

## Research Article

### A Signal Processing Technique for Heart Murmur Extraction and Classification Using Fuzzy Logic Controller

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**Abstract:** The aim of this study is to present a system which uses a new signal processing technique for extracting and identifying different types of systolic and diastolic heart murmurs as well as normal heart sound, depending on their relevant energies and frequencies values. Heart auscultation is one of the most commonly method that cardiologists used to examine the heart murmurs. In order to overcome the deficiency of cardiologists for heart auscultation the numbers of signal processing techniques have been introduced, such as ECG (Electrocardiography), MRI (Magnetic Resonance Imaging) and CT-Skin etc. The system uses the wav heart sound samples taking from Littman 3M electronic stethoscope and based on Fuzzy controller. The system reveals important information of cardiovascular disorders and can assist general physician to come up with more accurate and reliable diagnosis at early stages.

**Keywords:** Diastolic heart murmur, electronic stethoscope, fuzzy controller, heart murmur, systolic heart murmur

## INTRODUCTION

Cardiac arrest or heart failure is one of the two largest causes of fatalities. Cardiac malfunction, called the “Silent Killer,” lingers in the victim’s body without exhibiting external symptoms. It does leave telltale indications of its presence. One of these is termed Heart Murmur. These are heart sounds that are produced as a result of turbulent blood flow. Murmur can be physiological benign (innocent) or pathological (life threatening). Pathological murmur indicates heart problems like narrowing or leaking valves, valvular lesion, or intra-cardiac shunt, etc. If pathological murmur is detected at an early stage of its onset, a physician can suggest an appropriate regime of medication for its cure. If it remains undetected it can ultimately lead to fatality. Unfortunately both murmurs produce identical sounds and can be easily confused. There are numerous occasions when pathological murmur was mistaken for innocent murmur and no medication was prescribed.

The visual analysis of heart sound can give evidence of particular anomalies. Techniques like the Magnetic Resonance Imaging, the Cardiac Computed Tomography or the Echocardiogram allow to give an image of the heart and cardiac valves activities (Grebe *et al.*, 2002) showing many detailed information on possible symptom of diseases. Though very exhaustive, such techniques require sophisticated, expensive and cumbersome equipment. Therefore, these analyses can

be performed in medical facilities only by trained specialist technicians (Fanfulla *et al.*, 2011).

Phonocardiography (PCG) waveforms make medical professionals easy to interpret disorders and make a better diagnosis. A piezo electric heart sound transducer is used to pick up the vibrations of the four heart valves. The PCG is then interfaced to a PC for processing after which the frequency spectrum and time period analysis is done. The PCG, along with its data, is provided on the screen for detecting the disorders associated with the heart Valves (Mahabuba *et al.*, 2009).

In Ahlstrom *et al.* (2006) proposed a method for distinguishing innocent murmurs from murmurs caused by aortic stenosis, using a dog model; phonocardiographic recordings were obtained from 27 boxer dogs with various degrees of Aortic Stenosis (AS) severity. As a reference for severity, assessment, continuous wave Doppler was used. The data were analyzed with Recurrence Quantification Analysis (RQA) with the aim to find features able to distinguish innocent murmurs from murmurs caused by AS.

The discrimination of ECG signals using statistical parameters is of crucial importance in the cardiac disease therapy. The four statistical parameters considered for cardiac arrhythmia classification of the ECG signals are the Standard Deviation Of The NN Intervals (SDNN), the standard deviation of differences between adjacent NN intervals (SDSD), the root mean square successive difference of intervals which are extracted from heart rate signals (RMSSD) and the

proportion derived by dividing NN50 by the total number of NN intervals (pNN50) (Anuradha *et al.*, 2008).

De Vos and Blanckenberg (2007) designed a model based on automated artificial neural network as well as a direct ratio and a wavelet analysis technique, to discriminate between pathological and non-pathological heart sounds. To test the performance of the three techniques, auscultation data and Electrocardiogram (ECG)-data of 163 patients, aged between 2 mo and 16 yr, were digitized.

Strunic *et al.* (2007) developed a working classifier system using Artificial Neural Networks (ANNs) that accepts heart sound recordings directly, processes the sounds and classifies the inputs to identify the type of cardiac event that is present in the heart sounds.

The variability of the chaos features is linked with the analysis of a complete heartbeat, which defines the periodicity of the cardiac cycle. Concerning the perceptual and spectral features, their estimation may be focused on each biological event, so the four segments per heartbeat ought to be analyzed, S1 sound, systole, S2 sound and diastole (Delgado-Trejos *et al.*, 2009).

The neural network encodes the expertise of the doctor. The neural network is unable to tell the doctor why it makes any particular diagnosis. If a bad diagnosis is made there is no direct path by which the doctor can either understand the problem or rectify it (Jeharon *et al.*, 2006).

Noponen *et al.* (2007) designed a system consisting of an electronic stethoscope and a multimedia laptop computer was used for the recording, monitoring and analysis of auscultation findings. The recorded sounds were examined graphically and numerically using combined phono-spectrograms. The data consisted of heart sound recordings from 807 pediatric patients, including 88 normal cases without any murmur, 447 innocent murmurs and 272 pathological murmurs. The phono-spectrographic features of heart murmurs were examined visually and numerically. From this database, 50 innocent vibratory murmurs, 25 innocent ejection murmurs and 50 easily confusable, mildly pathological systolic murmurs were selected to test whether quantitative phono-spectrographic analysis could be used as an accurate screening tool for systolic heart murmurs in children.

This study is mainly focused on implementing an algorithm for heart murmur extraction and heart impairments identification through a signal processing technique, which would lead to implement a device that perform process auscultation and diagnosis of heart defects much Simpler and more user friendly. It would distinguish normal heart sound from pathological heart murmurs as well as innocent murmurs.

## HEART PHYSIOLOGY AND HEART SOUND PARTS

Human heart consists of four chambers; left ventricles, right ventricles, left atria and right atria. The blood enters from right side of heart through atrium and leave from left side through aorta during one complete cycle. The heart has four valves named as; tricuspid valve, mitral (bicuspid) valve, pulmonary valve and aortic valve. These valves play main role for generating heart sound.

The heart sound contains much useful information, physicians can use this information to check the condition of heart and heart defects such as heart murmur. The heart sound is made up of four components S1, S2, S3, S4 and two intervals systole and diastole (Fig. 1):

- **S1:** First heart sound generated due to closure of mitral and tricuspid valves.
- **S2:** Second heart sound generated due to closure of aortic and pulmonary valves.
- **S3:** Third heart sound caused by oscillation of blood between the roots of aorta and the ventricular walls.
- **S4:** Fourth heart sound generated due to vibration caused by turbulence in ejected blood flowing rapidly through the ascending aorta and pulmonary artery.
- Diastole interval is blood filling stage of heart when atria collect blood from the body circulation or lungs.
- Systole interval is blood leaving stage of heart.

The heart sound components S3 and S4 can be heard at the end of diastole interval and usually ignore these components in signal processing techniques, due to their low frequency range (10-100 Hz), overlap with normal heart sound frequency components. The normal

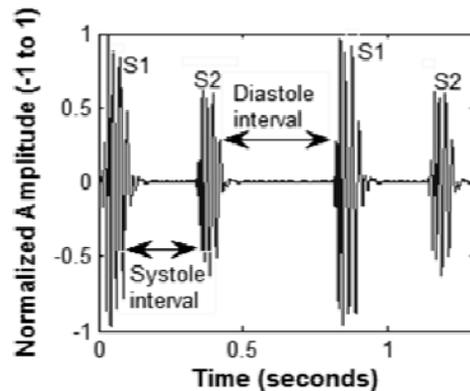


Fig. 1: Normal heart sound signal

heart sound and innocent murmur had frequencies, below 200Hz (Mahabuba *et al.*, 2009).

Heart murmur is an extra sound generated by heart during heartbeat. Murmurs range from very low to very loud sounds and lie between the frequency ranges of 75-1500 Hz (Delgado-Trejos *et al.*, 2009).

The interval between S1 and S2 is systole interval and the murmur lie between these intervals is systolic murmur, similarly the interval between S2 and S1 of next cycle is diastole interval and their corresponding murmur is known as diastolic murmur.

### METHOD FOR DATA ACQUISITION AND PROCESSING

The heart sounds were acquired through 3M Littman Electronic stethoscope, from patients with various pathologies. All data (heart sound of patients) were acquired under the supervision of experienced physician, who has pointed out the correct locations of heart for data (heart sound) acquisition and also indicate the presence of murmur type that patients suffering for. The sounds were recorded at 11025 Hz sampling frequency with duration of 8-12 seconds and stored in computer with .wav format. After collection of data it is passing through processing block (Fig. 2).

The algorithm was implemented using MATLAB simulation tools. The first step of processing block, to read the stored.wav sample of heart sound and pass it to low pass filter with cutoff frequency of 0-1500 Hz and normalized the signal. Before wavelet

decomposition and reconstruction the signal was down-sampled by a factor of four so that the details and approximations can results in frequency band which contain the maximum power of S1 and S2 (Javed *et al.*, 2006).

Apply wavelet decomposition and reconstruction to the down-sampled signal and collect level 4<sup>th</sup> and 5<sup>th</sup> (d4, d5) details (Fig. 3), because that contains maximum power of S1 and S2 and then calculate average Shannon energy of the reconstructed signal as:

$$E_s = \frac{-1}{N} \cdot \sum_{i=1}^N x_w^2(j) \cdot \log x_w^2(j) \quad (1)$$

where,  $x_w$  is the signal after wavelet reconstruction and N is signal length.

Then the normalized average Shannon energy is computed as follows:

$$E_{norm}(t) = \frac{E_s(t) - M(E_s(t))}{S(E_s(t))} \quad (2)$$

where,

$M(E_s(t))$  = The mean value of  $E_s(t)$

$S(E_s(t))$  = The standard deviation of  $E_s(t)$

$E_{norm}(t)$  Emphasizes the medium intensity signal and attenuates the effect of low intensity signal much more than that of high intensity signal (Nazeran, 2007; Liang *et al.*, 1997). The Shannon energy enhances the

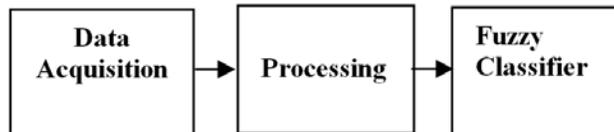


Fig. 2: Block diagram of signal processing technique

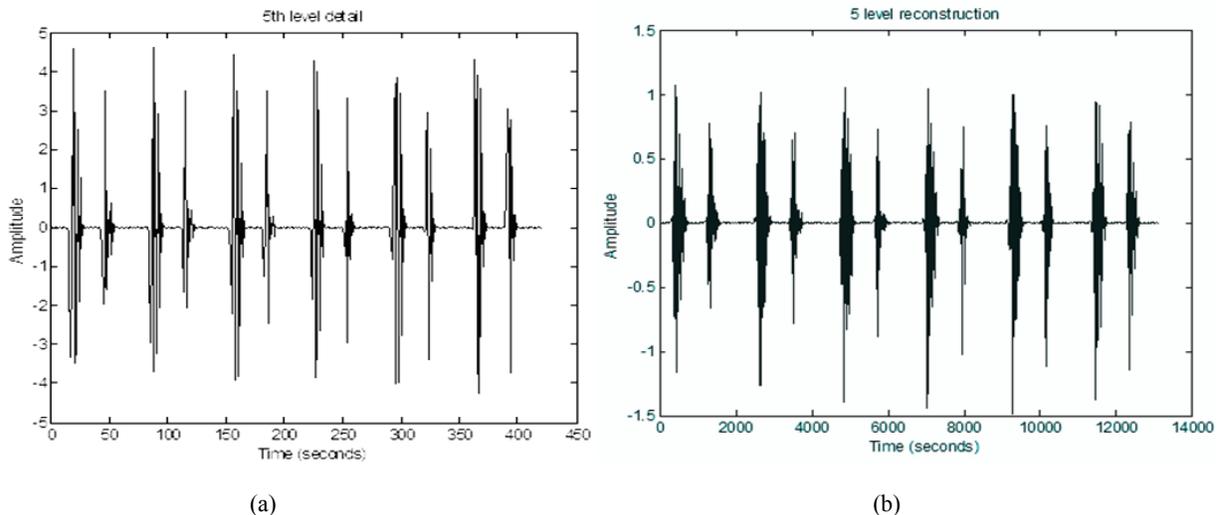


Fig. 3: Wavelet 5<sup>th</sup> level detail and 5<sup>th</sup> level reconstruction

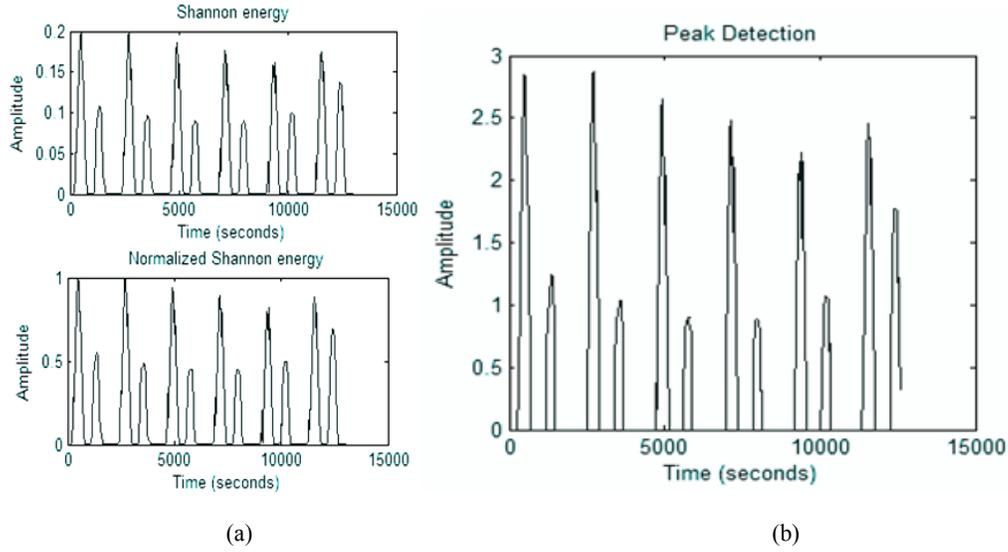


Fig. 4: (a) Shannon energy and (b) Peak detection

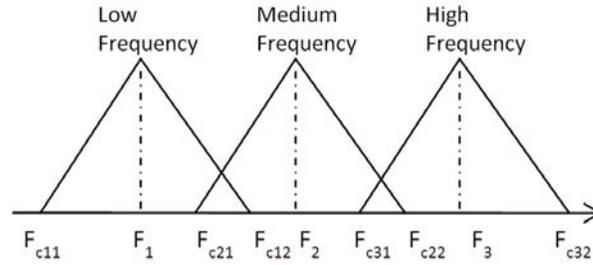


Fig. 5: Filter bands

frequency range where normal sounds S1 and S2 located (Fig. 4a).

The specific threshold was applied to and takes only those peaks whose amplitude is above the specified threshold and rejects other peaks (Fig. 4b).

The next step was to identify S1 and S2 by calculating the time duration between first interval and second interval of peaks. Normally systole interval (time from S1 to S2) takes less time than diastole interval (time from S2 to S1) (Strunic *et al.*, 2007; Park, 2007; Bronzino, 2006) and S1 comes before systole interval and S2 comes after systole interval in the heart signal. Separate the systole and diastole intervals according to that criterion and pass these intervals to three filter banks and calculate their relevant frequency and energy values. The cutoff frequencies of filters were selected according to the frequency ranges of normal heart sound, physiological and pathological murmur (Fig. 5).

The energy of the signal after passing through above filters calculated as follows:

$$Se(i) = \sum_{n=-\infty}^{\infty} |x[n]|^2 \quad (3)$$

$$De(i) = \sum_{n=-\infty}^{\infty} |x[n]|^2 \quad (4)$$

where,  $Se(i)$  represent energy of systole intervals of signal after passing through 1<sup>st</sup>, 2<sup>nd</sup> and 3<sup>rd</sup> filter respectively. Similarly  $De(i)$  represent energy of diastole intervals of signal after passing through 1<sup>st</sup>, 2<sup>nd</sup> and 3<sup>rd</sup> filter respectively.

There corresponding frequency values calculated as:

$$F1 = \frac{F_{c11} + F_{c12}}{2} \quad (5)$$

$$F2 = \frac{F_{c21} + F_{c22}}{2} \quad (6)$$

$$F3 = \frac{F_{c31} + F_{c32}}{2} \quad (7)$$

### FUZZY LOGIC CONTROLLER FOR MURMUR CLASSIFICATION

Fuzzy Logic Controller (FLC) is based on principles of fuzzy logic, which by the mean of membership functions, linguistic terms, such as “fast”, “slow”, “high” and “low” etc, not only to the values 0 and 1, but to the whole interval [0,1] (Werner *et al.*, 2007).

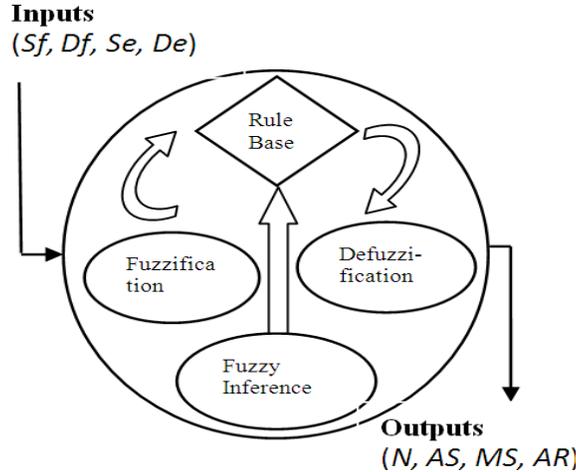


Fig. 6: Structure of fuzzy logic controller

There are three sub procedures in fuzzy logic controller (Fig. 6), fuzzification, fuzzy inference and defuzzification (Homnan and Benjapolakul, 2004; Sivanandam and Deepa, 2006; Leondes, 1998).

The inputs of FLC are systole interval frequency (Sf), systole interval energy (Se), diastole interval frequency (Df) and diastole interval energy (De) was calculated as follows:

$$S_f = \frac{F_1 * Se_1 + F_2 * Se_2 + F_3 * Se_3}{F_1 + F_2 + F_3} \quad (8)$$

$$D_f = \frac{F_1 * De_1 + F_2 * De_2 + F_3 * De_3}{F_1 + F_2 + F_3} \quad (9)$$

where,

$S_f$  = Average frequency of systole intervals

$D_f$  = Average frequency of diastole intervals

Similar to frequency calculation for the input of fuzzy logic controller, calculate systole and diastole intervals energy value by using:

$$S_e = \max [S_{e1} \ S_{e2} \ S_{e3} ] \quad (10)$$

$$D_e = \max [D_{e1} \ D_{e2} \ D_{e3} ] \quad (11)$$

where,

$S_e$  = Maximum value of systole intervals

$D_e$  = Maximum value of diastole intervals

The input port of fuzzy logic controller accepts the four calculated values of systole, diastole intervals frequencies and energies and perform fuzzification. These four calculated value are for different training samples are shown in Table 1. It is clearly seen that a normal heart sounds exhibit lower frequencies and have much lower energy in the systole and diastole regions. Aortic Stenosis exhibit have much higher dominant frequencies with considerably more energies within

Table 1: Calculated systole, diastole interval frequency and relative energy values

S.#	Sf	Df	Se	De
Normal heart sound				
1	175.64	192.02	0.070	0.0716
2	199.67	395.36	0.062	0.2292
3	174.96	189.34	0.070	0.0721
4	194.64	396.70	0.064	0.2212
5	179.64	198.01	0.056	0.2124
Mitral stenosis				
1	360.57	550.18	0.1947	163.97
2	500.23	489.07	0.1267	0.0968
3	537.72	557.96	67.032	32.264
4	509.45	569.45	15.164	6.1467
Aortic stenosis				
1	542.78	229.21	6.1931	0.0932
2	571.71	571.72	45.345	45.331
3	560.51	563.06	198.04	161.91
4	471.89	294.43	111.53	0.1363
5	334.49	444.94	0.4712	7.0842
Aortic regurgitation				
1	166.30	499.72	0.0998	59.212
2	166.09	499.66	0.0996	59.202
3	161.15	416.15	1.0254	55.456
4	169.6478	504.46	0.8976	67.156

these two regions while Aortic Regurgitation has its most of its energy only in the diastole interval.

- Fuzzification:** Fuzzification is the process of translating the real world values (crisp values) in to fuzzy world values (low, medium, high), by the mean of different membership functions and linguistic regions. The type of the membership functions can be choosing according to the circumstances. This paper uses triangular and trapezoidal type of membership functions and three linguistic regions “low”, “medium”, “high” for each input (Fig. 7).
- Inference engine:** After performing fuzzification the next step of FLC is inference engine, which is used to apply the rules from the rule base and produce fuzzy value output. The inserted rules in the rule base are completely based on background knowledge and experience of fuzzy logic controller designer.

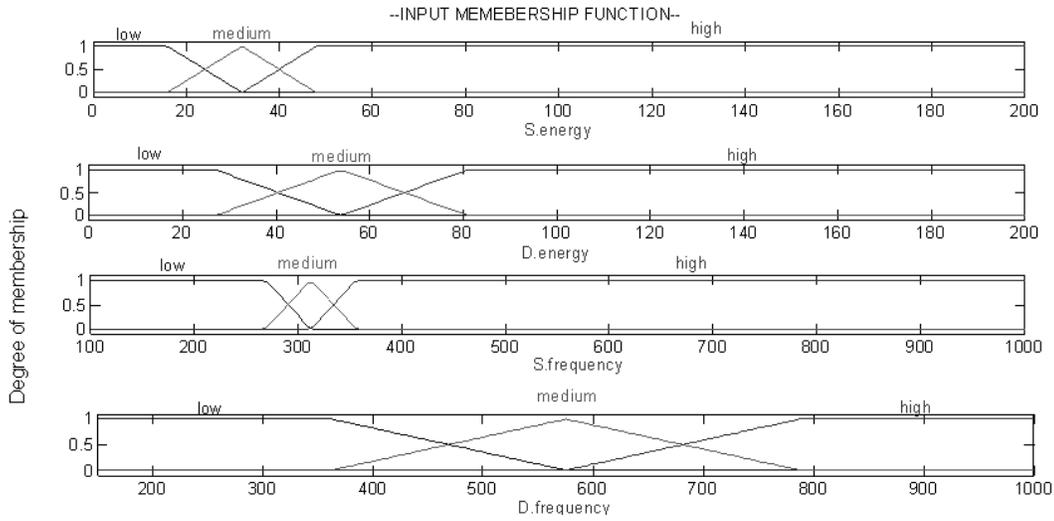


Fig. 7: Input membership functions

Table 2: Rule base (L = Low, M = Medium = High)

Rule No.	$S_f$	$D_f$	$S_e$	$D_e$	o/p 1 Normal	o/p 2 AR	o/p 3 MS	o/p 4 AS
1	L	L	L	L	H	L	L	L
2	L	L	L	M	L	M	H	L
3	L	L	L	H	L	H	M	L
4	L	L	M	L	L	L	L	H
5	L	L	M	M	L	L	M	M
6	L	L	M	H	L	H	M	L
7	L	L	H	L	L	L	L	H
8	L	L	H	M	L	L	M	H
9	L	L	H	H	L	L	M	H
10	L	M	L	L	H	L	L	L
11	L	M	L	M	L	H	L	L
12	L	M	L	H	L	H	L	L
13	L	M	M	L	L	M	H	M
14	L	M	M	M	L	L	H	M
15	L	M	M	H	L	H	M	L
16	L	M	H	L	L	L	L	H
17	L	M	H	M	L	L	H	M
18	L	M	H	H	L	H	L	M
19	L	H	L	L	H	L	L	L
20	L	H	L	M	L	M	H	M
21	.	.	.	.	.	.	.	.
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70	H	M	H	L	L	L	L	H
71	H	M	H	M	L	L	M	H
72	H	M	H	H	L	H	M	L
73	H	H	L	L	H	L	L	L
74	H	H	L	M	L	M	H	L
75	H	H	L	H	L	H	M	L
76	H	H	M	L	L	L	L	H
77	H	H	M	M	L	L	H	M
78	H	H	M	H	L	H	M	L
79	H	H	H	L	L	L	L	H
80	H	H	H	M	L	L	M	H
81	H	H	H	H	L	H	M	L

**Rule base:** The controller uses mamdani inference method and applies the rule base on fuzzy world values. The rule base is collection of IF-THEN rules. The size of rule base depends on the number of inputs and linguistic regions use for fuzzy logic controller. Table 2 represents a sample rule base using four inputs

( $S_e, D_e, S_f, D_f$ ), three linguistic regions and four outputs one is normal heart sound and other three representing the following heart defects:

**AR:** Aortic Regurgitation  
**MS:** Mitral Stenosis

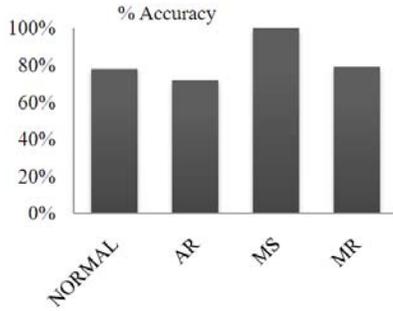


Fig. 8: Results for detection and classification of heart murmur

**AS: Aortic Stenosis**

This study uses 81 rules. The maximum number of rules for rule table calculated as:

$$N = L_1 * L_2 * L_3 * \dots * L_n \tag{12}$$

where,

L = The total number of linguistic regions of each input

N = Total size of rule base

- **Defuzzification:** Defuzzification is the process of converting fuzzy world values into crisp values (Sivanandam and Deepa, 2006; Leondes, 1998). The last step of FLC is applying defuzzification method centre of gravity to perform defuzzification as:

$$X^* = \frac{\sum \mu_c(x)x}{\sum \mu_c(x)} \tag{13}$$

where,

x = The value of running variable on x-axis

$\mu_c(x)$  = The corresponding value of probability

The algorithm use comparators for the controller outputs and declare the heart disease, against which the output value is largest among them.

**RESULTS AND DISCUSSION**

The detection and classification results have been presented in Fig. 8 for two hundred innocent as well as pathological heart murmur sound samples acquired from the patients at Ayub Teaching Hospital Abbottabad using 3M Littman electronic stethoscope. The results show reasonably good performance of around 80% for innocent heart murmur while the best results (approaching 100%) are obtained for Mitral Stenosis.

**CONCLUSION**

Human heart play main role to control and balance all body organs. This paper presents a genera algorithm

to diagnose heart defects caused by murmur in a much simpler and more efficient manner as compare to the complicated algorithms. We can develop a prototype that can be used by the medical industry. The segmentation process used to identify the locations of S1, S2 as well as systole and diastole intervals. A method for heart murmur extraction has been implemented and simulation results confirm the ability of proposed method. To pass the systole, diastole intervals of signal from filter banks before feature extraction make algorithm robust as previous methods. Extracted features used to feed in fuzzy logic controller for detection and classification of heart defects.

Future work will emphasize initial processing steps that will minimize ambient as well as humming noise present ins recorded signal. Additionally, the results of algorithm will be improved by changing of rules in the rule base and membership functions.

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