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CLASSIFICATION OF CARDIAC ARRHYTHMIAS WITH ARTIFICIAL NEURAL NETWORKS ACCORDING TO GENDER DIFFERENCES

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Abstract

Cardiac arrhythmias are common heart diseases. Electrocardiography (ECG) is an important measure for diagnosing arrhythmias. Researchers use the ECG signals in order to train artificial neural networks (ANN). In previous studies the ECG signals of males and females were analysed together. We know that there are some differences between male and female ECG signals. This paper suggests that classifying the arrhythmias according to gender differences gives more accurate results. In this study we classify the subjects as normal and right bundle branch block (RBBB) using cascade forward back algorithm in MATLAB. The accuracy of network simulations are as follow: 81.25% only male, 80% only female, 40% male and female together.

Keywords: Arrhythmia, Cascade forward back propagation, Gender differences, MATLAB.

1. Introduction

Cardiac diseases are worldwide problem. Arrhythmias are common cardiac diseases. There are several arrhythmias, such as coronary artery disease, tachycardy, bradycardy, left bundle branch block and right bundle branch block. ECG is one of the most commonly used tests to diagnose the arrhythmia. One cycle of ECG signal consists of the P-QRS-T waves. Abnormalities of these waves help the cardiologist to diagnose the arrhythmias. A lot of studies have been carried to classify arrhythmia using artificial neural networks. Researchers use the ECG signals in order to train networks. They use male and female ECG

Abbreviations

a	Amplitude
ANN	Artificial Neural Networks
ECG	Electrocardiography
MSE	Mean Squared Error
nntool	Neural Network Tool
RBBB	Right Bundle Branch Block
trainbfg	Quasi-Newton Algorithm

data together for training. However, there are some differences between male and female ECG signals. Women have a higher heart rate than men, along with a longer corrected QT interval and a shorter sinus nodal recovery time [1]. The faster resting heart rate in women appears to be primarily related to differences in physical conditioning [2].

The objective of this study is to understand the role of gender factor classifying the arrhythmias using ANN. MATLAB neural network tool is used in this study. It is preferred cascade forward back algorithm for classification of ECG signals. We have focused on normal and RBBB subjects in this paper. Three simulations were carried out that using only male data, only female data, male and female data together.

2. Material and Methods

The database provided by UCI Machine Learning Repository [3]. Data consists 245 normal subjects and 207 arrhythmia subjects ECG records. Each record contains clinical measurements, from ECG signals, such as QRS duration, RR, P-R and Q-T intervals and some other information such as sex, age, weight. Neural network was created in MATLAB. MATLAB has strong tools for ECG processing [4] and ANN [5, 6].

2.1. Data

Data of 28 normal male subjects (mean age; 48.5), 28 normal female subjects (mean age; 43.6), 28 RBBB male subjects (mean age; 42.8) and 22 RBBB female subjects (mean age; 34.4) has been selected from whole data set. The reason of selecting RBBB subjects is the large number of patients in the Guvenir *et al.* study. ECG signals have been collected 12 lead derivations (DI, DII, DIII, aVR, aVL, aVF, V1, V2, V3, V4, V5 and V6). Amplitude of ECG signal has been measured in millivolts.

2.2. Preprocessing of data for neural network

Raw data including only 12 derivations has been extracted from whole data which includes extra information such as sex, age, height, average QRS duration. The data matrices after the extracting are as follow: normal male; 120x28, normal female; 120x28, RBBB male; 120x28, RBBB female; 120x22. This process was performed in MATLAB.

2.3. Definition and simulation of the neural network

The first training matrix for analysing only male data has been composed using the 20 normal male subjects and 20 RBBB male subjects. The remaining 16 subjects data (8 normal and 8 RBBB subjects) have been used for the classification. The second training matrix for only female consists of 20 normal female subjects and 15 RBBB female subjects. The classification has been done with the remaining 15 subjects data. The third training matrix for both male and female consists of 46 normal (male and female together) subjects and 40 RBBB (male and female together). The remaining 20 subjects data have been used for the classification. The raw data has been normalized using Yule-Walker estimation method [7, 8]. This normalization has been performed on MATLAB with "aryule" function. The normalized train matrices are shown in Table 1.

Table 1. The normalized train matrices after Yule-Walker estimation.

Training Mat.	Row-Column	Min. Value	Max. Value
Only Male	9x40	-0.5769	1
Only Female	9x35	-0.7111	1
Male and Female	9x86	-0.7111	1

Defining the neural network has been carried out by MATLAB neural network tool (nntool). The tools for network of the MATLAB provides structure development adjustment according to requirements as well as tools to analyse the results, makes it a good option to solve this complex problem in a simple way. The cascade forward neural network with back propagation algorithm has been used in this study. Back propagation algorithm has simple structure, multi-adjustable parameters, much training algorithm and good operational performance [5, 9].

Quasi-Newton algorithm (trainbfg) has been chosen for training function. The network and training parameters are shown in Table 2 for three analyses. The following images (Figs. 1 and 2) are the analysis figures for male data where each of them interprets different properties about the network.

Nine epochs mean network has learnt in low repetitions. The progress time (2 seconds) means network achieved goal easily and very fast. When analyzing female data, training has stopped six epochs number and the progress time is one second. The training progress has stopped six epochs number analyzing the male and female data together. The progress time is one second.

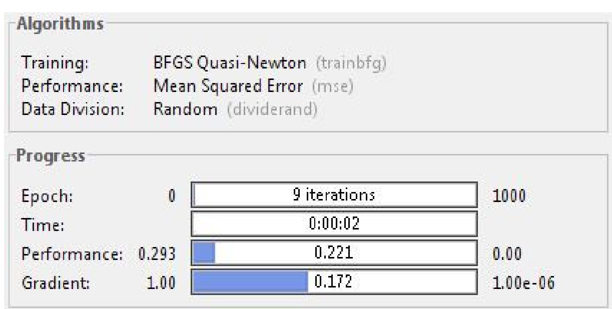


Fig. 1. Training process of the male data.

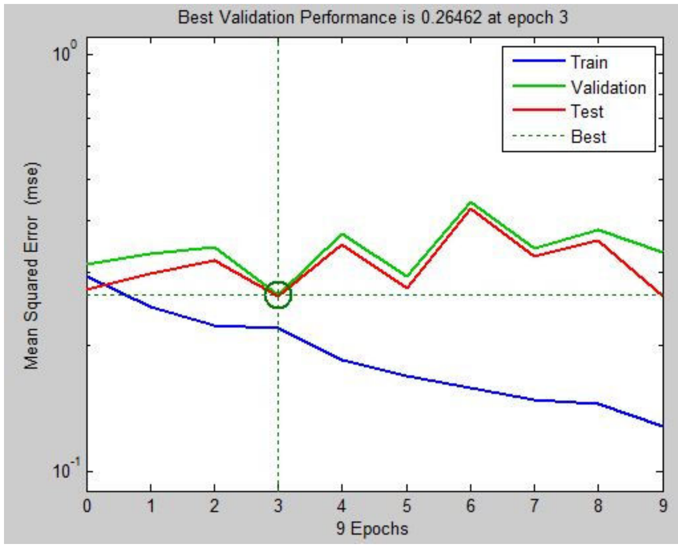


Fig. 2. Mean squared error (MSE) plot of the male data.

Table 2. Parameters of network and training.

Network type	Cascade-forward backprop
Training function	TRAINBFG
Adaptation learning function	LEARNGDM
Performance function	MSE
Number of layers	2
Number of neurons	30
Transfer function	TANSIG
show	1
max_fail	6
min_grad	1e-006

3. Results and Discussion

Three training processes have been carried out using three different datasets (male, female, male and female) with same train and network parameters. After the simulation of first network, 13 male subjects have been classified correctly from among 16 subjects. The simulation of the second network estimates 12 female subjects correctly from among 15 subjects. Only eight female and male subjects have been classified correctly from among 20 subjects. Accuracy of three simulations is shown in Fig. 3.

It is clear that using male and female subjects data do not work for clear training. Nine subjects have RBBB arrhythmia but they have been estimated as normal after the third simulation. Thus third simulation has only 10% accuracy in terms of classifying the subject who has arrhythmia (Fig. 4).

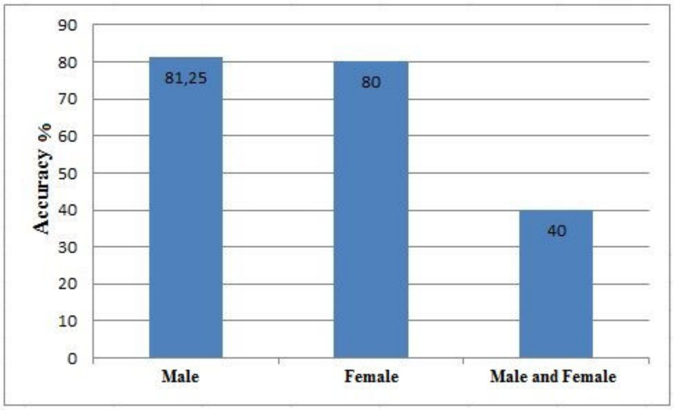
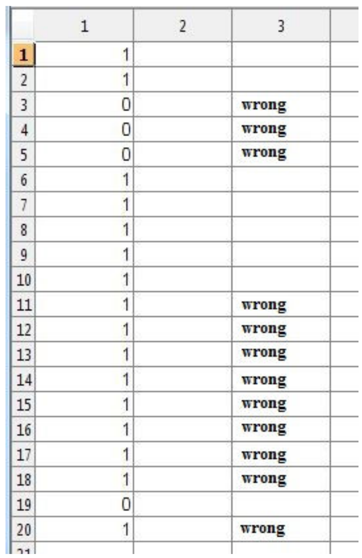


Fig. 3. Accuracy of three different simulations.



	1	2	3
1	1		
2	1		
3	0		wrong
4	0		wrong
5	0		wrong
6	1		
7	1		
8	1		
9	1		
10	1		
11	1		wrong
12	1		wrong
13	1		wrong
14	1		wrong
15	1		wrong
16	1		wrong
17	1		wrong
18	1		wrong
19	0		
20	1		wrong

Fig. 4. Results of the third simulation. Column 1 shows classification of the subjects. 1; Normal, 0; RBBB, Column 3 shows classification status.

4. Conclusions

This paper suggests a new approach for classifying the arrhythmias. There is a significant difference between first two simulations and third simulation. Classifying with neural networks according to gender differences presents more accurate results. We show that MATLAB has a very beneficial tool for ANN. On the other hand the cascade forward back propagation and Quasi-Newton training algorithm provides correct results when using male and female subjects separately. Training process takes a few seconds thanks to Yule-Walker estimation. The limitation of this study could be classifying two categories which are normal and RBBB.

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