# Heart Valve Disease Classification Using Neural Network

Ashish Shelke<sup>1</sup>, V.B. Baru<sup>2</sup>

<sup>1, 2</sup>Sinhgad College of Engineering, Savitribai Phule Pune University, Opposite to Sinhgad Road, Vadgaon Pune-041, India

Abstract: Heart valve diseases such as aortic stenosis, mitral regurgitation, mitral stenosis and aortic regurgitation can be audible directly by stethoscope. Valve diseases are characterized by systolic murmur and diastolic murmur features. Segment heart sound wave into S1, S2 systolic murmur and diastolic murmur then segments features given to artificial neural network to classify disease. Instead of giving complete PCG wave to ANN give segments and test disease for those segment only then cumulative results of each segment will give final valve disease name. ANN is trained with 49 S1 components, 43 systolic segments consists of 15 of aortic stenosis and 11 of mitral regurgitation. 37 diastolic segments used to classify mitral stenosis and aortic regurgitation. These ANN are giving 84.93 % accuracy for S1 test signals having 12 test segments. Systolic gives 88.73 % accuracy and diastolic gives 91.72 % accuracy

**Keywords:** Empirical Mode Decomposition, First heart sound (S1), Gaussian distribution, Intrinsic Mode Function, Kurtosis, Second heart sound (S2), neural Network, Back propagation algorithm.

## 1. Introduction

Stethoscope is basic diagnosis tool in medical tools. Acoustic waves heard through stethoscope are essential for recognizing heart valve diseases such Aortic Stenosis (AS), Mitral Regurgitation (MR), Mitral Stenosis (MS) and Aortic regurgitation (AR). Electronic stethoscope are developed which are capable of capturing these acoustic waves and its features such as loudness, frequency and its intensity useful for diseases recognition using signal processing algorithm.

Each heart valve diseases are having its own systolic and diastolic different features as shown in figure 1. As seen figure 1 systolic murmur and diastolic murmurs diamond shaped in aortic stenosis, S1 sound is splitted in mitral regurgitation. Such different shapes can be distinguished using statistical properties such as kurtosis and skewness, mean and root mean square.

Here Heart sounds of 17 normal and 19 abnormal sound waves are segmented using Empirical Mode Decomposition (EMD) based on kurtosis. S1, S2, systolic and diastolic murmurs are segmented. These segments are given to back propagation artificial neural network (ANN) [3]. Different neural networks used for S1, systolic murmurs and diastolic murmurs then cumulative results of these network are used for distinguishing heart valve diseases. Neural networks architectures are different for S1, systolic and diastolic murmurs.

# 2. Mathematical Background

Paper ID: SUB155159

Before classification heart sounds are given to neural network given to heart sound segmentation tool Empirical Mode Decomposition (EMD). Heart sounds undergone sifting algorithm [5] and decomposed into oscillations. These oscillations are analysed using kurtosis analysis. These selected oscillations are used to segments S1, S2, systolic murmur and diastolic murmur.

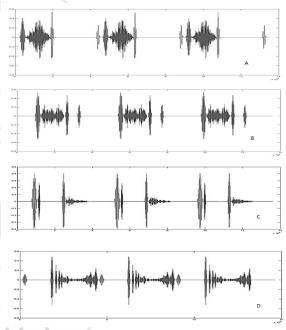


Figure 1: EMD flow to extract heart segments [2]

# 3.1 Empirical Mode Decomposition (EMD) and Segmentation

Empirical mode decomposition (EMD) decomposes signal into fast oscillation and slow oscillation [3]. It is iterative process until all oscillations are extracted. These finite numbers of oscillation are called as Intrinsic Mode Function (IMF). IMFs are obtained from signal by algorithm called as sifting algorithm. Sifting algorithm is having two constraints: each IMF has same number of zero-crossing and extremes, and also has symmetric envelope obtained by the local maxima, and minima respectively. It assumes that the signal has at least two extremes [5] [3]. So, for any 1-D discrete signal  $I_{\rm ori}$ , EMD can be represented with following representation:

$$I_{ori} = \sum_{j=0}^{J} IMF(j) + I_{res} \dots (1)$$

Volume 4 Issue 6, June 2015

Where IMF (j) is the j<sup>th</sup> mode (or IMF) of the signal, and I<sub>res</sub> is residual trend. The sifting procedure generates a finite number of IMFs which are nearly orthogonal to each other [5]. These IMFs are processed using kurtosis, instantaneous frequency and Shannon energy criterions. Segments which lies outside Gaussian distribution are correspond to heart sound [3]. S1, S2, systolic and diastolic segments separated from heart sounds.

## 3.2 Back Propagation Artificial Neural Network (ANN)

Back propagation is systematic method for training multi—layer artificial neural networks [1]. It has mathematical foundation. It multi-layer forward network using extend gradient-descent based delta-learning rule, commonly known as back-propagation algorithm [1]. Back propagation provides a computationally efficient method for changing the weights [1] in feed forward network, with differential activation functions, to learn a training set of input output examples. Network is trained using supervised learning method [1]. The aim of this network is to achieve balance between ability to respond correctly to the input patterns that are used for training and the ability to provide [1] good response to input that are similar [1]. As shown in fig 2 errors at output is measured and it is propagating in back ward direction so it is called back propagation neural network.

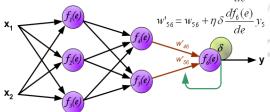


Figure 2: Back propagation algorithm [4]

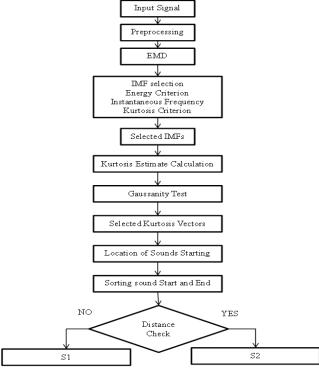


Figure 3: EMD flow to extract heart segments [2]

Paper ID: SUB155159

# 3. Proposed Approach

# 3.1 Pre-processing

Input signal x[n] is normalized by making it zero-mean signal and down-sampled to 12 kHz for time efficient computation. This normalized input undergoes 3rd order median filtering to enhance quality of signal followed by 10th order Butterworth filtering with cut off frequency 150Hz [2]. It gives filtered signal  $x_f[n]$ . Due to filtering with at cut off 150 Hz removes high frequency noise and high frequency murmur that help for detection of S1 and S2 points.

### 3.2 Empirical Mode Decomposition

Pre-processed heart sound undergoes empirical mode decomposition and gives S1, S2, systolic and diastolic murmurs as an output by following flowchart given in fig 3. Statistical parameters mean, standard deviation, kurtosis and skewness are extracted from segmented components for each sound. These features are used for neural network training and classification.

#### 3.3 Neural Network Classifier

As shown in fig 1 different sound follows different distribution in their time representation. AS, MR, MR and AS mainly depends on systolic and diastolic behaviour. In AS systolic murmur is diamond shaped distribution and diastolic murmur is having fourth sound present. Now is considering third and fourth sound as part of diastolic murmur only. Aortic Stenosis and Mitral Regurgitation are characterised by systolic murmur. Aortic Regurgitation and Mitral Stenosis are characterised by diastolic murmur only. S1sounds low loudness only characterise Mitral Stenosis. S2 sound is normal in all four heart diseases so it is not useful for classification. While developing neural network three back propagation neural network architecture is developed.

#### 1) Systolic and diastolic Neural Network

Systolic murmur is three levels architecture. It is having four inputs, six hidden layers and two output layers. Each layer is having activation function 'tansigmoid' and training 'trainrp'. Tough network classify only two disease output neurons are two because some patients may have both diseases.

#### 2) S1 based Neural Network

S1 neural network is two levels architecture. It is having four inputs and two output layers. Each layer is having activation function 'logsigmoid' and 'tansigmoid' respectively with training 'trainlm'.

Output of three neurons gives cumulative decisions. Patients may have two or three different heart valve disease. So output of neural architecture gives eight combinations. Patient with any of combinations is considered.

### 4. Results

As discussed heart sounds are segmented into S1, S2, systolic and diastolic murmurs. These segments are given to neural network.

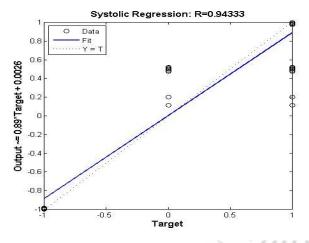
Table 1 shows training set used for training of neural network architectures. Number in tables indicated that number of segments used for training. Table 2 shows testing set used for testing of neural network. Accuracy column indicates accuracy using neural networks. Fig 4, fig 5, fig 6 shows regression graphs for given testing dataset which indicates accuracy of particular neural network.

Table 1: Margin specifications

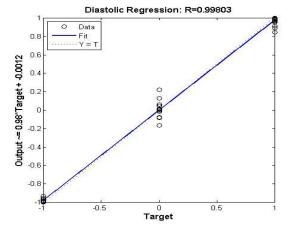
Tubit it iting in specifications							
Training Set	AS	MR	MS	AR			
S1 (49)	12	13	12	12			
S2 (47)	11	12	13	10			
Systolic Murmur	15	11	9	3			
Diastolic Murmur	7	3	15	13			

Table 2: Testing Set

Tuble 21 Testing Set							
Testing Set	AS	MR	MS	AR	Accuracy		
S1 (31)	8	8	7	8	21/31		
S2 (31)	8	8	7	8	-		
Systolic Murmur	6	/ 7	3	3	16/19		
Diastolic Murmur	2 /	3	9	6	17/21		



**Figure 4:** Systolic Murmur neural network's regression graph



**Figure 5:** Diastolic Murmur neural network's regression graph

Paper ID: SUB155159

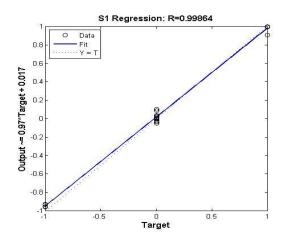


Figure 6: S1 neural network's regression graph

#### References

- [1] S.N. Sivanandam and S Sumathi, *Introduction to Neural Networks using Matlab* 6.0, MC Graw Hill, 2014.
- [2] Chrysa D. Papadaniil, Leontios J. Hadjileontiadis, "Efficient Heart Sound Segmentation and Extraction Using Ensemble Empirical Mode Decompositon and Kurtosis features," *IEEE Journal* of Biomedical and Health Informatics, vol. 18, no. 4, pp. 2168-2194, July 2014.
- [3] Mahesh C. Shashtry, "An Empirical Mode Decomposition Based Approach For Through The Wall Radar Sensing of Human Technology," Master's dissertation, Dept. of Electrical Eng., The Pennsylvania state Univ., Cambridge, August 2009.
- [4] Faizan Javed, P A Venkatachalam "A Signal Processing Module for the Analysis of Heart Sounds and Heart Murmurs," Journal of Physics: Conference Series 34 (2006) 1098–1105
- [5] http://home.agh.edu.pl/~vlsi/AI/backp\_t\_en/backprop.htm
- [6] Jean Claude, Eric delechelle, "Empirical Mode Decomposition: Applications on signal and Image Processing," *Advances in Adaptive Data Analysis*, vol. 1, no. 1, pp. 125-175, 2009.

## **Author Profile**



Ashish Shelke received the B.E. degrees in Electronics & Telecommunication Engineering from Savitribai Phule Pune University in 2012. Now is pursuing M.E. degree in Signal Processing (E&TC) from Savitribai

Phule Pune University. His area of interest is signal processing, video processing.



**Prof. V. B. Baru** is an Associate Professor in Electronics and Telecommunication Department at Sinhgad College of Engineering, Pune. He has done BE in 1993 and completed ME in 1999 in Electronics

and Telecommunications. He is pursuing Ph. D from College of Engineering, Pune. He has 20 years of Teaching Experience and published more than 50 papers in national and International level journals. He is author of two books 'Electronic Product Design' by Wiley Publication and 'Basic Electronics' by Dreamtech Publication. He has guided more than 100 UG students and about 25 PG students for their Dissertations