ISCHEMIC STROKE DETECTION SYSTEM WITH COMPUTER AIDED DIAGNOSTIC CAPABILITY

by

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Thesis submitted in partial fulfilment of the requirements
for the degree of
Bachelor of Engineering (Electronic Engineering)

JUNE 2017

ACKNOWLEDGEMENT

This dissertation is dedicated to everyone in the field of ultrasound signal processing system who embarks the journey of expanding the collection of knowledge and transcendent passion for improving emboli detection system.

My uttermost gratitude goes to Assc. Prof. Dr. Dzati Athiar Bt Ramli, my thesis advisor and project supervisor, for her invaluable support and guidance that were crucial for the completion of this project. Dr. Dzati has been supportive during the process of brainstorming. Her guidance and immense knowledge throughout all the time of research and writing this thesis are highly appreciated.

My special thanks reach out to Pn. Najah Bt Ghazali and Pn. Norsalina Bt Hassan, whom had supported me as technical advisors. Besides, I would like to thank my thesis examiners, Assc. Prof. Dr. Haidi bin Ibrahim for examining the thesis. My sincere thanks go to Universiti Sains Malaysia for supporting this wonder the Fundamental Research Grant Scheme (6071266).

Extensive acknowledgement need to be paid to my friends and family for their endless love and support in any aspect during the completion of this project and thesis. Last but not least, my special individual recognition goes to to Mr. Chiang Yi Fan, whom had helped me in proofreading the thesis.

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LIST OF ABBREVIATIONS

DCT	Discrete Cosine Transform
DFT	Discrete Fourier Transform
FAR	False Acceptance Rate
FFT	Fast Fourier Transform
FRR	False Rejection Rate
GAR	Genuine Acceptance Rate
GUI	Graphical User Interface
ICA	Internal Carotid Artery
LPC	Linear Prediction Coefficient
MCA	Middle Cerebral Artery
MEBR	Measured Embolus-to-Blood Ratio
MFCC	Mel Frequency Cepstral Coefficient
PCA	Posterior Cerebral Artery
RBF	Radial Basis Function
STAZCR	Short Time Average Zero Crossing Rate
STE	Short Time Energy
STFT	Short Time Fourier Transform
SVM	Support Vector Machine
TCD	Transcranial Doppler
ZCR	Zero Crossing Rate

SYSTEM PENGESAHAN STROKE ISKEMIK DENGAN KEUPAYAAN DIAGNOSTIK BANTUAN KOMPUTER

ABSTRAK

Strok iskemik berpunca daripada penyempitan saluran darah akibat perjalanan embolus sepanjang salur darah yang akhirnya terperangkap berhampiran dinding saluran darah dan menjadi stenosis. Ultrabunyi Doppler Transcranial (TCD) digunakan sebagai alat untuk mengesan embolus. Tetapi, proses pemantauan TCD adalah memakan masa dan menyebabkan keletihan. Oleh sebab penilaian memerlukan pakar-pakar, bilangan pakar yang terhad juga menyebabkan pengesanan embolus manual satu tugas yang mencabar. Oleh itu, projek ini adalah untuk mereka program untuk pengesan embolus automatik. MATLAB digunakan untuk mengembangkan algoritma pemprosesan isyarat system. Dalam projek ini, terdapat empat kaedah pengesanan telah dikaji. Kaedah pertama adalah kaedah pemodelan sinusoidal di mana spektrum frekuensi diperiksa untuk mencari komponen frekuensi yang bermagnitud tinggi. Kaedah kedua membandingkan kadar tenaga dan kadar lintasan sifar isyarat embolus dengan tahap ambang. Seterusnya, kaedah tenaga masa singkat dan kadar lintasan sifar purata masa singkat diambil untuk membandingkan kedua-dua ciri tersebut dengan tahap ambang dikira. Kaedah terakhir ialah pengelas Mesin Penyokong Vector (SVM) di mana Pekali Kepstrum Frekuensi Mel (MFCC) ialah ciri-ciri yang diekstrak untuk melatih pengelas. Penilaian prestasi kaedah pengesanan diukur dengan peratusan ketepatan dan masa pemprosesan. Keputusan terbaik adalah dicapai dengan kaedah pemodelan sinusoidal dengan kadar penerimaan tulen tinggi pada 84.2% dan kadar penolakan palsu rendah pada 33.14%. Selepas sistem perisian yang dicadangkan

disahkan, sistem ini diubah suai dan dijadikan aplikasi antara muka grafik pengguna (GUI).

ISCHEMIC STROKE DETECTION SYSTEM WITH COMPUTER AIDED DIAGNOSTIC CAPABILITY

ABSTRACT

Ischemic stroke is caused by narrowing of the blood vessel due to emboli travel along the blood vessel that eventually trapped near the vessel wall and become stenosis. Transcranial Doppler (TCD) Ultrasound is used as a tool to detect emboli. However, the TCD monitoring process is time-consuming and fatigue. Since the evaluation requires human experts, limited number of experts makes the manual emboli detection a challenging task. Therefore, this project is to develop program for automated emboli detection. MATLAB are used to develop signal processing algorithm of the system. In this project, there are four detection methods investigated. The first method is sinusoidal modelling method where the frequency spectrum were inspected to search for the frequency components with high magnitude. The second method compares the energy and zero crossing rate of embolic signal with the threshold level. Subsequently, the short time energy and short time average zero crossing rate method is employed to compare two characteristic with threshold level computed. The last method is the Support Vector Machine (SVM) classifier where Mel Frequency Cepstral Coefficients (MFCC) is the extracted features used to train the classifier. The performance evaluations of the detection methods are measured by accuracy percentage and processing time. The best result is achieved by the sinusoidal modelling method with high genuine acceptance rate at 84.2% and low false rejection rate of 33.14%. After the proposed software system is validated, the system is modified and employed into a graphical user interface (GUI) application.

CHAPTER 1

INTRODUCTION

1.1 Research Background

Stroke is a global health issue. It is one of the top five leading causes of death in Malaysia. It is also considered as the largest cause of disability. Stroke can happen to anyone at any age. According to the World Health Organization data published in May 2014, stroke deaths in Malaysia reached 12.19% of total deaths [1]. From the data collected by Global Health Observatory as shown in Figure 1.1, stroke was ranked as second leading cause of death globally, which accounted for a 6.24 million deaths in 2015 [2].

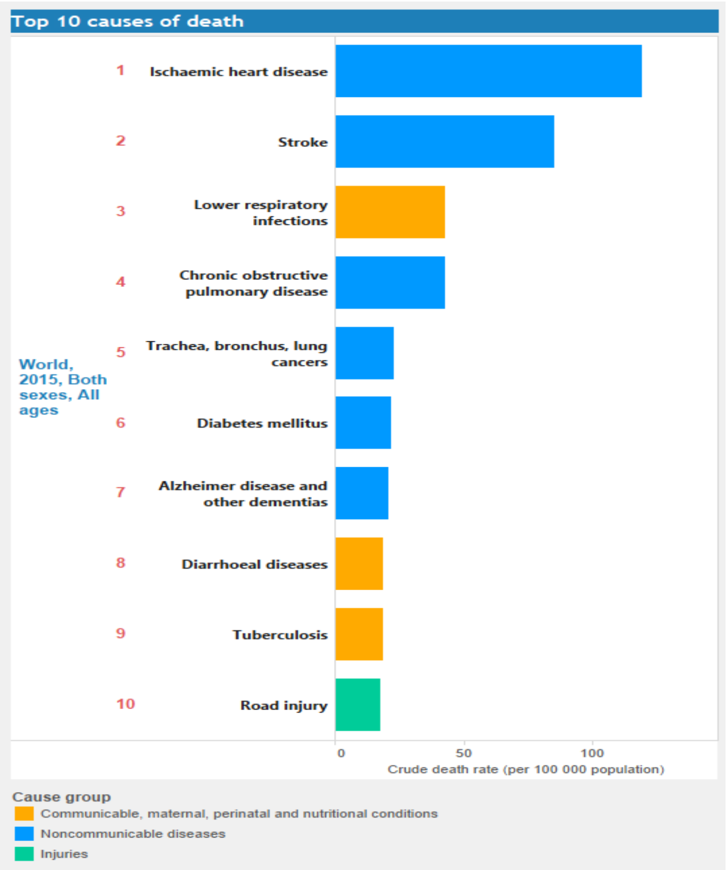

Figure 1.1: The top 10 causes of death globally in 2015 [2].

Stroke normally occurs when the brain cells are lacking of blood supply. There are two major types of stroke. Hemorrhagic stroke occurs when the blood vessel in the brain ruptures while ischemic stroke occurs when the blood vessel carrying blood to the brain is blocked by an obstruction. The illustration of ischemic stroke event is shown in Figure 1.2. According to American Stroke Association, ischemic stroke accounted for 87% of all strokes events [3] .

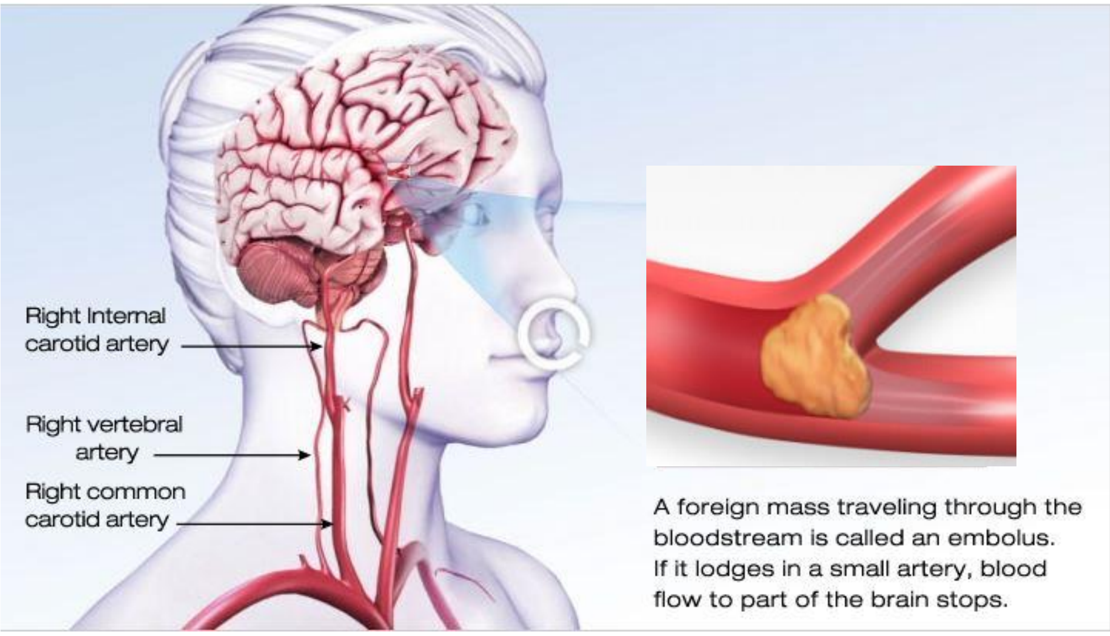

Figure 1.2: Illustration of ischemic stroke by American Stroke Association [4].

An ischemic stroke can occur in two ways: cerebral thrombosis and cerebral embolism. Ischemic stroke caused by cerebral thrombosis happens when diseased or damaged cerebral arteries become blocked by the formation of a blood clot within the brain. For ischemic stroke caused by cerebral embolism, the embolus is a clot that forms somewhere in the body and travels in the bloodstream which will later get lodged when the brain blood vessels are too small to allow its passage [3]. The emboli can be solid or gaseous. Solid emboli can be calcified plague, thrombus, or cholesterol flown from other parts of body. Gaseous embolism can be caused from small amount of air get into the blood circulation during clinical procedures such as surgeries [5]. The different phases in human blood vessel of stroke patient is shown in Figure 1.3. Emboli present in the blood vessel indicate the early stage of ischemic stroke.

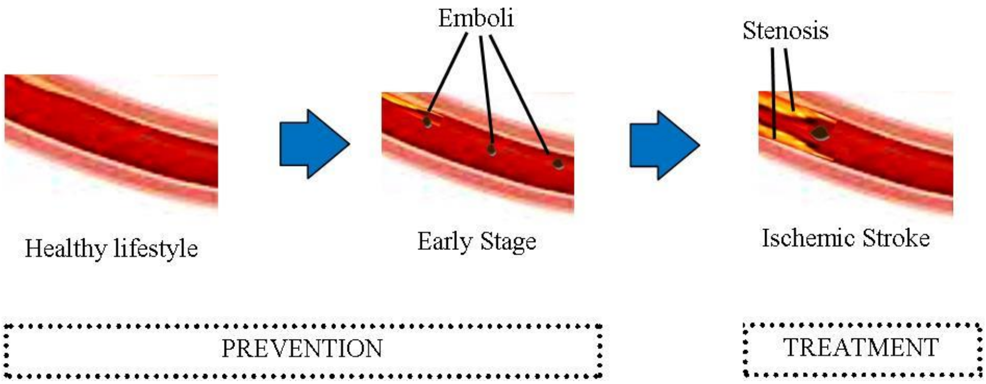

Figure 1.3: Different phases in human blood vessel of stroke patients.

Transcranial Doppler (TCD) ultrasound can be used to detect presence of emboli. A piezoelectric transducer is used to propagate ultrasound beam to the arteries and receive the echoes. The theory behind Doppler Effect shows that the velocity of flow inside the blood vessels can be calculated. Majority of the echoes is contributed by erythrocytes in the blood. The received signal will be processed and shown in the form of audio signal and sonogram. When there is presence of embolus, a short pure-tone audio signal will be generated and the intensity of the sonogram will have a brief increase in intensity for the particular frequency that corresponds to the velocity of embolus [6].

1.2 Problem Statement

Clinicians can monitor the patient with TCD to allow early detection of embolism during surgeries. The detection of emboli is performed by human expert and this is currently considered as the “gold standard” [7]. However, current practice of manual monitoring is time consuming and have a possibility of high error rate.

Traditional TCD machine requires long hour of manual monitoring as clinicians have to listen carefully and look closely on the sonogram to detect the presence of emboli. The TCD monitoring process usually takes 40 minutes [8]. After the test, a specifically trained physician is required to analyse and interpret the examination results. This is undesired as the professional manpower in hospital is limited [9].

The recording of TCD examination is long but the embolic signal only occurs for a very short period. The clinicians might easily miss the embolic due to the loss of concentration. Thus, the accuracy of detection depends on the skill and experience of clinicians [10].

1.3 Objectives

The objectives of this project are:

1. To develop detection program for automated emboli detection using sinusoidal modelling, energy and zero crossing rate, short time energy and short time average zero crossing rate and support vector machine.
2. To evaluate and compare the performance of the emboli detection methods in terms of accuracy and processing time.

1.4 Scope of Project

This project is software-based and the focus of this project is to determine methods to identify embolic signals in TCD signals. The data collected from in-vitro experiment that mimics human blood vessel for stroke case are provided by Ghazali *et* *al.*[11]. The TCD signal database are made up of 40 middle cerebral artery (MCA), 40 posterior cerebral artery (PCA), and 40 internal carotid artery (ICA) arterial signals of human brain. Four detection methods are implemented to detect the presence of emboli. MATLAB will be used to implement signal processing algorithm of the system.

The first method will involve the frequency information of the TCD signal in detecting embolic signal. The second method detects the emboli by evaluating the energy and zero crossing rate level of the TCD signal. The third method is improved from the second method by evaluating the short time energy and short time average zero crossing rate level. The last method requires training of SVM model to classify the embolic signal. After evaluate the performance of each of the methods, the system will be modified and deployed into a Graphical User Interface (GUI) application.

The priority of this project is to develop a program for ischemic stroke detection system. Accuracy and timing behaviour of the system to detect emboli are the focused performance parameters.

1.5 Outline of Report

This report is organized as follows:

Chapter one will unveil the background of the problems under investigation. The current status of the problems and the shortcomings will be highlighted. The objectives of the study will be shared in this chapter. The project scope will be defined and the tools required in this study will be identified.

Chapter two will summarize the research information from past works on signal processing. The different methods used by other researchers will be studied and compared. The fundamental academical background, such as tools and algorithms that related to this study will fall in this chapter as well.

Chapter three is where the implementation of the project will be included. Each step taken to achieve the objectives of the project will be explained. The flow charts, block diagrams and operational methods will be explained in this chapter.

Chapter four focuses on the analysis of the results of the implemented approach. The discussion will be made based on the accuracy and the performance of the system.

Chapter five concludes the project from the planning stage until the stage of verification. The limitations found in this project will also be concluded in this chapter. Future works which might help in enhancing this project will be suggested here.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter is about the study of TCD signals and research done previously on signal processing and automated emboli detection system. Section 2.2 will explain about how the ultrasound examination carried out in hospital, working principle of Transcranial Doppler Ultrasound and the challenges faced in automating the detection and classification of embolic signal. Section 2.3 will discuss the review of various detection methods, which are Sinusoidal Modelling, Energy and Zero Crossing Rate, Short Time Energy and Short Time Average Zero Crossing Rate and Support Vector Machine. Section 2.4 will be explaining about Mel Frequency Cepstral Coefficient (MFCC), which is a way to extract features from the raw TCD signal to train the classifier. Section 2.5 summarizes some of the projects that try to solve this problem with different methods applied. Section 2.6 will be the summary of this chapter.

2.2 Transcranial Doppler Ultrasound

Transcranial Doppler (TCD) Ultrasound machine is a non-invasive method to examine the blood circulation in the major cerebral arteries of the brain. TCD may be used by itself or with other diagnostic exams. The potential stroke patient can undergo TCD test in order to identify signs of embolization and allows physicians to provide early treatment. A TCD machine usually consists of a console containing a computer, a video display screen and a transducer that is used to do the scanning. Figure 2.1 shows an example of a TCD machine.

Figure 2.1: An example of the TCD machine [12].

2.2.1 Ultrasound Examination

During a TCD test, the patient is positioned on an examination table. A small amount of acoustic coupling gel is applied to the skin over the area to be examined. The transducer is gently pressed over the examine areas to measure the direction and speed of the flowing blood.

The patient has to remain still during the examination, which may take up to 40 minutes. Talking is avoided as it will affect the results of the test. The TCD test is performed by specially trained technologists and the result is interpreted by a board-certified radiologist [8].

2.2.2 Working Principle of TCD Ultrasound Machine

TCD monitoring requires a small transducer being placed at the cranium of the patient and ultrasound gel placed directly on the skin as shown in Figure 2.2. The transducer will generate a repetitive ultrasound pulse and its echo will be recorded at the same time.

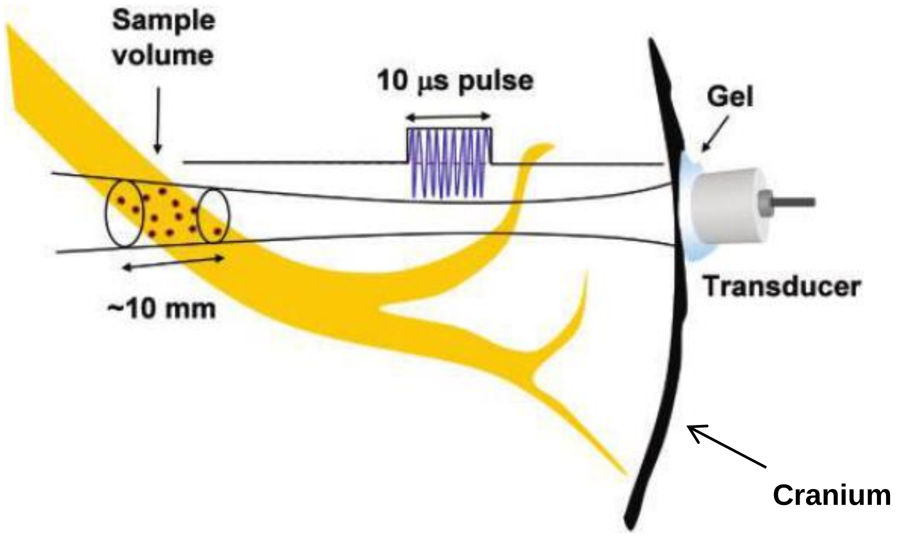

Figure 2.2: TCD insonation of an artery of the patient [6].

Ultrasonic detection of emboli is based on Doppler effect, which was proposed by physicist Christian Andreas Doppler in 1842 [13]. Doppler effect shows that the apparent frequency of a wave will be higher if the source is moving towards the receiver and vice versa. Doppler shift which is the difference in frequency of the wave, allows us to calculate the velocity of a moving object by measuring the difference in frequency between incident wave and reflected wave.

In 1982, a 2 MHz Doppler was introduced by Aaslid and colleagues, which allowed adequate penetration through the intact skull [14]. The ultrasound probe emits a high-frequency sound wave that bounces off the surfaces of red-blood cells in the vessels. These echoes are detected by a sensor in the probe. This information is then processed and analysed by the computer and displayed in the form of audio signal and sonogram.

The red-blood cells and emboli in the blood are able to scatter the projected ultrasonic beam, thus measuring the frequency of the reflected ultrasonic wave will allow the calculation of the velocity of blood and emboli in the blood vessel. As shown in Figure 2.3, the reflected signal will be processed by the TCD machine. By multiplying the emitted and received signals through demodulation, the signals will then be filtered to separate out the Doppler audio signal. Fourier Transform will be performed on the time domain signal to obtain the different frequency components that collectively make up the signal. The distribution of frequencies will be displayed against time as Doppler sonogram.

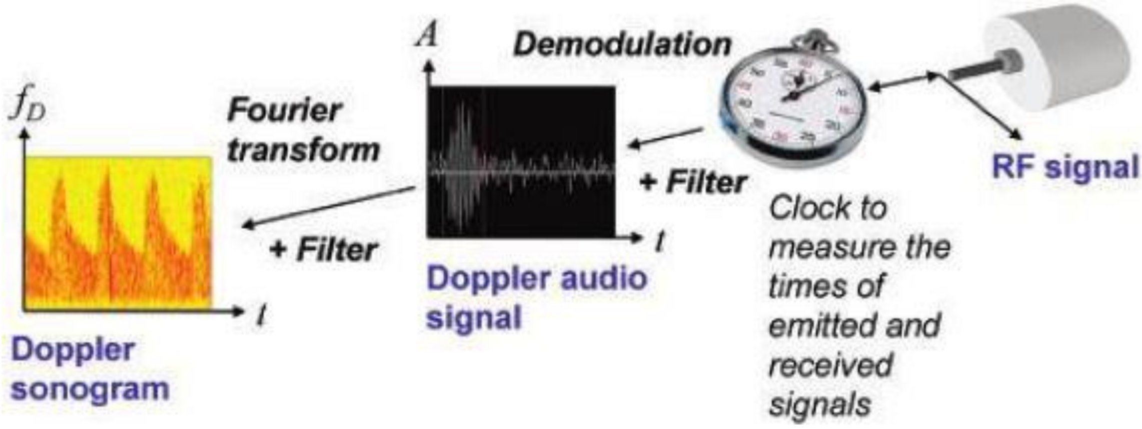

Figure 2.3: Post processing of TCD machine [6].

The velocity of the blood in the arteries is not constant all the time. It will be different at different position and different time due to the heartbeat and viscosity of blood. The blood will travel slower near the artery walls and faster in the centre due to the viscosity of blood. The velocity will be higher when the heart contracts and pumps the blood to all the cells. This will cause a continuous distribution of velocity, thus a distribution of frequency in the Doppler sonogram.

When there is a presence of emboli, it will be shown on both audio signal and the sonogram. For audio signal, there will be a short pure-tone audio signal produced, which may sound like ‘snap’, ‘chirp’ or ‘moan’. For sonogram, there will be an increase in intensity in a small range of frequency. The embolic signal typically will be very brief, depending on how the embolus passes through. The difference in audio signal and sonogram when an embolus is detected is shown in Figure 2.4.

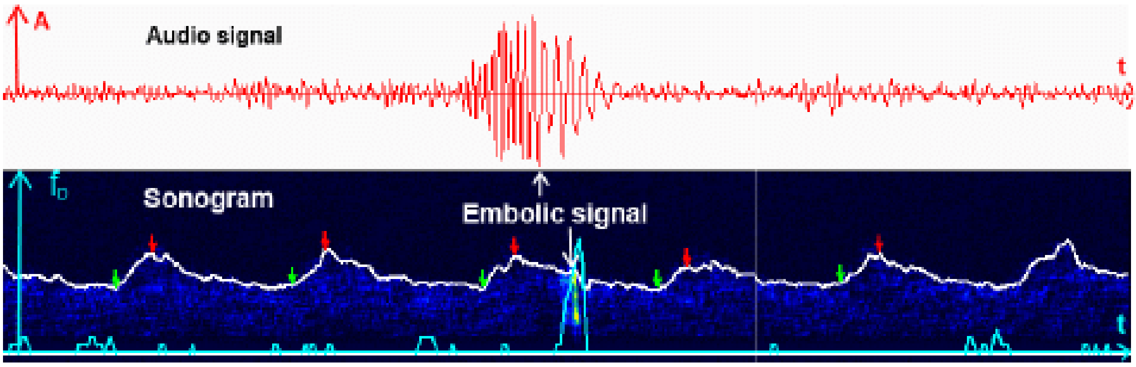

Figure 2.4: Appearance of Doppler embolic audio signal and the corresponding sonogram [15].

2.3 Review of Detection Methods

In this section, the detection methods used in signal processing are discussed. The goal of this stage is to identify the boundary between desired object and background to distinguish the desired object from the background. In this project, the desired object is embolic signal and the background is the blood flow. The first three method reviewed are based on thresholding while the last method are based on machine learning.

2.3.1 Sinusoidal Modelling

There have been many detection techniques proposed in the past. One of the analysis techniques proposed by McAulay *et al*. [16] was Sinusoidal Modelling (SM). This frequency-domain technique was applied widely in speech [17, 18] and audio signal processing, such as bioacoustics application [19-21] and music synthesis [22-24]. SM was applied by Harma *et al*. [19] to detect and segment syllables of continuous bird song of 14 species. The SM technique is described as below:

Step 1: The spectrogram on the syllables is computed by using Short Time Fourier

Transform (STFT). The spectrogram is expressed as matrix $S(f,t)$ where f is frequency index and t is the frame index.

Step 2: Both of f_n and t_n are determined, where n=0,1,…, N-1 and N is the number of syllables, such that $|S(f_n, t_n)|$ is the maximum value in the spectrogram.

Step 3: The following amplitude, $A_n(0) = 20\log_{10}|S(f_n, t_n)|$ and the frequency parameter, $\omega_n(0) = f_n$ are set.

Step 4: The maximum peak of $S(f,t)$ is traced from $|S(f_n, t_n)|$, for $t > t_n$ and $t < t_n$ until $A_n(t) < A_n(0) - \alpha$dB where α is the stopping criteria. This step is used to determine the starting time, t_s and the ending time t_e around the maximum amplitude at t_n.

Step 5: The amplitude trajectories are saved corresponding to the nth syllable by setting $S(f, [t_n - t_s, \dots, t_n + t_e]) = 0$. Steps 2-5 are repeated for new syllable.

2.3.2 Energy and Zero Crossing Rate

One of the simplest time-domain detection technique approached by researches is energy-based segmentation. This technique has been commonly used in segmentation process of speech and voice recognition [25-27]. A suitable threshold is decided for the energy level. Any part of the signal with energy higher than the threshold will be considered as the desired signal. The energy is expressed as follow [28]:

$$E = \sum_{k=1}^{N} |x(k)|^2 \tag{2.1}$$

where, E = the energy for input signal, $x(k)$

An improvement was made by Tian *et al*. [29] by combining the energy technique with Zero Crossing Rate (ZCR) to improve noise robustness. ZCR is the rate at which the amplitude of signal changes from positives to negative values and pass through the value of zero. This technique was implemented for end-point detection with the characteristic where ZCR of unvoiced signal and environmental noise are usually larger than voiced signal. It was reported that this technique works well in clean speech but performed poorly under high noise level. The ZCR is expressed as follows:

$$Z = \frac{1}{2N}\sum_{k=1}^{N}|sgn[x(k)] - sgn[x(k-1)]| \tag{2.2}$$

where, Z = the ZCR value of input signal, $x(k)$

$sgn[x(k)] = \begin{cases} 1, x(k) \geq 0 \\ -1, x(k) < 0 \end{cases}$

2.3.3 Short Time Energy and Short Time Average Zero Crossing Rate

It was reported that the E+ZCR technique only works well for stationary background noise. Therefore, another technique was proposed by Ramli *et al.*[30] by combining Short Time Energy (STE) and the Short Time Average Zero Crossing Rate (STAZCR) techniques and applied peak finding algorithm to overcome the problem.

STE is the energy of a desired signal segment used to estimate the initial signal in the detection of desired and undesired signal segments. It assumed that the signal under processing is stationary when the signal is viewed in blocks of short segments. Meanwhile, STAZCR is used to indicate whether the sound is present or absent in the input signal. The frame is considered to be undesired signal if STAZCR value is high and the frame is considered to be desired signal frame if STAZCR is low. The STE+STAZCR technique is described as below [30]:

Step 1: The input signal is framed and windowed by using Hamming window which defined as below:

$$w(k) = \begin{cases} 0.54 - 0.46\cos\left({2\pi k}/{N-1}\right) & k = 0, \dots, N-1 \\ 0 & otherwise \end{cases} \quad (2.3)$$

where, $w(k)$ = the window function

N = length of each frame

The signal after the above process is expressed as:

$$x_w(m) = x(k)w(m-k) \quad (2.4)$$

where, $x_w(m)$ = input signal after framing and windowing process

m = temporal length of each frame

$w(m-k)$ = frequency shifted window sequence

Step 2: The E_m and Z_m values are computed as below:

$$E_m = \frac{1}{N}\sum_{k=1}^{N}[x(k)w(m-k)]^2 \quad (2.5)$$

$$Z_m = \frac{1}{2N}\sum_{k=1}^{N}|sgn[x(k)] - sgn[x(k-1)]|w(m-k) \quad (2.6)$$

where, E_m = the value of STE

Z_m = the value of STZACR

Step 3: The first derivative of E_m and Z_m are calculated and their potential points are detemined where there are changes in the sign of the difference.

Step 4: A selective point is calculated to ensure the local maxima selected are above $1/4$ of the range of the data for both STE and STAZCR. The selective point for STE and STAZCR are stated in Equation (2.7) and (2.8) respectively as below:

$$E_{ms} = \frac{E_{m\,max} - E_{m\,min}}{4} \tag{2.7}$$

where, E_{ms} = the selective point for STE

$E_{m\,max}$ = maximum value of STE

$E_{m\,min}$ = minimum value of STE

$$Z_{ms} = \frac{Z_{m\,max} - Z_{m\,min}}{4} \tag{2.8}$$

where, Z_{ms} = the selective point for STAZCR

$Z_{m\,max}$ = maximum value of STAZCR

$Z_{m\,min}$ = minimum value of STAZCR

Step 5: The reference points for STE and STAZCR are set to be $E_{m\,min}$ and $Z_{m\,min}$ respectively at initial. For STE and STAZCR, a new reference point is set if the potential point satisfies the following conditions and selected to be local maxima:

$$E_{mp} > E_{ms} + E_{mr} \tag{2.9}$$

$$Z_{mp} > Z_{ms} + Z_{mr} \tag{2.10}$$

where, E_{mp} = the value of STE at current test point

E_{mr} = the value at the reference point of STE

Z_{mp} = the value of STAZCR at current test point

Z_{mr} = the value at the reference point of STAZCR

All potential points are tested and the final local maxima are obtained.

Step 6: The threshold level of STE and STAZCR are computed as follow:

$$T_E = \frac{W\left(E_{m\,max,1}\right) + E_{m\,max,2}}{W + 1} \tag{2.11}$$

$$T_Z = \frac{W\left(Z_{m\,max,1}\right) + Z_{m\,max,2}}{W + 1} \tag{2.12}$$

where, T_E = threshold level for STE

$E_{m\,max,1}$ = the value of first local maximum for STE

$E_{m\,max,2}$ = the value of second local maximum for STE

T_Z = threshold level for STAZCR

$Z_{m\,max,1}$ = the value of first local maximum for STAZCR

$Z_{m\,max,2}$ = the value of second local maximum for STAZCR

W = weight parameter

2.3.4 Support Vector Machine

Support Vector Machine (SVM) is a machine learning tool used to recognise patterns from the training data. It is useful because the way it learns from the examples is simple and the performance in practical applications is considered satisfying. SVM is based on statistical learning theory where it can be described as a system that receives data as input and outputs a function that can used to predict some features of future data. A set of training input and output data is first used to build the support vector machine model. The trained model is then used for classifying new data to its category. The training data must have a respectable size with enough variations in order to ensure the level of performance [31].

The training patterns or the support vectors possess the information required for classifications. These support vectors are mapped to a multidimensional space non-linearly. An optimal hyperplane will be constructed so that it has maximum margin between two classes of vectors to separate them. Kernel functions are used to compute the hyperplane without mapping all the support vectors on the feature space. By selecting different kernel functions, such as radial basis function (RBF) and polynomial kernel, the hyperplane yielded will have different shapes. The optimal choice of kernel is chosen to suit the input training patterns. For classification, the new input testing data will be assessed with respect to the hyperplane and the class can be determined accordingly by determining which side of the hyperplane it falls into [32, 33].

2.4 Mel Frequency Cepstral Coefficient

Mel Frequency Cepstrum is a collection that made up of Mel Frequency Cepstral Coefficients (MFCC). It is a representation of the short-term power spectrum of a sound, based on a linear cosine transform of a log power spectrum on a nonlinear Mel scale of frequency. MFCC is widely used as features in speech recognition and it approximates the way human perceives the audio signal more closely. The filters are spaced according to Mel scale where Mel scale is a non-linear scale of pitches based on human perception experiments. This is because humans are more aware of changes in lower frequency than higher frequencies. In this project, MFCC will be used to extract features of embolic signal before classification process. The computational steps involve in MFCC [34] are shown in Figure 2.5.

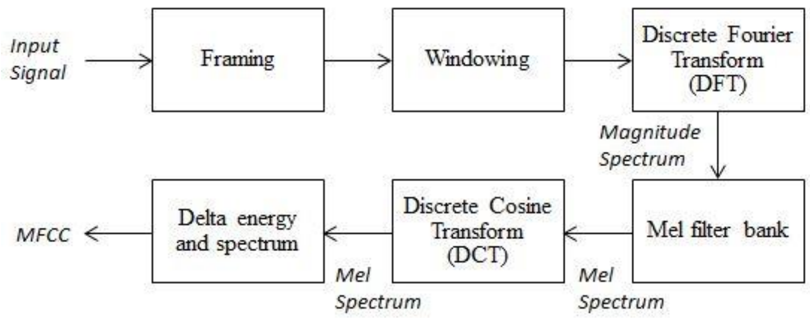

Figure 2.5: Block diagram of MFCC.

Step 1: The signal is framed into short frames with the time length within the range of 20-40ms. This is done because the audio signal is constantly changing and an assumption is made that in a shorter period, the audio signal exhibits quasi-stationary behaviour. However, the frame length must not be too short that the sample size is too small to provide reliable features.

Step 2: The power spectrum of each frame is calculated to identify the intensity of the signal at different frequencies. In this step, Discrete Fourier Transform (DFT) are applied to each frame:

$$X_t(\omega) = \sum_{k=0}^{N-1} x_t(n) e^{-\frac{j2\pi kn}{N}}, k \in intergar \tag{2.13}$$

where, $x_t(n)$ = discrete signal of length N samples

n = number of samples in each frames

k = domain index of the DFT

N = number of points in DFT

Step 3: The signal spectrum is multiplied with the Mel filter bank. The Mel filter bank is made of a set of triangular filters as shown in Figure 2.6. Each filter will only be non-zero at its designated frequency range and the width of each filter is not constant. The filters will be narrower at lower frequencies and getting wider at higher frequencies, which is exactly how human ears perceive the pitch of sound. The relationship between actual frequency and Mel scale is expressed in [34]:

$$f_{mel} = 2595 \log_{10}\left(1 + \frac{f}{700}\right) \tag{2.14}$$

where, f_{mel} = Mel scale

f = actual frequency

Step 4: After that, the logarithm of filter bank energies is obtained. The reason behind this is that humans do not perceive loudness linearly. Taking the logarithm of the energy will give us a better relationship between energy and loudness to be heard. It will also help to reduce the computational effort.

Step 5: The MFCC can be obtained by applying Discrete Cosine Transform (DCT) and the logarithm of the energy of the coefficients as follows:

$$y_t^{(m)}(k) = \sum_{m=1}^{M} \log_{10}\{|Y_t(m)|\} \cdot \cos\left(\frac{k(m-0.5)\pi}{m}\right), k = 0, \dots, L \tag{2.15}$$

where, $y_t^{(m)}(k)$ = Mel Frequency Cepstral Coefficients value

$Y_t(m)$ = energy of the filter bank

M = number of filters in the Mel filter bank

L = number of Mel Frequency Cepstral Coefficients

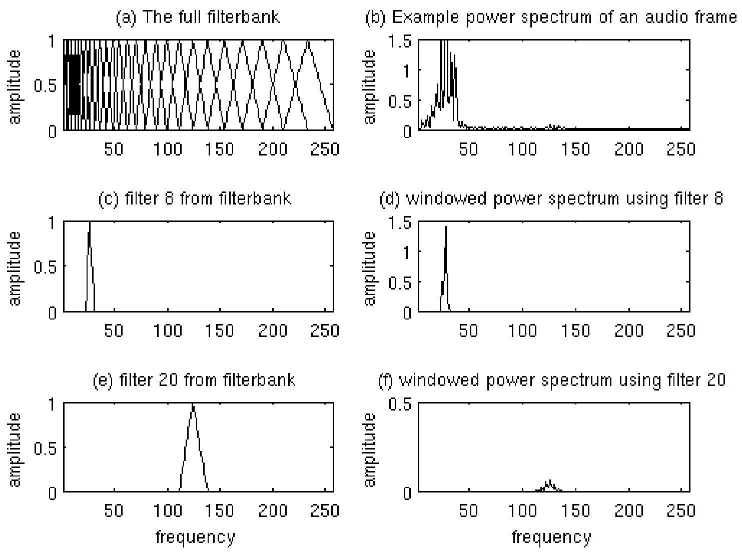

Figure 2.6: Plot of Mel filter bank and windowed power spectrum [34].

2.5 Computer Aided Embolic Detection System

Automating the emboli detection has been researched for long time and different approaches have been studied. However, it was reported that there is no current system of automatic embolus detection has the required sensitivity and specificity for clinical use [10]. The most basic method will be depending on the Measured Embolus-to-Blood Ratio (MEBR) value. A suitable threshold for the MEBR was decided. Any part of the TCD signal with its intensity higher than the threshold will be considered as embolic signal.

More sophisticated methods have been applied to achieve better results. A study from Kemeny *et al.* [35] used a trained neural network to discriminate emboli from background blood and artefacts. Out of the 1342 provoked artefacts, their system managed to label 85% of them correctly. When testing with patients with confirmed embolism, the software detected 282 events as emboli where 122 of them were actually artefacts. Another 58 of the real embolic signals have been missed.

Cullinane *et al.* [36] used frequency domain data instead of time domain data to distinguish the embolic signal from the artefacts. The signal was broken into small columns and Fast Fourier Transform (FFT) was applied to analyse the signal. Any columns with intensity higher than the predetermined background level will be considered as candidate and 9 meaningful parameters were obtained. Fuzzy logic was applied to the parameters to obtain the embolus probability and artefacts probability. The result given by the algorithm was slightly lower than the result observed by the human experts, which is the gold standard.

Research from Marvasti *et al.* [37] used novel auto regression modelling to shortlist the possible events as the candidates, then used a multiple wavelet denoising method to improve the signal over noise ratio. Unlike traditional threshold method which will remove the blood flow information, the denoising method they developed was superior. The selective wavelet amplification process will selectively enhance the signal strength of the possible candidate of the embolic signal. This method showed an increase of 2dB in embolic signal strength and it also improved detection accuracy.

Ghazali *et al.* [38] compared the use of features extracted from Linear Prediction Coefficient (LPC) and Mel Frequency Cepstral Coefficient (MFCC) for emboli classification. The result showed that features extracted from the LPC method achieved higher classification accuracy of 83.04% than those from MFCC method with 81.95% accuracy. Another study from Ghazali *et al.* [11] compared the performance of unsupervised and supervised classification method used in emboli detection. The methods used were *k*-means clustering technique and Support Vector Machine (SVM). From the results of the work, *k*-means clustering technique performed better than SVM.

2.6 Summary

The studies of TCD and related computer aided embolic detection process have been outlined in this chapter. From the studies, the ischemic stroke detection system can be organized as follows: The TCD signal is first fed into the system. The resultant signal is then processed and the features of the signal are extracted and compared with threshold or trained classifier. Finally, the decision is made to determine whether the input signal is embolic or non-embolic.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This project consists of software implementation. Hence, the outline of this chapter will be the software development methods. Section 3.2 will explain about the framework of the project. In Section 3.3, the pre-processing steps will be explained. Section 3.4 will explain the steps taken to employ the detection method to detect embolic signal. Section 3.5 will explain the performance measurement used to evaluate each detection method. Section 3.6 will shows the steps in building GUI.

3.2 Project Framework

The goal of this project is to develop an automated system to distinguish embolic and non-embolic TCD signals. Figure 3.1 shows the flowchart of the project. The project flow starts with literature review of TCD signal which is used to detect ischemic stroke and the detection method approached by other researchers.

For automated emboli detection, the first method will involve the frequency information of the TCD signal in detecting embolic signal. The second method detect the emboli by evaluating the E and ZCR level of the TCD signal. The third method will be improved from the second method by evaluating the STE and STAZCR level. The last method will require machine learning tool, SVM. The methods mentioned will be applied on TCD signals collected by Ghazali *et al.*[11] by using MATLAB R2016b.

The performance of each method will be measured and compared by accuracy and processing speed. After the simulation of the algorithms to detect embolic signal is satisfied, the system will be developed into a GUI application. Further improvement will be done to the system based on the performance measured.

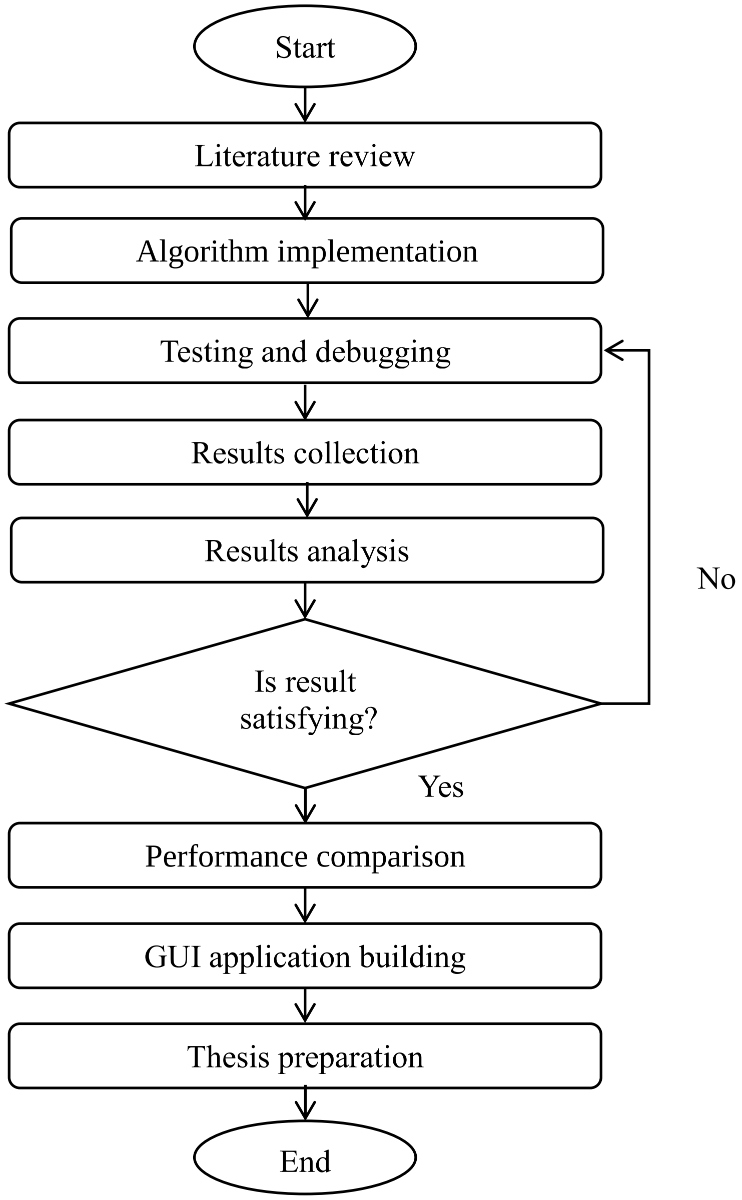

Figure 3.1: Project Flowchart

3.3 Pre-Processing Stage

The fundamental steps in pre-processing of signal are shown in Figure 3.2. To process the TCD signals recorded, every data need to undergo pre-processing before