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ARRHYTHMIA CLASSIFICATION USING NEURAL NETWROK

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Abstract:

This paper presents an effective application of artificial neural network for diagnosis of cardiac arrhythmia. Comparison of the result generated by Backpropagation and Conjugate gradient algorithm. The classifier was developed and tested with the MIT-BIH Arrhythmia Database. Automatic analysis is performed by using artificial neural network. Following three consecutive steps are required for automatic detection: 1) R-R interval detection 2) Heart Rate Calculation and 3) Classification.

***Keywords**: ECG, Neural Network, Back propagation algorithm, Training, Learning parameter, Testing,*

I. INTRODUCTION

The diseases that affect the cardiovascular system are the main cause of deaths in developed countries. Most of these deaths are due to sudden cardiac arrest and severe cardiac arrhythmia. Therefore, the automatic detection of cardiac arrhythmias from the bedside or ambulatories ECG becomes an important tool for risk assessment.

Computer based diagnostic system hold promising mean to meet the challenges of the clinical situation. The application of Artificial finds its use to supplement the decision making of the clinician. Artificial neural network captures the basic knowledge that allows the clinician to act as an expert while dealing with such complicated problem [1].

Hyper tension and low heart rate is a common clinical diseases and major risk to the human health. One emerging type of anti-aging treatment has recently gained popularity, but has shown amazing results for years.

II. MATERIALS AND METHODOLOGY

The classifier is developed using artificial neural network for analysis of cardiac arrhythmia. From the standard ECG database MIT-BIH data is selected for analysis. All samples of RR intervals are collected from the data base. All RR intervals are converted in terms of corresponding heart rate. Out of total RR intervals and heart rate the minimum and maximum samples of RR intervals and heart rate are extracted and extracted heart rate is given as input to the train neural network for further analysis. Neural network perform the analysis and classify the input data either as normal heart when heart rate is in between 60 to 100 BPM or high heart

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rate if heart rate is more than 100BPM (Tachycardia) , slow heart rate if heart rate less than 60 BPM (Bradycardia).

The basic backpropagation algorithm adjusts the weights in the steepest descent direction (negative of the gradient), the direction in which the performance function is decreasing most rapidly. It turns out that, although the function decreases most rapidly along the negative of the gradient, this does not necessarily produce the fastest convergence. In the conjugate gradient algorithms a search is performed along conjugate directions, which produces generally faster convergence than steepest descent directions.

In most of the training algorithms, a learning rate is used to determine the length of the weight update (step size). In most of the conjugate gradient algorithms, the step size is adjusted in each iteration.

Fletcher-Reeves Update (traincgf)

All the conjugate gradient algorithms start out by searching in the steepest descent direction (negative of the gradient) on the first iteration.

$$\mathbf{p}_0 = -\mathbf{g}_0$$

A line search is then performed to determine the optimal distance to move along the current search direction:

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \alpha_k \mathbf{p}_k$$

Then the next search direction is determined so that it is conjugate to previous search directions. The general procedure for determining the new search direction is to combine the new steepest descent direction with the previous search direction:

$$\mathbf{p}_k = -\mathbf{g}_k + \beta_k \mathbf{p}_{k-1}$$

The various versions of the conjugate gradient algorithm are distinguished by the manner in which the constant β_k is computed. For the Fletcher-Reeves update the procedure is

$$\beta_k = \frac{\mathbf{g}_k^T \mathbf{g}_k}{\mathbf{g}_{k-1}^T \mathbf{g}_{k-1}}$$

This is the ratio of the norm squared of the current gradient to the norm squared of the previous gradient.

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III. RESULT AND DISCUSSION

Figure(1) show 10 min sample of ECG wave from standered ECG MIT-BIH data base. Analysis is perfored on the basis of RR intervals availeble from standered database which are converted into corresponding heart rate and given as input to train neural network

Figure (1) ECG wave form

Extracted RR intervals are converted into corresponding heart rate and applied as input 'P' to the train neural network for analysis

Extracted Minimum Heart Rate 39 Bpm

Extracted Maximum Heart Rate 177 Bpm

Extracted Maximum Heart Rates 40 values

Columns 1 through 27

177 168 167 165 164 162 159 159 159 158 158 158 158 157 157 157 157 157 157 156 156 156 156 156 155 155 154

Columns 28 through 40

154 154 154 154 154 153 153 153 153 153 152 152 152

Extracted Minimum Heart Rates 40 values

Columns 1 through 27

39 40 41 42 43 43 43 44 44 44 44 44 44 45 45 45 45 45 45 45 45 45 46 46 46 46 46

Columns 28 through 40

46 46 46 46 46 46 46 46 46 46 46 46 47

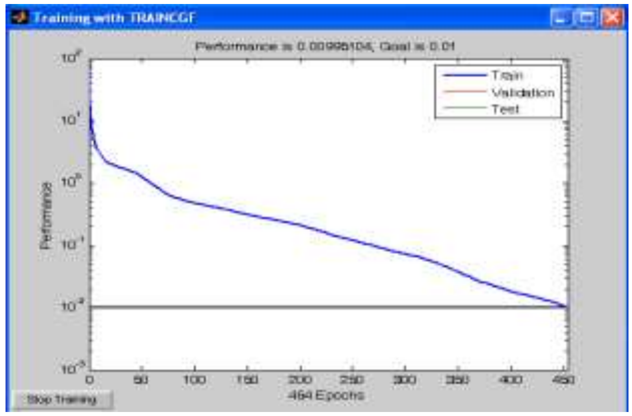

Figure (2) Error Graph for Testing of Neural Network

TRAINGD, Performance goal met.

Figure (2) shows testing error graph of neural network. Figure (1) shows 10 min sample of ECG wave form, for which complete RR intervals are from Columns 1 to columns 2260 are converted into corresponding heart rate hence heart rate columns are also from 1 to 2260. Out of total 2260 only 40 samples of high heart rate and 40 samples of low heart rate are extracted. These extracted 40 samples of high heart rate and low heart rate are given to the input P of the neural network for testing. After performing the analysis of given input sample network generate output 'a= 10.0412. Network required 454epochs out of 2000, it reduces the error up to set error 0.299998/0.3 and for that it required 2.50 sec time. As most of heart rates from given input are above 100 BPM and below 60 BPM i.e High and Slow heart rate, network perform the analysis and observer symptoms of tachycardia and bradycardia.

IV.CONCLUSION

A fundamental architecture of ANN based arrhythmia diagnosing consists of signal feature extraction, automatic ECG signal detecting, and criteria modelling for arrhythmia diagnosing.Feed forward multilayer neural networks trained with Back-propagation algorithm and conjugate gradient algorithm, have been reported to exhibit improved clinical diagnosis. The main advantage of this approach is that it is simple algorithm, faster convergence and effective result. The conjugate gradient algorithms are much faster than variable learning rate backpropagation algorithm.

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