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Prediction of ECG Signals Using Feedforward Neural Networks

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Abstract: The Electrocardiogram (ECG) signal could be modelled or analysed using time series prediction methods. This study considered neural networks models trained with ECG data, so that the trained models could then predict ECG for the purpose of diagnosis and prevention of cardiac troubles. Predicting the ECG is necessary in order to assist the heart specialist to provide early measures that could avert the likely cardiac crises thereby improving life's longevity, productivity and standard of living. The research utilised the application of backpropagation algorithm feedforward neural networks to predict the ECG of heart rhythm disorders. The ECG data for very slow heartbeat (sinus bradycardia), low blood reaching the heart (myocardial ischemia) and very fast heartbeat (ventricular tachycardia) were obtained from Massachusetts Institute of Technology, Biomedical Institute of Health Sciences (MIT-BIH). Feedforward neural networks (FFNN) using Levenberg-Marquart training algorithm were investigated in this research using neural network toolbox in MATLAB and were found to be good predictors of ECG. Feedforward neural network prediction performance however proved that FFNN could effectively predict the ECG. The research was based on short-term prediction of ECG using single-point prediction.
Keywords: Electrocardiogram, Predicting, Feedforward.

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Introduction

Neural networks (NN) are nonlinear mapping structures that mimic the function of the human brain. Neural networks are implemented in computer programmes that are able to handle the large number of necessary calculations during the learning process. They are powerful tools for modelling especially when the underlying data relationship is nonlinear. Neural networks exhibit universal approximation properties, Multi-Layer Perceptrons (MLPs) are often successful in modelling nonlinear systems such as electrocardiogram (ECG) which describe the electrical heart activities and may be used by heart specialist to assess heart rhythm, diagnose poor blood flow to the heart muscle (ischemia), diagnose an impending heart attack, diagnose abnormalities of the heart, such as heart chamber enlargement and abnormal electrical conduction.The ECG signal is a time series in nature and as such could be modelled or analysed using time series prediction methods.

Some of these methods that are used in predicting ECG time series are genetic algorithm, fuzzy logic, wavelets and neural networks. Recently neural networks proved to be promising alternatives. This research dwelt on the application of backpropagation algorithm feedforward neural networks to predict the ECG of heart rhythm disorders. The classic feedforward neural networks (FFNN) were used for the experimentation. The task is to determine if FFNN can be trained to predict common heart conditions for diagnostic and prevention purposes using large ECG data.

The primary function of the heart is to supply nutrients to the body as it moves the blood around the body and this is accomplished by the regular contraction of the heart, which is controlled by electrical impulses. Normally, these impulses occur in regular intervals. When something goes wrong, however, the impulses or contraction becomes irregular, resulting in a rhythm disorder, or arrhythmia (Nordqvist, 2009).

Arrhythmia can occur with a normal heart rate or with fast or slow heart rates. Causes may include coronary artery disease, heart attack, heart surgery, blood imbalances and so on. There are many types of arrhythmias. These include sinus bradycardia (very low heart beat), ventricular tachycardia (very fast heart beat), myocardial ischemia (low blood reaching the heart) and atria hypertrophy (enlargement of the atrium) and so forth. An electrocardiogram (ECG) is required to establish if rhythm problem is present and the exact type.

An ECG signal is a time series representing the electrical activity of the human heart. It can be detected by placing small metal discs called electrodes on the skin of the chest, arms, and legs (Abbas *et al*., 2004). A typical ECG signal of a normal heart rhythm is plotted from ECG data presented in Figure 1. A single heart beat comprises of one P wave, PR interval, QRS complex, Q wave, ST segment, T wave and U wave. Each of these components represents the electrical activity in the heart during a portion of the heart beat (Roberts *et al*., 2010).

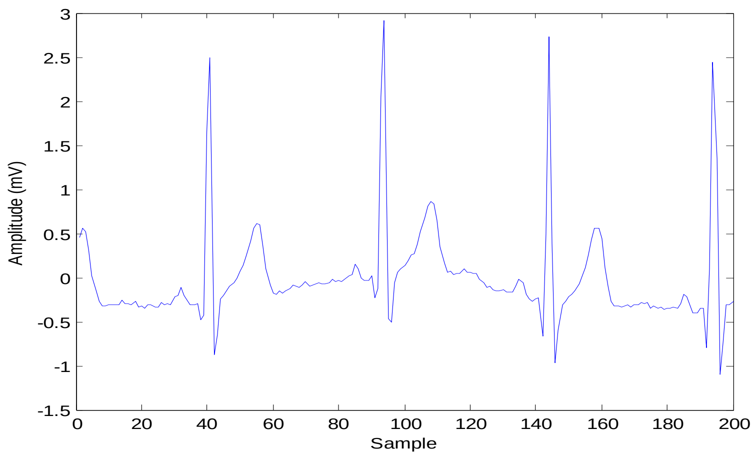

Figure 1. Typical Normal Heart ECG Wave (Source: MIT-BIH Database, 2009)

Three cases of arrhythmias namely sinus bradycardia, myocardial ischemia and ventricular tachycardia are considered in this study.

Sinus bradycardia:"Sinus" refers to the sinus node, the heart's natural heartbeat regulator which creates the normal regular heartbeat while "bradycardia" means that the heart beat rate is slower than normal. Fainting can occur with sinus bradycardia if the heart slows down even more (Christiansen, 1995).

*Myocardial ischemia:*Myocardial ischemia (also known as angina) is a heart condition caused by a temporary lack of oxygen-rich blood to the heart. The term refers to chest pain or discomfort that occurs when the heart muscle is not getting enough oxygen-rich blood for a short period of time (Cohn and Kim, 2003).

*Ventricular tachycardia:*Ventricular tachycardia causes fast and usually regular impulses which come from the ventricles and cause a very rapid heart rate. This is usually a life-threatening tachycardia and needs immediate medical attention (Abbas *et al*., 2004).

German-Sallo and Gyorgy (2010) used the feedforward neural network for the prediction of ECG which resulted in a good correlation between the predicted values and the actual outputs. Mohsenifar and Sadr (2011) simulations showed that RBF neural networks predicted ECG signals with 94% accuracy which further confirms that neural networks are suitable for predicting ECG. Nevertheless, there is much to be studied about the feedforward MLP with backpropagation algorithm.

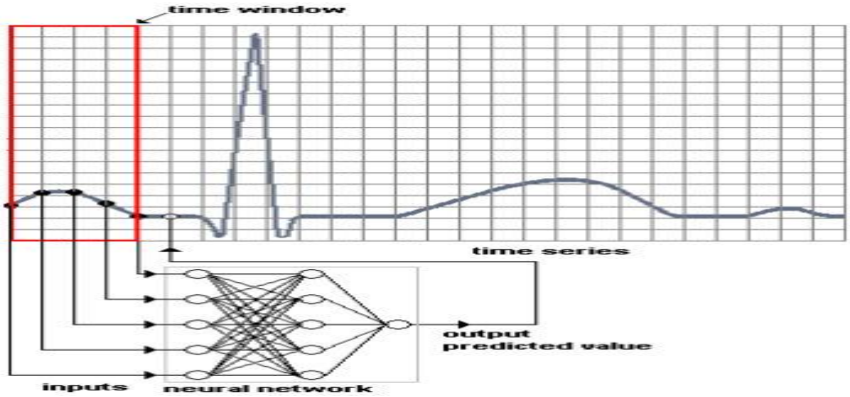

Figure 2. Input Samples to Trained NN to Predict Next Samples (Source: German-Sallo and Gyorgy, 2010)

Simulation, Results and Discussion

Neural network toolbox in MATLAB software (Mathworks, 2009) was used to create the feedforward neural networks (FFNN) for the modelling of ECG signals. The first step in training a feedforward network is to create the network object. A feedforward neural network have neurons in the hidden layers and a single neuron in the output layer. Tansigmoid transfer (‘tansig’) functions could be used in the hidden layer and linear transfer (‘purelin’) function in the output layer. A typical structure of the feedforward neural network created is shown in Figure 10 having three neurons, three tansigmoid nonlinear transfer functions in the hidden layer and a single output neuron with a linear transfer function (purelin). Where p_1, p_2 and p_3 are the inputs where ECG data for the training of the network is applied.

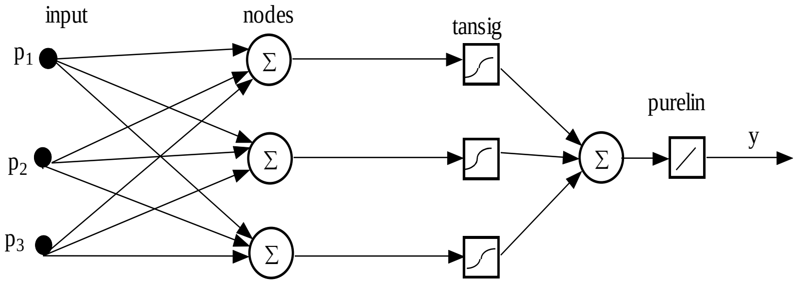

Figure 3. FFNN with Three Neurons in the Hidden Layer

For the training of the backpropagation feedforward networks, the Levenberg-Marquart algorithm was used. This algorithm appears to be the fastest method for training moderate-sized feedforward neural networks (Mathworks, 2009). It also has a very efficient MATLAB implementation, because the solution of the matrix equation is a built-in function, so its attributes become even more pronounced in a MATLAB setting.

The typical performance function used for training feedforward neural networks is the mean squared error (mse) and is defined by equation:

$$mse = \frac{1}{N}\sum_{i=1}^{N}(t_i - y_i)^2$$

where t_i is the desired output of the network and y_i is the predicted output

To use feedforward neural networks for the prediction of ECG signals, the data for three hearts rythms were considered. Each data has 1000 values, 600 of these were used as training data set while the remaining 400 were used as testing data. The heart conditions were sinus bradycardia which was taken as Case 1, while myocardial ischemia was Case 2, and ventricular tachycardia as Case 3. All simulations were carried out in the MATLAB neural network toolbox environment.

The results of training performance, plots of actual versus neural networks generated for the simulation for Case 1(sinus bradycardia), Case 2 (myocardial ischemia) and Case 3 (ventricular tachycardia) and the discussion of results are presented.

The ECG signals Cases 1, Case 2and Case 2 shown in Figures 4, 5, and 6 while the implemented feedforward neural network for the purpose of modelling the signal is shown in Figure 7. The performance of the network improved as a result of training, the progress of the mean squared error as performance index is shown in Figure 8, 9, 10 for Cases 1, 2, and 3 respectively and it was observed that acceptable performance was achieved at epochs indicated on the training plots. The comparison of the predicted signal of Cases 1, 2, and 3 with the actual signal is as shown in Figures 11, 12, and 13 respectively and the predicted signal is observed to have closely fit the actual signal.

The performances of the networks mean squared error (MSE) were observed and presented in Table 1 for various number of elements (nodes) in the hidden layer. It was observed that at node 3, FFNN prediction was better with the lowest MSE for all the three cases.

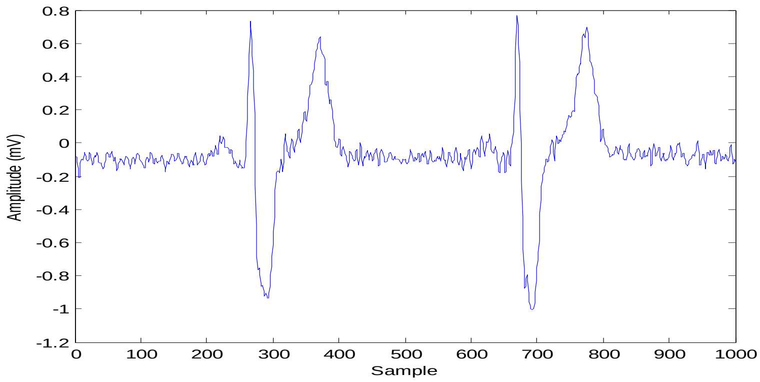

Figure 4. Case 1 ECG Signal(sinus bradycardia)

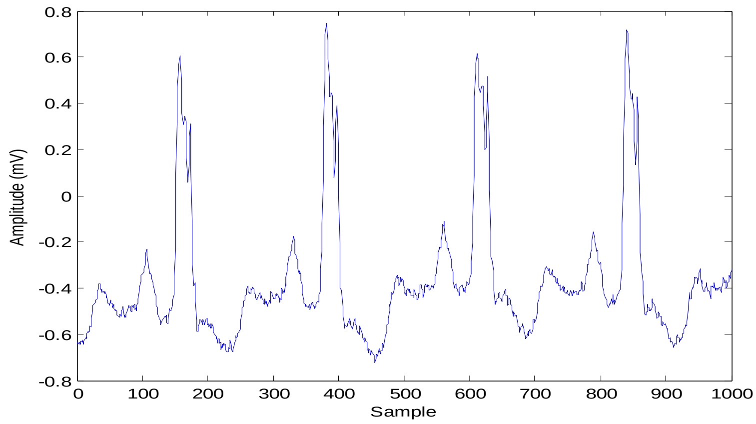

Figure 5. Case 2 ECG Signal(myocardial ischemia)

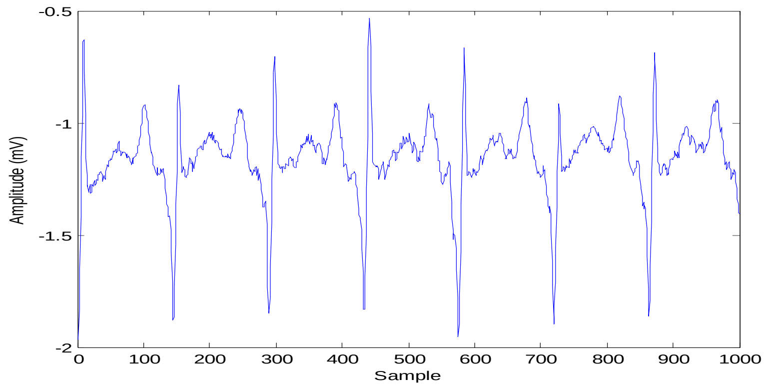

Figure 6. Case 3 ECG Signal (ventricular tachycardia)

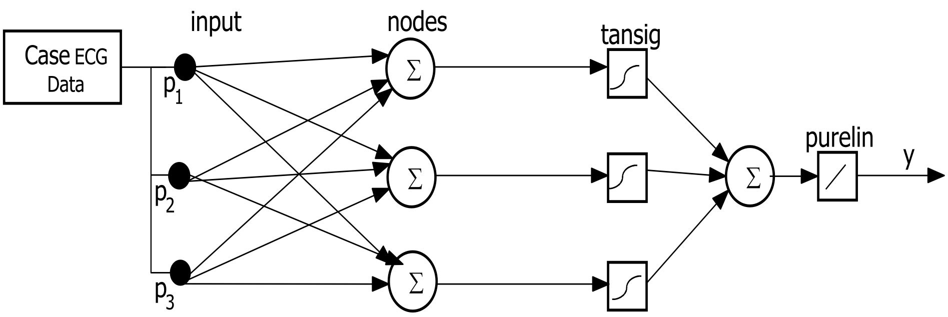

Figure 7. Topology of 3-Node FFNN

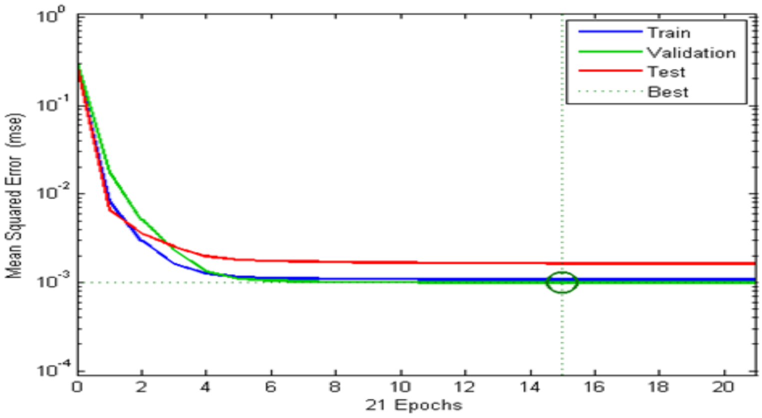

Figure 8. FFNN Training Performance for Case 1

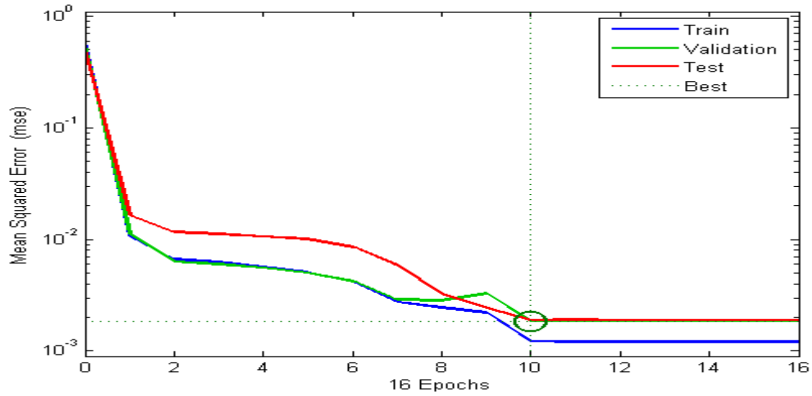

Figure 9. FFNN Training Performance of Case 2

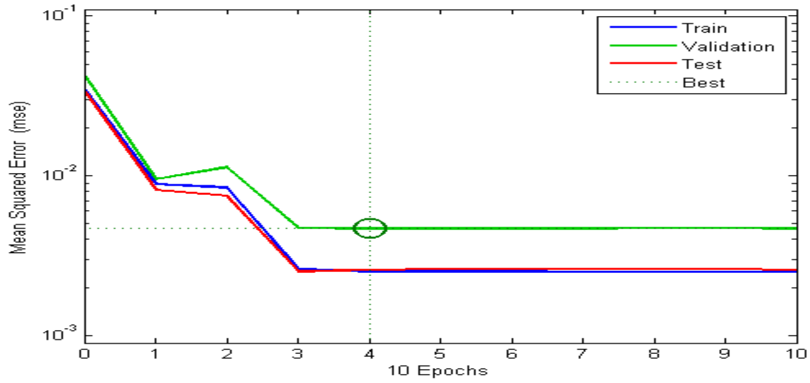

Figure 10. FFNN Training Performance of Case 3

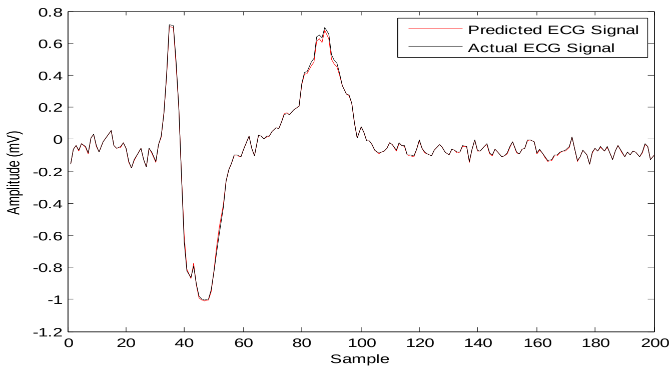

Figure 11. 3-Node FFNN Prediction of Case 1 Signal with the Actual ECG Signal

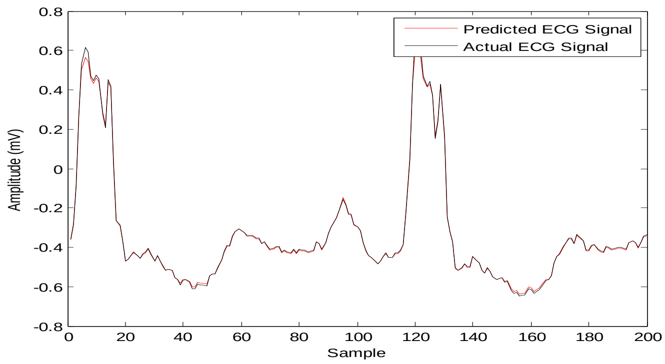

Figure 12. 3-Node FFNN Prediction of Case 2 Signal with the Actual ECG Signal

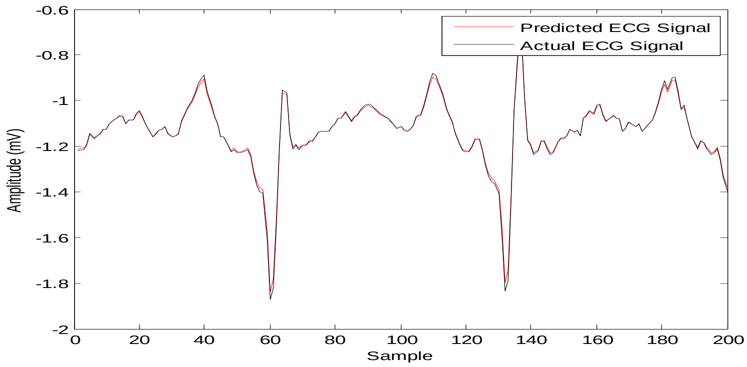

Figure 13. 3-Node FFNN Prediction of Case 3 Signal with the Actual ECG Signal

Table 1. FFNN Prediction Performance

Nodes	***Case 1***		***Case 2***		***Case 3***	
	Epochs	*MSE*	*Epochs*	*MSE*	*Epochs*	*MSE*
3	15	0.0017	10	0.0021	4	0.0016
4	9	0.0022	4	0.0022	25	0.0021
5	29	0.0020	5	0.0021	5	0.0017
8	15	0.0022	8	0.0022	2	0.0023
10	6	0.0021	26	0.0034	5	0.0026

The feedforward neural networks modelling for three hearts conditions; very slow heartbeat (sinus bradycardia), low blood reaching the heart (myocardial ischemia) and very fast heartbeat (ventricular tachycardia) were investigated and the results were presented in Tables 1. The performance index (mean squared error) was lowest when the network had three neurons in its hidden layer. FFNN predicted each heart case and comparisons were made with the actual signals. FFNN therefore is capable of predicting the heart conditions when trained with backpropagation algorithm. It is however observed that:

i) FFNN successfully predicted the ECG signals; sinus bradycardia, myocardial ischemia and ventricular tachycardia had higher accuracy when it had three elements in its hidden layer.
ii) FFNN prediction error for myocardial ischemia was higher compared to the other ECG signals. This shows that the performance of these networks depends on the dynamics of the ECG signals.

Babusiak and Mohylova (2008) compared MLP neural networks with linear neural network in modelling ECG. MLP network performed better than the linear neural network. In this research FFNN nonlinear MLP networks were investigated and proved successful in the prediction of ECG. This finding also agreed with German-Sallo and Gyorgy (2010) that feedforward neural networks are good predictors of ECG.

Conclusion

The feedforward neural networks implemented in this research successfully modelled the ECG signals of three cases understudy; namely very low heartbeat (sinus bradycardia), low blood reaching the heart (myocardial ischemia), and very fast heartbeat (ventricular tachycardia) irrespective of changes made in their parameters. Hence, neural network has proved to be a promising alternative to traditional techniques for ECG time series prediction. Feedforward neural network with backpropagation learning algorithm has shown that ECG could be modelled successfully.The prediction achieved in this study is termed short-term prediction which is based on single-point prediction, further work may be necessary for long-term prediction.

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