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Research Article

Time Delay Neural Networks Modelling of Heart Rhythms

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Abstract: The Electrocardiogram (ECG) signal could be modelled using neural networks models because of their universal approximation properties. 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 thereby leading to sustainable development. 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). Time delay neural networks (TDNN) 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. However, the comparison of TDNN with the feedforward neural network (FFNN) prediction performance shows that time delay neural network performance is better. The research was based on short-term prediction of ECG using single-point prediction. Real time application of neural network in the prediction of ECG is recommended for further work.
Keywords: Electrocardiogram, heart rhythm, time delay neural networks, prediction.

Introduction

Neural networks (NN) 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. An ECG signal is a time series representing the electrical activity of the human heart and are known as deterministic chaotic systems. The goal of time series prediction is to model the underlying mechanism that generates the series so that the value of the series for a short to intermediate term into the future can be predicted (Liao *et al*., 2002). Time series analysis find applications in economic forecasting, sales forecasting, budgetary analysis, stock market analysis, process and quality control, population analysis, monitoring of physiological signals such as patient heart's activity.

Cardiovascular disease strikes the younger working-age population at higher rates in developing countries than in developed countries; the economic impact is more severe due to low productivity as a result of illness and premature death. A study of patients attending a

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cardiac service in Nigeria showed that 57 percent suffered hypertension while 12 percent suffered some other forms of cardiovascular disease (Lamptey, 2009). This and other studies made it clear that ECG prediction could be a way forward in reducing occurrence of cardiac arrests, stroke and other heart related problems which will contribute in sustaining the nation's economic development. An ECG wave of a single heart beat is shown in simplified diagram of 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 heartbeat. It is these features of the ECG signal by which a cardiologist uses to analyse the health of the heart and note various disorders.

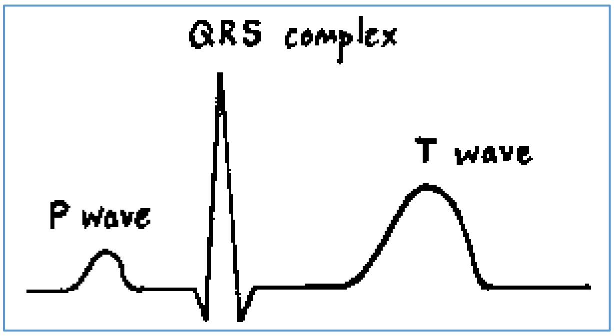

Figure 1. A Sketch of a Single Heart Beat

Arrhythmia (irregular heartbeat) can occur with a normal heart rate or with fast or slow heart rates. Arrhythmias 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.

The focus of this study is to train a time-delay neural network (TDNN) with backpropagation algorithm and implement the optimum network input delay vector and appropriate network size for the modelling of ECG time series; and to compare the FFNN and TDNN networks performances and their effectiveness to predict ECG time series for the purpose of heart diagnosis in order to minimise the possibility of heart attack.

ECG data used in this study was acquired from Massachusetts Institute of Technology, Biomedical Institute of Health Science (MIT-BIH) database at web address (MIT-BIH Database, 2009). In particular, the data obtained for low heart beat (sinus bradycardia), very fast heart beat (ventricular tachycardia), and low blood reaching the heart (myocardial ischemia) were used for the experiments in this research.

This study employed simulation method in which a neural network model is first created and trained with the ECG data then predictions are made using the model. These predictions are recursive in nature, that is, the previous predictions are used in making more short-term predictions. Thus, the current inputs to the neural network are used to predict the next value (German-Sallo and Gyorgy, 2010); this is known as single point prediction.

Signal Prediction Using Neural Networks

Various techniques have been used for time series modelling. These include neural networks (Bengio *et al*., 1995), embedding (Suer, 1993), genetic algorithm (Abraham and Nath, 2001), ARIMA (Brockwell and Davis, 2003), and fuzzy logic (Song and Chissom, 1993).

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Neural networks ability to predict time series has been based on short-term prediction which proved to yield better performance than long-term prediction. This study considered short-term prediction. The prediction of the next value based on the real input points is known as single-point prediction (Li, 1997).

Similarly, Li (1997) confirmed that single-point prediction of ECG signals could be achieved with neural networks using real-time recurrent learning (RTRL) algorithm. The effectiveness of the BPA has been demonstrated in the prediction of various heart diseases such as stroke (Shanti *et al*., 2008) and cardiac arrest (Sierra, 1997). Large ECG data could be compressed for easy transmission for clinical information using neural network prediction algorithm (Al-Hujazi and Al-Nashaas, 1996).

Gómez-Gill and Ramirez-Cortes (2006) proposed hybrid-complex neural networks for long-term prediction of ECGs. MLP neural networks proved to model ECG signals more successfully than the linear neural network (Babusiak and Mohylova, 2008). Recently, Adams and Choi (2012) were able to achieve 98.6% prediction accuracy of cardiac arrhythmias on test data which could result in improvements in the diagnosis of heart abnormalities.

Kwembe *et al.,* (2016) using single step prediction noted that classic feedforward neural network modelled digitised record of ECG effectively. Nevertheless, there is much to be studied about the feedforward MLP with backpropagation algorithm. The variant of a feedforward neural network, TDNN is considered in this study so as to ascertain its effectiveness in modelling ECG signal relative to the classic FFNN.

Simulation, Results and Discussion

Neural network toolbox in MATLAB software (Mathworks, 2009) was used to create the time delay neural network (TDNN) for the modelling of ECG signals. The structure of the neural network thus created is shown in Figure 2 having a time delay input vector [0 1], three neurons, three tansigmoid nonlinear transfer functions in the hidden layer and a single output neuron with a linear transfer function (purelin). p(t) is the input where ECG data is applied for the training of the network.

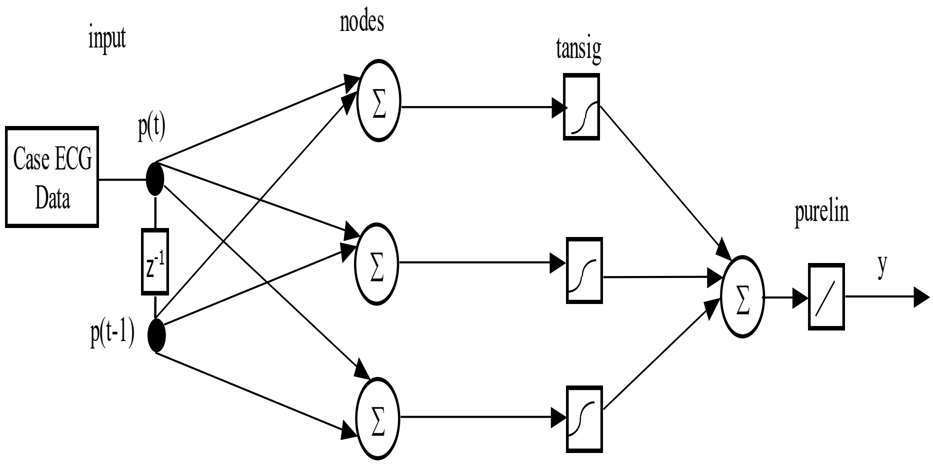

Figure 2. Topology of 3-Node TDNN

In training the networks, part of the ECG data was used as training data set and the remaining data were used as test data set. The odd training and test data sets were used as inputs data

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while the even values were used as targets data for the training and testing respectively. The data length for each of the three hearts condition cases considered in this work is 1000 while 600 of data were used as the training data set; the odd values were used as inputs for the training and the even values were used as target values. Similarly, 400 of the 1000 data length were used as test data having the odd values as inputs and even values as target values. The heart rhythms conditions for sinus bradycardia was considered as Case 1, while myocardial ischemia was considered as Case 2, and ventricular tachycardia as Case 3. The p is the training input vector and t is the target vector of the network with data length of 300 respectively.

During the simulation network output error was propagated to the input of the network and minimised by the Levenberg-Marquart algorithm. The mean squared error (mse) was used as the performance function for the training of the time delay neural network defined by the 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

The ECG signals of Cases 1, 2 and 3 shown in Figures 3, 4, and 5. The network performance improved as the training progresses, and the progress of the mean squared error as performance index was plotted as shown in Figures 6, 7, 8 for Cases 1, 2, and 3 respectively. It was however, observed that acceptable performance was achieved during the training at epochs indicated on the training plots.

The predicted signal was compared with that actual ECG signal and plotted as shown for each case in Figure 9, 10, and 11 and the predicted signal is observed to have closely fit the actual signal.

The network nodes (neurons) were varied at a given time delay and the performance index was observed and presented in Table 1 for all the cases considered. The performance index shows that TDNN modelled the heart rhythm cases better at node 3 and at [0 1] delay.

Kwembe *et al*, (2016) considered Feedforward neural networks as good models of ECG cases used in this study, the results are compared with that of the time delay networks at 3 nodes at [0 1] delay and presented in Table 2.

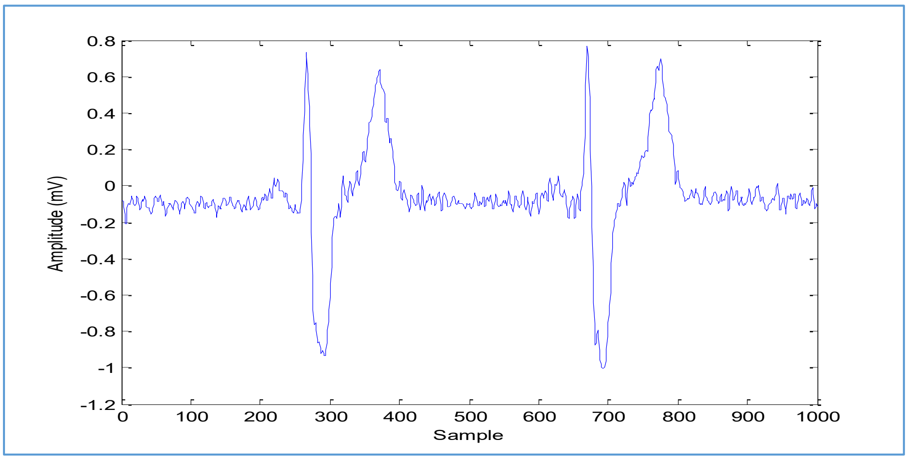

Figure 3. Case 1 ECG Signal

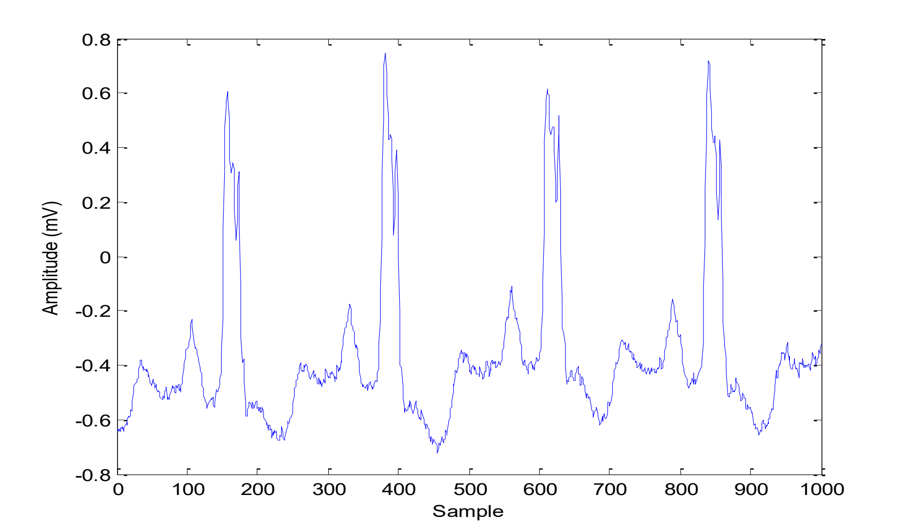

Figure 4. Case 2 ECG Signal

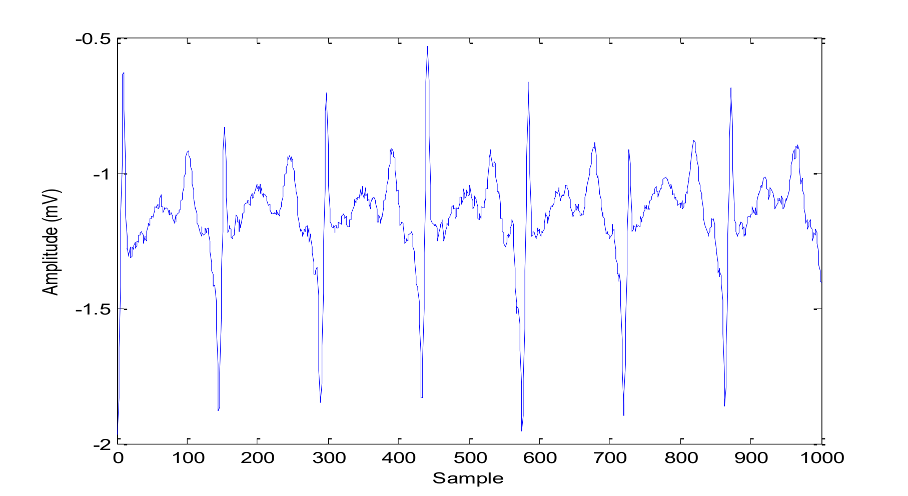

Figure 5. Case 3 ECG Signal

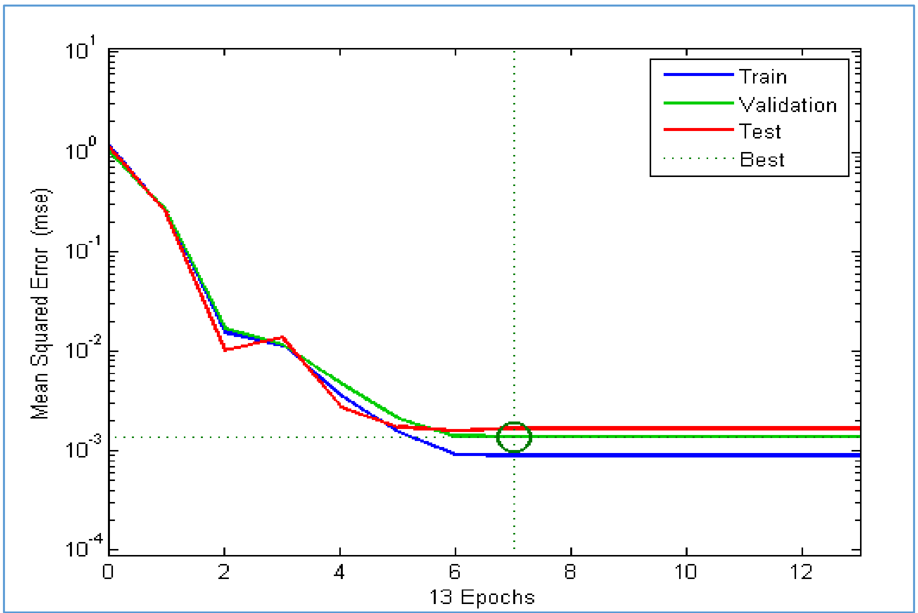

Figure 6. TDNN Training Performance for Case 1

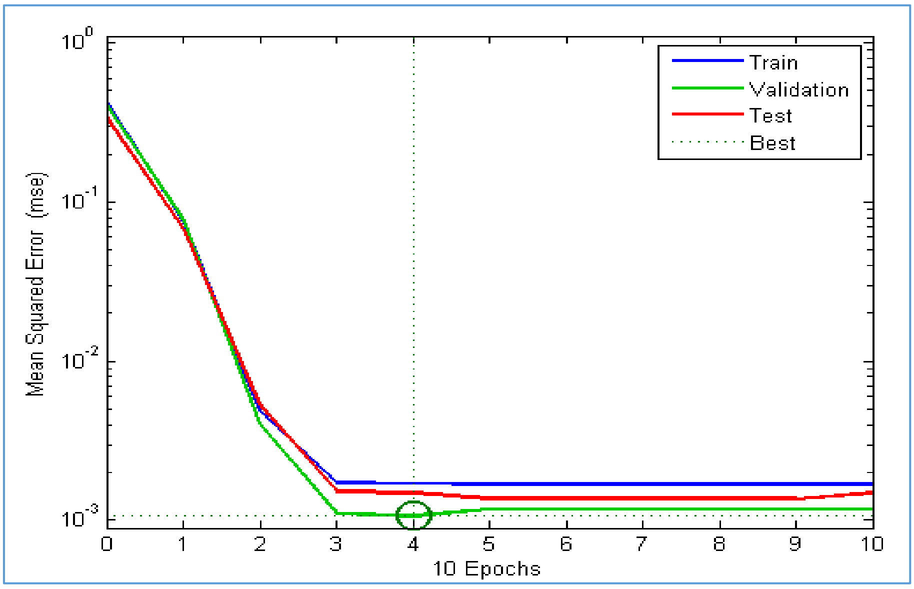

Figure 7. TDNN Training Performance of Case 2

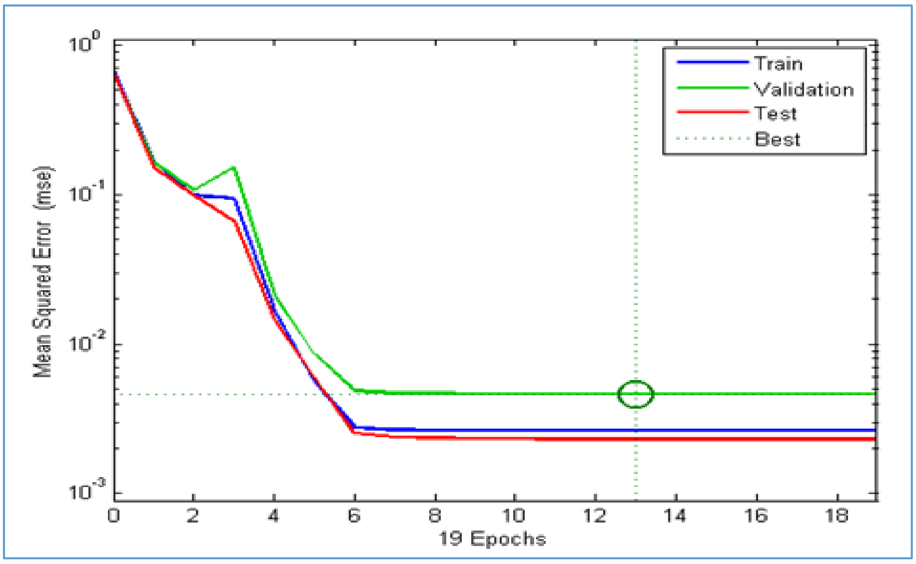

Figure 8. TDNN Training Performance of Case 3

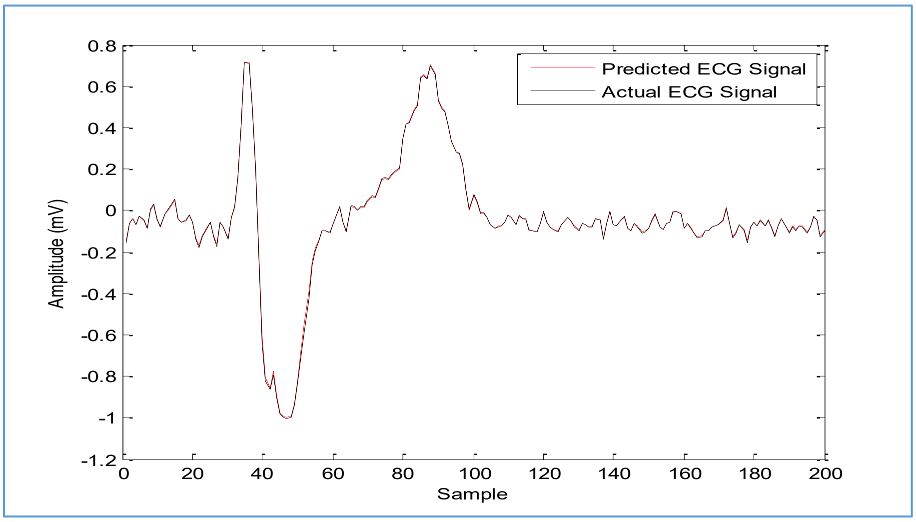

Figure 9. 3-Node TDNN Prediction of Case 1 with the Actual ECG Signal

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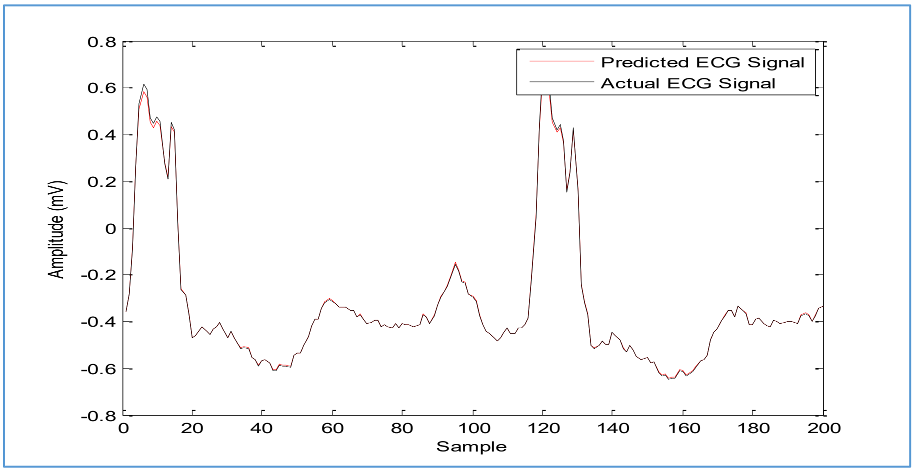

Figure 10. 3-Node TDNN Prediction of Case 2 Signal with the Actual ECG Signal

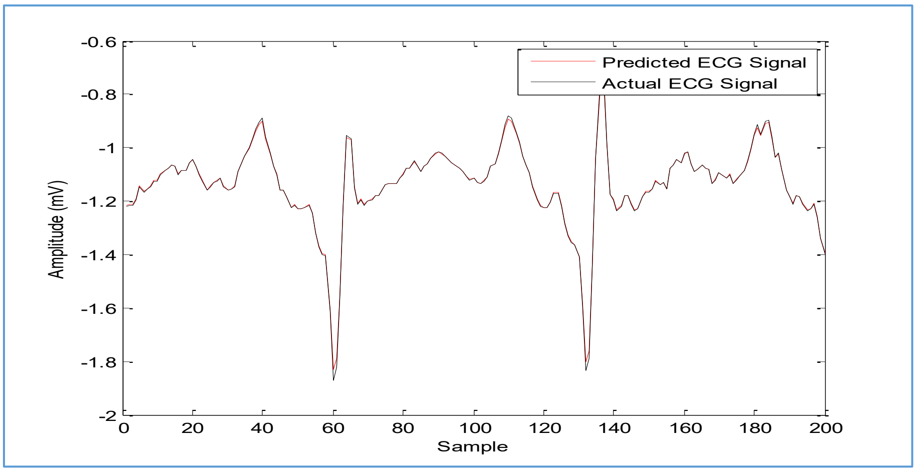

Figure 11. 3-Node TDNN Prediction of Case 3 Signal with the Actual ECG Signal

Table 1. TDNN Prediction Performance

Time Delay Input Vector	*Nodes*	*Case 1 MSE*	*Case 2 MSE*	*Case 3 MSE*
	3	0.0016	0.0021	0.0016
	4	0.0017	0.0021	0.0016
[0 1]	5	0.0017	0.0024	0.0016
	8	0.0017	0.0023	0.0016
	10	0.0021	0.0027	0.0016
	3	0.0016	0.0021	0.0016
	4	0.0017	0.0021	0.0016
[0 2]	5	0.0017	0.0023	0.0016
	8	0.0017	0.0027	0.0016
	10	0.0017	0.0027	0.0016
	3	0.0016	0.0021	0.0016
	4	0.0017	0.0022	0.0016
[0 3]	5	0.0017	0.0021	0.0016
	8	0.0017	0.0024	0.0016
	10	0.0022	0.0023	0.0016

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Table 2. FFNN and TDNN Prediction Performance Compared

	Case 1		*Case 2*		*Case 3*	
Node Elements	*FFNN MSE*	*TDNN MSE*	*FFNN MSE*	*TDNN MSE*	*FFNN MSE*	*TDNN MSE*
3	0.0017	0.0016	0.0021	0.0021	0.0016	0.0016
4	0.0022	0.0017	0.0022	0.0021	0.0021	0.0016
5	0.002	0.0017	0.0021	0.0024	0.0017	0.0016
8	0.0022	0.0017	0.0022	0.0023	0.0023	0.0016
10	0.0021	0.0021	0.0034	0.0027	0.0026	0.0016

The followings are observed from the results:
i) Time delay neural networks successfully predicted the ECG signals; sinus bradycardia, myocardial ischemia and ventricular tachycardia.

ii) Time delay networks predicted the ECG signal with higher accuracy when they had three elements in their hidden layers.

iii) Feedforward neural networks had larger mean squared error when elements in its hidden layer increases beyond three (Kwembe *et al.*, 2016) while TDNN had relative stable prediction error even though the elements in the hidden layer were increased.

iv) Time delay neural network has demonstrated to be more stable in its prediction despite changes in its internal structure and hence it's more reliable for the modelling of ECG signals compare to the feedforward neural network.

Kwembe *et al.,* (2019) demonstrated that feedforward neural networks successfully modelled ECG, however, TDNN performance is found to be more stable than that of FFNN.

Conclusion

The research study dwelt on the application of backpropagation algorithm time delay neural networks to predict the ECG of heart rhythm disorders. The time delay neural network was trained with backpropagation algorithm to minimise the training error. The network performance with three elements in the hidden layer and single time delay in its input layer proved successful. Comparatively, time delay neural network performance in predicting heart conditions is more desirable than that of the feedforward neural network.

The neural networks modelling of the ECG time series may be improved upon by extending its application to real time. In this case, ECG could be monitored on individuals and interfaced with the computer for the training and prediction.

Conflicts of interest

The authors declare no conflicts of interest.

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