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AUTOMATIC MODULATION CLASSIFICATION IN FADING ENVIRONMENT USING STATISTICAL FEATURES

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Research Article

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ABSTRACT:
The development of Fourth Generation (4G) wireless communication systems is anticipated to heavily rely on software radio technology. One of the main responsibilities of an intelligent receiver is the signal identification process, which is a stage in between signal interception and demodulation. The method of determining what modulation is being used at the transmitter based on observations of the received signal is known as Automatic Modulation Classification (AMC). Ten candidate signals were produced, including 2ASK, 4ASK, 2PSK, 4PSK, 2FSK, 4FSK, 16 QAM, GMSK, 64QAM, and 256 QAM. AWGN and the multipath Rayleigh fading effect were simulated in order to mimic channel conditions. Initially, instantaneous characteristics including amplitude, phase, and frequency were obtained. Instantaneous features were used to create stochastic features. The classifier was developed using seven essential characteristics. Higher order statistical features like moments and cumulants were used to classify higher order QAM signals like 64QAM and 256QAM. Threshold values were used in the development of the Decision Tree classifier. For SNR=3dB, the overall classification result was more than 97%. For SNR=5dB, the success rate was almost 99% (no fading condition). Ten modulated signals with different channel characteristics and SNRs as low as -5dB may be classified using the created classifier.

Keywords: SNR, Decision Tree, Automatic Modulation Classification, and Digital Modulation

INTRODUCTION

When the receiver is unaware of the modulation format, Automatic Modulation Recognition (AMR) is a process that is carried out based on the received signal prior to demodulation. One significant benefit in a wireless network is the capacity to automatically choose the appropriate modulation scheme utilized in an unknown received signal. Blind identification is a challenging process with numerous unknown characteristics at the receiver and no knowledge of the sent data. Real-world situations with multipath fading, frequency selection, and time-varying channels make the recognition process much more difficult.

Based on how categorization issues are approached, the recognizers are split into two subsets: Likelihood-Based (LB) or decision-theoretic approaches. Feature-based (FB) or statistical pattern recognition. The likelihood ratio is the foundation of the decision-theoretic, or LB, method, which uses the greatest likelihood ratio of chosen signals and known signals to determine a signal's modulation style. There are two components to the statistical pattern recognition, or FB, technique. The first phase is called feature extraction, and its function is to take the preset feature out of the data that was received. The second is a pattern recognition component that uses the retrieved information to categorize a signal's modulation type.

There is some prior research on feature-based categorization [1–5]. A cohesive perspective on modulation categorization was put forward. There was discussion of the basic principle kinds of characteristics utilized for algorithm structure and classification [6-7].A thorough summary of feature-based digital modulation methods has been provided [8]. Instantaneous amplitude, phase, and frequency [9–11], wavelet transformations [12–13], higher order moments and higher order cumulants (HOCs) [14–17], and cyclo-stationarity [18] are just

a few of the many characteristics that have been used in AMC. Numerous kinds

AMC has made use of Pattern Recognition (PR) techniques. Artificial neural networks [19–21], clustering, support vector machines [12], and decision trees [22] are examples of PR techniques. The outcomes of simulations for classifiers created with various attributes were compared [23].

Ten digitally modulated signals that are adaptable to Software Defined Radio (SDR) in the presence of AWGN and the multipath fading effect are classified in this study. Based on threshold values, a hybrid feature-based decision tree classifier has been created. Signals with SNRs as low as -5dB may be classified by the classifier.

SIGNAL MODEL IN AMR

The Modulation Classification model is presented in Fig. 1 The received signal is represented as

$$r_i(t) = s_i(t) + n(t) \quad (1)$$

Where $r_i(t)$ is the received signal, $s_i(t)$ is the transmitted signal, and n(t) is the additive white Gaussian noise. The discrete expression of received signal in Rayleigh fading environment is given by

$$r_i = \alpha_i s_i + n_i \quad (2)$$

Where α_i is a Rayleigh random variable, s_i is the signal sequence and n_i is noise

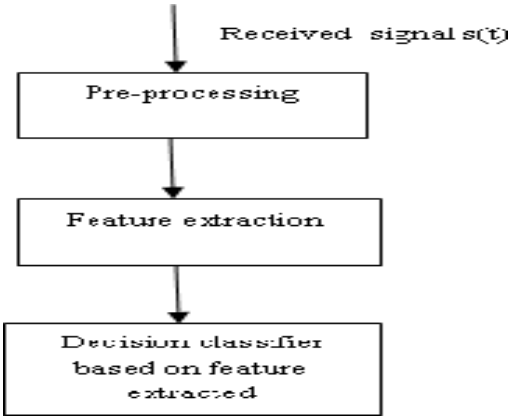


Fig. 1 Modulation Clsssification Model

The model shows three stages:

A. *Preprocessing*
B. *Feature Extraction*
C. *Modulation classification*

A .Preprocessing

The pre-processor's job is to improve the classifier's performance. By eliminating signal disruptions like interfering signals, the pre-processor raises the signal strength (SNR).This work's preprocessing tasks include blind equalization using the Constant Modulus algorithm (CMA) and signal denoising using wavelet decomposition [24].

The signal denoising algorithm is

i) Wavelet coefficients were calculated.
ii) Detail coefficients were used to estimate noise standard deviation
iii) Global threshold value was selected, which is used for signal denoising.

Without knowing the channel itself, the channel effect was reversed using the Constant Modulus Algorithm–Fractionally Spaced Equalizer (CMA-FSE) approach. The equalization weights are forced to maintain a constant envelope of the incoming signal via the constant modulus method, a stochastic gradient technique.

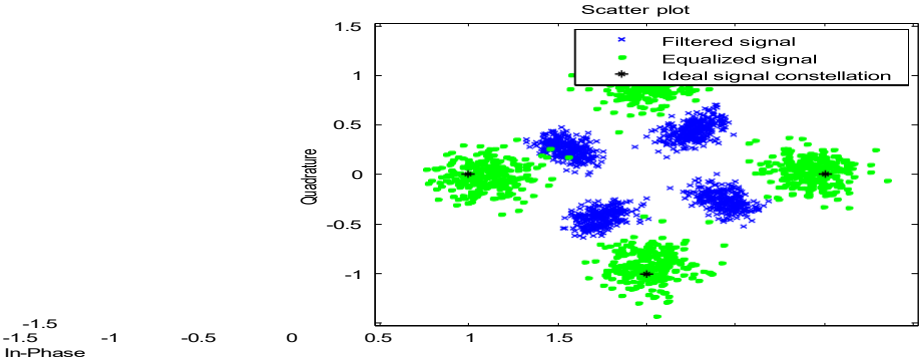


Fig. 2 Constellation plot of 4PSK

This study examined the CMA-FSE algorithm on 4PSK, 8PSK, 16QAM, 64QAM, and 256QAM. According to simulation findings, this technique almost eliminates the channel impact in 2PSK, 4PSK, 8PSK, and 16QAM. Additionally, the constellation may be recovered for 64 QAM, but not for symbol orders higher than 64 QAM. Figure 2 shows a constellation plot of a 4PSK signal. The signal plot in the figure is ideal, dispersed, and equalized. Higher order constellation plots were shown to be more severely affected by noise and fading.

B. Feature Extraction

The properties of various digital signal types vary. Finding the right characteristics for digital signal detection is thus a significant challenge, especially when dealing with higher order and/or nonsquare digital signal types. It is necessary to choose the essential characteristics for modulation categorization in the pattern recognition method. Robust characteristics that are responsive to modulation types and insensitive to variations in SNR should be included in these features. Initially, the whole set of signals' instantaneous characteristics, including amplitude, frequency, and phase, were determined. Instantaneous features were used to derive stochastic features like amplitude mean, standard deviation of the absolute value of the normalized-centered instantaneous amplitude, standard deviation of the centered non-linear component of the absolute instantaneous phase, standard deviation of the centered non-linear component of the direct (not absolute) instantaneous phase, and standard deviation of the absolute value of the normalized-centered instantaneous frequency of a signal as feature vectors 1, 2, 3, 4, and 5, respectively. Additionally, cumulants and higher order moments were computed. Higher order QAM signals were categorized using these. The classifier was developed using seven essential characteristics.

i) Stochastic features

Five Stochastic features were calculated as follows:

Feature vector 1 is the maximum value of Power Spectral Density (PSD) of normalized-centered instantaneous amplitude [3]

$$\gamma_{max} = \frac{max\ |FFT(a_{cn}\ (i))|^2}{N_S} \quad (3)$$

where Ns is the number of samples, m_a is the sample mean of a(i) and $a_{cn}\ (i) = \frac{a(i)}{m_a} - 1$

This feature classifies PSK modulations as one group, and FSK modulations as another group.

Feature vector 2 is the standard deviation of the absolute value of the normalized- centered instantaneous amplitude of a signal segment

$$\sigma_{aa} = \sqrt{\frac{1}{N_s}\sum_{i=1}^{N_s} a^2_{cn}(i) - \left[\frac{1}{N_s}\sum_{i=1}^{N_s} |a_{cn}(i)|\right]^2} \quad (4)$$

σ_{aa} captures the variation of modulated signal amplitude. Hence, they are used for determining ASK order and to distinguish ASK signals from PSK signals.

Feature vector 3 is the standard deviation of the centered non-linear component of the absolute instantaneous phase

$$\sigma_{ap} = \sqrt{\frac{1}{L}\sum_{a(i)>t_{th}} \varphi^2_{NL}(i) + \left[\frac{1}{L}\sum_{a(i)>t_{th}} \varphi^2_{NL}(i)\right]^2} \quad (5)$$

where t_{th} the threshold value of the non weak is signal in and L is the length of non weak values.

Feature vector 4 is the standard deviation of the centered non-linear component of the direct (not absolute) instantaneous phase

$$\sigma_{dp} = \sqrt{\frac{1}{L}\sum_{a(i)>t_{th}} \varphi^2_{NL}(i) + \left[\frac{1}{L}\sum_{a(i)>t_{th}} \varphi^2_{NL}(i)\right]^2} \quad (6)$$

Feature vector 5 is the standard deviation of the absolute value of the normalized- centered instantaneous frequency of a signal segment

$$\sigma_{af} = \sqrt{\frac{1}{N_s}\sum_{i=1}^{N_s} f^2_N(i) - \left[\frac{1}{N_s}\sum_{i=1}^{N_s} |f_N(i)|\right]^2} \quad (7)$$

ii) Higher Order Statistical Features

Moments and cumulants are examples of higher order statistical parameters that are used as features to find unique qualities in data. Cumulants are simply a different way of examining the moments of a particular distribution, while moments are a way of "measuring the shape" of a group of points.

a) Moments

Probability distribution moments are a generalization of the concept of the expected value, and can be used to define the characteristics of a probability density function. The k^{th} moment of a random variable is given by:

$$\mu_k = \int_{-\infty}^{\infty} (s-\mu)^k \, f(s) ds, \quad (8)$$

where μ is the mean of the random variable .The definition for the k^{th} moment for a finite length discrete is given by

$$\mu_k = \sum_{i=1}^{N} (s_i - \mu)^k \, f(s_i) \quad (9)$$

where N is the data length. Here signals are assumed to be zero mean . Equation(9) thus becomes

$$\mu_k = \sum_{i=1}^{N} (s_i)^k \, f(s_i) \quad (10)$$

The auto-moment of the random variable may be defined as

$$E_{s,p+q,p} = E[s^p (s^*)^q] \quad (11)$$

Where p and q represent the number of non conjugated terms and number of the congugated terms, respectively, and p+q is called the moment order. Equation (11) becomes

$$E_{s,2,2} = E[s^2 (s^*)^0] = E[s^2] = \mu_2 = {s_i}^2 f(s_i) \quad (12)$$

which is the second moment or the variance of random variable. In a similar way expressions for $E_{s,2,1}$, $E_{s,4,4}$ $E_{s,8,4}$ were derived. The normalized momemts $E_{s,3,3}$ and $E_{s,4,4}$ are called skewness and kurtosis resp. Skewness is the measure of symmetry of pdf, where as kurtosis is the degree of peakedness (density of peaks) of the pdf.[20]

b) Cumulants

A scalar zero mean random variable has characteristic function given by:

$$\hat{f}(t) = E\{e^{its}\}. \tag{13}$$

Expanding the logarithm of the characteristic function as a Taylor series one obtains

$$\log \hat{f}(t) = k_1(t) + \frac{k_2(it)^2}{2} + \cdots + \frac{k_r(it)^r}{r!} + \cdots, \tag{14}$$

Where the constant k_r are called the cumulants . The first three cumulants are identical to first three moments.

Feature Vector 6 $E_{S8,8}$ Eight Order moment

Table 1 Eighth order Statistical Moment of the form a_i+jb_i

$E_{S,8,8}$	$E\,[a^8 + b^8 - 28a^6\,b^2 + 70a^4b^4 - 28a^2b^6]$
$E_{S,8,7}$	$E\,[a^8 - b^8 - 14a^6\,b^2 + 14a^2b^6]$
$E_{S,8,6}$	$E\,[a^8 + b^8 - 4a^6\,b^2 - 10a^4b^4 - 4a^2b^6]$
$E_{S,8,5}$	$E\,[a^8 - b^8 + 2a^6\,b^2 - 2a^2b^6]$
$E_{S,8,4}$	$E\,[a^8 + b^8 + 4a^6\,b^2 + 6a^4b^4 + 4a^2b^6]$

Feature Vector 7 $C_{s,8,8}$ Eighth order cumulant

Table 2 Relation Between Eighth order Cumulant and Moment

$$C_{s,8,8} = E_{s,8,8} - 35E_{s,4,4^2} - 630E_{s,2,2^4} + 420E_{s,2,2^2}E_{s,4,4}$$

Where

$E_{S,8,8}$	$E\,[a^8 + b^8 - 28a^6\,b^2 + 70a^4b^4 - 28a^2b^6]$
$E_{S,4,4}$	$E\,[a^4 + b^4 - 6a^2\,b^2]$
$E_{S,2,2}$	$E\,[a^2 - b^2]$

Calculation of eighth order moment and sixth order cumulant is presented in Table 1 and Table 2 resp. The moment and cumulant were used as features to classify16QAM, 64QAM and 256QAM signal.

C. Modulation Classification

It is necessary to choose characteristics for AMR that are responsive to the modulation types of interest. The classifier will use the retrieved characteristics to determine the kind of modulation. Linear classifiers, tree classifiers, neural network-based classifiers, hypothesis testing-based classifiers, and ad hoc classifiers are some of the pattern matching approaches available. It was shown that the majority of classifiers based on different characteristics are based on decision trees or neural networks, while only a small number are based on Support Vector Machines (SVMs).

a) Decision Tree (DT) Classifier

One of the fundamental classification techniques is decision tree approaches, where decisions are made at each level based on predetermined threshold values. The primary factors influencing the classifier's performance in these techniques are predetermined threshold values. By include more decision branches, DT techniques may also be improved to support more modulations.

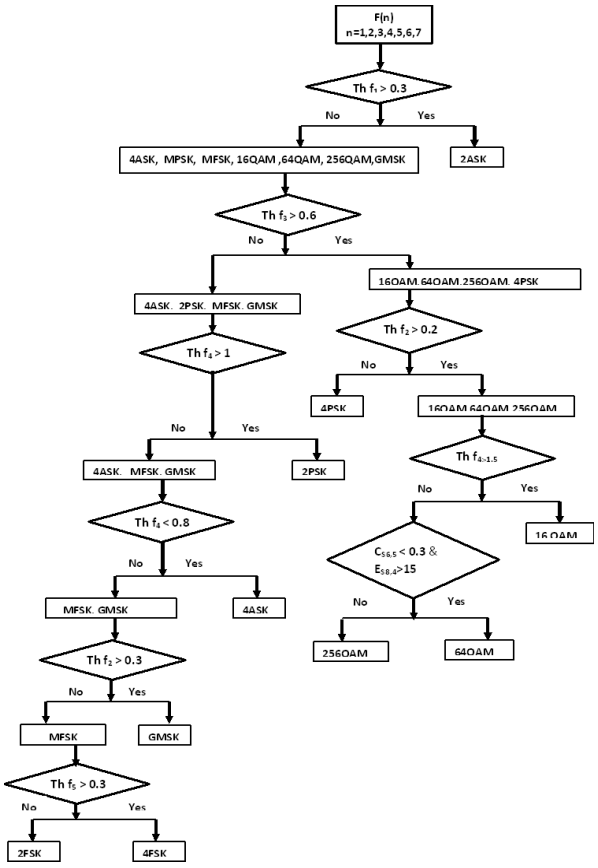


Fig. 3 Decision Tree Classifier

To clearly categorize the collection of modulated signals, the decision tree classifier was fed seven of the previously mentioned attributes. Fig. 3 displays the built decision tree classifier.The signals are divided into two groups by feature vector 1, and only 2ASK can be distinguished by a threshold value. Other characteristics were used to further categorize the signals. Once again, the signals are divided into two groups by the threshold value provided by feature vector 3. 4PSK and M-QAM make up one group, while 4ASK, 2PSK, MFSK, and GMSK make up another. To properly define each group, threshold values were also determined for each characteristic. Moments and cumulants were employed to categorize M-QAM signals because they could not be distinguished clearly from stochastic characteristics.

RESULTS AND DISCUSSION

First, a variety of digitally modulated signals were created, including 2ASK, 4ASK, 2PSK, 4PSK, 2FSK, 4FSK, 16QAM, 64QAM, 256QAM, and GMSK. After then, signals were distorted by mimicking a multipath Rayleigh fading channel after passing via an AWGN channel. The carrier frequency that was used was fc = 1000 Hz.Ten thousand samples were collected in total. The random number generator provided the binary data stream used for modulation.

For every modulation type, a random binary signal was produced for every repetition. Three different kinds of channel conditions were taken into account. For every channel type, 26 SNR values (-5dB to 20dB) were simulated. For every SNR, a confusion matrix was acquired. Confusion matrices were used to display the decision tree classifier's performance. A confusion matrix is a matrix that gives details about the recognition system's output for a certain modulation type. The confusion matrix for -5 dB SNR under no fading conditions is shown in Table 3.

Input/ Identified as	2ASK	4ASK	2FSK	4FSK	2PSK	4PSK	16QAM	GMSK	64QAM	256QAM
2ASK	92	8								
4ASK	10	90								
2FSK			91	5				4		
4FSK			8	92						
2PSK					100					
4PSK						100				
16QAM						6	94			
GMSK				5			10	85		10
64QAM								8	82	80
256QAM							10		10	

Table 3. Confusion matrix of decision tree classifier (SNR=-5dB) each SNR 100 trials

It is evident that out of 100 trials, 92 trials have the 2ASK signal properly categorized, whereas 8 trials have the signal incorrectly classified. The classification of 2PSK and 4PSK signals was 100% accurate.For 91 trials, 2FSK was properly categorized; for five and four trials, respectively, it was incorrectly labeled as 4FSK and GMSK.

For different SNRs, a confusion matrix was generated. Table 4 shows the percentage of accurate categorization for ten modulated signals with different SNRs (from -5 dB to 20 dB). Even with SNR as low as -5 dB, it is evident that a large proportion of outcomes were achieved with certain characteristics.

Table 4 . Percentage identification results for Decision Tree classifier (No fading, each SNR 100 trials)

SNR/mod signal	2ASK	4ASK	2FSK	4FSK	2PSK	4PSK	16QAM	GMSK	64QAM	256QAM
-5	92	90	91	92	100	100	94	85	82	80
-3	94	92	93	93	100	100	95	95	88	83
0	95	94	96	95	100	100	97	96	91	85
3	96	97	98	98	100	100	100	97	94	90
5	100	100	100	99	100	100	100	98	96	94
10	100	100	100	100	100	100	100	100	100	100
15	100	100	100	100	100	100	100	100	100	100
20	100	100	100	100	100	100	100	100	100	100

Table 5. Overall Percentage of correct classification

SNR/ %Classification	No fading	Low fading	Medium fading	High fading
-5	90.6	89	82	70
-3	93.3	90.4	85.3	74.8
0	94.9	92.3	88	83
3	97	94	91	87.2
5	98.7	96	94	91.6
10	100	100	96.6	94
15	100	100	100	96.5
20	100	100	100	100

Table 5 displays the overall classification results of the built decision tree classifier. Different simulation setups were used to examine the categorization findings. Only in the presence of AWGN is classification performance implied by no fading condition.Low Doppler shift is implied by low fading conditions. A Doppler shift of up to 100 Hz was used to approximate a strong fading situation.

CONCLUSION

Simulation findings showed that this method performs effectively even at low SNR. Overall, 97% of 3dB SNR for no fading situations—that is, just when AWGN is present—94% for mild fading, 91% for medium fading, and 87.2% for severe fading conditions were correctly classified.However, higher order QAM signals, which are negatively impacted by fading, were primarily responsible for the decline in the percentage of accurate categorization. Even after equalization, the constellations of 64 QAM and 256 QAM could not be fully restored. For -5dB SNR, 2PSK and 4PSK were 100% properly identified. For SNRs as low as 0 dB and for certain signals as low as -5 dB, a high proportion of accurate classification results were achieved.

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