FEATURE BASED MODULATION RECOGNITION FOR INTRAPULSE MODULATIONS

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Prof. Dr. Canan Özgen
Director

I certify that this thesis satisfies all the requirements as a thesis for the degree of Master of Science

Prof. Dr. İsmet Erkmen
Head of Department

This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science.

Assoc.Prof.Dr.Gözde Bozdağı Akar
Supervisor

Examining Committee Members

Assoc. Prof. Dr. Engin Tuncer	(METU, EEE)	
Assoc. Prof. Dr. Gözde Bozdağı Akar	(METU, EEE)	
Assist. Prof. Dr. Çağatay Candan	(METU, EEE)	
Assist. Prof. Dr. Özgür Yılmaz	(METU, EEE)	
Alaattin Dökmen (M. Sc.)	(ASELSAN)	

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Name, Last name: Gözde ÇEVİK

Signature :

ABSTRACT

FEATURE BASED MODULATION RECOGNITION
FOR INTRAPULSE MODULATIONS

Çevik, Gözde

M.S., Department of Electrical and Electronics Engineering
Supervisor : Assoc. Prof. Dr. Gözde Bozdağı Akar

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In this thesis study, a new method for automatic recognition of intrapulse modulations has been proposed. This new method deals the problem of modulation recognition with a feature-based approach.

The features used to recognize the modulation type are Instantaneous Frequency, Instantaneous Bandwidth, Amplitude Modulation Depth, Box Dimension and Information Dimension. Instantaneous Bandwidth and Instantaneous Frequency features are extracted via Autoregressive Spectrum Modeling. Amplitude Modulation Depth is used to express the depth of amplitude change on the signal. The other features, Box Dimension and Information Dimension, are extracted using Fractal Theory in order to classify the modulations on signals depending on their shapes. A modulation database is used in association with Fractal Theory to decide on the modulation type of the analyzed signal, by means of a distance metric among fractal dimensions. Utilizing these features in a hierarchical flow, the new modulation recognition method is achieved.

The proposed method has been tested for various intrapulse modulation types. It has been observed that the method has acceptably good performance even for low SNR cases and for signals with small PW.

Keywords: Automatic Modulation Recognition, Feature Extraction, Fractal Theory, Autoregressive Model, Intrapulse modulation

ÖZ

DARBE İÇİ MODÜLASYONLARIN
ÖZNİTELİKLERE BAĞLI OLARAK TANIMLANMASI

Çevik, Gözde

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Tez Yöneticisi : Doç. Dr. Gözde Bozdağı Akar

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Bu tez çalışmasında darbe içi modülasyonların otomatik olarak tanımlanması için yeni bir metot önerilmiştir. Bu metot, modülasyon tanımlama problemini özniteliklere bağlı bir yaklaşımla ele almaktadır.

Modülasyon tipinin tanımlanması için kullanılan öznitelikler Anlık Frekans, Anlık Bant Genişliği, Genlik Üzerindeki Modülasyon Yüzdesi ve Kutu Boyutu ile Bilgi Boyutudur. Anlık Frekans ve Anlık Bant Genişliği bilgileri Otoregrasyon Spektrum Modeli kullanılarak elde edilmiştir. Genlik Modülasyon Yüzdesi parametresi ile sinyalin genliğindeki değişimin derinliği ifade edilmektedir. Diğer öznitelikler olan Kutu Boyutu ve Bilgi Boyutu bilgileri Fraktal Teori yaklaşımı ile çıkarılmış ve bu bilgiler modülasyonların sinyal şekillerine göre ayrıştırılmasında kullanılmıştır. Fraktal ölçülerle şekli ifade edilen sinyalin en çok benzediği modülasyon tipini bulabilmek amacıyla, farklı modülasyon tiplerine ait ölçülerin bulunduğu bir veritabanı kullanılmıştır. Çıkarılan özniteliklerin hiyerarşik bir akışta kullanılması sonucunda, yeni bir modülasyon tanımlama metodu elde edilmiştir.

Önerilen metot farklı modülasyon tiplerindeki çok sayıda sinyal ile test edilmiştir. Bu testler sonucunda, önerilen metodun yüksek gürültülü ortamlarda ve küçük darbe genişlikli sinyallerde bile kabul edilebilir düzeyde iyi sonuçlar verdiği gözlenmiştir.

Anahtar Kelimeler: Otomatik Modülasyon Tanımlama, Öznitelik Çıkarımı, Fraktal Teori, Otoregrasyon Modeli, Darbe İçi Modülasyon

To My Parents,

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LIST OF ABBREVIATIONS

AMOP	: Amplitude Modulation On Pulse
AWGN	: Additive White Gaussian Noise
BPSK	: Binary Phase Shift Keying
BW	: Band Width
CD	: Correlation Dimension
CF	: Complexity Feature
CSF	: Chirp Stepped Frequency
CW	: Continuous Wave
DSB	: Double Side Band
ECCM	: Electronic Counter Counter Measure
ECM	: Electronic Counter Measure
ELINT	: Electronic Intelligence
ESM	: Electronic Support Measure
EW	: Electronic Warfare
FD	: Frequency Diversity
FIR	: Finite Impulse Response
FMOP	: Frequency Modulation On Pulse
FSK	: Frequency Shift Keying
GMLC	: General Maximum Likelihood Classifier
GUI	: Graphical User Interface
IF	: Intermediate Frequency
IMOP	: Intentional Modulation On Pulse
IPFE	: Intra-Pulse Frequency Encoding
LFM	: Linear Frequency Modulation
LRT	: Likelihood Ratio Test
LZC	: Lempel-Ziv Complexity
MCR	: Matlab Component Runtime
ML	: Maximum Likelihood
MPSK	: M-ary Phase Shift Keying
NED	: Normalized Euclidean Distance
NLFM	: Nonlinear Frequency Modulation
PMOP	: Phase Modulation On Pulse
PRI	: Pulse Repetition Interval
PSK	: Phase Shift Keying

PW	: Pulse Width
QAM	: Quadrature Amplitude Modulation
QFSK	: Quadrature Frequency Shift Keying
QPSK	: Quadrature Phase Shift Keying
RF	: Radio Frequency
SEI	: Specific Emitter Identification
SNR	: Signal to Noise Ratio
SPRT	: Sequential Probability Ratio Test
TCM	: Trellis-Coded Modulation
UMOP	: Unintentional Modulation On Pulse
VSB-C	: Vestigial Side Band with Carrier

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

RADAR is mainly the abbreviated form of the words “Radio Detection and Ranging”. Radars are systems which have the ability to sense a remote object by transmitting a particular type of electromagnetic wave and examining the nature of the signal reflected back from the object.

Every radar has some descriptive characteristics such as modulation type, scan type, pulse repetition interval (PRI) pattern and polarization.

Scan type describes how the radar beam sent from the antenna scans the environment, and how it tracks a certain target. Circular scan, sector scan, raster scan and conical scan can be listed as main types of scan for a radar. PRI is the time duration that passes between the transmissions of two consecutive pulses of a radar. PRI determines the maximum range at which the radar can make unambiguous range measurements. Constant, Staggered, Dwell-and-Switch and Jittered PRIs are among the types of PRI patterns. Polarization describes how the radar antenna is polarized. Vertical, Horizontal and Circular are listed as main polarization types.

Being mentioned above, the modulation type employed by a transmitter can be very helpful in establishing a radar's use and purpose. Depending on the complexity of the radar system, various kinds of modulations can be applied to the pulse train [1]. There are two basic types of modulation—interpulse and intrapulse.

Interpulse modulations refer to variations seen on the PRI, Frequency, Amplitude or Angle of Arrival values between pulses. In other words, interpulse modulations separate the radar pulses from a fixed PRI, constant pulse radar. Interpulse modulation helps the radar reduce range ambiguities. This is due to the fact that echo of each pulse must be received by the radar before a new pulse is transmitted. Hence, modifying the PRI of the radar, one can improve the maximum range that a specific target can be detected. Another point is that, Radio Frequency (RF) Jammers usually save the pulse received from a radar and then sends it back to that radar at an unexpected time to make the radar misunderstand the location of the target. For this reason, if interpulse modulation is applied on the radar signal, this will help the radar to distinguish between a real echo-signal and a synthetic one, improving the anti-jamming characteristics of the radar.

The second type of modulation applied on radar signals is the intrapulse modulation, or Intentional Modulation on Pulse (IMOP). IMOP radars, also named as Pulse Compression Radars, apply intentional changes in the amplitude, frequency or phase of the generated pulse. In other words, instead of the pulse being a burst of RF energy at a given carrier frequency, the pulse is a form of RF energy at a carrier frequency that varies in phase (PMOP), frequency (FMOP), or amplitude (AMOP). Intrapulse modulation techniques make it possible to simultaneously maximize the target range, the range resolution, and the velocity resolution of the radar [1]. The concept of intrapulse modulations and the effects of intrapulse modulations on radar performance are described in the next chapter in detail.

As described above, radars change their pulse characteristics and transmission styles in different ways for several benefits. On the other hand Electronic Warfare (EW) Systems aim to extract the descriptive characteristics of a radar from the RF signal and use them to determine other aspects of that radar, such as mission and capability.

In the past, EW systems such as Electronic Intelligence (ELINT) systems have relied on the operator interpretation (manual modulation recognition) of measured parameters to provide classification of different modulations [2]. This means that signals received by the ELINT system were analyzed by the operator manually and also radar tone was listened to by the operator, then several decisions about the source radar were made due to what the analyst sees and hears.

Later on, modulation recognizers began to develop. One of the oldest versions of modulation recognizers uses a bank of demodulators, each designed for only one type of modulation. However the number of modulation types that can be recognized is limited by the number of demodulators used.

Afterwards, to make modulation recognition independent of operator skills, automatic modulation recognition algorithms came to the scene. These algorithms firstly differ in the type of modulation they can classify: Analog or Digital Modulation.

For analog modulation classification, readers are referred to [2].

On the other hand, in digital modulation recognition part lies two main branches: “Recognition based on the Predetection Signal itself” and “Recognition based on Features extracted from the Predetection Signal”.

In the first one, the aim is to group the signals of similar modulation type together from a bunch of RF signals according to their own properties and parameters. An additional decision block must follow this “classification” in order to recognize the modulation type of each class. “Maximum Likelihood Approach” [3], “Fixed-Sample-Size Classifier” [4] and the “Fixed- Error- Rate Classifier” [4] can be listed in this type.

In the Maximum Likelihood approach, average log-likelihood function of the signal is derived and some rules are developed from this function. However, as mentioned in the work of Boiteau and Le Martret, this development is only valid for baseband pulse of duration equal to the symbol period [3].

Fixed-Sample-Size Classifier is also known as the Likelihood Ratio Test. This classifier uses a fixed amount of data to in order to make classification, but correct ratio is varying depending on the data size. On the other hand, the Fixed- Error- Rate Classifier, also known as the Sequential Probability Ratio Test uses a variable amount of data just enough to achieve a certain correct rate. Both classifiers claim that they classify the modulation scheme of a signal waveform modeled by a finite state Markov Chain [4].

In the second branch, the method is to extract some features from the RF signal which will somehow represent the signal, and use them for recognition of the modulation type. There are three main steps in feature based modulation recognition. In the first step preprocessing takes place, the second is the extraction of significant features and the third is a pattern classifier. In the preprocessing part mostly cyclostationarity of signals is used [14]. For the feature extraction step many methods as “Constellation Shape Recognition” [5], “Complexity Feature Extraction” [6], “Fractal Feature Extraction” [7], “Instantaneous Frequency and Bandwidth Extraction” [8] can be listed.

The Constellation Shape Recognition method proposes a technique that treats modulation recognition as a kind of “*shape recognition”*. This is possible by treating constellation shape as the key feature for modulation recognition. “Experiments are made for various modulation standards including V.29, V.29_fallback, QPSK, 8-PSK and 16QAM. For most cases, the method shows consistent performance above 90% for Eb/No ~0dB and above” [5]. This method is consistent but is concentrated on recognition of QPSK, 8-PSK and 16QAM only, which introduces a nonflexible method.

Complexity Feature Extraction Method says that the Complexity Feature, including Lempel-Ziv complexity and Correlation Dimension can measure the complexity and irregularity of radar signals effectively. These features are chosen because intrapulse modulation characteristics of signals are reflected directly on the regularity and the complexity dimensions of the waveform [6].

In the Fractal Feature Extraction Method, Box Dimension and Information Dimension are used as classification features to recognize the types of intrapulse modulation of radar signals. It is proved that features are not sensitive to noise [7].

Both Complexity Feature Extraction method and the Fractal Feature Extraction method are said to recognize up to 10 different modulation types. Being insensitive to noise, the Fractal Dimensions seem the most effective features to be used in digital modulation recognition.

Additionally, the Autoregressive Model approach provides a signal representation that is convenient for subsequent analysis. This model uses the instantaneous frequency and bandwidth parameters that are obtained from the roots of an autoregressive polynomial. These parameters are claimed to provide excellent measures for modulation type in addition to being noise robust [8]. Being independent of the SNR value, the instantaneous frequency and bandwidth parameters obtained by this method seem to be beneficial for the modulation recognition process.

As a result, the “Modulation Recognition of Radar Signals” topic plays a very important role in emitter identification which is one of the musts of Electronic Support Measures (ESM), Electronic Counter Measures (ECM), and Electronic Counter Counter Measures (ECCM) systems. In the sub-branch of “Intra-pulse Digital Modulations”, several approaches have been developed, and this will continue being a “hot” topic for a long time because an EW system need to know the modulation type in order to demodulate the received signal, understand the threat of the emitter, and determine the suitable jamming.

1.2 OUTLINE OF THESIS

The thesis consists of six chapters.

In Chapter 2, a general overview on the modulation subject and intrapulse modulations is given.

In Chapter 3, previous works among the “Modulation Recognition” subject that are encountered through the literature-search phase are summarized.

In Chapter 4, “Feature Based Modulation Recognition” concept is investigated in depth. First of all, methodologies of the extraction of features that are used in this thesis are described referring to the published papers. Then, the Modulation Recognition System offered by the author is presented and described in detail.

In Chapter 5, computer simulations made for testing the offered system, and the results of these performance tests are given.

And for the last, Chapter 6 contains some concluding remarks.

CHAPTER 2

INTRAPULSE MODULATIONS

2.1. *PURPOSE OF RADAR SYSTEMS FOR APPLYING MODULATIONS ON PULSE*

Radars are systems that find the location and many other properties of an object that reflects the electromagnetic wave sent by the radar. Radars process these echo signals, and extract various information about the target. Distance, size and velocity of the target may be listed among this information.

Distance between the radar and the target is the time duration between the radar pulse was sent and the echo signal came back to the radar. In the case that an echo pulse is received back by the radar *T* seconds after it was sent, the distance to the target *(R)* is calculated as;

$$R = \frac{T.c}{2} \tag{2.1}$$

where *c* is the speed of light.

For instance, the range *(R)* corresponding to 1msec time difference is 150 kilometers.

PRI of a radar is determined using this formula. This is due to the fact that; between two consecutive emissions, the radar must wait long enough for the echo of the first pulse to reach the radar. If the reflected wave reaches the radar after the second pulse is sent, distance of the target cannot be measured certainly, because the radar can never be sure if the reflected signal corresponds to the first pulse or the second pulse. For this reason, for a desired maximum range value (*Rmax)*; the PRI of the radar (*PRIreq),* must be chosen as;

$$PRIreq = \frac{2R\max}{c} \tag{2.2}$$

Furthermore, if there are two targets close to each other, this introduces another ambiguity. For the targets to be perceived as **two distinct targets** by the radar, the echo pulses reflected from these two targets must not overlap when they reach the radar. For this reason, for a radar pulse with a predefined Pulse Width (PW) value (τ), minimum distance between two targets that can be correctly distinguished can be;

$$\Delta d \min = \frac{c\tau}{2} \tag{2.3}$$

For instance, if the PW of the radar is 1μsec, this radar can distinguish between two targets as long as they are far from each other more than 150 meters.

As it is seen from the last example, PW of a radar must become shorter in order to increase the range resolution. However, peak power required for correct transmission must be increased as the width of the radar pulse is decreased. This “high peak power” requirement hardens the process of transmitter and receiver design.

Fortunately, the parameter that determines the range resolution is actually the PW that is used in the receiver of the radar, not the width of the pulse transmitted by the radar. Depending on this fact, transmitter applies intentional modulations on the pulse with large PW, and at the receiver end, this pulse is processed with the corresponding modulation technique. Hence, the pulse observed by the receiver has smaller PW. This technique is known as “Pulse Compression”, and it is applied at the receiver part of the radar.

However, radars also aim to distinguish between moving targets. This requirement introduces the subject of “Frequency resolution”, since velocities of the targets are found with the Doppler Frequency effect.

The phenomena of improving both range resolution and frequency resolution is known as the “Ambiguity Problem”, and radar parameters are chosen depending on the requirements on the ambiguity diagram.

The ambiguity diagram is actually a three dimensional diagram that shows the amplitude value corresponding to a certain Doppler shift and at a certain time shift.

Ideally, the ambiguity diagram must be an impulse. In the ideal case, however close the targets to each other, and whatever their velocities are, they will have their peaks at distinct “points” on the diagram, thus they will be distinguishable.

However, in real life applications, the ambiguity diagram has some width along the time and frequency axes.

In frequency axis, the first zero-crossing of the diagram occurs at;

$$f_{zero\_cross} = \pm \frac{1}{PW} \tag{2.4}$$

Referring to equations (2.3) and (2.4) it is seen that, **frequency resolution** is improved with **increasing** PW, in spite of the fact that **range resolution** is improved with **decreasing** PW. To overcome this problem, i.e. to make the ambiguity diagram approach the ideal case, “Pulse Compression Techniques” have been developed.

Pulse Compression refers to intentional modulations applied to the frequency or phase values inside the pulse. By the help of this technique, the “Band Width” of the pulse is increased without decreasing the Pulse Width of the signal. Thus, required resolution is achieved both at range and frequency.

Modulations on frequency or phase of the pulse will increase the Bandwidth (BW) of the signal, and the first zero-crossing of the ambiguity diagram in frequency axis will occur at

$$f_{zero\_cross} = \pm \frac{1}{BW} \tag{2.5}$$

It is seen from equation (2.5) that, although the PW of the radar is not affected, the ambiguity diagram in the frequency domain becomes narrower.

Hence, pulse compression radars can achieve good range resolution and good velocity resolution at the same time, applying intrapulse modulations on their pulses.

In the next section, detailed descriptions about intrapulse modulation types are given.

2.2. INTRAPULSE MODULATIONS

Intrapulse modulations are classified according to the part of the signal where modulation is applied. Mainly, they can be grouped as;

- AMOP (Amplitude Modulation On Pulse)
- FMOP (Frequency Modulation On Pulse)
- PMOP (Phase Modulation On Pulse)

2.2.1. AMPLITUDE MODULATION ON PULSE

As the name implies, in this type of signals, the Amplitude of the signal is intentionally modulated while the Frequency or Phase of the signal is kept constant.

These modulation shapes can be mainly divided into two groups as; Linear AMOP and Nonlinear AMOP. Modulation shapes such as Parabolic, Sinusoidal, Ramp, Triangular, and Square may be counted as Nonlinear AMOP types.

Amplitude, Frequency and Phase components corresponding to AMOP shapes which are considered in this thesis are included in the Appendix A, in AMPLITUDE MODULATION SHAPES section.

2.2.2. FREQUENCY MODULATION ON PULSE

In this class of signals, Amplitude is kept constant, and intentional modulation is applied on the Frequency component of the radar signal.

FMOP modulation types are mainly divided into two groups as; Linear FMOP and Nonlinear FMOP. Linear FMOP signals are also named as “Chirp” signals. Modulation shapes such as Parabolic, Sinusoidal, Ramp, Triangular, Square and FSK may be counted as Nonlinear FMOP types.

As mentioned in the previous section, Frequency Modulation is applied to the signals so that Pulse Compression is achieved and the Ambiguity diagram is approximated to the ideal case.

Amplitude, Frequency and Phase components corresponding to FMOP shapes which are considered in this thesis are included in the Appendix A, in FREQUENCY MODULATION SHAPES section.

2.2.3. PHASE MODULATION ON PULSE

Phase Modulation on Pulse is another method for Pulse Compression. In this modulation type, Phase of the signal is modulated depending on a binary or M-ary code, while the Amplitude of the signal is kept constant.

PMOP modulations are named depending on the minimum phase shift applied on the modulated phase. For instance, in **BPSK** codes minimum phase shift is **π radians**, whereas in **QPSK** codes minimum phase shift is **π/2 radians**. Compression rate for the signal depends on the number of sub-pulses (number of bits in the code) in the phase.

For BPSK modulations, Barker Codes are the mostly used codes in literature. The most favorable property of Barker codes is that, after the pulse is passed through the matched filter at the receiver end, the pulse has its maximum peak at the main lobe and all its side lobes have the same energy. This fact is illustrated in the figure below.

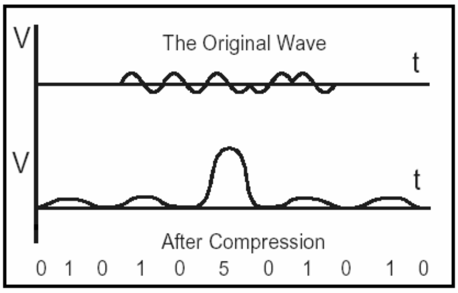

Figure 2.1. Comparison of the BPSK signal and its matched filter output [11]

In Figure 2.1 the signal is binary phase coded with 5-bit Barker code. It is seen that after the signal is demodulated at the receiver end, the frequency axis cut of the ambiguity diagram is approximated to the ideal case.

A lookup table is given in Appendix C, with number of bits in the Barker code and their corresponding binary codes.

On the other hand, Frank code is the mostly used coding technique for M-ary Phase Shift Keying. In this technique, if the number of phase steps is set as *N*, the pulse is first divided into *N* groups, and then each group is again divided into *N* sub-groups. Minimum phase shift is **2π/N radians**. Namely, for a QPSK signal, *N* is chosen as 4. Frank coding technique is described with the following matrix.

$$\begin{bmatrix} 0 & 0 & 0 & 0 & \ldots & 0 \\ 0 & 1 & 2 & 3 & \ldots & N-1 \\ 0 & 2 & 4 & 6 & \ldots & 2(N-1) \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ 0 & (N-1) & 2(N-1) & 3(N-1) & \ldots & (N-1)^2 \end{bmatrix} \Delta\varphi \qquad (2.6)$$

A lookup table is given in Appendix C, with phase difference matrices and their corresponding Frank code types for *N* = 2, 4, 6 and 8.

There are many other coding techniques in literature such as Combined Barker (as a type of BPSK coding); Pseudorandom Codes, P1-P2-P3 and P4 codes (as types of Polyphase codes) to generate PMOP signals, but only Barker and Frank codes are considered in the scope of this thesis.

Amplitude, Frequency and Phase components corresponding to PMOP shapes which are used in this thesis can be seen in Appendix A, in the PHASE MODULATION SHAPES section

CHAPTER 3

AUTOMATIC RECOGNITION OF INTRAPULSE MODULATIONS

Automatic modulation recognition algorithms mainly differ in the type of modulation they can classify: Analog or Digital Modulation.

For analog modulation classification, readers are referred to [2]. In [2] firstly the center frequency of the incoming signal is estimated, and then several feature extraction methods were used for signal classification. The key features are:

- Envelope standard deviation, $\sigma_{a(n)}$
- Similarity measure of the coherent demodulation result and envelope, μ
- Difference between the standard deviation of the instantaneous frequency of the signal and that of the squared signal, D, and
- Carrier information, C.

After extraction, these key features were given to the decision block as inputs. In the decision block, employing suitable weighting coefficients, the Euclidean distance of these key features with respect to all modulation types were calculated. Then the modulation type with the smallest Euclidean distance was chosen as the correct modulation type. This recognizer was used to discriminate between AM, FM, DSB, VSB-C, and CW modulations. The algorithm was tested with 1500 signal segments of each 279msec time length, at SNR levels 34.8dB, 14.8dB and 12.8dB. It is claimed that the algorithm performs over 80% success for AM, DSB and VSB-C signals even at low SNR values. However, the algorithm was not so powerful for AM-CW discrimination and FM-DSB discrimination at low SNRs. In order to increase the performance of AM-CW modulation discrimination at low SNR values an additional block was introduced to the system, which increased the success rate to 99% at low SNR values.

Even though we gave a brief summary of recognition of analog modulations, we mainly deal with digital modulation recognition techniques in this thesis. We also insert some additional blocks in order to identify AM and FM analog modulations.

In recognition of digital modulations, there are two main approaches: “Recognition based on the Predetection Signal itself” and “Recognition based on Features extracted from the Predetection Signal”.

In the first approach, the aim is to group the signals of similar modulation type together from a bunch of RF signals according to their own properties and parameters. An additional decision block must be used after this “classification” in order to recognize the modulation type of each class. “Maximum Likelihood Approach” [3], “Fixed-Sample-Size Classifier” [4] and the “Fixed- Error- Rate Classifier” [4] can be listed in this type.

In the work of Boiteau and Le Martret [3], a General Maximum Likelihood Classifier (GMLC) was introduced, based on an approximation of the likelihood function. In the classical Maximum Likelihood (ML) approach, quasi-optimal rules were derived from the development of the average log-likelihood function of the signal. However, that approach was only valid for baseband pulse of duration equal to the symbol period. Boiteau and Le Martret, with the introduction of GMLC, removed the restriction of signal duration, thus GMLC could be applied to any baseband signal. GMLC was tested for PSK and QAM signals, and the algorithm was also applied to M PSK / M^{I}PSK classification. It is claimed that, test results had shown that the GMLC approach gives equivalent result to ML tests, so GMLC provides a general theoretical framework for the modulation recognition approach.

Lin and Kuo, worked on the sequential modulation classification of dependent samples, using a finite state Markov Chain model [4]. They compared the Fixed-Sample-Size Classifier and the Fixed- Error- Rate Classifier in their work. The initial one is also known as the Likelihood Ratio Test (LRT), and uses a given fixed amount of data to decide for the modulation type. Its performance can be measured by the average decision error probability. The disadvantages of LRT are that the number of samples required to make decision is related to the computational complexity and decision time delay, and that although LRT tries to minimize the average decision error probability, it has no control on the individual error rate.

The second one is also known as the Sequential Probability Ratio Test (SPRT), and uses a variable amount of data just enough to achieve a certain correct ratio. This approach has many advantages over the LRT test, such as reduced computational complexity, less decision delay, and controllable individual classification error rate.

One of the tests was handled for classification of 8-PSK and 16-PSK, for SNR ranging from 8dB to 17dB. The claim is that, SPRT needs approximately the half of the samples to achieve the same correct decision level with respect to LRT.

Another test was handled for the performance comparison of SPRT and LRT, using 8-PSK TCM shapes. Yu-Chuan Lin and C.-C. Jay Kuo claimed that for a low SNR value of 4dB, LRT gives 90% performance for 4-state TCM, but only 29% performance for the 2-state TCM. Thus, although the average correct rate is at 60%, individual error rates differ in a wide range. And the average optimum correct rate is achieved at 100 – symbol – periods. On the other hand, SPRT gave 99% individual correct rate with the same number of symbols.

Finally, Lin and Kuo mentioned that number of symbols required for correct decision directly affects the delay in communication links and the computational complexity. For this reason, requiring less number of samples for correct decision, SPRT is more efficient and more appropriate for practical use than LRT.

In the second approach of digital modulation classification, the method is to extract some features from the RF signal, and use them for recognition of the modulation type. There are three main steps in feature based modulation recognition. In the first step preprocessing takes place, the second is the extraction of significant features and the third is a pattern classifier.

In the preprocessing part cyclostationarity property of signals is used. In communications many signals have an underlying periodicity due to factors such as sampling, scanning, modulating, multiplexing and coding. This periodicity is not always obvious. In some cases it is hidden and then manipulation on the incoming data is necessary to bring it out. Cyclostationarity calculations bring out this periodicity. For instance, a cyclostationary signal of second order, is a stationary signal that exhibits second order periodicity [14].

For the feature extraction step many methods as “Constellation Shape Recognition” [5], “Complexity Feature Extraction” [6], “Fractal Feature Extraction” [7], “Instantaneous Frequency and Bandwidth Extraction” [8] can be listed.

Mobasseri, proposed the Constellation Shape Recognition method [5]. This method proposes a technique that casts modulation recognition into *shape* recognition. In this approach Constellation Shape is chosen as the key modulation feature. From a shape perspective, a constellation is characterized by a particular and regular pattern of points on a *p*-dimensional grid. It is the recognition and identification of this pattern that reveals the underlying modulation. For this purpose, the proposed method firstly concentrates on recovery of the constellation shape. The constellation of the received signal is considered as a multidimensional random process.

The constellation recovery method used in the algorithm is *fuzzy c-means*. This is a typical clustering algorithm, which takes the symbols taken from the signal as inputs, and in the end outputs some key points revealing information about the modulation type of the signal, the most important being the number and position of clusters. This knowledge is then used to narrow down the search space of candidate modulations considerably. For each candidate modulation, a constellation space is formed up with the samples corresponding to that cluster. Constellation space can be thought of as a binary space; zeros everywhere except on modulation state vectors.

For the last step in modulation classification, development of an optimal decision rule was employed. An optimum Bayes classifier that selects the most likely modulation class based on a single observation was selected for the classification engine. For this classification phase, 500 instances of the reconstructed constellations for each modulation type, each corrupted with Gaussian noise, were generated and cataloged. For the recognition step, 1000 samples of the unknown signal were processed through the constellation reconstruction algorithm and a single constellation was recovered.

Experiments were made for various modulation standards including QPSK, 8-PSK and 16QAM. For most cases, the method has performance above 90%. This method is consistent but is concentrated on recognition of QPSK, 8-PSK and 16QAM, which introduces a nonflexible method.

Zhang et. al. proposed two new methods for the modulation recognition problem: Complexity Feature Extraction Method [6] and Fractal Feature Extraction Method [7].

Complexity Feature Extraction Method [6] utilizes the Complexity Feature (CF) as the key feature, which is composed of two other features as Lempel-Ziv complexity (LZC) and Correlation Dimension (CD). Intra-pulse modulations of radar signals are reflected directly on the signal waveform, as the regularity and the complexity of the waveform.

It is mentioned that the LZC can reflect the changes of phase, frequency and amplitude of a signal, thus it is used to measure quantitatively the complexity and irregularity of radar emitter signals. In LZC measure, only two simple operations (**copy** and **add**) are used to describe a signal sequence and the number of required add operations is the LZC measure value.

Fractal Theory is claimed to depict the complexity and irregularity of signals. CD is one of the fractal dimensions, and is chosen as a classifying feature in this work for its easiness to be obtained from signal samples directly.

For the simulations, ten typical modulation types as CW, BPSK, QPSK, MPSK, LFM, NLFM, FD(Frequency Diversity), FSK, IPFE(intra-pulse frequency encoding) and CSF(Chirp stepped-frequency) were chosen. Numerous signals were generated for different SNR values.

Mean and variance values of LZC and CD features were calculated for each modulation type. It is claimed that the measured values for different modulation types have obvious separations and there is nearly no overlapping. However, variations in the features with respect to changing SNR can not be neglected.

As mentioned above, the second method which was introduced by Zhang et. al. was the Fractal Feature Extraction Method [7]. In this method, Box Dimension and Information Dimension are used as classification features to recognize the types of intra-pulse modulation of radar signals. It is claimed that Fractal dimensions can depict the complexity and irregularity of signals quantitatively. Box dimension can reflect the geometric distribution of a fractal set, and information dimension can reflect the distribution density of a fractal set in space. Also it was proved that these features were insensitive to noise.

Since radar signals are time sequences, it is said that these sequences can be represented effectively by fractal theory, and these modulation shapes can be extracted by the help of fractal dimensions.

This method was tested with the same set of data that were used to test the Complexity Feature Extraction Method.

Both Complexity Feature Extraction method and the Fractal Feature Extraction method are said to recognize up to 10 different modulation types. Being insensitive to noise, the Fractal Dimensions seem to be suitable features to use in digital modulation recognition.

Additionally, Assaleh et. al. had proposed another method in 1992 [8]. This method is the Autoregressive Model approach, and it provides a signal representation that is convenient for subsequent analysis. In this model the instantaneous frequency and the instantaneous bandwidth parameters are used as the key features and these features are obtained by using autoregressive spectrum analysis. It is said that autoregressive spectrum estimation is an alternative to Fourier analysis for obtaining the frequency spectrum of a signal. The angle and the magnitude terms of the poles of the autoregressive polynomial correspond to the instantaneous frequency and instantaneous bandwidth for the signal respectively. It is claimed that these features provide excellent measures for modulation type in addition to being noise robust.

The algorithm was tested for CW, BPSK, QPSK, BFSK and QFSK signals. It is shown that the algorithm correctly classifies modulation type at least 99% correct for an input SNR of 15dB.

In the light of knowledge above, the Fractal Feature Extraction Method [7] and the Autoregressive Model [8] approach were chosen to form up a complete system for the intrapulse modulation recognition problem, since both of them claim to be noise robust. The methods and formulations are described in detail in the following chapter.

CHAPTER 4

FEATURE BASED MODULATION RECOGNITION

4.1 METHODOLOGY FOR FEATURE EXTRACTION

Mainly five parameters are selected as key features for modulation recognition in this thesis. These features are:

- Instantaneous Frequency
- Instantaneous Bandwidth
- Box Dimension
- Information Dimension
- Percent AM Depth

The process for extracting these features is described in detail in the following sections.

4.1.1. INSTANTANEOUS FREQUENCY AND BANDWIDTH

The method proposed in [8], is used in order to extract the instantaneous frequency and instantaneous bandwidth features of the signal.

In that method a signal representation known as the modulation model is used in order to extract the frequency and bandwidth properties of the signal via autoregressive spectrum modeling. This model represents a signal that has numerous modulations as the sum of signals each having individual amplitude modulations or phase modulations. It must be noticed that frequency modulation can also be depicted as phase modulation because frequency deviation of a signal from the center frequency is the derivative of the phase of that signal. Referring to this model, a signal is represented as follows:

$$s(t) = \sum_i A_i(t)\cos(\omega_i t + \phi_i(t)) \tag{4.1}$$

where *i* denotes the signal interval, $A_i(t)$ is the signal envelope, ω_i is the center frequency of the i^{th} interval, $\varphi_i(t)$ is the instantaneous phase. $A_i(t)$ reflects the amplitude modulation measure and $\varphi_i(t)$ reflects the phase modulation measure of the signal.

AM signals are not considered in [8]. Also, it is assumed that only one modulation type is present in the received signal. Within these categories, the modulation model representation of a signal will be as follows:

$$s(k) = A\cos(\omega_c k + \phi(k) + \theta) \tag{4.2}$$

where A is the constant amplitude of the signal, ω_c is the center frequency, θ is the phase difference at the receiver, and $\Phi(k)$ is:

$$\phi(k) = \begin{cases} 0 & & CW \\ 0, \pi & & BPSK \\ 0, \pm\frac{\pi}{2}, \pi & for & QPSK \\ \pm\omega_d k & & BFSK \\ \pm\frac{\omega_d}{2}k, \pm\omega_d k & & QFSK \end{cases} \tag{4.3}$$

Here, ω_d is the frequency deviation from the center frequency for the FSK modulation type.

In this method, instantaneous frequency is computed using autoregressive spectrum analysis [8]. It is claimed that autoregressive spectrum estimation is an alternative to Fourier analysis for obtaining the frequency spectrum of a signal. Given an input signal;

$$x(k) = s(k) + n(k) \tag{4.4}$$

autoregressive spectrum modeling can be accomplished by solving the following system of equations;

$$\begin{bmatrix} \hat{R}_{xx}(0) & \hat{R}_{xx}(1) & \dots & \hat{R}_{xx}(N-1) \\ \hat{R}_{xx}(1) & \hat{R}_{xx}(0) & \dots & \hat{R}_{xx}(N-2) \\ \vdots & \vdots & \ddots & \vdots \\ \hat{R}_{xx}(N-1) & \hat{R}_{xx}(N-2) & \dots & \hat{R}_{xx}(0) \end{bmatrix} \cdot \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_N \end{bmatrix} = \begin{bmatrix} \hat{R}_{xx}(1) \\ \hat{R}_{xx}(2) \\ \vdots \\ \hat{R}_{xx}(N) \end{bmatrix} \tag{4.5}$$

where,

$$\hat{R}_{xx}(k) = \sum_{n=0}^{M} x(n).x(n+k) \tag{4.6}$$

Here M is the number of samples existing in the analysis frame, and a is a vector that represents the coefficients for the polynomial that best fits the frequency spectrum. Phase of a pole of this polynomial corresponds to the frequency of that signal, and the magnitude of a pole corresponds to the bandwidth of that signal. These relations are given with the following formula;

$$F_i = \frac{F_s}{2\pi}\theta_i = \frac{F_s}{2\pi}\tan^{-1}\left[\frac{\mathrm{Im}(Z_i)}{\mathrm{Re}(Z_i)}\right] \tag{4.7}$$

and

$$BW_i = -\frac{F_s}{\pi}10\log_{10}\left[\frac{1}{\mathrm{Im}(Z_i)^2 + \mathrm{Re}(Z_i)^2}\right] \tag{4.8}$$

where F_i is the instantaneous frequency and BW_i is the instantaneous bandwidth of the corresponding samples in the analysis frame, F_s is the sampling rate, θ_i is the phase angle between the real and imaginary components of Z_i, and Z_i is the i^{th} complex pole of the autoregressive polynomial.

In the beginning of these calculations, the whole signal is partitioned into overlapping analysis frames of a fixed length. Each of these segments is called an “instant” of the signal. Then, F_i and BW_i values are calculated for all these signal segments. The concatenation of these instantaneous frequency and bandwidth values reflects the frequency and bandwidth properties of the corresponding pulse.

4.1.2. BOX DIMENSION AND INFORMATION DIMENSION

The method proposed in [7], employs Fractal Theory in order to extract the box dimension and information dimension features of the signal.

First of all, a brief information about Fractal Theory should be given [9]:

- Fractals are of rough or fragmented geometric shape that can be subdivided in parts, each of which is (at least approximately) a reduced copy of the whole.
- They are crinkly objects that defy conventional measures, such as length and are most often characterized by their fractal dimension.
- Fractal Dimension measures the degree of fractal boundary fragmentation or irregularity over multiple scales. (Modulation creates irregularities on the signal waveform.)
- Fractal Dimensions are relatively insensible to image scaling.
- Very often, fractal dimension is a quite unique classifier for similar shapes.

Thus, if we consider a signal, as a composition of infinitely small fractals, we can represent the “length” of this signal and the irregularities in the signal in terms of its fractal dimensions. The last two bullets confirm that fractal dimensions correctly fit the aim of modulation recognition, as finding the similarities of the current signal’s modulation shape with previously known modulation shapes.

In [7], Box Dimension and Information Dimension are chosen as the key features for modulation recognition.

Box Dimension gives a measure about the area that the image (signal waveform) covers in space. The issue of box dimension-calculation is given below [10];

- Cover the image (signal waveform) with square boxes of a side length *r*.
- Measure the number of nonempty boxes for different *r*;

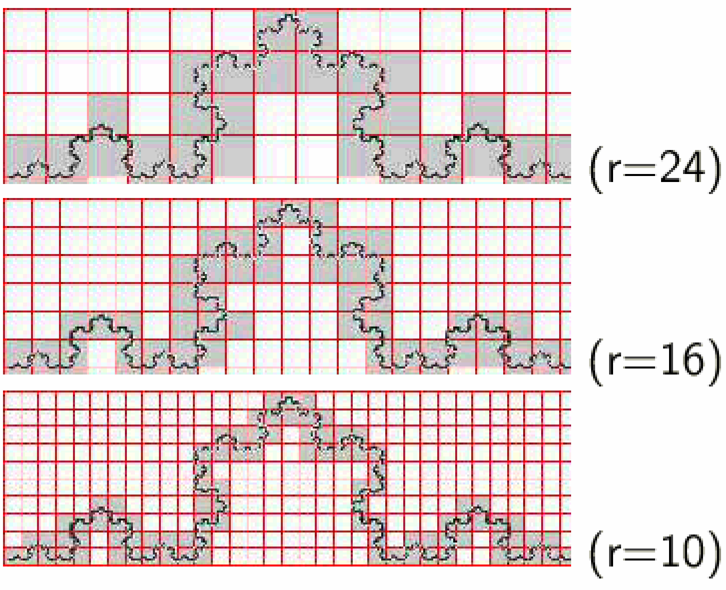

Figure 4.1. Representation of Box Dimension for different *r* values [10]

- *n(r)* is the number of boxes that cover the image (signal waveform), changing with respect to *r*.
- Then box dimension is;

$$D_B = \lim_{r \to 0} \frac{\log\left(\frac{1}{n(r)}\right)}{\log(r)} \tag{4.9}$$

The description above is given for images, and this calculation method must be adapted to the signal waveform case. In [7], the following method is proposed;

- First of all the signal is passed through a preprocess. In this phase the signal is transformed to a sequence in frequency domain. The received signal is a discrete time sequence. By Fourier transform the signal is transformed to a discrete signal in frequency domain. Then the energy of the signal is normalized so that the effect of the distance of radar emitter and the signal is eliminated.
- After the signal preprocessing, the sequence *g(i)* is obtained. Then, for a certain box size, the number of boxes that cover the signal waveform *N(q)* is calculated as;

$$N(q) = N + \frac{\left[\sum_{i=1}^{N-1} \max\{g(i), g(i+1)\} q - \sum_{i=1}^{N-1} \min\{g(i), g(i+1)\} q \right]}{q^2} \tag{4.10}$$

  where *N* is the length of the sequence, and *q* is the size of the boxes chosen to cover the signal.

  Investigating the formula, we see that if the signal had constant value through all samples, only *N* boxes would be sufficient to cover the signal in space. Then, considering the discontinuities found in the signal shape, the second part of the addition is generated. This part calculates the absolute difference between two consecutive samples of the signal and calculates the number of boxes of size *q* that will cover this difference. Making this calculation for all consecutive samples of the signal, the total number of boxes that will cover the signal waveform is obtained.

  After certain trials the ideal box size is found as *q = 1/Fs*, where *Fs* is the sampling rate. This is because the signal is composed of samples each *1/Fs* seconds apart. A larger box size selection would result in data loss and a smaller box size selection would require interpolation between two real samples.

- After the calculation of *N(q)*, the box dimension is calculated as;

$$D_b = -\frac{\ln N(q)}{\ln q} \tag{4.11}$$

The second key feature is the Information Dimension. The issue of box dimension calculation is given below [10];

- Cover the image by squares of size *r*.
- Count the number of points in each square *i*; $n_i(r)$.

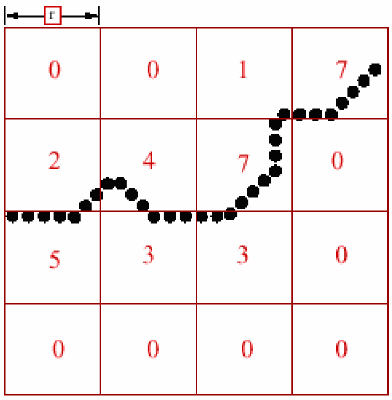

Figure 4.2. Interpretation of Information Dimension [10]

- Divide by the sum of all points to get a probability measure; $p_i(r)$.

$$p_i(r) = \frac{n_i(r)}{\sum_i n_i(r)} \tag{4.12}$$

- Compute Shannon's Entropy; $E(r)$.

$$E(r) = -\sum_i p_i(r) \log_2 p_i(r) \tag{4.13}$$

- Then information dimension is calculated as;

$$D_i = \lim_{r \to 0} \frac{-E(r)}{\log_2 r} \tag{4.14}$$

In [7], the method of Information Dimension calculation is handled as follows;

- First of all the signal is passed through the same preprocess that was described in Box Dimension calculation.
- Then the sequence in frequency domain is reconstructed in the following way;

$$s(i) = f_s(i+1) - f_s(i), \quad i = 1,2,\ldots,N-1 \tag{4.15}$$

Authors claim that this reconstruction method can eliminate a part of noise. Since the noise in our system is AWGN, it is spread overall the frequency spectrum, thus by differentiating the signal we can reduce the effect of this noise by a certain amount.

- Finally, Information dimension is calculated by using the following formulas in the frequency domain signal.

$$D_i = \sum_{i=1}^{N-1} P_i . \log(1/P_i) \tag{4.16}$$

where,

$$L = \sum_{i=1}^{N-1} s_i \tag{4.17}$$

$$P_i = \frac{s_i}{L} \tag{4.18}$$

Here s_i is the reconstructed signal, N is the length of the signal, and P_i is the probability that all the irregularities present in the signal can be represented by the corresponding individual irregularity, s_i. Here, the box size is chosen as $q=1/Fs$, same as the Box Dimension calculations. This choice eliminates the usage of the **limit** function present in the definition of Information Dimension.

As a result it is seen that Box Dimension of a fractal set can reflect the geometric distribution, and Information Dimension can reflect the distribution density of the fractal set in space.

It is claimed by the authors that these features, reflecting the complexity and irregularity of the radar signal, depict the modulation property of that signal and are not easily affected by noise.

In the figure below, we can see the distribution of fractal dimensions among various modulation types. It is seen that Box Dimension and Information dimension give a useful measure for distinguishing between different modulation types.

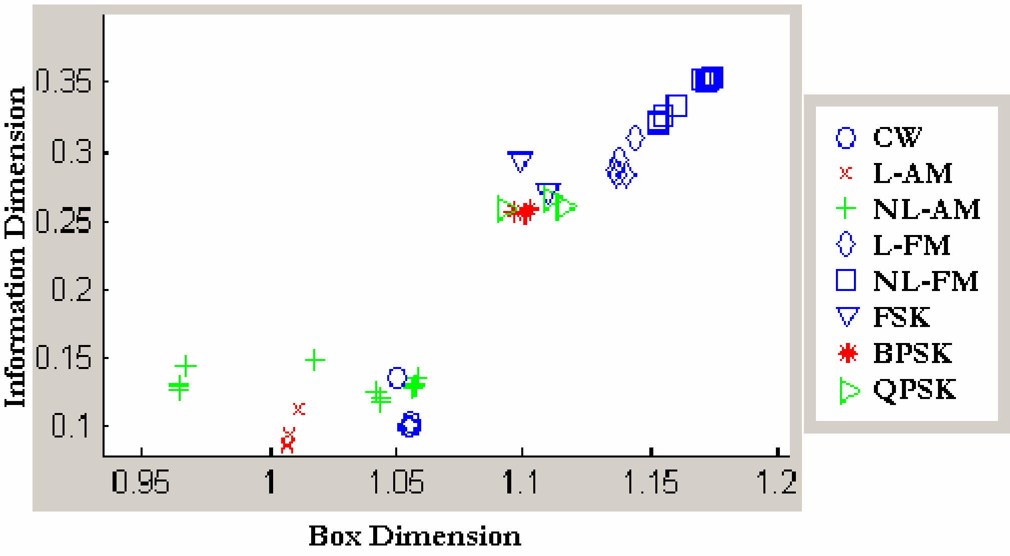

Figure 4.3. Distribution of Fractal Dimensions for various modulation types.

4.1.3. PERCENT AM DEPTH

Percent AM Depth is the measure of the modulation on the envelope of the signal. It is the rate of the maximum irregularity in the shape of the amplitude throughout the pulse, calculated in the percent scale. Formula for calculating this feature is given below:

$$AM\% = \left[\frac{(\max(amplitude) - \min(amplitude))}{(\max(amplitude) + \min(amplitude))} \right] .100 \qquad (4.19)$$

It is agreed in literature that if this value is greater than 10%, this depicts either some intentional amplitude modulation is applied on the signal, or the signal envelope is affected by another intentional modulation present in Frequency or Phase of the signal, or the signal amplitude is affected by some unintentional modulation.

4.2 PROPOSED SYSTEM

The system proposed in this thesis consists of three main parts: Signal Generator, Receiver, and Modulation Recognizer. This structure is represented in Figure 4.3. The other two blocks, i.e. Basic Feature Extraction & Database Update and Signal Decomposition are blocks presented to the user as auxiliary blocks, but not obligatory for the system to achieve its Modulation Recognition issue.

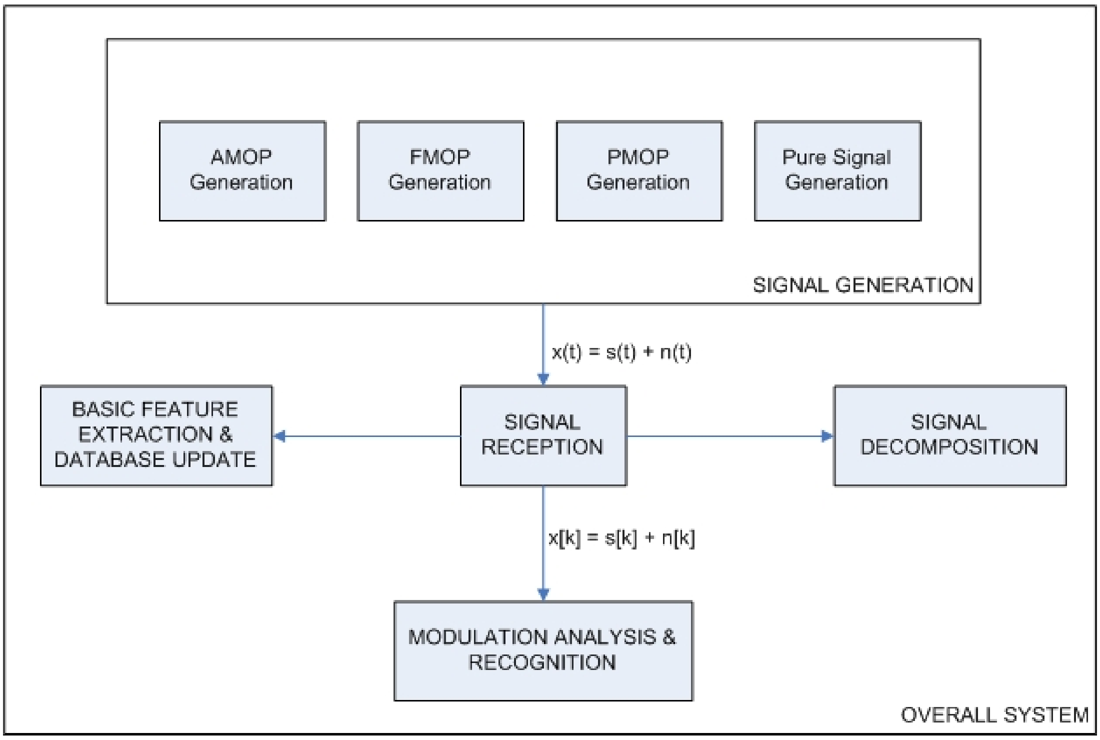

Figure 4.4. Blocks of the system.

4.2.1. SIGNAL GENERATION

In the Signal Generator block, AMOP – FMOP – PMOP or Modulationless Pure Signals are produced depending on the operator's choice, with the parameters entered via the Graphical User Interface (GUI). The signal is generated with a symbol rate of 1024 Msamples/second. Since the system is implemented in Matlab, we cannot generate "continuous" signals. However, with 1024 Msamples/second symbol rate, time resolution is more than 1 nsec, and this signal is "assumed to be continuous". The desired signal is generated at the Center Frequency (fc) entered by the user. Also some Additive White Gaussian Noise (AWGN) is added to the generated signal at the SNR value entered from the GUI. According to this SNR, the required noise power is calculated with respect to the power of the noiseless signal. This SNR value corresponds to the noise measured at the front end of the receiver of the system.

4.2.2. SIGNAL RECEPTION

After the continuous signal is generated, this signal is sent to the Receiver block. Structure of the Receiver block is given in Figure 4.4.

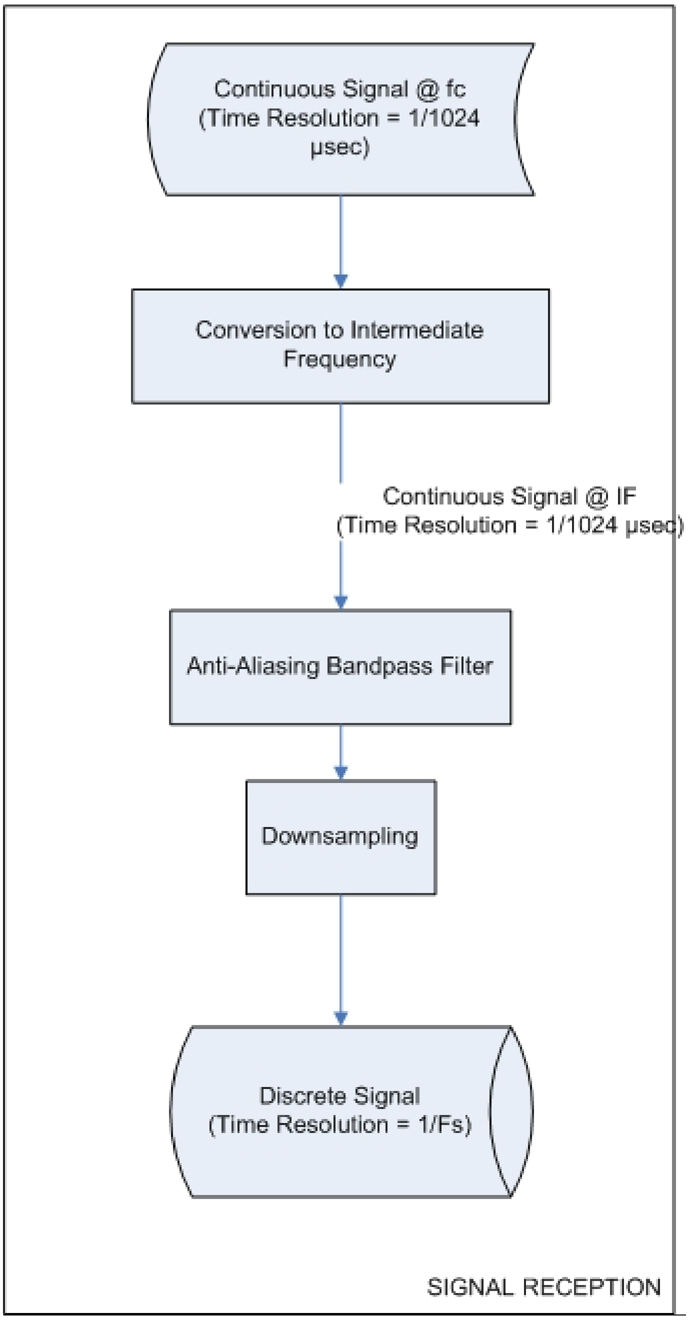

Figure 4.5. Receiver block of the system

In the Receiver block, continuous signal is first carried to the Intermediate Frequency (IF). IF of the system is 160 MHz. In this process, we assume that the center frequency of the incoming signal is known. In real systems, the center frequency of the signal can be extracted with a precision rate of a few kHz, thus our assumption does not diverge from the real case. After this process, signal is passed through a Bandpass Filter in order to avoid aliasing that may occur during downsampling. This filter is a 50th-order linear-phase FIR filter. The pass-band of the filter is 128 MHz around the intermediate frequency. Following the filter, signal is sampled with the Sampling Rate preferred by the user. Sampling Rate choices are 256 MHz and 128 MHz. Two choices were presented to the operator in order to observe the effect of different sampling speeds in modulation recognition.

4.2.3. SIGNAL DECOMPOSITION

After the signal is received and sampled, this signal is decomposed into its envelope, phase and frequency components, to be presented to the operator. This Signal Decomposer block is given in Figure 4.5 in detail.

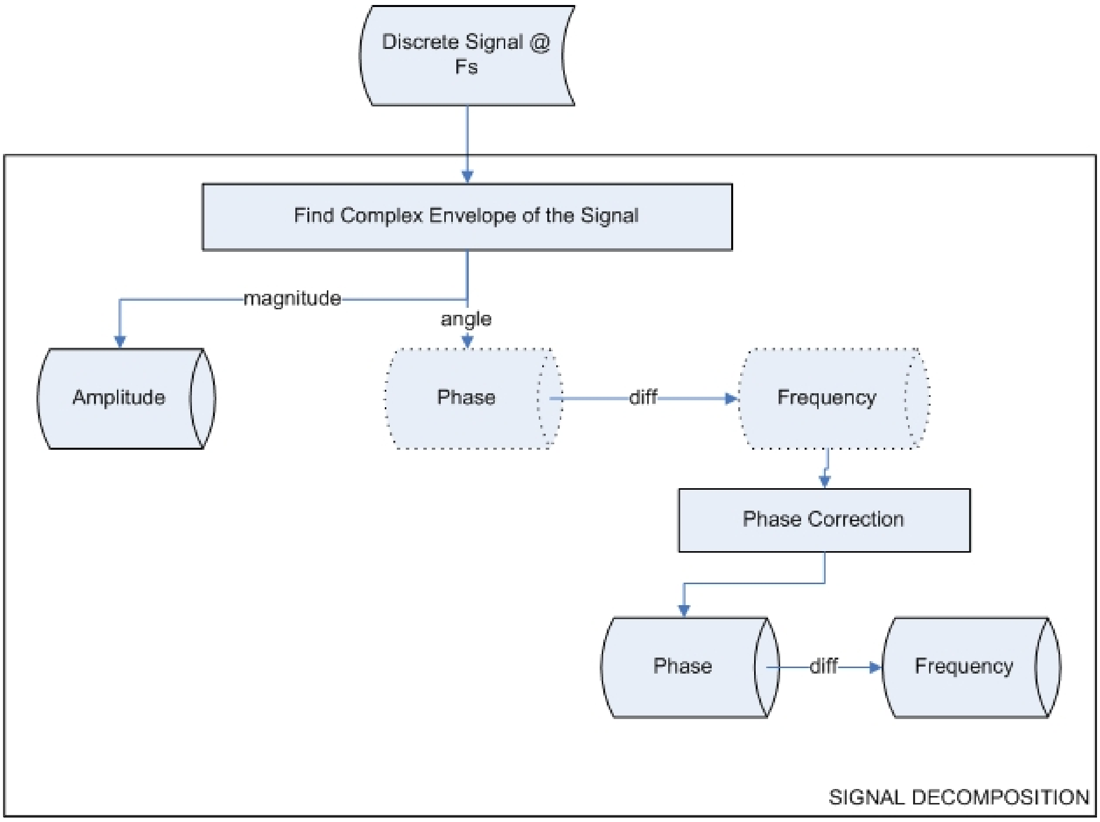

Figure 4.6. Decomposer block of the system

In this block, complex envelope of the signal is calculated. Magnitude of this complex envelope corresponds to the Amplitude, and Angle of the complex envelope corresponds to the Phase of the signal. Frequency of the signal is found by differentiating the Phase of the signal.

Throughout the algorithms, it is assumed that we know the center frequency of the original signal. However, if there were some discrepancy between the original center frequency value and the extracted center frequency value, this effect would be seen in the output of the Decomposer block as a deviation in the Pulse Frequency from the IF. Taking this probability into account, Phase of the pulse is corrected according to the deviation of mean of the extracted Pulse Frequency from IF. For this purpose the following method is used;

$$If \quad (F > 0)$$
$$Corrected\_Phase = \tan^{-1}\left(\frac{\sin(\omega_c + \omega_0)}{\cos(\omega_c + \omega_0)}\right) = \omega_c + \omega_0$$

$$If \quad (F < 0)$$
$$Corrected\_Phase = \tan^{-1}\left(\frac{\sin(\omega_c - \omega_0)}{\cos(\omega_c - \omega_0)}\right) = \omega_c - \omega_0$$

where,

$$F = mean(Pulse\_Freq) - IF \Rightarrow Deviation\ from\ IF$$
$$\omega_c = Pulse\ Phase\ Values$$
$$N = length(Pulse) \Rightarrow Number\ of\ samples\ in\ the\ Pulse$$
$$F_s = Sampling\ Rate$$
$$\omega_0 = \frac{2\pi F}{F_s} \cdot \begin{bmatrix} 1 & 2 & \cdots & N \end{bmatrix}$$

Phase of the Pulse is corrected with the method described above, and the Frequency of the pulse is calculated again due to this corrected phase.

At this point, there are two preferences for the user: “Basic Feature Extraction & Database Update” or “Modulation Analysis & Recognition”.

4.2.4. BASIC FEATURE EXTRACTION AND DATABASE UPDATE

User may choose to analyze the signal step by step and save the analysis results in the IMOP database.

IMOP Database is implemented in Ms Access. Below is given the details of this database.

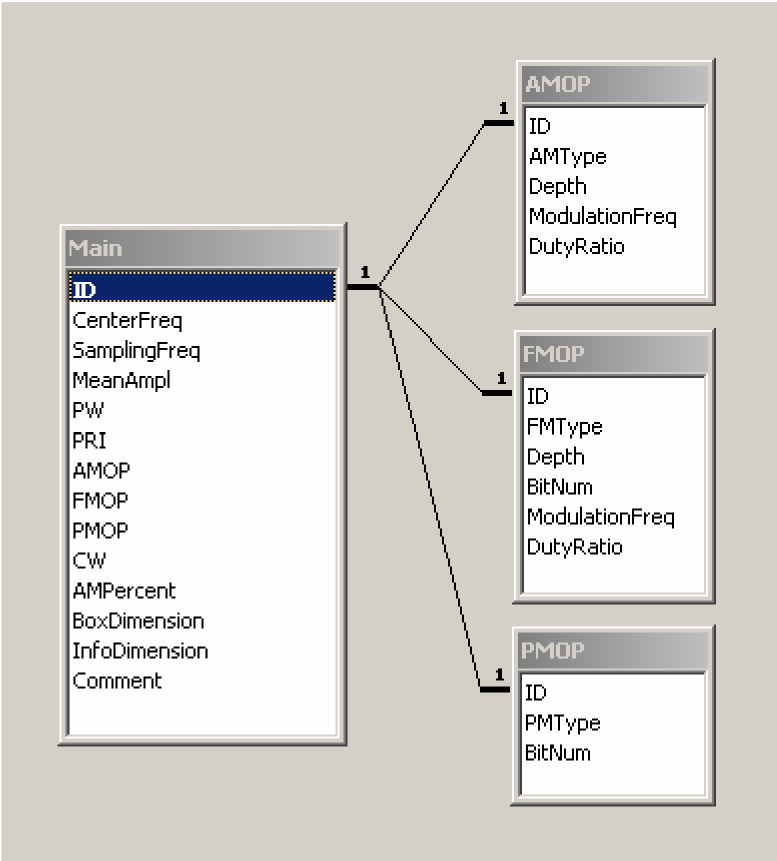

Figure 4.7. Structure of the IMOP Database

For each signal entering the database, a new row is opened in the Main table with a unique ID, which is the primary key for the database. In the Main table; Center Frequency, Sampling Frequency, Mean Amplitude, PW and PRI values are stored. Also the AM Percent, Box Dimension and Information Dimension values of the entered signals are saved in this table, to be used in signal comparison in the Fractal Theory Decision block. Details of AM Percent extraction is given in 4.1.3. PERCENT AM DEPTH, and details of Fractal Dimension extraction are given in the 4.1.2. BOX DIMENSION AND INFORMATION DIMENSION sections of this chapter. Also there are AMOP, FMOP, PMOP, CW flags in this table. User selects the modulation type of the signal from the GUI before sending the analyzed signal to the database. Referring to these flags the corresponding sub-table is filled, i.e. if AMOP flag is set to 1, then a row is opened in the AMOP sub-table with the same ID on the Main table, and corresponding properties of the signal are filled to this row on the AMOP sub-table.

As mentioned in the preceding paragraph, there are sub-tables related to the Main table with the ID parameter. This relationship is 1-1, thus an element in the AMOP table can be related to only one element that has the same ID in the Main table.

AM Type, AM Depth, Modulation Frequency and Duty Ratio fields exist in the AMOP sub-table. AM Type can be “Linear-Increasing”, “Linear-Decreasing”, “Positive Parabolic”, “Negative Parabolic”, ”Sinusoidal”, ”Triangular”, “Ramp” or ”Square”. AM Depth value is valid for all these types, however “Modulation Frequency” field is filled if the modulation is Periodic (”Sinusoidal”, ”Triangular”, “Ramp” or ”Square”), and “Duty Ratio” field is filled if the modulation is ”Square”.

FM Type, FM Depth, BitNum (Number of Bits in the modulating code), Frequency and Duty Ratio fields exist in the FMOP sub-table. FM Type can be “Linear-Increasing”, “Linear-Decreasing”, “Positive Parabolic”, “Negative Parabolic”, ”Sinusoidal”, ”Triangular”, “Ramp”, ”Square” or “BFSK”. FM Depth value is valid for all these types, however “Modulation Frequency” field is filled if the modulation is Periodic (”Sinusoidal”, ”Triangular”, “Ramp” or ”Square”), “Duty Ratio” field is filled if the modulation is ”Square”, and “BitNum” field is filled if the modulation is BFSK.

PM Type and BitNum (Number of Bits in the modulating code) fields exist in the PMOP sub-table. PM Type can be BPSK or MPSK.

There is no sub-table for the “No Modulation” or “CW” case, because the parameters in the Main table are enough to totally describe the CW signal.

On the other hand, if the user chooses to find the modulation type of the incoming signal without making manual analysis, the signal is sent to the Modulation Analyzer and Recognizer block.

4.2.5. MODULATION ANALYSIS AND RECOGNITION

Details of the Modulation Recognition block is given in Figure 4.7.

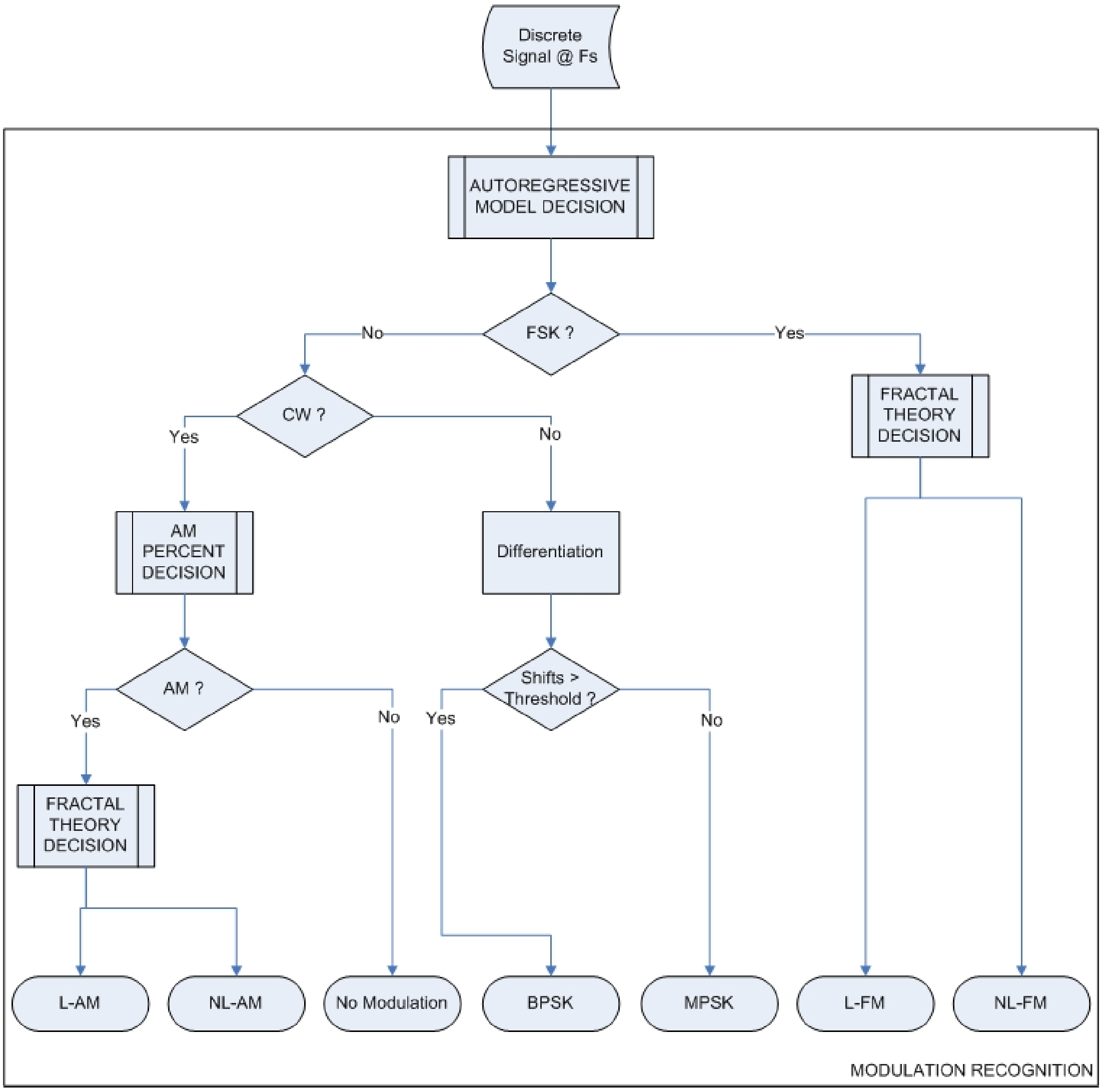

Figure 4.8. Modulation Recognizer block of the system

4.2.5.1. *AUTOREGRESSIVE MODEL DECISION*

Discrete signal entering the Recognizer block is first passed into the Autoregressive Model Decision block. Details of this sub-block is given in Figure 4.8.

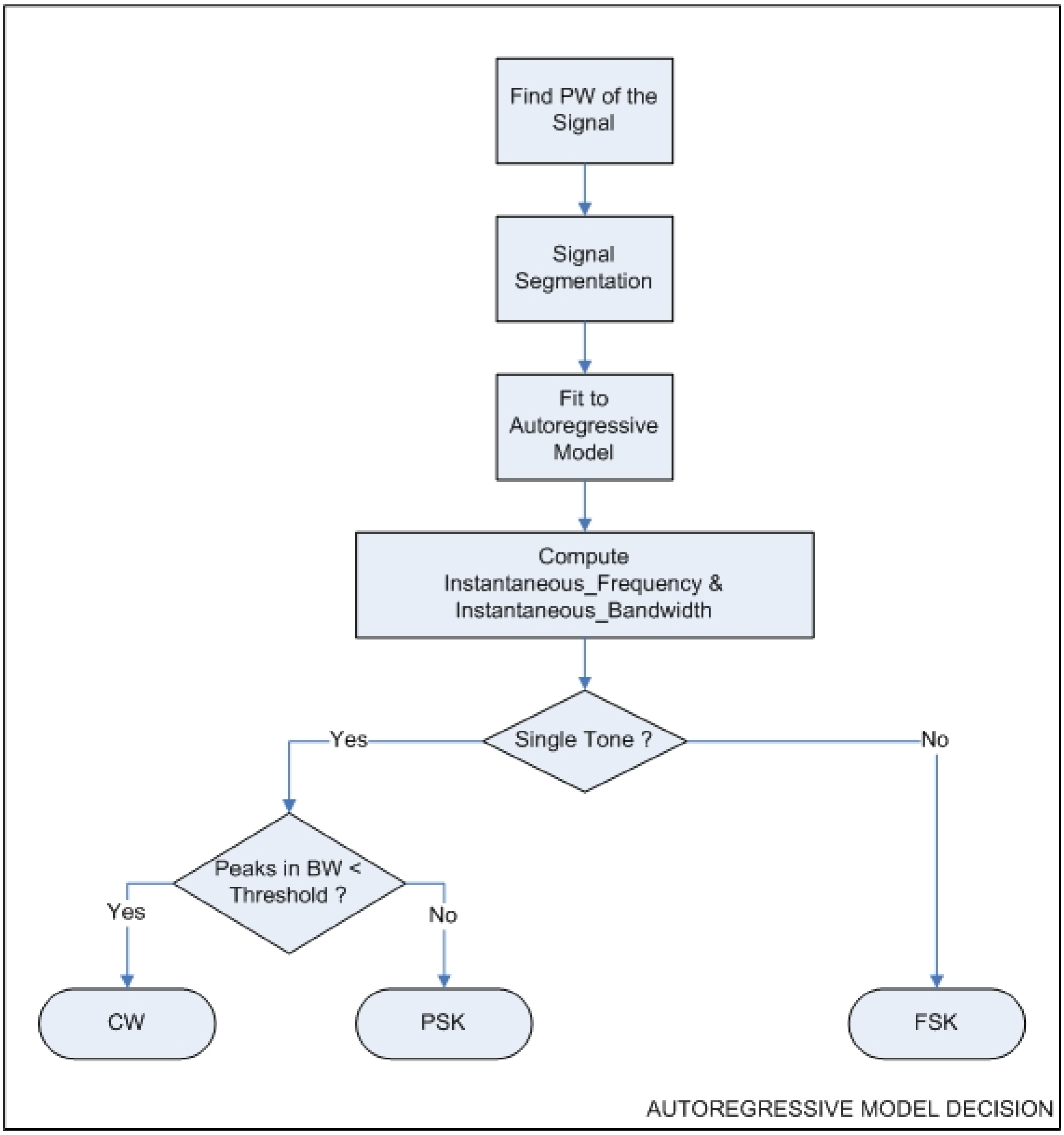

Figure 4.9. Autoregressive Model Decision sub-block of the Recognizer block

In the Autoregressive Model Decision block, first of all PW of the signal is found and with the help of this PW value initial and final points of the pulse is calculated. This process is made to avoid the overshoot effect that may be encountered at the very beginning points of a pulse. After this process, signal is segmented into overlapping parts. Then instantaneous frequency and instantaneous bandwidth is calculated for each signal segment. Details of these calculations are given in 4.1.1. INSTANTANEOUS FREQUENCY AND BANDWIDTH section of this chapter. Union of the instantaneous values for each parameter is assumed to resemble the behavior of that parameter through the pulse. Referring to the union of instantaneous frequency values, it is decided whether the signal is single tone or multi tone. If the signal is found to be multi tone, it is said that this signal is either BFSK or QFSK [8].

However, the proposed system is also capable of discriminating other types of FM, so we consider this output as “FSK” only, and keep on recognition by other techniques. On the other hand, if the signal is found to be single tone, this means that signal is either CW (modulationless pure signal) or PSK. Referring to the union of instantaneous bandwidth values, discrimination between CW and PSK is made [8]. However, our system is also capable of AM recognition, which is included in the “CW” answer of this block. For this reason if the signal is found to be CW in this block, recognition algorithm is continued outside this block. Also, if the signal is found to be PSK, signal is processed outside this block in order to make BPSK or MPSK decision.

After the Autoregressive Model Decision block, if the signal is found to be CW, this signal is passed to the AM Percent Decision Block.

4.2.5.2. AM PERCENT DECISION

Details of the AM Percent Decision block is given in Figure 4.9.

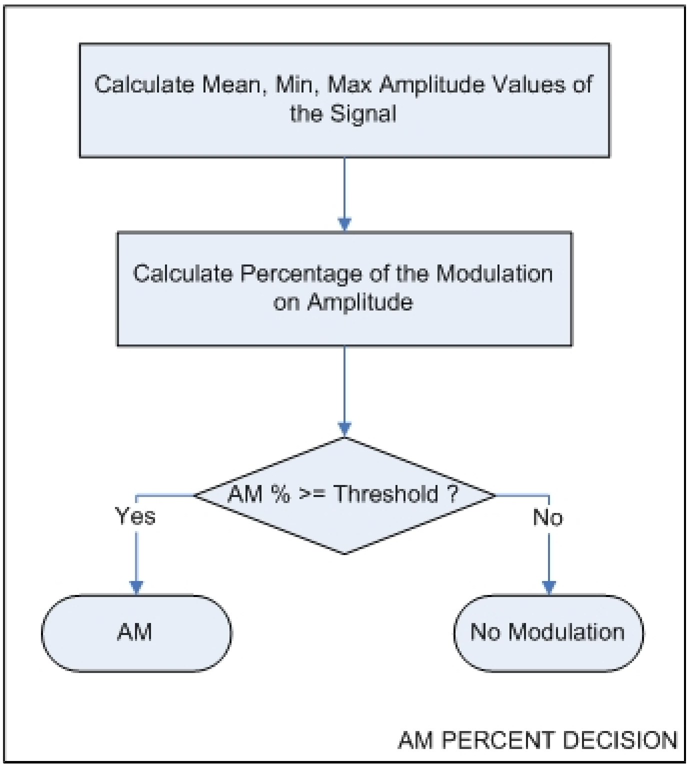

Figure 4.10. AM Percent Decision sub-block of the Recognizer block

In this block, the mean, minimum and maximum Amplitude values of the entered Pulse is calculated. Then, from these values, Amplitude Modulation Percent is calculated. If this value is greater than a threshold, it is assumed that the signal has amplitude modulation. Otherwise, we say that signal has “No Modulation”. This threshold value is selected as 10%, which is accepted as a valid value in literature.

If the output of the AM Percent Decision sub-block is “AM”, then the signal is sent to the Fractal Theory Decision sub-block in order to decide whether it is Linear AM or Nonlinear AM.

4.2.5.3. FRACTAL THEORY DECISION

Details of the Fractal Theory Decision block is given in Figure 4.10.

In the Fractal Theory Decision block, first of all PW of the signal is found and with the help of this PW value initial and final points of the pulse are determined. This process is made to avoid the overshoot effect that may be encountered at the very beginning points of a pulse. After this process, three features of the signal are calculated;

- AM Depth %
- Box Dimension
- Information Dimension

AM Depth% value is calculated as the way described in AM Percent Decision sub-block.

Box Dimension and Information Dimension are the Fractal Features of the signal. Details of the calculation of these parameters are given in the 4.1.2. BOX DIMENSION AND INFORMATION DIMENSION section of this chapter.

To find the modulation type of the entered signal, a database search is handled. Normalized Euclidean Distances (NEDs) between the entered signal parameters and the signals in the database are calculated, with the following method;

$$NED = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(Vector_{2i} - Vector_{1i})^2}}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(Vector_{1i})^2} + \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Vector_{2i})^2}} \tag{4.20}$$

where

Vector = [AMDepth%   BoxDimension   InformationDimension],
(if Modulation Type is 'AM');
Vector = [BoxDimension   InformationDimension],
(if Modulation Type is 'FM')

If the calculated NED is less than a threshold value, that modulation type is saved as a "Candidate Modulation Type". This process is repeated for all records present in the database.

After the database search, histogram of the "Candidate Modulation Type" is formed, and the Modulation type that has the maximum weight is chosen as the "Most Probable Modulation Type". If there are more than one modulation types having this weight, the one with the least NED is chosen for the "Most Probable Modulation Type". Furthermore, if any of the NEDs is very close to zero, then these signals' shapes are assumed to be "very close to each other", and independent of the histogram result, that signal's modulation type is given as the "Most Probable Modulation Type".

Outputs of this block may be one of the types; "Linear AM", "Nonlinear AM", "Linear FM" or "Nonlinear FM".

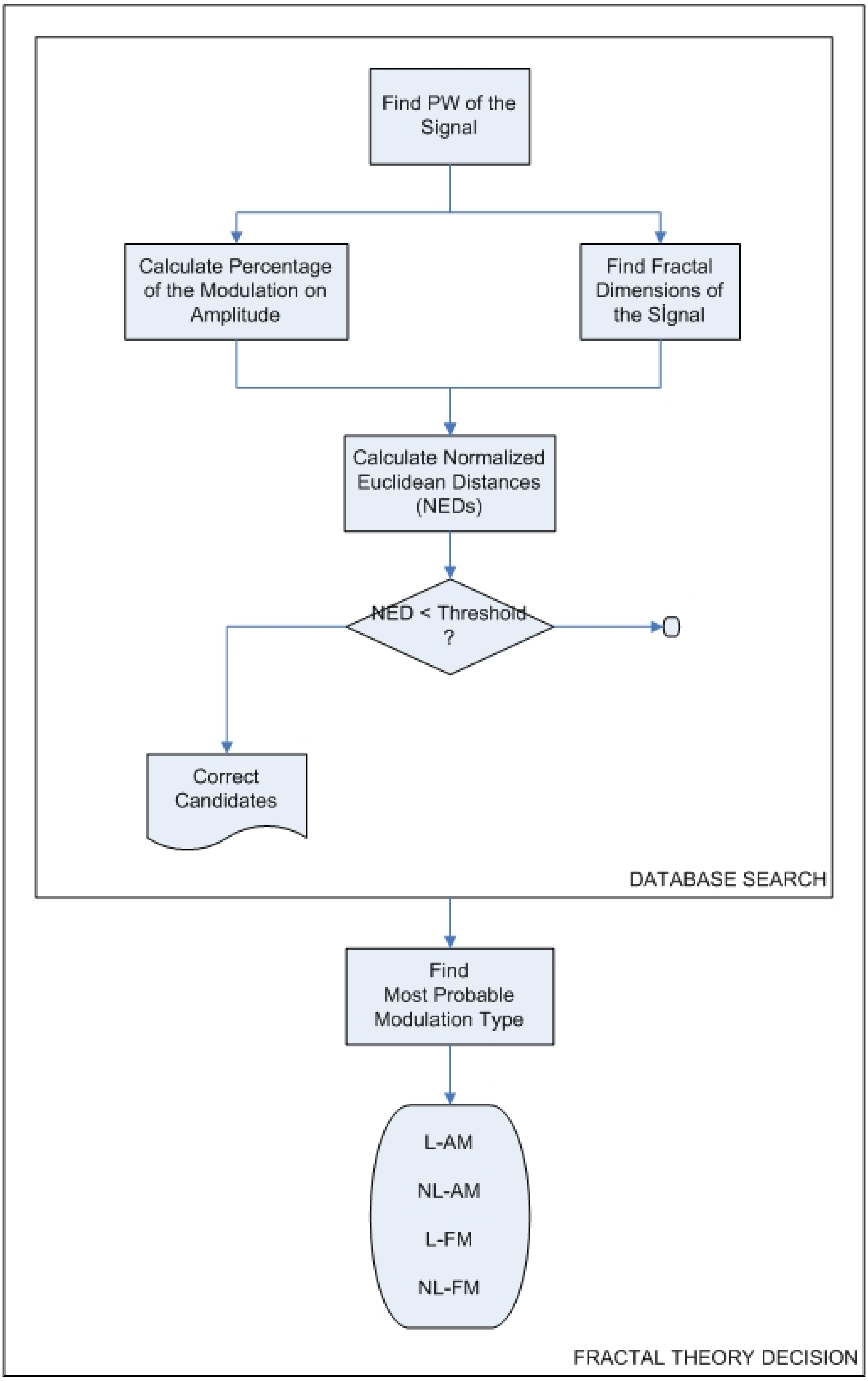

Figure 4.11. Fractal Theory Decision sub-block of the Recognizer block

If the output of the AM Percent Decision sub-block is “No Modulation”, then no further processing is required; signal is said to have no modulation, i.e. the signal is a pure sinusoid.

If the output of the Autoregressive Model Decision sub-block is “PSK”, then the Phase of the pulse is differentiated. If any of the differences is less than π radians, the signal is said to have MPSK modulation. Otherwise the signal is decided to have BPSK modulation.

After the Autoregressive Model Decision block, if the signal is found to be FSK, this signal is passed to the Fractal Theory Decision Block. By the help of this block, the signal is decided whether it is Linear FM or Nonlinear FM.

In order to make the simulations of the proposed system easier, a graphical user interface is also designed and presented to the user. Details about this interface is given in Appendix B.

CHAPTER 5

PERFORMANCE TESTS

In order to test the performance of the system, computer simulations were carried out using the Graphical User Interface created in MATLAB.

5.1. SIGNAL TYPES USED IN SIMULATIONS

Proposed algorithm was tested for AMOP, FMOP, PMOP modulation types and for signals without modulation. All signals were constructed using MATLAB programming language.

Signals were constructed at the given center frequency with a symbol rate of 1024MHz at first, so that they could be assumed to be continuous signals coming to the receiver of the system from the surrounding, with approximately 1nsec time resolution. In order to model the noise effects, Additive White Gaussian Noise was generated and added to the incoming signal, at the SNR value entered from the User Interface. This SNR value corresponds to the noise measured at the front end of the receiver of the system.

In the receiver part of the system, it is assumed that center frequency of the signal was recovered correctly and the signal was moved to the intermediate frequency (IF). IF value for the system was chosen to be 160MHz. In this process, we assume that the center frequency of the incoming signal is known. In real systems, the center frequency of the signal can be extracted with a precision rate of a few kHz, thus our assumption does not diverge from the real case.

The signal at IF which was assumed to resemble the continuous signal model, was filtered with a 50th order Bandpass filter, before sampling in order to avoid aliasing. This filter was designed with the “fir1” command of Matlab. Filtered signal was then sampled at one of the two different Sampling Frequency (Fs) choices, depending on the user selection. Fs values offered to the user were 256MHz and 128MHz respectively.

Modulation Types and the corresponding variable parameters used in the performance tests are given in Table 5.1.

Table 5.1. Variable Parameters Corresponding to Different Modulation Shapes

MODULATION TYPE	NO MOD.	AMOP				FMOP					PMOP	
		Linear	Nonlinear			Linear	Nonlinear				BPSK	MPSK
			Parabolic	*Periodic*	*Square*		*Parabolic*	*Periodic*	*Square*	*BFSK*		
VARIABLE PARAMETERS	Pulse Width (PW)	Pulse Width (PW)	Pulse Width (PW)	Pulse Width (PW)	Pulse Width (PW)	Pulse Width (PW)	Pulse Width (PW)	Pulse Width (PW)	Pulse Width (PW)	Pulse Width (PW)	Pulse Width (PW)	Pulse Width (PW)
	Sampling Rate (Fs)	Sampling Rate (Fs)	Sampling Rate (Fs)	Sampling Rate (Fs)	Sampling Rate (Fs)	Sampling Rate (Fs)	Sampling Rate (Fs)	Sampling Rate (Fs)	Sampling Rate (Fs)	Sampling Rate (Fs)	Sampling Rate (Fs)	Sampling Rate (Fs)
	Mean Amplitude	Modulation Shape (Linear Increasing / Linear Decreasing)	Modulation Shape (Positive Parabolic / Negative Parabolic)	Modulation Shape (Sinusoidal / Triangular / Ramp)	Duty Ratio Percent	Modulation Shape (Linear Increasing / Linear Decreasing)	Modulation Shape (Positive Parabolic / Negative Parabolic)	Modulation Shape (Sinusoidal / Triangular / Ramp)	Duty Ratio Percent	Barker Code Selection	Barker Code Selection	Number of Phase Steps in the Frank Code
	SNR	Percent AM Depth	Percent AM Depth	Percent AM Depth	Percent AM Depth	Frequency Deviation	Frequency Deviation	Frequency Deviation	Frequency Deviation	Frequency Shift	Mean Amplitude	Mean Amplitude
		Mean Amplitude	Mean Amplitude	Mean Amplitude	Mean Amplitude	Mean Amplitude	Mean Amplitude	Mean Amplitude	Mean Amplitude	Mean Amplitude	SNR	SNR
		SNR	SNR	SNR	SNR	SNR	SNR	SNR	SNR	SNR		
				Modulation Frequency	Modulation Frequency			Modulation Frequency	Modulation Frequency			

Each combination of these parameters formed a new signal version, and each version was sent to the modulation recognition block, in order to identify the modulation type.

5.2. RESULTS OF SIMULATIONS

5.2.1. NO MODULATION CASE

With different combinations of Sampling Rate, PW, Mean Amplitude and SNR values, a total of 36 distinct signals without modulation were formed. These signals were generated 100 times with and a new noise was added to each of them in order to achieve correct recognition percentages given in the graphs.

In order to test the effect of PW on recognition of “No Modulation” type signals, PW was swept through 0,1µsec to 100µsec, and other parameters were kept fixed. Test results are given in Table 5.2.

Table 5.2. Effect of PW on recognition of “No Modulation” type signals

Fs (MHz)	**PW (µsec)**	**Mean Amplitude (mV)**	**SNR**	**Result**
256	0,1	10	35	**NL-AM**
256	0,5; 1; 2; 5; 10; 20; 30; 50; 100	10	35	**No Mod.**

As it is seen from the table, recognizer makes correct decision for PW values greater than 0,5µsec, when the signal is sampled at 256MHz.

For the tests of sampling rate, tests given in Table 5.2 were repeated for Fs = 128MHz. Test results are given in Table 5.3.

Table 5.3. Effect of Fs on recognition of “No Modulation” type signals

Fs (MHz)	**PW (µsec)**	**Mean Amplitude (mV)**	**SNR**	**Result**
128	0,1	10	35	**NL-AM**
128	0,5; 1	10	35	**L-AM**
128	2; 5; 10; 20; 30; 50; 100	10	35	**No Mod.**

Referring to the table, recognizer makes correct decision for PW values greater than 2µsec, when the signal is sampled at 128MHz. System performance for two sampling rates are illustrated in Figure 5.1.

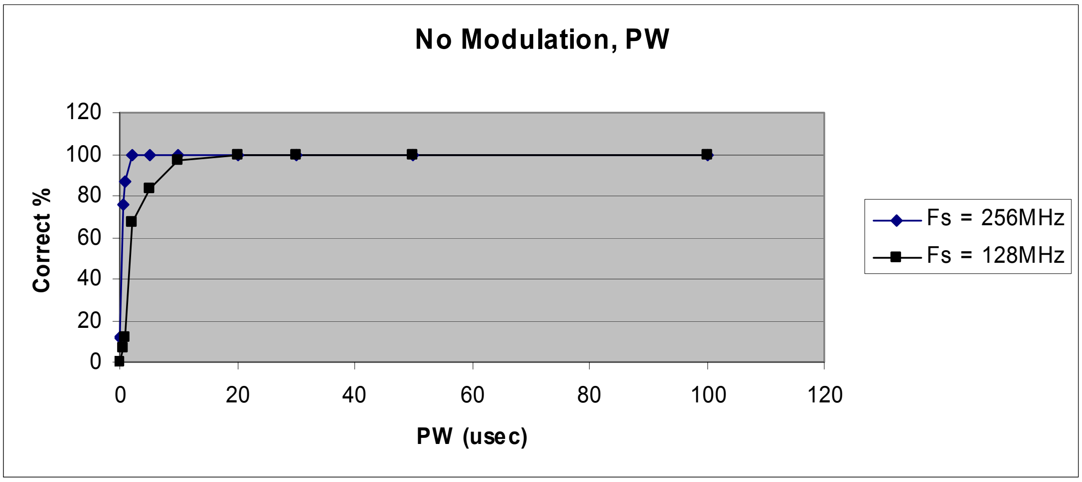

Figure 5.1. System performance at different sampling rates for No Modulation signals.

To see the effect of Mean Amplitude on pure signals' modulation recognition, Mean Amplitude was swept through 0,1mV to 100mV, with all other parameters fixed. Test results are given in Table 5.4.

Table 5.4. Effect of Mean Amplitude on recognition of "No Modulation" type signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	SNR	Result
256	10	0,1; 0,5; 1; 2; 5; 10; 20; 30; 50; 100	35	**No Mod.**

It is obvious that system performance is independent of the Mean Amplitude value for recognition of "No Modulation" type signals.

SNR is one of the most important parameters in modulation recognition. For this reason, tests were handled to see the effect of noise on modulation recognition of pure signals. For fixed values of Fs, PW and Mean Amplitude, SNR was swept through 35dB to 0dB. Test results are given in Table 5.5.

Table 5.5. Effect of SNR on recognition of "No Modulation" type signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	SNR	Result
256	10	10	35; 30; 25; 20; 15	**No Mod.**
256	10	10	10	**BPSK**
256	10	10	5	**MPSK**
256	10	10	0	**NL-FM**

As seen from the table, system performance decays as the SNR decreases. System makes correct decision for SNR greater than 15dB. This fact can also be observed from Figure 5.2.

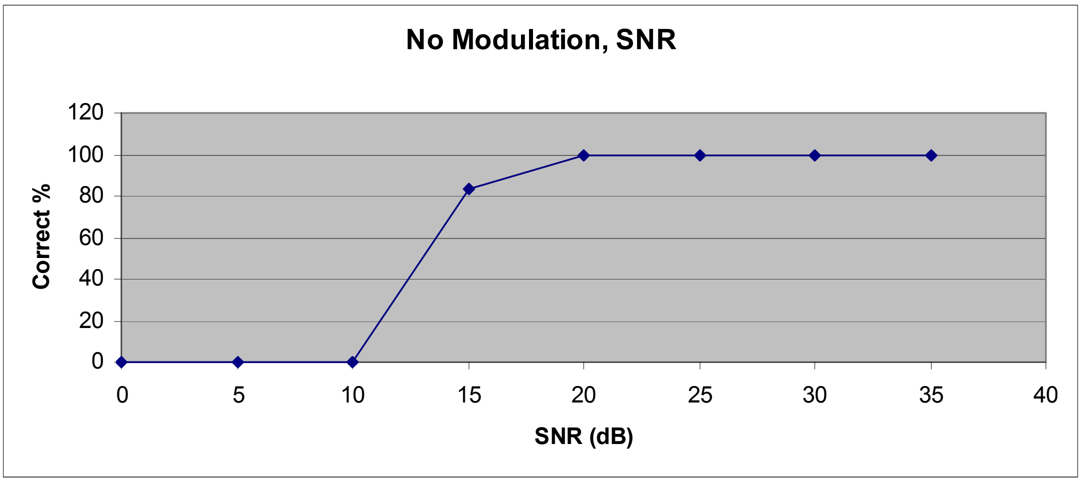

Figure 5.2. System performance at different SNR values for No Modulation signals.

5.2.2. AMOP CASE

5.2.2.1. Linear AMOP Case

With different combinations of Sampling Rate, PW, Modulation Shape, % AM Depth, Mean Amplitude and SNR values, a total of 53 distinct Linear AM signal type was formed. These signals were generated 100 times with and a new noise was added to each of them in order to achieve correct recognition percentages given in the graphs.

Through the tests for Linear AM recognition, it is seen that Linear AM is mostly confused with Nonlinear AM signals. However, Linear modulation shape is also equivalent to half period of

Triangular and Ramp modulation shapes. So, one should investigate the tables below taking this fact into account.

In order to test the effect of PW on recognition of Linear AM signals, PW of the signals was swept through 0,1μsec to 100μsec as we kept all other parameters constant. Test results are given in Table 5.6.

Table 5.6. Effect of PW on recognition of Linear AM signals

Fs (MHz)	**PW (μsec)**	**Mean Amplitude (mV)**	**AM Type**	**%AM Depth**	**SNR**	**Result**
256	0,1	10	L-inc	30	35	**NL-AM (Triangular)**
256	0,5 ; 1	10	L-inc	30	35	**L-AM**
256	2 ; 5	10	L-inc	30	35	**NL-AM**
256	10 ; 20 ; 30	10	L-inc	30	35	**L-AM**
256	50 ; 100	10	L-inc	30	35	**NL-AM**

Referring to the table, it is seen that system can recognize Linear AM modulation for even very small PW values. However, some fluctuations between Linear and Nonlinear AM were detected due to the variations in the randomly generated noise.

For the tests of sampling rate, tests given in Table 5.6 were repeated for 128MHz sampling rate. Test results are given in Table 5.7.

Table 5.7. Effect of Fs on recognition of Linear AM signals

Fs (MHz)	**PW (μsec)**	**Mean Amplitude (mV)**	**AM Type**	**%AM Depth**	**SNR**	**Result**
128	0,1 ; 0,5 ; 1	10	L-inc	30	35	**L-AM**
128	2	10	L-inc	30	35	**NL-AM**
128	5 ; 10 ; 20	10	L-inc	30	35	**L-AM**
128	30	10	L-inc	30	35	**NL-AM**
128	50 ; 100	10	L-inc	30	35	**L-AM**

As it is given in the table, system shows similar behavior for both of the sampling rates. System performance for two sampling rates are also illustrated in Figure 5.3.

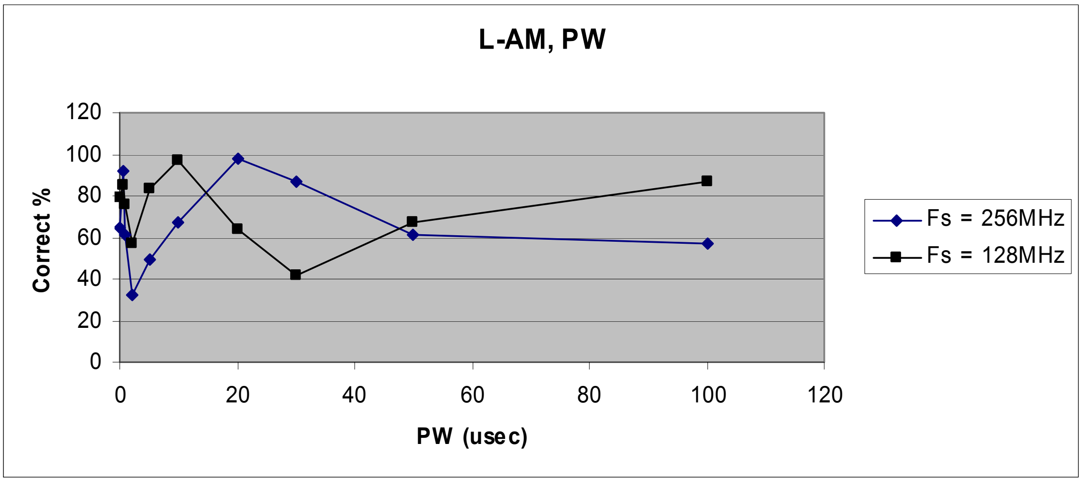

Figure 5.3. System performance at different sampling rates for Linear AM signals.

To observe the effects of modulation shape on Linear AM recognition, tests in Table 5.6 were repeated for “Linear Decreasing” AM type. Results are given in Table 5.8 and Figure 5.4.

Table 5.8. Effect of Modulation Shape on recognition of Linear AM signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	AM Type	%AM Depth	SNR	Result
256	0,1	10	L-dec	30	35	**L-AM**
256	0,5	10	L-dec	30	35	**NL-AM**
256	1 ; 2 ; 5	10	L-dec	30	35	**L-AM**
256	10 ; 20	10	L-dec	30	35	**NL-AM (Triangular)**
256	30; 50; 100	10	L-dec	30	35	**L-AM**

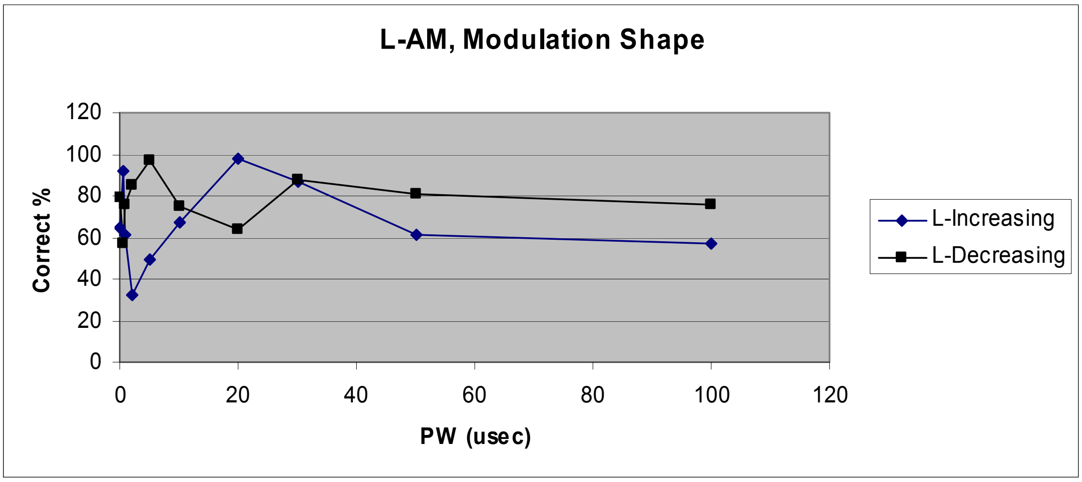

Figure 5.4. System performance at different modulation shapes for Linear AM signals.

It is seen that modulation shape does not make a significant change in system performance for Linear AM recognition, which is an expected case.

In order to test the effect of Percentage AM Depth, Percentage AM Depth was swept through 50% to 1%, and other parameters were kept constant. Test results are given in Table 5.9 and Figure 5.5.

Table 5.9. Effect of Percentage AM Depth on recognition of Linear AM signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	AM Type	%AM Depth	SNR	Result
256	10	10	L-inc	50 ; 40	35	**NL-AM (Ramp)**
256	10	10	L-inc	30	35	**L-AM**
256	10	10	L-inc	20	35	**NL-AM**
256	10	10	L-inc	15; 10; 5; 1	35	**No Mod.**

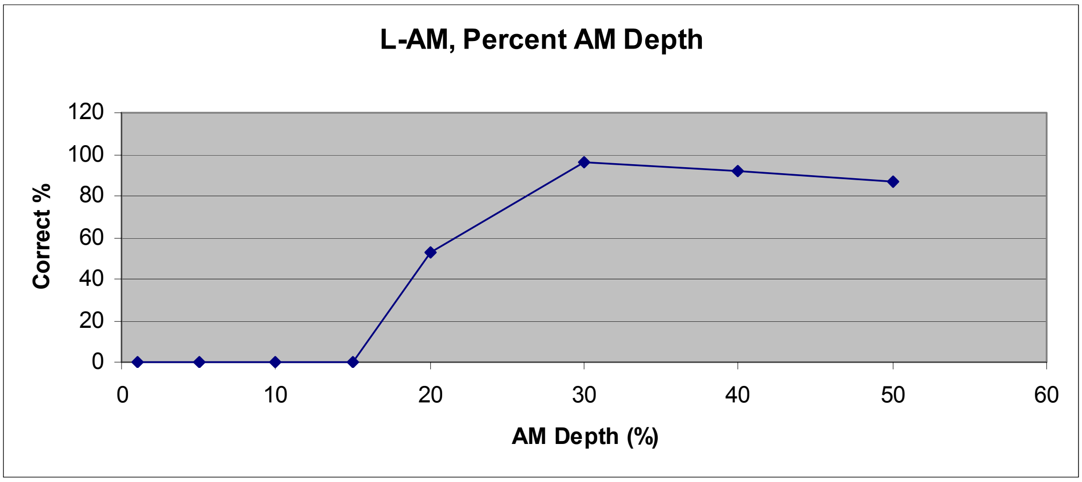

Figure 5.5. System performance at different modulation depth values for Linear AM signals.

As AM depth percent increases, amplitude change through the pulse gets steeper, which makes modulation more observable. Furthermore PW value is also very important for the modulation to be recognized, wider the pulse less steep the modulation. For instance 30% AM depth is recognized for 10μsec PW as given in the table, however it would not be recognized if the PW was 500μsec. Parallel to these facts, for the fixed PW value of 10μsec, system can recognize L-AM type for Percent AM Depths greater than 20%. For AM depth values less than 15%, system confuses the signal with modulationless pure signals, as expected.

To see the effect of Mean Amplitude on recognition of Linear AM signals, other parameters were kept constant and Mean Amplitude was swept through 0,1mV to 100mV. Test results are given in Table 5.10.

Table 5.10. Effect of Mean Amplitude on recognition of Linear AM type signals

Fs (MHz)	**PW (μsec)**	**Mean Amplitude (mV)**	**AM Type**	**%AM Depth**	**SNR**	**Result**
256	10	0,1; 0,5; 1; 2; 5; 10; 20; 30; 50; 100	L-inc	30	35	**L-AM**

It is clearly seen from Table 5.10 that system performance is independent of Mean Amplitude value, for Linear AM signals.

Finally, to see the result of changing SNR on system decision, SNR was swept through 35dB to 0dB for fixed values of other signal parameters. Test results are given in Table 5.11.

Table 5.11. Effect of SNR on recognition of Linear AM type signals

Fs (MHz)	PW (μsec)	Mean Amplitude (mV)	AM Type	%AM Depth	SNR	Result
256	10	10	L-inc	30	35	**L-AM**
256	10	10	L-inc	30	30; 25; 20	**NL-AM (Ramp)**
256	10	10	L-inc	30	15	**NL-FM**
256	10	10	L-inc	30	10	**BPSK**
256	10	10	L-inc	30	5	**MPSK**
256	10	10	L-inc	30	0	**NL-FM**

As seen from the table, system performance decays as the SNR decreases. System makes correct decision for SNR greater than 15dB. This fact can also be observed from Figure 5.6.

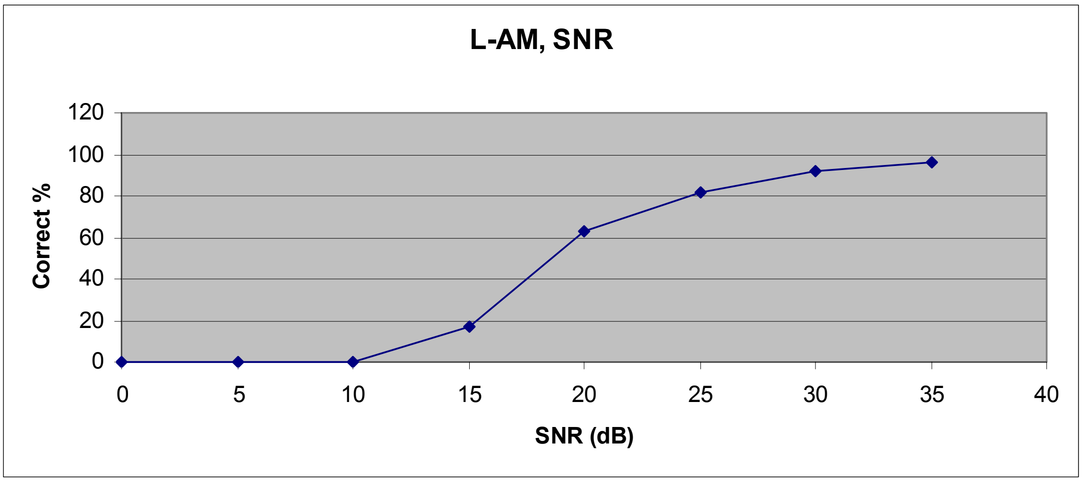

Figure 5.6. System performance at different SNR values for Linear AM signals.

5.2.2.2. Nonlinear AMOP Case

This type of tests can be classified into three groups depending on the modulation shape.

➢ *Parabolic AMOP Case*

With different combinations of Sampling Rate, PW, Modulation Shape, % AM Depth and SNR values, a total of 55 distinct Parabolic AM signal type was formed. These signals were generated 100 times with and a new noise was added to each of them in order to achieve correct recognition percentages given in the graphs.

To observe the effect of PW on recognition of Parabolic AM signals, PW was swept through 0,1μsec to 100μsec, and other parameters were kept fixed. Test results are given in Table 5.12.

Table 5.12. Effect of PW on recognition of Parabolic AM signals

Fs (MHz)	PW (μsec)	Mean Amplitude (mV)	AM Type	%AM Depth	SNR	Result
256	0,1	10	P-parabolic	50	35	**NL-AM**
256	0,5	10	P-parabolic	50	35	**L-AM**
256	1 ; 2	10	P-parabolic	50	35	**NL-AM**
256	5	10	P-parabolic	50	35	**L-AM**
256	10; 20; 30; 50; 100	10	P-parabolic	50	35	**NL-AM**

Additionally, same tests were handled with 128MHz sampling rate in order to see the effect of sampling rate on Parabolic AM recognition. Results are presented in Table 5.13.

Table 5.13. Effect of Fs on recognition of Parabolic AM signals

Fs (MHz)	PW (μsec)	Mean Amplitude (mV)	AM Type	%AM Depth	SNR	Result
128	0,1	10	P-parabolic	50	35	**NL-AM**
128	0,5; 1; 2; 5	10	P-parabolic	50	35	**L-AM**
128	10	10	P-parabolic	50	35	**NL-AM**
128	20	10	P-parabolic	50	35	**L-AM**
128	30; 50; 100	10	P-parabolic	50	35	**NL-AM**

From Table 5.12 and Table 5.13 it is seen that system can recognize “Parabolic AMOP” type signals even for very small PW values. However, it is observed that the system performance decreases as the sampling rate changes from 256MHz to 128MHz. This is due to the fact that number of samples that can be supplied to the algorithm for modulation recognition increases with increasing sampling rate. Performance of the system for the two sampling rates can be seen comparatively in Figure 5.7.

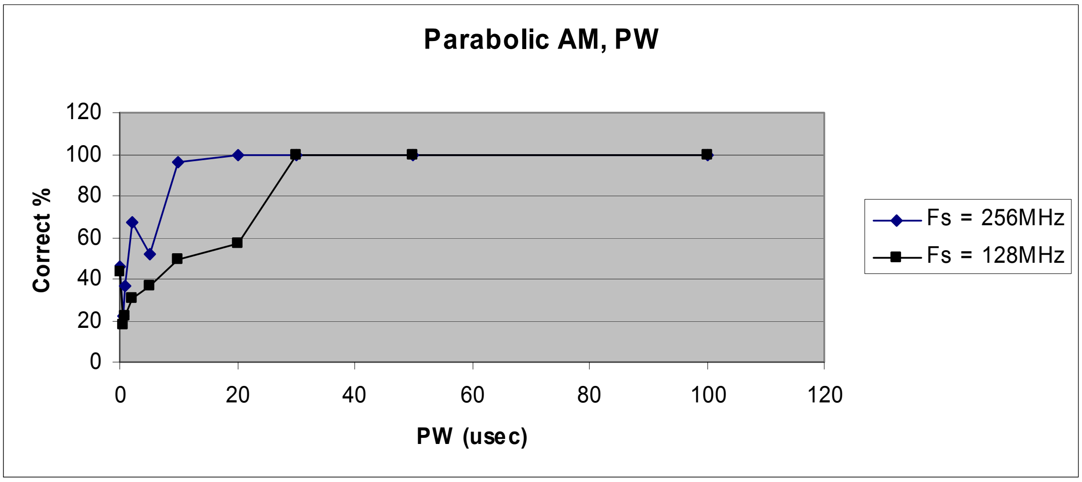

Figure 5.7. System performance at different sampling rates values for Parabolic AM signals.

PW is another parameter that effects the number of samples taken from the pulse, number of samples increases with increasing PW.

Furthermore, Percent AM Depth effects the recognition performance of the system. To measure this effect, Percentage AM Depth was swept through 70% to 1%, with all other parameters fixed. Test results are given in Table 5.14 and Figure 5.8.

Table 5.14. Effect of Percentage AM Depth on recognition of Parabolic AM signals

Fs (MHz)	**PW (µsec)**	**Mean Amplitude (mV)**	**AM Type**	**%AM Depth**	**SNR**	**Result**
256	10	10	P-parabolic	70	35	**NL-AM**
256	10	10	P-parabolic	60	35	**L-AM**
256	10	10	P-parabolic	50	35	**NL-AM**
256	10	10	P-parabolic	40 ; 30	35	**L-AM**
256	10	10	P-parabolic	20; 15; 10; 5; 1	35	**No Mod.**

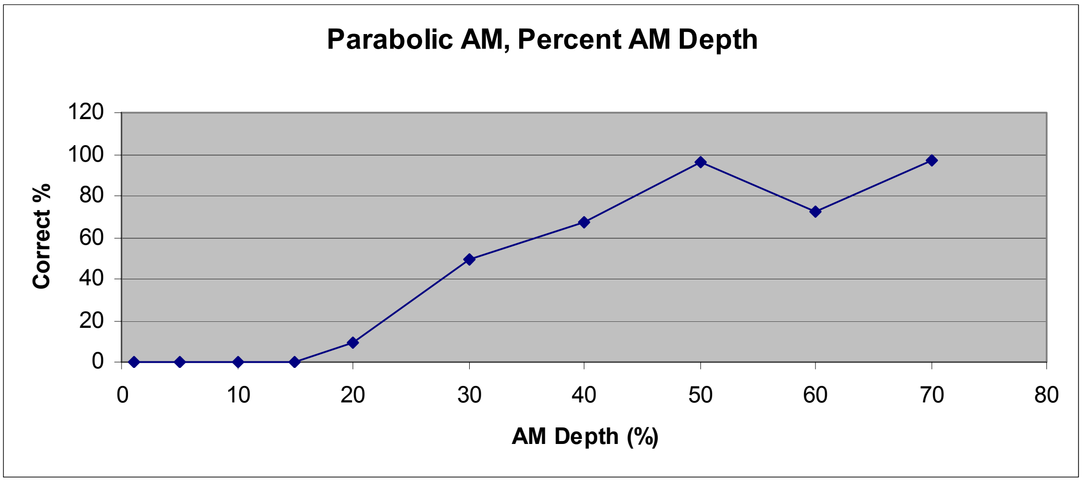

Figure 5.8. System performance at different modulation depths for Parabolic AM signals.

As given in the table above, for a fixed PW value system performance gets better as the Percent AM Depth increases, since the change in the signal amplitude becomes more obvious.

To sum up, performance of the system is improved when amplitude change through the pulse is large enough with respect to the PW, and when the continuous signal is sampled well enough to resemble the original signal's behavior.

To observe the effects of modulation shape on Parabolic AM recognition, tests in Table 5.12 were repeated for "Negative Parabolic" AM type. Results are given in Table 5.15.

Table 5.15. Effect of Modulation Shape on recognition of Parabolic AM signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	AM Type	%AM Depth	SNR	Result
256	0,1; 0,5; 1; 2; 5	10	N-parabolic	50	35	**L-AM**
256	10; 20	10	N-parabolic	50	35	**NL-AM**
256	30; 50; 100	10	N-parabolic	50	35	**L-AM**

If we compare the shapes of the envelopes of "Positive Parabolic" and "Negative Parabolic" signals, we see that "Positive Parabolic" has sharp edges at the beginning and end of the pulse. On the other hand, “Negative Parabolic” has a smoother shape. This explains why “Negative Parabolic” signals are mostly confused with Linear AM signals, as seen in the table. This effect can also be observed from Figure 5.9.

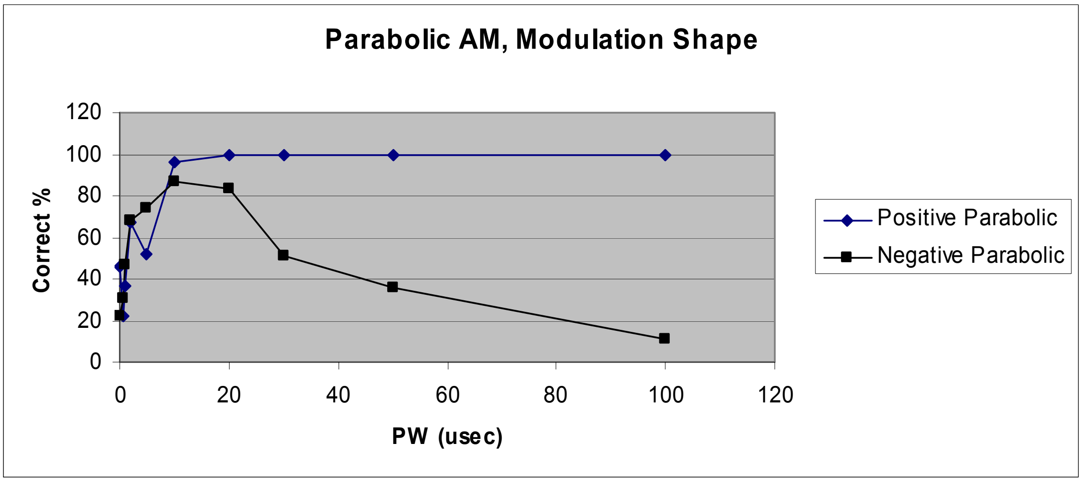

Figure 5.9. System performance at different modulation shapes for Parabolic AM signals.

To see the effect of Mean Amplitude on recognition of Parabolic AM signals, for fixed values of other parameters Mean Amplitude was swept through 0,1mV to 100mV. Test results are given in Table 5.16.

Table 5.16. Effect of Mean Amplitude on recognition of Parabolic AM type signals

Fs (MHz)	**PW (µsec)**	**Mean Amplitude (mV)**	**AM Type**	**%AM Depth**	**SNR**	**Result**
256	10	0,1; 0,5; 1; 2; 5; 10; 20; 30; 50; 100	P-parabolic	50	35	**NL-AM**

It is clearly seen from Table 5.16 that system performance is independent of Mean Amplitude value, for Parabolic AM signals.

Finally, to see the result of changing SNR on system decision, SNR was swept through 35dB to 0dB and all other parameters constant were kept constant. Test results are given in Table 5.17 and Figure 5.10.

Table 5.17. Effect of SNR on recognition of Parabolic AM signals

Fs (MHz)	**PW (µsec)**	**Mean Amplitude (mV)**	**AM Type**	**%AM Depth**	**SNR**	**Result**
256	10	10	P-parabolic	50	35; 30; 25; 20	**NL-AM**
256	10	10	P-parabolic	50	15	**NL-FM**
256	10	10	P-parabolic	50	10	**BPSK**
256	10	10	P-parabolic	50	5	**MPSK**
256	10	10	P-parabolic	50	1	**NL-FM**

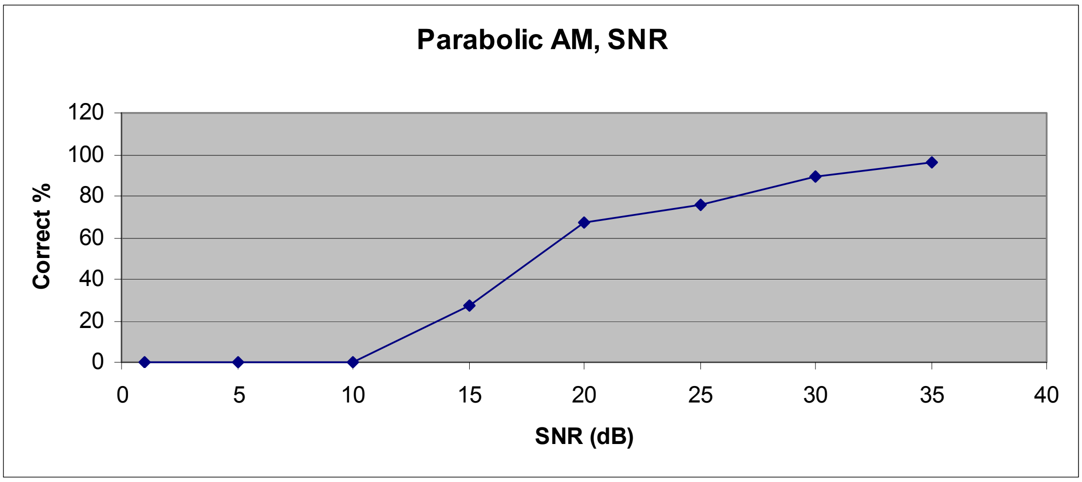

Figure 5.10. System performance at different SNR values for Parabolic AM signals.

As seen from the table and graph, system performance decays as the SNR decreases. System makes correct decision for SNR greater than 15dB.

- *Periodic AMOP Case*

A total of 74 distinct Periodic AM signal type was formed with different combinations of Sampling Rate, PW, Modulation Shape, % AM Depth, Frequency of the Modulating Wave and SNR values. These signals were generated 100 times with and a new noise was added to each of them in order to achieve correct recognition percentages given in the graphs.

To observe the effect of PW on recognition of Periodic AM signals, PW was swept through 0,1µsec to 100µsec, and Modulation Frequency was adjusted so that 2 periods of the modulating wave would be included in one pulse. Test results are given in Table 5.18.

Table 5.18. Effect of PW on recognition of Periodic AM signals

Fs (MHz)	**PW (µsec)**	**Mean Amplitude (mV)**	**AM Type**	**%AM Depth**	**Modulation Freq(MHz)**	**SNR**	**Result**
256	0,1; 0,5	10	Sinusoidal	50	20	35	**NL-AM**
256	1	10	Sinusoidal	50	2	35	**L-AM**
256	2; 5; 10; 20; 30; 50	10	Sinusoidal	50	1	35	**NL-AM**
256	100	10	Sinusoidal	50	0,02	35	**L-AM**

Same signals were also sampled with 128MHz, in order to observe the effect of sampling rate on recognition of Periodic AM. Results are given in Table 5.19 and illustrated in Figure 5.11.

Table 5.19. Effect of Fs on recognition of Periodic AM signals

Fs (MHz)	**PW (µsec)**	**Mean Amplitude (mV)**	**AM Type**	**%AM Depth**	**Modulation Freq(MHz)**	**SNR**	**Result**
128	0,1; 0,5; 1; 2; 5; 10	10	Sinusoidal	50	20	35	**NL-AM**
128	20	10	Sinusoidal	50	0,1	35	**L-AM**
128	30; 50; 100	10	Sinusoidal	50	0,067	35	**NL-AM**

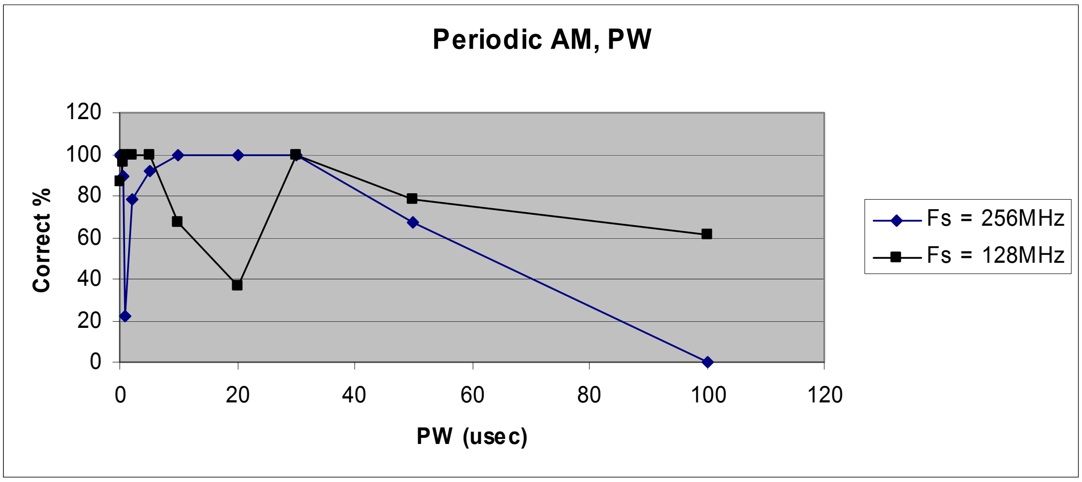

Figure 5.11. System performance at different sampling rates for Periodic AM signals.

Referring to the Table 5.18 and Table 5.19 it is seen that system can recognize "Periodic AMOP" type signals even for very small PW values. However, as the PW increases the change throughout the pulse becomes smoother, and this causes the modulation to be confused with Linear AM signals. Also we see that, system performance is approximately the same for both of the sampling rates.

Additionally, Percent AM Depth effects the recognition performance of the system. To measure this effect, Percentage AM Depth was swept through 70% to 1%, and other parameters were kept constant. Test results are given in Table 5.20.

Table 5.20. Effect of Percentage AM Depth on recognition of Periodic AM signals

Fs (MHz)	**PW (μsec)**	**Mean Amplitude (mV)**	**AM Type**	**%AM Depth**	**Modulation Freq(MHz)**	**SNR**	**Result**
256	10	10	Sinusoidal	70; 60; 50; 40	0,2	35	**NL-AM**
256	10	10	Sinusoidal	30; 20	0,2	35	**L-AM**
256	10	10	Sinusoidal	15	0,2	35	**NL-AM**
256	10	10	Sinusoidal	10; 5; 1	0,2	35	**No Mod.**

From Table 5.20 it is seen that system performance gets worse with decreasing AM depth. As AM depth decreases, system begins to confuse the NL-AM signal with

Linear AM signals. If AM depth is further decreased, modulation on the amplitude becomes unobservable and the system makes “No Modulation” decision. This fact is also demonstrated in the figure below.

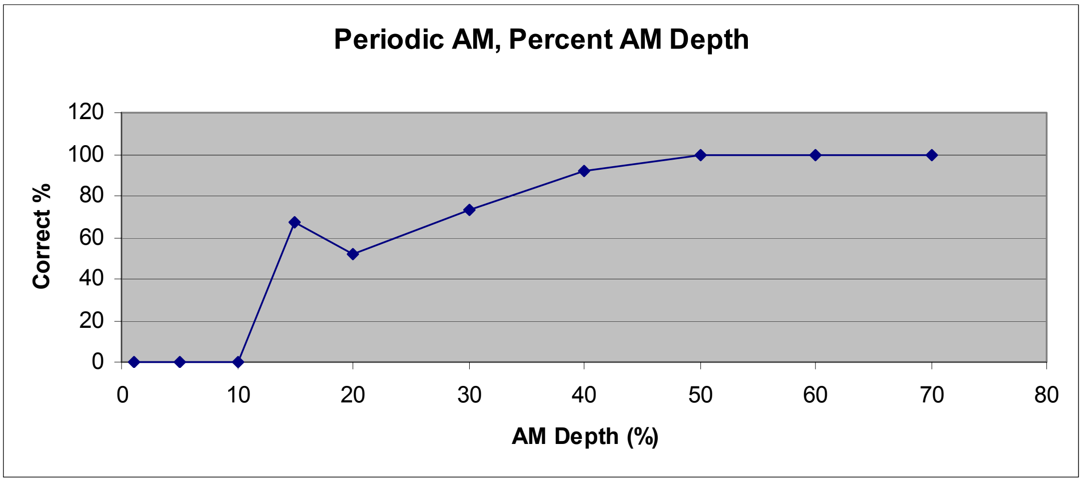

Figure 5.12. System performance at different modulation depths for Periodic AM signals.

To sum up, performance of the system is improved when amplitude change through the pulse is large enough with respect to the PW, and when the continuous signal is sampled well enough to resemble the original signal’s behavior.

To observe the effects of modulation shape on Periodic AM recognition, tests in Table 5.18 were repeated for “Triangular” and “Ramp” type AM signals. Results are given in Table 5.21.

Table 5.21. Effect of Modulation Shape on recognition of Periodic AM signals

Fs (MHz)	PW (μsec)	Mean Amplitude (mV)	AM Type	%AM Depth	Modulation Freq(MHz)	SNR	Result
256	0,1; 0,5; 1	10	Triangular	50	20	35	**NL-AM**
256	2	10	Triangular	50	1	35	**L-AM**
256	5; 10	10	Triangular	50	0,4	35	**NL-AM**
256	20	10	Triangular	50	0,1	35	**L-FM**

Table 5.21 (cont'd)

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	AM Type	%AM Depth	Modulation Freq(MHz)	SNR	Result
256	30; 50; 100	10	Triangular	50	0,067	35	**NL-AM**
256	*0,1; 0,5*	*10*	*Ramp*	*50*	*20*	*35*	***L-AM***
256	*1; 2*	*10*	*Ramp*	*50*	*2*	*35*	***NL-AM***
256	*5*	*10*	*Ramp*	*50*	*0,4*	*35*	***L-FM***
256	*10*	*10*	*Ramp*	*50*	*0,2*	*35*	***NL-AM***
256	*20*	*10*	*Ramp*	*50*	*0,1*	*35*	***NL-FM***
256	*30; 50; 100*	*10*	*Ramp*	*50*	*0,067*	*35*	***BPSK***

First of all, it is seen that this type of modulation is mostly confused with Linear AM, for all of the modulation shapes. However, due to the "linear" inclines and declines in the shape of "Triangular" and "Ramp" modulations, these are more exposed to confusion with Linear AM. Furthermore, the sharp vertices of the Triangular and Ramp waveforms in the envelope of pulse are reflected as jumps to the phase and frequency of these signals. This causes Triangular and especially Ramp waveforms to be confused with FM or PM signals, which is not encountered with Sinusoidal waveforms. System performance for different modulation shapes can be comparatively seen in Figure 5.13.

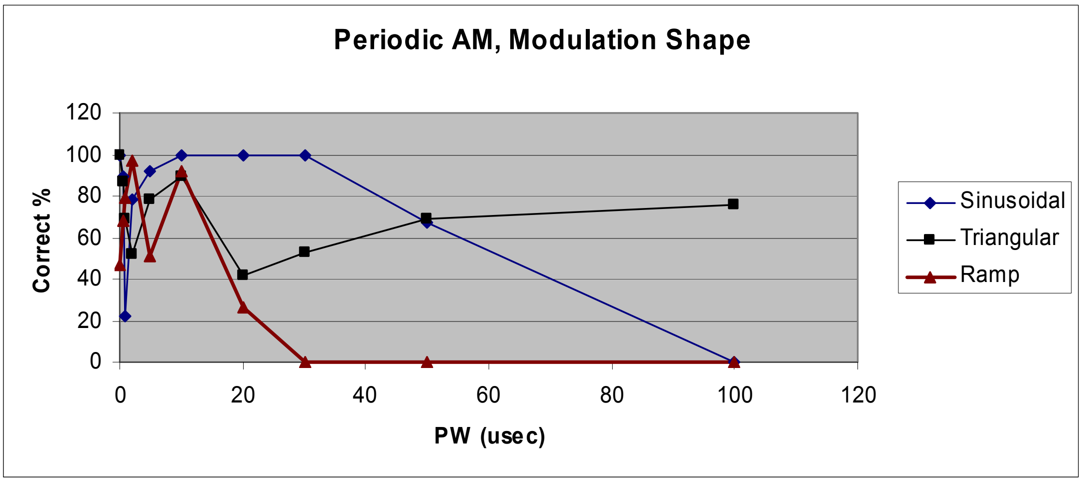

Figure 5.13. System performance at different modulation shapes for Periodic AM signals.

To see the effect of Mean Amplitude on recognition of Periodic AM signals, other parameters were kept constant and Mean Amplitude was swept through 0,1mV to 100mV. Test results are given in Table 5.22.

Table 5.22. Effect of Mean Amplitude on recognition of Periodic AM type signals

Fs (MHz)	**PW (μsec)**	**Mean Amplitude (mV)**	**AM Type**	**%AM Depth**	**Modulation Freq(MHz)**	**SNR**	**Result**
256	10	0,1; 0,5; 1; 2; 5; 10; 20; 30; 50; 100	Sinusoidal	50	0,2	35	**NL-AM**

As it is seen from Table 5.22, system performance is independent of Mean Amplitude value, for Periodic AM signals.

In order to see the result of changing SNR on system decision, SNR was swept through 35dB to 0dB for fixed values of other signal parameters. Test results are given in Table 5.23.

Table 5.23. Effect of SNR on recognition of Periodic AM signals

Fs (MHz)	**PW (μsec)**	**Mean Amplitude (mV)**	**AM Type**	**%AM Depth**	**Modulation Freq(MHz)**	**SNR**	**Result**
256	10	10	Sinusoidal	50	0,2	35; 30; 25; 20	**NL-AM**
256	10	10	Sinusoidal	50	0,2	15	**NL-FM**
256	10	10	Sinusoidal	50	0,2	10	**BPSK**
256	10	10	Sinusoidal	50	0,2	5	**MPSK**
256	10	10	Sinusoidal	50	0,2	0	**NL-FM**

It is seen from the table that system performance decays as the SNR decreases. System makes correct decision for SNR greater than 15dB. System performance for different SNR values are also given in Figure 5. 14.

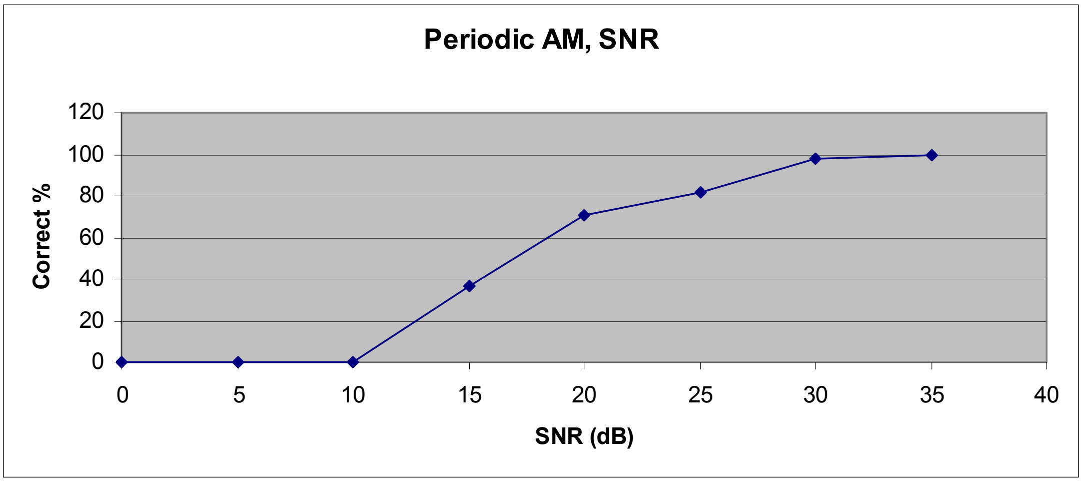

Figure 5.14. System performance at different SNR values for Periodic AM signals.

Finally, several tests were handled for the effect of Modulation Frequency. For this purpose, other parameters were kept fixed and the Modulation Frequency was swept from 0,1MHz to 1MHz, so that 1 to 10 periods of the modulating wave would be included in one pulse. Test results are given both in Table 5.24 and in Figure 5.15.

Table 5.24. Effect of Modulation Frequency on recognition of Periodic AM type signals

Fs (MHz)	**PW (µsec)**	**Mean Amplitude (mV)**	**AM Type**	**%AM Depth**	**Modulation Freq(MHz)**	**SNR**	**Result**
256	10	10	Sinusoidal	50	0,1	35	**L-AM**
256	10	10	Sinusoidal	50	0,2; 0,3; 0,4	35	**NL-AM**
256	10	10	Sinusoidal	50	0,5	35	**L-AM**
256	10	10	Sinusoidal	50	0,6; 0,7; 0,8	35	**NL-AM**
256	10	10	Sinusoidal	50	0,9	35	**L-FM**
256	10	10	Sinusoidal	50	1	35	**NL-AM**

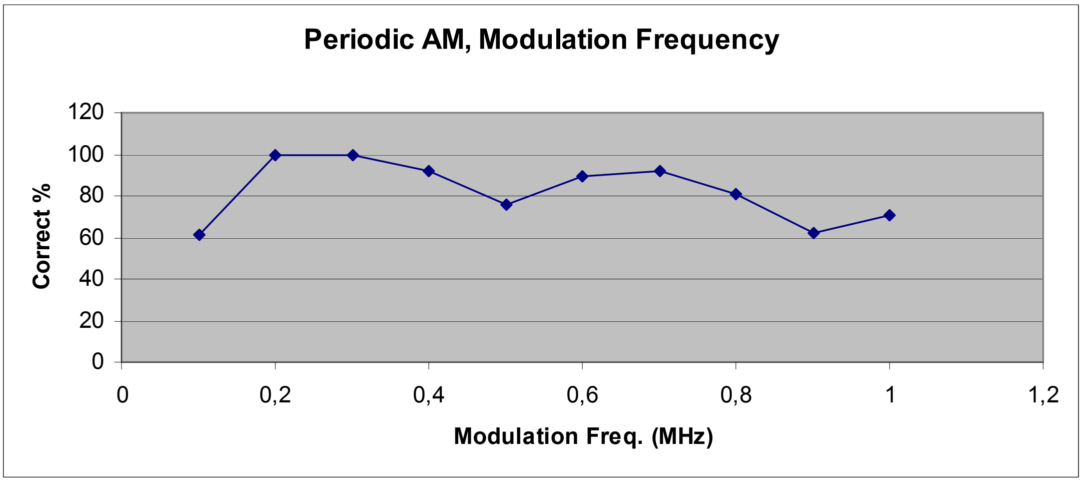

Figure 5.15. System performance at different Modulation Frequency values for Periodic AM signals.

Referring to the table we see that system makes Linear AM decision when Modulation Frequency is 0,1MHz, i.e. 1 period of the sine wave is seen in the amplitude of the pulse. This means that change in the amplitude is very smooth, hence it is confused with Linear AM. Furthermore, for very high Modulation Frequencies, due to the reason that changes in the amplitude occur very fast, system becomes more apt to make wrong decisions.

➢ *Square AMOP Case*

A total of 66 distinct Square AM signal type was generated with different combinations of Sampling Rate, PW, Modulation Shape, % AM Depth, Frequency and Duty Ratio of the Modulating Wave, and SNR values. These signals were generated 100 times with and a new noise was added to each of them in order to achieve correct recognition percentages given in the graphs.

To observe the effect of PW on recognition of Square AM signals, PW was swept through 0,1μsec to 100μsec, and Modulation Frequency was adjusted so that 2 periods of the modulating wave would be included in one pulse. Test results are given in Table 5.25.

Table 5.25. Effect of PW on recognition of Square AM signals

Fs (MHz)	PW (μsec)	Mean Amplitude (mV)	Duty Ratio	%AM Depth	Modulation Freq(MHz)	SNR	Result
256	0,1	10	50	20	20	35	**NL-AM**
256	0,5	10	50	20	4	35	**L-AM**
256	1; 2; 5; 10; 20; 30; 50	10	50	20	2	35	**NL-AM**
256	100	10	50	20	0,02	35	**BPSK**

Same signals were also sampled with 128MHz, in order to observe the effect of sampling rate on recognition of Square AM. Results are given in Table 5.26.

Table 5.26. Effect of Fs on recognition of Square AM signals

Fs (MHz)	PW (μsec)	Mean Amplitude (mV)	Duty Ratio	%AM Depth	Modulation Freq(MHz)	SNR	Result
128	0,1	10	50	20	20	35	**NL-AM**
128	0,5	10	50	20	4	35	**L-AM**
128	1; 2; 5; 10	10	50	20	2	35	**NL-AM**
128	20	10	50	20	0,1	35	**L-FM**
128	30; 50; 100	10	50	20	0,067	35	**NL-AM**

Referring to the Tables 5.24 and 5.25 it is seen that system performance is similar to the performance in Periodic AM case. Like Periodic AM, system can recognize “Square AMOP” type signals even for very small PW values. However, as the PW increases the change throughout the pulse becomes smoother. Additionally, just like Triangular and Ramp waveforms, sharp edges of the Square waveform in the envelope of pulse are reflected as jumps to the phase and frequency of the signals. This causes Square AM waveforms to be confused with FM or PM signals. Also we see that, system performance is approximately the same for both of the sampling rates. This fact can be observed from the graph in Figure 5.16.

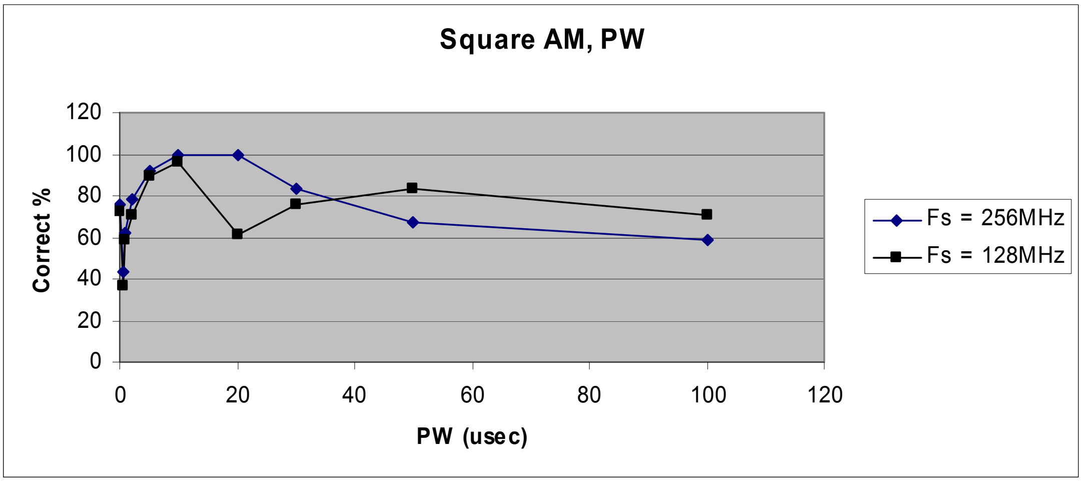

Figure 5.16. System performance at different sampling rates for Square AM signals.

Percent AM Depth is another factor that effects recognition performance. In order to see this effect, Percentage AM Depth was swept through 70% to 1%, and other parameters were kept fixed. Test results are given in Table 5.27 and illustrated in Figure 5.17.

Table 5.27. Effect of Percentage AM Depth on recognition of Square AM signals

Fs (MHz)	PW (μsec)	Mean Amplitude (mV)	Duty Ratio	%AM Depth	Modulation Freq(MHz)	SNR	Result
256	10	10	50	70; 60; 50	0,2	35	**BPSK**
256	10	10	50	40	0,2	35	**NL-AM**
256	10	10	50	30	0,2	35	**NL-FM**
256	10	10	50	20; 15; 10	0,2	35	**NL-AM**
256	10	10	50	5; 1	0,2	35	**No Mod.**

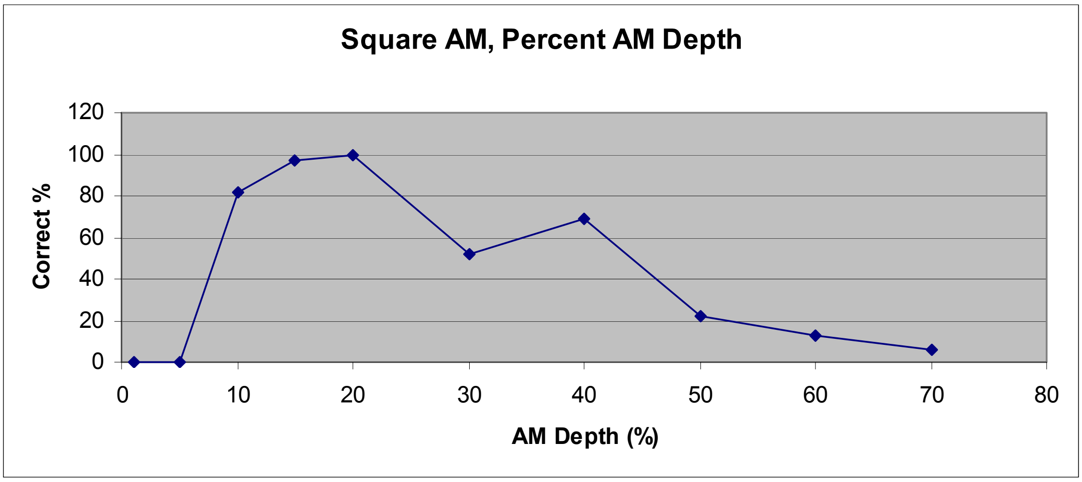

Figure 5.17. System performance at different modulation depths for Square AM signals.

For very large AM depths (greater than %50) splits in the envelope of the signal becomes drastically large. This causes the sharp edges of the Square waveform in the envelope of pulse to be reflected as jumps to the phase and frequency of the signals, thus Square AM waveforms are confused with FM or PM signals. Also for very small AM depths (less than 5%), it is seen that system begins to confuse the NL-AM signal with “No Modulation” type signals. Because, for these AM depths modulation on the amplitude becomes unobservable.

Duty Ratio of the Square wave is the ratio of the positive portion of the wave to the negative portion, in one period of the square. In order to observe the effects of this parameter on modulation recognition, Duty Ratio of the modulating square wave was swept from 5% to 90% for constant values of all other parameters. Results are given in Table 5.28 and Figure 5.18.

Table 5.28. Effect of Duty Ratio on recognition of Square AM signals

Fs (MHz)	PW (μsec)	Mean Amplitude (mV)	Duty Ratio	%AM Depth	Modulation Freq(MHz)	SNR	Result
256	10	10	5	20	0,2	35	**NL-AM**
256	10	10	10	20	0,2	35	**NL-FM**
256	10	10	15 to 90	20	0,2	35	**NL-AM**

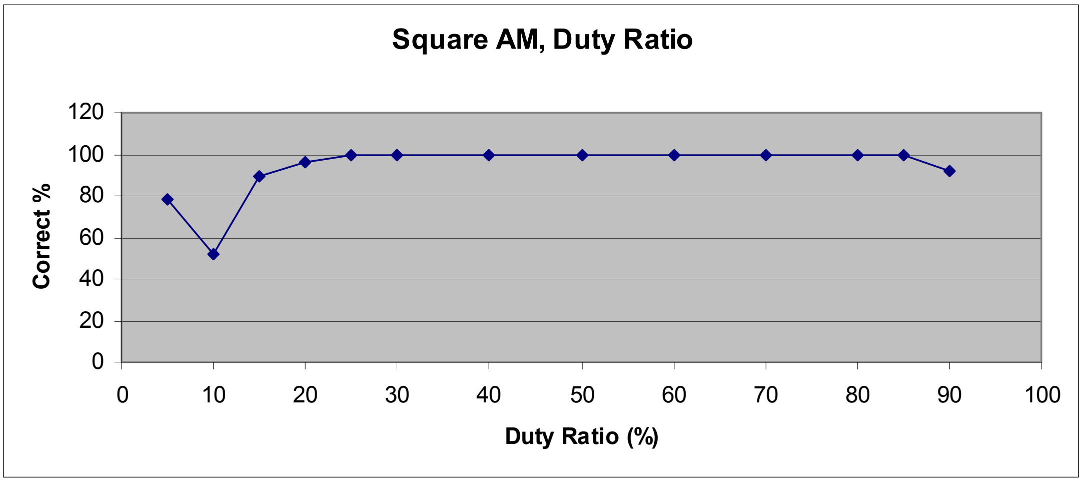

Figure 5.18. System performance at different duty ratio values for Square AM signals.

From the table and figure above, it is seen that system performance is not effected much by the change of the duty ratio of the square waveform.

To see the effect of Mean Amplitude on recognition of Square AM signals, Mean Amplitude was swept through 0,1mV to 100mV, with all other parameters fixed. Test results are given in Table 5.29.

Table 5.29. Effect of Mean Amplitude on recognition of Square AM type signals

Fs (MHz)	**PW (μsec)**	**Mean Amplitude (mV)**	**Duty Ratio**	**%AM Depth**	**Modulation Freq(MHz)**	**SNR**	**Result**
256	10	0,1; 0,5; 1; 2; 5; 10; 20; 30; 50; 100	50	20	0,2	35	**NL-AM**

As it is seen from Table 5.29, system performance is independent of Mean Amplitude value, for Square AM signals.

In order to see the result of changing SNR on system decision, for fixed values of other parameters SNR was swept through 35dB to 0dB. Test results are given in Table 5.30.

Table 5.30. Effect of SNR on recognition of Square AM signals

Fs (MHz)	PW (μsec)	Mean Amplitude (mV)	Duty Ratio	%AM Depth	Modulation Freq(MHz)	SNR	Result
256	10	10	50	20	0,2	35; 30; 25; 20	**NL-AM**
256	10	10	50	20	0,2	15	**NL-FM**
256	10	10	50	20	0,2	10	**BPSK**
256	10	10	50	20	0,2	5	**MPSK**
256	10	10	50	20	0,2	0	**BPSK**

As seen from Table 5.30, system performance decays as the SNR decreases. System makes correct decision for SNR greater than 10dB. This fact can also be seen in Figure 5.19.

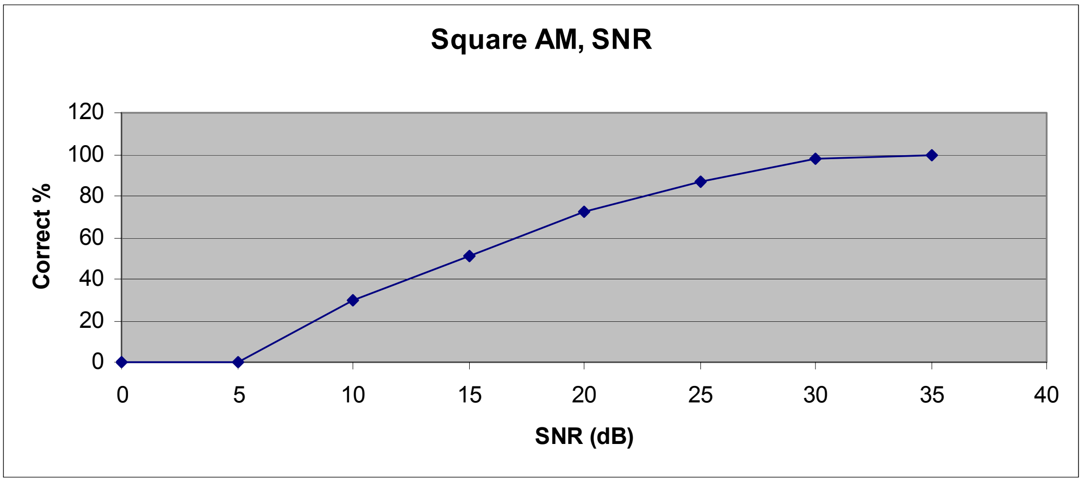

Figure 5.19. System performance at different SNR values for Square AM signals.

Additionally, tests were handled for the purpose of measuring effect of Modulation Frequency on modulation recognition. All other parameters constant were kept constant and Modulation Frequency was swept from 0,1MHz to 1MHz, so that 1 to 10 periods of the modulating wave would be included in one pulse. Test results are given in Table 5.31 and Figure 5.20.

Table 5.31. Effect of Modulation Frequency on recognition of Square AM type signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	Duty Ratio	%AM Depth	Modulation Freq(MHz)	SNR	Result
256	10	10	50	20	0,1; 0,2; 0,3; 0,4	35	**NL-AM**
256	10	10	50	20	0,5	35	**L-FM**
256	10	10	50	20	0,6; 0,7; 0,8	35	**NL-AM**
256	10	10	50	20	0,9; 1	35	**L-FM**

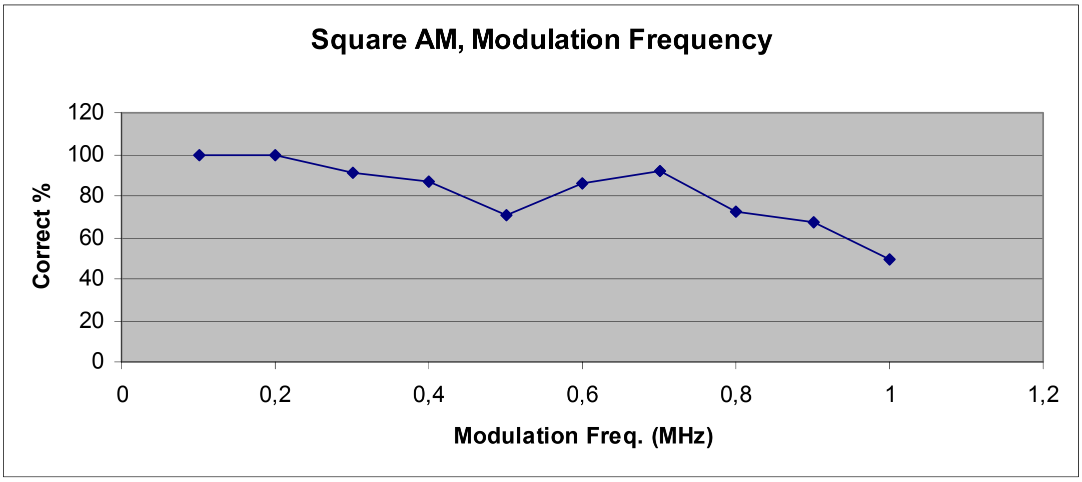

Figure 5.20. System performance at different modulation frequencies for Square AM signals.

Referring to the table and figure it is seen that, for very high Modulation Frequencies, due to the reason that changes in the amplitude occur very fast, system begins to make wrong decisions.

5.2.3. FMOP CASE

5.2.3.1. Linear FMOP Case

With different combinations of Sampling Rate, PW, Modulation Shape, Frequency Deviation, Mean Amplitude and SNR values, a total of 53 distinct Linear FM signal type was formed. These signals were generated 100 times with and a new noise was added to each of them in order to achieve correct recognition percentages given in the graphs.

Through the tests for Linear FM recognition, it is seen that Linear FM is mostly confused with Nonlinear FM signals. However, Linear modulation shape is also equivalent to half period of Triangular and Ramp modulation shapes. So, one should investigate the tables below taking this fact into account.

In order to test the effect of PW on recognition of Linear FM signals, PW was swept through 0,1μsec to 100μsec, and other parameters were kept constant. Test results are given in Table 5.32.

Table 5.32. Effect of PW on recognition of Linear FM signals

Fs (MHz)	PW (μsec)	Mean Amplitude (mV)	FM Type	Freq. Deviation(MHz)	SNR	Result
256	0,1	10	L-inc	30	35	**NL-AM**
256	0,5; 1	10	L-inc	30	35	**L-FM**
256	2; 5	10	L-inc	30	35	**NL-FM**
256	10	10	L-inc	30	35	**L-FM**
256	20; 30	10	L-inc	30	35	**NL-FM**
256	50; 100	10	L-inc	30	35	**NL-FM (Triangular)**

Referring to the table, it is seen that system can recognize Linear FM modulation for PW values greater than 0.5μsec. However, some fluctuations between Linear and Nonlinear FM were detected due to the variations in the randomly generated noise.

For the tests of sampling rate, tests given in Table 5.32 were repeated for 128MHz sampling rate. Test results are given in Table 5.33. Additionally, we can observe the performance of the system for Fs values comparatively in Figure 5.21.

Table 5.33. Effect of Fs on recognition of Linear FM signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	FM Type	Freq. Deviation(MHz)	SNR	Result
128	0,1; 0,5	10	L-inc	30	35	**NL-AM**
128	1	10	L-inc	30	35	**NL-FM**
128	2; 5	10	L-inc	30	35	**NL-FM**
128	10	10	L-inc	30	35	**L-FM**
128	20; 30	10	L-inc	30	35	**NL-FM**
128	50; 100	10	L-inc	30	35	**NL-FM (Triangular)**

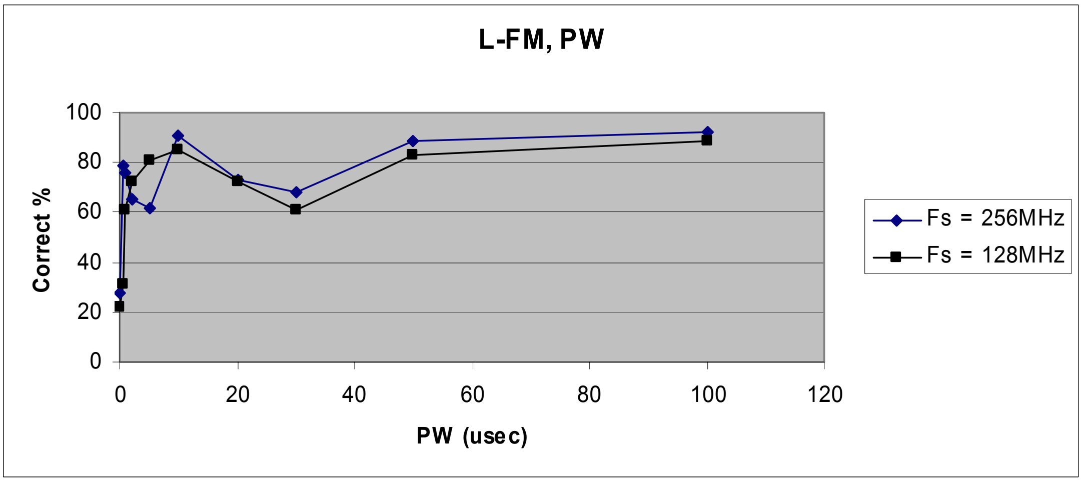

Figure 5.21. System performance at different sampling frequencies for Linear FM signals.

As it is seen in the table, system shows similar performance for both of the sampling rates. Additionally we see that recognition limit for PW is higher for Fs = 128MHz than Fs = 256MHz. This is an expected result because signal bandwidth is larger for small PW values, thus requires higher sampling rates due to the Nyquist rate.

To observe the effects of modulation shape on Linear FM recognition, tests in Table 5.32 were repeated for “Linear Decreasing” FM type. Results are given in Table 5.34.

Table 5.34. Effect of Modulation Shape on recognition of Linear FM signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	FM Type	Freq. Deviation(MHz)	SNR	Result
256	0,1; 0,5	10	L-dec	30	35	**NL-AM**
256	1	10	L-dec	30	35	**L-FM**
256	2; 5	10	L-dec	30	35	**NL-FM**
256	10	10	L-dec	30	35	**L-FM**
256	20; 30	10	L-dec	30	35	**NL-FM**
256	50; 100	10	L-dec	30	35	**NL-FM (Triangular)**

It is seen that modulation shape does not make a significant change in system performance for Linear FM recognition, which is also illustrated in Figure 5.22.

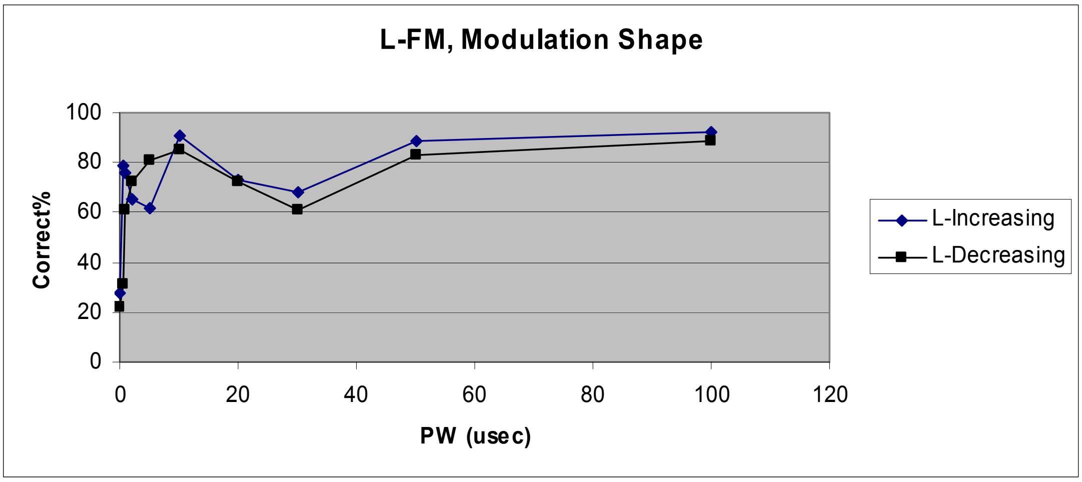

Figure 5.22. System performance at different modulation shapes for Linear FM signals.

In order to test the effect of Frequency Deviation, other parameters were kept constant and Frequency Deviation was swept through 50MHz to 1MHz. Test results are given in Table 5.35 and in Figure 5.23.

Table 5.35. Effect of Frequency Deviation on recognition of Linear FM signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	FM Type	Freq. Deviation(MHz)	SNR	Result
256	10	10	L-inc	50; 40	35	**NL-FM (Triangular)**
256	10	10	L-inc	30	35	**L-FM**
256	10	10	L-inc	20; 15	35	**NL-FM**
256	10	10	L-inc	10; 5; 1	35	**No Mod.**

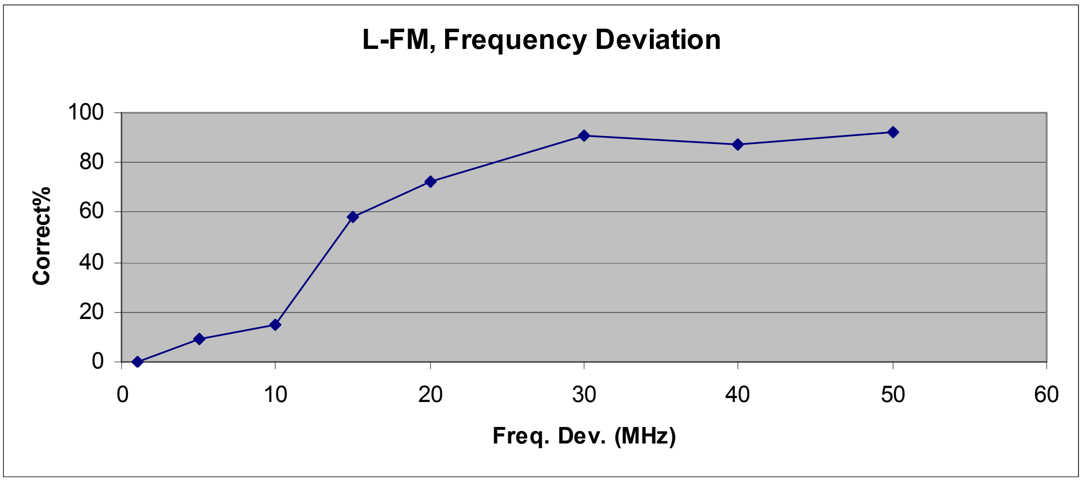

Figure 5.23. System performance at different frequency deviation values for Linear FM signals.

As Frequency Deviation increases, frequency change through the pulse gets steeper, which makes modulation more observable. It is seen from the table that, for the fixed PW value of 10µsec, system can recognize L-FM type for Frequency Deviations greater than 20MHz. As the Frequency Deviation keeps decreasing, first of all system confuses the modulation with NL-FM. For Frequency Deviation values less than 10MHz, system confuses the signal with modulationless pure signals, as expected.

To see the effect of Mean Amplitude on recognition of Linear FM signals, Mean Amplitude was swept through 0,1mV to 100mV for fixed values of other signal parameters. Test results are given in Table 5.36.

Table 5.36. Effect of Mean Amplitude on recognition of Linear FM type signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	FM Type	Freq. Deviation(MHz)	SNR	Result
256	10	0,1; 0,5; 1; 2; 5; 10; 20; 30; 50; 100	L-inc	30	35	**L-FM**

It is seen from the table that performance is independent of Mean Amplitude value, for Linear FM signals.

Finally, to see the result of changing SNR on system decision, SNR was swept through 35dB to 0dB, and other parameters were kept fixed. Test results are given in Table 5.37.

Table 5.37. Effect of SNR on recognition of Linear FM type signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	FM Type	Freq. Deviation(MHz)	SNR	Result
256	10	10	L-inc	30	35; 30; 25; 20; 15	**L-FM**
256	10	10	L-inc	30	10	**NL-FM (Ramp)**
256	10	10	L-inc	30	5; 0	**NL-FM**

As seen from the table, system performance decays for very small SNR values. System makes correct decision for SNR greater than 5dB. This fact is also seen in Figure 5.24.

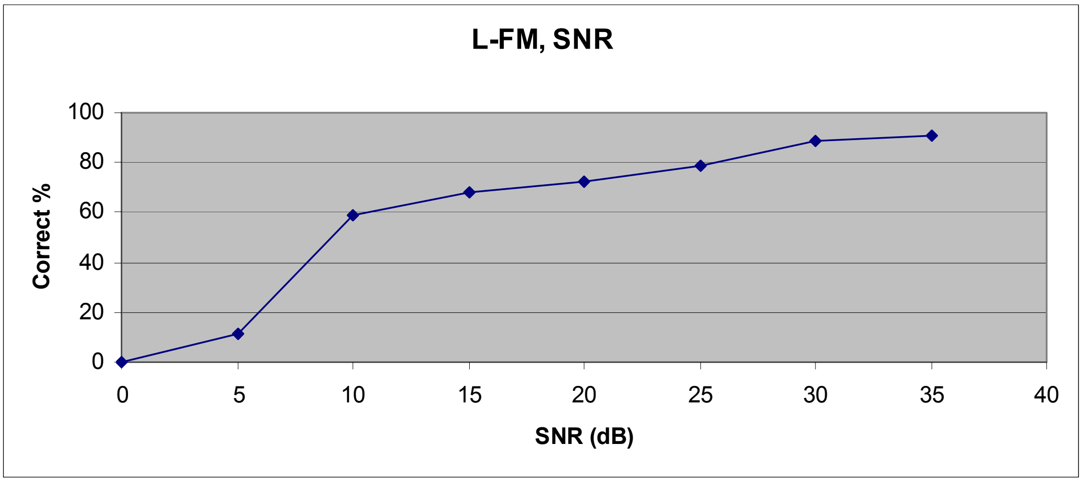

Figure 5.24. System performance at different SNR values for Linear FM signals.

5.2.3.2. Nonlinear FMOP Case

This type of tests can be classified into three groups depending on the modulation shape.

- *Parabolic FMOP Case*

  With different combinations of Sampling Rate, PW, Modulation Shape, Frequency Deviations and SNR values, a total of 55 distinct Parabolic FM signal type was formed. These signals were generated 100 times with and a new noise was added to each of them in order to achieve correct recognition percentages given in the graphs.

  To observe the effect of PW on recognition of Parabolic FM signals, PW was swept through 0,1µsec to 100µsec, and other parameters were kept fixed. Test results are given in Table 5.38.

  Additionally, same tests were handled with 128MHz sampling rate in order to see the effect of sampling rate on Parabolic FM recognition. Results are presented in Table 5.39 and in Figure 5.25.

Table 5.38. Effect of PW on recognition of Parabolic FM signals

Fs (MHz)	PW (μsec)	Mean Amplitude (mV)	FM Type	Freq. Deviation(MHz)	SNR	Result
256	0,1	10	P-parabolic	30	35	**NL-AM**
256	0,5	10	P-parabolic	30	35	**L-FM**
256	1	10	P-parabolic	30	35	**NL-FM**
256	2; 5	10	P-parabolic	30	35	**L-FM**
256	10; 20; 30; 50; 100	10	P-parabolic	30	35	**NL-FM**

Table 5.39. Effect of Fs on recognition of Parabolic FM signals

Fs (MHz)	PW (μsec)	Mean Amplitude (mV)	FM Type	Freq. Deviation(MHz)	SNR	Result
128	0,1; 0,5	10	P-parabolic	30	35	**NL-AM**
128	1; 2; 5; 10; 20; 30; 50; 100	10	P-parabolic	30	35	**NL-FM**

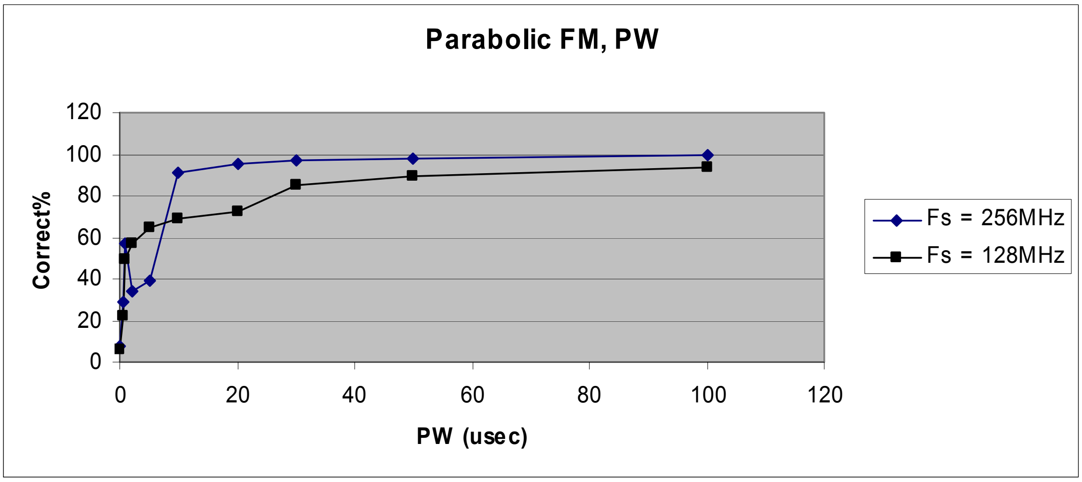

Figure 5.25. System performance at different sampling rates for Parabolic FM signals.

Referring to Tables 5.37 and 5.38, we see that system can make correct decision for PW values greater than 0,5μsec. Also it is seen that system behaves in a similar way for both sampling rates.

Another data set was produced to see the effect of Frequency Deviation value on the recognition performance of the system. To measure this effect, Frequency Deviation was swept through 70MHz to 1MHz for constant values of all other parameters. Test results are given in Table 5.40.

Table 5.40. Effect of Frequency Deviation on recognition of Parabolic FM signals

Fs (MHz)	**PW (μsec)**	**Mean Amplitude (mV)**	**FM Type**	**Freq. Deviation(MHz)**	**SNR**	**Result**
256	10	10	P-parabolic	70; 60; 50; 40; 30; 20	35	**NL-FM**
256	10	10	P-parabolic	15	35	**L-FM**
256	10	10	P-parabolic	10	35	**NL-FM**
256	10	10	P-parabolic	5; 1	35	**No Mod.**

As given in the table above, for a fixed PW value system performance gets better as the Frequency Deviation increases, since the change in the signal frequency becomes more obvious. For Frequency Deviation values less than 5MHz, modulation on frequency becomes unobservable such that signal is confused with modulationless pure signals. These facts can also be observed from the figure below.

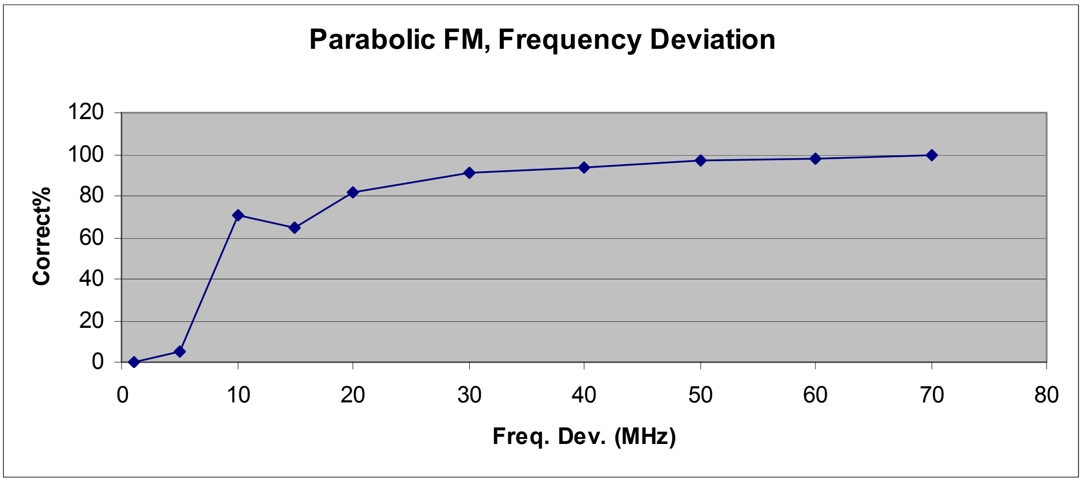

Figure 5.26. System performance at different frequency deviation values for Parabolic FM signals.

To observe the effects of modulation shape on Parabolic FM recognition, tests in Table 5.38 were repeated for “Negative Parabolic” FM type. Results are given in Table 5.41and Figure 5.27.

Table 5.41. Effect of Modulation Shape on recognition of Parabolic FM signals

Fs (MHz)	**PW (μsec)**	**Mean Amplitude (mV)**	**FM Type**	**Freq. Deviation(MHz)**	**SNR**	**Result**
256	0,1	10	N-parabolic	30	35	**NL-AM**
256	0,5	10	N-parabolic	30	35	**L-FM**
256	1; 2; 5; 10; 20; 30; 50; 100	10	N-parabolic	30	35	**NL-FM**

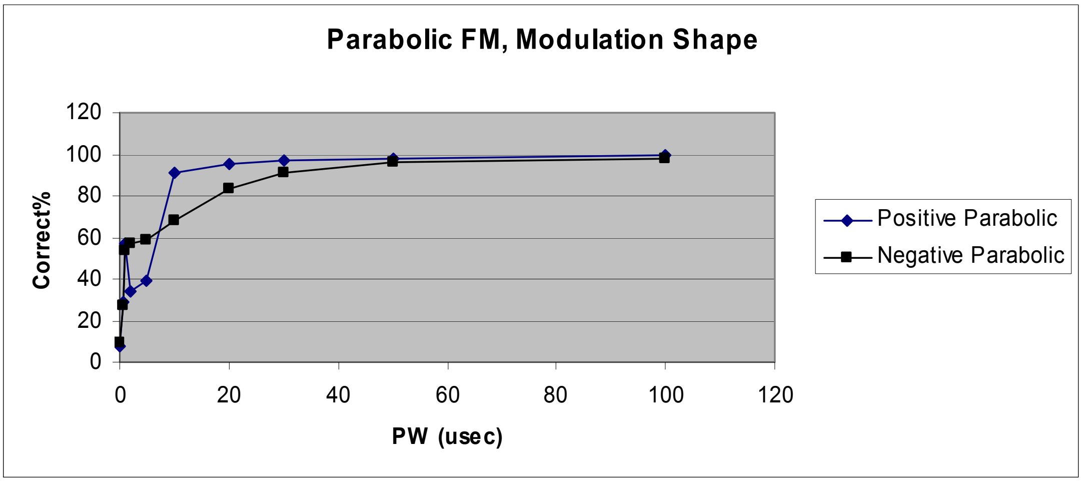

Figure 5.27. System performance at different modulation shapes for Parabolic FM signals.

It is seen that system performance does not change among Positive and Negative Parabolic shaped frequency modulated signals.

To see the effect of Mean Amplitude on recognition of Parabolic FM signals, Mean Amplitude was swept through 0,1mV to 100mV, with all other parameters fixed. Test results are given in Table 5.42.

Table 5.42. Effect of Mean Amplitude on recognition of Parabolic FM type signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	FM Type	Freq. Deviation(MHz)	SNR	Result
256	10	0,1; 0,5; 1; 2; 5; 10; 20; 30; 50; 100	P-parabolic	30	35	**NL-FM**

Finally, to see the result of changing SNR on system decision, for fixed values of other parameters SNR was swept through 35dB to 0dB. Test results are given in Table 5.43 and Figure 5.28.

Table 5.43. Effect of SNR on recognition of Parabolic FM signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	FM Type	Freq. Deviation(MHz)	SNR	Result
256	10	10	P-parabolic	30	35; 30; 25; 20; 15; 10; 5; 0	**NL-FM**

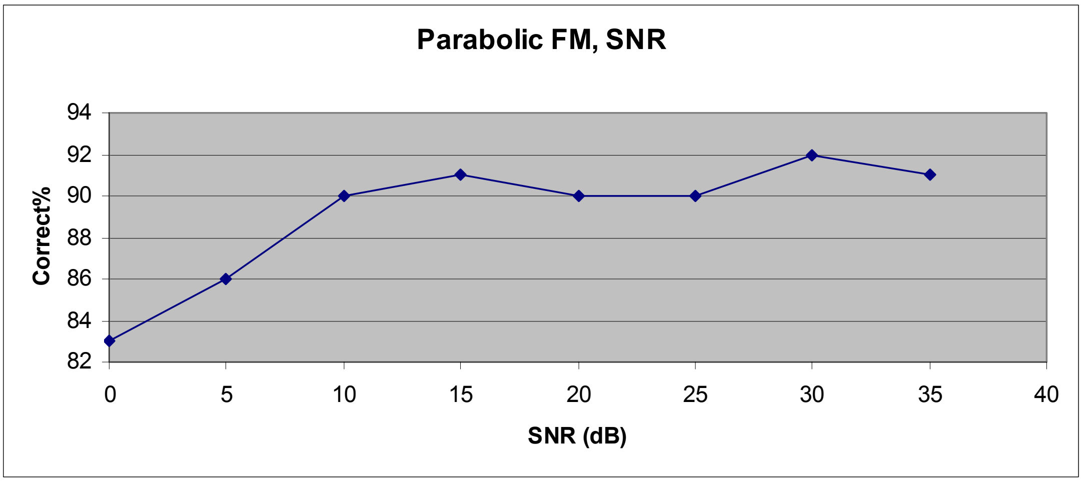

Figure 5.28. System performance at different SNR values for Parabolic FM signals.

It is clearly seen from Tables 5.42 and 5.43 that system performance is independent of Mean Amplitude and SNR values, for Parabolic FM signals.

- *Periodic FMOP Case*

A total of 74 distinct Periodic AM signal type was generated with different combinations of Sampling Rate, PW, Modulation Shape, Frequency Deviation, Frequency of the Modulating Wave and SNR values. These signals were generated 100 times with and a new noise was added to each of them in order to achieve correct recognition percentages given in the graphs.

To observe the effect of PW on recognition of Periodic FM signals, all other parameters constant were kept constant and PW was swept through 0,1µsec to 100µsec, and Modulation Frequency was adjusted so that 2 periods of the modulating wave would be included in one pulse. Test results are given in Table 5.44.

Table 5.44. Effect of PW on recognition of Periodic FM signals

Fs (MHz)	PW (μsec)	Mean Amplitude (mV)	FM Type	Freq. Deviation (MHz)	Modulation Freq(MHz)	SNR	Result
256	0,1	10	Sinusoidal	30	20	35	**NL-AM**
256	0,5	10	Sinusoidal	30	4	35	**NL-FM**
256	1	10	Sinusoidal	30	2	35	**L-FM**
256	2; 5; 10; 20; 30; 50; 100	10	Sinusoidal	30	1	35	**NL-FM**

Same signals were also sampled with 128MHz, in order to observe the effect of sampling rate on recognition of Periodic FM. Results are given in Table 5.45.

Table 5.45. Effect of Fs on recognition of Periodic FM signals

Fs (MHz)	PW (μsec)	Mean Amplitude (mV)	FM Type	Freq. Deviation (MHz)	Modulation Freq(MHz)	SNR	Result
128	0,1	10	Sinusoidal	30	20	35	**L-AM**
128	0,5; 1; 2	10	Sinusoidal	30	4	35	**NL-FM**
128	5	10	Sinusoidal	30	0,4	35	**L-FM**
128	10; 20; 30; 50; 100	10	Sinusoidal	30	0,2	35	**NL-FM**

Referring to the Tables 5.44 and 5.45 it is seen that system can recognize “Periodic FMOP” type signals even for PW values greater than 2μsec. Also we see that, system performance is approximately the same for both of the sampling rates, which can be observed from the figure below.

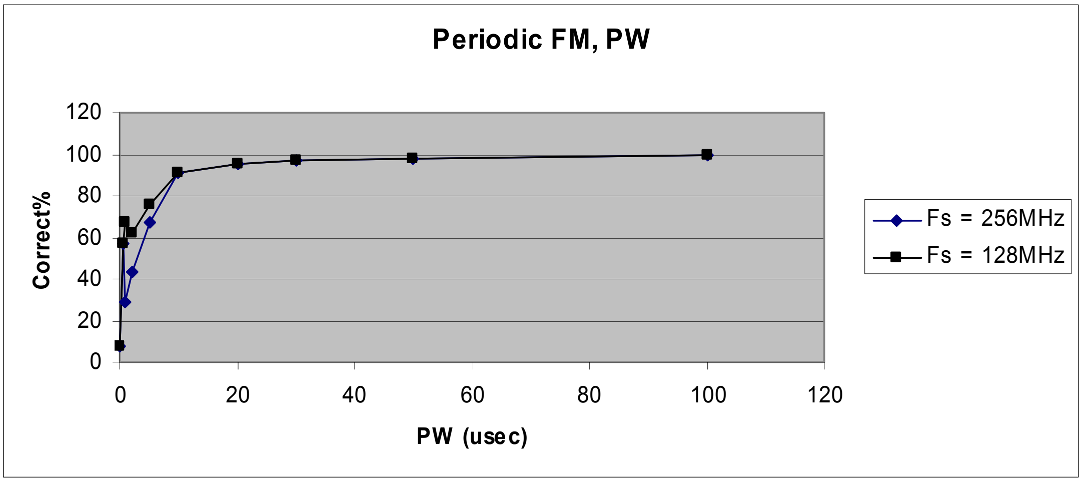

Figure 5.29. System performance at different sampling rates for Periodic FM signals.

Additionally, Frequency Deviation effects the recognition performance of the system. To measure this effect, Frequency Deviation was swept through 70MHz to 1MHz, and other parameters were kept constant. Test results are given in Table 5.46.

Table 5.46. Effect of Frequency Deviation on recognition of Periodic FM signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	FM Type	Freq. Deviation (MHz)	Modulation Freq(MHz)	SNR	Result
256	10	10	Sinusoidal	70; 60; 50; 40; 30; 20; 15; 10	0,2	35	**NL-FM**
256	10	10	Sinusoidal	5	0,2	35	**L-FM**
256	10	10	Sinusoidal	1	0,2	35	**No Mod.**

It is given in Table 5.46 that system makes correct decision for Frequency Deviation values greater than 5MHz. For smaller values, modulation on the frequency becomes unobservable and the system begins to make "Linear FM" decision. If the Frequency Deviation is further decreased, system makes "No Modulation" decision. This fact can be seen from Figure 5.30.

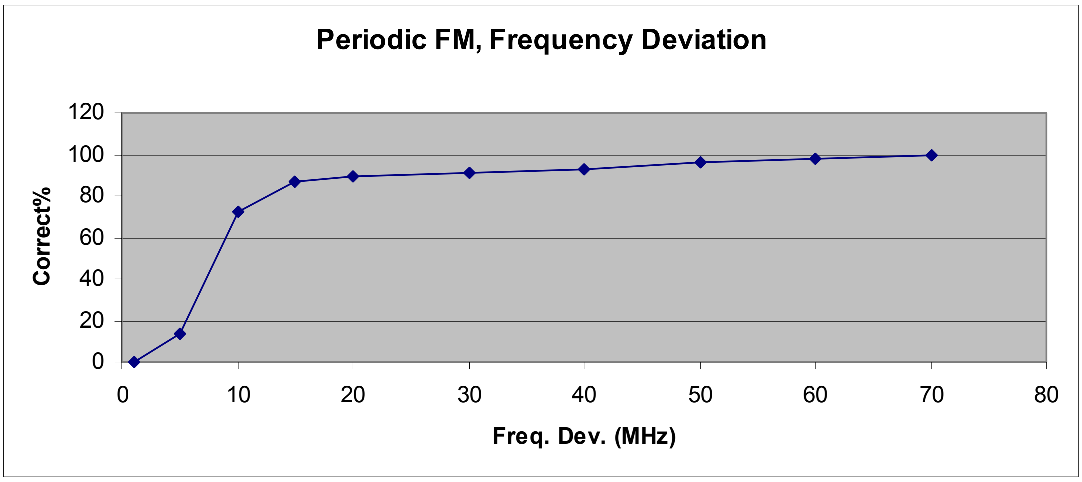

Figure 5.30. System performance at different Frequency Deviation values for Periodic FM signals.

To observe the effects of modulation shape on Periodic FM recognition, tests in Table 5.44 were repeated for “Triangular” and “Ramp” type FM signals. Results are given in Table 5.47 and Figure 5.31.

Table 5.47. Effect of Modulation Shape on recognition of Periodic FM signals

Fs (MHz)	**PW (µsec)**	**Mean Amplitude (mV)**	**FM Type**	**Freq. Deviation (MHz)**	**Modulation Freq(MHz)**	**SNR**	**Result**
256	0,1	10	Triangular	30	20	35	**NL-AM**
256	0,5	10	Triangular	30	4	35	**NL-FM**
256	1	10	Triangular	30	2	35	**L-FM**
256	2; 5; 10; 20; 30; 50; 100	10	Triangular	30	1	35	**NL-FM**
256	*0,1*	*10*	*Ramp*	*30*	*20*	*35*	***NL-AM***
256	*0,5; 1; 2; 5; 10*	*10*	*Ramp*	*30*	*4*	*35*	***NL-FM***
256	*20*	*10*	*Ramp*	*30*	*0,1*	*35*	***BPSK***
256	*30*	*10*	*Ramp*	*30*	*0,067*	*35*	***MPSK***
256	*50; 100*	*10*	*Ramp*	*30*	*0,04*	*35*	***No Mod.***

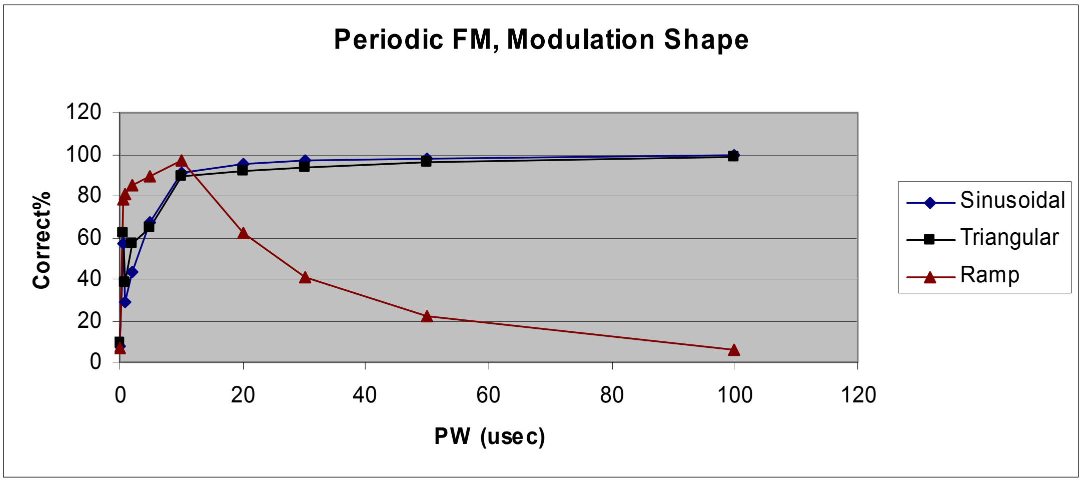

Figure 5.31. System performance at different modulation shapes for Periodic FM signals.

It is seen from Table 5.44 and 47 that system behavior is similar for Sinusoidal and Triangular waveforms. Apart from these, as PW increases in Ramp modulations, change in frequency becomes smoother and the system recognizes it as “single tone”, not “multi tone”. Thus, Ramp signals are confused with PM and No Modulation signals for PW values greater than 20µsec.

To see the effect of Mean Amplitude on recognition of Periodic FM signals, other parameters were kept constant and Mean Amplitude was swept through 0,1mV to 100mV, and each signal was sampled at 256MHz. Test results are given in Table 5.48.

Table 5.48. Effect of Mean Amplitude on recognition of Periodic FM type signals

Fs (MHz)	**PW (µsec)**	**Mean Amplitude (mV)**	**FM Type**	**Freq. Deviation (MHz)**	**Modulation Freq(MHz)**	**SNR**	**Result**
256	10	0,1; 0,5; 1; 2; 5; 10; 20; 30; 50; 100	Sinusoidal	30	0,2	35	**NL-FM**

As it is seen from Table 5.48, system performance is independent of Mean Amplitude value, for Periodic FM signals.

In order to see the result of changing SNR on system decision, SNR was swept through 35dB to 0dB for fixed values of other signal parameters. Test results are given in Table 5.49.

Table 5.49. Effect of SNR on recognition of Periodic FM signals

Fs (MHz)	PW (μsec)	Mean Amplitude (mV)	FM Type	Freq. Deviation (MHz)	Modulation Freq(MHz)	SNR	Result
256	10	10	Sinusoidal	30	0,2	35; 30; 25; 20; 15; 10; 5; 0	**NL-FM**

It is seen from the table that system performance remains unchanged for different SNR values, which can also be seen in Figure 5.32.

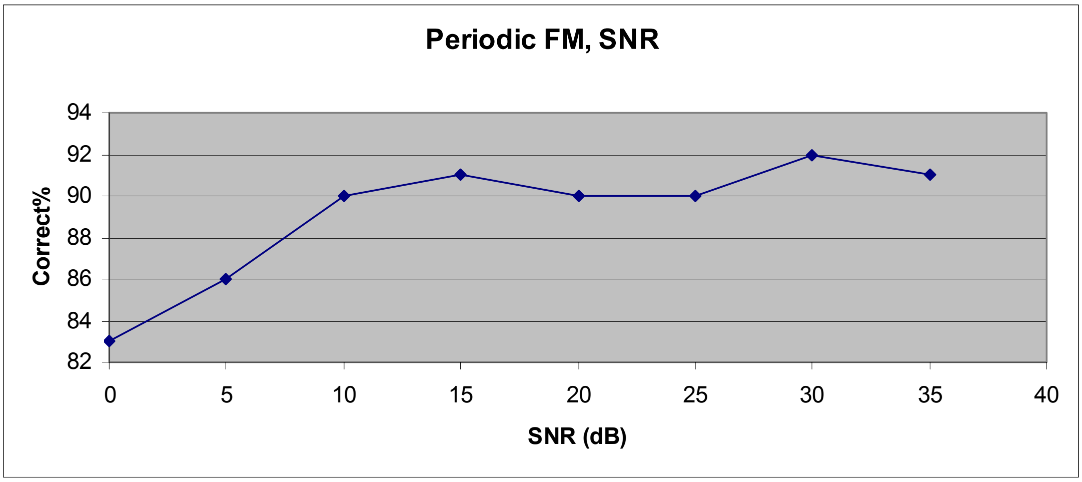

Figure 5.32. System performance at different SNR values for Periodic FM signals.

Finally, several tests were handled for the effect of Modulation Frequency. For this purpose, Modulation Frequency was swept from 0,1MHz to 1MHz, so that 1 to 10 periods of the modulating wave would be included in one pulse, and other parameters were kept fixed. Test results are given in Table 5.50 and Figure 5.33.

Table 5.50. Effect of Modulation Frequency on recognition of Periodic FM type signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	FM Type	Freq. Deviation (MHz)	Modulation Freq(MHz)	SNR	Result
256	10	10	Sinusoidal	30	0,1	35	**L-FM**
256	10	10	Sinusoidal	30	0,2 to 1	35	**NL-FM**

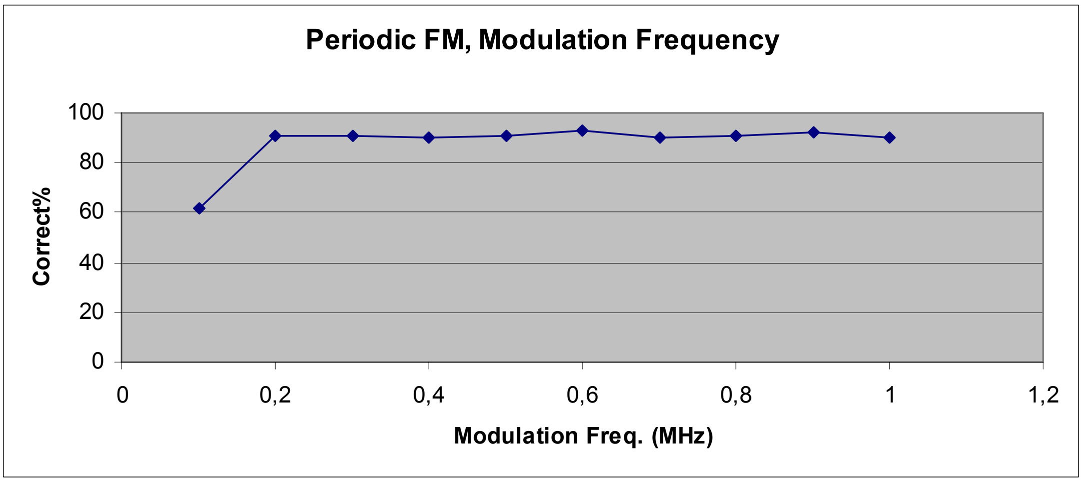

Figure 5.32. System performance at different modulation frequencies for Periodic FM signals.

Referring to the table we see that system makes Linear FM decision when Modulation Frequency is 0,1MHz, i.e. 1 period of the sine wave is seen in the frequency of the pulse. This means that change in the frequency is very smooth, hence it is confused with Linear FM.

- *Square FMOP Case*

A total of 68 distinct Square FM signal type was generated with different combinations of Sampling Rate, PW, Modulation Shape, Frequency Deviation, Frequency and Duty Ratio of the Modulating Wave, and SNR values. These signals were generated 100 times with and a new noise was added to each of them in order to achieve correct recognition percentages given in the graphs.

To observe the effect of PW on recognition of Square FM signals, PW was swept through 0,1µsec to 100µsec, and Modulation Frequency was adjusted so that 2 periods of the modulating wave would be included in one pulse. Test results are given in Table 5.51.

Table 5.51. Effect of PW on recognition of Square FM signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	Duty Ratio	Freq. Deviation (MHz)	Modulation Freq(MHz)	SNR	Result
256	0,1	10	50	30	20	35	**L-FM**
256	0,5; 1; 2; 5; 10; 20; 30; 50; 100	10	50	30	4	35	**NL-FM**

Same signals were also sampled with 128MHz, in order to observe the effect of sampling rate on recognition of Square FM. Results are given in Table 5.52.

Table 5.52. Effect of Fs on recognition of Square FM signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	Duty Ratio	Freq. Deviation (MHz)	Modulation Freq(MHz)	SNR	Result
128	0,1	10	50	30	20	35	**NL-AM**
128	0,5	10	50	30	4	35	**L-FM**
128	1; 2	10	50	30	2	35	**NL-FM**
128	5; 10; 20; 30; 50; 100	10	50	30	0,4	35	**BPSK**

From Tables 5.51 and 5.52 it is seen that system can recognize Square AM signals correctly for PW values greater than 0,5µsec. On the other hand, it is observed that system performance is better for large sampling rate. This fact is also seen from Figure 5.33.

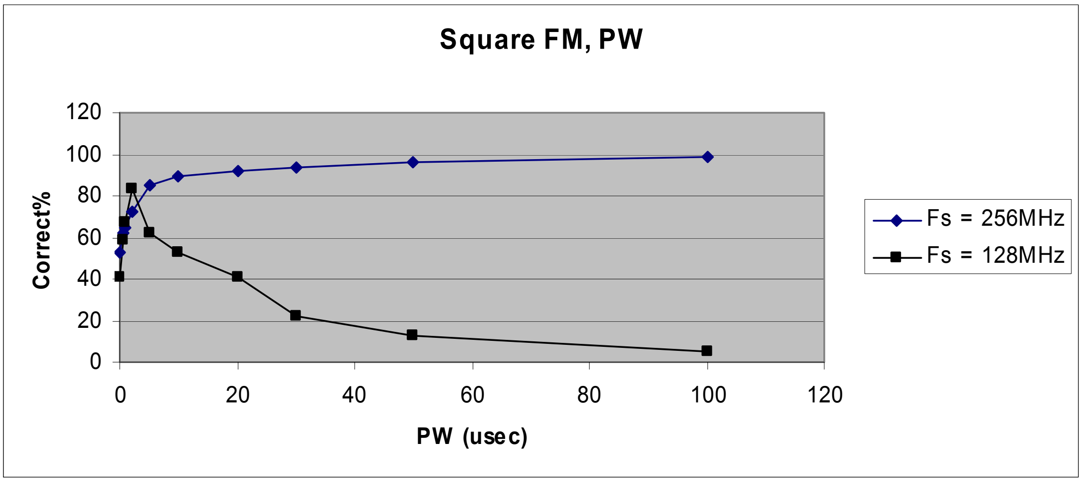

Figure 5.33. System performance at different sampling frequencies for Square FM signals.

Frequency Deviation is another factor that effects recognition performance. In order to see this effect, Frequency Deviation was swept through 70MHz to 1MHz, and other parameters were kept fixed. Test results are given in Table 5.53.

Table 5.53. Effect of Frequency Deviation on recognition of Square FM signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	Duty Ratio	Freq. Deviation (MHz)	Modulation Freq(MHz)	SNR	Result
256	10	10	50	70; 60; 50; 40; 30; 20; 15; 10	0,2	35	**NL-FM**
256	10	10	50	5	0,2	35	**BPSK**
256	10	10	50	1	0,2	35	**NL-FM**

According to Table 5.53, system performance is not effected much by the value of Frequency Deviation. However, for very small Frequency Deviation values (less than 5MHz), it is seen that system begins to confuse the NL-FM signal with PM type signals. Because, for these Frequency Deviations modulation on the frequency becomes unobservable. We can observe this from Figure 5.34 too.

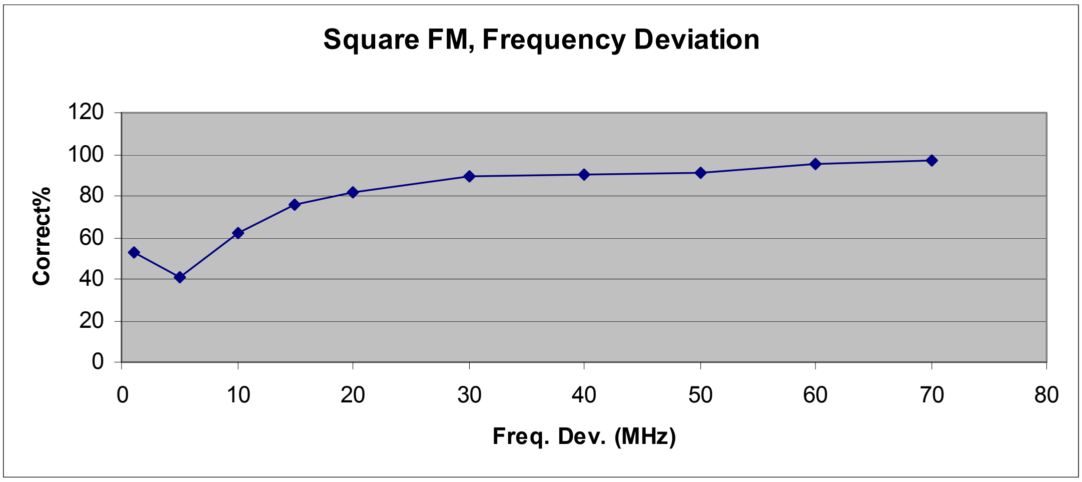

Figure 5.34. System performance at different frequency deviations for Square FM signals.

In order to observe the effects of Duty Ratio parameter on modulation recognition, Duty Ratio of the modulating square wave was swept from 5% to 99% for constant values of all other parameters. Results are given both in Table 5.54 and in Figure 5.35.

Table 5.54. Effect of Duty Ratio on recognition of Square FM signals

Fs (MHz)	**PW (μsec)**	**Mean Amplitude (mV)**	**Duty Ratio**	**Freq. Deviation (MHz)**	**Modulation Freq(MHz)**	**SNR**	**Result**
256	10	10	5 to 90	30	0,2	35	**NL-FM**
256	10	10	97; 99	30	0,2	35	**BPSK**

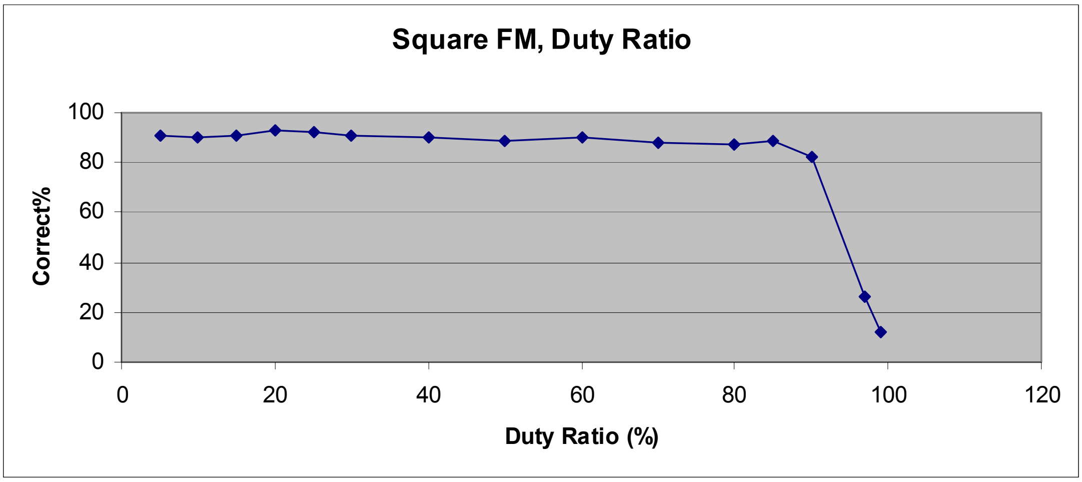

Figure 5.35. System performance at different duty ratio values for Square FM signals.

From Table 5.54 and Figure 5.35, it is seen that system performance is not effected much by the change of the duty ratio of the square waveform. However, if the duty ratio is too small (less than 5%) or too large (greater than 97%), waveform begins to lose its characteristic shape. For this reason system begins to make wrong decisions at the very high and very low limits of duty ratio.

To see the effect of Mean Amplitude on recognition of Square FM signals, Mean Amplitude was swept through 0,1mV to 100mV, with all other parameters fixed. Test results are given in Table 5.55.

Table 5.55. Effect of Mean Amplitude on recognition of Square FM type signals

Fs (MHz)	**PW (µsec)**	**Mean Amplitude (mV)**	**Duty Ratio**	**Freq. Deviation (MHz)**	**Modulation Freq(MHz)**	**SNR**	**Result**
256	10	0,1; 0,5; 1; 2; 5; 10; 20; 30; 50; 100	50	30	0,2	35	**NL-FM**

In order to see the result of changing SNR on system decision, for fixed values of other parameters SNR was swept through 35dB to 0dB. Test results are given in Table 5.56.

Table 5.56. Effect of SNR on recognition of Square FM signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	Duty Ratio	Freq. Deviation (MHz)	Modulation Freq(MHz)	SNR	Result
256	10	10	50	30	0,2	35; 30; 25; 20; 15; 10; 5; 0	**NL-FM**

As it is seen from Table 5.55 and Table 5.56, system performance is independent of Mean Amplitude and SNR values, for Square FM signals.

Finally, tests were handled for the purpose of measuring effect of Modulation Frequency on modulation recognition. For this purpose, Modulation Frequency was swept from 0,1MHz to 1MHz, so that 1 to 10 periods of the modulating wave would be included in one pulse. Test results are given in Table 5.57.

Table 5.57. Effect of Modulation Frequency on recognition of Square FM type

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	Duty Ratio	Freq. Deviation(MHz)	Modulatio n Freq(MHz)	SNR	Result
256	10	10	50	30	0,1 to 1	35	**NL-FM**

We see from Table 5.57 that system gives correct decision through the 0,1MHz – 1MHz Modulation Frequency range. We can conclude that system performance is not effected by the Modulation Frequency, if the parameter is in an acceptable range, i.e. 1-10 periods range.

➢ *BFSK Case*

With different combinations of Sampling Rate, PW, Frequency Deviation, Frequency of the Modulating Signal, Barker Code and SNR values, a total of 105 distinct BFSK signal type was generated. These signals were generated 100 times with and a new noise was added to each of them in order to achieve correct recognition percentages given in the graphs. These data were then fed to the recognizer block, in order to find the modulation type.

In order to test the effect of PW on recognition of BFSK signals, all other parameters constant were kept constant and PW was swept through 0,1μsec to 100μsec. Test results are given in Table 5.58.

Table 5.58. Effect of PW on recognition of BFSK signals

Fs (MHz)	PW (μsec)	Mean Amplitude (mV)	Barker Type	Freq. Deviation(MHz)	SNR	Result
256	0,1	10	5	30	35	**L-AM**
256	0,5	10	5	30	35	**L-FM**
256	1; 2; 5; 10; 20; 30; 50; 100	10	5	30	35	**NL-FM**

Referring to the table, it is seen that system can recognize BFSK modulation for PW values greater than 1μsec.

Tests given in Table 5.58 were repeated with 128MHz sampling rate, in order to see the effect of sampling frequency on system recognition for BFSK signals. Test results are given in Table 5.59 and Figure 5.36.

Table 5.59. Effect of Fs on recognition of BFSK signals

Fs (MHz)	PW (μsec)	Mean Amplitude (mV)	Barker Type	Freq. Deviation(MHz)	SNR	Result
128	0,1	10	5	30	35	**NL-AM**
128	0,5	10	5	30	35	**NL-AM**
128	1; 2; 5; 10	10	5	30	35	**NL-FM**
128	20	10	5	30	35	**L-FM**
128	30; 50; 100	10	5	30	35	**NL-FM**

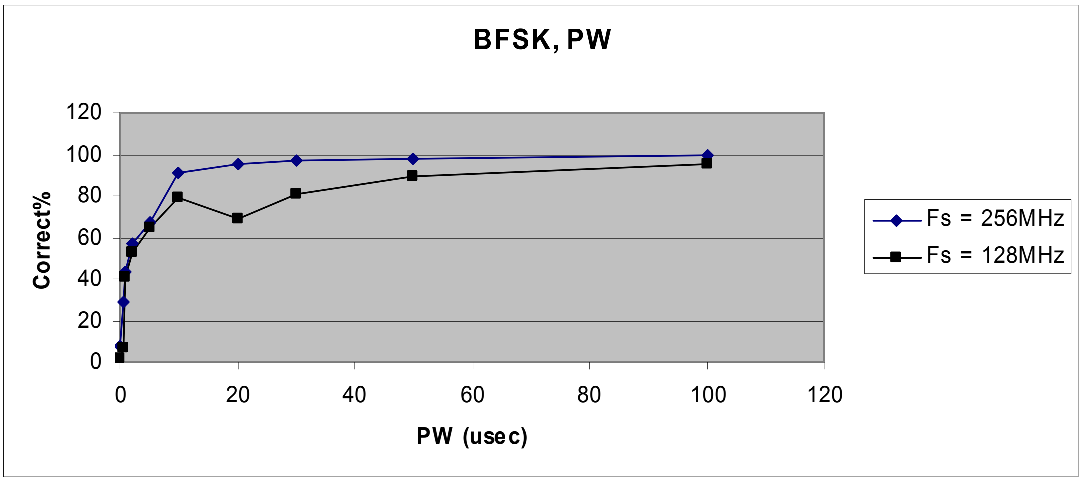

Figure 5.36. System performance at different duty ratio values for BFSK signals.

Comparing Tables 5.58 and 5.59, it is seen that system behaves in similar ways for 256MHz and 128MHz Sampling Rates.

To observe the effects of modulation shape on BFSK recognition, tests in Table 5.58 were repeated for all Barker Types. Results are given in Table 5.60.

Table 5.60. Effect of Modulation Shape on recognition of BFSK signals

Fs (MHz)	PW (μsec)	Mean Amplitude (mV)	Barker Type	Freq. Deviation(MHz)	SNR	Result
256	0,1	10	2	30	35	**NL-AM**
256	0,5	10	2	30	35	**L-FM**
256	1; 2; 5; 10; 20; 30; 50; 100	10	2	30	35	**NL-FM**
256	*0,1; 0,5*	*10*	*3*	*30*	*35*	***NL-AM***
256	*1*	*10*	*3*	*30*	*35*	***L-FM***
256	2; 5; 10; 20; 30; 50; 100	*10*	*3*	*30*	*35*	***NL-FM***
256	0,1	10	4	30	35	**L-AM**
256	0,5	10	4	30	35	**L-FM**

Table 5.60 (cont'd)

Fs (MHz)	PW (μsec)	Mean Amplitude (mV)	Barker Type	Freq. Deviation(MHz)	SNR	Result
256	1; 2; 5; 10; 20; 30; 50; 100	10	4	30	35	**NL-FM**
256	*0,1; 0,5*	*10*	*7*	*30*	*35*	***NL-AM***
256	1; 2; 5; 10; 20; 30; 50; 100	*10*	*7*	*30*	*35*	***NL-FM***
256	0,1	10	11	30	35	**L-FM**
256	0,5	10	11	30	35	**NL-AM**
256	1; 2; 5; 10; 20; 30; 50; 100	10	11	30	35	**NL-FM**
256	*0,1*	*10*	*13*	*30*	*35*	***NL-AM***
256	0,5; 1; 2; 5; 10; 20; 30; 50; 100	*10*	*13*	*30*	*35*	***NL-FM***

Readers are referred to the lookup table given in Appendix C, which consists of binary codes and their corresponding Barker code types.

We see that system performance is nearly the same for 2-3-4-5-7-11 bit Barker Codes. Furthermore system performance is improved with 13 bit Barker Code, because number of frequency jumps in this code is greater than other codes. Test results for different modulation shapes are also illustrated in the figure below.

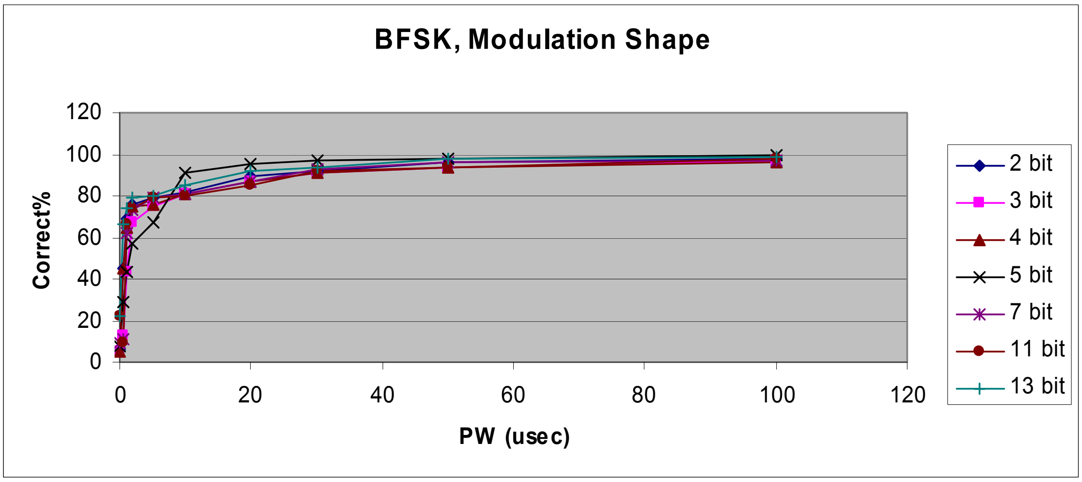

Figure 5.37. System performance at different modulation shapes for BFSK signals.

In order to test the effect of Frequency Deviation, Frequency Deviation was swept through 70MHz to 1MHz, and other parameters were kept constant. Test results are given in Table 5.61 and Figure 5.38.

Table 5.61. Effect of Frequency Deviation on recognition of BFSK signals

Fs (MHz)	PW (μsec)	Mean Amplitude (mV)	Barker Type	Freq. Deviation(MHz)	SNR	Result
256	10	10	5	70; 60; 50; 40; 30; 20; 15; 10; 5	35	**NL-FM**
256	10	10	5	1	35	**No Mod.**

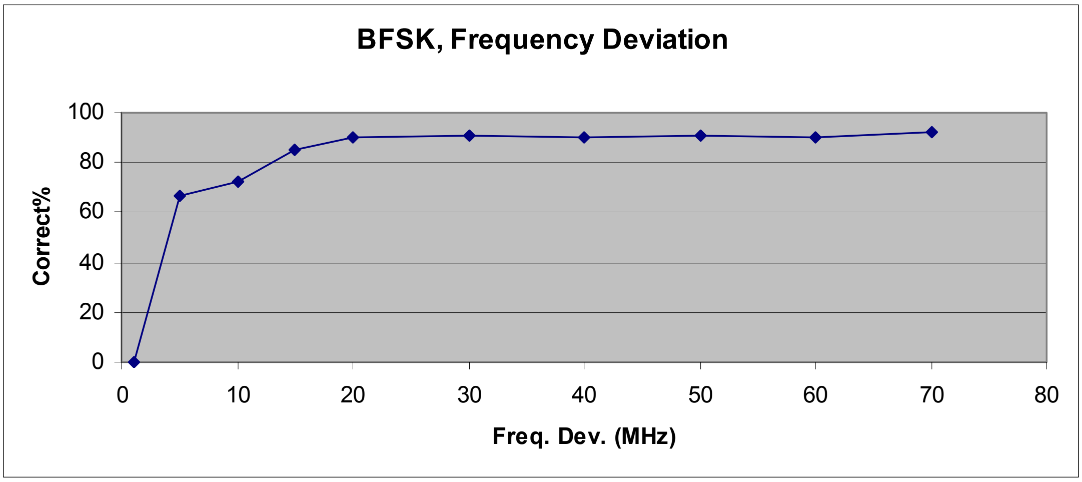

Figure 5.38. System performance at different Frequency Deviation values for BFSK signals.

As given in the table above, for a fixed PW value system performance gets better as the Frequency Deviation increases, since the change in the signal frequency becomes more obvious. For Frequency Deviation values less than 1MHz, modulation on frequency becomes unobservable such that signal is confused with modulationless pure signals.

To see the effect of Mean Amplitude on recognition of BFSK signals, other parameters were kept constant and Mean Amplitude was swept through 0,1mV to 100mV. Test results are given in Table 5.62.

Table 5.62. Effect of Mean Amplitude on recognition of BFSK signals

Fs (MHz)	PW (μsec)	Mean Amplitude (mV)	Barker Type	Freq. Deviation(MHz)	SNR	Result
256	10	0,1; 0,5; 1; 2; 5; 10; 20; 30; 50; 100	5	30	35	**NL-FM**

Finally, to see the result of changing SNR on system decision, SNR was swept through 35dB to 0dB for fixed values of other signal parameters. Test results are given in Table 5.63.

Table 5.63. Effect of SNR on recognition of BFSK signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	Barker Type	Freq. Deviation(MHz)	SNR	Result
256	10	10	5	30	35; 30; 25; 20; 15; 10; 5; 0	**NL-FM**

It is clearly seen from Tables 5.62 and 5.63 that system performance is independent of Mean Amplitude and SNR values, for BFSK signals.

5.2.4. PMOP CASE

5.2.4.1. BPSK Case

With different combinations of Sampling Rate, PW, Barker Type and SNR values, a total of 96 distinct BPSK signal type was generated. These signals were generated 100 times with and a new noise was added to each of them in order to achieve correct recognition percentages given in the graphs. These data were then fed to the recognizer block, in order to find the modulation type.

In order to test the effects of signal PW, PW was swept through 0,1µsec to 100µsec, and other parameters were kept fixed. Test results are given in Table 5.64.

Table 5.64. Effect of PW on recognition of BPSK signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	Barker Type	SNR	Result
256	0,1	10	5	35	**NL-AM**
256	0,5; 1; 2	10	5	35	**NL-FM**
256	5; 10; 20; 30; 50; 100	10	5	35	**BPSK**

From the table it is seen that system confuses BFSK signals with Nonlinear FM signals for small PW values. Since frequency of a signal is the derivative of its phase value, it is very natural that modulation on phase may be confused with modulation on frequency, and vice versa. Also, we see that system makes the correct “BPSK” decision for PW values greater than 5μsec.

To see the effect of Sampling Frequency on recognition of BPSK signals, tests given in Table 5.64 were repeated with Fs = 128MHz. Results are given in Table 5.65.

Table 5.65. Effect of Fs on recognition of BPSK signals

Fs (MHz)	**PW (μsec)**	**Mean Amplitude (mV)**	**Barker Type**	**SNR**	**Result**
128	0,1	10	5	35	**NL-AM**
128	0,5; 1; 2	10	5	35	**NL-FM**
128	5; 10; 20; 30; 50; 100	10	5	35	**BPSK**

If we make a comparison between Tables 5.64 and 5.65, we see that system performance is absolutely the same for both Sampling Rates. This comparison can also be observed from Figure 5.39

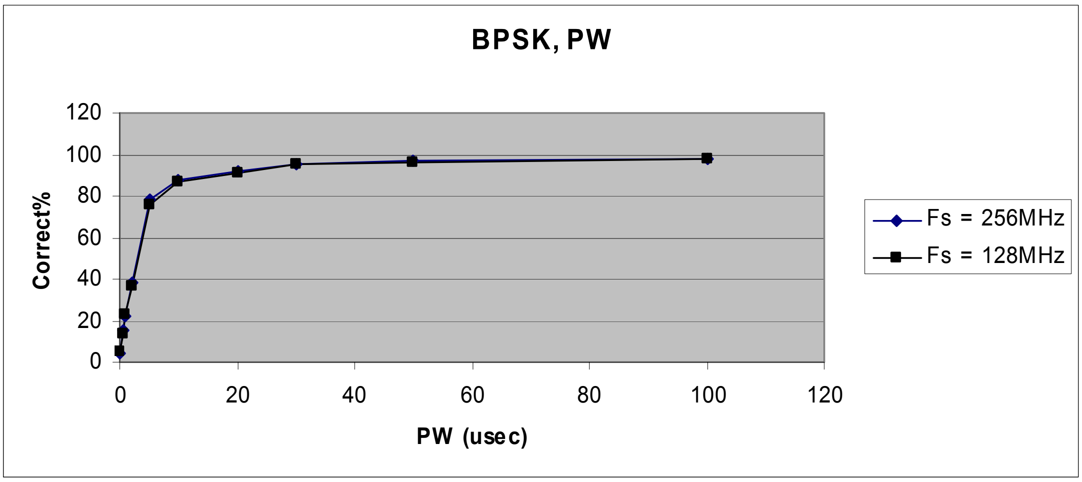

Figure 5.39. System performance at different sampling rates for BPSK signals.

To observe the effects of modulation shape on BPSK recognition, tests in Table 5.64 were repeated for all Barker Types. Results are given in Table 5.66 and Figure 5.40.

Table 5.66. Effect of Modulation Shape on recognition of BPSK signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	Barker Type	SNR	Result
256	0,1	10	2	35	**NL-AM**
256	0,5	10	2	35	**L-FM**
256	1; 2	10	2	35	**NL-FM**
256	5; 10; 20; 30; 50; 100	10	2	35	**BPSK**
256	*0,1*	*10*	*3*	*35*	***NL-AM***
256	*0,5; 1*	*10*	*3*	*35*	***L-FM***
256	*2*	*10*	*3*	*35*	***NL-FM***
256	5; 10; 20; 30; 50; 100	*10*	*3*	*35*	***BPSK***
256	0,1	10	4	35	**L-AM**
256	0,5	10	4	35	**L-FM**
256	1; 2	10	4	35	**NL-FM**
256	5; 10; 20; 30; 50; 100	10	4	35	**BPSK**
256	*0,1*	*10*	*7*	*35*	***NL-AM***
256	*0,5*	*10*	*7*	*35*	***L-FM***
256	*1*	*10*	*7*	*35*	***NL-FM***
256	2; 5; 10; 20; 30; 50; 100	*10*	*7*	*35*	***BPSK***
256	0,1; 0,5	10	11	35	**L-FM**
256	1; 2	10	11	35	**NL-FM**
256	5; 10; 20; 30; 50; 100	10	11	35	**BPSK**
256	*0,1; 0,5*	*10*	*13*	*35*	***L-FM***
256	*1; 2*	*10*	*13*	*35*	***NL-FM***
256	5; 10; 20; 30; 50; 100	*10*	*13*	*35*	***BPSK***

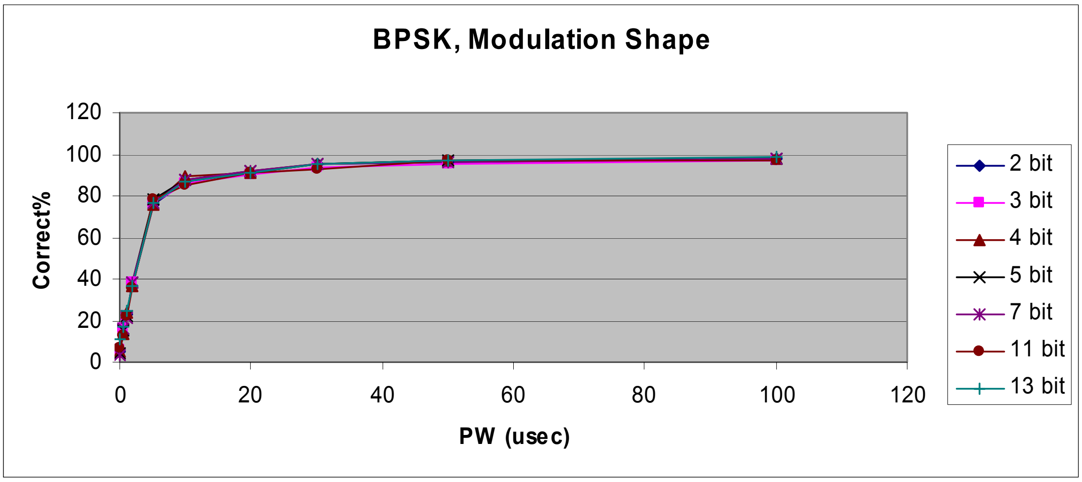

Figure 5.40. System performance at different modulation shapes for BPSK signals.

Readers are referred to the lookup table in Appendix C, which includes binary codes and their corresponding Barker code types.

It is seen that system performance remains the same for different Barker code types. For all types, system makes correct decision for PW values greater than 5μsec.

To see the effect of Mean Amplitude on recognition of BPSK signals, Mean Amplitude was swept through 0,1mV to 100mV, and other parameters were kept constant. Test results are given in Table 5.67.

Table 5.67. Effect of Mean Amplitude on recognition of BPSK signals

Fs (MHz)	**PW (μsec)**	**Mean Amplitude (mV)**	**Barker Type**	**SNR**	**Result**
256	10	0,1; 0,5; 1; 2; 5; 10; 20; 30; 50; 100	5	35	**BPSK**

It is clearly seen from Table 5.67 that system performance is independent of Mean Amplitude values, for BPSK signals.

Finally, to see the result of changing SNR on system decision, other parameters were fixed and SNR was swept through 35dB to 0dB. Test results are given in Table 5.68.

Table 5.68. Effect of SNR on recognition of BPSK signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	Barker Type	SNR	Result
256	10	10	5	35; 30; 25; 20; 15; 10	**BPSK**
256	10	10	5	5	**MPSK**
256	10	10	5	0	**NL-FM**

It can be seen in Table 5.68 that system performance decays with decreasing SNR, especially for SNR values less than 5dB. This can also be observed in Figure 5.41.

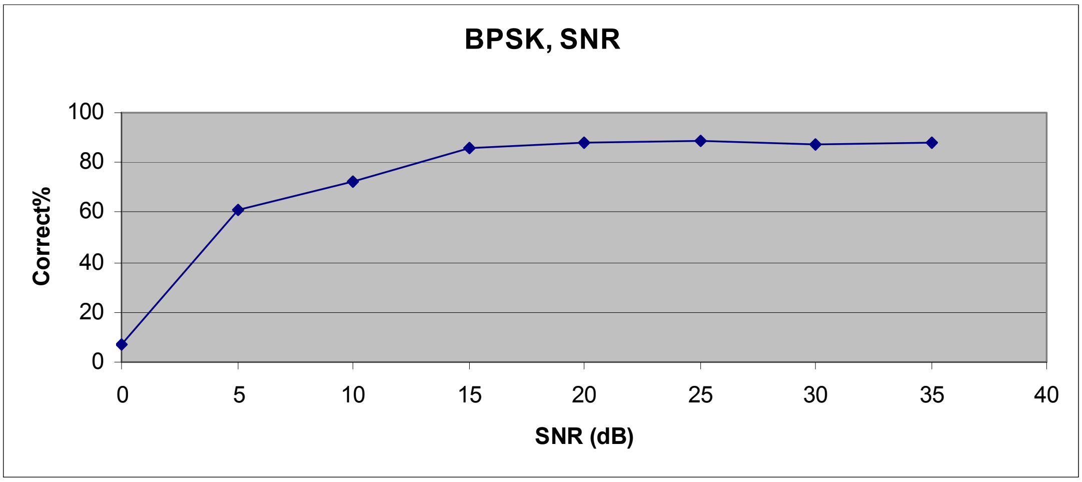

Figure 5.41. System performance at different SNR values for BPSK signals.

5.2.4.2. MPSK Case

With different combinations of Sampling Rate, PW, Number of Phase Steps and SNR values, a total of 66 distinct MPSK signal type was generated. 4, 6 and 8 step Frank codes are used in order to generate MPSK signals for the performance tests. In other words QPSK, 6-PSK and 8-PSK signals are used in the MPSK signal tests. These signals were generated

100 times with and a new noise was added to each of them in order to achieve correct recognition percentages given in the graphs.

In order to test the effects of PW, QPSK signals were generated for PW values between 0,1µsec and 100µsec. Test results are given in Table 5.69.

Table 5.69. Effect of PW on recognition of MPSK signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	Frank Type	SNR	Result
256	0,1	10	4	35	**NL-AM**
256	0,5	10	4	35	**L-FM**
256	1	10	4	35	**NL-FM**
256	2	10	4	35	**L-FM**
256	5; 10; 20; 30; 50; 100	10	4	35	**MPSK**

From Table 5.67 it is seen that system behavior is similar to the BPSK case. System makes the correct decision of "MPSK" for PW values greater than 5µsec.

Tests given in Table 5.69 were repeated with Fs = 128MHz in order to see the effect of Sampling Frequency on recognition of MPSK signals,. Results are given in Table 5.70 and Figure 5.42.

Table 5.70. Effect of Fs on recognition of MPSK signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	Frank Type	SNR	Result
128	0,1	10	4	35	**NL-AM**
128	0,5	10	4	35	**L-FM**
128	1	10	4	35	**NL-FM**
128	2	10	4	35	**L-FM**
128	5; 10; 20; 30; 50; 100	10	4	35	**MPSK**

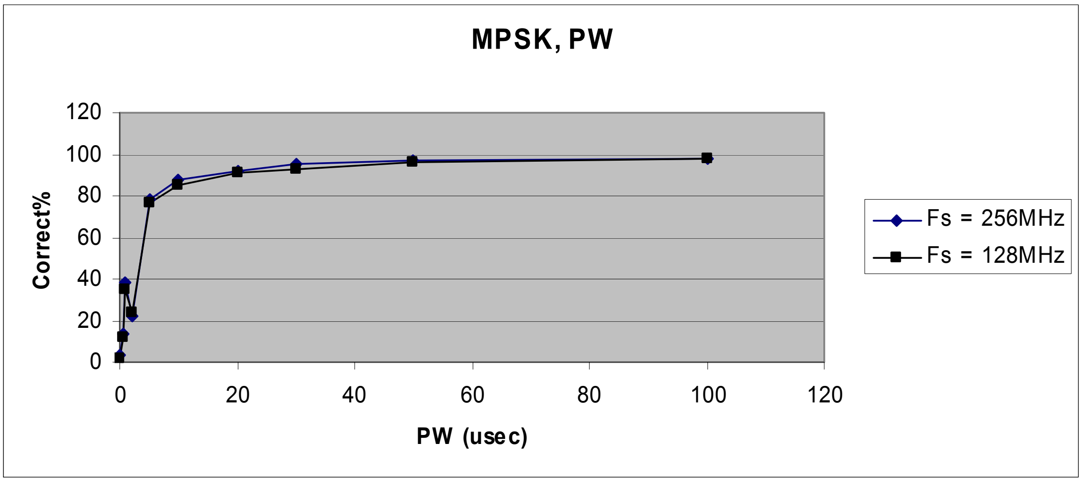

Figure 5.42. System performance at different sampling rates for MPSK signals.

We see that system performance remains unchanged with respect to different sampling rates.

To observe the effects of modulation shape on MPSK recognition, tests in Table 5.69 were repeated for both 6-step and 8-step Frank codes. Results are given in Table 5.71.

Table 5.71. Effect of Modulation Shape on recognition of MPSK signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	Frank Type	SNR	Result
256	0,1	10	6	35	**NL-AM**
256	0,5; 1; 2	10	6	35	**NL-FM**
256	5; 10; 20; 30; 50; 100	10	6	35	**MPSK**
256	*0,1*	*10*	*8*	*35*	***NL-AM***
256	*0,5; 1; 2; 5*	*10*	*8*	*35*	***NL-FM***
256	10; 20; 30; 50; 100	*10*	*8*	*35*	***MPSK***

Readers are referred to the lookup table in Appendix C, which contains phase difference matrices and their corresponding Frank code types.

System performance at different modulation shapes for MPSK signals is also illustrated in Figure 5.43.

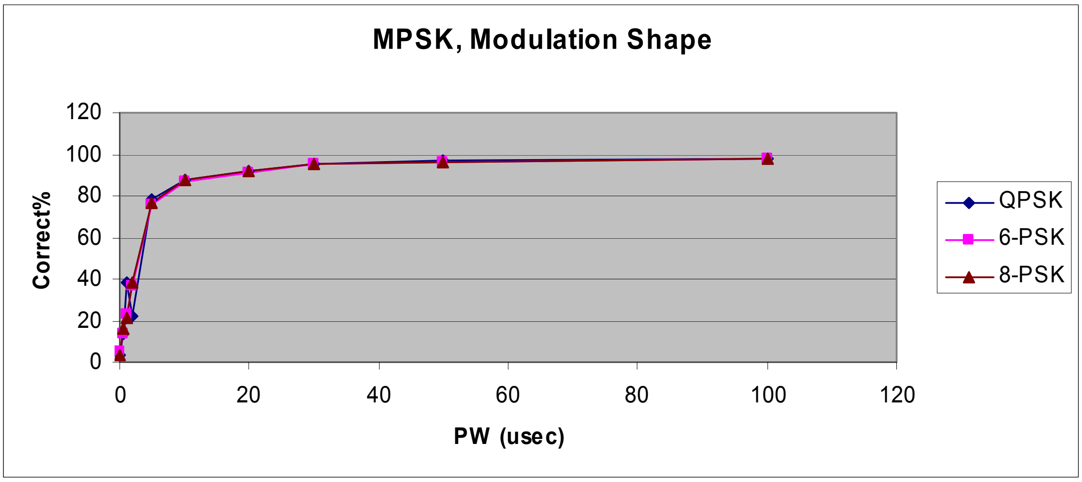

Figure 5.43. System performance at different modulation shapes for MPSK signals.

First of all it is seen that same performance is observed for 4-step, 6-step and 8-step Frank coded MPSK signals. Furthermore, system performance with respect to modulation shape in MPSK signals is similar to that of BPSK signals.

To see the effect of Mean Amplitude on recognition of MPSK signals, Mean Amplitude was swept through 0,1mV to 100mV, and other parameters were kept constant. Test results are given in Table 5.72.

Table 5.72. Effect of Mean Amplitude on recognition of MPSK signals

Fs (MHz)	**PW (µsec)**	**Mean Amplitude (mV)**	**Frank Type**	**SNR**	**Result**
256	10	0,1; 0,5; 1; 2; 5; 10; 20; 30; 50; 100	4	35	**MPSK**

It is clearly seen from Table 5.72 that system performance is independent of Mean Amplitude values, for MPSK signals.

Finally, to see the result of changing SNR on system decision, other parameters were fixed and SNR was swept through 35dB to 0dB. Test results are given in Table 5.73 and Figure 5.44.

Table 5.73. Effect of SNR on recognition of MPSK signals

Fs (MHz)	PW (µsec)	Mean Amplitude (mV)	Frank Type	SNR	Result
256	10	10	4	35; 30; 25; 20; 15; 10; 5	**MPSK**
256	10	10	4	0	**NL-FM**

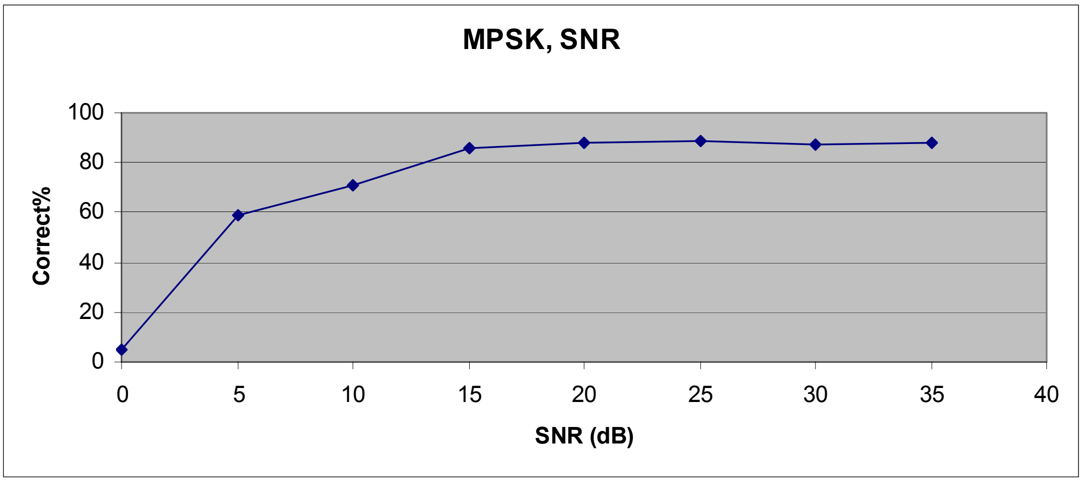

Figure 5.44. System performance at different SNR values for MPSK signals.

It can be seen in Figure 5.44 that system performance decays for very low SNR, especially for SNR values less than 5dB.

5.3. OVERALL PERFORMANCE

A total of 800 signals were generated including all the modulation types. Distribution of these signals among their modulation types are given in the table below:

Table 5.74. Classification of the signals used in performance tests according to their modulation types

MODULATION TYPE	NO MOD.	AMOP				FMOP				PMOP	
		Linear	Nonlinear			**Linear**	Nonlinear				
			Parabolic	*Periodic*	*Square*		*Parabolic*	*Periodic*	*BFSK*	*BPSK*	*MPSK*
Number of Signals	200	100 *(Linear increasing)*	20 *(Positive Parabolic)*	20 *(Sinusoidal)* 20 *(Triangular)* 20 *(Ramp)*	20 *(%50 Duty Ratio)*	100 *(Linear increasing)*	20 *(Positive Parabolic)*	20 *(Sinusoidal)* 20 *(Triangular)* 20 *(Ramp)*	20 *(5-bit Barker code)*	100 *(5-bit Barker code)*	100 *(4-step Frank code)*

Signals were generated with 5µsec PW, 10mV Mean Amplitude and 25dB SNR value. For all modulation types, half of the signals were sampled with 256MHz and the remaining half were sampled with 128MHz. A different Additive White Gaussian noise was generated for each signal.

The confusion matrix reflecting the results of the tests is given in Table 5.75.

Table 5.75. Confusion Matrix for the Overall System

	Estimated Modulation						
Actual Modulation	No Modulation	L-AM	NL-AM	L-FM	NL-FM	BPSK	MPSK
No Modulation	200/200	0	0	0	0	0	0
L-AM	0	100/100	0	0	0	0	0
NL-AM	0	13/100	69/100	18/100	0	0	0
L-FM	0	0	0	100/100	0	0	0
NL-FM	0	0	0	18/100	72/100	3/100	7/100
BPSK	0	0	0	0	0	100/100	0
MPSK	0	0	0	0	0	1/100	99/100

It is seen that system can recognize “Modulationless”, “Linear AM”, “Linear FM”, “BPSK”, “MPSK” with approximately 100% rates.

Test results may be summarized as follows;

- 200 of the 800 signals were modulationless pure signals. System made the correct decision of ”No Modulation” with 100% rate.
- 100 of the 800 signals were Linear AM signals. System made the correct decision of ” Linear AM” with 100% rate.
- 700 of the 800 signals were not Linear AM signals. However, system made “Linear AM ” decision for 13 of these 700 signals. False Alarm Rate for Linear AM signals is 1,85%.
- 100 of the 800 signals were Nonlinear AM signals. System made the correct decision of ” Nonlinear AM” with 69% rate. System confused this type of signals mostly with “Linear AM” and “Linear FM”.
- 100 of the 800 signals were Linear FM signals. System made the correct decision of ” Linear FM” with 100% rate.

- 700 of the 800 signals were not Linear FM signals. However, system made “Linear FM ” decision for 36 of these 700 signals. False Alarm Rate for Linear FM signals is 5,14%.
- 100 of the 800 signals were Nonlinear FM signals. System made the correct decision of ” Nonlinear FM” with 69% rate. System confused this type of signals mostly with “Linear FM” signals.
- 100 of the 100 signals were MPSK signals. System made the correct decision of ” MPSK” with 99% rate.
- 700 of the 800 signals were not MPSK signals. However, system made “MPSK” decision for 7 of these 700 signals. False Alarm Rate for MPSK signals is 1%.

Correct decision rates and false alarm rates of corresponding modulation types are summarized in the table below.

Table 5.76. Overall Performance of the System

Modulation Type	Correct Decision Rate	False Alarm Rate
No Modulation	100,00%	0,00%
L-AM	100,00%	1,86%
NL-AM	69,00%	0,00%
L-FM	100,00%	5,14%
NL-FM	72,00%	0,00%
BPSK	100,00%	0,57%
MPSK	99,00%	1,00%

As it is seen in Table 5.76, system behavior is much better than an acceptable modulation recognition performance; for No Modulation, Linear AM, Linear FM, BPSK and MPSK signals. Nonlinear AM is mostly confused with Linear AM, and Nonlinear FM is mostly confused with Linear FM. These confusions may be decreased if the Euclidean distance, which is calculated between Fractal dimensions of the current signal and the database signal, is replaced with a more talented decision method.

In order to evaluate the performance of this system, the same set of 800 signals were given to the Autoregressive Model Decision block and the Fractal Theory Decision block separately, and their decision results were collected. Below is given the results of Autoregressive Model Decision block.

Table 5.77. Confusion Matrix for Autoregressive Model Decision

	Estimated Modulation				
Actual Modulation	No Modulation	BFSK	QFSK	BPSK	QPSK
No Modulation	200/200	0	0	0	0
L-AM	100/100	0	0	0	0
NL-AM	100/100	0	0	0	0
L-FM	0	82/100	18/100	0	0
NL-FM	0	50/100	40/100	10/100	0
BPSK	0	0	0	100/100	0
MPSK	0	0	0	100/100	0

As is it seen from Table 5.77, Autoregressive Model can not recognize AMOP signals. Also it is not capable of recognizing Linear FM signals; it can make only BFSK or QFSK decision which constitute a small portion of Nonlinear FM types. Also, the method recommended in the Autoregressive Model to separate between BPSK and QPSK signals fails to separate **M**PSK signals.

Results of Fractal Theory Decision block is given in the table below.

Table 5.78. Confusion Matrix for Fractal Theory Decision

	Estimated Modulation						
Actual Modulation	No Modulation	L-AM	NL-AM	L-FM	NL-FM	BPSK	MPSK
No Modulation	188/200	10/200	2/200	0	0	0	0
L-AM	0	100/100	0	0	0	0	0
NL-AM	0	3/100	68/100	27/100	2/100	0	0
L-FM	0	0	0	100/100	0	0	0
NL-FM	0	0	0	19/100	70/100	7/100	4/100
BPSK	0	0	0	100/100	0	0	0
MPSK	0	0	0	0	100/100	0	0

Referring to the table we see that, Fractal Theory Decision method confuses “No Modulation signals” with AMOP signals. Performance of this method for AM and FM signals are the same as the performance of the overall system, because this method is issued for AM and

FM recognition in the whole system too. However, Fractal Theory Decision method itself is not capable of recognizing PSK signals, thus confuses PSK signals with FMOP types.

CHAPTER 6

CONCLUSIONS

In this thesis, the problem of automatic modulation recognition is considered. First of all an investigation was made in order to understand the reason for radar systems to apply modulation on their signals. Then a detailed literature search was made among the subject of Intra-pulse Modulation Recognition. After all, a complete system has been proposed to recognize the modulation type of IMOP signals.

In this system, benefits of the Auto Regressive Model Decision [8] and Fractal Theory Decision [7] are combined, and the AM Depth Percent is added as a new feature for more accurate classification.

The method based on Fractal Theory decision has good performance for CW (no modulation) and FMOP signals. However during the tests, three main problems are encountered. The results show that;

- The method fails to distinguish PMOP signals with FMOP signals.
- AMOP signals are mostly confused with FMOP signals.
- The results are sensitive to noise.

This method also cannot classify AM signals. However, being a class of intrapulse modulations, recognition of AMOP signals is in scope of our work. To overcome this problem, a new feature as “AM Depth Percent” is inserted to the algorithm. This feature gives a measure of the modulation on the envelope of the pulse. Together with the “Box Dimension” and “Information Dimension”, “AM Depth Percent” is used to find the modulation type of the AMOP signals. However, this requires a pre-knowledge of whether the signal has FMOP or AMOP property.

To solve this problem, and to be able to recognize PMOP signals, the Autoregressive Model Decision method is used in corporation with the Fractal Theory Decision method.

The Autoregressive Model Decision method solves the problem of mixing PMOP signals with FMOP signals. However, the method is not successful for distinguishing between BPSK and MPSK signals. To overcome this problem, a new decision block is inserted to the system. In this block, magnitudes of the jumps in the phase of the pulse is calculated. Then, if the minimum magnitude is less than π radians, the signal is decided to have MPSK modulation, otherwise BPSK modulation. However, for the success of the differentiation method, correct retrieval of the signal phase from the predetection signal is essential. Correct retrieval of the signal phase is directly dependent on the accuracy of the estimated center frequency. To eliminate the effect of the error in estimated center frequency, phase of the signal is corrected according to the deviation of the extracted Pulse Frequency Mean from the IF.

Furthermore, before all these decision blocks the signal is passed through a bandpass filter centered on the intermediate frequency. By this way noise is suppressed more and this improves the system performance for low SNR applications.

Performance tests were made for the resultant system. Same set of signals were input to the Fractal Theory Decision block and Autoregressive Model Decision block individually. It is observed that the proposed system shows better performance than the other two systems.

The system we propose shows good performance for SNR values greater than 10-15dB. Improving system performance for more noisy environments can be considered as a future work.

Additionally, for AMOP and FMOP signals, we can make Linear or Nonlinear decision for the last. Decision of the exact modulation shape for these signals can be another future work to be considered.

As a result, Modulation Recognition solution offered in this thesis collects the beneficial points of the Autoregressive Model Decision Method and Fractal Theory Decision Method, and together with the usage of AM Depth Percent value and the IMOP Database, gives a more comprehensive solution for the “Modulation Recognition of IMOP Signals” problem.

Moreover, if the recognition of Unintentional Modulations on Pulse (UMOP) is also studied, analysis of IMOP and UMOP signals will introduce a compact solution for the Specific Emitter Identification (SEI) problem.

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APPENDICES

A. MODULATION SHAPES

AMPLITUDE MODULATION SHAPES

Amplitude, Frequency and Phase components and the baseband signal corresponding to AM shapes which are considered in this thesis are illustrated in the figures below.

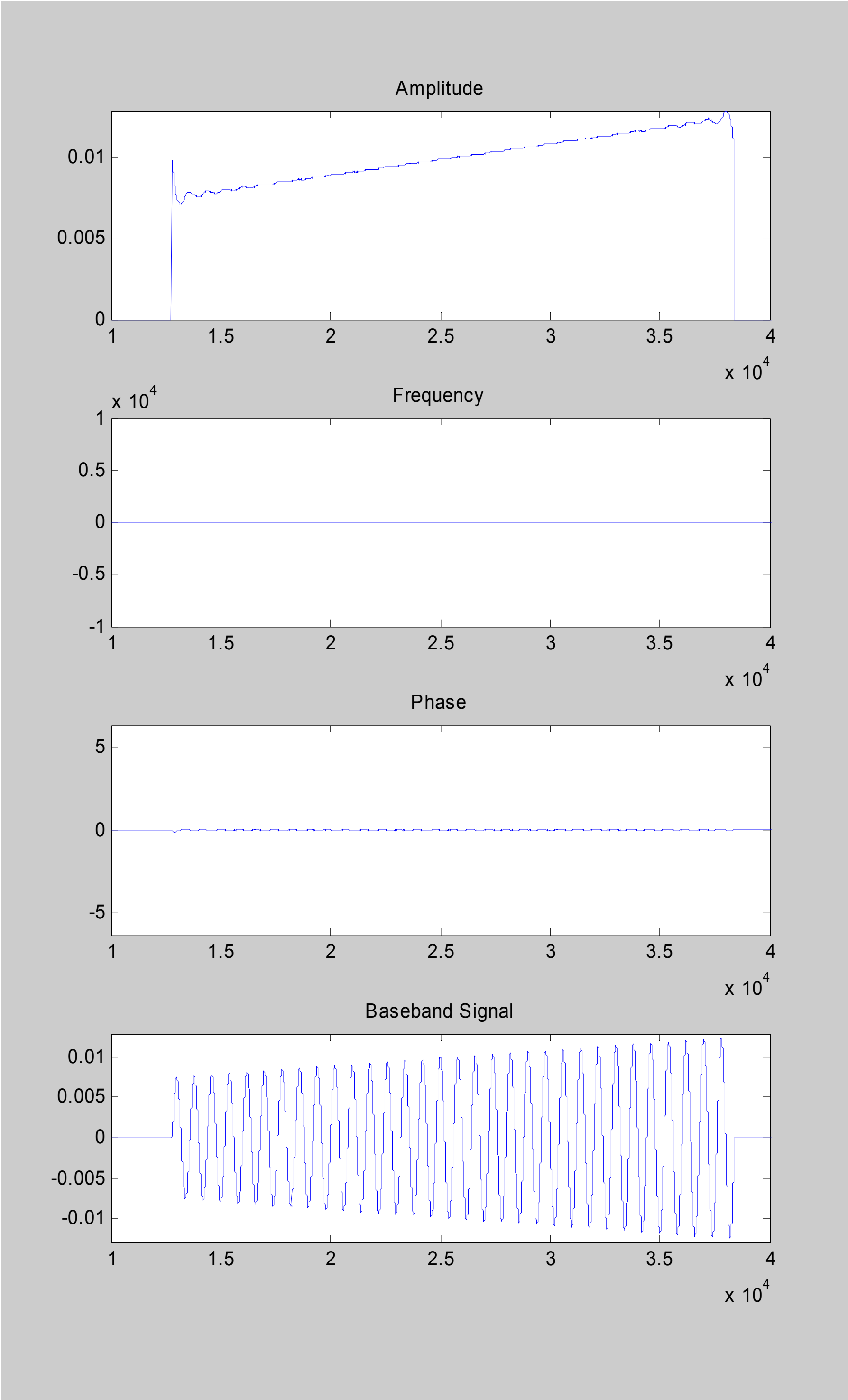

Figure A.1. Linear Increasing Amplitude Modulation (PW = 100µsec, Fs = 320kHz, AM Depth = 50%)

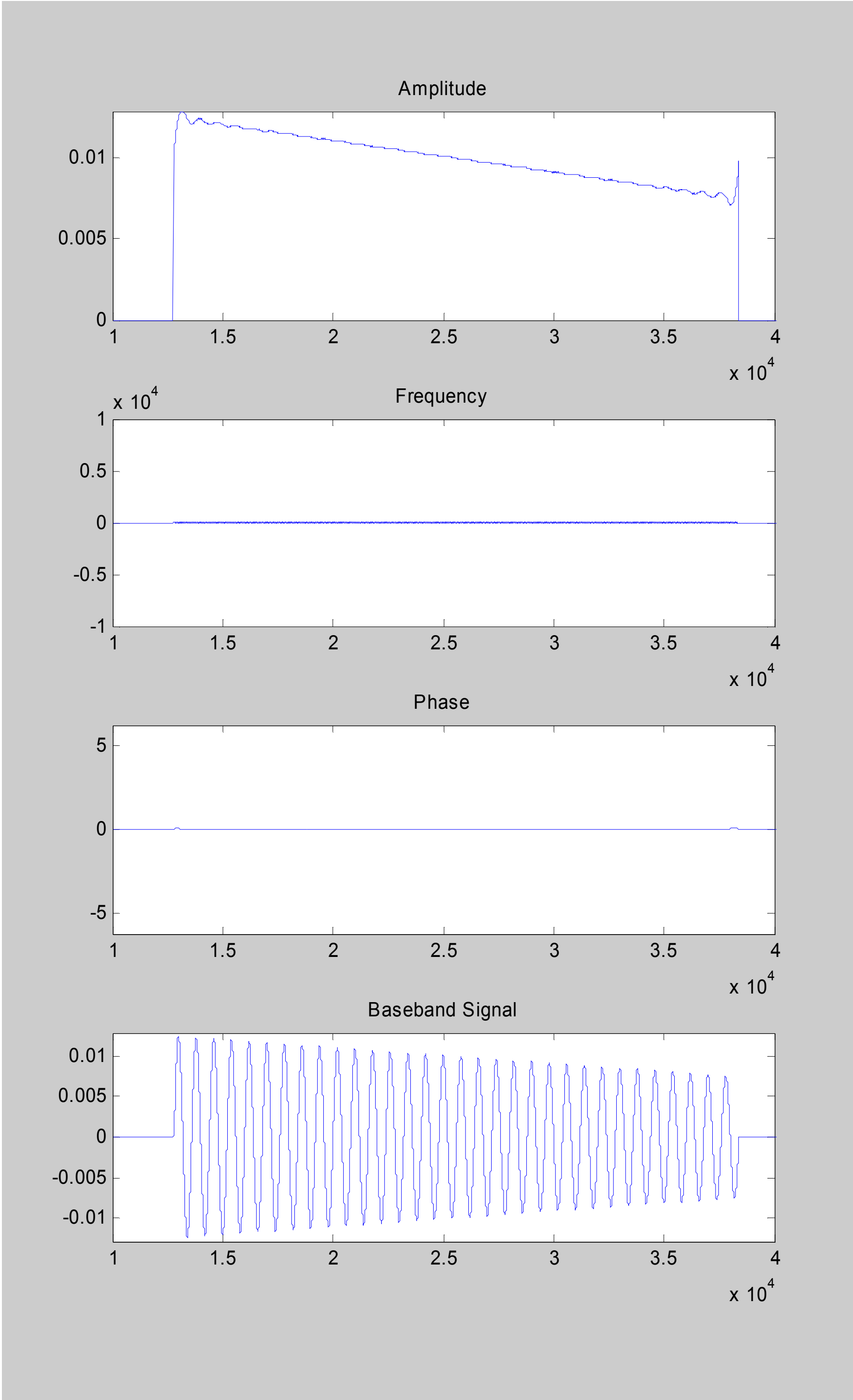

Figure A.2. Linear Decreasing Amplitude Modulation (PW = 100μsec, Fs = 320kHz, AM Depth = 50%)

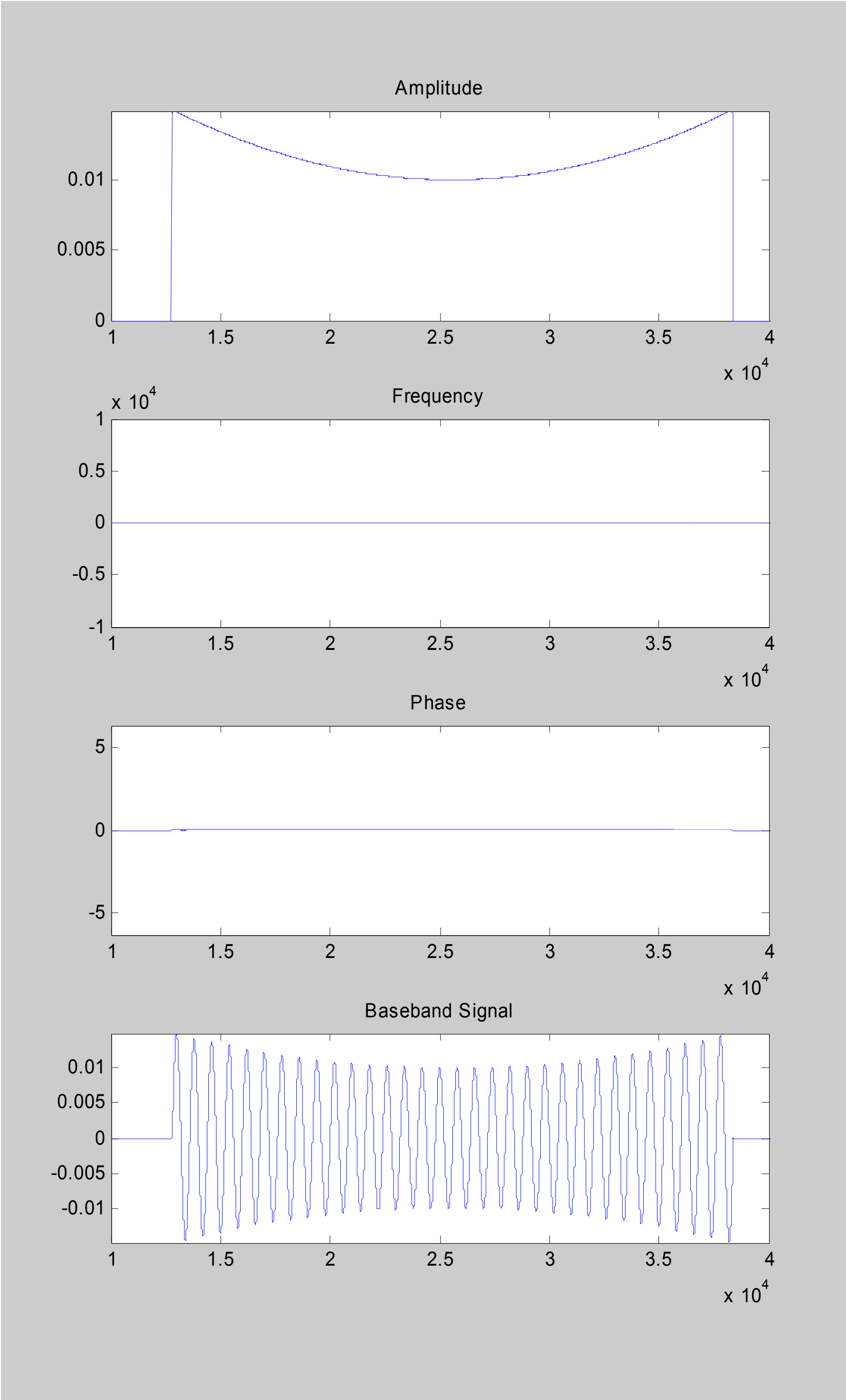

Figure A.3. Positive Parabolic Amplitude Modulation (PW = 100μsec, Fs = 320kHz, AM Depth = 50%)

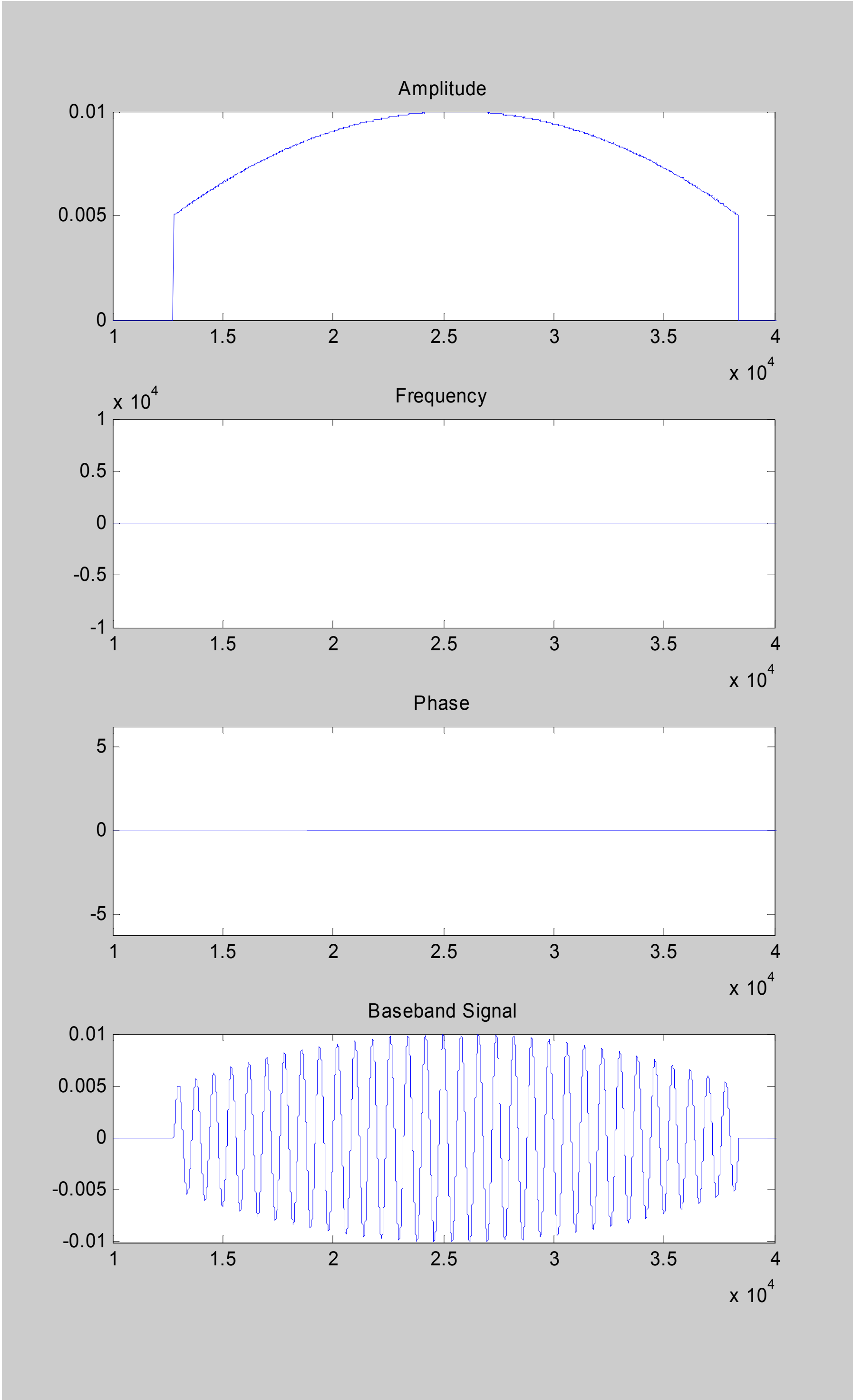

Figure A.4. Negative Parabolic Amplitude Modulation (PW = 100µsec, Fs = 320kHz, AM Depth = 50%)

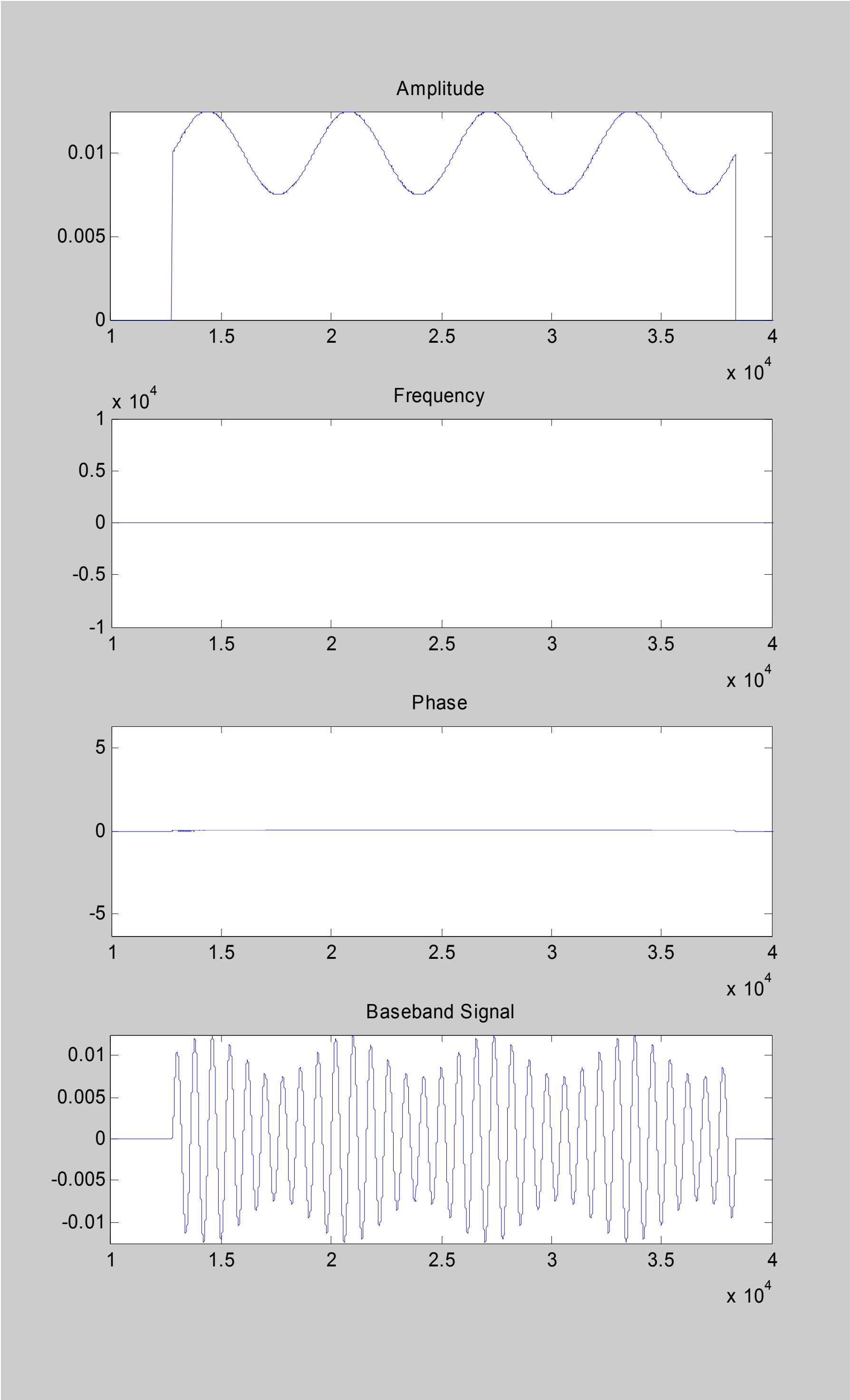

Figure A.5. Sinusoidal Amplitude Modulation (PW = 100μsec, Fs = 320kHz, AM Depth = 50%)

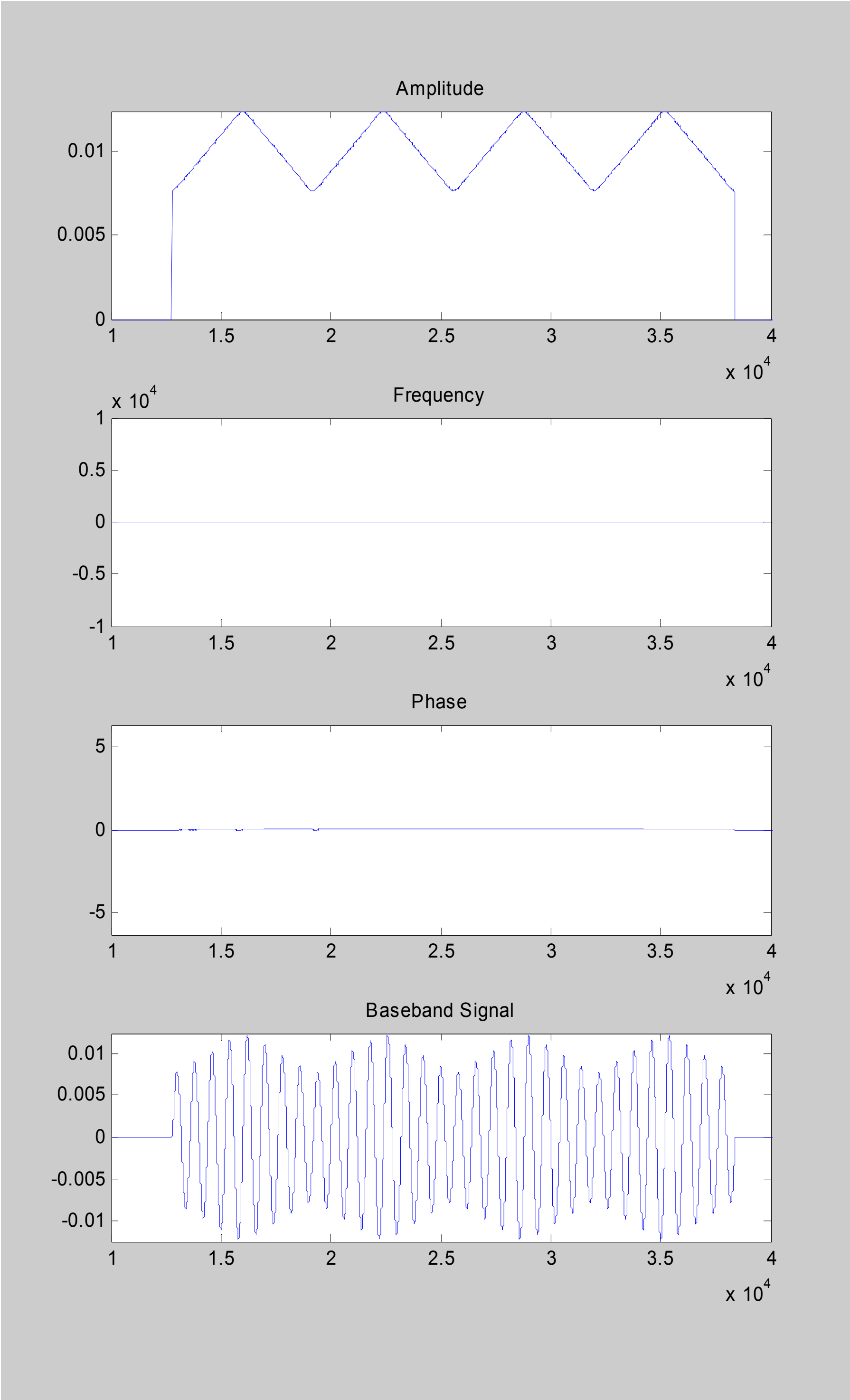

Figure A.6. Triangular Amplitude Modulation (PW = 100µsec, Fs = 320kHz, AM Depth = 50%)

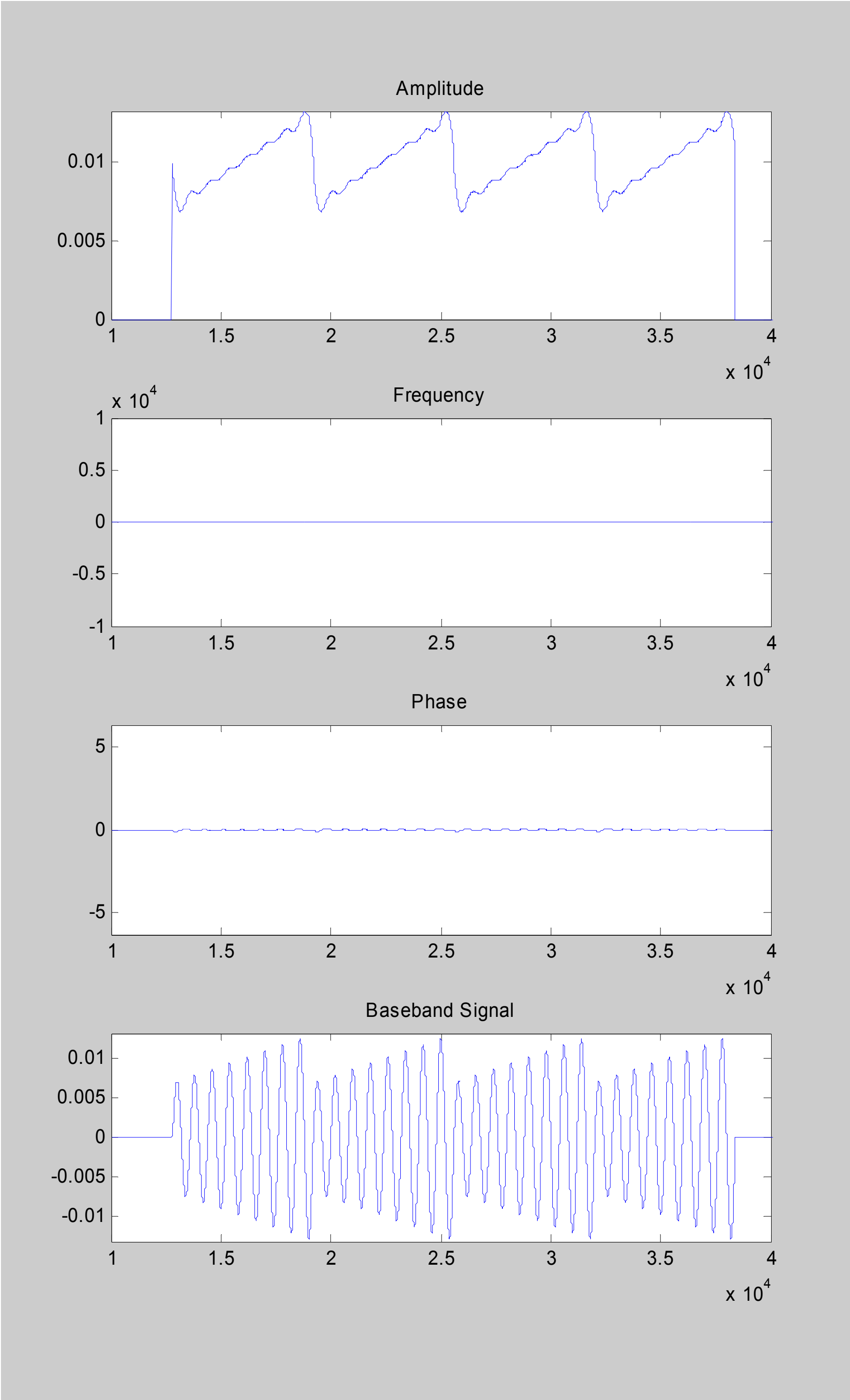

Figure A.7. Ramp Amplitude Modulation (PW = 100µsec, Fs = 320kHz, AM Depth = 50%)

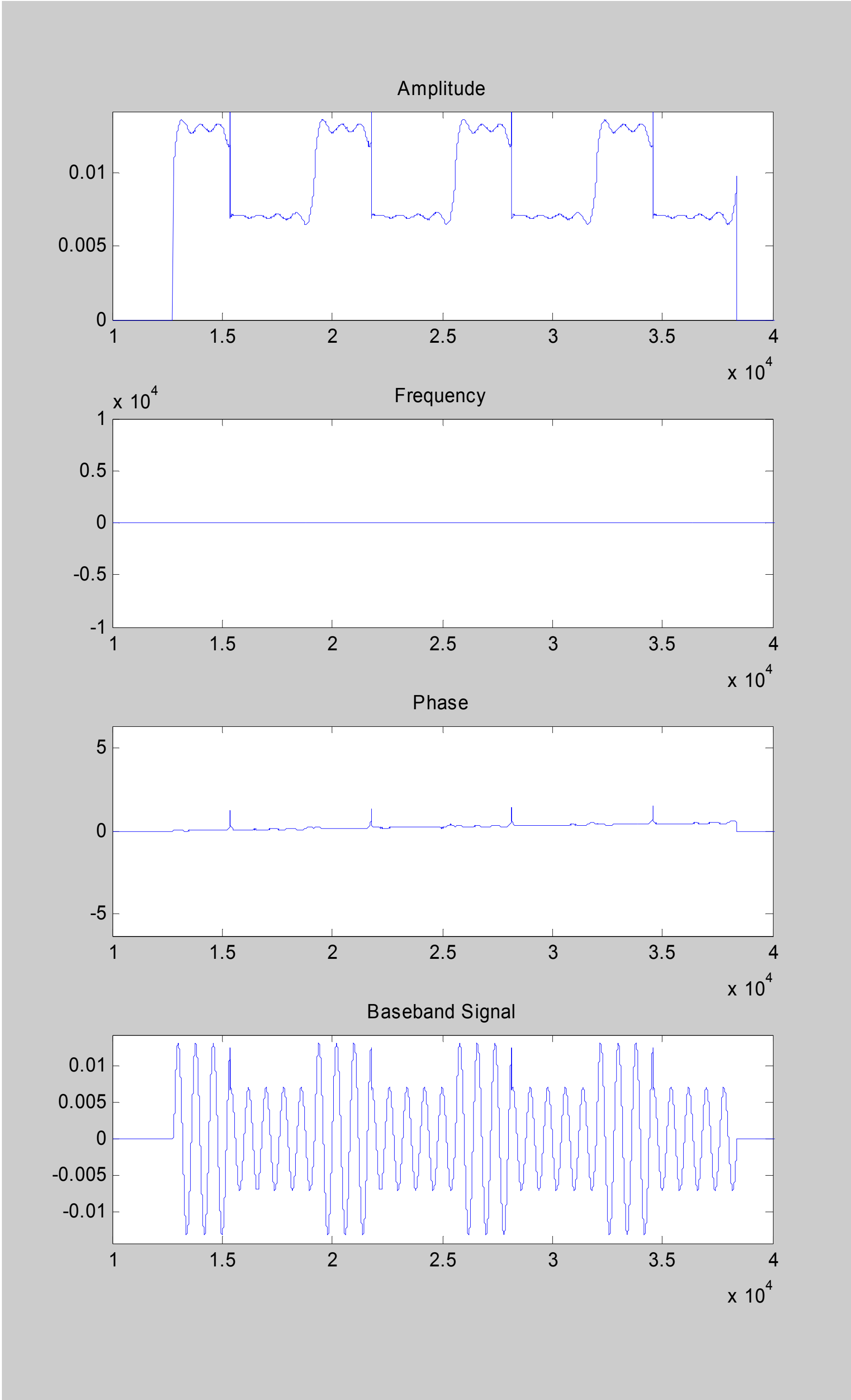

Figure A.8. Square Amplitude Modulation (Duty Ratio = 40%, PW = 100μsec, Fs = 320kHz, AM Depth = 50%)

FREQUENCY MODULATION SHAPES

Amplitude, Frequency and Phase components and the baseband signal corresponding to FM shapes which are considered in this thesis are illustrated in the figures below

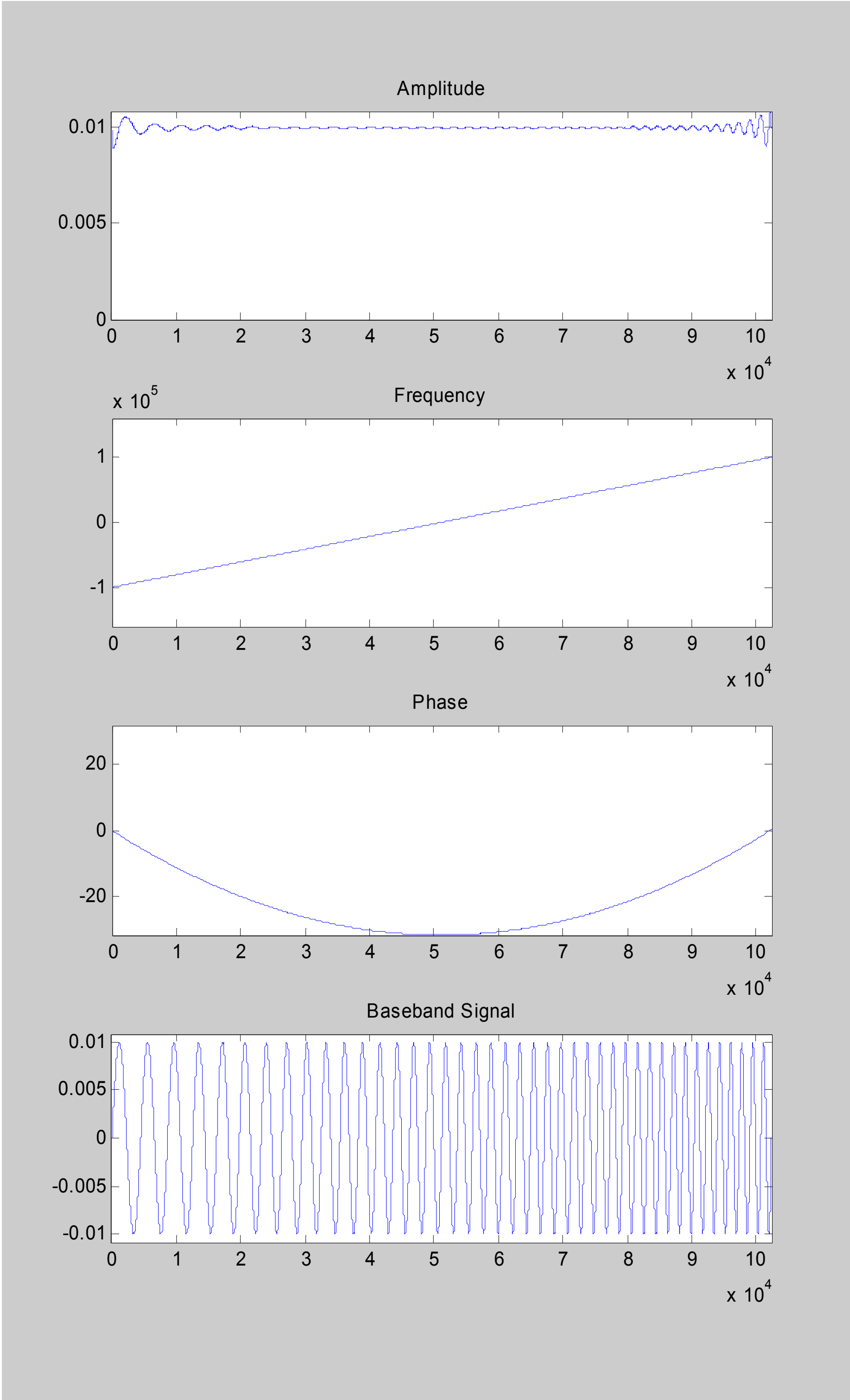

Figure A.9. Linear Increasing Frequency Modulation (PW = 100µsec, Fs = 320kHz, Frequency Deviation = 200kHz)

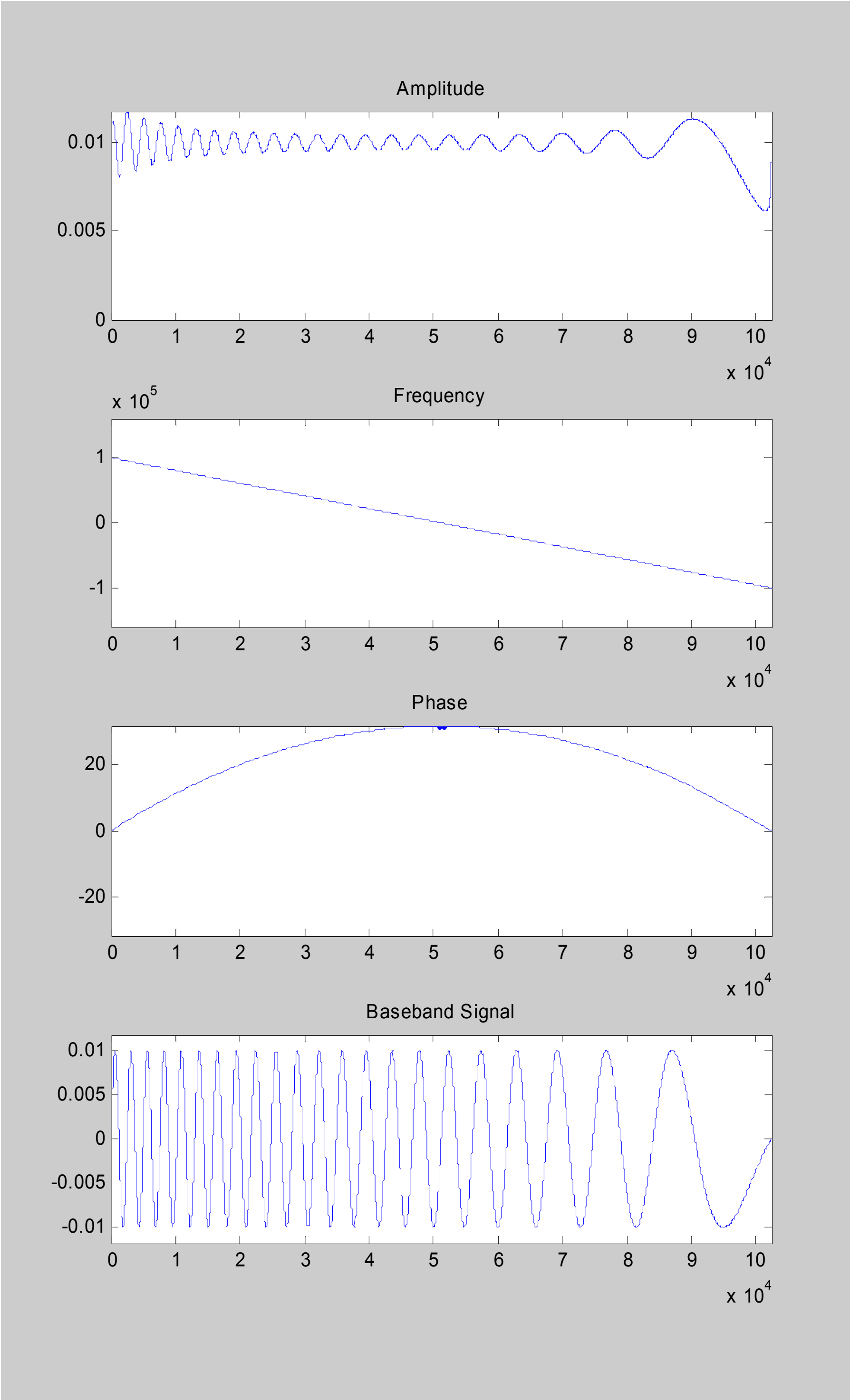

Figure A.10. Linear Decreasing Frequency Modulation (PW = 100μsec, Fs = 320kHz, Frequency Deviation = 200kHz)

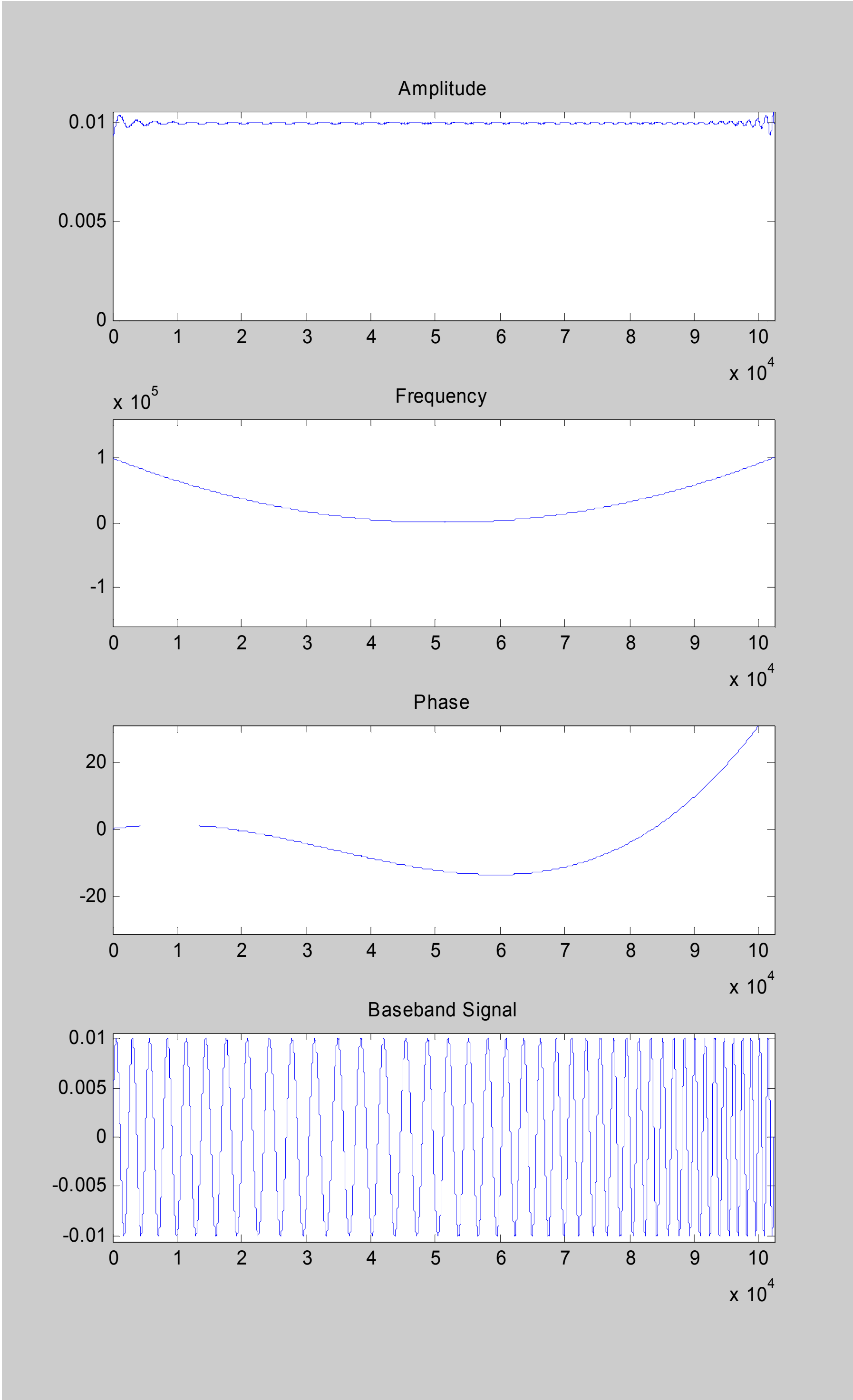

Figure A.11. Positive Parabolic Frequency Modulation (PW = 100µsec, Fs = 320kHz, Frequency Deviation = 100kHz)

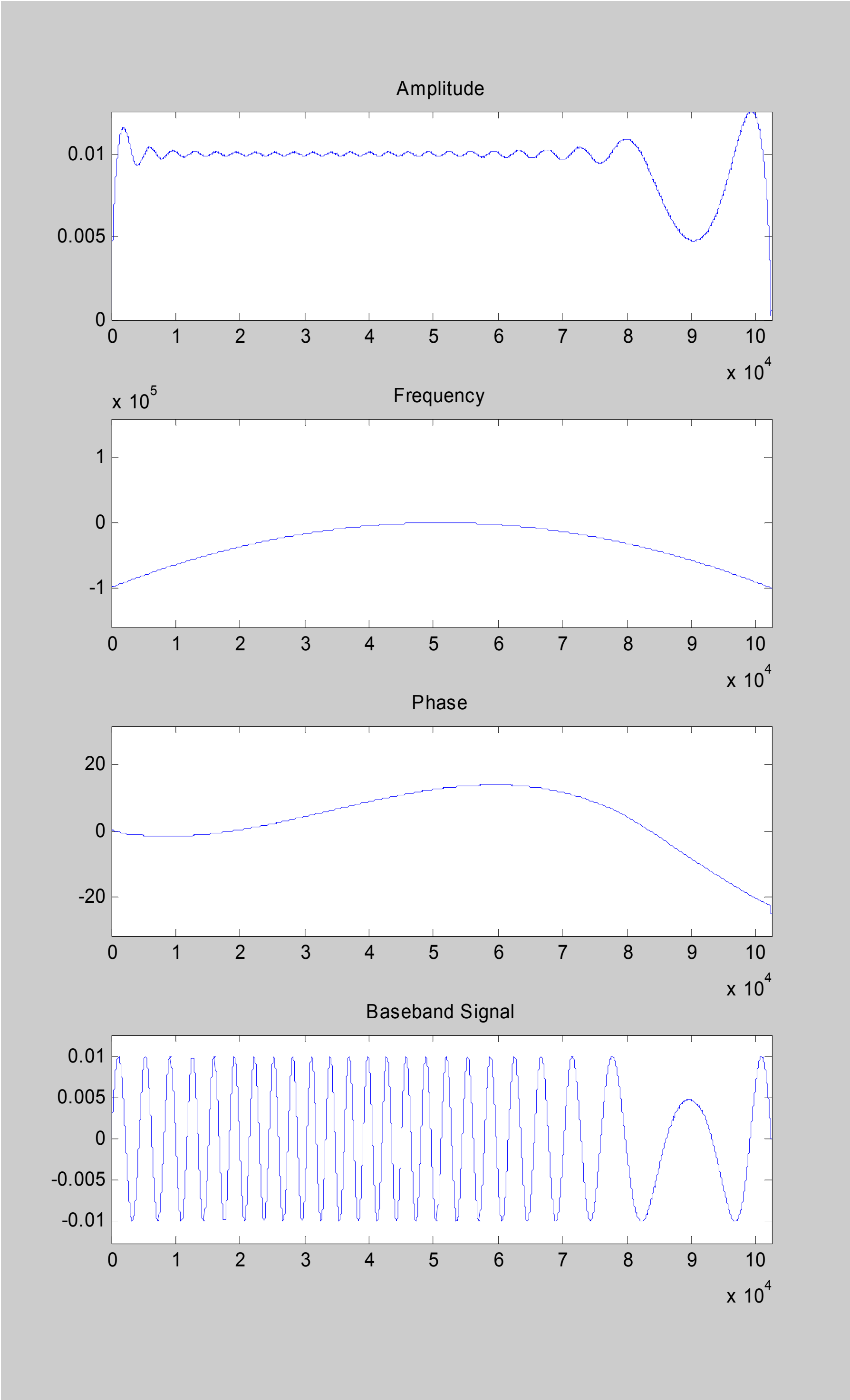

Figure A.12. Negative Parabolic Frequency Modulation (PW = 100μsec, Fs = 320kHz, Frequency Deviation = 100kHz)

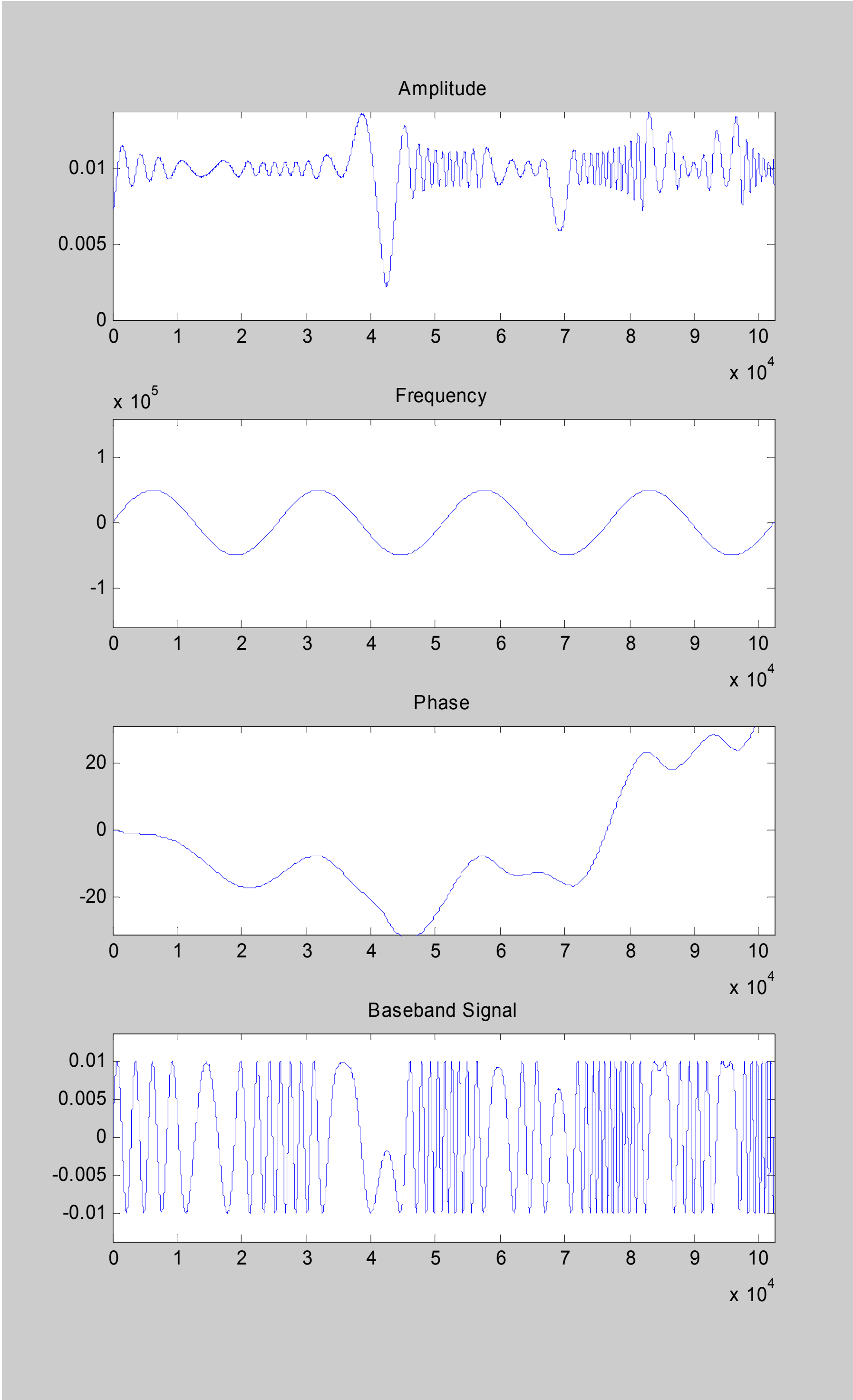

Figure A.13. Sinusoidal Frequency Modulation (PW = 100μsec, Fs = 320kHz, Frequency Deviation = 100kHz)

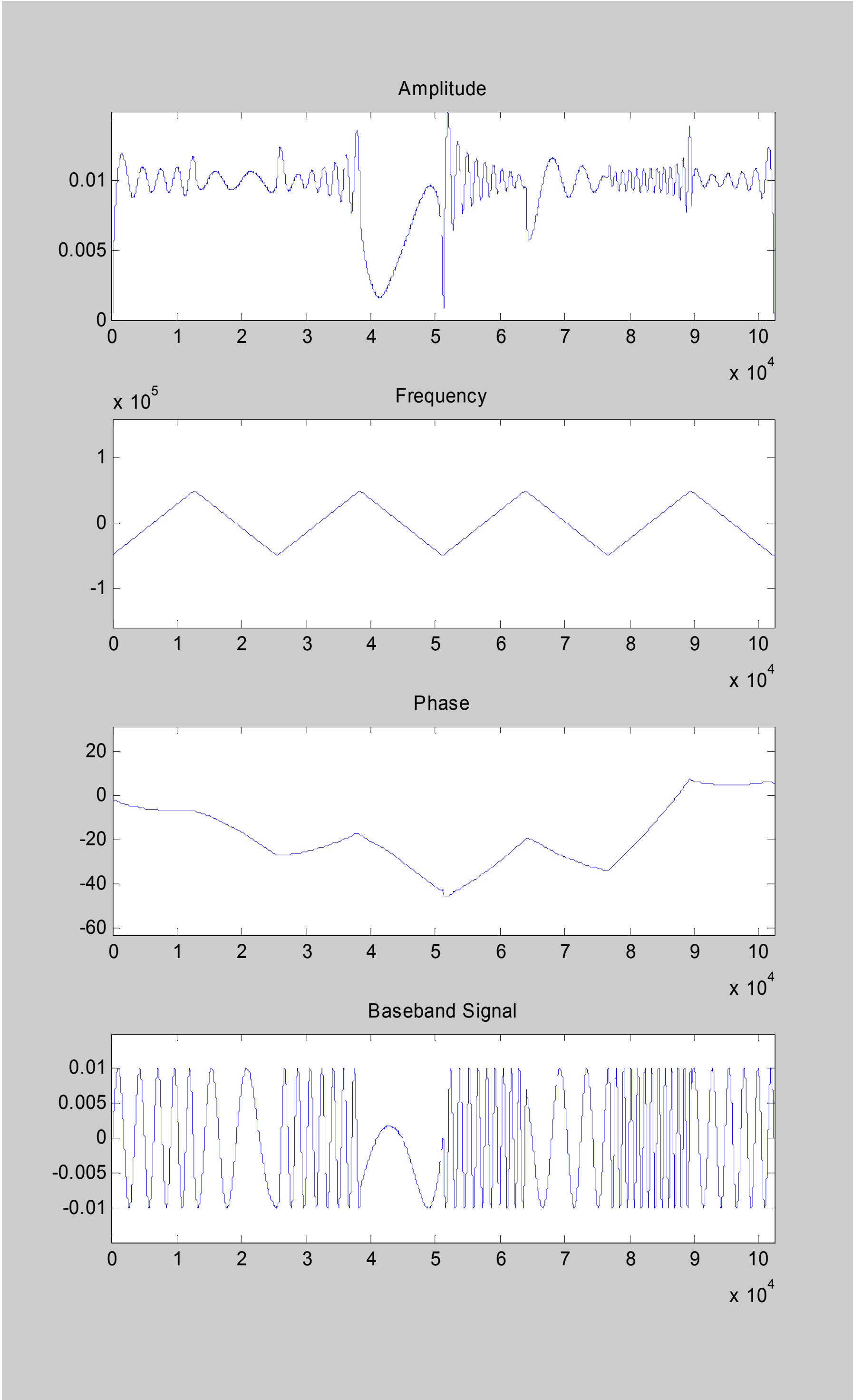

Figure A.14. Triangular Frequency Modulation (PW = 100µsec, Fs = 320kHz, Frequency Deviation = 100kHz)

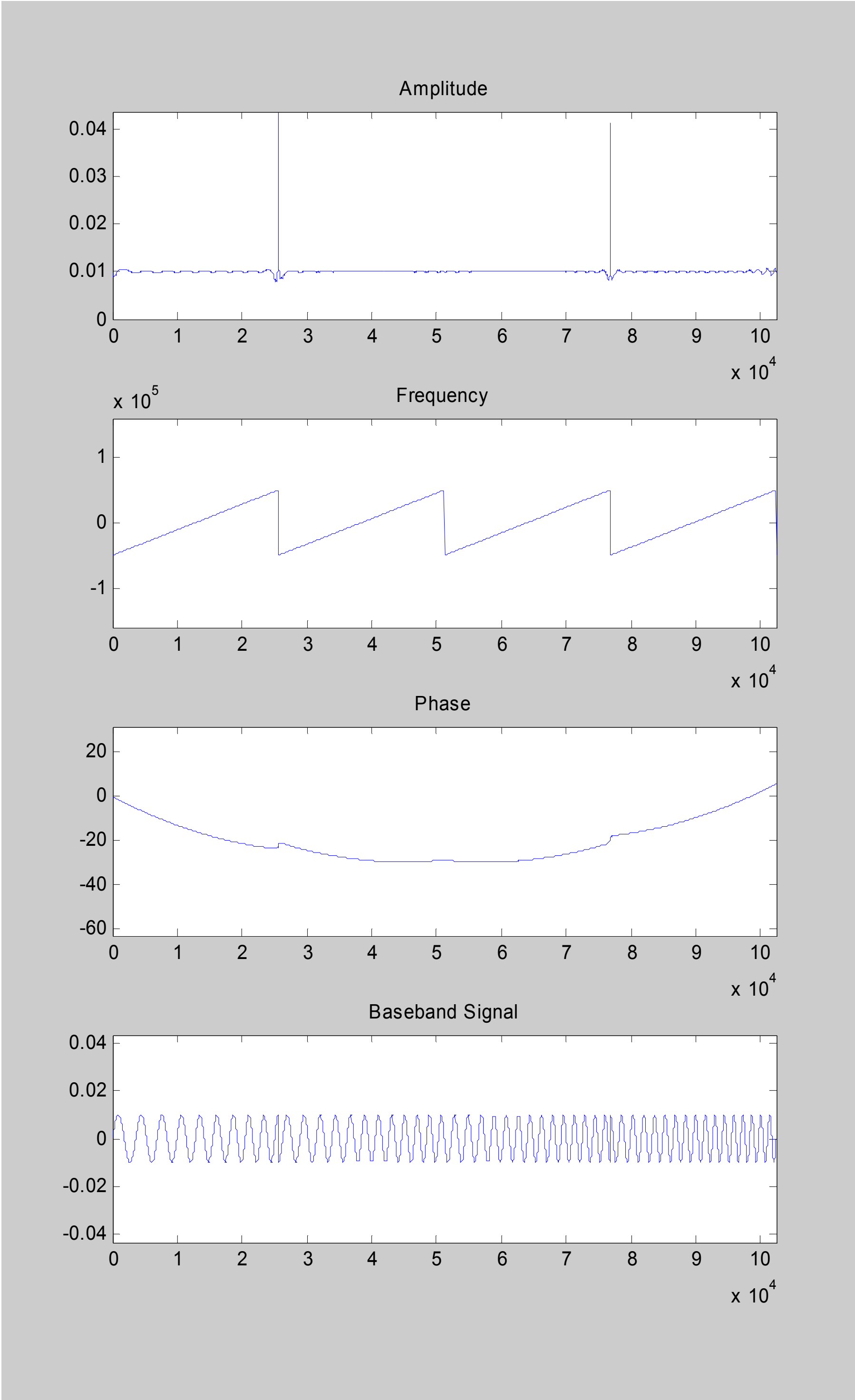

Figure A.15. Ramp Frequency Modulation (PW = 100µsec, Fs = 320kHz, Frequency Deviation = 100kHz)

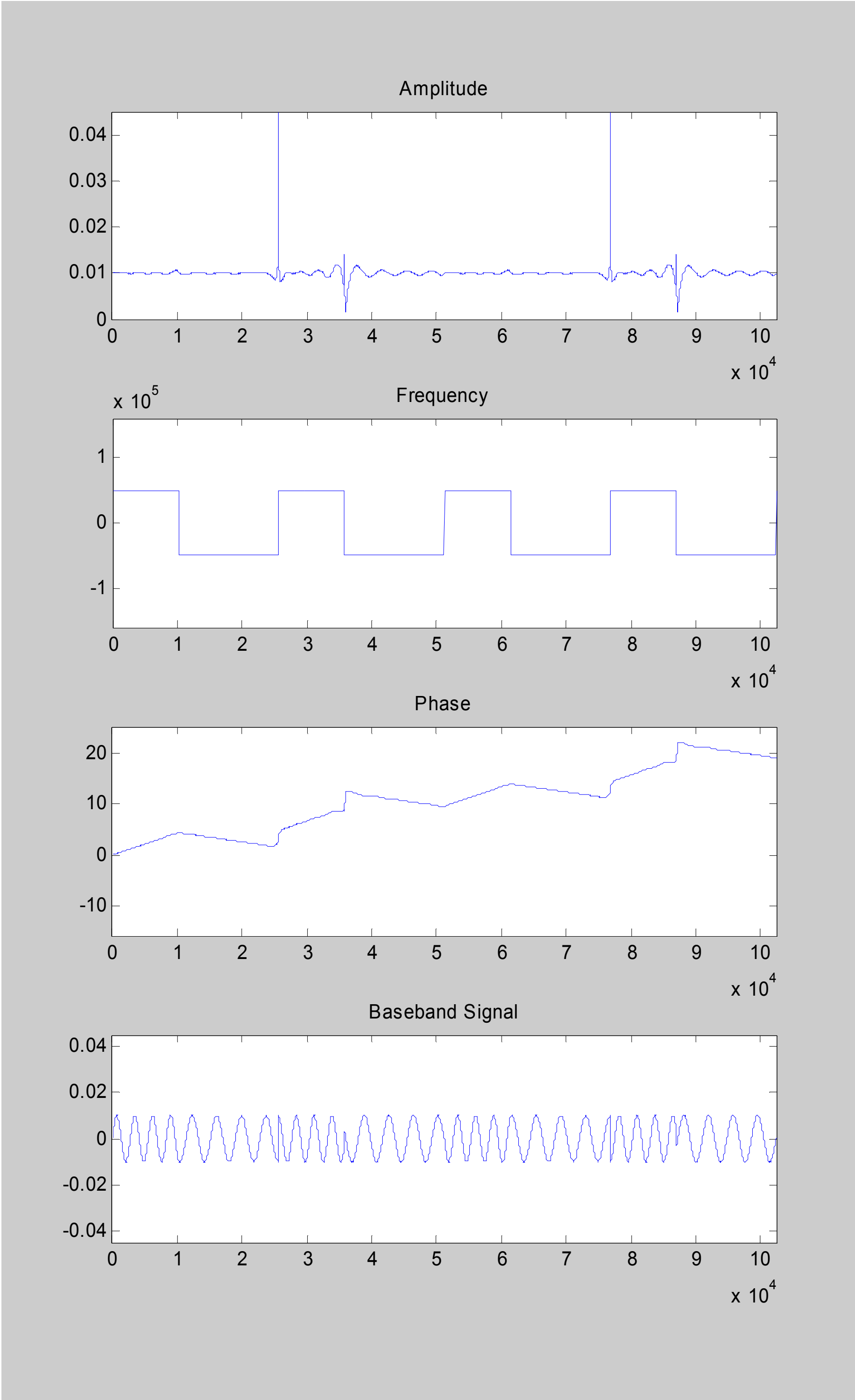

Figure A.16. Square Frequency Modulation (PW = 100μsec, Fs = 320kHz, Frequency Deviation = 100kHz, Duty Ratio = 40%)

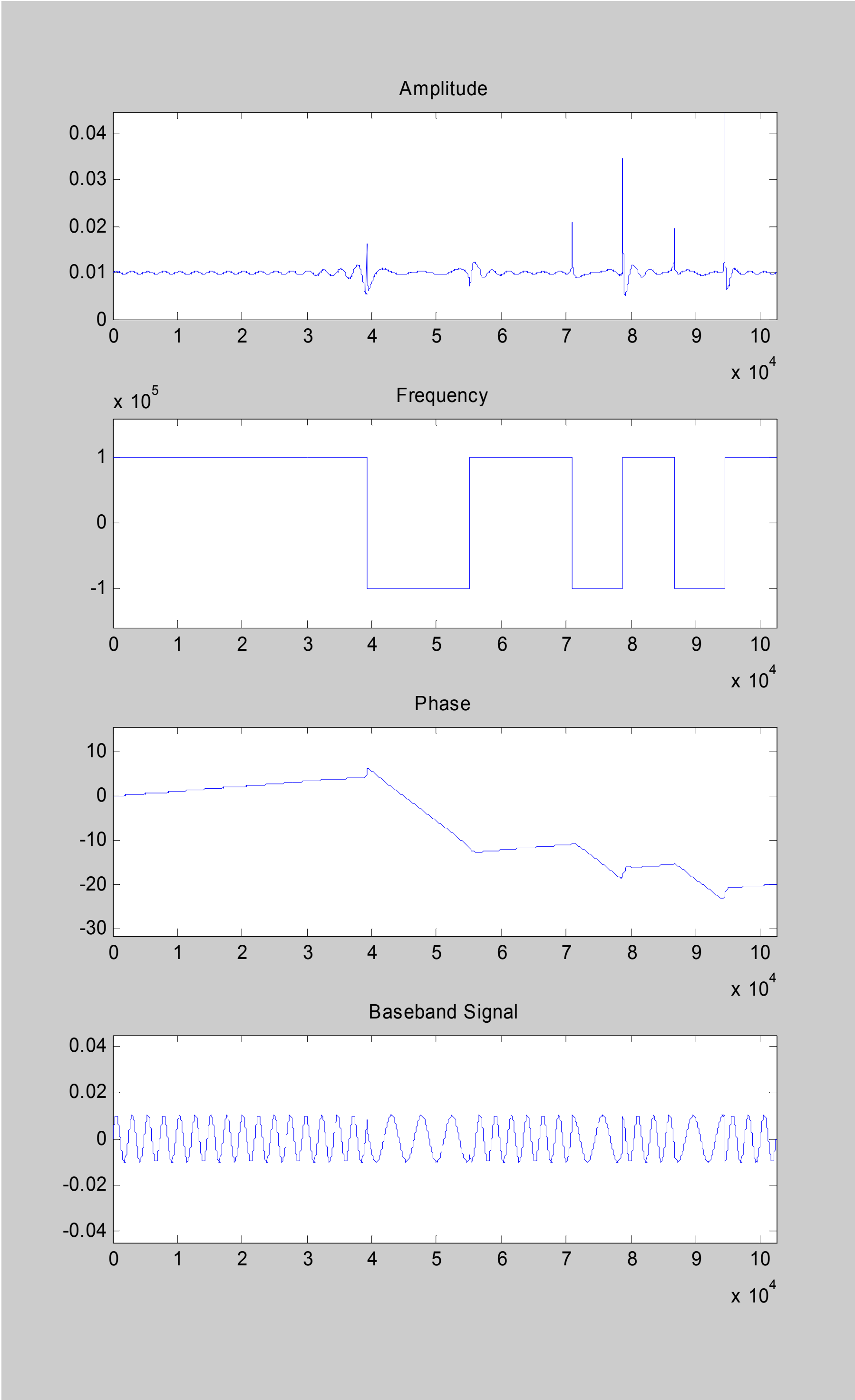

Figure A.17. BFSK Modulation (PW = 100μsec, Fs = 320kHz, 13-bit Barker, Frequency Deviation = 100kHz)

PHASE MODULATION SHAPES

Amplitude, Frequency and Phase components and the baseband signal corresponding to PM shapes which are examples of the modulation shapes considered in this thesis are illustrated in the figures below

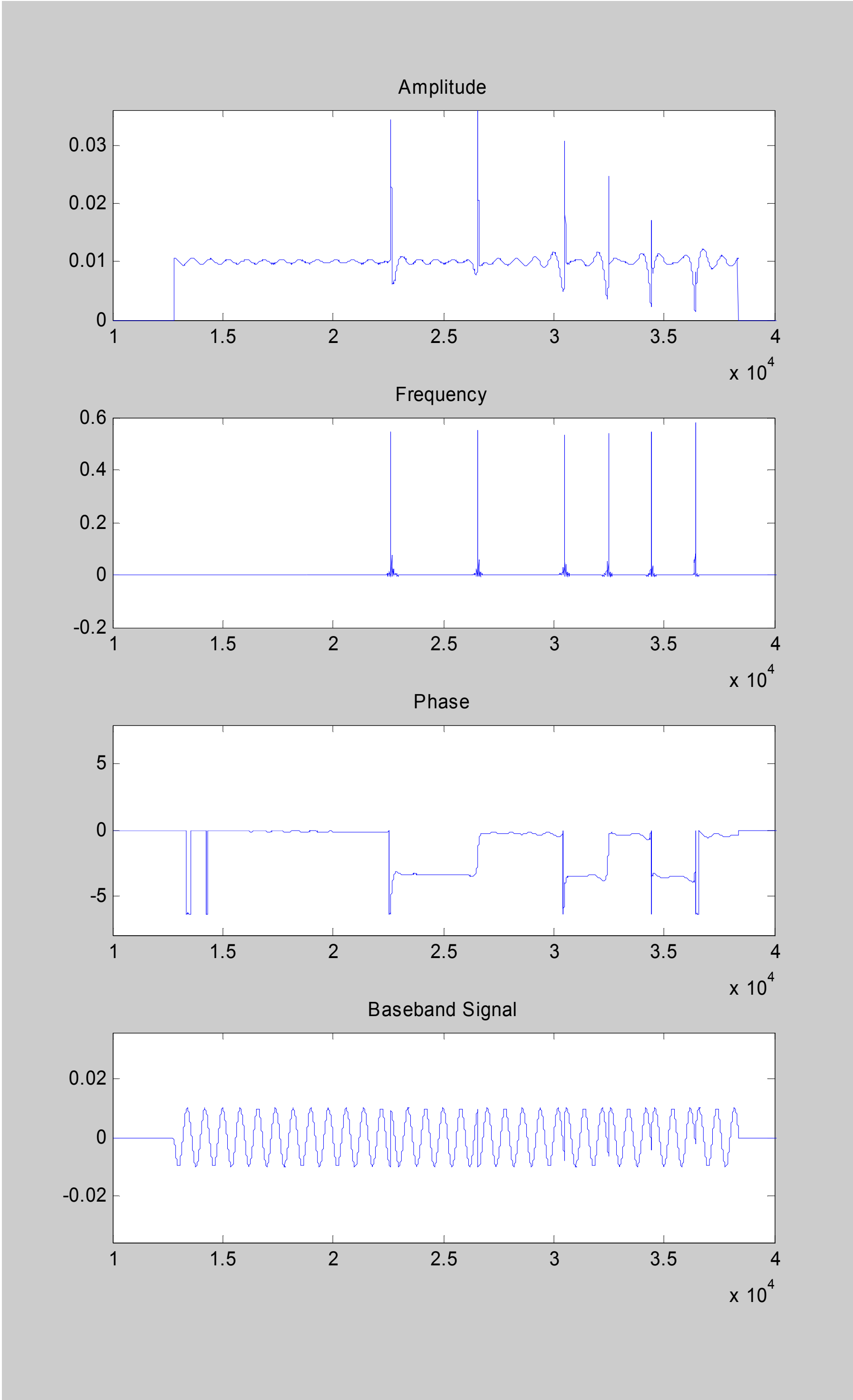

Figure A.18. BPSK Modulation (PW = 100µsec, Fs = 320kHz, 13-bit Barker)

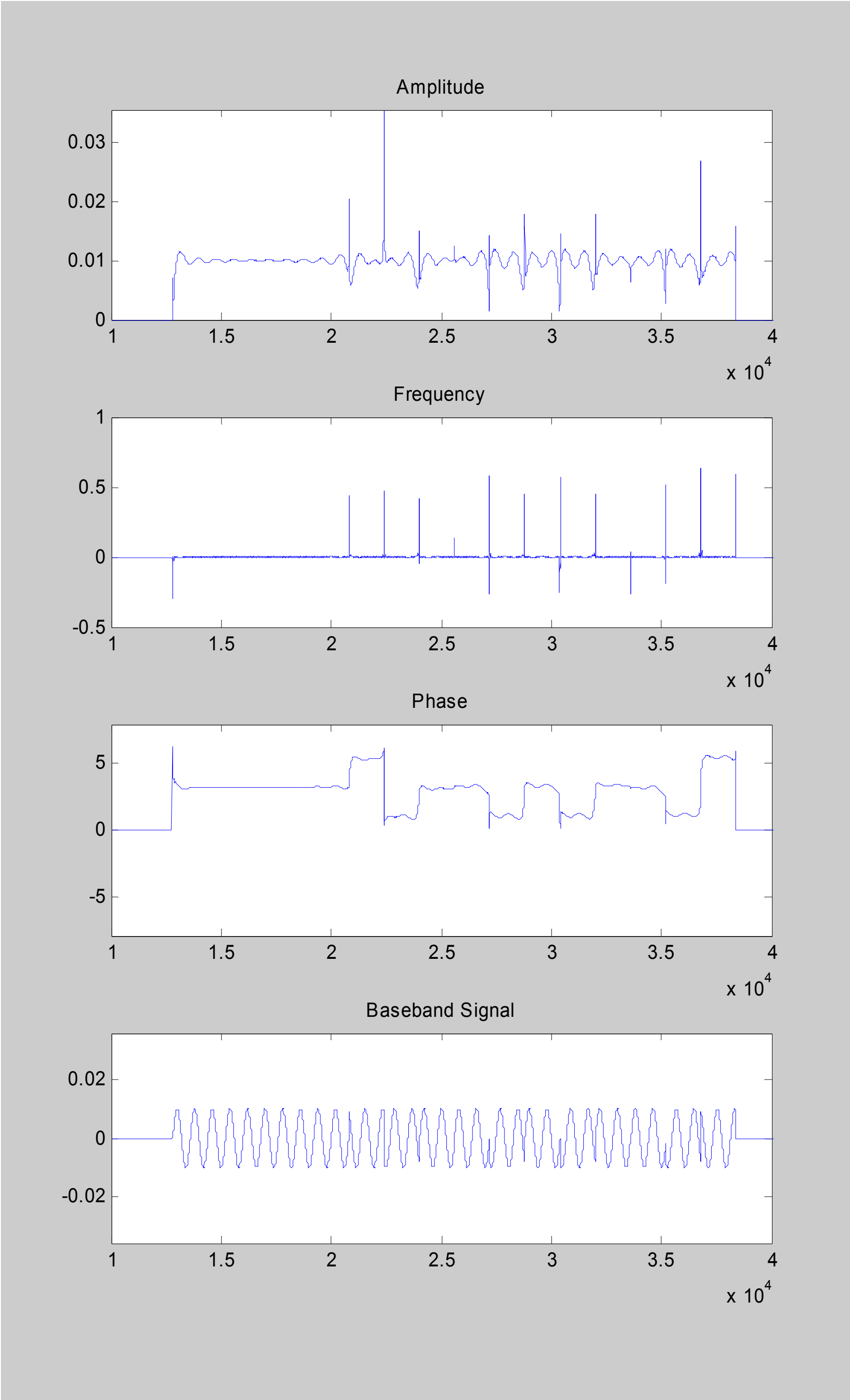

Figure A.19. QPSK Modulation (PW = 100µsec, Fs = 320kHz, 4-step Frank Code)

B. GRAPHICAL USER INTERFACE

Screenshot of the “Modulation Recognizer-GUI” is given in the figure below.

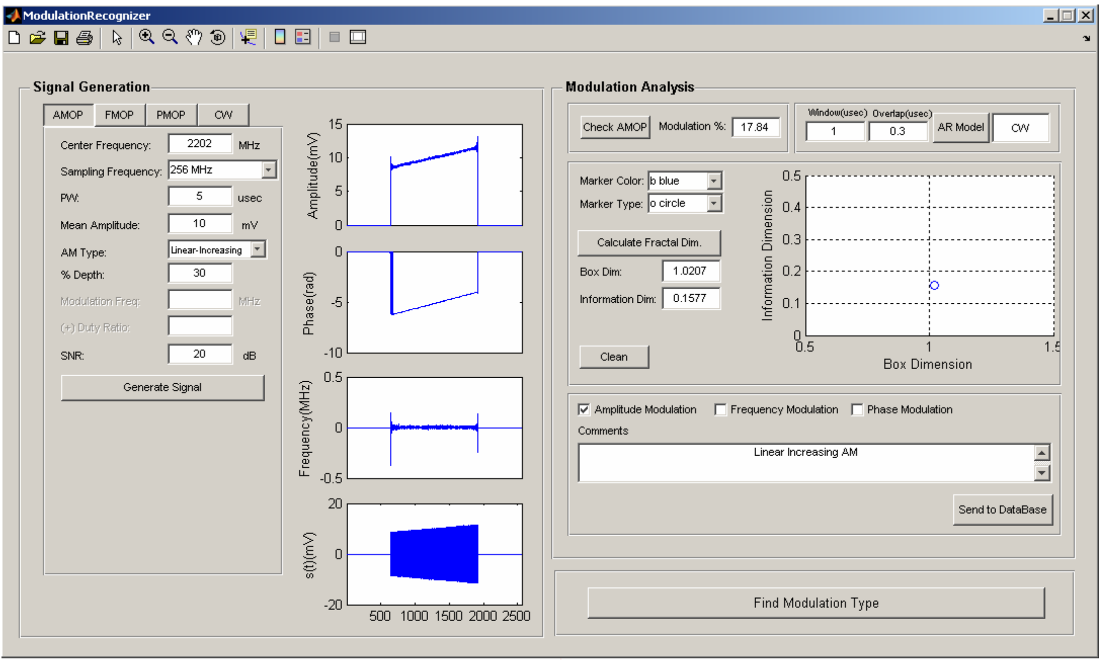

Figure B.1. Screenshot of the “Modulation Recognizer-GUI”

This screen is composed of the “Signal Generator”, “Signal Decomposer”, “Modulation Analyzer”, “Database Update” and “Modulation Recognizer” parts.

❖ SIGNAL GENERATOR

Signal Generator enables the system to generate signals with various modulation properties. This part is marked on the GUI in Figure B.2. Details of this part is given in Figure B.3.

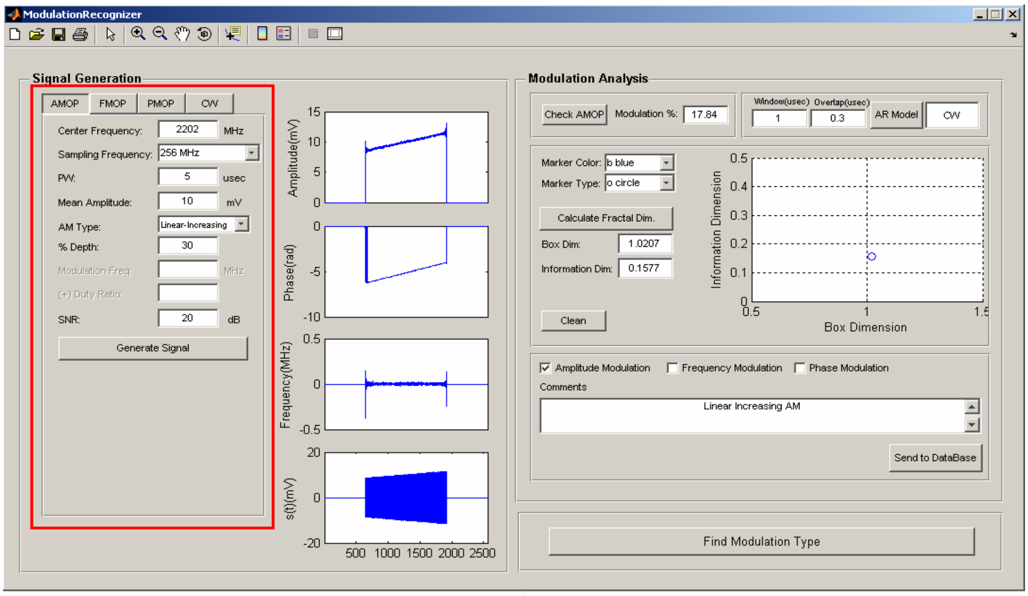

Figure B.2. Signal Generator of the GUI

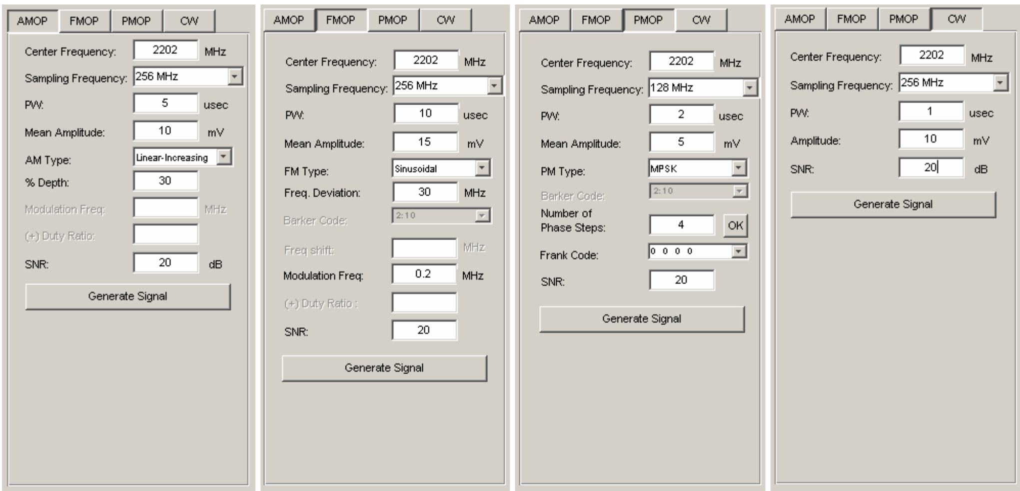

Figure B.3. Details of the Signal Generator.

As given in Figure B.3, there are 4 tab-panels of the Signal Generator, for different modulation types. In each tab, different modulation shapes are presented to the user, and user can generate any type of signal by choosing the Modulation Shape and entering the corresponding parameter's values. Modulation Shape choices with their corresponding tabs are given in the table below.

Table B.1. Modulation Shape choices corresponding to different tabs.

TAB	AMOP	FMOP	PMOP
MODULATION SHAPE CHOICES	Linear-Increasing	Linear-Increasing	BPSK
	Linear-Decreasing	Linear-Decreasing	MPSK
	Positive Parabolic	Positive Parabolic	
	Negative Parabolic	Negative Parabolic	
	Sinusoidal	Sinusoidal	
	Triangular	Triangular	
	Ramp	Ramp	
	Square	Square	
		BFSK	

Since CW has “no modulation”, there is not a modulation shape choice for the CW tab.

Once the required parameters are entered for the selected modulation type, user presses the “Generate Signal” button on the corresponding tab, and the desired continuous signal is generated.

- SIGNAL DECOMPOSER

After the continuous signal is generated, signal receiver block runs on the backplane. After this block the continuous signal is converted to a discrete signal sampled at the rate entered by the user at the Signal Generation part. Then this signal is behaved as the “received signal”, and in the Signal Decomposer part the “received signal” is decomposed into its Envelope(Amplitude) – Phase – Frequency components to be presented to the user. This part is marked on the GUI in Figure B.4.

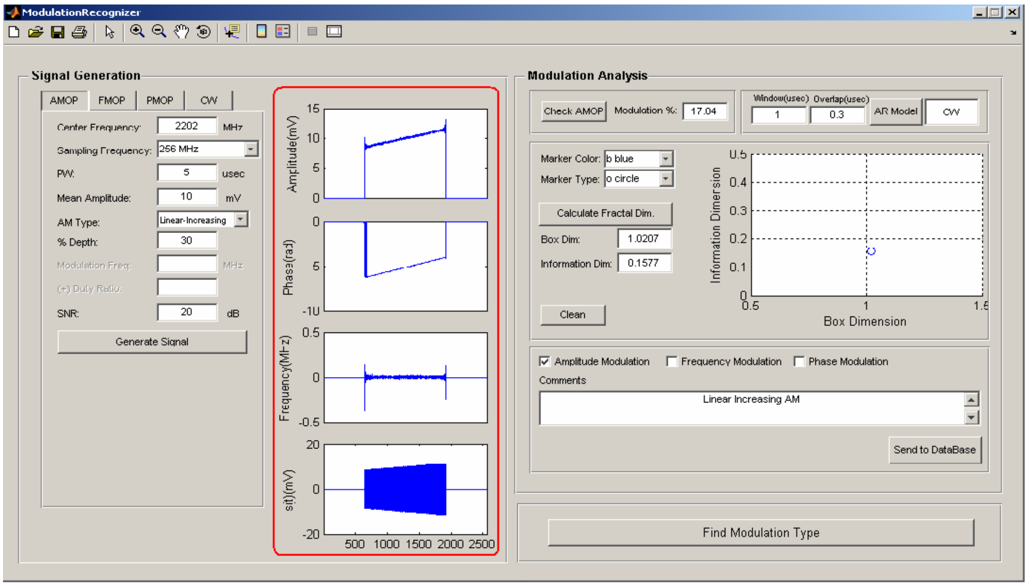

Figure B.4. Signal Decomposer of the GUI

❖ MODULATION ANALYZER AND DATABASE UPDATE

Modulation Analyzer part enables the user to manually analyze the received signal's modulation properties. This part is marked on the GUI in Figure B.5.

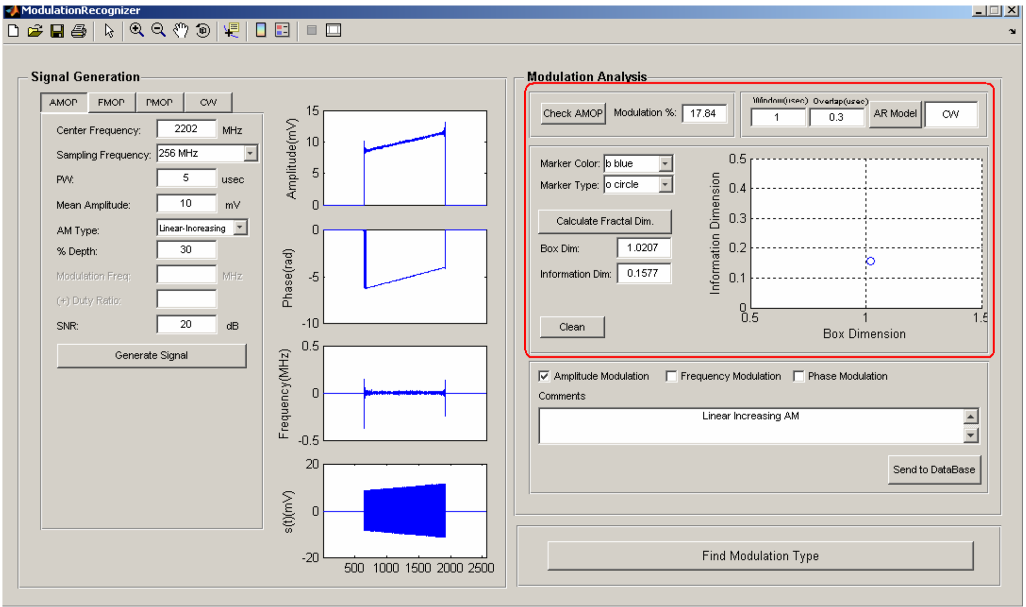

Figure B.5. Modulation Analyzer Part of the GUI.

Each section gives opportunity to the user to analyze the signal in a different point of view.

Pressing the “Check AMOP” button, one can check the modulation percent on the amplitude of the received signal.

In the Autoregressive Model section, signal is segmented into overlapping parts according to the values entered by the user. Then pressing the “AR Model” button, one can learn the Autoregressive Model’s decision about this signal.

In the Fractal Theory section, Fractal Dimensions of the received signal is calculated and plotted on the axis to the right with the Marker Color & Type chosen by the user. Unless the user presses the “Clean” button, this axes is not cleaned, so one can analyze various signals and see whether they are grouped on the axes with respect to their modulation types.

Once the user calculates the signal’s AM % and Fractal Dimension values, he can save the properties of this signal in the database by selecting its corresponding modulation type. User can also enter some comments related to the signal, to be saved in the database. This part is marked on the GUI in Figure B.6.

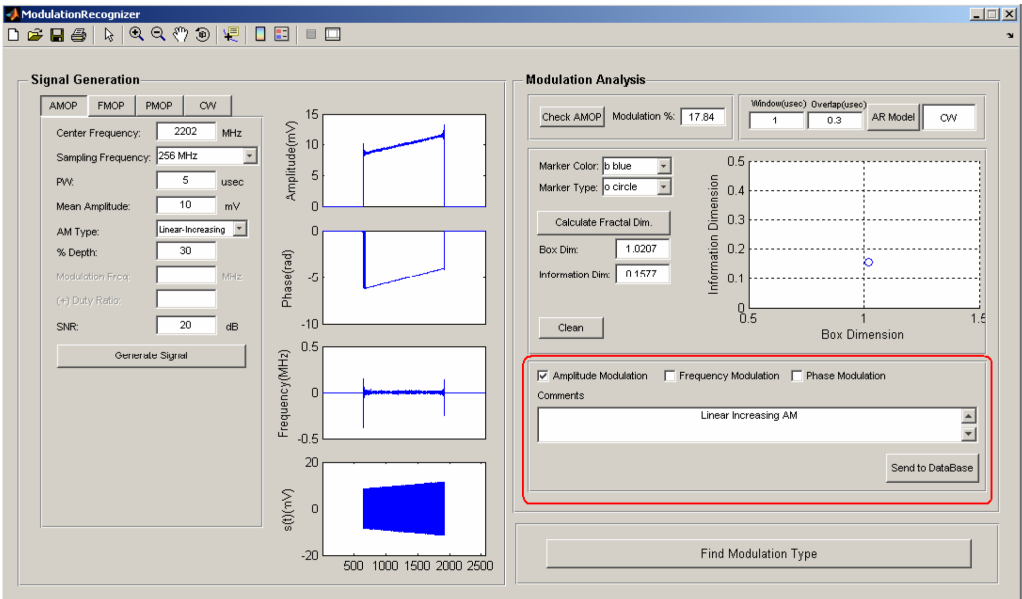

Figure B.6. Database Update Part of the GUI.

❖ MODULATION RECOGNIZER

If the user presses the “Find Modulation Type” button on the GUI, system begins to run modulation analysis tools on the received signal automatically. By this way, user can learn the system’s decision about the modulation type of the received signal, without making any manual analysis.

Depending on the signal’s modulation property, system makes a decision about the signal and reports this decision by the use of a dialog box, seen in Figure B.7.

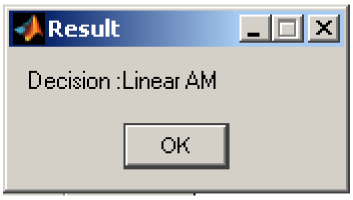

Figure B.7. Modulation Recognizer Decision Box

If the modulation type of the signal is AM or FM, these signals are analyzed by the help of Fractal Theory Decision Block. While this block makes decision depending on a database search, Another window reporting the database search results are also opened for AM and FM modulation types. This window is shown in Figure B.8.

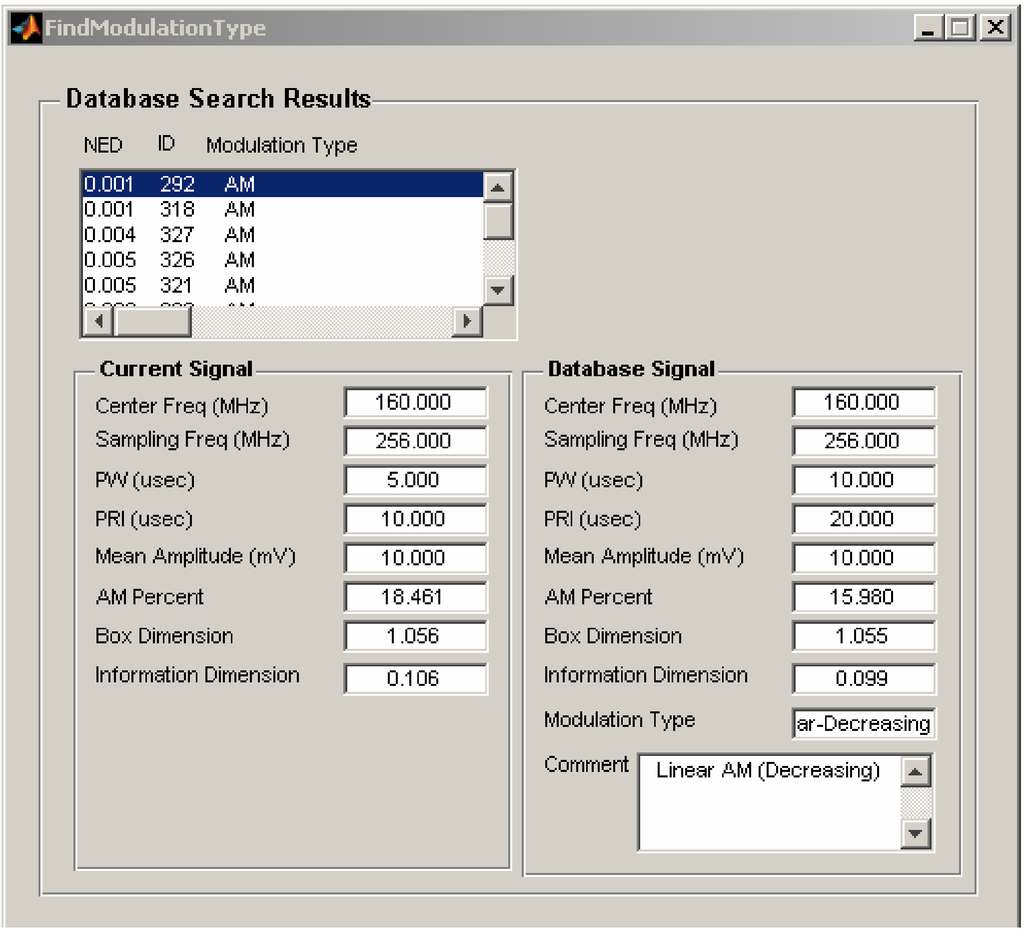

Figure B.8. Database Search Results of the Fractal Theory Decision Method.

In this window, signals from the database which are found to be close to the currently analyzed signal are listed, with an ascending order of their Normalized Euclidean Distances. Also signal properties of the currently analyzed signal, and the signals from the database are shown respectively, so that one can make a comparison between them.

A CD containing the standalone executable version of the Modulation Recognizer application is also included at the end of this thesis. The application is compiled with Matlab R2006a, thus in order to run the software it is essential that you install the MCR (Matlab Component Runtime) 7.4 on your PC. Since this is a standalone version, you do not need to install Matlab to your computer.

Furthermore, for the Modulation Recognizer application to operate correctly, it is essential that you add the IMOP database given in the CD to your computer's data sources. To achieve this, from **Start** menu of your computer, enter **Settings** -> **Control Panel** -> **Administrative Tools**. In this menu click on the **Data Sources (ODBC)** shortcut. In the opening **ODBC Data Source Administrator** window (Figure B.9), **add** the **IMOPDatabase** selecting **Microsoft Access Driver (*.mdb)** option (Figure B.10).

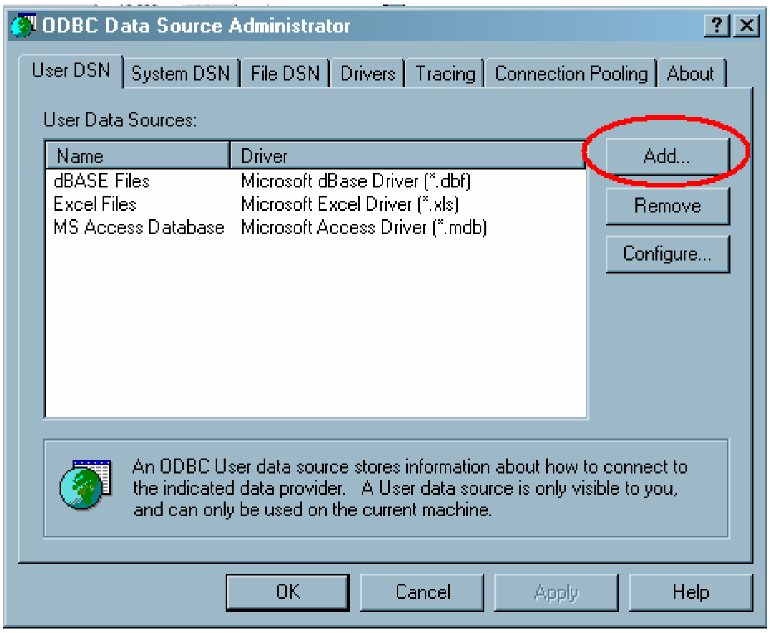

Figure B.9. ODBC Data Source Administrator window.

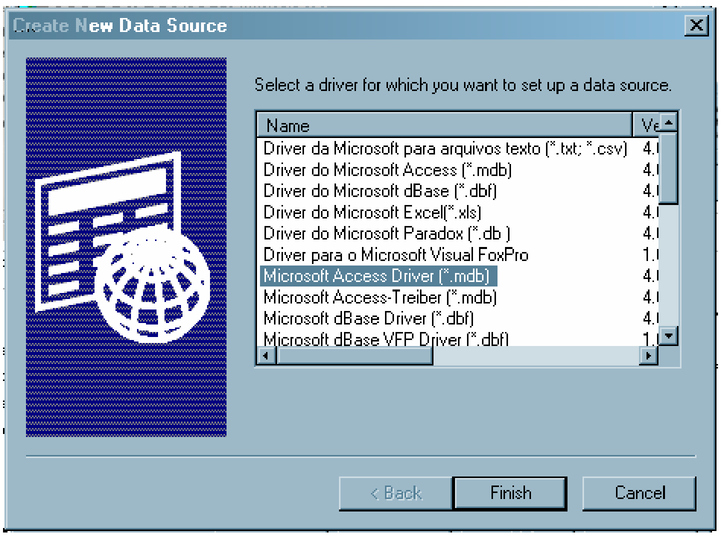

Figure B.10. Create New Data Source window.

In the opening **ODBC Microsoft Access Setup** window, add the **IMOPDatabase** to your computer's data sources. The resultant form of this window should look like the one in Figure B.11.

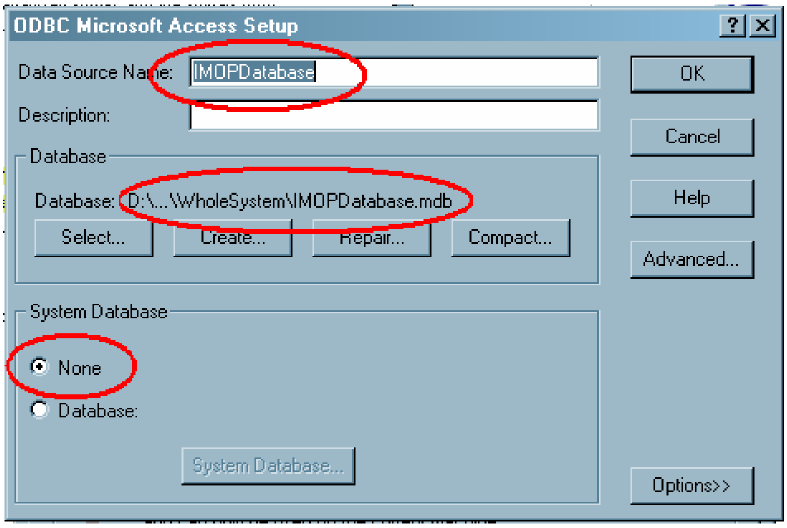

Figure B.11. ODBC Microsoft Access Setup window.

C. PSK CODES

Table C.1. Binary Codes corresponding to Barker code Types

Number of Bits in the Barker Code	**Binary Code**
2	1 0
3	1 1 0
4	1 1 0 1
5	1 1 1 0 1
7	1 1 1 0 0 1 0
11	1 1 1 0 0 0 1 0 0 1 0
13	1 1 1 1 1 0 0 1 1 0 1 0 1

Table C.2. Phase Difference Matrices corresponding to Frank Code Types

Number of Phase Steps in the Frank Code	**Phase Difference Matrix**
2	$\begin{pmatrix} 0 & 0 \\ 0 & 180 \end{pmatrix}$
4	$\begin{pmatrix} 0 & 0 & 0 & 0 \\ 0 & 90 & 180 & 270 \\ 0 & 180 & 0 & 180 \\ 0 & 270 & 180 & 90 \end{pmatrix}$
6	$\begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 60 & 120 & 180 & 240 & 300 \\ 0 & 120 & 240 & 0 & 120 & 240 \\ 0 & 180 & 0 & 180 & 0 & 180 \\ 0 & 240 & 120 & 0 & 240 & 120 \\ 0 & 300 & 240 & 180 & 120 & 60 \end{pmatrix}$
8	$\begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 45 & 90 & 135 & 180 & 225 & 270 & 315 \\ 0 & 90 & 180 & 270 & 0 & 90 & 180 & 270 \\ 0 & 135 & 270 & 45 & 180 & 315 & 90 & 225 \\ 0 & 180 & 0 & 180 & 0 & 180 & 0 & 180 \\ 0 & 225 & 90 & 315 & 180 & 45 & 270 & 135 \\ 0 & 270 & 180 & 90 & 0 & 270 & 180 & 90 \\ 0 & 315 & 270 & 225 & 180 & 135 & 90 & 45 \end{pmatrix}$