ADDIS ABABA UNIVERSITY
ADDIS ABABA INSTITUTE OF TECHNOLOGY (AAiT)
SCHOOL OF ELECTRICAL AND COMPUTER ENGINEERING

Digital Modulation Identification and Modulation orders Estimation using Wavelet Transform

BY

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Approval by Board of Examiners

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Declaration

Declaration I, the undersigned, declare that this thesis is my original work, has not been presented for a degree in this or any other university, and all sources of materials used for the thesis have been fully acknowledged.

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Place: Addis Ababa

This thesis has been submitted for examination with my approval as a university advisor.

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Abstract

Automatic modulation identification is rapidly evolving in many areas mainly in military applications and research institutions. The identification methods are basically categorized as likelihood based (LB) and feature based (FB) approaches.

In this thesis FB is proposed to study modulation identification of received signals in the presence of additive white Gaussian noise (AWGN) using wavelets. The Haar wavelet was used as the mother wavelet. The algorithm identifies 13 modulation schemes 4 for FSK, 3 for QAM, 3 for ASK and 3 for PSK modulation types without prior knowledge. The correct identification ratio has been analyzed based on the confusion matrix for different modulation type at different signal to noise ratio (SNR) and the intra-class and inter-class identification of those modulation schemes are evaluted. The correct intra-class identification ratio was greater than 99%, 97%, 96% and 83% at thier lowerest SNR bounds 5dB, 8dB, 8dB and 25dB for FSK, QAM, ASK and PSK modulations respectively. The proposed method is relatively robust for noisy signal and identifies more modulation schemes compared to related exsiting works.

Key words: Feature based, Modulation identification, Wavelet and Histogram

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Nomenclature

ALRT Average Likelihood Ratio Test

AM Amplitude Modulation

AMI Automatic Modulation Identification

ASK Amplitude Shifting Keying

AWGN Additive White Gaussian Noise

BER Bit Error Rate

BPSK Binary Phase Shift Keying

CC Cyclic Cumulants

CNR Carrier to Noise Ratio

COMINT Communication Intelligence

CW Continous Wave

CWT Continous wavelet transform

dB Daubechies

DC Direct Current

DWT Discrete Wavelet Transform

ECCM Electronic Counter Counter Measure

ECM Electronic Counter Measure

ESM Electronic Support Measure

FB Feature Based

FSK Frequency Shifting Keying

FT Fourier Transform

GLRT General Likelihood Ratio Test

HWT Haar Wavelet Transform

JPEG Joint Photographic Experts Group

LB Likelihood Based

OFDM Orthogonal Frequency Division Multiplexing

pdf probability density function

PSK Phase Shifting Keying

QAM Quadrature Ampitude Modulation

qLRT qausi Likelihood Ratio Test

QPSK Quadrature Phse Keying

SNR Signal to Noise Ratio

STFT Short Time Fourier Transform

SVM Support Vector Machine

WT Wavelet Transform

1 Introduction

1.1 Digital modulation

The digital data produced by mobile radio, audio or television programmes needs to be modulated onto a carrier for transmission[40]. The basic concept behind digital modulation is to identify efficient schemes taking M different symbols in a given digital alphabet and transforming them into waveforms that can successfully transmit the data over the transmission channel. Modulation involves changing the amplitude, frequency and/or the phase of the carrier wave traveling over the channel.

There are three basic types of modulation schemes: frequency shift keying (FSK), amplitude shift keying (ASK), and phase-shift keying (PSK). The quadrature amplitude modulated (QAM) signal is an expansion of the amplitude shift keying modulation types.

The simplest modulation technique is ASK, where a carrier is simply turned on and off. ASK is not normally used for radio frequency transmissions. In FSK, the frequency of the carrier is varied with the data. FSK is thus the same as frequency modulation but since the binary data only has 2 levels, only 2 frequencies are used. Four level FSK (4FSK) is a technique where the digital data is changed to a 4 level signal allowing 2 bits to be transmitted at a time. This technique provides a reasonable spectral efficiency and is implemented cheaply[40].

While higher order modulation rates ($M > 2$) are able to offer much faster data rates and higher levels of spectral efficiency for the radio communications system, this comes at cost of less resilient to noise and interference[40].

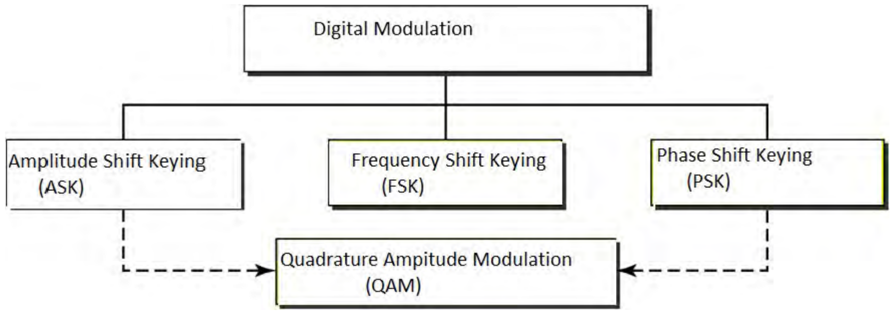


Figure 1.1: Digital modulation types [38]

1.1.1 M-ary Amplitude Shift Keying (M-ASK)

ASK is the simplest digital modulation scheme. The alphabet consists of $M = 2^b$ points in the real line of the signal space where each point represents a sequence of b bits. Therefore, the symbols are represented by different amplitude levels of the modulated signal [46].

ASK in the context of digital communications is a modulation process, which imparts to a sinusoid two or more discrete amplitude levels. These are related to the number of levels adopted by the digital message.

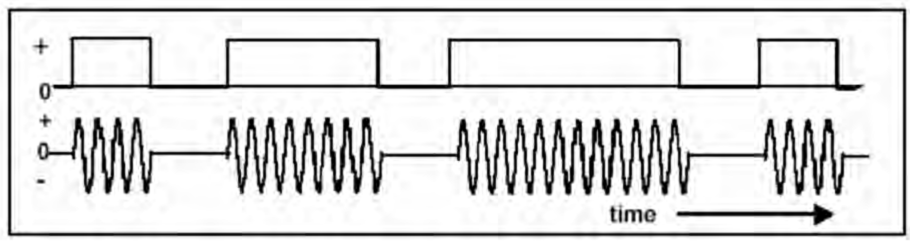


Figure 1.2: BinaryASK signal (below) and the message (above) [37]

An M-ary amplitude-shift keying (M-ASK) signal can be defined by

$$s_i(t) = \begin{cases} A_i \cos(w_c t + \phi) & 0 \le t \le T \\ 0 & elsewhere \end{cases} \quad (1.1)$$

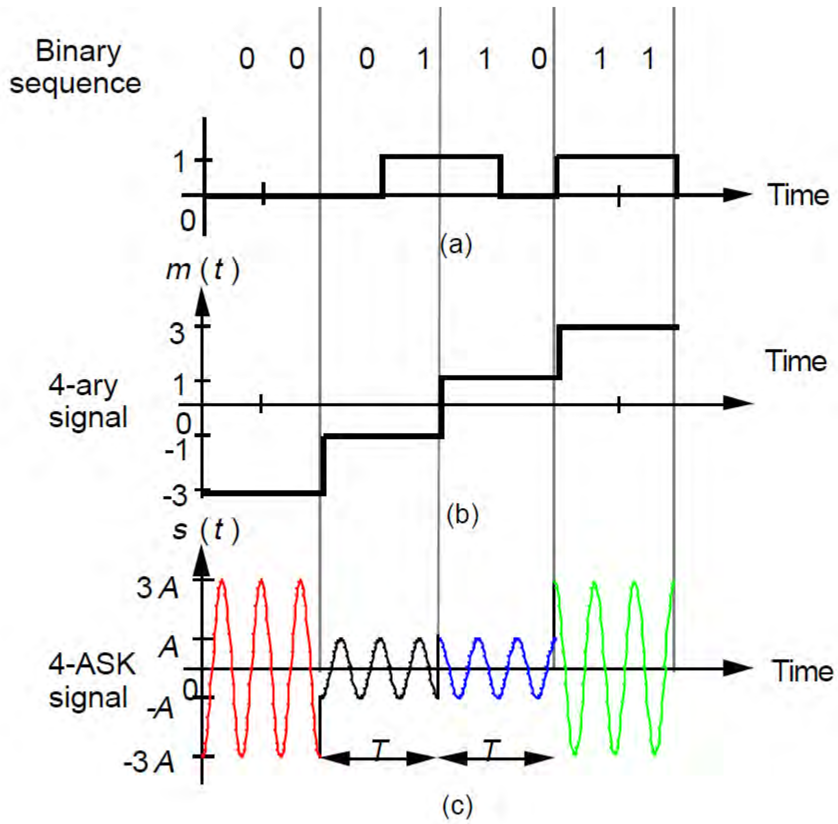


Figure 1.3: 4-ASK modulation: (a) binary sequence, (b) 4-ary signal, and (b) 4-ASK signal

where A_i = A[2i - (M - 1)] for i = 0, 1, ..., M - 1 and M > 4. Here, A is a constant, w_c is the carrier frequency, and T is the symbol duration.

One of the disadvantages of ASK, compared with FSK and PSK, is that it does not have a constant envelope. This makes its processing (eg, power amplification) more difficult, since linearity becomes an important factor.

1.1.2 M-ary Frequency Shift Keying (M-FSK)

In an M -ary FSK modulation, the binary data stream is divided into b-tuples of M bits. We denote all M possible b -tuples as M messages. There are M signals with different frequencies to represent these m messages. The expression of the i^{th} signal is using the following sinusoidal formulas [40].

$$S_i(t) = A\cos(2\pi f_i t + \phi)$$

The simplest form of FSK is known as the binary frequency-shift keying (2-FSK), where the symbols 0 and 1 are distinguished from each other.

$$\begin{cases} S_1(t) = A\cos(2\pi f_1 t + \phi) & binary'1' \\ S_2(t) = A\cos(2\pi f_2 t + \phi) & binary'0' \end{cases} \tag{1.2}$$

where f_1 and f_2 are usually offset from the carrier frequency(fc) by equal but opposite amounts.

A more bandwidth efficient signal (with increased probability of error) is the M-FSK signal where more than two frequencies are used. The number of bits in the binary data stream of ones and zeroes is determined by $b = \log M$.

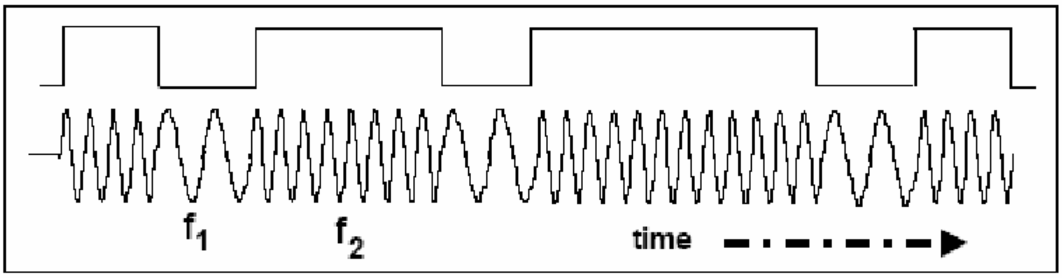


Figure 1.4: Binary FSK signal
[37]

1.1.3 M-ary Phase Shift Keying (M-PSK)

In PSK modulation, the phase of the carrier signal is shifted to represent data. In binary phase-shift keying (BPSK), a pair of signals are used to represent symbols 1 and 0. These signals are 180 degrees out of phase with each other.

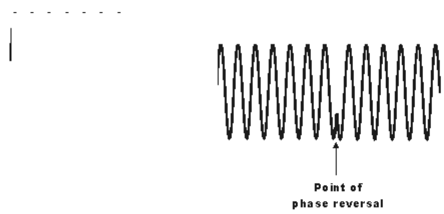


Figure 1.5: Binary phase shift keying
[37]

Similary, bandwidth efficiency of the PSK modulation scheme is increased by using M-PSK modulation. Note that a more efficient use of bandwidth is achieved when each signaling element represents more than one bit.

However, increasing the bandwidth efficiency in this way usually increases the bit error rate. This thesis considers M-PSK modulation types where M = 2, 4, and 8, which corresponds to n = 1, 2, or 3 data bits. A M-PSK signal can be represented mathematically as

$$S_i(t) = A\cos(2\pi f_c t + \tfrac{2\pi i}{M}) \qquad (1.3)$$

i=1,2...M

where A is the signal pulse shape, M is the number of possible phases of the carrier, and fc is the carrier frequency.

Among all MPSK schemes, QPSK is the most often used scheme since it does not suffer from BER(bit error rate) degradation while the bandwidth efficiency is increased [46].

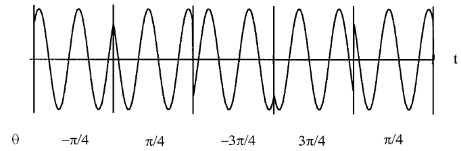


Figure 1.6: QPSK wave form [46]

The problem with phase shift keying is that the receiver cannot know the exact phase of the transmitted signal even if the transmitter and receiver clocks are accurately linked. The exact phase of the received signal is determined by path length. To overcome this problem PSK systems use a differential method for encoding the data onto the carrier. This is accomplished, for example, by making a change in phase equal to a one, and no phase change equal to a zero. Phase shift keyed systems use a constant amplitude and therefore points appear on one constant amplitude circle and the changes in state being represented by movement around the circle. For binary shift keying using phase reversals the two points appear at opposite points on the circle. Other forms of phase shift keying may use different points on the circle and there will be more points on the circle. Errors may be seen from the ideal positions on the phase diagram. These errors may appear as the result of in accuracies in the modulator and transmission and reception equipment, or as noise that enters the system. It can be imagined that if the position of the real measurement when compared to the ideal position becomes too large, then data errors will appear as the receiving demodulator is unable to correctly detect the intended position of the point around the circle.

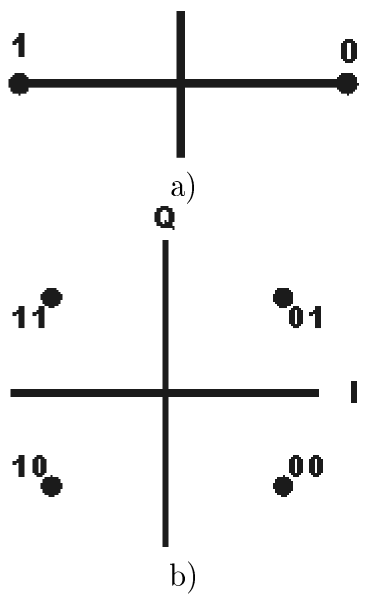


Figure 1.7: Constellation diagram for PSK signal a) BPSK b)QPSK [37]

Each form has its own advantages and disadvantages, and a choice of the optimum format has to be made for each radio communications system that is designed. To make the right choice it is necessary to have a knowledge and understanding of the way in which PSK works.

1.1.4 M-ary Quadrature Ampitude Modulation (M-QAM)

This modulation technique, which combines PSK with ASK techniques, sends two different signals simultaneously using same but orthogonal carrier frequencies. In this way, a binary 1 can be represented whenever a constant envelope carrier is present and a binary 0 is represented as the absence of a carrier wave. The two separate signals are then transmitted independently with the same carrier frequency by using two quadrature carriers.

These two separate modulated signals are then added and transmitted. This structure of QAM allows for M discrete amplitude levels (M-QAM), and thus permits a symbol to contain more than one bit of information. The general form for an M-QAM signal is given by

$$s_i(t) = s_{Ii}(t)\cos(2\pi f_c t + \phi_1) - s_{Qi}(t)\sin(2\pi f_c t + \phi_1) \tag{1.4}$$

i=1,2...M

s_{Ii} and s_{Qi} are the information-bearing discrete amplitudes of the two quadrature carriers, ϕ_1 intial phase of signal.

QAM is in many radio communications and data delivery applications[35]. However some specific variants of QAM are used in some specific applications and standards. For domestic broadcast applications for example, 64 QAM and 256 QAM are often used in digital cable television and cable modem applications.

1.2 Problem Statement

Modulation identification of digital communication signals is an important signal processing problem in communications, and its related fields. Modulation identification can be considered as an intermediate step between signal interception and information recovery or demodulation. Applications of such algorithms are primary military ones in COMINT (communication intelligence), one need to recognize the applied modulation type to more reliably identify the source of an emission (ESM electronic support measure). It is also useful in choosing the appropriate method of jamming (ECM electronic counter measure), or to protect oneself (ECCM electronic counter counter measure). In addition to military application, modulation identification also applicable in civil works such as signal confirmation, interference identification, and spectrum management.

In recent years, wavelet analysis has attracted attention for its ability to analyze rapidly changing transient signals. Any application using the Fourier transform can be formulated using wavelets to provide more accurately localized temporal and frequency information. It is known that different types of modulation signals have different actual values amplitude, frequency and phase. The wavelet transform has the ability to extract these instantaneous values, allowing thus the implementation of simple and rapid calculation algorithms, which ensure the recognition of modulation of the input signal in real time. Some very standard wavelets are the Morlet, the Haar and Shannon.

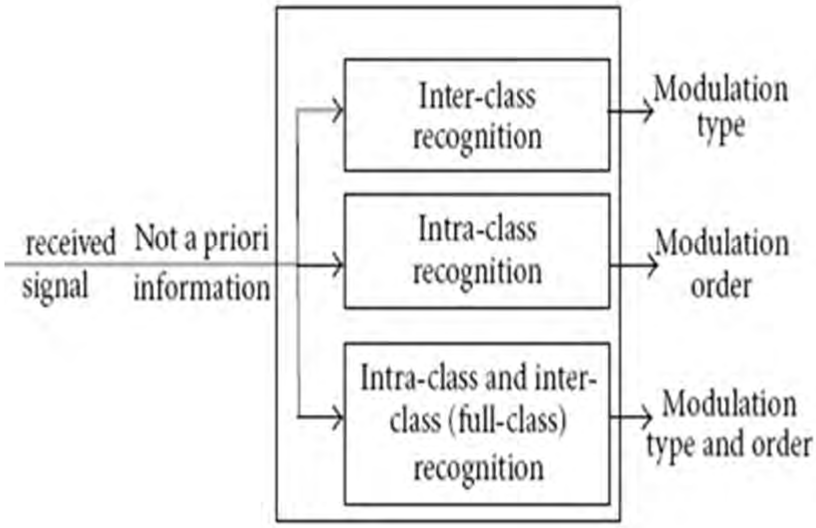


Figure 1.8: Categories of Modulation Identificcation [14]

Problems in modulation identification can be divided into two categories, the inter-class recognition and intra-class recognition. Specically, the inter- class recognition distinguish between different types of modulation (ASK, PSK, FSK and QAM), while the intra-class finally acknowledged a distinction between different levels of the same type settings, such as FSK2 and FSK4. Once the modulation scheme and the order of modulation are identifed, an appropriate demodulator can be selected to demodulate the signal and then to recover the information if it is needed. Any work in modulation identification aims to identfy wider modulation schemes with highest success rate of inra-class and inter-class identification by automatically adapting SNR changes with less complex algorithm. These are the key problems to be improved by modulation identification algorithms.

1.3 Objective

To study automatic modulation identification identifying modulation type of signal is not enough. Even within given modulation type, there are different variants.

The geneal objectives of this thesis are:

- To study and implement an algorithm, that identifies different types of modulation (ASK, PSK, FSK and QAM) using wavelet transform
- To estimate modulation order of a given modulation type at noisy AWGN channel

The specific objective of this thesis is:

- To develope less complex algorithm, which identifies wider modulation schemes at lower SNR compared to existing works

Thirteen different modulation schemes are considered: three for PSK: {2PSK, 4PSK, 8PSK); four for FSK: {2FSK, 4FSK, 8FSK, 16FSK); three for QAM: {8QAM, 16QAM, 32QAM}; and three for ASK: {2ASK, 4ASK, 8ASK}.

1.4 Related Works

Automatic signal identification is one of the most important parts in military and civil domains. Due to the increasing usage of digital signals in novel technology such as wireless communications, the recent researches have been focused on identifying these signal types. Generally, digital modulation type identification methods fall into two main categories: Likelihood based approach, and feature based approaches. LB methods use probabilistic and hypothesis testing arguments to formulate the identification problem [21-23]. These algorithms make a decision based on the comparison of a likelihood ratio with a predefined threshold, minimizing the probability of false decision. They demand significant computational workload and a priori knowledge of probability functions [8]. Another approaches for modulation classification based on a combination of the likelihood approach and other computational techniques such as Support Vector Machines (SVM) [30]-[31] and Artificial Neural Networks (ANN) [33]-[34] have been developed. These new methods provide higher accuracy of classification when communication signals are subject to noise and channel impairments. ANN and SVM techniques have also been used in conjunction with WTs [24]. SVM is a mathematical technique which maps the input data, which are the statistical parameters of the received signals in this case, to a higher-dimensional space. ANNs are a rather new technique used in applications requiring computational decision-making. Multiple input stimuli are provided to an ANN and are propagated through an interconnected network of nodes. Each node has the ability to assign a weight to each input signal. However, ANNs also have the ability to adaptively change these weights based on the specific decision-making mathematical model chosen for the ANN. Using signal parameters obtained from either the decision-theoretic, or pattern recognition-based methods, ANNs can be used for modulation classification. In addition, the adaptive learning ability of ANNs is especially useful for the classification of communications signals that are subject to noise and channel impairments.

In [24], an SVM-based modulation classification method was developed. In that method, the Haar wavelet was used as the kernel function. BPSK, QPSK, and AM signals, corrupted by additive band-limited Gaussian noise, were used as test signals in the reported work. The rate of correct classification was 84% in the presence of band-limited Gaussian noise.

The WT has capability to extract transient information and thereby allowing simple methods to perform modulation identification. One popular WT-based approach involves computing the histogram of the wavelet coefficients of the received signals and then counting the number of peaks in the histogram in order to distinguish between PSK and FSK [27]; QPSK and GMSK [25], and M-QAM and M-ASK [28].

Jin, J-D [27], the method used to distinguish PSK and FSK signals is to determine the number of distinct histogram ordinate levels reached by the histogram data peaks. The distinct levels are used as thresholds in a subsequent decision-making step. Hence, the number M of distinct levels is used to identify the M-ary modulated signals.Most WT-based AMI methods use the Haar Wavelet for the extraction of wavelet coefficients to be used in computing either the desired histograms, or other statistical parameters as needed [24] [28][29]. Other wavelets, such as the Daubechies (dB) family, and the complex Shannon wavelet, may also be used to obtain the wavelet coefficients of a signal that will be used for AMI.

Chen, et al., proposed [32] an algorithm which could identify signals in either the inter-class, or intra-class by combining both WT and likelihood functions, which is known as the decision-theoretic approach in the literature. The success rate of this method is above 90% with a Carrier-to-Noise Ratio (CNR) of 13 dB and above. But these methods are difficult to compare with this work, since they belong to two different approches.

The second approach, FB methods can be further divided in two main subsystems: the feature extraction subsystem and the decision making subsystem. Several studies on AMI using FB approaches that have been reported in the literature are presented below. The following litreatures are more related to this thesis relative the above ones. Alogorithms are discussed and compared thier achievement to the alogorithms proposed by this work.

K.C.Ho, W.Prokopiw and Y.T.Chan [5]-[6] used three identifiers for classifying PSK and FSK, M-ary PSK and M-ary FSK but M-ary ASK and QAM are not considered. Symbol time is first estimated before modulation identication is performed and the algorithm identified only 6 modulation schemes at 15dB and above [6].

In 2004, Jin, J-D. [27]: A new noise-robust modulation identification method for an adaptive receiver based on software defined radio. But the method only distinguishes M-ary FSK from M-ary PSK by using the characteristics obtained from the wavelet coefficients of each modulated signal.

In 2005, Xin Zhou, Ying Wu [4]: Studied a digital modulation identifier using wavelet transform for M-ary FSK signals. In this work, algorithm identified only intra-class identification of MFSK signal. Results showed that, the lowest identification accuracy is 90% and lowest SNR is 85% 20dB. In this year, Konstantinos Maliatsos, [7]: Recognized the intra-class and inter-class recogination for higher than 12dB SNR for about 12 modulation schemes. But MPSK signal is identified by first estimate carrier frequency ofrecieved signal for lower SNR (<22dB). In addition, algorithm is helped by Likelihood based approach in order to improve accuracy of correct identification. This adds computational workload to the algorithm.

In 2007, Prakasam, P. [25]: Developed algorithm has been tested by introducing additive white Gaussian noise (AWGN) in the modulated signal. Only identified QPSK and GMSK using histogram peaks. The performance has been computed by estimating the bit error rate (BER) and reconstruction efficiency. Modulation identification is possible to a lower bound of 15 dB and 6 dB for GMSK and QPSK respectively.The same Author in 2008 [2]: Developed an algorithm to test 10 modulation schemes with different SNR. The correct modulation scheme identification is possible even at low channel SNR of 5 dB and the percentage of correct modulation identification is higher than 96.8%. The drawback of this work is, it assumed misclafication of modulation schemes and 10 thresholds setting is used to identfy 10 modulation schemes, which decreases correct modulation identification as number of modulation schemes increased for furher work.

In 2010, HU You-qiang [1]: Algorithm first denoised the instantaneous information using optimized wavelet filter, which can improve the recognition ability at low SNR.Three new key feature parameters are proposed to distinguish seven modulation schemes. It is found that the success rate is over 99 % when SNR is 10 dB, while the success rate is over 95 % when SNR is 5 dB. Only 7 modulation schemes are identified in this work.

The algorithm proposed by this thesis considers 13 modulation schemes, without the need of prior knowledge of the modulated signal which is much higher than all discussed in second approach (FB) [1,2,3,4,5,25]. It is also used less complex algorithms which don't perform the above additional methods [4,5,7] and number of threshold are minimized [1,2]. In addition more modulation types(QAM,ASK,FSK, and PSK) are identified.

1.5 Contributions of the Work

Determining the identified effects and computational complexity of the algorithm are key steps for automatic modulation identication. Any work in modulation identification intends to identify wider modulation schemes at noisy channel with higher identification rate and at the same time with less complex algorithm.

Most of existing works are either computationally intensive, not robust for noisy signal or require some known modulation parameters such as carrier frequency and symbol time of the signal. Computationally intensive algorithms may perform phase extraction, center frequency recovery, SNR and symbol rate estimation and so on. Since identification of wider modulation schemes affects the accuracy of correct identification most of existing methods limit their modulation schemes so that their efficiency of correct identification stayed higher.

This thesis considers the application of the wavelet transform (WT) to modulation identification at relatively low SNR , without the need of prior knowledge of the modulated signal. It is also used less complex algorithms which don't perform the above additional methods and number of threshold are minimized. In addition more modulation types(QAM,ASK,FSK, and PSK) and wider modulation schemes are identified.

1.6 Thesis Outline

The rest of this thesis is organized as follows: Chapter 2 discusses about the two methods used in modulation identification. Chapter 3 covers about background, theories and applications of wavelet transform. Chapter 4 covers mathematical modeling of modulation identification using wavelet transform. Chapter 5 describes the identifier structure and the realization. Implementation of the identifier and the simulation results are also discussed in this chapter.

Finally, conclusions and suggestions for further work are presented in Chapter 6.

2 Modulation Identification

Modulation identification is the process of deciding, based on observations of the received signal, what modulation is being used at the transmitter. It is an intermediate step between signal interception and demodulation. In the pre-processin block, the modulated signal is pass through filter, designed to eliminate noise which can improve the modulation identification ability at low SNR. The AMI block gives modulation format of recieved signal to demodulator block sothat, appropriate demodulator will be selected. For ECM application, the modulation format is used to choose effective method of jamming for the incoming signal.

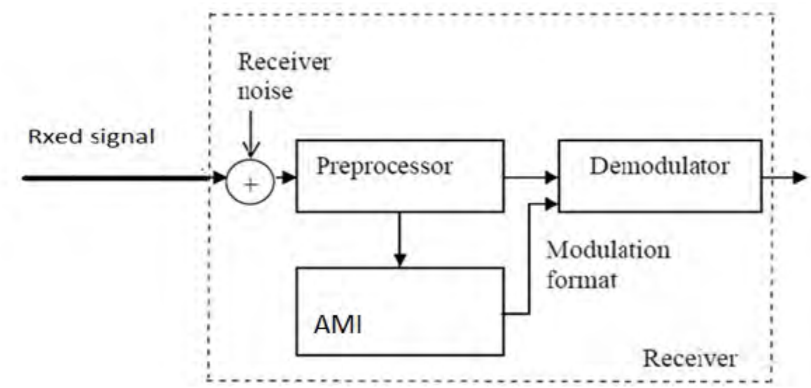


Figure 2.1: General block diagram of receiver system with AMI [14]

It has long been an important component of non cooperative communications in which a listener desires to intercept an unknown signal from an adversary. It is also becoming increasingly important in cooperative communications, with the advent of the software-defined autonomous radio. Such a radio must configure itself, including what demodulator to use, based on the incoming signal[8].

Any modulation identification algorithm is required to achieve the following [9]:

- Identifying the modulation type automatically, and high recognition rate;
- Adapting the SNR changes in noisy channel;

- Wider range of modulation types can be identified automatically;
- Reducing the complexity of the algorithm, and achieving real-time analysis;

The key steps are to automatically identify the modulation type of feature extraction and classification method, determining the identified effects and the complexity of the algorithm. To achieve the above function different methods are being used in area of modulation identification.

The identification methods are basically categorized into two general classes:

Likelihood based approach and feature based approaches. In AMI problems, it is generally assumed that each possible modulation format happens with the same probability.

While feature-based classifiers are generally easier to implement, they are sub-optimal. Likelihood-based classifiers, on the other hand, are optimal in the Bayesian sense, as they minimize the probability of classification error [17].

2.1 Likelihood based approach

The maximum likelihood function of the received signal and the decision is made comparing the likelihood ratio against a threshold. A solution offered by the LB algorithms is optimal in the Bayesian sense. It minimizes the probability of false classification. But the optimal solution suffers from computational complexity.

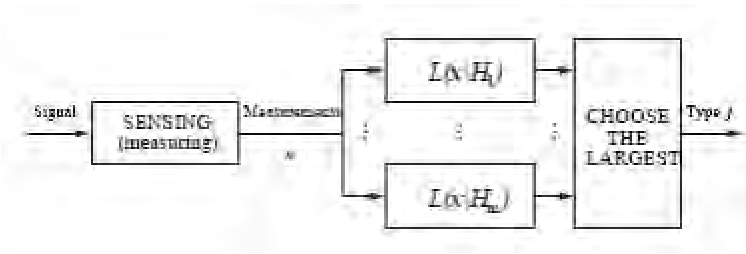


Figure 2.2: General maximum likelihood classfier [17]

In the maximum likelihood approach, the classification is analyzed as a multiple hypothesis testing problem, where a hypothesis H_i is arbitrarily assigned to the i^{th} modulation type of m possible types[8]. The LB identifier is established on the conditional probability density function (pdf) [8], $p(r/H_i)$

$i = 1, 2..m$, r is the observation. If the observation sequence r[k] k=1,2...n, is independent and identically distributed (i.i.d), the likelihood function, $L(r/H_i)$

$$p(r/H_i) = \prod_{i=1}^{n} p(r[k]/H_i) \triangleq L(r/H_i) \quad (2.1)$$

The LB identifier reports the; j^{th} modulation type based on the observation when $L(r/H_j) > L(r/H_i)$ $i \neq j$, $i, j = 1, 2..m$

There are different approaches for LB classifiers to handle unknown variables in $p(r/H_i)$, including the Average Likelihood Ratio Test (ALRT), Generalized LRT, Hybrid LRT (HLRT), and quasi-HLRT (qHLRT) [8]. In these approaches, through a standard hypothesis testing procedure the unknowns are either estimated, averaged by using their probability density function or a combination of both.The LB-based classifier is sensitive to model mismatches, such as carrier frequency and timing errors. In the paper[8] the theory behind and their application are discussed in detail.

2.2 Feature based approaches

The statistical pattern recognition or FB approach is divided into two parts. The first is a feature extraction part and its role is to extract the predefined feature from the received data. The second is a pattern recognition part, whose function is to classify the modulation type of a signal from the extracted features.

In this methods, features are first extracted from the received signal and then applied to a classifier in order to recognize the modulation type.

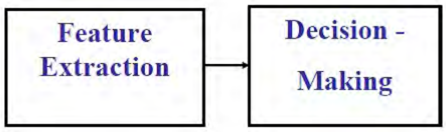


Figure 2.3: Genaral block diagram FB approaches [18]

The features show unique characteristics for every specific modulation. Decision-making is based on the difference of the features for diverse modulations.

Some examples of feature FB are Instantaneous values of signal (Amplitude, Phase, and Frequency), Wavelet Transform, Signal Statistics: Moments, Cumulants, Cyclic Cumulants (CC), Information in the Zero-Crossing Sequence and so on. And decision is made using decision criteria,

Examples of decision criteria: Euclidian distance between estimated and prescribed values of the features, Correlation between estimated and theoretical features, the probability density function of a feature estimator.

2.2.1 Instantaneous values

The most intuitive way to identify the modulation class of the incoming signal is to use the information contained in its instantaneous amplitude, phase and frequency [8]. FSK signals are characterized by constant instantaneous amplitude, whereas ASK signals have amplitude fluctuations, and PSK signals have information in the phase.

The features are derived from the signal spectrum and the instantaneous amplitude, frequency and phase. Two different approaches are used in classifying the modulated signals[19]. The first approach was a decision theoretic tree classier where each feature was tested against a certain threshold value at a time. The success rate of the tree classifier depends on the order of the features tested in these branches. The second approach was based on an artificial neural network.

With the help of wavelet filters for denoising the instantaneous values recognition ability at low SNR is improved. Besides the existing three new key feature parameters are proposed to distinigush seven modulation schemes. It is found that the success rate is over 99 % when SNR is higher than 10 dB.

2.2.2 Zero-Crossings

The zero-crossing sampler has the advantage of providing accurate phase transition information over a wide dynamic frequency range [19]. In these techniques zero-crossing variance, carrier-to-noise ratio (CNR), and carrier frequency are estimated. The phase difference and zero-crossing interval histograms were used as the features for recognition of the continous wave (CW), MPSK and MFSK modulated signals. However, these techniques are unsuitable for the complex envelope representation. Phase difference and zero-crossing interval histograms play the role of features for modulation recognition. The classifier [44] performance is given in the form of a confusion matrix. The simulation results obtained demonstrate that a reasonable average probability of correct classification is achievable for CNR greater than15 dB.

2.2.3 Wavelet transform based algorithm

Different modulated signals give rise to different sets of peak values in the magnitude of the wavelet transform. The histogram of the peak magnitudes was employed to identify the order of a modulated signal, with the decision made by comparing the histogram with the theoretical PDFs corresponding to different orders[8]. A lot of wok have been done using wavelet transform. WT based approach can involve computing the histogram of the wavelet coefficients of the received signals and then counting the number of peaks in the histogram in order to distinguish different modulation types [26]-[27]. Some of those methods and thier reults are discussed and compared with proposed system in section 5.5.

2.2.4 Classification based on distance functions

A classification algorithm can be developed which used the counts of the signals falling into different parts of the signal plane. The feature is far more easier to compute and much faster than the likelihood methods and methods based on higher-order statistics. Algorithm is thus dependent on the orientation of the symbols in the signal space and could only be used for binary classification.

The author [43]; studied the Euclidean distance is found between the ideal and the calculated cyclic cumulants; however, the distance is left squared, which speeds up computation in a practical environment. In the multichannel case, four signals [BPSK, QPSK, 8-PSK, and minimum shift keying (MSK)] are simultaneously transmitted within close proximity in frequency. Signal power ranged from 7 to 10 dB above the noise power.

2.2.5 Signal cyclostationarity

A stochastic process r(t) is said to be cyclostationary of order n (for a given conjugation configuration, i.e., q conjugate) if its cumulants up to order n (assuming they exist) are (almost) periodic functions of time. The nth-order/q-conjugate moments are also (almost)periodic functions of time.

Signal cyclostationarity is exploited for linear modulation identification , via two approaches: spectral line generation when passing the signal through different nonlinearities, and periodic fluctuations with time of cumulants up to the nth-order.The cyclostationarity of the received signal is used for modulation identification through a pattern of sine-wave frequencies in signal polynomial transformations. The algorithm given [44] processes the baseband signal entirely in the digital domain on an FPGA. The FPGA is run-time reconfigurable, which allows for more efficient usage of the FPGA slices when performing the computationally complex algorithm. Another step that allows real-time classification is the addition of a mask to the cyclic spectrum so that only certain points are calculated, greatly reducing the complexity, but this requires prior knowledge of which modulations are likely. also,the classifier was tested only with QPSK signals of known bandwidth, center frequency, and rolloff factor.

3 Wavelet Transform

3.1 Introduction to time-frequency domain

Mathematical transformations are applied to signals to obtain further information from that signal that is not readily available in the raw signal.There are a number of transformations that can be applied, among which the Fourier transforms are probably by far the most popular.

Most of the signals in practice, are time domain signals in their raw format. This representation is not always the best representation of the signal for most signal processing related applications. In many cases, the most distinguished information is hidden in the frequency content of the signal. The frequency spectrum of a signal shows what frequencies exist in the signal[10].

If the Fourier transform (FT) of a signal in time domain is taken, the frequency-amplitude representation of that signal is obtained. In other words, the plot with one axis being the frequency and the other being the amplitude tells us how much of each frequency exists in our signal.

Although FT is probably the most popular transform being used, there are many other transforms that are used quite often by engineers and mathematicians. Hilbert transform, short-time Fourier transform (STFT), Wigner distributions, the Radon transform, and of course our featured transformation, the wavelet transform, constitute only a small portion of a huge list of transforms that are available at engineer's and mathematician's disposal. Every transformation technique has its own area of application, with advantages and disadvantages, including wavelet transform (WT) .

The need of transformation depends on the particular application, and the nature of the signal in hand. Recall that the FT gives the frequency information of the signal, which means that it tells us how much of each frequency exists in the signal, but it does not tell us when in time these frequency components exist. This information is not required when the signal is so-called stationary. The frequency content of stationary signals do not change in time. In this case, one does not need to know at what times frequency components exist, since all frequency components exist at all times.

3.2 From short time Fourier time to wavelet

The Fourier transform gives us the signal as a function of frequency only in the Fourier transform space. This means that it is possible to have a good time resolution by choosing a small time increment, with corresponding poor frequency information.

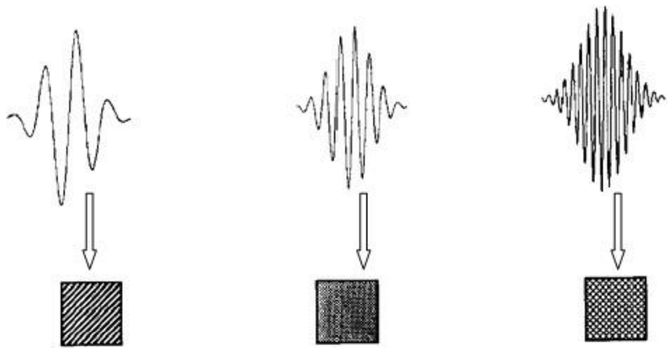
There is only a minor difference between STFT and FT. In STFT, the signal is divided into small enough segments, where these portions of the signal can be assumed to be stationary. For this purpose, a window function is chosen. The width of this window must be equal to the segment of the signal where its stationary is valid.

This window function is first located to the very beginning of the signal. Example, suppose that the width of the window is “T" s. At this time instant (t=0), the window function will overlap with the first T/2 seconds. The window function and the signal are then multiplied. By doing this, only the first T/2 seconds of the signal is being chosen, with the appropriate weighting of the window.Then this product is assumed to be just another signal, whose FT is to be taken. In other words, FT of this product is taken, just as taking the FT of any signal. The result of this transformation is the FT of the first T/2 seconds of the signal. If this portion of the signal is stationary, as it is assumed, then there will be no problem and the obtained result will be a true frequency representation of the first T/2 seconds of the signal.The next step, would be shifting this window (for some t1 seconds) to a new location, multiplying with the signal, and taking the FT of the product. This procedure is followed, until the end of the signal is reached by shifting the window with "t1" seconds intervals.

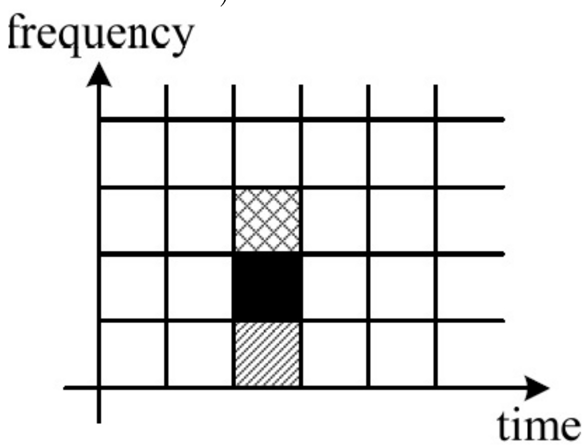
$$STFT_x^w(t,f) = \int_t [x(t)w^*(t-t')e^{-j2\pi ft}dt \tag{3.1}$$

x(t) is the signal itself, w(t) is the window function, and * is the complex conjugate. The STFT of the signal is nothing but the FT of the signal multiplied by a window function.

FT of a real signal is always symmetric, since STFT is nothing but a windowed version of the FT, it should come as no surprise that STFT is also symmetric in frequency. The symmetric part is said to be associated with negative frequencies, an odd concept which is difficult to comprehend, fortunately, it is not important; it suffices to know that STFT and FT are symmetric.



a) Basis functions



b)Coverage of time-frequency plane

Figure 3.1: Basis functions and time- frequency resolution of the Short-Time Fourier Transform (STFT) [13]

For example, if there are four peaks corresponding to four different frequency components. Unlike FT, these four peaks are located at different time intervals along the time axis. Remember that the original signal had four spectral components located at different times.

In this case, frequency components are present in the signal, but we also know where they are located in time.The problem with the STFT has something to do with the width of the window function that is used. This width of the window function is known as the support of the window. If the window function is narrow, then it is known as compactly supported . This terminology is more often used in the wavelet world.

3.3 Theory of Wavelet

In 1982 Jean Morlet a French geophysicist, introduced the concept of a 'wavelet. The wavelet means small wave and the study of wavelet transform is a new tool for seismic signal analysis. Immediately, Alex Grossmann theoretical physicists studied inverse formula for the wavelet transform.

Wavelet analysis is originally introduced in order to improve seismic signal analysis by switching from shortime Fourier analysis to new better algorithms to detect and analyze abrupt changes in signals Daubechies , Mallat .

A wavelet means a small wave (the sinusoids used in Fourier analysis are big waves) and in brief, a wavelet is an oscillation that decays quickly[12].Equivalent mathematical conditions for wavelet are :

$$\begin{cases} \int_{-\infty}^{\infty} |\psi(t)|^2 dt < \infty \\ \int_{-\infty}^{\infty} |\psi(t)| dt = 0 \\ \int_{-\infty}^{\infty} \frac{|\psi(w)|^2}{w} dw < \infty \end{cases} \tag{3.2}$$

The most applicable wavelets are those that die out to identically zero after a few oscillations on a finite interval [a,b), i.e., ψ(t) = 0 outside the interval[a,b).

The basic wavelet since it will be equipped with two parameters, namely, a "scale" . and τ "translation" to result in a "family" of wavelets $\psi(\frac{t-\tau}{a})$. The construction of basic wavelets is established in terms of their associated building blocks or scaling functions $\phi(t)$.

Jean Morlet in 1982, introduced the idea of the wavelet transform and provided a new mathematical tool for seismic wave analysis. Morlet first considered wavelets as a family of functions constructed from translations and dilation of a single function called the "mother wavelet" $\psi(t)$. They are defined by

$$\psi_{a,\tau}(t) = \frac{1}{\sqrt{|\alpha|}}\psi(\frac{t-\tau}{a}) \tag{3.3}$$

$a, \tau \in \Re \; \alpha \neq 0$

The parameter a is the scaling parameter or scale, and it measures the degree of compression. The parameter b is the translation parameter which determines the time location of the wavelet. If $|a| < 1$, then the wavelet in the above equation is the compressed version of the mother wavelet and corresponds mainly to higher frequencies.On the other hand, when $|a| > 1$, then $\psi_{a,\tau}(t)$ has a larger time-width than $\psi(t)$ and corresponds to lower frequencies. Thus, wavelets have time-widths adapted to their frequencies.

There are an infinity of possible bases for function space, what makes the wavelet basis interesting is that, unlike sines and cosines, individual wavelet functions are quite localized in space; simultaneously, like sines and cosines, individual wavelet functions are quite localized in frequency or (more precisely) characteristic scale. Unlike sines and cosines, which define a unique Fourier transform, there is not one single unique set of wavelets; in fact, there are infinitely many possible sets. Roughly, the different sets of wavelets make different trade-offs between how compactly they are localized in space and how smooth they are.

3.3.1 Mother wavelets

A wavelet is a mathematical function used to divide a given function into different frequency components. A wavelet transform is the representation of a function by wavelets, which represent scaled and translated copies of a finite length or fast-decaying oscillating waveform (known as the mother wavelet). The term mother implies that the functions with different region of support that are used in the transformation process are derived from one main function, or the mother wavelet. In other words, the mother wavelet is a prototype for generating the other window functions. Some examples of mother wavelet are listed below.

Haar wavelets The Haar transform is one of the earliest examples of what is known now as a compact, dyadic, orthonormal wavelet transform[37].The Haar wavelet's mother wavelet function can be described as

$$\psi(t) = \begin{cases} +1 & 0 < t < 1/2 \\ -1 & 1/2 < t < 1 \\ 0 & otherwise \end{cases} \quad (3.4)$$

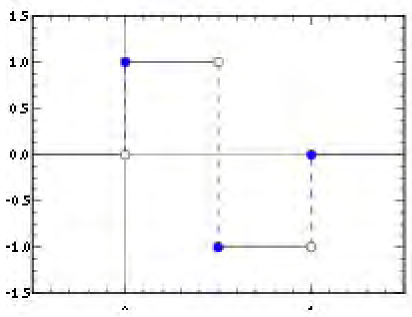


Figure 3.2: Haar wavelet [40]

Due to its low computing requirements, the Haar transform has been mainly used for pattern recognition and image processing.Hence, two dimensional signal and image processing is an area of efficient applications of Haar transforms due to their wavelet-like structure. In addition to this, due to its relative similar shape to most of signals wave form it is applied in most signal analysis.The advantages of computational and memory requirements of the Haar transform make it of a considerable interest to VLSI designers as well.The shapes of discontinuities that can be identified by the smallest wavelets are simpler than those that can be identified by the longest wavelets to identify. This signal discontinuity detected using haar wavelet easily. For the sake of simplicity the haar family wavelets are the most frequently used wavelets.

The Haar wavelet is the easiest Wavelet transform, and it is a kind of the continuous wavelet transform with discrete coefficients[38]. We can see clearly that this mother wavelet is a high pass filter and the scaling function is a low pass filter indeed. There are some advantages of the Haar wavelet: one is it is simple and Fast algorithm.

The main disadvantage is both the mother wavelet and the scaling function are not enough smooth. Since there are less rectangular signals in nature, and in general it hope the basis seem to the signal we want to analysis in the signal processing.

Daubechies wavelets The Daubechies wavelet transforms are defined in the same way as the Haar wavelet transform by computing running averages and differences via scalar products with scaling signals and wavelets the only difference between them consists in how these scaling signals and wavelets are defined.

In general the Daubechies wavelets are chosen to have the highest number A of vanishing moments, (this does not imply the best smoothness) for given support width N=2A. There are two naming schemes in use, DN using the length or number of taps, and dbA referring to the number of vanishing moments. So D4 and db2 are the same wavelet transform.

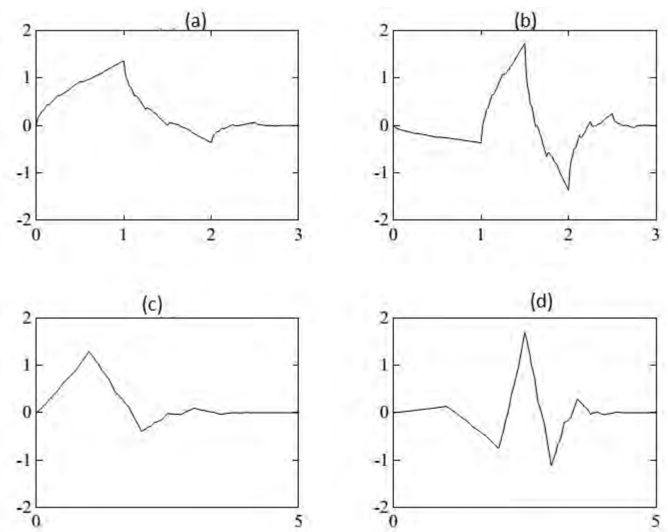


Figure 3.3: Daubechies wavelet
(a) Daubechies D4 scaling function (b) Daubechies D4 wavelet (c) Daubechies D6 scaling function (d) Daubechies D6 wavelet [40]

Morlet wavelets The Morlet wavelet is the most popular complex wavelet used in practice, which mother wavelet is defined as

$$\psi(t) = \frac{1}{\sqrt[4]{\pi}}(e^{jw_0 t} - e^{-\frac{w_0^2}{2}})e^{-\frac{t^2}{2}} \tag{3.5}$$

w_0 is the central frequency of the mother wavelet

$e^{-\frac{w_0^2}{2}}$ is used for correcting the non-zero mean of the complex sinusoid, and it can be negligible when $w_0 > 5$. Therefore in some research the mother wavelet definition of the Morlet wavelet is:

$$\psi(t) = \frac{1}{\sqrt[4]{\pi}}e^{jw_0 t}e^{-\frac{t^2}{2}} \tag{3.6}$$

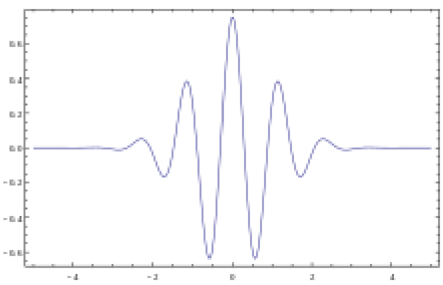


Figure 3.4: Real-valued Morlet wavelet [39]

The Morlet wavelet has a form very similar to the Gabor transform. The important difference is that, the window function also be scaled by the scaling parameter, while the size of window in Gabor transform is fixed. The application of the Morlet wavelet analysis in the electrocardiogram (ECG) is mainly to discriminate the abnormal heartbeat behavior[39]. Since the variation of the abnormal heartbeat is a non-stationary signal, then this signal is suitable for wavelet-based analysis.

3.3.2 The continuous wavelet transform (CWT)

The continuous wavelet transform was developed as an alternative approach to the short time Fourier transform to overcome the resolution problem. The wavelet analysis is done in a similar way to the STFT analysis, in the sense that the signal is multiplied with a function similar to the window function in the STFT, and the transform is computed separately for different segments of the time-domain signal. However, there are two main differences between the STFT and the CWT[10]:

1. The Fourier transforms of the windowed signals are not taken, and therefore single peak will be seen corresponding to a sinusoid, i.e., negative frequencies are not computed.

2. The width of the window is changed as the transform is computed for every single spectral component, which is probably the most significant characteristic of the wavelet transform.

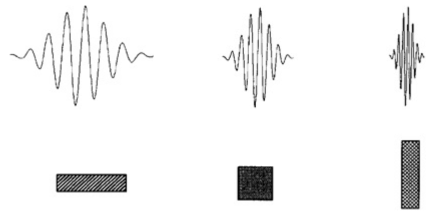
The continuous wavelet transform is defined as follow

$$CWT_x^{\psi}(\tau, a) = \Psi_x^{\psi}(\tau, a) = \frac{1}{\sqrt{|\alpha|}} \int x(t)\psi^*(\tfrac{t-T}{\alpha})dt \qquad (3.7)$$

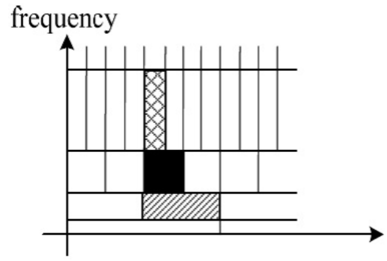
The transformed signal is a function of two variables, τ and a, the translation and scale parameters, respectively. $\psi(t)$ is the transforming function, and it is called the mother wavelet. Mother wavelet gets its name due to two important properties of the wavelet analysis as explained below:

The term wavelet means a small wave and the smallness refers to the condition that this (window) function is of finite length (compactly supported). The wave refers to the condition that this function is oscillatory. The term mother implies that the functions with different region of support that are used in the transformation process are derived from one main function, or the mother wavelet [13]. In other words, the mother wavelet is a prototype for generating the other window functions and translation is related to the location of the window, as the window is shifted through the signal. This term, obviously, corresponds to time information in the transform domain.

The time-frequency resolution of the WT involves a different tradeoff to the one used by the STFT: at high frequencies the WT is sharper in time, while at low frequencies, the WT is sharper in frequency as shown in Figure 3.5.



a)Basis functions



b)Coverage of time-frequency plane

Figure 3.5: Basis functions and time-frequency resolution of the wavelet transform [13]

The parameter scale in the wavelet analysis is similar to the scale used in maps. As in the case of maps, high scales correspond to a non-detailed global view (of the signal), and low scales correspond to *a* detailed view. Similarly, in terms of frequency, low frequencies (high scales) correspond to a global information of a signal (that usually spans the entire signal), whereas high frequencies (low scales) correspond to a detailed information of a hidden pattern in the signal.

The definition of the wavelet transform, the scaling term is used in the denominator, and therefore, the opposite of the above statements holds, i.e., scales $a > 1$ dilates the signals whereas scales $a < 1$, compresses the signal.

Let x(t) in Equation (3.7) is the signal to be analyzed. The mother wavelet is chosen to serve as a prototype for all windows in the process. All the windows that are used are the dilated (or compressed) and shifted versions of the mother wavelet. There are a number of functions that are used for this purpose.

This definition of the CWT shows that the wavelet analysis is a measure of similarity between the basis functions (wavelets) and the signal itself. Here the similarity is in the sense of similar frequency content. The calculated CWT coefficients refer to the closeness of the signal to the wavelet at the current scale.If the signal has a major component of the frequency corresponding to the current scale, then the wavelet (the basis function) at the current scale will be similar or close to the signal at the particular location where this frequency component occurs. Therefore, the CWT coefficient computed at this point in the time-scale plane will be a relatively large number.

The continuous wavelet transform is reversible if the above mathematical conditions in Section 3.3 are satisfied, even though the basis functions are in general may not be orthonormal. The reconstruction is possible by using the following reconstruction formula:

$$x(t) = \frac{1}{c_\psi^2} \int_a \int_\tau \psi_x^\psi(\tau, a) \frac{1}{a^2} \psi\left(\frac{t-\tau}{a}\right) d\tau da \qquad (3.8)$$

where c_ψ is a constant that depends on the wavelet used. The success of the reconstruction depends on this const ant called, the admissibility constant , to satisfy the following admissibility condition :

$$c_\psi = \left\{2\pi \int_{-\infty}^{\infty} \frac{|\hat{\psi(\xi)}|^2}{|\xi|} d\xi\right\}^{1/2} < \infty$$

where $\hat{\psi(\xi)}$ is FT of $\psi(t)$.

$\int \psi(t)dt < \infty$, this is not a very restrictive requirement since many wavelet functions can be found whose integral is zero. For this equation to be satisfied, the wavelet must be oscillatory.

3.3.3 The discrete wavelet transform (DWT)

Wavelet Transform merely performs the convolution operation of the signal and the basis function.High frequencies (low scales) do not last for a long duration, but instead, appear as short bursts, while low frequencies (high scales) usually last for entire duration of the signal.

In CWT, the signals are analyzed using a set of basis functions which relate to each other by simple scaling and translation. In the case of DWT, a time-scale representation of the digital signal is obtained using digital filtering techniques. The signal to be analyzed is passed through filters with different cutoff frequencies at different scales. The Wavelet Series is obtained by discretizing CWT. This aids in computation of CWT using computers and is obtained by sampling the time-scale plane. The sampling rate can be changed accordingly with scale change without violating the Nyquist criterion. Nyquist criterion states that, the minimum sampling rate that allows reconstruction of the original signal is 2ω radians, where ω is the highest frequency in the signal. Therefore, as the scale goes higher (lower frequencies), the sampling rate can be decreased thus reducing the number of computations.

Wavelet Series is just a sampled version of CWT and its computation may consume significant amount of time and resources, depending on the resolution required. The Discrete Wavelet Transform (DWT), which is based on sub-band coding is found to yield a fast computation of Wavelet Transform. It is easy to implement and reduces the computation time and resources required.

DWT provides sufficient information both for analysis and synthesis of the original signal, with a significant reduction in the computation time.The DWT is considerably easier to implement when compared to the CWT.

3.4 Application wavelet in wireless communication

Wavelet Transforms are applied in different fields ranging from signal processing to biometrics, and the list is still growing. The wavelet transforms enables high compression ratios with good quality of reconstruction. The application of wavelets for image compression is one the hottest areas of research and the wavelet transforms have been chosen for the JPEG 2000 compression standard.

It is highly applied in different signal processing application. Processing may involve compression, encoding, de-noising etc. The processed signal is either stored or transmitted. For most compression applications, processing involves quantization and entropy coding to yield a compressed image [10]. During this process, all the wavelet coefficients that are below a chosen threshold are discarded. These discarded coefficients are replaced with zeros during reconstruction at the other end. To reconstruct the signal, the entropy coding is decoded, then quantized and then finally Inverse Wavelet Transformed.

Wavelets also find application in speech compression, which reduces transmission time in mobile applications. They are used in de-noising, edge detection, feature extraction, speech recognition, echo cancellation and others. They are very promising for real time audio and video compression applications. Wavelets also have numerous applications in digital communications. Orthogonal Frequency Division Multiplexing (OFDM) is one of them. Wavelets are used in biomedical imaging.

Modulation identification using WT has been reported recently. It is mainly used to extract the features of an incoming signal[20]. The number of modulation types which can be identified by the previous research is limited because the same features are used for the identification of different modulation types. Different features have been used for identification in different papers, which make the identifier easy to design and realize [2]. In 2010, wavelet also used to denoise the instantaneous information of incoming signal, which improves identification ratio of low SNR signals [1].

Based on the localize ability in time-domain and frequency-domain, WT has been widely used for extracting the features of a signal. There are two ways. One is called multi-resolution analysis, decomposing the signal at different levels. The other way is to look for the local maximum of the magnitude by CWT [6]. Wavelet decomposing means that the signal is divided into two parts, by filtering it through the low pass and high pass filters. The high pass filter picks up the small details, the low pass filter picks up everything else. The process continues with the low pass portion of the signal. With the continuing of the process, signals are decomposed at different levels; different discrete details can be got at different frequency channels.

4 Mathematical modeling using wavelet transform

We consider the received waveform r (t), 0 <= t <= T, and r(t) can be expressed as:

$$r(t) = s'(t) + n(t) \qquad (4.1)$$

where $s'(t)$ is the signal, n(t) is white Gaussian noise and T is symbol period.

The signal s(t) in Chapter one expressed in cos and sine form can be expressed in exponential form as follows

$$s(t) = s'(t)exp(j(w_c t + \theta_c)) \qquad (4.2)$$

where w_c is the carrier frequency and θ_c is the carrier phase. Different modulated signals are represented as following

$$\begin{cases} s_{FSK}(t) = \sqrt{S}(\sum_{i=1}^{N}(e^{j(w_i t+\theta_i)})) & Where\ \omega_i \in \{\omega_1, \omega_2, ..., \omega_M\}\ \theta_i \in (0, 2\pi) \\ s_{PSK}(t) = \sqrt{S}(\sum_{i=1}^{N}(e^{j\phi_i})) & Where\ \phi i \in \frac{2\pi(m-1)}{M}, m = 1, 2, \ldots, M \\ s_{ASK}(t) = \sqrt{S}(\sum_{i=1}^{N} v(i)) & Where\ v(i) \in 1, M\ is\ the\ data\ produced\ by\ the\ source \\ s_{QAM}(t) = \sum(Ai + jBi) & Where\ Ai, Bi \in \{2m - 1 - M, m = 1, 2, ..M\} \end{cases} \qquad (4.3)$$

In these Equations, S is the signal strength, N is the number of symbols

The signal to noise ratio given by the relationship

$$SNR = 10\log(\frac{S}{Np}) \qquad (4.4)$$

where S is the signal strength and Np is the noise power. Since, in this algorithm we are taking normalized signal essentially S=1, the effect of noise will force

$$Np = 10^{-\frac{SNR}{10}} \qquad (4.5)$$

We have the continuous wavelet transform of a signal s(t) in Equation (3.7)

$$CWT(a,\tau) = \int s(t)\psi_a^*(t)dt = \frac{1}{\sqrt{a}}\int s(t)\psi_a^*(\frac{(t-\tau)}{a})dt \qquad (4.6)$$

where a is the scale part of the shift and symbol "*" represents complex conjugate of the function. The function ψ(t) is the mother function wavelet, the choice of which depends on the application, and $CWT(a,\tau)$ the resulting function wavelet, resulting from scaling time and the displacement function of the parent wavelet. As we are interested in digital signals, we take discrete values continuous transformation, replacing the existing integrated press the sum of these terms. In this case, as the mother function will use the wavelet of Haar, so that the resulting wavelet function in Equation (3.2) can be generalized as following [7]:

$$\frac{1}{\sqrt{a}}\psi(\frac{k}{a}) = \begin{cases} \frac{1}{\sqrt{a}} & -a/2 < k < 0 \\ -\frac{1}{\sqrt{a}} & 0 < k < a/2 \\ 0 & otherwise \end{cases} \qquad (4.7)$$

For discrete time s(t)=s(k) then for $t \in [k,\ k_1]$

$$C_{a,\tau} = \frac{1}{\sqrt{a}}\sum_k s(k)\int_k^{k+1}\psi^*(\frac{(t-\tau)}{a})dt \qquad (4.8)$$

$$C_{a,\tau} = \frac{1}{\sqrt{a}}\sum_k s(k)(\int_{-\infty}^{k+1}\psi^*(\frac{(t-\tau)}{a})dt - \int_{-\infty}^{k}\psi^*(\frac{(t-\tau)}{a})dt) \qquad (4.9)$$

For PSK signal

During the time (i- 1)Tb $+\frac{\alpha}{2} \leq$ n $\leq$ iTb $+\frac{\alpha}{2}$ (if there is no symbol chnage), the Haar wavelet transform (HWT) of the PSK signal is given by the formula:

$$WT_{PSK}(a,nT_s) = \sqrt{\frac{s}{\alpha}}\left(\sum_{k=n-\alpha/2}^{n-1} exp(j(w_c kT_s+\theta_c+\phi_i)) - \sum_{k=n}^{k-\alpha/2-1} exp(j(w_c kT_s+\theta_c+\phi_i))\right) \quad (4.10)$$

Then we change the variable, setting k-n = 0

Resulting in the following formula for the wavelet transform Haar.

$$WT_{PSK}(a,nT_s) = \sqrt{\frac{s}{\alpha}}\left(\sum_{k=-\alpha/2}^{-1} exp(j(w_c(k+n)T_s+\theta_c+\phi_i)) - \sum_{k=0}^{\alpha/2-1} exp(j(w_c(k+n)T_s+\theta_c+\phi_i))\right)$$

T_s is the sampling period and Tb is the duration of a modulation symbol

$$= \sqrt{\frac{s}{\alpha}}\left(\sum_{k=0}^{\alpha/2-1} exp(j(w_c(k+n-\alpha/2)T_s+\theta_c+\phi_i)) - \sum_{k=0}^{\alpha/2-1} exp(j(w_c(k+n)T_s+\theta_c+\phi_i))\right)$$

$$= \sqrt{\frac{s}{\alpha}} exp(j(w_c nT_s+\theta_c+\phi_i)\left(\sum_{k=0}^{\alpha/2-1} exp(j(w_c(k-\alpha/2)T_s)) - \sum_{k=0}^{\alpha/2-1} exp(j(w_c kT_s))\right)$$

$$= \sqrt{\frac{s}{\alpha}} exp(j(w_c nT_s+\theta_c+\phi_i)\left(\sum_{k=0}^{\alpha/2-1} \frac{exp(j(w_c(kT_s))}{exp(j(w_c\alpha/2)T_s))}\right) - \sum_{k=0}^{\alpha/2-1} exp(j(w_c kT_s)))$$

$$= \sqrt{\frac{s}{\alpha}} exp(j(w_c nT_s+\theta_c+\phi_i)\left[\sum_{k=0}^{\alpha/2-1} \frac{1}{exp(j(w_c\alpha/2)T_s))} - 1\right] \sum_{k=0}^{\alpha/2-1} exp(j(w_c kT_s)))$$

Taking the magnitude we have

For (i-1)Tb+$\frac{\alpha}{2}$≤n≤iTb $+\frac{\alpha}{2}$

$$|WT_{PSK}(a,n)| = 2\sqrt{\frac{s}{\alpha}}\left|\frac{\sin^2(w_c\alpha/4)}{\sin((w_c/2)}\right| \quad (4.11)$$

Specifically, for the time n = iT When a phase transition happens, the above

Equations are not valid. Instead a noticeable peak appears as the following

$$\begin{cases} S(kT_s) = \sqrt{S}exp(j(w_c nT_s)\exp(j\phi_i) & (i-1)Ts \leq n \leq iTs \\ S(kT_s) = \sqrt{S}exp(j(w_c nT_s)\exp(j\phi_i+\delta) & iTs \leq n \leq (i+1)Ts \end{cases} \quad (4.12)$$

where

$$\delta = \varphi_{i+1} - \varphi_i,\ \delta\epsilon(\frac{(m-1)2\pi i}{M})$$

Then the continuous wavelet transformation to apply

$$WT_{PSK}(a,\tau) = \sqrt{\frac{s}{\alpha}}\left(\sum_{k=n-\alpha/2}^{n-1} exp(j(w_c kT_s+\theta_c+\phi_i)) - \sum_{k=n}^{n-\alpha/2-1} exp(j(w_c kT_s+\theta_c+\phi_i+\delta))\right)$$

$$= \sqrt{\frac{s}{\alpha}}\left(\sum_{k=-\alpha/2}^{-1} exp(j(w_c(k+n)T_s+\theta_c+\phi_i)) - \sum_{k=0}^{\alpha/2-1} exp(j(w_c(k+n)T_s+\theta_c+\phi_i+\delta))\right)$$

$$= \sqrt{\tfrac{s}{\alpha}}(\sum_{k=0}^{\alpha/2-1} exp(j(w_c(k+n-\alpha/2)T_s+\theta_c+\phi_i)) - \sum_{k=0}^{\alpha/2-1} exp(j(w_c(k+n)T_s+\theta_c+\phi_i+\delta)))$$

$$= \sqrt{\tfrac{s}{\alpha}} exp(j(w_c n)T_s+\theta_c+\phi_i)(\sum_{k=0}^{\alpha/2-1} exp(j(w_c(k-\alpha/2)T_s)) - \sum_{k=0}^{\alpha/2-1} exp(j(w_c kT_s+\delta)))$$

$$= \sqrt{\tfrac{s}{\alpha}} exp(j(w_c nT_s + \theta_c + \phi_i)(\sum_{k=0}^{\alpha/2-1} \tfrac{exp(j(w_c(kT_s))}{exp(j(w_c\alpha/2)T_s))})) - \sum_{k=0}^{\alpha/2-1} exp(j(w_c kT_s)exp(j\delta)))$$

$$= \sqrt{\tfrac{s}{\alpha}} exp(j(w_c nT_s + \theta_c + \phi_i)[\sum_{k=0}^{\alpha/2-1} \tfrac{1}{exp(j(w_c\alpha/2)T_s))} - exp(j\delta)] \sum_{k=0}^{\alpha/2-1} exp(j(w_c kT_s))) \tag{4.13}$$

For FSK

During the time (i- 1)Tb $+\frac{\alpha}{2} \leq$ n $\leq$ iTb $+\frac{\alpha}{2}$ the continuous wavelet transform of the FSK signal is given by the formula:

$$WT_{FSK}(a, nT_s) = \sqrt{\tfrac{s}{\alpha}}(\sum_{k=n-\alpha/2}^{n-1} exp(j((w_c+wi)kT_s+\theta_c+\phi_i)) - \sum_{k=n}^{k-\alpha/2-1} exp(j((w_c+wi)kT_s+\theta_c+\phi_i)))$$

$$WT_{FSK}(a, nT_s) = \sqrt{\tfrac{s}{\alpha}}(\sum_{k=-\alpha/2}^{-1} exp(j(w_c(k+n)T_s+\theta_c+\phi_i)) - \sum_{k=0}^{\alpha/2-1} exp(j(w_c(k+n)T_s+\theta_c+\phi_i)))$$

$$= \sqrt{\frac{s}{\alpha}}(\sum_{k=0}^{\alpha/2-1} exp(j((w_c+w_i)(k+n-\alpha/2)T_s+\theta_c+\phi_i)) - \sum_{k=0}^{\alpha/2-1} exp(j((w_c+w_i)(k+n)T_s+\theta_c+\phi_i)))$$

$$= \sqrt{\frac{s}{\alpha}} exp(j(w_c+w_i)nT_s+\theta_c+\phi_i)(\sum_{k=0}^{\alpha/2-1} exp(j(w_c+w_i)(k-\alpha/2)T_s)) - \sum_{k=0}^{\alpha/2-1} exp(j(w_c+w_i)kT_s)))$$

$$= \sqrt{\frac{s}{\alpha}} exp(j((w_c+w_i)nT_s+\theta_c+\phi_i)(\sum_{k=0}^{\alpha/2-1} \frac{exp(j((w_c+w_i)(kT_s))}{exp(j((w_c+w_i)\alpha/2)T_s))})) - \sum_{k=0}^{\alpha/2-1} exp(j((w_c+w_i)kT_s))$$

$$= \sqrt{\frac{s}{\alpha}} exp(j(w_c+w_i)nT_s+\theta_c+\phi_i)[\sum_{k=0}^{\alpha/2-1} \frac{1}{exp(j(w_c+w_i)\alpha/2)T_s))} - 1] \sum_{k=0}^{\alpha/2-1} exp(j((w_c+w_i)kT_s)))$$

For (i- 1)Tb $+\frac{\alpha}{2}\leq$ n $\leq$ iTb $+\frac{\alpha}{2}$

$$|WT_{FSK}(a,n)| = 2\sqrt{\tfrac{s}{\alpha}}\left|\tfrac{\sin^2(w_c+w_i)\alpha/4)}{\sin((w_c+w_i)/2)}\right| \qquad (4.14)$$

While the transition of the signal in time n = iT, the Haar wavelet transform of is given by

$$WT_{FSK}(a,nT_s) =$$
$$\sqrt{\tfrac{s}{\alpha}}(\sum_{k=n-\alpha/2}^{n-1} exp(j((w_c+w_i)kT_s+\theta_c+\phi_i)) - \sum_{k=n}^{n-\alpha/2-1} exp(j((w_c+w_i)kT_s+\theta_c+\phi_i+\delta)))$$

$$= \sqrt{\tfrac{s}{\alpha}}(\sum_{k=-\alpha/2}^{-1} exp(j((w_c+w_i)(k+n)T_s+\theta_c+\phi_i)) - \sum_{k=0}^{\alpha/2-1} exp(j((w_c+w_i)(k+n)T_s+\theta_c+\phi_i+\delta)))$$

$$= \sqrt{\tfrac{s}{\alpha}}(\sum_{k=0}^{\alpha/2-1} exp(j((w_c+w_i)(k+n-\alpha/2)T_s+\theta_c+\phi_i)) - \sum_{k=0}^{\alpha/2-1} exp(j((w_c+w_i)(k+n)T_s+\theta_c+\phi_i+\delta)))$$

$$= \sqrt{\tfrac{s}{\alpha}} exp(j((w_c+w_i)n)T_s+\theta_c+\phi_i)(\sum_{k=0}^{\alpha/2-1} exp(j((w_c+w_i)(k-\alpha/2)T_s)) - \sum_{k=0}^{\alpha/2-1} exp(j((w_c+w_i)kT_s+\delta)))$$

$$= \sqrt{\tfrac{s}{\alpha}} exp(j((w_c+w_i)nT_s+\theta_c+\phi_i)(\sum_{k=0}^{\alpha/2-1} \tfrac{exp(j((w_c+w_i)(kT_s))}{exp(j((w_c+w_i)\alpha/2)T_s))})) - \sum_{k=0}^{\alpha/2-1} exp(j((w_c+w_i)kT_s) exp(j\delta)))$$

$$= \sqrt{\tfrac{s}{\alpha}} exp(j((w_c+w_i)nT_s+\theta_c+\phi_i)[\sum_{k=0}^{\alpha/2-1} \tfrac{1}{exp(j((w_c+w_i)\alpha/2)T_s))} - exp(j\delta)] \sum_{k=0}^{\alpha/2-1} exp(j((w_c+w_i)kT_s))) \qquad (4.15)$$

For QAM signal

The WT of QAM signal will be as follows:

$$WT_{QAM}(a,nT_s) = \sqrt{\tfrac{1}{\alpha}}(\sum_{k=n-\alpha/2}^{n-1} \sqrt{A_i^2+B_i^2} exp(j(w_c kT_s + \theta_c + \phi_i)) - \sum_{k=n}^{k-\alpha/2-1} \sqrt{A_i^2+B_i^2} exp(j(w_c kT_s + \theta_c + \phi_i)))$$

$$= \tfrac{1}{\sqrt{\alpha}}(\sum_{k=-\alpha/2}^{-1} \sqrt{A_i^2+B_i^2} exp(j(w_c(k+n)T_s + \theta_c + \phi_i)) - \sum_{k=0}^{\alpha/2-1} \sqrt{A_i^2+B_i^2} exp(j(w_c(k+n)T_s + \theta_c + \phi_i)))$$

$$= \tfrac{1}{\sqrt{\alpha}}(\sum_{k=0}^{\alpha/2-1} \sqrt{A_i^2+B_i^2} exp(j(w_c(k+n-\alpha/2)T_s + \theta_c + \phi_i)) - \sum_{k=0}^{\alpha/2-1} \sqrt{A_i^2+B_i^2} exp(j(w_c(k+n)T_s + \theta_c + \phi_i)))$$

$$= (\sqrt{\tfrac{A_i^2+B_i^2}{\alpha}} exp(j(w_c+n)T_s + \theta_c + \phi_i)(\sum_{k=0}^{\alpha/2-1} \tfrac{1}{exp(j(w_c\alpha/2T_s)} - 1)(\tfrac{-1+exp(j\alpha w_c)}{-1+exp(jw_c)}))$$

For (i- 1)Tb $+\frac{\alpha}{2} \leq$ n $\leq$ iTb $+\frac{\alpha}{2}$

$$|WT_{QAM}(a,n)| = 2\sqrt{\frac{S}{\alpha}} \left| \frac{\sin^2(w_c)\alpha/4)}{\sin(w_c)/2)} \right| \quad (4.16)$$

For the time n = iT in the transition of signal the formula will be as follows:

$$s(kTs) = \sqrt{\frac{S_i^2}{\alpha}} exp(j(w_c)T_s exp(\phi_i) \text{ for } (i-1)T_s \leq n \leq iT_s$$

$$s(kTs) = \sqrt{\frac{S"_i^2}{\alpha}} exp(j(w_c)T_s exp(\phi_i+\delta) \text{ for } iT_s \leq n \leq (i+1)T_s$$

$$\delta \in \left\{ (\tfrac{2\pi(m-1)}{M}) \right\}$$

$$S_i^2 = A_i^2 + B_i^2$$

$$S"_i^2 = A_i'^2 + B_i'^2$$

Then the continuous wavelet transform will be

$$WT_{QAM}(a, nT_s) = \sqrt{\tfrac{1}{\alpha}}(\sum_{k=n-\alpha/2}^{n-1} \sqrt{S_i} exp(j(w_c kT_s + \theta_c + \phi_i)) - \sum_{k=n}^{k-\alpha/2-1} \sqrt{S_i^{"}} exp(j(w_c kT_s + \theta_c + \phi_i + \delta)))$$

$$= \tfrac{1}{\sqrt{\alpha}}(\sum_{k=-\alpha/2}^{-1} \sqrt{A_i^2 + B_i^2} exp(j(w_c(k+n)T_s + \theta_c + \phi_i)) - \sum_{k=0}^{\alpha/2-1} \sqrt{S_i^{"}} exp(j(w_c(k + n)T_s + \theta_c + \phi_i + \delta)))$$

$$= \tfrac{1}{\sqrt{\alpha}}(\sum_{k=0}^{\alpha/2-1} \sqrt{S_i} exp(j(w_c(k + n - \alpha/2)T_s + \theta_c + \phi_i)) - \sum_{k=0}^{\alpha/2-1} \sqrt{S_i^{"}} exp(j(w_c(k + n)T_s + \theta_c + \phi_i + \delta)))$$

$$= (\sqrt{\tfrac{S_i}{\alpha}} exp(j(w_c nT_s + \theta_c + \phi_i))(\sum_{k=0}^{\alpha/2-1} \tfrac{exp(j(w_c kT_s)}{exp(j(w_c \alpha/2T_s)} - \sqrt{S_i^{"}} exp(j\delta)) \sum_{k=0}^{\alpha/2-1} exp(j(w_c kT_s))$$

$$= (\sqrt{\tfrac{S_i}{\alpha}} exp(j(w_c + n)T_s + \theta_c + \phi_i)(\sum_{k=0}^{\alpha/2-1} \tfrac{1}{exp(j(w_c \alpha/2T_s)} - \sqrt{\tfrac{S_i^{"}}{\alpha}} exp(jw_c\delta))(\tfrac{-1+exp(j\alpha w_c)}{-1+exp(jw_c)})) \tag{4.17}$$

For ASK signal

$$WT_{ASK}(n, Ts) = \sqrt{\tfrac{1}{\alpha}}(\sum_{k=n-\alpha/2}^{n-1} \sqrt{A_i^2 + B_i^2} exp(j(w_c kT_s + \theta_c + \phi_i)) - \sum_{k=n}^{k-\alpha/2-1} \sqrt{A_i^2 + B_i^2} exp(j(w_c kT_s + \theta_c + \phi_i)))$$

$$= \tfrac{1}{\sqrt{\alpha}}(\sum_{k=-\alpha/2}^{-1} \sqrt{A_i^2 + B_i^2} exp(j(w_c(k + n)T_s + \theta_c + \phi_i)) - \sum_{k=0}^{\alpha/2-1} \sqrt{A_i^2 + B_i^2} exp(j(w_c(k + n)T_s + \theta_c + \phi_i)))$$

$$= \tfrac{1}{\sqrt{\alpha}}(\sum_{k=0}^{\alpha/2-1} \sqrt{A_i^2 + B_i^2} exp(j(w_c(k + n - \alpha/2)T_s + \theta_c + \phi_i)) - \sum_{k=0}^{\alpha/2-1} \sqrt{A_i^2 + B_i^2} exp(j(w_c(k + n)T_s + \theta_c + \phi_i)))$$

$$= (\sqrt{\tfrac{A_i^2+B_i^2}{\alpha}} exp(j(w_c + n)T_s + \theta_c + \phi_i)(\sum_{k=0}^{\alpha/2-1} \tfrac{1}{exp(j(w_c \alpha/2T_s)} - 1)(\tfrac{-1+exp(j\alpha w_c)}{-1+exp(jw_c)}))$$

For(i- 1)Tb $+\frac{\alpha}{2}\leq$ n $\leq$ iTb $+\frac{\alpha}{2}$

$$|WT_{ASK}(a,n)| = 2\sqrt{\frac{s}{\alpha}}\left|\frac{\sin^2(w_c\alpha/4)}{\sin((w_c/2)}\right| \tag{4.18}$$

For the time n = iT:

$$S(kTs) = \sqrt{\frac{A_i^2+B_i^2}{\alpha}}exp(j(w_c)T_s exp(\phi_i) \text{ for}(i-1)T_s \leq n \leq iT_s$$

$$S(kTs) = \sqrt{\frac{{A'}_i^2+{B'}_i^2}{\alpha}}exp(j(w_c)T_s exp(\phi_i) \text{ for} iT_s \leq n \leq (i+1)T_s$$

$$\delta \in \left\{(\frac{2\pi(m-1)}{M})\right\}$$

The continuous wavelet transformation will be :

$$WT_{ASK}(a,nTs) = \sqrt{\frac{1}{\alpha}}(\sum_{k=n-\alpha/2}^{n-1}\sqrt{A_i^2+B_i^2}exp(j(w_ckT_s+\theta_c+\phi_i)) - \sum_{k=n}^{k-\alpha/2-1}\sqrt{A_i'^2+B_i'^2}exp(j(w_ckT_s+\theta_c+\phi_i+\delta)))$$

$$= \frac{1}{\sqrt{\alpha}}(\sum_{k=-\alpha/2}^{-1}\sqrt{A_i^2+B_i^2}exp(j(w_c(k+n)T_s+\theta_c+\phi_i)) - \sum_{k=0}^{\alpha/2-1}\sqrt{A_i'^2+B_i'^2}exp(j(w_c(k+n)T_s+\theta_c+\phi_i+\delta)))$$

$$= \frac{1}{\sqrt{\alpha}}(\sum_{k=0}^{\alpha/2-1}\sqrt{A_i^2+B_i^2}exp(j(w_c(k+n-\alpha/2)T_s+\theta_c+\phi_i)) - \sum_{k=0}^{\alpha/2-1}\sqrt{A_i'^2+B_i'^2}exp(j(w_c(k+n)T_s+\theta_c+\phi_i+\delta)))$$

$$= (\sqrt{\frac{A_i^2+B_i^2}{\alpha}}exp(j(w_cnT_s+\theta_c+\phi_i))(\sum_{k=0}^{\alpha/2-1}\frac{exp(j(w_ckT_s)}{exp(j(w_c\alpha/2T_s)} - \sqrt{\frac{A_i'^2+B_i'^2}{\alpha}}exp(j\delta))\sum_{k=0}^{\alpha/2-1}exp(j(w_ckT_s))$$

$$= (\sqrt{\frac{A_i^2+B_i^2}{\alpha}}exp(j(w_c+n)T_s+\theta_c+\phi_i)(\sum_{k=0}^{\alpha/2-1}\frac{1}{exp(j(w_c\alpha/2T_s)} - \sqrt{\frac{{A'}_i^2+{B'}_i^2}{\alpha}}exp(jw_c\delta))(\frac{-1+exp(j\alpha w_c)}{-1+exp(jw_c)})) \tag{4.19}$$

From the above Equations it is clear that, the wavelet transform of modulated signal at symbol transition (n=iT) is different from when transition is not occur. The output is clearly distinguishable from the constant output of CWT of signal derived at time iTs$\leq$ n $\leq$ (i+1)Ts. Since WT of a signal has different output, the final derived formulas given in (4.11), (4.14), (4.16) and (4.18) are different from that of (4.13), (4.15), (4.17) and (4.19).

5 Simulation Results

The simulation parameters and environment of the algorithm were as follows.

Carrier frequency (fc)	1 kHz
Sampling rate (fs)	8 kHz
symbol time(T)	0.01 second
Symbol rate (rs)	12.5kbaud/s
Order median filter (M(.))	25
Wavelet scale	4

Table 5.1: Simulation parameters

The mother wavelet was the Haar wavelet discussed in Chapter four. The test set contained thirteen modulation types: Three for PSK: {2PSK, 4PSK, 8PSK); four for FSK: {4FSK, 4FSK, 8FSK, 16FSK); three for QAM: {8QAM, 16QAM, 32QAM}; and Three for ASK: {2ASK, 4ASK, 8ASK).The above specified modulation schemes were simulated using software tool MATLAB 7.9.0 (R2009b) and AWGN noise was simulated and added with a transmitting signal as a channel noise.

5.1 Pre-processing

In low SNR environment, signal parameters and transient information are usually affected by noise and other interferences, which reduces the recognition ability. The basic idea behind denoising (or filtering) is to separate the noisy signal into its constituent components. That is, separation into parts primarily associated with the signal components and those that are not. The noise removal tends to retain the signal related components and remove as much as is possible the components that relate to the noise only[35]. Because Gaussian noise and other transient interference signal are evenly distributed throughout the frequency band of the useful signals, the denoising method of the classical linear filter cannot achieve satisfactory performance for modulation recognition at low SNR. Wavelet decomposes recieved signals at different frequency intervals with various resolutions and analyze a signal into rough approximation (low frequency) and detail (high frequency) components.

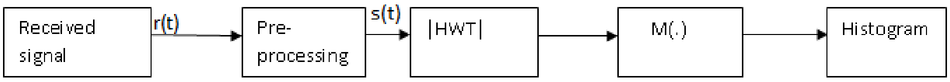


Figure 5.1: General block diagram of AMI system

The modulated signal is pass through wavelet filter is designed to eliminate noise which can improve the modulation identification ability at low SNR. Identification ability at low SNR can be improved by almost 5dB if we use wavelet filter instead of linear filters [1]. In this work, recieved signal is denoised using order 4 haar wavelet filter which means, wavelet coefficients are 4 levels.

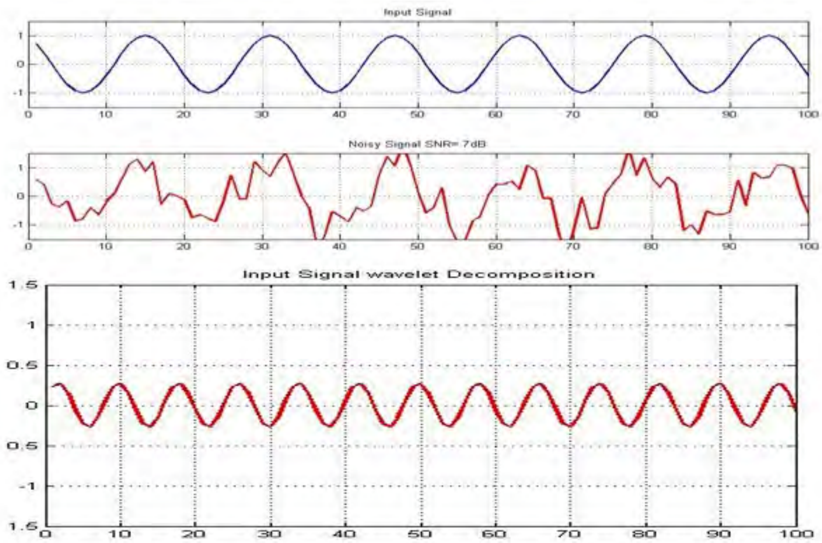


Figure 5.2: Signal pre-processing using wavelet filter

After signal denoised using wavelet filter, the distorted peaks of output is smoothed using order 25 median filter. The median filter takes several sequential data points and uses as the filtered output the data point that is obtained as the middle point when ranking is invoked. The median filter replaces the center point of the window with the median value of all the points contained in the window. Ranking the values and selecting the central value achieves this so that, the undesired peaks of signal will be removed or round off. The median filter is used as classifying block of PSK signal from remianing modulation types. This is because of peaks are diminished, when signal is pass through median filter. It is also used as processing block for the three modulaion types (FSK, ASK, and QAM) to smooth undesired peaks created by noise as we can see in Figure (5.3).

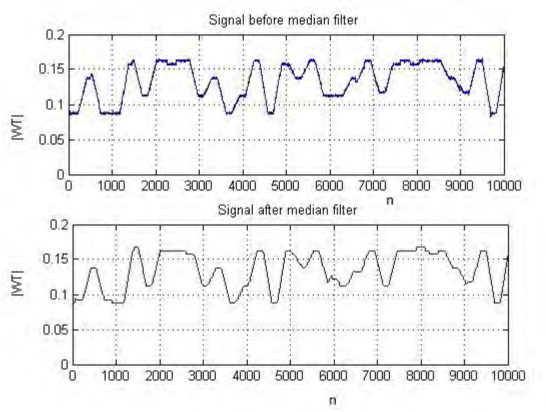


Figure 5.3: Signal before and after median filter

5.2 Inter-Class Classification

Different types of modulation signals have different actual values amplitude, frequency and phase. The wavelet transform has the ability to extract these instantaneous values or transient change in any of the instantaneous amplitude, frequency or phase.

Modulation type	With out amplitude normalization	With amplitude normalization
PSK	Constant function	Constant function
ASK	Multi-level function	Single-level function
QAM	Multi-level function	Constant function
FSK	Multi-tone function	Multi-tone function

Table 5.2: Characteristics of different modulation signals types
HWT

In this case, there are two algorithms which determine the total modulation identification system. The first algorithm calculates the number of tones of amplitude normalized signal. Second algorithm calculate the number of amplitude levels of signal before amplitude normalization. This can distinguish whether the received signal is multi-level function or not. Finally, if the signal is neither a multi-level nor multi-tone function, the algorithm at inter-class level recognizes the signal as PSK signal.

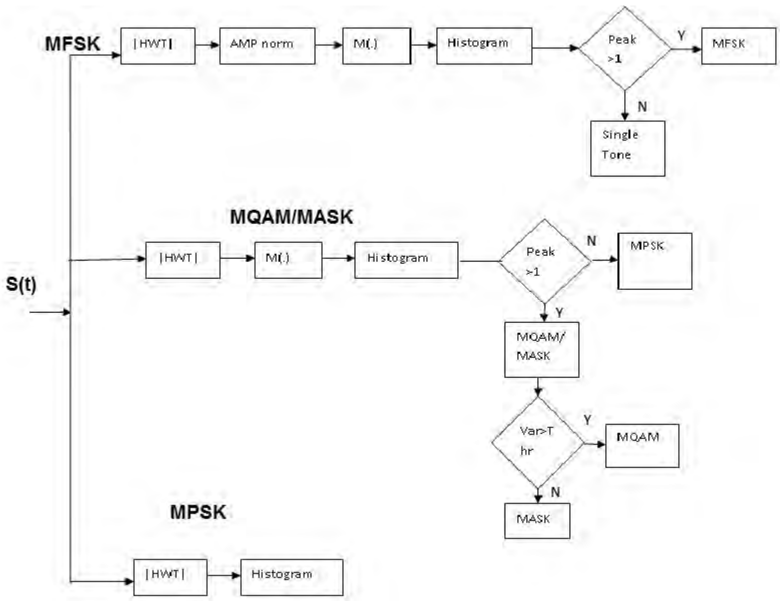
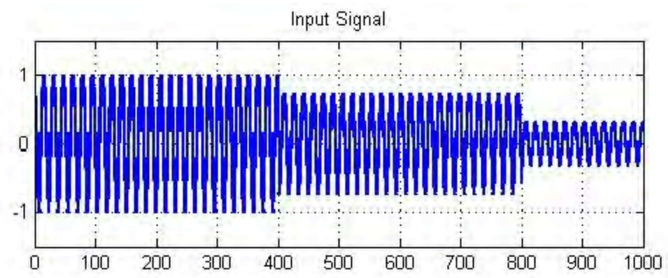
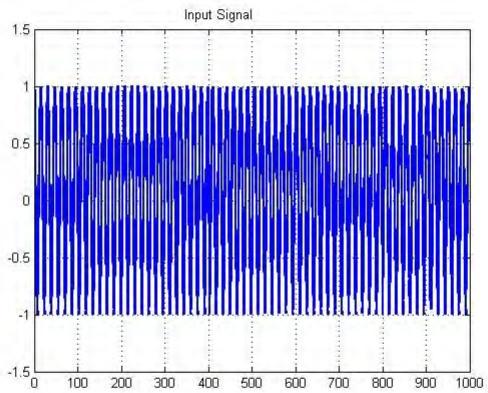


Figure 5.4: Flow chart of automatic modulation identifier

Figure5.4 is the WT modulation identifier for FSK,QAM,ASK and PSK signals. The identifier consists of three branches: One branch is without amplitude normalization and second branch is with amplitude normalization. These two branches include median filter. The third branch is with out median filter. The identifier first finds the |HWT| of an input signal. After removing the peaks of |HWT| by a median filter, the identifier computes the number peaks of histogram which is used as decision block. After signal received for the first time, the magnitude of HWT with amplitude normalization was used to discriminate FSK from PSK and QAM/ASK. Because the multli-level funictions ASK and QAM signals are constant function signal after amplitude normalization.As we can see in Figure 5.5, signal without amplitude normalization is tested to distinguish between multi-level functions signals (QAM/ASK) and constant function signal PSK. The identifier block is discussed in the following sub-sections.



(a) 16 QAM before amplitude normalization



(b)16 QAM after amplitude normalization

Figure 5.5: QAM signal before and after amplitude normalization

5.2.1 M-FSK Classification

Based on the characteristics of signal discussed on the Table 5.2, the normalized histogram generation of wavelet transform coefficient is used to classify the FSK from the other modulation types (QAM,ASK and PSK).

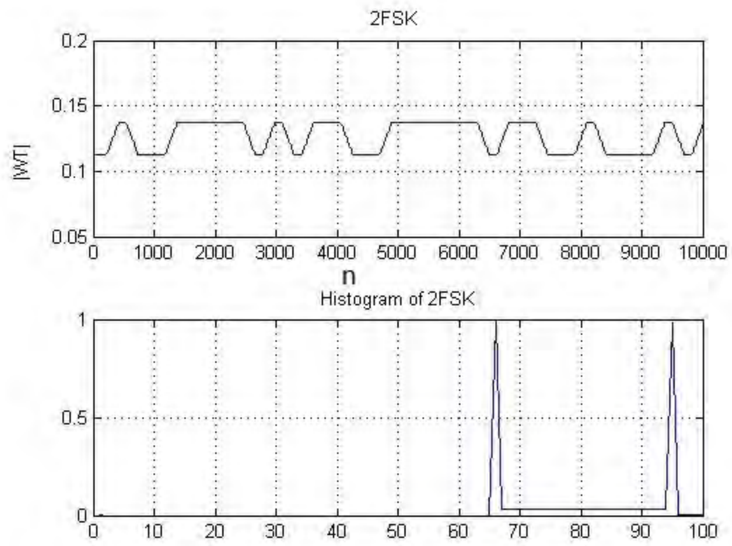


Figure 5.6: 2FSK Identification

By taking the magnitude of the wavelet transform FSK modulation easily distinguishable due to its multi-frequency component so that it has multiple histogram peaks irrespective of signal is amplitude normalized or not.

5.2.2 Multi-level Signal Classification

Amplitude normalization does not affect modulation signals of PSK and FSK. On the other hand, changes in the case of QAM and ASK signals disappear after the amplitude normalization. M-ary ASK/ M-ary QAM signal is classified from single level (M-PSK) using median filter with out normalization. |HWT| M-ary ASK and M-ary QAM has a multi-level function with out amplitude normalization but |HWT| M-PSK has one histogram peak after passed through median filter.

5.2.3 M-ASK and M-QAM classification

After multi-level signal is classified from constant function PSK signal, it should further test whether the signal is ASK or QAM signal. This requires an additional criterion for distinguishing between these two types of modulations. QAM signal will contain both phase and amplitude changes during symbol transition. But ASK will contain only amplitude changes. Consequently variance of QAM will be higher than ASKas we can see in Figure 5.7. Hence, by putting a threshold over, incoming signal can be classified as ASK or QAM (Figure 5.8).

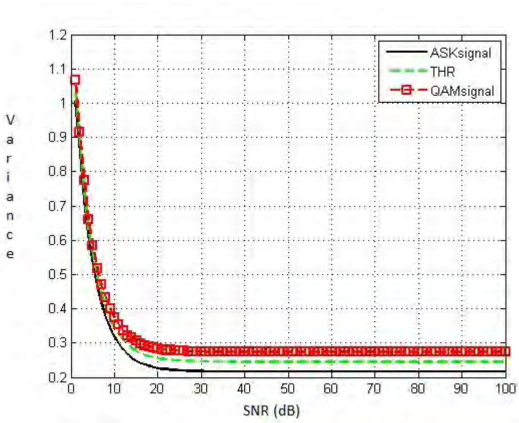


Figure 5.7: Threshold, QAM and ASK curves

Specifically to distinguish the two types of modulation variance of |HWT| before the median filter and amplitude normalization is used. The curve in the case of ASK signals consisting of a dc level without peaks and its phase does not change, while for QAM signals consisting of both dc level and change in phase between symbols. Therefore value variance for ASK signals is less than the variance QAM signals. Following the same procedure,it can found a curve with values threshold versus SNR. Threshold setting is function of SNR and is approximated using polynomial approximation degree 3 .

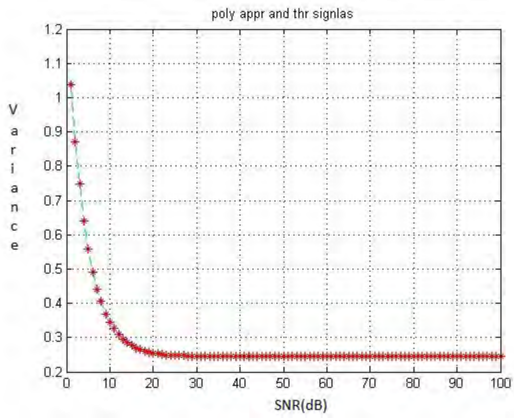


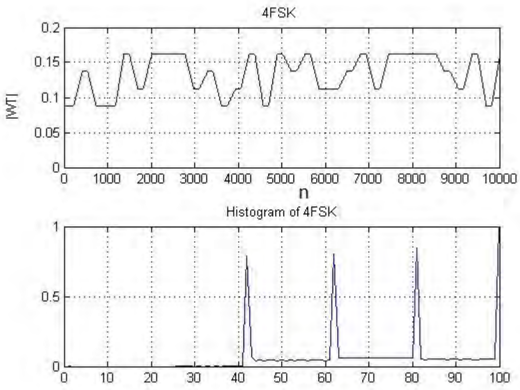
Figure 5.8: polynomial approximation

PSK signal is constant but peaks appear when a phase change occurs as far as signal is not passed through median filter. Peaks are diminished when median filter is used.

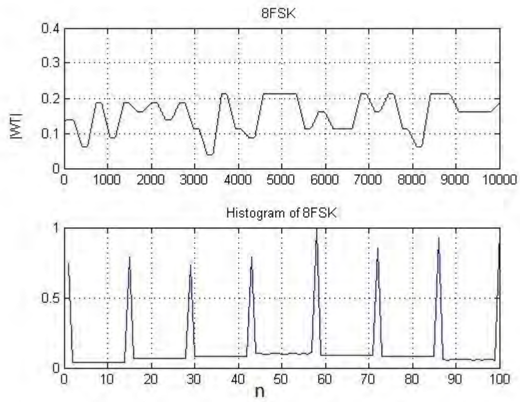
5.3 Intra-Class Identification

5.3.1 M-FSK Identification

|HWT| of M-ary FSK has M dc levels, it is identified by generating histogram of the HWT magnitude. The number of DC levels equals to the number of modulation frequencies. Identification is achieved by finding the number of DC levels in the WT magnitude and histogram is used to calculate it.



a) 4FSK



b)8FSK

Figure 5.9: M-FSK Identification

Ideally, for M-FSK signal there will be M peaks in the histogram. The peaks are however, spread out due to noise. For example, algorithm can identify 3FSK, 5FSK and so on even though we don't have such modulations in reality. The algorithm rounds off such undesired outputs due to noise to the actual modulation schemes. The input is identified as M-ary if there are $M/2 + 1$ to M and also up to half point of next one peaks in the histogram.

5.3.2 M-QAM Identification

When M>4, |HWT| of QAM signals have multi-level amplitude and the number of levels represents the order of QAM modulation. If the amplitude is with two levels, signal is identified as 8-QAM signal since generated histogram peaks are two as seen Figure below.

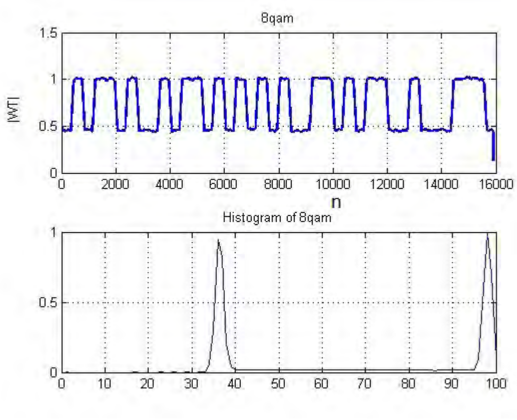


Figure 5.10: 8QAM Identification

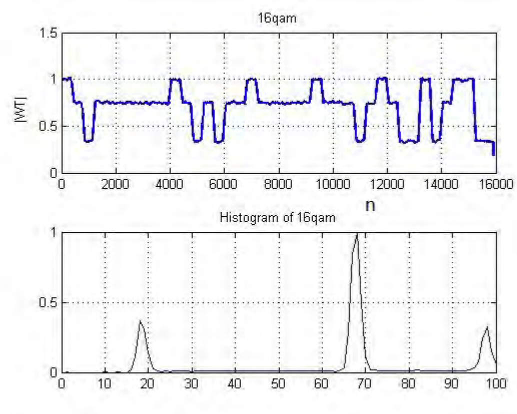


Figure 5.11: 16QAM Identification

But there are special case, for example 32-QAM has two possible amplitude levels which is 5 and 6 levels of amplitude.

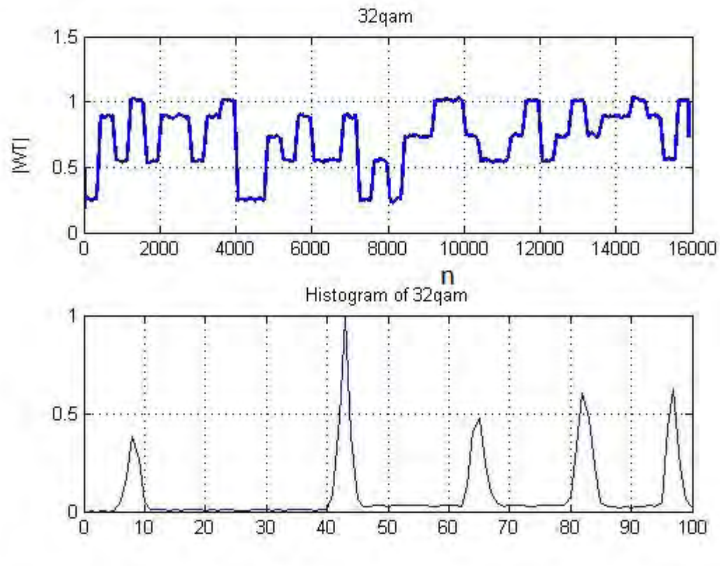


Figure 5.12: 32QAM Identification

5.3.3 M-ASK Identification

The magnitude of wavelet transform without amplitude normalization is a multi-level function which has so many dc levels and the possible levels can get the signal amplitude.

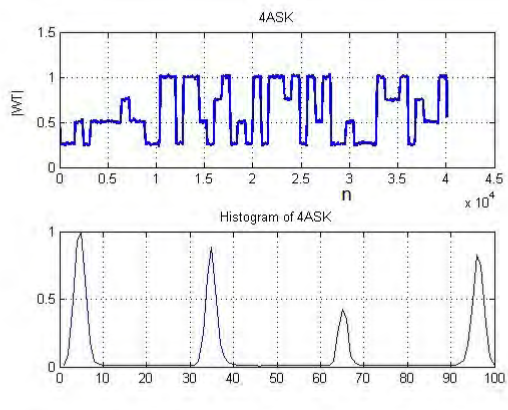


Figure 5.13: 4ASK Identification

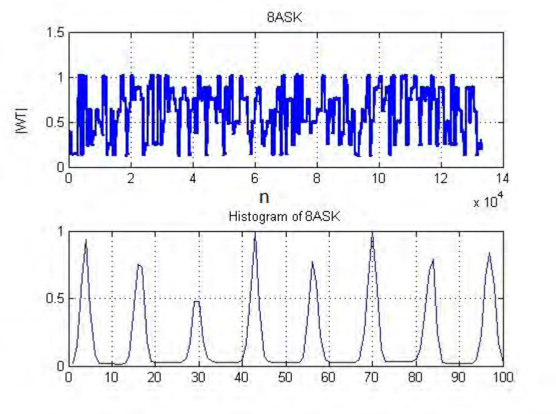


Figure 5.14: 8ASK Identification

Similar to FSK, ASK signal is identified by counting the number of peaks occurred during histogram generation. If there are M /2 to 2 M peaks, the signal will be identified as M-ASK.

5.3.4 M-PSK Identification

It is difficult to identify M-PSK signal at lower dB compared to other modulation types. As discussed above |HWT| of a PSK signal is constant. However peaks appear when a phase change occurs and peaks in |HWT| are quite large and peak to noise ratio is high.The peaks follow the Ricean distribution and for low SNR, Ricean distribution can be approximated by a Gaussian[7].

$$f(p/M-PSK) = \frac{1}{M-1}\sum_{m=2}^{M}\frac{1}{\sqrt{2\Pi}\sigma_n}\exp\left\{\frac{1}{2\sigma_n^2}(p-\mu_m)^2\right\} \tag{5.1}$$

Random variable p denotes the peak value and μ_m are the unknown mean peak values.

When PSK signal received and symbol changes occurs, a phase shift $\delta = \varphi_{i+1} - \varphi_i$ is noticed. When a phase transition happens, noticeable peak appears. Assuming that the symbol change happen, the following will be HWT for PSK signal:

$$WT_{PSK}(\alpha,T) = \sqrt{\tfrac{s}{\alpha}}exp(j(w_c nT_s + \theta_c + \phi_i)[\sum_{k=0}^{\alpha/2-1} \tfrac{1}{exp(j(w_c\alpha/2)T_s))} - exp(j\delta)] \sum_{k=0}^{\alpha/2-1} exp(j(w_c kT_s)))$$

δ are phase parameters controlled by information, a finite number of discrete values normalized within a symbol. Taking the same component is i(n), the orthogonal component is q (n) of the receiver outputting IQ signal,

x(n) = i(n) + jq(n), n = 0,1, , N -1

According to the definition of the complex signal, the instantaneous phase of the signal is as follows:

$\phi(n) = \arctan(\frac{q(n)}{i(n)})$

arctan is periodic function of π , but the phase of the communication signal is a 2π cycle, (-π ,π]. Function arctan value change to the range (-π ,π] according to the symbol in the quadrant q(n) and i(n) [9].

$$\phi(n) = \begin{cases} \delta & q(n) \geq 0, i(n) > 0 \\ \delta - \pi & q(n) \geq 0, i(n) < 0 \\ \delta + \pi & q(n) \leq 0, i(n) < 0 \\ \delta & q(n) \leq 0, i(n) > 0 \end{cases} \quad (5..2)$$

Signal phase increase linearly over the range (-π ,π], when the phase exceeds (-π ,π) phase wrapped occurs, so the original phase of signal needs to be unwrapped and phase should be unwrapped .

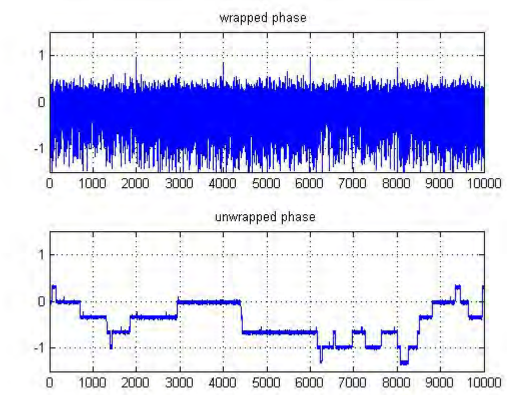
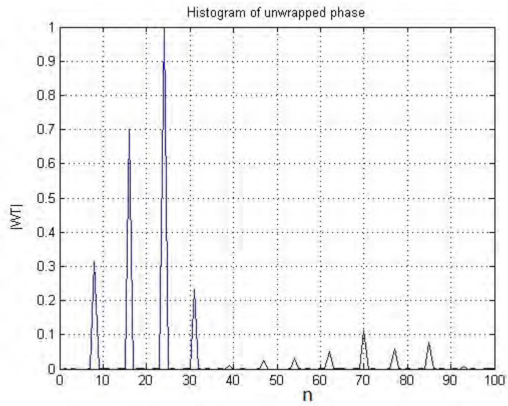


Figure 5.15: Phase unwrapping

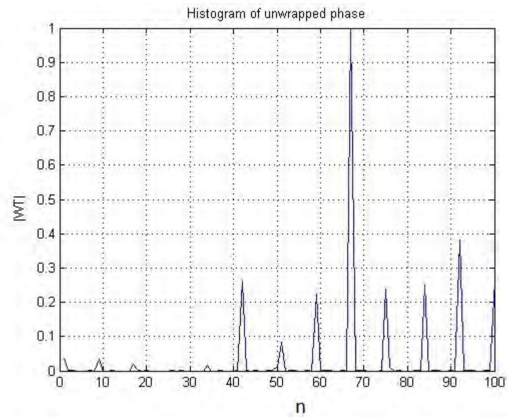
The 2π jumps that are present in the wrapped phase signal must be removed in order to return the phase signal to a continuous form and hence make the phase usable in any analysis or further processing. This process is called phase unwrapping and has the effect of returning a wrapped phase signal to a continuous phase signal that is free from 2πjumps. The basic phase unwrapping process can be explained by splitting the task down into the following steps.

1. Start with the second sample from the left in the wrapped phase signal
2. Calculate the difference between the current sample and its directly adjacent left-hand neighbor.
3. If the difference between the two is larger than $+\pi$, then subtract 2π from this sample and also from all the samples to the right of it.
4. If the difference between the two is smaller than -π, then add 2π to this sample and also to all the samples to the right of it.
5. Have all the samples in signal been processed? If No then go back to step 2. If Yes then stop.

This unwrapping process improves the identification of M-PSK signal. If M/2 to M-1 Gaussian exists in the histogram of peaks, input is identified as M-PSK. This is because the at zero degree is not counted . Figure 5.16 shows histograms of M-PSK signals.



a) 4PSK



b)8PSK

Figure 5.16: Histogram of PSK signal a) 4PSK b)8PSK

5.4 Efficiency evaluation

Perfomance is evaluated using Confusion matrix in the following tables shown below. A confusion matrix compares the input signal with actual output signal. Results of the simulation for total modulation identification at two different SNR for each modulation types are presented. The identifier has been tested for average 1000 independent simulations. The success rate is more than 96% for the the three modulation types (FSK,ASK and QAM) and more than 83% for PSK signal. Success rate decreases as SNR decreases.

FSK

In Table (5.3) the results of the simulation for intr-aclass and inter-class identifaction at SNR=10dB and SNR=5 are presented. The success rate was 100% for inter-class identification and greater than 99% for intra-class identification. The results are quite better than those presented in [2] and [5].

SNR=10dB

In/Out	**FSK2**	**FSK4**	**FSK8**	**FSK16**	**ASK2**	**ASK4**	**ASK8**	**QAM8**	**QAM16**	**QAM32**	**PSK2**	**PSK4**	**PSK8**
FSK2	**100%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**
FSK4	**0%**	**99%**	**1%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**
FSK8	**0%**	**0%**	**99%**	**1%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**
FSK16	**0%**	**0%**	**0%**	**100%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**

SNR=5dB

In/Out	**FSK2**	**FSK4**	**FSK8**	**FSK16**	**ASK2**	**ASK4**	**ASK8**	**QAM8**	**QAM16**	**QAM32**	**PSK2**	**PSK4**	**PSK8**
FSK2	**100%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**
FSK4	**0%**	**99%**	**1%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**
FSK8	**0%**	**0%**	**99%**	**1%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**
FSK16	**0%**	**0%**	**0%**	**100%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**

Table 5.3: FSK Identification

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ASK

Confusion matrix in the table (5.4) shows the results of the simulation for intraclass and inter-class identifaction at SNR=12dB and SNR= 8dB. The success rate was greater than 99% for inter-class identification and 96% for intra-class identification. One of the improvements in this work is, it can classify QAM and ASK modulations.

SNR=8dB

In/Out	**ASK2**	**ASK4**	**ASK8**	**QAM8**	**QAM16**	**QAM32**	**FSK2**	**FSK4**	**FSK8**	**FSK16**	**PSK2**	**PSK4**	**PSK8**
ASK2	**96%**	**3%**	**0%**	**1%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**
ASK4	**1%**	**97.4%**	**2%**	**0%**	**0.6%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**
ASK8	**0.2%**	**2%**	**97%**	**0%**	**0%**	**0.8%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**

SNR=12dB

In/Out	**ASK2**	**ASK4**	**ASK8**	**QAM8**	**QAM16**	**QAM32**	**FSK2**	**FSK4**	**FSK8**	**FSK16**	**PSK2**	**PSK4**	**PSK8**
ASK2	**98%**	**2%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**
ASK4	**0.1%**	**98.5%**	**1%**	**0.5%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**
ASK8	**0%**	**1.8%**	**97%**	**0%**	**0%**	**1.2%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**	**0%**

Table 5.4: ASK Identification

QAM

The success rate of QAM signal was 98% for inter-class identification and greater than 97% for intra-class identification. The results better than those presented in [2] and [7].

SNR=8dB

In/Out	QAM8	QAM16	QAM32	ASK2	ASK4	ASK8	FSK2	FSK4	FSK8	FSK16	PSK2	PSK4	PSK8
QAM8	98%	1.8%	0.2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
QAM16	0%	97.5%	1.5%	0.5%	0%	0%	0%	0%	0%	0%	0.5%	0%	0%
QAM32	97.6%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

SNR=12dB

In/Out	QAM8	QAM16	QAM32	ASK2	ASK4	ASK8	FSK2	FSK4	FSK8	FSK16	PSK2	PSK4	PSK8
QAM8	97.5%	1%	0%	1%	0%	0%	0%	0%	0%	0%	0.5%	0%	0%
QAM16	1%	98%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
QAM32	0%	2%	97%	0%	0%	0%	0%	0%	0%	0%	1%	0%	0%

Table 5.5: QAM Identification

PSK

The algorithm less efficient to identify MPSK signal at lower dB compared to other modulation types . The results of simulation PSK signal is discussed in table (5.6). The sucess rate was at an average of 83% for intra-class identification and higher than 95% for inter-class identification. To compare the results with other works [5-6] is difficult since the other works consider some prior knowladge in their algorithm such as center frequency, symbol rate and so on.

SNR=25dB

In/Out	PSK2	PSK4	PSK8	QAM8	QAM16	QAM32	ASK2	ASK4	ASK8	FSK2	FSK4	FSK8	FSK16
PSK2	82%	6%	5%	0%	0%	0%	7%	0%	0%	0%	0%	0%	0%
PSK4	8%	83%	6%	2%	0%	0%	0%	1%	0%	0%	0%	0%	0%
PSK8	6.7%	7%	82.3%	2%	0%	0%	0%	0%	0%	0%	2%	0%	0%

SNR=29dB

In/Out	PSK2	PSK4	PSK8	QAM8	QAM16	QAM32	ASK2	ASK4	ASK8	FSK2	FSK4	FSK8	FSK16
PSK2	86%	5.3%	5.2%	0%	0%	0%	3.5%	0%	0%	0%	0%	0%	0%
PSK4	2%	86.8%	5%	1.2%	0%	0%	0%	0%	0%	2%	3%	0%	0%
PSK8	3%	4%	87%	3%	0%	0%	0%	0%	0%	0%	1%	2%	0%

Table 5.6: PSK Identification

5.5 Comparison of various methods

Performance of several methods reported for classifying various digital modulation schemes is presented in table below

Author	Used Techniques	Modulation schemes	Lowest SNR bound	%Correct Identification
HU Youqiang, LIU Juan TAN Xiaoheng	instantaneous information, decision theory[1]	2ASK,4ASK, 16QAM,2FSK,4FSK	10	99
P. Prakasam and M.Madheswaran	Histogram peaks in WT magnitude, mean & variance of normalized histogram[2]	BPSK, QPSK, 8PSK, 16PSK, 2QAM,4QAM 8QAM, 16QAM, GMSK, M-FSK	5	96.5
K.C.Ho, W.Prokopiw and Y.T.Chan	Histogram peaks WT symbol period synchronisation time[6]	BPSK, QPSK, 8PSK,		
		BFSK, QFSK, 8FSK	15	98
Xin Zhou, Ying Wu	Variance of HWT magnitude and normalized HWT magnitude[4]	BFSK, QFSK, 8FSK	20	98
Proposed System	normalized HWT magnitude, histogram , instantaneous values	2FSK,4FSK,8FSK,16FSK 2ASK,4ASK, 8ASK 8QAM, 16QAM,32QAM 2PSK, 4PSK, 8PSK,	5 8 8 25	99 96 97 83

Table 5.7: Performance comparison of various methods

The above methods are either computationally intensive which require some known modulation parameters such as carrier frequency, symbol rate, and so on... [6] or not efficient for low dB signals[4,5] . In addition, they identify less modulation schemes[1,4] and need some prior knowledge[2]. The methodology in this thesis is computationally easy,and relatively robust for noisy signal at the same time, it identifies a wider modulation schemes compared to other methods.

6 Conclusion and Summary of Results

6.1 Summary of Results

In this thesis, the AMI algorithm was tested and proved to give excellent results of FSK signal for SNR$\geq$ 5 dB and $\geq$ 8dB for both QAM and ASK signals for intra-class and inter-class identification. FSK signal is identified at higher than 99% of correct identification ratio where as, QAM and ASK signals are identified at higher than 97% and 96% correct identification ratio respectively. The algorithm identifies PSK signal for SNR of greater than 25dB and at an average of 83% correct identification ratio for intra-class identification and higher than 93% for inter-class identification.

6.2 Conclusion

In this work, it has been demonstrated that the use of wavelet filter and wavelet transform for modulation identification of digital signals. The identifier consists of inter-class and intra-class identification. The algorithm is less computationally intensive which is, it doesn't performs phase extraction, center frequency recovery, SNR and symbol rate estimation and so on. It is relatively robust for noisy signal with out required some known modulation parameters such as carrier frequency and symbol time of the signal. The system was tested with 13 modulation schemes with different SNR. The simulated results using wavelet transform technique and histogram generation show that the correct modulation scheme identification is possible even at low channel SNR. The inter-class identification of all modulation types is identified successfully at high rate of identification even at their lower boundary of SNR. This algorithm is most suitable for FSK modulation among others due to multi-tone property of FSK function. FSK signal is identified efficiently at higher rate and lower SNR compared to other modulation types. In the other hand, PSK identification is remained as challenging problem in automatic modulation identification including in this work. Even though, the inter-class is identified successfully, the intra-class identification is less efficient and needs higher SNR. But, The comparison entire system with existing methods shows that, the proposed system is capable of identifying the wider digital modulation schemes with low SNR.

6.3 Future Work

It is expected that combining the results from several scales will improve the identification accuracy. It will also be interesting to study the performance of a WT identifier when mother wavelets other than Haar especially to improve PSK signal identification. The signal identification by wavelet transform is worth for further investigation.

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