The number of hidden nodes is selected based on experience and the number of output nodes is set to be 25 which are corresponding to the number of predicted samples. A schematic of the applied networks in this paper has been shown in figure 4.

Here, we have employed a database consists of 50 signals taken from 50 persons in the intensive care unit (ICU) that 10% of them were healthy and 90% of them were patient. First, All signals have been noise canceled using wavelet transformation. Then, all data were normalized to lie between 0 and 1. After that they have been divided into three datasets named as: training (60% of all data), test (20% of all data) and validation (20% of all data). Figure 5 shows some instances of denoised signals from the mentioned database.

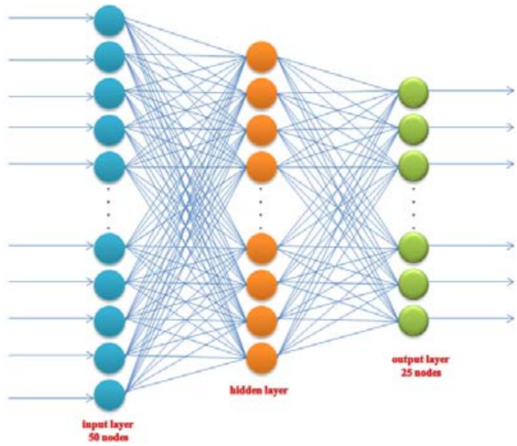

Fig. 4 The common MLP and RBF network

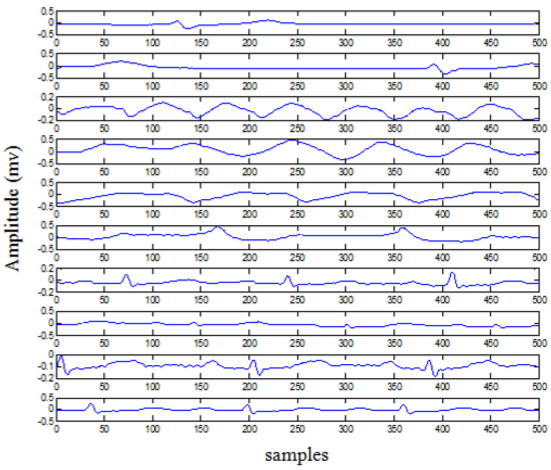

Fig. 5 Actual ECG signals

4. Results

To verify the performance of the ECG prediction systems, the difference between the output and target values is calculated using Mean Square Error (MSE). The MSE parameter is expressed as:

$$mse = \frac{1}{n}\sum_i (y_d(t_i) - y_o(t_i))^2 \tag{6}$$

Where $y_o(t_i)$ is the ith network output, $y_d(t_i)$ is the ith desired output and n is equal to the number of predicted samples.

Figure 6 and figure 7 show the MSE parameter for different MLP neural networks using two groups of database include 40 and 50 signals, respectively. In these neural networks we aim to achieve the minimum mean square errors. As shown in figure 6, the best MLP network using a database of 40 signals has four layers with 50-30-30-25 structure. However, in the case of 50 signals, the number of hidden neurons was chosen to be 30 for which the MSE was minimum. So, 50-30-25 structure was the most suitable network for the task.

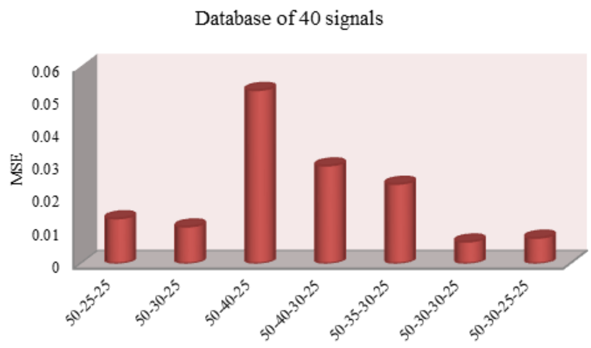

Fig. 6 MSE of MLP networks with a database of 40 signals

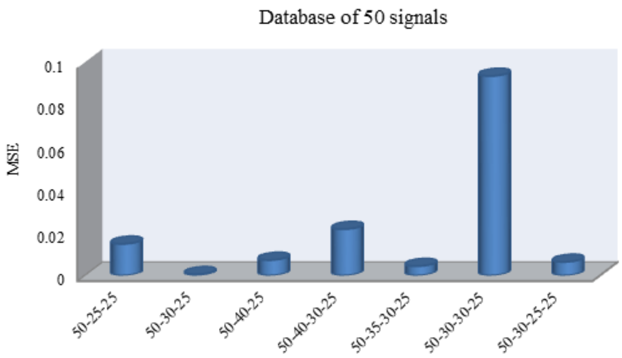

Fig. 7 MSE of MLP networks with a database of 50 signals.

The results of trained RBF neural networks with two groups of database consist of 40 and 50 signals are presented in the following figures. As shown in figures 8 and 9, the RBF networks with 35 nodes in its hidden layer are the best one to achieve the minimum MSE.

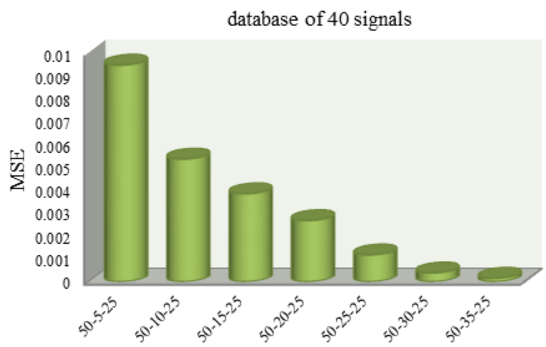

Fig. 8 MSE of RBF networks with a database of 40 signals

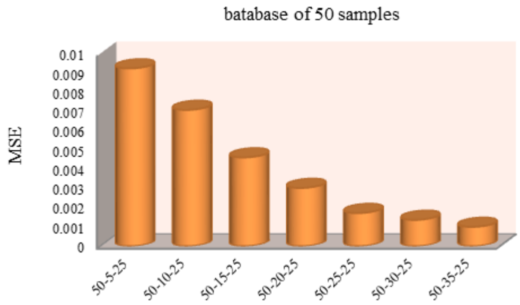

Fig. 9 MSE of RBF networks with a database of 50 signals

All results are presented in Table 1. Although both types of neural networks are good at prediction problems, it is clear from the table that the best results are obtained by the RBF neural network. According to the simulations, RBF neural network with 35 neurons in the hidden layer reconstructs ECG signals with 94% accuracy which is 2% better than MLP architecture with 30 hidden neurons.

Table 1:MSE in MLP and RBF comparison

No. of signals	***MSE in MLP NN***	***MLP NN Regression***	***MSE in RBF NN***	***RBF NN Regression***
10 signals	$2.1 * 10^{-3}$	0.8356	$2.00282 * 10^{-4}$	0.8752
20 signals	$2.46 * 10^{-3}$	0.8997	$2.53066 * 10^{-5}$	0.9026
30 signals	$9.8 * 10^{-5}$	0.9134	$3.1567 * 10^{-6}$	0.9154
40 signals	0.00661	0.7856	$1.12179 * 10^{-4}$	0.8512
50 signals	0.000488	0.9269	$2.85156 * 10^{-4}$	0.9467

Two predicted ECG signals for healthy and unhealthy persons are shown in figures 10 and 11, respectively. These results obtained from the best RBF neural network. In this procedure, 20 seconds of signal are predicted in 0.7 second.

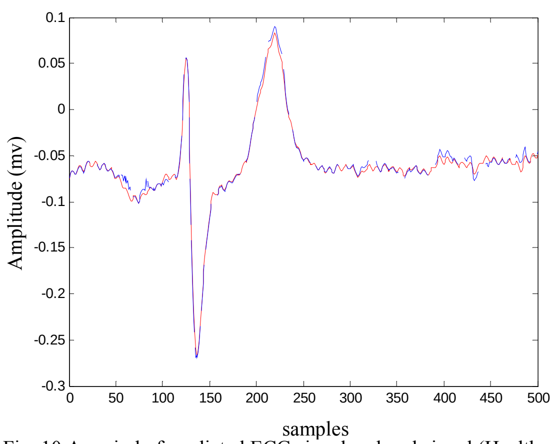

Fig. 10 A period of predicted ECG signal and real signal (Healthy signal)

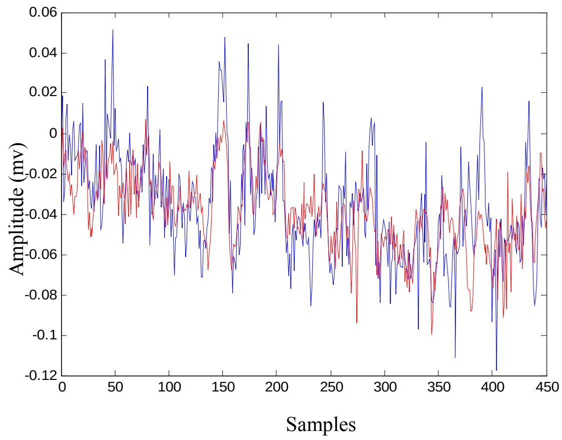

Fig. 11 A period of predicted ECG signal and real signal (unhealthy signal)

5. Conclusions

This paper compared the performance of multilayer perceptron network (MLPN) and radial basis function network (RBFN) in terms of ECG signal prediction. Both neural networks were able to predict the future of the signal from the recorded part. However, The RBF architecture shows better results than MLP architecture. Our simulations confirm that RBF neural network reconstructs ECG signals with 94% accuracy which is 2% better than MLP architecture.

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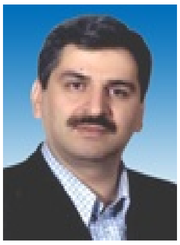

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