

The classification of heart sound by using ANNS

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Abstract

Heart auscultation (the interpretation by a physician of heart sounds) is a fundamental component in cardiac diagnosis. It is, however, a difficult skill to acquire. In this work, we present a study for a system intended to aid in heart sound classification based on a FFT of the sounds and a neural network. This work contain three step. The information acquire is the first step which included recording the heart and can record by small recode instrument. The sound from the patient by the sonoketle phone , where the sound heart can be heard and can record by small recoded instrument _ the second step is analysis step ,in this step we analysis the sound wave file to get (11) parameter which represent the input to to the third step (classification step) .

In classification step we can recognize the class which the sound wave file belong to it. heart sounds of 21 subjects divided in to groups normal (6) and heart valve diseases (14)analysis and take times and frequencies as 11 parameters that interred to input of network . The accurate result was obtained.

Keywords :heart sound, cardiae diagnosis, nevrnal network, classification

الخلاصة

اصوات القلب هي الجزء اساسي في تشخيص امراض القلب. في هذا العمل تم تقديم دراسة عن طريق نظام اعد للمساعدة في تصنيف اصوات القلب اعتماداً على محول FF+ والشبكات العصبية وهذا النظام يتكون من ثلاث مراحل المرحلة الاولى تتضمن تسجيل اصوات القلب من مرضى القلب عن طريق جهاز sonoketle . المرحلة الثانية هي مرحلة تحليل الاصوات وقد تم تجميع احد عشر متغير او معامل وهذه المعاملات تمثل المدخلات للمرحلة الثالثة. المرحلة الثالثة هي مرحلة التصنيف حيث يتم في هذه المرحلة تحديد الصنف التي يعود اليها الصوت المسجل. اصوات القلب تم تقسيمها الى مجاميع، المجاميع العادية (6) ومجموعة امراض الصمامات (14) حيث تم تجميع الوقت والتردد لـ (11) متغير والتي تكون كمدخلات للشبكات العصبية.

الكلمات المفتاحية: الشبكات العصبية، امراض القلب، اصوات القلب.

INTRODUCTION

Heart auscultation (the interpretation of sounds produced by the heart) is a fundamental tools in the diagnosis of heart diseaseu)(Curry *et al.*, 1990). It is the most commonly used technique for screening and diagnosis in primary health care(Cameron *et al.*, 1987). In some circumstances, particularly in remote areas or developing countries, auscultation may be the only method available. However, detecting relevant symptoms and forming a diagnosis based on sounds heard through a stethoscope is a skill that can take years to acquire and refine (Curry *et al.*, 1990). Because this skill is difficult to teach in a structured way, the majority of internal medicine and cardiology programs offer no such instruction(Braun, 1998). It would be very advantageous if the benefits of auscultation could be obtained with a computer programs, using equipment that is low-cost, robust, and easy to use. The complex and highly nonstationary nature of heart sound signals can make them challenging to analyze in an automated way. However, in this technological used have made extremely powerful digital signal processing techniques both widely accessible and practical. Local frequency analysis by using FFT (local scale analysis) approaches are particularly applicable to problems of this type, and take these methods have been applied to study the correlation between

these sounds and one valve diseases by ANNs(Curt ,2001).

Where in this work we combine local signal analysis methods with classification techniques to detect, characterize and interpret sounds corresponding to symptoms important for cardiac diagnosis. It is hoped that the results of this analysis may prove valuable in themselves as a diagnostic aid, and as input to more sophisticated method diagnosis systems.

How do the heart valves function?

As the heart muscle contracts and relaxes, the valves open and shut, letting blood flow into the ventricles and atria at alternate times. The following is a step- by-step illustration of how the valves function normally in the left ventricle (Davidson *et al.*, 1995):

- After the left ventricle completes its contraction phase, the aortic valve closes and the mitral valve opens, to allow blood to flow from the left atrium into the left ventricle.
- As the left atrium contracts, more blood flows into the left ventricle.
- When the left ventricle completes its contraction phase again , the mitral valve closes and the aortic valve opens, so blood flows into the aorta.

What is heart valve disease?

Heart valves can have one of two malfunctions:

1- regurgitation

The valve(s) does not close completely or do not come together Causing the blood to flow backward instead of forward through the valve.

2- stenosis

The valve(s) opening becomes narrowed or does not form properly, inhibiting the ability of the heart to pump blood to the chamber or blood vessel ahead of it, and increased force is required to pump blood through the stiff (stenotic) valve (s) (Harvey ,1995).

Heart valves can have both malfunctions at the same time (regurgitation and stenosis). When heart valves fail to open and close properly, the implications for the heart and the body can be serious, possibly hampering the heart's ability to pump blood sufficiently to maintain the body's normal requirements(Katz ,1977).

In this project we deal with two valve only (in the left side of the heart) aortic and mitral valve where the stenosis case are valuable according to the this study requirement.

The Perceptron Network

The perceptron was presented in 1958 by F .Rosenblatt in a psychological magazine. Originally it was a two-stage networks, in which the weight of the lower stage were constant and those of the upper stage could learn. Rosenblatt create this concept for the classification of visual patterns, which came from the human retina. Today, one mostly associates a single-stage, learning network with the term “perceptron”. The single-stage network has got many restrictions in their application area. Hence it become necessary to examine the features of multi-stage networks.

Multi-layer perceptron are feed-forward nets with one or more layers of nodes between the input and output node. These additional layers contain hidden units or nodes that are not directly connected to both the input and output nodes. Multi-layer perception overcome many of limitations of single-layer perception, but were generally not used in the past because effective training algorithms were not available. This was recently changed with the development of new training algorithm.

To use multi-layered networks efficiently, one needs a method to determine their synaptic efficacious and threshold potentials. A very successfully method, usually called error back-propagation was developed independently around _ It is based on generalization of gradient method.(Fausett,1994)

The back-propagation learning method can be applied to any multi-layer network that uses differentiable activation function and supervised learning(Lippmann, 1987; Mehta, 1995) .

The learning Process

Multi layer perceptron always consist of at least three layers of neurons. As a result, the network will have an input layer, an output layer, and a middle layer(sometimes referred to as a hidden layer. (Zurada,1996)

Neurons communicate analog signals over the synaptic links. In general, all neurons in a layer are fully interconnected to neuron in adjacent layers. Information flows unidirectional from input through hidden and output layers. However, it flows in the reverse direction during training. Associated with each synapse a weight V_{ik} connecting input neuron i to hidden neuron k , and a weight w_k , connecting hidden neuron k to output neuron j .

Each neuron cell receives a net signal, which is the linear weighted sum of all its inputs.

A logistic activation output function $1/(1+e^{-x})$ converts this to a smooth approximation to the classic step neuron of McCulloch and Pitts. The output h_k of hidden neuron k is given by

$$H_k = 1/(1 + e^{-\sum v_{iks} s_i})$$

Similarly, the activation u_j of output neuron j is given by

$$U_j = 1/(1 + e^{-\sum w_{kj} h_k})$$

Since network weights are initially undetermined, a training process is needed to set their value. Backpropagation refers to an iterative training process in which an output error signal is propagated back through the network and is used to modify weight values. The error signal ε

$$\varepsilon = \frac{1}{2} \sum (t_j - u_j)^2$$

where the summation is performed over all output nodes j , and t_i is the desired or target value of output u_j for a given input pattern.

Training is begun by presenting a sample pattern to the sensor inputs of a network primed with random initial weights. For an output neuron, δ_j is defined by $\delta_j = u_j(1 - u_j)(t_j - u_j)$

Weights w_{kj} are changed according to

$$\Delta w_{kj}(n) = \eta \delta_j h_k$$

δ The variable η in the weight-adjustment equation is the learning rate. Its value (commonly between 0.25 and 0.75) is chosen by the neural network user, and usually reflects the rate of learning of the network. Values that are very large can lead to instability in the network, and unsatisfactory learning. Values that are too small can lead to excessively slow learning. Sometimes the learning rate is varied in an attempt to produce more efficient learning of the network; for example, allowing the value of η to begin at a high value and to decrease during the learning session can sometimes produce better learning performance. Usually a momentum term is included to improve the convergence, which determines the effect of previous weight change on present changes in the weight space. The weight change after n th iteration is

$$\Delta w_{kj}(n) = \eta \delta_j h_k + \alpha \Delta w_{kj}(n-1)$$

where α is the momentum term and lies between 0 and 1.

After computing δ_j in the output layer, hidden layer values δ_k^* can be obtained. For a hidden neuron, the rule changes to

$$\delta_k^* = h_k(1 - h_k) \sum \delta_j w_{kj}$$

Where h_k is the activation of hidden neuron k and summation is over the j neurons in the output layer. The weight correction for v_{ik} is similarly,

$$\Delta v_{ik}(n) = \eta \delta_k^* s_i + \alpha \Delta v_{ik}(n+1)$$

The total error in the performance of the network with particular set of weight can be computed by comparing the actual y , and the desired, d , output patterns for every case. The total error, E , is define by

$$\varepsilon_c = \frac{1}{2} \sum (t_j - u_j)^2$$

where j is an index over output units (with in a training pair).

Before starting the training process, all of the weights must he initialized to small random numbers, these ensure that the network is not saturated by large values of the weights, and prevents certain other training pathologies. For example if the weights all start at equal value, and the desired performance requires unequal value, the network will not learn. After training is stopped, the performance requires of the network is tested. (Paterson,1995)

Material and method

The system for heart sound classification which was used in this project consisted of the following component :-

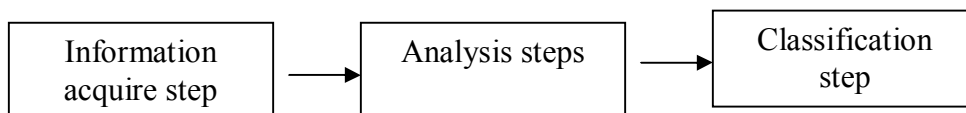


Figure 1. A Simple Heart Sound Classification System

1- information acquire step

This step is started when we have to ask the patient to lie on the supine position ,the sonokette probe are first connected to the patients chest and then a gel is put on the proper location where heart sound is heard and can recorded by small recorded instrument and transition from the analog to digital (sound wave tile) in order to fed to the computer by sound recorder software

The sound wave tiles were divided in to three class according to our study requirement and they were investigated with the echo C.G. The class are:

A-control class

The control class involve from many normal persons in both sexes , they had no history of heart disease.

B- Mitral stenosis class

This class contain many patients had mitral stenosis disease where the mitral valve opening indicates that the tips of leaflets are restricted in their ability to open can be detected with echocardiographic examination and no had any complication heart diseases.

C- Aortic stenosis class

This class contain many patients had aortic stenosis disease where the aortic valve opening indicates that the tips of leaflets are restricted in their ability to open can be detected with echocardiographic examination and had no any complication heart diseases.

2- The analysis step

- sound wave

The two major sounds heard in the normal heart sound like “lub dub”. The “ lub” is the first heart sound , commonly termed S1 , and is caused by turbulence caused by the closure of mitral

and tricuspid valves at the start of systole. The second sound , “dub” or S2 , is caused by the closure of aortic and pulmonic valves, marking the end of the systole. Thus the time period elapsing between the first heart sound and second sound defines systole (ventricular ejection) and the time between the second sound and the following first sound defines diastole (Ventricular filling).

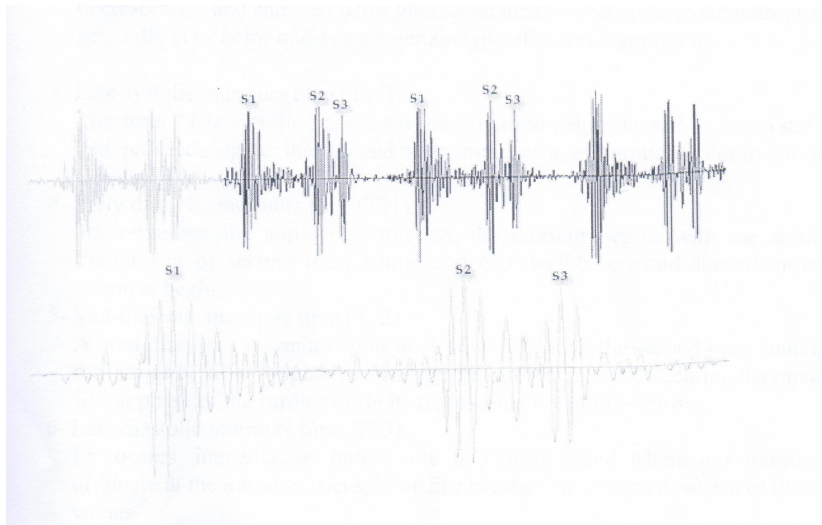


Figure (2) heart sound signal

Parameter

The parameter in this step divided in three type according to the our study requirement which are :-

measured parameters

Which includes all the parameter take directed from the signal (include time component in second) and its

a-systolic heart sound time (T1)

b- diastolic heart sound time (T2)

A systolic heart sound time begins with or after the first heart sound and ends at or before the subsequent second heart sound. Diastolic heart sound time begins with or after the second heart sound and ends before the subsequent first heart heart sound also its can be classification according to their time of on set as

1- Mid-systolic murmurs time (T12)

Midsystolic murmurs occur in several setting such as the aortic valve stenosis , its began after the first heart sound (s1) , rises in crescendo as flow diminishes, ending just before the second heart sound.

2- Early systolic murmurs time (T11)

Murmurs confined to early systole begin with first heart sound , diminish in decrescendo, and end well before the second heart sound midsystolic murmurs, generally at or before mid-systole, certain type of mitral regurgitation.

3- Late systolic murmurs time (T13)

The term “ late systolic “ applies when a murmur begins in mid-to-late systole and proceeds up to the second heart sound such as murmurs occur in mitral valve prolapse.

4- Early diastolic murmurs time (T21)

Its represented by aortic regurgitation, the murmur begins with the aortic component of second heart sound and end Well before mid-diastolic heart sound is begins.

5- Mid-diastolic murmurs time (T22)

A mid-diastolic murmur begins at clear interval after the second heart sound, the majority of it originate across mitral or tricuspid values during the rapid filling phase of the cardiac cycle its represented by mitral stenosis.

6- Late-diastolic murmurs time (T23)

Its occurs immediately before the first heart sound Where this murmur originate at the mitral or tricuspid orifice because od abnormal pattern of these values.

Analysis and calculated parameters

Which includes all the parameters take from the result of FFT and calculate the statistical tested which are:-

1- Medain

Is that value that occurs in the middle of a set of values the values are arranged in increasing magnitude

2- confidence intervals

- pulse confidence intervals
- minus confidence intervals

3-classification step

In this step We are use a single multi layer perceptron network. The output of the analysis step represent the input to this step (11 parameter) . The number of node in the input layer equal to the number of input parameters (11 node) , the number of hidden layer - in this Work We used variable number and find the best result We obtained with 11 node , The output layer represented by three node corresponding to the number of classes. We are using binary code to represent the class , We are refer to the class 1 by 000, class 2 by 001, and class 3 by 011.

Conclusion .

An ANN classifier was constructed for the task of discriminating among normal , systolic and diastolic heart sound .The data set comprised 21 example, recorded from 21 patient ,18 example used as training set and the remaining used as test set. The extracted parameters from sound wave file refer to as (T1,T11,T12,T13, T2,T21,T22,T23,M,C+,C-).

Table (1) represent example of the parameter of normal wave

T1	T11	T12	T13	T2	T21	T22	T23	M	C+	C-
0.26	0	0	0	0.33	0	0	0	0	0	0
0.23	0	0	0	0.32	0	0	0	0	0	0

Table (2) represent example of the parameter of aortic stenosis Wave

T1	T11	T12	T13	T2	T21	T22	T23	M	C+	C-
0	0.05	0.2	0.05	0.38	0	0	0	0.0722	0.2021	-0.1865
0	0.06	0.22	0.06	0.39	0	0	0	0.0065	0.0271	-0.0271

Table (3) represent example of the parameter of mitral stenosis Wave

T1	T11	T12	T13	T2	T21	T22	T23	M	C+	C-
0.45	0	0	0	0	0.163	0.16	0.272	0.0059	0.0818	-0.0506
0.31	0	0	0	0	0.246	0.206	0.17	0.0211	0.1289	-0.0195

We obtained accurate classifier with hidden node equal to 11 ,momentum and learning rate equal to 0.2,0.7,0.3 and 0.5 respectively with total error equal to 0.39. Figure 3 represented the relation between the number of epoch and the decreasing total error .

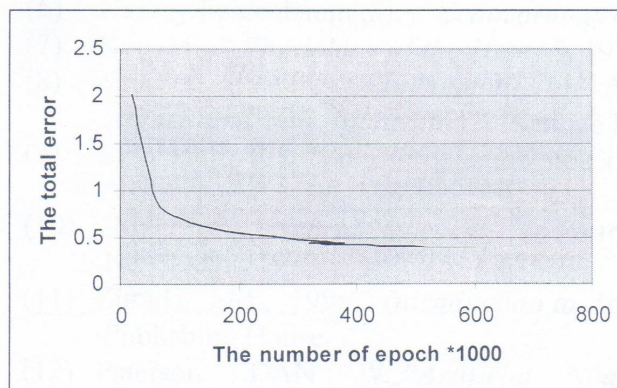


Figure (3)

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