

**SIMULTANEOUS DETERMINATION OF  
MODULATION TYPES AND SIGNAL-TO-NOISE  
RATIOS IN WIRELESS COMMUNICATION  
SYSTEMS**

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SIGNAL-TO-NOISE RATIOS IN WIRELESS COMMUNICATION  
SYSTEMS**

**by**

**TARIK ADNAN ALMOHAMAD**

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# LIST OF ABBREVIATIONS

2D	Two-Dimensional
2D-ASIQHs	Two-Dimensional Asynchronous Sampled In-Phase-Quadrature Histograms
4G	Fourth Generation
5G	Fifth Generation
AAH	Asynchronous Sampling Amplitude Histograms
ADTPs	Asynchronous Delay Tap Plots
AI	Artificial Intelligent
ALRT	Average Likelihood Ratio Test
AMR	Automatic Modulation Classification
ANN	Artificial Neural Networks
ASK	Amplitude Shift Keying
AWGN	Additive White Gaussian Noise
CR	Cognitive Radios
CRLB	Cramer-Rao Lower Bound
CWT	Continuous Wavelet Transform
DA	Data-Aided
dB	Decibel
DNN	Deep Neural Network
EM	Expectation-Maximization
FB	Feature-Based Approach
FC	Fusion Centre
FSK	Frequency Shift Keying

FT	Fourier Transform
Gbps	Gigabit per second
GLRT	Generalized Likelihood Ratio Test
HLRT	Hybrid Likelihood Ratio Test
HOCs	Higher Order Cumulants
HOMs	Higher Order Moments
LB	Likelihood-Based Approach
LOS	Line-of-Sight
MATLAB	Matrix Laboratory
Mbps	Megabit per second
MIMO	Multiple-Input Multiple-Output
ML	Maximum Likelihood
MLP-NN	Multi-Layer Perceptron Neural Network
NDA	NonData-Aided
OFDM	Orthogonal Frequency Division Multiplexing
PCA	Principal Component Analysis
PCs	Principal Components
PDF	Probability Density Function
PSK	Phase Shift Keying
QAM	Quadrature Amplitude Modulation
QoS	quality of Service
SAE	Sparse Auto-Encoder
SCD	Spectral-Correlation Density Function
SC-FDMA	Single-Carrier Frequency-Division Multiple-Access
SNR	Signal to Noise Ratio

SPD	Signal Parameters Determination
STBC	Space-Time Block Code
StVR	Signal-to-Variation Ratio
SVC	Support Vector Classifier
SVM	Support Vector Machine
SVR	Support Vector Regressor
WT	Wavelet Transform

# **PENENTUAN SERENTAK JENIS PEMODULATAN DAN NISBAH ISYARAT-KEPADA-HINGAR DALAM SISTEM KOMUNIKASI TANPA WAYAR**

## **ABSTRAK**

Teknik penentuan automatik parameter isyarat boleh menawarkan lebih kebolehpercayaan, lebar jalur yang lebih besar, dan keselamatan yang lebih tinggi kepada sistem tanpa wayar moden. Walau bagaimanapun, perbandingan prestasi teknik penentuan sedemikian tidaklah mudah. Hal ini boleh disebabkan oleh kurangnya set data penanda aras dalam komuniti penyelidikan komunikasi tanpa wayar berbanding dengan bidang penyelidikan lain. Oleh itu, terdapat keperluan untuk mencadangkan set data berpotensi-penanda aras yang boleh menjadi pilihan bagi penyelidik dalam domain komunikasi tanpa wayar pada masa hadapan, mencetuskan sumbangan pertama dalam tesis ini. Kebanyakan penyelesaian terkini bagi teknik penentuan parameter isyarat memberi tumpuan kepada menentukan hanya satu parameter tunggal contohnya, jenis modulasi dan menganggap parameter lain, seperti nisbah isyarat-kepada-hingar (SNR) diketahui dan bukannya menganggarkan pelbagai parameter isyarat secara serentak. Oleh itu, keinginan untuk membolehkan keupayaan automatik dalam penentuan serentak pelbagai parameter isyarat telah mencetuskan sumbangan kedua dan ketiga yang menangani penerima bukan koheren dan koheren. Oleh itu, objektif dalam tesis ini adalah seperti berikut, pertama, untuk membangunkan tiga set data untuk penerima yang telah dinyatakan terdahulu dan digunakan bagi penentuan secara serentak jenis modulasi dan nisbah isyarat-kepada-hingar, iaitu Set data berasaskan histogram amplitud tak segerak (AAHs), Set data 1 berasaskan pensampelan tak segerak dua-dimensi dalam histogram fasa-kuadratur (2D-ASIQHs) dan Set data 2 berasaskan 2D-ASIQHs. Kedua, untuk membangunkan satu skema yang dapat menentukan secara serentak jenis modulasi dan nisbah isyarat-kepada-hingar dalam penerima tanpa koheren dengan menggunakan satu jenis ciri (ciri-berasaskan AAH) di bawah senario pemudaran multipath. Akhir sekali, untuk membangunkan satu

skema yang boleh menentukan secara serentak jenis modulasi dan nisbah isyarat-kepada-hingar dalam penerima yang koheren dengan menggunakan ciri-ciri 2D-ASIQH di bawah pemudaran Rician dan Rayleigh. Bagi pembentukan set data, ketiga-tiga set data dibangunkan di bawah saluran pemudaran multipath dan digunakan untuk mengesahkan skema penentuan yang dicadangkan dalam sumbangan kedua dan ketiga. Skema penentuan serentak berasaskan AAH membolehkan penerima pintar generik untuk mengenalpasti pelbagai modulasi yang dimiliki oleh kategori modulasi yang berbeza dan menunjukkan bahawa keupayaan pengenalpastian boleh dikembangkan lagi kepada jenis isyarat yang lain. Skema ini juga boleh menganggarkan secara serentak nilai-nilai SNR dengan tepat. Skema penentuan serentak berasaskan 2D-ASIQH menangani penerima koheren untuk menentukan sembilan jenis modulasi dan pelbagai jenis SNR secara serentak. Ciri-ciri yang paling penting diekstrak menggunakan analisis komponen utama (PCA) dan kemudian dijadikan input kepada mesin vektor sokongan (SVM) untuk proses pembelajaran automatik. Dalam hasil simulasi, sampel set data mencerminkan histogram sampul-1D dan imej berasaskan fasa-kuadratur yang mengandungi pelbagai jenis modulasi dan SNR dengan kombinasi gandaan dan penundaan jalur yang berlainan. Dari segi ketepatan pengenalpastian modulasi dan purata kesilapan penganggaran SNR, skema berasaskan AAH yang dicadangkan masing-masing mencapai 99.83% dan 0.79 dB. Begitu juga, skema berasaskan 2D-ASIQH yang dicadangkan masing-masing mencapai 99.06% dan 1.10 dB. Hasil yang diperoleh menunjukkan bahawa skema yang dicadangkan mengatasi kerja terkini yang sedia ada.

# **SIMULTANEOUS DETERMINATION OF MODULATION TYPES AND SIGNAL-TO-NOISE RATIOS IN WIRELESS COMMUNICATION SYSTEMS**

## **ABSTRACT**

Signal parameters determination techniques can offer more reliability, larger bandwidth, and higher security to the modern wireless systems. However, the performance comparison of such determination techniques is not straightforward. This can be attributed to the lack of having benchmarks datasets in the wireless communication research community as compared to other research fields. Hence, there is a need to propose potentially-benchmark datasets that can be a future choice for researchers in the wireless communication domain, motivating the first contribution in this thesis. Most of the up-to-date solutions of signal parameters determination techniques focus on determining only one single parameter for example modulation type and assuming the other parameters e.g. signal-to-noise ratio (SNR) are known rather than on determining multiple signal parameters jointly. Hence, the desire to enable an autonomous capability of simultaneous determination of multiple signal parameters has motivated the second and third contributions that tackle the non-coherent and coherent receivers, respectively. Therefore, the objectives in this thesis are as follows, firstly, to construct three datasets for the aforesaid receivers to be utilized for joint determination of modulation types and signal-to-noise ratios, namely asynchronous amplitudes histograms (AAHs)-based Dataset, two-dimensional asynchronous sampling in-phase-quadrature histograms (2D-ASIQHs)-based Dataset 1 and 2D-ASIQHs-based Dataset 2. Secondly, to develop a scheme that can simultaneously determine the modulation type and signal-to-noise ratio in non-coherent receivers by using one features' type (AAHs-based features) under a multipath fading scenario. Lastly, to develop a scheme that can simultaneously determine the modulation type and signal-to-noise ratio in coherent receivers by employing 2D-ASIQHs features under Rician and Rayleigh fading. For datasets formation, the three datasets are developed under multipath

fading channels and used to validate the proposed determination schemes in the second and third contributions. The simultaneous determination AAHs-based scheme enables a generic intelligent receiver to recognize various modulations that belong to different categories and reveals that the recognition capability can be extendable further to other more signal types. The scheme can also simultaneously estimate the SNR values accurately. The simultaneous determination 2D-ASIQHs-based scheme tackles the coherent receivers to jointly determine nine modulation types and a wide range of SNRs. The most significant features are extracted using principal component analysis (PCA) and then fed to a support vector machine (SVM) tool for the automatic learning process. In the simulation results, the samples of the datasets reflect 1D-envelope histograms and in-phase-quadrature-based images which comprise various modulation types and SNRs with different combinations of path gains and delays. In term of modulation recognition accuracy and mean SNR estimation error, the proposed AAHs-based scheme attains 99.83% and 0.79 dB, respectively. Similarly, the proposed 2D-ASIQHs-based scheme achieves 99.06% and 1.10 dB, respectively. The obtained results showed that the proposed schemes outperform the existing state-of-the-art work.

# CHAPTER ONE

## INTRODUCTION

### 1.1 Motivation

Advanced technologies of wireless communications systems have been lately emerged. Recently, a tremendous demand for more secure, reliable, efficient, high-quality and cost-effective wireless and mobile applications and services has been witnessed. Future wireless applications and services are envisaged to lead to continuous growth of demand for high data rates, quality of service (QoS) and mobility. Tackling the aforementioned demands is always a critical concern and a challenging mission for the designers of any modern wireless network in both societies of academia and industry. Due to such a scenario in the wireless telecommunication industries, researchers and communication designers have to develop advanced wireless communication systems that can meet the needs of the aforementioned societies. For instance, many wireless companies are developing fifth-generation wireless communications system (5G) as the next generation of the wireless system to be implemented in the world. The 5G cellular networks target to attain improvement in the capacity of the communication network by 1000 times (Liu et al., 2016, Zhang et al., 2016). Moreover, they aim to increase the entire throughput of the cellular cell 25 times of that of the current's fourth-generation (4G) networks and 10 times the data rates, energy and spectral efficiencies (Bogucka et al., 2015). However, with the rapid growth of telecommunication systems, it seems that there are many challenges which still cannot be addressed by the current 4G cellular system and even would be

challenging in the upcoming 5G enabling technologies (Wang et al., 2014) such as enhancing the QoS of the wireless schemes, securing wireless communication, reducing implementation complexity, and providing accurate channel state estimation. Automatic determination techniques of signals' parameters, such as modulation type, signal-to-noise ratio (SNR), bit-rate, transmitted signal power, etc., can be a suitable and potential platform that provides solutions to the abovementioned challenges in the modern wireless networks. This is because these automatic determination schemes, such as automatic modulation recognition (AMR) techniques and SNR estimation methods, can offer more reliability, larger bandwidth space, and higher security to these modern wireless networks. This is by exempting the transmitters involved in these networks from: 1) preserving a space in the bandwidth for sending modulation and SNR knowledge, 2) broadcasting such crucial secretive information over wireless mediums which are vulnerable to penetration at any time. Instead, the automatic determination schemes enable the receivers to carry the responsibility to automatically determine these parameters successfully.

Recently, many techniques in wireless communication systems for the AMR and also for the SNR estimation have been presented in the literature (Azim et al., 2012, Dobre, 2015, Eldemerdash et al., 2016b, Li et al., 2016, Ming Zhang, 2017, Shah et al., 2019, Zhang et al., 2019, Zhu et al., 2015). Modulation type knowledge is crucial information that enables the receiver in the wireless networks to correctly recover the received signal. It is important that this knowledge is not hacked or detected by third parties during the transmission over wireless links which have a broadcasting process in nature. Thus, AMR capability can exempt the transmitters from sending this information and hence, provide a high level of security to the upcoming wireless communications

systems (i.e. 5G). Moreover, AMR can enable the receiver in these modern systems to be ready and more aware of the unexpected changes that may occur on the transmitted signal such as varying its modulation types, bit rates or SNRs. In addition, AMR techniques can enable the modern-generation wireless communication systems (i.e. 5G and beyond) to possess a sole generic and intelligent receiver that is able to automatically establish the knowledge of various modulations types without receiving any prior knowledge from the transmitter. It is rather than possessing a specific receiver for each modulation type as the case in our current wireless networks (i.e. 4G).

Furthermore, accurate information of the channel state (i.e. SNR) has a significant impact on the wireless communication system as it is vital knowledge to the receivers in these systems to notably improve their performance (Li et al., 2016, Riba et al., 2010). In addition, SNR estimation enables the receivers to know the quality of the transmission channels and optimally decode the received message. Many other functions like link adaption (i.e., adaptive modulation and coding) and diversity reception relating their procedures to the estimated SNR information (Riba et al., 2010). Most of the current SNR estimation techniques rely on pilot sequences information (Socheleau et al., 2008) which this information in turn has to be adjusted every time the end-to-end terminals sensing new variations in the medium quality ( i.e., SNR values). Also, these pilot signals are power and bandwidth consuming. As mentioned earlier, the receivers in the future wireless systems (i.e. 5G) are required to track these variations that may occur in the network. Thus, the automatic SNR estimation capability will enable the receivers in the modern generation wireless networks to blindly estimate the instantaneous SNR value without any prior knowledge (i.e., pilot sequence) required.

Therefore, the work of this thesis will be the development of schemes that are capable of having an accurate modulation type recognition and SNR estimation for modern generations of wireless communication systems.

In this thesis, three realistic datasets are promoted to be a potential standard choice for the research community. In addition, different low-complexity schemes of automatic simultaneous determination of modulation types and SNRs are proposed to overcome existing challenges and provide reliable solutions to the research community. More details will be deeply discussed in the next section of the problem statement. The remainder of this chapter is arranged as follows: Section 1.2 elaborates the problem statements. Sections 1.3 and 1.4 outline the thesis objectives and the scope of the research, respectively. Eventually, the arrangement of the thesis is presented in Section 1.5.

## **1.2 Problem Statement**

Many signal's parameters determination techniques are proposed in the literature. In order to signify their contrasts, a fair comparison among them has to be made in order to decide which signal parameters identification scheme has the best performance whether for classification problem (for modulation type) or regression (for SNR). However, the performance comparison in term of many criteria such as modulation recognition accuracy or computational complexity among the existing methods in literature is not straightforward (Dobre et al., 2007, Hazza et al., 2013). This is due to the following reasons that control the performance of automatic determination techniques of the signal's parameters. First, each technique has its own assumptions and settings. For instance, the modulation types' pool is not identical as different techniques

consider different modulations' pool. Additionally, their simulations conducted over different ranges of SNRs, some algorithms assess the performance at a single/specific value of SNR and some other algorithms evaluate their performance over a few values or short range of SNRs. Second, each classifier in the existing methods is designed to treat specific unknown factors such as data rates, carrier frequencies, phase offsets, channel parameters, etc. In other words, these parameters are not identical among the existing algorithms and sometimes they are ambiguous or not clearly defined. Third and most importantly, the aforementioned two reasons exist because there is a lack of having standard or benchmark datasets for the researchers in wireless communication research community unlike the scenario followed in computer and image processing domains, where the existence of benchmark datasets in their fields allows for direct implementation and comparison of their proposed methods. The previous challenges will result in unfair performance contrast among the classifiers in the existing work and will lead to incorrect inferences on evaluating such identification techniques. Consequently, it is timely to propose solutions to the aforementioned challenges and address the emerging needs of the research community by the attempt to propose new datasets that would be useful to the wireless communication research community.

The transmitters in the next-generations of wireless networks (i.e. cognitive radio systems, 5G networks and beyond) are envisaged to vary and adjust some of the signal parameters based on the existing status of the transmitting medium (Dobre, 2015, Eldemerdash et al., 2017). For instance, if the channel condition between the transmitter and the receiver is good (i.e. low fading effects), then the transmitter will exploit this situation and select some advance modulation schemes which allow for transmitting more bits in each symbol (i.e. high data-rates) whereas, if the scenario

was adverse and the channel condition is worse due to severe fading impairments, then the transmitter needs to adapt itself to the new interim scenario and choose a lower modulation type that transmits less data in order to avoid more errors occurring on the transmitting symbols due to the new harsh environment. This, in turn, will demand the receivers in these systems to adapt to these fluctuations and to be successfully equipped with the autonomous determination schemes of various signal parameters like the modulation types and SNRs in our case.

The majority of the existing schemes in the literature focuses on identifying one signal parameter but either ignoring the other crucial parameters or assuming that they are known for e.g. modulation type (Ali et al., 2017, Shah et al., 2019, Sherme, 2012, Tayakout et al., 2018, Zhang et al., 2019) or signal-to-noise ratio (SNR) (Hao et al., 2013, Krishnamurthy et al., 2016, Li et al., 2016, Pauluzzi et al., 2000, Socheleau et al., 2008), rather than on determining both parameters simultaneously using one technique. For instance, the features type exploited in Ali et al. (2017) which was the fourth-order cumulants enabled the receiver to recognize only PSK and QAM-based signals and was unable to estimate the SNR value, where they assumed the SNR value is known. The acquisition of SNR knowledge is very precious in many advanced communication technologies such as cognitive systems where cognitive terminals require to sense the medium quality from the surrounding systems environment in order to judge which channel is the most suitable to connect with. Similarly, the work in (Shah et al., 2019, Tayakout et al., 2018) used a combination of many types of features in order to enable the receiver in their systems to recognize PSK and QAM-based signals. Their work assumed that the SNR parameter is known to the receiver. Furthermore, in Li et al. (2016), they exploited frozen bits of polar codes-based features. These features were

able to provide the receiver only SNR information. They assumed that modulation type is known at the receiver which is essential knowledge for data recovery. The gap in the up-to-date methods for the incapability of performing parallel recognition of multiple signal parameters at the same time using one sole algorithm, remains deep and still requires lots of investigations and developments. To fill this gap, the aspiration on the potential capability of simultaneous determination of multiple signal parameters has inspired and reinforced the enthusiasm for the proposed schemes and motivated the second and third contributions of this thesis. As it will be seen in the literature, vast existing research methods focus on identifying one of the above-mentioned parameters and neglect or assume the other one is known to the receiver (Ali et al., 2017, Li et al., 2016, Shah et al., 2019, Sherme, 2012, Tayakout et al., 2018, Zhang et al., 2019). However, a very few techniques of parallel determination schemes of signals' parameters are also reported in the literature (Khan et al., 2015) but they still suffer from considerable computational complexity and limitations. For instance, they had to change the structure of the receiver by using extra samplers in order to obtain enough samples from the detected signals. Additionally, the channel effect on these signals was limited to AWGN only which is impractical in real-world scenarios.

Receivers in wireless communication systems can be categorized based on the detection process into non-coherent and coherent receivers as in Proakis et al. (2012) (refer to Appendix B). Both types of receivers are widely exploited in wireless communication systems depending on the considered applications (Sklar, 2001, Yong Soo Cho, 2010). Majority of the current AMR techniques built their algorithms based on the assumption that the received signals are already in the baseband form (Aslam et al., 2012, Shah et al., 2019, Sherme, 2012, Tayakout et al., 2018, Zhang et al., 2019),

and ignored to analyze the detection environment itself (which precedes the acquisition of a baseband signal). This makes a designer of wireless network incapable to decide whether such techniques are applicable to coherent or non-coherent based-receiver. It remains vague in the literature although both detection-based receivers are used in the real-world (Sklar, 2001, Yong Soo Cho, 2010). Therefore, the problem of signal parameters determination in this research will be tackled for both types of receivers through the second and third contributions in the presented thesis.

The size of modulation types' pool is a very important factor to consider in AMR techniques. It gives a clue on how capable a receiver employed in a wireless network to identify different types of detected signals. The existing work in AMR field designed to handle only a few types of signals i.e., small variety of modulation types, such as in (Aslam et al., 2012, Shah et al., 2019, Sherme, 2012, Tayakout et al., 2018, Yan et al., 2019). For example, the work in (Ali et al., 2017) was able to recognize only PSK and QAM-based signals. Similarly, the work presented in (Shah et al., 2019, Tayakout et al., 2018) used a combination of many types of features to recognize PSK and QAM-based signals. This in turn, will constrain the receivers employed in next-generations wireless systems to track the adaptive variations of selecting a suitable modulation which occur at the transmitter, and limit their abilities to recognize various types of modulations.

Moreover, signal-to-noise ratio (SNR) is also a crucial factor to be considered in signal parameters identification techniques and their simulations. Its values indicate the strength of the transmitted signals and the level of noise imposed on these signals. Furthermore, accurate information of SNR has a profound impact on the wireless

communications networks, the acquisition of SNR information is critical to the receivers in these systems to notably improve their performance (Li et al., 2016, Riba et al., 2010). In addition, it plays a major role in analyzing the performance of AMR techniques. Plenty of the current AMR methods training their receivers and calculating their modulation recognition accuracies based on few specific values of SNRs (Kim et al., 2016, Sherme, 2012, Tayakout et al., 2018) which this, in practice, does not reflect the actual scenarios in real applications where SNR value varies based on the distortion imposed on the power of the propagated signal. A broad range of SNRs from low to high values which mimic all the potential variations of the wireless medium quality, is considered in the proposed schemes of this thesis.

Channel impairments type is a very essential factor to be considered in AMR techniques as it directly affects the accuracies of modulation recognition and SNR estimation. Plenty of existing automatic modulation recognition techniques and also SNR estimation methods consider only AWGN (which is an ideal channel) in their proposed algorithms (Aslam et al., 2012, Khan et al., 2015, Li et al., 2016, Sherme, 2012, Yan et al., 2019, Zhang et al., 2019) and ignore the real-world channel impairments (i.e., multipath fading channels) which certainly exist and experienced in real-world applications. Multipath fading channels impact which causes a severe deterioration on the performance of the signal's parameters determination schemes, has not yet been completely and thoroughly solved up to the present. The following Figure 1.1 illustrates the link between the statement of the existing problems and their corresponding solutions proposed in the presented thesis.

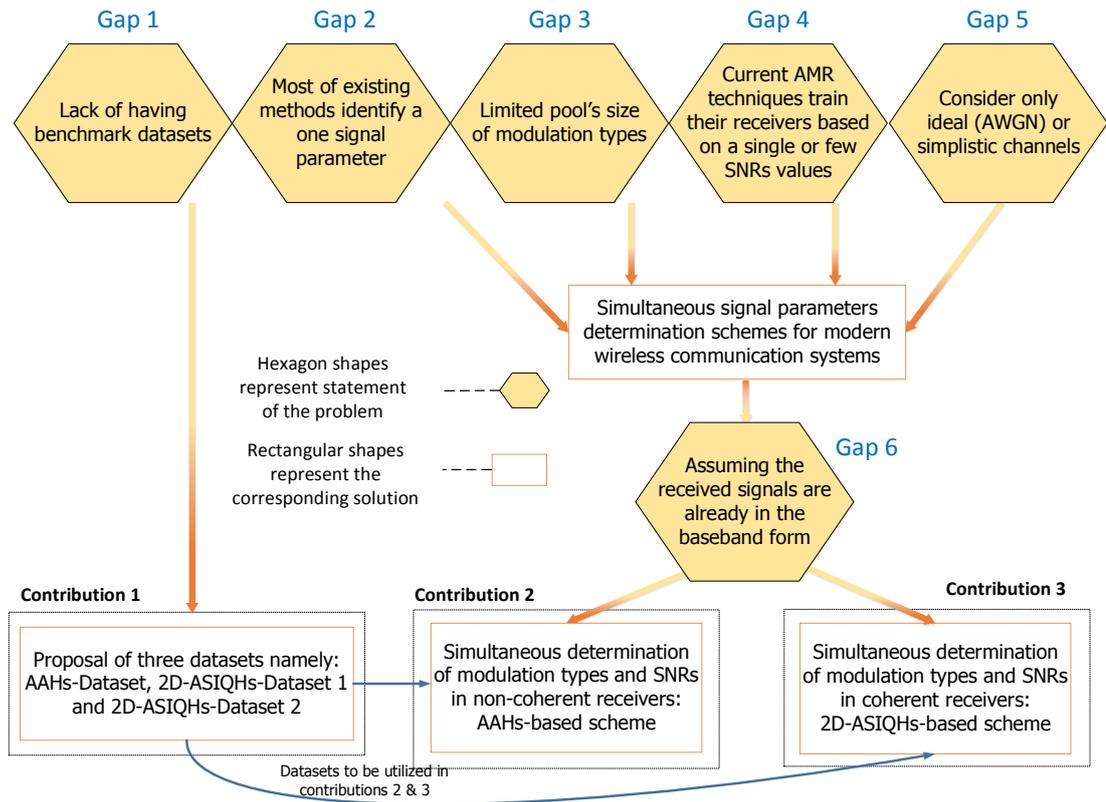


Figure 1.1: A block diagram describes the link between the existing problems and pertaining solutions proposed in this thesis.

where in Figure 1.1, the term *AAHs* stands for asynchronous sampling amplitudes histograms and *2D-ASIQHs* refers to two-dimensional asynchronous sampling in-phase-quadrature histograms.

### 1.3 Thesis Objectives

- 1- To construct three datasets for non-coherent and coherent receivers to be utilized for joint determination of modulation types and signal-to-noise ratios.
- 2- To develop a scheme that can simultaneously determine the modulation type and signal-to-noise ratio in non-coherent receivers by exploiting AAHs

features under multipath fading scenario with improved accuracies and reduced complexity.

- 3- To develop a scheme that can simultaneously determine the modulation type and signal-to-noise ratio in coherent receivers by employing 2D-ASIQHs features under multipath fading scenario with improved determination accuracies.

#### **1.4 Scope of the Work**

The scope of this thesis is confined to the development of the proposed schemes that aim to simultaneously determine the modulation types (based on commonly-utilized modulations namely, BPSK, 2-ASK, QPSK, 4-ASK, 8-PSK, 4-QAM, 16-QAM, 32-QAM, 64-QAM-based signals) and the SNRs of the received signals in wireless communication systems. MATLAB is used to conduct the simulations and analyze the results, and the hardware implementation is out of the thesis's scope. The proposed schemes in this thesis are envisaged to be attractive choices for the new generations of wireless communications systems.

The scope of the artificial intelligent (AI) and features extraction techniques to facilitate the determination process (i.e., classification and regression) are limited to the support vector machine (SVM) and principal component analysis (PCA) tools only, and thereby leaving the use of the other techniques for future research work. This thesis does not aim to enhance the AI machine tool itself, rather it exploits them as fresh paradigms to support intelligent wireless communication terminals.

## 1.5 Thesis Outlines

The thesis consists of five chapters. This chapter presents the introduction, problem statement, thesis objectives, the research scope and the thesis arrangement. In Chapter 2, the background of modern wireless communication and a thorough review of the related work of the automatic signals' parameters determination techniques is introduced. In Chapter 3, three methods namely, Datasets formation in which three datasets are generated, Simultaneous Determination of Modulation Types and SNRs in Non-coherent Receivers: AAHs-based scheme, and Simultaneous Determination of Modulation Types and SNRs in Coherent Receivers: 2D-ASIQHs-based scheme, are proposed in detail. In Chapter 4, the results of simulations of the proposed schemes are presented and compared with the state-of-the-art related recognition algorithms. Finally, in Chapter 5, the conclusions are drawn, and the summary of the contributions is presented. In addition, future open issues and research directions are highlighted.

# CHAPTER TWO

## LITERATURE REVIEW

### 2.1 Introduction

The recent decades have witnessed a rapid growth in the advent of wireless mobile systems coinciding with increasing demands in our lives. Such advancement has attracted a tremendous interest in many societies, such as in academia, civilian and military. Future wireless applications and services lead to a growing demand for high-speed data rates quality of service (QoS) and mobility. The bandwidth exploitation is always a critical concern and challenging mission for any modern wireless networks. Due to such development in telecommunication industry, researchers and telecommunication engineers have to accommodate modern wireless telecommunication networks that can satisfy the requirements of above-mentioned societies. For example, the fifth-generation (5G) wireless communication system is soon going to be implemented in the world. The enhancements in 5G will facilitate the targets of achieving energy efficiency, massive multiple-input multiple-output (MIMO), channel estimation, user location, etc., (Jiang et al., 2017). The 5G general design is depicted in Figure 2.1.

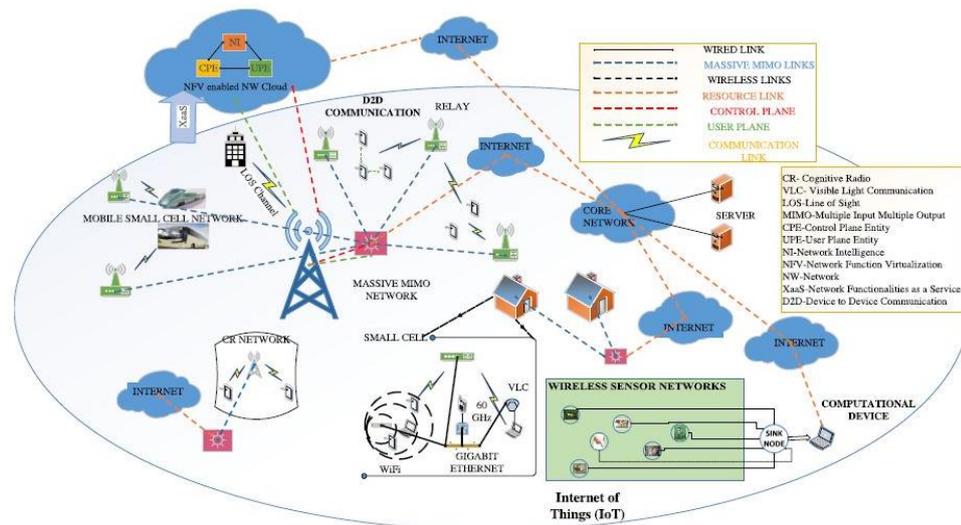


Figure 2.1: Overall potential structure of 5G cellular systems (Gupta et al., 2015).

The future next-generation cellular networks aim at accomplishing enhancement in the capacity of the telecommunication systems 1000 times (Liu et al., 2016, Zhang et al., 2016). Furthermore, they target enlarging the total throughput of the cellular system's cell 25 times of today's 4G systems and 10 times the data rates, energy and spectral efficiencies (Bogucka et al., 2015). Nevertheless, with the swift progression of telecommunication systems, there are several challenges which are still short of being tackled by the 4G networks and even by the upcoming 5G enabling technologies (Wang et al., 2014) such as improving the QoS of wireless networks, the congestion in their reserved bandwidth, implementation complexity, and accurate knowledge of the channel state.

Automatic determination techniques of signals parameters are envisaged by a suitable and potential platform that provides solutions to the abovementioned challenges. Before digging deeply on this, there are some basic concepts need to be addressed and explained earlier. Figure 2.2 depicts an overview of the entire structure of the literature review reported in this thesis.

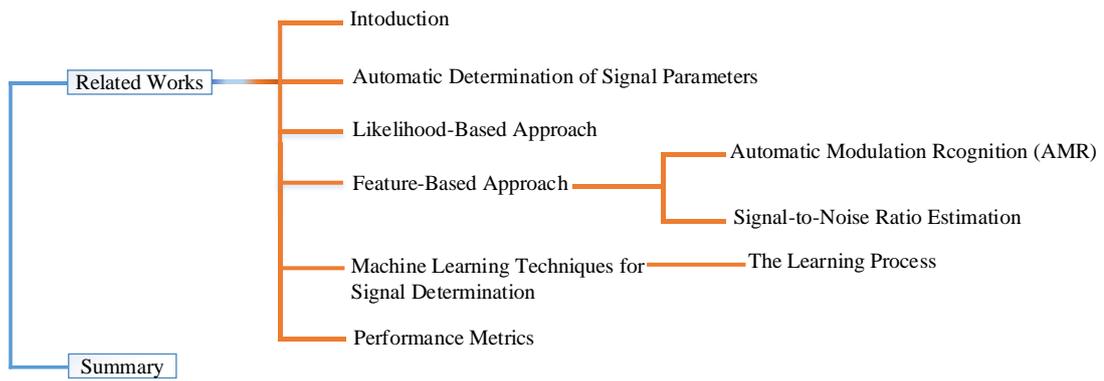


Figure 2.2: The structure of the literature review.

This chapter starts with a general broad literature on state-of-the-art work for automatic identification of digital signal parameters associated. More specifically, it shows a categorization of automatic digital modulation identification methods and channel state estimation techniques associated with their pros and cons. In addition, Section 2.2.3 reports on the existing machine learning techniques employed in the research field. In Section 2.2.4, the performance metrics of the techniques are presented. Lastly, Section 2.3 summarized the chapter.

## 2.2 Automatic Determination of Signal Parameters

The last few decades have witnessed many techniques for the estimation of signals' parameters such as modulation type, signal-to-noise ratio (SNR), bit-rate, transmitted signal power, etc., in wireless communications (Azim et al., 2012, Dobre, 2015, Eldemerdash et al., 2016b, Ming Zhang, 2017, Zhu et al., 2015). The transmitters in future wireless networks are anticipated to vary these parameters according to the given channel conditions. This, in turn, will necessitate the receivers employed in these networks to be effectively prepared of autonomous estimation of various signal parameters. Figure 2.3 illustrates an overview of a basic wireless system including the stage of signal parameters determination (SPD). More details can be found in

Appendix A.1. The term SPD onwards refers to the identification/determination of multiple signal's parameters, that is, this abbreviation includes the automatic modulation recognition (AMR) and SNR estimation.

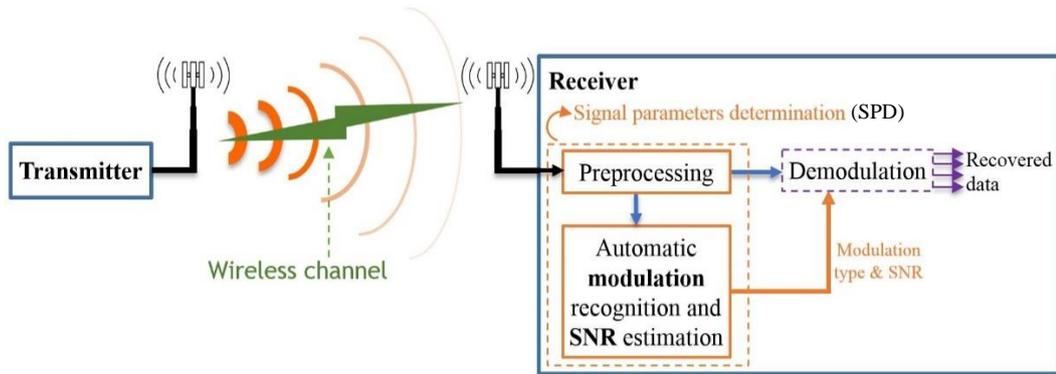


Figure 2.3: An overview of wireless communication system including SPD model

The design of a determination technique of signal's parameters usually comprises of two stages: 1) pre-processing of the received signal, 2) appropriate selection of identification tool as shown in Figure 2.3.

The following literature review aims to present the state-of-the-art existing methods. In addition, it targets to provide the reader with comprehensive knowledge about the signal's parameters identification techniques, their distinguished features extracted from the signals and utilized for the identification process, and eventually the machine learning methods deployed for the automatic identification stage of the targeted signal's parameters.

AMR has recently received a huge prominence over the past few decades. It is a crucial phase between detecting and demodulating the received signal in wireless communication system. In order to determine a signal's parameter (i.e., modulation type or SNR), two different approaches of signal's parameters identification schemes

can be generally categorized into two categories, namely, Likelihood-Based (LB) approach and Feature-Based (FB) approach (Dobre et al., 2007). Each approach has its own operating mechanism, its ability to handle certain types of data, its advantages and disadvantages. The former approach treats AMR as a hypothesis testing problem and provides an optimal solution to AMR in Bayesian sense. Furthermore, LB method targets to reduce the probability of misclassification (Xu et al., 2011) as it computes the probability of the detected signals. It is worth to mention that, yet LB provides optimal identification performance, but typically this computations process is complex and exhaustive when lots of considered parameters are unknown (Tayakout et al., 2018, Wong et al., 2008). Moreover, it necessitates a prior knowledge of many parameters of the signal in order to start the identification process of modulation (Chavali et al., 2013, Hameed et al., 2009, Wen et al., 2000). The latter approach (i.e., FB) excerpts useful statistical features of detected signals. Although it offers a sub-optimal solution to the AMR but it enjoys a very good robustness against channel impairments and also low computational complexity. Hence the FB approach is adopted in this thesis. Figure 2.4 shows the pros and cons of LB and FB approaches.

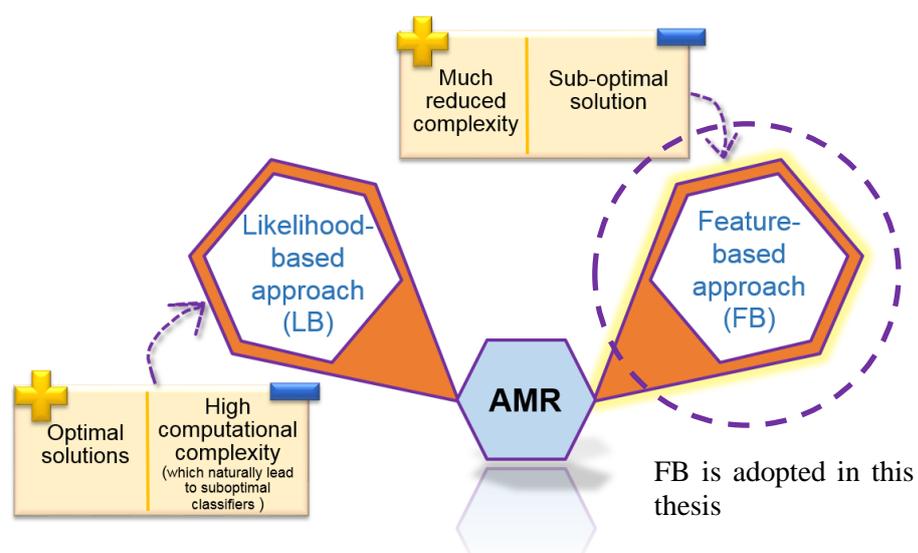


Figure 2.4: The pros and cons of LB and FB approaches

On the other hand, there are few existing techniques adopted in the literature which propose a fusion model of both FB and LB schemes together for modulation formats classification (Huang et al., 2017, Yu et al., 2017). Our major focus in this thesis will be given to FB techniques in Section 2.2.2. However, a short overview of LB methods is provided briefly in Section 2.2.1 as follows:

### 2.2.1 Likelihood-Based (LB) Approach

A broad survey in Xu et al. (2011) reports on likelihood techniques for automatic modulation classification. Likelihood-based approach (LB) works efficiently with the machine learning classifiers when it is provided with knowledge of channel parameters and complete channel model (Hameed et al., 2009, Ramezani-Kebrya et al., 2013, Wallayt et al., 2014). In LB framework, there are usually two pivotal stages for the modulation identification. Firstly, critical assessment of the likelihood for every modulation hypothesis with detected signal. Next, from other diverse modulation hypotheses, the likelihood is derived and compared in order to finalize the classification decision. Furthermore, decision-making step is empowered either through the calculation of ratio test between two hypotheses or finding the maximum likelihood (ML) among all potential candidates. The former requires a threshold which in turn will necessitate other processing algorithms to optimize the threshold while the latter is much less complex to implement and does not involve a careful selection of thresholds. The process of computing the probabilities of detected signal samples can be referred by the term called likelihood assessment. Considered that a pool of modulation candidates  $\mathfrak{M}$  and a targeted modulation  $\mathcal{M} \in \mathfrak{M}$  under a hypothesis  $\mathcal{H}$ , the likelihood function can be explicitly expressed as follows (Xu et al., 2011, Zhu et al., 2015):

$$\mathcal{L}(r[\mathbf{d}]|\mathcal{H}, \sigma) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{|r[\mathbf{d}] - A_m|^2}{2\sigma^2}\right) \quad (2.1)$$

Without realizing the waveform sample  $r[\mathbf{d}]$  returns to which modulation symbol, the likelihood value is computed by taking the mean of the likelihood value between the detected waveform sample  $r[\mathbf{d}]$  modulated  $\mathcal{M}$  and every modulation symbol  $A_m$ , where  $\sigma$  is the standard deviation and  $\sigma^2$  is the variance.

In maximum likelihood-based machine learning model, with typical channel information, all parameters are mostly have to be known to the receiver such as knowledge of SNR and channel coefficients, except the modulation type. Hence, the identification task (i.e., decision making  $\widehat{\mathcal{M}}$ ) of a modulation type that belongs to a limited pool of candidates, can be expressed as a maximum likelihood prediction by obtaining the hypothesis  $\mathcal{H}_{\mathcal{M}}$  that has a highest likelihood value among all likelihood values  $\mathcal{L}(\cdot)$  as shown in (2.2) (Zhu et al., 2015).

$$\widehat{\mathcal{M}} = \arg \max (\mathcal{L}(r[\mathbf{d}]|\mathcal{H}_{\mathcal{M}})) \quad (2.2)$$

The policy of recognizing modulation types in LB methods is to maximize the likelihoods among several hypotheses of predefined potential modulation types. Three types of LB algorithms are reported in the literature, namely, average likelihood ratio test (ALRT) (Abdi et al., 2004, Chung-Yu et al., 1995, Hong et al., 2000, Wen et al., 2000, Zheng et al., 2018), generalized likelihood ratio test (GLRT) (Panagiotou et al., 2000, Xu et al., 2011) and hybrid likelihood ratio test (HLRT) (Derakhtian et al., 2011, Dulek, 2017, Hameed et al., 2009, Xu et al., 2011, Zheng et al., 2018).

ALRT classifier finds a use in Zheng et al. (2018) to recognize orthogonal frequency division multiplexing (OFDM) signals. As ALRT classifier calculates the likelihood values of the detected signals, its exponential complexity correlated with signal length was reported in Huang et al. (2017). Furthermore, huge arithmetical operations are encompassed under the ALRT process, and hence it is not applicable in SDR systems Su et al. (2008). To report some solutions to this burden, GLRT-based and HLRT estimators were reviewed in (Dobre et al., 2007, Xu et al., 2011). They are widely exploited in modulation recognition for maximum likelihood approach. Despite this fact, GLRT classifier is still impractical for advanced modulations schemes. The authors in Zhu et al. (2014) proposed an enhancement scheme to overcome the drawbacks of GLRT by adopting non-parametric likelihood function. Their LB classifier aimed to classify between PSK and QAM-based signals. The resulted recognition accuracy at 10 dB of SNR for 64-QAM signal was only 71.6% despite the use of ideal channel (i.e., AWGN). However, there are several drawbacks of likelihood-based approach (i.e., maximum-likelihood), one of the problems found in LB classifiers that they generally experience unbearable computational complexity and necessitate prior information about SNR (Wong et al., 2008). Furthermore, their modulation recognition accuracies are sensitive to the noisy signals and demand a perfect synchronization (Zhang et al., 2019). Additionally, they undergo very high computational complexity and requires high power (Dobre et al., 2007, Tayakout et al., 2018). In contrast to LB approach, FB algorithms provide a near-optimal solution but very less computational complexity.

The following section will present the existing work that identifying the modulation types using feature-based approach in Section 2.2.2(a). In addition, the

techniques that estimate SNRs based on the same approach are presented in Section 2.2.2(b).

## **2.2.2 Feature-Based (FB) Approach**

### **2.2.2(a) Automatic Modulation Recognition (AMR)**

The transmitters in the next-generations of wireless systems (i.e., cognitive radios (CR), 5G networks and beyond) are envisaged to vary and adjust the signal parameters such as modulation types or signal and/or noise ratio (SNR) based on the present status of the transmitting link (Dobre, 2015, Eldemerdash et al., 2017). Thus it is crucial for receivers in the next generation wireless communication systems to be adaptive to these changes and able to automatically detect the knowledge of modulation type and SNR. Such vital knowledge can empower many tasks at the receivers, for instance, assisting the demodulators and predicting possible variations at the transmitters' side such as adaptive schemes of modulations, dynamic power allocation, etc. Furthermore, it is not essential to recover the data rather than only its modulation type in some practical implementations. For instance, in electronic warfare, an attack can be blocked and reversely responded by generating jamming signals with identical modulation type if the receiver correctly recognizes the transmitter's modulation type.

Automatic modulation recognition (AMR) is widely investigated through feature-based approach. In FB algorithms, the identification is made based on the extraction of single or multiple statistical features from the received signal. There are various types of features exploited in the AMR techniques. The features that have been widely used in the existing methods are listed as follows: 1) high order cumulants (Ali et al., 2017, Eldemerdash et al., 2016a), 2) higher order moments (Lopatka et al., 2000,

Tayakout et al., 2018), 3) spectral features (Qian et al., 2010, Shah et al., 2019, Sherme, 2012, Zhu et al., 2015), 4) cyclostationary (Fehske et al., 2005, Kim et al., 2007, Ramkumar, 2009, Sutton et al., 2008), and 5) wavelet transform-based features (Avci et al., 2008, Avci et al., 2007, Hassan et al., 2010, Türk et al., 2011).

For instance, high order cumulants (HOCs) features in combination with false-alarm rate test are considered in (Eldemerdash et al., 2016a) to discern space-time block code (STBC) for SC-FDMA signals. In their work, the fourth order statistic (which is one form of HOCs) of the detected signals was exploited while the false-alarm rate decision criterion was needed to recognize the peaks of these statistics. PSK and QAM-based modulations were considered in their algorithm. The results in their work showed degradation in the identification performance for QAM signals compared with PSK signal types. This was attributed to the convergence in the peaks' values of the statistics features for QAM signals.

HOCs features are also adopted in (Abdelbar et al., 2018, Swami et al., 2000) in order to identify the modulation types. In Abdelbar et al., 2018 work, they utilized a fusion center (FC) unit to assemble the votes from all distributed terminals. Their QAM, PSK and ASK signals were impaired by simplistic fading channel i.e., flat fading, and the achieved classification accuracy was not very encouraging at low SNR range, less than 90% over the range of 0–5.5 dB. The classification accuracy approaches 95% at higher range of SNR values i.e. after SNR= 6 dB onwards. One drawback of their work is that the terminals or nodes are involved in the decision voting independently in different times through repeated exchange of their votes on what modulation to decide. This will result in huge processing time and power

necessities and impose higher overhead on the cellular communication system. In addition, their FC unit utilized a maximum likelihood classifier which will add more computational complexity to the classification process as it needs to calculate the likelihood function for each received vote and extract the maximum value i.e. final decision. Moreover, the adopted HOCs in the work (Abdelbar et al., 2018) assumed that SNR estimation is to be perfect/known as their adopted features were unable to estimate this parameter.

The utilization of averaged instantaneous amplitude values in conjunction with the maximum value of spectral power density was reviewed in (Azzouz et al., 1997) for the recognition of analog and digital modulation types. The authors observed that the overall recognition accuracy of all considered signals was 93% at SNR = 15dB. However, the presented algorithm in (Swami et al., 2000), which exploits high-order cumulants to discriminate modulation signals, outperforms the method in (Azzouz et al., 1997) due to its robustness to the noise. Despite its robustness, it also offers poor recognition performance when the detected signal belongs to high-order modulation category, for instance, 16-QAM and above.

In (Wu et al., 2008), the authors proposed a cumulant-based technique to identify only PSK and QAM-based signals, and their results showed that for SNR= 10 dB, the classification accuracies above 90% restricted to modulation order up to 4 (i.e. QPSK) while 80% for 64QAM, this is after the necessity of having perfect channel information.

Obtaining HOCs features is not an easy process as their extraction yield unbearable computational complexity (Yan et al., 2019). Another drawback of HOCs is that they require a huge number of samples (Tsakmalis et al., 2014). Besides, poor performances and high computational complexity were shown in the results of the work (Abdelbar et al., 2018, Swami et al., 2000) for higher order QAM modulation when adopting these features. Furthermore, cumulants features are not optimal choice in non-ideal channels such as fading. This brings motivations to the researchers in wireless communication field to exploit and implement artificial intelligent techniques aiming to reap great enhancements on the recognition accuracies of AMR techniques (Aslam et al., 2012, Du et al., 2018, Hassan et al., 2012, West et al., 2017).

Identification of PSK and QAM signals continues to be investigated in (Tayakout et al., 2018, Yang et al., 2007). The scheme presented in (Tayakout et al., 2018) identified basically PSK and QAM-based signals. The authors used a combination of many types of features in order to enable the receiver in their systems to recognize PSK and QAM-based signals. These features were the fourth and sixth higher order moments and higher order cumulates. Then their considered features were utilized to train the support vector machine (SVM) for the automatic recognition of the received signals. Their proposed scheme achieved quite a good recognition modulation accuracy, it reaches 98.25% at best condition i.e. assuming a perfect channel state knowledge. In addition, the communication channel between the transmitter and the receiver in their system was impaired by simplistic fading channel i.e. flat fading impairment. The proposed scheme in their work however suffered from some drawbacks. In their method, they required two-time slots to perform successful AMR. Additionally, simulations conducted over single value of SNR between source and