FEATURES EXTRACTION OF HEART SOUNDS USING TIME-FREQUENCY DISTRIBUTION AND MEL-FREQUENCY CEPSTRUM COEFFICIENT

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A thesis submitted in fulfillment of the requirements for the award of the degree of Master of Engineering (Electrical – Electronic & Telecommunication)

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MAY 2006

To my beloved parents, Mohamed B. Shafie and Siti Zaharah Bt. Othman, my lovely brothers and sisters

ACKNOWLEDGEMENTS

I would like to thank my supervisor, Prof. Ir. Dr. Sheikh Hussain B. Shaikh Salleh for giving me the opportunity to work on this project and always giving me lots of good advices. I would also like to thank En. Kamarulafizam B. Ismail for giving me the opportunity to cooperate with him. He has been a great source of information and his invaluable guidance and timely input has helped me throughout my Master's project. His good guidance has given me an exposure to learn a lot of new things.

A great thank to Mr. Asasul Islam for providing me the heart sounds data for my analysis. I would also like to thank all my colleagues in UTM & KUITTHO for their supports and helping me to complete this project successfully. Last but not least, a special thanks to my family especially my beloved parents, brothers and sisters who have supported me all through their life and provided constant encouragement.

ABSTRACT

Heart sounds analysis can provide lots of information about heart condition whether it is normal or abnormal. Heart sounds signals are time-varying signals where they exhibit some degree of non-stationary. Due to these characteristics, therefore, two techniques have been proposed to analyze them. The first technique is the Time-Frequency Distribution using B-Distribution, used to resolve signal's components in the time-frequency domain and specifies the frequency components of the signal that changing over time. Another proposed technique is the Mel-Frequency Cepstrum Coefficient, used to obtain the cepstrums coefficients by resolving signal's components in the frequency domain. An experiment is presented to extract features of heart sounds using both mentioned techniques and compare their performances. Both techniques are discussed in details and tested against ideal simulations of 50 heart sound signals including normal and abnormal signals. All simulations are done using Matlab software except for MFCC where it has used the Microsoft Visual C++ software. A brief description of SVD is included to the technique using time-frequency distribution. Also, a brief description of Neural Network is used to verify and to compare the performances results of the two techniques with regard to the values of hidden node, learning rate and momentum coefficient. The results showed that performance of the TFD can be achieved up to 90% whereas MFCC is only 80%. Therefore, the TFD technique is chosen as the best technique to analyze and to extract features of the non-stationary signals such as the heart sounds signals.

ABSTRAK

Analysis degupan jantung dapat memberikan banyak maklumat tentang keadaan jantung sama ada ia normal atau tidak. Isyarat degupan jantung sentiasa berubah-ubah, menunjukkan bahawa ia adalah isyarat yang tidak pegun. Disebabkan oleh ciri-ciri tersebut, maka dua teknik khas telah disarankan untuk menganalisanya. Teknik yang pertama adalah menggunakan taburan masa-frekuensi (TFD) dengan jenis taburan-B (B-Distribution) untuk merungkaikan komponen-komponen isyarat dalam domain masa-frekuensi. Satu lagi teknik yang disarankan adalah mengunakan pekali Mel-Frekuensi Sepstrum (MFCC) bagi mendapatkan pekali sepstrum dengan merungkaikan komponen-komponen isyarat dalam domain frekuensi. Satu eksperimen telah dilakukan bagi mengekstrak ciri-ciri yang ada pada bunyi degupan jantung menggunakan dua teknik tersebut dan membandingkan tahap pencapaian yang diperolehi. Kedua-dua teknik telah dibincangkan dengan terperinci dan telah diuji dengan mensimulasi sebanyak 50 isyarat degupan jantung yang terdiri daripada isyarat normal dan abnormal. Kesemua teknik simulasi tersebut telah dilakukan menggunakan perisian Matlab kecuali MFCC menggunakan perisian Microsoft Visual C++. Terdapat penerangan ringkas tentang penguraian nilai tunggal (SVD) yang digunakan bersama teknik TFD. Juga disertakan huraian mengenai rangkaian saraf tiruan (ANN) untuk menentukan pencapaian kedua-dua teknik tersebut berdasarkan kepada jumlah lapisan tersembunyi, kadar latihan dan kadar momentum. Keputusan telah menunjukkan bahawa pencapaian teknik TFD telah mencecah 90% manakala teknik MFCC pula hanya 80%. Jadi, teknik TFD merupakan teknik yang terbaik untuk menganalisa dan mengekstrak ciri-ciri yang ada pada isyarat yang tidak pegun seperti isyarat degupan jantung.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLE

LIST OF ABBREVIATIONS

AF	-	Ambiguity Function
ANN	-	Artificial Neural Network
BoF	-	Bank of filters
BP	-	Backpropagation
BPN	-	Backpropagation Neural Network
DCT	-	Discrete Cosine Transform
DFT	-	Discrete Fourier Transform
DSP	-	Digital Signal Processing
FFT	-	Fast Fourier Transform
G.D.R	-	Generalized Delta Rule
GMM	-	Gaussian Mixture Model
IDFT	-	Inverse Discrete Fourier Transform
IF	-	Instantaneous Frequency
Im	-	Imaginary
MFCC	-	Mel Frequency Cepstrum Coefficient
MLP	-	Multilayer Perceptron
MLSA	-	Mel Log Spectrum Approximation
PC	-	Principal Component
PCA	-	Pricipal component analysis
PCG	-	Phono-cardiographic
PE	-	Processing element
PWVD	-	Pseudo-Wigner-Ville distribution
Re	-	Real
RMS	-	Root Mean Square
SBC	-	Subband Based Cepstral

SCG	-	Scaled Conjugate Gradient
SNR	-	Signal-to-noise ratio
STFT	-	Short-Time Fourier Transform
SVD	-	Singular Value Decomposition
SWWVD	-	Smooth windowed Wigner-Ville distribution
TFA	-	Time Frequency Analysis
TFD	-	Time-Frequency Distribution
TFR	-	Time-Frequency Representation
VQ	-	Vector Quantization
WVD	-	Wigner-Ville distribution
WWVD	-	Windowed Wigner-Ville distribution

LIST OF SYMBOLS

$A_z(v,\tau)$	-	symmetrical ambiguity function
c	-	firing angle control
C_k	-	cosine function
E_i	-	instantaneous energy
E_{min}	-	minimum error
f	-	frequency
f_i	-	instantaneous frequency
$f(net_j)$	-	sigmoid function
$G(n,m)$	-	discrete-time expression of time-lag kernel
$G(t,\tau)$	-	time-lag kernel
$g(v,\tau)$	-	Kernel function
$h[i]$	-	number of samples of long system's impulse response flipped left-or-right
$H_j[k]$	-	transfer function of filter j
Hz	-	hertz
i,D	-	number of cepstrum coefficient
j,p	-	number of filter outputs
J(w)	-	lower threshold on the sum squared error
k	-	samples
kHz	-	kilo Hertz
$\boldsymbol{l}$	-	latent variables dimension
m	-	number of rows of matrix $\boldsymbol{X}$
$Mag[k]$	-	magnitudes notation
$Mel(f)$	-	Mel frequency
m_j	-	log band-pass filter output amplitudes

ms	-	millisecond
n	-	number of columns of matrix $\boldsymbol{X}$
N	-	number of filters
N_s	-	number of samples
N_w	-	window size
O_j	-	output of neuron j
O_k	-	output of neuron k
$P(f)$	-	magnitude spectrum
$Phase[k]$	-	phase notation
$P(M)$	-	Mel spectrum
r	-	rank of matrix $\boldsymbol{X}$
$R_z(t,\tau)$	-	instantaneous autocorrelation function
s	-	second
$\boldsymbol{S}$, σ_j	-	singular values
$S(f)$	-	frequency domain representation of a signal
S_k	-	sine function
$s(t)$	-	time domain representation of a signal
T	-	iteration number
t, τ	-	time
T_z	-	total signal duration
$\boldsymbol{U}$	-	left singular vectors
$\boldsymbol{V}$	-	right singular vectors
v	-	frequency variable
W_{ji} (t+1)	-	adaptation weight between input (i) and hidden (j) layers
W_{kj} (t+1)	-	adaptation weight between output (k) and hidden (j) layers
$w(n)$	-	Hamming window function
$\boldsymbol{X}$	-	dataset in matrix *mxn*
$x[i]$	-	input discrete signal
$\boldsymbol{X}^T$	-	transpose of matrix $\boldsymbol{X}$
$y[i]$	-	output discrete signal
$z(n)$	-	discrete-time expression of analytic signal
$z(t)$	-	analytic signal (associated with real)
Δw	-	adaptation weights
θ_j	-	bias weights of neuron j

θ_k	-	bias weights of neuron k
$\rho(t,f)$	-	Cohen's class of distributions
ϕ, f_c, α	-	constant argument
λ_j	-	eigenvalues
δ_j	-	error signal through layer j
δ_k	-	error signal between the output and hidden layers
$\Gamma(.)$	-	gamma function
$\tau_g(f)$	-	group delay
$\theta(f)$	-	instantaneous phase in frequency domain
φ	-	instantaneous phase in time domain
η	-	learning rate
$\theta(M)$	-	log mel spectrum
α_m	-	momentum rate
$\Re\{\beta\}$	-	real value of β
$\Re\{\gamma\}$	-	real value of γ
β	-	smoothing parameter

CHAPTER 1

INTRODUCTION

1.1 Project Background

This project is focused on the problem of heart sounds analysis using an integration of signal processing techniques and artificial neural networks. This includes feature extraction technique, verification technique and estimation of performance with related parameters. It has proposed two techniques for feature extraction analysis. The first technique is emphasizing on Time-Frequency Distributions (TFD). It used to choose a distribution from a group of bilinear time-frequency distributions that satisfies the TFD properties. In that case, the B-distribution was chosen because it satisfied the properties of TFD and it performed well in reducing the cross-terms. Another technique is using Mel Frequency Cepstrum Coefficient where the outputs are in terms of cepstrum coefficients. For verification analysis, both of the techniques mentioned above are further simulating using neural network and after that the performances were compared between the both proposed techniques.

1.2 Project Objectives

The main objective of this work is to choose the best technique to extract features of heart sounds signals. This can be achieved by comparing two proposed techniques; Time-Frequency Distribution (B-distribution) and Mel Frequency Cepstrum Coefficient. The best technique will be chosen according to the performance accuracy.

1.3 Scope of Work

Different heart sounds were produced when the cardiac system is not in a proper manner of working, which will produce the heart irregularities or heart diseases. A good technique needs to be used to extract the features of heart sounds in order to detect the diseases. Different features will represent different heart diseases.

This project has proposed two techniques that can be used for feature extraction of heart sound signals. Both of them are outperformed their own classes compared to others. The first technique is using Time-Frequency Distribution with Singular Value Decomposition. The second technique is focusing on the Mel Frequency Cepstrum Coefficient. The data used to implement both techniques are taken from Centre of Biomedical in UTM, Skudai. They are actually the heart sound signals including normal and abnormal signals. The normal heart sounds are taken from healthy persons and the abnormal heart sounds are taken from patients that are suffering from various kinds of diseases.

For the first technique, the heart sound signals are transformed into time-frequency domain using bilinear time-frequency distribution. The transformation is done using B-distribution with some parameters setting and the outputs from that particular distribtuion are then dimensionality reduced using Singular Value Decomposition. The results after that simulated further using neural network for verification and performance analysis. All simulations are done using Matlab. The second technique is different from the first one because the analysis is done based on frequency analysis using Mel Frequency Cepstrum Coefficient. The heart sound signals are extracted using MFCC with mel-frequency scaled. The simulation is done using Microsoft Visual C++. The outputs of MFCC are actually the cepstrum coefficients that were going to be simulated further using neural network for performance analysis. Lastly, the performances accuracies from both techniques are then compared to each other.

1.4 Heart Sounds

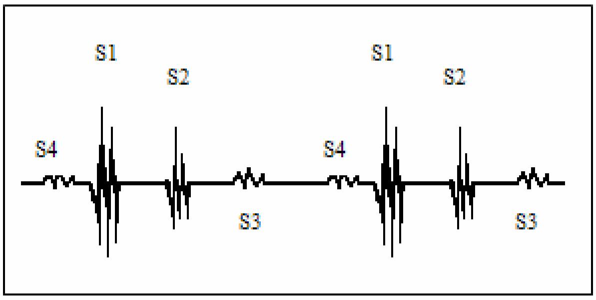

Figure1.1 Heart sound components

The heart sounds are generated by mechanical vibration of heart and cardiovascular where they provide abundant information about them while the measurement is noninvasive and low cost. Heart sounds and murmurs are the important parameter used in diagnosing the heart condition and it can be captured by using phonocardiogram or heart auscultation. Classically the sounds made by a healthy heart are conceived as being a nearly periodic signal consisting of four components. These four parts are referred to as the first, second, third and fourth heart sounds. The first two heart sounds give rise to the familiar 'lub-dup' beating sound of the heart and tend to dominate the Phono-CardioGraphic (PCG) signals. The first heart sound is caused by the closure of the mitral and tricuspid valves. The second heart sound is due to the closure of the aortic and pulmonary valves. The four components of heart sounds are stated below:

1. First Heart Sound;

   First heart sound is the effect of closing the tricuspid and mitral valve at the beginning of ventricle systolic. There are four component of the first heart sounds [22]:

   (i) The first component is the effect of ventricular contraction and blood movement towards atrio-ventricular valve. This occur at beginning of ventricle systolic.

   (ii) The second component is the effect of atrioventricle clossure.

   (iii) The third component is reflected the opening of semilunar valve and the beginning of blood ejection.

   (iv) The fourth component represent the maximum blood ejection from ventricle to aorta.

2. Second Heart Sound;

   Second heart sound represents the vibrations as a result from closure of semilunar valve at the end of ventricle systolic. Since there are two component of semilunar valve, the second heart sound is a combination of two components. The aortic valve closed earlier than the closing of pulmonary valve.

3. Third Heart Sound;

   The third heart sound result from vibration setting by early filling of ventricle during ventricle diastole.

4. Fourth Heart Sound;

   The fourth heart sound is caused by rapid filling of ventricle with blood during atrium systole. It also marked the end of ventricle diastole.

Each beat is separated by an interval of the order of 1s, with each heart sound having duration of roughly 50ms. The interval between beats varies even in a patient at rest because of respiration. Similarly the exact nature of each beat varies from beat to beat. The result is a signal which is non-periodic, even though it has a repetitive character.

The heart murmurs occur as the additional components in the PCG signal, most often arising in the interval between the first and second heart sound. Heart murmurs are the result of turbulent blood flow, which produces a series of many vibrations. The murmur signal is often of much smaller amplitude than either of the heart sounds. Many murmurs are described as "whooshing" sounds and are believed to be derived from flow noise. The heart murmurs will produce the abnormal heart sounds. There are four main factor of producing murmurs [17]:

(i) High rates of flow through normal and abnormal valves
(ii) Forward flow through a constricted or irregular valve or into dilated vessels.
(iii) Backward flow through an incompetent valve, septal defect, or patient ductus arteriosus.
(iv) Decreased viscosity, which causes increased turbulent and contributes to the production and intensity of murmurs.

1.5 Time-Frequency Distributions

Many signals encountered in real-world situations are exhibit some degree of non-stationarity where the frequency content changes over time. One of the most common applications is heart sound signals processing. Classical signal analysis tools, however, do not take this into account, assuming that the signal characteristics are stationary. A solution to the problem of representing non-stationary signals is found in their joint time and frequency representations which characterized the exact behavior of the time-varying frequency content of the signal. Time-frequency analysis methods are capable of detecting heart murmurs and vital information to the classification of heart sounds and murmurs. Therefore, Time-Frequency Analysis is used to represent the heart sounds in time-frequency domain by mapping the one-dimensional time-domain signal into a two-dimensional function of time and frequency.

The introduction of time-frequency analysis (TFA) has led to define new tools to represent and characterize the time-varying contents of non-stationary signals using time-frequency distributions (TFDs) [2, 7, 15], also for removing noise and interference from a signal. Among the most studied time-frequency distributions are the quadratic distributions. In this paper, a member of the quadratic class of TFDs is proposed, referred to as the B-distribution, which can resolve close signals in the time-frequency domain that other members fail to do so. In addition to that, the B-distribution is shown to outperform existing reduced interference distributions in suppressing the cross-terms of a multicomponent signal, while keeping a high time-frequency resolution. The performance of this technique is depending on the value of smoothing parameter applied to the signal analysis. This condition is evaluated using the simulation on the heart sound signals using Matlab.

1.6 Mel-Frequency Cepstrum Coefficient

A representation of heart sounds using Mel-Frequency Cepstrum Coefficient (MFCC) would be provided by a set of cepstrum coefficients. These coefficients are the results of a cosine transform of the real logarithm of the short-term energy spectrum expressed on a mel-frequency scale [32]. The MFCC are also an efficient method to extract any kind of features [8]. The number of resulting mel-frequency cepstrum coefficients is practically chosen relatively low, in the order of 12 to 20 coefficients. However, in many cases of MFCC analysis, the 0th coefficient of the

MFCC cepstrum is ignored because of its unreliability [24]. In fact, the 0th coefficient can be regarded as a collection of average energies of each frequency bands in the signal that is being analyzed. The energy of heart sound signal is also a very important feature for pattern recognition. Many experiments have shown that the performance can be improved when the energy information is added as another model feature in addition to cepstrums.

Mel Frequency Cepstrum Coefficients (MFCC) is also used as a method that analyzes how the Fourier transform extracts frequency components of a signal in the time-domain. In addition, it is a representation defined as the real cepstrum of a windowed short-time signal derived from the Discrete Fourier Transform (DFT) of that signal. The difference from the real cepstrum is that a non-linear frequency, a mel-scale is used. The mapping from linear frequency to mel frequency is done using an equation as follows:

$$Mel(f) = 2595 \log10 (1 + f/700) \tag{1.1}$$

Basically, the analysis of the signal is done using Frequency Domain Analysis where it converts a temporal signal to a frequency domain representation. The keywords involve in this analysis as below:

- <u>Cepstrum</u>: a homomorphic signal processing technique that converts the signal into a domain in which short-term and long-term variations in the signal can be separated.

- <u>FourierTransform</u>: implements a variety of techniques for performing Fourier Transforms, including the most effective fast transforms

- <u>Spectrum</u>: an umbrella class that encapsulates most of the frequency domain techniques, and provides a uniform interface. This capability is used extensively in many of our front end implementations.

1.7 Thesis Outline

This report has been organized into eight chapters. Chapter 1 outlines the entire project giving a brief introduction to the time-frequency distribution technique and Mel Frequency Cepstrum Coefficient technique. Chapter 2 provides the literature reviews where the common references with some information that related to the project are collected. Chapter 3 describes the time-frequency technique used in this project by specifically elaborate the B-Distribution and its kernel. In addition, a brief description about SVD is also included in this chapter. Chapter 4 is an explanation about the MFCC principle and the steps involve in getting the MFCC. Chapter 5 is having a detail explanation about neural network. The important parameters involve in this chapter is explained further in order to get some ideas of verification technique used in this project. Chapter 7 presents and explains the results of signal processing experiments conducted on heart sound data including normal and abnormal based on time-frequency distribution technique and MFCC technique. The verification results are also attached to this chapter for performances comparison. Chapter 8 is the last chapter of this thesis where it concludes this project and provides suggestions for future recommendations and improvement.

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