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

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UNIVERSITI TEKNOLOGI MALAYSIA

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MASNANI BT MOHAMED

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

Faculty of Electrical Engineering
Universiti Teknologi Malaysia

MAY 2006

I declare that this thesis entitled "*Features Extraction of Heart Sounds using Time-Frequency Distribution and Mel-Frequency Cepstrum Coefficient*" is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

Signature : ....

Name : Masnani Bt. Mohamed

Date : 2 May 2006

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

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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.

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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

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLE

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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

$A_z(\nu,\tau)$	-	symmetrical ambiguity function
c	-	firing angle control
C_k	-	cosine function
E_i	-	instantaneous energy
$\mathrm{E}_{\mathrm{min}}$	-	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
$g(\nu,\tau)$	-	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
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
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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

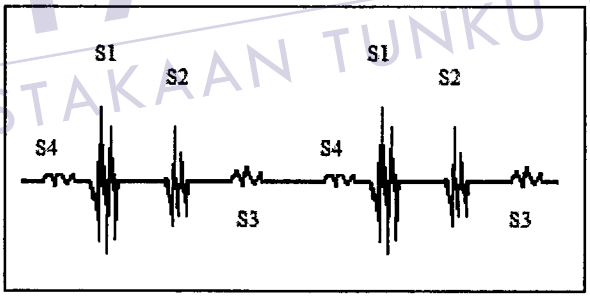

Figure1.1 Heart sound components

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:

$$Mel(f) = 2595 \log 10 \, (1 + f/700) \tag{1.1}$$

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:

- Cepstrum: 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.

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

- Spectrum: 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.

CHAPTER 2

LITERATURE REVIEW

2.1 Time-Frequency Representations/Distributions

Hlawatsch and Boudreaux-Bartels (1992) have studied that Time-frequency representations (TFRs) are powerful tools for the analysis and processing of "non-stationary" signals for which separate time-domain and frequency-domain analyses are not adequate. They have combined time-domain and frequency-domain analyses to yield a potentially more revealing picture of temporal localization of a signal's spectral components. The TFRs are including both linear and quadratic representations. The found that numerous TFRs which have been proposed may be interpreted as smoothed versions of the WD, with the type of smoothing determining the amount of attenuation of interference terms, loss of time-frequency concentration and mathematical properties. Hence, the choice of the "best" TFR depends on the nature of the signals to be analyzed. Once a specific TFR has been selected, the user often has to select certain TFR parameters. Finally, the analysis result will also depend upon the graphical representation of the TFR surface (e.g. 3D plots versus contour-line plots).

White, Collis and Salmon (1996) have studied the use of time-frequency methods in the detection and analysis of heart murmurs in Phono-CardioGraphic (PCG) signals. These heart sounds can yield important diagnostic information. An abnormality between the heart sounds is generically termed a murmur. Heart sounds are clearly non-stationary signals and hence the natural analysis methods are those of time-frequency and time-scale. In this application there is no evidence to suggest that the analysis technique would benefit from a multi-resolution type analysis, so they concentrated on time-frequency, rather than time-scale, methods. The method exploits averaged versions of the Pseudo-Wigner-Ville distribution (PWVD). The algorithms were shown to detect two types of heart murmurs and to be able to distinguish between them. The general processing strategy they adopted consists of initially segmenting the signal into individual beats. This segmentation process can be performed in a variety of ways; the success of each approach depends critically on the signal to noise ratio (SNR) of the recording under consideration. They have presented the results illustrating that time-frequency methods are capable of detecting heart murmurs and also of yielding information vital to the classification of such murmurs. The methods used involved averaging of time-frequency plots, which has intuitive value and can be interpreted in a theoretical fashion exploiting the concepts of cyclo-stationarity.

Haghighi-Mood, and Torry (1997) have addressed the characteristics of heart murmurs from signal theory point of view and suggests an appropriate signal analysis method which is capable of describing the dynamics of heart murmurs. The result of a pilot study using the proposed method indicates a distinctive pattern for time-frequency distribution of heart murmurs which is expected to provide information of diagnostic importance. The choice of time-frequency method is mainly dictated by the time-bandwidth product of the signal under investigation. While traditional Time-Frequency methods such as Short Time Fourier Transform (STFT) and bank of filters (BoF) are known to be robust for signals of large time-bandwidth product, their performance degrades when used with signals of fast-varying spectra and short duration. An alternative approach to study such signals is joint Time-Frequency Distribution (TFDs) methods which, unlike traditional methods, make no assumption of stationarity at any time interval. For their study, a number of TFD methods belonging to the Cohen class of distributions were applied to heart murmurs. They found that the Choi-Williams distribution (CWD) with an exponential kernel also can provide the best compromise between spectro-temporal resolution and cross-term suppression and therefore the detection of time-frequency dynamics of heart murmurs. Considering the generation mechanism and the hydrodynamic models proposed for various types of murmurs, it is logical to predict that the time-frequency pattern of murmurs contains valuable information which may lead to non-invasive diagnosis of certain cardiac diseases such as valvular stenosis and ventricular or atrial septal defect.

Cohen (1989) has presented a review and tutorial of the fundamental ideas and methods of joint time-frequency distributions. He has introduced the types of distributions and the method to obtain them. The objective of the field is to describe how the spectral content of a signal is changing in time, and to develop the physical and mathematical ideas needed to understand what a time-varying spectrum is. The basic goal is to devise a distribution that represents the energy or intensity of a signal simultaneously in time and frequency. The basic idea is to devise a joint function of time and frequency, a distribution that will describe the energy density or intensity of a signal simultaneously in time and frequency. This review is presented to be understandable to the non-specialist with emphasis on the diversity of concepts and motivations that have gone into the formation of the field.

2.2 Cross-terms Elimination (Signal-to-Interference Ratio)

Daliman and Sha'ameri (2003) have done the analysis of the heart sound and murmurs using time frequency distribution method. The reason why they were using time-frequency distribution because the heart sound signals are actually non-stationary signals and time-varying signals that would be best analyzed in time-frequency domain. The Windowed Wigner-Ville distribution (WWVD) and smooth windowed Wigner-Ville distribution (SWWVD) have been used to obtain the time-frequency representation of the signal. Determination of parameter setting of WWVD and SWWVD will eliminate the cross-terms and improve time-frequency representation. The accuracy of time-frequency representation is determined based on the mainlobe width and signal-to-interference ratio. By comparing the two types of the distributions, they found that the most accurate time-frequency representation can be achieved using the SWWVD.

Sha'ameri and Salleh (2000) have performed an analysis of heart sounds and murmur using time-frequency signal analysis. They used the technique using Wigner-Ville distribution (WVD) and windowed Wigner-Ville distribution (WWVD) that belonged to the bilinear class of time-frequency distribution. They developed these techniques to provide high-resolution time-frequency representation for time-varying signals. Due to the nonlinear operation involved, interference terms were introduced in the time-frequency representation. The signals of' interest are modeled as multicomponent signals and the characteristics of the signal in time-lag plane are observed. From the time-lag plane, the interference components are identified, and the appropriate window width is selected in the WWVD to remove the interference. Results analyses showed that WWVD produced more accurate time-frequency representation compared to the WVD and the signal-to-interference is used to quantify the improvement. This happened because the WWVD has used the window function to control the amount of interference present in the time-frequency representation by removing the cross bilinear product terms.

2.3 B-Distribution

Sucic, Barkat and Boashash (1999) proved that B-distribution can resolve close signals in the time-frequency domain that other members fail to do so. They showed that the B-distribution is real, time and frequency shift invariant and its first moment with respect to frequency yields the instantaneous frequency of the signal. Using synthetic and real-life multicomponent signals, it has been shown that the B-distribution achieves a better time-frequency resolution and energy concentration around the instantaneous frequency of a signal, while still significantly suppressing the cross-terms, than other commonly-chosen distributions for multicomponent signals analysis. They have reviewed the fundamental concepts of the cross-terms elimination using the ambiguity domain filtering, based on the B-distribution kernel. The kernel has been defined in both the time-lag and the Doppler-lag domain and they have proved that B-Distribution has satisfied most of the desirable properties sought for a time-frequency distribution.

Boashash and Sucic (2000) have presented two novel results which are significant for the application of time-frequency signal analysis techniques to real life signals. First, they introduced a measure for comparing the resolution performance of TFDs in separating closely spaced components in the time-frequency domain. The measure takes into account key attributes of TFDs such as main-lobes, side-lobes, and cross-terms. The introduction of this measure is an improvement of some techniques that rely on visual inspection of plots. The performance comparison of quadratic TFDs using the proposed resolution measure shows that the B-distribution outperforms existing quadratic TFDs in resolving closely spaced components in the time-frequency domain. The second part consists in proposing a methodology for designing high resolution quadratic TFDs for the time-frequency analysis of multicomponent signals when components are close to each other. By removing limitations in the way desirable properties of quadratic TFDs were previously chosen, a new set of design criteria has been defined. The combination of these two results is an important break-through for the field of time-frequency signal analysis. They have concluded that the B-Distribution outperforms other existing distributions in terms of time-frequency resolution, as well as cross-terms suppression, when used to represent signals with closely-spaced components in the time-frequency domain.

2.4 Singular Value Decomposition

Wall, Rechtsteiner and Rocha (2003) have described SVD methods for visualization of gene expression data, representation of the data using a smaller number of variables, and detection of patterns in noisy gene expression data. In addition, they also described the precise relation between SVD analysis and Principal Component Analysis (PCA). Their aimed is actually to provide definitions, interpretations, examples, and references that will serve as resources for understanding and extending the application of SVD and PCA to gene expression analysis. An important capability distinguishing SVD and related methods from other analysis methods is the ability to detect weak signals in the data. Even when the structure of the data does not allow separation of data points, causing clustering algorithms to fail, it may be possible to detect biologically meaningful patterns. SVD allows obtaining the true dimensionality of the data, which is the rank r of matrix X and a representation is using a reduced number of variables. This property of the SVD is commonly referred to as dimensionality reduction.

2.5 Mel-Frequency Cepstrum Coefficient

Garcia and Garcia (2003) have done the experiments to present the development of an automatic recognition system of infant cry, with the objective to classify two types of cry: normal and pathological cry from dear babies. In this study, they used acoustic characteristics obtained by the Mel-Frequency Cepstrum technique and a feed-forward neural network as a classifier that was trained with several learning methods, resulting better the Scaled Conjugate Gradient (SCG) algorithm. The SCG method avoids a time consuming line-search per learning iteration, which makes the algorithm faster than other second order Conjugate Gradient algorithms. This work has shown good results, with the MFCC technique, using neural network architecture.

Bahoura and Pelletier, (2004) have proposed a new tool based on the cepstral analysis as feature extractor and the Gaussian Mixture Model for the classification process. The Cepstral analysis is proposed with Gaussian Mixture Models (GMM) method to classify respiratory sounds in two categories: normal and wheezing. The sound signal is divided in overlapped segments, which are characterized by a reduced dimension feature vectors using Mel-Frequency Cepstral Coefficients (MFCC) or Subband based Cepstral parameters (SBC). The proposed schema is compared with other classifiers: Vector Quantization (VQ) and Multi-Layer Perceptron (MLP) neural networks. In order to improve the classification results, they also proposed the postprocessing technique. There are also some explanation about two feature extractors based on cepstral analysis (MFCC and SBC) are briefly presented in this work. The best result is obtained by the MFCCGMM combination and note that the postprocessing improves the classification result for all combinations.

Imai (1983) has presented a new technique of cepstral analysis synthesis on the mel frequency scale. The log spectrum on the mel frequency scale (the mel log spectrum) is considered to be an effective representation of the spectral envelope of speech. This analysis synthesis system uses the mel log spectrum approximation (MLSA) filter which was devised for the cepstral synthesis on the mel frequency scale. The filter coefficients are easily obtained through a simple linear transform from the mel cepstrum that defined as the Fourier cosine coefficients of the mel log spectral envelope of speech. The MLSA filter has low coefficient sensitivity and good coefficient quantization characteristics. The spectral distortion caused by interpolation of the filter parameters of two successive frames is small. Accordingly, the data rate of this system is very low. The log spectrum on a mel frequency scale (the mel log spectrum) is considered to be a more effective representation of the spectral envelope of speech than that on the linear frequency scale. The mel cepstrum which is defined as the Fourier transform of a spectral envelope of the mel log spectrum has a comparatively low order, hence it is an efficient parameter. The Mel cepstrum also has the same good features as those of the conventional cepstrum. By using the MLSA filter, a low bit rate mel cepstral analysis synthesis system was obtained. In this system, the spectral envelope information is transmitted by the filter parameter of the MLSA filter. The filter parameter is obtained by a simple linear transform from the mel cepstrum which is defined as the Fourier cosine coefficients of the mel log spectral envelope. The filter parameter has almost the same good statistical properties as those of the mel cepstrum. Since the filter parameter sensitivity of the mel log spectrum is very small, the filter parameter can be roughly quantized. The system has fairly small spectral distortions.

2.6 Neural Network

Upadhyaya and Yan (1993) have explained about artificial neural networks that are developed to simulate the most elementary functions of neurons in the human brain, based on the present understanding of biological nervous systems. These network models attempt to achieve good human-like performance such as: learning from experiments and generalization from previous samples. A processing element (PE) is analogous to a neuron in that it has many inputs from input signals or from other PEs and combines (sum up) the values of the inputs, adjusted by their weights. This sum is then subjected to a nonlinear transformation, often called a transfer function that controls the output in accordance with the prescribed nonlinear relationship. Back-propagation neural networks (BPN) were used to develop the neural network models for artifact classification and defect parameters estimation.

There are several issues that need to be considered when utilizing the back-propagation algorithm to train a neural network such as the selection of hidden layers and nodes, and the learning options. The selection of number of hidden layers and hidden nodes is one of the most important issues in back-propagation network applications. The selection of hidden nodes for a fully-connected, feedforward networks with one hidden layer is based on the two types of Rule-of-thumb.The important algorithms for backpropagation network training are actually the learning coefficient, momentum term that used to smooth the learning, the nonlinear transfer function, the learning rule that specifies how connection weights are changed during the learning process and Gaussian noise and RMS threshold value that adds a random number within a special range to each node summation value in the layer.

CHAPTER 3

TIME-FREQUENCY DISTRIBUTION TECHNIQUE

3.1 Introduction

Time-frequency representations are used to analyze or characterize signals whose energy distribution varies in time and frequency. They map the one-dimensional time-domain signal into a two-dimensional function of time and frequency. A time-frequency representation describes the variation of spectral energy over time.

Time-frequency analysis provides time-localized spectral information for a non-stationary signal as a distribution function in terms of time and frequency. Non-stationary signal in this paper implies a signal which has time-varying frequency components, not a statistically stationary signal. Due to the uncertainty principle, which restricts the resolution in time and frequency, the time-frequency distribution functions have been developed for the purpose of analysis. The basic idea is to devise a joint function of time and frequency, a distribution, that will describe the energy density or intensity of a signal simultaneously in time and frequency. In addition, the method of relating a joint time-frequency distribution to a signal will be a powerful tool for the construction of signals with desirable properties.

3.1.1 Time-Frequency Transforms

The Fourier Transform has become one of the most widely used signal-analysis tools across many disciplines of science and engineering. The basic idea of the Fourier Transform is that any arbitrary signal (of time, for instance) can always be decomposed into a set of sinusoids of different frequencies. The Fourier transform is generated by the process of projecting the signal onto a set of basis functions, each of which is a sinusoid with a unique frequency. The resulting projection values form the Fourier transform (or the frequency spectrum) of the original signal. Its value at a particular frequency is a measure of the similarity of the signal to the sinusoidal basis at that frequency. Therefore, the frequency attributes of the signal can be revealed via the Fourier transform. In many engineering applications, this has proven to be extremely useful in the characterization, interpretation, and identification of signals.

While the Fourier transform is a very useful concept for stationary signals, many signals encountered in real-world situations have frequency contents that change over time. In this case, it is not always best to use simple sinusoids as basis functions and characterize a signal by its frequency spectrum. Joint time-frequency transforms were developed for the purpose of characterizing the time-varying frequency content of a signal. The best-known time-frequency representation of a time signal is known as the Short-Time Fourier Transforms (STFT). It is basically a moving window Fourier transforms. By examining the frequency content of the signal as the time window is moved, a two-dimensional time-frequency distribution called the spectrogram is generated. The spectrogram contains information on the frequency content of the signal at different time instances. One well-known drawback of the STFT is the resolution limit imposed by the window function. A shorter time window results in better time resolution, but leads to worse frequency resolution, and vice versa. To overcome the resolution limit of the STFT, a wealth of alternative time-frequency representations have been proposed.

There are various time-frequency transforms developed by researchers in the signal processing community. They are broadly divided into two classes: linear time-frequency transforms and quadratic (or bilinear) transforms. In this project, the discussion is only concentrated on the quadratic time-frequency transform, that is B-Distribution.

3.2 General Signal Representations

Heart sounds are actually generated by mechanical vibration of heart and cardiovascular system. Commonly, vibration signals are represented in either the time domain or the frequency domain. In general, the time domain representation of a signal,

$$s(t) = a(t)e^{j\varphi(t)} = a(t)e^{j\left(\phi_0 + 2\pi\int_0^t f_i(\tau)d\tau\right)} \tag{3.1}$$

allows a simple characterization of a signal in terms of its (instantaneous) energy,

$$E_i(t) = a(t)^2 = |s(t)|^2 = s(t)s^*(t) \tag{3.2}$$

and instantaneous frequency,

$$f_i = \frac{1}{2\pi}\frac{d(\varphi(t))}{dt} \tag{3.3}$$

that is, at time t the signal has an energy density of $E_i(t)$ at a frequency of $f_i(t)$. For multicomponent signals (i.e., signals which have more than one frequency at a given instance of time) the 'instantaneous frequency' is the average frequency of the signal at that time. The frequency domain representation of a signal,

$$S(f) = A(f)e^{j\theta(f)} = \int s(t)e^{-j2\pi ft}dt \tag{3.4}$$

gives a perfect representation of a signal which consist of multiple harmonic oscillators (i.e., with no amplitude or frequency modulation). However, it is not an adequate representation of non-stationary signals (i.e., signals whose content change with time).

A multicomponent non-stationary signal can be described as the superposition of a number of monocomponent non-stationary signals, giving

$$s(t) = \sum_c s_c(t) = \sum_c a_c(t)e^{j\varphi_c(t)} = \sum_c a_c(t)e^{j\left(\phi_c + 2\pi\int_0^t f_c(\tau)d\tau\right)} \tag{3.5}$$

In order to decompose (and understand) a signal of the form given, a joint time-frequency domain representation of the signal is required.

3.3 General Form of Time-Frequency Distributions

In 1966, Cohen developed a generalized form of 'phase-space' distributions from which all other time-frequency energy distributions could be derived. The general form, which has since become known as Cohen's class of distributions is

$$\rho(t,f) = \iiint g(v,\tau)z\left(u+\frac{\tau}{2}\right)z^*\left(u-\frac{\tau}{2}\right)e^{j2\pi(vu-vt-f\tau)}dv\,du\,d\tau \tag{3.6}$$

where $g(v, \tau)$ is referred to as the kernel function that is used to define the properties of the distribution and $z(t)$ is the analytic signal associated with the real one. For example, by setting the kernel $g(v, \tau) = 1$, equation (3.6) becomes

$$\rho(t,f) = \iiint z\left(u+\frac{\tau}{2}\right)z^*\left(u-\frac{\tau}{2}\right)e^{j2\pi(vu-vt-f\tau)}dv\,du\,d\tau$$

$$= \int z\left(t+\frac{\tau}{2}\right)z^*\left(t-\frac{\tau}{2}\right)e^{-j2\pi f\tau}d\tau \qquad (3.7)$$

which is the Wigner-Ville distribution and setting $g(v, \tau) = |\tau|^{\beta}\cosh^{-2\beta}(t)$ will give the B-Distribution as shown below:

$$\rho(t,f) = \iiint \frac{|\tau|^{\beta}}{\cosh^{2\beta}(t)} z\left(u+\frac{\tau}{2}\right)z^*\left(u-\frac{\tau}{2}\right)e^{j2\pi(vu-vt-f\tau)}dv\,du\,d\tau$$

$$= \iint \frac{|\tau|^{\beta}}{\cosh^{2\beta}(t-u)} z\left(u+\frac{\tau}{2}\right)z^*\left(u-\frac{\tau}{2}\right)e^{-j2\pi f\tau}du\,d\tau \qquad (3.8)$$

$R_z(t,\tau)$ is used to be the instantaneous autocorrelation function of $z(t)$ and it is defined as:

$$R_z(t,\tau) = z\left(t+\frac{\tau}{2}\right)z^*\left(t-\frac{\tau}{2}\right) \qquad (3.9)$$

The symmetrical ("Sussman's") ambiguity function (AF), on the other hand, is defined as the Fourier transform of $R_z(t,\tau)$ with respect to time t:

$$A_z(v,\tau) = \int z\left(t+\frac{\tau}{2}\right)z^*\left(t-\frac{\tau}{2}\right)e^{-j2\pi vt}dt \qquad (3.10)$$

3.3.1 Properties of the Cohen Class of Distributions

The number of distributions which can be generated from equation (3.6) is infinite. Cohen proposed a number of restrictions on the properties of the distributions to be studied and showed that certain constraints could be placed on the kernel function, $g(v,\tau)$ in equation (3.6) to ensure that a distribution meets the restrictions. The constraints on the kernel function required to give certain desirable properties have been studied and the range of desirable properties and the kernels required to meet then is being continuously expended. An extensive range of properties is given by [5] and [7]. Some of these are:

a) *The signal energy is preserved*

The signal energy is preserved if $g(0,0)=1$

b) *The marginal condition in time*

for integration over frequency=energy density in time, $g(v,0)=1$

c) *The marginal condition in frequency*

for integration over time=energy density in frequency, $g(0,\tau)=1$

d) *Real valued distributions*

the distribution will be real valued if $g(v,\tau)=g^*(v,\tau)$

e) *Invariance to time and frequency shifts*

if two signals are identical except for a shift in time or frequency then the distributions of the signals should also be identical except for a similar shift in time or frequency. Cohen [7] showed this is true as long as the kernel function is independent of time and frequency.

f) *The first moment of the distribution equal the instantaneous frequency and group delay*

Boashash [5] showed that the first moment of a distribution in frequency is equal to the *instantaneous frequency* and the first moment in time equals the *group-delay,*

$$\tau_g(f) = -\frac{1}{2\pi}\frac{d(\theta(f))}{df} \tag{3.11}$$

$$\frac{\int f\rho(t,f)df}{\int \rho(t,f)df} = f_i(t) \quad \text{and} \quad \frac{\int t\rho(t,f)dt}{\int \rho(t,f)dt} = \tau_g(f) \tag{3.12}$$

if

$$\frac{\partial g(v,t)}{\partial t}\Big|_{t=0} = \frac{\partial g(v,t)}{\partial v}\Big|_{v=0} = 0, \tag{3.13}$$

$g(v,0)$ = constant for all ν and $g(0,\tau)$ = constant for all τ

g) *Recovery of signal*

Cohen [7] showed that a signal could be recovered up to a constant phase factor if kernel function $g(v, \tau)$ is well defined at every point or has isolated zeros but not regions where it is zero.

h) *Finite time support*

a distribution has finite time support if it is zero before the signal starts and zero after the signal ends. For a signal to have finite time support the kernel must met the condition:

$$\int g(v,\tau)e^{-j2\pi vt}dv = 0 \quad \text{for } |\tau|<2|t| \tag{3.14}$$

3.3.2 Reduced Interference Distributions

Some of time-frequency distributions posses a number of mathematically satisfying properties such as the Wigner-Ville distribution, however, it actually produces large cross-terms when applied to multicomponent signals. This can make interpretation difficult. Therefore, other type of distribution is used to overcome this

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