# EFFICIENT DENOISING, ALIGMENT AND SEGMENTATION ALGORITHM FOR MULTIVARIATE HEART SOUND DIAGNOSTIC

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# DEDICATION

This thesis is dedicated to my family, who have always loved me unconditionally and whose good examples have taught me to work hard for the things that I aspire to achieve.

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## ABSTRACT

Heart auscultation is still the most commonly used method for diagnosing heart diseases caused by heart valve abnormalities, but it is highly subjective and heavily relies on the interpretation of physicians. Pattern recognition techniques have been applied to biomedical data (heart sound) provide high performances in terms of its accuracy, time complexity, and allowing clinicians to make a better decision for early diagnosis. Thus, it would be very desirable to develop a Efficient Denoising Alignment And Segmentation Algorithm For Multivariate Heart Diagnostic (DAS-HD) that could provide objective diagnostic results. Heart sound processing algorithms are not completely robust in the presence of noise, requiring clean segments of heart sounds to extract reliable features. Hence, this thesis presented a new approach to detect noises interference from heart sound. The majority of the filters did not only remove the noisy samples, but also the clean training samples that were incorrectly classified using different types of filtering, thus, lowering the system's accuracy. The purpose of this study was to investigate different filtering techniques which exploited non-stationary heart sound signals. This study examined the classification performance of an Mel Frequency Cepstral Coefficient (MFCC) based on Hidden Markov Model (HMM) heart sound signals by varying the model's number of states, the number of mixtures, and analysis of a few filtering techniques to obtain clean heart sound. DAS-HD of Framework 1 performance at Location 3 (tricuspid), displayed a total performance of 90.1%, while the worst result was noted for Location 4 (mitral), having an overall performance of 91%. In Framework 2, the DAS-HD framework with a focus on heart sound denoising, segmentation, and information retrieval for pathology detection and classification was enhanced. The proposed Kalman, Wavelet, and Kalman-Wavelet filtering as a pre-processed signal to evaluate system performance based on MFCC, and Gaussian mixture model classifier showed improvement of performance for the DAS-HD. Comparing the three types of filtering, the Wavelet-Kalman filter showed the highest percentage accuracy of 95.4% at location 3 Tricuspid with state 5 of 16 GMM. Different locations with different types of filters will give different accuracy performance. The previously suggested approach had superior performance in estimating single-trial signals. The limitation of the univariate models of Framework 1 and Framework 2 was that the process included only correlation in time precedence of the signal, while the correlation between multi auscultation points was ignored. The inter-regional could not be assessed directly from the univariate model. The work proposed a new approach of DAS-HD (Framework 3) which used State-Space Model (SSM) with Time-Varying Vector Autoregressive (TV-VAR). The inter-regionals correlation was suspected to discriminate between the 4 auscultation points in which the models could measure the synchronization and coherency between the auscultation regions. Based on the comparison between these two different feature extraction performances, TV-VAR produced a better overalls performance compared to MFCC. The best percentage accuracy, sensitivity, and specificity for TV-VAR were 99.5%, 100%, and 99.48% respectively which was more significant than MFCC performance. However, even though the computation and complexity of the TV-VAR model of Framework 3 were higher than MFCC-model Framework 2, the performance improvement on its accuracy, sensitivity, and specificity was significantly better.

# ABSTRAK

Auskultasi jantung merupakan kaedah konvensional yang digunakan untuk mendiagnosis penyakit jantung yang disebabkan oleh keabnormalan injap jantung, tetapi ia sangat subjektif dan bergantung pada tafsiran doktor. Teknik pengecaman corak telah diaplikasikan pada data bioperubatan (bunyi jantung) yang mampu menghasilkan keputusan yang lebih baik dari segi ketepatan, kerumitan masa dan seterusnya membantu doktor dalam mengdiagnosis pesakit pada peringkat awal.Oleh itu adalah suatu kewajaran untuk membangunkan Pelbagai Diagnostik Jantung Berdasarkan Algoritma Kecekapan Penjajaran Hingar dan Segmentasi (PAKJD) yang dapat memberikan hasil diagnostik objektif. Algoritma pemprosesan bunyi jantung tidak teguh sepenuhnya dengan kehadiran hingar memerlukan segmen bunyi jantung yang bersih untuk mengekstrak ciri yang boleh diandai. Oleh itu, kajian ini membincangkan pendekatan baharu untuk mengesan gangguan bunyi daripada bunyi jantung. Majoriti penyaring bukan sahaja mengalih keluar sampel yang hingar, tetapi juga sampel yang tepat yang dikelaskan secara salah menggunakan penapisan berkelompok, dan dengan itu ia menurunkan ketepatan sistem. Tujuan kajian ini adalah untuk mengkaji teknik penapisan berkelompok yang mengeksploitasi isyarat bunyi jantung yang tidak pegun. Kajian ini mengkaji prestasi klasifikasi Model Tersembunyi Markov (HMM) berasaskan Pekali Cepstral Frekuensi Mel (MFCC) dengan isyarat bunyi jantung melalui variasi kepelbagaian situasi dan keberadaan model, dan menganalisis beberapa teknik penyaringan untuk mendapatkan data bunyi denyutan jantung yang lebih tepat. Prestasi PAKJD Rangka Kerja 1 di Lokasi 3 (tricuspid), menunjukkan prestasi keseluruhan 90.1%, manakala hasil terendah dicatatkan untuk Lokasi 4 (mitral), dengan prestasi keseluruhan sebanyak 91%. Dalam Rangka Kerja 2, kerangka kerja PAKJD memberi tumpuan pada pengurangan gangguan bunyi pada denyutan jantung, segmentasi dan penjanaan maklumat untuk pengesanan dan pengklasifikasian patologi telah dipertingkatkan. Penyaringan Kalman, Wavelet, dan Kalman-Wavelet yang dicadangkan sebagai isyarat pra-pemprosesan untuk menilai prestasi sistem berdasarkan MFCC, dan penyaringan Model Gabungan Gaussian (GMM) menunjukkan peningkatan prestasi untuk PAKJD. Membandingkan ketiga-tiga jenis saringan, penyaring Wavelet-Kalman menunjukkan ketepatan peratusan tertinggi sebanyak 95.4% di lokasi 3 (Tricuspid) pada tahap 5 dengan 16 Model Gabungan Gaussian. Lokasi yang berlainan dengan pelbagai jenis saringan akan memberikan prestasi ketepatan yang berbeza. Pendekatan yang dicadangkan sebelum ini mempunyai prestasi lebih unggul dalam penganggaran isyarat percubaan tunggal. Keterbatasan model univariasi Rangka Kerja 1 dan Rangka Kerja 2 adalah proses itu hanya melibatkan korelasi dalam masa terdahulu, manakala korelasi antara multi-auskultasi diabaikan. Antara lokasi tidak dapat dinilai terus dari model univariasi. Kaedah baharu PAKJD (Rangka Kerja 3) yang disarankan menggunakan Model Ruang Keberadaan (SSM) dengan Autoregresif Vektor Variasi Masa (TV-VAR). Penyelarasan antara lokasi di dapati membezakan antara 4 titik auskultasi yang mana model boleh mengukur pergerakan dan koherensi antara lokasi auskultasi. Berdasarkan perbandingan antara kedua-dua persembahan pengekstrakan ciri yang berbeza ini, Autoregresif Vektor Variasi Masa menghasilkan prestasi keseluruhan yang lebih baik berbanding MFCC. Peratusan ketepatan, kepekaan dan kekhususan terbaik untuk Autoregresif Vektor Variasi Masa masing-masing ialah 99.5%, 100% dan 99.48% yang lebih penting daripada prestasi MFCC. Walau bagaimanapun, walaupun komputasi dan kerumitan model Autoregresif Vektor Variasi Masa bagi Rangka Kerja 3 adalah lebih tinggi daripada Rangka Kerja Model 2 MFCC , peningkatan prestasi terhadap ketepatan, kepekaan dan kekhususannya adalah jauh lebih baik.

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| | | |
|---|---|---|
| AB | - | Abnormal |
| ACF | - | Auto-correlation function |
| AF | - | Atrial fibrillation |
| AR | - | Auto-regressive |
| AV | - | Atroventricle |
| AC | - | Autocorrelation |
| ACS | - | Accurate Coronary Syndrome |
| BPF | - | Band-pass filter |
| CAD | - | Coronary artery disease |
| CHF | - | Chronic heart failure |
| CinC | - | Computing in cardiology |
| CNN | - | Convolutional neural network |
| CQA | - | Cycle quality assessment |
| CSC | - | Cost-sensitive classifier |
| CT | - | Central terminal |
| CV | - | Cross-validation |
| CWT | - | Continuous wavelet transform |
| CT | - | Computed Tomography |
| DFT | - | Discrete Fourier transform |
| DNN | - | Deep neural network |
| DAS-HD | - | Denoising, Aligment And Segmentation Algorithm Heart Diagnostic |
| DSP | - | Digital signal processing |
| DTW | - | Dynamic time warping |
| DWT | - | Discrete wavelet transform |
| DCT | - | Discrete Cosine Transform |
| EEMD | - | Ensemble empirical mode decomposition |
| EKF | - | Extended Kalman filter |
| ELM | - | Extreme learning machines |
| EM | - | Expectation maximization |

| | | |
|---|---|---|
| EMD | - | Empirical mode decomposition |
| ERBNN | - | Error backpropagation neural network |
| ERP | - | Event Related Potentials |
| ECG | - | Electrocardiogram |
| FFT | - | Fast Fourier transform |
| FHS | - | Fundamental heart sounds |
| FN | - | False negative |
| FT | - | Fourier transform |
| GM | - | Gaussian mixture |
| GMF | - | Gaussian mesa function |
| GMM | - | Gaussian mixture models |
| GOFR | - | Generalized orthogonal forward regression |
| GP | - | Gaussian process |
| GPU | - | Graphical processing unit |
| GSF | - | Gaussian smoothing filter |
| GUI | - | Graphical user interface |
| GP | - | General Practioners |
| HHT | - | Hilbert Huang transform |
| HMM | - | Hidden Markov models |
| HOS | - | Higher order statistics |
| HPC | - | High-performance computing |
| HR | - | Heart rate |
| HSMM | - | Hidden semi-Markov model |
| HT | - | Hilbert transform |
| HS | - | Heart Sound |
| HSS | - | Heart Sound Signal |
| Hz | - | Hertz |
| ICA | - | Independent Component Analysis |
| KF | - | Kalman filters |
| ME | - | Mixture of Expert |
| MFCC | - | Mel frequency cepstral coefficients |
| MI | - | Myocardial infarction |
| MRI | - | Magnetic resonance imaging |

| | | |
|---|---|---|
| MSAR | - | Markov switching auto-regressive |
| MVN | - | Multivariate normal |
| MVP | - | Mitral valve prolapse |
| MLP | - | Multilayer perceptron |
| MOH | - | Ministry Of Health |
| $M_1$ | - | Mitral component of $S_1$ |
| NB | - | Naive Bayes |
| NSR | - | Normal sinus rhythm |
| NN | - | Neural network |
| PCA | - | Principal component analysis |
| P wave | - | Part of ECG tracing that represents atrial depolarization |
| RA | - | Right arm |
| RF | - | Random Forests |
| RNN | - | Recurrent neural network |
| SKF | - | Switching Kalman filter |
| SKS | - | Switching Kalman smoother |
| SLDS | - | Switching linear dynamic systems |
| SQI | - | Signal quality index |
| SSM | - | State space models |
| STFT | - | Short-term Fourier transform |
| SVD | - | Singular value decomposition |
| SVM | - | Support vector machine |
| $S_1$ | - | First Heart Sound; produced by closure of Mitral ($M_1$) and Tricuspid ($T_1$) valves. |
| $S_2$ | - | Second Heart Sound; produced by closure of aortic ($A_2$) and pulmonic ($P_2$) valves. |
| $S_3$ | - | Third Heart Sound; created by vibrations caused by the rapid, passive filling of the ventricles.$S_3$ is abnormal in adults older than age 20. |
| $S_4$ | - | Fourth heart sound; generated by stretching and filling of ventricle during late diastole; associated with atrial contraction. |
| $S_1$ | - | First Heart Sound; produced by closure of Mitral ($M_1$) and Tricuspid ($T_1$) valves. |

| | | |
|---|---|---|
| $S_2$ | - | Second Heart Sound; produced by closure of aortic ($A_2$) and pulmonic ($P_2$) valves. |
| $S_3$ | - | Third Heart Sound; created by vibrations caused by the rapid, passive filling of the ventricles. $S_3$ is abnormal in adults older than age 20. |
| ST segments | - | Connects the QRS complex and T wave. The ST segment represents the period when the ventricles are depolarized present. |
| SA | - | Sinoatrial |
| SNR | - | Signal-to-noise ratio |
| $T_1$ | - | Tricuspid component of $S_1$ |
| T wave | - | Part of the ECG tracing that represents ventricular repolarization. |
| TN | - | True negative |
| TP | - | True positive |
| TFR | - | Time Frequency Resolution |
| WDV | - | Wigner Ville Distribution |
| VQ | - | Vector quantization |
| VSD | - | Ventricular septal defects |
| WHO | - | World health organization |
| WT | - | Wavelet transform |
| WVD | - | Wigner-Ville distribution |

## LIST OF SYMBOLS

| | | |
|---|---|---|
| $A$ | - | State space AR coefficients |
| $a_{ij}$ | - | Transition matrix of HMM model |
| $D$ | - | Dictionary matrix |
| $d_x$ | - | Dictionary atom with index $k$ |
| $dP$ | - | Viterbi state duration probabilities |
| $e$ | - | Exponential |
| $F$ | - | Fusion ECG beats |
| $Fs$ | - | Sampling frequency |
| $GM$ | - | Gaussian mixture |
| $O$ | - | Observation probability of HMM |
| $p$ | - | Auto-regressive model order |
| $Q$ | - | State covariance matrix |
| $QT_c$ | - | Corrected $QT$ interval |
| $R$ | - | Observation covariance matrix |
| $Q$ | - | State covariance matrix |
| $w_t$ | - | Gaussian state noise |
| $X$ | - | Sparse coefficient matrix |
| $x_k$ | - | Sparse coefficients vector of index $k$ |
| $x_t$ | - | Mean of Kalman filter prediction error |
| $y$ | - | Observation data EG/PCG |
| $Y$ | - | Multivariate ECG beats stack |
| $\beta$ | - | RR interval/duration factor |
| $\gamma_1$ | - | The first adaptive threshold for QRS detector |
| $\gamma_2$ | - | The second adaptive threshold for QRS detector |
| $\Delta$ | - | Slope maxima |
| $\hat{\sigma}$ | - | The Wavelet estimated noise variance |
| $\sigma_i$ | - | Gaussian standard deviation |
| $\delta$ | - | Viterbi state probabilities |
| $\mu_i$ | - | Gaussian mean |
| $\beta$ | - | RR interval/duration factor |
| $\varphi_p$ | - | Auto-regressive model coefficients |

| | | |
|---|---|---|
| $\varepsilon_t$ | - | Auto-regressive model error |
| $\Theta$ | - | MSAR model parameters |
| $\pi_0$ | - | Initial state probability |
| $\varphi_p$ | - | Auto-regressive model coefficients |
| sgn | - | Sign |
| $\lambda$ | - | HMM model parameters |
| $\mu_{jm}$ | - | Vector quantization Gaussian mixture mean |
| $\Sigma_{jm}$ | - | Vector quantization Gaussian mixture variance |
| $f_s$ | - | Sampling frequency |
| $\lambda$ | - | HMM model parameters |
| $a_{ij}$ | - | Probability Of making transition from state *i* to *j* |
| $N$ | - | State Transition |
| $O_t$ | - | Vector |
| $C_{jm}$ | - | Mixture Coefficient |
| $s[n]$ | - | Signal value at sample *n* |
| $N$ | - | Frame size |
| $a_{ij}$ | - | Probability Of making transition from state *i* to *j* |
| $l$ | - | Lag |
| $R_y$ | - | Average magnitude difference function value |
| X2 | - | Doubling error |
| $\sigma_v^2$ | - | State noise |
| $\sigma_w^2$ | - | Observation noise |
| S error | - | Standard deviation error |
| $f_H$ | - | Highest frequency |
| $F_H$ | - | Real value for highest frequency |
| $N_H$ | - | Consecutive number of the highest harmonic peak |
| $Q_N$ | - | the $K^{th}$ root of the multiplication of spectral coefficients (amplitudes) |
| L | - | Number of points used for the FFT |
| X(f) | - | Log spectrum |
| S(f) | - | Cepstral smoothed log spectrum |

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# CHAPTER 1

# INTRODUCTION

## 1.1 Introduction

When it comes to pattern recognition using deep learning, there are two major issues to consider. The first is feature selection.There is no guarantee that the features will be prominent in previously unseen data.Second, the selection of training data does not guarantee coverage of previously unseen data.Probability models, such as the Markov model and deep learning, have demonstrated superiority in computer-aided classification of heart sound signals, but it also faces some challenges .For starters, these models have far too many parameters, requiring a large amount of data to be optimised, a long and complex execution time, and a large training data set.Second, the modelling necessitates a more powerful computer configuration with a powerful CPU and GPU for calculation, which increase the experiment cost and renders the model unsuitable for home computers and microcomputers.However, portable heart sound devices have significant development potential as well as promising application prospects.At present, intelligent auscultation technology is not widely used in clinical diagnosis, and manual auscultation is the primary method for detecting heart sounds.As a result, the development and application of computer-aided techniques for heart sound detection based on pattern recognition will significantly advance the field of cardiovascular disease diagnosis.

Statistically, heart disease is regarded as one of the major mortality causes in the world and also the leading cause of death in Malaysia based on the National Health and Morbidity Survey 2011 which ranked the Coronary Heart Disease as the number one killer with 25.4% of the total mortality rate. Based on that, the Yayasan Jantung Malaysia stresses on the significant need for cultivating healthier lifestyle choice as to reduce the potential of suffering from cardiovascular diseases (Yayasan

Jantung Malaysia, 2014) (Kaur, 2020). It is rather alarming to see an escalating health care cost and increasing number of hospitalization which result in a mounting burden on healthcare system. Generally speaking, patients with heart problems need to undergo a cardiac test at the hospital by using the electrocardiographic device or instrument. The electrocardiogram (ECG) produced by an electrocardiographic device is a time varying signal reflecting the ionic flow which causes the cardiac valve to contract and subsequently relax. Moreover, a cardiologist after examination conducts a diagnosis that combines the ECG and Heart Sound (HS) with the clinical symptoms to take into consideration whether there has been an abnormality in the patient's heart condition. Auscultation is a vital diagnostic technique for heart disease, inexpensive and non-invasive, but greatly reliant on the experience and expertise of the listener General Practioner.

Thanks to the advancement of technology, the world can witness the introduction of new complex diagnostic modalities like echocardiography and chest x-rays, phonocardiography (PCG), MRI and FMRI and other diagnostic techniques which positively improve the field phonocardiography. Besides that, the apparent lacking in the teaching of asuculation by medical schools and accuracy of heart sounds and murmur identification has also led to the development of such new modalities (Kaphingst, 2010). Generally, it is known that there are some limitations found in use the conventional mechanical stethoscopes in studying the phonocardiogram (PCG) whereby such stethoscopes cannot store and playback sounds and visual display, and is unable to process the acoustic signal. The presence of PCG CAD systems in the design of new electronic stethoscopes helps to tackle the drawbacks faced as the intelligent Computer Aided Diagnosis (CAD) system is proven to improve the physician diagnostic abilities and lessen the time taken for performing precise diagnosis (Nabih-Ali, 2017).Even though they improve accurateness of diagnosis is usually performed by employing the electrocardiogram, computed tomography scan and magnetic resonance imaging, unfortunately these tools require considerable investment costs that are only available in big hospitals. Therefore, there is a need to support the development of CAD auscultation technique that is inexpensive and capable of improving the reliability and accuracy of diagnosis on initial stages as proposed by this author. In order to recognize and classify the heart sound signal (HS) advanced methods such as signal processing and filtering technique are used. The heart signal (HS) reveals information regarding cardiac function via vibrations instigated by the working heart. The data modalities can be found in the form of time series containing the dynamics heart activities which is important for diagnosing and monitoring different types of heart murmurs. In normal practice, the data is presented as single recording, but the multi-dimensional recording such as multichannel HS signal from different location provides an advantage to produce a new improved diagnostic aid which forms the motivation behind the work in this thesis.

It is normal for the low and high amplitudes of HS signal to be obscured by varied arficats and background noises originating either from physiological or technical origin. The causality effects that one region say the first heart sound (S1) which is resulted from closure of the atrioventricular (mitral and tricuspid) has on another region, the second heart sound (aortic and pulmonary) sound within the four valves is imperative to be analysed from the observed signals in order to understand the fundamental physiological process of the heart during particular circumstances. Therefore, this thesis strives to propose an intelligent computer aided denoising alignment and segmentation heart diagnostic (DAS-HD) with efficient multivariate modelling that caters dynamics heart sound signals with the presence of noise and artefacts.However, in heart sound recordings, the noise is a key problem. The sensor, the auscultation area, the sensor contact surface, the position of the patient, the background noise and the respiration phase all impact the sound quality. This in practice means that the recordings often contain noise, for example, rumbling sounds from the stomach, friction rubs, background noise from the clinical environment and respiratory sounds from the lungs. Therefore, this study aims to improve the operational efficiency with specific focus on the heart sound denoising, segmentation information retrieval for pathology detection and classification. However, for the techniques mentioned to work effectively and produce great result, they heavily rely on the quality of the heart analysis sound. As such, through the adaptation of the noise detection algorithm, this study attempts to conduct noise detection for heart sound analysis which is found to be greatly contaminated by various sources. This adaptation aims to improve the quality of the heart sound analysis through substantial noise detection algorithm in order to effectively process the signal and retrieve the information.

At present, numerous methods and approaches have been proposed for examining, retrieving and processing data from the heart sound signal collected at Hospital Tun Aminah, Johor Bahru. However, all the data collected at Hospital Tun Aminah, Johor Bahru reliy on the quality of the sound of the examined heart signals to produce appropriate outcomes. Using the State Space Modelling (SSM), this study proposes a new method for modelling the dynamics of multivariate HS signal in time series. It is a statistical model which comprises a time series analysis specific to HS. It has the ability to track, predict and forecast the underlying dynamic phenominal which is imperative for the hidden dynamics of the HS analysis and understanding. This study proposes several models based on feature extraction such as MFCC and VAR filters such as Kalman Filter with wavelet and the classifier based on HMM. The main contribution of this thesis is the introduction of state space model based on Time Varying-Vector Autogressive (TV-VAR) process and the use of multi-channel HS,non-stationary signal as a multivariate modelling for effective classification of HS data.

## 1.2 Problem Statement

There are numerous research in biomedical engineering that described the use of machine learning techniques to develop the preprocessing of biomedical signal and classifier for detection or diagnosis of the heart disease.However, machine learning models for diagnosing heart murmurs to predict patient risk are incapable to fit for clinical use due to incorrect assumptions about the data as the trained models did not work as claimed.. However, proper consideration in developing clinically validated diagnostic techniques which have its limitation and the methods are prone to over fitting and other problems which may not be immediately apparent to the work carried in this thesis. Thus, this thesis is aware of some potential pitfalls in the development of classifiers, and considers steps that help avoid these problems.As opposed to removing and separating the non-heart sound constituents of the noise contaminated PCG, this study aims to examine the PCG and retrieves the information categorized as clean heart sounds and appropriate for more detailed analysis of the signal. The discovery of such information is achieved in reference the criteria of sound quality described in Chapter 5. The new forms of features include the frequency, pitch, timing, energy, and splitting of heart sounds which become the basis for the proposed new approach to clinical implementation and testing. Chapter 4 will explain the new framework of DAS-HD (Framework 1) which is believed to offer substantial contribution to cardiac auscultation as the GPs will be presented with valuable information on heart sounds and its murmurs. Few limitations can be found from the use of conventional method in distinguishing murmurs from auscultation which include:

(i) Absence of information on frequency (pitch) of heart sounds. Frequency content contains valuable information of the first and second heart sounds as well as its murmurs which can be a vital deciding factor for clinically interpreting murmur.

(ii) The inability of capturing the dynamic changes (energy and frequency) of the heart sounds. The proposed method employs Mel Frequency Cepstrum Coefficient features to retrieve significant information from the raw data of heart sound. The dynamics signals can be addressed with SSM and TV-VAR.

(iii) Exposure towards many undesirable factors such as breathing noise, artifacts, voice and external noise. Pre-processing of the raw signals with specific filters is essential in order to highlight the mentioned concerns as discussed in Chapter 4.

(iv) The tediousness and impracticality of manual segmentation used in conventional clinical practice as it is known that the characteristics of the heart sound signals and its features of S1 and S2 location, number of components for each sound, the frequency content and time interval must be comprehensively measured and quantified. As an alternative, segmentation of ECG with R-R peaks is proposed to segment every cycle of the cardiac signals.

The detection of QRS complex P wave and T wave can be a crucial step to automatic analysis of ECG signals. Most of the research in this area uses the QRS complex as it is the easiest symbol to detect in the first stage. The QRS complex represents the ventricular depolarization and consists of three consequences wave. However, the main challenge in any algorithm design is the large variation of QRS, P and T waveform leading to some form of failure for each method. The QRS complex may only occupy only R waves QR(no R),QR(no S),S(no Q) or RSR depending on the ECG lead (Friganovic, 2018) (Xiang, Lin, & Meng, 2018) (Mohamed Elgendi, Marianna, & Abbott, 2016) (Bhoi1 & Sherpa, 2014).

This work in this thesis suggests a new algorithm to extract the relevant characteristic of the ECG signal. The new approach handles the delineation of the ECG waveforms which can be  a complicated task due to the varying wave duration and amplitudes with unknown drift source. To handle these complications, the QRS complexes delineation algorithm is based on temporal detection of shape changes, where as a non overlapped window is passed along the ECG signal calculating the angle of each window.In general, the heart disease into several categories, like coronary artery disease, congenital heart disease, valvular cardiomyopathy, rheumatic heart disease or any number of heart diseases (Saras Ramiya, 2011). However, this knowledge provided by the author is not supported by any database of heart sound that has been collected in Malaysia. Moreover, international database can be obtained but at a high cost and also the database might not be comprehensive enough to cover the different types of murmurs. In order to address such issue, there has been great effort to collect heart murmurs in Malaysia hospital. The data gathered by the Center for Biomedical Engineering (CBE) can serve as clinical data, and utilized for the purpose of teaching and research regarding cardiac auscultation.

This can negatively impact the mastering of physical examination skill among healthcare personnel which is a vital basic skill in the medical examination and an essential step before referring a person for examination by specialist. The auscultation has distinct advantage over these technologies. Auscultation is a simple non-invasive clinical skill used by general practitioner (GP) for patient evaluation and management.

Auscultation is practiced for evaluating the functional status of a complex human system such as the heart, lungs, abdomen etc (Mangrulkar & Judge, 2017) .Looking at the defined advantages of auscultation over other technologies, the researcher is keen to further investigate the possibility of using advanced signal processing algorithm to improve the auscultation diagnostic procedures.It is important to note that apart from S1 and S2 heart sounds, the abnormal heart sounds with murmurs is associated with other pathological conditions of the cardiovascular system. The skills of auscultation are usually obtained after years of training and practice with patients' heart sound. It is evidential that newly graduated medical students are less proficient in performing diagnosis for detecting abnormal heart sound. (Montinari & Minelli, 2019) argued that if two issues are not addressed properly the consequences can be that:

(i) Patients who are incorrectly diagnosed as false negative will endure health complications or the possibility of death in later stage.

(ii) Despite the benefits and advantages of Echocardiogram, Computerized Tomography (CT) and Magnetic Resonance Imaging (MRI) in cardiac diagnosis, these technologies are extremely costly and require expert operators which limit the possibility of equiping all district hospitals nationwide with such technologies.

(iii) Cardiac patients face the risk of fatality due to the long hour queue for echocardiogram screening.

The major limitation of the auscultation process occurs in human auditory system where collected heart sounds are detected. The human auditory system is particularly inefficient with low frequency and low intensity sound when analysed. The motivation behind the work in this thesis is the fact that by addressing the non-stationary signal of HS with advance signal processing algorithm, it is possible to take advantage on the improved electronic data of the HS while maintaining a clear relationship to auscultation methods. By maintaining this connection, it is envisaged that the advantages of electronic data capture and the advanced signal processing diagnosis can be combined to develop an intelligent phonocardiograph (PCG) Computer Aided Diagnostic (CAD) system (Li, Li, & Tang, 2020).

## 1.3 Research Question

This study aims to overcome the above mentioned problems. The key question is whether auscultation by normal stethoscopes can be implemented as a primary screening for heart abnormality. This has led this research to answer the following research questions.

(i) How to address the efficiency of multichannel heart sound as a multivariate signal when compared to traditional technique?

(ii) How to segment the heart sound signal as well as enhance the signal quality of the multivariate signal?

(iii) How to detect noise using different filtering technique to enhance heart sound data quality and classification performance?

(iv) How to estimate the clean heart sound signal x(t) from the observe signal y(t) and used different features to improve the performance of the DAS-HD?

## 1.4 Objective

The aim of this thesis is to investigate the suitability of linear and nonlinear as well as stationary and non-stationary of heart sound (HS). The specific objective to achieve are as follows:

(i) To evaluate and compare at different auscultation point between univariate and multivariate model.

(ii) To compare different filtering technique to exploit noisy signal of the heart sound in order to enhance accuracy of the technique.

(iii) To design and develop the non-stationary var technique into state space model to understand the correlation between the multivariate HS signal and also to reduce noise effect of the signal.

## 1.5 Scope of the Research

A proper measure to explore the issue of noise contamination in heart sound signal will be studied in detail. The algorithm for heart sound denoising will be considered in designing solution for the noise problem and variability due to the acquisition of heart sound in real clinical environment. As each point of auscultation normally correlates with a cardiac valve, this allows the detection of murmurs to only be associated with valvular abnormalities. There are a number of techniques when it comes to denoising and measuring the biomedical signals. The performance of the filters is largely affected by the statistical properties of biomedical signals and background noise whereby the background noise overlaps the spectral of the biomedical signals. This thesis highlights the use of Kalman Filter (KF) and wavelet transform to measure the underlying non-stationary process and given observation in minimum square error sense. As this technique enables the use of simultaneous time frequency information, it is widely utilized in analysing the heart sound. Filtering heart sound will be proposed based on Kalman Filtering and wavelet which is the time and frequency domain respectively.

New features are developed based on TV-VAR coefficient which is different from the available studies on stationary signal. Time varying features will become the basis for the new features. The time series features based on state-space methods and its estimates will adhere to certain procedures. The hidden state parameter estimation is resolved analytically through the use of closed form Kalman Filter (KF), and the model parameter is measured using maximum likelihood (ML) approach, the EM algorithm. The DAS-HD non gaussian state space model (Framework 3) will be compared with the traditional DAS-HD based on MFCC-HMM (Framework 1) and the filtered version with (Framework 2).In this study, the different heart sounds and the ECG data was gathered from the patients at Hospital Sultanah Aminah, Johor Bahru with the help of Physician who is a paediatric cardiologist. The consent of the patients was taken before collecting the data. In addition, additional data was recorded at CBE, Universiti Teknologi Malaysia, Skudai for the patients with normal heart sounds. Information plays an important role in this modern technology. People discover amazing invention at rapid pace;

with data sizes are becoming larger day by day. So, it is challenging to deal with large amounts of data stored in database. Medical diagnosis is a complicated task which requires accuracy and efficiency. In tackling this issue, the 2016 Physio Net/Cinc Challenge invented a large database by gathering data from various research groups worldwide; recorded in various actual clinical and non-clinical settings. The PhysioNet/Computing in Cardiology Challenge 2016 tried to highlight several of these issues by gathering the research community to accumulate plentiful promising databases (Clifford et al 2016). The PhysioNet/Computing contains 3 heart sound databases which are used in Chapter 4 for the DAS-HD. The summary of these three databases (Liu, et al., 2016) is as follows:

(i) The Michigan heart sound and murmur database (UMHS)

The Michigan heart sound and murmur database (MHSDB) was contributed by the University of Michigan Health System. It encompasses 23 heart sound recordings with a total of time length of 1496.8 s and was retrieved from www.med.umich.edu/lrc/psb/ heartsounds/index.htm

(ii) The PASCAL database (Bentley et al 2011)

The PASCAL database contains 176 recordings for heart sound segmentation and 656 recordings for heart sound classification. Despite having massive numbers of the recordings, there is limited time-length for each recording ranging from 1s to 30 s. The frequency is also limited to below 195 Hz because of the applied low-pass filter, which discards majority of the valuable heart sound components for clinical diagnosis. It was retrieved from www.peterjbentley.com/heartchallenge.

(iii) The Cardiac Auscultation of Heart Murmurs database (eGeneralMedical)

The Cardiac Auscultation of Heart Murmurs database was provided by eGeneral Medical Inc., which includes 64 recordings. It is not open and requires payment for access from www.egeneralmedical.com.The

PhysioNet/Computing Challenges database was also used in this study to evaluate the proposed methods in this thesis.

## 1.6 Contribution of study

The study investigates the mechanical (phonocardiogram) activity where the heart sound amplitude and frequency contexts are possibly the essential elements in a non-invasive assessment of heart activity. The PCG categorises four main components of the heart sound cycle period namely the first heart sound (S1) corresponding to the closure of mitral and tricuspid valves, the systolic period, the second heart sound (S2) corresponding to the closure of the aortic and pulmonary valves and the diastolic period. There four segments represent the full cycle of cardiac heart sound that is used by DAS-HD to predict the abnormality or the normal behaviour of the heart sound.However, determing the cardiac cycle for the long duration can be problematic.In this theis,the reserarch gap was address by designing and developing a new segmentation algorithm that is capable to automatically detect the cycles of HS.

The first part of the work also used univariate method for example MFCC - HMM modelling to interface the dynamics of the heart activity. This approach has shown to provide significant performance in estimating single-trial signal (example: mitral valve). The setback of univariate model is the process only correlates in time precedence of signal whereby the correlations between other signal regions is unable to be assessed directly from univariate model.Most current studies in this area are mainly focus on univariate modelling and in order to tackle the research gap, further work in this thesis enhance the generalization of univariate model to multivariate modelling. .Significant review has been carried out related to this multivariate study and it is found that this study is one of the few studies that employ the state space methods to model and measure the heart sound signal dynamics. The work proposes a new method to analyse the dynamics changes in a multivariate heart sound signal in reference to state-space modelling which consists the following contributions:

(i) Multi channel heart sounds (HS) with its introduction of linear dynamics model and proposed the EM algorithm in order to solve the estimation problem. The multivariate TVAR and its classification provide significantly better performance than the conventional MFCC-HMM model. The model estimation used the Kalman Filter.

(ii) The thesis proposed a new framework as dynamic time varying VAR model. formulated in a state-space form with EM estimation to identify the varying changes within the four valves. The method was applied to 40 normal patients and 6 abnormal patients.

## 1.7 Content of thesis

This study focuses on the filtering technique for ECG analysis and heart modelling. In order to acquire the intended results, an ECG and heart sound processing method utilizing an iterative filtering and parameter estimation technique is proposed in this study. This study also proposes new framework based on state space modelling (SSM) to measure changes in multivariate signals of the HS. This proposed algorithm can appropriately fine-tune itself according to the patient’s specific demands. On the bright side, this feature-specific heart sound estimation method can manage nearly all perturbed waveforms compared to the direct or transformation-based processing methods which cannot process the uncommon waveforms even though large sample databases are utilized. Moreover, a priori determined medical parameter greatly correlates with the signal estimation and efficient of the suggested algorithm. Adaptive modification of noisy signals can be done through the advanced distortion analysis which can provide the analysis with a high quality and clean signal. The structure of this study is in the following ways:

- **Chapter 1** Introduces briefly the history of heart diseases, the objective of study scope of research and methods used in the thesis which is the main focus of research.

- **Chapter 2** highlights the brief summary on the physiology of the heart, heart diseases, types of heart diseases, and feature extractions and classification model. This chapter explores numbers of theories and applications which involves averaging, extraction of heart cycle, alignment of the extracted heart cycle, segmentation and filtering technique. This chapter also provides comprehensive review of past work performed in the field automated and computer based heart sound analysis.

- **Chapter 3** explore overall methodology on framework 1,2 and 3.Framework 1 discussed the traditional method of features extraction and classifier in designing the DAS-HD(Framework 2) provides the methodology used for filtering the heart sound and finally Framework 3, shows the methodology of converting to univariate signal at each auscultation point to multivariate signal.These section emphasize the overall.

- **Chapter 4** explores the theory of a well-known heart sound segmentation algorithm and its application, and proposes practical improvement for actual clinical settings. This chapter also explains the required mathematical approaches in order to comprehensively comprehend this study. In order to realise the aims of this study, the methods proposed are thoroughly and comprehensively discussed which include statistical analysis and measurement on the performance of the methods.

- **Chapter 5** discusses in detail methods for denoising of HS signals. The Chapter describes the proposed methodology namely the Kalman, Wavelet and Wavelet-Kalman filtering. There approaches are investigated and validated with the standard database.

- **Chapter 6** describes the detail use of State Space Model (SSM) applied to non-stationary and multivariate HS signal the classification which is validated with different evaluation paradigms including kfold-splitting, accuracy, specitivity and sensitivity of the performance.

- **Chapter 7** provides the conclusion for the results presented in the previous chapter. From the findings of the results, special attention is given on the objective presented in Chapter 1. Finally, suggestions are made for possible areas of further research and summarised the findings and contribution discussed in this thesis.

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# LIST OF PUBLICATIONS

## Indexed Journal with Impact Factors

1. Sh-Hussain, H., Mohamad, M. M., Zahilah, R., Ting, C. M., Ismail, K., Numan, F., & Rasul, S. (2017). Classification of heart sound signals using autoregressive model and hidden Markov model. *Journal of Medical Imaging and Health Informatics*, 7(4), 755-763.
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