Use the ANNs as a Tool for Diagnosis of Mitral Regurgitation and Aortic Regurgitation

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Abstract

For many centuries ,machines development was one of the mostly important goals for human kind, where the engineers and scientists are trying to develop intelligent machines . Artificial neural systems are present-day examples of such machines that have great potential to further improve the quality of our life.

Stethoscope is a tool of interpretation for a physician heart impless are fundamental component in cardiac diagnosis. In this work, we present a study for a system intended to aid in heart sound classification based on artificial neural network .Where it is contain on three steps. The information acquire is the first step which included recording the heart sound from the patient by the sonoketle phone , where the sound heart can be heard and can record by small record instrument . the second step is analysis step , in this step we analyzed 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 (38) subjects divided in two groups normal (20) and heart valve diseases (18)analysis and take times and frequencies as 11 parameters that interred to input of network .The accurate result was obtained from 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.

الخلاصة

بقي تطوير الالة واحدة من الاهداف التي سعى اليها الانسان على مر العصور, حيث قام المهندسون والعلماء بمحاولة تطوير الالات الذكية فنظم الشبكات العصبية تعتبر مثال لهذة الالات التي رفدت التقدم الحاصل في حياتنا اليومية.

سماعة الطبيب تعتبر وسيلة تمكن الاطباء من سماع صوت القلب كمرحلة اساسية من مراحل تشخيص القلب لذلك ففي هذا البحث صممت طريقة لتصنيف أصوات القلب بواسطة الشبكات العصبية التي تتضمن ثلاث مراحل.

ففي المحلة الاولى يتم تشجيل صوت القلب من المريض مباشرة بواسطة السونوكيت والمرحلة الثانية تحليل الصوت الى احد عشر متغير تعتبر كمدخلات في الشبكة العصبية التي تصنف هذة المتغيرات كمرحلة ثالثة.

الغاية من البحث أيجاد منظومة تستطيع تشخيص اصوات القلب بنسبة خطأ قليلة لذلك فقد اخذت اصوات (38)عينة قسمت الى مجموعتين المجموعة الطبيعية(20) ومجموعة امراض الصمامات القلبية(18) ,حلل كل صوت الى احد عشر متغير للزمن والتردد اعتبرت كمدخلات للشبكة العصبية.

النتيجة النهائية كانت الحصول تصنيف اصوات القلب بصورة دقيقة بـ 11 عقدة خفية بنسبة تعلم تساوي 0.5, 0.2,0.7,0.3 ونسبة خطأ تساوي 0.39 .

Introduction

A vibrating object will produce a sequence of compressions and rarefactions in the air surrounding it. These small fluctuations in air pressure travel away from the source at relatively high speed, gradually dying off as their energy is absorbed by the medium. What we call sound is simply the sensation produced by the ear when stimulated by these vibrations. (Halliday and Walker, 2007).

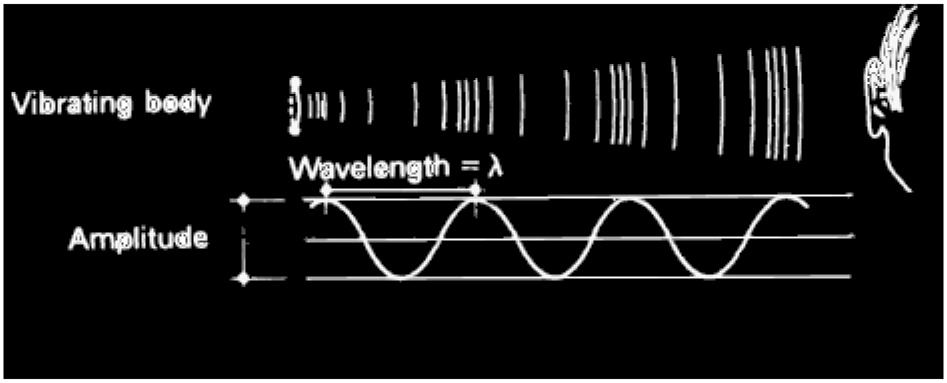

Figure (1) Sound Wave Characteristics

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: 1.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. 2.As the left atrium contracts, more blood flows into the left ventricle. 3.When the left ventricle completes it's contraction phase again, the mitral valve closes and the aortic valve opens, so blood flows into the aorta.

Valvular heart disease

The job of a valve is to make sure that fluid flows only in the right direction. Your heart is a muscle which pumps blood around your lungs and the rest of your body. There are four valves in your heart. These valves guard the entrances and exits of the two pumping chambers in your heart (the right and left ventricles). The valves at the entrances are there to make sure that the blood only goes into the ventricles. The valves at the exits only let blood out. A diseased or damaged valve can affect the flow of blood in two ways.

1. If the valve does not open fully, it will obstruct the flow of blood. This is called 'valve stenosis'.
2. If the valve does not close properly, it will allow blood to leak backwards. This is called 'valve incompetence' or 'regurgitation'.

Both stenosis and incompetence put an extra strain on the heart. If you have stenosis, the valve will obstruct the flow of blood, so your heart will have to pump harder to force the blood past the obstruction. If you have incompetence, a leaking valve will mean that your heart has to do extra work to pump the required volume of blood forwards. This is because your heart will be wasting energy as some of the blood is going backwards too. (Halliday and Walker, 2007).

Stethoscope

Heart auscultation (the interpretation of sounds produced by the heart) is a fundamental tools in the diagnosis of heart disease. It is the most commonly used technique for screening and diagnosis in primary health care. 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.

Because this skill is difficult to teach in a structured way, the majority of internal medicine and cardiology programs offer no such instruction.(Beichner,2006)

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 no stationary 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.(Fausett,1994)

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.(Paterson,1995)

The Perceptron Network

The perceptron was presented in 1958 by F.Rosenblatt in apsychological 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-stag, 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. (Zurada,1997)

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 (1985 by several research groups). It is based on generalization of gradient method.

The back-propagation learning method can be applied to any multi-layer network that uses differentiable activation function and supervised learning. (D.Bouche,1997)

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). [computer program that learn].

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 vik connecting input neuron i to hidden neuron k, and a weight wkj 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
McCullah and Pitts. The output hk of hidden neuron k is given by

$$hk = 1/(1+e^{-\sum i viksi}) \quad \ldots\ldots\ldots\ldots(1)$$

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

$$Uj=1/(1+e^{-\sum kwkjhk}) \quad \ldots\ldots\ldots\ldots(2)$$

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 εϵ

$$\varepsilon = ½ \sum(tj-uj)^2 \quad \ldots\ldots\ldots\ldots(3)$$

where the summation is performed over all output nodes j, and tj is the desired or target value of output uj 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, δj is defined by

$$\delta j= uj(1-uj)(tj-uj) \quad \ldots\ldots\ldots\ldots(4)$$

Weights wkJ are changed according to

$$\Delta wkj\ (n)= \eta\delta jhk \quad \ldots\ldots\ldots\ldots(5)$$

δThe 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 nth iteration is δ

$$\Delta wkj\ (n)= \eta\delta jhk + \alpha\Delta wkj\ (n-1) \quad \ldots\ldots\ldots\ldots(6)$$

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

After computing δj in the output layer, hidden layer values δ*k can be obtained. For a hidden neuron, the rule changes to

$$\delta^*k = hk(1-hk)\sum \delta jwkj \quad \ldots\ldots\ldots\ldots(7)$$

Where hk is the activation of hidden neuron k and summation is over the j neurons in the output layer. The weight correction for vik is similarly,

$$\Delta vik(n)= \eta\delta^*k\ si + \alpha\Delta vik(n+1) \quad \ldots\ldots\ldots\ldots(8)$$

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

$$E=\sum c\ \varepsilon c \quad \ldots\ldots\ldots\ldots(9)$$

where (c) is an index over all of input-output pairs on training set and local error

$$\varepsilon c = ½ \sum(tj-uj)^2 \quad \ldots\ldots\ldots\ldots(10)$$

where, j is an index over output units(with in a training pair).
Before starting the training process, all of the weights must be 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 (Nurr,1988,Dayhoff,1990)

Materiel and method

The system for heart sound classification which was used in this project consisted of the following component .(Al-Ramadhni *et. al.*,2004)

Figure 2. 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 can be heard and can recorded by small recording instrument and transition from the analog to digital (sound wave file) in order to fed the computer by sound recorder software

The sound wave files 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 consist from many normal persons in both sexes , they had no history of heart disease.

B-Mitral regurgitation class

This class contain many patients had mitral regurgitation disease where the mitral valve opening indicates does not close completely or do not come together can be detected with echocardiographic examination and had no any complication heart diseases

C-Aortic regurgitation class

This class contain many patients had aortic regurgitation disease where the aortic valve opening indicates does not close completely or do not come together can be detected with echocardiographic examination and had no any complication heart diseases

2. The analysis step

A. 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 flow 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).

B. Parameter

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

1.Measured Parameters

Which includes all the parameter taking directly 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 befor the subsequent second heart sound. Diastolic heart sound time begins with or after the second heart sound and ends befor the subsequent first heart sound also its can be classification according to their time of onset as classified

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 befor 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 befor the second heart sound midsystolic murmurs, generally at or befor 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 prolase.

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 abnormal pattern of these values.

2.Analysis and Calculated Parameters

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

1.Median

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

2.confidence intervals (CI)

A.pluse confidence intervals (CI+)

B.minus confidence intervals (CI-)

As shown in below

1.Normal heart sound signal

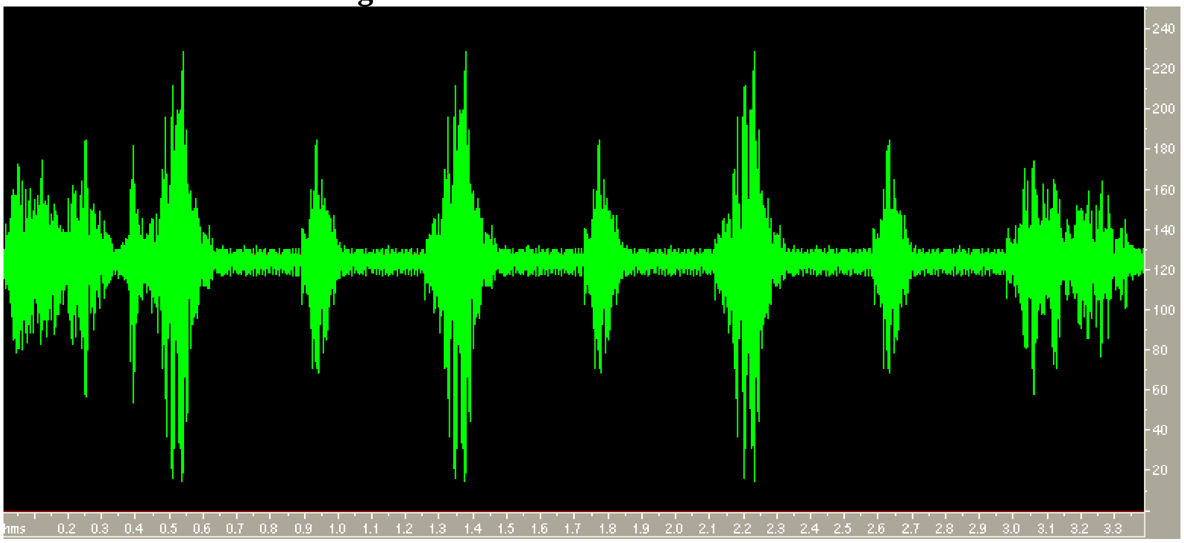

Figure (3).Normal heart sound wave

We can take one signal from this wave to get analysis of it such as the following

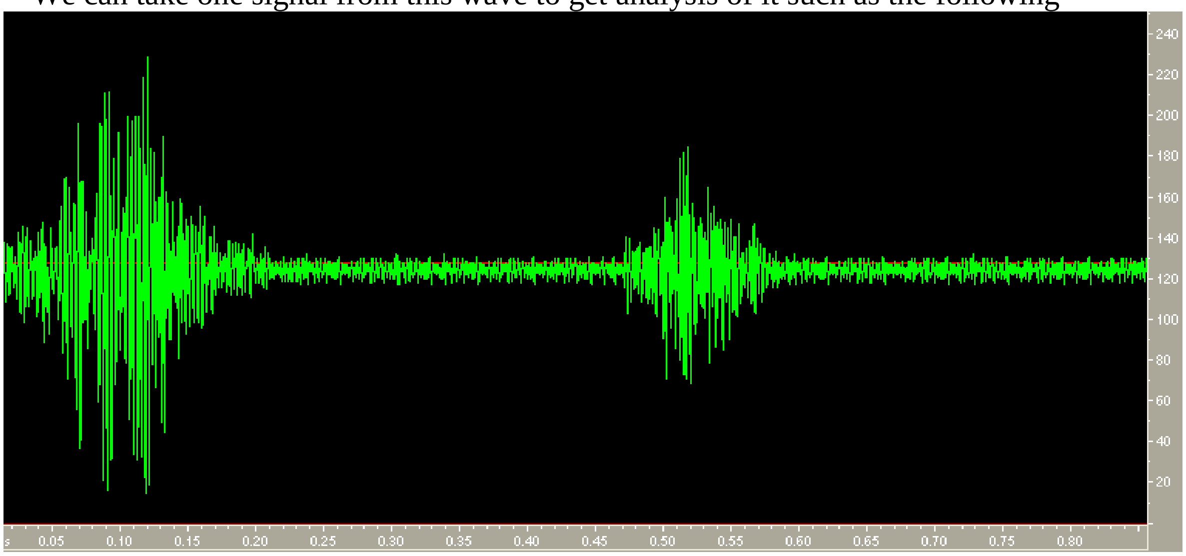

Figure (4).Single wave cutter from wave above

Table (1).The parameters analysis of the wave in figure (4)

T21	T2	T13	T12	T11	T1
0	0.31	0	0	0	0.23
CI -	CI +	Medain s3	T23	T22	
0	0	0	0	0	

2. Abnormal heart sound signal

There are five type of wave represented to five type of valvular heart diseases according to our study requirements

1.Aortic regurgitation wave

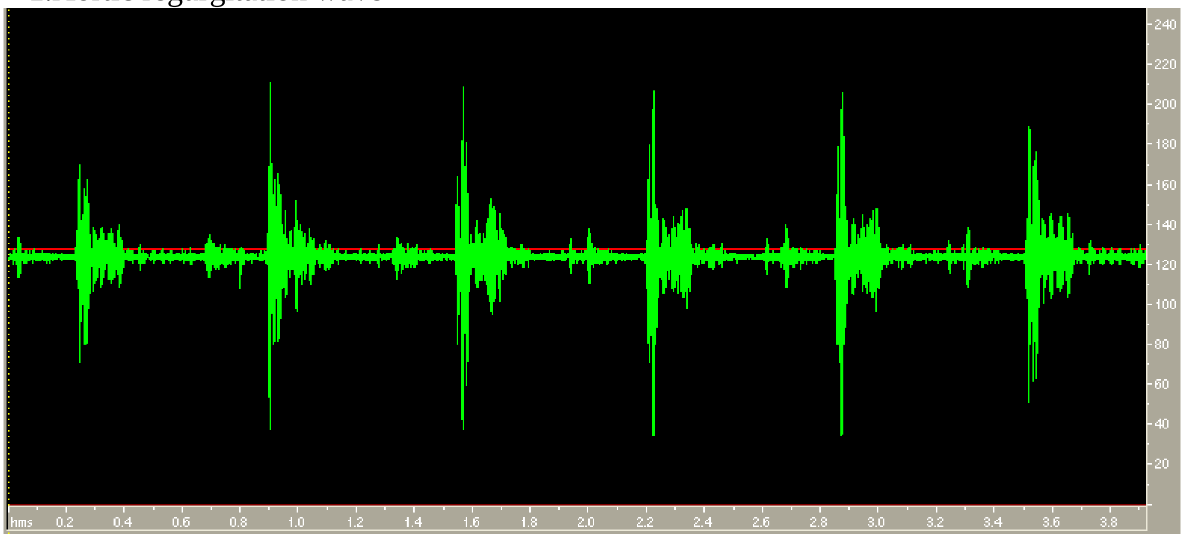

Figure (5). Aortic regurgitation disease wave

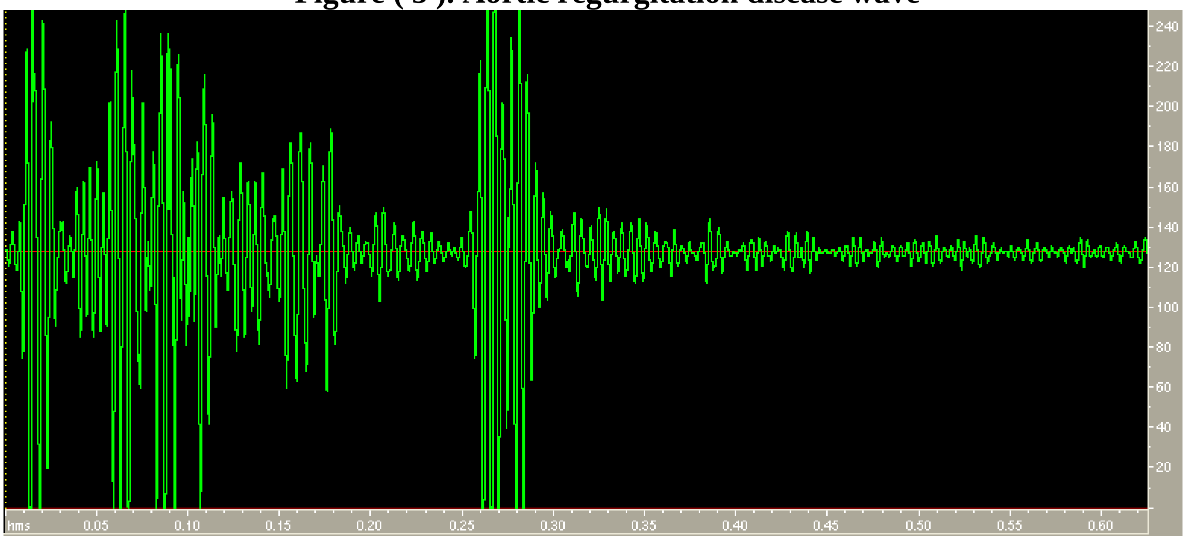

Figure (6).Single wave cutter from wave above

The parameters analysis of this wave can be tabulated as in below

Table (2).The parameters analysis of this wave in figure(6)

T21(M)	T2	T13	T12	T11	T1
0.16	0	0	0	0	0.27
CI -	CI +	Medain s3	T23	T22	
0.0147	0.1103	0.0436	0.06	0	

2.Mitral regurgitation wave

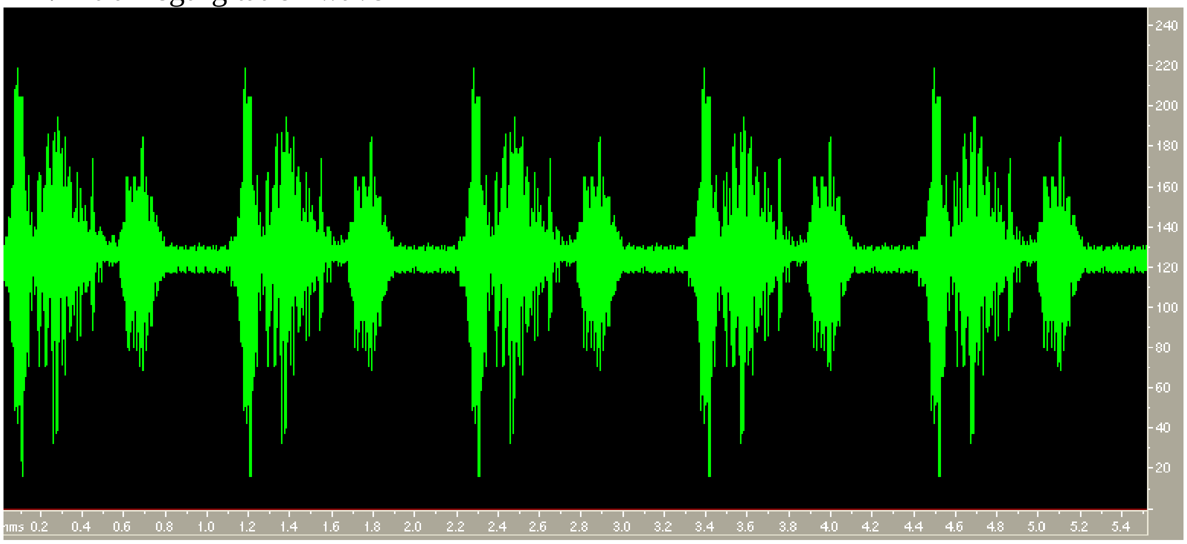

Figure (7). Mitral regurgitation wave

We can take one signal from this wave to get analysis of it such as the following

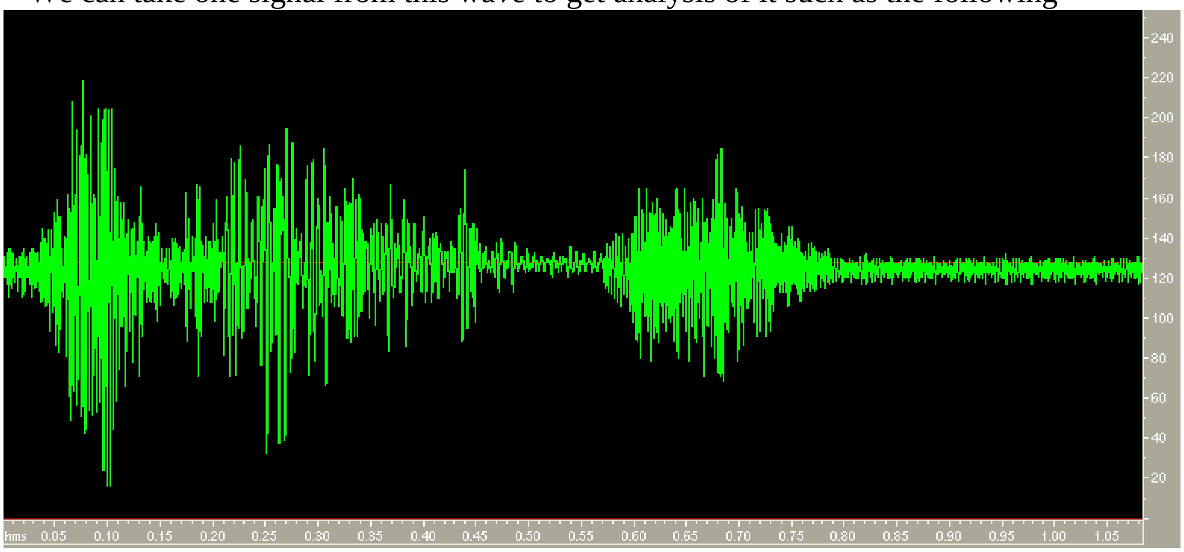

Figure (8).Single wave cutter from wave above

The parameters analysis of this wave can be tabulated as in below

Table (3).The parameters analysis of this wave figure(8)

T21	T2	T13(M)	T12	T11	T1
0	0.37	0.06	0	0.317	0
CI -	CI +	Medain s3	T23	T22	
-0.0768	0.1236	0.0149	0	0	

There for we can tabulated the studies parameters of all subjects waves for each group of disease as shown in below studied

1.Normal waves parameters

Table (4) Normal waves parameters

wave no.	T1	T11	T12	T13	T2	T21	T22	T23	Medain s3	CI +	CI -
1	0.26	0	0	0	0.33	0	0	0	0	0	0
2	0.23	0	0	0	0.32	0	0	0	0	0	0
3	0.25	0	0	0	0.3	0	0	0	0	0	0
4	0.26	0	0	0	0.31	0	0	0	0	0	0
5	0.32	0	0	0	0.28	0	0	0	0	0	0
6	0.22	0	0	0	0.32	0	0	0	0	0	0
7	0.25	0	0	0	0.55	0	0	0	0	0	0
8	0.24	0	0	0	0.38	0	0	0	0	0	0
9	0.3	0	0	0	0.3	0	0	0	0	0	0
10	0.26	0	0	0	0.31	0	0	0	0	0	0
11	0.275	0	0	0	0.31	0	0	0	0	0	0
12	0.275	0	0	0	0.28	0	0	0	0	0	0
13	0.22	0	0	0	0.29	0	0	0	0	0	0
14	0.21	0	0	0	0.28	0	0	0	0	0	0
15	0.25	0	0	0	0.29	0	0	0	0	0	0
16	0.22	0	0	0	0.29	0	0	0	0	0	0
17	0.24	0	0	0	0.3	0	0	0	0	0	0
18	0.28	0	0	0	0.33	0	0	0	0	0	0
19	0.3	0	0	0	0.31	0	0	0	0	0	0
20	0.23	0	0	0	0.31	0	0	0	0	0	0

2.Aortic regurgitation waves parameters

Table (5) Aortic regurgitation waves parameters

wave no.	T1	T11	T12	T13	T2	T21(M)	T22	T23	Medain s3	CI +	CI -
1	0.27	0	0	0	0	0.16	0	0.06	0.0436	0.11	0.0147
2	0.172	0	0	0	0	0.155	0	0.235	0.0316	0.119	-0.041
3	0.45	0	0	0	0	0.31	0	0.179	0.6243	1.008	-0.9919
4	0.248	0	0	0	0	0.268	0	0.197	0.0523	0.072	-0.0412
5	0.247	0	0	0	0	0.247	0	0.98	0.052	0.191	-0.0036
6	0.278	0	0	0	0	0.355	0	0.174	0.0137	0.148	-0.0856
7	0.316	0	0	0	0	0.319	0	0.163	0.0327	0.152	0.0042
8	0.411	0	0	0	0	0.487	0	0.141	0.0219	0.65	-0.2437
9	0.18	0	0	0	0	0.241	0	0.17	0.0512	0.124	-0.0297
10	0.27	0	0	0	0	0.31	0	0.17	0.0109	0.17	-0.0607

3.Mitral regurgitation waves parameters

Table (6). Mitral regurgitation waves parameters

wave no.	T1	T11(M)	T12	T13	T2	T21	T22	T23	Medain s3	CI +	CI -
1	0	0.283	0	0.1	0.3	0	0	0	0.0425	0.3	-0.07
2	0	0.173	0	0.2	0.5	0	0	0	0.0673	0.2	-0.02
3	0	0.26	0	0.1	0.3	0	0	0	0.0062	0.1	-0.03
4	0	0.258	0	0.1	0.3	0	0	0	0.0382	0.1	-0.06
5	0	0.218	0	0.1	0.3	0	0	0	0.125	0.3	-0.12
6	0	0.235	0	0.1	0.4	0	0	0	0.0516	0.1	-0.07
7	0	0.317	0	0.1	0.4	0	0	0	0.0149	0.1	-0.08
8	0	0.194	0	0.2	0.3	0	0	0	0.0365	0.1	0

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 as shown in figure below.

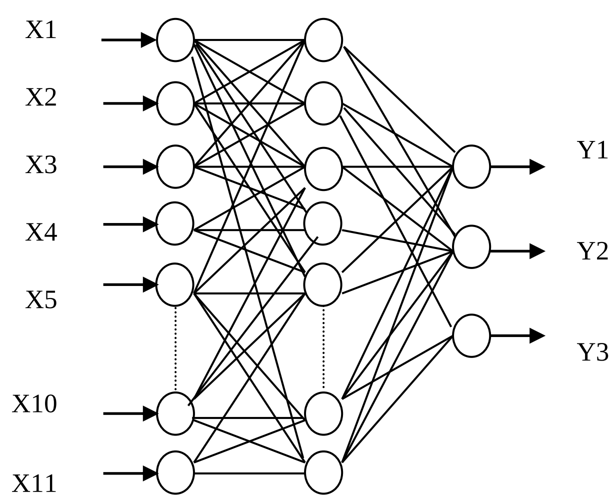

Figure (9).Multi layer perceptron network

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,T2,T11,T12,T13,T21,T22,T23,M,C+,C).

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(9) represented the relation between the number of epoch and the decreasing total error

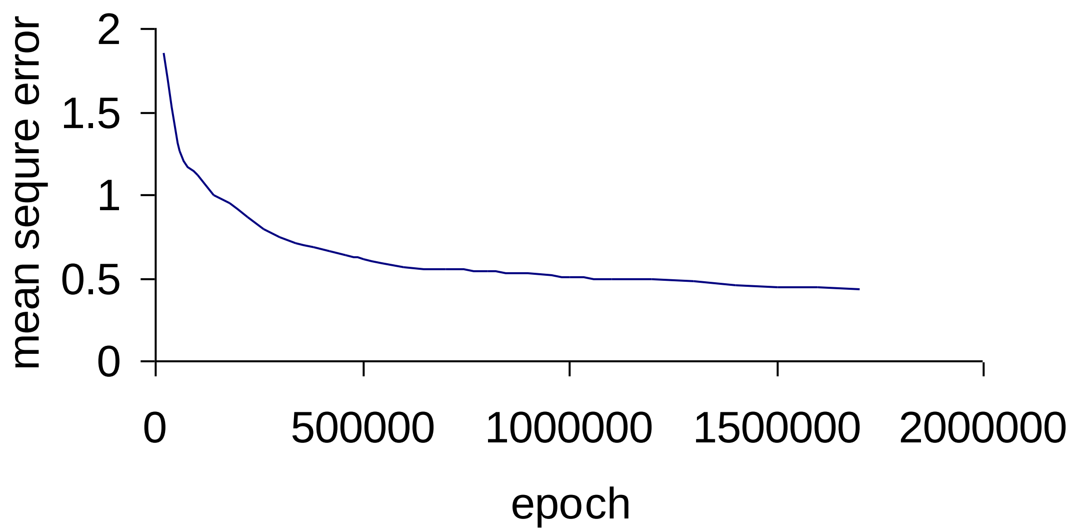

Fig.(10)relationshap between mean sequire error and number of epoch.

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