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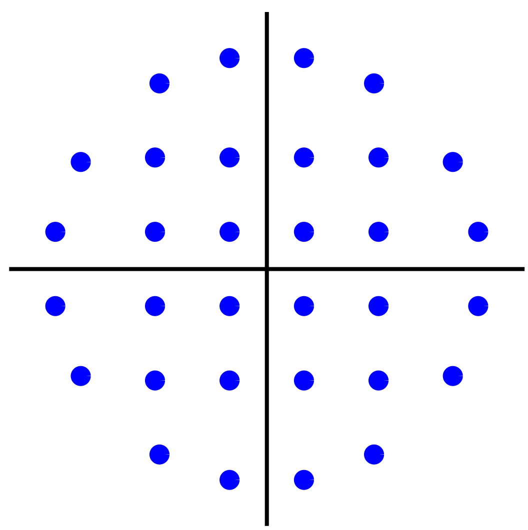
Methodology report

Maria Wikström

A Survey of Modulation Classification Methods for QAM Signals



Command and Control Systems
SE-581 11 Linköping

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SE-581 11 Linköping

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Peter Nagy</td></tr>
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Classification of the modulation type of a signal is a rapidly evolving research area with interests in both civilian and military applications.

Quadrature Amplitude Modulation (QAM) is a modulation scheme where both the amplitude and phase of the signal is shifted in accordance with the message. Because of its bandwidth efficiency QAM has become more frequently used especially in high capacity radio communications. Since there is a recent increase of QAM signals, methods for classifying such signals are of great importance.

This report is a result of a study performed to survey existing methods for QAM classification. Both pattern recognition and decision theoretic methods based on for example higher order statistics, wavelets and maximum-likelihood, are presented. The proposed methods are discussed and fundamental advantages and drawbacks are identified. In general, the approaches to QAM classification are only at its first stage towards practical implementation since ideal conditions, i.e. additive white Gaussian noise and perfect signal parameter recovery, are assumed and current analysis of the considered methods lacks studies in robustness.</td></tr>
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Maria Wikström

Projektledare
Peter Nagy

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En Översikt av Metoder för Modulationsklassificering av QAM Signaler

Sammanfattning (högst 200 ord)

Bestämning av modulationstypen hos en signal är ett snabbt framskridande forskningsområde med tillämpningar inom både civil kommunikation och militär signalspaning.

Quadrature Amplitude Modulation (QAM) är en modulationstyp där både amplituden och fasen hos signalen varieras i enlighet med meddelandesignalen. Tack vare den bandbreddseffektivitet QAM erbjuder har användandet av denna modulationstyp ökat vilket aktualiserar behovet av metoder för att kunna klassificera QAM signaler.

Denna rapport är resultatet av en litteraturstudie av existerande metoder för QAM-klassificering med utgångspunkt både från mönsterigenkänning och beslutsteori. Metoder baserade på högre ordningens statistik, neurala nätverk, wavelets och maximum-likelihood, presenteras och grundläggande fördelar och nackdelar identifieras. Generellt sett så har den tidigare forskningen på de föreslagna metoderna antagit ideala förhållanden, d.v.s. signaler mottagna i additivt Gaussiskt brus och perfekt återskapande av signalparametrar. Således krävs mer omfattande utvärderingar t.ex. robusthetsanalys av de föreslagna metoderna innan en praktisk implementering kan genomföras.

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Abbreviations

ASK	Amplitude Shift Keying
AWGN	Additive White Gaussian Noise
CNR	Carrier to Noise Ratio
FL	Fuzzy Logic
FSK	Frequency Shift Keying
IQ	In-phase and Quadrature
HWT	Haar Wavelet Transform
MC	Modulation Classification
ML	Maximum Likelihood
PAM	Pulse Amplitude Modulation
PCC	Probability of Correct Classification
PDF	Probability Density Function
PMM	Power Moment Matrix
PSK	Phase Shift Keying
QAM	Quadrature Amplitude Modulation
SNR	Signal-to-Noise Ratio

Chapter 1

Introduction

When detecting a radio communication signal, the signal characteristics needs to be identified to enable demodulation to obtain the message hidden in the signal. In cooperative communication theory the modulation type is supposed to be known at the detector but in non-cooperative communications no information about the signal is assumed to be known.

A system which identifies the modulation type of an input signal automatically and reports the estimation results is defined as an automatic modulation classifier. Automatic identification of the modulation type of a signal is a rapidly evolving area. It has found applications in military areas such as electronic warfare, surveillance and threat analysis as well as programmable and reconfigurable radio systems realized by software, what is called software radio.

Since the early 1980s many investigations about automatic classification of digitally modulated communication signals have been carried out. The majority of them have not included classification of quadrature amplitude modulation (QAM) which is a mix of amplitude and phase modulation of the carrier, since it has not been generally used in the past. However, with the recent advance of communication technologies, QAM has become used especially for high capacity radio communications. Therefore there is a need to examine the different techniques available to classify QAM signals.

This survey is intended to give an overview of the subject modulation classification for QAM signals. First the basics behind digital modulation and modulation classification are described. In chapter 2 the features of QAM signals are introduced to provide for better understanding on how to discriminate them from other modulation types. Some recent modem standards using QAM are briefly presented. Several interesting algorithms and approaches to modulation classification of QAM signals are outlined in chapter 3. In the final chapter some fundamental similarities and differences between the methods are explored and some conclusions on the topic are drawn.

1.1 Digital modulation techniques

To transmit digital information on bandpass channels, a sinusoidal carrier is required to perform frequency translation of the transmitted signal spectrum. Bandlimited channels most frequently encountered in practice are telephone channels, microwave line-of-sight radio channels and satellite channels. A modulated signal can be expressed as

$$s(t) = \mathrm{Re}[z(t)e^{j2\pi f_c t}] \tag{1.1}$$

where $e^{j2\pi f_c t}$ is the complex carrier signal with frequency f_c. The *complex envelope* $z(t)$ contains the message signal and is basically the equivalent baseband signal, can be written as

$$z(t) = A(t)e^{i\theta(t)} \tag{1.2}$$

where $A(t)$ is the amplitude and $\theta(t)$ the phase of the message signal. Another way of representing the modulated signal is in form of its inphase (I) and quadrature (Q) components

$$s(t) = I(t)\cos 2\pi f_c t + Q(t)\sin 2\pi f_c t$$

The amplitude and the phase can therefore be expressed in terms of the I and Q components according to

$$\begin{aligned} A(t) &= |z(t)| \\ &= \sqrt{I^2(t) + Q^2(t)} \end{aligned} \quad (1.3)$$

and

$$\begin{aligned} \theta(t) &= \angle z(t) \\ &= \tan^{-1}\frac{Q(t)}{I(t)} \end{aligned} \quad (1.4)$$

Modulation means that the carrier is altered by the message signal by switching or keying the amplitude, frequency or phase of the carrier. The three basic digital modulation techniques for the transmission are *amplitude shift keying* (ASK), *frequency shift keying* (FSK) and *phase shift keying* (PSK). The features are changed in M discrete steps to produce $M = 2^k$ possible signals, where k bits represent a symbol. If the signalling rate or bit rate is R bits/s the symbols are transmitted at a rate of R/k symbols/s, which is commonly called baudrate.

The general representation of a MPSK signal is

$$s(t) = \cos\left(2\pi f_c t + \frac{2\pi k}{M}\right), \qquad k = 0, 1, ..., M-1 \quad (1.5)$$

Ideally FSK and PSK signals have constant envelope which makes them insensitive to amplitude nonlinearities and are widely used in for example telephone modems and on microwave radio links. ASK is not used for data communications because it is very susceptible to electrical noise interference. Radio amateurs and some military system especially in the marine use ASK but within those applications Morse code or OOK (on-off keying) are more common terms for this modulation scheme.

The basic modulation techniques only modulate one feature of the carrier. By changing both amplitude and phase of the carrier a more efficient modulation scheme is obtained, namely QAM. To illustrate this consider consider the 8PSK and 8QAM constellations shown in figure 1.1. The probability of error is dominated by the minimum distance between pairs of signal points. The considered constellations have the same minimum distance, $d_{\min} = 2A$ .The average transmitted power for an M-ary signal, assuming that all signal points are equally probable is given by

$$P_{av} = \frac{1}{M}\sum_{m=1}^{M}(A_{mc}^2 + A_{ms}^2) \quad (1.6)$$

where A_{mc} and A_{ms} are the signal amplitudes for the quadrature qarriers. The 8PSK requires an average transmitted power of $P_{avg,8PSK} = 6.83A^2$ while the 8QAM only requires $P_{avg,8QAM} = 4.73A^2$. This specific QAM constellation is known to be the best 8QAM constellation.

For a complete overview of the basic principles behind digital communication systems including modulation, see Proakis [1].

1.2 Modulation classification

A modulation classifier estimates characteristics of a radio signal and determines the modulation type based on these characteristics. The modulation classification process is described more thoroughly in [2] by Nagy.

At the receiver the intercepted signal consits of the modulated signal perturbed by noise that has been introduced anywhere along the transmission line. On the channel the signal is exposed to e.g. fading, multipath components and internal receiver noise. The receiver has the task of observing the received

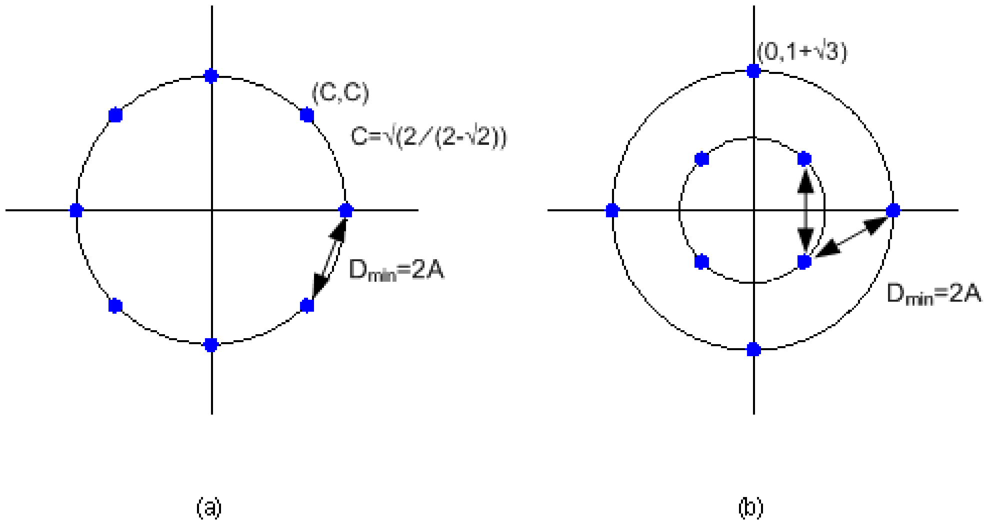

Figure 1.1: 8PSK and 8QAM constellation with the same minimum distance between signal points.

signal, $r(t)$ for a duration of T seconds and trying to estimate the transmitted signal $s_m(t)$. The received signal corrupted by noise $n(t)$ can be expressed as

$$r(t) = s_m(t) + n(t), \qquad 0 \leq t \leq T \tag{1.7}$$

In communication theory it is common to assume that the noise is additive white Gaussian noise (AWGN) with zero mean and power spectral density of $N_0/2$. The reasons for this assumption are that it makes calculations tractable and it is also a reasonable description of the receiver noise present in many communication systems.

Given the measurement $r(t)$ the modulation classifier recognizes the modulation type of $r(t)$ from L possible modulations $\{\mathcal{I}_1, \mathcal{I}_2, ..., \mathcal{I}_L\}$. A modulation classifier can be described as a system comprising three parts as seen in figure 1.2.

The work of the *pre-processor* is crucial for the performance of the classifier. The pre-processor removes disturbances from the signal such as outliers and interfering signals and increases the signal-to-noise ratio (SNR) and compensates for fading on the channel. This is only preparation for the *feature processor* which extracts discriminating features of the signal before the *classifier* makes the decision about the modulation type given the data available. The techniques for making the decision are pattern recognition and decision theoretic approach.

This report only covers methods for the actual classification. It is worth noting the distinction between identifying a signal as for example a PSK signal or a QAM signal, *inter-class*, and identifying it as an 8-QAM or a 16-QAM signal which is *intra-class* modulation classification.

1.2.1 Pattern recognition approach

Modulation classification is a problem well suited for pattern recognition. One set of features is to be matched with a pre-determined set of the same features. In the pattern recognition approach, the classifier is composed of two subsystems. The first is a feature extraction subsystem to extract available information from the signal and the second is a pattern recognition subsystem whose function is to indicate the modulation types. A training and adaptation process is necessary during the development of a pattern recognition technique. In many cases, the techniques are designed on an intuitive basis, and the attention is focused on practical implementation rather than theoretical background. Many

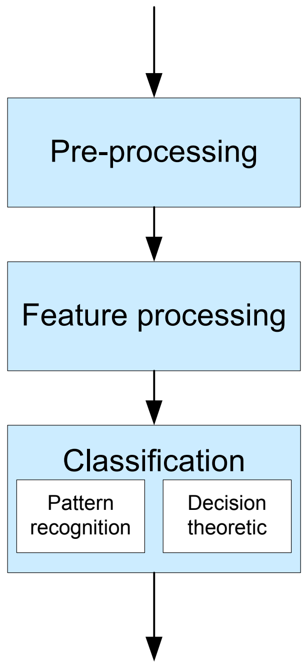

Figure 1.2: The steps in the modulation classification process.

different features have been suggested for pattern recognition for example time domain features based on amplitude, frequency and phase as well as higher order statistics.

1.2.2 Decision-theoretic approach

The decision-theoretic approach is based on statistical properties of the received signal and hypothesis testing to formulate the classification problem. Concretely to that approach, threshold values of key features are established previously and modulation signals are classified by comparing those values.

An L-hypothesis test problem is formulated as

$$\begin{aligned} H_\alpha \quad &: \quad r_i = s_{mi} + n_i, \qquad \alpha = 1,2,...,L \\ i \quad &= \quad 1,2,...,N, \qquad m = 1,2,...M \end{aligned} \tag{1.8}$$

where $\mathbf{r} = [r_1, r_2, ..., r_N]$ is a signal vector formed at the receiver. Choose the hypothesis H_α over H_β if the following holds

$$P(H_\alpha|\mathbf{r}) > P(H_\beta|\mathbf{r})$$

Performance is often measured in probability of correct classification (PCC) as a function of the SNR of the signal according to.

$$PCC \triangleq \frac{\Pr(H_1|H_1) + \Pr(H_2|H_2) + ... + \Pr(H_L|H_L)}{L} \tag{1.9}$$

The decision theoretic approach requires some a priori information of the signal, that is the probability of each hypothesis. It is therefore common to assume that the hypotheses are equally likely. A lot of research has been conducted within the decision-theoretic approach since it can ensure optimality. In an ideal situation, a decision theoretic classifier may outperform a classifier based on pattern recognition.

Chapter 2

Quadrature amplitude modulation

One of the basic forms of bandpass modulation is pulse amplitude modulation (PAM). The information is conveyed by the amplitude of the pulse so that the waveforms may be represented as

$$s_m = \mathrm{Re}[A_m g_T(t) e^{j2\pi f_c t}] \tag{2.1}$$
$$= A_m g_T(t)\cos(2\pi f_c t) \qquad m = 1, 2, ..., M \quad 0 \le t \le T \tag{2.2}$$

where A_m is the signal amplitude that takes on discrete values and $g_T(t)$ is the transmitting filter impulse response whose shape determines the spectral characteristics of the transmitted signal. ASK is a form of digital PAM with a rectangular pulse shape.

A quadrature amplitude modulation (QAM) signal is obtained by simultaneously impressing two separate symbols from the information sequence on two quadrature carrier $\cos 2\pi f_c t$ and $\sin 2\pi f_c t$. The resulting waveforms may be expressed as

$$s_m(t) = \mathrm{Re}[(A_{mc} + jA_{ms}) g_T(t) e^{j2\pi f_c t}] \tag{2.3}$$
$$= A_{mc} g_T(t)\cos(2\pi f_c t) + A_{ms} g_T(t)\sin(2\pi f_c t) \tag{2.4}$$

where A_{mc} and A_{ms} are the information-bearing signal amplitudes of the quadrature carriers. The modulator for QAM is schematically described in figure 2.1. Alternatively, the QAM signal waveforms

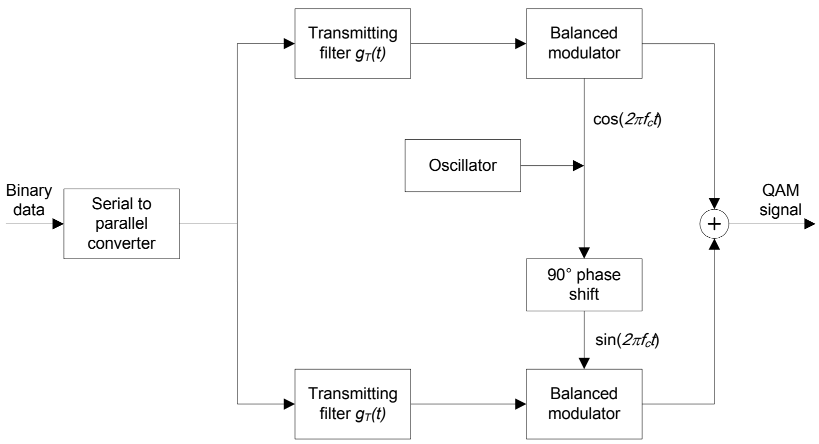

Figure 2.1: Block diagram of QAM modulator.

may be expressed as

$$s_m(t) = \mathrm{Re}[V_m g(t) e^{j2\pi f_c t + \theta_m}] \tag{2.5}$$
$$= V_m g_T(t)\cos(2\pi f_c t + \theta_m) \tag{2.6}$$

where $V_m = \sqrt{A_{mc}^2 + A_{ms}^2}$ and $\theta_m = \tan^{-1}(A_{ms}/A_{mc})$ which makes it apparent that the QAM waveforms can be expressed as a form of combined digital amplitude and digital phase modulation as seen in figures 2.2 and 2.3.

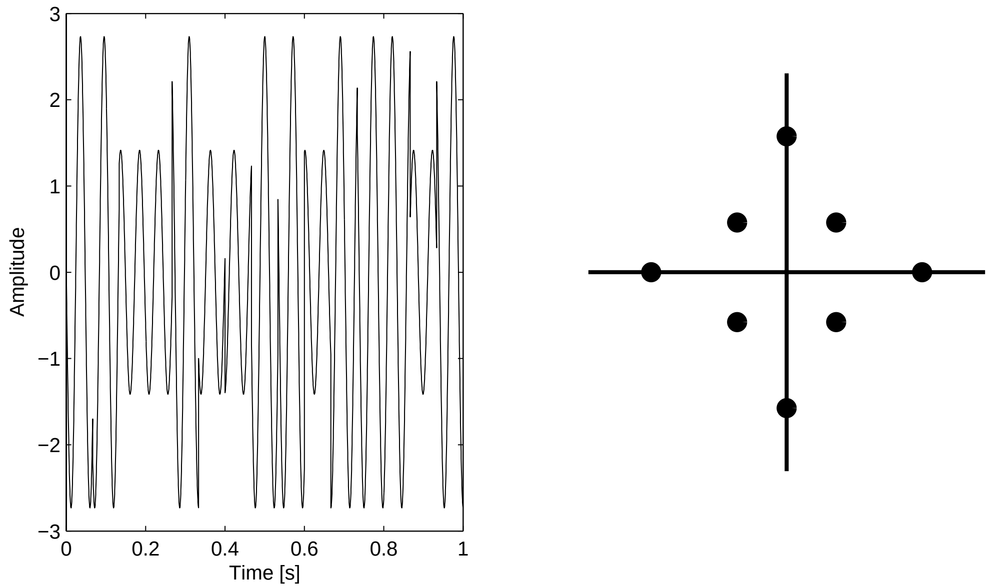

Figure 2.2: The realpart of an 8QAM signal in the time domain and the corresponding constellation diagram.

As mentioned in section 1.1 modulated signals may be expressed in terms of their in-phase and quadrature components

$$s(t) = s_I(t)\cos(2\pi f_c t) - s_Q(t)\sin(2\pi f_c t) \tag{2.7}$$

where $s_I(t)$ is the in-phase component of the modulated wave, and $s_Q(t)$ is the quadrature component. In QAM the in-phase and quadrature components are independent of each other so that the complex envelope is not held constant for QAM signals as in for example in PSK and FSK modulation schemes.

In some literature, e.g. Haykin [3], the general form of combined amplitude and phase modulation is referred to *amplitude-phase keying (APK)* where QAM is defined as a special form of this hybrid. The signal constellation of a QAM signal consists of a square lattice of the message signal according to that definition. In some of the standards for telephone modems the term QAM is used for amplitude and phase modulated carriers with no constraint on the shape of the signal constellation. The latter is also the most common definition in literature and is therefore adopted in this report.

2.1 Signal constellation

By projecting the signal onto a two-dimensional orthogonal vector space a constellation shape is obtained. For a QAM signal there are many different signal constellation shapes for a given number of signal points since the envelope is not constant. For QAM signal sets that have only $M = 4$ points there are two variations on the signal constellation. As seen in figure 2.4 one case with a four-phase modulated signal and a second case is a QAM signal with two amplitude levels.

With increasing number of signal points the number of possible constellations escalates and constellation shapes becomes more complex. The best constellation is the one that requires the least power for a given minimum distance between signal points. In section 2.2 constellation shapes for the modulation types used in some modem standards are shown. Rectangular signal constellations have the distinct

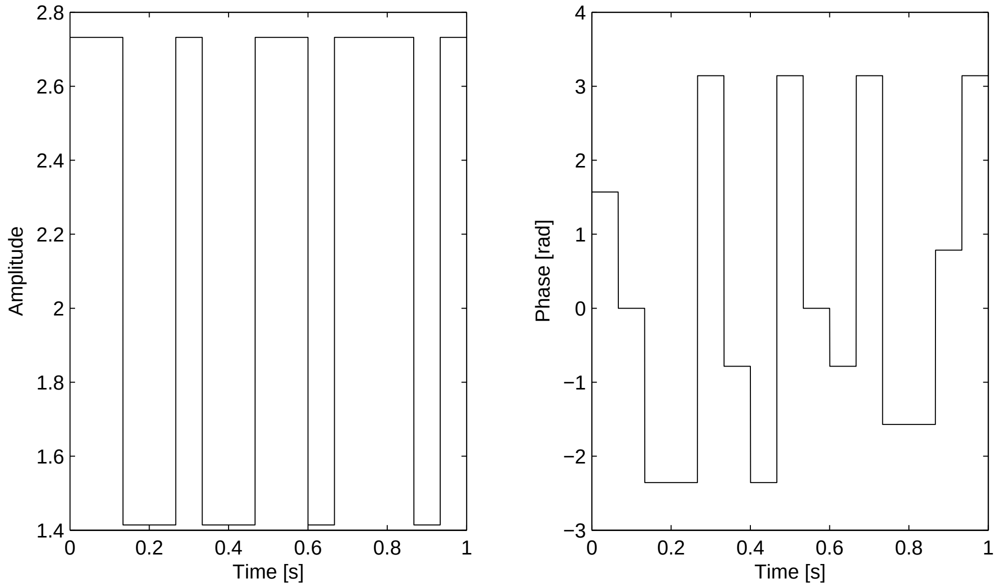

Figure 2.3: Amplitude and phase plots of the QAM signal from figure 2.2.

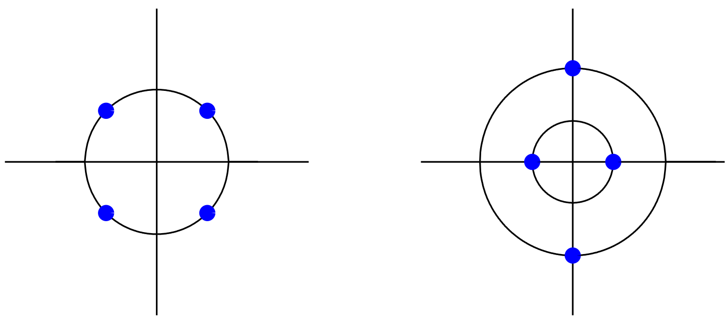

Figure 2.4: Two different 4-point signal constellations.

advantage of being easily generated and demodulated. For $M \geq 16$ they are not the best signal constellations but the average transmitted power required to achieve a given minimum distance is only slightly greater than for the best M-ary QAM signal constellation. Therefore, rectangular M-ary QAM signals are commonly used in practice according to [1].

2.2 Modem standards using QAM

QAM is one of the modulation methods commonly used in modem standards, on its own or together with Trellis coded modulation (TCM) which means that extra bits are added for error correction. Most high-speed modems incorporate fallback capabilities which allows the modem to lower the transmission rate in difficult environments if reliable communication at the highest communication speed can not be established. Modem standards are for instance issued by the international Telecommunication Union (ITU), NATO and the US Military. A few examples of modem standards using QAM are shortly introduced below.

2.2.1 MIL-STD-188-110B Appendix C

This US Military modem standard, [4], for HF data modem waveforms for data rates above 2400 bps uses QAM for data rates above 6400 bps as specified in table 2.1.

Data Rate (bps)	Modulation
3200	QPSK
4800	8PSK
6400	16QAM
8000	32QAM
9600	64QAM
12800	64QAM

Table 2.1: Data rates included in the MIL-STD-188-110B Appendix C

The constellation points which shall be used for the 32QAM modulation are shown in figure 2.5.

2.2.2 V.22bis

The V.22bis modem, [5], uses a square signal constellation of 16 points. The standard calls for 600 baud with 4 bits per baud, giving a data rate of 2400bps.

2.2.3 V.29

With a carrier frequency at 1700 Hz the V.29 operates at 2400 bauds and 9600 bps. This ITU-T Recommendation uses 16QAM with 8 phases and 4 amplitudes in a circular constellation shape as shown in figure 2.6..

2.2.4 V.32

The family of V.32 modems with three different signalling rates may be implemented by the recommendation from the ITU, [6]. The maximum signalling rate of 9600 bps have two alternate modulation schemes, one using 16QAM and one 32QAM as seen in figure 2.7. The 16QAM is a square constellation with nonredundant coding and 4 bits per baud while the 32-point signal structure uses Trellis coding so that each group of 4 consecutive data bits are transmitted together with a redundant bit for error control. Signalling rates of 4800 bit/s and 2400bit/s may also be implemented according to the standard.

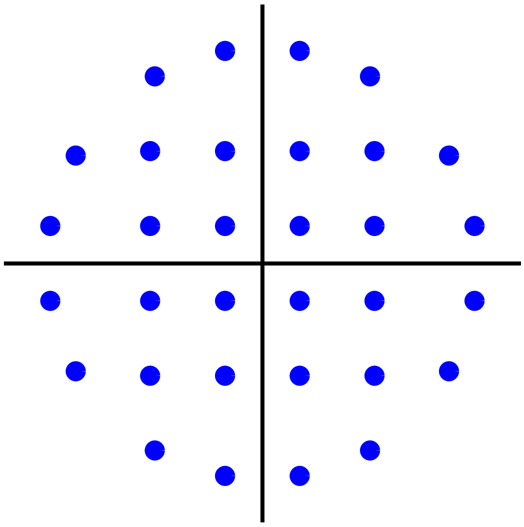

Figure 2.5: A 32-point signal constellation used in the MIL-STD-188-110B Appendix C.

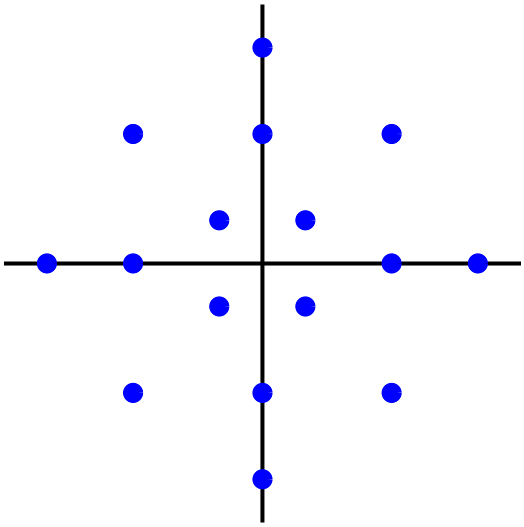

Figure 2.6: The ITU-T V.29 constellation.

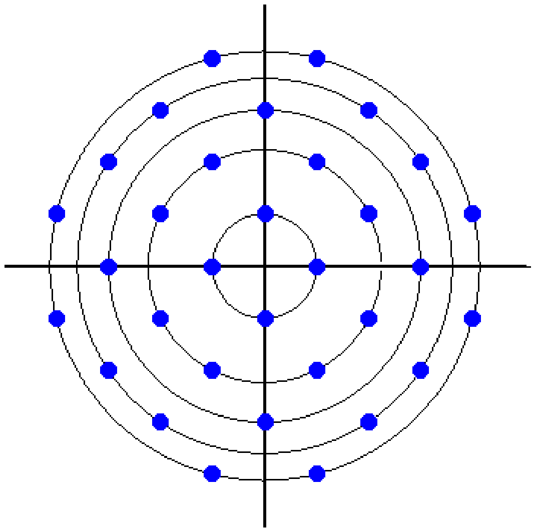

Figure 2.7: 32-QAM signal constellation in the V.32 standard.

2.2.5 V.32bis

Higher transfer rates use much more complex QAM methods. For example, V.32bis uses a 64 point constellation to transfer 6 bits per baud and can achieve 14.4 kbps .

2.2.6 V.34

The highest rate modem, [7], for audio channels uses the QAM modulation which supports signalling rates up to 33.6 kbps and symbol rate of 3429 symbols/s. V.34 requires 3430Hz of bandwidth (244 - 3674) Hz. All signal constellations in the standard are subsets of a 1664-point superconstellation. One quarter of the points in this constellation are shown in figure 2.8. Depending on the symbol rate the modulation carrier frequency varies from 1600 Hz to 1959 Hz. In addition the V.34 modem can perform compression when communicating with another V.34 modem.

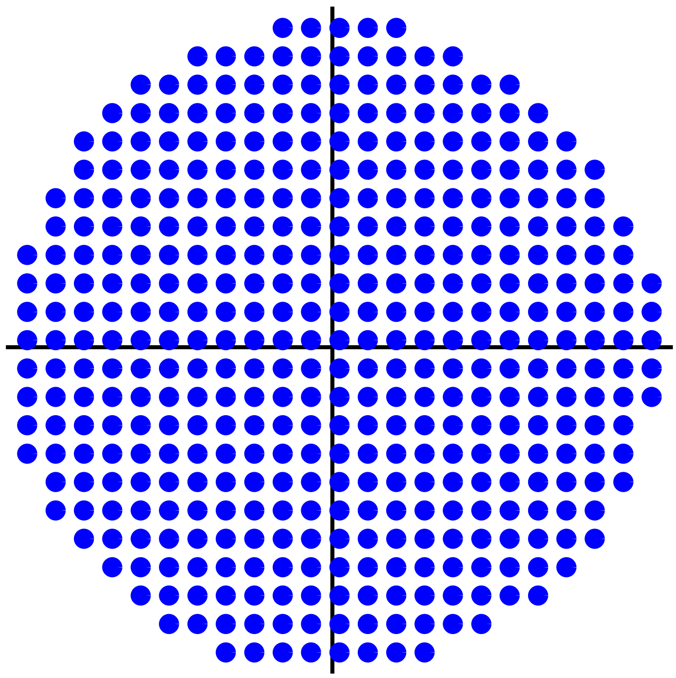

Figure 2.8: One quarter of the 1664-point superconstellation which all constellations used in the V.34 standard are subsets of.

Chapter 3

Modulation classification of QAM

Numerous research articles have been published over the years about automatic modulation classification. Most of them cover identification of FSK and PSK signals with some additions on how to expand the methods for classification for QAM signals as well, now that the interest for QAM has increased. Many of them have been focused on developing signal features rather than providing an overview of existing methods. In [8] Su et al. investigated several well-known methods for digital modulation recognition. The methods were categorized depending on whether baseband conversion was necessary or not. Their survey is brief since it covers modulation classification as a whole and few of the methods investigated deal with QAM classification. Therefore there is a need to study methods proposed for the classification of QAM signals.

3.1 Discriminating features

The most straightforward approache in discriminating different modulation types is using time and/or frequency domain parameters. One of the most referred papers within the research area of modulation classification is Aisbett, [9] from 1987. Five simple functions were used successfully in simulations to discriminate between AM, FM, DSB and CW in the presence of Gaussian noise. It was emphasized that the SNR needs to be considered in modulation classification since noisy signals are more similar to each other, regardless of modulation type, than they are to strong signals of the same modulation type. It was theoretically shown that features based on the standard time-domain parameters of signal envelope and instantaneous frequency are biased estimators of the true signal parameters in the presence of bandlimited Gaussian noise. Instead five simple functions (polynomials of order two) of the quadrature components and their derivatives were suggested since these parameters are unbiased in the presence of AWGN.

In [10] Azzouz and Nandi developed five key features based on the standard deviation of modulation parameters such as nonlinear component of the phase. Then, a decision-tree is used to compare the modulation features with pre-determined thresholds to recognize binary and 4-ary ASK, FSK and PSK.

To classify PSK and QAM signals Taira and Murakami used in [11] the instantaneous amplitude as the discriminating parameter. The instantaneous amplitude of PSK signals at the symbol points is constant, but those of QAM signals take on at least two values for M-ary QAM if $M \geq 8$. A signal is therefore classified as QAM if the computed standard deviation of the instantaneous amplitude at symbol points, is above the predetermined threshold.

3.1.1 Cross Margenau-Hill distribution

Since the Margenau-Hill (time-frequency) distribution (MHD) is known to preserve phase information it can be used to distinguish phase changes in the signal for classification as proposed by Ketterer et al. in [12]. The cross MHD is given by

$$CMHD_{x,y}(t,f) = \frac{1}{2}\int_{-\infty}^{\infty} [x(t+\tau)y^*(t) + x(t)y^*(t-\tau)]e^{-j2\pi f t} d\tau \quad (3.1)$$

If $y(t) = e^{j2\pi f_c t}$ where f_c is the carrier frequency which needs to be estimated if it is not known a priori, the CMDH expression simplifies to

$$CMHD_x(t,f) = \frac{1}{2}\int_{-\infty}^{\infty}[x(t+\tau)e^{-j2\pi f_c t} + x(t)e^{-j2\pi f_c(t-\tau)}]e^{-j2\pi f t}d\tau \tag{3.2}$$

Terms that are related to phase shifts of the signal are shown in the CMHD in a row along time that is located at the carrier frequency. A feature vector, $q(t)$, is formed by taking the absolute value of the cross section of the CMHD along the carrier frequency. This feature vector, defined by

$$q(t) = |CMHD(t, f = f_c)| \tag{3.3}$$

reveals the number of phase values as different amplitude levels. The CMHD is also used in the carrier frequency estimation. A rough estimate is obtained via an autoregressive model of order three and by choosing the frequency with the highest peak in the power spectral density. For several closely spaced frequency the CMHD is computed, the feature vector $q(t)$ will have constant amplitude for the correct frequency and otherwise a superimposed sinusoidal component.

3.1.2 Higher-order statistics

The received signal vector can also be described by its histogram, which is an approximation of the probability density function that describes the probability of different values of the amplitude or phase to occur. The PDF has many parameters to handle so it is often convenient to replace it with fewer parameters as the expected value, variance etc.

Statistics of higher order, i.e. moment and cumulant spectra also reveal characteristics of the received signal and a number of researchers have suggested the use of higher order statistics of the received signal to classify it regarding to modulation type. Cumulants of order greater than two can suppress Gaussian noise processes of unknown spectral characteristics from the signal, and are therefore interesting features from a classification point of view. In appendix A the definitions of joint moments and cumulants are given. A complete introduction to higher-order statistics are found in [13].

Since all cumulant spectra of a Gaussian process of order greater than two are identically zero, a transform to a higher order cumulant will in theory, eliminate the noise when a non-Gaussian process is received along with additive Gaussian noise. Cumulant spectra can become high SNR domains in which one may perform detection, parameter estimation etc.

Soliman and Hsue developed in [14] a classification algorithm to classify M-ary PSK signals. Based on the property that the nth moment (n even) of the phase of the PSK signal is a monotonic increasing function of M, a general hypothesis problem was formulated using the eighth-order moment of the phase.

The nth order moments of normalized instantaneous amplitudes at the estimated symbol points was used by Taira et al. in [11] to discriminate among QAM signals, after performing inter-class modulation classification. Using a decision-theoretic framework the nth order moments were implemented since for even n the nth order moments are monotonic increasing functions of M. Simulations with 16QAM, 64QAM and 256QAM where their 10th order moments were estimated, showed that at SNRs below 20dB classification results were not reliable.

P. Marchand et al. presented in [15] a classifier whos discriminating feature is a vector containing the samples of mixed-orders cyclic cumulants of the signal. This classifier is designed within a decision-theoretic framework so that the feature vector is compared to the possible theoretical features in the maximum likelihood sense. If the received signal $r(t)$ is assumed to be a cyclostationary process, the cyclic cumulant of order $p+q$ at cycle frequency β is defined as

$$c_{r,p+q,p}(\tau) = \lim_{T\to+\infty}\sum_{t=0}^{T-1} C_{r,p+q,p}(t;\tau)e^{-j2\pi\beta t}dt \tag{3.4}$$

where the $C_{r,p+q,p}(t,\tau)$ is the$(p+q)$th order cumulant-based correlation of $r(t)$ with p conjugations given by

$$C^{\beta}_{r,p+q,p}(t;\tau) = Cum[r(t), r(t+\tau_1), ..., r(t+\tau_{p-1}), r^*(t-\tau_p), ..., r^*(t-\tau_{p+q-1})] \tag{3.5}$$

The feature vector to distinguish between modulation types is defined as

$$\mathbf{f}_i = [\, \left| c^{1/T_b}_{r_i,4,2}(a\tau, b\tau, c\tau) \right| + \lambda \left| c^{1/T_b}_{r_i,2,1}(\tau) \right|^2 \,] \tag{3.6}$$

where (a, b, c) are $(\in \mathbb{Z})$, and $\lambda \in \mathbb{R}$ and $\tau = 0, ..., T_b$. The parameters a, b, c and λ will be adjusted to maximize the distance between the $\mathbf{f}_i$'s, so that the minimum achievable probability of error be as low as possible. An expression for computing the optimum value of the mentioned parameters was given in [15]. The proposed classifier was applied to the classification of 4QAM *vs.* 16QAM *vs.* 64QAM and set up as a 3-ary testing problem. Simulations with signals corrupted by Gaussian noise showed up to 90% probability of correct classification for SNR=10dB but most confusions occurred between 16QAM and 64QAM. To improve performance of the classifier the feature vector needs to be extended with more elements.

In [16] by Dobre et al. cyclic cumulants (CCs) up to the eighth order were employed to include the classification of higher-order QAM signals. In this method the received signal power, carrier frequency, symbol period, pulse shape and carrier frequency offset needs to be estimated in a pre-processing step. Three feature vectors, whose components are the magnitudes of the fourth, sixth and eighth order CCs for conjugations ranging from 0 to n are estimated from data by equation (3.4). Only even cumulants are considered since odd-order cumulants are equal to zero due to the symmetry of he considered signal constellations. For all candidate modulation types these feature vectors are computed in advance for comparison with the measured features vectors. The modulation type i, whose feature vector f_i minimizes the Euclidian distance to the measured feature $\hat{f}$ according to

$$\hat{\imath} = \arg\min d(f_i, \hat{f}) \tag{3.7}$$

The analysis of the results of simulations for various signal constellations suggests the use of a hierarchical classification scheme. Fourth order CCs are sufficient to distinguish between real-valued constellations (BPSK, 4ASK, 8ASK) and complex-valued (4PSK, 8PSK, 16QAM, 64QAM and 256QAM) while eight order CCs are suitable to discriminate signals within each class.

3.1.3 Wavelet transform

Another feature for digital modulation identification is wavelet transforms (WT). It makes use of the fact that different digital modulation signals contain different transients in amplitude, frequency or phase because of symbol changes in the signal. The WT has capability to extract the transient characteristics in a signal and thereby allowing simple methods to perform modulation identification. This is because there will be distinct peaks in the magnitude of the WT when it covers a symbol change. Hong and Ho applied in [17] the Haar WT to the signal to be identified due to its simple form and ease of computation. QAM, PSK and FSK signals can be distinguished by computing the variances of the magnitude of the Haar WT, |HWT| with and without applying amplitude normalization and comparing the two cases.

The continuous WT (CWT) of a signal $s(t)$ is defined as

$$\begin{aligned} CWT(a,\tau) &= \int s(t)\Psi_a^*(t)dt \\ &= \frac{1}{\sqrt{a}} \int s(t)\Psi^*(\frac{t-\tau}{a})dt \end{aligned}$$

where a is the scale, τ is the translation and the superscript $*$ denotes complex conjugate. The function $\Psi(t)$ is the mother wavelet and the baby wavelet $\Psi_a(t)$ is a time-scaled and translated copy of the mother wavelet. The Haar wavelet, which is one of the simplest wavelets, is given by

$$\Psi(t) = \left\{ \begin{array}{cc} 1 & 0 \le t < \frac{1}{2} \\ -1 & \frac{1}{2} \le t < 1 \end{array} \right\}$$

In the ideal case, the magnitude of the $|HWT|$ of a PSK signal is constant and that of a FSK and QAM signal is a multistep function. When amplitude normalization is applied the $|HWT|$ of a QAM signal the amplitude variations disappear and the signal becomes a dc, while the amplitudes of the PSK and FSK signals are not affected since they are constant amplitude modulations.

The classifier consists of two branches and a common decision block as seen in figure 3.1, where the second branch includes amplitude normalization. The |HWT| of the input signal is computed and a median filter is applied to remove the peaks. The variances of the outputs are computed and the decision block compares the variances with two thresholds to decide the modulation type of the input signal. If the variance produced by the branch without amplitude normalization is larger than the threshold while the other variance is smaller than the threshold, the input is classified as a QAM signal. The input is classified as a PSK signal if both variances are lower than the thresholds. If both variances are higher than the threshold, the input is classified as a FSK signal.

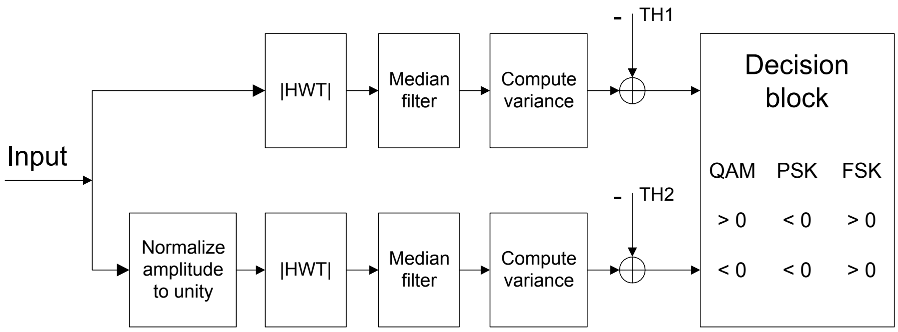

Figure 3.1: Block diagram of the modulation classifier based on the Haar wavelet transform.

Simulation results presented in [17] show 97% correct identification or higher for 16-QAM, QPSK and QFSK at CNR = 5dB in the presence of white Gaussian noise.

3.2 Pattern recognition methods

After some discriminating features in the received signal have been extracted the classifier needs to compare these with the ones of the possible constellation schemes and make a decision. This can be done by pattern recognition. One way of making the decision is by simply deciding a threshold, for example if one feature exceeds the predetermined threshold it belongs to the modulation type $\mathcal{I}_\alpha$.

3.2.1 FCM clustering

Another pattern recognition approach to classify signals is to consider the constellation shape rather than the signal, as the key modulation signature. As stated by B.G. Mobasseri in [18] "if a modulated signal can be uniquely characterized by its constellation it should also be identifiable by the recovered constellation at the receiver". The recovered constellation is distorted in various ways depending on the receiver structure as well as the channel. For example an error in the carrier phase will rotate the symbol. Figure 3.2 shows a 4-QAM constellation corrupted with AWGN.

To recover the constellation shape a fuzzy c-means (FCM) clustering algorithm was proposed by B.G. Mobasseri in [18] and [19]. It is a minimum distance, minimum variance iterative algorithm used to group the signal points in to clusters. The inputs needed are 1) $Nx2$ vector of measurements at correlation detector output 2) initial number of clusters (larger than expected) 3) a termination threshold. Some post-processing might be needed to merge unsupported clusters. The algorithm links each symbol to an individual cluster via a pointer.

The reconstructed constellation is then modeled by a discrete spatial random field. Corresponding random fields are computed in advance for all candidate modulations. An optimum Bayes classifier selects

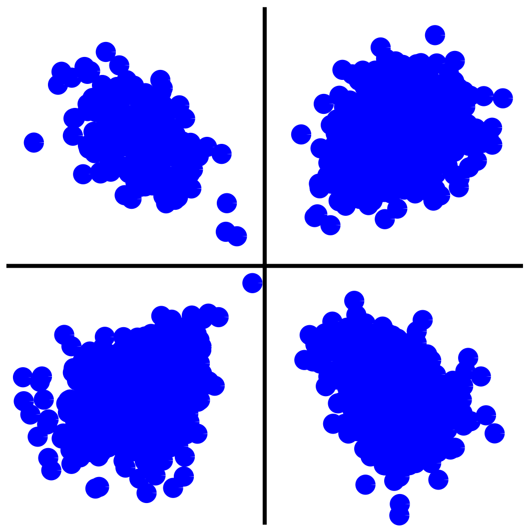

Figure 3.2: 2000 realizations of a 4-QAM signal constellation under Gaussian noise.

the most likely modulation class by maximizing the a posteriori probability for the observed constellation.

The classifier was evaluated and experimental results showed 90% correct separation of an 8PSK from an 8QAM at SNR 0dB. The 8QAM was derived from the fallback provision of v.29 so that the modulations were similar in number of states as well as the circularity of their constellations. In another experiment the effect of carrier phase lock error was examined. V.29 modulation was matched to 16QAM with random carrier phase error with its peak at $\frac{\pi}{8}$. Even at this peak error the classifier exceeds 90% correct classification at SNR of 3dB.

3.2.2 Power moment matrices

With the constellation shape in focus H. Hadinejad-Mahram et al. developed in a series of papers [20]-[22] an algorithm for modulation classification by viewing the constellation diagram as a gray scale picture. Higher-order statistics has already been presented as a discriminating feature in section 3.1.2; here linear combinations of a large number of different orders of joint phase and magnitude moments are arranged in a moment matrix to enable classification of M-ary PSK and QAM signals.

Similar to the definition of moments in Appendix A the $(p+q)$th order spatial moment of an image irradiance distribution $f(x, y)$ is defined by

$$m^{p,q} = \int \int_{-\infty}^{\infty} x^p y^p f(x, y) dx dy \tag{3.8}$$

By extending a moment matrix to gray scale images, which are represented by three variables $\underline{x} = (x, y, z)$, where x, y are the coordinates of each pixel and z is the grey level of this pixel. The spatial power moments (PM) $\mu(p, q, s)$ of order p, q, s of positive integer random variables $\mathbf{x}$, $\mathbf{y}$, and $\mathbf{z}$ are defined as

$$\mu(p, q, s) = E[\mathbf{x}^p \mathbf{y}^q \mathbf{z}^s] \tag{3.9}$$

It can be shown that the set of L^3 power moments $\{\mu(p, q, s)\}_{p,q,s=1}^{L}$ completely characterizes the density in the limit as $L \to \infty$.

Because of the structure of IQ-plane measurements are represented in polar coordinates of the complex plane. The PM rewritten in polar coordinates gives

$$\mu(p,q,s) = E[\mathbf{r}^p e^{j\boldsymbol{\theta}q}\mathbf{z}^s] \quad (3.10)$$

Given a vector of pairwise higher-order moments $\mathbf{U} = [1, \mathbf{r}, \mathbf{r}^2, ..., \mathbf{r}^L, e^{-j\boldsymbol{\theta}}, e^{-j2\boldsymbol{\theta}}, ..., e^{-jL\boldsymbol{\theta}}, \mathbf{z}, \mathbf{z}^2, ..., \mathbf{z}^L]^T$ a power moment matrix (PMM) for a three-dimensional random vector $(\mathbf{x}, \mathbf{y}, \mathbf{z})$ is defined as the expectation over $\mathbf{x}, \mathbf{y}, \mathbf{z}$ of the dyadic outer product of $\mathbf{U}\mathbf{U}^*$. The resulting $(3L+1)\times(3L+1)$ PMM is the expectation over

$$\begin{bmatrix} 1 & \mathbf{r} & \dots & \mathbf{r}^L & e^{-j\boldsymbol{\theta}} & \dots & e^{-jL\boldsymbol{\theta}} & \mathbf{z} & \dots & \mathbf{z}^L \\ \mathbf{r} & \mathbf{r}^2 & \dots & \mathbf{r}^{L+1} & \mathbf{r}e^{-j\boldsymbol{\theta}} & \dots & \mathbf{r}e^{-jL\boldsymbol{\theta}} & \mathbf{rz} & \dots & \mathbf{rz}^L \\ \vdots & \ddots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{r}^L & \mathbf{r}^{L+1} & \dots & \mathbf{r}^{2L} & \mathbf{r}^L e^{-j\boldsymbol{\theta}} & \dots & \mathbf{r}^L e^{-jL\boldsymbol{\theta}} & \mathbf{r}^L\mathbf{z} & \dots & \mathbf{r}^L\mathbf{z}^L \\ e^{-j\boldsymbol{\theta}} & \mathbf{r}e^{-j\boldsymbol{\theta}} & \dots & \mathbf{r}^L e^{-j\boldsymbol{\theta}} & 1 & \dots & e^{-j(1-L)\boldsymbol{\theta}} & \mathbf{z}e^{j\boldsymbol{\theta}} & \dots & \mathbf{z}^L e^{j\boldsymbol{\theta}} \\ \vdots & \ddots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ e^{-jL\boldsymbol{\theta}} & \mathbf{r}e^{-jL\boldsymbol{\theta}} & \dots & \mathbf{r}^L e^{-jL\boldsymbol{\theta}} & e^{-j(L-1)\boldsymbol{\theta}} & \dots & 1 & \mathbf{z}e^{jL\boldsymbol{\theta}} & \dots & \mathbf{z}^L e^{jL\boldsymbol{\theta}} \\ \mathbf{z} & \mathbf{rz} & \dots & \mathbf{r}^L\mathbf{z} & \mathbf{z}e^{-j\boldsymbol{\theta}} & \dots & \mathbf{z}e^{-jL\boldsymbol{\theta}} & \mathbf{z}^2 & \dots & \mathbf{z}^{L+1} \\ \vdots & \ddots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{z}^L & \mathbf{rz}^L & \dots & \mathbf{r}^L\mathbf{z}^L & \mathbf{z}^L e^{-j\boldsymbol{\theta}} & \dots & \mathbf{z}^L e^{-jL\boldsymbol{\theta}} & \mathbf{z}^{L+1} & \dots & \mathbf{z}^{2L} \end{bmatrix} \quad (3.11)$$

In order to make these moments invariant to magnitude changes $\mathbf{r}$ is divided by r_0, where $r_0 = \frac{1}{n}\sum_{i=0}^{n} r_i$ is the arithmetic mean of the magnitudes. To achieve invariance with respect to unknown phase angles element-to-element multiplication of the above matrix with its conjugate is used.

Signal components in the PMM can be separated from the noise background via eigendecomposition. Let $\mathbf{M}$, $\mathbf{M}_s$, and $\mathbf{M}_n$ denote the signal plus noise, signal alone and noise alone moment matrices. The assumed relationship between received signal and noise is given by the mixture model

$$\mathbf{M} = \beta\mathbf{M}_s + (1-\beta)\mathbf{M}_n \quad (3.12)$$

where β is an unknown constant.

Let $\mathbf{C}$ be the known Cholesky factor of the noise alone moment matrix $\mathbf{M}_n$, i.e. $\mathbf{M}_n = \mathbf{C}\mathbf{C}^T$. By defining $\tilde{\mathbf{M}} = \mathbf{C}^{-1}\mathbf{M}\mathbf{C}^{-T}$ we get

$$\tilde{\mathbf{M}} = \beta\tilde{\mathbf{M}}_s + (1-\beta)\mathbf{I} \quad (3.13)$$

where $\mathbf{I}$ is the $(3L+1)\times(3L+1)$ identity matrix and $\tilde{\mathbf{M}}_s = \mathbf{C}^{-1}\mathbf{M}_s\mathbf{C}^{-T}$ is the whitened moment matrix of the signal pattern. Eigendecomposition of the PMM:

$$\tilde{\mathbf{M}} = \sum_{i=1}^{2p+1} \gamma_i \boldsymbol{\xi}_i \boldsymbol{\xi}_i^T \quad (3.14)$$

where γ_i and $\boldsymbol{\xi}_i$ are eigenvalues and eigenvectors. From equation (3.12)

$$\tilde{\mathbf{M}} = \sum_{i=1}^{q} [\beta\gamma_i^s + (1-\beta)]\, \boldsymbol{\xi}_i \boldsymbol{\xi}_i^T + (1-\beta) \sum_{i=q+1}^{2p+1} \boldsymbol{\xi}_i \boldsymbol{\xi}_i^T \quad (3.15)$$

where $\{\gamma_i^s\}_{i=1}^q$ are the non-zero eigenvalues of $\tilde{\mathbf{M}}_s$. Only the q largest eigenvalues $\gamma_i = \beta\gamma_i^s + (1-\beta)$ of $\tilde{\mathbf{M}}$ are related to the signal itself and the rest are pure noise eigenvalues. Therefore $\tilde{\mathbf{M}}_s$ can theoretically be exactly recovered from the eigendecomposition of $\tilde{\mathbf{M}}$ via

$$\tilde{\mathbf{M}}_s = \frac{1}{\beta} \sum_{i=1}^{q} [\gamma_i - (1-\beta)]\, \boldsymbol{\xi}_i \boldsymbol{\xi}_i^T \quad (3.16)$$

Simulation results showed that the PMM method performs better than the classifier developed by Soliman et al. briefly described in section 3.1.2, which used solely the eighth-order phase moment and the log-likelihood function classifier proposed by Polydros et al. in [23]. Note that the Cholesky factor used to denoise the PMM requires knowledge of the noise distribution in the IQ plane and even though simulations presented in [21] were performed with mismatched noise distribution only a moderate amount of mismatched is allowed.

The referred research articles do not reveal the procedure of the actual classification decision but assumable some sort of image processing is used to compare the PMM of the received signal to those of signals in a signal library.

3.2.3 Neural networks

Neural networks have often been applied to classification problems as a technique to use a computed vector and arrive at a classification decision. In [24] a neural network method was presented with the histogram distribution of instantaneous amplitude at symbol points is the input. This works as a inter-class modulation classification method that can separate between, since only the signal amplitude is considered. A three layer neural network with a hidden association layer for the classification is suggested since three layers are sufficient to obtain arbitrary decision regions.

To estimate the symbol timings of the input signal a block demodulation method is used. I and Q components form the square sum component. Symbol rate components can be obtained by FFT processing of these square sum data and choice of maximum peak component.

Histograms of possible modulation schemes are used as learning data sets to initialize the neural network. Updates are performed by an iterative learning algorithm. If the system fails to recognize the modulation after a set number of trial, a unit is added to the association layer and learning continues. It is shown that good classification results for computer simulations can be obtained at SNR 10dB for the synchronous case and at 15dB in the asynchronous case.

3.3 Decision-theoretic approach

A modulation classification problem can be formulated as a hypothesis problem where each hypotheses represents a candidate modulation scheme. The maximum likelihood (ML) classification method chooses the hypothesis under which the likelihood or log-likelihood function is maximized. An L-hypothesis testing problem is written as

$$\begin{aligned} H_\alpha \quad &: \quad r_i = s_{mi} + n_i, \qquad \alpha = 1, 2, ..., L \\ i \quad &= \quad 1, 2, ..., N, \qquad m = 1, 2, ...M \end{aligned} \tag{3.17}$$

where $\mathbf{r} = [r_1, r_2, ..., r_N]$ is a signal vector formed at the receiver. The decision rule is to choose the hypothesis under which the posterior probability is maximized given he observed signal vector $\mathbf{r}$. An overview of the building blocks of the ML MC is shown in figure 3.3. The decision rule is more concretely to choose H_α if

$$P(H_\alpha|\mathbf{r}) > P(H_\beta|\mathbf{r}) \tag{3.18}$$

The posterior probabilities are expressed as

$$P(H_\alpha|\mathbf{r}) = \frac{p(\mathbf{r}|H_\alpha)P(H_\alpha)}{p(\mathbf{r})} \tag{3.19}$$

Since $p(\mathbf{r})$ is independent of H_α and if the a priori probabilities of H_α are assumed equally likely, the maximization of the conditional probability is equivalent of finding the signal that maximizes the likelihood function $p(\mathbf{r}|H_\alpha)$, which is the conditional PDF of the observed vector under hypothesis H_α. Since the noise samples n_i are assumed to be independent and identically distributed the conditional

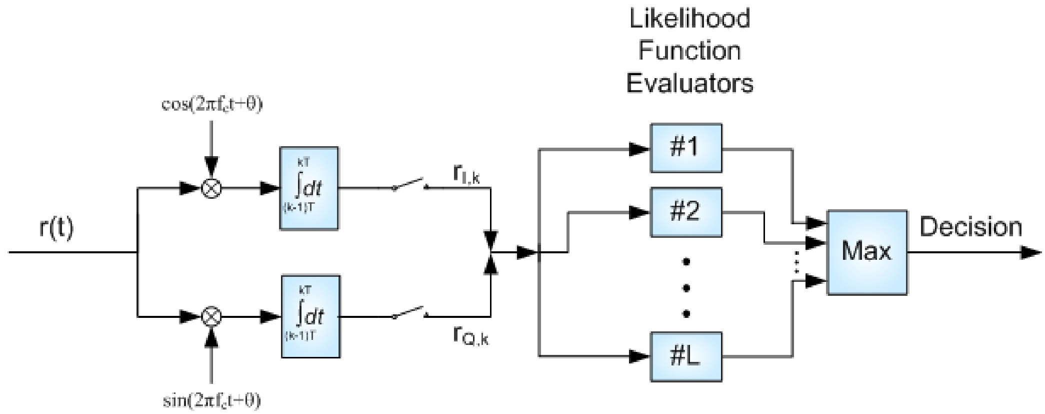

Figure 3.3: Block diagram of a maximum-likelihood modulation classifier.

PDF of the random vector $\mathbf{r}$ is the product of N individual PDF's as

$$p(\mathbf{r}|H_\alpha) = p(r_1, r_2, ..., r_N|H_\alpha) \tag{3.20}$$

$$= \prod_{i=1}^{N} p(r_i|H_\alpha) \tag{3.21}$$

When all constellations are equally likely, the ML criterion is equivalent to the maximum a posteriori criterion (MAP); therefore, the ML MC is optimal in the sense of minimum error rate. Wei and Mendel studied in [25] the asymptotic performance of a maximum-likelihood classifier capable of classifying PSK, PAM and QAM. The results show that the classifier achieves 100% probability of correct classification when classifying a finite set of distinctive constellations when the number of available data symbols goes to infinite. This is only true in an ideal situation where all signal parameters as well as noise power are known, data symbols are independent and the pulse shape is rectangular. The theoretic results are supported by Monte Carlo simulations with four different QAM constellations. Because the maximum-likelihood classifier is optimal and show asymptotic performance it is an interesting approach to the classification problem. Therefore many papers within this field have been published in recent years.

Early research within maximum-likelihood modulation classification performed by Polydros and Kim resulted in [23]. Under the assumption that some communication parameter such as CNR and symbol rate are available, an approximate likelihood ratio modulation classifier was derived to separate BPSK and QPSK and proven to work well even for low SNR. This approach was extended to QAM signals in [26] by Long et al. The modulation classification problem was formulated as a binary hypothesis testing problem with two general quadrature modulated signals. Given the signal $s(t)$, the average log-likelihood function (ALLF) of the received waveform $r(t)$ is

$$l(r(t)|s(t)) = \ln << \exp\left\{\frac{2}{N_0}\int_0^T r(t)s(t)dt\right\} >_{\tilde{s}_k}>_\theta \tag{3.22}$$

where $N_0/2$ is the power spectral density of the additive white Gaussian noise corrupting the signal. $< . >_{\tilde{s}_k}$ and $< . >_\theta$ denote averaging with respect to input data symbols and carrier phase respectively. It can be shown that for any two-dimensional QAM signal constellation set, the ALLF can be approximated by an infinite series, which can be used for classification. This series can be simplified to a classifying statistic Q_m, expressed as

$$Q_m = \left|\sum_{k=1}^{N}(\tilde{r}_k)^m\right|^2 \tag{3.23}$$

The design parameter m is dependent on the power of $s(t)$ and $\tilde{r}_k$ is the sampled output of the bandpass matched filter according to

$$\tilde{r}_k = \int_{(k-1)T_s}^{kT_s} r(t)\sqrt{2}e^{j2\pi f_c t}dt \tag{3.24}$$

where known symbol timing and common symbol duration T_s have been assumed. Acceptable classifier performance is obtained. The classification decision between the two modulated signal QAM$_i$ and QAM$_j$ is the made by the average log-likelihood ratio (ALLR) test. Given the threshold value T_q, the test can be expressed as

$$\begin{aligned} Q_m &> T_q \qquad for \quad \mathcal{I}^* = QAM_i \\ Q_m &< T_q \qquad for \quad \mathcal{I}^* = QAM_j \end{aligned} \tag{3.25}$$

The threshold setting has decisive influence on the performance of the classifier. In [26] an expression for the optimal threshold was derived but analytical determination of the threshold is often difficult. A practical method for setting the threshold of the ALLR test is presented, simulations confirm that it only suffers slightly in performance relative to the optimal setting The PCC for the proposed classifier in the two cases 16PSK/16QAM and 16PSK/V.29 is higher than 95% for SNR>10dB.

To simplify computations and using the fact that the natural logarithm is a monotonic function Yang et. al. developed in [27] a classifier that chooses the hypothesis under with the log-likelihood function is maximized. The PDF of the amplitude of the received signal is used to classify QAM signals. The ith received sample can be expressed as

$$R(i) = A_m(i) + \xi(i) \tag{3.26}$$

where $A_m(i)$ is the sampled amplitude component of the message signal and $\xi(i)$ is the random amplitude component due to noise. It was shown that the amplitude, R, is Rician distributed as

$$p(R) = \frac{R}{\sigma^2}e^{-(R^2+S^2)/2\sigma^2} I_0\left(\frac{RS}{\sigma^2}\right), \qquad R \geq 0$$

where S is the magnitude of the modulated signal $s_m(t)$ and $I_0(x)$ is the well-known modified Bessel function of order 0. Given the weight vector w_{16}, the amplitude PDF of a rectangular 16QAM is expressed as

$$\begin{aligned} p(R) &= \sum_{j=1}^{3} w_{16}[j]Re^{-(R^2+S^2_{16,j})/2} I_0\left(RS_{16,j}\right) \\ w_{16} &= \left[\frac{4}{16}, \frac{8}{16}, \frac{4}{16}\right] \qquad R \geq 0 \end{aligned} \tag{3.27}$$

The decision-function for a M-ary QAM is expressed as

$$\begin{aligned} l_\alpha &= \ln[p(R_1, R_2, ..., R_N|H_\alpha)] \\ &= \sum_{i=1}^{N} \left\{ \ln \sum_{j=1}^{k} w_M[j]R_i e^{-(R^2+S^2_{M,j})/2} I_0\left(RS_{M,j}\right) \right\} \end{aligned} \tag{3.28}$$

Since R_i and $e^{-R^2/2}$ are common in each hypothesis the test statistic can be further simplified

$$l_\alpha = \sum_{i=1}^{N} \left\{ \ln \sum_{j=1}^{k} w_M[j] e^{-S^2_{M,j}/2} I_0\left(RS_{M,j}\right) \right\} \tag{3.29}$$

For each hypothesis l_α is estimated so the classifier chooses the largest and reports back the modulation type.

To utilize the complete information in the signal and not only the amplitude Yang et al. presented in [28] a classifier based on the joint PDF of the amplitude and phase of the received signal. If z is the complex envelope and φ the phase of the received signal, the joint PDF of amplitudes and phases can be written as

$$p(z,\varphi) = \frac{z}{2\pi\sigma^2} e^{-\frac{z^2+A_m^2-2A_m z\cos(\theta_m-\varphi)}{2\sigma^2}} \tag{3.30}$$

where A_m and θ_m represent the amplitude and the phase of the mth message point of the signal. The noise corrupting the signal is assumed to be AWGN with zero mean and variance of σ^2. For example the joint PDF of amplitudes and phases for a 16QAM is given by

$$p_{16}(z,\varphi) = \frac{1}{16}\sum_{m=1}^{16} \frac{z}{2\pi\sigma^2} e^{-\frac{z^2+A_{16,m}^2-2A_{16,m} z\cos(\theta_{16,m}-\varphi)}{2\sigma^2}} \tag{3.31}$$

The set of amplitudes and phases can be written as $\{\mathbf{A}_{16,m}, \boldsymbol{\theta}_{16,m}\}$ where the specific values are given by table 3.1.

$\mathbf{A}_{16,m}$	$\boldsymbol{\theta}_{16,m}$
$\sqrt{5}A$	$tan^{-1}[1/3]$
A	$\pi/4$
$3A$	$\pi/4$
$\sqrt{5}A$	$tan^{-1}[3]$
$\sqrt{5}A$	$tan^{-1}[3]+\pi/2$
A	$3\pi/4$
$3A$	$3\pi/4$
$\sqrt{5}A$	$tan^{-1}[1/3]+\pi/2$
$\sqrt{5}A$	$tan^{-1}[1/3]+\pi$
A	$5\pi/4$
$3A$	$5\pi/4$
$\sqrt{5}A$	$tan^{-1}[3]+\pi$
$\sqrt{5}A$	$tan^{-1}[3]+3\pi/2$
A	$7\pi/4$
$3A$	$7\pi/4$
$\sqrt{5}A$	$tan^{-1}[1/3]+3\pi/2$

Table 3.1: The set of amplitude and phases of rectangular 16QAM

Taking the natural logarithm of (3.31) gives the new test statistic. Simulations with two hypothesis show good classification results even at low SNR. The classifier algorithm based on the joint PDF of amplitude and phases proves to be superior to the amplitude PDF based classifier.

Since the ML approach provides an optimized solution for modulation classification it may result in a high probability of correct classification in an ideal situation compared to other methods. However the performance is based on the assumption that the signal is transmitted in a perfect channel only disturbed by AWGN and the receiver has perfect knowledge of many critical signal parameters such as: symbol rate, carrier frequency, carrier phase, pulse shape, SNR, timing offset and transmission channel. In practice, those parameters are not always available in non-cooperative communication and the estimation of some parameters is not trivial. In [29] Sills presented a maximum-likelihood framework for both the coherent and non-coherent classification of PSK/QAM signals in the latter which all signal parameters are known to the receiver except the carrier phase. The algorithms performance was evaluated for various constellations where the demodulated symbols were rotated by an unknown carrier phase. The results show that the non-coherent classifier suffers a performance loss of approximately 3dB. With more than one unknown signal parameters even greater losses would be expected but no analysis on the robustness of the ML classifier in the case of unknown signal parameters has been found in literature.

3.4 Decision-making based on fuzzy logic

In classic logic everything can be expressed in binary terms (0 or 1, true or false) while fuzzy logic allows for values between 0 and 1. Fuzzy logic is used to describe degrees of truth which is useful in the classification process. Since the classification process consists of many decisions it is useful to keep as much of the information which led to the decision by making a soft decision rather than a hard decision.

The maximum likelihood modulation classifier assumes ideal conditions, i.e. Gaussian noise and known signal parameters (e.g. carrier frequency and phase, symbol timing, signal and noise power). This is typically not the case in the real world, non-Gaussian noise exists in many communication environments and signal parameters are not completely time-invariant and need therefore to be estimated and . Wei and Mendel developed in [30] a fuzzy logic modulation classifier to outperform existing ML classifiers in a non-ideal environment. The architecture of the fuzzy logic modulation classifier is illustrated in figure 3.4. A two-dimensional fuzzy logic system (FLS) constitutes the core building block of the modulation classifier. It processes one input complex symbol x_k at a time and produces a fuzzy output O_k for each input. Since each O_k is based only on one symbol it is highly uncertain. The N O_k's are then combined by fuzzy intersection that results in the overall fuzzy decision Y, which is then defuzzified to produce a hard decision.

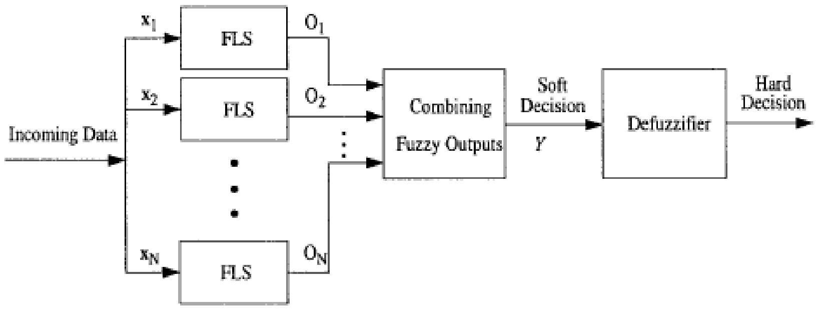

Figure 3.4: The architecture of a fuzzy logic modulation classifier.

The classifier proposed in [30] use heuristic interpretations of the ML MC as training data for generating fuzzy rules. The rules are based on the geometric formation of the complex-domain data. If $\mathcal{I}^*$ is the true constellation the data points form M^*clusters centered at the original constellation points. So an indication that $\mathcal{I}_l$ is the true constellation is if each data point in $\mathcal{I}_l$ falls into at least on of the M_l clusters. This observation can be described as "*If* every data point (x_k) belongs to one or more of the M_l clusters *then* the constellation is probably $\mathcal{I}_l$". Each cluster is modeled by a fuzzy set with a membership function. It depends on the distance metric (e.g. Euclidean or Hamming) of the data point and the cluster center as well as a selected kernel function (e.g. triangular, Gaussian or exponential) and a scale factor to control the dispersion of the fuzzy set. The membership functions of the clusters are combined by compositional fuzzy inference that results in a fuzzy modulation O_k.

Wei and Mendel show through simulations that when ideal conditions hold, the ML and FL classifiers perform equally but when impulsive noise is present the FL classifier performed consistently better than the ML MC. The FL classifier has much more flexibility because it is not dependent on a priori information and the distance metric and kernel functions can be chosen to make the classifier adapt to different non-ideal environments.

Chapter 4

Discussion

Increasing interest in QAM signals and classification of the same has led to increasing numbers of published work on the subject. Because of the classified nature of signal intelligence, the open literature does not contain all the information on modulation identification. Therefore a survey of existing methods can never be complete. This report has presented a variety of methods for the classification of QAM signals.

Most papers published within this field are directed towards developing new features for classification. Few discuss the signal classification problem using a system approach, where for example, it is required to perform a real-time classification within defined computational constraints. In many of the proposed methods, the noise corrupting the signal is assumed to be AWGN. This might be an acceptable assumption at high frequency communications but at lower frequencies, e.g. the HF band, noise with other spectral characteristics is present.

Comparing the performance of different methods presented in this report is not a straight-forward task. These methods have been tested in channel conditions of the authors' choice. The stated probabilities of correct classification are in many ways dependent on the other modulations in the library and are therefore not comparable to each other.

4.1 Conclusions

The first step in the classification process is to extract the discriminating features of the incoming signal. Time and frequency parameters are easy to implement and makes up a flexible classifier, which easily can be increased with more features. When making the decision, too many features make it significant to optimize the features so that the most important features are computed and tested first. The cross Margenau-Hill distribution and higher order statistics are more computationally intensive and might be to abstract and difficult to manually tell if they are reasonable or not. The CMDH is nevertheless a powerful tool for extracting the phase information from a signal. Higher order statistics are interesting features thanks to their behavior in AWGN.

The pattern recognition approach is straightforward and relatively easy to implement but determining well-balanced threshold values require a lot of training. A hypothesis-testing method on the other hand can guarantee optimality but only if the hypothesis are adequately set out. ML MC is based on assumptions that typically do not hold in a real-world modulation classification problem. In the presence of impulsive noise the presented classifier based on fuzzy logic performs better than the ML MC.

QAM signal are challenging to classify since their notations are not unambigiuous unlike FSK and PSK constellation. A QAM signal is uniquely defined only by its constellation shape, i.e. the amplitude and phases of signal points. Even for a small number of signal points there exist many variations in the constellation shape. Both the classifier based on the FCM clustering algorithm and power moment matrices solve this problem by treating the constellation shape as the discriminating feature. These methods require reasonable SNR to distinguish signal points especially when the number of signal point increases.

The use of the Haar wavelet transform to distinguish transient characteristics in a signal is a new and interesting approach to modulation classification. Because the decision relies on thresholds, training is crucial for the performance.

Fuzzy logic and neural networks are frameworks that can be used in modulation classification. These together with other methods would form a classifier applicable to all modulation types. Training data is needed in the initial step but these approaches are very flexible and easy to expand to other modulation types.

In most of these presentations no robustness studies of modulation recognition performance in regards to symbol rate error, symbol timing error, symbol resampling error and channel distortion are found.

Since there is no modulation classification approach superior to all others the nature of the application must determine the optimum method to use.

4.2 Recommendations for further research

As pointed out before no studies of robustness were found for many of the suggested methods. It is relevant to examine the performance of the methods under other conditions than AWGN and with no knowledge of signal parameters such as baudrate and carrier phase for example.

No papers that deal with the classification of higher order QAM, for example the modem standards V.32 or V.34, were found in this study even though their respective recommendations were published some years ago. It would be interesting to investigate the performance of the presented methods with these complex signals.

For practical implementation of a modulation classifier capable of dealing with QAM signals the preprocessor step must be carefully implemented for satisfying performance. A hierarchical decision might be implemented by classifying in two steps; first a coarse classification to distinguish QAM from other modulation types by for example a pattern recognition method and then a fine classification by a decision-theoretic intra-class modulation, where the number of possible modulation types is more restricted.

When implementing a QAM classifier it becomes important to investigate how to represent different QAM constellations in a transmission database, with different entries for possible combinations.

Appendix A

Definition of joint moments and cumulants

Given a set of N real random variables $\{r_1, r_2, ..., r_N\}$ their joint moments of order $p = k_1 + k_2 + ... + k_n$ are defined as

$$\begin{aligned} Mom[r_1^{k_1}, r_2^{k_2}, ..., r_N^{k_N}] &\triangleq E\{r_1^{k_1} r_2^{k_2} ... r_N^{k_N}\} \\ &= (-i)^p \frac{\partial^p \Phi(\omega_1, \omega_2, ..., \omega_N)}{\partial \omega_1^{k_1} \partial \omega_2^{k_2} ... \partial \omega_N^{k_N}}|_{\omega_1=\omega_2=...=\omega_N=0} \end{aligned} \tag{A.1}$$

where $\Phi(\omega_1, \omega_2, ..., \omega_N) \triangleq E[\exp(i(\omega_1 r_1 + \omega_2 r_2 + ... + \omega_N r_N))]$ is their joint characteristic function. The natural logarithm of $\Phi(\omega_1, \omega_2, ..., \omega_N)$ provide for another form of the characteristic function i.e. $\tilde{\Psi}(\omega_1, \omega_2, ..., \omega_N) \triangleq \ln[\Phi(\omega_1, \omega_2, ..., \omega_N)]$ that defines the joint cumulants of order p:

$$Cum[r_1^{k_1}, r_2^{k_2}, ..., r_N^{k_N}] \triangleq (-i)^p \frac{\partial^p \tilde{\Psi}(\omega_1, \omega_2, ..., \omega_N)}{\partial \omega_1^{k_1} \partial \omega_2^{k_2} ... \partial \omega_N^{k_N}}|_{\omega_1=\omega_2=...=\omega_N=0} \tag{A.2}$$

For a stationary random process $\{R(k)\}, \quad k = 0, \pm 1, \pm 2, ...$ the moments and of order p are defined as

$$\begin{aligned} Mom[R(k), R(k+\tau_1), ..., R(k+\tau_{p-1})] &= m_p^r(\tau_1, \tau_2, ..., \tau_{p-1}) \\ &\triangleq E\{R(k) \cdot R(k+\tau_1) ... R(k+\tau_{p-1})\} \end{aligned} \tag{A.3}$$

Similarly the cumulants are given by

$$c_p^r(\tau_1, \tau_2, ..., \tau_{p-1}) \triangleq Cum[R(k) \cdot R(k+\tau_1) ... R(k+\tau_{p-1})] \tag{A.4}$$

where $\tau_1, \tau_2, ..., \tau_{p-1}, \quad \tau_i = 0, \pm 1, \pm 2, ...$ denote the time differences.

Given the set $\mathbf{r} = \{r_1, r_2, ..., r_N\}$, the mean value of this set also defined as the moment of 1st order

$$\bar{r} = m_1^r \tag{A.5}$$

$$= E\{R(k)\} \tag{A.6}$$

where $E\{\cdot\}$ is the expected value of the argument. The variance of the set is a measure of the variation of the set of variables, defined as

$$\sigma^2 = E\{(r - \bar{r})^2\} \tag{A.7}$$

Given that the mean value defined in equation (A.5) is zero, definitions of commonly used statistics to described the probability density function of the signal set, are listed in table A.1.

Name	Definition
Variance	$\gamma_2^r = E(R^2(k)) = c_2^r(0),$
Skewness	$\gamma_3^r = E(R^3(k)) = c_3^r(0,0),$
Kurtosis	$\gamma_4^r = E(R^4(k)) - 3(\gamma_2^r)^2 = c_4^r(0,0,0)$
	$if\ m_1^r = 0$

Table A.1: Example of higher-order statistics useful in modulation classification

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