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HEART DISEASES DIAGNOSIS USING HEART SOUNDS

Onsy Abdel-Alim*, Nadder Hamdy and Mohammed A. El-Hanjouri****

*Alexandria University, Alexandria. Egypt. **AAST. Alexandria, Egypt. <E-mail: Alhanjouri@hotmail.com.

Abstract:

Heart Sound is one of the oldest means for assessing the function of its valves. It helps, together with Echocardiograms and Electrocardiographs, giving a clear and proper diagnostic of several diseases.

In this paper artificial neural networks are used to classify several valves-related heart disorders. A library of heart sound files, recorded via the traditional Stethoscope, are used to extract relevant features using several signal processing tools e.g Discrete Wavelet Transfer (DWT), Fast Fourier Transform (FFT) and Linear Prediction Coding (LPC). The achieved recognition rates were around 95.7%.

I. Introduction

Proper diagnosis of heart diseases is important for patients to survive heart attacks. Physicians have to know clearly heart conditions to decide for invasive (surgery) or non-invasive treatment [1]. Electrocardiograph ECG's serve as guide for the diagnostics of most heart diseases that are more or less related to blood circulation and blood vessels [2,3]. It fails, however, to detect valve-related diseases. Historically, the bare ear and the Stethoscope were of great help to classify most of the diseases [4]. The recently developed echocardiography does present a rather important and precise diagnostic means in this respect. It is, however, bulky and expensive.

In this paper, a portable system for automatic diagnostics of heart valves problems is described. It is based on a feed forward neural network classifier [5]. Different feature extraction tools e.g. FFT [6,7], LPC [6,8], and wavelet decomposition and reconstruction are used.

II. Sources of Heart Sounds

Blood circulation to and out of the heart is controlled by a set of valves, these are [9]: -

- The Tricuspid valve that allows the flow of blood from the right atrium to the right ventricle
- The Mitral valve that allows the blood flow from the left atrium to left ventricle.
- The Pulmonary valve that admits the blood flow to the pulmonary artery from the right ventricle.
- The Aortic valve that allows the blood flow to the aorta from the left ventricle.

The cardiac cycle of the heart, Fig.1, involves the opening and closure of the above-mentioned valves. Due to blood pressure in the systolic and diastolic phases, audible sounds are produced [1,4].

Four heart sounds are to be detected. As depicted in fig.2, the First Heart Sound (FHS) that results from the consecutive closure of the mitral and tricuspid valves. Opening of the pulmonary and aortic valves occurs next and are normally inaudible [4].

The Second Heart Sound (SHS) has two components due to the closure of the aortic and pulmonary valves. The opening of the mitral and tricuspid valves then follows inaudibly. The systolic period starts from the closure of the mitral and tricuspid valves and extends to the closure of the aortic and pulmonary valves. The diastolic period, on other hand, includes the time from the closure of the aortic and pulmonary valves to the start of the next cycle, i.e. the closure of the mitral and tricuspid valves. It is evident from fig.2that the frequency components in the FHS are higher then those of the SHS. Usually valves problems result in the production of strange sounds called murmurs [4].

III. Features Extraction

A 1-minute long record of heartbeats representing each disease (that obtained from a tape produced by Prof. Dr. Mohammed Khairy Abdel-Daeem, faculty of medicine, Ain Shams University, Cairo, Egypt) is used to extract representative and unique features. This raw data should be processed in order to extract the necessary features by:

- Denoising using wavelet analysis.
- Separating one beat out of each record.
- Identifying each of the FHS and the SHS.

It was found that diseases related to valve problems could be classified according to the time separation T_{fs}, between the FHS and the SHS relative to cardiac cycle time T_{cs}, namely whether it is greater or smaller than 20% of T_{cs}, (see fig. 2).

Characteristic features of the first group

To get distinct features for the group, the following operations should be carried out:

- Measuring the duration T_f and T_s of the first and second heart sounds.
- Calculating the ratio (T_f/T_s) and the time difference (T_f-T_s).
- Taking the | FFT | for both of the FHS and the SHS.
- Taking the | FFT | to the outputs of preceeding step.
- Determining the maximum significant component I_1 and I_2, in the resulting spectra of both heart sounds by setting a proper threshold, then calculating the ratio I_1/I_2
- Taking the | FFT | of the early diastolic sound.
- Selecting a second threshold to get the maximum significant component I_3 of the spectrum obtained in the preceeding step

Experiments have shown that the following features

① T_s	② T_f/T_s	③ T_f-T_s
④ I_1	⑤ I_1/I_2	⑥ I_3

Can be used efficiently as characteristic features for classification

Characteristic features of the Second group

The wavelet transform (Daubechies 6) can be used to get appropriate features namely the details **D4, D5, D6** and the approximation **A5** for the second group of diseases. These sounds are first divided into frames of 40 ms duration each before being windowed using a hamming window. 12 LPC coefficients for each output are then calculated. Furthermore, the location of the stethoscope on the chest during recording is considered as an additional feature and it should therefore be included in the feature set.

IV. Classification

A feed forward neural network (NN) classifier is used to classify the 16 diseases of both groups [10,11]. For the **first group**, the neural network comprises 6 nodes at both ends, with one hidden layer containing 10 nodes. It was possible to correctly classify the following diseases: Normal, Split, Open snap, Third HS, Early diastolic and Two component in FHS. For the **second group**, the resulting 216 LPC coefficients for each event are fed to two separate neural networks containing 50 hidden neurons. The NN designed for classifying systolic diseases should have 4 output neurons while that for classifying diastolic diseases can contain 2 neurons only [12,13,14].

The complete classification algorithm is illustrated in the flow chart of fig. 3.

V. Results

For the first group of diseases, 650 cases are used for training the NN while 200 cases for testing. The proposed algorithm has successfully classified 190 cases of them, which corresponds to a recognition rate of 95%. All normal cases have been correctly detected. For the second group, the training data included 320 cases and 100 for testing.

Based on the location of Stethoscope (as shown in fig. 4) and the output of the NN (table 1) exact diagnosis was obtained for 94% of the cases.

The location of the Stethoscope is fed beforehand to exclude other groups of diseases (table 2). The obtained average recognition rate (RR) was in this case about 97%.

Table.1 Classifying the HS according to the timing of murmurs (2nd group)

Murmurs	The location	RR%
I-Systolic Murmurs		96
1-Ejection (Mid) systolic		
Aortic stenosis	Aortic area (1)	
Pulmonary stenosis	Pulmonary area (2)	
Atrial Septal defect	Left sternal edge (5)	
2-Pan systolic		
Mitral regurgitation	Mitral area (3)	
Tricuspid regurgitation	Tricuspid area (4)	
Ventricular Septal defect	Left sternal edge (5)	
3-Late systolic		
Mitral valve prolapse	Mitral area (3)	
II-Diastolic Murmurs		98
1-Ejection(Mid)diastolic		
Mitral stenosis	Mitral area (3)	
Tricuspid stenosis	Tricuspid area (4)	
2-Early diastolic		
Aortic regurgitation	Aortic area (1)	
Pulmonary regurgitation	Pulmonary area (2)	
Overall RR		94

Table.2 Classification according to the location of the stethoscope on the chest (2nd group)

Location	Murmurs	%RR
Aortic area (1) or Pulmonary area (2)	Ejection (Mid) Systolic Early Diastolic	100
Left Sternal edge area (5)	Ejection (Mid) Systolic Pan Systolic	98
Tricuspid area (4)	Pan Systolic Ejection (Mid) Diastolic	100
Mitral area (3)	Pan Systolic Late Systolic Ejection (Mid) diastolic	99
Overall RR		97

VI. Conclusions

Heart Sound is an important guide for assessing the cardiac valves conditions. Due to the diversity of their diseases, reliable diagnosis that does not rely on the bare ear is needed [4]. In this paper a system is developed that can classify almost all valve-associated diseases. Several signal processing tools e.g. artificial neural networks, Discrete Wavelet Transfer (DWT), Fast Fourier Transform (FFT) and Linear Prediction Coding (LPC) were used to extract representative features using a library of heart sound files. The achieved recognition rates were around 95.7%.

VII. References

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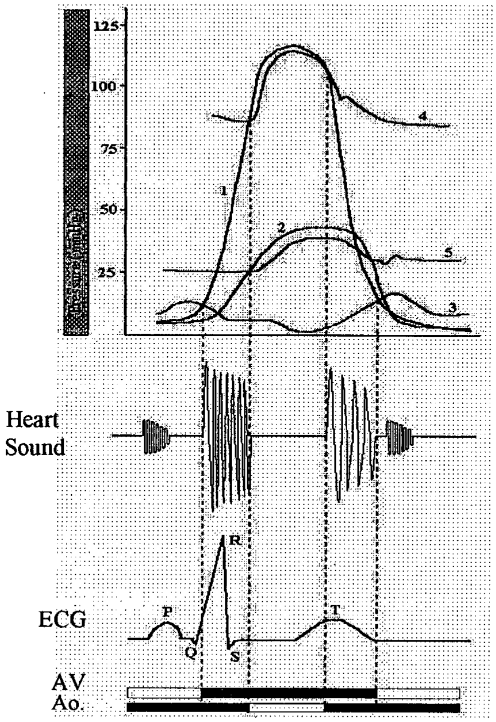
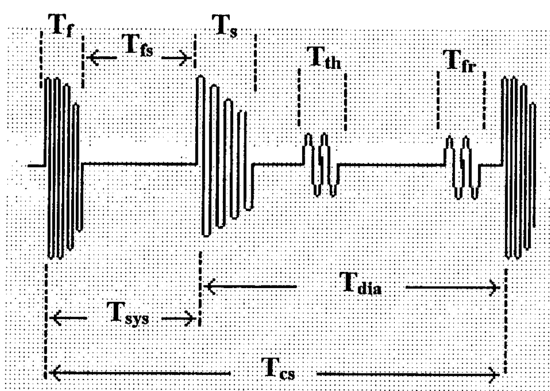


1-Left Ventricle Presure
2-Right Ventricle Presure
3-Left and right atria Presure
4-Aorta Presure
5-Pulmonary artery Presure
AV=Atria Ventricular valve
Ao. =Aortic valve
Closed
Open

Fig.1. The Cardiac Cycle



T_f= First Heart Sound duration.
T_s = Second Heart Sound duration.
T_{th} = Third Heart Sound duration.
T_{fr}= Fourth Heart sound duration.
T_{sys} = Systolic duration.
T_{dia} = Diastolic duration.
T_{fs} = Separation between FHS & SHS

Fig. 2. Heart Sounds

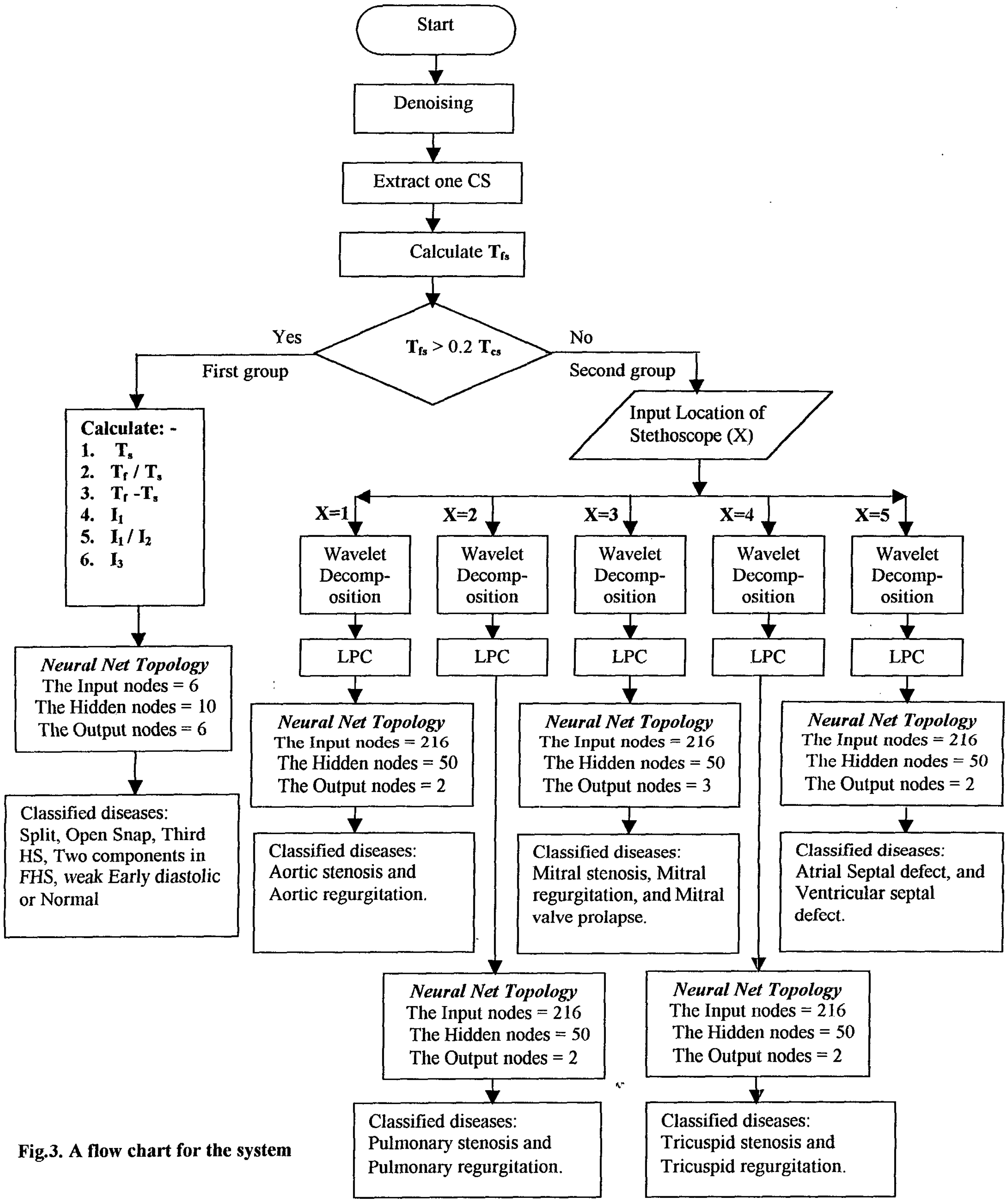


Fig.3. A flow chart for the system

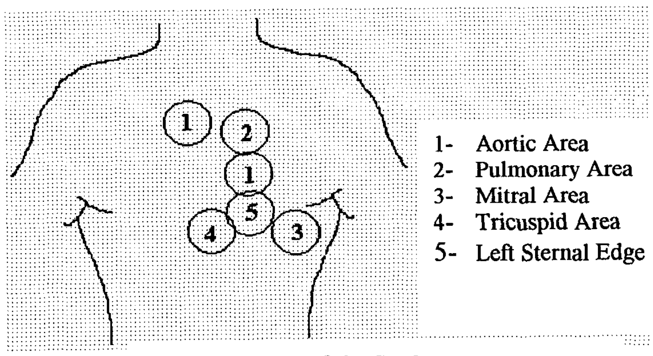


Fig. 4. Location of the Stethoscope