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A Signal Processing Module for the Analysis of Heart Sounds and Heart Murmurs

Faizan Javed[1], P A Venkatachalam[2] and Ahmad Fadzil M H

Signal & Imaging Processing and Tele-Medicine Technology Research Group, Department of Electrical & Electronics Engineering, Universiti Teknologi PETRONAS, 31750 Tronoh, Perak, Malaysia

E-mail: paruvachiammasai_venkatachala@petronas.com.my

Abstract. In this paper a Signal Processing Module (SPM) for the computer-aided analysis of heart sounds has been developed. The module reveals important information of cardiovascular disorders and can assist general physician to come up with more accurate and reliable diagnosis at early stages. It can overcome the deficiency of expert doctors in rural as well as urban clinics and hospitals. The module has five main blocks: Data Acquisition & Pre-processing, Segmentation, Feature Extraction, Murmur Detection and Murmur Classification. The heart sounds are first acquired using an electronic stethoscope which has the capability of transferring these signals to the near by workstation using wireless media. Then the signals are segmented into individual cycles as well as individual components using the spectral analysis of heart without using any reference signal like ECG. Then the features are extracted from the individual components using Spectrogram and are used as an input to a MLP (Multiple Layer Perceptron) Neural Network that is trained to detect the presence of heart murmurs. Once the murmur is detected they are classified into seven classes depending on their timing within the cardiac cycle using Smoothed Pseudo Wigner-Ville distribution. The module has been tested with real heart sounds from 40 patients and has proved to be quite efficient and robust while dealing with a large variety of pathological conditions.

1. Introduction

Heart Auscultation, defined as the process of interpreting acoustic waves produced by the mechanical action of heart is a non-invasive, low-cost screening method and is used as a fundamental tool in the diagnosis of cardiac diseases. It can provide valuable information concerning the function of heart valves and the hemo-dynamics of the heart and has high potential for detecting various heart disorders especially valvular problems. New advanced imaging techniques like EKG, MRI and CT although can provide more direct evidence but require expensive equipment, specialized technicians to operate, experienced cardiologists to interpret the results, high maintenance cost, a permanent place to be installed and generally require more resources to function properly. These requirements are usually met in advanced hospitals and are not suitable in homecare, in rural hospitals and rural as well as urban clinics [1]. Therefore in numerous cases the heart sound diagnosis is the possible economical and quick alternative to detect the heart condition under emergency conditions.

1 and 2 for correspondence.

Heart sound analysis by auscultation depends highly on the skills and experience of the listener. Despite the importance of auscultation the internal medicine and cardiology training programs underestimate the value of cardiac auscultation and the new clinicians are not well trained in this filed [2]. It has been reported that extremely high percentages (as much as 87 %) of patients referred to cardiologists for evaluation have benign heart sounds [3]. So a computer assisted system can help the general physician in coming up to a more accurate and reliable diagnosis at early stages and also can reduce unnecessary referrals of patients to expert cardiologists at a distant.

As part of our major effort towards developing a system for tele-diagnosing heart diseases, a signal processing module has been developed that can assist the general physicians. The module uses heart sound signals that are taken as input from an electronic stethoscope which can be made available to the primary healthcare units. These signals are then processed through embedded sophisticated signal processing algorithms before a final diagnosis can be made. The block diagram of the module is depicted in figure 1.

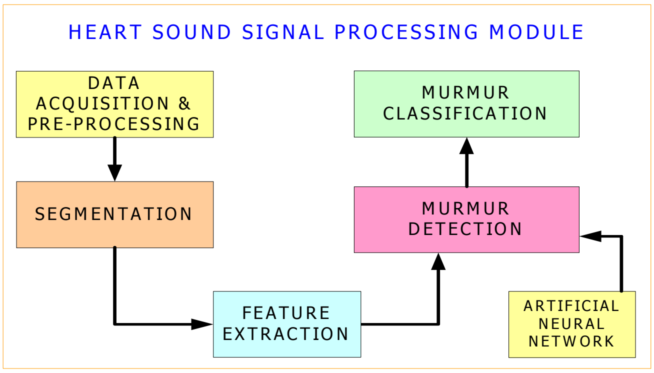
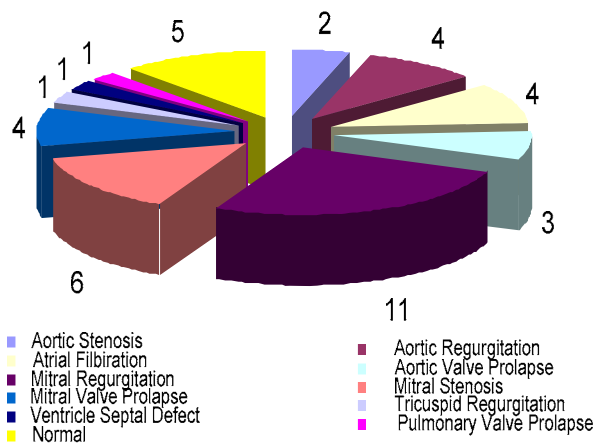


Figure 1: Block Diagram of Signal Processing Module

2. Methodology

2.1. Data Acquisition & Pre-Processing

The heart sounds were collected from Institute Jantung Negara (National Heart Institute) Kuala Lumpur and Hospital Fatimah Ipoh, Malaysia. The recordings were made using 3M Littmann Electronic Stethoscope for about 8 seconds each. A total of 40 patients aged from 16 to 79 years with various pathologies as shown in figure 2 were used in the current study. Patient's willingness to contribute in the study was taken in the form of written consent. Heart sounds were recorded in a quite room with assistance from the patients. No sedation was used. A Senior Cardiologist has listened to all the recording to assure good quality of recordings. The recordings were then transferred to the nearby workstation with wireless infra-red media. The recordings were saved in a **.e4k* format which is a propriety format by the manufacturer of the stethoscope (a 16 bit signed integer (little endian) code not recognized by common audio software [4]). The recordings were then transferred to **.wav* format using the software provided with the stethoscope. The software also saves the patient's information inside the wave file.



Note: Some patients has multiple pathologies as well

Figure 2: Distribution of Pathologies in data collected

The sounds were then digitized with a sampling rate of 8 KHz, 16 bits/sample. The digitized signal was then used as input to the segmentation algorithm.

2.2. Heart Sound Segmentation

The segmentation algorithm is based on the spectral analysis of heart sounds and separates the heart sound into individual cycles with each cycle containing First Heart Sound (S1), Systolic Period, Second Heart Sound (S2) and Diastolic Period in time. Most of the techniques used previously depend on the reference of ECG signal or/and carotid pulse for segmentation [5-7]. However to avoid the time synchronization of both heart sounds and ECG signal and to simplify the data collection procedure no reference signal was used. The main idea is that first the location of S1 and S2 were computed and then based on that information the location of systolic and diastolic periods were calculated. The whole algorithm was implemented in Matlab. The steps involved in the segmentation algorithm are shown in figure 3 [8] and its implementation on a real heart sound is shown in figure 4. Before wavelet decomposition and reconstruction the original signal was downsampled by a factor of four so that the details and approximations can result in frequency bands which contain the maximum power of S1 and S2 which in our case was d4, d5.

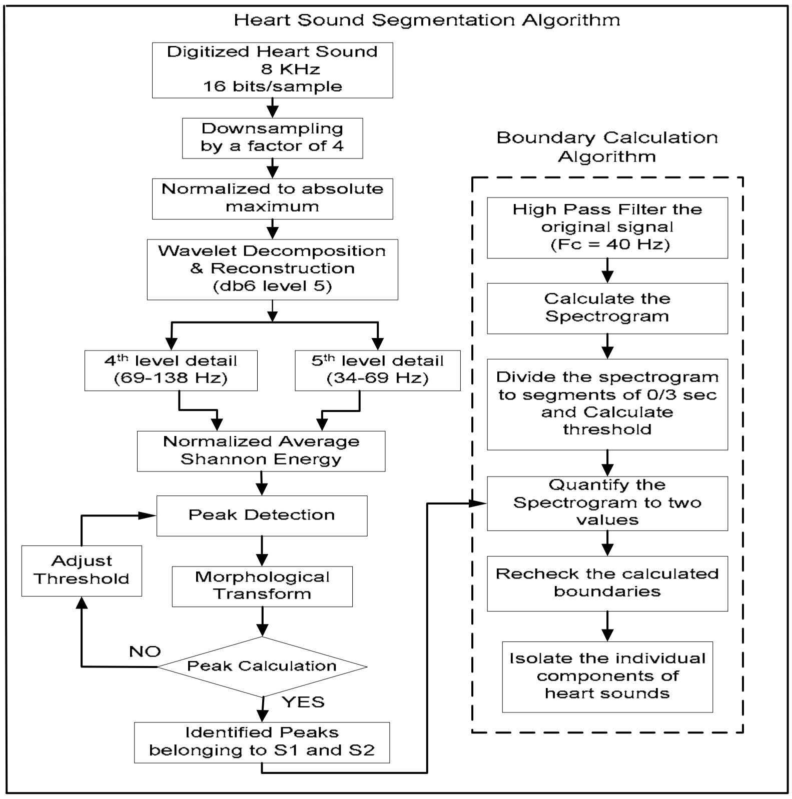


Fig 3: Steps involved in segmentation algorithm

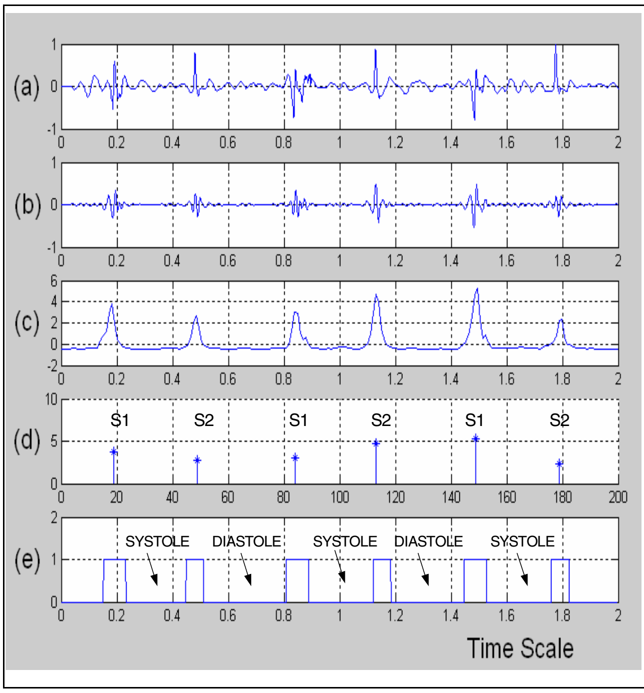


Figure4: Implementation of Segmentation Algorithm. (a) Original heart sound signal. (b) 5th level detail of the signal calculated by wavelet decomposition and reconstruction using dB6 (level 5) filter. (c) Normalized Average Shannon Energy. (d) Peaks belonging to S1 and S2. (e) Calculated boundaries of S1 and S2.

2.3. Feature Extraction using Spectrogram

The features are extracted from individual systolic and diastolic periods using Spectrogram which is a window based Fast Fourier Transform (FFT). Matlab command to calculate the windowed discrete-time Fourier transform using a sliding window called *specgram* was used in the current work. The Hanning Window which has smooth edges compared to rectangular window was used to prevent oscillations in the spectrum known as the Gibbs phenomenon. However due to smooth edges the Hanning window tapers the signal at the edges that eliminates important information present in the signal. Inorder to avoid this, the windows were overlapped by half the window length. Next the spectrogram was divided into 10 segments of equal length and the maximum amplitude in each segment was taken as a feature as shown in figure 5.

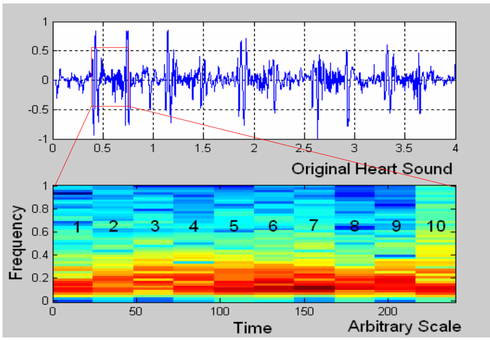


Figure 5: Feature extraction using spectrogram

In order to automate the whole feature extraction step, Matlab was linked with Microsoft Access. The features were then exported to the database directly.

2.4. Detection using Artificial Neural Networks

The Bio-medical Signals have a very complex and un-predictable characteristics so they cannot be modeled analytically in a straight forward manner and conventional signal processing methods are inappropriate for their processing and analysis. Neural Networks, with their inherent non-linear characteristics can provide a powerful framework for performing medical signal processing. Such non-linear signal processing helps to reveal hidden information in biomedical systems [9]. This has led to the integration of signal processing with intelligent techniques such as neural networks to improve performance [10].

Previous researchers have efficiently used the ANN for detecting and classifying the heart sounds and murmur but the network size being used was quite large that takes time for training and testing the system [10, 11]. In the current work a three layer perceptron neural network with 10 neurons in the input layer, 10 in the hidden layer and one in the output layer was used. The network detects the presence of murmur and the output is quantified to two values by using a threshold. A backpropagation learning algorithm based on a least mean square error in conjunction with a gradient descent technique was used. The network was trained using batch steepest descent function, that updates the weights and biases of the network only after all the training data has been provided. The goal and the learning rate were chosen carefully to optimize computational complexity while maintaining stability by hit and trial method.

2.5. Classification Using Smoothed Pseudo Wigner Ville Distribution

Due to the complex nature of heart sounds, the spectral contents are changing so rapidly that traditional time-frequency analysis techniques does not give good resolution. In the current work the application of Smoothed Pseudo Wigner Ville Distribution (SPWVD) was used which uses two windowing functions; one in time domain and other in frequency domain to suppress the interference terms in the WVD and defined as:

$$SPWVD_x[n,k] = \sum_m h[m] \sum_l g[l] * (x[n+m-l]\, x^*[n-m-l])\, e^{(-j4\pi km)} \quad (1)$$

Where *SPWVD[n,k]* is the SPWVD function, *n* is the time domain representation, *k* is the frequency domain representation, *h[m]* and *g[l]* are the windowing functions in time and frequency domain respectively, *x[n]* is the original signal and *x[n+m-l].x*[n-m-l]* is the bi-linear product of the *x[n]*.

3. Results & Discussion

3.1. Results and Discussion of ANN Prediction

A total of 120 individual systolic periods were used to train and test the ANN. The data was grouped into pathological and non-pathological cases. First half of the data was used to train the network and then the network was tested using full data. The results are shown in figure 6. The green circled areas are the misclassifications where the ANN misclassified the murmur. The red areas show a high fluctuation in the pathological cases, this is because any type of murmur no matter how severe, was used as a pathological case. These fluctuations can be reduced by further grouping the pathological murmur cases.

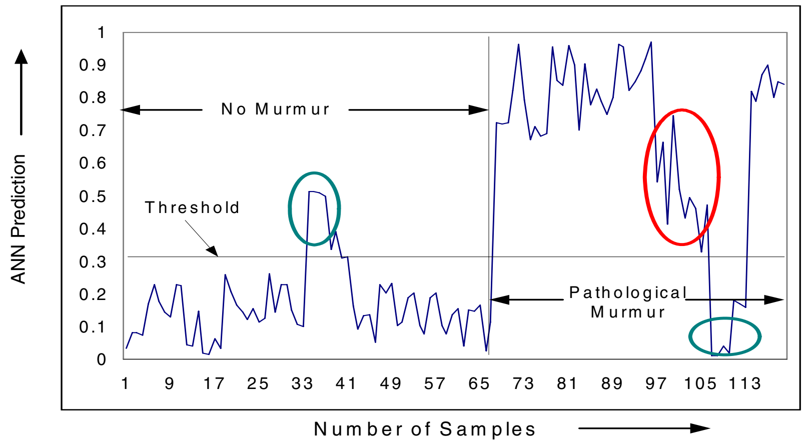


Figure 6 Results of ANN Prediction

Next to compare the performance of network accuracy, sensitivity and specificity defined in [10] were calculated and tabulated in table 1.

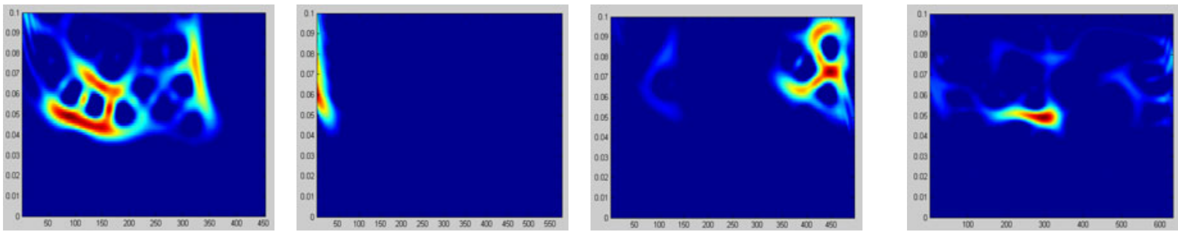
Table 1: ANN Performance

Performance Measure	Percentage
Accuracy	86.4
Sensitivity	85.1
Specificity	87.5

3.2. Results and Discussion of Classification Block

The individual systolic and diastolic periods on applying the SPWVD are shown in figure 7. Figure 7(a) and 7(b) show the systolic and diastolic periods of patient (PT124) suffering from VSD (Ventricle Septal Defect) respectively. The symptoms indicate Pan Systolic Murmur and No Diastolic Murmur. However there are some energy contents in the edges of Diastolic period that might be because of S2 since the boundary calculation algorithm was based on a relative measure of energy and not an exact value. However this problem can be avoided by using some tolerance factor while calculating the boundaries. Figure 7(c) and 7(d) show the systolic and diastolic periods of patient (PT118) suffering from Aortic Regurgitation/ Mitral Regurgitation (AR/MR) respectively. This is a case of multiple murmur and the symptoms indicate Pan Systolic Murmur followed by a quite loud Mid Diastolic Murmur.

The Classification block can classify the murmur into seven different classes depending on the timing of the murmur within the cardiac cycle as shown in table 2.



(a) (b) (c) (d)

Figure 7: Results of SPWVD

Table 2: Classified Groups

Systolic Murmur	**Diastolic Murmur**
Early Systolic (ESM)	Early Diastolic (EDM)
Mid Systolic (MSM)	Mid Diastolic (MDM)
Late Systolic (LSM)	Late Diastolic (LDM)
Pan Systolic (PSM)	

The collected data was grouped in the above mentioned classes and is shown in figure 8.

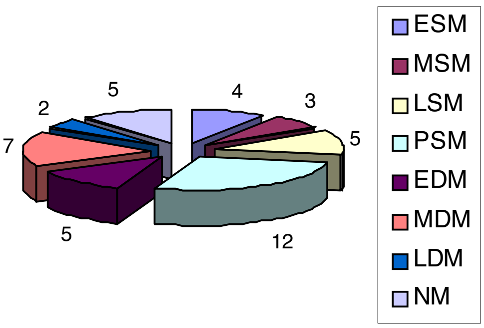


Figure 8: Murmur cases in grouped form

Some of the patients had multiple murmurs which are also added separately in the grouped form.

3. Conclusions

A Signal Processing Module which will get the tele-signal from an electronic stethoscope has been developed. A general physician can interact with the module and get quick preliminary diagnosis of heart problems of patients who cannot be easily shifted to advanced hospitals which are at a distance and also who cannot afford high consultation fee and traveling cost. The Module has a provision of extracting information at the end of every step instead of working as a black box to the user. Such module will be a step towards the development of efficient medical care. It will overcome the deficiency of expert cardiologist in both urban and rural areas.

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