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Coronary Artery Diagnosis Aided by Neural Network

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Coronary artery disease is due to atheromatous narrowing and subsequent occlusion of the coronary vessel. Application of optimised feed forward multi-layer back propagation neural network (MLBP) for detection of narrowing in coronary artery vessels is presented in this paper. The research was performed using 580 data records from traditional ECG exercise test confirmed by coronary arteriography results. Each record of training database included description of the state of a patient providing input data for the neural network. Level and slope of ST segment of a 12 lead ECG signal recorded at rest and after effort (48 floating point values) was the main component of input data for neural network was. Coronary arteriography results (verified the existence or absence of more than 50% stenosis of the particular coronary vessels) were used as a correct neural network training output pattern. More than 96% of cases were correctly recognised by especially optimised and a thoroughly verified neural network. Leave one out method was used for neural network verification so 580 data records could be used for training as well as for verification of neural network.

Key words: coronary artery disease, ECG exercise test, MLBP, computer aided diagnosis, artificial neural networks.

Introduction

Coronary artery disease causes severe disability and more death than any other disease including cancer. Coronary artery disease is due to atheromatous narrowing and subsequent occlusion of the coronary vessel. It manifests as angina, silent ischaemia, unstable angina, myocardial infraction, arrhythmias, heart failure and sudden death.

An abnormal electrocardiogram increases the suspicion of significant coronary disease, but a normal result does not exclude it. Therefore the exercise electrocardiography is the most widely used non-invasive test in evaluating patients with suspected angina. It is generally safe method and provides diagnostic as well as prognostic information. The average sensitivity and specificity is 68% and respectively 77% [5]. The test is interrupted in terms of achieved workload, symptoms and elecrocardiographic response. A 1 mm depression in the horizontal ST segment is usual cut-off point for significant ischaemia. Poor exercise capacity, an abnormal blood pressure response and profound ischaemic electrocardiographic changes are associated with a poor prognosis [1].

In this paper application of feed forward Multi-Layer neural network (NN) trained with Back Propagation algorithm (MLBP) applied to interpretation of results of traditional ECG exercise test is presented. The database used for training and verification of neural network contains 580 data records from exercise test (training input data) and results of coronarography as a pattern of correct answer of neural network (training output data).

Application of "leave one out" erification method is a very important aspect of this experiment. This method gives the best generalisation estimate but due to very high computation demand is applied for small datasets only.

Materials and method

Neural network

Neural network methods attempt to define decision regions in feature space, according to their interconnection of weights within the network. The weights are determined in the iterative training phase, during which samples are presented to the NN input. After passing through the network, resulting signal is compared with the desired output to obtain an error expression, which is then back-propagated and used as a factor to correct weights. Error is iteratively minimised until the network converges on the solution.

In this experiment, feed forward perceptron type neural network was implemented. Artificial neural networks consist of simple processing units, called neurons, and weighted connections between them. In a feed forward multilayer perceptron architecture (Figure 1) the neurons are arranged in layers and a neuron from one layer is

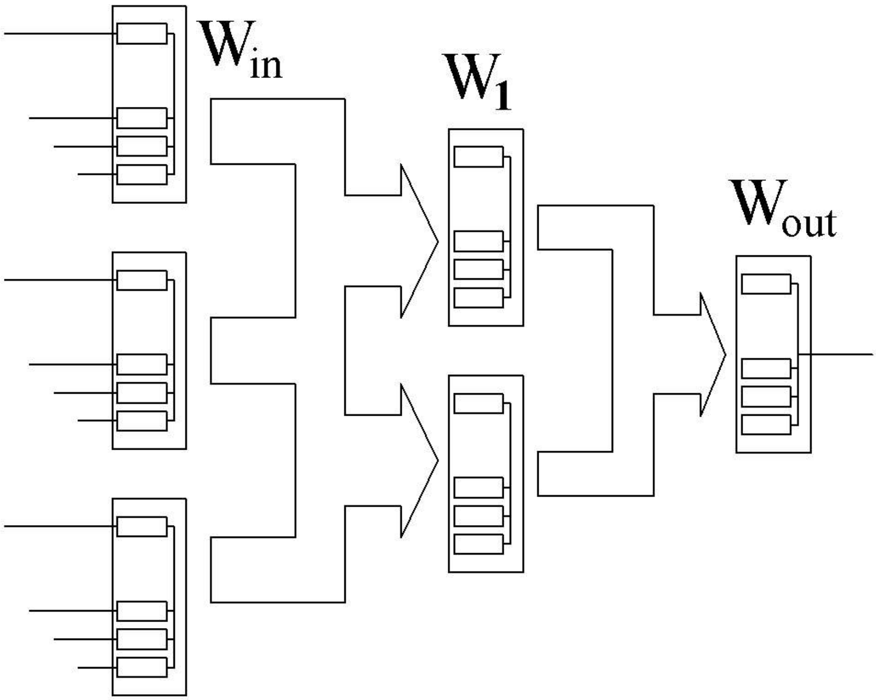

Figure 1. Schematic view of the weights layers of the neural network.

fully connected only to each neuron of the next layer. The first and last layer are the input respectively output layer. The layers between them are called hidden. Values are given to the neurons in the input layer and the results are taken from the output layer. The outputs of the input neurons are propagated through the hidden layer of the net. Figure 2 shows the schematics of algorithm each neuron performs.

Neural network trained with back propagation algorithm with momentum term and adaptive learning rate was especially optimised. Neural network has one hidden layer, 60 input units, and four decision neurons in the output layer to indicate the state of particular coronary vessel.

The optimum configuration of feedforward multilayer perceptron network with its input, hidden and output layers are very difficult to find. Too many hidden neurons cause disability of neural network to extract the function rule and take more time for learning. With a lack in hidden neurons it is not possible to reach any error limit. Input

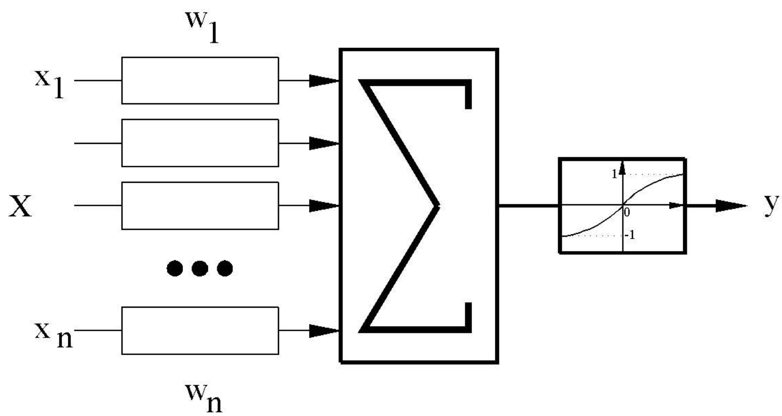

Figure 2. Schematic view of the architecture of the single neuron.

and output layers are determined by the problem and the hidden layer neuron count and determined by the function that is to be approximated. Finally neural network with 5 neurones in the hidden layer (60-5-4 architecture) was applied.

The basic back propagation algorithm was used with added momentum term which allows the network to ignore small changes in the error surface. Beside that, the adaptive learning rate was used which attempts to keep the learning step as large as possible while keeping learning process to converge to solution.

Medical database

The research was performed using 580 data records from traditional ECG exercise test confirmed by coronary arteriography results. Each record of training database contained description of the state of a patient, provided input data for the neural network. Level and slope of ST segment of a 12 lead ECG signal recorded at rest and after effort (48 floating point values) was the main component of input data for neural network.

Coronary arteriography results of verified existence or absence of more than 50% stenosis of the particular coronary vessels were used as a correct neural network training output pattern. Due to non-specific results of ECG exercise test result of female patient, only male patient data were included in training database.

Detailed description of the applied medical database is described by Lewenstein in Ref. 4, where the generalisation possibility of different NN architectures was evaluated.

Neural network with MLBP architecture was the first one investigated. This network obtained correctness of simple diagnosis equal 88% and 75% correctness of patient state diagnosis.

Results and discussion

One of the most important aspects of NN application is how well the NN generalises to unseen data. The best generalisation possibility has that one neural network that offers the smallest probability of misclassification, which can be estimated by the “leave one out” (LOO) method. This method is based on classification of each input record from the database by neural network trained with the whole database reduced by classified record. Thus the number of NN training sessions equals to the numerical force of the reference set.

Generalisation error is better for smaller nets. They need more epochs to learn the rule of coronary artery disease, but because of this they can generalise their behaviour better. Beside that, with neural network with lower neurone count in the network, it was very difficult to obtain trained network. Training algorithm will not converge to result within desired number of training epochs.

In Table 1, summary results of our experiment are shown. Three hundred neural network training experiments were performed with fixed, optimum neural network architecture (60-5-4) and fixed training parameters. While majority of training experiments failed to finish training process, for clinical application only one neural network is needed, that one which was marked by the best generalisation possibility. In

Table 1. Average generalisation possibilities of applied neural network estimated with live one out method.

Diagnosis type	SD	PST	SENS	SP	LCA	LAD	LCX	RCA
Generalisation possibility [%]	99.17	96.58	100.0	75.83	99.17	99.51	98.65	99.20
Standard deviation	1.30	1.83	0.00	37.74	1.30	0.33	1.14	0.84

Table 1, generalisation possibility as well as standard deviation computed for five best performing neural networks is shown.

As a main indicator of neural network quality, the PST (Patient STate) parameter was used. This parameter is a generalisation possibility of the one neural network that classifies four coronary archeries as narrowed or healthy.

Tested with database of 580 medical cases, the 96% of probability of proper indication was obtained. This result proved the thesis that in ECG exercise test data there is information about the narrowing in the particular coronary artery vessels. Cardiologists said that there is no enough information in results of ECG exercise test for sough a diagnosis, and they do not make it.

All of the other indicators shown in Table 1 were computed for reference only.

Those parameters are sensibility (SENS), specificity (SP) and simple diagnosis (SD). It is known from medical literature that sensitivity of the exercise test is from 44 to 88%, average 68% and specificity is from 52% to 89%, average 77% [5, 2]. The result of this research of 100% sensibility indicates increase of 32%. The lower specificity obtained in this experiment (76%) is due to insufficient count of sane patient data in training base.

SD parameter is just a simple classification of a patient as sick or healthy. Patient is classified as a sick while at last one coronary vessel is narrowed. Probability of correct diagnosis of 99% is a very good result. The last four entries in the table represent possibility of four main coronary arteries (Left coronary artery (LCA), Left anterior descending artery (LAD), Left circumflex artery (LCX) and Right coronary artery (RCA)) to be classified as a narrowed or healthy independent each of the other.

Conclusion

Our experiment confirmed that it is possible to localize narrowing in the particular coronary artery of four main coronary vessels with aid of MLBP neural network applied for traditional ECG exercise test interpretation. The obtained result of 96% of probability of the correct answer of MLBP neural network introduces 21% improvement to the result obtained by Lewenstein [4] for the same neural network architecture.

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