H. AL-SUDANI

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HIGH-ORDER CUMULANTS BASED CLASSIFICATION FOR COGNITIVE RADIO APPLICATIONS

THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
OF
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HAIDER JALIL SAHIB AL-SUDANI

A MASTER OF SCIENCE THESIS
IN
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Approval of the Graduate School of Natural and Applied Sciences, Atilim University.

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ABSTRACT

HIGH-ORDER CUMULANTS BASED CLASSIFICATION FOR COGNITIVE RADIO APPLICATIONS

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Modern communication systems have witnessed dramatic changes due to the huge development of wireless technologies applications. These developments caused the scarceness of the spectrum and its inefficiency. However, cognitive radio (CR) is proposed as one of the best solutions to maintain high spectral efficiency (SE), and to treat spectrum scarcity. CR delivers the service to the unauthorized user to utilize the spectrum channel when the channel is out of the needs of the authorized user. However, spectrum sharing needs to be completed without signal interference. Thus, CR has many detection techniques for proper management of the frequency spectrum and interference avoidance. The major detection techniques of CR are Energy Detection (ED), Matched-filter Detection (MFD), and Feature-based Detection (FBD). In practice, each one of them has its own advantages and limitations. In this thesis, the use of statistical features in Machine Learning (ML) is proposed for a FBD. A MATLAB simulation is conducted to evaluate the effectiveness of the proposed detector. To this end, firstly, various modulation schemes with various noisy channels are generated. Then, the high-order moments and cumulants are extracted from the corrupted signals in noisy channels. In fact, these features are selected according to their strength in distinguishing between the signal and noise. The detection outcomes are employed in the support vector machine (SVM) classifier and the probability of detection (Pd) is obtained. The highest Pd value is achieved with 3 high-order cumulants in statistical detection. The same Pd value is obtained using SVM classifier by 1 high-order cumulant which reduces the amount of the processed data and simplify the detector complexity.

Keywords: Wireless Communication, Cognitive Radio, Feature-Based Detection, Cyclostationary, SVM , and Machine Learning.

ÖZ

BİLİŞSEL RADYO UYGULAMALARI İÇİN YÜKSEK DÜZEY KÜMÜLANT TABANLI SINIFLANDIRMA

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Ocak 2023, 68 sayfa

Modern iletişim sistemleri, kablosuz teknoloji uygulamalarındaki büyük gelişme nedeniyle çok hızlı değişikliklere tanık olmuştur. Bu gelişmeler spektrumun kıtlığına ve verimsizliğine neden olmuştur. Bilişsel Radyo (BR), yüksek spektral verimliliği korumak ve spektrum kıtlığını tedavi etmek için en iyi çözümlerden biri olarak önerilmektedir. BR, kanal yetkili kullanıcısının spektrum kanalını ihtiyaçlarının dışında kaldığında yetkisiz kullanıcıya kullanabilmesi için tahsis eder. Fakat spektrum paylaşımı sinyal paraziti olmadan tamamlanmalıdır. Bu nedenle, BR, frekans spektrumunun düzgün yönetimi ve parazitten kaçınma için birçok algılama tekniğine sahiptir. Başlıca algılama teknikleri; Enerji Algılama (EA), Eşleştirilmiş Filtre Algılama (EFA) ve Özellik Tabanlı Algılama (ÖTA) olarak sınıflandırılabilir. Genel olarak algılama tekniklerinin özellikleri irdelendiğinde uygulama alnına göre her birinin avantajları ve sınırlamaları olduğu söylenebilir. Bu tezde, bir ÖTA için makine öğrenmenin kullanıldığı yeni bir yöntem önerilmiştir. Önerilen yöntemin etkinliğinin değerlendirilebilmesi için bir MATLAB ortamında benzetimler gerçekleştirilmiştir. Bu amaçla, öncelikle çeşitli gürültülü kanallarla farklı modülasyon şemaları oluşturulmuştur. Daha sonra, gürültülü kanallarındaki bozuk sinyallerden yüksek dereceli momentlerin ve kümülantların çıkarılması sağlanmıştır. Bu özellikler, sinyal

ve gürültüyü ayırt etmedeki güçlerine göre seçilmiştir. Tespit sonuçları, destek vektör makine (DVM) sınıflandırıcısında kullanılarak dedektörden elde edilen tespit olasılıkları (Pd) hesaplanmıştır. En yüksek Pd değerinin, istatistiksel tespitte 3 yüksek dereceli kümülant ile elde edilebileceği gösterilmiştir. Aynı Pd değeri, işlenen veri miktarını azaltan ve detektör karmaşıklığını basitleştiren 1 yüksek dereceli kümülant ile DVM sınıflandırıcısı kullanılarak elde edilebilmektedir.

Anahtar Sözcükler: Kablosuz Haberleşme, Bilişsel Radyo, Özellik Tabanlı Tespit, Döngüsel Durağan, Destek Vektör Makine ve Makine Öğrenme.

To My Family

To the memory of the special and unique icon in my life My Father. May God have mercy on him. Even though his place is vacant, his existence in my heart and my mind has guided me to overcome the difficult moments.

To the supportive and motivating one who keeps our lives colored and bright My Mother. May God save her to keep our days shiny.

To my sisters Rusul and Rafal. They should be thanked for enduring the distance from home and family during my study. Your closeness gives warmth to our family, accept my gratitude.

To My Little Family

To my life partner, who keeps supporting, motivating, and granting with love. My Lovely Wife Nooralhuda, You are the nice half of me and my success.

To the one who makes this life valuable, worthy, and meaningful. My lovely Son Aldhurgham. Your company during this journey has made it easier.

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LIST OF SYMBOLS/ABBREVIATIONS

FCC	Federal communication committee
SE	Spectral Efficiency
CR	Cognitive Radio
SDR	Software Defined Radio
PU	Primary User
DSA	Dynamic Spectrum Access
SU	Secondary User
ED	Energy Detection
FBD	Feature-Based Detection
MFD	Matched-Filter Detection
SNR	Signal-to-Noise Ratio
SS	Spectrum Sensing
CSS	Cooperative Spectrum Sensing
FC	Fusion Center
CDF	Cyclic Density Function
NN	Neural Network
CNN	Convolution Neural Network
ICNN	Improved Convolution Neural Network
BPNN	Back-Propagation Neural Network
MLP	Multi-Layer perceptron
MSE	Mean Square Error
KNN	K-Nearest Neighbor
SVM	Support Vector Machine
BW	Bandwidth
Pfa	Probability of False Alarm
Pd	Probability of Detection

CFAR	Constant False Alarm Ratio
RBF	Radial Base Function
QAM	Quadrature Amplitude Modulation
PSK	Phase Shift Keying
AWGN	Additive White Gaussian Noise
FGPA	Field-Programmable Gate Array
FSK	Frequency Shift Keying
ASK	Amplitude Shift Keying
ML	Machine Learning

CHAPTER 1

INTRODUCTION

High quality in wireless network services requires a high data rate communication channel [1]. In general, a communication channel utilizes a spectrum assigned by authorized organizations [2]. Static spectrums' allocation produces spectrum scarceness meanwhile, the spectrum owner's absence underutilized the assigned spectrum [3]. The federal communication committee (FCC) has surveyed spectrum utilization, the survey outcomes clearly proved that the spectrum suffers from low use efficiency [5]. This increases the difficulties and challenges to fulfill user demands. Moreover, many emerging technologies have appeared in couple of recent decades significantly increasing the demand for new spectrum [4]. Therefore, spectrum sharing is proposed to increase SE by two or more users [6]. It is important to note that random spectrum sharing without using a regulator will cause interference. Evidently, to provide high-quality services, interference should extremely be avoided.

Coordination between the users who aim to share the spectrum is the key solution to avoid interference. Thus, coordinated spectrum sharing is proposed for safe spectrum sharing. CR is one of the main tools for efficient coordinated spectrum sharing [7]. For this reason, IEEE has initiated 802.22 WRAN to standardize and develop CR networks [8]. CR is a software-defined radio (SDR) that can sense and detect the spectrum status to allow other users to share the allocated spectrum during the authorized user or primary user (PU) absence [9]. CR is responsible for managing and controlling spectrum-sharing operations without causing any harm to the PU signal, and returning the spectrum once the PU attends [10]. In 1999, CR was introduced as a marvel solution to overcome the low SE and spectrum paucity problem [11]. Nowadays, in the most recent generation 4G, 5G, and beyond networks. CR is one of the enabling key technologies that help to achieve the high demand fulfillment to network services by dynamic spectrum access (DSA) [12]. The cognitive cycle guides the CR for successful DSA, depending on the sensing's data channel status decision will be taken. Thus, sensing is the first step in the cognitive cycle and the core step for spectrum sharing [13]. During the sensing step of the cognitive cycle, CR tries to detect the spectrum holes from the allocated spectrum and assign the vacant channel to a secondary user (SU). Channel assignment to the SU does not end the sensing activity since no harm should occur to the PU's signal. CR should be able to detect the PU's signal in case of coming back [14]. In addition, CR must prevent communication interruption for SU, thus sensing is continuing to find more vacant channels to move SU while returning the assigned channel [15]. Three main detection techniques are employed for the sensing step, namely ED, FBD, and MFD [38]. Detection performance varies according to the radio environment and detection techniques [16]. When the detection techniques are compared in terms of performance, implementation fidelity, and cost. FBD is a powerful detection technique in a noisy radio environment. However, it has a drawback regarding its computational complexity in comparison with the other techniques. ED is simple and fast with low accuracy in a low SNR. On the other hand, MFD is designed for one signal with high detection accuracy, and for this reason, it is expensive in terms of cost [17]. Performance comparison clearly shows that FBD or Cyclostationary detection technique can be employed for more than one signal and provides a high detection performance in low SNR [18]. Moreover, FBD can employ instantaneous or statistical features in the detection operation. Statistical features perform better than instantaneous features [19]. There are some statistical features like covariance matrices [20], eigenvalue [21], statistical mean and variance [22], and high-order cumulants [23]. Challenging detection operations lie in low SNR value, FBD is the best candidate to handle the challenging detection radio environment. But it requires fixing the slowness and high amount of processed data [24]. Thus, ML is proposed to overcome FBD weakness and gain high accuracy performance in a noisy radio environment [25].

The earlier-mentioned drawback of FBD increasing the sensing time which might cause interference and reduce channel throughput. In addition, the highly processed data requires a more complex hardware structure. A new combination of high-order cumulants and SVM Classifier is proposed to achieve a high Pd using FBD. Thereafter, statistical detection data will be fed into SVM to enhance performance.

High Pd is achieved using three high-order cumulants for different noisy channel types, and different modulation schemes. Then, SVM Classifier provides the same Pd with a training accuracy of 100% using one high-order cumulant instead of three. The simulation results of the proposed detector reduce the processed data of the employed feature which will reduce the computational complexity.

The rest of the thesis is organized as follows. Chapter 2 investigates the background information and related works. The third chapter mentions the theoretical analysis in addition to the proposed detection system. The fourth chapter includes the simulation steps of the proposed detector. The fifth chapter discusses the simulation results. Finally, the researchers' conclusions will be briefed in the sixth chapter in addition to the suggested future directions.

CHAPTER 2

BACKGROUND INFORMATION AND RELATED WORKS

2.1. Spectral Efficiency and CR

Modern generations of networks are designed to provide communication services to many emerging technologies wirelessly. In addition, static spectrum allocations cause spectrum scarceness [26]. 5G researches have come up with proposed key solutions for relieving spectrum scarcity. Meanwhile, these solutions have increased network architecture and made it more complex. Moreover, 5G involved many technologies to reduce interferences for better spectrum sharing [27]. CR is the proposed solution for enhancing the SE and spectrum paucity, while other involved solutions focus on spectrum scarcity like beam forming and millimeter waves [28]. CR was introduced by Mitola and Maguire to scavenge on spectrum holes and looks for an underutilized spectrum channel to allow the SU to use the vacant channel opportunistically during the absence of the PU [29]. However, the proposed solutions need some enhancement to overcome the obstacles. Millimeter waves suffer from penetration through high buildings in urban and highly populated areas. Thus, 5G network architecture has many base stations and repeaters [30]. Meanwhile, CR performance varies because of noise uncertainty and the selected detection technique [18]. Even though, CR has a drawback like other solutions. But CR is preferred more than other solutions. Since it can remedy the spectrum scarcity and SE at the same time [31].

2.2. CR Definition

CR is a combination of SDR and artificial intelligence that can sense and detect the channel status and use it opportunistically. CR technology is designed to share the spectrum between the spectrum owner PU the licensed user and SU the unlicensed user. Moreover, SU must use the available vacant channel and return it once PU asks to reclaim it. The cognitive cycle stated the necessary steps of CR for efficient spectrum sharing as shown in Figure 2.1 [32].

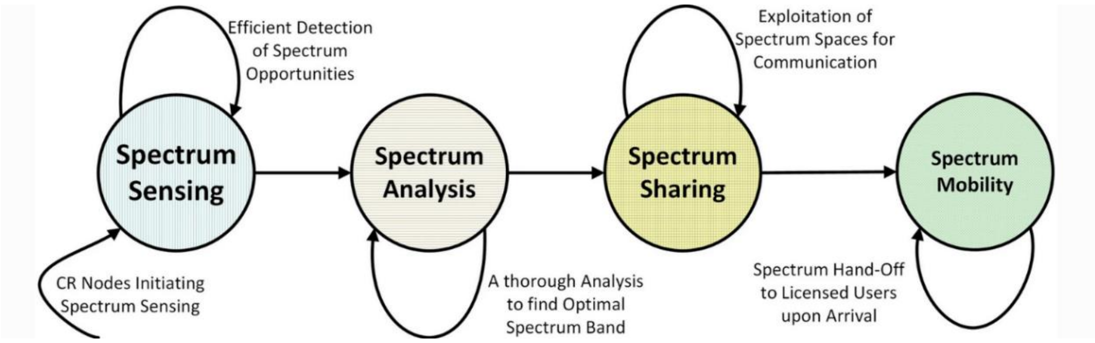


Figure 2.1 Cognitive cycle [32].

CR's main characteristics are awareness, locating radio sources, and changing the parameters to complete a successful cognitive cycle. CR must be aware of the radio environment and locate the radio sources of the transmitter and receiver. In addition to the ability to change the parameter according to the parameter of the available channel [33].

2.3. Spectrum Sensing

Sensing is the most critical step in the cognitive cycle. Since the spectrum sharing must be done without interference or causing any kind of harm to the PU signal. Thus, SS stands as a challenging step because of the noisy radio environment. Meanwhile, CR must recognize the signal of the PU even if the power of noise is greater than the signal. Thereafter, many detection techniques were proposed to overcome the problem of the noisy environment [34]. SS might be done by one SU or by the effort of many users and subjected to the fusion center (FC) decision in cooperative spectrum sensing (CSS). Accurate sensing data are important to find the vacant channel or finding the best vacant channel among the underutilized channels [35].

2.4. Detection Techniques

Many detection techniques were designed to determine the PU status. Therefore, choosing the best detection technique depends on the radio environment noise level.

In addition to the implementation's cost and required performance speed [36]. Moreover, detection accuracy is extremely associated with detection techniques and environmental radio circumstances [37]. There are three main detection techniques that have different points of strength and weakness [38].

2.4.1. Energy Detection

ED is the simplest detection technique and is easy to implement. In addition, prior knowledge is not required for the PU signal. ED suffers from high false alarms and low Pd in low SNR [39]. Since a high noise level leads the detector to report a false alarm. Meanwhile, a low signal level will report misdetection. ED performs as follows, SU keeps observing samples from the desired channel that needs to be shared. Then, performing FFT to extract the frequency component of the collected samples. Thereafter, computing the magnitude value of the collected sample. Finally, comparing to the threshold and concluding the sensing decision. Figure 2.2 illustrates the ED steps to find the channel status [40].

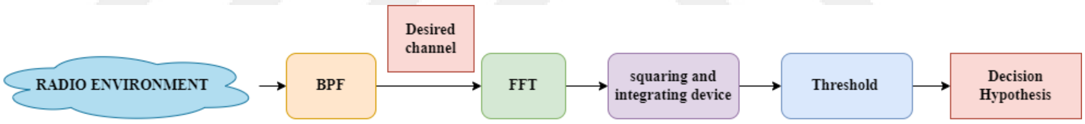


Figure 2.2 ED block diagram [40].

2.4.2 Feature-Based Detection

FBD or Cyclostationary detection is robust against noise. The detector monitors the channel and analyzes the observed samples to find a cyclic event of the PU signal. Meanwhile, all monitoring data must be processed to find the detection's feature. Data processing leads to performance slowness which is an undesirable property of FBD [41]. The technique works as follows, SU collects samples from the monitored channel. Then, find the correlation among the collected samples. Thereafter, the observed samples for a specific time will be subject to the decision criteria to calculate the channel's status. Increasing the number of samples will provide a clearer vision for the detector. However, a longer time is needed to achieve this, while optimal performance requires to have the sensing outcomes within a lower sensing time [42].

A shorter sensing time needs a robust feature that can be detected with the fewest possible samples. Figure 2.3 briefs FBD general steps for detection [43].

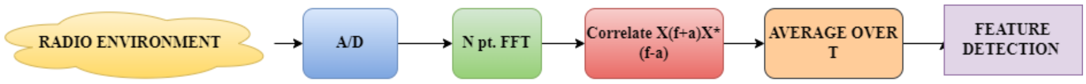


Figure 2.3 FBD steps block diagram [34].

2.4.3. Matched-Filter Detection

MFD is designed for a predefined signal which means prior knowledge of the PU signal is required. MFD has a high Pd in low SNR and low false alarms. But, designing a detector for each signal causes a high implementation cost [44]. Moreover, MFD is a sensor that uses the pilot stream of the PU's signal to detect its presence. PU sends a pilot stream with the message to be received by the receiver and interpreted. MFD needs to have prior knowledge about the PU pilot stream. SU will verify the pilot stream of the observed sample and decide whether PU exists or is absent. In addition, any change in the PU signal parameters needs to update the detector parameter in SU. Each signal has its pilot stream and its parameters thus, utilizing MFD does not provide the required flexibility in detection performance. Figure 2.4 represents the core steps of MFD [45].

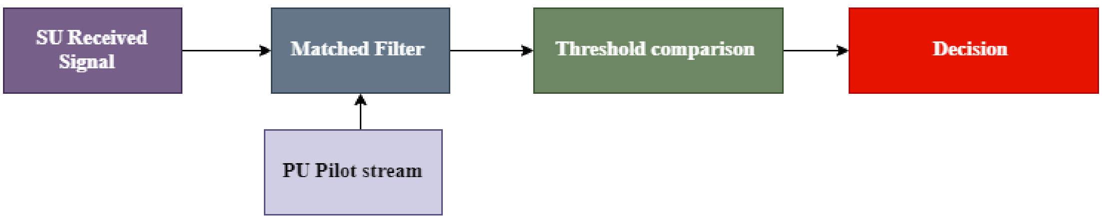


Figure 2.4 MFD steps block diagram [45].

2.5. Detection Techniques Combination

The three main detection techniques have different bright faces for each. On the other hand, each detection technique has an unwanted side. Thus, combining more than one detection technique in a single detector is proposed to overcome the drawbacks [38]. ED and FBD are employed to have a high detection accuracy in low SNR for two stages of detection [46]. However, this combination rises the detection accuracy while sensing time increases accordingly.

2.6. Detection Accuracy Influencers

High Pd is constrained by selecting the right detection technique and accurate calculation of some critical parameters like Threshold. Since a high threshold will produce a miss detection while a low threshold can cause a false alarm [47]. In addition, minimizing the confused region which is clarified in Figure 2.5 by dividing the region into smaller regions. Then applying more than a single threshold will reduce the wrong decisions regarding channel status [48]. Moreover, selecting suitable detection techniques or selecting the right features for the FBD according to the measured noise level will enhance the detection accuracy. But, the radio environment has rapid dramatic changes in noise levels. Thus, adaptivity is proposed to have a fixed detection performance during radio environmental changes [49].

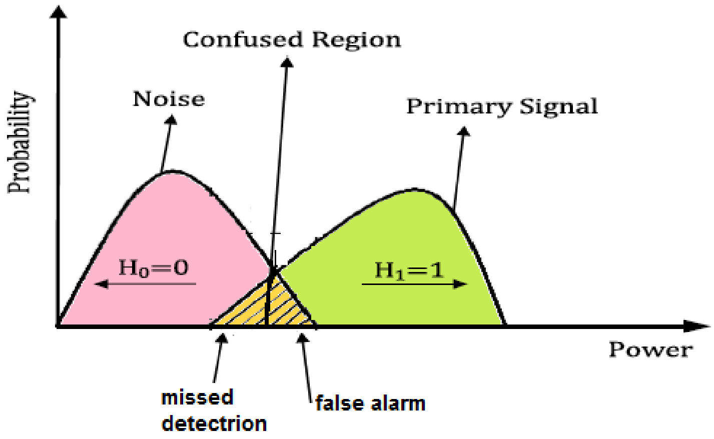


Figure 2.5 Detection confused region [48].

2.7. Experiential Detection and ML Utilization

Experiential detection is proposed to use historical sensing data and decisions in future detection activity. Furthermore, slow detection techniques with a high Pd, low false alarm, and miss detection are the best candidate for experiential detection. FBD is usually integrated with ML to produce an experienced detector that saves data processing time [50]. In addition, Some features perform well with some kinds of ML while other types do not provide the same performance [51]. Thus, selecting the best feature and combining it with the appropriate ML technique is a kind of topic that needs to be judged experimentally. ML has many other utilizations in CR for adapting thresholds or optimizing the overall performance. In the cognitive cycle steps, ML can be involved at any step to achieve the desired performance. ML might involve in classification based on previous detection decisions. ML algorithms are suitable for optimizing in addition to granting the system human reasoning while the channel status decision-making [52].

2.8. Sensing and Feature Extraction

The signals who are repeating and not changing over time are called stationary signals. Spectral components of the stationary signals are carried the detection features. Therefore, feature extraction from the spectral content in low SNR is quite difficult due to the signal's corruption. However, the cyclic density function (CDF) represents the key point for detecting the PU signal and feature extraction [53]. The detector continuously keeps sensing the channel to find out a cyclic event. Then, analyzes this cyclic event for feature extraction of the PU's signal from noise and decides the channel's status. Meanwhile, declaring an available channel will require more sensing operations after the SU channel assignment. The detector needs to be aware of cyclic event reappearance by sensing to move to another channel. [54]. Thus, feature extraction must be done rapidly and accurately to avoid the PU and SU signal interference when the PU's signal reappears in the channel. There are two categories of sensing wideband sensing and narrowband sensing. Wideband sensing requires more time and computation. Narrowband sensing is preferred in CR applications due to the lower sensing time for feature extraction [55].

2.9. Digital Modulation

Modulation of data inside a carrier signal is necessary for efficient transmission through the wireless medium between the transmitter and receiver [78]. Modulation methods have a couple of important quantities or more. The first quantity is the modulated waveform that includes the data while the second wave is the carrier's frequency. The carrier frequency is higher than the data wave frequency. The carrier wave characteristics are used for modulation [79]. In general, modulation is the operation of changing some parameters of the carrier wave according to modulated wave.

Modulated waves have binary data or M-ary encoded versions of binary data. Carrier characteristics are changing to construct the modulated wave. The main characteristics that are employed for the modulation in the carrier wave are amplitude, frequency, and phase. In this context, amplitude shift keying (ASK) refers to amplitude changes. Meanwhile, FSK means the varied parameter in the carrier wave is the frequency. PSK indicates that the phase angle of the carrier wave is the modified parameter. Furthermore, some modulation schemes change two characteristics or parameters of the carrier wave. In QAM amplitude and phase of the carrier wave are changed to construct the modulated waveform.

2.9.1. Phase Shift Keying

The digital information is represented by different phase angles in PSK. If the modulated data is binary data groups of bits are called symbols. Each symbol will have a unique phase in the baseband. The number of bits in each symbol will identify the number of phase angles. The binary phase shift keying (BPSK) symbol contains one bit. Thus, two phases are employed to represent the information. Meanwhile, two bits per symbol in 4-PSK. Therefore, four phases are required to represent the information. The PSK waveform can be found by equation (1) [80]

$$s_i(t) = \left\{ \sqrt{\frac{2E_s}{T_s}} \cos\left(2\pi f_c t + \frac{2\pi}{M_s} i\right) \quad i = 0,1,\ldots,M_s - 1 \right. \tag{1}$$
$$M_s = 2^{N_b}$$

Where Es denotes the symbol's energy, Ms denotes the number of symbols, Nb denotes bits' number per symbol, fc represents carrier's frequency, and Ts denotes symbol's interval.

For $Ms = 2$(BPSK). To represents the logic 0 and 1, two-phase angles are generated and separated by π. Then, the reference carrier waveform will be shown in equation (2) [80].

$$s_i(t) = \begin{cases} \sqrt{\frac{2E_s}{T_s}}\cos(2\pi f_c t) & for\ symbol\ 0 \\ \sqrt{\frac{2E_s}{T_s}}\cos(2\pi f_c t + \pi) = -\sqrt{\frac{2E_s}{T_s}}\cos(2\pi f_c t) & for\ symbol\ 1 \end{cases} \tag{2}$$

If Ms = 4, four-phase angles are expected to be represented in carrier waveform. The four phases for four symbols, two bits in each. The expected phase angles are mathematically represented in (3) [80].

$$s_i(t) = \begin{cases} \sqrt{\frac{2E_s}{T_s}}\cos(2\pi f_c t) & for\ symbol\ \ 00 \\ \sqrt{\frac{2E_s}{T_s}}\sin(2\pi f_c t) & for\ symbol\ \ 01 \\ -\sqrt{\frac{2E_s}{T_s}}\cos(2\pi f_c t) & for\ symbol\ \ 10 \\ -\sqrt{\frac{2E_s}{T_s}}\sin(2\pi f_c t) & for\ symbol\ \ 11 \end{cases} \tag{3}$$

Phase characteristic is preferred more than amplitude and frequency since PSK has less sensitivity to noise. Figure 2.6 shows the PSK constellation diagram [81].

Figure 2.6 PSK Constellation Diagram [81]

2.9.2 Quadrature Amplitude Modulation

The receiver's ability to recognize the tiny differences in phase represents the limits of PSK in bit numbers and symbols. The limitation is due to using one characteristic of the waveform which is the phase [81]. However, QAM uses two characteristics of the carrier waveform to represent the information. The QAM uses phase and amplitude variation to represent symbols and overcome the potential bit rate limits drawback in PSK. The mathematical description of QAM is in equation (4) [80].

$$s_i(t) = \sqrt{\frac{2E_s}{T_s}}\, a_i \cos(2\pi f_c t) - \sqrt{\frac{2E_s}{T_s}}\, b_i \sin(2\pi f_c t) \qquad (4)$$

where: ai denotes the in-phase content, and the parameter bi denotes the quadrature contents that are independent of each other for all i.

The M-ray's symbols distribution is shown in Figure 2.7 when $Ms = 16$ [81].

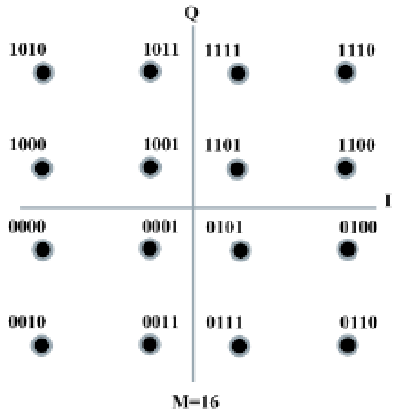


Figure 2.7 QAM Constellation Diagram When $Ms = 16$ [81]

2.9.3 Frequency Shift Keying

In FSK amplitude and phase are kept constant. Meanwhile, symbols are represented by changing the carrier frequency. The binary information is represented by two numbers 0, and 1. The carrier frequency is flapping up and down according to the binary digits. Then each symbol has a unique carrier frequency shift. The FSK mathematical description is shown in equation (5) [80].

$$s_i(t) = \sqrt{\frac{2E_s}{T_s}}\cos(2\pi f_i t) \qquad i = 0,1,\dots,M_s - 1 \qquad (5)$$

The most important features of FSK are it is simple, easy to be recognized, and provides a good performance against interference.

2.10. Noisy and Faded Channels

A wireless signal travel through the spectrum channels. If there is a high noise level inside the channel, the signal will be corrupted before arriving at the receiver. Then, the receiver can not interpret the signal. Noisy channels are divided into fading channels and AWGN channels [82]. In Rayleigh fading channel, the signal arrives at the receiver through multipath due to scattering. Then the signal will be received with a doppler shift. The probability density function (PDF) of the Rayleigh channel can be expressed by using equation (6) [83].

$$P_R\,(r) = \frac{r^2}{\sigma^2}\ exp\,(-\frac{r^2}{2\sigma^2})\ for\ r \geq 0 \tag{6}$$

Where σ^2 denotes the variance, and r denotes the envelope's amplitude of the received signal. In the rician fading channel, the signal arrives in multi-path also with a small exception. This exception is that one of the paths of the same signal provides a dominant signal. The dominant signal might be the signal that arrives from the line-of-sight path while other signals came from this signal reflection on the grounds or any other object. The Rician fading channel can be modeled by the PDF shown in equation (7) [84].

$$P_R\,(r) = \frac{s}{r^2}\ exp\,-\frac{(r^2+s^2)}{\sigma^2}\,I_0\,(\frac{rs}{\sigma^2}) \quad for\ r \geq 0,\ s \geq 0 \tag{7}$$

Where I_0 denotes the modified Bessel function with order zero, and (s) represents the direct signal envelope's amplitude.

2.11. Signal Features

Radio signals mainly have two types of features. Instantaneous and statistical features, the first type of features are the power of the signal or frequency. These features are not reliable for detection due to dramatic changes in those features in noise uncertainty [19]. Meanwhile, statistical features like covariance matrices [20], eigenvalue [21], statistical mean and variance [22], and high-order cumulants [23]. Are preferred more than the instantaneous features for detection due to solid performance in noise uncertainty. In this context, this research is interested in statistical cumulants of the signal as a detection feature due to its high Pd in low SNR [57]. In addition, individual or sets of cumulants provides different performance due to different behaviors of cumulants since it depends on cumulant order [58].

2.12. ML Employment in CR

ML is discussed for many purposes in the CR topic to add adaptively, reduce complexity, and train the detection system. Moreover, faster and more reliable performance can be obtained by learning using ML. A High accuracy performance needs to feed the ML by high accuracy training data set [59]. Thus, ML performance in CR counts on detection technique performance. Meanwhile different kinds of ML algorithms and techniques like neural networks (NN), classifiers, and ML algorithms produce different performances Figure 2.8 shows the ML algorithms that have been utilized in CR for different purposes and in many steps of the cognitive cycle [60]. Furthermore, ML algorithms are proposed for spectrum management not only for SS. Whenever PU asks to reclaim the channel the Genetic algorithm has been employed for finding another channel for SU to avoid communication interruption [61]. Convolution neural networks (CNN) have been utilized in CR to optimize the detection performance of CSS applying rules [62]. In general, ML contributes positively to CR networks. Regarding this thesis, SS requires combining the FBD with the appropriate ML classifier to support the detection in a noisy environment, and achieve efficient signal and noise sample separation.

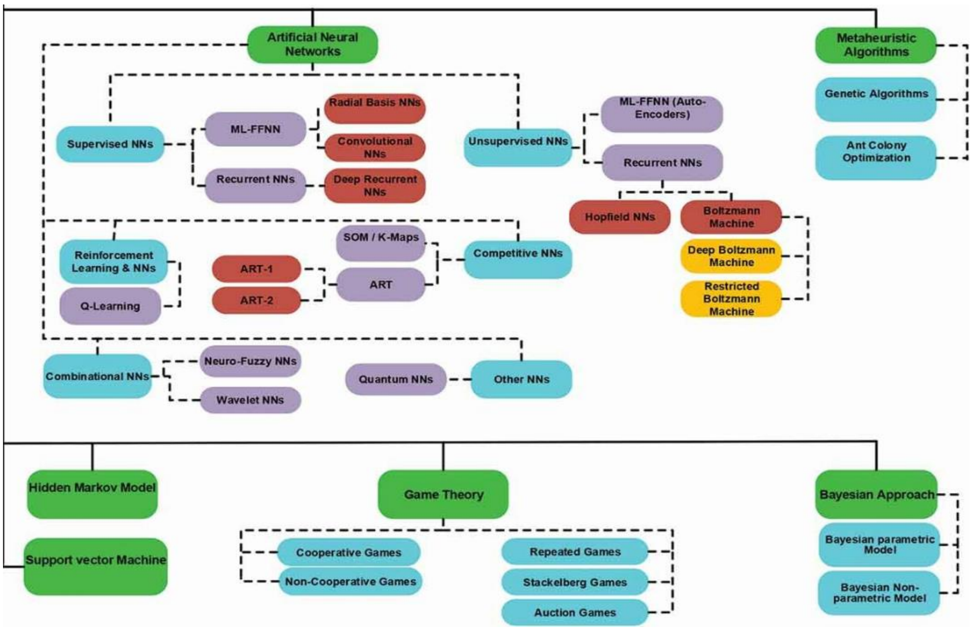


Figure 2.8 ML and CR [60].

2.13. ML and Detection in Noisy Environment

The signal observations and detection decisions represent the whole detection system outcomes. Meanwhile, outcomes contents should contain the presence and the absence of PU. Then, data can be qualified to be utilized in ML algorithms. Thereafter, ML will deal with new observations after finishing the training as classification problems [65]. FBD comes as the best candidate to overcome detection inaccuracy in noise uncertainty. FBD provides the high Pd with long-time sensing. Thus, CNN reduces the consumed time in FBD [63]. As well as, improved convolution neural networks (ICNN) have performed well in the same circumstances [64]. Moreover, the back-propagation neural network (BPNN) has reduced the consumed time, consumed energy for sensing and providing high detection accuracy [65]. the employment of multi-layer perceptron (MLP) in detection system training reduces the mean square error (MSE) to the best level in decision prediction for the next observation after a few epochs as shown in Figure 2.9 the detection enhanced as well [66].

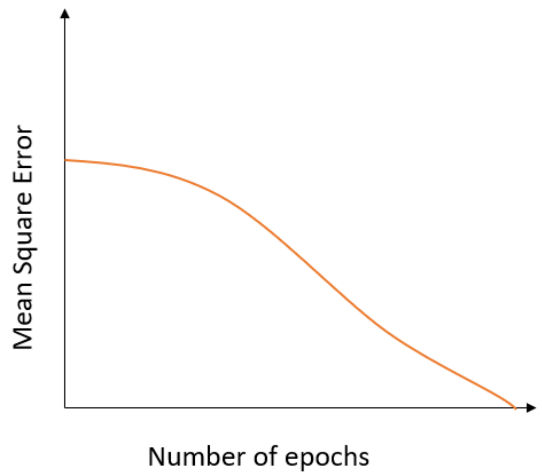


Figure 2.9 Minimizing MSE using MLP [66].

Among many ML algorithms, the challenge is finding the right algorithm for the right problem to be solved. However, several types of research have been conducted to evaluate ML algorithms in different parts of the CR networks.

It was found that in the SS area the best candidate ML algorithms among the tested techniques are Q-learning, k-nearest neighbor (KNN), random forest, and support

SVM [67]. Moreover, SVM is one of the best ML classifiers among the tested ML classifiers for SS and detection problems [74].

CHAPTER 3

THEORETICAL ANALYSIS FOR THE PROPOSED DETECTOR

In this chapter, high-order cumulants will be discussed as detection features for the proposed FBD. Moreover, a brief discussion about the necessary parameters that need to be considered and estimated in advance before starting the simulation works. ML employment in the proposed detection system in addition to the clarification of the way of using the detection outcomes in the ML part of the proposed detector will be explained at the end of this chapter.

3.1. Statistical Features and Detection Hypothesis

Features that represent random variables embedded in the signals. The PU signal is usually generated by software, the software will modulate the signal inside a sinusoidal carrier and then transmit it to the receiver. Thereafter, the signal will pass through the medium. In general, medium immunity is represented by noise, fading, and shadowing. Thus, the received signal will be corrupted by noise. The detection system will face some difficulties to recognizes the signal from the noise, especially in low SNR values. The received signal might be either a corrupted signal or noise only as shown in equations (8) and (9) [68]. The proposed detector needs to calculate high-order cumulants from the collected samples.

$$X(m) = S(m) + w(m) \tag{8}$$

$$X(m) = w(m) \tag{9}$$

Where m denotes the number of samples, $X(m)$ denotes the received sample at the SU, $S(m)$ denotes the PU signal, and $w(m)$ denotes the noise.

The proposed detector decision mainly depends on two hypotheses as clarified in equation (10).

$$G_k = \begin{cases} X(m) \geq \gamma, \ldots H_1 \\ X(m) < \gamma, \ldots H_0 \end{cases} \tag{10}$$

Where (γ) represents the estimated threshold, (H_1) means spectrum status is busy, and (H_0) spectrum is vacant and ready to be assigned to SU. While (G_k) denotes status decision.

As mentioned in the previous chapter FBD is a powerful detection technique for noise uncertainty and ML algorithms are involved to overcome the slowness. Hight-order cumulants are the detections' features for the proposed detector in this thesis. Meanwhile, the ML part will utilize SVM classifier.

3.2. Statistics and High-Order Cumulants

Cumulants or high-order moments are commonly used in detection and estimation theories. These theories are working to estimate the unknown parameters from the collected observation. The unknown parameters are embedded in the moments in different orders. Moreover, the first moment is known as the mean, and the second moment is known as the variance. The third one is called skewness while the fourth-moment name is kurtosis. Primarily, signal features are divided into two main categories instantaneous and statistical. Cumulants are statistical features of the signal [70]. On the receiver side, the collected signals' samples will be complex random variables. Equations (11) and (12) are the general formulas to calculate the moments while equation (13) is the complex random variable moments formula[66].

$$\mu = E(x) \tag{11}$$

$$\sigma^2 = (\mu - E(x))^2 \tag{12}$$

Where μ represents the mean of the random variable (x) samples, while (σ^2) represents the variance same random variable.

$$(E_{i,j}) = E\,[(x)^i.((x)^*)^j] \tag{13}$$

Where (x) is a complex random variable of equation (6), (i, j) identifies the moment order, and $(*)$ denotes the conjugate. Then, the higher-order cumulants formula can be written as shown in equations (14) and (15).

$$C_{1,0} = E_{1,0} \tag{14}$$

$$C_{i,j} = E_{i,j} \tag{15}$$

Where $(C_{i,j})$ denotes cumulant at $(i+j)^{th}$ order. by using equation (15) higher-order cumulant can be obtained by using the Maclaren series [71]. Thus, High-order cumulants that will be used in this thesis will be calculated as follows:

$$C_{1,1} = E_{1,1}$$

$$C_{2,0} = E_{2,0}$$

$$C_{3,1} = E_{3,1} - 3\, E_{2,0} * \; E_{1,1}$$

$$C_{3,3} = E_{3,3} - 6\, E_{2,0} * \; E_{3,1} - 9\, E_{1,1} * E_{2,2} + 18(E_{2,0})^2 * E_{1,1} + 12(E_{1,1})^3$$

$$C_{6,0} = E_{6,0} - 15\, E_{2,0} * \; E_{4,0} + 30\; (E_{2,0})^3$$

Where $E_{i,j}$ Represents the moments and $C_{i,j}$ denotes the high-order cumulants.

3.3. Threshold Selection

In statistical-based detection, thresholds are estimated experimentally by generating a corrupted signal by different noise levels. Then, find the statistics of the signal at each noise level. Particularly, in high-order cumulants, each cumulant statistic needs to be obtained experimentally then deciding how many cumulants will be employed for the detector. The detector will have a threshold for each cumulant. Thus, the detection operation will be subjected to more than one threshold. For this reason, high-order cumulants are preferred in addition to the solid performance in the negative SNR region for some cumulants. Figure 3.1 shows the high-order cumulant $C_{3,1}$.

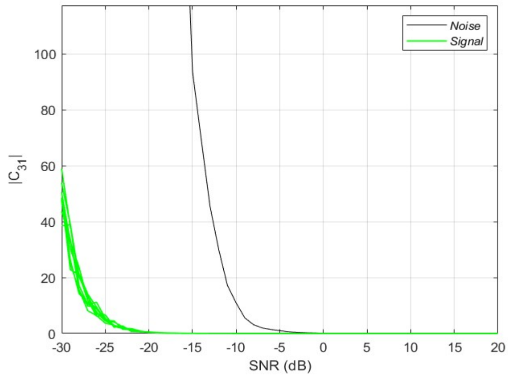


Figure 3.1 $C_{3,1}$values vs SNR.

The green curves represent the $C_{3,1}$ values for different SNR levels while the black curve denotes the $C_{3,1}$ for the noise. In Figure 3.1 several signals were generated using different modulation schemes. To estimate the threshold from $C_{3,1}$ value the following procedure is used to estimate the threshold. By looking at the figure, the black curve does not exist in the SNR region (-30 to -14). Signal curves start rising at SNR (-22). Thus, if ($C_{3,1}$< 60) in the mentioned SNR range, the channel status will be busy which means the channel is utilized. $C_{3,1}$ has the operational range mentioned above which is not enough for the whole detection process. However, A combination of cumulants is proposed to cover a wider SNR range. Meanwhile, the detection process in positive SNR values is an easy task for the detector. Cumulants are necessary for negative SNR values due to the high separation margin between noise and signal. Moreover, a combination of high-order cumulants allows the detector to apply a series of thresholds to verify channel status.

3.4. Sensing Time

Sensing time is a crucial parameter for the detection system since CR needs to complete a cognitive cycle in a very short time, and keep sensing according to FCC standards. Thus, lower sensing time represents one of the key points to avoiding signal interference between SU and PU. In addition, long sensing time for vacant channels reduces channel utilization. Therefore, lower sensing time produces a higher throughput. Sensing time is mainly related to channel bandwidth (BW), and the sample amount which represents message length. According to the Nyquist sampler, the minimum number of samples is twice of BW frequency to reconstruct the sinusoidal signal. In these regards, longer message lengths carried more details for the detector. But, sensing time will be increased while lower sensing time is required extremely. Therefore, balancing message length and sensing time is necessary to have optimal performance. Adaptive systems are proposed in many researches for better performance and higher throughput by reducing sensing time. SNR stands as the regulator to adapt the sensing time in low SNR values, higher sensing time is required, while normal SNR values need a shorter sensing time. Furthermore, the maximum sensing time is about 2 ms for CR. By using equation (16) sensing time can be estimated [72].

$$N = Ts * Fs \tag{16}$$

Where (N) denotes message length by the number of samples, (Ts) sensing time, (Fs) is the sampling frequency.
As it is obvious the minimum necessary number of samples to reconstruct a sinusoidal signal is to observe two points to plot the negative and positive peaks of the signal according to the sub-Nyquist sampler [73]. By substituting the necessary number of the samples in equation (16) in addition to considering the BW of the channel sensing time can be found using equation (17).

$$Ts = \frac{2N}{BW} \tag{17}$$

Thus, shorter sensing time can be obtained by selecting the right message length according to the channel's BW.

3.5. Variable Parameters for The Detection Systems

Some parameters need to be set before conducting the simulation trials**.** However, setting those parameters or assigning values to part of them must be close to real environmental measurement. So the detector can meet the expected performance during the implementation.

3.5.1. SNR Setting

Firstly, different SNR values must be chosen for monitoring the behavior of the detection system. In addition, most of the selected SNR range is preferred to be located in the negative region. The wider range will help to identify the operational SNR range for the detection system.

3.5.2. Probability of False Alarm

Different false alarm values need to be set to be tested with SNR values then monitor the detection system performance for each tested Pfa. the considered Pfa(s) <= 0.1. since the minimum required Pd > = 0.9.

The Pfa is the probability of a wrong decision that could be taken by the detector. The detection system might have wrong decisions when the noise level exceeds the threshold. Thus the detector will declare a signal while it was just a high level of noise. However, the constant false alarm ratio (CFAR) approach comes to keep a constant false alarm rate in the detection system which produces a fixed Pfa.

3.5.3 Message Length

A longer message carried out more details about the signal. Detailed information increases detection decision reliability. But, a longer message needs more time and resources to be processed. Thus, different message lengths need to be tested to figure out the detection performance and balance the message length according to the required sensing time.

3.6. ML Classifier for The Proposed Detector

As mentioned in chapter 2 ML algorithms and classifiers have been employed in many aspects. In detection problems, ML is proposed to classify the observed data into two classes either noise or signal. SVM classifier stands as one of the best classifiers in detection problems. Moreover, SVM can be employed to classify more than two classes from many features by plotting a hyperplane among the observed features. Figure 3.2 shows the SVM classifier hyperplane between two classes.

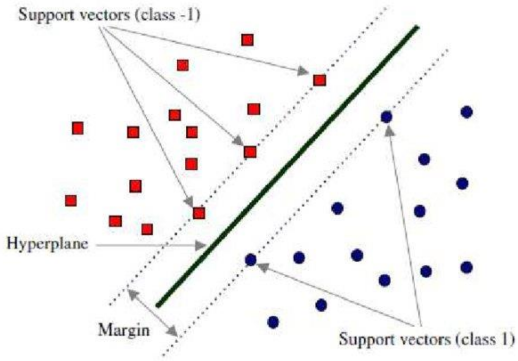


Figure 3.2 SVM classifier hyperplane

The closest observations to the hyperplane are named the edge observation or the support vectors. Meanwhile, the distance between the edge observation of the class is called the margin. Better classification performance comes from a larger margin.

3.6.1. SVM Classifier Kernel Function

There are many kinds of kernel functions in SVM classifier, some of them linear while others are non-linear. The radial base function (RBF) is widely used in vector, text, and image classification. Simply kernel functions are responsible for transforming input data to the required data form that meet SVM requirement for classification. There are two important parameters used in RBF (ξ) gamma and (C) c-value [75]. These two parameters are used to evaluate each single input training entry. Whenever (ξ) has a high-value mean close while a low value means far from the classification model. (C) value has an inverse relation with the decision function margin. Moreover (C) value refers to the correct classification of each training example.

3.6.2. Cross-Validation

Cross-validation is a mandatory step in ML classifiers. It uses to evaluate the input training data. Cross-validation is necessary to diagnose over-fitting. The over-fitting occurs when the classifier fails to establish a pattern for the input training data.

3.7. Proposed Detection System

Due to the solid detection performance in the noisy radio environment of the FBD as mentioned in the previous chapter, and the strong separation between noise and signal samples. In this thesis, the proposed FBD will utilize high-order cumulants because of the different characteristics of each cumulant. Moreover, high-order cumulants allow the detector to apply a series of thresholds depending on the number of employed cumulants in the detection operation. As clarified in the related works, there are many approaches to high-order cumulants employment in detection like using a single cumulant, a couple of cumulants, or 3 cumulants. Certainly, 3 cumulants will provide better detection performance in a wider SNR range than using single or 2 cumulants. In order to achieve better detection performance cumulants selection must be done experimentally and tested with different SNR values. Therefore, 3 high-order cumulant detectors will need a longer time than a single cumulant or couple of cumulants to achieve higher detection performance. In addition to more complex hardware design. However, SVM classifier is proposed to overcome mentioned drawbacks. Furthermore, several parameters need to be modified and tested during the simulation to evaluate the detection performance.

3.7.1. Detection Parameters and Constraints

As mentioned earlier in this chapter and the previous chapter, there are some standards for any proposed detection system. Firstly, Pfa acceptable value, Pfa should be <= 0.1. Secondly, the Pd acceptable value must be => 0.9. Pd and Pfa are not the only constraints. Sensing time is the most critical parameter. In this context, sensing time is mainly related to the message length and BW. Sensing time can be increased because of the number of trials of samples examination or as they commonly called the number of trials. Sensing outcomes should be obtained with minimum possible trials from the well-designed detector. Meanwhile, increasing sample examination trials will produce more accurate detection decisions. The number of trials is a very powerful tool for noisy channels. Anyway, sensing time should not exceed 2 ms.

3.7.2. Selecting Modulation Schemes

Detection performance differs from one modulation scheme to another. However, using many types of modulation is a mandatory criterion for FBD. In addition, randomizing the modulation scheme in each trail is very necessary to CR since SU will scan the channel without any knowledge of the PU signal modulation scheme.

Modulation is an essential step between the RF transmitter and receiver. In general, The transmitter modulates the data inside the RF carrier for many reasons some of them related to data protection, data security, avoiding environmental impact, and transmission distance. Modulation schemes keep developing according to new network requirements. Some of the old modulation schemes have faded out while new schemes have been established a well-designed detector should consider the modern modulation schemes in addition to legacy modulation schemes. So that the detector will be able to detect signals with different modulation schemes. Moreover, the detector will be operatable for a longer time. The considered modulation schemes in the proposed detector are QAM, PSK, and FSK.

3.7.3. Noisy Channels

Radio channels represent the workspace of the CR's detector. The radio channel has different types of noise, fading, and shadowing. Some channels have noise only, fading only, or shadowing only. Meanwhile, other channels have all of them. Thus, noise, fading, and shadowing are described by the word noise. Signal corruption usually comes from noise. The corrupted signal is more difficult to be detected because of noise. Furthermore, when the noise level is greater than the signal that confuses the detector, sometimes in FBD the high level of noise hides the cyclic event that could be used as a detection feature. However, a designer must consider the noise, fading, and shadowing while selecting the detection feature. In addition, testing Pd in radio channels with different types of noise and different noise levels to figure out the detection performance. The additive white gaussian noise (AWGN) and fading will help to have the RF channel close to reality. The AWGN has a normal distribution $\mathcal{N}(0,\sigma^2)$ and it has the same impact on all frequencies in the spectrum [6]. Thus, AWGN is commonly used in detection problems. In addition, consider the most common types of fading and mix them with AWGN to evaluate the detector performance under different channel types. Moreover, randomizing the noise and fading in each trail of detection gives more adaptivity to the detector. therefore, solutions could be found for detection enhancement if the detector did not perform well in noisy channels. AWGN, Rayleigh fading, and Rice fading will be considered in the proposed detector.

3.7.4. Feature Extraction and Detection Decision

The Pfa values and SNR range will be selected. Then, the Modulated signal will be generated and passed through the noisy channel. SU will act as the receiver. The observed samples by the receiver will be corrupted according to a predefined SNR value. 3 high-order cumulants will be calculated from the observed samples. The high-order cumulants calculation will be the feature extraction. Cumulants values will be compared to the predefined thresholds. Finally, the detection decision will be compared to the generated signal to find the Pd.

3.8. SVM Classifier and Proposed Detection System Training

SVM classifier mainly requires two data sets. Namely, the training data set and the testing data set. The training data set is used to build the classification model. Each entry in the training data set will be evaluated according to ($\boldsymbol{\xi}$) and (**C**) values. As mentioned earlier ($\boldsymbol{\xi}$) and (**C**) values are used to measure the classification model influenced by each training entry. Thus, training accuracy mainly depends on the training data set. The training data set contains features that are represented by high-order cumulants. Features will be collected from the statistical FBD outcomes. As well as testing data sets that have the same features. The training and testing data sets have two classes, these classes are the detection decision. training and testing data sets are generated by selecting the Pfa. The generated signal for a specific Pfa will be examined for the specified SNR range, testing will start from the lower SNR value toward the higher SNR value in the range with a fixed incremental step. A shorter step produces more detailed data since cumulants, and detection decisions will be calculated at each step. Detailed data is necessary for the training data set to build an efficient classification model. In order to find the best training scenario, the training and testing data will be generated into two cases as follows:

- The training data set and testing data set will have the same SNR incremental step.
- The training data set will have a shorter step than the testing data set.

Then classifier simulation trials will be conducted with different hypotheses. Firstly, SVM classifier will be forced to use all the cumulants. Secondly, SVM will be allowed to select the included features and performs the classification activity. Finally, SVM classifier will be allowed to select included features by adding some randomly generated features, in addition to the real features while performing the cross-validation. Then, classify the testing data according to the classification model. The core steps for the proposed detector are shown in Figure 3.3.

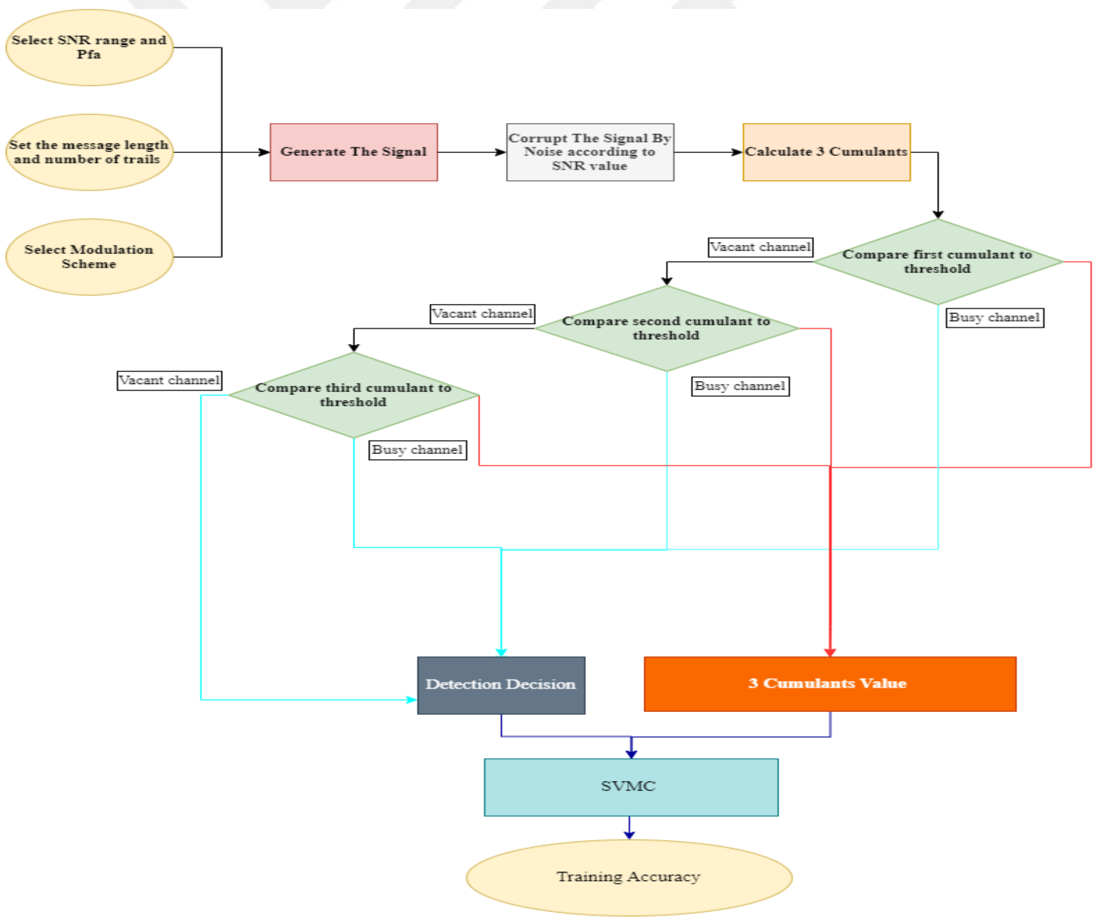


Figure 3.3 Proposed detector block diagram.

CHAPTER 4

PROPOSED DETECTION SYSTEM SIMULATION

This chapter includes the simulation steps. Changing some parameters during the simulation process may have a major effect to enhance the detection accuracy. Moreover, applying more than a single approach during ML classification using SVM might produce different results. 3 cumulants are required for the detection as mentioned in chapter 3. Thus, the simulation will be conducted to find out the best 3 high-order cumulants for the detection process. Then, conducting SVM classification using the same cumulants. In addition, to find the best training approach. The simulation studies have mentioned that Matlab is a powerful tool for CR networks and detection problems due to the accurate results. Evidently, Matlab has many tools for modulation schemes and noise generation that facilitate the simulation process regarding detection and training. Thus, Matlab is the simulation tool for the proposed detection system.

4.1 Threshold Estimation

Cumulants' threshold values need to be estimated experimentally. Moreover, different types of modulation schemes are employed for threshold estimation, to guarantee the same performance for all generated signals during the detection as mentioned in the previous chapter. Thus, thresholds need to be estimated for different SNR values. Figure 4.1 shows the simulation steps for the threshold estimation. The generated modulation schemes are 2,4, and 8 PSK, in addition to 16,32,64,128, 265 QAM, and FSK. The generated modulation schemes were passed through the noisy channels that contain AWGN, Rayleigh fading, and Ricean fading. In this thesis, 5 cumulants are proposed to be examined. The 5 cumulants are ($C_{2,0}$, $C_{1,1}$, $C_{3,1}$, $C_{3,3}$, and $C_{6,0}$).

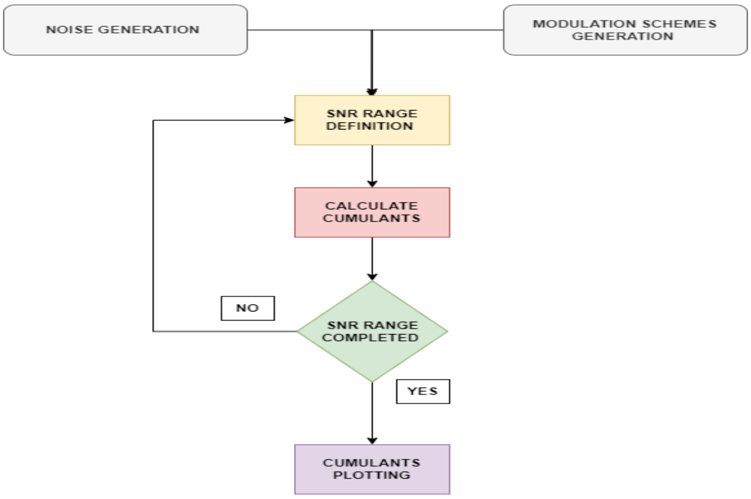


Figure 4.1 Threshold estimation simulation steps

The method of threshold estimation is explained in chapter 3. The proposed cumulants have different SNR operational ranges, in other words, each cumulant provides the required separation between signals and noise in different SNR regions as shown in Table 4.1. The green curves represent the modulated signal while the red curve is for noise. From the simulation outcomes, the proposed high-order cumulants have different operational SNR regions. Evidently, most of the operational regions are in the negative part of the proposed SNR range. It was clearly noted that $C_{2,0}$ provide the best range in negative SNR region (-30 to -14).

Table 4.1 High-order cumulants values for various modulations schemes vs noise

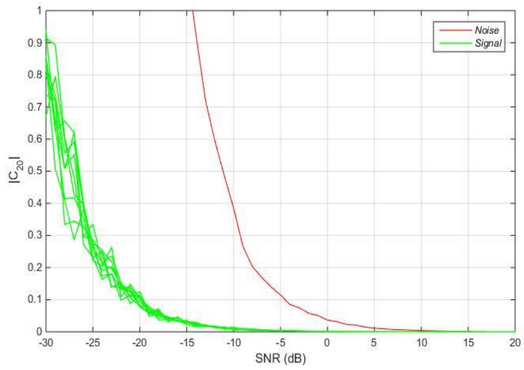
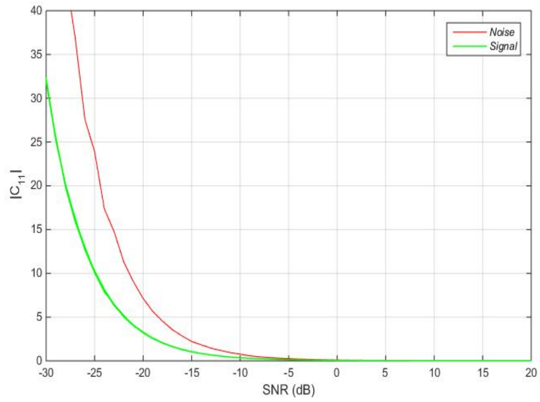
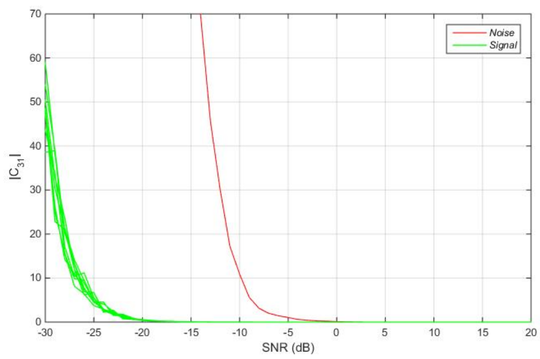
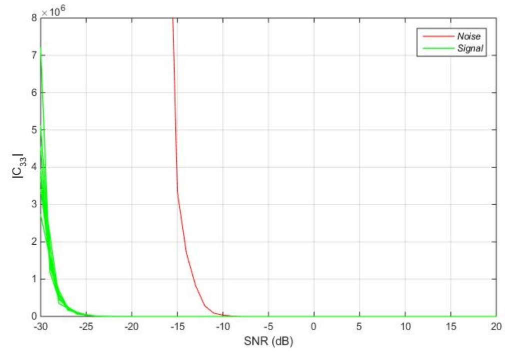
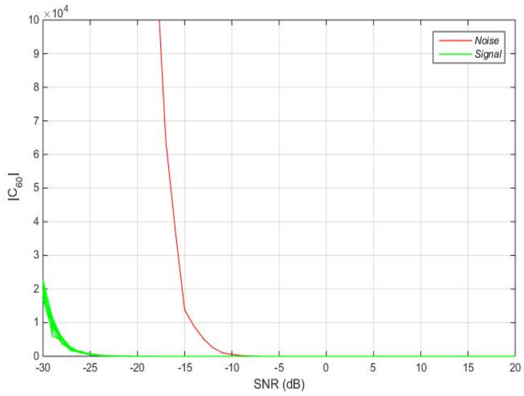
High-order cumulants	Simulation results plot	Comment
$C_{2,0}$		If $C_{2,0}$ < = 0.9 in the SNR range (-30 to -15) means a signal detected anything else means noise.
$C_{1,1}$		If $C_{1,1}$ =<32 in the SNR range (-30 to -27) means a signal anything else means noise
$C_{3,1}$		If $C_{3,1}$< 60 in the SNR range (-30 to -14) means signal anything else means noise

Table 4.1 continue

$C_{3,3}$		If $C_{3,3}$ =< $(7 * 10^6)$ in the SNR range (-30 to -16) means a signal anything else means noise
$C_{6,0}$		If $C_{6,0}$< $(2.2 * 10^4)$ in the SNR range (-30 to -18) means signal anything else means noise.

By identifying the SNR value of the noise cumulant ending and the operational SNR range for the same cumulant. Thresholds can be estimated.

4.2. Modulated Signal Generation

As mentioned in the previous chapter digital modulation schemes will be used for signals generation by Matlab. The FSK signal is generated according to equation (5) with a separation frequency of 16 Hz between the successive frequencies, 16 samples per symbol, and a sampling frequency of 128 Hz. The QAM signals are generated according to equation (4) without phase offset and symbol input. The PSK signals are generated according to equation (1) without phase offset and symbol input.

4.3. Faded channels simulation

The Rayleigh and Rician fading channels are simulated via Matlab using equations (6) and (7) with a doppler shift equal to 50 Hz and a sample time equal to 1 microsecond. In addition, AWGN is generated with normal distribution $\mathcal{N}(0, 1)$.

4.4. The Proposed Detector Simulation

The high Pd at a low SNR level is the main purpose behind a high-order cumulant-based detector. As mentioned earlier 5 high-order cumulants are proposed. The proposed high-order cumulants will be divided into sets. Each set contains 3 high-order cumulants out of the 5. In order to discover the best 3 cumulants, simulation trials will be conducted via Matlab. Simulation steps are clarified in Figure 4.2 while simulation parameters are shown in Table 4.2. The simulation will start by generating various modulation schemes for a specific Pfa according to the details mentioned in chapter 3. Then, trials will start from the lower SNR value from the specified range with a fixed incremental step toward the highest value. The high-order cumulants and Pd will be calculated for the whole range after each SNR incremental step. A modulation scheme will be selected randomly. The modulated signal will be corrupted by noise and fading according to the selected channel. The randomly selected modulation scheme is one of the modulation schemes mentioned in Table 4.2. Thereafter corrupted signal in Matlab will be a 1 by N matrix containing complex variable entries. Then, equation (13) will be used to calculate the 3 selected high-order cumulants. The cumulants values will be compared to the pre-estimated thresholds. The decision will be compared to the generated signal if it was a signal, and the detector decision matches then Pd will be increased. If the detector decision mismatch the generated signal Pd will be decreased. After completing all trials for the whole SNR range for the specified Pfa. Pd will be plotted and the process will be repeated for the next Pfa until plotting the Pd for the last specified Pfa. The whole process will be repeated using different high-order cumulants.

The necessary calculation for detector performance can be made for the SNR value, Pd, and Pfa by using equations (18), (19), and (20) [41].

$$SNR = \frac{|R(t)|^2}{|N(t)|^2} \tag{18}$$

Where (R(t)) denotes the observed signal magnitude, while (N(t)) denotes the noise level magnitude.

$$Pd = Q\left(\sqrt{2(SNR)}\right).\sqrt{\frac{\gamma}{\sigma^2}} \tag{19}$$

Where (γ) refers to the threshold and (σ^2) denotes the noise variance. Q denotes the generalized Marcum Q-function.

$$Pfa = 1 - (\frac{\gamma}{\boldsymbol{\sigma}} ,2) \tag{20}$$

Table 4.2 Simulation parameters

Parameter	**Values**
Pfa	0.003, 0.007, 0.05, 0.07, 0.1
Message length	1000, 3000, 5000, 10000 Sample
SNR Range in dB.	-50 to 10
Modulation Schemes	2,4,8 (PSK), 16, 32, 64, 128, 265 (QAM), and FSK
Noise	AWGN, Rayleigh Fading, Rician Fading
Number of trails Per sample	various iterations
Employed Cumulants	$C_{2,0}$, $C_{1,1}$, $C_{3,1}$, $C_{3,3}$, $C_{6,0}$

All simulation trials were conducted using a fixed number of trials, message lengths, and the same type of noisy channels. The reason behind fixing parameters is to provide the same environment for all cumulants. Therefore, comparison can be made for the simulation outcomes.

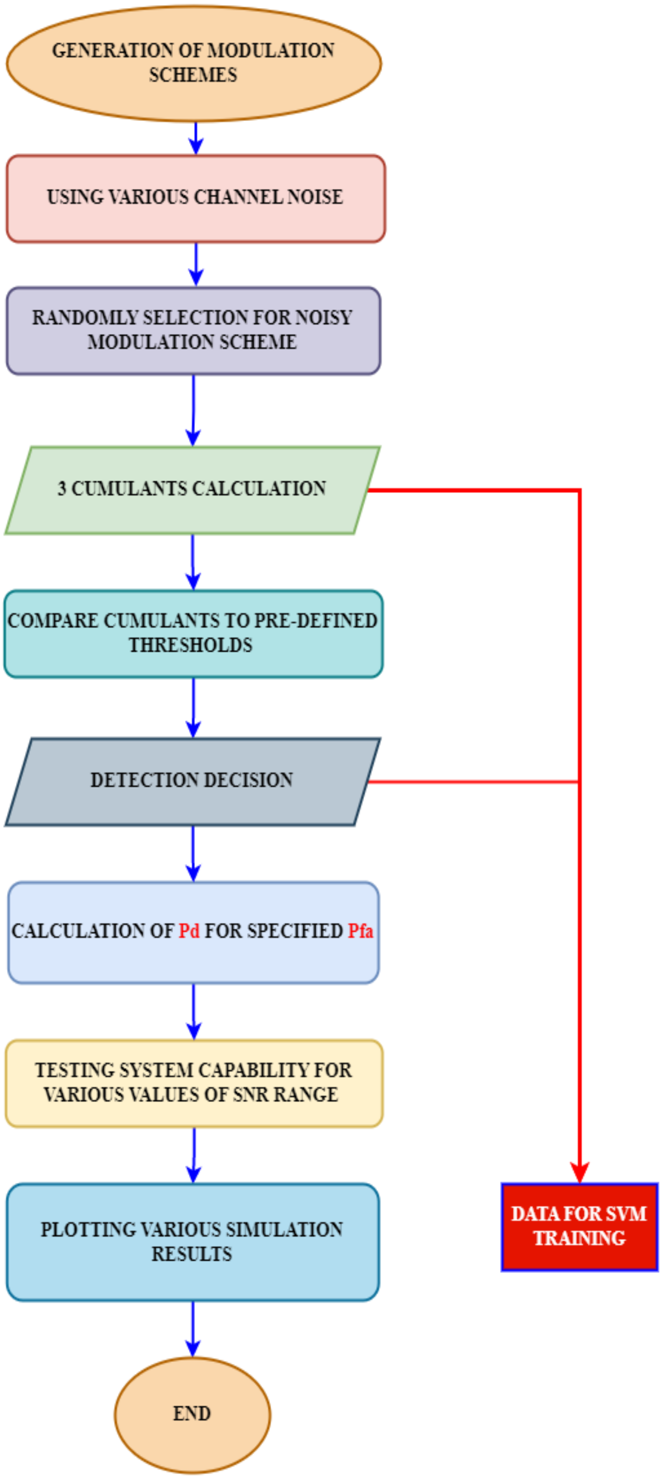
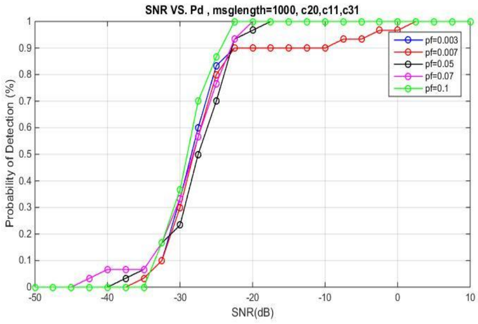
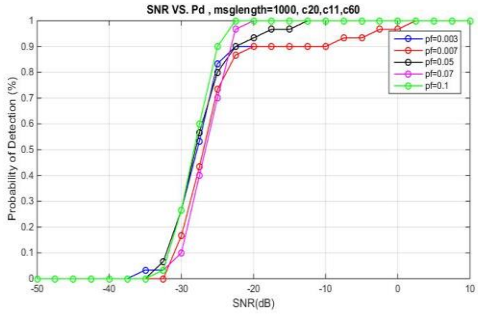


Figure 4.2 Proposed detector simulation steps

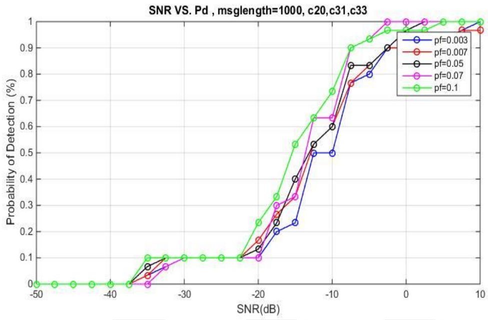
Simulation trials have been conducted the obtained results are shown in Figure 4.3.



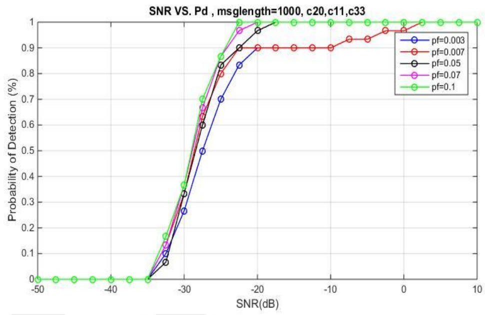
(a)



(b)



(c)

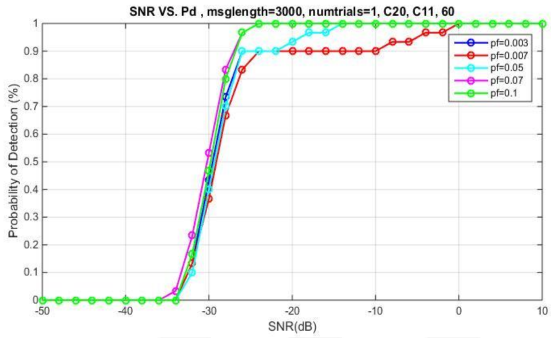


(d)

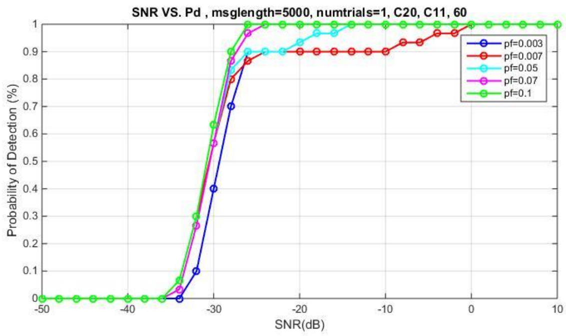
Figure 4.3 Various cumulants sets' Pd vs. SNR

In Figure 4.3 (a) simulation results of the high-order cumulants set ($C_{2,0}$, $C_{1,1}$, $C_{3,1}$). Meanwhile, part (b) of the same figure shows the simulation results of the high-order cumulants set ($C_{2,0}$, $C_{1,1}$, $C_{6,0}$). The cumulants set ($C_{2,0}$, $C_{3,1}$, C_{33}) simulation results are shown in Figure 4.3 (c). Finally, the (d) part of the mentioned figure contains the simulation results of ($C_{2,0}$, $C_{1,1}$, $C_{3,0}$). Different detection performances have been provided by each high-order cumulants set. It was noted during the simulation, removing ($C_{2,0}$, $C_{1,1}$) affects the Pd negatively. However, further investigations will be done using the high-order cumulants set ($C_{2,0}$, $C_{1,1}$, $C_{6,0}$), due to high performance as clearly shown in Figure 4.3 B. The set ($C_{2,0}$, $C_{1,1}$, $C_{6,0}$) achieves Pd = 0.9 at SNR level = -24. Evidently, ($C_{2,0}$, $C_{1,1}$, $C_{6,0}$) performs better than other tested sets.

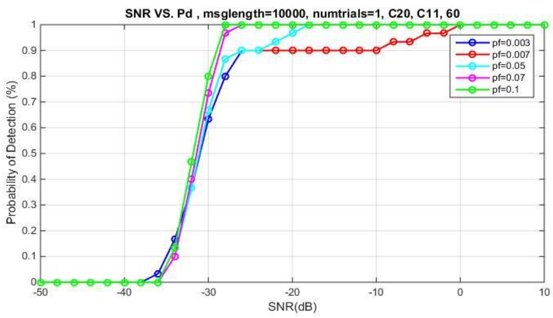
$C_{2,0}$, $C_{1,1}$, $C_{6,0}$ will be employed to perform a further investigation into the effect of message length, noisy channel type, and the number of trails. Simulation for three different message lengths is proposed to check the message length effects on the Pd for the proposed detection system. Different message lengths are proposed with the same number of trails and fixed noise types in each case. The message lengths are 3000, 5000, and 10000 samples with AWGN and a single trail of sample examinations Figure. 4.4 shows the simulation results of the message length effect on Pd.



(a)



(b)

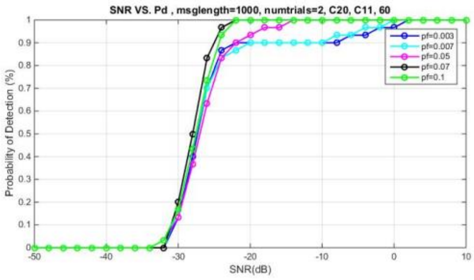


(c)

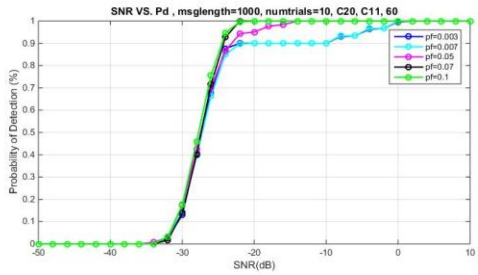
Figure 4.4 Message length vs. Pd

Figure 4.4 (a) is the result of a 3000 sample message length while Figure 4.4 (b) is the result of a 5000 samples message length. Finally, the 10000 samples message length is in part (c).

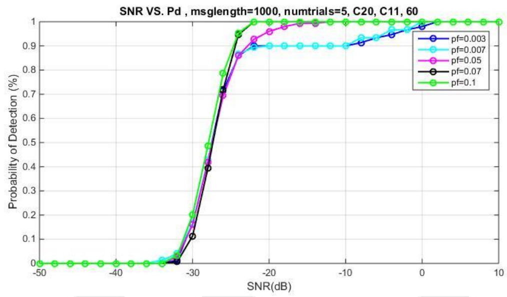
To investigate the number of trials effect on the Pd a fixed message length and one noise type are employed with different 3 iterations number. Simulations of the 2, 5, and 10 trials of sample examination are described in Figure 4.5.



(a)



(b)

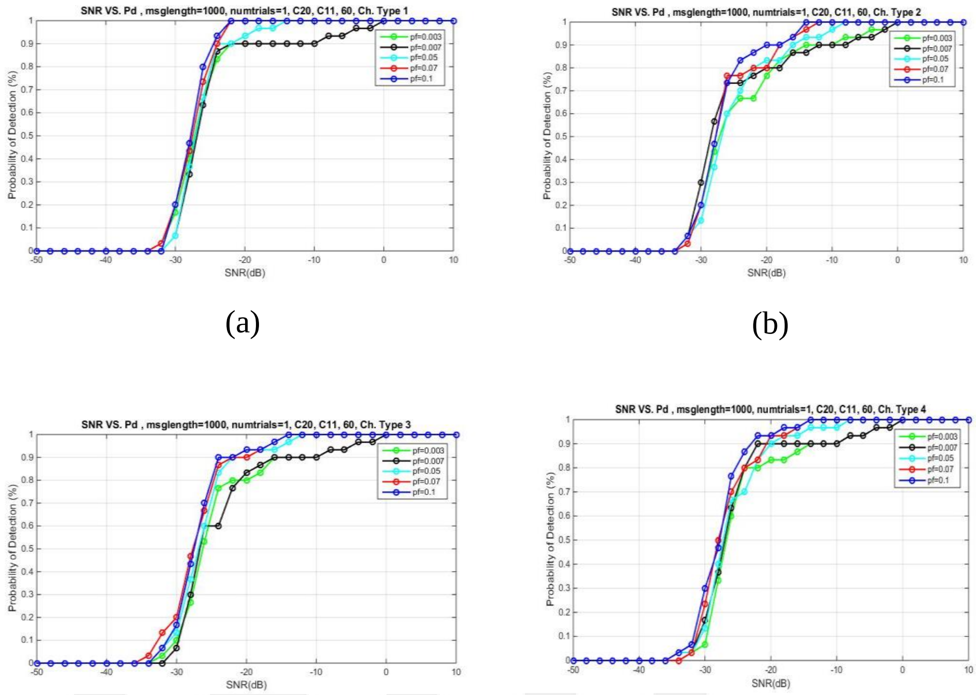


(c)

Figure 4.5 Number of trials vs Pd

Figure 4.5, (a) shows the results of 2 trials of samples examination. 5 trials results are shown in (b). Lastly, 10 trials are shown in (c). results are asymptotic.

In the previous simulations, trials were performed through a channel containing AWGN. To investigate the detection performance of the proposed detector in different noisy environments 4 noisy channels are designed. The next trials will be performed through 4 noisy channel types. The first channel type will contain AWGN. The second channel type is designed to contain Rayleigh fading and AWGN. The third channel type is designed to contain Rice fading and AWGN. The fourth channel type contains AWGN, Rayleigh, and Rice fading. Moreover, the noisy channel type will vary during the next trials. Meanwhile, other parameters will be kept constant at the same values. The simulation results of noise-type effects on the Pd for the proposed detector are shown in Figure 4.6.



(a) (b)

(c) (d)

Figure 4.6 Different noisy channels vs Pd

The simulation results show that fading effect the detection performance of the proposed detector. Figure 4,5 (a) is the result of the first channel type, while (b) is the second channel type, (c) for the third channel type, and the fourth channel simulation result is part (d) of the mentioned figure.

To discuss the noise effect from the results it was clearly found that Rayleigh's fading has a major effect to decrease the Pd. Meanwhile, Rice fading has a lower effect than Rayleigh.

To overcome the noise and fading impact, the message length was increased to 3000 samples, and raising the number of trials was to 2 trials in the fourth type of noisy channels. The simulation results are shown in Figure 4.7.

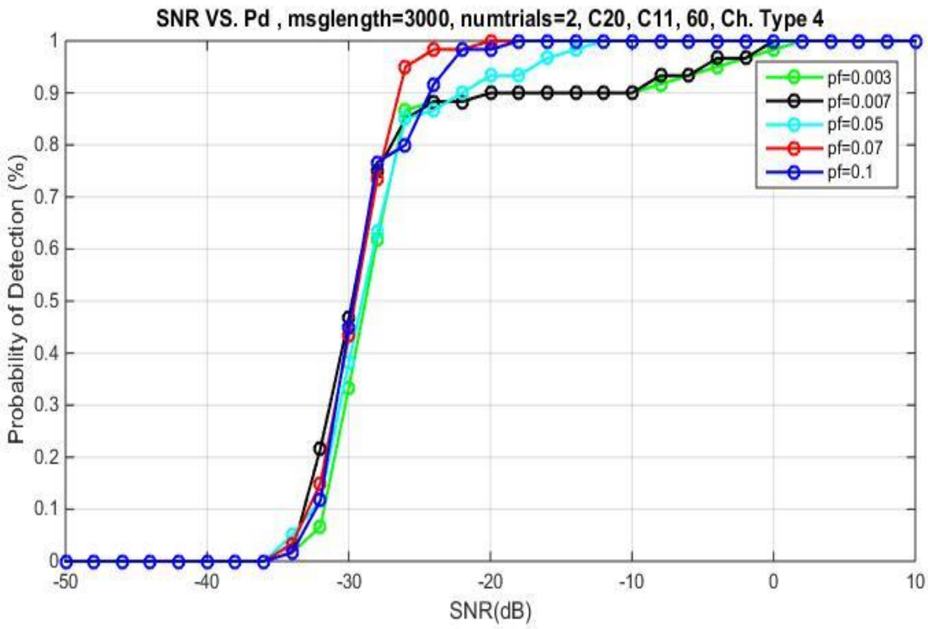


Figure 4.7 Enhanced Pd using a longer message and extra sample examination trial

By comparing the simulation results in Figures 4.7 and 4.6 D. Evidently, the Pd enhanced. The results prove that checking the samples many times is necessary and will make difference in detection outcomes in extremely noisy channels. But, there is an inversely proportional relation between the message length, the number of trials, and the sensing time. However, selecting the right number of trials and the right message length can be decided when utilizing the proposed detector. The employment of the proposed detector will provide the required information about the frequency and BW. Then, the maximum sensing time can be calculated accordingly.

4.5. SVM Classifier Simulation

Detection outcomes have been collected to be used in classification by SVM. $C_{2,0}$, $C_{1,1}$, and $C_{6,0}$ are the three features that will be employed for classification. Meanwhile, the detection decision will be the classes. SVM is the classification tool with Kernel RBF. As mentioned in the previous chapters SVM classifier needs a training data set and a testing data set. A high-accuracy prediction requires an efficient data set to be used by the classifier to build a robust classification model. As mentioned earlier, the statistical detector starts from the lowest SNR value toward the highest SNR value. The detector calculates the Pd, high-order cumulants, and makes a sensing decision after completing each SNR incremental step. Thus, by reducing the step the detector will calculate the required parameters more times to reach the highest SNR value. Therefore, detection outcomes data can be more detailed by decreasing the SNR step when measuring the Pd. SNR step in the statistical detection process was 2 dB in each measurement. To have more detailed data SNR step decreased to 0.5 dB. Both scenarios will be examined to find the best data set creation for accurate prediction. Moreover, specifying the number of included features in classification represents another important step to build the classification model. The classification model will be visualized during the construction in MATLAB. Figure 4.8 shows the simulation steps.

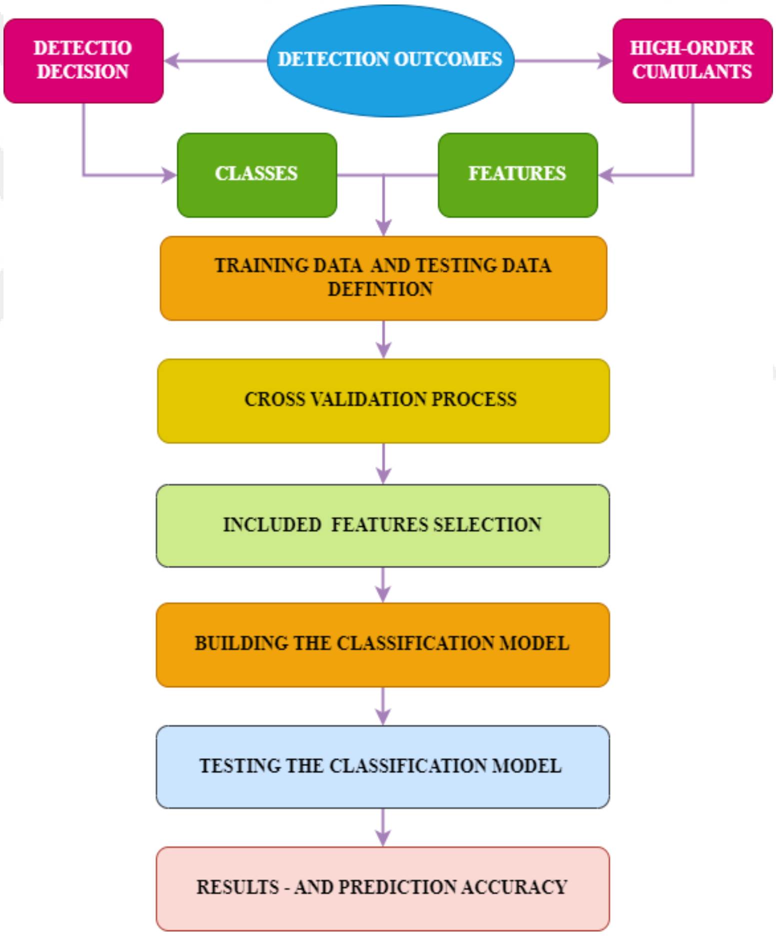


Figure 4.8 SVM classification steps

SVM classifier analyzes every single entry in the training data set. To find the amount of influencing that might be caused by the entry to the classification model As shown in Figure 4.9.

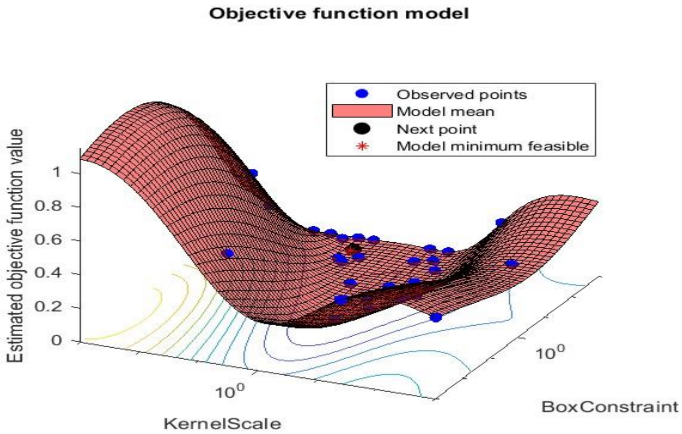


Figure 4.9 SVM classifier objective function model

Detection data with different message lengths have been tested for classification. As mentioned, three cumulants represent the features. At the first simulation, SVM classifier was forced to use the three features for classification. SNR incremental steps are the same for training and testing data, with 3 independent classification trials for each message length. In each trial, the classifier randomizes the training data set entries and rebuilds the classification model. Then, randomizes the testing data set entries and reclassifies the testing data. The trials average results for each message length are shown in Table 4.3.

Table 4.3 Same SNR increment vs. training accuracy

Message Length (samples)	Training Data SNR Increment dB	Test Data SNR Increment dB	Trials	Prediction Accuracy %
1000	0.5	0.5	3	70.9
5000				73.1
10000				64.5

To increase the prediction accuracy of the classifier, training data sets for the considered message lengths are generated with shorter SNR incremental steps. Thus, the training data set in the next classification trials will be more intense than the testing data set. In other words, high-order cumulants and decisions are calculated at each 0.5 dB in the training data sets. Meanwhile, the testing data sets are calculated at each 2 dB. The same 3 independent trials are repeated for each message length. The prediction accuracy average of the 3 trials for each message length is shown in Table 4.4.

Table 4.4 Different SNR increment vs training accuracy

Message Length	Training Data SNR Increment dB	Test Data SNR Increment dB	Trails	Prediction Accuracy %
1000	0.5	2	3	83.9
5000				73.1
10000				70.9

In Table 4.4, prediction accuracy is enhanced when the training data set had more detailed data than the testing data set. The results show that the data of shorter message lengths provide higher prediction accuracy than long messages. In other words, statistical detection prefers the longer message as shown in the statistical detection simulation earlier in this chapter. Meanwhile, SVM classifier prefers shorter messages for higher prediction accuracy. This means some features are not qualified for the classification task. To overcome the mentioned problem in the next trials, SVM classifier will be allowed to select the 3 included features in classification model building. For this reason, 7 random features will be added to previous features. Then SVM classifier needs to select 3 features out of 10 features. Moreover, 3000 sample message length will be involved in the next classification trials. The classification results are shown in Table 4.5.

Table 4.5 Random feature selection vs training accuracy

Message Length	Training Data SNR Increment dB	Test Data SNR Increment dB	Trials	Prediction Accuracy %
1000	0.5	2	3	98.9
3000				100
5000				100
10000				98.9

It was notified that during the included feature selection, $C_{2,0}$ was selected as included features in classification model building. In all three independent iterations $C_{2,0}$ was included in addition to selecting two randomly generated features. The simulation scenario is repeated by asking the classifier to include a single feature. $C_{2,0}$ was the only selected feature in each trial. The obtained results were the same results mentioned in Table 4.5.

CHAPTER 5

RESULT AND DISCUSSION

5.1. Statistical Detection Results

The obtained results in the previous chapter are mainly depending on high-order cumulants combinations. Moreover, the cumulants set ($C_{2,0}, C_{1,1}, and\ C_{6,0}$) provided better performance than other high-order cumulant sets in terms of detection probability. The detection performance is varying according to noise type and noise level. By comparing the obtained results, the best detection performance has been obtained in the first proposed channel type which has AWGN only. Meanwhile, other channel types which have AWGN, Rayleigh fading, and Rice fading more challenging in terms of detection accuracy. However, the proposed detector can achieve the minimum acceptable Pd for 1000 samples when Pfa is 0.1 at good SNR levels in different noisy channels. The results are summarized in Table 5.1.

Table 5.1 Minimum Pd in different noisy channels with SNR level

Channel type	**SNR LEVEL in dB**	**Pd %**
1	-25.5	90
2	-20	
3	-24	
4	-23	

By comparing the obtained results, it seems that the worst performance was in the type 2 channel which contains Rayleigh fading and AWGN. Increasing the examination attempts of message samples did not affect the detection performance in the first designed channel. Therefore, simulation results have been showed that increasing the number of samples examination is necessary to reduce the fading effect as shown in

Figure 4.7. Finally, the longer message has a positive effect on Pd as shown in Table 5.2.

Table 5.2 Message length with SNR and minimum acceptable Pd at 0.1 Pfa

Message length	SNR LEVEL in dB	Pd%
3000	-27	90
5000	-28	
10000	-29	

Thus, message length and number of trials are important for noise effect reduction. But, these two solutions will increase sensing time meanwhile longer sensing time may cause interference between PU and SU signals. So making an accurate calculation must be done before specifying the message length and number of trails. Moreover, necessary calculations could be done after defining the BW and frequency of the targeted channel in addition to the maximum desired sensing time.

5.2. SVM Classification Results

SVM classifier has provided a good classification performance in a specific direction while prediction accuracy is not meet the desired outcomes in other directions. However, cumulants set ($C_{2,0}, C_{1,1}, and\ C_{6,0}$) is performing well in statistical detection. $C_{1,1}$, and $C_{6,0}$ harm the prediction accuracy. Once features selection authority turned to SVM classifier, the classifier preferred to select the randomly generated features instead of $C_{1,1}, and\ C_{6,0}$. Moreover, prediction accuracy has been checked in 3 trials. There were slight differences in training accuracy which means SVM classifier final results can be obtained with few iterations. The final simulation scenario results were 100 % prediction accuracy when the message length was 3000 samples and 5000 samples. In addition, when SVM classifier is provided with more dense training data higher classification performance with higher prediction accuracy was obtained. $C_{2,0}$ was the suitable feature for SVM classifier to provide the best outcomes among the tested cumulants.

5.3. Recent Similar Works Comparison

The proposed FBD in this thesis using high-order cumulants delivered enhancement in terms of the Pd better than the proposed high-order statistical detector [76]. A higher Pd has been achieved in high-order cumulant-based detectors in lower SNR regions. Moreover, many modulation schemes have been considered in this thesis simulation while the high-order statistics proposed detector has been investigated for 16 QAM only. Regarding the classification works, high-order cumulants with SVM classifier have achieved 100 % of prediction accuracy for noise and signal. Moreover, SVM classifier needed only one cumulant for efficient classification. In [77] classifiers have been surveyed regarding the accuracy and mean square error for the modulation techniques classification. SVM classifier in this thesis has achieved higher classification accuracy for different modulation schemes signals in different noisy channels.

In [85], second-order and third-order cyclic cumulants are proposed for a FBD, The proposed detector used each feature separately. The proposed detector is achieving a Pd equal to 90% at the SNR level (-14) at Pfa (0.01) using the third-order cyclic cumulant. Furthermore, the proposed detector used Neyman-Pearson Theorem and asymptotic optimal estimation. In this thesis, a higher Pd is achieved using 3 high-order cumulants. The closest comparable results can be found in Figure 4.3 (b) at Pfa (0.03) the same Pd achieved at the SNR level (-22). Moreover, in this thesis, more modulation schemes are used. The employment of the SVM classifier reduces the employed cumulant in other words, the high-order cumulant $C_{2,0}$ provides superior performance with lower complexity than third-order cumulant. In addition, this work includes ML classification and statistical detection.

In [86], high-order statistics are proposed for spectrum sensing., and different sensing schemes have been tested. The best-obtained results for CSS from the tested methods is Pd equal to 0.9 at the SNR level (-3.15) when Pfa (0.01), and message length (8000) samples. Comparing to this thesis's results a higher Pd was achieved with a lower message length as shown in Figure 4.3 (b).

CHAPTER 6

CONCLUSION AND FUTURE WORKS

6.1. Conclusion

FBD is a powerful detection technique in noisy environments. The high-order cumulants are promising features for detection and classification. The cumulants set ($C_{2,0}$, $C_{1,1}, and\ C_{6,0}$) has provided the best detection performance among the tested sets. Moreover, increasing message length and the number of trials is a magical tool to overcome the noise uncertainty problem in CR. In addition to making the necessary calculation for the right message length and sensing consumed time in advance to avoid interference and guarantee accuracy. Three cumulant-based detectors allow applying of three different thresholds which produce more accurate detection decisions. CFAR guarantees the number of false decisions thus, it is very necessary to control the number of wrong decisions. Regarding the classification part, SVM achieved 100% of classification accuracy by considering the high-order cumulants as classification features. Some cumulants were causing low accuracy which makes them undesirable features in SVM. As shown in the results ($C_{1,1}, and\ C_{6,0}$) were not preferable by the classifier. Meanwhile, randomly generated features were better than mentioned two cumulants. However, ($C_{1,1}, and\ C_{6,0}$) were marvel features in statistical detection but weak performance in classification leading to say that good statistical detection features may not perform the same in classification. For the message length parameter, simulation results show that the best-obtained performance was achieved by two message lengths 3000 sample and 5000 sample. Moreover, the training data amount should be intense more than the test data. In other words, testing data preferred to be partially included in training data for higher accuracy. Finally, high-order cumulants statistical detection combined with SVM is a very promising detection system according to simulation results due to the high Pd and high prediction accuracy. Meanwhile, SVM classifier reduces the amount of calculation and system complexity. Since the best-obtained performance was using one cumulant which is equivalent to three cumulants' performance in statistical detection.

6.2. Future Works

Due to this thesis's outcomes and the obtained results several approaches can be suggested to be tested and verified. A hardware implementation for the high-order cumulants and SVM classifier proposed detector in this thesis using field-programmable gate array (FGPA) for cumulants calculation. In addition to automation using a powerful programming language. Moreover, employ other combinations of high-order cumulants to check other sets and use the detection outcomes for classification. Utilizing other classifiers with the same proposed high-order cumulants sets in this thesis. Lastly, other features like covariance matrices can be combined with SVM classifier. To investigate if the SVM classifier can contribute to other detectors that utilize other features.

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APPENDIX A

SVM CLASSIFIER SIMULATION CODE

```
clc
clear;
close all;
#loading the training and testing data.
load('Training_data.mat');
load('Testing_data.mat')
# Generating 10 columns of random values that will be used as randomly generated
features for 121 rows matrix.
X=randn(121,10)
# Specifying features.
Z=”Features_Data”;
#Replacing the 3 random features with 3 real features.
 X(:,[9,1,5]) = Z(1:121,:);
# Specifying the classes
Y=”Classes_Data”;
# Randomyzing rows data sequence.
rand_num=randperm(121);

# Specifying training data set.

X_train=X(rand_num(1:90),:);
Y_train=Y(rand_num(1:90),:);

# Specifying testing data set
X_test=X(rand_num(91:end),:);
Y_test=Y(rand_num(91:end),:);
#Cross-Validatio Partitioning data by 5 in each set.
C=cvpartition(Y_train,'k',5);
# Included features selection by setting option and building the function
opts = statset('display','iter');
classf = @(train_data, train_labels, test_data, test_labels)... %build function
    sum(predict(fitcsvm(train_data, train_labels,'KernelFunction','rbf'), test_data) ~=
test_labels);
```

```
#Subsequential Feature selection
[fs, history] = sequentialfs(classf, X_train, Y_train, 'cv', C, 'options',
opts,'nfeatures',"insert the number of features")

# Finding best hyper parameter from the included features
X_train_w_best_feature = X_train(:,fs)
# Selecting the best feature(s) for classification
Md1 =
fitcsvm(X_train_w_best_feature,Y_train,'KernelFunction','rbf','OptimizeHyperparam
eters','auto',...
    'HyperparameterOptimizationOptions',struct('AcquisitionFunctionName',...
    'expected-improvement-plus','ShowPlots',true));
#Testing the model and finding the prediction accuracy
X_test_w_best_feature = X_test(:,fs);
test_accuracy_for_iter = sum((predict(Md1,X_test_w_best_feature) ==
Y_test))/length(Y_test)*100;
```

APPENDIX B

STATISTICAL DETECTION CODE MAIN

```
clc
clear
cl='brkmg';
# Define SNR range.
sn=[-50:2.5:10];
#Specifying The Pfa(s).
p=[Pfa values equal to j];
# Set the first loop equal to the number of Pfas.
for j=1:length of j
# set the second loop for SNR range.
for i=1:length(sn)
# define the variable SymSNR.
SymSNR=sn(i);
# specify the message length.
msglength=;
# define the system order.
symorder='bin';
# Setting the number of trial for samples examination.
numtrials=1;
# define the modulation schemes 2,4,8 PSK, 2,4,8,16,64,256 QAM, 1 for noise only.
ModSchemes=[2 4 8 2 4 8 16 64 256 1];
#Selecting the channel type it can be 1,2,3, or 4.
channeltype=1;
# Call the function linear tester 3 which contains the tracker and Pd, msgb is the
features, modguess mean detection decision as the output of this function.
[tracker,percent,msgb,modguess]=lineartester_3_pf(numtrials,msglength,ModSchem
es,symorder,SymSNR,channeltype,pf);
#Calculating the mean of trails
R(i,2)=(mean(tracker(1:9,1)))/(numtrials);
#SNR value
R(i,1)=sn(i);
# Collecting features
A(:,i)=msgb;
#Collecting detection decision
B(:,i)=modguess;
```

```
Features = A';
Classes = B';
# Saving detection outcomes
save ('Training_Or_Testing', 'Features', 'Classes');
end
# Plotting the Pd for a completed SNR range
plot(R(:,1),sort(smooth(R(:,2),4)),[cl(j) '-o'],'LineWidth',1);
# keeps the previous outcomes
hold on
xlabel('SNR(dB)')
ylabel('Probability of Detection (%)')
ylim([0 1])
grid on
hFig = figure(1);
title('SNR VS. Pd , msglength=10000, c20,c11,c31')
set(hFig, 'Position', [100 100 800 400])
legend('pf=0.003','pf=0.007','pf=0.05','pf=0.07','pf=0.1'); end;
```

APPENDIX C

STATISTICAL DETECTION FUNCTION 1

```
function[tracker,percent,msgb,modguess]=lineartester_3_pf(numtrials,msglength,Mo
dSchemes,symorder,SymSNR,channeltype,pf)
# define the variable Num schemes
NumSchemes = length(ModSchemes);
# tracker will keep track of the results as a confusion matrix
tracker = zeros(NumSchemes,2);
#define modulator objects for PSK and QAM signals
bpskmodulator =
modem.pskmod('M',2,'PhaseOffset',0,'SymbolOrder',symorder,'InputType','integer');
qpskmodulator =
modem.pskmod('M',4,'PhaseOffset',0,'SymbolOrder',symorder,'InputType','integer');
epskmodulator =
modem.pskmod('M',8,'PhaseOffset',0,'SymbolOrder',symorder,'InputType','integer');
modulator16 =
modem.qammod('M',16,'PhaseOffset',0,'SymbolOrder',symorder,'InputType','integer'
);
modulator32 =
modem.qammod('M',32,'PhaseOffset',0,'SymbolOrder',symorder,'InputType','integer'
);
modulator64 =
modem.qammod('M',64,'PhaseOffset',0,'SymbolOrder',symorder,'InputType','integer'
);
modulator128 =
modem.qammod('M',128,'PhaseOffset',0,'SymbolOrder',symorder,'InputType','intege
r');
modulator256 =
modem.qammod('M',256,'PhaseOffset',0,'SymbolOrder',symorder,'InputType','intege
r');
# define parameters for FSK signals
freqsep = 16;
Nsamp = 16;
Fx = 128;
# Define fading channel parameters and Symrate variable
symrate = 1e6;
raychan = rayleighchan(1/symrate,5000,[0, 2e-6], [0,-10]);
```

```
richan = ricianchan(1/symrate,5000,3,[0, 2e-6], [0,-10]);
# conducting the trail
h=waitbar(0,'Conducting Trials...');
# define the modetype variable which is start from one to the length of ModSchemes
vector and starting the loop
for modtype=1:NumSchemes
# starting the trails number fron 1 to the defined number in (linear tester 1)
  for n = 1:numtrials
 # Pick modulation scheme at random and generate msg
      %    modtype = randsrc(1,1,1:NumSchemes);
      M = ModSchemes(modtype);
      msg = randsrc(msglength,1,[0:M-1]);
# modulating the message according to randomly selected Modscheme
      switch modtype
        case {1,2,3}
          modmsg = fskmod(msg,M,freqsep,Nsamp,Fx,'cont',symorder);
        case 4
          modmsg = modulate(bpskmodulator,msg);
        case 5
          modmsg = modulate(qpskmodulator,msg);
        case 6
          modmsg = modulate(epskmodulator,msg);
        case 7
          modmsg = modulate(modulator16,msg)./sqrt(10);
        case 8
          modmsg = modulate(modulator64,msg)./sqrt(42);
        case 9
          modmsg = modulate(modulator256,msg)./sqrt(170);
        case 10
          modmsg = msg;
      end
 # Use channel type to determine the propagation model to use (according to selected
channel type in linear_tester_1)
      xUp = modmsg;
# when modtype = 10 channel will contain noise only for this reason all message bits
will be zeros.
      if modtype==10
        xUp = zeros(1,length(modmsg));
      end
 #Use channel type to determine the propagation model to use and adding the pf and
corrupting the signal
      if modtype==2
        xUp2=xUp(1:fix(length(xUp)*pf));
      end
      if channeltype == 4
        propmodel = randsrc(1,1,1:3);
```

```
else
    propmodel = channeltype;
end
switch propmodel
    case 1
        if modtype==10
            yUp = awgn(xUp, SymSNR);

            if pf~=0
                v = awgn(xUp2, SymSNR,'measured');

                yUp(1:length(v))=v;
            end

        else
            yUp = awgn(xUp, SymSNR,'measured'); %,'measured'
        end

    case 2
        multipath = filter(raychan,xUp);
        if modtype==10
            yUp = awgn(multipath,SymSNR);

            if pf~=0
                multipath = filter(raychan,xUp2);
                v = awgn(multipath,SymSNR,'measured');

                yUp(1:length(v))=v;
            end

        else
            yUp = awgn(multipath,SymSNR,'measured'); %,'measured'
        end

    case 3
        multipath = filter(richan,xUp);
        if modtype==10
            yUp = awgn(multipath,SymSNR);

            if pf~=0
                multipath = filter(raychan,xUp2);
                v = awgn(multipath,SymSNR,'measured');

                yUp(1:length(v))=v;
            end
```

```
            else
                yUp = awgn(multipath,SymSNR,'measured'); %,'measured'
            end
        end
# Calculating High-order cumulants and compare them to thresholds
        msgb=profgen(yUp(1:msglength));
        A(:,n)=msgb
if (msgb(2)<=0.9)
    modguess=2;
elseif msgb(1)==msgb(2)
    modguess=2;
elseif msgb(1)>1.2
    if msgb(1)>=25
        modguess=2;
    elseif msgb(3)<60
        modguess=1;
    else
        modguess=2;
    end
else
    modguess=1;
end

    end

       tracker(modtype,modguess) = tracker(modtype,modguess) + 1;
       waitbar(n/numtrials);

    tracker
    # Calculate overall performance
end
percent = sum(diag(tracker))/(numtrials*NumSchemes)*100;
close(h);
```

APPENDIX D

STATISTICAL DETECTION FUNCTION 2

```
# Define the Function Name
function profile = profgen(s)
# First ensure that mean of s is 0 and define the signal
[r,c] = size(s);
s = s - ones(r,1)*mean(s);
# define the complex conjigate for the complex variables
sbar = conj(s);
spower = mean(s.*sbar);
# Calculate higher order moments
e20 = (mean(s.^2));
e11 = (mean(s.*sbar));
e40 = (mean(s.^4));
e31 = (mean((s.^3).*sbar));
e22 = (mean((s.^2).*(sbar.^2)));
e60 = (mean(s.^6));
e33 = (mean((s.^3).*(sbar.^3)));
# Calculate cumulants
c20 = e20;
c11 = e11;
c31 = e31 - 3*e20.*e11;
c60 = e60 - 15*e20.*e40 + 30*e20.^3;
c33 = e33 - 6*e20.*e31 - 9*e11.*e22 + 18*(e20.^2).*e11 + 12*e11.^3;
profile=abs([c33;c31;c60]);
```