ADAPTIVE CROSS WIGNER-VILLE DISTRIBUTION FOR PARAMETER ESTIMATION OF DIGITALLY MODULATED SIGNALS

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To my beloved family, friends and
all those who have contributed in this project

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ABSTRACT

Spectrum monitoring is important, not only to regulatory bodies for spectrum management, but also to the military for intelligence gathering. In recent years, it has become part of spectrum sensing process which is the key in cognitive radio system. Among the features of a spectrum monitoring system is to obtain spectrum usage characteristics and determining signal modulation parameters. All these required a powerful signal analysis technique suitable for use with classifier network. The loss of phase information in the Quadratic Time–Frequency Distributions (QTFDs) makes it an incomplete solution as Phase Shift Keying (PSK) modulation is widely employed in many wireless communication applications nowadays. Therefore, Cross Time–Frequency Distribution (XTFD) which can provide localised phase information is proposed in this research. The Adaptive Windowed Cross Wigner–Ville Distribution (AW–XWVD) and Adaptive Smoothed Windowed Cross Wigner–Ville Distribution (ASW–XWVD) are developed to analyse a broader class of signals such as PSK, Quadrature Amplitude Modulation (QAM), Amplitude Shift Keying (ASK) and Frequency Shift Keying (FSK) signals without any prior knowledge. In non–cooperative environment, two kernel adaptation methods are proposed: local and global adaptive. The developed XTFD is proven to be an efficient estimator as it meets the Cramer–Rao Lower Bound (CRLB) for phase estimation at Signal-to-Noise Ratio (SNR) ≥4 dB and Instantaneous Frequency (IF) estimation at SNR ≥–3 dB. Other TFDs such as the S–transform never meet the CRLB in both phase and frequency estimation. A complete signal analysis and classification system is implemented by combining the AW–XWVD and ASW–XWVD for signal analysis. In the presence of Additive White Gaussian Noise, the classifier gives 90% correct classification for all the signals at SNR of about 6 dB. Thus, it has been demonstrated that the XTFD is a complete solution for the analysis and classification of digitally modulated signals.

ABSTRAK

Pemantauan spektrum bukan sahaja penting bagi pihak penguatkuasa dalam pengurusan spektrum, tetapi juga untuk angkatan tentera dalam aktiviti perisikan. Di akhir ini, ia telah menjadi sebahagian daripada pengesanan spektrum yang merupakan kunci kepada sistem radio kognitif. Antara fungsi dalam sistem pemantauan spektrum adalah pengumpulan maklumat penggunaan spektrum dan penentuan parameter modulasi isyarat. Semua ini memerlukan teknik analisis isyarat yang sesuai untuk digunakan bersama rangkaian klasifikasi isyarat. Kehilangan informasi fasa dalam taburan masa–frekuensi quadratik menjadikan ia bukan satu solusi yang menyeluruh memandangkan modulasi *Phase Shift Keying* (PSK) banyak digunakan dalam aplikasi komunikasi wayarles pada masa kini. Oleh itu, taburan masa–frekuensi bersilang yang memberikan informasi fasa setempat dicadangkan dalam penyelidikan ini. Taburan *Adaptive Windowed Cross Wigner–Ville Distribution* (AW–XWVD) dan *Adaptive Smoothed Windowed Cross Wigner–Ville Distribution* (ASW–XWVD) telah direka tanpa pra–pengetahuan bagi meliputi kelas isyarat yang lebih luas seperti PSK, quadratur modulasi amplitud (QAM), *Amplitude Shift Keying* (ASK) dan *Frequency Shift Keying* (FSK). Dalam keadaan tiada kerjasama, dua kaedah adaptasi kernel dicadangkan: adaptasi setempat dan global. Taburan XTFD yang direka telah dibuktikan sebagai penganggar efisien kerana ia mencecah limit *Cramer–Rao Lower Bound* (CRLB) untuk fasa pada *Signal-to-Noise Ratio* (SNR) ≥4dB dan untuk frekuensi pada SNR≥–3dB. Taburan lain seperti *S–transform* tidak mencecah CRLB untuk kedua–dua fasa dan frekuensi. Sistem analisis dan klasifikasi yang menyeluruh telah dibentuk dengan menggabungkan AW–XWVD dan ASW–XWVD. Pengelas tersebut memberikan 90% klasifikasi tepat bagi semua isyarat pada SNR 6 dB dengan kehadiran *Additive White Gaussian Noise*. Maka, taburan XTFD telah dibuktikan sebagai sistem analisis dan klasifikasi yang menyeluruh bagi isyarat modulasi digital.

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LIST OF ABBREVIATIONS

3GPP–LTE - Third Generation Partnership Program Long Term Evolution
ALRT - Average likelihood ratio test
AMC - Adaptive modulation and coding
AMPS - Advanced Mobile Phone Services
AOK - Adaptive optimal kernel
APE - Absolute percentage error
ASK - Amplitude shift keying
ASWWVB - Adaptive smoothed windowed Wigner–Ville bispectrum
ASWWVD - Adaptive smooth–windowed Wigner Ville distribution
ASW–XWVD - Adaptive smoothed windowed cross Wigner–Ville distribution
AWGN - Additive white Gaussian noise
AW–XWVD - Adaptive windowed cross Wigner–Ville distribution
BD - B–distribution
BJ - Born–Jordan
BPSK - Binary phase shift keying
CDMA - Code Division Multiple Access
COMINT - Communication intelligence
CRLB - Cramer–Rao lower bound
CWD - Choi–Williams distribution
FFT - Fast Fourier transform
FM - Frequency modulation
FSK - Frequency shift keying
GLRT - Generalized likelihood ratio test
GPRS - General Packet Radio Service
GSM - Global System for Mobile communications
GUI - graphic user interface
HF - High frequency

HLRT	-	Hybrid likelihood ratio test
IA	-	Instantaneous amplitude
IAF	-	Instantaneous autocorrelation function
ICF	-	Instantaneous cross correlation function
IE	-	Instantaneous energy
IF	-	Instantaneous frequency
IIB–phase	-	Instantaneous information bearing phase
ITU	-	International Telecommunications Union
LF	-	Low Frequency
LLAC	-	Localized lag autocorrelation
LTAC	-	Localized time autocorrelation
MAP	-	Maximum a posteriori probability
MBD	-	Modified B–distribution
MCMC	-	Malaysian Communication and Multimedia Commission
MF	-	Medium Frequency
MLW	-	main–lobe-width
MSK	-	Minimum shift keying
NMT	-	Nordic Mobile Telephony
OFDM	-	Orthogonal Frequency Division Multiplexing
PLL	-	Phase–locked loop
PSK	-	Phase shift keying
PSLR	-	Peak–to–side lobe ratio
QAM	-	Quadrature amplitude modulation
QPSK	-	Quadrature phase shift keying
QTFD	-	Quadratic time–frequency distribution
RID	-	Reduced interference distribution
SCR	-	Signal–to–cross terms ratio
SD	-	Symbol duration
SDR	-	Software defined radio
SHF	-	Super High Frequency
SIGINT	-	Signal intelligence
SNR	-	Signal–to–noise ratio
STFT	-	Short–time Fourier transform
SWWVD	-	Smooth windowed Wigner–Ville distribution

TACS	-	Total Access Communication System
TDMA	-	Time division multiple access
TFA	-	Time–frequency analysis
TFD	-	Time–frequency distribution
TFR	-	Time–frequency representation
TS	-	Time–smooth function
UHF	-	Ultra High Frequency
VHF	-	Very High Frequency
VLF	-	Very Low Frequency
WD	-	Wigner–Distribution
WiMax	-	Worldwide Interoperability for Microwave Access
WVD	-	Wigner–Ville distribution
WWVD	-	Windowed Wigner–Ville distribution
WXWVD	-	Windowed cross Wigner–Ville distribution
XTFD	-	Cross time–frequency distribution
XWVD	-	Cross Wigner–Ville distribution
ZAM	-	Zhao–Atlas–Marks

LIST OF SYMBOLS

f - Signal frequency.

f_{samp} - Sampling frequency

$\phi(t)$ - Instantaneous phase.

k - Symbol sequence.

A_k - Signal amplitude.

φ_k - Instantaneous information bearing phase of the k^{th} symbol.

T_s - Symbol duration.

$\Pi(t)$ - Box function.

$\rho_z(t,f)$ - Quadratic time–frequency distribution.

$K_Z(t,\tau)$ - Bilinear product.

$G(t,\tau)$ - Time–lag kernel.

$\underset{t}{*}$ - Convolution in time.

$z^*(t)$ - Signal of interest complex conjugate.

$z(t)$ - Analytical form of the signal of interest.

$\rho_{zr}(t,f)$ - Quadratic time–frequency distribution.

$K_{zr}(t,\tau)$ - Cross bilinear product.

$r^*(t)$ - Analytical form of reference signal.

$r(t)$ - Reference signal.

$w(\tau)$ - Fixed lag window.

$S(t,f)$ - S–transform.

$g(t,f)$ - Frequency dependent window in the S–transform.

τ - Lag domain or time delay.

$Z(f)$ - Frequency representation of signal of interest.

$K_{zr,auto}(t,\tau)$ - Cross bilinear product of the auto term.

$K_{zr,duplicated}(t,\tau)$ - Cross bilinear product of the duplicated term.

K_{Π} - Bilinear product of the box function.

$w(t,\tau)$ - Time-dependent lag window.

$\tau_g(t)$ - Time-dependent lag window width.

$R_{KK}(t,\varsigma)$ - Localized lag autocorrelation function.

$R_{KK,norm}(t,\varsigma)$ - Normalized localized lag autocorrelation function.

$w_{\mathrm{a}}(\tau)$ - Analysis window.

T - Signal duration.

ς - Lag running instant.

τ_{a} - Analysis window width.

$\tau(k)$ - Occurance time of local minima for localized time autocorrelation function.

$R_{zz}(t)$ - Localized time autocorrelation.

$H(t)$ - Time smooth function.

$\rho_{SWWVD}(t,f)$ - Smoothed windowed Wigner-Ville distribution.

T_{sm} - Time smooth parameter.

T_g - Fixed lag window parameter.

$h(\upsilon)$ - Doppler frequency representation of TS function.

υ_c - Doppler cut–off frequency.

$\rho_{zr,ASW-XWVD}$ - Adaptive smoothed windowed Wigner–Ville distribution.

$\rho_{zr,AW-XWVD}$ - Adaptive windowed Wigner–Ville distribution.

f_k - k^{th} subcarrier frequency.

$S(f)$ - Power spectrum.

$E_{zr}(t)$ - Cross instantaneous energy.

$E_{zr,normalized}(t)$ - Normalized cross instantaneous energy.

$\hat{f}_i(t)$ - Instantaneous frequency.

$\hat{\varphi}(t)$ - Estimated instantaneous information bearing phase.

μ_{IE} - Mean of the instantaneous energy .

$\sigma_{IE}{}^{2}$ - Variance of the instantaneous energy.

γ - Signal-to-noise ratio (SNR).

$W_z[n,k]$ - Discrete time formulation of the Windowed Wigner-Ville distribution.

$\rho_{zr,AWXWVD,}[n,k]$ - Discrete time formulation of the adaptive windowed cross Wigner-Ville distribution.

$\rho_z[n,k]$ - Discrete time formulation of quadratic time-frequency distribution.

$\rho_z[n,k]_{ASW-XWVD}$ - Discrete time formulation of the adaptive smoothed windowed cross Wigner-Ville distribution.

$H(n)$ - Discrete time representation of time smooth function.

$S[n,k]$ - Discrete time formulation of the S-transform.

N - Number of symbol or signal length.

N_τ - Lag window length.

N_A - Length of the analysis window.

N_w - Average length of time–dependent lag window.

N_{sm} - Length of smoothing function.

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CHAPTER 1

INTRODUCTION

1.1 Background

Wireless communication is a fast growing technology that was stimulated by various emerging applications from commercial use, specialized application in public protection, disaster relief and wireless communication [1]. The development of wireless communications technologies from the first generations to today's fourth generation results in the explosion of the number of wireless communication users. According to the International Telecommunications Union (ITU) statistics, the total number of mobile cellular users is 6000 million up to year 2011 [2]. For Malaysia, the total number of mobile subscribers recorded until June 2012 can be found in [3]. Users communicate in new ways through the internet and multimedia communications where speeds and communication reliability are crucial. Therefore, various modulation and coding techniques such as M-ary modulation, Orthogonal Frequency Division Multiplexing (OFDM), Code Division Multiple Access (CDMA), multicarrier–CDMA [4–8] were introduced to cater for the increase of the users' demand. Technologies such as cellular network, wireless local area network (WLAN), wireless metropolitan network (WMAN), Bluetooth, Zigbee, radio frequency identification (RFID), ultra-wideband (UWB), WiMax, TV broadcast and satellites require radio spectrum to operate [9]. Other than those applications, the available spectrum is also used for military, maritime and aeronautical applications.

Since the availability of the spectrum is very limited, hence there is a need to manage the usage of the frequencies. This can be done through spectrum monitoring which is usually conducted by the regulatory bodies, military, wireless operators and security agencies. General features of a spectrum monitoring system are the measurement of signal carrier frequency, power, direction, estimation of modulation parameters and symbol rate [10]. Regulatory bodies such as Malaysian Communication and Multimedia Commission (MCMC) and the United States Federal Communication Commission (FCC) perform spectrum monitoring as a mean of spectrum management and surveillance to ensure the conformance to the frequency planning [11]. From military applications perspective, spectrum monitoring is part of electronic warfare and threat assessment [12–15]. Cognitive radio which arises recently as a solution to the spectral congestion problem has adopted spectrum monitoring or spectrum sensing to sense the spectral environment for unoccupied band [16, 17]. Other than detecting the radio frequency over the spectrum, spectrum sensing also involves measurement of the signal characteristics such as the modulation parameters, carrier frequency and waveform [18]. Thus, a powerful and efficient signal analysis tool is required to perform all the tasks of a spectrum monitoring system.

1.2 Problem Statement and its Significance

Any information bearing signal in communication system needs to be modulated so that it could be transmitted through the frequency band of interest. Due to the development of wireless communication, various modulation schemes were introduced to provide efficient use of the available spectrum. The modulation schemes can be classified into three general classes: amplitude shift keying (ASK), frequency shift keying (FSK) and phase shift keying (PSK). Other modulation schemes such as minimum shift keying (MSK), quadrature PSK (QPSK), quadrature amplitude modulation (QAM) and OFDM are derived from any one of these three general classes. The type of modulation and the data format must be known at the receiver before information can be recovered from the received signal. Signal analysis and classification represents an intermediate step between signal interception and demodulation. Other than that, it is also part of a spectrum monitoring system where it provides information such as the instantaneous parameters of a signal. The task is more challenging in non–cooperative environment where there is no prior information of the received signals available. Therefore, there is a need to develop a method to perform signal analysis and classification of digital modulation suitable for a non–cooperative environment.

Digital communication signals are exposed to channel impairment such as multipath fading, path loss, noise and interference [19]. Multipath fading occurs due to the presence of reflectors and scatterers in the transmission channel causing signals arriving from multiple propagation paths [20]. The resulting signals exhibit time–varying amplitude and phase and is attenuated or delayed. Flat fading can result in amplitude reduction as multiple received signals cancel out each other [19]. This phenomenon reduces the signal–to–noise ratio (SNR) and leads to the inaccuracy of the analysis and classification process. In this case, the cross time–frequency distribution (XTFD) provides a better solution in estimating instantaneous parameters compared to quadratic time–frequency distribution (QTFD) for low SNR [21].

Since digital communications signals are time–varying, hence time–frequency analysis (TFA) is a suitable method to analyze these signals. The problem with power spectrum estimation method is that it assumes signals to be time–invariant and stationary. The conventional power spectrum estimate provides only frequency content of the signal but not its temporal characteristics. Previous work based on the QTFD has demonstrated that this method is capable to analyze ASK and FSK signals accurately at SNR as low as –2 dB [22, 23]. Since the QTFD represents the distribution of the signal power over the time and frequency plane, hence the phase information of a signal is not represented and could not be used to analyze PSK and QAM signals completely. The XTFD which is capable to extract phase information of a signal is proposed in this research. Similar to the cross terms which appeared in the QTFD, interference terms are introduced in the XTFD. The interference terms are referred to as duplicated terms instead of cross terms in QTFD because it carry the same information as the auto terms but shifted in both time and lag in the time–lag representation. Both cross terms and duplicated terms cause misinterpretation of a signal and must be suppressed. This justifies the need for an optimal kernel that minimizes the effect of the cross terms and duplicated terms to produce an accurate TFR of a signal.

Adaptive modulation and coding (AMC) scheme is a resource allocation technique used in WiMax and HSDPA to enhance the data throughput [24, 25]. It is also applied in modern high frequency (HF) communication systems such as PACTOR I/II/III and MIL STD 188-110B [26]. By varying the type of modulation, level of modulation, coding techniques and transmission symbol rate according to time–varying channel, spectral efficiency is achieved while maintaining good connection quality and link stability [27, 28]. Due to the time–varying characteristic of these signals, an adaptive cross time–frequency analysis is the most comprehensive technique to estimate the signal instantaneous parameters such as instantaneous frequency (IF), instantaneous amplitude (IA) and instantaneous information bearing phase (IIB–phase). Therefore, an optimum signal analysis and classification method that can adaptively change its kernel parameters to be used with systems employing AMC scheme is required.

Instantaneous parameters such as IF, IA and IIB–phase are important parameters in many applications. In seismic, radar, sonar, communications, and biomedical applications, the IF and IIB–phase are good descriptors of some physical phenomena [29, 30]. In this research, these parameters are used as input to classify digitally modulated signals. Estimation of these parameters is a challenging task as in practice signals are exposed to noise and interference. Accurate parameters estimation is crucial as it significantly affects the classification accuracy. The QTFD can accurately estimate IF but it is less robust to noise as compared to XTFD [21]. Moreover, the XTFD can estimate both IF and IIB–phase which makes it a complete optimum instantaneous parameters estimator.

1.3 Research Philosophy and Motivation

The traditional power spectrum estimation method which assumes that signals to be stationary has a limitation in analyzing signals with time-varying contents. Therefore, it fails to provide a useful representation for precise characterization and identification of digital communication signals which are time-varying in nature. In this research, the time-frequency distribution which gives representation of signal jointly in time and frequency arises as the motivation for devising a more sophisticated and practical analysis tool for time-varying signals. It has been proven in the previous work [22, 23] that the QTFD is practically useful in analyzing digitally modulated signals. However, success is limited only for ASK and FSK signals as the phase information is lost in the computation of the bilinear product. Thus, there is a necessity to derive a comprehensive distribution which is capable to analyze a broader class of signals while maintaining the IIB-phase in the PSK and QAM signals. The XTFD gives the complex distribution of the signal over the time-frequency plane. Thus, it is capable to represent phase information in the signal. Due to the presence of duplicated terms and cross terms in the time-lag representation, the adaptive XWVD is proposed in this research to provide an accurate TFR for digitally modulated signals.

An accurate TFR is necessary as the parameter estimation is derived using peak detection method. In practice, signals are subjected to impairments such as noise, interference and fading which causes variance in the estimation of instantaneous parameters. Therefore, an optimum parameter estimator for digitally modulated signals is required. In order to benchmark the developed parameter estimation performance, the CRLB is used as the theoretical limit. An optimum parameter estimator is crucial as it translates to a good classification results especially in the low SNR range of less than 10dB. Further outcome of this work is applicable to any frequency band since the limitation is on the sampling frequency and also in radar where similar signals are used in pulse compression.

1.4 Objectives

The objectives of this research are:

1. To develop a XTFD with an adaptive window function which yields accurate TFR for PSK, QAM and ASK signals. Then, together with a time-smooth function this adaptive window is capable to produce accurate TFR for FSK signals.

2. To estimate the instantaneous parameters of digitally modulated signals using the peak detection method from the TFR.

3. To benchmark the instantaneous parameter estimation with the Cramer–Rao lower bound (CRLB) to verify the optimality of the estimation method.

1.5 Scope of Work

This research focuses mainly on the analysis and classification of digitally modulated signal using TFA method. The scopes of this project are as follows:

1. Signals considered here are the digitally modulated signals which include the class of ASK, FSK, PSK and QAM signals. This research is extensions of the previous work done on the QTFD where only ASK and FSK signals had been considered [22, 23].

2. Intercepted signals are HF communications signals due to the availability of the Perseus software defined radio (SDR) at the Digital Signal Processing Lab, Universiti Teknologi Malaysia. With the suitable receiving equipment, the research findings could be applied to receive signals from other frequency bands.

3. In this research, the received signal is demodulated to baseband and the analysis is performed at baseband. The choice of sampling frequency must meet the Nyquist sampling theorem. The sampling frequency used throughout this research is normalized to 1 Hz to show that the developed methods are not limited to communication applications in the HF band solely.

4. A reference signal is required in the computation of the XTFD. In this research, it is assumed a pure sinusoid signal with the same carrier frequency as the signal of interest. This reference signal is generated synthetically based on the estimated frequency of the received signal using traditional power spectrum estimation technique.

5. Pattern recognition method [31] is employed in this research as the signals parameters are first estimated before classification of the signal is performed

6. The main interest of this research is to focus on developing an efficient and accurate signal analysis techniques based on the XTFD and not on the classification algorithm. The purpose for selecting the rule based classifier is to demonstrate the performance of complete signal analysis and classification system which is a component of a spectrum monitoring system.

7. Since all digital communication signals suffer from channel impairments, simulation is performed in the presence of additive white Gaussian noise

(AWGN). The developed signal analysis method is then benchmarked to the CRLB to determine the optimality of the developed methods.

8. In this research, it is assumed that the fading rate is slow compared to the received signal packet length as such that the signal instantaneous energy is approximately constant.

9. The developed method is compared with other time–frequency distributions (TFDs) such as S–transform and adaptive smooth–windowed Wigner Ville distribution (ASWWVD) for IF estimates. Since the S–transform is capable to provide localized phase information of a signal, it is compared with the XTFD in terms of the IIB–phase estimate.

1.6 Research Methodology

The overall procedure and methodology carried out through this research can be represented as a flow chart as shown in Figure 1.1. This research begins with the studies and reviews on digital communications, spectrum monitoring, TFA, signal analysis and classification. The purposes of conducting literature review on these areas are to gain better understanding and generate new ideas to resolve the problems encountered in the research. On top of that, review of other works done is beneficiary in benchmarking this research. Then, analysis of the cross bilinear product of the PSK and QAM signals with time–varying IIB–phase in the time–lag representation. Based on the signal characteristics, an optimum kernel function and parameters that gives accurate TFR is designed. Adaptive algorithms for estimating the kernel parameters suitable for non–cooperative communication environment are developed. Two methodologies are proposed: local adaptation method and global adaptation method.

Next, the previously developed methods are then extended for the analysis of digitally modulated signals such as the ASK and FSK signals. Analysis of the cross bilinear product for these signals in the time–lag representation is performed and a mathematical model is developed to represent these signals. A generalized XTFD which capable to analyze all digitally modulated signals is formed by combining both distributions. Thus, this formulation can be used to analyze broader class of signals such as ASK, FSK, PSK and QAM signals. The performance of the XTFR is evaluated using a set of comparison criteria: main–lobe-width (MLW), peak–to–side lobe ratio (PSLR), symbol duration (SD) and signal–to–cross terms ratio (SCR). All these performance measures are quantified in terms of the absolute percentage error (APE) for further comparison.

The instantaneous parameters such as IIB–phase and IF are estimated from the peak of the TFR. Monte Carlo simulations of 100 realizations are carried out at various SNR level and the performance of the XTFD, S–transform and ASWWVD is then benchmarked to the CRLB. Followed by that, a signal analysis and classification system is designed. The analysis is done using the XTFD and classification is done based on the rule based classifier. Signals parameters' estimated are used as inputs to the classifier. Classification is done based on the type of modulation, subcarrier frequency, IIB–phase and symbol duration. Monte Carlo simulation is used to verify the performance of the signal analysis and classification system. Simulation is run at SNR range from –5 dB to 12 dB to classify ASK, FSK, PSK and QAM signals. The performance of the signal analysis and classification system is evaluated based on the percentage of correct classification. In order to validate the proposed system, field testing is conducted using equipment available in the DSP laboratory.

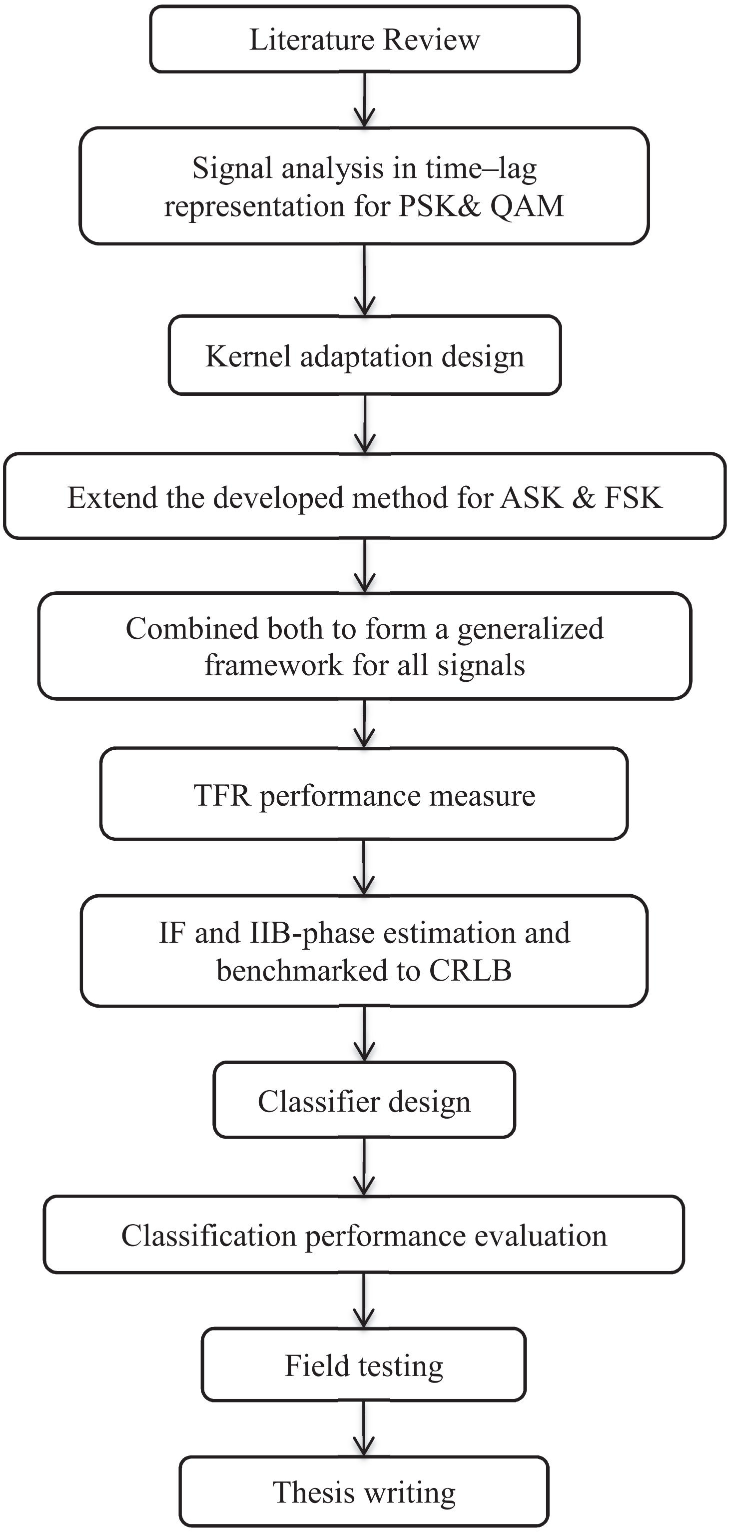

Figure 1.1 Research procedures

1.7 Contributions of Work

In this work, a signal analysis and classification system for digitally modulated signals using the XTFD is proposed. The XTFD overcomes the limitation of previous work on the QTFD where it is capable to retain phase information of a signal. Design of the kernel function of the XTFD is done in a systematic way where the signal characteristics is first analyzed and then used to develop the appropriate kernel function. It is demonstrated that the XTFD is capable to analyze phase bearing signals such as PSK and QAM signals. Various works were reported using this distribution but most of them were used for IF estimate in biomedical applications [21,30]. So far, there is no work presented based on this distribution for communication applications.

An optimum formulation for XTFD which is capable in analyzing a broader class of signals such as the ASK, FSK, PSK and QAM signals is proposed. This significantly overcomes the limitation of previous work on QTFD for digitally modulated signals which is applicable only for ASK and FSK signals. Two adaptation methods namely local adaptation and global adaptation are proposed to estimate the kernel parameters. Between these two methods, the local adaptation method which changes its kernel parameter every time instant gives better performance at low SNR at the expense of computation cost. However, with the advances of current technologies such as parallel processing this adaptation method is still feasible.

Comparison is made with other TFDs such as the S–transform and ASWWVD. The S–transform has received major attention recently due to its capability to provide localized phase information of a signal. The ASWWVD provides accurate TFR for ASK and FSK signals. As an IF estimator, it is capable to work at low SNR of –3 dB. The proposed optimum XTFD is proven to be an efficient phase estimator as it meets the CRLB at minimum SNR of 4 dB whereas the S–transform did not meet the CRLB even at SNR of 12 dB for all PSK and QAM signals. Since, the ASWWVD cannot represent phase, it is compared to the optimum XTFD as an IF estimator. Both the optimum XTFD and ASWWVD are efficient IF estimators as both meet the CRLB at SNR –3 dB for FSK signals. The optimum XTFD is both efficient frequency and phase estimator which makes it a complete solution to analyze digitally modulated signals.

A comprehensive signal analysis and classification system is proposed based on the optimum XTFD method that works at low SNR of 6 dB. Signals modulation parameters such as the IIB–phase, carrier frequency and symbol duration are estimated from the peak of the TFR. These modulation parameters are then used as input to the classifier to determine the signal type from a set of possible signals. Most of the automatic modulation classification system classifies the modulation type alone without any addition information on signals available. Thus, the proposed signal analysis and classification system can provide other information on signals such as the instantaneous energy, IIB–phase, carrier frequency and symbol rate.

1.8 Thesis Organization

This thesis is organized as follows. Overview of this research is given in the Chapter 1. Chapter 2 discusses on some recent work on spectrum monitoring, cognitive radio, phase estimation, IF estimation, TFA, signal analysis and classification. The mathematical model for signals carrying phase information such as PSK and QAM signals are given in Chapter 3. Selection of the kernel is done based on the analysis of the signal in the time–lag domain. The kernel function for PSK and QAM signals is a time–dependent lag window. In the same chapter, the adaptation algorithm used for estimating the time–dependent lag window is discussed. In Chapter 4, the analysis method is extended to include ASK and FSK signals. The mathematical representation of these signals in the time–lag domain and the kernel function is given. Chapter 5 presents the benchmark of the proposed

XTFD with other TFDs and the CRLB for parameters estimation. In the same chapter, the classification performance of the designed system is discussed. Conclusion and recommendations for future work are presented in Chapter 6.

REFERENCES

1. Poor, H. V. and Wornell, G. W. *Wireless Communications: Signal Processing Perspectives*. New Jersey: Prentice Hall. 1998.
2. International Telecommunications Union (ITU) Statistics. Global mobile-cellular subscriptions, total and per 100 inhabitants, 2001-2011. Retrieved on 17 July, 2012, from http://www.itu.int/ict/statistics.
3. Malaysian Communications and Multimedia Commission (MCMC). Statistics and Records. Retrieved on 14 Jan, 2013, from http://www.skmm.gov.my.
4. Smith, C. and Collins, D. 3G wireless network. New York: The McGraw-Hill. 2002.
5. William, C. Y. Wireless and Cellular Communications. Third Edition New York : McGRAW-HILL. 2006. pp.1-27
6. Singal, T.L. Wireless communication. India: McGraw–Hill. 2010. pp 1-16
7. Das, S.K. Mobile Handset Design. Singapore: John Wiley & Sons. 2010. pp 509-536
8. Himayat, N., Talwar S., Rao A. and Soni R. Interference management for 4G cellular standards [WIMAX/LTE UPDATE]. IEEE Communications Magazine, IEEE, 2010. 48(8): 86-92
9. Volakis, J.L. Antenna Engineering Handbook, Fourth Edition. New York: McGraw-Hill. 2007.
10. Tan, J.L. and Sha'ameri, A.Z. Automatic Analysis and Classification of Digital Modulation Signals Using Spectogram Time Frequency Analysis. IEEE International Symposium on Communication and Information Technology ISCIT 2007, 17-19 Oct, 2007. Sydney, NSW: IEEE, 2007. 916- 920
11. Malaysian Communication & Multimedia Commission (MCMC). Spectrum Plan. 2011.

12. Shklyaeva, A., Kovar, P. and Kubanek, D. Classification of Digital Modulations Mainly Used in Mobile Radio Networks by means of Spectrogram Analysis. IFIP International Federation for Information Processing, 2007, 245: 341-348.
13. Yuan, J., Zhang, Z.Y. and Qiu, P.L. Modulation Classification of Communication Signals. IEEE Military Communication Conference MILCOM, 31 Oct.-3 Nov, 2004. 1470-1476.
14. Ramkumar, B. Automatic Modulation Classification for Cognitive Radios Using Cyclic Feature Detection. IEEE Circuits and Systems Magazine, IEEE , Second Quarter 2009, 9(2): 27-45.
15. El-Mahdy, A.E. Automatic Modulation Classification of Composite FM/PM Speech Signals in Sensor Arrays Over Flat Fading Channel. IET Communications, Institution of Engineering and Technology, IET April 2007, 1(2): 157-164.
16. Yucek, T. and Arslan, H. A Survey of Spectrum Sensing Algorithms for Cognitive Radio Applications. IEEE Communications Surveys & Tutorials, IEEE, First Quarter 2009, 11(1): 116-130.
17. Axell, E., Leus, G., Larsson, E.G. and Poor, H.V. Spectrum Sensing for Cognitive Radio. IEEE Signal Processing Magazine, May 2012.
18. Lee, W.Y., Chowdhury, K.R. and Vuran, M.C. Cognitive Radio Networks. USA : Auerbach Publications, CRC Press, 2008. 9-16.
19. Sklar, B. Digital Communications, Fundamentals and Applications. Second edition. United State: Prentice Hall. 2006.
20. Bagad, V.S. Wireless Communication. India: Technical Publications Pune, India. 2009. 1-16
21. Ristic, B. and Boashash, B. Use of the Cross Polynomial Wigner-Ville Distribution for Instantaneous Frequency Estimation of Non-Linear FM Signals. International Symposium on Proceedings of the IEEE-SP Time-Frequency and Time-Scale Analysis, 25-28 Oct, 1994. Philadelphia, PA: IEEE, 1994. 252-255.
22. Tan, J.L and Sha’ameri, A.Z. Adaptive Optimal Kernel Smooth-Windowed Wigner-Ville Distribution for Digital Communication Signals. EURASIP Journal on Advances in Signal Processing, Hindawi Publications Corp, Nov 2008.

23. Tan, J.L and Sha’ameri A.Z. Adaptive optimal kernel smooth-windowed Wigner-Ville Bispectrum for digital communication signals. Signal Processing, Elsevier. 2011. 91(4), 931–937 (2011).
24. Fantacci, R., Marabissi, D., Tarchi, D. and Habib, I. Adaptive Modulation and Coding Techniques for OFDMA Systems, IEEE Transactions On Wireless Communications, IEEE, September 2009. 8(9): 4876-4883.
25. Shayea, I., Ismail, M., Sultan, J. and Misran, N. Spectral Efficiency of Mobile WiMAX Networks Employing Adaptive Modulation and Coding, IEEE 10th Malaysia International Conference on Communications (MICC). 2-5 October 2011. Sabah, Malaysia, IEEE. 2011.
26. Proesch, R. Technical Handbook for Radio monitoring HF. Germany: Books on Demand GmbH. 2009.
27. Marabissi, D., Tarchi, D., Fantacci, R. and Balleri, F. Efficient Adaptive Modulation and Coding Techniques for WiMAX Systems. IEEE International Conference on Communications. 19-23 May, 2008. Beijing, China: IEEE, 2008. 3383-3387.
28. Simon, M.K. and Alouini, M.S. Digital Communication over Fading Channels. Canada: John Wiley and Sons. 2005.
29. Boashash, B. Estimating and interpreting the instantaneous frequency of a signal-part 1: fundamentals, IEEE Proc. IEEE, 1992. 80 (4): 520–538.
30. Shin, Y.-J., Gobert, D., Sung, S.-H., Powers, E.J. and Park J. B. Application Of Cross Time-Frequency Analysis to Postural Sway Behavior: the Effects of Aging and Visual Systems. IEEE Transactions on Biomedical Engineering, May 2005. 52(5): 859-868.
31. Dobre, O.A., Abdi, A., Bar-Ness, Y. and Su, W. Survey of automatic modulation classification techniques: classical approaches and new trends. IET Communications, April 2007. IET. 2007. 1(2): 137-156.
32. Elbert, B.R. Introduction to Satellite Communication. 3rd edition. Norwood: Artech House Inc. 2008.
33. Sorrentino, R. and Bianchi, G. Microwave and RF Engineering. United Kingdom: John Wiley & Sons. 2010.
34. Martine, C., Adrian, F. and Robert, W.J. Radio Spectrum Management: Overview and Trends. ITU Workshop on Market Mechanisms for Spectrum Management. 22-23 January, 2007. ITU Headquarters, Geneva, Switzerland.

35. Ziemer, R. and Peterson, R.L. Introduction to Digital Communication. New Jersey: Prentice-Hall. 2001. 284-296
36. Gaiwak, A., Jain, A. and Vyavahare, P.D. Spectrum management for wireless communication an overview. IEEE International Conference on Personal Wireless Communications. 23-25 Jan, 2005. IEEE, 2005. 441- 445.
37. Matic, V., Lestar, B. and Tadic, V. The use of digital signal processing for a modulation classification. 11th Mediterranean Electrotechnical Conference. 07 August, 2002. 126- 130.
38. Ramakomar, V., Habibi, D. and Bouzerdoum, A. Automatic recognition of digitally modulated communications signals. Proceedings of the Fifth International Symposium on Signal Processing and Its Applications. 22 Aug-25 Aug, 1999. Brisbane, Qld: IEEE, 2008. 753-756.
39. Mukherjee, A., Bandyopadhyay, S. and Saha, D. Location Management and Routing In Mobile Wireless Networks. Norwood, MA: Artech house inc. 2003. 39-41.
40. Çayirci, E. and Rong, C.-M. Security in Wireless Ad Hoc and Sensor Networks. UK: John Wiley & Sons. 2009.
41. Lakhmi C.J, Gabrys, B. and Robert J. H. Knowledge-based intelligent information and engineering systems, Part 2. New York: Springer-Verlag Berlin Heidelberg. 2006. 523-530.
42. Neri, F. Introduction to Electronic Defense Systems, 2nd edition. Raleigh, NC: SciTech Publishing Inc. 2006.
43. Luo, T., Lin, F., Jiang, T., Guizani, M. and Chen, W. Multicarrier modulation and cooperative communication in multihop cognitive radio networks. IEEE Wireless Communications, IEEE, February 2011. 18(1). 38-45.
44. Sridhara, K., Chandra, A. and Tripathi, P.S.M. Spectrum Challenges and Solutions by Cognitive Radio: An Overview. Wireless Personal Commununications, Springer, May 2008. 45(3): 281–291.
45. ElRamly, S., Newagy, F., Yousry, H. and Elezabi, A. Novel modified energy detection spectrum sensing technique for FM wireless microphone signals. IEEE 3rd International Conference on Communication Software and Networks (ICCSN), 27-29 May, 2011. Xi'an, China: IEEE. 59-63.
46. Imani, S., Dehkordi, A.B. and Kamarei, M. Adaptive sub-optimal energy detection based wideband spectrum sensing for cognitive radios. International

Conference on Electrical, Control and Computer Engineering (INECCE). 21-22 June, 2011. Pahang, Malaysia: IEEE. 22-26.

47. Gholamipour, A.H., Gorcin, A., Celebi, H., Toreyin, B.U., Saghir, M.A.R., Kurdahi, F. and Eltawil, A. Reconfigurable filter implementation of a matched-filter based spectrum sensor for Cognitive Radio systems. IEEE International Symposium on Circuits and Systems (ISCAS). 15-18 May, 2011. Rio de Janeiro: IEEE. 2457-2460.
48. Kapoor, S., Rao, S.V.R.K. and Singh, G. Opportunistic Spectrum Sensing by Employing Matched Filter in Cognitive Radio Network. International Conference on Communication Systems and Network Technologies (CSNT). 3-5 June, 2011. Katra, Jammu: IEEE. 580-583.
49. Geirhofer, S., Tong, L. and Sadler, B.M. A Measurement-Based Model for Dynamic Spectrum Access in WLAN Channels. IEEE Military Communications Conference. 23-25 Oct, 2006. Washington, DC: IEEE. 1-7.
50. Li, J.J., Tan, Z.H., Xu, S.Y. and Wang, H.B. Cooperative Correlation Based Spectrum Sensing for DMB-T Systems. IEEE Vehicular Technology Conference. 16-19 May, 2010. Taipei: IEEE. 1-5.
51. Ali, O., Nasir, F. and Tahir, A.A. Analysis of OFDM parameters using Cyclostationary spectrum sensing in cognitive radio. IEEE 14th International Multitopic Conference. 22-24 Dec, 2011. Karachi: IEEE. 301-305,
52. Derakhshani, M., Tho L.-N. and Nasiri-Kenari, M. Efficient Cooperative Cyclostationary Spectrum Sensing in Cognitive Radios at Low SNR Regimes. IEEE Transactions on Wireless Communications, IEEE, November 2011. 10(11): 3754-3764.
53. Karthik, D., Manikandan, P.N., Hari, R.R.S. and Srinivas, A.R. A novel algorithm for spectrum sensing using adaptive Wavelet Edge Detection scheme. 3rd International Conference on Electronics Computer Technology (ICECT). 8-10 April, 2011. Kanyakumari: IEEE.118-122.
54. Chandran, A., Anantha K.R., Kumar, A., Subramania S.M., Iyer, U.S., Ramanathan, R. and Naidu, R.C. Discrete Wavelet Transform Based Spectrum Sensing in Futuristic Cognitive Radios. International Conference on Devices and Communications (ICDeCom). 24-25 Feb, 2011. Mesra, Ranchi: IEEE .1-4.
55. Javed, F. and Mahmood, A. The use of time frequency analysis for spectrum sensing in cognitive radios. International Conference on Signal Processing and

Communication Systems (ICSPCS). 13-15 Dec, 2010. Gold Coast, QLD: IEEE. 1-7,

56. Luo, Y.H. and Bu, Z.Y. Distributed spectrum sensing based on the Gabor time-frequency analysis for cognitive networks. IET International Communication Conference Wireless Mobile and Computing. 7-9 Dec, 2009. Shanghai, China: IEEE. 690-693,
57. Sutton, P.D., Lotze, J., Nolan, K.E. and Doyle, L.E. Cyclostationary Signature Detection in Multipath Rayleigh Fading Environments. International Conference on Cognitive Radio Oriented Wireless Networks and Communications. 1-3 Aug, 2007. Orlando, USA: IEEE. 408-413,
58. Semenov E.K.S. Modulation and Coding Techniques in Wireless Communications. United Kingdom: John Wiley & Sons Ltd. 2011.
59. Franz Hlawatsch, Gerald Matz. Wireless Communications over Rapidly Time-Varying Channels. USA: Elsevier. 2011.
60. Saunders, S.R. and Arag´on-Zavala, A. Antennas and Propagation for Wireless Communication Systems, 2nd edition, Chichester: John Wiley & Sons, Ltd. 2007.
61. Oetting, J. The Effects of Fading on Antijam Performance Requirements. IEEE Journal on Selected Areas in Communications, Feb 1987. 5(2): 155-161.
62. Sklar, B. Rayleigh fading channels in mobile digital communication systems .I. Characterization. IEEE Communications Magazine, Jul 1997. 35(7): 90-100.
63. Watterson, C., Jurosheck, J. and Bensema, W. Experimental Confirmation of an HF Channel Model. IEEE Transactions on Communications Technology. 1970. 18 (6): 792-803.
64. International Telecommunication Union. Recommendation 520-1 Use of High Frequency Channel Simulator. Recommendation and Reports of the CCIR. 1986. 3: 57-58.
65. Pahlavan, K. and Allen H. L. Wireless information networks, 2nd Edition. New Jersey, USA: John Wiley & Sons Inc. 2005.
66. Xu, J.L., Su, W. and Zhou, M.C. Likelihood-Ratio Approaches to Automatic Modulation Classification. IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE, July 2011. 41(4): 455-469.

67. Jie, Y., Ye, C.Z. and Yue, Z. Modulation classification based on spectrogram. Journal of Systems Engineering and Electronics, IEEE, September 2005. 16(3): 475-488.

68. Zeng, D., Zeng, X., Lu, G., and Tang, B. Automatic modulation classification of radar signals using the generalised time-frequency representation of Zhao, Atlas and Marks. Radar, Sonar & Navigation, IET, April 2011. 5(4): 507-516.

69. Beidas, B.F. and Weber, C.L. Higher-order correlation-based approach to modulation classification of digitally frequency-modulated signals. IEEE Journal on Selected Areas in Communications, IEEE, Jan 1995. 13(1): 89-101.

70. Beidas, B.F. and Weber, C.L. Asynchronous classification of MFSK signals using the higher order correlation domain. IEEE Transactions on Communications, IEEE, Apr 1998. 46(4): 480-493,

71. Hero, A.O., and Hadinejad-Mahram, H. Digital modulation classification using power moment matrices. IEEE International Conference on Acoustics, Speech and Signal Processing, 12-15 May, 1998. Seattle, WA: IEEE. 3285-3288

72. Hsue, S.Z. and Soliman, S.S. Automatic Modulation Classification using Zero Crossing. IEE Proceedings F: Radar and Signal Processing, IEEE, December 1990. 137(6): 459-46.

73. Assaleh, K., Farrell, K. and Mammone, R.J. A New Method of Modulation Classification for Digitally Modulated Signals. IEEE Military Communications Conference, 11-14 October, 1992. San Diego, CA: IEEE. 712-716.

74. Polydoros, A. and Kim, K. On the detection and classification of quadrature digital modulations in broad-band noise. IEEE Transaction on Communications, IEEE, August 1990. 38(8): 1199–1211

75. El-Mahdy, A.E. and Namazi, N.M. Classification of Multiple M-ary Frequency-Shift Keying Signals over a Rayleigh Fading Channel. IEEE Transactions on Communications, IEEE, June 2002. 50 (6): 967-974.

76. Hong, L. and Ho, K.C. BPSK and QPSK modulation classification with unknown signal level. 21st Century Military Communications Conference Proceedings, 22 -25 Oct, 2000. Los Angeles, CA: IEEE. 976–980.

77. Panagiotou, P., Anastasoupoulos, A., and Polydoros, A. Likelihood ratio tests for modulation classification. 21st Century Military Communications Conference Proceedings, 22 -25 Oct, 2000. Los Angeles, CA: IEEE. 670–674

78. Lay, N. and Polydoros, A. Modulation classification of signals in unknown ISI environments. Military Communications Conference, 05-08 Nov 1995, San Diego, CA: IEEE. 170–174.
79. Dobre, O.A., Zarzoso, J., Bar-Ness, Y., and Su, W. On the classification of linearly modulated signals in fading channel. Proc. CISS Conference, Princeton, March 2004.
80. Abdi, A., Dobre, O.A., Choudhry, R., Bar-Ness, Y., and Su, W. Modulation classification in fading channels using antenna arrays. Military Communications Conference, 31 Oct-3 Nov, 2004. IEEE. 211- 217.
81. Ho, K.C., Prokopiw, W. and Chan, Y.T. Modulation Identification by the Wavelet Transform. Proc. IEEE Military Communication Conference MILCOM, 05-08 Nov, 1995. San Diego, CA: IEEE. 886-890.
82. Soliman, S.S. and Hsue, S.Z. Signal Classification using Statistical Moments. IEEE Transactions on Communications, IEEE, May 1992. 40 (5): 908-916.
83. Azzouz, E.E. and Nandi, A.K. Procedure for Automatic Recognition of Analogue and Digital Modulations. IEE Proceedings-Communications, IET, October 1996. 143 (5): 259-266.
84. Haring, L., Chen, Y. and Czylwik, A. Automatic Modulation Classification Methods for Wireless OFDM Systems in TDD Mode. IEEE Transactions on Communications, IEEE, September 2010. 58(9): 2480-2485.
85. Nandi, A.K. and Azzouz, E.E. Algorithms for Automatic Modulation Recognition of Communication Signals. IEEE Transactions on Communications, IEEE, April 1998. 46 (4): 431-436.
86. Zong, W., Edmund, M.K and Quek, C. Digital Modulation Classification using Fuzzy Neural Networks. Studies in Computational Intelligence (SCI). Berlin: Springer. 2006. 101–116
87. Ahmadi, N. and Berangi, R. Modulation Classification of QAM and PSK From Their Constellation Using Genetic Algorithm And Hierarchical Clustering. International Conference on Information and Communication Technologies: From Theory to Applications, 7-11 April, 2008. Damascus: IEEE. 1-5.
88. Popoola, J.J. and VanOlst, R. Automatic classification of combined analog and digital modulation schemes using feedforward neural network. AFRICON, 13-15 Sept, 2011. Livingstone: IEEE. 1-6.

89. Xiao, H.F., Shi, Y.Q., Su, W. and Kosinski, J.A. Automatic classification of analog modulation schemes. Radio and Wireless Symposium (RWS), 15-18 Jan, 2012. Santa Clara, CA: IEEE. 5-8,

90. Orlic, V.D. and Dukic, M.L. Automatic modulation classification algorithm using higher-order cumulants under real-world channel conditions. IEEE Communications Letters, IEEE , December 2009.13(12): 917-919.

91. Narendar, M., Vinod, A.P., Madhukumar, A.S. and Krishna, A.K. Automatic modulation classification for cognitive radios using cumulants based on fractional lower order statistics. General Assembly and Scientific Symposium, 13-20 Aug, 2011. Istanbul: IEEE. 1-4.

92. Tan, J.L. Bilinear Time–Frequency Distribution. PhD Dissertation. Universiti Teknologi Malaysia. 2009.

93. Haq, K.N., Mansour, A. and Nordholm, S. Classification of digital modulated signals based on time frequency representation. 4th International Conference on Signal Processing and Communication Systems, 13-15 Dec, 2010. Gold Coast, QLD :IEEE. 1-5.

94. Liu M., Li J.Q. and Jiang H. Automatic Classification of Modulations in the Flat Fading HF Channel Based on Watterson Model. Second International Workshop on Education Technology and Computer Science (ETCS), 6-7 March 2010. Wuhan, China: IEEE. 218-221,

95. Hazza, A., Shoaib, M., Saleh, A. and Fahd, A. A novel approach for automatic classification of digitally modulated signals in HF communications. IEEE International Symposium on Signal Processing and Information Technology (ISSPIT), 15-18 Dec, 2010. Luxor: IEEE. 271-276.

96. Boashash, B. Time Frequency Signal Analysis and Processing: A Comprehensive Reference. UK: Elsevier. 2003.

97. Abdullah, A.R. and Sha'ameri, A.Z. Power Quality Analysis Using Bilinear Time-Frequency Distributions Journal on Advances in Signal Processing, Hindawi Publications Corp, Jan 2011.

98. Boashash, B. Time Frequency Signal Analysis: Past, present and future trends Control and Dynamics Systems, Academic Press, Inc., 1996. 78: 1–69.

99. Lin, H.B. Varying-Window-Length Time-Frequency Peak Filtering And Its Application To Seismic Data. International Conference on Computational Intelligence and Security. 13-17 Dec, 2008. Suzhou, China: IEEE. 429-432.

100. Sheng, H.S., Xu, J. and Zheng, C.X. Time-Frequency Analysis of Vascular Dementia EEG Signals Using Generalized S-Transform. 4th International Conference on Bioinformatics and Biomedical Engineering, 18-20 June, 2010. Chengdu, China: IEEE. 1-4.
101. Terao, Y. and Wada, S. Time-frequency analysis of driving sound and application to electric machinery diagnosis. 7th International Conference on Signal Processing, 31 Aug.-4 Sept, 2004. Japan: IEEE. 203- 206.
102. Antonino-Daviu, J.A., Climente-Alarcon, V., Pons-Llinares, J., Pineda-Sanchez, M., Jover-Rodriguez, P. and Arkkio, A. Application of TFD tools for the tracing of eccentricity-related components in induction machines. 35th Annual Conference of IEEE Industrial Electronics, 3-5 Nov. 2009. Porto: IEEE. 1039-1044,
103. Tantibundhit, C., Pernkopf, F. and Kubin, G. Joint Time–Frequency Segmentation Algorithm for Transient Speech Decomposition and Speech Enhancement. IEEE Transactions on Audio, Speech, and Language Processing, IEEE, Aug. 2010, 18(6): 1417-1428.
104. Antonia P.-S. Applications in Time–Frequency Signal Processing. Arizona State University: CRC Press LLC. 2003.
105. Jones, D.L. and Parks, T.W. A High Resolution Data-Adaptive Time-Frequency Representation. IEEE Transactions on Acoustics, Speech and Signal Processing, IEEE, Dec 1990. 38(12): 2127-2135.
106. Wexler, J. and Raz, S. Discrete Gabor expansions. Signal Processing, Elsevier, November 1990. 21(3): 207–220
107. O'Toole, A.J., Phillips, P.J., Jiang, F., Ayyad, J., Penard, N. and Abdi, H. Face Recognition Algorithms Surpass Humans Matching Faces Over Changes in Illumination. IEEE Transactions on Pattern Analysis and Machine Intelligence, IEEE, Sept. 2007. 29(9): 1642-1646.
108. Boogaart, C.G. and Lienhart, R. Fast Gabor Transformation for processing high quality audio. ICASSP 2006 IEEE International Conference on Acoustics, Speech and Signal Processing. 14-19 May, 2006. Toulouse, France: IEEE. 161-164.
109. Pinnegar, C.R. and Mansinha, L. The S-transform with windows of arbitrary and varying shape. Geophysics, 2003. 68(1): 381-385.

110. Nguyen, T. and Liao, Y. Power quality disturbance classification utilizing S-transform and binary feature matrix method. Electric Power Systems Research, Elsevier, April 2009. 79(4): 569-575.
111. Assous, S., Humeau, A., Tartas, M., Abraham, P. and L'Huillier, J.P. S-transform applied to laser Doppler flowmetry reactive hyperemia signals. IEEE Transactions on Biomedical Engineering, June 2006. 53(6): 1032-1037.
112. Stockwell, R.G., Mansinha, L. and Lowe, R.P. Localization of the complex spectrum: The S-transform. IEEE Transaction on Signal Processing. April 1996. 44(4): 998–1001.
113. Jones, G. and Boashash, B. Window matching in the time-frequency plane and the adaptive spectrogram. Proceedings of the IEEE-SP International Symposium: Time-Frequency and Time-Scale Analysis, 4-6 Oct 1992. Victoria, BC: IEEE. 87-90.
114. Vargas-Rubio, J.G. and Santhanam, B. An improved spectrogram using the multiangle centered discrete fractional Fourier transform. IEEE International Conference on Acoustics, Speech, and Signal Processing, 18-23 March, 2005. Pennsylvania, USA: IEEE. 505- 508.
115. Sejdić, E., Djurović, I. and Jiang, J. Time–frequency feature representation using energy concentration: An overview of recent advances, Digital Signal Processing, Elsevier, Jan 2009. 19 (2009): 153–183.
116. Cohen, L. Time-Frequency Signal Analysis. New York: Prentice Hall. 1995.
117. Pachori, R.B. and Sircar, P. A new technique to reduce cross terms in the Wigner distribution. Digital Signal Processing, Elsevier, March 2007. 17(2007): 466–474.
118. J. Jeong, J. and William J.W. Kernel Design for Reduced Interference Distributions. IEEE Transactions on Signal Processing, IEEE, Feb 1992. 40(2): 402-412.
119. Jones, D.L. and Baraniuk, R.G. A Simple Scheme for Adaptive Time-Frequency Representations. IEEE Transactions on Signal Processing. IEEE, Dec 1994. 42(12): 3530-3535.
120. Arce G.R. and Hasan, S.R. Elimination of Interference Terms of the Discrete Wigner Distribution using Nonlinear Filtering. IEEE Transactions on Signal Processing. IEEE, August 2000. 48(8): 2321-2331.

121. Sucic, V. A separable kernel filter design procedure for signal time-frequency analysis in: Proc. of IEEE 6th International Symposium on Communication Systems, Networks and Digital Signal Processing, 25-25 July, 2008. Graz: IEEE. 234-238.
122. Barkat B. and Boashash. B. A High-Resolution Quadratic Time-Frequency Distribution for Multicomponent Signals Analysis. IEEE Transactions on Signal Processing. IEEE, Oct 2001. 49 (10): 2232-2239.
123. Williams, W.J. Reduced interference distributions: biological applications and interpretations. Proceedings of the IEEE, Sep 1996. 84(9): 1264-1280.
124. Xu, R. and Liu, J. Optimal time-frequency distribution of arterial blood pressure for assessing cerebral auto regulation. International Conference on Biomedical and Health Informatics. 5-7 Jan. 2012. Hong Kong: IEEE. 767-770.
125. Moreira, L.A.E. An approach to ultrasonic fault machinery monitoring by using the Wigner-Wille and Choi-Williams distributions. Proceedings of the International Conference on Electrical Machines. 6-9 Sept, 2008. Vilamoura: IEEE. 1-6.
126. Barkat, B. and Attallah, S. A study of time-frequency based detectors for FSK modulated signals in a flat fading channel. IEEE Signal Processing Workshop on Statistical Signal Processing. 06-08 Aug 2001. Singapore: IEEE. 206-209.
127. Li, Y., Zhao, W.G., Bai, P., Bai, Y.Q., Zhang, Q. and Zhu, F. Extraction of radar LFM signal parameter based on B-distribution. IEEE International Conference on Signal Processing, Communications and Computing. 14-16 Sept. 2011. Xi'an, China: IEEE. 1-4.
128. Sahmoudi, M. and Abed-Meraim, K. Robust quadratic time-frequency distributions for the analysis of mulicomponent FM signals in heavy-tailed noise. IEEE/SP 13th Workshop on Statistical Signal Processing. 17-20 July 2005. Novosibirsk: IEEE. 871-876,
129. Zhao, Y., Atlas, L.E., and Marks, R.J. The use of cone-shaped kernels for generalized time-frequency representations of non-stationary signals. IEEE Transactions on Acoustics, Speech and Signal Processing, IEEE, Jul 1990. 38(7): 1084-1091.
130. Urresty, J., Riba, J., Ortega, J. and Cardenas, J. Stator short circuits detection in PMSM by means of Zhao-Atlas-Marks distribution and energy calculation.

13th European Conference on Power Electronics and Applications. 8-10 Sept. 2009. Barcelona: IEEE. 1-9.

131. Rajagopalan, S., Restrepo, J.A., Aller, J.M., Habetler, T.G. and Harley, R.G. Nonstationary Motor Fault Detection Using Recent Quadratic Time–Frequency Representations. IEEE Transactions on Industry Applications, IEEE, June 2008. 44(3): 735-744.

132. Thomas, M., Lethakumary, B. and Jacob, R. Performance comparison of multi-component signals using WVD and Cohen's class variants. International Conference on Computing, Electronics and Electrical Technologies. 21-22 March 2012. Kumaracoil: IEEE. 717-722.

133. Czerwinski, R. N. and Jones, D.L. Adaptive cone-kernel time-frequency analysis. IEEE Transaction on Signal Processing, IEEE, July 1995. 43(7): 1715-1719.

134. Stankovic, L. and Katkovnik, V. Algorithm for the instantaneous frequency estimation using time-frequency distributions with adaptive window width. IEEE Signal Processing Letters, IEEE, Sept 1998. 5(9): 224-227.

135. Stankovic, L. and Katkovnik, V. The Wigner distribution of noisy signals with adaptive time-frequency varying window. IEEE Transactions on Signal Processing, IEEE, Apr 1999. 47(4): 1099-1108.

136. Zhong, J.G. and Huang, Y. Time-Frequency Representation Based on an Adaptive Short-Time Fourier Transform. IEEE Transactions on Signal Processing, IEEE, Oct. 2010. 58(10): 5118-5128.

137. Li N., Dong S., Yang D.M. and Hao Z.H. The Research on Frequency-Hopping Signals Analysis Methods Based on Adaptive Optimal Kernel Time-Frequency Representation. International Conference on Measuring Technology and Mechatronics Automation, 11-12 April, 2009. Zhangjiajie, Hunan: IEEE. 544-547,

138. Boashash, B. and O'Shea, P. Use of the Cross Wigner-Ville Distribution for Estimation of Instantaneous Frequency. IEEE Transactions on Signal Processing, IEEE, Mar 1993. 41(3): 1439-1445.

139. O'Shea, P. and Boashash, B. Instantaneous Frequency Estimation Using the Cross Wigner-Ville Distribution with Application to Nonstationary Transient Detection. International Conference on Acoustics, Speech, and Signal Processing, 3-6 Apr, 1990. Albuquerque, NM: IEEE. 2887-2890.

140. Boles, P. and Boashash, B. Practical Use of the Cross Wigner-Ville Distribution to Process Vibroseis VSP Data. International Conference on Acoustics, Speech, and Signal Processing. 3-6 Apr, 1990. Albuquerque, NM: IEEE. 1941-1944.

141. Boashash, B. and O'Shea, P. A Methodology for Detection and Classification of Some Underwater Acoustic Signals Using Time-Frequency Analysis Techniques. IEEE Transactions on Acoustics, Speech and Signal Processing, IEEE, Nov 1990. 38(11): 1829-1841.

142. Boashash, B. and O'Shea, P. Time-Frequency Analysis Applied to Signaturing of Underwater Acoustic Signals. International Conference on Acoustics, Speech, and Signal Processing, 11-14 Apr 1988. New York, NY: IEEE. 2817-2820.

143. McHale, T.J. and Boudreaux-Bartels, G.F. An algorithm for synthesizing signals from partial time-frequency models using the cross Wigner distribution. IEEE Transactions on Signal Processing, IEEE, May 1993. 41(5): 1986-1990.

144. Kersten, P.R., Jansen, R.W. and Ainsworth, T.L. The Cross Time-Frequency Distribution Series for Synthetic Aperture Radar (SAR) Applications. IEEE International Geoscience and Remote Sensing Symposium. 23-28 July 2007. Barcelona: IEEE. 5178-5181.

145. Shui, P.L., Liu, H.W. and Bao, Z. Range-Spread Target Detection Based on Cross Time-Frequency Distribution Features of Two Adjacent Received Signals. IEEE Transactions on Signal Processing, IEEE, Oct. 2009. 57(10): 3733-3745.

146. Orini, M., Pelaez-Coca, M.D., Bailon, R. and Gil, E. Estimation of spontaneous respiratory rate from photoplethysmography by cross time-frequency analysis. Computing in Cardiology. 18-21 Sept. 2011. Hangzhou, China: IEEE. 661-664.

147. Riter, S. An Optimum Phase Reference Detector for Fully Modulated Phase-Shift Keyed Signals. IEEE Transactions on Aerospace and Electronic Systems, IEEE, July 1969. 5(4): 627-631.

148. Viterbi, A.J. and Viterbi, A.M. Nonlinear Estimation of PSK Modulated Carrier Phase with Application to Burst Digital Transmission. IEEE Transaction on Information Theory, IEEE, July 1983. 29(4): 543-551.

149. Kim, Y. H. and Lee, H.S. New total carrier phase estimator in fully phase modulated signals", IEEE Electronics Letters, IEEE, Oct 1993. 29(22): 1921-1922.

150. Huq, A.T., Panayirci, E. and Georghiades, C.N. ML NDA carrier phase recovery for OFDM systems. IEEE International Conference on Communications, 6-10 Jun 1999. Vancouver, BC: IEEE. 786-790.

151. Panagirci, E and Georghiades, C.H. Joint ML timing and phase estimation in OFDM systems using the EM algorithm. IEEE International Conference on Acoustics, Speech, and Signal Processing, 5-9 Jun 2000. Istanbul: IEEE. 2949-2952.

152. Linn, Y. Robust M-PSK phase detectors for carrier synchronization PLLs in coherent receivers: theory and simulations. IEEE Transactions on Communications, June 2009. 57(6): 1794-1805.

153. Rohde & Schwarz. Spectrum monitoring the ITU way. Germany: News from Rohde & Schwarz. 1(153). 1997.

154. Boashash, B. Estimating and interpreting the instantaneous frequency of a signal-part 2: algorithms and applications. Proceeding of the IEEE, April 1992. 80(4): 540–568.

155. Boashash, B and O'Shea, P. Polynomial Wigner-Ville distributions and their relationship to time-varying higher order spectra. IEEE Transactions on Signal Processing, Jan 1994. 42(1): 216-220.

156. Hussain, Z. and Boashash, B. Adaptive instantaneous frequency estimation of multicomponent FM signals using quadratic time–frequency distributions. IEEE Transaction on Signal Processing. IEEE, August 2002. 50 (8): 1866-1876.

157. Rankine, L., Mesbah, M. and Boashash, B. IF estimation for multicomponent signals using image processing techniques in the time–frequency domain. Signal Processing, Elsevier, June 2007. 87(6): 1234-1250.

158. Lerga, L., Sucic, V. and Boashash, B. An efficient algorithm for instantaneous frequency estimation of nonstationary multicomponent signals in low SNR", EURASIP Journal on Advances in Signal Processing, Hindawi Publications Corp, Dec 2011.

159. Stankovic, L., Dakovic, M., Jiang, J., Sejdic, E. Instantaneous Frequency Estimation Using the S-Transform. IEEE Signal Processing Letters, February 2008. 15(1): 309-312.
160. Wang, L. and Meng, X.F. An adaptive generalized S-transform for instantaneous frequency estimation. Signal Processing, Elsevier, August 2011. 91(8): 1876–1886.
161. Hua, F., and Kam, P.Y. MAP/ML Estimation of the Frequency and Phase of a Single Sinusoid in Noise. IEEE Transactions on Signal Processing, IEEE, March 2007. 55(3): 834-845.
162. Ghartey, K., Papandreou-Suppappola, A. and Cochran, D. Time-varying techniques for multisensor signal detection. IEEE Transactions on Signal Processing, IEEE, Sept. 2006.54(9): 3353-3362.
163. Jabloun, M., Leonard, F., Vieira, M. and Martin, N. A New Flexible Approach to Estimate the IA and IF of Nonstationary Signals of Long-Time Duration. IEEE Transactions on Signal Processing, IEEE, July 2007. 55(7): 3633-3644.
164. Lee, H.Y., and Bien, Z.Z. A Variable Bandwidth Filter for Estimation of Instantaneous Frequency and Reconstruction of Signals With Time-Varying Spectral Content. IEEE Transactions on Signal Processing, May 2011. 59(5): 2052-2071.
165. Reilly, A., Frazer, G. and Boashash, B. Analytic signal generation-tips and traps. IEEE Transactions on Signal Processing, IEEE, Nov 1994. 42(11): 3241-3245.
166. Best, R.E. Phase-Locked Loops: Design, Simulation and Applications, 5th Edition. USA: McGraw-Hill. 2003.
167. White, L.B. and Boashash, B. Cross spectral analysis of nonstationary processes. IEEE Transaction on Information Theory, IEEE, Jul 1990. 36(4): 830–835.
168. Jones, G., and Boashash, B. Generalized instantaneous parameters and window matching in the time-frequency plane. IEEE Transaction on Signal Processing, IEEE, May 1997.45(5):1264–1275.
169. Harris, F.J. On the use of windows for harmonic analysis with the discrete Fourier transform. Proceedings of the IEEE, Jan 1978. 66 (1): 51-83.

170. Sha'ameri, A.Z. The lag windowed Wigner-Ville Distribution: An Analysis Method for HF Data Communication Signals. Jurnal Teknologi, Universiti Teknologi Malaysia, 1999. 30(D): 33-54.
171. Drake, J. Cramer-Rao bounds for M-PSK packets with random phase. Proceedings of the Fifth International Symposium on Signal Processing and Its Applications, 22 -25 Aug 1999. Brisbane, Qld: IEEE. 725-728.
172. Barbier, A. and Colavolpe, G. On the Cramer-Rao bound for carrier frequency estimation in the presence of phase noise. IEEE Transactions on Wireless Communications, IEEE, Feb 2007. 6(2): 575-582.
173. Kay, S.M. Fundamentals of statistical signal processing: Estimation theory. Englewood Cliffs: Prentice Hall. 1993.
174. Rao, P. and Taylor, F.J. Estimation of IF using the discrete Wigner–Ville distribution. Electronics Letters. Feb 1990. 26(4): 246–248.
175. Barkat, B. and Boashash, B. Instantaneous frequency estimation of polynomial FM signals using the peak of the PWVD: Statistical performance in the presence of additive Gaussian noise. IEEE Transactions on Signal Processing, IEEE, September 1999. 47(9): 2480 - 2490.
176. Cowley, W.G. Phase and frequency estimation for PSK packets: bounds and algorithms. IEEE Transactions on Communications, IEEE, Jan 1996. 44(1): 26-28.
177. Tavares, G.N., Tavares, L.A. and Piedade, M.S. Improved Cramer-Rao lower bounds for phase and frequency estimation with M-PSK signals. IEEE Transactions on Communications, IEEE, Dec 2001. 49(12): 2083-2087.
178. Rice, F., Cowley, B., Moran, B. and Rice, M. Cramér–Rao Lower Bounds for QAM Phase and Frequency Estimation. IEEE Transactions On Communications, IEEE, Sept 2001. 49(9): 1582-1591.
179. Abdul Rahim Abdullah. Time-Frequency Analysis for Power Quality Monitoring. Ph.D. Dissertation. Universiti Teknologi Malaysia. 2012.
180. Bhujade, M.R. Parellel computing, 2nd edition .UK: New Age Science. 2009.
181. Boashash, B. Note on the Use of the Wigner Distribution for Time Frequency Signal Analysis. IEEE Transactions on Acoustics, Speech, and Signal Processing, IEEE, Sept 1988. 36(9): 1518-1521.