Modulation Classification Based Spectrum Sensing Using High Order Statistics

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The results of Chapter 3 of this thesis has been published as an article during the course of the author's masters research period, the most up-to-date version of which being:

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The author of this thesis states that the research, including the collection, processing and presentation of data, addressing and comparing to previous research, etc., was done entirely in an honest way, as expected from scientific research that is conducted according to the ethical standards of the academic world. Also, reporting the research and its results in this thesis was done in an honest and complete manner, according to the same standards.

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Contents

List of Figures

Abstract

In this thesis, we explore modulation classification within the spectrum sensing domain of cognitive radio systems. Spectrum sensing, a critical component of cognitive radio networks, requires the transceiver to adapt to its environment. This adaptation entails scanning and identifying optimal frequency channels and modulation schemes for communication. By integrating modulation classification into spectrum sensing, the radio can distinguish various users in proximity—whether from a different network or the same network—based on the modulation scheme of the signal. This integration also aids in adjusting the demodulation process if the signal is meant for the radio. With advancements in technology, cognitive radio has become a practical reality, enhancing the relevance of spectrum sensing research and highlighting the significance of modulation classification. This thesis aims to investigate this aspect using a feature-based machine learning algorithm, focusing on the signal's high-order statistics.

Our method starts with calculating and analyzing high-order statistics for different modulation schemes, including both analog and digital formats. We concentrate on cumulant statistics, a robust alternative to statistical moments. These statistics are vital for designing our model for modulation classification and offer a significant advantage: they effectively differentiate between signal and noise with minimal computational requirements, allowing for efficient isolation of each modulation scheme.

Our study uses a well-established dataset of radio signal samples for training and testing our model. The methodology involves a detailed analysis of various hyperparameters in the machine learning model. Extensive testing and fine-tuning of these parameters with the training set are followed by comprehensive experimentation on the testing set. This approach confirms the model's robustness and adaptability, showcasing improved performance across various signal-to-noise ratios (SNRs) and channel conditions, and achieving notable classification accuracy.

We compare our model and results with contemporary deep learning methods to demonstrate the superiority of our high-order statistic-based classifier. Through a comprehensive comparison, we highlight the advantages of our proposed method over existing approaches. Our experiments show that our model's exceptional efficiency and high performance make it an excellent choice for deployment in cognitive radio network end units. The importance of our findings lies in providing a cost-effective, high-quality solution for modulation classification, a crucial function in spectrum sensing.

Abbreviations

AM	:	Amplitude modulation
AMC	:	Automatic modulation Classification
ASK	:	Amplitude-shift keying
AWGN	:	Additive white Gaussian noise
CGF	:	Cumulant generating function
CR	:	Cognitive radio
DSB	:	Double-side band
FB	:	Feature based
FM	:	Frequency modulation
GMSK	:	Gaussian minimum-shift keying
HOC	:	High order cumulants
HOS	:	High order statistical moments
LSTM	:	Long short-term memory
MGF	:	Moment generating function
OOK	:	On-off keying
PSK	:	Phase-shift keying
QAM	:	Quadrature amplitude modulation
SDR	:	Software defined radio
SNR	:	Signal to Noise Ratio
SSB	:	Single-side band

Notations

$C_t(x)$	:	cumulant-generating function of random variable x
$c_n(x)$	:	The n'th order cumulant of random variable x
$c_{i,j}$	:	The i,j mixed cumulant of a random variable
$G(A)$	:	The Gini impurity of random variable A
$M_n(\Pi {x_i}^{n_i})$	:	The n'th mixed moment of jointly distributed random variables x_i
m_k	:	The k'th moment of a random variable
$m_{i,j}$	:	The i,j mixed moment of a random variable
$m_n(x)$	:	The n'th moment of a random variable
P_d	:	Total number of nodes in a tree of depth d
$x_d[n]$	:	The discrete derivative of sampled signal x

Chapter 1

Introduction

1.1 Background and Motivation

The evolution of smart transmitters, adaptive receivers, and the concept of intelligent communication networks have significantly altered the landscape of radio communication in recent years. These technological advancements have streamlined our use of wireless channels, particularly emphasizing the importance of intelligent radio systems. Within this area, Automatic Modulation Classification (AMC) has emerged as a key task, proving to be important in a variety of both civilian, emergency and military applications. For long-established radio networks, the need for rapid adaptability and efficiency in handling diverse communication tasks has never been more critical. In addressing these requirements, Software Defined Radio (SDR) stands out as a prominent and effective solution.

SDR, a communication platform functioning through software programs rather than conventional hardware components, offers a transformative approach to radio functions. It allows for dynamic adjustments to different networks and specific operational demands. This approach, originating from Mitola's conceptualization of ”software radio” [1], shifts signal processing to the digital realm, thereby amplifying communication effectiveness in terms of rate, accuracy, and operational range.

A notable application of SDR technology is the idea of Cognitive Radio (CR), introduced by Mitola in 1999 [2]. Cognitive Radio represents an innovative step towards creating a radio unit capable of autonomously managing its communication network through advanced software algorithms. This technology addresses the pressing issue of spectral congestion in contemporary communication systems, a problem intensified by the ever-increasing number of users and the consequent scarcity of spectrum resources. Cognitive Radio emerges as a strategic solution, efficiently facilitating communication for unlicensed users such as military and emergency services by enabling the creation of shared, unlicensed communication networks.

The essence of Cognitive Radio is its spectrum sensing capability, a critical function for efficiently utilizing the radio frequency spectrum. Spectrum sensing involves scanning for unused frequency bands, commonly termed as ”empty holes,” to optimize the usage of available spectrum. This process is crucial as it enables CR systems to dynamically modify their modulation schemes and central frequencies in response to environmental conditions. A key component of this dynamic approach is automatic modulation classification (AMC), a method for identifying the modulation scheme of incoming signals. AMC plays a vital role in adapting CR systems to varied signal conditions, ensuring efficient and effective communication. This concept of AMC has been thoroughly explored in the literature [3–5], underscoring its significance in the field of Cognitive Radio networks. Effective spectrum sensing is crucial for adaptive networks, particularly in ensuring seamless communication during emergencies without causing disruption to local users.

AMC research exists in the literature since the 1980s [6, 7], while the concept itself raised popularity following the introduction of Cognitive Radio networks. Traditional AMC algorithms are generally splitted between likelihood-based algorithms [8]—noted for their accuracy but high computational cost—and Feature-based (FB) methods which are cost-efficient and simple. The recent years in AMC studies started to include deep learning methods for the task. [9–11].

The emergence of neural networks in the field of AMC has been remarkable, particularly in their application for feature extraction and classification tasks. Despite their high accuracy and efficacy, particularly at low signal-to-noise ratios (SNRs), neural networks can be quite resource-intensive, especially when implementing deep network models. This becomes a significant concern in scenarios requiring rapid deployment of radio networks that depend on efficient end units, such as in emergency services where quick adaptability to the spectral environment is crucial.

In a strong contrast to NN methods, feature-based methods present a less complex approach, employing features such as high-order statistical moments (HOS) or instantaneous frequency and phase parameters to analyze signals more efficiently. The FB methodology involves an initial step of feature extraction from the signal, followed by the training of a classification algorithm, which is optimal when considering minimized complexity and runtime.

This thesis places its focus on the FB approach for AMC, specifically leveraging high-order cumulants (HOCs) as the primary features. These cumulants, which are statistical metrics that can be seen as alternatives to more conventional measures such as mean and variance, are recognized in the AMC literature for their unique ability to differentiate the desired signal from additive noise [12, 13]. Our research extends beyond the usual emphasis on digital modulation classification [14, 15], by also encompassing analog modulation schemes. We engage in a detailed analysis of eleven different modulation schemes, aiming to discern the most effective classification features for each and to elucidate the statistical interconnections that exist between various modulation types. Through this exploration, we seek to contribute a deeper understanding of the complexities and nuances inherent in the field of modulation classification, thereby enhancing the potential applications and effectiveness of cognitive radio systems in a variety of critical contexts.

1.2 Main Contributions

This research addresses the challenges and limitations highlighted in the previous section, making several notable contributions to the field of modulation classification within cognitive radio networks. The key contributions of our study include:

- We have provided a novel feature extraction methodology that approximates the cumulants of a received signal without computing the Cumulant Generating Function (CGF). This innovative approach leverages the inherent benefits of cumulants and the mathematical relationship between statistical moments and high-order cumulants. It simplify the extraction of each cumulant, enhancing efficiency and simplicity, which could transform signal analysis in cognitive radio systems.

- The research introduces a straightforward machine learning model, particularly a decision tree, for tasks usually handled by more complex and resource-heavy deep learning methods. This strategic move towards simpler and more efficient models is a significant shift. The performance of our decision tree model has been thoroughly evaluated and compared with various established methods from the literature. Our results demonstrate notable improvements in areas such as computational speed and memory usage, highlighting the potential of simpler models in intricate modulation classification tasks.

- This study key aspect is the comprehensive examination of the statistical behaviors of a wide array of analog and digital modulation schemes in the time domain. This exploration reveals striking similarities in statistical patterns among related modulation groups, while also distinguishing clear differences between them. These insights into the statistical characteristics of different modulation schemes open the door for more sophisticated and targeted classification strategies, thereby increasing the adaptability and efficiency of cognitive radio networks.

1.3 Research Overview

This research delves into the realm of feature-based modulation classification, utilizing high-order statistics for spectrum sensing within cognitive radio networks. The study encompasses a thorough examination of the statistical behavior of various modulation schemes, both analog and digital, and evaluates the efficiency of the feature-based classification method in comparison with other classification models documented in the literature.

This study contributes to the development of an innovative feature extraction method designed to approximate the cumulants of received signals, thereby eliminating the need for calculating the Cumulant Generating Function (CGF). This method ingeniously capitalizes on the inherent benefits of cumulants and exploits the mathematical relationships between statistical moments and high-order cumulants. Such an approach facilitates the extraction of individual cumulants with remarkable ease. The research also marks a significant deviation from conventional practices by employing a straightforward yet effective machine learning model, namely the decision tree, for tasks typically managed using more complex and computationally intensive deep learning methods. The efficacy of this model is thoroughly evaluated through rigorous testing and comparative analysis against established methods from the literature. The results underscore improvements in key areas such as computational runtime and memory efficiency.

Furthermore, this study extends its analytical lens to the statistical behavior of various analog and digital modulation schemes within the time domain. Through this exploration, it uncovers striking similarities among groups of related modulations, while also highlighting the distinct characteristics that differentiate each group. These findings are not only instrumental in addressing the existing limitations and challenges within the domain of modulation classification but also in charting a course towards more efficient, practical, and nuanced solutions.

The overarching aim of this research is to contribute meaningful insights, innovative methodologies, and practical models that significantly enhance the performance and applicability of modulation classification in real-world scenarios, particularly in the ever-evolving field of Cognitive Radio networks. This endeavor seeks to provide a comprehensive and significant advancement in the understanding and application of modulation classification, poised to have a profound impact on the efficiency and adaptability of cognitive radio systems.

1.4 Organization

The structure of this thesis is methodically arranged to facilitate a clear and comprehensive understanding of the research conducted. The organization is as follows:

Chapter 2 lays the foundational groundwork for the study. It presents the problem formulation and delves into the related scientific background, setting the stage for the subsequent chapters.

Chapter 3 is dedicated to the core contributions of this thesis. It details the proposed Automatic Modulation Classification (AMC) method, emphasizing the use of high-order cumulants (HOCs) as classification features. Additionally, this chapter includes a comparative analysis of the proposed method against state-of-the-art deep learning models, highlighting the advancements and efficiencies achieved by our approach.

Chapter 4 serves as the culmination of the thesis. It provides a concise summary of the main contributions and findings of the research. Furthermore, it offers a perspective on potential future research directions, suggesting avenues for further exploration and development in the field.

Chapter 2

Preliminaries

In this chapter, we establish the essential groundwork necessary for an in-depth understanding of the algorithms and methods utilized in our research. The chapter is systematically structured to introduce the key concepts and theoretical frameworks that are vital to our study. We begin with a comprehensive exploration of cumulants. These statistical measures are fundamental to our classification task, making it essential to grasp their mathematical properties and significance. The section on cumulants delves into their theory, explaining how they are computed and their particular relevance in the context of our research. Following the cumulants, the focus shifts to the various classification algorithms pivotal in our study. For each algorithm, we present a detailed theoretical background, accompanied by pseudo-code to demonstrate their operational processes. This section aims not only to familiarize the reader with these algorithms but also to provide insights into their relative effectiveness, as evidenced by our research findings. The chapter concludes with an exhaustive review of the digital and analog modulation schemes implemented in our study. We detail each modulation scheme, elucidating their operational principles and significance in relation to our research objectives. As the thesis progresses, the topics and concepts introduced in this chapter will become foundational knowledge for the reader. This approach allows subsequent chapters to build upon this base, facilitating a deeper and more targeted examination of our research findings and contributions.

2.1 Problem Formulation

Modulation classification within the spectrum sensing framework is a crucial task in cognitive radio networks. The overarching aim is to precisely identify the modulation scheme of incoming signals, optimizing electromagnetic spectrum usage. This objective becomes increasingly complex in environments characterized by noise and interference, conditions that are commonplace in real-world scenarios.

The typical model of a received signal in an Additive White Gaussian Noise (AWGN) channel is represented by the following equation:

$$r(t) = s(t) + n(t) \tag{2.1}$$

In this model, $r(t)$ denotes the received signal, $s(t)$ symbolizes the transmitted signal modulated with an unidentified scheme, and $n(t)$ signifies the noise, generally modeled as a Gaussian process with zero mean and a variance of σ^2.

The process of spectrum sensing in cognitive radio involves scrutinizing this received signal $r(t)$ to not only detect the presence of primary users but also to classify the modulation type of the signal. This classification task entails extracting features from $r(t)$ and applying statistical or machine learning algorithms to determine the modulation scheme.

A pivotal aspect of addressing this challenge involves the utilization of statistical measures for feature extraction. The high-order statistics of the received signal, particularly the cumulants, are essential in this context and will be discussed in further detail in Section 3.1.

The core challenge in modulation classification is the precise extraction and accurate interpretation of these features under diverse channel conditions and varying levels of noise. Environmental factors such as multipath propagation, signal fading, and the dynamic nature of the radio spectrum further complicate this task. These conditions necessitate a modulation classification algorithm that is not only accurate but also robust and adaptable to changing scenarios.

Thus, the ultimate goal of this research is to develop an algorithm that can reliably and efficiently classify the modulation scheme of the received signal in a cognitive radio setting. Such an algorithm would significantly contribute to the efficiency and reliability of spectrum sensing, a critical function in the dynamic and ever-evolving landscape of cognitive radio networks.

2.2 High Order Statistics

In the field of statistics, the moments of a random variable are quantitative measures related to the shape of its probability density graph and the behavior of the distribution. The n'th order moment of a random variable x is defined by:

$$m_n(x) = \int x^n f(x)dx \tag{2.2}$$

where $f(x)$ is the probability density function of x. If the n'th order moment integral diverges, the n'th order moment of the variable does not exist. If the $n'th$ order moment of x exists, so do the $(n-1)'th$ order moment, and all lower order moments as well. We define a central moment by $m_n(x-\mu)$, which is the mean value of x, and define the normalized moment as $m_n(x/\sigma)$ where σ is the standard deviation.

Following the definition above, the first order moment is the mean value, and the second central moment is the variance. The normalized third central moment is the skewness, which is related to the symmetry of the distribution. The normalized fourth central moment is the kurtosis, which measures the heaviness of the tail of the distribution compared to a normal distribution of the same variance. The fifth and higher order moments are related to other non-linear properties of the distribution, but they are not as notable as the first four. The mixed moment of jointly distributed random variables $x_1, x_2, \ldots$ of order n will be defined by $M_n(\Pi x_i^{n_i})$ where $\Sigma n_i = n$. For example, the second order mixed moment is the covariance.

The cumulants k_n of a probability distribution are an alternative to the moments of the distribution. Any two probability distributions whose moments are identical will have identical cumulants as well, and vice versa. The first, second, and third cumulants are the same as the central moments, but fourth and higher-order cumulants are not equal to central moments. The cumulant of a random variable x is defined using the cumulant-generating function (CGF):

$$C_t(x) = \log(E[e^{tx}]) \tag{2.3}$$

The cumulants c_n are obtained from a power series expansion of the CGF:

$$C_t(x) = \sum c_n \frac{t^n}{n!} \tag{2.4}$$

Since this expansion is a Maclaurin series, the nth order cumulant can be obtained by differentiating the expansion n times at $t = 0$. An important property of cumulants, which is particularly useful in our analysis, is their additive nature. For two independent random variables X and Y, the cumulant of the sum $(X + Y)$ is simply the sum of their individual cumulants. This additive property is formally expressed as:

$$c_n(X + Y) = c_n(X) + c_n(Y) \tag{2.5}$$

This relationship stems from the logarithmic transformation applied to the moments in the cumulant-generating function. When considering the moments of a sum of random variables, such as $X+Y$, the moment-generating function leads to a product of individual moments. The logarithm of this product then translates into the sum of the logarithms, thereby making the cumulants additive.

This additive property of cumulants is particularly beneficial when dealing with Additive White Gaussian Noise (AWGN) channels. In AWGN channels, the noise is modeled as a normal distribution, $\mathcal{N}(\mu, \sigma^2)$. The cumulant-generating function (CGF) of a normal distribution [16, 17], as proved by theorem 2.1 is given by:

$$C_t(\mathcal{N}(\mu, \sigma^2)) = \mu t + \sigma^2 \frac{t^2}{2} \tag{2.6}$$

A notable characteristic of the normal distribution is that its CGF is a second-order polynomial. Consequently, when differentiating this polynomial, the cumulants of order three and above for the normal distribution are all zero. This property greatly simplifies the analysis of signals in AWGN channels. In these contexts, the higher-order cumulants of the noise do not contribute to the overall cumulants of the received signal. As a result, in such environments, the cumulants of the received signal predominantly reflect the characteristics of the signal itself rather than the noise. This aspect provides a significant advantage for signal processing and classification tasks, particularly in noisy environments, as it allows for a more accurate isolation and analysis of the signal's properties.

$$c_n(X+Y) = c_n(X) + c_n(Y) \tag{2.7}$$

Theorem 2.1. *For the normal distribution with expected value μ and variance σ^2, the CGF is:*

$$C_t(\mathcal{N}(\mu, \sigma^2)) = \mu t + \sigma^2 \frac{t^2}{2} \tag{2.8}$$

proof: Recall that the probability density function of a normally distributed random variable x with a mean of μ and a variance of σ^2 is:

$$\mathcal{N}(x; \mu, \sigma^2) = \frac{1}{\sqrt{(2\pi\sigma^2)}} e^{\frac{(x-\mu)^2}{2\sigma^2}} \tag{2.9}$$

Consider the case where $\mu = 0$, the moment generating function (MGF) by definition is:

$$M_t(x) = E(e^{xt}) = \int e^{xt} \frac{1}{\sqrt{(2\pi\sigma^2)}} e^{\frac{(x-\mu)^2}{2\sigma^2}} dx \tag{2.10}$$

Using the change-of-variable technique we define $z = \frac{x-\mu}{\sigma}$, which implies $x = z\sigma + \mu$ and $dx/dz) = \sigma$. So, we get:

$$M_t(x) = e^{\mu t} \int e^{z\sigma t} \frac{1}{\sqrt{(2\pi\sigma^2)}} e^{\frac{1}{2}z^2} |\frac{dx}{dz}| dz = e^{\mu t} \int e^{z\sigma t} \frac{1}{\sqrt{(2\pi)}} e^{\frac{1}{2}z^2} dz = e^{\mu t} e^{\frac{1}{2}\sigma^2 t^2} \tag{2.11}$$

The conclusion is that the MGF corresponding to the normal probability density function $\mathcal{N}(x; \mu, \sigma^2)$ is:

$$M_t(x) = e^{\mu t + \frac{\sigma^2 t^2}{2}} \tag{2.12}$$

Hence, the matching CGF is:

$$C_t(x) = log(M_t(x)) = \mu t + \sigma^2 \frac{t^2}{2} \tag{2.13}$$

2.3 Waveform Modulation

Modulation is a fundamental process in communication systems, where the properties of a carrier signal are varied according to the information signal to facilitate efficient transmission over a medium. It is crucial in overcoming the limitations imposed by the physical medium and the constraints of the communication channel. Modulation allows for the optimization of bandwidth usage, improves signal-to-noise ratio, and enables multiple signals to be transmitted simultaneously over the same channel, a process known as multiplexing. Different modulation techniques are developed to meet various requirements such as power efficiency, bandwidth efficiency, and resilience against noise and interference in the communication channel.

This section delves into several key modulation methods, detailing their operational principles and applications:

- **On-Off Keying (OOK):** The simplest form of amplitude-shift keying (ASK), OOK modulates the presence (1) or absence (0) of a carrier wave to represent binary data. Its simplicity makes it ideal for optical fiber communication where only two states are needed.
- **4-Amplitude Shift Keying (4ASK):** An extension of ASK, 4ASK uses four distinct amplitude levels (e.g., A_1, A_2, A_3, A_4) to encode two bits per symbol, enhancing data rate while maintaining simplicity.
- **Binary Phase Shift Keying (BPSK):** This technique modulates the phase of the carrier wave with two distinct phases (e.g., $\phi_1, \phi_2 = 0, \pi$). BPSK is robust against noise, making it suitable for satellite and radio frequency communications.
- **Quadrature Phase Shift Keying (QPSK):** QPSK uses four phase shifts (e.g., $0, \frac{\pi}{2}, \pi, \frac{3\pi}{2}$) to encode data. It is more bandwidth-efficient than BPSK and commonly used in wireless communication systems.
- **8-Phase Shift Keying (8PSK):** 8PSK builds on QPSK by employing eight phase shifts, enabling three bits per symbol encoding. It offers higher data rates but requires a higher signal-to-noise ratio.
- **16-Quadrature Amplitude Modulation (16QAM):** A combination of amplitude and phase modulation, 16QAM uses sixteen different amplitude-phase combinations for signal representation, making it highly bandwidth-efficient.
- **Amplitude Modulation - Single Sideband Suppressed Carrier (AM-SSB-SC):** In AM-SSB-SC, only one sideband is transmitted, and the carrier is suppressed. This technique is bandwidth-efficient and used in long-range radio communication.
- **Amplitude Modulation - Double Sideband Suppressed Carrier (AM-DSB-SC):** This method transmits both sidebands while suppressing the carrier, optimizing power usage and suitable for specific data transmission applications.
- **Frequency Modulation (FM):** FM modulates the frequency of the carrier signal according to the information signal. Represented as $f(t) = f_c + \Delta f \sin(\omega_m t)$, FM is resistant to signal amplitude variations and is extensively used in high-fidelity radio broadcasting.

- **Gaussian Minimum Shift Keying (GMSK):** A bandwidth-efficient form of frequency modulation, GMSK applies a Gaussian filter to minimize phase shift variations and is a key technique in GSM networks.
- **Offset Quadrature Phase Shift Keying (OQPSK):** OQPSK, a variant of QPSK, offsets the phase shifts of the I and Q components by a quarter symbol period, reducing signal distortion and suitable for high-data-rate applications.

Chapter 3

Modulation Classification Based on Higher-Order Statistics

This chapter introduces a modulation classification methodology centered around the higher-order statistics of the received signal. The primary research focus in this chapter is the extraction of cumulants as key features for classification, coupled with an analysis of each modulation's statistics derived from these cumulants. Typically, cumulants are computed using the cumulant generating function and its derivatives. However, due to the absence of an exact statistical model of the signal, we adopt an approximation approach for cumulant calculation, grounded in methodologies presented in various literature sources. Section 3.1 delves into a detailed explanation of the cumulant extraction process, establishing how these statistical measures serve as effective classification features. Following this, Section 3.2 outlines the classification methodology applied in our research, including the hyperparameters selected for optimization during the experimental phase. In Section 3.3, we discuss the setup for the simulations conducted based on the proposed algorithm, providing insight into the practical implementation aspects. The experimental outcomes, along with a comparative analysis of various systems and conditions, are presented in Section 3.4. Finally, the chapter concludes with a summary in Section 3.5, encapsulating the key findings and contributions of our research in this domain.

3.1 Cumulants Calculation

The computation of cumulants is central to our classification methodology. Cumulants offer a nuanced statistical perspective of the signal, which is critical in distinguishing modulation schemes. The conventional approach involves using the Cumulant Generating Function (CGF), as shown in equation 2.3. However, calculating the CGF necessitates an expected value integral over the signal's unknown probability distribution, a task that can be quite challenging when dealing with signals of unknown modulation schemes.

To address this challenge, our study employs high-order statistics. MGF and the CGF uniquely define a distribution, implying that the total set of statistical moments correlates one-to-one with the total set of cumulants. Hence, by deriving moments from the sampled signal, we can infer the cumulants. In the case of discrete signals, the central moments can be conveniently obtained as follows:

$$m_k(x) = \frac{1}{N}\sum_{n=1}^{N} x^k[n] \tag{3.1}$$

Based on the discrete moments from equation 3.1, the cumulants are calculated using approximations derived from mixed moments, inspired by the works of [13, 18]. The following equations provide these approximations:

$$\begin{aligned}
c_{2,0} &= m_{2,0} && (3.2)\\
c_{2,1} &= m_{2,1} && (3.3)\\
c_{4,0} &= m_{4,0} - 3m_{2,0}^2 && (3.4)\\
c_{4,1} &= m_{4,1} - 3m_{2,1}m_{2,0} && (3.5)\\
c_{4,2} &= m_{4,2} - |m_{2,0}|^2 - 2m_{2,1}^2 && (3.6)\\
c_{6,0} &= m_{6,0} - 15m_{4,0}m_{2,0} + 30m_{2,0}^3 && (3.7)\\
c_{6,3} &= m_{6,3} - 9c_{4,2}m_{2,1} - 6m_{2,1}^2 && (3.8)\\
c_{8,0} &= m_{8,0} - 28m_{6,0}m_{2,0} - 35m_{4,2}^2 + 420m_{4,0}m_{2,0}^2 - 630m_{2,0}^4 && (3.9)
\end{aligned}$$

Here, $m_{q,p}$ denotes the mixed moment of the signal, defined as $E(x^q * \bar{x}^{p-q})$. This formulation allows for a simple and efficient computation of High-Order Cumulants (HOC), which serve as the features for our classification algorithm.

Given the digital nature of our signals, the discrete approximation for the mixed moment of N samples from a signal is utilized:

$$m_{q,p} = \frac{1}{N}\sum_{n=1}^{N} x^q[n] * \bar{x}^{p-q}[n]. \tag{3.10}$$

In our classification method, we use the discrete approximation of cumulants as input features. Additionally, we include a matching set of cumulants $C_{p,q}(x_d)$, derived from the derivative of the signal:

$$x_d[n] = x[n+1] - x[n]. \tag{3.11}$$

This comprehensive approach to cumulant calculation and application allows for robust modulation classification, effectively leveraging the statistical properties of the signal.

3.2 Classification Method

In this research, we employ the decision tree model for classification, owing to its simplicity and effectiveness. A decision tree is a model in supervised learning, resembling a flowchart, where each internal node signifies a decision test on a feature, branches represent the test's outcome, and leaf nodes indicate class labels. This structure translates input features into classification rules.

The decision tree model used in this study, implemented via the Python scikit-learn library, is trained using Gini impurity, a measure of classification error probability. Given a random variable A with k labels $(a_1, a_2, ..., a_k)$, the Gini impurity $G(A)$ is defined as:

$$G(A) = 1 - \sum_{i=1}^{k} (P(a_i))^2. \tag{3.12}$$

The training of the decision tree involves the following steps, presented here as pseudo-code:

```
Algorithm: Training a Decision Tree
Input: Training Data, Tree Depth (d)
Output: Trained Decision Tree

function TRAIN_DECISION_TREE(Data, d)
    if Tree Depth (d) is reached or Data is homogeneous:
        return Leaf Node with Class Label
    else
        BestFeature, BestThreshold = FIND_BEST_SPLIT(Data)
        LeftData, RightData = SPLIT_DATA(Data, BestFeature, BestThreshold)
        LeftTree = TRAIN_DECISION_TREE(LeftData, d-1)
        RightTree = TRAIN_DECISION_TREE(RightData, d-1)
        return Node(BestFeature, BestThreshold, LeftTree, RightTree)
    end if
end function

function FIND_BEST_SPLIT(Data)
    BestGini = Inf
    for each Feature in Data:
        for each Threshold in Feature:
            Gini = CALCULATE_GINI_IMPURITY(Feature, Threshold, Data)
            if Gini < BestGini:
                BestGini = Gini
                BestFeature = Feature
                BestThreshold = Threshold
```

```
            end if
        end for
    end for
    return BestFeature, BestThreshold
end function
```

The algorithm starts by checking whether the maximum tree depth or a homogeneous data segment (all samples belonging to one class) is reached. If either condition is met, a leaf node is returned. Otherwise, it identifies the best feature and threshold to split the data by minimizing Gini impurity. The data is then split accordingly, and the process repeats recursively for each subset until the specified tree depth is reached.

This decision tree model's parameters, excluding the leaves, are the comparison thresholds at each node. For a tree of depth d, the total number of parameters is given by:

$$P_d = 2^{d+1} - 1, \tag{3.13}$$

This number represents the count of operations needed for classification, as the tree performs only comparisons without requiring additional calculations.

Enhancing this model, we incorporated more complex decision models at each node, augmenting the decision tree's ability to handle intricate classification scenarios, particularly relevant in signal modulation classification within cognitive radio networks.

In this research, our classification algorithm is specifically tailored for integration with Software Defined Radio (SDR) systems in Cognitive Radio networks. The operational workflow begins with the signal acquisition by the SDR. The acquired signals are then segmented into discrete packets. The standard packet length is set to 1024 samples, although this can be adjusted based on network requirements and design specifications. These packets form the input data for our classification algorithm.

For each received packet, we employ the set of equations from 3.2 to 3.9 to extract the feature vector, which comprises the cumulants. This feature extraction process is designed for computational efficiency, requiring only a single pass through the packet data. The process is aligned with the packet length as determined by the communication network's configuration.

Once the features are extracted, they are passed to the classification phase, where the decision tree model is applied. The output from this stage is the identification of the modulation scheme used, from a set of 11 ”Normal” modulations. The identified modulation scheme is of significant importance in the Cognitive Radio context. It enables dynamic functionalities such as adaptive frequency channel selection and network usage detection, which are crucial for efficient and flexible operation within cognitive radio environments.

The training of the system can be conducted proactively in a controlled environment or dynamically during operational use. This flexibility allows for real-time adaptation to the changing conditions of the network. Such adaptability is essential to ensure that the system remains efficient and responsive to various operational scenarios, facilitating seamless integration into dynamic spectrum environments typical of Cognitive Radio networks.

3.3 Experimental Setup

3.3.1 Datasets

The dataset employed for this study is the comprehensive RadioML2018.01A dataset [19]. This dataset is a significant compilation in the field, containing 2,555,904 frames. Each frame in this dataset comprises 1024 IQ samples from a signal modulated using various schemes. The dataset captures a broad spectrum of SNR values, ranging from -20 dB to 30 dB, to mimic realistic communication scenarios.

The RadioML2018.01A dataset is notable for its diversity in modulation types and the range of channel conditions it simulates. The dataset encompasses 24 different modulation schemes, all generated using Software Defined Radio (SDR) under a variety of channel specifications:

- Selective multipath Rician fading, simulating a common real-world propagation environment;
- Carrier frequency offset, representing the discrepancies between the transmitter and receiver frequency;
- Symbol rate offset, accounting for synchronization variances;
- Non-impulsive delay spread, indicative of multi-path effects;
- Doppler shift, simulating the impact of relative motion on the frequency of the signal;
- Additive White Gaussian Noise (AWGN), a fundamental component in channel modeling.

For our research, we focus on a subset of this dataset, referred to as the "Normal" set. This subset includes 11 modulation schemes: OOK, 4ASK, BPSK, QPSK, 8PSK, 16QAM, AM-SSB-SC (SSB), AM-DSB-SC (DSB), FM, GMSK, and OQPSK. The selection of these 11 modulations is intentional, as they represent a wide spectrum of commonly used modulation techniques in practical communication systems, encompassing both analog and digital methods.

The "Normal" set is particularly significant for our study as it serves as a benchmark for classification models in the literature. This subset provides a balanced mix of modulation types, allowing for a comprehensive evaluation of our classification algorithm's performance. By focusing on these 11 modulations, we aim to develop and test a model that is both robust and versatile, capable of accurately identifying a diverse range of signal types under various channel conditions.

In contrast, the ”hard” set in the RadioML2018.01A dataset, which contains all 24 modulation schemes, presents a more challenging scenario. While it offers a broader range of modulations, the complexity and similarity among some of the additional schemes can introduce additional challenges in classification. By prioritizing the ”Normal” set, our study aims to establish a strong foundational model, which could be further extended and refined for more complex scenarios in future work.

3.3.2 Algorithm Implementation

The complete algorithm for modulation classification was implemented using Python 3 on an Ubuntu-based platform. The initial step involves extracting relevant samples from the RadioML2018.01A dataset, as provided by O'Shea et al. [19]. These samples form the foundation for our analysis and classification tasks.

Following sample selection, the algorithm proceeds to the feature extraction phase. In this phase, we compute the cumulants and their derivatives for each signal in the dataset. The computed cumulants are assembled into feature vectors, which are essential for the subsequent classification process.

To facilitate training and testing, the dataset's feature vectors are divided into two primary groups: a training set and a test set. Within the training set, we perform a further subdivision based on a predetermined Signal-to-Noise Ratio (SNR) threshold. This SNR threshold allows us to segregate the data into two distinct subsets - The first subset consists of signals with SNR values exceeding the established threshold. These signals are presumed to have higher quality and clarity, potentially making them easier to classify accurately. The second subset contains signals with SNR values falling below the specified threshold. These are typically more challenging due to increased noise levels, providing a rigorous test of the algorithm's robustness.

This strategic division of the data based on SNR thresholds is instrumental for conducting experiments. It aids in determining the optimal SNR threshold that yields effective classification, enabling us to assess the algorithm's performance under varying signal conditions. Such an approach ensures that our classification model is not only accurate but also adaptable to different SNR scenarios commonly encountered in practical communication systems.

3.4 Experimental results

The suggested classification method is initiated with a preliminary experiment aimed at determining the most effective features for the classification of each modulation scheme within the selected set of 11. This initial phase involves a small-scale simulation using a basic decision tree model, where each run (consisting of training and testing) utilizes only one feature at a time, either from the cumulants or the derivative cumulants.

Table 3.1: Best two features for each modulation at SNR=10dB.

Modulation	**1st Feature**	P_d	**2nd Feature**	P_d
SSB	$C_{4,1}$	100%	$C_{4,0}$	100%
DSB	$C^d_{4,1}$	74.69%	$C^d_{4,0}$	73.34%
BPSK	$C_{2,0}$	99.57%	$C_{4,0}$	92.73%
FM	$C_{4,1}$	99.63%	$C_{2,0}$	99.27%
GMSK	$C_{4,2}$	96.09%	$C_{8,0}$	81.23%
OOK	$C_{2,0}$	95.82%	$C_{2,1}$	93.61%
4ASK	$C_{2,1}$	95.84%	$C_{2,0}$	93.71%
QPSK	$C^d_{4,0}$	87.95%	$C^d_{8,0}$	86.69%
OQPSK	$C_{4,2}$	76.39%	$C_{4,0}$	60.53%
16QAM	$C^d_{6,0}$	100%	$C^d_{6,3}$	99.74%
8PSK	$C^d_{4,0}$	100%	$C^d_{4,2}$	99.87%

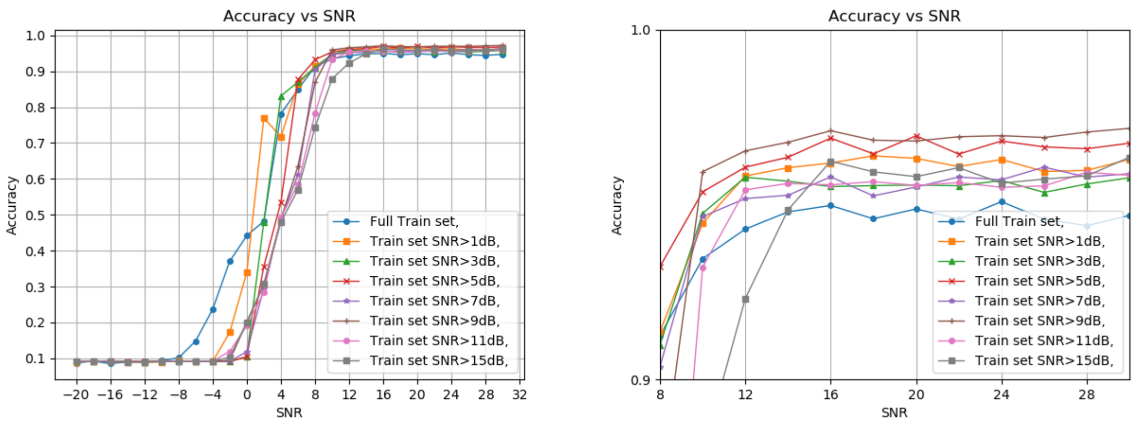
Table 3.1 presents the top two features for each modulation scheme, ranked according to their detection accuracy with the simple decision tree model. The results shown in table are based on average outcomes achieved when classifying signals at a specific SNR of 10 dB. This SNR level is chosen as it is generally considered adequate for a receiver to effectively detect and demodulate signals with a high degree of accuracy.

Informed by the insights from these initial results, we then proceed to construct the definitive feature vector. This vector is carefully crafted, combining a selection of cumulants that have demonstrated optimal performance at the chosen 10 dB SNR threshold. The process of selecting these cumulants is crucial in forming an efficient and discriminative feature set, specifically tailored for signal classification within this SNR range. By integrating these selected cumulants into a single, comprehensive feature vector, our aim is to capture the most informative and distinguishing characteristics of the signals. This integrated approach is designed to enhance the accuracy of modulation classification, ensuring that our algorithm effectively identifies the modulation scheme at the specified SNR level. The combination of these cumulants into one feature vector represents a strategic decision to balance efficiency with the nuanced requirements of accurate signal classification.

The next phase of our simulation involves the critical process of selecting the training set for the model. Conventionally, training sets for machine learning models are randomly picked from the entire database. However, in our approach, we adopt a more targeted strategy by choosing to train our model with only a subset of the data. This subset comprises sampled signals with SNR values exceeding a specific threshold.

The rationale behind this decision stems from an understanding of the unique characteristics of different modulation schemes. It is recognized that each modulation scheme has a minimum SNR requirement for effective demodulation. Consequently, incorporating signals with SNR values below this threshold into the training set could potentially impair the model's learning process. In light of this, we divide the data into two distinct groups: one with high SNR signals and the other with low SNR signals.

To determine the appropriate SNR threshold for this separation, we conducted a second experiment. This experiment aimed to assess the impact of varying SNR thresholds on the classification accuracy of the model. The results of this experiment are depicted in Figure 3.1, which illustrates the classification performance when the model is trained using signals with SNR values above different thresholds. A zoomed-in view of the figure highlights the section where classification accuracy peaks. This detailed analysis allows us to identify the optimal SNR threshold for training, ensuring that the model is exposed to high-quality data that aligns with the practical requirements of effective modulation classification.



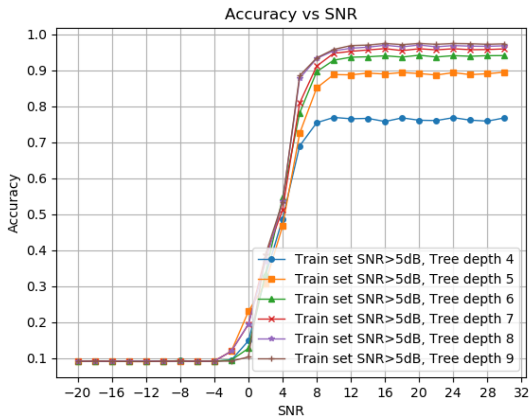
(a) Full view.

(b) Zoomed in.

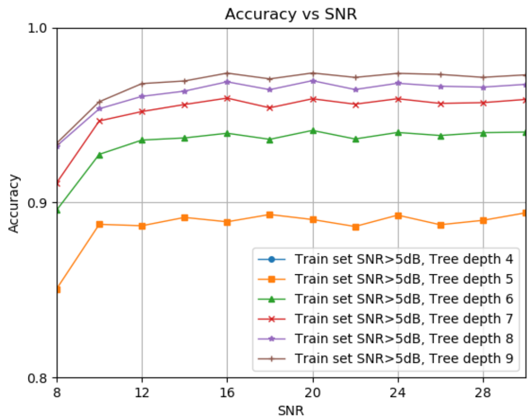
Figure 3.1: P_d based on train set SNR threshold.

The process of selecting the optimal training set and configuring the decision tree involved several critical observations and decisions. We observed that using a training set encompassing all SNR values resulted in better accuracy at negative SNRs but showed a decline in performance at positive SNR levels. This trend aligns with expectations, as signals with higher SNR typically provide clearer information for classification. Additionaly, It was found that setting the SNR threshold above 5 dB led to reduced accuracy for both high and low SNR test samples. After careful evaluation, we narrowed down our choice of threshold to a range between 1 dB and 5 dB. While the 1 dB threshold offered better accuracy at lower SNR levels, there was a noticeable improvement in detection accuracy from 4 dB and above when using the 5 dB threshold. This finding corroborates the hypothesis that different modulation schemes have specific minimum SNR requirements for effective demodulation. Furthermore, In our initial tests, the depth of the decision tree was not a primary factor. However, for subsequent tests, we aimed to select a balanced tree depth. The goal was to ensure the tree is deep enough to encompass all the selected features without being overly deep, which could lead to overfitting and increased complexity. A well-balanced tree depth is crucial for achieving a model that is both accurate and generalizable, capable of handling diverse modulation schemes effectively.

These insights guided us in refining our approach, leading to a more targeted and effective classification model. By judiciously selecting the training set based on SNR values and optimizing the decision tree depth, we aimed to strike a balance between accuracy, generalizability, and computational efficiency.



(a) Full view.



(b) Zoomed in.

Figure 3.2: P_d based on tree depth.

Figure 3.2 illustrates the variation in detection probability with different decision tree depths. Our analysis begins with a tree depth of four layers, the minimum required to accommodate 11 labels, and extends up to nine layers. Beyond eight layers, no significant improvement in performance was observed. The optimal depth for practical application can be determined based on the specific memory and runtime constraints of the system. For our purposes, we selected a decision tree with a depth of eight layers and trained it using a dataset with SNR values higher than 5 dB.

Figure 3.3 the confusion matrix for SNR=10 dB, utilizing a decision tree with a depth of 8 and a positive threshold, showcases excellent classification results. This matrix highlights the algorithm's effectiveness in accurately identifying modulation schemes using a cumulants based decision tree. The high accuracy observed across various modulation types at this SNR level indicates the robustness and reliability of the proposed method, affirming its suitability for practical applications in spectrum sensing and modulation classification tasks.

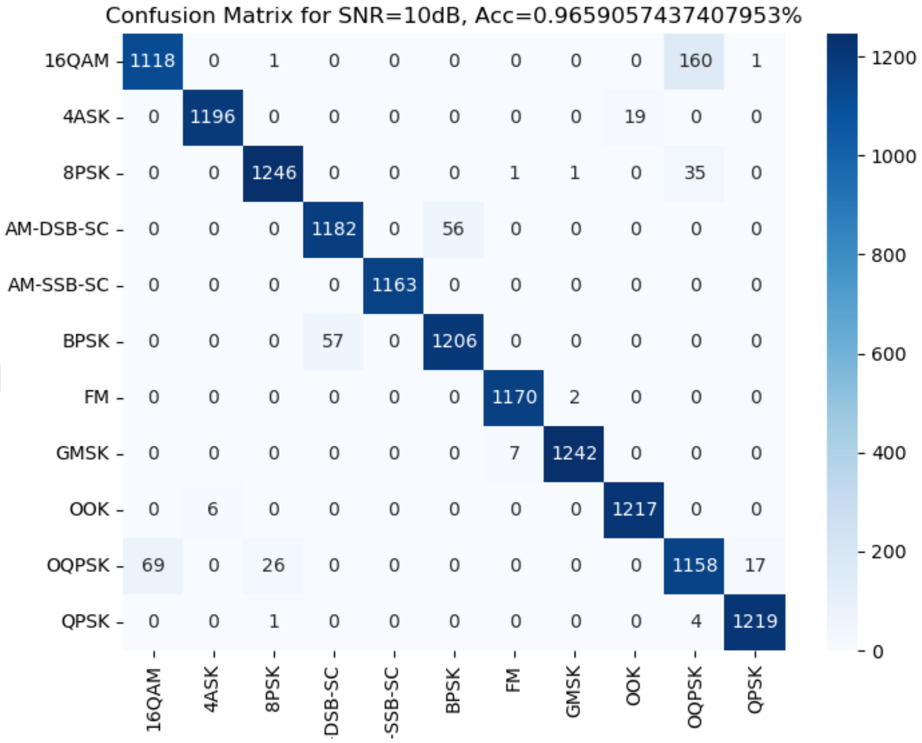


Figure 3.3: Confusion Matrix for treshold SNR=0dB, depth=8.

In order to benchmark our results, we aim to compare our method with various state-of-the-art deep learning models. The models chosen for this comparison include ResNet [20], DenseNet [21], LSTM [11], FLANs [9], and VGG [22].In our research, we take the suggested NN models and adjust them to the modulation classification task, using the sampled signal as the input and the label as output. Figure 3.4 depicting classification accuracy across different models.

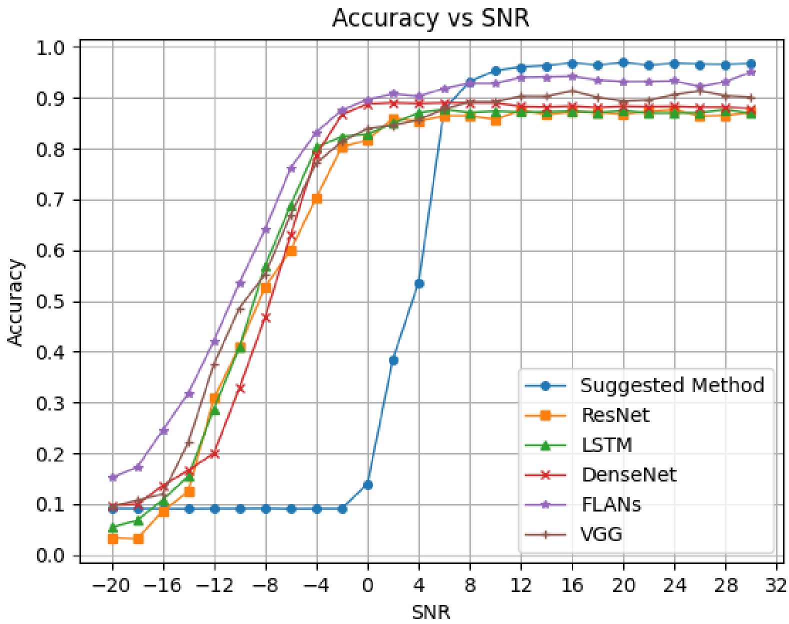


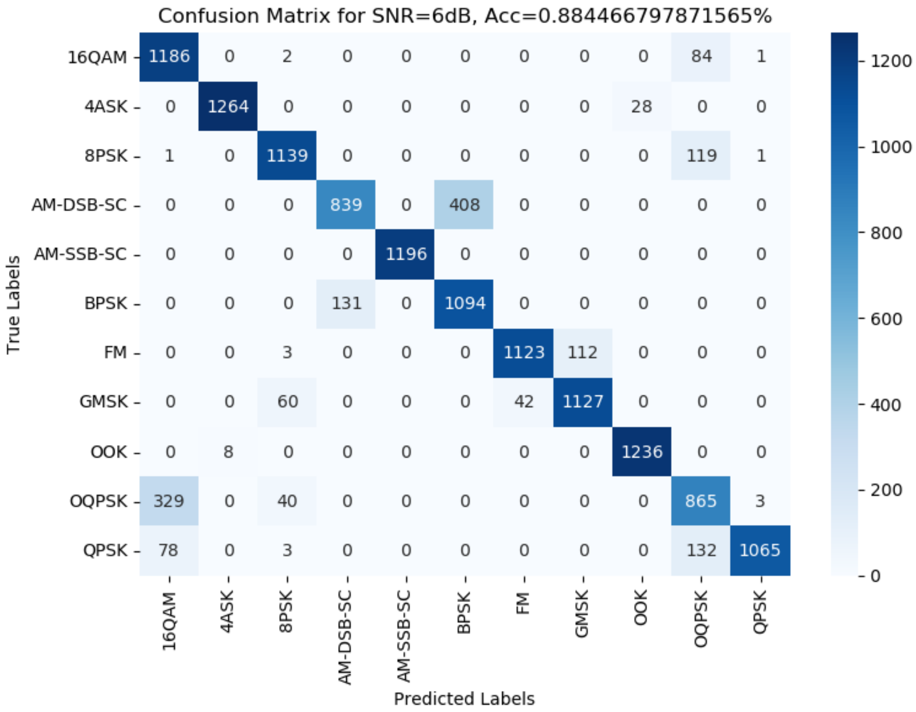
Figure 3.4: P_d comparison for the suggested method.

The comparison reveals that deep neural networks have an edge in scenarios with negative SNR values, an area where our method shows limitations. Nonetheless, the relevance of classification at negative SNR is often negligible in the context of perfect demodulation, as previously discussed. Interestingly, when the data is split at a threshold of 6 dB SNR, our proposed method demonstrates superior detection accuracy over the popular neural network models, outperforming them by almost 8%. This outcome underscores the efficacy of our method in environments with SNR values conducive to accurate signal demodulation.

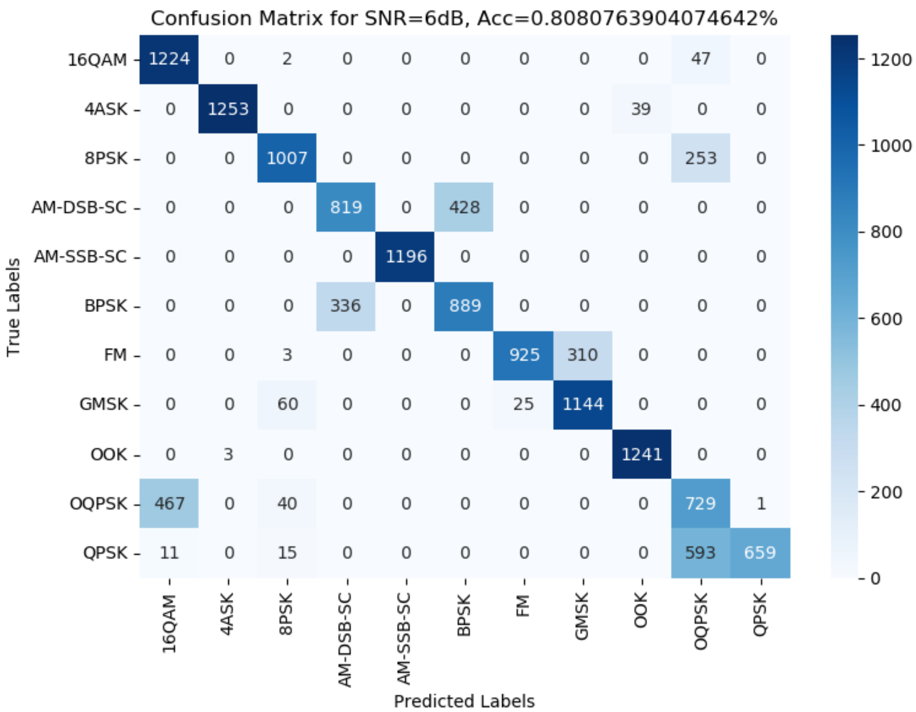
Table 3.2: Parameter size of different models.

Model	**Total Parameters**
6 Deep Tree	63
7 Deep Tree	127
8 Deep Tree	255
ResNet	214,922
LSTM	770,378
DenseNet	542,850
VGG	1,621,780
FLANs	954,747

The secondary comparison of our classification model with Neural Network (NN) models focuses on the parameters or memory requirements. Utilizing Equation (3.13), we calculate the total number of parameters required for decision trees of various depths. The results of these calculations are presented in Table 3.2, where we compared the parameter count of our model against that of the selected NN models. The chosen decision tree model, even with the inclusion of additional layers, maintains a parameter count in the range of a few hundred. This is in stark contrast to NN models, which typically have parameters numbering in the hundreds of thousands. This significant difference in parameter count underscores the memory efficiency of our model. Such sparse memory usage is particularly beneficial in scenarios where low complexity and quick runtime are essential. It is especially advantageous when considering the integration of multiple models to improve accuracy, a common requirement in real-world applications. The minimal memory requirements of our model compared to NN models make it highly suitable for deployment within SDR systems. NN architectures, with their extensive parameter count often reaching millions, can be impractical for many SDR implementations due to their heavy memory demands. On the other hand, our model's operation within the range of hundreds to thousands of parameters makes it much more feasible for integration in SDR systems. This presents a significant advantage for our approach, making it particularly apt for real-world applications in contexts where memory and computational efficiency are critical, such as in SDR-based Cognitive Radio networks.



(a) depth=7



(b) depth=8

Figure 3.5: Confusion Matrices for different tree depth.

We conducted an in-depth examination of the confusion matrix resulting from our proposed method. Figure 3.5 illustrates the confusion matrices at 6 dB for decision trees with depths of 7 and 8, trained on the dataset with an SNR threshold of 5 dB. A consistent pattern of mislabeling emerges from these matrices, and similar patterns are observed across other matrices we analyzed. This consistency allows us to categorize the modulation schemes into distinct subgroups based on their misclassification tendencies:

- Group 0: AM-SSB.
- Group 1: AM-DSB and BPSK.
- Group 2: 4ASK and OOK.
- Group 3: FM and GMSK.
- Group 4: 8PSK, 16QAM, QPSK, and OQPSK.

Group 0, with its exclusive composition of SSB modulation, demonstrates nearly instantaneous classification, even at relatively low SNR values. This group's consistent and rapid detection is a hallmark of its unique and easily recognizable modulation characteristics. Groups 1, 2, and 3 represent combinations of modulations that are statistically similar, leading to frequent misclassifications, particularly at lower SNR levels. This similarity suggests that the signal models within these groups share comparable statistical behaviors, complicating their differentiation under challenging SNR conditions. Group 4, encompassing the remaining modulations, portrays a scenario of higher complexity. Here, multiple modulation schemes exhibit overlapping statistical features, making individual identification more challenging. The lack of distinct differentiation within this group signifies a higher level of complexity, where distinguishing characteristics are blurred due to similarities in statistical behavior.

This categorization into subgroups based on confusion matrix analysis provides valuable insights into the behavior and detectability of various modulation schemes. It highlights distinct characteristics observed across different SNR levels and establishes patterns of similarity and complexity among the modulation types.

3.5 Summary

This chapter presented a comprehensive simulation study to validate the effectiveness of a classic Feature-Based algorithm in Automatic Modulation Classification. Initially, we focused on assessing the impact of individual features on detection accuracy. This analysis led to the elimination of unnecessary or redundant features during the training phase of our model, streamlining the feature set for enhanced performance. The dataset was divided into high and low SNR groups, revealing that certain modulation schemes are detectable only above specific SNR thresholds. This insight allowed us to refine our model, concentrating on SNR levels that are most pertinent in practical communication scenarios. The final phase of our simulation involved fine-tuning the decision tree's hyperparameters. Our objective was to achieve the highest possible accuracy while maintaining optimal complexity and avoiding overfitting. When compared against three state-of-the-art neural network models, our method demonstrated superior detection accuracy at higher SNR levels, albeit struggling at lower SNR values where NN models were more effective. This variance underscores the importance of considering SNR thresholds in real-world modulation detection. A significant advantage of our FB classifier over NN models lies in its memory efficiency. While NN models required millions of parameters, our model operated with a few hundred parameters, translating to reduced memory usage and faster runtime, essential for practical deployment in Cognitive Radio systems.

Despite these promising results, our method has limitations, particularly in low SNR scenarios and for certain modulation schemes that exhibit similar carriers or statistical properties, leading to potential misclassification. These limitations notwithstanding, the outcomes of our research affirm the viability and advantages of employing a classic FB classifier for AMC in real-world Cognitive Radio networks. The effectiveness, efficiency, and practicality of our approach make it a valuable tool for modulation classification in diverse operational environments.

Chapter 4

Conclusion

4.1 Summary

Our research endeavored to develop a straightforward yet robust method for automatic modulation classification (AMC) within the realm of spectrum sensing in cognitive radio networks. Our proposed method demonstrated superior performance compared to several widely used neural network models. This advantage was notable not only in terms of classification accuracy but also in memory efficiency, a critical factor for practical applications in cognitive radio systems. The choice of the decision tree classifier was pivotal due to its simplicity and effectiveness. This facilitated the identification and utilization of High-Order Cumulants (HOC) as efficient statistical features tailored for each modulation scheme. This approach was instrumental in achieving the desired balance between accuracy and computational efficiency. Our study ventured beyond the conventional focus on digital modulations. We explored the classification of analog modulations using cumulants, an area that has not been extensively examined in previous research. This exploration provided new insights into the classification of both digital and analog modulation schemes. Through our research, we discovered subsets of modulations that exhibited similar statistical behaviors. This finding not only enhanced our understanding of modulation characteristics but also laid the groundwork for future advancements in classification methodologies. The approach we developed is particularly suitable for end units in Cognitive Radio (CR) networks. It achieves high accuracy while requiring minimal parameters, addressing the crucial needs for memory and speed efficiency in such networks. Looking ahead, our future work aims to leverage the identified modulation subgroups to develop an even more sophisticated classification method that further enhances accuracy. Additionally, we plan to broaden our approach to encompass a more extensive range of modulations, thereby making our classification framework more comprehensive and applicable across various modulation scenarios in cognitive radio environments.

4.2 Future Research

The research presented in this thesis introduces an efficient modulation classification method for spectrum sensing in cognitive radio networks, with a particular focus on high-order statistics as classification features. While our method shows improved performance in certain comparison parameters, there remain several areas ripe for future research:

- **Complex Channel Models:** Our research primarily addressed the classic modulation classification task within the AWGN (Additive White Gaussian Noise) channel model. Future studies should explore more complex channel models that more closely resemble real-world environments. As cognitive radio applications move towards real-time operation, adapting to these more realistic channel conditions becomes essential. Understanding how our method performs under various channel impairments will be crucial for its practical deployment.

- **Advanced Feature-Based Classification Methods:** While this study demonstrated the efficacy of cumulants as classification features using a basic decision tree classifier, there is potential for further enhancement. Future research could explore more sophisticated and novel feature-based classification methods that utilize cumulants. Investigating the integration of cumulants with advanced machine learning algorithms could lead to even more robust classification models.

- **Real-World Applicability:** Our work discusses the relevance of real-time applications where power consumption and memory allocation are critical yet limited resources. A complementary study focusing on the viability of our proposed method in actual end-unit deployments within cognitive radio networks would be beneficial. This investigation should assess the practicality of our method in terms of computational efficiency, power usage, and memory constraints, ensuring its suitability for real-world cognitive radio applications.

These potential research directions not only extend the scope of our current work but also align with the evolving needs and challenges in the field of cognitive radio networks. Addressing these areas could significantly contribute to the development of more adaptive, efficient, and practical spectrum sensing solutions.

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המחקר כולל כמה חלקים. תחילה, חולצו ונשמרו כל המאפיינים מתוך סט נרחב של אותות הדגומים, כך שיהוו מסד נתונים עצמאי, ללא צורך לחלץ אותם מחדש בכל ניסוי. לאחר מכן, בוצעה סדרה מקיפה של בדיקות וניסויים שמטרתם כוונון עדין של כל הפרמטרים עבור מודל הסיווג המוצע. בסיום שלב זה התקבל את המודל הסופי של המסווג, ובאמצעותו נבדקו אחוזי הסיווג של אפנונים שונים ברמות רעש שונות. בכדי לבסס את איכות המודל המוצע במחקר זה, נערכה השוואה של תוצאות הסיווג אל מול מודלים נבחרים מהספרות. ההשוואה נערכה מול שני מדדים - הראשון הוא בדיקת אחוז הסיווג, כאשר המיקוד הוא אותות הניתנים לפענוח. השני הוא השוואת יעילות המודלים בהיבט של בהקצאת זיכרון ושל יעילות חישובית. בחלק האחרון של המחקר, ראינו כיצד אפנונים בעלי דמיון מתנהגים דומה גם במובן הסטטיסטי, לפי שיוך של טעויות הסיווג למספר קבוצות. להערכתנו, השיטות היעילות שהוצעו במחקר מהוות בסיס חשוב להמשך מחקר בתחומי הרדיו חכם וסטטיסטיקה של אפנונים, זאת בהתאם לתוצאות הניסויים וההשוואות שקיבלנו.

תקציר

בתזה זו, אנו חוקרים שיטה יעילה של סיווג אפנונים עבור פונקציית חישת הספקטרום של מערכות רדיו חכם. חישת ספקטרום היא חלק מרכזי ברשתות תקשורת של רדיו חכם, מכיוון שקיים הצורך להתאים את הקליטה והשידור אל סביבת הספקטרום הזמינה. התאמה זו כוללת סריקה של כלל התדרים, מציאת ערוצי תדר פנויים וזיהוי של משתמשים פעילים בתחום התדר. על מנת לבצע זיהוי משתמשים והבדלה ביניהם בצורה חכמה, יש צורך לסווג את האפנון של כל אות בתדר. זיהוי האפנון של האות מאפשר גם להבחין בין משתמשים ברשתות שונות, וגם כדי לאתר משתמשים באותה הרשת, ולהתאים את שיטת הפענוח של האפנון לפי הסכמה המתאימה. הקדמה הטכנולוגית פתחה את הדלת לרשתות רדיו חכמות, הן בצד התוכנה והן בצד החומרה. פיתוח ושיווק של יחידות רדיו מסתגלות אשר מבוססות על רכיבי חומרה יעילים וחכמים יחד עם כלים תוכנתיים המאפשרים פיתוח טכניקות חכמות בקליטה ובשידור. בין טכניקות אלה נמצאת גם המשימה של סיווג האפנונים, אשר הפכה ליותר נפוצה ומוכרת בעולמות המחקר, גם עבור חישה ספקטרלית וגם עבור משימות אחרות הדורשות זיהוי אפנון.

מחקרים בנושא סיווג אפנונים מתחלקים לשלושה סוגים של אלגוריתמים. במחקר זה, בחרנו אלגוריתם המבוסס על סיווג באמצעות סט מאפיינים. משפחה זו של אלגוריתם עדיפה כאשר בוחנים יעילות חישובית, הקצאות זיכרון ועומס על רכיבי המערכת. המאפיינים בהם נעשה שימוש בשיטות אלה מחולצים מתוך האות הדגום, כך שנדרש להתאים אלגוריתם סיווג למימד קלט הרבה יותר קטן מאשר האות הדגום בעצמו. המאפיינים בהם עשינו שימוש בתזה זו נבחרו להיות הקומולנטים מסדר גבוה של האות. הקומולנטים הם מאפיינים סטטיסטים של סיגנל ובדומה למומנטים סטטיסטיים, הם מהווים מדד איכותי לצורת הפילוג של האות. היתרון של השימוש בקומולנטים נובע כאשר לוקחים בחשבון את תכונת החיבור שלהם תחת מודל הרעש של ערוץ לבן קלאסי. שיטה זו מאפשרת ניתוח סטטיסטי של האות המשודר באמצעות הדגימות של האות הנקלט.

הגישה המוצעת מתחילה עם חילוץ המאפיינים באמצעות שערוך הקומולנטים של האות הנקלט, על ידי שימוש בקירוב המבוסס על המומנטים הסטטיסטיים. בשלב השני, נלקח סט המאפיינים הסטטיסטיים למטרת אימון ובדיקה של מודל למידה חכמה יעיל ופשוט אשר נבחר במטרה לתת את הדגש במחקר להתנהגות הסטטיסטית של האותות תחת אפנונים שונים. בנוסף, המחקר בדק את השפעת סט האימון על יכולת הסיווג, כאשר תהליך אימון המודל כולל רק אותות עם יחס אות לרעש חיובי, זאת על מנת למנוע מאותות רועשים, בהם המידע אבוד, מלהוות גורם המשפיע על הצלחת המסווג. האפנונים אשר נבדקו במהלך מחקר כוללים ביניהם גם אפנונים דיגיטליים וגם אפנונים אנלוגיים, הנפוצים פחות בסיווג מבוסס קומולנטים. רוב האפנונים שנבחנו במהלך המחקר מהווים אפנונים נפוצים במערכות תקשורת, לכן נדרשת יכולת לסווג אותם עם דיוק גבוה.

המחקר בוצע בהנחייתו של פרופסור ישראל כהן בפקולטה להנדסת חשמל ומחשבים.

התוצאות של פרק 3 של חיבור זה פורסמו בכתב-עת במהלך תקופת מחקר המגיסטר של המחבר, אשר גרסתו העדכנית ביותר הינה:

Ben Dgani and Israel Cohen. Efficient cumulant-based automatic modulation classification using machine learning. *Sensors*, 24(2), 2024.

מחבר חיבור זה מצהיר כי המחקר, כולל איסוף הנתונים, עיבודם והצגתם, התייחסות והשוואה למחקרים קודמים וכו', נעשה כולו בצורה ישרה, כמצופה ממחקר מדעי המבוצע לפי אמות המידה האתיות של העולם האקדמי. כמו כן, הדיווח על המחקר ותוצאותיו בחיבור זה נעשה בצורה ישרה ומלאה, לפי אותן אמות מידה.

תודות

ברצוני להביע את הכרת התודה והערכתי הרבה למנחה המחקר שלי, פרופסור ישראל כהן. המחקר הזה לא היה מתאפשר ללא התמיכה וההכוונה שלו. במהלך המסע הזה, הוא לימד אותי איך להיות חוקר טוב יותר, איפשר לי ללמוד כישורים משמעותיים, ועזר לי להתגבר על הקשיים הרבים שבדרך, ועל זה אני מוקיר תודה.

ברצוני גם להודות לבת זוגתי מירית ולמשפחה שלי, שליוו אותי ותמכו בי ברגעים הקשים וחלקו איתי את הרגעים הטובים של התהליך הזה. ההישג הזה לא היה מתאפשר בלעדיהם.

חישת ספקטרום מבוססת על סיווג אפנון באמצעות סטטיסטיקות מסדר גבוה

חיבור על מחקר

לשם מילוי חלקי של הדרישות לקבלת התואר
מגיסטר למדעים בהנדסת חשמל

בן דגני

הוגש לסנט הטכניון — מכון טכנולוגי לישראל
אדר התשפ"ד חיפה מרץ 2024

חישת ספקטרום מבוססת על סיווג אפנון באמצעות סטטיסטיקות מסדר גבוה

בן דגני