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HEART SOUND MONITORING SYSTEM

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ABSTRACT

Cardiovascular disease (CVD) is among the leading life threatening ailments [1] [2] .Under normal circumstances, a cardiac examination utilizing electrocardiogram appliances or tools is proposed for a person stricken with a heart disorder. The logging of irregular heart behaviour and morphology is frequently achieved through an electrocardiogram (ECG) produced by an electrocardiographic appliance for tracing cardiac activity. For the most part, gauging of this activity is achieved through a non-invasive procedure i.e. through skin electrodes. Taking into consideration the ECG and heart sound together with clinical indications, the cardiologist arrives at a diagnosis on the condition of the patient's heart. This paper focuses on the concerns stated above and utilizes the signal processing theory to pave the way for better heart auscultation performance by GPs. The objective is to take note of heart sounds in correspondence to the valves as these sounds are a source of critical information. Comparative investigations regarding MFCC features with varying numbers of HMM states and varying numbers of Gaussian mixtures were carried out for the purpose of determining the impact of these features on the classification implementation at the sites of heart sound auscultation. We employ new strategy to evaluate and denoise the heart and ecg signal with a specific end goal to address specific issues.

Keywords: heart sound, HMM, MFCC, heart murmurs.

INTRODUCTION

Cardiovascular disease (CVD) is among the leading life threatening ailments [1][2].Under normal circumstances, a cardiac examination utilizing electrocardiogram appliances or tools is proposed for a person stricken with a heart disorder. The logging of irregular heart behaviour and morphology is frequently achieved through an electrocardiogram (ECG) produced by an electrocardiographic appliance for tracing cardiac activity. For the most part, gauging of this activity is achieved through a non-invasive procedure i.e. through skin electrodes. Taking into consideration the ECG and heart sound together with clinical indications, the cardiologist arrives at a diagnosis on the condition of the patient's heart. This paper focuses on the concerns stated above and utilizes the signal processing theory to pave the way for better heart auscultation performance by GPs.

The objective is to take note of heart sounds in correspondence to the valves as these sounds are a source of critical information. Comparative investigations regarding MFCC features with varying numbers of HMM states and varying numbers of Gaussian mixtures were carried out for the purpose of determining the impact of these features on the classification implementation at the sites of heart sound auscultation.

Data acquisition and pre-processing

Heart sounds are gathered from hospitals, clinics and a range of other establishments. An electronic stethoscope is utilized for a period of one minute to document these sounds. This stethoscope is appropriate for the reading of body sounds as it is equipped with sensors that have an elevated frequency response. The recordings are conducted in a WAV arrangement utilizing the software language (Meditron) that comes with the stethoscope. In the course of our endeavour to generate a procedure for heart sound analysis, a signal processing module that can prove to be useful to GPs was developed. The block illustration of this module is displayed in Figure-1.

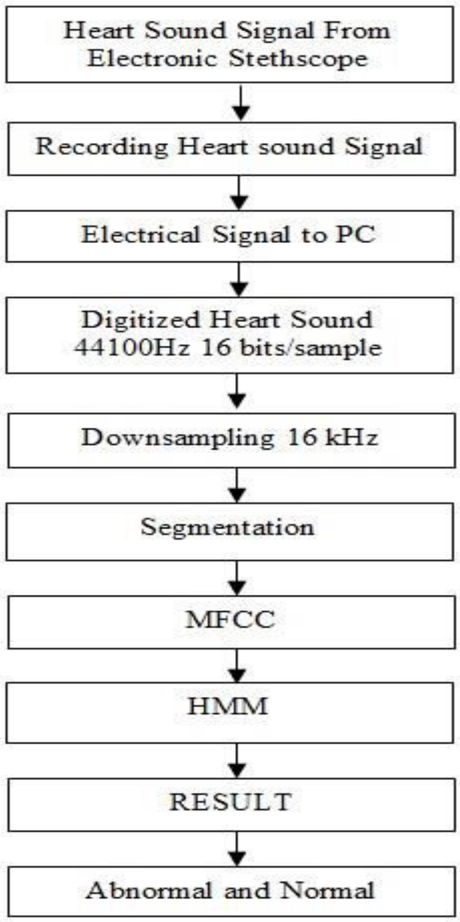

Figure-1. The flowchart of the Heart mumur analysis.

Segmentation

The segmentation algorithm is derived from the spectral analysis of heart sounds. This algorithm breaks up the heart sounds into separate cycles with every cycle comprising First Heart Sound (S1), Systolic Period, Second Heart Sound (S2) and Diastolic Period in time. For the most part, segmentation methods employed in the past were reliant on the reference of the ECG signal or/and the carotid pulse [3] [4].

Feature extraction

Heart murmurs are an indication of valvular disorders. More often than not, this ailment identified by way of an investigation into the spectral trait of the heart sound. Data related to amplitude and timing is significant as it reveals occurrences that are relevant to the causal activity of the heart. A variety of procedures have been adapted by investigators in this sphere to deal with the abovementioned predicaments. Among them are the wavelet based approach [5] [6][7] and the time frequency technique. These procedures were employed for the segmentation of the signals.

These researchers utilized short windows for the purpose of isolating signal discontinuities and long windows to acquire a comprehensive frequency breakdown to pave the way for feature extraction. A portrayal of heart sounds is made available through a set of cepstrum coefficients. For this study,mel-frequency ceptrum coefficients (MFCCs) were utilized as the feature depiction of the heart signal.In the past, MFCCs were mostly implemented in the speech processing but due its ability to remain robust when subjected to a range of adverse situations, MFCCs have consistently delivered outstanding result [8][9].MFCCs were then computed by taking a discrete cosine transform (DCT) of the logarithmic spectrum scale subsequent to its warping to the Mel scale [10].

$$mel(f) = 2595\log(1 + f / 700) \quad (1)$$

In order to attain a superior quality heart sound, a number of issues need to be taken into account. Among them are the need for a quiet workplace and setting for exclusion of background noises. The objective of this endeavour is to conduct a Heart Murmur Analysis for identification of heart sound irregularities. The unprocessed data are compressed 10 efficient for each frame prior to diagnosis at a research centre UTM.This procedure utilizes the mel-frequency cepstrum technique for the features of the heart sound.Eventually,the analysis is carried out at the research centre with employment of hidden markov model to train and distinguish the murmurs. The investigation utilized 12 MFCCs per frame for the execution of the categorization stage.

Hidden Markov model

The Hidden Markov model is recognized as an efficient instrument in the speech processing domain [11].The flexibility of this model for stochastic processes allows its employment for a wide range of biomedical signals. The Hidden Markov model was utilized by this study for the classification of heart disorders. Investigations on the impact of laryngeal ailments on the human voice have been on-going from the early 1960s [12].

According to a recent report, the application of the Hidden Markov Model can be highly effective for the diagnosis of heart disorders [13].The following are the parameters that distinguish the HMM:

i. $A = [a_{ij}]$, $1 \le i, j \le N$ the state transition matrix where aij is the probability of achieving a conversion from state i to state j.
ii . B the observation probability function related to each state j. The observation probability distribution of HMM is modelled through the uninterrupted probability density function (pdf), B = {bj(x)}, for 1≤ j ≤ N and x signifies the uninterrupted observations of the K-dimensional random vectors.
iii. Generally, a depiction of the pdf of HMM is a finite Gaussian mixture density of the form:

$$b_{jt}(O_t) = \sum_{m=1}^{M} d_{jm} N(O_t, U_{jm}, C_{jm}), 1 \le j \le N \quad (2)$$

where O_t is the vectors (in this situation, MFCCs) being modelled, C_{jm} is the mixture coefficient for the mixture component in state. N represents the typical density (Gaussian) given by U_{jm} and ∑jm are the mean vector and covariance matrix related to state j and mixture m.

$$N(O_t, U_{jm}, \Sigma_{jm}) = \frac{1}{\sqrt{(2\pi)^n |\Sigma_{jm}|}} \exp\left\{-\frac{1}{2}(O_t - Ujm)^T \sum^{-1}(O_t - Ujm)\right\} \quad (3)$$

Filtering technique

The filtering techniques are primarily used for pre-processing of the signal and have been implemented in a wide variety of systems for ECG and Heart Sound analysis. Filtering of the ECG and Heart Sound is contextual and should be performed only when the desired information remains ambiguous. Many researches have worked towards reduction of noise in ECG signal. Most types of interference that affect ECG signals may be removed by band pass filters; but the limitation with band pass filter is discouraging, as they do not give best result. At the same time, the filtering method depends on the type of noises in ECG signal [14].

Unfortunately, the heart sound also prone to noise interference, either internal (e.g. physiological noises) or external (e.g. surrounding noises). Noise sources exhibit very complex time-frequency characteristics. Furthermore, due to time-varying propagation routes inside the thorax, these sources tend to mix in highly complex ways with the heart sound [15]

Biomedical signal are often affected and corrupted by various types of noise and artifact. Any image, pattern, or signal other than that of interest could

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be termed as interference, artifacts or simply noise. For example ECG signal due movement of the patient muscle. Usually the alternative using filtering technique for removing noise and interference are important to medical practice [16], [17].

In order to be successful, any noise removal procedure for biomedical signals must be adaptive, i.e., it must track the changing signal characteristics. In some signals the noise level is very high and it is not possible to recognize it by single recording, it is important to gain a good understanding of the noise processes involved before one attempt to filter or pre-process a signal. The ECG and Heart Sound signal is very sensitive in nature, and even if small noise mixed with original signal the characteristics of the signal changes. Data corrupted with noise must either filtered or discarded, filtering is important issue for design consideration of real time heart monitoring systems.

The application of digital filters on heart sound signals provides an overview of the behavior of these to the output of digital filters. A part of this work is to apply methods of Kalman filtering on the heart sound signals with the objective aim to make possible discrimination between heart sounds for abnormal and normal.

Kalman Filter is essentially a set of mathematical equation that implement a prediction type estimator that is optimal in sense that minimize the estimated error covariance-when its required has meet its objective. Hypothetically, the Kalman channel is an estimator for what is known as the direct quadratic problem, which is the issue of evaluating the immediate "state"(a idea that will be made more exact in the following chapter)of straight element framework overturned by background noise utilizing estimation directly identified with the state yet adulterated by repetitive sound. The resulting estimator is statistically optimal with respect to any quadratic function of estimation error. Practically, the Kalman filter is one of the greater discoveries in the history of statistical estimation theory and possibly the greatest discovery in the twentieth century [18] [19].

The Kalman Filter utilizes a parametric portrayal of probility appropriation of estimation mistake in deciding the ideal sifting picks up, and this likelihood dispersion might be utilized as a part of surveying its execution as an element of the "configuration parameter" of an estimation framework, for example[20]:

- The sorts of sensors to be utilized
- The area and introductions of the different sensor sorts as for framework to be assessed
- The allowable noise characteristic of the sensor
- The prefiltering methods for smoothing sensor noise.

The use of Kalman separating envelop numerous field, but its utilization as an instrument is only for two purpose: estimation and execution investigation of estimators. The Kalman channel permits us to appraise the condition of element framework with specific sorts of arbitrary conduct by utilizing such factual information.

Generally, the filters' performances are naturally reliant on the past information associated with the statistical features of the signal and the background noise. Nonetheless, to denoising measurable heart sound, this study proposes Kalman Filtering. Keeping in mind the end goal to take after first request.

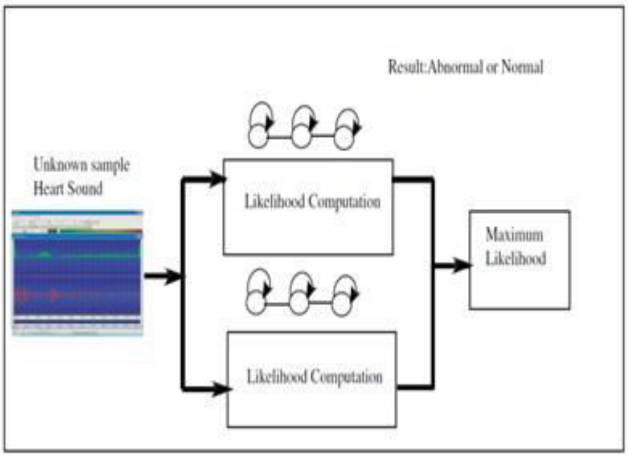

Figure-2. Training and testing for heart sound classification.

Gaussion Markov prepare, the cycles of heart sounds are ensured. These cycles are seen with additional clamor for the predefined estimation.. The model is expressed in state space form to allow use of Kalman filter to assess the clean cycles of heart sounds. The guesstimates acquired by Kalman Filter are optimum in a mean squared sensor. [21][22]The Kalman Filter address the general issue estimating the statex of a discrete heart signal that is governed by the linear stochastic difference equation [23].

$$y_k = Ay_{k-1} + V_{k-1} \tag{4}$$

$$Z_k = Ay_k + V_k \tag{5}$$

The random variable W_k and Z_k represent the process and measurement noise (respectively).They are assumed to be independent(of each other),white and with normal probability distribution.

$$p(w) \sim N(0,Q) \tag{6}$$

$$p(v) \sim N(0,R) \tag{7}$$

In practice, the process noise covariance Q and measurement noise R matrices might change with each time or measurement, however we assume they are constant. The measurement noise here is the heart sound signal. The process noise takes into account the inaccuracies due to state transform model is completely unknown and uncertainty incorporated because of the process models. The state x here is weight which multiplied with the heart sound samples gives the desired heart sounds [24].

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DISCUSSION AND RESULT

Analysis of Heart Sound classification

Table-1. Average gaussion mixture model for different state.

	No of Gaussion mixture components					
S/GM	1	2	4	6	8	16
State 1	94%	98%	97%	95%	97%	94%
State 2	88%	98%	95%	95%	99%	88%
State 3	93%	94%	99%	98%	100%	93%
State 4	99%	96%	96%	98%	99%	99%
State 5	97%	99%	99%	100%	99%	97%

Figure-2 displays the preparation and classification process for the generation of the heart sound signals. Utilizing MFCC with 12 coefficient facets, an arrangement with each HMM comparing to a specific heart disease is produced.

This study involved the manual segmentation of 754 cycles corresponding to 5 kinds of heart disorders, namely, mitral reguration, mitral valve prolapse, diastolic dysfunction grade 2, systolic murmurs and tricuspid reguration. The training set for normal and abnormal cycles comprise 240 and 250 cycles while classification entails 104 and 160 cycles (refer to Table-2).

Table-2. Training data for normal and abnormal.

Training	Normal	Abnormal
1	50	50
2	50	50
3	40	50
4	50	50
5	50	50
Total Cycle	240	250
6	21	60
7	32	34
8	11	8
9	11	38
10	29	20
Total Cycle	104	160

Comparative tests were conducted with regard to varying parameter values of MFCC feature extraction analysis, varying quantity of HMM states and varying gaussion mixtures to examine the impact of these elements on the classification process. Table-1 depicts the characterization results in regards to the HMM states (S1, S2, S3, S4, S5) with every line delineating the quantity of mixtures (1, 2, 4, 8, 16).

The highest level of achievement was realized with the number of the mixture model set at 16 and state 3. The accuracy level peaked at 100% while the lowest level was observed to be 88%. Table-3 displays the average computation of varying gaussion mixtures for each state. The peak percentages for each state are as follows: 97% for state one, 99% for state two, 100% for state three, 99.56% for state four and 100% for state 5.

Table-3. Patient data.

Name: Patient 1
Data Type: Heart Sound
Total Cycle :79
Average per cycle: 5
Averaging = 79/5 = 15.8 =15
Averaging 5 cycle first

Analysis of Heart Sound filtering

Averaging and wavelet in GUI was developed with the utilization of Matlab toolbox. As can be observed, although the procedure led to a reduction in noise, it was left wanting in its capacity for filtering. More in-depth studies are required for the generation of a high-quality filtration procedure.

Conversely, the wavelet filters extend the sum energy of the low pass filtered signal in the decomposing procedure. Apparently, as illustrated in the figure above, the propagation of energy occurs at low frequencies while at elevated frequency levels energy is essentially decreased when compared to orthogonal filters of a similar length [25], [26].

In the case of discrete wavelet transform, the signal is initially decomposed into a predetermined number of levels with each level holding its individual particulars and approximation coefficients.

A 3-level bior5.5 wavelet decomposition method is employed to denoise the heart sound signal. This is achieved through the mining of the third level approximation coefficients and the reconstruction of the heart signal with the utilization of just these coefficients. This test was conducted in a MATLAB setting [27], [28].

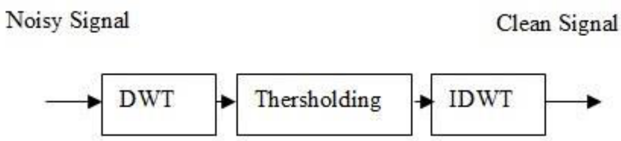

Figure-3. A 3 level bior5.5 wavelet.

The software, which includes averaging, wavelet, kalman filter and wavelet kalman filter, has the capacity to load ECG and heart sounds.

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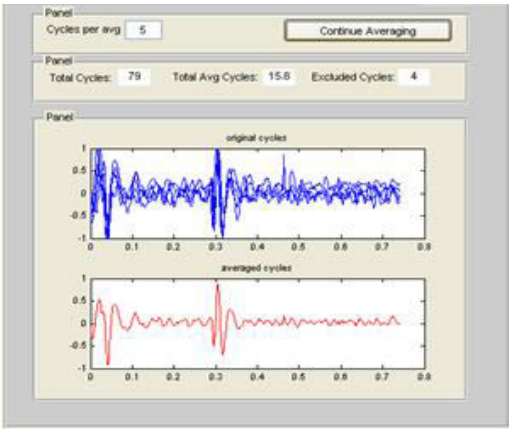

Figure-4. The heart signal before averaging (blue) and averaging (red).

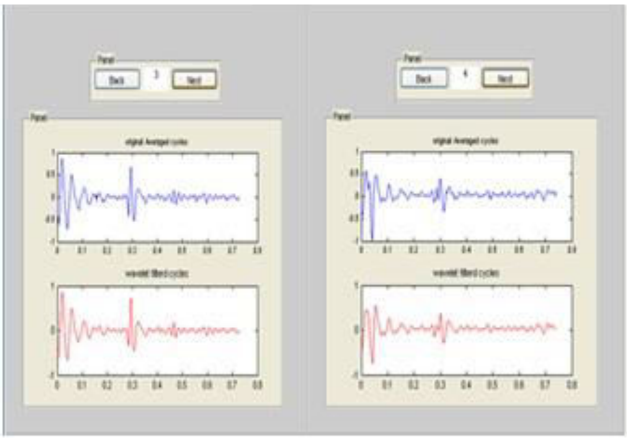

Figure-5. Cycle 1 and 2 wavelet transformation.

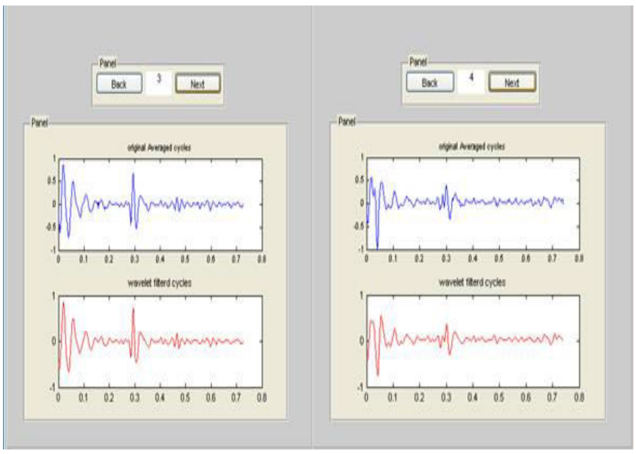

Figure-6. Cycle 3 an d 4 wavelet transformation

The result exhibited above portrays the heart sound data of a normal patient and Table 4 shows the detail heart sound information of the patient data. The averaging of every 5 cycles out of 79 cycles will result in a total amount of 15 cycles. Figure-4 exhibits the general primary signal before averaging (blue), and after averaging (red). The standings of 4 cycles that were subjected to wavelet transform can be observed in Figures-5 and 6. The amplitude of the signal reveals that it had been diminished.

RESULT ON KALMAN FILTER

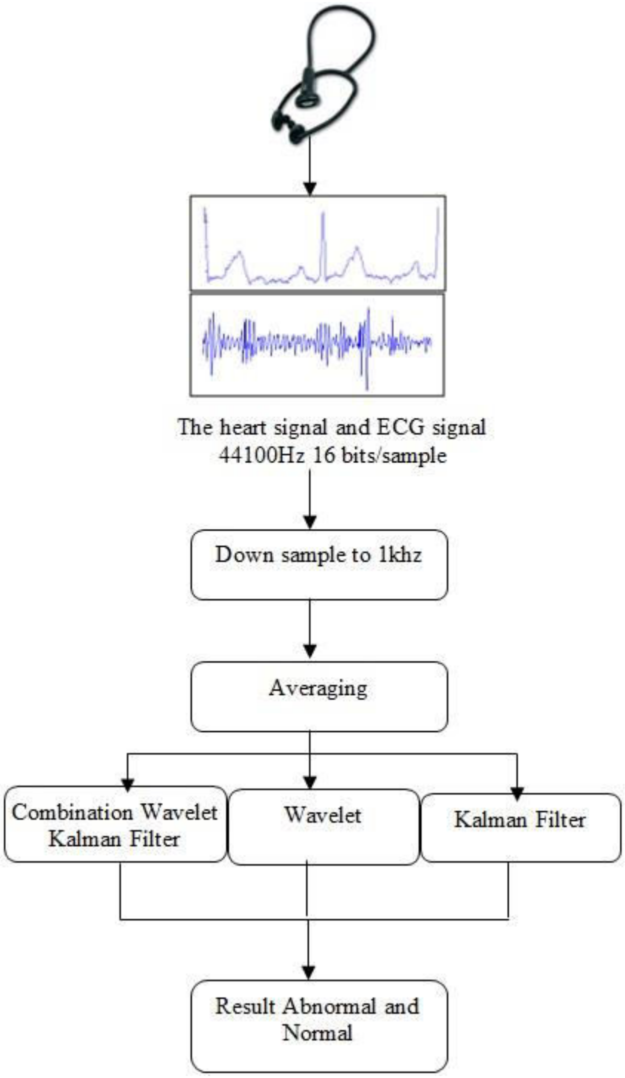

Figure-7. Filtering framework on Heart Sound and Ecg.

Figure-7 shows the extension of the work raw ECG and Heart Sound which goes through the different denoising process.

The signal is process with three different filter which include the wavelet analysis, kalman filter and the combination of wavelet and Kalman Filter. Three filters are capable of giving reliable estimate of the processed signal.

Figure-8 and 9 shows signal recorded for patient 1 with abnormal heart sound and ECG respectively. Figure-10 and 11 on the other hand shows another patient 2 with normal heart and Ecg signals. The same characteristic of the signal can be observed from the two patients. The averaged signal as well as the wavelet

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technique resulted in some shrink of several factor in amplitude. On the other when applying kalman filter and wavelet kalman filter significant shrink of several factor with amplitude can be clearly visible.

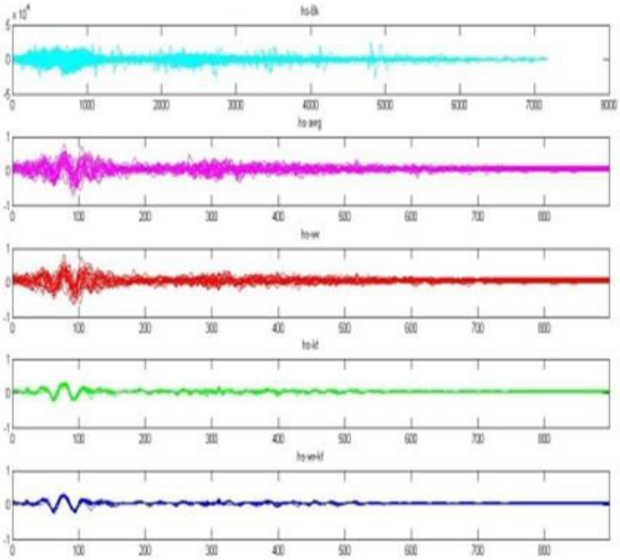

Figure-8. Patient 1 Abnormal heart sound.

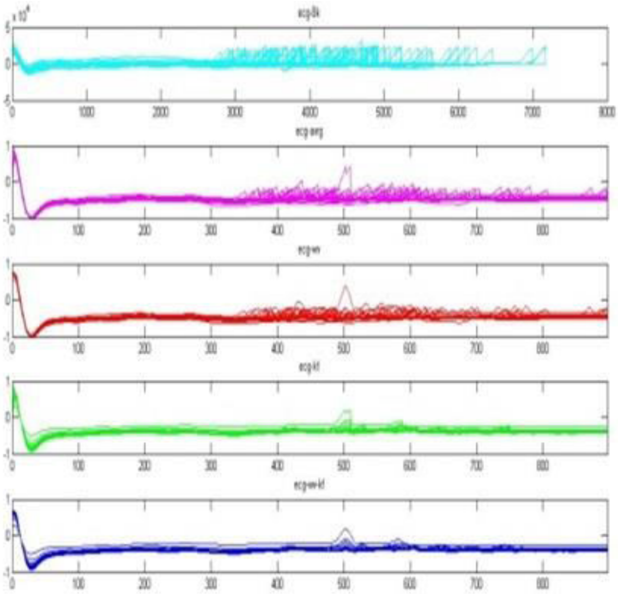

Figure-9. Patient 1 Abnormal Ecg.

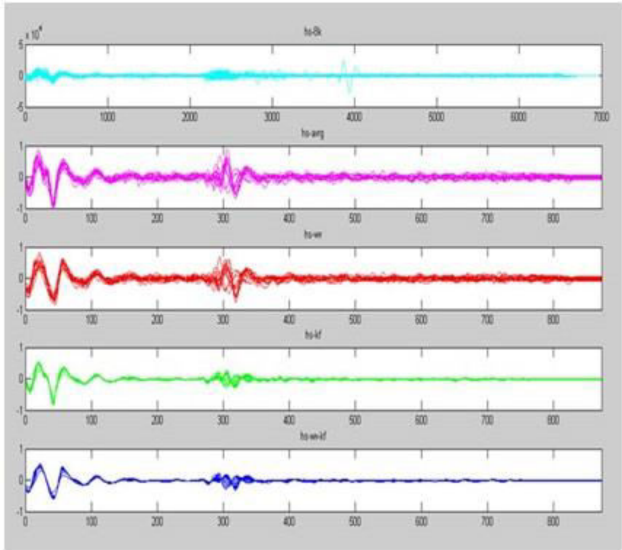

Figure-10. Patient 2 Normal heart sound.

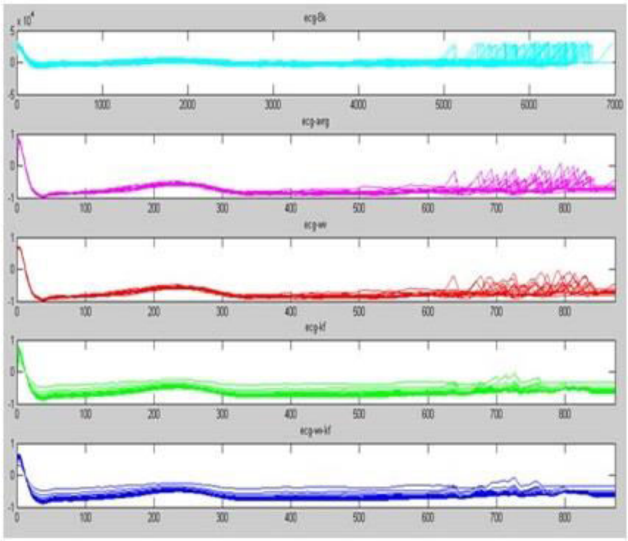

Figure-11. Patient 2 Normal Ecg.

However, care must be taken to understand the amount of shrink on the amplitude since too much filtering can cause useful information to taken out and classification of murmurs would not successful. Also if the noise signal was not properly removed, it would affect significant to performance of the classification process. Thus there is a need to study these methods to increase the SNR and obtain a meaningful result in order to increase the performance of the heart sound classification.

CONCLUSIONS

Heart signals are obtained through the utilization of an acoustic stethoscope. A wide range of methods are utilized in this area for the reading of acoustic cardiac signals. Gauging the effectiveness of classification can prove to be a formidable undertaking due to the extensive variety of heart murmur and the wide selection of classification techniques. Taking these issues into consideration, it was decided that this study be confined to identifying the disparities between normal and abnormal heart sound murmurs. This research offers an assessment of various processing units that are currently available for fixed classification and extraction. The parameter values from MFCC testing were scrutinized to establish the impact of these elements on operations related to telemedicine On the other hand the Kalman filtering technique is for detection and extraction of periodic noises. The study exhibited in this research affirms that the standard Kalman Filter definition can likewise adapt to the circumstances unknown and/or varying frequency components are encountered**.**

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