A Study and Design of an Automated Heart Sound Analysis Framework

Anindo Chatterjee, Debasmriti Ghosh

Abstract— Heart auscultation is a fundamental component of cardiac diagnosis. However, forming a diagnosis based on sounds heard through either a conventional acoustic or an electronic stethoscope is itself a very special skill, one that can take years to acquire. Because this skill is also very difficult to teach in a structured way, the majority of internal medicine and cardiology programs offer little or no such instruction. Despite its obvious utility, primary care physicians are documented to have poor auscultatory skills.Computer-aided electronic auscultatory devices have been developed that acquire, record, and analyze the acoustic signals of the heart. Using acoustic signal processing algorithms, a computer analyzes the recording to identify specific heart sounds that may be present, including S1, S2 and suspected murmurs. A graphic user interface displays the results. These computer-aided electronic auscultatory devices are intended to provide support to the physician in the evaluation of heart signals for the identification of the normal and abnormal heart signals. Certain sounds pertaining to the heart and lungs are heard in all normal persons. These normal sounds vary in quality and intensity for different individuals depending on the physical make-up of the particular organs producing them and also on the structure of bone and flesh through which the sounds are transmitted to the surface of the body. Pathological changes can often be detected by the modification of the normal sounds or by the appearance of abnormal sounds. In this article, consideration is given to the nature of normal and abnormal heart signals with a view to presenting preliminary information relative to their amplitude of the frequency and power-spectrum characteristics.

Index Terms— Artificial Neural Networks(ANN)-are computational models inspired by animals' central nervous systems that are capable of machine learning and pattern recognition, Fourier Transform(FT)-A transformation from time to frequency domain or vice versa, Fast Fourier Transform(FFT)-Time to frequency (vice versa) transformations are computed rapidly, Heart Auscultation-interpretation of heart sounds by a physician, S1-the first heart sound during systole, S2-the second heart heart sound during diastole, Short Time Foirier Transform(STFT)- It is obtained by sliding a window function along the signal, and for each portion of the signal multiplied by the window function, a Fourier transform (FT) is found.

1 INTRODUCTION

In today medical prevention, the early diagnosis of cardiac disease is one of the most important topics. To detect cardiac diseases the first and foremost thing is to differentiate between normal and abnormal heart sound signals. The recent availability of intelligent electronic systems, supporting the automatic detection of cardiac pathologies, represents indeed a very useful way to shorten and make more reliable diagnostic procedures. There are many methods to extract information about pathologies.

The visual analysis of heart sounds can give evidence of particular anomalies. Techniques like the Magnetic Resonance Imaging, the Cardiac Computed Tomography or the Echocardigram allow giving an image of the heart and cardiac valves activities showing many detailed information. Though very exaustive such technique require sophisticated, expensive and cumbersome equipment. Moreover, results are not immediate and therefore these exams do not fit both for domestic and emergency context. Other techniques rely on 'electrical characterization' of the heart. The analysis of electrocardiogram (ECG) signals does not require expensive equipment and test results are instantaneously avalible. An alternative approach is based on direct auscultation of heart sounds by means of stethoscopes. Amandeep Cheema and Mandeep Singh [1] show that phonocardiogram or PCG signals are the heart sound signals which carry tremendous information about the condition of the heart and the abnormal heart sounds can also be detected from these signals. Phonocardiogram (PCG) requires very affordable equipments and skills common to all physicians. Such a technique is almost cost free and gives immediate results, even though not completely exhaustive. Its main draw back is that diagnoses are based on the experience and abilities of the physician.

The availability of electronic stethoscopes opens the way to an automatic ananlysis of cardiac sounds, which may overcome the limitation of the subjective diagnosis. Amandeep Cheema, Mandeep Singh [1] and Ilias Maglogiannis, Euripidis Loukis, Elias Zafiropoulos, Antonis Stasis [3] show that an effective automated diagnosis can be based upon the extraction of features from the heart sounds and on the basis of those features the abnormal heart sounds can be differentiated from the normal ones. Each and every heart signal consists of mainly two sounds- S1 and s2. Now we already have some normal and abnormal heart signals with us. According to Sumeth Yuenyong, Akinori Nishihara, Waree Kongprawechnon and Kanokvate Tungpimolrut [6] we will differentiate these signals based on the peak amplitude and power spectrum of those signals. To have these frequency and power sprctrum features we have applied FFT and STFT on these time domain signals. Depending on these frequency and power spectrum features, we can say whether two signlals are same or different. We have also used Back Propagation Neural Network (BPN) which can easily clas-

- *Anindo Chatterjee, B.Tech in CSE from Institute of Engineering & Management, is currently pursuing Post Graduate Diploma in Management in Indian Institute of Management, Lucknow, India, PH-8052813691. E-mail: chatterjeeanindo.ac@gmail.com*
- *Debasmriti Ghosh, B.Tech in CSE from Institute of Engineering & Management, Kolkata, India, PH-9433909728. E-mail: rumpa.debasmriti@gmail.com*

sify the normal and abnormal signals into two different classes.

2 Theoritical Background

2.1 Heart Sound Description

The human heart is a four chambered pump with two atria for the collection of blood from the veins and two ventricles for pumping out the blood to the arteries. The right side of the heart pumps blood to the pulmonary circulation (lungs) and the left side pumps blood to the systemic circulation (rest of the body). The blood from pulmonary circulation returns to the left atrium (through the pulmonary veins) and the blood from the systemic circulation returns to the right atrium (through the superior/inferior vena cava).

Two sets of valves control the flow of blood: the AV valves (mitral and tricuspid) between the atria and the ventricles, and the semilunar valves (aortic and pulmonary) between the ventricles and the arteries.

Prakash D, Uma Mageshwari T, Prabakaran K and Suguna A [2] show that cardiac sounds are generated by a plurality of complex mechanisms. In particular, they include: Sounds and Mummurs.Mainly, two intense sounds are audible in all subjects. The first tone S1 is generated by the deceleration of blood due to closure of atria ventricular valves when ventricular blood pressure exceeds the atria one during heart contraction (systole). The second tone (S2) is generated by the decontraction of the heart(diastole), which closes the semi lunar valves.

2.2 Fast Fourier Transform

Fourier transforms convert time to frequency and vice versa; Fast Fourier transform rapidly computes such transformations. This is an algorithm to compute the Discrete Fourier Transform and its inverse. The DFT is obtained by decomposing a sequence of values into components of different frequencies. This operation is useful in many fields but computing it directly from the definition is often too slow. An FFT is a way to compute the same result more quickly. The idea behindthe FFT is the divide and conquer approach, to break up the original N point sample into two N/2 sequences. Computing the DFT of N points in the naïve way, using the definition takes O (N*N) operations, while a FFT can compute the same DFT in only O (N log N) operations.

2.3 Short Time Fourier Transform

The STFT is obtained by sliding a window function along the signal and for each portion of the signal multiplied by the window function, a FT is found. For each time location where the window is centered, we obtain a different FT- each FT provides the spectral information of a separate time slice of the heart signal, providing simultaneous time and frequency information. STFT maps 1-D time domain signals to 2-D time-frequency. Robi Polikar [5] shows that the STFT is a time frequency transformation that is highly dependent on the choice of the window function.

2.4 Artificial Neural Network

ANNs are computational models inspired by animals' central nervous systems that are capable of machine learning and pattern recognition. They are usually presented as systems of interconnected neurons that can compute values from inputs by feeding information through the network. Commonly, Gautam Saha [4] shows that ANN consists of three groups-a layer of 'input' units, connected to a layer of 'hidden' units, which is connected to a layer of 'output' units.

Amandeep Cheema and Mandeep Singh [1] show that the Back propagation neural network (BPN) is a common method of training artificial neural networks. For a desired output, the network learns from many inputs. It is a supervised learning method and is a generalization of the delta rule. It requires a dataset of the desired output for many inputs, making up the training set. It is most useful for feed forward networks. Back propagation requires that the activation function used by the artificial be differentiable.

The back propagation learning algorithm has two phases-propagation and weight update. Here the errors propagate backwards from the output nodes to the input nodes. Back propagation calculates the gradient of the error of the network.

3 Proposed Methodology

We have approached the project by transforming the time domain heart signals into frequency domain with the help of FFT and STFT and extracting the feature vectors that include peak amplitude, power spectrum of the signal. By using the feature vectors, the signals are classified by applying back propagation neural network.

Now we have different types of heart signals (in time domain) with us. From any of those signals we have taken the first 1024 samples (one can take more than that) and applied FFT and STFT on that signal. In case of STFT, we have taken window size as 256 and we have done 50% overlapping STFT and converted that signal into its frequency domain. From the frequency domain we can easily get the peak amplitude and the power spectrum (which takes the summation of the amplitude values of each block) of that signal.When we plot the outputs (amplitude and frequency) after doing FFT or STFT on the original signal we always get a symmetric graph from that. Now from the graph that we have plotted we can get the peak amplitude values of that heart signal (for its first 1024 samples).Using these peak amplitude values we can form a feature vector. Using FFT the feature vector looks like {21.32, 21.32} and using STFT the feature vector looks like {21.32, .043, .028, .028, .028, .043, 21.32}.

Besides the amplitude vector we have also computed power spectrum of the above mentioned signal by taking the summation of the amplitude values of each block by computing STFT on the original heart signal (time domain signal). The power spectrum vector for this heart signal looks like {67.36, 5.06, 3.92, 3.71, 4.31, 5.82, and 45.83}.

Now if we take another portion from the same heart signal (say its second 1024 samples) and compute FFT and STFT on this signal and calculate the feature vectors from this we will get nearly same values from where we can conclude that these two portions are a part of the same signal. But here if we take another 1024 samples from totally a different heart signal and form its feature vector we can see that how largely the feature vectors vary. So, using this methodology we can differentiate between two different heart signals.

Now, our aim is to differentiate between the normal and abnormal heart signals. As we have already stated that we have different types of heart signals with us. We also have a normal heart signal with us. So, from the normal heart signal we calculate the amplitude and power spectrum feature vectors. Now we take any other heart signal, compute its feature vectors and calculate the error=| (a-d) + (b-e) +(c-f)|, where {a, b, c}, {d, e, f} are feature vectors of the respective signals. If the error is small then we can conclude that the signal which we have tested later is a normal one and if the error is large then we will conclude that the signal is an abnormal heart signal.

Although we can differentiate the heart signals FFT and STFT but we can also use BPN to classify different heart signals into different classes. As an example we can say that we have input samples as {21.32, .043, .028, .028, .028, .043, and 21.32} (say, this is the amplitude vector for normal heart signal) and {.066, .009, .0084, .0084, .0084, .009, .066} (this one is arbitrary, different from the normal one). As Gautam Saha [4] shows that the network will be trained by these input samples (the more the training samples the more accurate the result will be). As output samples we have taken {0, 0} and {1, 1} as we need to classify the heart signals into normal and abnormal class.then we give some input vectors and neural network classify the signal. If the neural network classifies the signal in the same class as that of the normal signal then the testing signal is normal; otherwise it is an abnormal signal.

4 Experimental Result

After having performed FFT and STFT here we show a comparative result. The result shows how the feature vectors looks in each case, how much symmetric the feature vector values are. From this result we will be able to determine which feature vector is more accurate and how the values of the feature vectors change on changing the no. of samples and the window size.

Results for the amplitude vector and power spectrum vector are shown in table 1 and table 2 respectively:

TABLE1
AMPLITUDE FEATURE VECTOR

Signal	FFT	STFT
Heart signal1(first 1024 samples)	{21.32,21.32}	{21.32, .043, .028, .028, .028, .043, 21.32}
Heart Signal1(next 1024 samples)	{19.01,19.01}	{19.01, .05, .027, .021, .027, .05, 19.01}
Heart Signal2(first 1024 samples)	{.066,.066}	{.066, .009, .0084, .0084, .0084, .009, .066}

TABLE2
POWER SPECTRUM FEATURE VECTOR

Signal	STFT
Heart signal1(first 1024 samples)	{67.36, 5.06, 3.92, 3.71, 4.31, 5.82, 45.83}.
Heart Signal1(next 1024 samples)	{73.90, 4.28, 3.29, 3.09, 3.65, 4.58, 52.81}
Heart Signal2(first 1024 samples)	{1.83, .95, 1.41, 1.19, 1.04, 1.39, 2.69}

From these feature vectors we can easily differentiate between two different signals. Moreover if the feature vectors for the normal signals are known to us then we can easily conclude whether another signal is a normal one or not by looking at these feature vectors. We can also use BPN that we have mentioned earlier to distinguish the normal signals from the abnormal ones.

We have also studied how the STFT result changes on changing the window size and the no. of samples on STFT as discussed by Robi Polikar [5]. From there we have noticed that if we take higher no. of samples our result will be more accurate. Change in window size of STFT only makes the feature vector larger or smaller; but the amplitude or power spectrum values remain almost same in every case.

We have also done a comparison between the amplitude and power spectrum feature vectors. There we see that the values of the amplitude feature vectors are more accurate,they are more symmetric. But in case of power spectrum as they consider all the sample values within a block, the feature vector values are not exactly symmetric. So, power spectrum feature vectors contain some error.

5 Conclusion

Heart Auscultation is a complex practice that doctors are able to perfect after years of experience as there does not exist any direct method to teach it. The aim of the framework described in this paper is to identify arrhythmic heart signals from the rhythmic ones by tracking the heart signal and matching it with already present normal heart signal.

In a highly populated country like India, a major portion of the population suffers from cardiac diseases and stays deprived of proper health care. There is a shortage of trained medical specialists, poor access to diagnostic devices and a supply chain infrastructure that is unable to provide sufficient calibration and maintenance of medical equipment.

So, here we show how by the help of computer aided system the cardiac problems can be addressed and to detect any cardiac issue the firast and foremost thing is to differentiate between the normal and abnormal heart sound signals. Here we have done this using FFT, STFT and BPN.

6 Acknowledgment

Our study would not have been possible without the kind

ISSN 2229-5518

support and help of many individuals. The authors wish to thank all of them. We would like to express our gratitude towards our mentor and all the faculties of Institute of Engineering & Management for their kind co-operation and encouragement. Our thanks and appreciations also go to the fellow classmates who have willingly helped us when needed.

7 REFERENCES

[1] Amandeep Cheema and Mandeep Singh, "Steps Involved in Heart Sound Analysis-A Review of Existing Trends," *International Joural of Engineering Trends and Technology(IJETT),* vol. 4, issue 7, pp. 2921-2925, July 2013.

[2] Prakash D,Uma Mageshwari T,Prabakaran K and Suguna A, "Detection of Heart Diseases by Mathematical Artificial Intelligence Algorithm Using Phonocardiogram Signals," *International Joural of Innovation and Applied Studies,* vol. 3, no. 1, pp. 145-150, May 2013.

[3] Ilias Maglogiannis, Euripidis Loukis, Elias Zafiropoulos and Antonis Stasis, "Support Vector Machine-based Identification of Heart Valve Diseases Using Heart Sounds," *Computer Methods and Programs in Biomedicine,* 95 (2009) 47-6I.

[4] Gautam Saha, "Analysis and Characterization of Phonocardiogram Signal for Diagnosing Valvular Heart Disease," unpublished.

[5] Robi Polikar, "The Engineer's Ultimate Guide to Wavelet Analysis-The Wavelet Tutorial," unpublished.

[6] Sumeth Yuenyong, Akinori Nishihara, Waree Kongprawechnon and Kanokvate Tungpimolrut, "A Framework for Automatic Heart Sound Analysis without Segmentation," *Yuenyong et al. BioMedical Engineering OnLine 2011, 10:13*, available at http://www.biomedical-engineering-online.com/content/10/1/13.