

Automatic Modulation Classification through clustering in the I/Q plane

JP Mouton



orcid.org / 0000-0002-0148-3927

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Supervisor: Dr M Ferreira
Co-supervisor: Prof ASJ Helberg

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Abstract

Automatic Modulation Classification (AMC) refers to a process where the modulation scheme of a signal of interest is determined. It is not a requirement of an AMC system to recover the original data contained in the signal. AMC has several applications for both military and civilian use. The military may use AMC to determine the modulation scheme of a signal in order to demodulate or more efficiently jam the signal. AMC can also be used for threat identification as the modulation scheme of a signal can reveal additional information about the hardware being used. In civilian use, AMC can be used to create cognitive radios capable of sensing the electromagnetic spectrum in order to use the optimal modulation scheme in a co-operative environment. Regulatory agencies that are required to enforce band allocations can use AMC to ensure/determine compliance with regulations.

Most AMC methods typically use either Maximum Likelihood approaches with hypothesis testing or Feature-based approaches in conjunction with a decision tree or some form of machine learning. These techniques require training or threshold calibration that will need to be re-set if the operating environment changes significantly. Several of these techniques also have large computational complexity and long execution times. Most AMC methods are only evaluated in an Additive White Gaussian Noise (AWGN) channel and are not described to the extent that it can be replicated. Several methods may not function at all in a multipath environment.

In 2000 B.G. Mobasser [1] investigated using the location of symbol levels in the In-phase and Quadrature (I/Q) plane as a robust feature for AMC. This feature is, however, rarely used. We use this feature to develop an AMC method that does not require retraining a machine learning algorithm or extensive reconfiguration for different channel conditions.

A literature study was first conducted to find publications that utilise the location of I/Q samples as a feature. A simple multi-stage AMC method was then developed. The *Classification Accuracy*, execution time and scalability of k-means, k-medoids, fuzzy

c-means, Density-Based Spatial Clustering of Applications with Noise (DBSCAN), Ordering Points To Identify the Clustering Structure (OPTICS) and hierarchical clustering was evaluated for each stage in an AWGN channel. The best performing clustering algorithm (k-means) was then used to develop a new AMC method. The proposed method was then evaluated in an AWGN channel and compared to popular Feature-based and Likelihood-based techniques.

The proposed method was improved by extracting a parameter that we define as the *Classification Quality*. We use this parameter to detect and reject incorrect classifications. The proposed method was then re-evaluated in an AWGN channel while rejecting classifications with a low *Classification Quality* in order to prevent any incorrect classifications. The proposed method was then evaluated in a simulated multipath channel with the European Telecommunications Standards Institute (ETSI) Tap Delay Line (TDL) models.

The proposed method does not rely on machine learning, is deterministic in the number of operations and has low algorithmic complexity, resulting in low execution times while maintaining a large pool of possible modulation schemes. The proposed method addresses several of the drawbacks of the more popular methods in the literature, among others that minimal reconfiguration will be required with a significant change in the operating environment. The low execution time, linear scalability and the deterministic nature of the proposed method is also highly advantageous.

Keywords: *Automatic Modulation Classification, I/Q Plane, Constellation Diagram, Clustering Algorithms, K-means, Centroid Estimation, Multipath*

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List of Acronyms

AM Amplitude Modulation

ALRT Average Likelihood Ratio Test

AMC Automatic Modulation Classification

ANN Artificial Neural Network

ASK Amplitude Shift Keying

AWGN Additive White Gaussian Noise

CNN Convolutional Neural Network

COST European Cooperation in Science and Technology

CWT Continuous Wavelet Transform

DBSCAN Density-Based Spatial Clustering of Applications with Noise

DSL Digital Subscriber Line

ETSI European Telecommunications Standards Institute

EPA Extended Pedestrian A

EVA Extended Vehicular A

ETU Extended Typical Urban

FCM Fuzzy c-means

FIR Finite Impulse Response

FM Frequency Modulation

FSK Frequency Shift Keying

GLRT Generalised Likelihood Ratio Test

HLRT Hybrid Likelihood Ratio Test

I/Q In-phase and Quadrature

ITU International Telecommunication Union

KNN K-Nearest Neighbors

KS Kolmogorov Smirnov

ML Maximum Likelihood

NPLF Non-Parametric Likelihood Function

OFDM Orthogonal Frequency-Division Multiplexing

OPTICS Ordering Points To Identify the Clustering Structure

PAM Pulse Amplitude Modulation

PSK Phase Shift Keying

QAM Quadrature Amplitude Modulation

SNR Signal-to-Noise Ratio

SoS Sum of Sinusoids

SVM Support-Vector Machine

SUI Stanford University Interim

TDL Tap Delay Line

TTSAS Two Threshold Sequential Algorithmic Scheme

Chapter 1

Introduction

In this chapter, we discuss the shortcomings of popular Automatic Modulation Classification (AMC) methods and provide the research objectives of the study. A brief overview of the proposed method is then provided.

1.1 What is AMC?

Automatic Modulation Classification (AMC) refers to a process wherein the modulation scheme of an unknown signal is identified. It should be mentioned that at no point is it a requirement of an AMC system to demodulate the signal or recover the original data.

AMC can be used in a wide range of applications for both military and civilian use. The military may use AMC for threat identification, as the type of transmission can reveal information regarding the source of the signal. A signal of interest can also be more efficiently interfered with or even demodulated if the modulation scheme is known. AMC can further be used for cognitive radios or spectrum use enforcement

in civilian applications. A cognitive radio refers to a device that has the ability to sense the electromagnetic spectrum. The optimal modulation scheme can then be used based on the modulation type of nearby transmissions. Typically it would be required to communicate to all receiving devices which modulation scheme is being used if the transmitter switches to a new modulation scheme. AMC can be used to change modulation schemes without this handshake enabled transition.

The electromagnetic spectrum will need to be used more efficiently as more wireless devices are in use than ever before. Frequency bands in the electromagnetic spectrum are licensed out to entities that wish to transmit in a specific frequency range. The bandwidth used by a transmitter is highly dependent on the modulation scheme that is being used. AMC can be used to ensure that transmissions remain within their allocated frequency range. AMC methods can be split into two categories based on how the unknown signal is investigated, namely, Feature-based classification and Likelihood-based classification techniques.

Feature-based approaches use parameters extracted from the signal referred to as features. These features are then compared to those of known modulation schemes using a classification algorithm. The vast majority of classification algorithms in literature use some form of machine learning or a decision tree. The main drawback of this approach is that the machine learning algorithm needs to be trained to classify signals and thresholds need to be set for a decision tree. This training may be time consuming, depending on the machine learning algorithm, and require re-training if the operating environment changes significantly.

Likelihood-based approaches perform statistical hypothesis tests with known signal models. These models require accurate channel parametrisation. A Maximum Likelihood approach has been mathematically proven to be the most accurate method for AMC, assuming perfect channel parametrisation. The performance will degrade if accurate channel models are not available [3]. The sensitivity to changing channel conditions for both Feature-based classification and Likelihood-based classification approaches require the frequent retraining or re-calibration of both implementations.

We will develop an AMC method based on how a human may seek to identify digital modulation schemes. These modulated signals will not be recognisable to a person in the time domain. Instead, a person would rather aim to see a processed version of the signal in the In-phase and Quadrature (I/Q) plane. It should also be noted that this process of I/Q symbol recovery will be required if the originally transmitted data needs to be recovered. Figure 1.1(a) and 1.1(b) shows an 8-Phase Shift Keying (PSK) and 16-Quadrature Amplitude Modulation (QAM) signal in the I/Q plane with 15 dB Signal-to-Noise Ratio (SNR) in an Additive White Gaussian Noise (AWGN) channel. The geometry of constellations in the I/Q plane is rarely taken advantage of directly in popular AMC methods. Statistical features are typically extracted from the I/Q plane and not used directly. In our approach, we will use the locations of symbol levels to utilise the I/Q plane in a more direct way than extracting statistical features for use in a classification algorithm, as in other approaches in AMC literature.

1.2 Research Objectives

The study aims to develop a new AMC method to address the drawbacks found in well-known methods by using the location of estimated symbol levels as a feature. The proposed method should not rely on machine learning or widely varying thresholds to overcome the problems regarding most feature-based AMC methods. I/Q symbol recovery is outside the scope of this dissertation as it is seen as a separate research topic with broad applications and is typically not addressed in AMC literature.

1.2.1 Concept Outline

Figure 1.1(a) and 1.1(b) shows 8-PSK and 16-QAM with 15 dB SNR AWGN. A human mind can intuitively identify these two signals as 16-QAM and 8-PSK. The thought process of a person will be analysed in order to develop a method to classify unknown signals.

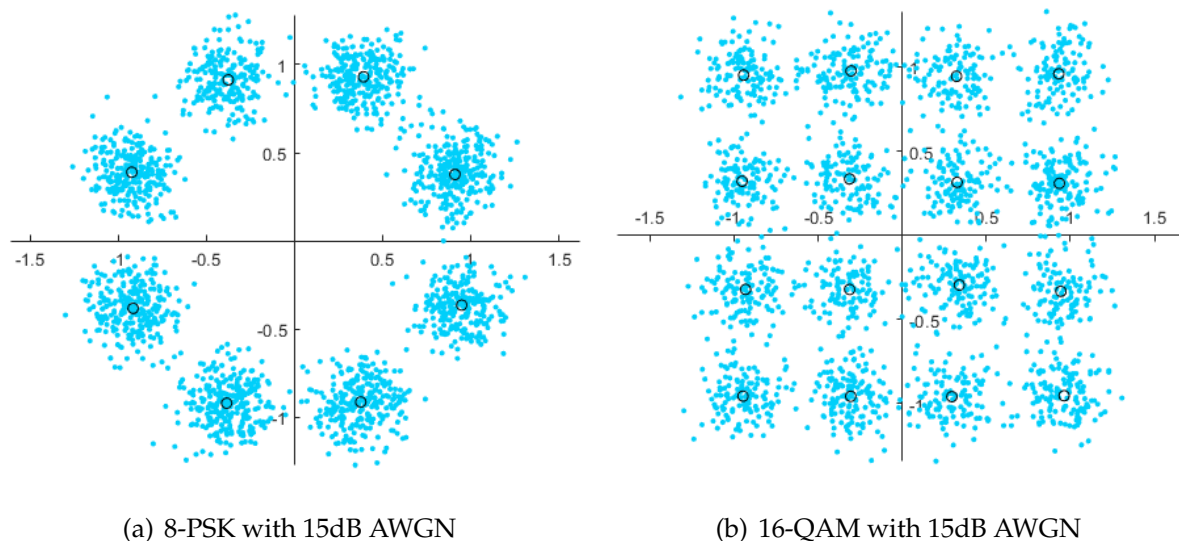


Figure 1.1: Constellations in an AWGN channel.

A blue dot represents a single I/Q sample; the reference symbol levels are indicated by a black circle. One can see that the I/Q samples are scattered around specific points. The correct modulation scheme can then be determined as the modulation scheme whose reference symbol levels are most similar to these points. This thought process can be replicated in software with the aid of clustering algorithms.

A human will, in low noise environments, be able to estimate the symbol locations without much effort. The modulation scheme of a signal can then be identified by comparing the location of these estimated symbol level locations with those of known modulation schemes. We emulate this in software by calculating the total distance between each estimated symbol level and its closest reference location for each modulation scheme in a pool of possible modulation schemes with the same number of symbol levels. The modulation scheme with the lowest distance error is then accepted as the correct modulation scheme. This is seen demonstrated in Figure 1.2 with 16-QAM, where an X represents the estimated location and O represents the known symbol levels of 16-QAM. The lengths of the red lines are summed to calculate the *Model Mismatch Error*. The modulation scheme with the lowest *Model Mismatch Error* is then accepted as the correct modulation scheme. We label this process as the Modulation Type Classification stage.

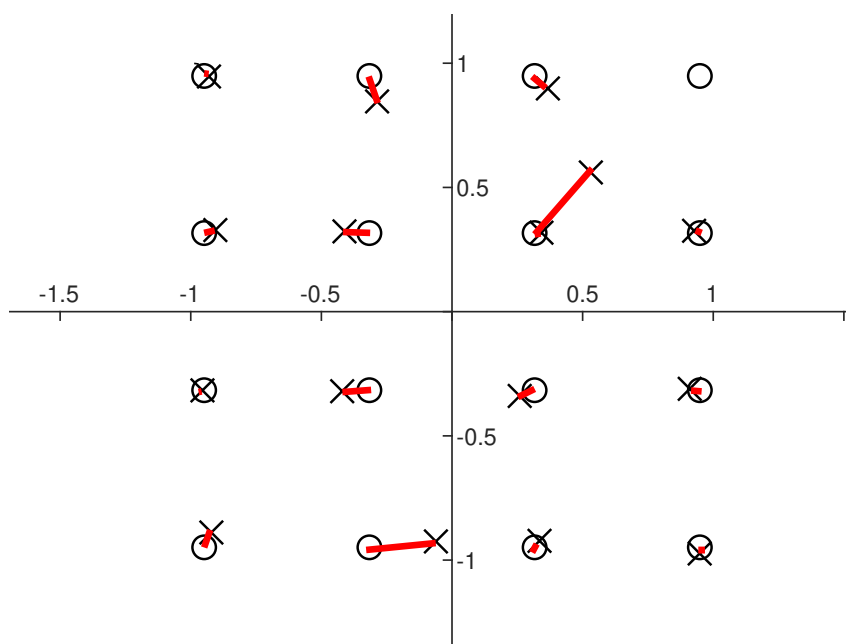


Figure 1.2: Comparing estimated symbol levels to reference locations

Clustering algorithms can be used in software to estimate the symbol level locations by grouping the noisy I/Q samples. Several clustering algorithms exist that can be used to estimate these locations. These algorithms will be divided into two categories based on input requirements. We will define algorithms that require the number of clusters as an input as Known Order Clustering algorithms and algorithms that do not as Unknown Order Clustering algorithms. We name this stage the Final Clustering stage.

All clustering algorithms will, however, require some parameterisation, whether it is estimating the number of clusters or some other parameters related to the density of the data. We use the number of estimated symbol levels as a way to compare several clustering algorithms. Density-based clustering algorithms will still need to be able to determine the correct number of clusters, even though some other set of input parameters is needed to be estimated rather than the number of symbol levels. We name this stage that either estimates the number of clusters or some other set of parameters as the Order Estimation stage. This whole process can be seen summarised in Figure 1.3, where a dotted line shows the scope of the proposed AMC method.

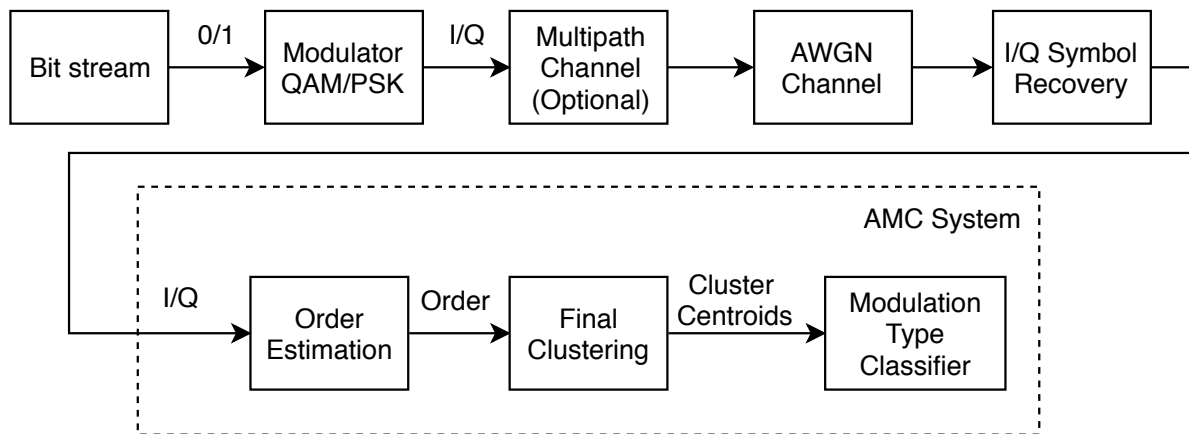


Figure 1.3: Proposed multi-stage approach

The individual objectives to construct the proposed method can be summarised as follows:

1. Perform a literature study to examine other classification methods that use a similar feature.
2. Identify clustering algorithms that do not rely on machine learning.
3. Create methods to utilise these clustering algorithms for each relevant stage in such a way that they can be used interchangeably without compromising the efficiency of each algorithm.
4. Evaluate the performance of each clustering algorithm for each relevant stage.
5. Identify the most suitable clustering algorithm for each stage and construct the proposed method according to Figure 1.3.
6. Evaluate the performance of the proposed method in an AWGN channel and compare the performance with other methods.
7. Evaluate the performance of the proposed method under multipath conditions.

1.2.2 Publications

The rest of the article-based dissertation is ordered as follows; required background information is given with a summary of similar AMC methods. From here, three publications are given in which the proposed AMC is developed and evaluated with progressively worsening channel conditions. After these papers, a discussion is given on verification and validation, and a final conclusion is drawn.

In the first paper, **A Comparison of Clustering Algorithms for Automatic Modulation Classification**, we examine and compare several clustering algorithms with a specific focus on AMC. We compare these algorithms in terms of the objectives of each stage by examining accuracy, algorithmic complexity and execution time. The best performing clustering algorithm of each stage is then used to construct the new proposed AMC method. The *Classification Accuracy* of the proposed method is thereafter compared to well-known AMC methods. An AWGN channel is used to allow a comparison with other methods. We show that 100% *Classification Accuracy* is achieved at a similar SNR as other popular methods, while addressing several of their drawbacks.

The second paper, **Performance Evaluation of a Clustering-based Automatic Modulation Classification Method**, builds on the first paper by extracting a parameter, the *Classification Quality* (ϵ), from the order estimation stage. This parameter is a measure of how much a noisy channel has corrupted the constellation and is used to identify and reject incorrect classifications to achieve 100% *Classification Accuracy*. The proposed method is then again compared to existing methods while rejecting low ϵ -value classifications in an AWGN channel. By rejecting low ϵ -value classifications, 100% *Classification Accuracy* is achieved at a lower SNR than in the previous paper, while not having incorrect classifications at any SNR.

The proposed method is evaluated in a multipath channel with European Telecommunications Standards Institute (ETSI) Tap Delay Line (TDL) models in the third and final paper, **Evaluation of a Clustering-based Modulation Classification under ETSI Multipath Channels**. In this paper, we show that 100% *Classification Accuracy* can be

achieved in channels that would typically not allow 100% *Classification Accuracy* at any SNR due to a short coherence time of the channel. The coherence time of the channel will shorten as the multipath conditions of the channel worsen. Classification Quality (ϵ) can be used to determine when the channel is most favourable and reject classifications during the time that it is not.

Chapter 2

Background

In this chapter, we provide background information required to understand the work presented as well as its connection to related work in literature. Digital modulation methods, communication channels, popular modulation classification methods, as well as clustering algorithms, are discussed. We end the chapter by examining and critiquing related work in literature that use the location of symbol levels in the I/Q plane.

2.1 Digital Modulation Methods

In the early days of wireless communication, data was sent using analogue methods such as Amplitude Modulation (AM) and Frequency Modulation (FM). These days, however, information is only sent using analogue techniques in specific applications such as broadcast radio. Digital modulation techniques are capable of sending more data while using less bandwidth by utilising the electromagnetic spectrum more efficiently. These common techniques include Phase Shift Keying (PSK), Quadrature Amplitude Modulation (QAM), Pulse Amplitude Modulation (PAM) and Frequency Shift Keying (FSK) where FSK is used with low data rates [2]. These modulation methods

are commonly used in conjunction with Orthogonal Frequency-Division Multiplexing (OFDM) in order to multiplex several sub-carriers rather close to each other and be more spectrally efficient.

In the work presented here, we will only focus on modulation schemes that can be represented in the I/Q plane. We will, therefore, only focus on PSK, QAM, and PAM rather than modulation such as FSK that cannot be represented in the I/Q plane. In the I/Q plane, signals can be decomposed into amplitude-modulated sinusoid signals that vary in phase. Figure 2.1 shows a block diagram of how a time-domain signal can be decomposed into I and Q streams.

In the I/Q plane, in-phase components are represented by one axis, with the distance from the centre representing the amplitude of the signal. Each combination of amplitude and phase represents a symbol level. Figure 2.2 illustrates the symbol mapping of popular modulation schemes. We can compare modulation schemes with the unit spectral efficiency defined as:

$$\text{SpectralEfficiency} = b/s/Hz \quad (2.1)$$

It can be observed that the spectral efficiency of a modulation scheme increases as the baud rate increases, for the same bandwidth and symbol time. This increase will, however, increase the density of the symbol levels in the I/Q plane, as seen in Figure 2.2, and reduce the robustness to noise. The spectral efficiency of a modulation scheme is, therefore, related to how the symbol levels are packed within the I/Q plane.

2.1.1 Phase Shift Keying (PSK)

In PSK, the amplitude of a sine wave is kept constant while the phase is varied in set increments. Figure 2.3 shows a BPSK appears in the time domain with two symbol levels. In the I/Q plane, PSK is spaced circularly around the origin, which can be seen in Figure 2.2 for two, four and eight symbol levels.

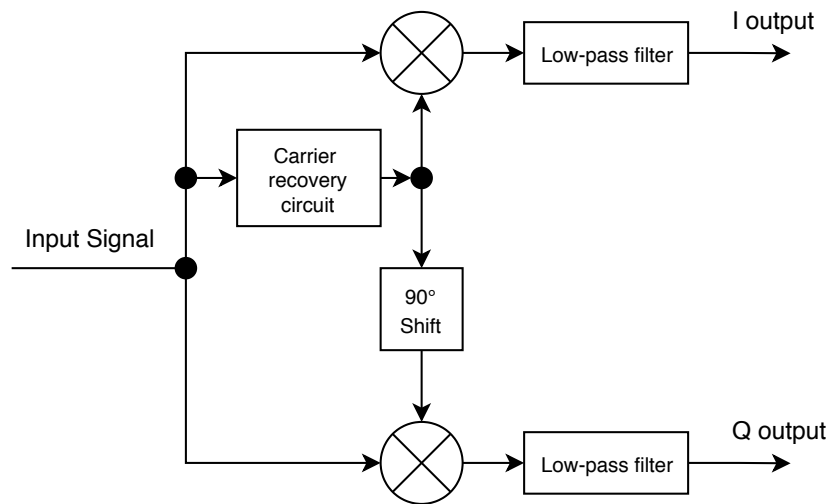


Figure 2.1: A QAM demodulator, redrawn from [2].

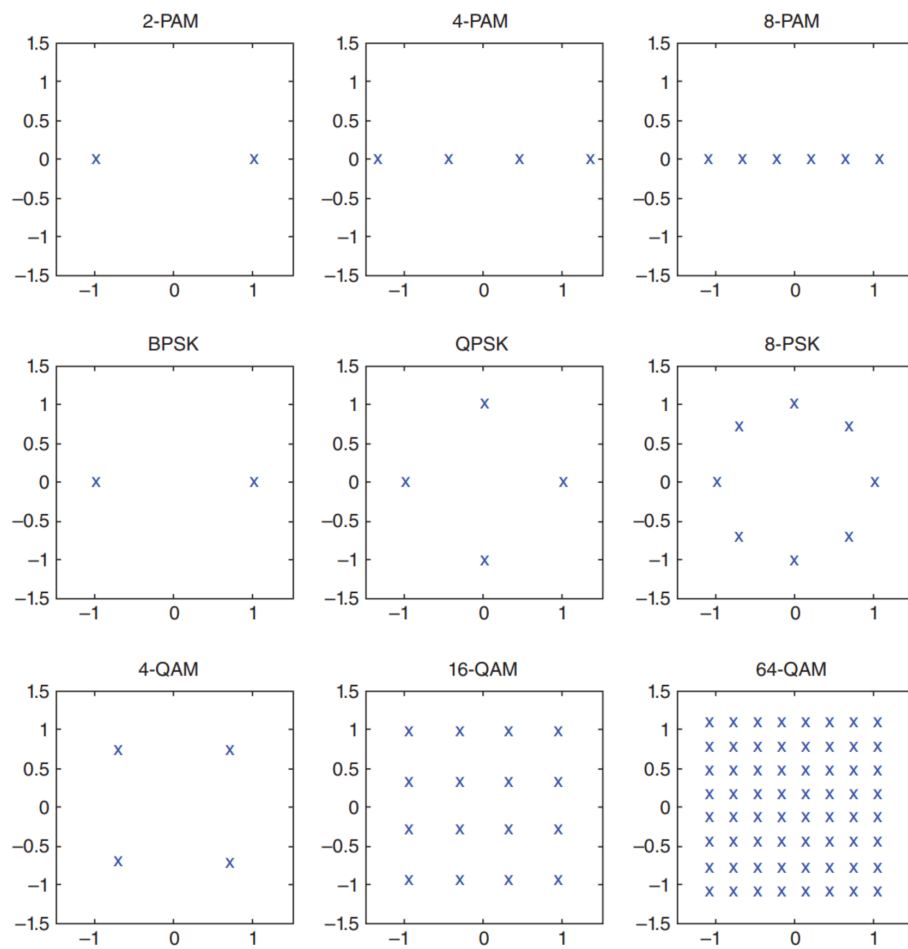


Figure 2.2: Symbol mapping of popular modulation schemes [3]

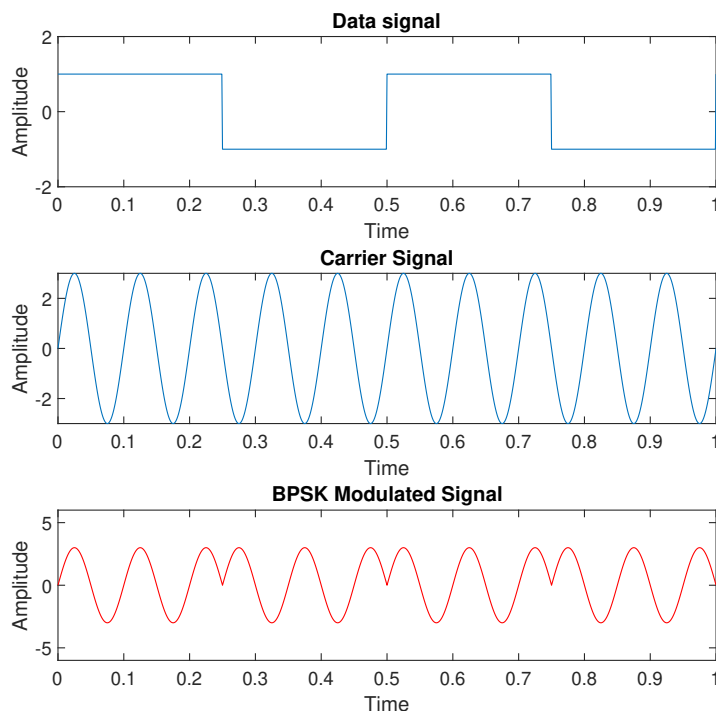


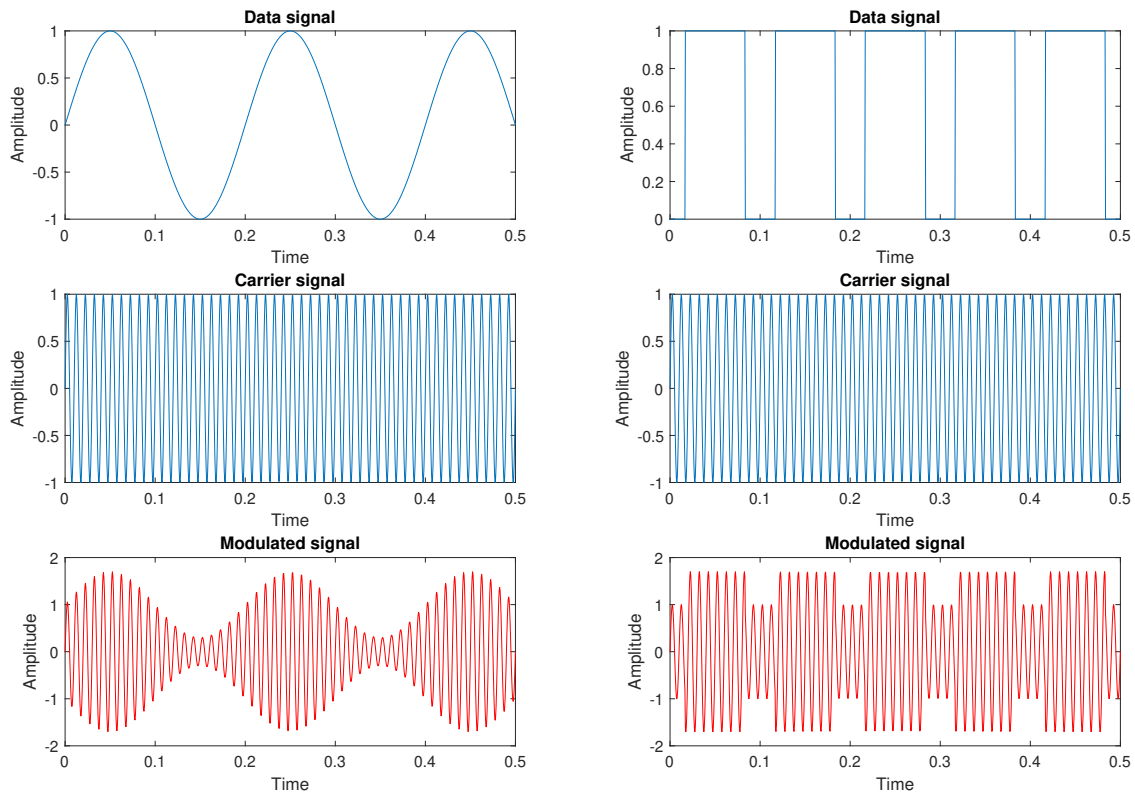
Figure 2.3: PSK in the time domain.

2.1.2 Pulse Amplitude Modulation (PAM)

With PAM, a carrier sinusoid's amplitude is varied in a similar way to AM. With AM, a carried sinusoid's amplitude is varied by an amount corresponding to the amplitude of another signal. In PAM, a sinusoid's amplitude is varied between discrete levels in order to represent a binary sequence. The difference between AM and PAM is demonstrated in Figure 2.4. From Figure 2.2, we observe that PAM appears as a series of linear dots in the I/Q plane since only amplitude is used to distinguish symbol levels and not phase, resulting in low spectral efficiency and increased bandwidth requirements [2].

2.1.3 Quadrature Amplitude Modulation (QAM)

With QAM, both the amplitude and phase of a sine wave are varied to create arbitrary symbol levels in the I/Q plane [2]. Several mappings are available. Figure 2.5(a) shows



(a) AM time domain

(b) PAM time domain

Figure 2.4: Comparison of AM and PAM in the time domain.

16-QAM in a star configuration that was used in Digital Subscriber Lines (DSLs), while Figure 2.5(b) shows the more common rectangular 16-QAM.

2.2 Communication Channels

All communication systems experience some level of noise that can originate from a large number of sources. One can mitigate or lessen the effect of several noise sources through improved antenna design and shielding. There will, however, always be noise, due to the nature of wireless communication.

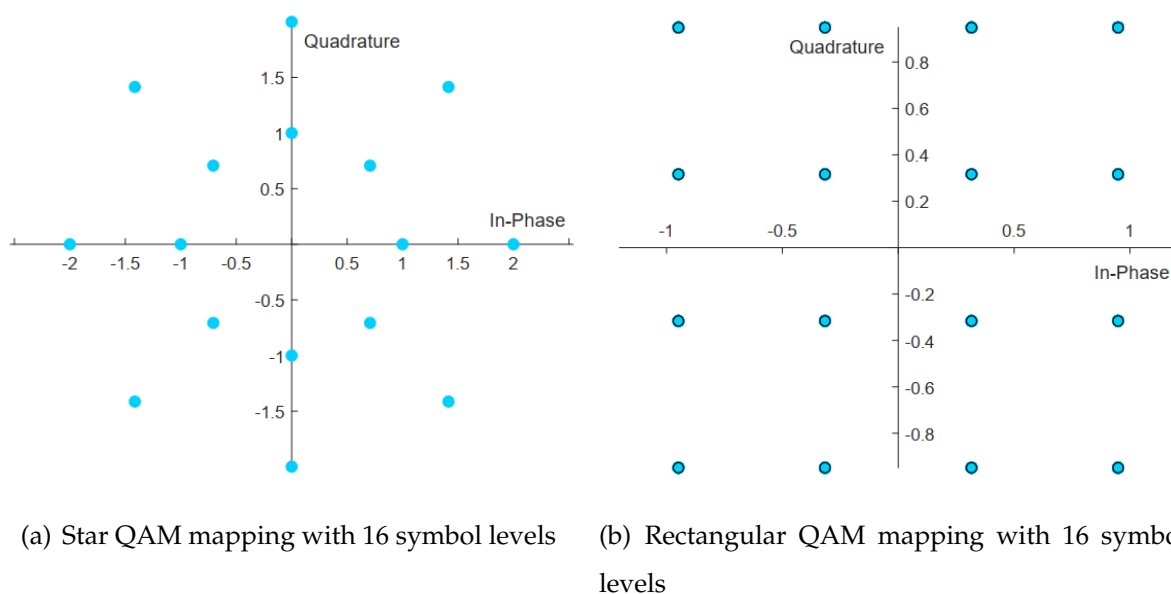


Figure 2.5: Comparison of QAM symbol mappings in the I/Q plane.

2.2.1 Fading

Fading occurs when a signal is affected by the medium through which it is sent. Fading can be caused by a signal following more than one path or a relative movement between the transmitter and receiver, causing a Doppler shift in the signal, referred to as fast fading. Fading caused by signals passing through obstacles or long transmission distances is referred to as slow fading [2]. These effects are demonstrated in Figure 2.6.

Path loss

According to the inverse square law, the power of a received signal is proportional to the square of the distance between the transmitter and the receiver. The free space path loss model can be described mathematically by [2]:

$$P_r = \frac{P_t G_t G_r \lambda^2}{16\pi^2 d^2} \quad (2.2)$$

Where:

- λ is the signal wavelength (m).
- d is the distance between the transmitter and the receiver (m).
- P_r is the received power.
- P_t is the transmitted power.
- G_r is the receiver gain, expressed as a power ratio.
- G_t is the transmitter gain, expressed as a power ratio.

This model does not take any obstacles into account. A signal sent between a transmitter and receiver will typically also reflect off of the ground, resulting in a 180-degree phase shift. These reflections can interfere destructively. The received power can then be expressed as [4]:

$$P_r = P_t \frac{G_t G_r h_t^2 h_r^2}{d^4} \quad (2.3)$$

Where h is the antenna height and the subscript t and r denoting the transmitter and receiver, respectively.

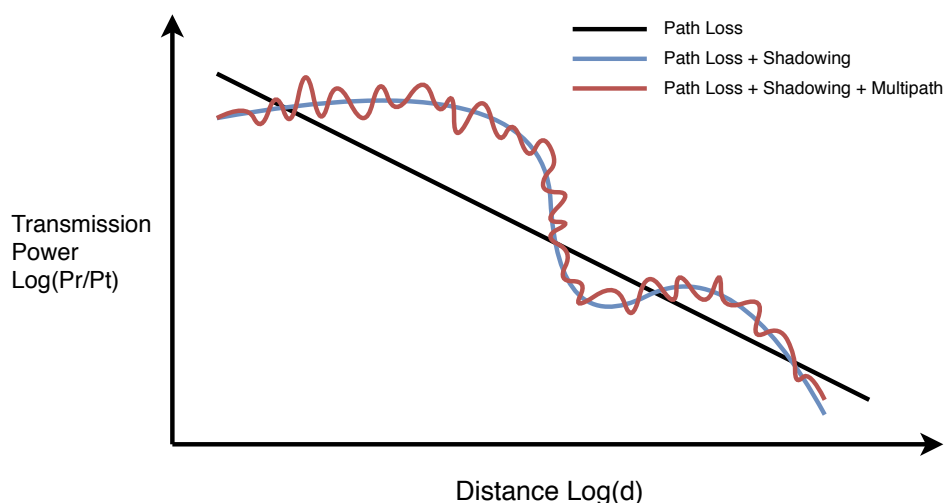


Figure 2.6: The effect of fading on a signal, redrawn from [4]

Shadowing

Shadowing occurs when a signal passes through an obstacle that attenuates the signal, as demonstrated in Figure 2.7. The path loss in decibels is defined as [4]:

$$PL_d = \overline{PL}(d_0) + 10\alpha \log \left(\frac{d}{d_0} \right) + \chi \quad (2.4)$$

Where:

- $\overline{PL}(d_0)$ is the mean path loss at distance d_0 in meter and can be derived from Eq. 2.3.
- α is the path loss exponent.
- χ is a normally (Gaussian) distributed random variable (in dB) with standard deviation σ .

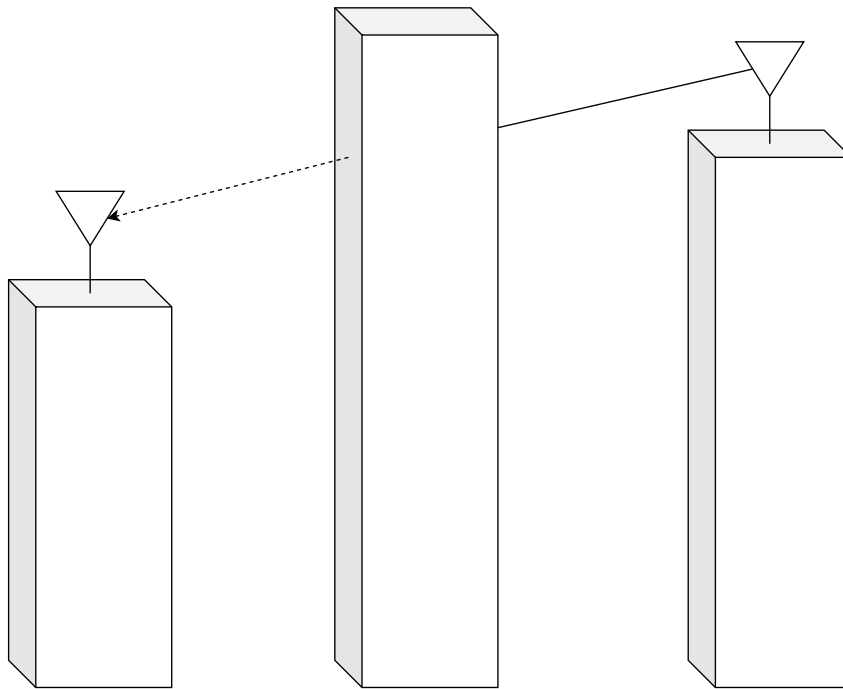


Figure 2.7: Shadowing, redrawn from [4]

2.2.2 Additive White Gaussian Noise (AWGN)

Sources not within our control include industrial noise from large machinery, atmospheric noise from sources such as lightning and extraterrestrial noise from sources in space. Noise can also originate from the communication system itself, referred to as internal noise. Internal noise sources include thermal noise and semiconductor noise. Internal noise may be much weaker than other sources, but it can still interfere with smaller signals [2], and cannot be easily shielded from. These noise sources cause AWGN [2], where:

- Additive refers to the fact that the noise is added to the signal.
- White refers to the fact that the noise has uniform power across the frequency spectrum, similar to how white light consists of all other wavelengths.
- Gaussian refers to the fact that the noise has a normal distribution.

AWGN is typically expressed in decibels in terms of the Signal-to-Noise Ratio (SNR) defined as [2]:

$$SNR_{dB} = 10 \log \left(\frac{S}{N} \right) \quad (2.5)$$

Where S is the signal amplitude and N is the noise. The effect of AWGN on received I/Q samples can be seen demonstrated in Figure 2.8(a) and 2.8(b) for 8-PSK and 16-QAM at 15dB SNR AWGN.

2.2.3 Multipath

It is rare that a signal only reaches a receiver when it is sent from a transmitter. It is a common occurrence for the signal to be reflected from several surfaces on its way to the receiver. This allows a signal to follow more than one path [4], as demonstrated in Figure 2.9. Each path that a signal can follow can have a different path length, resulting in a different time delay between when the signal is sent and when it is received. This

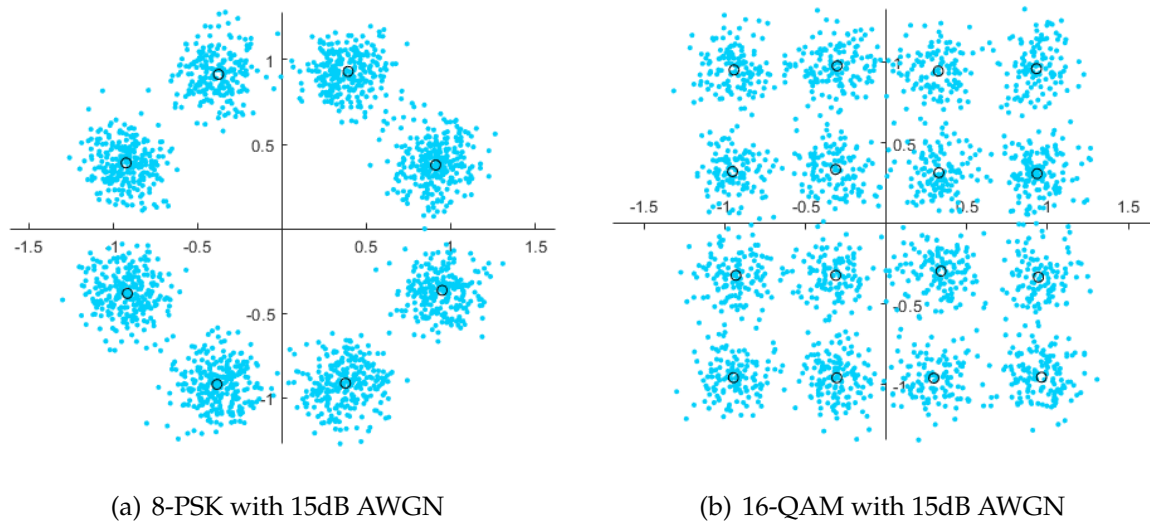


Figure 2.8: The effect of AWGN in the I/Q plane.

results in multiple echoes of the signal at the receiver. Each reflection also alters the phase of the signal.

If there is a direct line-of-sight component, the noise has a Rician distribution. If no line-of-sight component is present, the noise has a Rayleigh distribution [4]. A Rician channel approximates a Rayleigh channel as the line of sight component approaches zero [7].

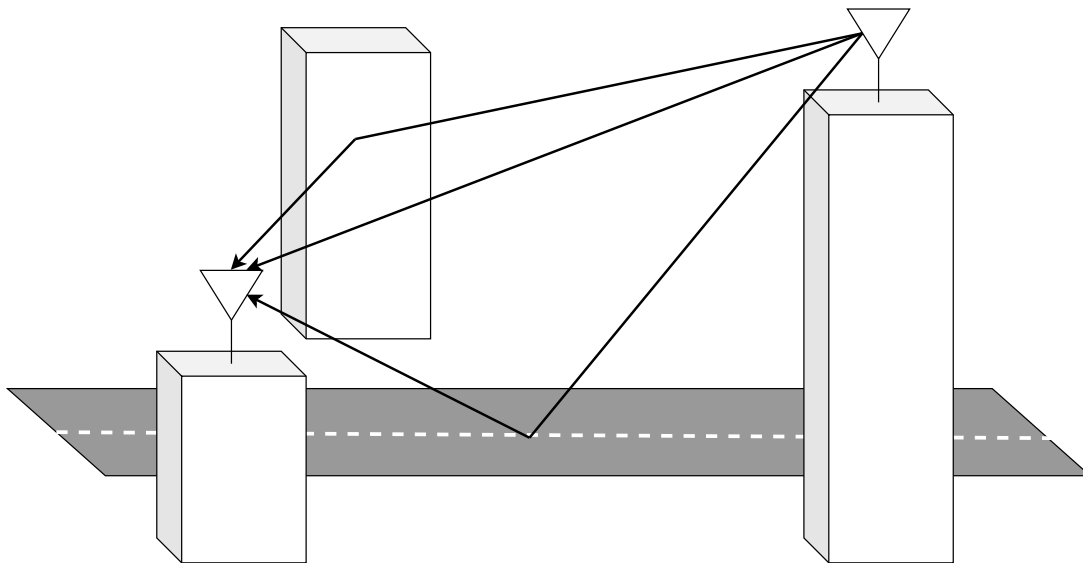


Figure 2.9: The path a signal can take, redrawn from [4]

Tap Delay Line

In a multipath channel, a signal can take multiple paths from a transmitter to a receiver where no path contains the full power of the signal. The signals from each path are summed at the receiver. Figure 2.10 illustrates this concept. At the transmitter the full power of the signal is available. The signal may then travel along more than one path to the receiver. Each of these paths has a different path length and attenuation and will, therefore, take a different amount of time to arrive at the transmitter with a different path loss.

A TDL model builds on this concept. Figure 2.11 shows the visual representation of a typical TDL model that can be mathematically expressed as [4]:

$$h(t, \tau) = \sum_{i=1}^N c_i(t) \delta(\tau - \tau_i) \quad (2.6)$$

Where:

- $h(t, \tau)$ is the received signal.
- c_i indicates the path power loss.
- τ_i indicates the path delay.

In a TDL model c_i changes with time where the number of coefficients is equal to the number of paths. The amount of time that the channel conditions remain constant is

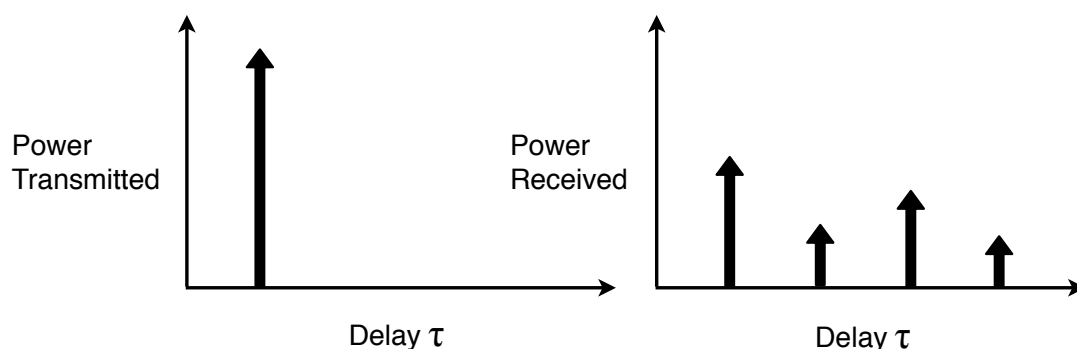


Figure 2.10: The recieved signal power in a multipath environment, redrawn from [4]

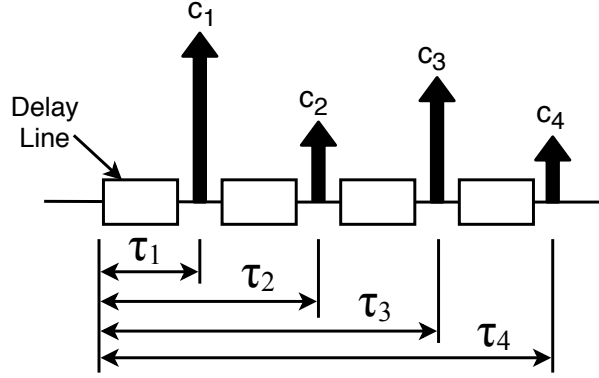


Figure 2.11: The received signal power in a multipath environment, redrawn from [4]

known as the coherence time. A TDL model can easily be implemented with a Finite Impulse Response (FIR) filter.

Sum of Sinusoids

Sum of Sinusoids (SoS) methods rely on the fact that a signal can be described by its amplitude, phase and angle of arrival. This allows a multipath channel to be simulated by summing sinusoids. In order to perfectly model a communication channel, an infinite number of sinusoids is required, in practice, a discrete number of paths is used [7]. A received signal in a multipath environment can be expressed mathematically with a SoS method as:

$$u_i(t) = \sum_{n=1}^{N_i} c_{i,n} \cos(2\pi f_{i,n}t + \Theta_{i,n}) \quad (2.7)$$

Where:

- $c_{i,n}$ represents the gain of each path as specified by a channel model.
- $f_{i,n}$ represents the frequency offset in (rad/s) of each path as specified by a channel model.
- $\Theta_{i,n}$ (rad) are random variables representing phase noise.

2.2.4 Channel Models

Several channel models have been developed over the years to simulate realistic communication channels based on both measured data and theoretical propagation models. Some of these methods include [4]:

- The Hata channel model was developed in 1968 in Japan based on empirical measurements for signals in the 150 - 1500 MHz range for first-generation cellular systems.
- The European European Cooperation in Science and Technology (COST) series of models is an extension of the Hata model developed in 1991. Several revisions are available for different situations, such as the COST231 model for large and small macro-cells, and the COST231-Walfish-Ikegami model for micro cells and small macro cells.
- The Erceg model was developed in 1999 based on data collected by AT&T for macro cells with signals at 1.9 GHz. The model has three available configurations based on the amount of hills and trees there in the area.
- The International Telecommunication Union (ITU) model was developed in 1997 with several configurations; indoor office, outdoor to indoor, and pedestrian as well as vehicular with a high antenna. Each of these configurations is available with a low and medium delay spread.
- The Stanford University Interim (SUI) model developed in 2001 comes in six different configurations based on three different terrain types.
- The European Telecommunications Standards Institute (ETSI) standardised models that have been incorporated in the 3GPP standard [6].

These channel models may not be a perfect representation of how a signal is affected by noise in the real world, but it is a much closer approximation than when only considering AWGN. However, AWGN channels are simpler to implement with fewer variables.

Many AMC methods in literature are only evaluated in an AWGN channel, as it is difficult to compare results with other AMC methods in a multipath environment due to the larger number of variables affecting the channel response. It is also more difficult for an AMC method to identify signals under multipath conditions compared to a pure AWGN channel.

2.3 Clustering Algorithms

The aim of clustering algorithms is to group data according to a set of rules in order to highlight a pattern. This can be achieved through a large number of methods. Clustering algorithms can be utilised in AMC. As discussed in Section 2.1, digital signals modulated with PSK, QAM or PAM can be represented in the I/Q plane akin to coordinates in a Cartesian plane. These I/Q samples can then be clustered together where each cluster centre represents a symbol level.

In this section, we distinguish between two different types of clustering algorithms based on input requirements. We define a known order clustering algorithm as any clustering algorithm where the number of clusters is a required input. In contrast, we define an unknown order clustering algorithm as any clustering algorithm that can function without this requirement.

2.3.1 Complexity and Big O notation

Big O notation is a way to describe how the execution time of an algorithm scales with different datasets [8]. Big O notation does not specify execution time, and algorithms with a low Big O complexity do not necessarily run faster than other algorithms with higher complexity on the same dataset. For example, an algorithm that sums all elements in a vector is said to be $O(n)$ linear complex. This shows that the execution time scales linearly with the number of elements in the dataset. In another case multiplying two numbers with n digits will have $O(n^2)$ quadratic complexity. With Big O notation,

only the highest complexity is considered. If one section of an algorithm shows $O(n)$ complexity and another shows $O(n^2)$ the algorithm is said to be $O(n^2)$ complex, but can have sections with $O(n)$ complexity.

2.3.2 Known Order Clustering Algorithms

K-means

One of the simplest and most well-known clustering algorithms is k-means, also known as Lloyd's algorithm, as proposed in [9]. The k-means clustering algorithm aims to minimise the sum of distances known as the objective function, where the Euclidean distance metric is defined as:

$$d(x, c) = \sum_{j=1}^p |x_j - c_j| \quad (2.8)$$

Where:

- p is the number of elements in x .
- x_j is a single data point.
- c_j is the cluster center assigned to x_j .

Several distance metrics can be used, such as squared Euclidean distance, one minus the sample correlation between points, Hamming, or one minus the cosine of the included angle between points. At a minimum, the algorithm requires the Cartesian data to be clustered, the number of clusters, the stopping condition and the distance metric. The k-means algorithm functions with just a few steps [9]; as follows:

1. Initialise starting cluster locations as random locations.
2. Assign each data point to the closest cluster centre using the distance metric.

3. Re-calculate the location of the centre of each cluster by calculating the mean of its assigned data points.
4. Calculate the objective function as the sum of the distances between each data point and its assigned cluster centre.
5. Repeat steps 2-4. Stop if the objective function is below the stopping condition threshold or the iteration limit is reached.

The k-means algorithm, has $O(knt)$ complexity, meaning that execution time scales linearly with the number of clusters (k), number of data points (n), and the number of iterations (t) [10]. In its original form, the k-means algorithm calls for the starting cluster locations to be random [9]. This proved to be inefficient and was improved on by [11] with the k-means++ algorithm that provides better initial cluster centre location estimations and was shown to improve the rate of convergence significantly.

K-means has been used previously for AMC in [12, 13] by using the algorithm to estimate the symbol level locations.

K-medoids

K-medoids functions on the same principle as k-means. However, each cluster's centre is limited to one of the locations of a data point within the cluster in order to make the clustering algorithm more robust to outliers [11]. This centre point can be determined by calculating the sum of distances between the cluster centre and each point within the cluster for each point as if it was the cluster centre. The point with the lowest sum of distances is then accepted as the centre. This increases the k-medoids algorithm's complexity to $O(k(n-k)^2)$, where k is the number of clusters and n the number of data points [11].

Fuzzy c-means (FCM)

The FCM algorithm was first proposed in [14] and used in [1, 15] for AMC. FCM also displays low complexity compared to other clustering algorithms, having only $O(n)$ complexity, where n is the number of samples [11]. In other known order clustering algorithms, the output is the cluster's centre locations along with which data points are associated with which clusters. FCM instead returns a degree of membership to each cluster for each data point. The degree of membership is related to an input, referred to as the fuzzy overlap exponent. This allows a data point to be associated with more than one cluster [11].

This behaviour allows the FCM algorithm to be used to estimate the number of clusters and their locations. To determine cluster locations, the cluster with the highest degree of membership for each data point is generally accepted as the cluster the data point belongs to. In order to determine the number of clusters present, the FCM algorithm runs iteratively, starting with a large number of clusters and merging clusters whose data points shows a large degree of membership overlap [15].

The elbow method

As proposed in [16], the elbow method can be used to estimate the number of clusters present in a dataset, and in our case, the number of symbol levels. This result can then be used in a known order clustering algorithm such as k-means, k-medoids or FCM.

The elbow method operates by using a known order clustering algorithm to cluster the data into a different number of clusters, as determined by a pool of possible number of clusters. The total sum of distances between all the points and their respective clusters (also known as the distance error) is then calculated for each number of clusters available in a pool. The distance error will always decrease as the number of clusters increase. If the noise levels are not too high, a sharp angle will form at the location of the most probable true number of clusters.

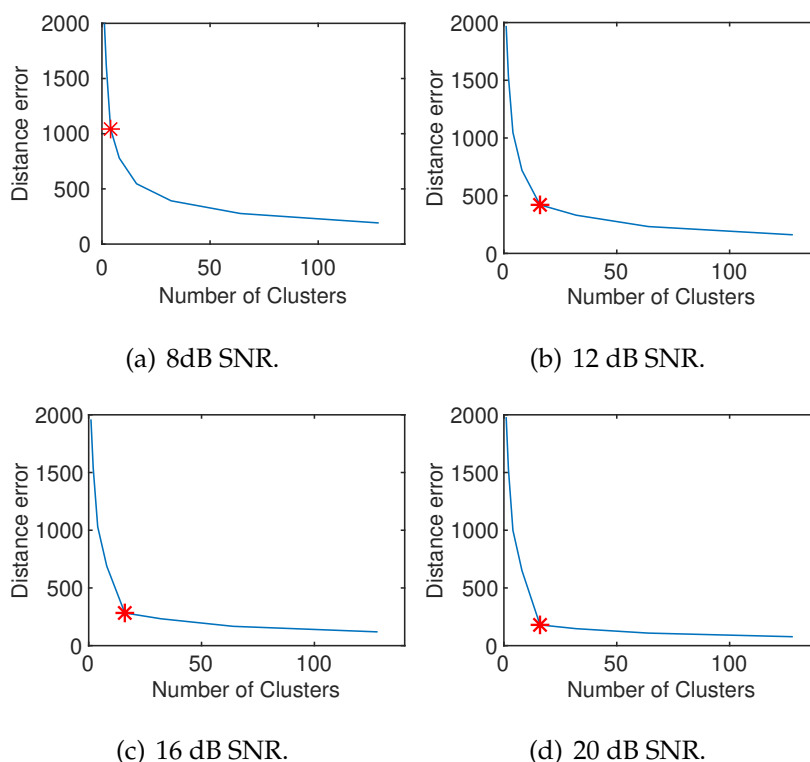


Figure 2.12: Effect of SNR on the elbow method with k-means for 16-QAM.

This behaviour is demonstrated in Figure 2.12, where the elbow method was used with the k-means algorithm on 2048 samples of a 16-QAM I/Q signal in an AWGN channel while increasing the SNR. We can see that the more pronounced the bend is, the more accurate the estimated order will be. The complexity of the elbow method is determined by the clustering algorithm used to cluster the data points in its configuration for the largest number of clusters in the pool.

2.3.3 Unknown Order Clustering Algorithms

Density-Based Spatial Clustering of Applications with Noise (DBSCAN)

As implemented by [17], DBSCAN is a clustering algorithm that is designed to cluster data based on density in a noisy environment with $O(n * \log(n))$ complexity, where n is the number of data points. One of the greatest benefits of DBSCAN is its ability to

isolate noise [11]. To illustrate this, Figure 2.13 shows 2048 I/Q samples of a 16-QAM signal with 12dB AWGN where we can see that the I/Q samples with the most noise have been isolated.

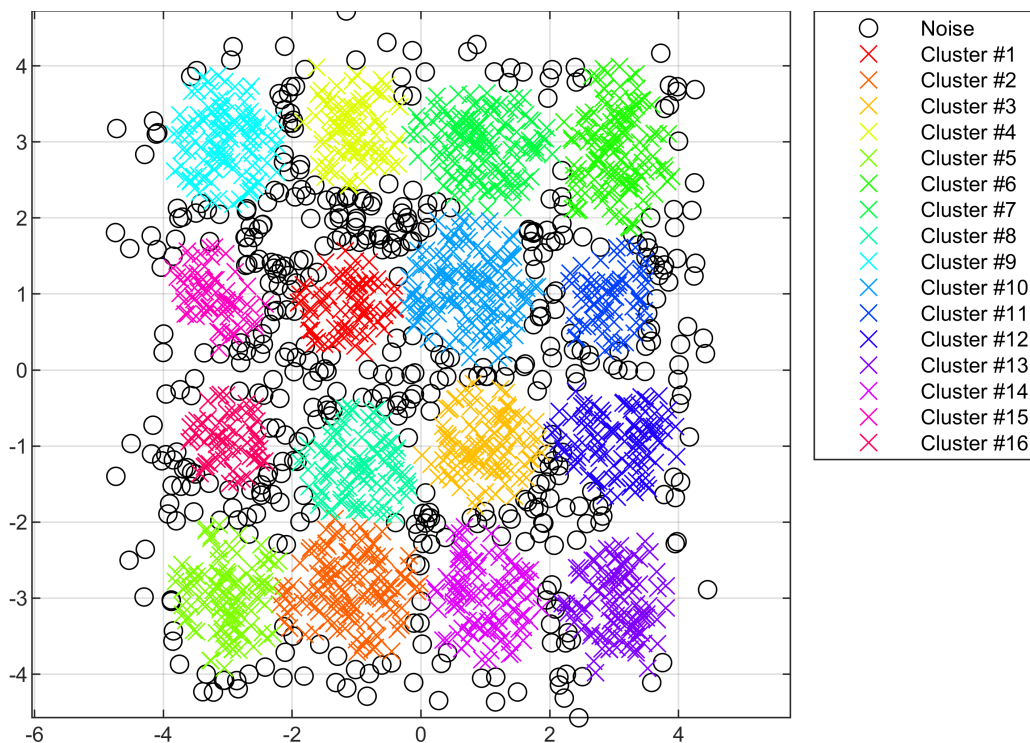
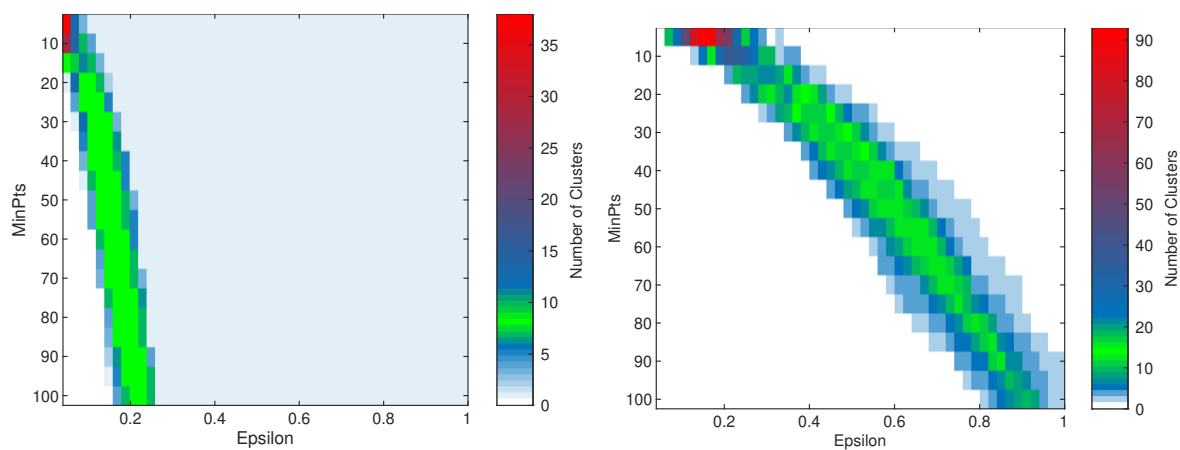


Figure 2.13: 16-QAM at 12dB clustered with DBSCAN



(a) A parameter sweep of DBSCAN for 8-PSK at 12dB SNR (b) A parameter sweep of DBSCAN for 16-QAM at 12dB SNR

Figure 2.14: The number of clusters detected by DBSCAN as a function of ϵ and MinPts.

In order to cluster data, DBSCAN relies on two parameters. The first parameter, MinPts, is the minimum number of data points required for a set of data points to form a cluster. The second parameter, ϵ , dictates how far away data points can be in a cluster. A well-known pitfall of DBSCAN is its sensitivity to change in these parameters [11]. This drawback is illustrated in Figure 2.14(a) and 2.14(b), where the number of clusters is shown as a function of ϵ and MinPts. These two figures illustrate that only a certain combination of these two parameters will result in the correct number of clusters, as indicated by the green region. This region will expand with a larger SNR.

Ordering Points To Identify the Clustering Structure (OPTICS)

OPTICS was designed by [18] to overcome the shortcomings of DBSCAN while maintaining $O(n * \log(n))$ complexity and was first used for AMC by [13]. As opposed to DBSCAN, OPTICS only requires the minimum number of points in a cluster to cluster data.

The data is not clustered in the traditional sense. Instead, OPTICS orders the data into regions where the reachability distance (similar to ϵ in DBSCAN) increases. The output of the OPTICS algorithm is demonstrated with the implementation from [19] in Figure 2.15 with 2048 samples of 16-QAM I/Q data and 12dB SNR AWGN. As seen in the figure, peaks form in the reachability distance as a function of the ordering of the data points. Each of these peaks represents a cluster with the region between the peaks being the points that are associated with that cluster. As proposed by [13], peaks can be determined without knowing the optimal reachability distance by using the maximum of regions that rise above 60% of the average of the two highest points, disregarding the large initial peak. OPTICS can also be used as a known order clustering algorithm by raising the reachability distance until the correct number of clusters is present.

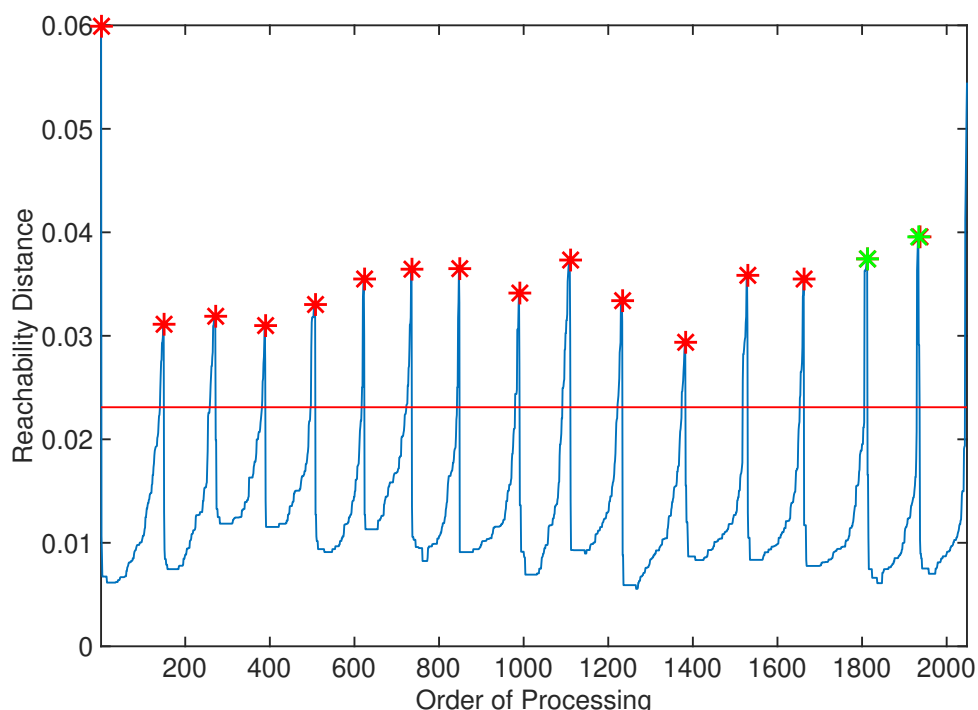


Figure 2.15: Extracting information from the OPTICS clustering algorithm. Input signal has 16 symbol levels at 15 dB SNR in an AWGN channel. Identified peaks (clusters) shown in red with two highest peaks indicated in green.

Hierarchical Clustering

In hierarchical clustering, all data points either begin as a cluster and is merged until only one remains (agglomerative), or begin as one cluster that is divided until each cluster only has one point (divisive) [20]. The merging information is represented in a dendrogram where the clusters being merged are represented by horizontal lines and the merging distance represented by vertical lines. A dendrogram can be seen in Figure 2.16. Clusters are formed/divided based on merging distance, so that points closest to each other will form a cluster. A minimum or maximum merging distance can be used to determine when to stop merging or dividing in order to determine the correct number of clusters. Alternatively, other methods such as the elbow method and the L-method can also be used to determine the correct number of clusters [21]. Hierarchical clustering has $O(n)$ complexity.

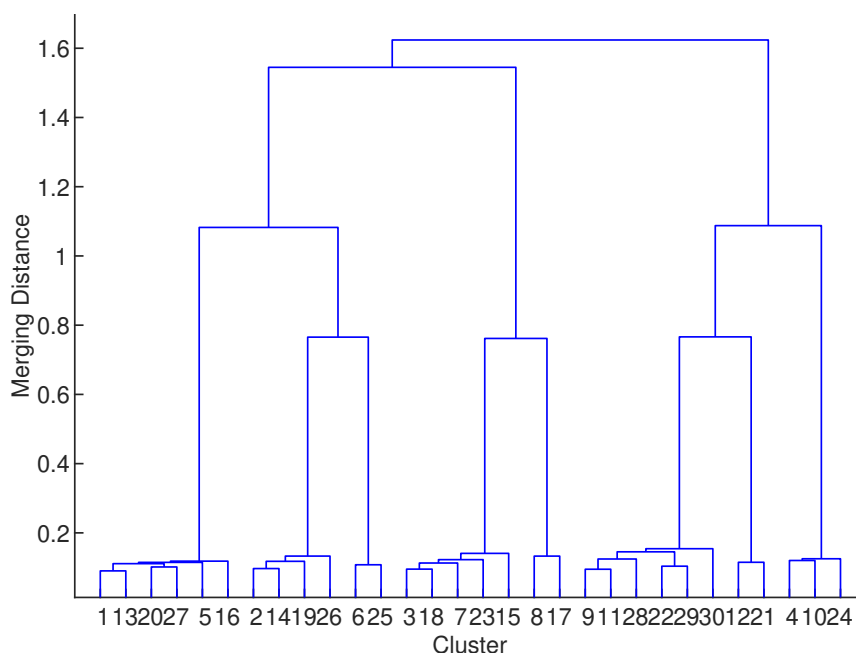


Figure 2.16: Dendrogram

2.4 Automatic Modulation Classification (AMC) in Literature

Several AMC methods have been proposed in literature with widely varying approaches, each with their advantages and drawbacks. AMC methods can typically be described as either being a Feature-based or Likelihood-based technique. In this section, we discuss the operation of several of the most popular methods in literature in order to contrast the operation of our proposed method with those in literature.

2.4.1 Likelihood Methods

Likelihood-based techniques are derived from known signal models. Statistical hypothesis testing techniques are used to classify a signal's modulation scheme. The main drawback of these techniques is the requirement of accurate channel parameter estimation [3]. The most popular techniques start with the Maximum Likelihood (ML) classifier and are then simplified and reduced to the Average Likelihood Ratio Test

(ALRT), Generalised Likelihood Ratio Test (GLRT), and the Hybrid Likelihood Ratio Test (HLRT).

The Maximum Likelihood (ML) classifier

When using a ML classifier, it is assumed that all parameters in a system, other than the modulation scheme, are known. The signal can then be tested against known modulation schemes with a magnitude likelihood function. A magnitude likelihood function is derived for QAM and PAM in [3]. The ML technique has been mathematically proven to be the most accurate approach when classifying signals. The main drawback of this technique is the strict channel state estimation, as accuracy will suffer with inaccurate parameters.

The Average Likelihood Ratio Test (ALRT)

The ML classifier fails if any single parameter, other than the modulation scheme, is unknown. The Average Likelihood Ratio Test (ALRT) was developed by Polydorus and Kim [22] in order to overcome this requirement. Unknown parameters are replaced by the average of all the possible values the parameter can assume. The ALRT function for a system with unknown constant carrier phase offset is derived in [3]. Each unknown parameter increases the computational complexity and run time of the method.

The Generalised Likelihood Ratio Test (GLRT)

The complexity of the ALRT increases as the unknown parameters increase. The accuracy of the ALRT is dependant on the accuracy of available models. If no accurate model is available, the accuracy of the ALRT will decrease. The GLRT was developed to overcome this shortcoming by substituting the average of all the possible values of an unknown parameter with the most probable value. The likelihood function is derived in [3]. The GLRT become biased towards certain modulation schemes.

The Hybrid Likelihood Ratio Test (HLRT)

At both low and high SNRs, the GLRT classifier becomes biased, where lower order modulation schemes are recognised as a higher order. The Hybrid Likelihood Ratio Test (HLRT) was developed in an attempt to overcome this by averaging over the received symbols and maximising the resulting likelihood function with respect to phase. The likelihood function is derived in [3].

2.4.2 Feature-Based Methods

As opposed to Likelihood-based methods, Feature-based methods extract some properties of the signal. These extracted properties, called features, are then used with some form of classification algorithm. Exact channel parameter estimation is not a strict requirement when using Feature-based methods.

Features

Features extracted from a signal can take many forms, with some of the most popular features including Higher Order Statistics-based features, Signal Spectral-based features, Wavelet Transform-based features, and Cyclostationary Analysis-based features. A summary of features in related work is provided in this section.

High Order Statistics-based features:

Moments are high order statistics first proposed for AMC by [23] and built upon by [24]. These statistics are derived from the complex-valued signal $r = r[1] + r[2] + \dots + r[N]$ [3]:

$$\mu_{xy}(r) = \frac{1}{N} \sum_{n=1}^N r^x[n] \cdot r^{*y}[n] \quad (2.9)$$

Where $x + y = k$ for the k th moment of r and $r^*[n]$ is the complex conjugate of $r[n]$.

Cumulants are high order statistical values derived from complex signals and were

first proposed by [25] for the use in AMC.

Second and fourth-order Cumulants are mathematically defined as [3]:

$$C_{20} = E \left\{ r^2 [n] \right\} \quad (2.10)$$

$$C_{21} = E \left\{ \left| r^2 [n] \right| \right\} \quad (2.11)$$

$$C_{40} = cum (r [n], r [n], r [n], r [n]) \quad (2.12)$$

$$C_{41} = cum (r [n], r [n], r [n], r^* [n]) \quad (2.13)$$

$$C_{42} = cum (r [n], r [n], r^* [n], r^* [n]) \quad (2.14)$$

Where $cum()$ is the joint cumulant function defined as:

$$cum(w, x, y, z) = E(wxyz) - E(wx)E(yz) - E(wy)E(xz) - E(wz)E(xy) \quad (2.15)$$

These Cumulants ($\hat{C}_{20}, \hat{C}_{21}, \hat{C}_{40}, \hat{C}_{41}, \hat{C}_{42}$) can be used to distinguish between PSK, QAM, and PAM [3]. These modulation schemes have some of these higher order features in common, but unique combinations can be formed to distinguish them from one another.

Signal Spectral-based features [3, 26]: Spectral-based features are related directly to the waveform of a signal.

- γ_{max} , the maximum spectral power density of the normalised and centred instantaneous amplitude of the received signal.
- σ_{ap} , the standard deviation of the absolute value of the non-linear component of the instantaneous phase.
- σ_{dp} , the standard deviation of the non-linear component of the direct instantaneous phase.

- P , an evaluation of the spectrum symmetry around the carrier frequency.
- σ_{aa} , the standard deviation of the absolute value of the normalised and centred instantaneous amplitude of the signal samples.
- σ_{af} , the standard deviation of the absolute value of the normalised and centred instantaneous frequency.
- σ_a , the standard deviation of the normalised and centred instantaneous amplitude.
- μ_{42}^a , the kurtosis of the normalised and centred instantaneous amplitude, also a form of high order statistics.
- μ_{42}^f , the compactness of the instantaneous frequency distribution, also a form of high order statistics.

Wavelet Transform-based features:

The Continuous Wavelet Transform (CWT) has a similar function as the Fourier transform. Rather than decomposing a signal into sinusoids, the CWT decomposes a signal into smaller non-infinite waveforms, referred to as wavelets. CWT features must be calculated for each different modulation scheme. PSK and FSK can be distinguished, QAM and PAM, however, can not be distinguished from one another [3].

Cyclostationary-based features:

Cyclostationary features were first proposed by [27] as a feature in signal processing. Cyclostationary-based features rely on the periodic properties of a cyclostationary process to distinguish between the Cyclic Spectrum Patterns of different modulation schemes [3]. These techniques are, however, inadequate when classifying higher-order modulation schemes [3]. Therefore, it is used in conjunction with other features, such as Cyclic Cumulants, when used for AMC, as proposed by [24].

Classifiers

Classifiers are used to match the features of an unknown signal to a known modulation scheme. Although several approaches exist, a decision tree or machine learning technique is the most commonly used.

Decision trees:

When using decision trees, features are matched against some predefined threshold in a multi-stage approach. At each stage, one or more feature is used to either exclude possible modulation schemes or match the unknown signal to a known modulation scheme. The main drawback of decision trees is the use of thresholds, as the optimal value for these thresholds could change depending on the operating environment [3].

Machine Learning:

In machine learning algorithms, sample data is used to train a classification algorithm. The algorithm then learns how to identify patterns using the available features in order to classify an unknown signal. Some of the most common machine learning algorithms include K-Nearest Neighbors (KNN), Support-Vector Machine (SVM), Artificial Neural Network (ANN) and Convolutional Neural Network (CNN).

The **KNN** algorithm uses the distance (L) between features (F) to match signal (A) to signal (B). Although several distance metrics exist, the Euclidean distance is the most commonly used [3], defined as:

$$D(F(A), F(B)) = \sqrt{\sum_{I=1}^L [F_I(A) - F_I(B)]^2} \quad (2.16)$$

K-sections of the test signal that is the closest to the reference signal using a distance metric are then used to classify the unknown signal. As the number of features increases, the computational complexity of KNNs will increase as well, resulting in it being impractical for some applications that rely on a large number of features [3].

An **SVM** algorithm uses the available features to create a multi-dimensional feature space. Machine learning techniques are then employed to construct a hyperplane capable of separating these features in order to classify unknown signals. Figure 2.17 shows

a theoretical feature space of two features, x_1 and x_2 separated by a hyperplane [3].

An **ANN** aims to emulate the function of a brain in order to make a decision or perform an action. In Figure 2.18, each extracted feature is represented on the left and the single classified modulation scheme is on the right. ANNs can be as deep or as shallow as required, with the depth represented by the number of layers. As with organic brains, connections are referred to as neurons, where each neuron has a weight value. The features (x_n) on the left are multiplied by the neuron weight (w_n) and summed to create a value for each node, which is then repeated for each layer. The value of these weights is optimised in accordance with a training algorithm over several iterations so that the final output has a unique value for each possible modulation scheme [3].

A **CNN** is a form of machine learning specifically designed for two-dimensional data that functions similarly to an ANN, as illustrated in Figure 2.19. The data is initially reduced with convolution layers, without losing features, before being sent through a pooling layer that sub-samples the data in order to further reduce the data dimensionality. This reduction allows for a much less computationally complex method and increases scalability with larger datasets. The data is then passed through a fully connected neural network layer in order to classify the data [5].

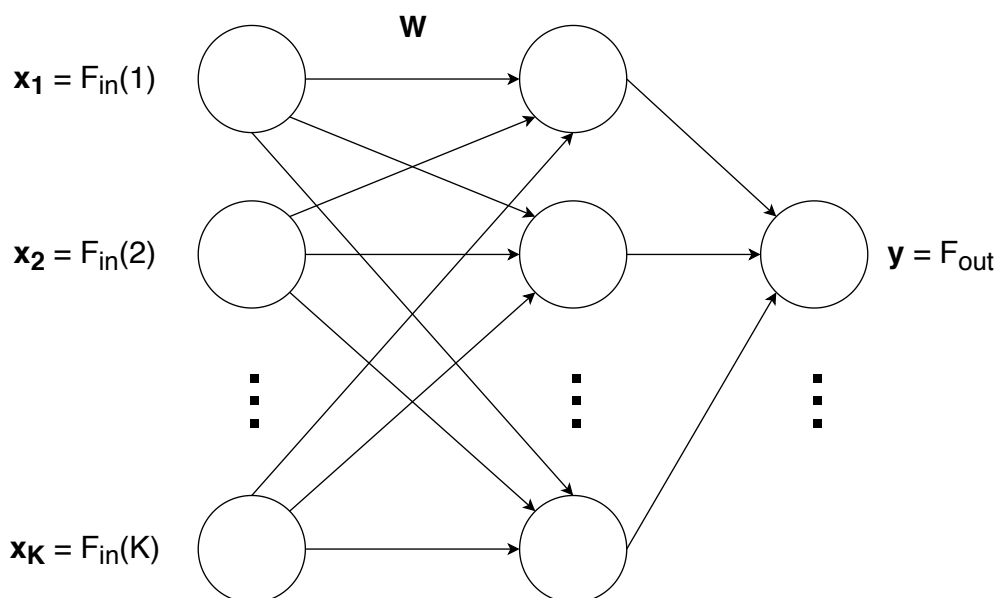


Figure 2.18: An Artificial Neural Network (ANN), redrawn from [3]

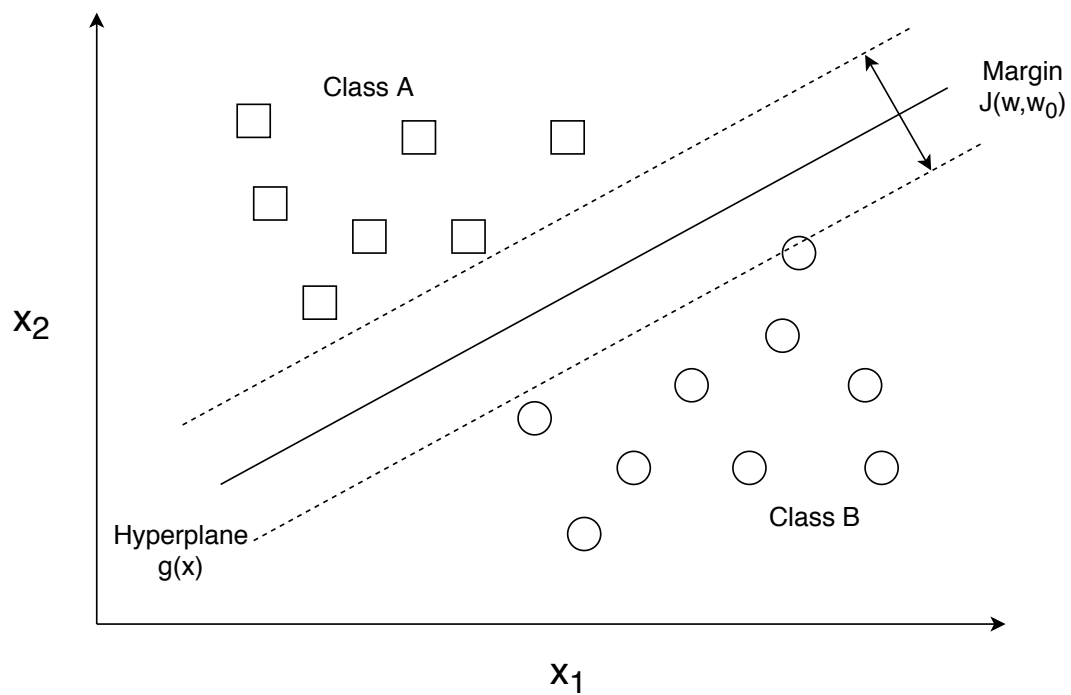


Figure 2.17: Feature Space Hyperplane, redrawn from [3]

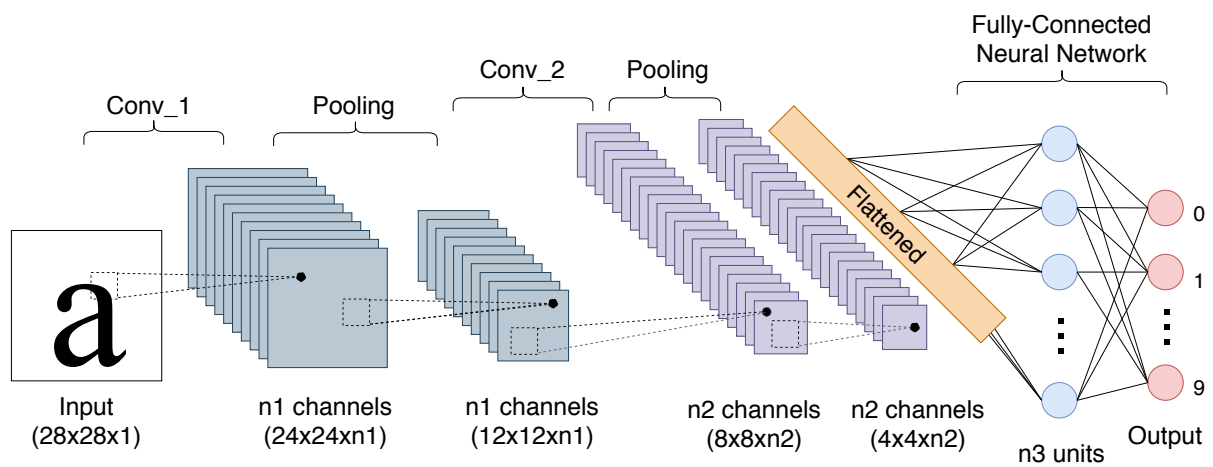


Figure 2.19: A Convolutional Neural Network (CNN) used to recognise handwriting, redrawn from [5]

2.4.3 Related Work on Clustering-Based AMC Methods

Clustering algorithms can be used to estimate the symbol level locations of an unknown signal, determine the number of clusters (and therefore the modulation order), or even classify a signal with a more statistical approach (where features of a signal are clustered together in a feature space). Some of the most noteworthy uses of clustering algorithms for the use of AMC in literature include:

Digital modulation classification using constellation shape

In 1999, B.G. Mobasseri used FCM to determine the modulation order. After the unknown signal is converted to its I/Q representation, the FCM algorithm is used to cluster the received symbols [28]. Initially, the data is clustered into a number of clusters larger than what is expected. A post-processing step then merges clusters with weak membership, which is then repeated until the I/Q symbols show satisfactory membership. Information related to the geometry of the estimated symbol levels is then extracted and used with an ML rule to classify the modulation type.

Using fuzzy clustering and TTSAS algorithm for modulation classification based on constellation diagram

In 2010, M. Ahmandi used FCM in a way similar to the approach of [28] and [15]. Only the data in the first quadrant is considered in order to take advantage of the symmetry of modulation schemes' constellation representation, thus reducing computational complexity. An initial number of clusters larger than the largest possible modulation scheme is used with FCM and iteratively reduced by merging clusters with a post-processing step relying on hierarchical and hard c-means clustering until the correct number of clusters is found. The I/Q data is then clustered with the Two Threshold Sequential Algorithmic Scheme (TTSAS), as implemented with a Hamming neural network. The Euclidean distance error between the estimated symbol levels and known

modulation schemes is then used to classify the modulation scheme.

I/Q diagram utilization in a novel modulation classification technique for cognitive radio applications

In 2013, O. Azarmanesh and S.G. Bilén proposed a way to detect and separate an OFDM signal into its subcarrier waveforms, by performing a Gaussianity test [12]. Initial points are then estimated with the greedy k-centre algorithm and used as a starting point for the k-means algorithm. A cumulative distance error is then used to distinguish between M-QAM and M-PSK.

Blind Digital Modulation Classification Using Minimum Distance Centroid Estimator and Non-Parametric Likelihood Function

In 2014, Z. Zhu and A.K. Nandi developed an AMC method that relies on the distance between I/Q samples in conjunction with a Non-Parametric Likelihood Function (NPLF) [29]. The Euclidean distance between received I/Q symbols and the known symbol levels of modulation schemes is first calculated in order to get a goodness of fit metric. An NPLF is then developed in order to overcome the fact that the GLRT assumes a Gaussian distribution.

Blind signal modulation recognition through clustering analysis of constellation signature

In 2017 G. Jajoo et al. used OPTICS clustering to estimate the modulation order [13]. In order to estimate the number of symbol levels, 2000 I/Q symbols are generated and passed through an AWGN channel and then clustered with OPTICS with the minimum number of points per cluster set to 30. A suitable Reachability Distance must then be chosen in order to find the correct number of peaks. This Reachability Distance value is then calculated as 60% of the average value between the two highest points. Peaks

are defined as regions above this point, with the number of these regions representing the number of symbol levels present. An error value is then calculated with linear regression to distinguish Amplitude Shift Keying (ASK) from PSK and QAM. K-means is used with the estimated order to calculate a distance error to distinguish QAM from PSK.

These aforementioned clustering-based AMC methods, as well as several other that use the location of I/Q samples, can be found summarised in Table 2.1.

2.4.4 Review of Related Work

As summarised in Table 2.1, it is apparent that several open problems still need to be addressed in the related work. Several of the proposed methods are solely evaluated with M-QAM in the pool of possible modulation schemes, reducing the complexity of the classification problem significantly by essentially only estimating the modulation order. Many of the methods are evaluated using only a small pool of possible modulation schemes.

In the following section, we will present the development of our proposed method over the course of three papers. In the first paper, we evaluate the performance of several clustering algorithms and present the first iteration of our proposed method. In the second paper, we expand on the first paper by extracting a parameter that allows us to identify incorrect classifications. The proposed method is evaluated with ETSI multipath conditions in the third paper.

Care has been taken throughout these papers to describe the proposed method in such a way that it can easily be replicated. The proposed method is also evaluated with a large pool of possible modulation schemes and presented in such a way that it can easily be compared to other AMC methods detailed in literature.

Table 2.1: Short summary of related work (1/4)

Year	Author	Title	Order Estimation Methodology	Modulation Classification Methodology	Channels	Comments
2000	Bijan G. Mobasser	Digital modulation classification using constellation shape [1]	The fuzzy c-means clustering algorithm is used. I/Q samples are clustered together into a high number of clusters. These clusters are then iteratively merged based on fuzzy membership overlap.	A Maximum Likelihood classifier is used to distinguish between modulation types.	AWGN, Phase Lock Error and Carrier Lock Error	Outstanding work, widely cited by others using clustering algorithms for Automatic Modulation Classification. Full results are only given for a small number of modulation schemes. The effect of several sub-optimal channel effects is discussed in depth.
2008	Negar Ahmadi; Reza Berangi	Modulation classification of QAM and PSK from their constellation using Genetic Algorithm and hierarchical clustering [30]	A Genetic Algorithm is used where an objective function is calculated with the hard c-means algorithm to provide a fitness value. The Genetic Algorithm is stopped when the improvement of the objective function falls below a certain value.	A post-processing step built on Hierarchical clustering is then used to assign I/Q samples to clusters.	AWGN	Little discussion is given on how the modulation family is identified. Results are given for M-QAM and M-PSK, but a small pool of possible modulation schemes is used.
2010	Negar Ahmadi	Using fuzzy clustering and TTSAS algorithm for modulation classification based on constellation diagram [30]	The fuzzy c-means clustering algorithm is used. I/Q samples are clustered together into a high number of clusters. These clusters are then iteratively merged based on a larger decision making process.	I/Q samples are clustered together with the Two Threshold Sequential Algorithm. The Euclidean distance error is then calculated and compared against known modulation schemes.	AWGN	Inadequate information is provided on the decision making when to merge clusters during order estimation. The method is tested with several modulation schemes, and the results are discussed in depth. The work is built on the previous article by N. Ahmadi in 2008 [30].

Table 2.2: Short summary of related work (Continued 2/4)

Year	Author	Title	Order Estimation Methodology	Modulation Classification Methodology	Type Channels	Comments
2013	Okhtay Azarmanesh and Sven G Bilén	I-Q diagram utilization in a novel modulation classification technique for cognitive radio applications [12]	"The greedy k-center algorithm"	A distance error metric coined the Cumulative Distance Error is used to compare the cluster centres with known modulation schemes.	AWGN	The main focus of this article is on the classification of OFDM sub-carriers; very little information is given on modulation order estimation.
2013	Chou Zhen-dong; Jiang Weining; Xiang Changbo; Li Min	Modulation recognition based on constellation diagram for M-QAM signals [31]	Frequency Offset, Baud-rate and Timing are first estimated and compensated for. I/Q samples are then normalised in terms of phase offset as well as amplitude and clustered together with k-means with all possible number of clusters. A distance error is then calculated for each result and compared to determine the correct modulation order.	Only M-QAM signals is considered.	AWGN and Multipath	Only M-QAM is considered with a small pool.
2014	Zhechen Zhu; Asoke K. Nandi	Blind Digital Modulation Classification Using Minimum Distance Centroid Estimator and Non-Parametric Likelihood Function [29]	Explicit order estimation is not required.	The distance error between all I/Q samples and their closest symbol level is calculated for each modulation scheme in a pool. This is then used with hypothesis testing using a Maximum Likelihood function.	AWGN	No clustering algorithm is used, instead the significance of distance error metrics is demonstrated. Results are given for several modulation schemes and compared to other popular methods.

Table 2.3: Short summary of related work (Continued 3/4)

Year	Author	Title	Order Estimation Methodology	Modulation Classification Methodology	Channels	Comments
2016	Xu Zhu; Takeo Fujii	A novel modulation classification method in cognitive radios based on features clustering of time-frequency [32]	DBSCAN is used to eliminate the need for order estimation.	Pseudo Wigner-Ville Distribution is used as a feature extraction approach and clustered with DBSCAN.	AWGN	Feature extraction is explained in detail while the exact use of DBSCAN and the classification strategy is insufficient. Classification accuracy is only given as a whole rather than for each modulation scheme.
2017	Gaurav Jajoo; Yogesh Kumar; Sandeep Kumar Yadav; Bibhas Adhikari and Ashok Kumar	Blind signal modulation recognition through clustering analysis of constellation signature [13]	The OPTICS clustering algorithm is used to estimate the modulation order.	An error value is then calculated with linear regression to distinguish ASK from PSK and QAM. K-means is used with the estimated order to calculate a distance error to distinguish QAM from PSK.	AWGN	The proposed method is well described and can be replicated. The results are only given for a few low order modulation schemes.
2017	Liu Wang; Yubai Li	Constellation based signal modulation recognition for MQAM [33]	Subtractive clustering is used to estimate I/Q symbol levels. Each sample is assigned a value to be a potential cluster centre where the point with the highest potential is selected as the cluster centre. This is repeated iteratively where a new cluster centre is created each time; until the potential value drops below a threshold.	Only M-QAM signals are used.	AWGN	Only M-QAM is considered. The decision making process is inadequately described and can't be replicated.

Table 2.4: Short summary of related work (Continued 4/4)

Year	Author	Title	Order Estimation Methodology	Modulation Classification Methodology	Type	Channels	Comments
2018	Guo-Yu Zhang, Xiao Yan, Shi-Hao Wang and Qian Wang	A Novel Automatic Modulation Classification for M-Qam Signals Using Adaptive Fuzzy Clustering Model [34]	Subtractive clustering is used to estimate I/Q symbol levels. Each sample is assigned a value to be a potential cluster centre where the point with the highest potential is selected as the cluster centre. This is repeated iteratively where a new cluster centre is created each time; until the potential value drops below a threshold. A distance error between the estimated symbol levels and known symbol levels is calculated. The classification is accepted if this distance metric is below a certain threshold.	Only M-QAM signals is used.		AWGN	Only M-QAM is considered. Results are given as a function of a method-specific metric that cannot be sufficiently compared to other methods.
2018	Faqian Yang; Ling Yang; Dong Wang; Peihan Qi and Haiyan Wang	Method of modulation recognition based on combination algorithm of K-means clustering and grading training SVM [35]	Explicit order estimation is not required.	I/Q data is clustered with k-means for different values of k corresponding to a pool of possible modulation orders. Features are then extracted from each result and used with a SVM to classify the unknown signal.		AWGN	Interesting approach. Extensive training is required.

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Chapter 3

Publications

In this chapter, we provide the papers written. A brief discussion is also given as a preamble to each paper, and how it affects the study as a whole.

3.1 Introduction

The proposed method, as described in the concept outline in 1.2, is divided into several stages. The *Final Clustering* stage uses clustering algorithms to estimate the location of the symbol levels in the I/Q plane. These estimated locations can then be compared to known modulation schemes. Several clustering algorithms require the number of clusters as an input parameter. Algorithms that do not rely on the number of clusters as an input use some other set of parameters specific to the algorithm. These parameters are then estimated in the *Order Estimation* stage for use in the subsequent stages.

The CRediT taxonomy is a method to assign roles and contributions. Each member can contribute in various degrees to fourteen roles [36]. For the papers presented in this chapter, we adopt the CRediT taxonomy for author contribution. Three authors

contributed to these three publications with their respective roles and contributions shown in Figure 3.1 in CRediT format.

	J Mouton	M Ferreira	A Helberg
Conceptualisation	e	e	e
Data curation	l		
Formal analysis	l	s	s
Funding acquisition		l	e
Investigation	l		
Methodology	l	s	s
Project administration		l	s
Resources		l	s
Software	l		
Supervision		l	s
Validation	l	s	s
Visualisation	l	s	s
Writing – original draft	l		
Writing – review & editing	s	l	l

Attribution Key:

l = lead

s = supporting

e = equal

Figure 3.1: Individual contribution in CRediT format for papers 1-3.

3.2 Paper 1

Title: A Comparison of Clustering Algorithms for Automatic Modulation Classification

Publication type: Journal

Publication: Expert Systems with Applications

Publisher: Elsevier

ISBN: 0957-4174

Publication date: Article in press, at the time of writing.

Published article Digital Object Identifier (DOI):

<https://doi.org/10.1016/j.eswa.2020.113317>

In the first paper, we examine the performance of the clustering algorithms in Section 2.3 for each stage of the proposed AMC method. Accuracy, execution time, and scalability are taken into account. From this, we conclude that the k-means clustering algorithm, in conjunction with the elbow method, outperformed the other clustering algorithms. We also show that the number of samples plays an important role, as the examples of each symbol level decreases as the modulation order increases for a constant number of samples. The number of samples should, therefore, be chosen as a function of the largest modulation scheme in the pool of possible modulation schemes.

The k-means algorithm was subsequently used to develop the proposed method. The proposed method was evaluated using the same testing conditions as in [3] in order to compare results in a meaningful way. From these results, we saw that we achieve 100% *Classification Accuracy* at a similar SNR as other popular methods, if an adequate number of samples is used.

The article presented in this section is a preprint of the manuscript that appeared in Expert Systems with Applications. Please refer to the DOI for the published manuscript.

A comparison of clustering algorithms for automatic modulation classification

JP Mouton^a, M Ferreira^{a,*}, ASJ Helberg^a

^a*School of Electrical, Electronic and Computer Engineering,
North-West University, Potchefstroom, South Africa*

Abstract

In this paper, the k-means, k-medoids, fuzzy c-means, Density-Based Spatial Clustering of Applications with Noise (DBSCAN), Ordering Points To Identify the Clustering Structure (OPTICS), and hierarchical clustering algorithms (with the addition of the elbow method) are examined for the purpose of Automatic Modulation Classification (AMC). This study compares these algorithms in terms of classification accuracy and execution time for either estimating the modulation order, determining centroid locations, or both. The best performing algorithms are combined to provide a simple AMC method which is then tested in an Additive White Gaussian Noise (AWGN) channel with M-Quadrature Amplitude Modulation (QAM) and M-Phase Shift Keying (PSK). Such an AMC method does not rely on any thresholds to be set by a human or machine learning algorithm, resulting in a highly flexible system. The proposed method can be configured to not give false positives, making it suitable for applications such as spectrum monitoring and regulatory enforcement.

Keywords: Automatic Modulation Classification, Constellation diagram, I/Q plane, Clustering algorithm, Centroid estimation

1. Introduction

Automatic modulation classification (AMC) refers to a process that identifies modulation schemes used to modulate an unknown signal without human input. AMC has several military and civilian applications. In civilian applications, spectrum users are assigned specific bands in the electromagnetic spectrum which depend on the regulatory domain, user application, radio technology used, and the transmitter. For example, 802.11 Wi-Fi commonly operates at 2.4 GHz in unlicensed spectrum, while most cellular providers have dedicated bands assigned in licensed spectrum operating at 900 MHz and 1800 MHz. AMC can be used in cognitive radios that can sense the spectrum in order to automatically switch to the optimal modulation scheme. In 5G networks it will also be necessary to continuously monitor the electromagnetic spectrum to ensure that only authorised transmissions occupy allocated frequency slots in space and time. In military applications, a signal could be intercepted and demodulated if the modulation scheme can be determined. Alternatively, signal jamming can be made more effective if the modulation scheme is known (Zhu & Nandi (2015)). AMC methods typically fall into two categories, likelihood-based and feature-based. Likelihood-based methods typically outperform feature-based methods when it comes to classification

accuracy but require accurate channel parameter estimation. Feature-based methods are typically used in situations where not all channel parameters can be determined (Zhu & Nandi (2015)).

In this paper, we extract features from the constellation representation in the In-phase and Quadrature (I/Q) plane by approximating the number and location of the received symbol levels and using clustering algorithms. These symbol level locations are then compared with a pool of possible modulation schemes' known symbol level locations in an Additive White Gaussian Noise (AWGN) channel.

The proposed AMC method in this study is composed of different functional blocks namely order estimation, final clustering, and modulation type classification as shown in Fig. 1. The rest of this paper is ordered as follows: Section 2 provides a background on several clustering algorithms. Related work in AMC is given in Section 3. Section 4 evaluates applicable algorithms for modulation order estimation, Section 6 evaluates the abilities of different clustering algorithms to determine symbol level locations, and Section 7 uses the best performing clustering algorithms from the prior evaluations to create the proposed AMC method. A comparative evaluation with popular AMC methods is shown Section 8. Finally, the benefits of the proposed method are discussed in Section 9.

2. Clustering algorithms

I/Q samples can be clustered together in a two-dimensional Cartesian plane to estimate the modulation

*Corresponding author

Email addresses: 24911658@student.nwu.ac.za (JP Mouton),
melvin.ferreira@nwu.ac.za (M Ferreira),
albert.helberg@nwu.ac.za (ASJ Helberg)

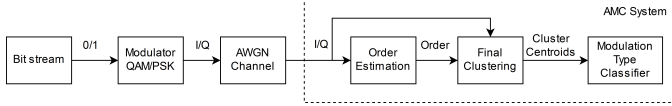


Figure 1: Stages of the proposed AMC method.

order and the unknown modulation scheme’s symbol locations where the number of clusters is equal to the modulation order. This feature is, however, rarely used and merits further investigation (Ali et al. (2017)).

In this section, brief background information is given on the operation of the examined clustering algorithms. For the purpose of this paper, clustering algorithms can be functionally split into two categories which will be defined as: *known-order*, where the number of clusters is used as an input parameter, and *unknown-order*, where this is not required. In known-order algorithms, data is partitioned under a specified number of clusters according to a set of rules. Unknown-order algorithms do not require the modulation order as input, instead relying on factors such as the density of received symbols in the I/Q plane to determine the number of clusters.

2.1. Unknown-order algorithms

2.1.1. Density-based spatial clustering of applications with noise (DBSCAN)

DBSCAN is a density based clustering algorithm that does not require the number of clusters as input as proposed by Ester et al. (1996) and implemented by Yarpiz (2015). Instead, the algorithm requires two input parameters in addition to data points that need to be clustered. The first is epsilon (ϵ), which represents the reachability distance related to the minimum distance between points in the same cluster; and the second is MinPts, which is the minimum number of points to be considered a single cluster. A significant benefit of DBSCAN is its ability to identify and isolate noise, thereby allowing cluster centres to be more representative of the data. DBSCAN has previously been used for modulation order estimation by Zhu & Fujii (2016).

During testing the optimal values of ϵ and MinPts were found to vary significantly between modulation schemes, modulation order as well as the amount of noise present in the system. Fig. 2(a) and Fig. 2(b) shows a sensitivity analysis conducted for 8-Phase Shift Keying (PSK) and 16-Quadrature Amplitude Modulation (QAM) respectively, by sweeping MinPts and ϵ over a range of values and recording the resulting number of clusters. The value of MinPts is shown on the y-axis and ϵ on the x-axis, with the number of clusters shown by the intersection of these two values. These two figures demonstrate that in noisy environments, only a narrow region between these two parameters will produce the correct number of clusters, implying the value of ϵ and MinPts will have to be uniquely determined for each run.

2.1.2. Ordering points to identify the clustering structure (OPTICS)

OPTICS is a modified version of DBSCAN proposed by Ankerst et al. (1999) and implemented by Daszykowski (2002). DBSCAN was used to estimate the modulation order in Jajoo et al. (2017). OPTICS does not necessarily cluster the data in the traditional sense—instead it provides an ordering of the data based on density. The initial purpose of OPTICS was to improve on DBSCAN by reducing its sensitivity to changing input parameters by only requiring MinPts. The reachability distance (ϵ) can then be chosen in a post-processing step. This can be seen in Fig. 3, with each peak representing a cluster and the points succeeding each peak belonging to that specific cluster. Peaks can be determined by identifying regions in which the reachability distance rises and drops again below a certain threshold. The threshold is determined as a fraction of the largest reachability distance. The maximum value between those regions can then be considered a peak. As proposed by Jajoo et al. (2017), this threshold is set as 60% of the average between the two highest peaks, marked with a green star, disregarding the large initial peak. A sensitivity analysis also verified this threshold value as suitable.

2.1.3. Hierarchical clustering

In hierarchical clustering, each data point starts either as its own cluster that is iteratively merged with its closest neighbour until only one cluster is present (agglomerative), or a single cluster comprising all data points which is then divided until each data point is its own cluster (divisive) (Xu & Tian (2015)). The distance between merging clusters is then represented in a dendrogram, as shown in Fig. 4. The number of clusters can be determined by using a maximum distance as a stop-criterion. Alternatively, the distance between the merging of clusters can be examined in a post-processing step by using a technique like the elbow method (Antunes et al. (2018)). Hierarchical clustering has not previously been presented in AMC literature.

2.2. Known-order algorithms

2.2.1. K-means

The k-means algorithm (also known as Lloyd’s algorithm) is an iterative clustering algorithm for minimising the total distance between data points and their assigned cluster’s centre (Lloyd (1982)). The only required inputs are the data points, the number of clusters required, and a stopping condition. In its original form initial clusters are distributed randomly, however Arthur & Vassilvitskii (2007) developed the k-means++ algorithm, which improves on the random initial clusters and significantly accelerates the k-means algorithm’s convergence rate.

The algorithm functions by determining which cluster’s centre is closest to each point. Each point is then assigned to its nearest cluster. Each cluster’s centre is recalculated as the average of all its assigned points’ locations. This process is repeated either until no points can

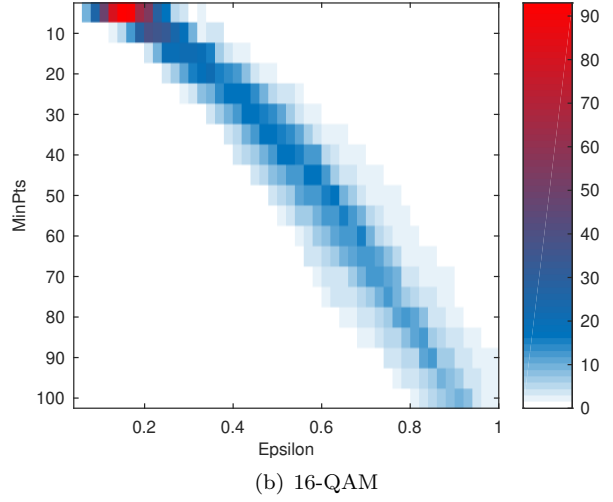
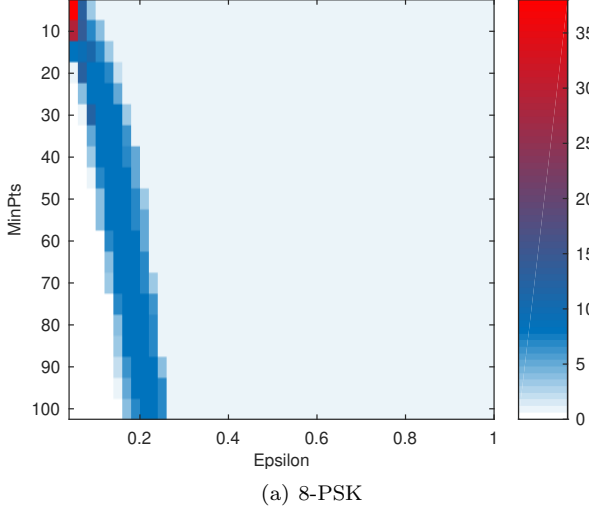


Figure 2: Sensitivity analysis of the number of clusters for the DBSCAN algorithm at 12 dB SNR.

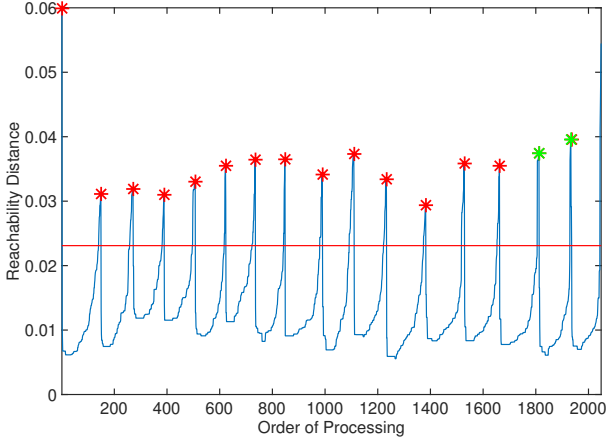


Figure 3: Extracting information from the OPTICS clustering algorithm. Input signal has 16 symbol levels at 15 dB SNR in an AWGN channel. Identified peaks (clusters) shown in red with two highest peaks indicated in green.

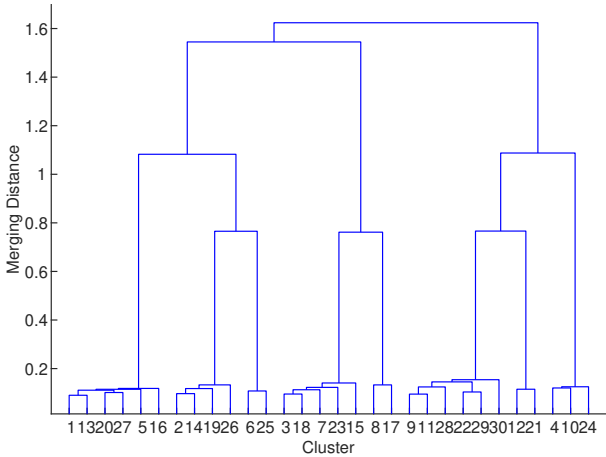


Figure 4: Dendrogram for eight symbol levels. Horizontal lines represent the linking of two data points or clusters. The vertical line represents the distance between the two merging clusters.

be assigned to a closer cluster or until the stopping condition has been reached. K-means is typically used in literature to estimate the symbol level locations (Azarmanesh & Bilén (2013); Jajoo et al. (2017)), but not to estimate the modulation order.

2.2.2. K-medoids

The k-medoids algorithm is similar to the k-means algorithm in the sense that data is iteratively partitioned to minimise the total distance error. The main difference between the k-means algorithm and the k-medoids algorithm is that the k-means uses the average of a cluster's data points as the cluster location, where the k-medoids uses the median data point belonging to the cluster. This is achieved by replacing the step in which the centre is determined with that of calculating the total in-cluster distance error for each point in a cluster and using the point with the lowest distance error as the cluster's centre. This allows k-medoids to be more robust to outliers and therefore more representative of the data (Xu & Tian (2015)). Variations of the k-medoids algorithm have been used in literature to determine the symbol position in the I/Q plane but not to estimate the modulation order.

2.2.3. Fuzzy c-means

The fuzzy c-means algorithm was first proposed in Bezdek et al. (1984) and used by Ahmadi (2010) and Mobasseri (2000) to estimate the number of symbol levels. Similar to the k-means algorithm, the fuzzy c-means algorithm aims to minimise the distance error. However the output of the fuzzy c-means algorithm is a degree of membership rather than a cluster number, allowing each point to belong to more than one cluster. The cluster with the highest degree of membership is generally accepted as the cluster that the point belongs to. The number of symbol levels can then be estimated by first clustering data with the highest number of symbol levels in the pool and

iteratively merging clusters whose points show a large degree of membership overlap. This process is repeated until points show majority membership to only one cluster. Fuzzy c-means has widely been used in literature for AMC (Mobasseri (2000); Ahmadi (2010)).

3. Related Work

The k-means, fuzzy c-means, DBSCAN and OPTICS algorithms have previously been used for AMC in literature in some capacity. However, these clustering algorithms have never been directly compared in the context of AMC. Clustering techniques can also be used in statistical approaches for pattern recognition that does not directly rely on the location of symbols in the I/Q plane. This study will limit its focus to clustering I/Q data for estimating the modulation order and symbol levels of an unknown digital modulation scheme.

Jajoo et al. (2017) were the first to use the OPTICS algorithm for AMC. First an error value (e), is calculated and compared with a threshold value to detect Amplitude Shift Keying (ASK). Incoming I/Q symbols are then clustered with OPTICS to estimate the number of symbol levels. The I/Q data is then reclustered with k-means using the estimated number of symbol levels. Next, a distance error is calculated and compared with a threshold to distinguish M-QAM from M-PSK.

Zhu & Nandi (2014) investigated the use of clustering algorithms for the purpose of AMC. In this approach, I/Q symbols are clustered together with a different number of clusters. For each number of clusters the distance error between each symbol and its cluster centroid is calculated. This information is then used to develop a “minimum distance centroid estimator”, incorporating a Non-Parametric Likelihood Function (NPLF) to blindly classify modulation schemes.

Azarmanesh & Bilén (2013) used k-means, k-means++, and k-centre to develop a method for classifying single carrier signals. In this work, specific attention is given to identifying Orthogonal Frequency-Division Multiplexing (OFDM) signals and the separation of sub-carriers into single carrier signals that can then be identified. After a single carrier signal is identified, the greedy k-centre algorithm is used rather than k-means++ for initialisation to improve accuracy. The symbols are then clustered together with k-means, and a cumulative deviation error is calculated and compared with a threshold to distinguish between modulation types such as M-QAM and M-PSK.

The fuzzy c-means clustering algorithm was used by Ahmadi (2010) to determine the modulation order. With this algorithm the I/Q symbols are clustered together with a varying number of samples. The distance error between the known symbol levels and estimated symbol levels is then used to determine the highest possible modulation order. The Two-Threshold Sequential Algorithm Scheme (TTSAS) is then used as it does not require the precise

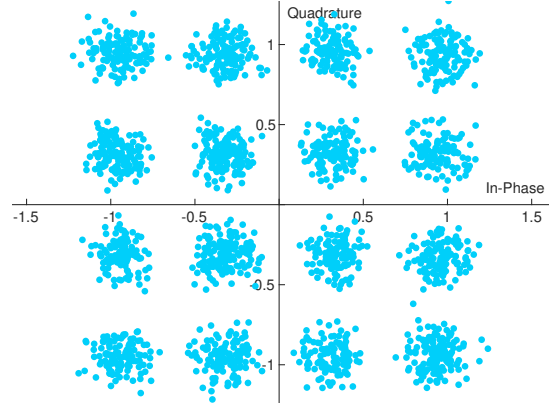


Figure 5: Received I/Q data for 16-QAM with 18dB SNR in an AWGN channel.

number of symbol levels, but does require two thresholds to be trained.

Mobasseri (2000) argues that the shape of a modulation scheme’s constellation representation is a robust feature in a noisy environment. The fuzzy c-means algorithm is used to cluster I/Q data into a different number of clusters, starting with the highest modulation in a pool and lowering the number of clusters until low membership overlap is shown. The modulation type is then identified using a Maximum Likelihood (ML) rule based on known modulation scheme models.

In the next two sections, we will evaluate the previously discussed clustering algorithm’s ability to estimate the modulation order and symbol location in the I/Q plane. The best performing algorithms will then be used to create a new method for AMC.

4. Order Estimation Evaluation

The first phase in this study’s proposed method, as shown in Fig. 1, requires the modulation order to be estimated. The modulation order is used as an input for the next stage that will re-cluster the data to estimate the symbol level locations. Fig. 5 shows I/Q symbols for a 16-QAM modulation scheme in an AWGN channel. Examining these data points, reveals that the received symbols are scattered around certain centres. The number of these centres corresponds with the modulation scheme’s order or number of symbol levels. Several algorithms can be used to determine how many of these reference points are present by clustering the received symbols. Unknown-order clustering algorithms will be capable of determining the modulation order directly, based on density. Known-order clustering algorithms will, however, require a post-processing step. We evaluate the available clustering algorithms in respect of accuracy as a function of Signal to Noise Ratio (SNR) in an AWGN channel and the number of samples in this section.

4.1. Implementation of the “elbow method”, for known-order algorithms

As proposed by Ketchen & Shook (1996), the elbow method can be used to determine the optimal numerical parameter in a system by examining the change in variance as this parameter changes. Therefore, this method can be used to determine the number of symbol levels present by clustering the received symbols into each possible number of symbol levels in a pool with a known-order clustering algorithm such as k-means, k-medoids, or fuzzy c-means. Where the total distance error is calculated and plotted as a function of the number of symbol levels present in the pool, a sharp elbow will form that indicates the probable number of symbol levels in the pool. This can be seen in Fig. 6 where 16 symbol levels are present with different SNRs. Fig. 6(a) illustrates that the SNR is too low and no pronounced elbow is present, causing the modulation order to be estimated incorrectly. As the SNR increases in Figs. 6(b), 6(c) and 6(d), a more pronounced elbow is formed where the data is clustered into 16 clusters. A sensitivity analysis was conducted to determine a sufficient iteration limit past, which there is very little increase in accuracy for each known-order clustering algorithm. A slightly larger iteration limit is then used for extra assurances.

Several methods exist to identify the elbow, such as the L-method where two straight lines are fit to the data or evaluating the curvature (Antunes et al. (2018)). These methods can, however, be computationally complex. We can use a much simpler method that is similar to the approach used by Handaka et al. (2018) since modulation orders come in 2^n steps allowing easier identification of the elbow due to a large separation between the possible number of clusters. We calculate what percentage the distance error changes for each number of clusters relative to the preceding one. The largest percentage difference indicates the position of the elbow.

4.2. Implementation of fuzzy c-means with fuzzy overlap

The degree of membership returned by the fuzzy c-means algorithm indicates how well the cluster centres fit the data for a certain number of clusters. Therefore, the data is clustered into the highest modulation order in the pool to determine the most likely number of clusters. The degree of membership is then summed for all data points belonging to each cluster to determine each cluster’s average degree of membership. Clusters are then merged where a large degree of membership is shown to more than one cluster. This is repeated until all points show predominant membership to only one cluster.

4.3. Unknown Order Algorithms

4.3.1. Implementation of DBSCAN

Fig. 2(a) and Fig. 2(b) demonstrate how only certain combinations of ϵ and MinPts deliver the correct number of clusters, as discussed in Section 2. To determine this region of correct MinPts and ϵ , MinPts is set to slightly

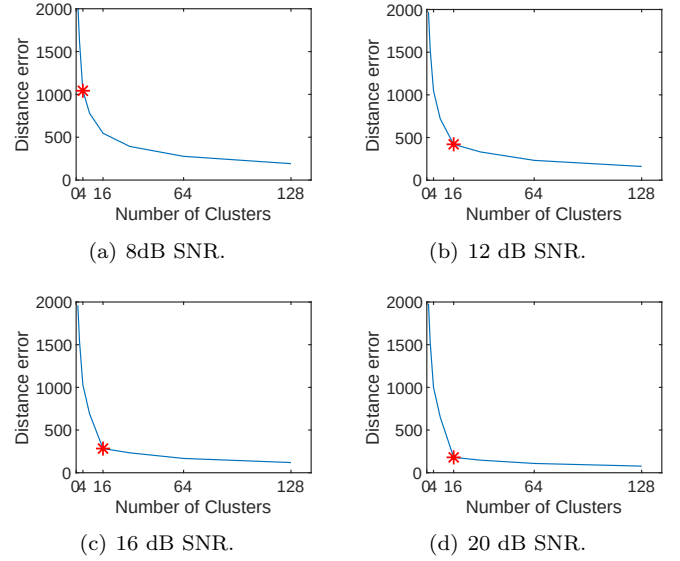


Figure 6: Effect of SNR on the elbow method with k-means for 16-QAM.

less than the number of samples divided by the largest modulation order in the pool. This allows MinPts to be slightly less than the number of samples in each cluster in the case where the largest modulation order in the pool is the correct one. DBSCAN is then applied with a constant MinPts, and ϵ is incremented from 0 at a set rate until a number of clusters greater than 0 is achieved- this value for ϵ represents the minimum ϵ value. The same process is repeated from an overestimated ϵ , where ϵ is decremented to find the maximum value for ϵ . If one of these points cannot be determined, MinPts is lowered and the process is repeated. The maximum number of clusters between these minimum and maximum values for ϵ is then accepted as the number of clusters.

4.3.2. Implementation of OPTICS

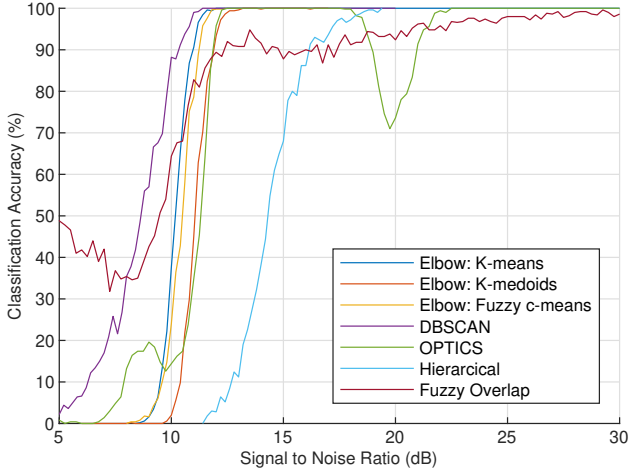
The only parameters required for OPTICS is the data to be clustered, and the minimum number of points to be considered as a cluster. The order is determined by counting the number of peaks greater than 60% of the average between the two highest peaks, as proposed by Jajoo et al. (2017). The minimum number of points is calculated in the same way as with DBSCAN.

4.3.3. Implementation of Hierarchical clustering

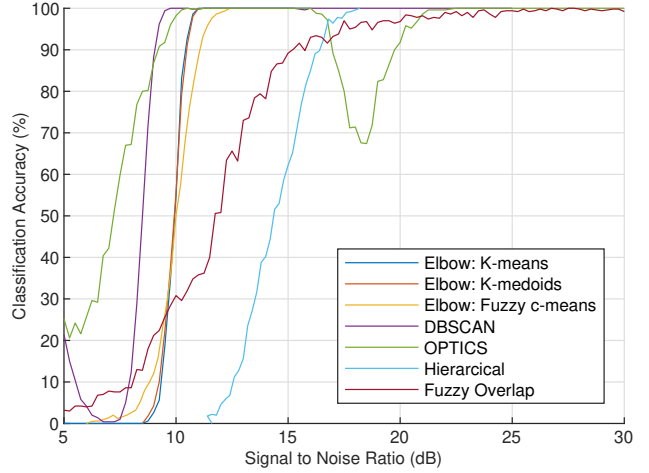
The number of clusters can be determined by examining the merging distances represented by vertical lines in a dendrogram, as shown in Fig. 4. The merging distance is plotted as a function of the number of clusters, after which the elbow method is applied.

4.4. Order estimation accuracy and execution time evaluation

The aforementioned clustering algorithms for estimating the modulation order was implemented in a Matlab



(a) 16-QAM.



(b) 8-PSK.

Figure 7: Order estimation accuracy for 2048 samples in an AWGN channel.

Table 1: SNR at which 90% Order Estimation Accuracy is achieved (dB)

Algorithm	8-PSK			16-QAM		
	1024 Samples	2048 Samples	4096 Samples	1024 Samples	2048 Samples	4096 Samples
Elbow: K-means	11.0	10.6	10.4	11.6	11.0	10.6
Elbow: K-medoids	11.0	10.8	10.4	12.2	11.8	11.6
Elbow: Fuzzy c-means	11.2	11.2	15.0	11.8	11.2	13.6
DBSCAN	9.5	9.2	9.5	9.6	10.4	10.5
OPTICS	12.0	9.2	8.2	12.0	11.8	12.0
Hierarchical	16.0	16.4	16.6	16.4	16.2	16.4
Fuzzy Overlap	17.0	15.3	15.0	30.0	12.5	12.5

Table 2: Order Estimation complexity and run time comparison with 16-QAM

Algorithm	Complexity ^a	Run Time (s)		
		1024 Samples	2048 Samples	4096 Samples
Elbow: K-means	$O(knt)$	0.998	2.346	5.737
Elbow: K-medoids	$O(k(n-k)^2)$	17.610	82.984	340.963
Elbow: Fuzzy c-means	$O(n)$	3.923	11.236	24.985
DBSCAN	$O(n * \log n)$	0.968	3.666	14.785
OPTICS	$O(n * \log n)$	0.172	0.536	1.915
Fuzzy c-means	$O(n)$	9.029	25.128	54.950
Hierarchical	$O(n)$	0.014	0.0775	0.420

^aSource: Xu & Tian (2015)

(2018a) simulation environment and run on an i7 6500u clocked at 2.6 GHz in Linux Mint 18.3. Randomly generated 8-PSK and 16-QAM data at various SNR levels were applied to each algorithm 500 times in an AWGN channel. The number of samples is varied between 1024, 2048, and 4096 samples. The possible pool of modulation schemes were M-QAM and M-PSK, with $M \in \{2, 4, 8, 16, 32, 64, 128, 256\}$.

Fig. 7(a), Fig. 7(b), and Table 1 illustrate that DBSCAN achieved the highest accuracy for modulation order estimation at a low SNRs. Table 2 shows that hierarchical clustering has the lowest execution time for a

various number of samples when all other variables are kept constant. Comparing each algorithm's complexity with its execution time reveals that there is little correlation between low complexity and execution time, mainly as a result of parameter estimation and iteration requirements. Table 1 shows the SNR in dB where 90% order estimation accuracy for 8-PSK and 16-PSK is achieved for various sample lengths.

The required minimum number of samples depends on the highest modulation order in the pool and the desired accuracy. More samples are required for higher-order modulation schemes to allow a sufficient number of samples per symbol level. Even though DBSCAN demonstrates the best accuracy at low SNR levels, Table 2 shows that it does not scale well when increasing the number of samples. K-means together with the elbow method is, however, only slightly less accurate and scales more linearly when keeping the number of allowed iterations constant, which is confirmed by its Big O complexity.

OPTICS and DBSCAN exhibit interesting behaviour due to their ability to identify noise, which can be seen in Fig. 7(a) and Fig. 7(b), where OPTICS undergoes a drop in accuracy after achieving 100% classification accuracy. However, for both DBSCAN and OPTICS, this behaviour dissipates with a larger number of samples.

5. Final Clustering accuracy and execution time evaluation

The I/Q symbols can be clustered together in order to determine the used modulation scheme's symbol levels in the I/Q plane with the estimated parameters from the order estimation stage (Section 4). These estimated symbol levels can then be used with a classifier in the final stage in order to determine the modulation scheme.

The true number of clusters is used for *known-order* clustering algorithms without estimation for evaluation

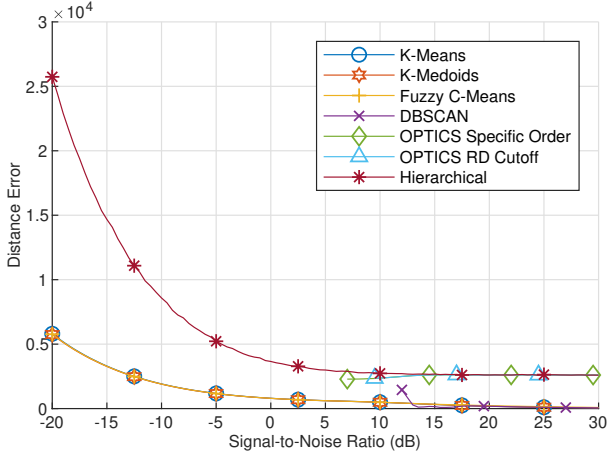


Figure 8: Final Clustering accuracy for 16-QAM.

purposes while the estimated parameters from the order estimation stage (see Fig. 1) are used for *unknown-order* clustering algorithms. OPTICS allows the value of ϵ to be chosen after the data has been clustered. This allows for either the use of a value for ϵ that has been determined in the previous stage or for choosing one that results in a set order. The unknown order clustering algorithms are only tested until the data cannot be clustered into the correct number of clusters, as the estimated symbol levels at that point no longer represent the data.

The clustering algorithms were implemented in a Matlab 2018a simulation environment where randomly-generated bit streams are modulated with the 16-QAM modulation scheme in an AWGN channel. The total distance error is then calculated between each sample and averaged over 500 iterations. The possible pool of modulation schemes were M-QAM and M-PSK, with $M \in \{2, 4, 8, 16, 32, 64, 128, 256\}$. As seen in Fig. 8, all known-order clustering algorithms are comparable in accuracy when determining symbol level locations. The unknown-order clustering algorithms, other than DBSCAN, are also equally accurate, with the only distinction being the lowest SNR where the algorithm can be used. Table 3 shows that, for the Final Clustering stage, hierarchical clustering has the lowest execution time and that k-means scales the best with the number of samples when keeping all other variables constant. This corresponds with the trend observed in Section 4. Execution times were evaluated with the same set up and hardware as in Section 4.4.

6. Final Clustering and Modulation Type Classification

The Modulation Type Classification stage compares the estimated symbol levels from the Final Clustering stage with known symbol levels of modulation schemes in a pool. We will use a simple, deterministic, minimum distance classifier to keep complexity and execution time low. Other classification algorithms can also be used with

Table 3: Final Clustering run time with 16-QAM (s)

Algorithm	Number of samples				
	512	1024	2048	4096	8192
K-means	0.115	0.179	0.269	0.691	2.408
K-medoids	0.148	0.730	2.712	11.256	59.312
Fuzzy c-means	0.053	0.129	0.300	0.650	1.592
DBSCAN	0.016	0.671	2.599	12.844	53.757
OPTICS (Specific Order)	0.072	0.240	0.779	3.536	23.701
OPTICS (RD Cutoff)	0.070	0.236	0.777	3.437	24.768
Hierarchical	0.004	0.010	0.043	0.282	2.131

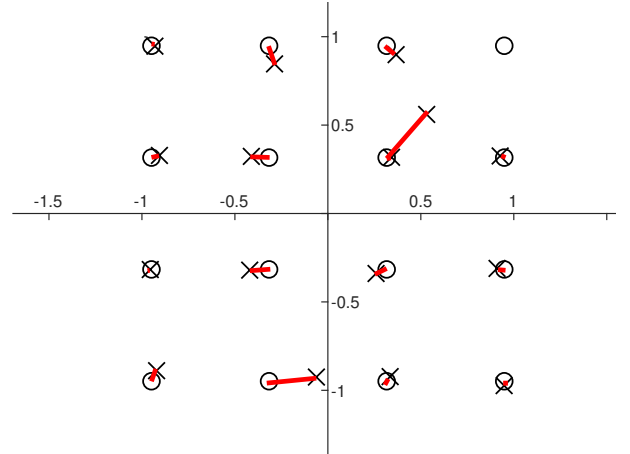
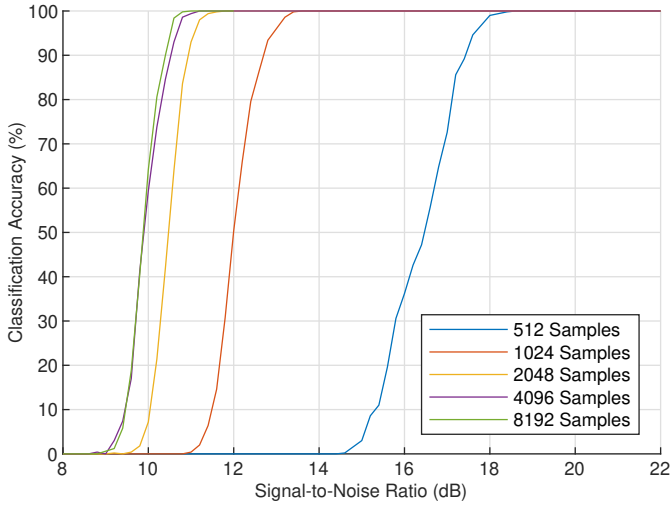


Figure 9: Minimum distance classifier. Estimated locations are marked with an X while actual locations are marked with an O.

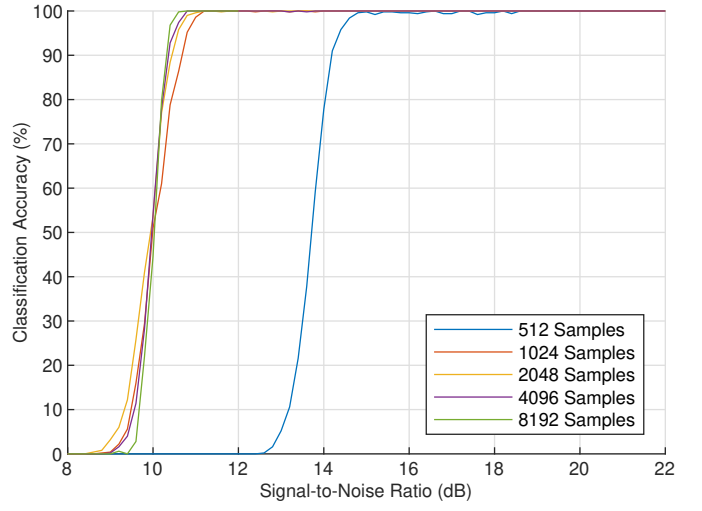
the output of the Final Clustering stage as a feature, as proposed by Ali et al. (2017). As shown in Fig. 9, the distance between each estimated symbol level (X) and its closest reference symbol level (O) can be calculated and summed together for a total distance error for each modulation scheme with the same number of symbols. The modulation scheme with the lowest score is then accepted as the most likely used modulation scheme.

7. Performance evaluation of the proposed AMC method

The AMC method described in Fig. 1 was created in a Matlab (2018a) simulation environment using the best performing algorithm from Section 4 and Section 6. The elbow method with k-means is proposed for order estimation and k-means for Final Clustering. The k-means clustering algorithm was chosen for its accuracy and scaling with a larger number of samples, as discussed in Section 4 and Section 6. The possible pool of modulation schemes were M-QAM and M-PSK, with $M \in \{2, 4, 8, 16, 32, 64, 128, 256\}$. An SNR step size of 0.2dB was used with each SNR level repeated 500 times. The number of samples was varied between 512, 1024, 2048, 4096, and 8192 samples. Fig. 10(a) and Fig. 10(b) show the classification accuracy for 16-QAM and 8-PSK respectively in an AWGN channel with a varying sample length.

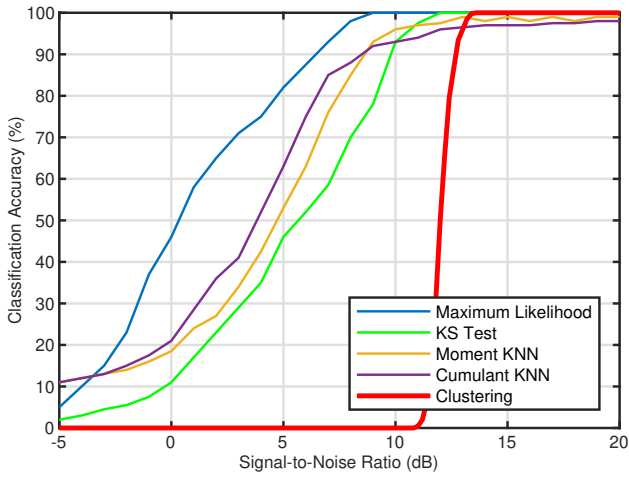


(a) 16-QAM.

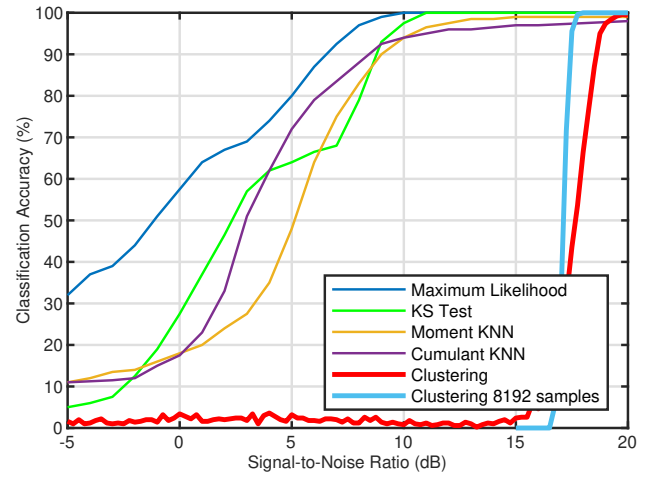


(b) 8-PSK.

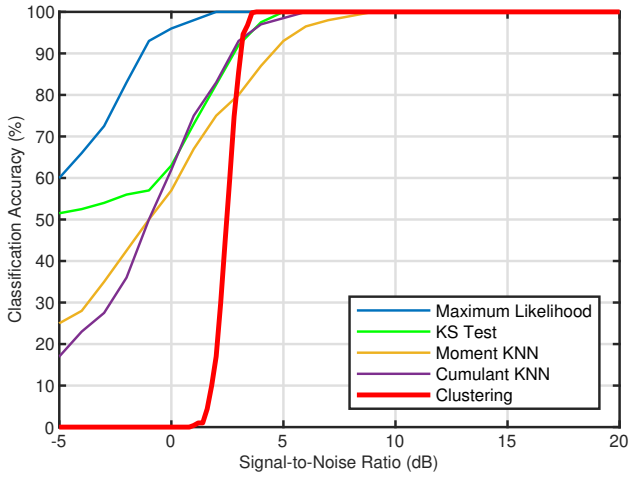
Figure 10: Classification accuracy of proposed AMC method at various sample sizes



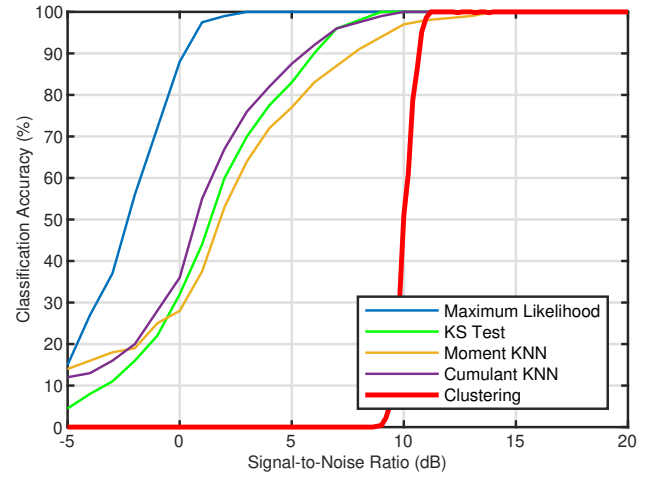
(a) 16-QAM.



(b) 64-QAM.



(c) Q-PSK.



(d) 8-PSK.

Figure 11: Classification accuracy of proposed AMC method (red) vs. popular AMC methods.

Fig. 10(a), Fig. 10(b), and Table 1 illustrate that the required minimum number of samples depends on the highest possible order in the pool of possible modulation schemes. Therefore, a certain minimum number of samples for each symbol level is required for clustering algorithms to be viable for AMC. However, the accuracy gain does not scale linearly when increasing the number of samples, leading to an optimal number of samples that depends on the highest order modulation scheme in the pool.

8. Comparison with popular AMC methods

In 2015, Zhu & Nandi (2015) published “Automatic Modulation Classification Principles, Algorithms and Applications” in which the most popular AMC methods were simulated on the same test platform to provide an equal comparison between the following methods:

- The Maximum Likelihood Ratio Test (MLRT)
- The Kolmogorov Smirnov (KS) Test
- High order cumulants with a K-Nearest Neighbour (KNN) classifier
- High order moments with a KNN classifier

Zhu & Nandi (2015) did not examine clustering techniques as these methods are relatively unexplored in literature. In Zhu’s comparison between the above mentioned AMC methods, 1024 samples were used for all methods and modulation orders. Accurate channel information was also used where required in order to represent ideal situations for each AMC method. The pool of possible modulation schemes evaluated were 2-PAM, 4-PAM, 8-PAM, BPSK, QPSK, 8-PSK, 4-QAM, 16-QAM, and 64-QAM. Figs. 11(a) - 11(d) show the classification accuracy for 16-QAM, 64-QAM, Q-PSK, and 8-PSK respectively. Execution times were not stated in the related work.

Figure 11(a)-11(d) show that the proposed clustering-based method’s classification accuracy drops off at a faster rate in low SNR situations when compared with the other methods. The proposed method is, however, capable of 100% classification accuracy at a similar SNR for lower order modulation schemes. The proposed method also has benefits not present in other AMC methods. A larger number of samples is recommended for higher-order modulation schemes like 64-QAM as each cluster will contain fewer samples. For example, if 1024 samples are used, 8-PSK will have 128 samples for each symbol level while 64-QAM will only have 16, assuming each symbol level appears equally often.

The nature of the operation of the elbow method allows it to also give a measurement of how intact the underlying geometry of the constellation remained during transmission depending on how pronounced the elbow is. This behaviour can allow the proposed method to fail in a way, that when the SNR is too low, a *could not classify* state

is given rather than a false positive. This will allow the proposed method to classify modulation schemes with a higher degree of confidence in sub-optimal environments than related work.

9. Conclusion

Clustering algorithms for the use of AMC are relatively unexplored in literature. The experiments conducted in Section 4, Section 6 and Section 7 show that clustering algorithms can be used in various ways that delivers benefits that other AMC methods do not.

In Section 4 and Section 6, the order estimation accuracy and classification accuracy were tested as functions of SNR and the number of samples. The best performing clustering algorithms from each section were then assembled to form a proposed AMC method based on clustering algorithms and compared to other popular methods in Section 7. The results show that increasing the number of samples allows for accurate classification at lower SNR levels. This will allow the proposed AMC method to be tuned for certain applications where either execution time or classification accuracy is preferred by changing the number of samples. Therefore, the low complexity and fast execution time will enable lower-end devices to classify lower order modulation schemes.

In Section 8 the proposed method was compared with popular techniques in literature. Figs. 11(a) - 11(d) show that clustering-based techniques have a sharper drop-off in accuracy compared to MLRT, the KS test, and moments and cumulants with a KNN classifier. These figures also show that the proposed method achieves 100% classification accuracy at a similar SNR compared other methods, if a sufficient number of samples is used.

As discussed in Section 4.1, we limit the allowed number of iterations in the k-means algorithm. This allows us to know the exact number of operations conducted and therefore allows the proposed method to be deterministic with a known consistent execution time. The proposed method also allows for a large pool of possible modulation schemes, only requiring a unique representation in the I/Q plane. In contrast to several methods in literature, the proposed method, does not rely on machine learning or absolute thresholds and therefore does not require training or threshold calibration. Future work will focus on exploring the proposed method’s ability to detect false positives and evaluating the performance under European Telecommunications Standards Institute (ETSI) multipath conditions.

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3.3 Paper 2

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In the second paper, we use the best-performing algorithms from the previous paper to construct the proposed method. An additional parameter, the *Classification Quality* (ϵ), is extracted that can be used to identify and reject incorrect classifications. The nature of this parameter is extensively evaluated and discussed. We show that a too low cut-off value will allow incorrect classifications at low SNRs, while a too high cut-off value only allows classification at higher SNRs. The *Classification Accuracy* is then again compared to other methods, as in the first paper, when rejecting low ϵ -value classifications. We demonstrate that a 100% *Classification Accuracy* can be achieved without incurring incorrect classifications at low SNRs, with a carefully chosen ϵ cut-off value.

Performance Evaluation of a Clustering-based Automatic Modulation Classification Method

Jacques Mouton, Melvin Ferreira, Albert Helberg
School of Electrical, Electronic and Computer Engineering,
North-West University, Potchefstroom Campus, South Africa

¹24911658@student.nwu.ac.za ²melvin.ferreira@nwu.ac.za ³albert.helberg@nwu.ac.za

Abstract—In this paper, we present an Automatic Modulation Classification (AMC) method based on the k-means clustering algorithm. The proposed AMC method is entirely deterministic and does not require any training. The proposed method is described in detail and then evaluated in an Additive White Gaussian Noise (AWGN) channel with M-Phase Shift Keying (PSK) as well as M-Quadrature Amplitude Modulation (QAM) for various sample lengths. We extract a parameter that we can use to detect incorrect classifications that we define as the *Classification Quality* (ϵ). The results are compared to other popular AMC methods. We show that 100% *Classification Accuracy* is achieved at similar Signal-to-Noise Ratios (SNRs) for lower order modulation schemes. The proposed method allows 100% *Classification Accuracy* by rejecting classifications with a low *Classification Quality* to eliminate false positives in a large pool of possible modulation schemes while maintaining low algorithmic complexity.

Index Terms—Automatic Modulation Classification, I/Q Plane, k-means, Clustering

I. INTRODUCTION

Automatic Modulation Classification (AMC) refers to a process where the modulation scheme of a signal is identified without the need for human interaction. At no point is it a requirement to demodulate the signal or recover the original data [1]. AMC has several applications in both the civilian and military sector. In the civilian sector, AMC can be used to monitor the electromagnetic spectrum and enforce frequency allocations. AMC can also be used to create cognitive radios that are capable of sensing the electromagnetic spectrum and automatically use the optimal modulation scheme. In the military sector, a signal of interest can be better jammed or even demodulated if the modulation scheme can be identified. AMC methods can typically be split into two different categories, namely, Likelihood-based and Feature-based methods. In Likelihood-based methods, a hypothesis test is performed against known models with the most popular approaches including the Average Likelihood Ratio Test (ALRT) [2], Generalised Likelihood Ratio Test (GLRT) [3] and the Hybrid Likelihood Ratio Test (HLRT) [3]. These approaches require accurate channel parameterisation, else *Classification Accuracy* will decrease severely with inaccurate parameters [1]. Feature-based approaches extract parameters of a signal, referred to as features, and compares them to known models with a classification algorithm. Some of the most popular features include higher-order moments and cumulants. In most approaches, a machine learning technique is used to match the features to a known modulation scheme. These machine

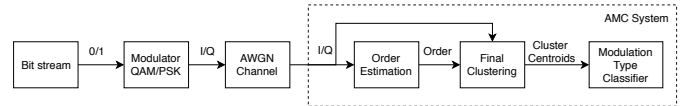


Fig. 1. Stages of the proposed AMC method

learning techniques require extensive training for specific channel conditions [1].

The proposed AMC method in this paper consists of multiple stages, shown in Fig. 1, with the scope of the AMC method shown inside the dotted line. The Order Estimation stage estimates the modulation order by detecting the number of symbol levels by using the *Elbow Method* [12]. This is then used in the Final Clustering stage to cluster the In-phase and Quadrature (I/Q) samples to estimate the symbol levels' location in the I/Q plane. Lastly, in the Modulation Type Classification stage, the estimated symbol locations are compared with the locations of known modulation schemes in order to classify the unknown signal's modulation scheme.

The rest of the paper is ordered as follows, a brief overview of the k-means clustering algorithm is given in Section II, the Order Estimation stage is described in Section III, and the exact implementation of the *Elbow Method* and the extraction of the *Classification Quality* parameter (ϵ) is discussed in detail. The Final Clustering stage, as well as the Modulation Type Classification stage, is described in Section IV. The performance of the proposed AMC method is then evaluated in an AWGN channel and compared to other methods in Section V with a conclusion drawn in Section VI.

II. THE K-MEANS CLUSTERING ALGORITHM

The k-means clustering algorithm [4], is one of the most well-known clustering algorithms. In its simplest form, the algorithm requires as input the data to be clustered, the number of clusters as well as the stopping condition. The algorithm can be summarised in a few steps:

- 1) Initialise starting clusters randomly.
- 2) Assign each data point to the closest cluster centre using a distance metric.
- 3) Re-calculate the location of the centre of each cluster as the average of its assigned data points.
- 4) Calculate the objective function as the sum of the distances between each data point and its assigned cluster centre.

- 5) Repeat steps 2-4. Stop if the objective function is below the stopping condition threshold or the iteration limit is reached.

The k-means algorithm is therefore said to be $O(knt)$ complex in Big O notation, meaning that it scales linearly with the number of samples (n), iterations (t) and the number of clusters (k). In its original form, the k-means algorithm begins with random cluster centres. This was improved upon with the k-means++ algorithm [5]. This algorithm can be seen as a pre-processing step to determine more suitable initial cluster centres. This improvement results in a significant increase in the rate of convergence of the k-means algorithm and therefore reduces the execution time. It has been observed during testing that increasing the iteration limit past 50 iterations does not increase the *Classification Accuracy*. The number of iterations is therefore limited to 50 iterations, making the proposed method deterministic, on operations. Other clustering algorithms could also be used rather than k-means. K-means was, however, chosen for its ability to accurately calculate cluster centres, low complexity and scalability with respect to the number of samples.

III. MODULATION ORDER ESTIMATION

Digital modulation schemes can be represented in the I/Q plane where each sample is represented by a single point. The I/Q samples are scattered around certain points (in an AWGN channel) where the centre of each cluster represents a symbol level. The objective of the Order Estimation stage is to determine the number of clusters present and therefore the modulation order.

A. Related Work

Some noteworthy methods of estimating the modulation order using I/Q data include:

- Density-based clustering algorithms like Ordering Points To Identify the Clustering Structure (OPTICS) and Density-Based Spatial Clustering of Applications with Noise (DBSCAN) [6], [7].
- Starting with a large number of clusters and using fuzzy c-means clustering and iteratively merge clusters based on the degree of membership [8], [9].
- Using Subtractive Clustering, a technique similar to Hierarchical Clustering [10], [11].

Many AMC methods do not explicitly estimate the modulation order as each possible combination of modulation order and modulation type can be regarded as a separate entity. Estimating the modulation can improve *Classification Accuracy* in some AMC methods by reducing the pool of possible modulation schemes.

B. The Elbow Method

The *Elbow Method* [12], is used to choose the optimal value of a parameter in a system by examining the effect of changing this parameter on some objective function. We will first define the distance error (e_d) as the sum of the Euclidean

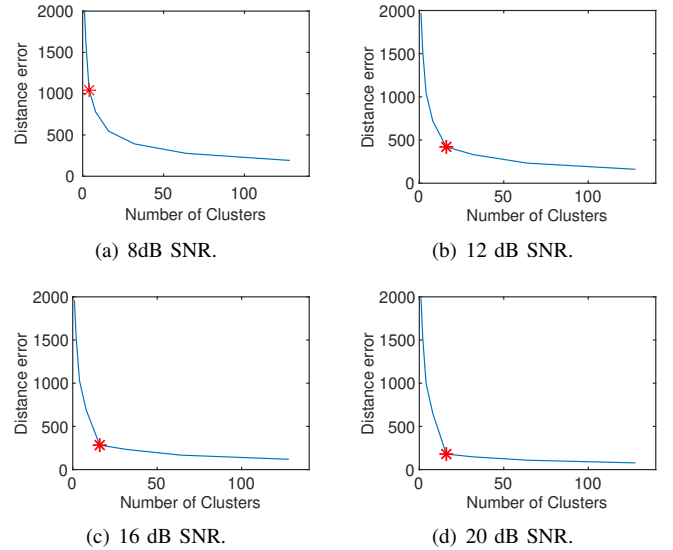


Fig. 2. Effect of SNR on the elbow method with k-means for 16-QAM.

distances between all I/Q samples and their assigned cluster's centre as given by:

$$e_d = \sum_{k=1}^N \sqrt{(C_{di} - D_{ki})^2 + (C_{dq} - D_{kq})^2} \quad (1)$$

where:

- N is the number of samples.
- D is an individual I/Q sample with i and q denoting the In-Phase and Quadrature values, respectively.
- C_d is the sample k 's assigned cluster's centre with i and q denoting the I/Q values, respectively.

We cluster I/Q data into all possible number of clusters in a pool using the k-means clustering algorithm and then calculate the distance error for each number of clusters. A sharp bend, or elbow, will form at the correct number of clusters; if the SNR is high enough.

Fig. 2 shows the elbow method applied to a 16-QAM signal with 8, 12, 16 and 20 dB SNR respectively in an AWGN channel. The elbow becomes more identifiable as the SNR increases. We measure how pronounced the elbow is and use it as the *Classification Quality*, that we will define as ϵ .

1) *Elbow Method algorithm*: The exact implementation of the elbow method can be summarised as follows:

- 1) Cluster the data into each number of clusters in a pool and calculate the distance error using Eq. (1).
- 2) Calculate what percentage each distance error differs from the previous one as:

$$\frac{e_d[n-1] - e_d[n]}{e_d[n-1]} * 100 \quad (2)$$

- 3) The number of clusters with the highest *Percentage Difference* is then accepted as the true number of clusters.
- 4) We define the difference between the highest and second highest *Percentage Difference* as the *Classification Quality* (ϵ).

TABLE I
THE ELBOW METHOD APPLIED TO 16-QAM

Number of Clusters	Distance Error	Percentage Difference
1	1975.50	-
2	1540.70	22.010
4	1034.60	32.847
8	676.92	34.573
16	286.65	57.653
32	231.86	19.114
64	166.72	28.097
128	118.82	28.731

We will use 16-QAM with 2048 samples and 16 dB SNR in an AWGN channel for illustration purposes. As shown in Table I the distance error is calculated for a number of clusters in $M \in \{1, 2, 4, 8, 16, 32, 64, 128\}$. Sixteen clusters have the highest *Percentage Difference* and eight clusters the second highest of 57.653% and 34.573%, respectively, resulting in an ϵ value of 23.8.

IV. MODULATION TYPE CLASSIFICATION

A parameter related to the goodness of fit, such as the previously mentioned distance error, is a powerful tool for extracting information from an arbitrary cartesian plane. Although the exact implementation of such a parameter is not alike for all instances, its frequent use in related literature shows its importance [6], [9], [13], [14].

In our implementation, the *I/Q* data is clustered together using the k-means algorithm in the Final Clustering stage, with the number of clusters estimated in the Order Estimation stage. The centres of these clusters represent the estimated symbol level locations.

These estimated symbols are first normalised in the *I/Q* plane. The Euclidean distance between each estimated symbol level and its closest symbol level for a known modulation scheme is then calculated and summed together to calculate a parameter that we will define as the *Model Mismatch Error*. This is then repeated for all modulation schemes in a pool with the same order. The modulation scheme with the lowest *Model Mismatch Error* is accepted as the correct modulation scheme. This can be seen as demonstrated in Fig. 3 where 16 estimated symbol levels (represented by X) are compared to the known symbol levels of 16-QAM (represented by O). The *Model Mismatch Error* is the distance of all the error vectors summed together. The modulation type with actual symbol levels most closely representing the estimated symbol levels will have the lowest *Model Mismatch Error*.

V. PERFORMANCE EVALUATION IN AN AWGN CHANNEL

Random *I/Q* samples are generated in Matlab 2018b and passed through an AWGN channel while varying the SNR. The test is repeated 1000 times for each SNR while recording the percentage of correct classifications as the *Classification Accuracy*. All constellations are normalised and set up as in [1]. The pool of possible modulation schemes consists of M-QAM and M-PSK with $M \in \{2, 4, 8, 16, 32, 64, 128, 256\}$.

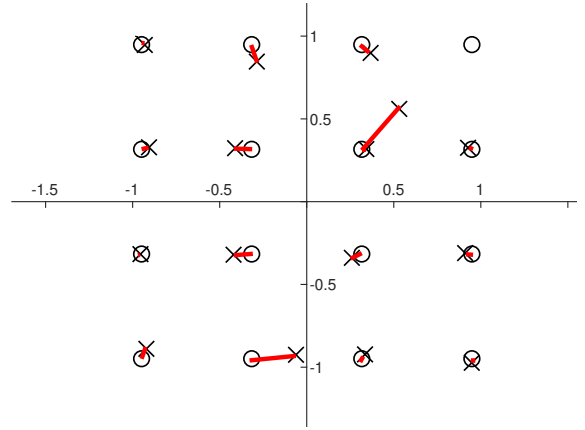


Fig. 3. Comparing 16 estimated symbol levels with 16-QAM

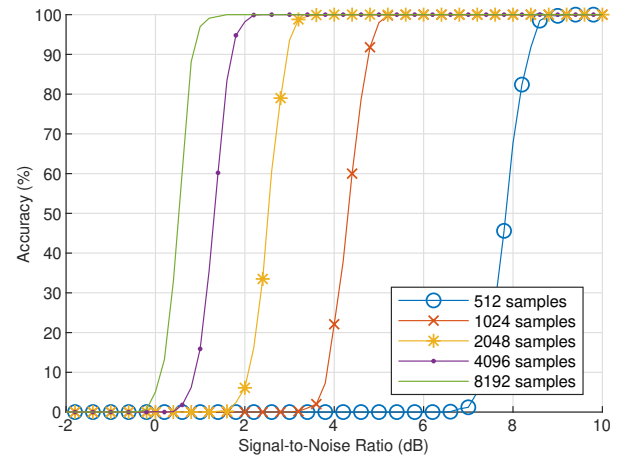


Fig. 4. QPSK Classification Accuracy

A. Effect of the number of samples

The number of samples has a substantial effect on both the run time and *Classification Accuracy*, as with other AMC methods. Fig. 4 and Fig. 5 shows the *Classification Accuracy* as a function of SNR for a different number of samples for QPSK and 64-QAM respectively. Table II shows the SNR where 95% *Classification Accuracy* is achieved for several other modulation schemes with a different number of samples. From these results, we can see that the *Classification Accuracy* has a near binary response and that the *Classification Accuracy* increases at low SNRs as the number of samples increase. This increase in *Classification Accuracy* is, however, not linear and not the same for all modulation schemes. This phenomenon is highlighted in Fig. 6, showing the SNR at which 100% *Classification Accuracy* is achieved as a function of the number of samples. A larger number of samples is therefore required for higher-order modulations due to the fact that as the modulation order increase, the number of examples of each symbol will decrease.

B. Classification Accuracy when rejecting low-quality classifications

A parameter, the *Classification Quality* (ϵ), can be extracted from the elbow method, as discussed in Section III-B. The

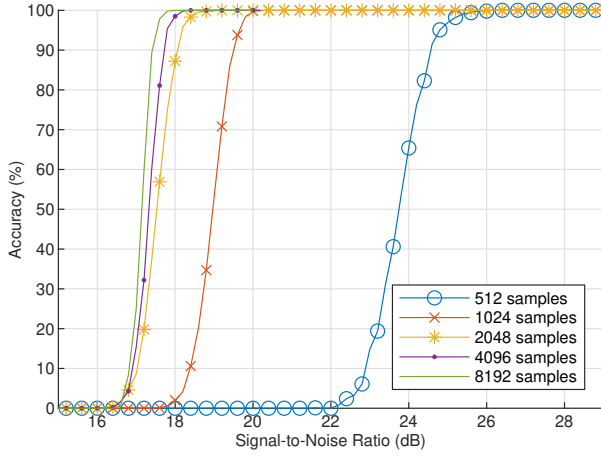


Fig. 5. 64-QAM Classification Accuracy

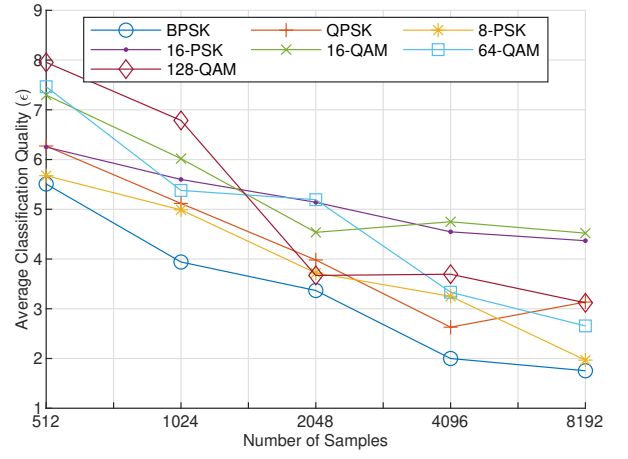


Fig. 7. Average ϵ at 100% Classification Accuracy

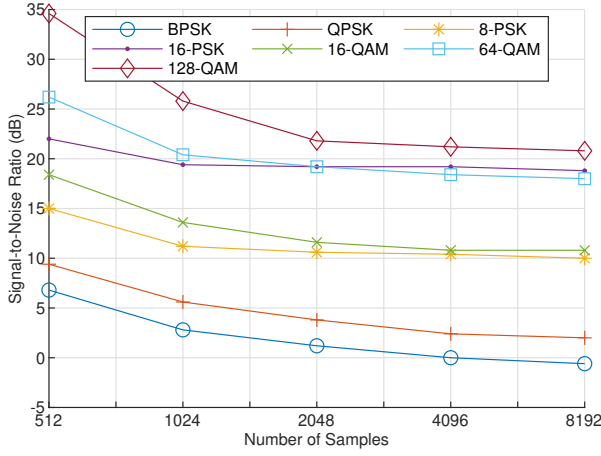


Fig. 6. The SNR at which 100% Classification Accuracy is achieved

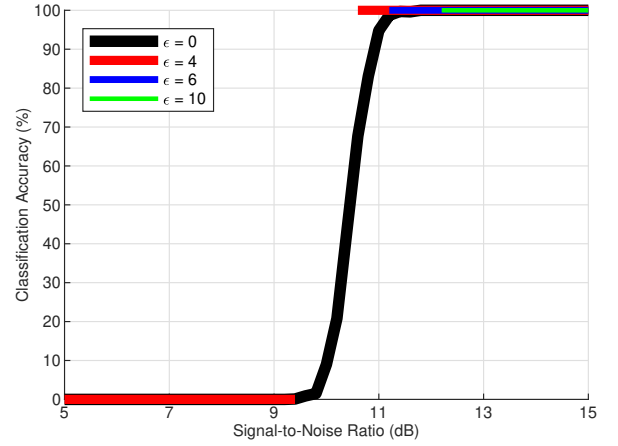


Fig. 8. 16-QAM Classification Accuracy with an ϵ cut-off

angle that the elbow forms will increase as the SNR increases, the classification can then be rejected if ϵ is below a specific value.

1) ϵ cut-off value selection: We can choose an adequate ϵ value by examining the average value where 100% Classification Accuracy is achieved. Fig. 7 shows these average ϵ values for several modulation schemes as a function of the number of samples. It can be seen that the average value of ϵ at 100% Classification Accuracy is dependant on the type of modulation, the modulation order as well as the number of samples. This is mainly due to the distance between the symbols in the I/Q plane for each modulation type and the fact

that the accuracy of cluster centre locations increases as the number of samples increase. A cut-off value higher than the highest average ϵ value at 100% Classification Accuracy for each number of samples should then be used for that specific number of samples. For example, classifications with 2048 samples with an ϵ value lower than 6 should be rejected.

2) Classification Accuracy with ϵ : A simulation was run using the same set up as in Section V-A with several ϵ cut-off values. Fig. 8 shows the Classification Accuracy for 16-QAM with different threshold values where an ϵ cut-off value of 0 represents accepting all classifications. Regions, where no classifications resulted in an ϵ value above this threshold, is not shown.

Fig. 9 shows the percentage of the classifications above the ϵ cut-off value as well as the average ϵ value. We can see that an ϵ cut-off value of 6, as previously suggested, allows 100% accurate Classification Accuracy above 11.2 dB SNR with no incorrect classifications. A too low cut-off value will allow incorrect classifications at lower SNRs while a too high cut-off value only allows classifications at higher SNRs.

TABLE II
SNR IN DB AT 95% CLASSIFICATION ACCURACY (%)

	512 Samples	1024 Samples	2048 Samples	4096 Samples	8192 Samples
BPSK	6.1	2.4	0.8	-0.2	-0.8
QPSK	8.5	4.9	3.1	1.8	1.0
8-PSK	14.3	10.6	10.1	9.9	9.8
16-PSK	21.6	19.0	18.8	18.7	18.7
16-QAM	17.6	12.8	11.0	10.7	10.4
64-QAM	24.8	19.6	18.2	17.8	17.6
128-QAM	32.0	23.7	21.2	20.4	20.1

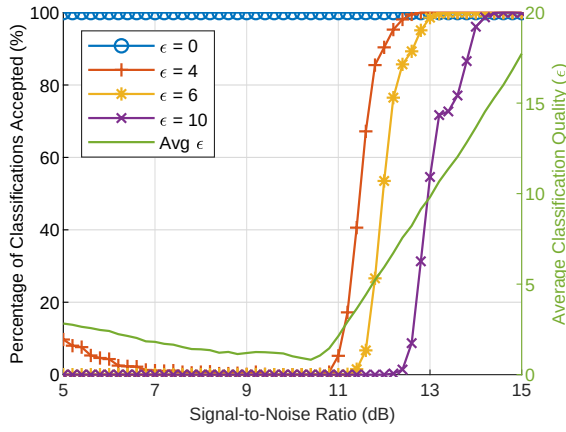


Fig. 9. Percentage 16-QAM Samples Classified

C. Classification Accuracy compared to other methods

Although AMC is a popular research topic, no standardised testing method exists for evaluating and comparing methods with each other. This is also true for clustering-based methods in literature [6]–[8], [10], [11], [13]–[17]. Several of these methods use an extremely small pool of possible modulation schemes which dramatically improves the *Classification Accuracy* at low SNRs. Several of these methods do not provide the complete experimental set-up or *Classification Accuracy* as a function of SNR making it difficult to compare AMC methods adequately. Several other factors that are commonly not stated could also influence the *Classification Accuracy*, such as the size of the pool of possible modulation orders; the pool of possible modulation techniques; and if the modulation's symbol mapping in the I/Q plane has been normalised. It is therefore essential to have a clearly defined experimental set-up.

In 2015 Zhu et al. [1], set up and compared a wide range of popular AMC methods including a Maximum Likelihood (ML) technique, the Kolmogorov Smirnov (KS) test as well as higher order moments and cumulants with a K-Nearest Neighbour (KNN) classifier. Clustering in the I/Q plane was not evaluated. This test environment was duplicated and tested with our proposed clustering based method. Zhu et al. used a reduced pool of possible modulation schemes compared to our previous results consisting of $Modulation \in \{2-PAM, 4-PAM, 8-PAM, BPSK, QPSK, 8-PSK, 4-QAM, 16-QAM, 64-QAM\}$ with 1024 samples for all of the AMC methods. These results can be seen in Fig. 10 through 13 for 4-QAM, 16-QAM, BPSK and 8-PSK respectively. 1024 samples were used in all tests with an appropriate cut-off value of 7.75 for ϵ chosen from Fig. 7. The *Classification Accuracy* without this consideration is also shown. It should be noted that increasing the number of samples will increase the *Classification Accuracy*, as shown in Table II and Fig. 6.

Comparing the *Classification Accuracy* of 4-QAM in Fig. 10 with the *Classification Accuracy* of QPSK with 1024 samples in Fig. 4 demonstrates the relevance of the size of the pool of possible modulation schemes. With the reduced pool of possible modulation schemes, 100% *Classification Accuracy*

is achieved at 4 dB SNR while the larger pool requires 5.2 dB SNR. The size of the pool of possible modulation schemes affects the vast majority of AMC methods and is a critical factor to consider when evaluating an AMC method.

From Fig. 10-13, we can see that 100% classification is achieved at a similar SNR while maintaining several other benefits. ϵ can be used to ensure that only correct classifications are accepted and improve accuracy at lower SNRs with a carefully selected ϵ cut-off value.

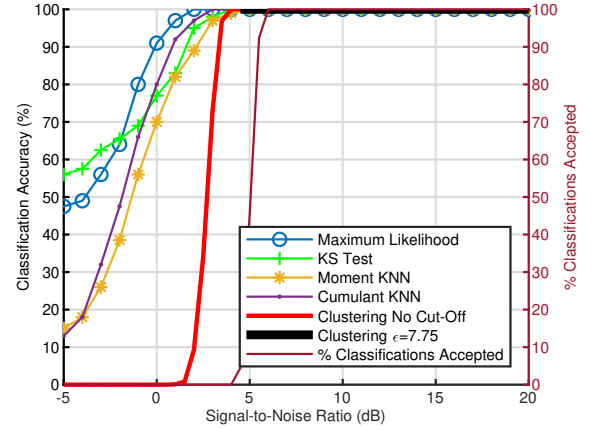


Fig. 10. AMC 4-QAM classification accuracy with [1]

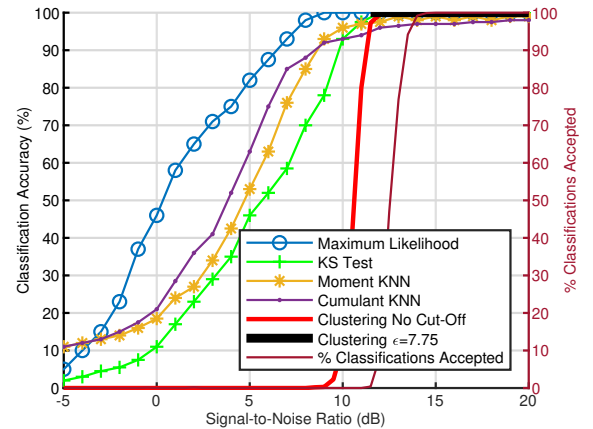


Fig. 11. AMC 16-QAM classification accuracy with [1]

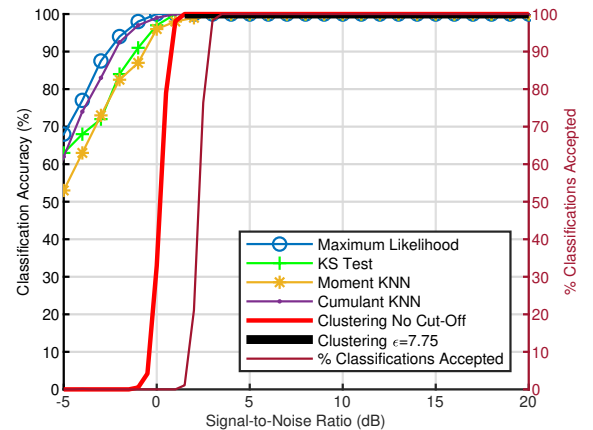


Fig. 12. AMC BPSK classification accuracy with [1]

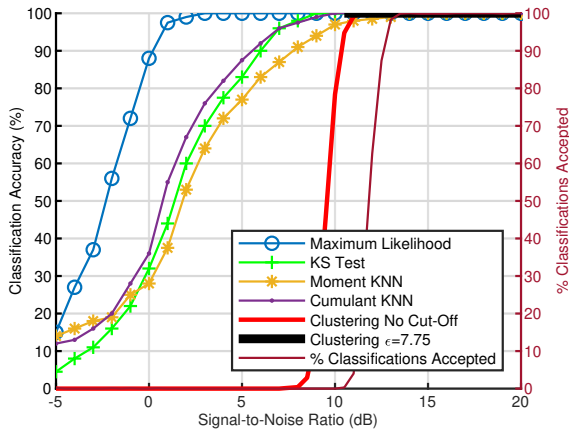


Fig. 13. AMC 8-PSK classification accuracy with [1]

VI. CONCLUSION

The proposed method has several significant benefits compared to other popular AMC methods:

- Low complexity with good scalability resulting in low execution time.
- No training is required.
- No thresholds need to be set by humans if ϵ is not taken into account.
- Incorrect classifications can be eliminated by rejecting classifications with a low ϵ value.
- The proposed method is deterministic in number of operations.
- The proposed method can be used with a large pool of possible modulation schemes.
- The proposed method can be used with any modulation scheme that has a unique representation in the I/Q plane.
- A balance between execution time and *Classification Accuracy* can be reached by changing the number of input samples.

These attributes can be extremely beneficial in applications where false classifications can't be allowed, such as spectrum use enforcement. The ideal implementation of this AMC method is envisioned as part of a larger AMC system where signals can be quickly classified with the proposed method. Classifications with a low ϵ value can then be classified by another AMC method that might have better *Classification Accuracy* at low SNRs at the cost of execution time. This will allow such an AMC system to classify a large number of signals in a small amount of time while the proposed method will allow 100% *Classification Accuracy* with a large pool with no false positives. Future work will focus on evaluating the proposed method in a simulated multipath channel environment as well as testing with real signals using a hardware in the loop configuration.

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Jacques Mouton received his engineering degree in 2017 and is currently a second year M.Eng student at the North West University in South Africa. Currently he is working on Automatic Modulation Classification as a member of the TeleNet research group in the Telkom CoE.

3.4 Paper 3

Title: Evaluation of a Clustering-based Modulation Classification under ETSI Multipath Channels

Publication type: Journal

Journal name: Transactions on Cognitive Communications and Networking (TCCN)

Publisher: IEEE

ISSN: 2332-7731

Publication date: Under review at the time of writing

In the third paper, we examine the proposed method under ETSI multipath conditions, while rejecting low ϵ -value classifications. We show that certain channel conditions result in a short enough coherence time that 100% *Classification Accuracy* is never achieved at any SNR. However, we can use ϵ to identify when the time of sampling aligns with the coherence time of the channel and reject classifications outside this time period, allowing in 100% *Classification Accuracy* without any incorrect classifications.

Both a single and a double-column version was submitted, with the double-column version being provided here.

Evaluation of a Clustering-based Modulation Classification Method under ETSI Multipath Channels

Jacques Mouton, Melvin Ferreira and Albert Helberg *School of Electrical, Electronic and Computer Engineering, North-West University, Potchefstroom Campus, South Africa*

Email: ¹24911658@student.nwu.ac.za ²melvin.ferreira@nwu.ac.za

³albert.helberg@nwu.ac.za

Abstract—In this paper, we present an Automatic Modulation Classification (AMC) method based on clustering samples in the In-phase and Quadrature (I/Q) plane using the k-means clustering algorithm. A parameter, the *Classification Quality*, ϵ , is extracted and used to detect and reject incorrect classifications. The effect of the number of samples on the performance, and ϵ is tested and discussed. Our proposed method is evaluated with 8-Phase Shift Keying (PSK) and 16-Quadrature Amplitude Modulation (QAM) using the European Telecommunications Standards Institute (ETSI) models for multipath environments as adopted for use in 3GPP version 15. We show that 100% *Classification Accuracy* can be achieved in sub-optimal channel conditions by detecting and eliminating false positives. The proposed method does not rely on machine learning, is deterministic in the number of operations and has low algorithmic complexity, which results in low execution times while maintaining a large pool of possible modulation schemes.

¹ **Index Terms**—Automatic Modulation Classification, I/Q plane, K-means clustering, Multipath, Constellation, Centroid estimation

I. INTRODUCTION

AMC (Automatic Modulation Classification) refers to a process where the modulation scheme of an unknown signal is identified without the need for human interaction. AMC can be used to monitor the electromagnetic spectrum and enforce frequency allocations or create cognitive radios capable of switching to the optimal modulation scheme based on bandwidth and noise restrictions [1].

AMC methods can typically be split into two categories, namely likelihood-based and feature-based methods. likelihood-based approaches require

accurate channel parametrisation for hypothesis testing. Inaccurate parameters will cause sub-optimal performance. Feature-based approaches extract statistical parameters from a signal for use in a classification algorithm, typically a decision tree or a machine learning algorithm. These usually require thresholds to be set or training for specific channel conditions [1].

The performance of an AMC method that uses I/Q samples with clustering algorithms to determine the modulation scheme has not yet been evaluated in multipath channels. Furthermore, there is no consensus in related work on a standard experimental set-up for evaluating the performance of AMC methods in multipath conditions [2]–[5]. We will use the European Telecommunications Standards Institute (ETSI) Version 15 channel models as adopted for use in 3GPP in a Matlab simulation environment.

The rest of the paper is ordered as follows. An overview of the three stages of our proposed method is given in Section II. The Order Estimation stage is described in Section III, and the implementation of the elbow method and the extraction of the *Classification Quality* parameter (ϵ) is discussed. The Final Clustering stage, and the Modulation Type Classification stage are described in Section IV. The selection of parameters used for simulations is discussed in Section V. The performance of the proposed method is then evaluated in multipath environments in Section VI with 16-QAM and 8-PSK in a large pool of possible modulation schemes. The benefits of the proposed method are discussed and a conclusion is drawn in Section VII.

¹Preprint submitted to IEEE TCCN, 26 November 2019

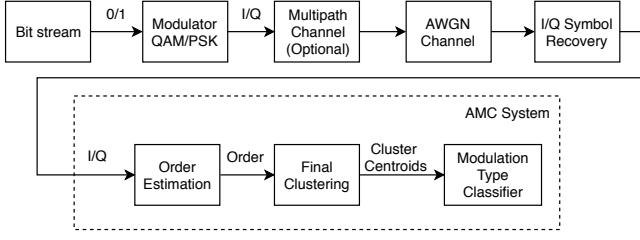


Fig. 1. Stages of the proposed AMC method

II. OVERVIEW OF PROPOSED AMC METHOD

Digital modulation schemes can be represented in the I/Q plane where each sample is represented by a single point. The I/Q samples are scattered around certain points (depending on channel conditions) where the centre of each cluster represents a symbol level. We extract and compare information from the geometry of these points with that of known modulation schemes.

Our proposed method can be split into several stages, as seen in Fig. 1. The Order Estimation stage accepts arbitrary I/Q samples, applies the elbow method with the k-means clustering algorithm and extracts the *Classification Quality* (ϵ) parameter. The Final Clustering stage clusters the I/Q samples into the number of clusters determined in the previous stage with the k-means clustering algorithm. The centres of these clusters are then compared to the constellation representation of known modulation schemes in the Modulation Type Classification stage. We do not consider I/Q symbol recovery as part of the proposed method, as it is considered a research topic on its own and is typically not addressed in the literature related to AMC. The proposed method has $O(knt)$ algorithmic complexity, which means that the execution time will scale linearly with the number of clusters (k), the number of samples (n) and the number of iterations (t). During testing, it was observed that allowing more than 50 iterations does not increase the *Classification Accuracy*. The maximum number of iterations is, therefore, limited to 50. This also allows the proposed method to be deterministic in the number of operations.

III. MODULATION ORDER ESTIMATION

The objective of the Order Estimation stage is to determine the number of clusters present and therefore the modulation order.

A. Related work on modulation order estimation in the I/Q Plane

Some noteworthy methods of estimating the modulation order using I/Q data include:

- Density-based clustering algorithms like Ordering Points To Identify the Clustering Structure (OPTICS) and Density-Based Spatial Clustering of Applications with Noise (DBSCAN) [6], [7].
- Starting with a large number of clusters and using fuzzy c-means clustering and iteratively merging clusters based on the degree of membership [8], [9].
- Using Subtractive Clustering, a technique similar to Hierarchical Clustering [10], [11].

These methods typically have long execution times, require accurate parameters for satisfactory performance or require complex pre-processing steps. We apply the elbow method to estimate the modulation order. Note that modulation order estimation is not necessarily a requirement for all AMC methods. It is also possible to regard each possible combination of modulation order and modulation type as a separate entity. Many AMC methods, therefore, do not explicitly estimate the modulation order.

B. The elbow method

The elbow method [12] is used to choose the optimal value of a parameter in a system by examining the effect of changing this parameter on some objective function.

We will first define the distance error (e_d) as the sum of the Euclidean distances between all I/Q samples and their assigned cluster's centre, as given by:

$$e_d = \sum_{k=1}^N \sqrt{(C_{di} - D_{ki})^2 + (C_{dq} - D_{kq})^2} \quad (1)$$

where:

- N is the number of samples.
- D_k is an individual I/Q sample with i and q denoting the In-Phase and Quadrature values, respectively.
- C_d is the sample k 's assigned cluster's centre with i and q denoting the I/Q values, respectively.

We cluster I/Q data into all possible modulation orders in a pool using the k-means clustering algorithm and then calculate the distance error for

each modulation order. A sharp bend, or elbow, will form at the most probable modulation order if the Signal-to-Noise Ratio (SNR) is high enough. We measure how pronounced the elbow is and define this measurement as the *Classification Quality* (ϵ). Several applications require more sophisticated analysis to correctly identify the elbow, since the algorithm is applied to a more continuous set of variables. Methods such as the L-method, where two lines are fit to the data or analysing the curvature, can be used on continuous variables but has a large computational complexity [13], [14]. We can use a much simpler approach due to the large separation of possible modulation orders as the pool of possible modulation orders increases in steps of 2^n .

The elbow method algorithm: The implementation of the elbow method can be summarised as follows:

- 1) Cluster the I/Q samples into each number of clusters in a pool and calculate the distance error using Eq. (1).
- 2) Calculate what percentage each distance error (n) differs from the previous one ($n - 1$), as:

$$\frac{e_d[n-1] - e_d[n]}{e_d[n-1]} * 100 \quad (2)$$

- 3) The number of clusters with the largest Percentage Difference is then accepted as the true number of clusters.
- 4) We assign ϵ as the difference between the highest and second-highest Percentage Difference.

IV. MODULATION TYPE CLASSIFICATION

A parameter related to the goodness of fit, such as e_d , is a powerful tool for extracting information from an arbitrary Cartesian plane. These parameters extracted from the distance between points in the I/Q plane are frequently used in different ways in related literature [6], [9], [15], [16].

In our implementation, the I/Q data is clustered together using the k-means algorithm in the Final Clustering stage, with the modulation order estimated in the Order Estimation stage. The centres of these clusters represent the estimated symbol level locations.

These estimated symbols are first normalised in the I/Q plane, initially only in terms of amplitude, but then also, optionally, in phase. Normalising the

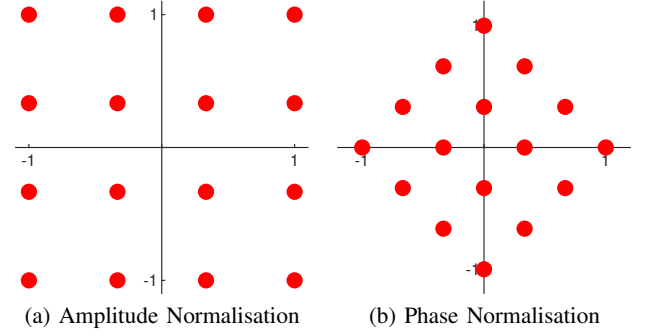


Fig. 2. Normalised 16-QAM Symbol Levels

amplitude involves scaling the symbol levels to a known distance from the centre of the I/Q plane, whereas phase normalisation will also rotate the symbol levels in the I/Q plane so that the furthest point from the centre makes a known angle with an axis. These normalisation methods are shown in Fig. 2 for 16-QAM. Normalising the amplitude only is sufficient for Gaussian environments, but a multipath channel will cause the constellation to rotate, and thus require phase normalisation. A requirement of the modulation schemes in the pool is that each should have a unique representation in the I/Q plane if the constellations are only normalised in terms of amplitude. If the constellation is also normalised in terms of phase, no modulation scheme in the pool should be able to undergo a transformation that will result in another modulation scheme. This means that BPSK and 2-QAM as well as Q-PSK and 4-QAM cannot exist in the same pool of possible modulation schemes, since they are indistinguishable under phase rotation.

The Euclidean distance between each estimated symbol level and its closest symbol level for a known modulation scheme is then calculated and summed to calculate a parameter that we define as the Model Mismatch Error. This is then repeated for all modulation schemes in a pool of the same order. The modulation scheme with the lowest Model Mismatch Error is accepted as the correct modulation scheme, as the symbol levels of the modulation scheme that most closely represent the estimated symbol levels will have the lowest Model Mismatch Error.

V. PARAMETER SELECTION

Several factors affect the performance of any AMC method, some of the most important being the

number of samples, the size of the pool of possible modulation schemes as well as the types of modulation schemes included in the pool. These three factors will affect both the *Classification Accuracy* as well as the execution time.

Simulations were run where various modulation schemes and the number of samples were evaluated with the proposed method in an Additive White Gaussian Noise (AWGN) channel while varying the SNR. The simulations were repeated 1000 times for each SNR with a step size of 0.2dB and with a large pool of possible modulation schemes consisting of M-QAM and M-PSK, with $M \in \{2, 4, 8, 16, 32, 64, 128, 256\}$. The constellations were normalised in terms of amplitude since only an AWGN channel is considered.

A. Effect of the number of samples

Fig. 3 shows the SNR where several modulation schemes could be classified with 100% accuracy as a function of the number of samples. In this figure, the *Classification Accuracy* can be seen to increase at lower SNRs as the number of samples increases. This increase is, however, non-linear and not the same for all modulation schemes. At some point, there is little to no benefit to increasing the number of samples. Higher-order modulation schemes will require a larger number of samples as fewer samples of each symbol level will be present than a lower-order modulation scheme for any fixed number of samples.

B. Classification Quality (ϵ) value selection

As discussed in Section III, the *Classification Quality* parameter ϵ can be extracted from the Order Estimation stage. Classifications with a low ϵ value can then be rejected to avoid incorrect classifications, as ϵ can be seen as a measurement of how intact the constellation remained during transmission. Fig. 4 shows the average value of ϵ where 100% *Classification Accuracy* is achieved for several modulation schemes as a function of the number of samples. It follows that the average value of ϵ is dependant on the number of samples as well as the modulation scheme. An appropriate minimum ϵ value can then be chosen as a value higher than the highest average ϵ value for a known number of samples. A too low ϵ cut-off value will allow incorrect classifications at lower SNRs while a too

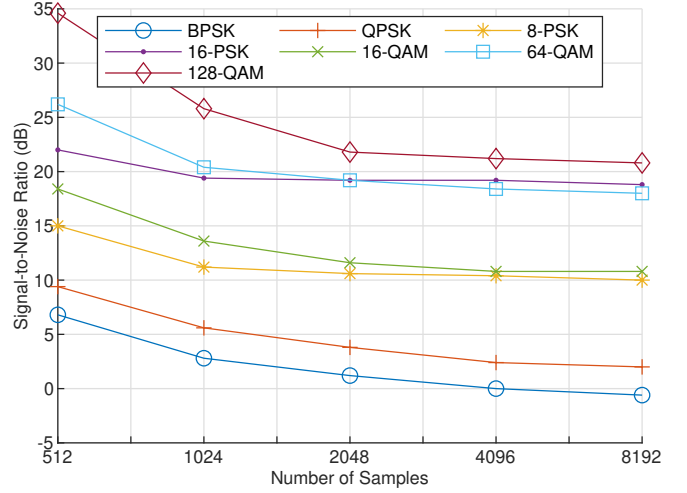


Fig. 3. The SNR at which 100% *Classification Accuracy* is achieved in an AWGN channel for a various number of samples and modulation schemes

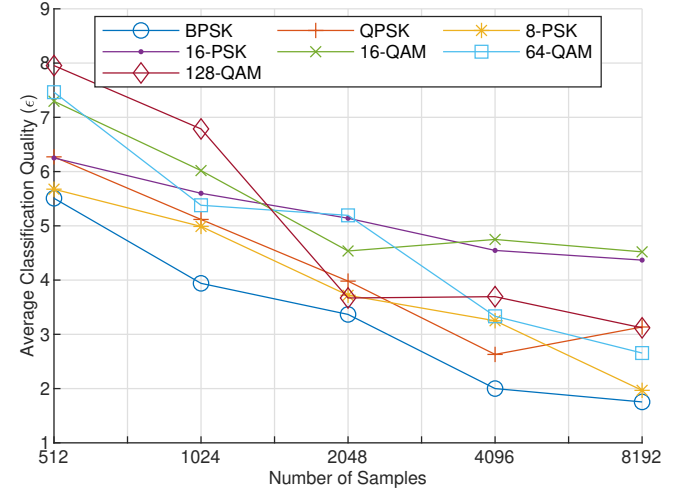


Fig. 4. Average ϵ at 100% *Classification Accuracy* in an AWGN channel

high ϵ cut-off value will only allow classifications at higher SNRs.

VI. PERFORMANCE EVALUATION IN ETSI MULTIPATH CHANNELS

Most AMC methods are typically only evaluated in AWGN channels, and most publications use their own methods for performance evaluation in multipath conditions [2]–[5]. It is, therefore, advisable to use a standardised channel that can be easily replicated to compare different methods. A Tap Delay Line (TDL) approximates a multipath channel by adding delayed versions of a signal where each delay is referred to as a tap [17]. Each tap is charac-

TABLE I
ETSI DELAY PROFILE FOR EPA, EVA AND ETU TDL MODELS
[19]

Tap	EPA		EVA		ETU	
	Tap Delay (ns)	Relative Power (dB)	Tap Delay (ns)	Relative Power (dB)	Tap Delay (ns)	Relative Power (dB)
1	0	0.0	0.0	0.0	0	-1.0
2	30	-1.0	30	-1.5	50	-1.0
3	70	-2.0	150	-1.4	120	-1.0
4	90	-3.0	310	-3.6	200	0.0
5	110	-8.0	370	-0.6	230	0.0
6	190	-17.2	710	-9.1	500	0.0
7	410	-20.8	1090	-7.0	1600	-3.0
8	-	-	1730	-12.0	2300	-5.0
9	-	-	2510	-16.9	5000	-7.0

terised by both a delay in seconds and gain, typically in dB. The delays of these taps typically vary between 1 ns and 100 ns for indoor channel conditions and between 100 ns 10 μ s for outdoor channel conditions. The gain typically varies between 0dB and -20dB [18]. Several AMC methods demonstrate poor performance under these conditions due to being sensitive to phase and frequency offsets [1].

The European Telecommunications Standards Institute (ETSI) provides a TDL model for typical multipath environments, specifically the Extended Pedestrian A (EPA), Extended Vehicular A (EVA) and Extended Typical Urban (ETU) models [19], as adopted in 3GPP version 15.4, with delay-profiles shown in Table I. These models can then be used with a combination of AWGN and maximum Doppler shift to describe a complex multipath channel. A large Doppler shift will have a significant impact on the received I/Q samples. Our proposed method requires that the received I/Q samples retain their geometry with respect to each other. Doppler shifts and multipath noise are typically addressed in a channel-equalisation stage and is typically not seen as part of an AMC method. We will, therefore, focus on lower residual Doppler shifts that may remain after using an equalisation technique [20].

The coherence time of a channel is defined as the duration of time for which the characteristics of the channel remains constant. Movement between the transmitter and receiver will shorten the coherence time [17]. In the I/Q plane, multipath

fading and, especially, phase error introduced by Doppler shifts differ from the diffuse scattering caused by AWGN. Multipath fading distributes the received I/Q samples in a range of arcs around the reference constellation points, due to the phase angle difference. I/Q samples are smeared away from the reference symbol levels in the I/Q plane rather than being scattered around them. This will cause ϵ to vary over a larger range of values, as the noisy I/Q samples may be scattered further from their initial locations when compared to an AWGN channel. A larger ϵ cut-off value is therefore required in multipath conditions. Sampling outside the coherence time of the channel will typically result in unusable data if these channel effects are not compensated for. Fig. 5 shows the channel impulse response and the 16-QAM I/Q data passed through the ETU model with a 5 Hz maximum Doppler shift. This figure demonstrates some of the more extreme channel conditions where the modulation scheme could still be correctly classified as 16-QAM. Note that it requires an intelligent choice of ϵ . This could be done by machine learning or another threshold-setting scheme. Good values of ϵ are also dependent on the channel conditions. Future work may investigate methods of selecting or dynamically varying ϵ cut-off values for desired classification characteristics under variable channel conditions.

The *Classification Accuracy* and the percentage of classifications above the ϵ cut-off value can be seen in Fig. 6 for the EPA, EVA and ETU models with 0 Hz and 5 Hz maximum Doppler shifts. All constellations were normalised both in terms of amplitude and phase, thus disqualifying only 2 – QAM and 4 – QAM from the pool of possible modulation schemes as defined in Section V. The simulations were repeated 1000 times for each SNR with a step size of 0.2dB. Fig. 3 shows that each modulation scheme has a sufficient number of samples, where increasing the number of samples (at the cost of execution time) does not yield a satisfactory increase in *Classification Accuracy*; 8-PSK was, therefore, tested with 1024 samples and 16-QAM was tested with 2048 samples.

We can use ϵ to determine when the sampling time aligns with the coherence time of the channel and only accept those classifications as certain noise conditions result in a short coherence time. From Fig 6, we can see that 100% *Classification Accuracy* can be achieved under conditions where

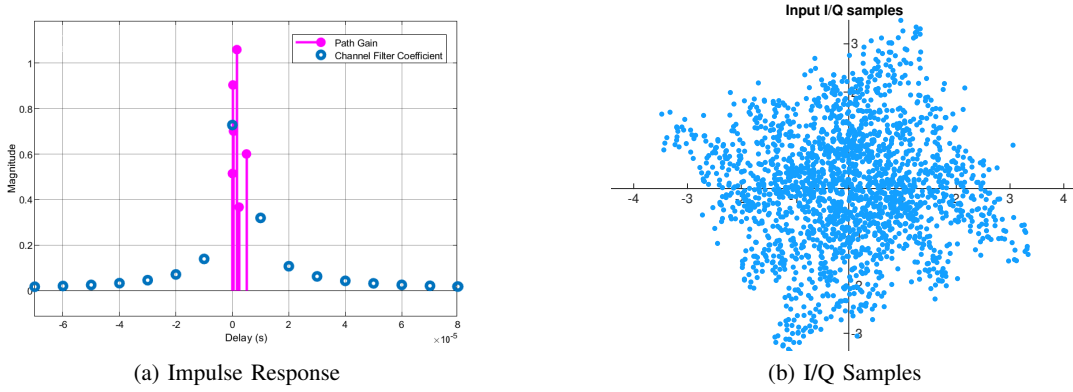


Fig. 5. The response of an ETU channel with a maximum of 5 Hz Doppler Shift

this is typically not possible due to the shortened coherence time induced by the multipath noise by rejecting low ϵ classifications. By doing so, we still achieve 100% *Classification Accuracy* without any false positives.

Any performance evaluation of an AMC method in multipath conditions can be seen as a multi-dimensional analysis where each author may employ their own methodology. We use the ETSI testing conditions in order to allow a basis of comparison for future work as there is currently no consensus in the literature on how to evaluate an AMC method in multipath conditions.

VII. CONCLUSION

Our proposed method does not rely on machine learning and, therefore, does not require any training. Instead, our proposed method relies on the k-means clustering algorithm that is well known for its relatively low complexity and linear scalability. A balance between *Classification Accuracy* and execution time can be reached by changing the number of samples. By limiting the number of iterations, we also allow our proposed method to be deterministic in the number of operations. A large pool of possible modulation schemes can also be used without it having a large impact on the execution time where any modulation scheme with a unique representation, independent of phase rotation, in the I/Q plane can be used. Incorrect classifications can be detected and rejected by rejecting classifications with a low ϵ value, as ϵ is a measurement of how well the constellation remained intact during transmission. The proposed method can function with large phase shifts, as long as the underlying geometry of the

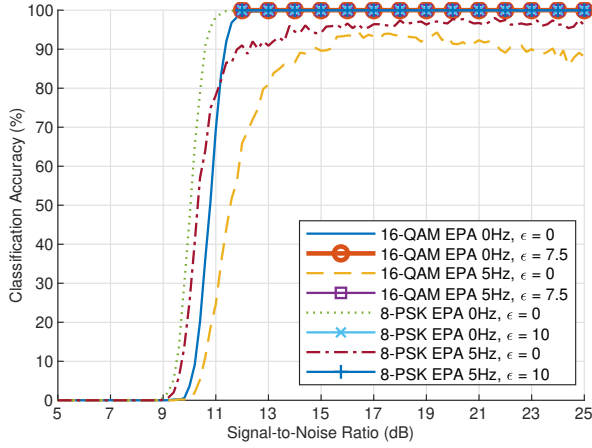
reference symbol levels remains intact with regard to each other.

These attributes are critical for applications where incorrect classifications cannot be allowed, such as spectrum use enforcement. The proposed method allows 100% *Classification Accuracy* in sub-optimal channel conditions and eliminates incorrect classifications while having fast execution times with a large pool of possible modulation schemes. It is, however, required that the geometry of the constellation remains intact during transmission for the proposed method to function. It will, therefore, operate favourably when there is little to no movement between the transmitter and receiver, as high levels of Doppler shifts violates this requirement.

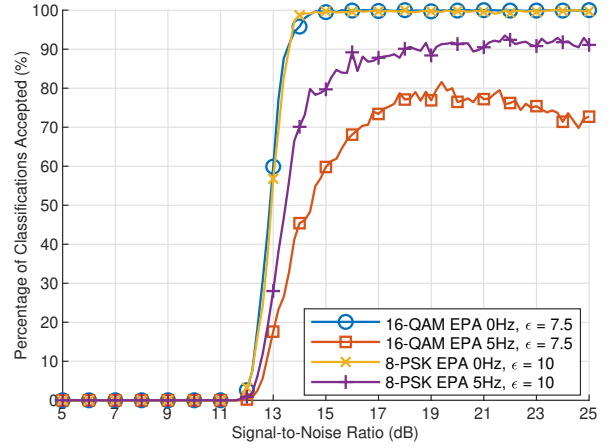
From the aforementioned benefits, the ideal real-world implementation would be as part of a larger AMC system. The proposed method will be able to quickly and accurately classify a large number of signals and refer the signals that have a low ϵ value to an AMC method with a better *Classification Accuracy* at the cost of execution time. Such a system would be able to accurately classify a large number of signals in a short amount of time. Future work will focus on dynamically adjusting ϵ cut-off values and evaluating the proposed method with measured I/Q data using a hardware-in-the-loop configuration.

ACKNOWLEDGEMENT

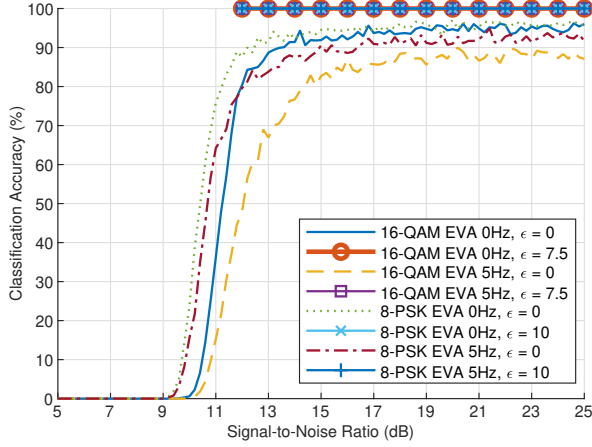
The authors gratefully acknowledge the financial support of this study by the Telkom CoE at the NWU and the National Research Foundation under grant nr TP14081892668.



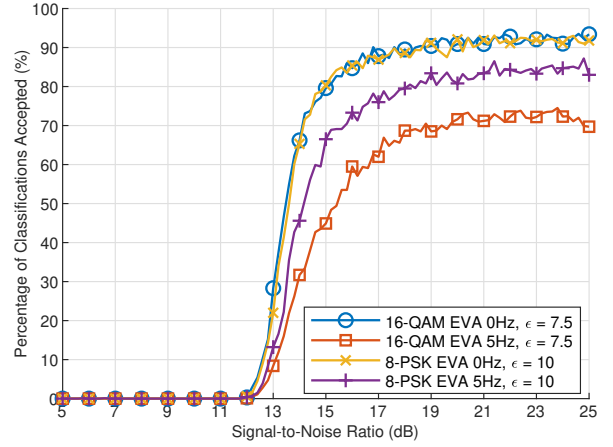
(a) EPA Classification Accuracy



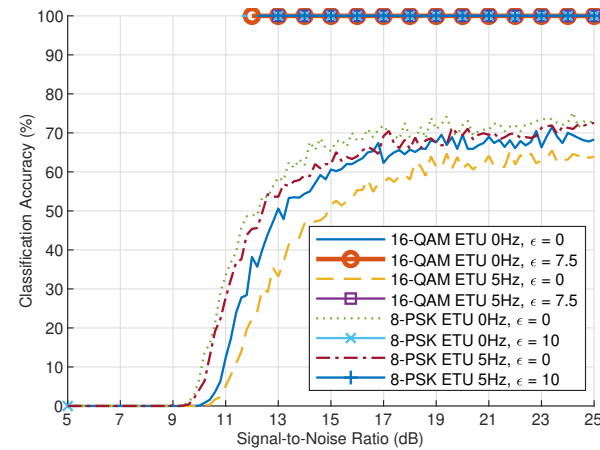
(b) EPA percentage classification



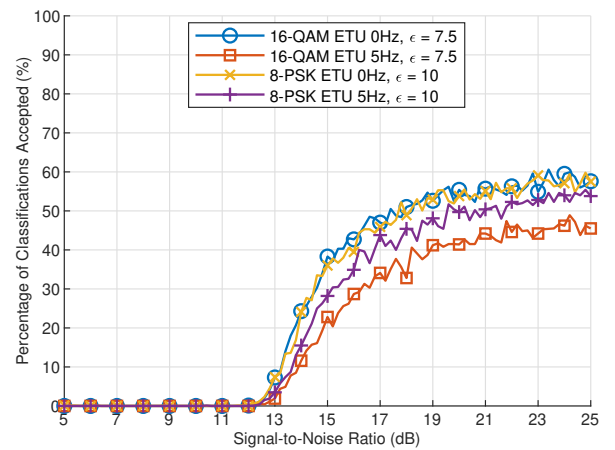
(c) EVA Classification Accuracy



(d) EVA percentage classification



(e) ETU Classification Accuracy



(f) ETU percentage classification

Fig. 6. Performance of the proposed AMC method in ETSI TDL multipath testing conditions

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Chapter 4

Verification and Validation

In this chapter, the verification and validation of the proposed AMC method and system models are discussed. Verification and validation are used to ensure that models are correctly implemented and that the results are trustworthy.

Verification can be described as a process to ensure models are correctly implemented, whereas validation refers to ensuring a process or system functions as expected within its domain [37]. In this study, we are mainly concerned with the verification of the implementation of digital modulation schemes and communication channels, as well as validating the operation of the proposed AMC method in a noisy channel.

4.1 Verification

We will examine the implementation of M-PSK, M-QAM, and M-PAM with the communication system toolbox in Matlab. The operation of the AWGN and multipath channels will also be examined and verified separately, based on the output of the respective models.

4.1.1 Modulation Schemes

Modulation schemes are used to encode a data signal onto a carrier signal that can be transmitted, as discussed in Section 2.1. The proposed AMC method relies on the constellation representation of a modulation scheme. Figure 4.1 illustrates the constellation representation of M-PSK, M-QAM, and M-PAM. We can compare these constellations with those generated by [3] in Figure 2.2 to ensure correct implementation. Any constellations not shown are generated similarly. These constellations are used to modulate a pseudo-randomly generated bit-stream in Matlab that has its own internal verification process.

4.1.2 AWGN channel

AWGN noise refers to noise that is added to a signal with a Gaussian distribution and equal power over all frequencies, as discussed in Section 2.2.2. We demonstrate that the noise has a Gaussian distribution with a histogram of the instantaneous amplitude of an 8-PSK signal with 10 dB SNR in an AWGN channel, shown in Figure 4.2. We also see the effect of various SNRs on the constellation of an 8-PSK signal in an AWGN channel in Figure 4.3.

The “measured” option was used in Matlab when adding AWGN to a signal that will identify the amplitude of a signal to ensure that the correct amount of noise is added for a specific SNR. This ensures that the actual amplitude of a signal is irrelevant as all constellations (with and without noise) is normalised in a later stage in the proposed AMC method.

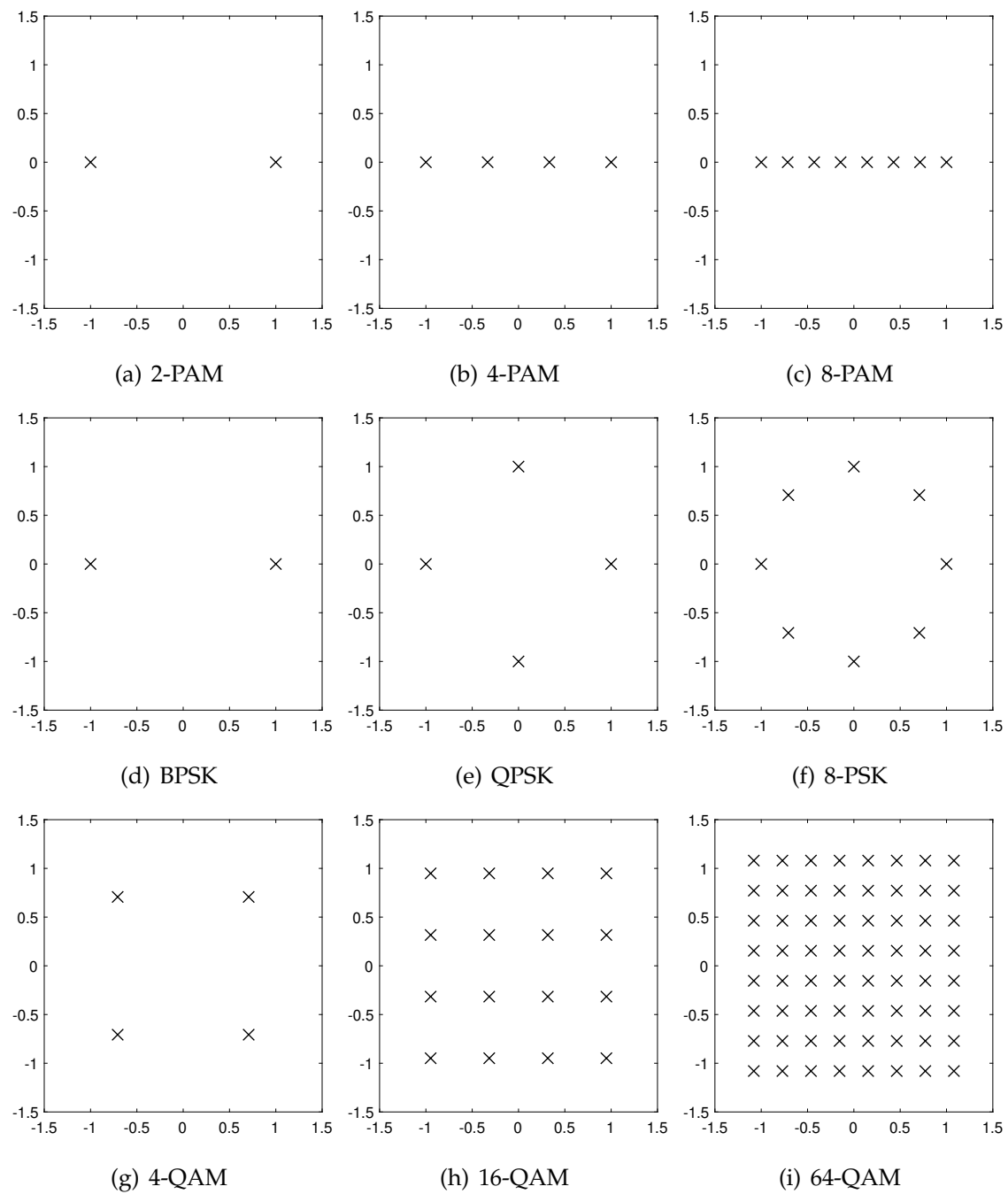


Figure 4.1: Reference modulation scheme constellations

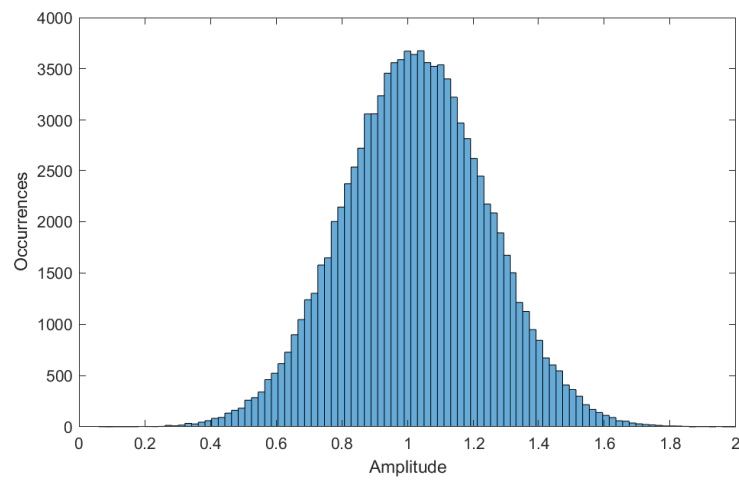


Figure 4.2: Histogram of the amplitude of 8-PSK with 10 dB SNR in an AWGN channel.

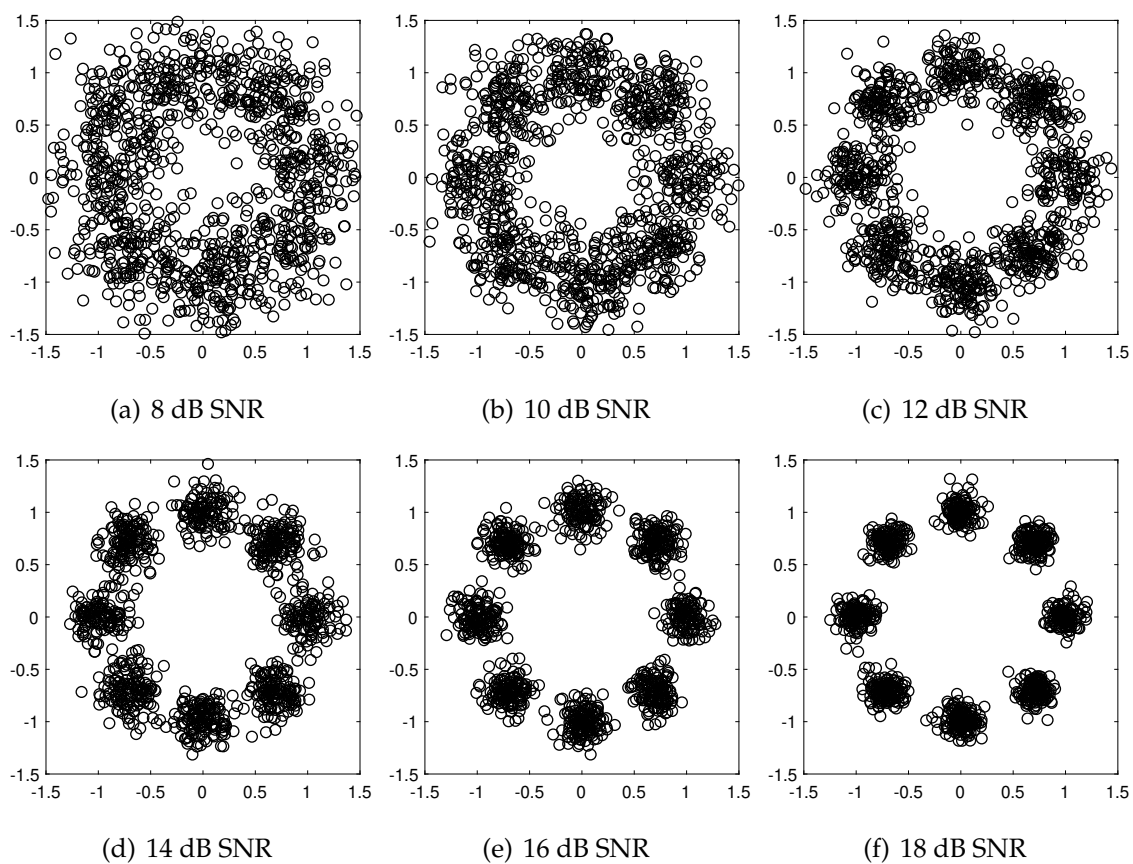


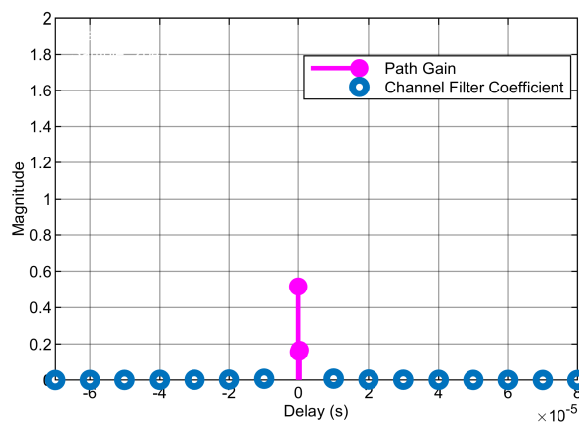
Figure 4.3: 8-PSK with AWGN

4.1.3 Multipath Channel

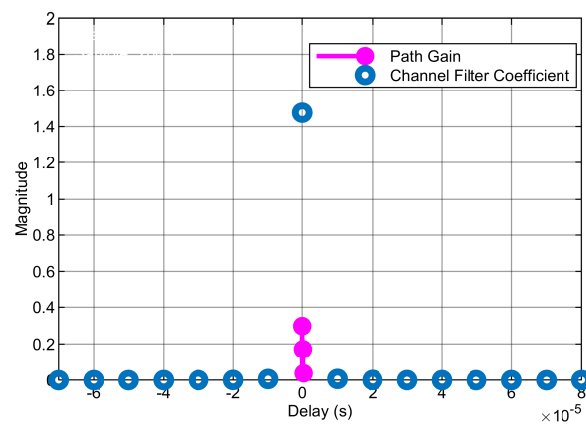
The European Telecommunications Standards Institute (ETSI) specifies TDL profiles for three different multipath environments in the latest 3GPP specification [6]. The Extended Pedestrian A (EPA), Extended Vehicular A (EVA), and Extended Typical Urban (ETU) models can be implemented with a maximum Doppler shift and AWGN in a Matlab simulation environment, using the Communication Toolbox. A maximum Doppler shift is indicated by a number following the model name, e.g. EVA5 indicates a maximum Doppler shift of 5Hz. Matlab specifies that an AWGN channel should follow the fading channel. The proposed AMC method is evaluated with these three models in the third publication in Section 3.4. The delay profiles are repeated in Table 4.1 for convenience. We can examine the magnitude delay and frequency response of each channel to validate the implementation. Figure 4.4, 4.5, and 4.6 show the delay magnitude response, frequency response, and the effect that it has in the I/Q plane with 20dB SNR AWGN for the EPA, EVA and ETU delay profiles. We observe that the channel becomes progressively worse, especially in terms of frequency response, as the delay spread increases, and even more so with the addition of Doppler shifts. Note that a new random channel is generated with each iteration during simulations based on an initial seed value.

Table 4.1: ETSI Delay profile for EPA, EVA and ETU TDL models [6]

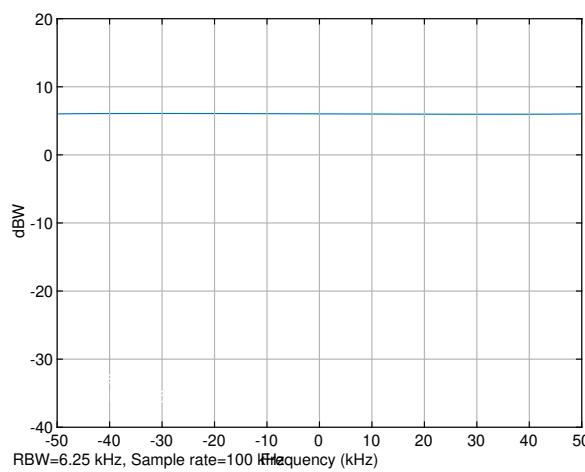
	EPA		EVA		ETU	
Tap	Tap Delay (ns)	Relative Power (dB)	Tap Delay (ns)	Relative Power (dB)	Tap Delay (ns)	Relative Power (dB)
1	0	0.0	0.0	0.0	0	-1.0
2	30	-1.0	30	-1.5	50	-1.0
3	70	-2.0	150	-1.4	120	-1.0
4	90	-3.0	310	-3.6	200	0.0
5	110	-8.0	370	-0.6	230	0.0
6	190	-17.2	710	-9.1	500	0.0
7	410	-20.8	1090	-7.0	1600	-3.0
8	-	-	1730	-12.0	2300	-5.0
9	-	-	2510	-16.9	5000	-7.0



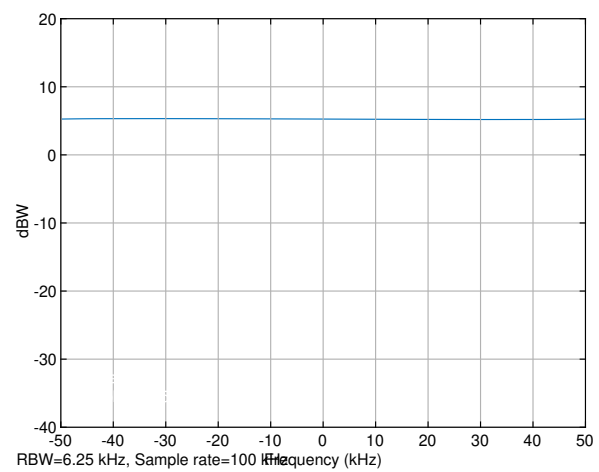
(a) EPA0 delay magnitude response



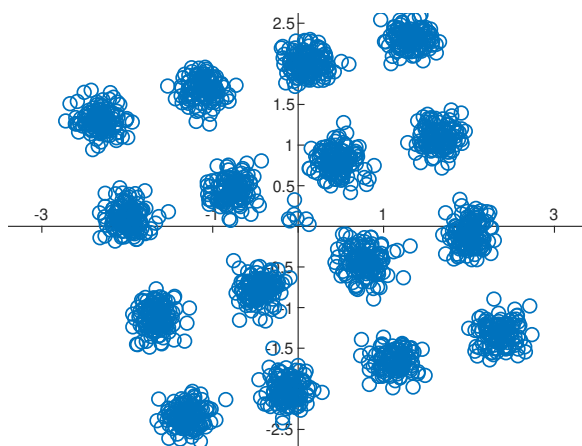
(b) EPA5 delay magnitude response



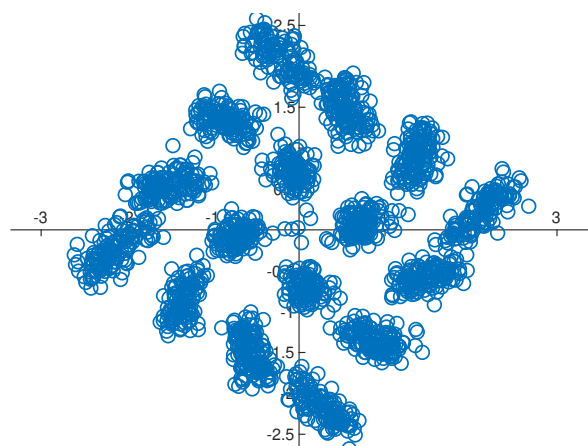
(c) EPA0 frequency response



(d) EPA5 frequency response

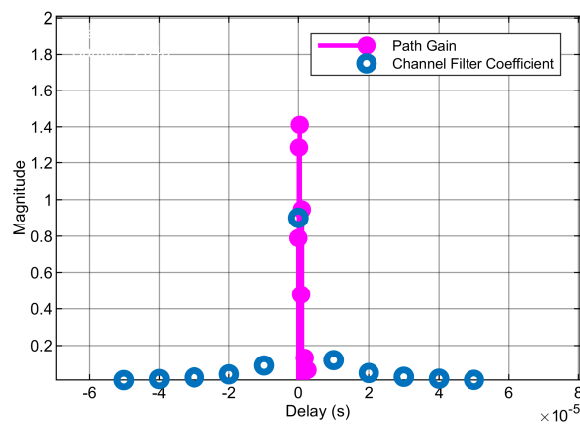


(e) EPA0 in the I/Q plane

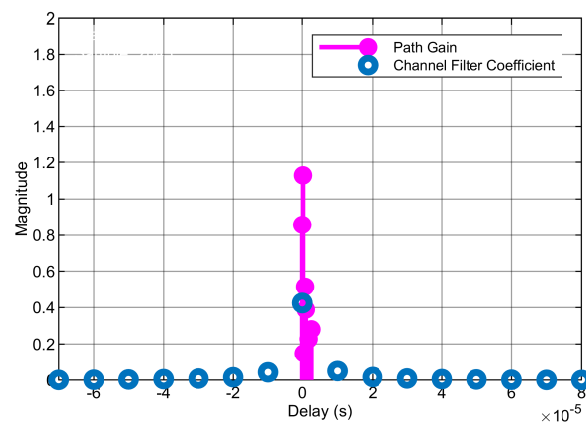


(f) EPA5 in the I/Q plane

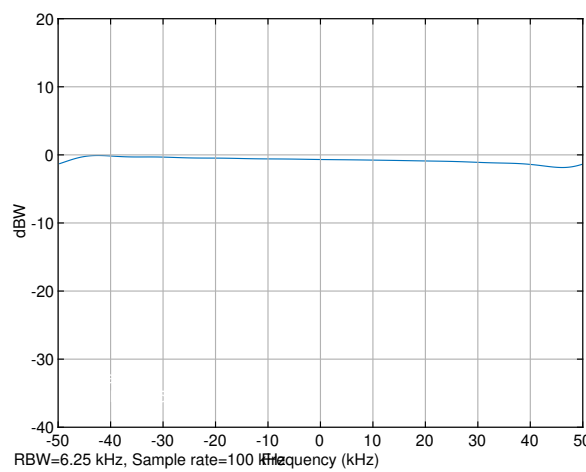
Figure 4.4: Channel response of EPA ETSI TDL profiles.



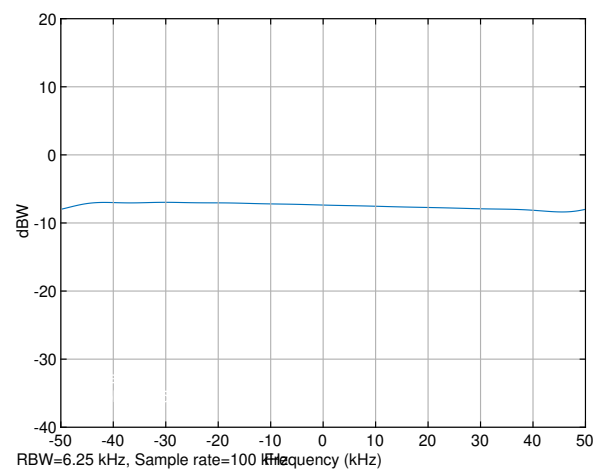
(a) EVA0 delay magnitude response



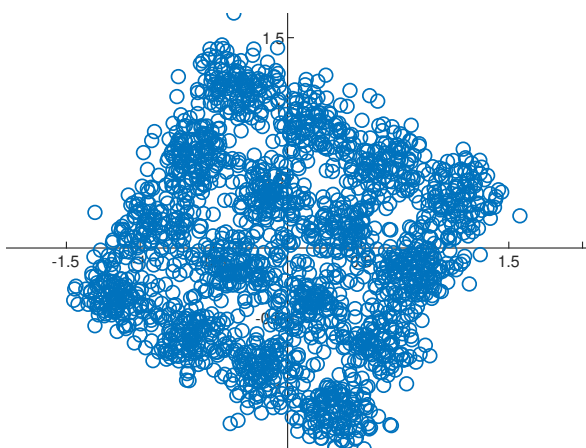
(b) EVA5 delay magnitude response



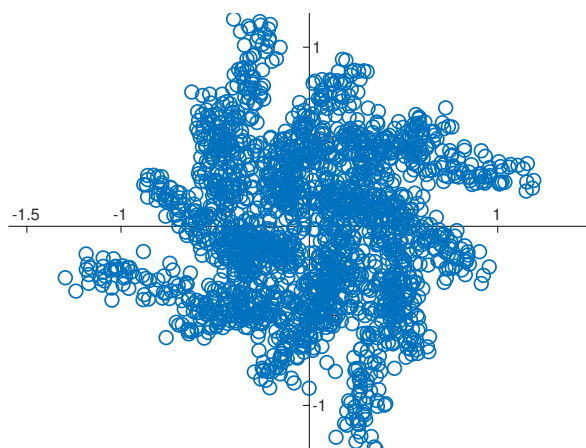
(c) EVA0 frequency response



(d) EVA5 frequency response

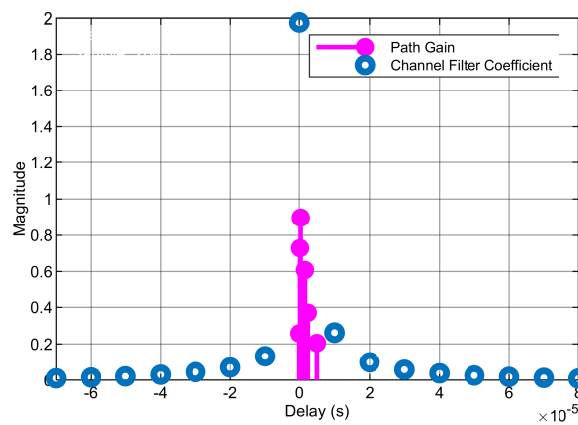


(e) EVA0 in the I/Q plane

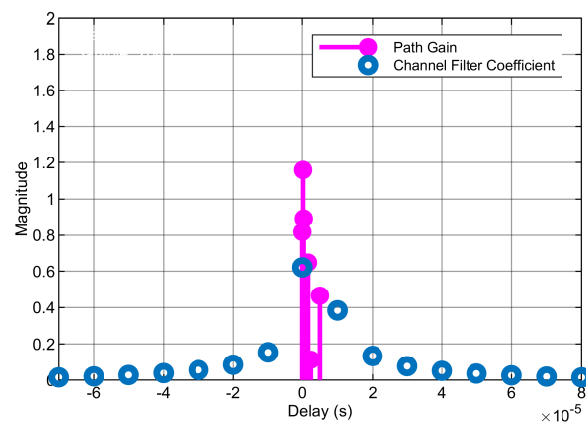


(f) EVA5 in the I/Q plane

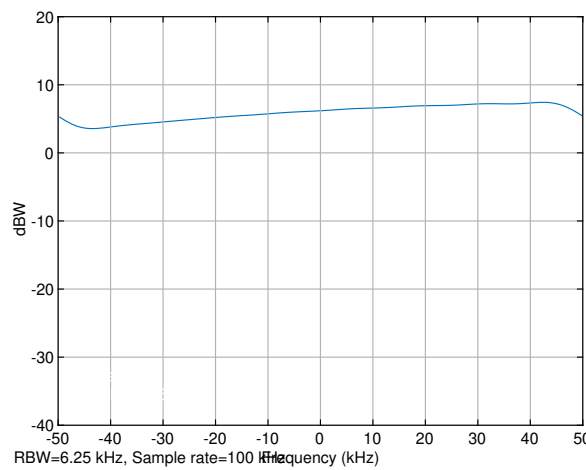
Figure 4.5: Channel response of EVA ETSI TDL profiles.



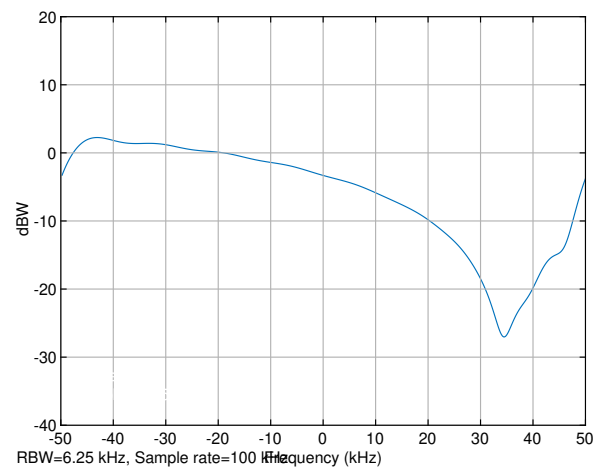
(a) ETU0 delay magnitude response



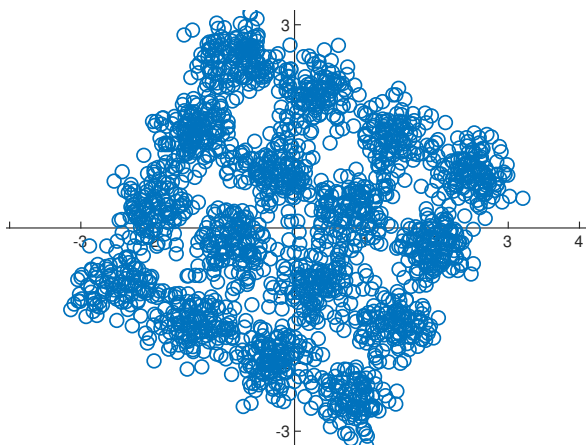
(b) ETU5 delay magnitude response



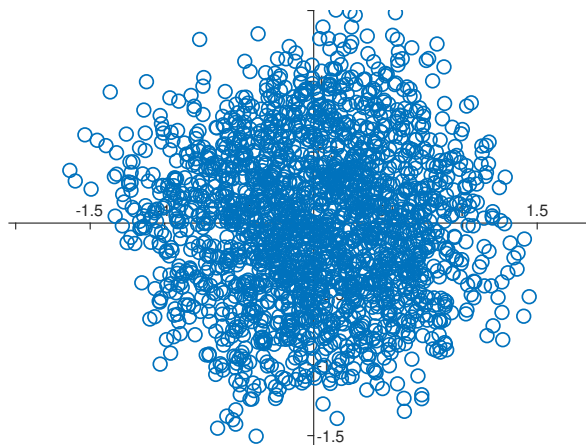
(c) ETU0 frequency response



(d) ETU5 frequency response



(e) ETU0 in the I/Q plane



(f) ETU5 in the I/Q plane

Figure 4.6: Channel response of ETU ETSI TDL profiles.

4.2 Validation

Sargent [37] outlines several methods of validation. We use a combination of extreme condition tests, comparing our results with other methods, and traces. Each stage of the proposed method in Figure 4.7 is individually validated using traces and extreme condition tests. The final proposed method is then compared with other methods.

4.2.1 Traces

The first paper in Section 3.2 evaluates the k-means, fuzzy c-means, k-medoids, DB-SCAN, OPTICS, and hierarchical clustering algorithms individually in terms of accuracy, execution time, and scalability for each stage in Figure 4.7. The effectiveness of each algorithm is discussed. The best performing clustering algorithm for each stage is then used in the proposed method.

4.2.2 Extreme condition tests

The *Classification Accuracy* of the proposed method was evaluated in all three publications in Section 3 under various noise conditions. In the first paper, in Section 3.2, the proposed method is evaluated with a large range of SNRs to determine a suitable range of operation. The second paper, in Section 3.3, repeats the previous evaluation with the

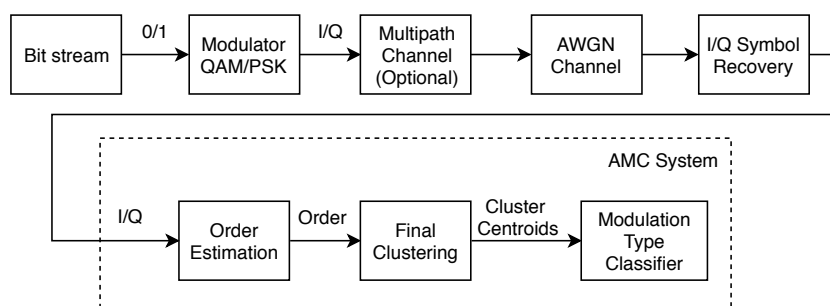


Figure 4.7: Proposed multi-stage approach

addition of the Classification Quality parameter (ϵ). The performance characteristics of ϵ are also examined in detail, with a discussion on the selection of appropriate cut-off values. The third paper, in Section 3.4, evaluates the proposed method under ETSI multipath conditions. A discussion is given on how this specific type of noise affects ϵ and the proposed method as a whole.

4.2.3 Comparing results with other methods

The proposed method's *Classification Accuracy* is compared with that of other popular methods in the first two papers, in Section 3.2 and 3.3. A discussion follows on how the proposed method compares with other methods in both papers.

We can, therefore, rely on the results generated by our simulation to be correct based on the preceding verification and validation process and draw a meaningful conclusion to the original research problem stated in Section 1.2.

Chapter 5

Conclusions and Recommendations

In this chapter, we reflect on the research and development of the proposed AMC method. We examine the benefits and limitations of the proposed method while keeping the original research problem in mind. Furthermore, recommendations for future work are discussed.

5.1 Overview

In Chapter 1, we introduce the concept of AMC and its use cases, ranging from spectrum use enforcement and cognitive radio to threat identification and interference. The importance of how we use the electromagnetic spectrum is discussed, as it is a finite resource. The research objectives are stated with a conceptual overview of the proposed method. A high-level architecture is provided that allowed us to develop the proposed method in separate stages in the subsequent chapters.

In Chapter 2, we provide required background information on digital modulation schemes, introduce the I/Q plane, and discuss communication channels. A summary is then provided of several clustering algorithms and their complexity that we can

use to cluster samples in the I/Q plane. We then investigate well-known AMC approaches. These approaches are divided into two categories, namely, Feature-based and Likelihood-based. We discuss each approach separately and summarise a few well-known methods in general AMC literature in order to contrast the operation of our proposed method. We then review AMC methods found in literature that use a feature set similar to our proposed method.

In Chapter 3, we present the papers submitted for publication. In the first paper, we evaluate the use of several clustering algorithms for each stage of the proposed method. These clustering algorithms are evaluated in terms of algorithmic complexity, scalability and execution time, and how well they can achieve the requirements of each stage in an AWGN channel. The best performing algorithms are then used to develop the proposed method, which is then compared to other well-known methods using the same conditions. The second paper expands on the first by extracting a parameter that is used to identify and reject incorrect classifications. We name this parameter as Classification Quality (ϵ). The nature of this parameter is examined and discussed. The performance of the proposed method is re-evaluated with the addition of this parameter and once again compared with other well-known methods. The proposed method is then evaluated with ETSI multipath conditions in the third paper.

In Chapter 4, we address the Verification and Validation of the operation of the system model and the proposed method. We use Operational Verification to examine the implementation of the modulation schemes by comparing our generated constellations with those of [3]. The output of the AWGN channel is shown to have a Gaussian distribution, and the channel response of the ETSI multipath channels are shown to behave as expected. A combination of three validation techniques is used to ensure the correct operation of the proposed method. Traces are used in the first paper in Chapter 3, where each stage of the proposed method is evaluated individually. Extreme condition testing is also employed in the first two papers to determine at which point there is too much noise to identify the modulation scheme. The results of our simulations are also compared to well-known methods. From these Verification and Validation investigations, we conclude that the implementation of these models and systems are correct

and that the results can be used to draw a sensible conclusion to the original research problem.

5.2 Reflection on Research Objectives

In Chapter 1, we state that we aim to develop a new AMC method that addresses the drawbacks of well-known AMC methods. Likelihood-based methods require accurate channel state estimation. Performance of these methods will degrade if these parameters cannot accurately be estimated. The majority of Feature-based methods in literature utilise machine learning to match features extracted from a signal of interest to a known modulation scheme. These approaches need to be trained for specific conditions and will need to be re-trained should a significant change in the operating environment occur. Feature-based approaches that use a decision tree, rather than a machine learning algorithm, will also need to be re-calibrated should a significant change in the operating environment occur.

Our proposed method can be used both with and without an ϵ cut-off. The proposed method fulfils all of the above requirements, if ϵ is not considered. The proposed method, in this form, does not rely on any machine learning or thresholds, resulting in a highly adaptable method. The proposed method does, however, require adequate I/Q symbol recovery, but this is outside the scope of this investigation. The proposed method can use a threshold for ϵ to identify probable incorrect classifications. This threshold has to be selected with care as a too low value will result in incorrect classifications at lower SNRs, while a too high value will only allow classifications at higher SNRs. An overestimated cut-off value can be used to assure correct classifications.

By looking back at the original research objectives in section 1.2.1 we can see that the first two objectives are completed in Chapter 2. Objectives three through six are completed in the first paper. The proposed method is then improved and objective six is repeated with the improved implementation in the second paper. The proposed method is then evaluated under ETSI multipath conditions to satisfy objective number

seven.

5.3 Performance Evaluation in an AWGN Channel

The proposed method is evaluated in an AWGN channel in the first two papers in Chapter 3 and compared to a Maximum Likelihood method, the Kolmogorov Smirnov (KS) Test, Moments with a KNN classifier, and Cumulants with a KNN classifier. From the results of these two papers, we demonstrate the importance of the number of samples. There will be fewer examples of each symbol level as the modulation order increases for a fixed number of samples. For example, 16-PSK with 1024 samples will have an average of 64 samples for each symbol level, but 64-QAM will only have 16, assuming each symbol level occurs equally often. A sufficient number of samples can be calculated as a function of the largest modulation order in the pool of possible modulations. This behaviour is reflected in the *Classification Accuracy*, where the performance will degrade at a higher SNR compared to when an adequate number of samples is used. The proposed method is, however, capable of achieving 100% *Classification Accuracy* at a similar SNR compared to the previously mentioned AMC methods whilst, having several additional benefits.

Furthermore, we can extract ϵ from the elbow method in the Order Estimation stage. This parameter can be regarded as a measurement of how intact the constellation remained during transmission and can be used to confidently classify the modulation scheme. We can detect these noise conditions and thereby avoid any incorrect classifications at any SNR, by rejecting classifications with a low ϵ -value.

5.4 Performance Evaluation with ETSI Multipath Conditions

A multipath channel is a far more accurate reflection of real-world wireless communication channels. All AMC methods will perform better in an AWGN channel than they would in a multipath channel. The majority of AMC methods in literature are only evaluated in an AWGN channel, and many may be unable to function in multipath conditions.

The proposed method was evaluated with ETSI multipath conditions in the third paper in Section 3. In this paper, we demonstrate that the coherence time of the channel decreases as the multipath conditions worsen. A short coherence time prevents 100% *Classification Accuracy* at any SNR, as the geometry of the modulation scheme's constellation representation is fully corrupted and unrecognisable. The proposed method is capable of detecting these conditions and rejecting those classifications in order to achieve 100% *Classification Accuracy*.

The envisioned real-world implementation of the proposed method sees the proposed method as part of a larger AMC system. The proposed method is able to quickly examine a large number of modulation schemes and refer those signals of interest with a low ϵ -value classification to another AMC method that may be more accurate at lower SNRs, at the cost of execution time. Such a system will be able to quickly identify a large number of signals with good accuracy.

5.5 Benefits and Limitations

5.5.1 Benefits

The proposed method has several benefits not present in other AMC methods:

1. The proposed method can function without any thresholds or parameters that require calibration, if ϵ is not taken into account.
2. Incorrect classifications can be detected by rejecting low ϵ classifications.
3. The proposed method has low algorithmic complexity with an execution time that scales linearly with the number of samples.
4. The proposed method can be used with a large pool of modulation schemes with little cost to execution time, as presented in the first paper in Section 3.2.
5. The execution time of the proposed method can be calculated as a function of the number of samples, number of iterations, and the modulation schemes in the pool.
6. The proposed method can be used with any modulation scheme that has a unique representation in the I/Q plane.

5.5.2 Limitations

The proposed method does, however, exhibit the following limitations:

Number of samples

In section 3.3, we investigated the connection between the number of I/Q samples and the SNR at which 100% *Classification Accuracy* is achieved. We found that the proposed

method achieves 100% *Classification Accuracy* at a similar SNR as other methods for lower modulation orders (See comparison with other methods in section 3.3 with 4-QAM, 16-QAM, BPSK and QPSK). The proposed method does, however, require a larger number of samples for higher order modulation schemes such as 64-QAM (See comparison with other methods in section 3.2 with 16-QAM, 64-QAM, QPSK and 8-PSK). Several other methods exist that are capable of classifying high order modulation schemes with fewer samples.

I/Q symbol recovery

The proposed method uses the location of the symbol levels of a modulation scheme's constellation representation as a feature. This means that the I/Q symbols must be recovered in such a way that the original constellation can be identified. It should be noted that the proposed method can function with a rotated constellation, as long as the position of the symbol levels remain the same relative to each other.

Doppler shifts

The proposed method requires adequate I/Q symbol recovery, as discussed in the previous limitation. Doppler noise has a different effect on the constellation of a modulation scheme than AWGN. Doppler noise corrupts the data in such a way that the I/Q samples can't be recovered in a manner that satisfies the previously mentioned condition. Further processes such as estimating channel state information and channel equalisation can be employed to compensate for this type of noise.

Unique constellations

The proposed method compares recovered I/Q samples to reference constellations to classify the modulation scheme. The proposed method is (optionally) configured to normalise the rotation of recovered I/Q samples so that the two symbol levels that are

farthest away from each other are placed on known points in an attempt to mitigate the effects of phase shifts. This process introduces two limitations. Each modulation scheme in the pool should have a unique constellation representation. No constellation in the pool must be able to be rotated or resized to result in a constellation representation of another modulation scheme in the pool. For example, Q-PSK and 4-QAM cannot be distinguished from each other after normalisation.

5.6 Recommendations for Future Work

We evaluated the performance of our proposed method in a simulated AWGN channel as well as a simulated multipath channel with ETSI TDL profiles. Several other communication channels, simulated or otherwise, also exist. It will be of value to evaluate the performance of the proposed method under unexplored channel conditions.

All blind AMC methods will require some degree of channel state information estimation, even if simply for I/Q symbol recovery. Further research should be conducted in techniques that will improve the performance of AMC with real-world signals. Once this has been accomplished, our proposed method, along with several other methods, should be re-evaluated under those conditions using real-world signals.

Machine learning is a rapidly advancing topic of research. It would certainly be of value to use the feature set that we used in our proposed method with some form of machine learning. Clustering algorithms are also continually being developed and should be evaluated in a similar manner as in the first paper in Chapter 3 for the purpose of AMC.

The optimisation of ϵ cut-off values should be further investigated, as well as the use of other figures of merit, such as the separability indices discussed in [38]. Computational complexity as well as accuracy should be taken into account when evaluating these figures of merit.

5.7 Conclusion

The research conducted in this investigation follows the development of a novel AMC method that can function without any machine learning or thresholds that need to be set, as specified in the original research objective. The proposed method is then expanded upon by extracting a parameter that allows for the identification of incorrect classifications. The proposed method shows performance comparable with other well-known AMC methods, while providing other benefits.

Appendix A

Matlab source code for the proposed method

The Matlab code is given for the proposed method in this appendix.

A.1 demo.m

A Matlab script that use the required functions to demonstrate the operation of the proposed AMC method in a multipath channel.

```
close all
% toSim input format (usefull for multiple simulations):
%toSim=AddAWGN?(1/0),AWGNinSNRdB,AddRaylei/Rician(ray/ric/none),PathDelays,PathGains,
    %SampleRate;MaxDoppler;NormalizePathGains;KFactor(Optional);Visualise

% Extended Pedestrian A Model (EPA5) + 20dB SNR AWGN:
toSim = "1,20.00,ray,0;30e-9;70e-9;90e-9;110e-9;190e-9;410e-9,"...
    +"0;-1.1;-2;-3;-8;-17.2;-20.8,100000;5;0";

% Extended Vehicular A Model (EVA5) + 20dB SNR AWGN:
%toSim = "1,20.00,ray,0;30e-9;150e-9;310e-9;370e-9;710e-9;1090e-9;1730e-9;2510e-9,"...
%
%    +"0;-1.5;-1.4;-3.6;-0.6;-9.1;-7;-12;-16.9,100000;5;0";

% Extended Typical Urban Model (ETU5) + 20dB SNR AWGN:
% toSim = "1,20.00,ray,0;50e-9;120e-9;200e-9;230e-9;500e-9;1600e-9;2300e-9;5000e-9,"...
```

```

%          +"-1;-1;-1;0;0;0;-3;-5;-7,100000;5;0";

M = 16 %Modulation order
modType = "QAM" %Modulation type
samples = 2048 %Number of samples
bps = log2(M); %Number of bits per symbol
bits = samples*bps; %Number of bits to process
orderPool = [1 2 4 8 16 32 64 128 256]; %Pool of possible modulation orders
%Pool of possible constellations:
modPool = [ "1" "PSK"; "2" "PSK"; "4" "PSK"; "8" "PSK"; "16" "PSK";
            "32" "PSK"; "64" "PSK"; "128" "PSK"; "256" "PSK";
            "1" "QAM"; "2" "QAM"; "4" "QAM"; "8" "QAM"; "16" "QAM";
            "32" "QAM"; "64" "QAM"; "128" "QAM"; "256" "QAM"];

%Process toSim
line = strsplit(toSim,',' );
addGaus = str2double(line{1});
gausNoise = str2double(line{2});
addRayRic = line{3};
pathDelays = str2double(strsplit(line{4},',' ));
pathGains = str2double(strsplit(line{5},',' ));
params = str2double(strsplit(line{6},',' ));

dataIn = randi([0 1],bits,1); % Generate vector of binary data
% Reshape data into binary k-tuples, k = log2(M):
dataInMatrix = reshape(dataIn,length(dataIn)/bps,bps);
dataSymbolsIn = bi2de(dataInMatrix); % Convert to integers
dataMod = [];
%Modulate
if modType == "QAM"
    dataMod = qammod(dataSymbolsIn,M,'UnitAveragePower',true);
end
if modType == "PSK"
    if M==4 || M == 2
        dataMod = pskmod(dataSymbolsIn,M,pi/2);
    else
        dataMod = pskmod(dataSymbolsIn,M);
    end
end

[X,chan]=addNoise(dataMod,false,addGaus,gausNoise,addRayRic,pathDelays,pathGains,params,true);
disp(chan)
figure
scatter(X(:,1),X(:,2))
points = gca;
points.XAxisLocation = 'origin';

```

```

points.YAxisLocation = 'origin';
title("Input I/Q samples")
axis equal

[EstimatedOrder, epsilon] = estimateOrderElbowKmean(X, orderPool, 15, true)
[C,idx] = clusterKmeans(X,EstimatedOrder,50);
figure
scatter(C(:,1),C(:,2))
title("Estimated Symbol Levels")
axis equal;

C = normalisePhase(C);
figure
scatter(C(:,1),C(:,2))
title("Normalised Estimated Symbol Levels")
axis equal
xlim([-1.5 1.5])
ylim([-1.5 1.5])

classifiedModulation = identifyModType(C, EstimatedOrder, modPool)

ref = makeRefConst(EstimatedOrder,classifiedModulation);
hold on
scatter(ref(:,1),ref(:,2),'x')
axis equal
xlim([-1.5 1.5])
ylim([-1.5 1.5])

if classifiedModulation == modType && EstimatedOrder == M
    fprintf("%d-%s is correct",EstimatedOrder,classifiedModulation)
else
    fprintf("%d-%s is incorrect",EstimatedOrder,classifiedModulation)
end

```

A.2 addNoise.m

A Matlab function that adds noise to a modulated signal.

```

function [X,chan]=addNoise(data,plot,addGaus,gausNoise,addRayRic,pathDelays,pathGains,params,visualise)
%Adds Gaussian and Rayleigh or Rician noise
% For Rayleigh: params = [bitRate, MaximumDopplerShift,
% NormalizePathGains] For Rician: params = [bitRate, MaximumDopplerShift,
% NormalizePathGains, KFactor]

```

```

chan = [];
switch addRayRic
    case "ray"
        bitRate = params(1);
        MaximumDopplerShift = params(2);
        NormalizePathGains = params(3);
        if visualise
            chan = comm.RayleighChannel('SampleRate',bitRate,'MaximumDopplerShift',MaximumDopplerShift,...
                'PathDelays',pathDelays,'AveragePathGains',pathGains,'NormalizePathGains',NormalizePathGains,...
                'Visualization','Impulse and frequency responses');
        else
            chan = comm.RayleighChannel('SampleRate',bitRate,'MaximumDopplerShift',MaximumDopplerShift,...
                'PathDelays',pathDelays,'AveragePathGains',pathGains,'NormalizePathGains',NormalizePathGains);
        end
        data = chan(data);
    case "ric"
        bitRate = params(1);
        MaximumDopplerShift = params(2);
        NormalizePathGains = params(3);
        KFactor = params(4);
        if visualise
            chan = comm.RicianChannel('SampleRate',bitRate, 'MaximumDopplerShift',MaximumDopplerShift,...
                'KFactor',KFactor,'NormalizePathGains',NormalizePathGains,'PathDelays',pathDelays,...
                'AveragePathGains',pathGains,'Visualization','Impulse and frequency responses');
        else
            chan = comm.RicianChannel('SampleRate',bitRate, 'MaximumDopplerShift',MaximumDopplerShift,...
                'KFactor',KFactor,'NormalizePathGains',NormalizePathGains,...
                'PathDelays',pathDelays,'AveragePathGains',pathGains);
        end
        data = chan(data);
    case "none"
        temp = "Do nothing";
    otherwise
        % Source: https://www.mathworks.com/help/comm/ref/stdchan.html
        fd = params(1);
        rs = params(2);
        chan = stdchan(addRayRic,rs,fd);
        data = chan(data);
end

if addGaus
    data = awgn(data,gausNoise,'measured');
end

X = [real(data) imag(data)];
if plot
    scatterplot(X)

```

```

    if addGaus
        title("Gaussian Noise")
    end
    if addRayRic == "ric"
        title("Rician Noise")
    end
    if addRayRic == "ray"
        title("Rayleigh Noise")
    end
end
end

```

A.2.1 normalisePhase.m

A Matlab helper function used in more than one place to normalise the constellation so that the two points farthest from each other are placed on -1 and 1 on the x-axis.

```

function out = normalisePhase(X)
%Normalise the phase of a constellation so that the 2 farthest points are
%on [-1 1] on the x axis.
out = X;
[point2, index2] = max(sqrt((out(:,1).^2) + (out(:,2).^2)));
angle = -atan2(out(index2,2),out(index2,1))*180/pi;
R = [cosd(angle) -sind(angle); sind(angle) cosd(angle)];
for i = 1:length(out)
    out(i,:) = (R*out(i,:))';
end
out = (out/(out(index2,1)));
end

```

A.3 estimateOrderElbowKmean.m

A Matlab function that use k-means with the elbow method to estimate the number of clusters.

```

function [order, confidence] = estimateOrderElbowKmean(X, orderPool, km_iter_order, showData)
%Estimate the number of clusters.
sizes = orderPool';
dists = zeros(size(sizes));
for j = 1:length(sizes)

```

```

[idx,C] = kmeans(X,sizes(j),'Distance','cityblock','Replicates',km_iter_order,'Display','off');
dist_error = 0;
for i = 1:length(X)
    tempX = X(i,:);
    tempC = C(idx(i),:);
    dist_error = dist_error + sqrt(power(tempX(1,1)-tempC(1,1),2) + power(tempX(1,2)-tempC(1,2),2));
end
dists(j) = dist_error;
end
[order, data, confidence] = elbow(sizes, dists, showData,...
    'Elbow Method - K means', 'Number of Clusters', 'Distance error');
end

```

A.3.1 clusterKmeans.m

A Matlab helper function used in more than one place that clusters data with the k-means clustering algorithm.

```

function [C,idx] = clusterKmeans(X,M,km_iter)
%Cluster data with k-means.
if ~exist('km_iter','var')
    km_iter = 25;
end
[idx,C] = kmeans(X,M,'Distance','cityblock','Replicates',km_iter,'Display','off');
end

```

A.3.2 elbow.m

A general purpose Matlab function for the elbow method.

```

function [val, data, confidence] = elbow(items, values, showData, tit, xlab, ylab)
%A general purpose elbow method.
difper = zeros(size(values));
for j = 1:length(difper)-1
    per = ((values(j)-values(j+1))/(values(j)))*100;
    difper(j+1) = per;
end
[maxVal, maxIndex] = max(difper);
val = items(maxIndex);
data = [items values difper];
confidence = sort(difper,'desc');

```

```
confidence = confidence(1)-confidence(2);

if(showData)
    disp(array2table(data,'VariableNames',{'Item','Value','PercentDif'}))
    fprintf("Most likely point: %d\n",val)
    fprintf("With confidence: %.2f\n",confidence)

    figure
    plot(data(:,1),data(:,2))
    hold on
    plot(val, values(maxIndex), 'r*')
    title(tit)
    xlabel(xlab)
    ylabel(ylab)
end
```

A.4 identifyModType.m

A Matlab function that identifies the most probable modulation scheme from a pool.

```
function [type, centroidError] = identifyModType(centres, M, types)
%Returns the most probable modulation scheme
centroidError = inf;
type = "Could not identify";
[rows cols] = size(types);
for i = 1:rows
    if M == str2double(types(i,1))
        temp = ref_dist_error(centres,makeRefConst(M,types(i,2)));
        if temp<centroidError
            centroidError = temp;
            type = types(i,2);
        end
    end
end
end
end
```

A.4.1 refDistError.m

A Matlab function that calculates the distance error between estimated symbol levels and a single reference constellation.

```
function [dist] = refDistError(C,refConst)
%Calculates the distance error between estimated symbol levels (C) and a
%reference constellation refConst.
dist = 0;
[height width] = size(C);
for i = 1:height
    ref_dist = zeros([height 1]);
    for j = 1:length(refConst)
        ref_dist(j) = sqrt((C(i,1)-refConst(j,1)).^2 + (C(i,2)-refConst(j,2)).^2);
    end
    dist = dist + min(ref_dist);
end
end
```

A.4.2 makeRefConst.m

A Matlab function that returns the constellation of a modulation scheme.

```
function [refConst] = makeRefConst(M,modType)
%Returns the reference constellation of a modulation scheme
refConst = ["Constellation type not available"];
if modType == "QAM" || modType == "qam"
    dataMod = qammod((0:M-1)',M,'UnitAveragePower',true);
    refConst = [real(dataMod) imag(dataMod)];
    refConst = normalisePhase(refConst);
end
if modType == "PSK" || modType == "psk"
    if M==4 || M==2
        dataMod = pskmod((0:M-1)',M,pi/2);
    else
        dataMod = pskmod((0:M-1)',M);
    end
    refConst = [real(dataMod) imag(dataMod)];
    refConst = normalisePhase(refConst);
end
if modType == "PAM" || modType == 'pam'
    refConst = pammod((0:M-1)',M,0);
    refConst = [real(refConst)/max(real(refConst)) imag(refConst)];
    refConst = normalisePhase(refConst);
end
end
```