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Automatic modulation classification using modulation fingerprint extraction

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Abstract: An automatic method for classifying frequency shift keying (FSK), minimum shift keying (MSK), phase shift keying (PSK), quadrature amplitude modulation (QAM), and orthogonal frequency division multiplexing (OFDM) is proposed by simultaneously using normality test, spectral analysis, and geometrical characteristics of in-phase-quadrature (I-Q) constellation diagram. Since the extracted features are unique for each modulation, they can be considered as a fingerprint of each modulation. We show that the proposed algorithm outperforms the previously published methods in terms of signal-to-noise ratio (SNR) and success rate. For example, the success rate of the proposed method for 64-QAM modulation at SNR=11 dB is 99%. Another advantage of the proposed method is its wide SNR range; such that the probability of classification for 16-QAM at SNR=3 dB is almost 1. The proposed method also provides a database for geometrical features of I-Q constellation diagram. By comparing and correlating the data of the provided database with the estimated I-Q diagram of the received signal, the processing gain of 4 dB is obtained. Whatever can be mentioned about the preference of the proposed algorithm are low complexity, low SNR, wide range of modulation set, and enhanced recognition at higher-order modulations.

Keywords: automatic modulation classification, in-phase-quadrature (I-Q) constellation diagram, spectral analysis, feature based modulation classification.

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1. Introduction

Modulation classification as an intermediate step between signal detection and demodulation can play a critical role in several applications. Recognition of the modulation type of the received signals is the most important task of modulation classification systems. Classification modulation is a challenging issue, especially in non-cooperative communication systems with unknown parameters such as carrier frequency and time duration of the samples. Noise removal and estimation of carrier frequency, symbol duration, and signal and noise powers are usually performed in the pre-processing steps. Classification algorithms are grouped into two general methods: likelihood-based (LB) methods and feature-based (FB) methods [1−4]. The LB methods compare the likelihood ratio of each possible hypothesis against a threshold, which is derived from the probability density function (PDF) of the received signal. Multiple likelihood ratio test (LRT) algorithms have been proposed among them: average likelihood ratio test (ALRT) [5,6], generalized likelihood ratio test (GLRT) [5,7], hybrid likelihood ratio test (HLRT) [5,8], and quasi-hybrid likelihood ratio test (Quasi-HLRT) [5,9].

LB methods providing the advantage of optimal solutions have high complexity. In addition, to use these methods, the received signal must be statistically well known. It means that some prior information must be known, which is practically impossible. An LB classification method considers a problem of composite hypothesis by assigning each type of modulation to the received signal and then by using the likelihood function to determine the correct modulation. Extraction of specific characteristics from the received signal and decision making based on separation of the received data are the methods used in the FB techniques. It can be said that the implementation of these methods is easier by creating optimal sub-solutions and does not require prior information of the received signal. In addition, FB can provide near optimal solutions if it is well designed. Generally, FB methods consist of two steps of extracting the characteristics of the received signal, and then selecting the appropriate classifiers to detect the type of modulation. Therefore, both steps affecting the performance of the FB method are features extraction and decision making[10]. FB techniques have less computational complexity than

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LB methods [7−11]. The ability of modulation recognition in low signal-to-noise ratio (SNR) conditions by using short observation intervals is the most important evaluation criteria of classifiers [12−15]. The classifiers must also be robust against processing errors and able to classify large number of modulations in different propagation conditions. In addition, real-time operation and low computational complexity should be considered [16−20].

In this paper, a method for modulation classification based on the received signal features is presented. The proposed method is designed based on the intrinsic properties of the modulated signals with low SNR and low sampling time. It is robust against channel noise and processing errors. In comparison to current methods, our algorithm has low complexity, low SNR, wide range of modulation set, and enhanced recognition at higher-order modulations.

The geometrical structure and distances between symbols in in-phase-quadrature (I-Q) constellation diagram are extracted as one part of features in this algorithm. Additionally, our method combines the derived results from the I-Q constellation diagram with the results of normality test and spectrum features of the received signal as another part of features. In other words, the extracted features which are used in the proposed method are as follows: normality test, spectrum analysing, and the geometrical structure of the I-Q constellation diagram. Since the combination of these features is unique for each modulation, they can be considered as a fingerprint of any one. Our results show that the proposed algorithm outperforms the previously presented modulation classifiers.

Following this introduction in Section 1, related works are presented in Section 2. Next, the basis of the proposed technique is explained in Section 3. This section includes a diagram of the main algorithm of the proposed method. The feature extraction techniques are also explained in this section. In Section 4, simulation results of the proposed method as an automatic modulation classifier are discussed. The final section presents the conclusions.

2. Related works

In FB approaches, modulation recognition is carried out in two modules. The first module is the feature extraction subsystem, in which features are extracted from the received signal. The second module is the pattern recognizer or the decision maker subsystem, which determines the modulation format [10].

In the first module of the feature-based automatic modulation classification (FB-AMC), some features are under more attention in literatures that generally include statistical, spectral, cyclo-stationary, and time-frequency features.

First, the statistical features involve the diverse range of cumulants and moments. For instance, in [11,21−23] different orders of cumulants were extracted as features of received signals. Some studies used high order cumulants as features in their algorithms [24−26]. In addition, moments’ extraction was implemented in [27], and a moment matrix technique was used for AMC in [28]. Second, the spectral features are obtained from three basic parameters, i.e., amplitude, phase, and frequency. For example, in [29,30] the variance of the centerd normalised signal amplitude, phase, and frequency were considered as features. In [31], the features consisted of statistical and spectral features to AMC. Third, most of the modulated signals have some parameters which change with time. In digital communications, these parameters may be amplitude, frequency and phase. Most of the signals have the cyclo-stationary property which can be exploited for classification of modulation formats. For instance, in [32,33] the cyclo-stationary properties such as cyclic frequency and phase were obtained. Fourth, frequency and time features are extracted by the aid of short time Fourier transform. In [31], discrete Fourier transform and instantaneous autocorrelation were used to recognize modulation types. Furthermore, I-Q constellation diagram properties are extremely noticed in researching. For example, some studies were performed based on constellation shape properties in [34,35]. In Table 1, summary of related FB approaches are described. It informs algorithm references, feature types, decision making methods, extracted features in each algorithm, and modulation set that can be recognized by any algorithm.

In the second module of the FB-AMC, some methods are reported for decision making [10]. Several common approaches, such as decision tree (DT) [22−24,30], artificial neural networks (ANNs) [27,32], machine learning (ML) and support vector machine (SVM) [25,29,34−36], k-nearest neighbour (KNN) [26,33], genetic programming (GP) [25,26,31], PDF-based algorithm [11], particle swarm optimization (PSO) [36], principal component analysis (PCA) [27], and combinations of some techniques have been used for decision making. The decision making schemes of these algorithms can be seen in Table 1.

Table 1 Summary of related FB approaches

Algorithm	Feature type	Decision making	Extracted feature	Modulation set
[36]	Time-frequency	Naive Bayesian and SVM	Discrete Fourier transform Instantaneous autocorrelation	Binary phase shift keying (BPSK), quadrature phase shift keying (QPSK), 16-QAM, LFM, SF, 2-FSK, 4-FSK
[29]	Spectral	Extreme learning machine	Amplitude Phase information	BPSK, QPSK, 8-PSK, 16-QAM, 64-QAM, 4-ASK
[37]	Statistical	Genetic programming	Original cumulants	BPSK, QPSK, 8-PSK, 16-QAM, 64-QAM
[11]	Statistical	PDF-based	Fourth-order cumulants	BPSK, 4-ASK, 16-QAM, 8-PSK, V32, V29, V29c
[32]	Cyclo-stationary	ANN	Cyclic frequency Spectral	2-ASK, 2-FSK, 4-FSK, 8-FSK, BPSK, QPSK, MSK
[31]	Spectral and statistical	SVM with PSO	Higher-order Statistical and wavelet	2-ASK, 4-ASK, 2-FSK, 4-FSK, 2-PSK, 4-PSK
[25]	Statistical	GP and SVM	Higher-order cumulants	16-QAM, 64-QAM
[27]	Statistical	PCA and ANN	Mean value and variance Central moments	4-ASK, 8-ASK, 16ASK, 2-PSK, 4-PSK, 8-PSK, 16-PSK, 4-FSK, 8-FSK, 16-FSK, 8-QAM, 16-QAM, MSK, on off keying (OOK)
[30]	Spectral	DT	Amplitude Phase and frequency	2-ASK, 4-ASK, 8-ASK, 2-FSK, 4-FSK, 8-FSK, 2-PSK, 4-PSK, 8-PSK
[22]	Statistical	DT	Fourth-order cumulant	BPSK, QPSK, FSK, MSK
[23]	Statistical	DT	Fourth-order Zero-conjugate cumulant	QPSK, offset quadrature phase shift keying (OQPSK), 8-PSK, 16-PSK
[24]	Statistical	DT	Instantaneous amplitude Higher-order cumulants	2-ASK, 4-ASK, 8-ASK, BPSK, QPSK, 8-PSK
[33]	Cyclo-stationary	KNN	Cyclo-stationarity	BPSK, QPSK, FSK, MSK
[26]	Statistical	GP and KNN	Higher-order cumulants	BPSK, QPSK, 16-QAM, 64-QAM
[34]	Time-frequency	ML	Constellation	4-QAM, 16-QAM, 32-QAM, 64-QAM, 128-QAM, 256-QAM.
[35]	Time-frequency	ML	Constellation	16-QAM, 32-QAM, 64-QAM

3. Basis of the proposed FB approaches

The proposed method is mainly based on the extraction of the signal features. In this research, I-Q constellation diagram, normality test, and frequency spectrum analysis are used to uniquely classify orthogonal frequency division multiplexing (OFDM), phase shift keying (PSK), quadrature amplitude modulations (QAM), frequency shift keying (FSK), and minimum-shift keying (MSK) modulations schemes. The three steps of the proposed feature extraction procedures, i.e., normality test, spectrum analysing, and geometrical analysis of the I-Q diagram are shown in Fig.1.

In fact, in the proposed method, a unique set of parameters including normality test, spectral features and geometrical structure of the I-Q diagram, acts as a fingerprint for each modulation scheme. With appropriate determination of these parameters, an accurate classification would be possible. In the following, the steps of the proposed algorithm are explained.

3.1 Normality test

In an OFDM modulation, a great number of dense spaced orthogonal sub-carrier signals with overlapping spectrum are transmitted simultaneously [38,39]. Thus, the transmitted signal can be considered as a combination of numerous independent identically distributed (IID) random variables. Therefore, due to the central limit theorem (CLT) the distribution of the received IID signal is normal [40,41]. Thus, this modulation is easily distinguishable from other carrier modulations by performing a normality test. Based on this explanation at the first step of the proposed algorithm, the normality test is performed to discriminate OFDM from other modulation schemes, as it is shown in Fig.1 . In other words, the normality test of the received signal is used to discriminate single-carrier modulations from multi-carrier modulations [19,20]. In this paper, we assume that multi-carrier modulation category includes only OFDM, and single-carrier modulation category includes QAM, PSK, FSK, and MSK. Therefore, the normality feature extraction step can distinguish OFDM signals clearly. For other modulations, complete recognition will be done in the next steps.

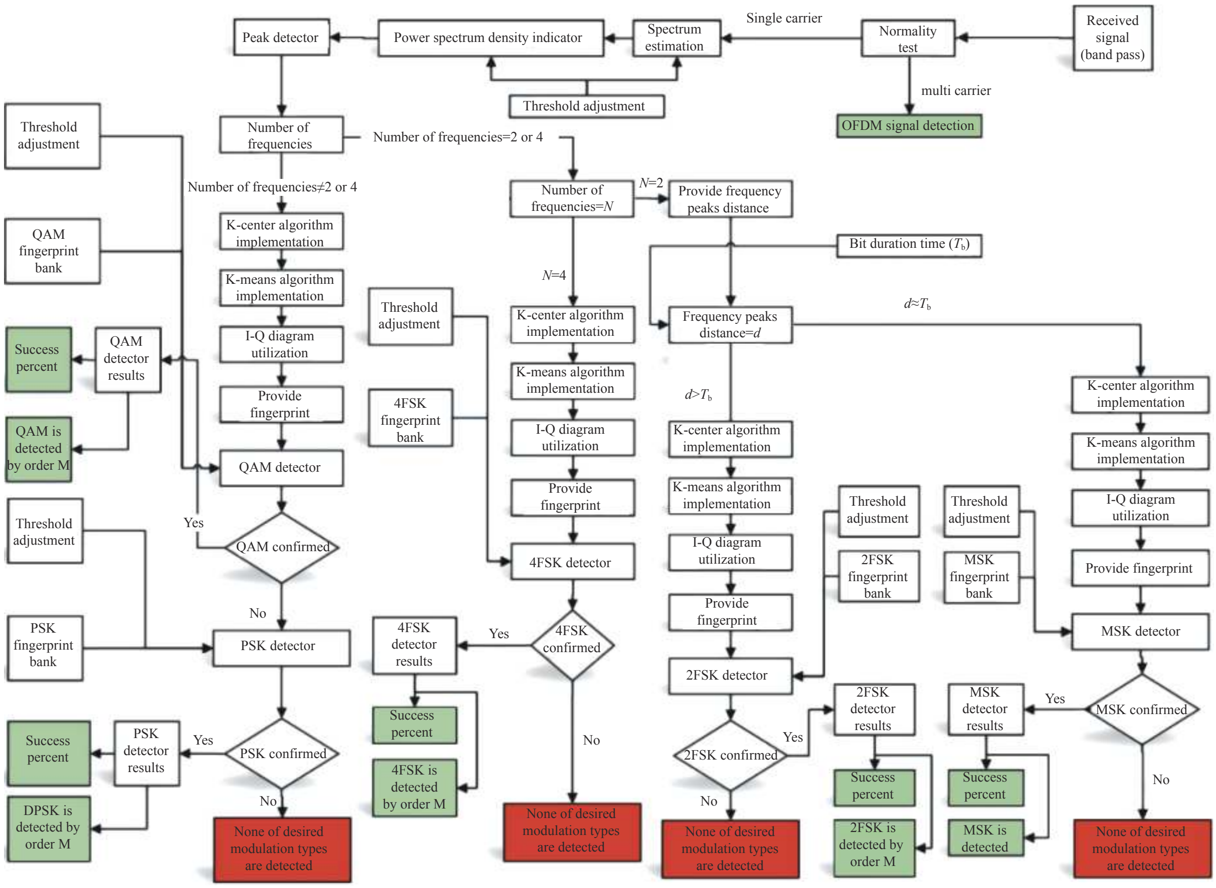


Fig. 1 Proposed feature-based automatic modulation classification algorithm

3.2 Frequency spectrum analysis

Spectrum analysis of the modulation classification has been previously considered in [42–45]. In this paper, we propose an approach that uses spectrum analysis in modulation classification. In our method, the spectrum analyzer performs an initial classification based on spectrum features. It classifies single-carrier modulations to two groups, regular-shape and irregular-shape spectrum modulations. Modulations with regular-shape spectrums always have a fixed and deterministic pattern, while the irregular-shape modulations do not have such properties. For instance, 4FSK modulation always has four peaks in its spectrum while QAM and PSK spectrums have several variable peaks with erratic frequency distances. Also, we define N for the number of peaks in the regular-shape spectrum of modulation. Thus, 4-FSK has N=4, and 2-FSK and MSK have N=2. Besides, their branches in Fig. 1 are indicated by their number of peaks resulted in spectrum analyzing. For more conceptual understanding, Fig. 2 shows spectrums of 16QAM, 16PSK, and 4FSK. 16QAM and 16PSK modulated signals have irregular-shape spectrum, and 4FSK modulated signal has regular-shape spectrum. Moreover, the order of modulation that is determined by the number of the different symbols that can be transmitted using it is defined by M.

According to Fig. 1, we can discriminate between single-carrier modulations by estimating and extracting the peaks of the frequency spectrum of the received signal and then comparing the results with the frequency spectrum of each modulation. In the next step, the proposed method classifies the irregular-shape spectrum modulation group to QAM or PSK subgroups. Then considering the number of peaks, it classifies regular-shape spectrum modulation signals to FSK or MSK subgroups. Furthermore, frequency spectrum analysis is done considering the number of peaks, to distinguish between 4FSK, 2FSK, and MSK in the regular-shape spectrum subgroups, as it is shown in Fig. 3. For example, a signal with four peaks in its spectrum belongs to 4FSK modulation. Equation (1) can be used to identify MSK and 2FSK, However, both of them have two peaks. In this situation, we need to use another characteristic to differentiate between MSK and 2FSK. As we know, MSK is a continuous phase frequency shift keying (CPFSK) modulation with the minimum frequency difference between its two peaks [46]. In fact, the decision rule in (1) is used to discriminate between 2FSK and MSK in frequency analysis.

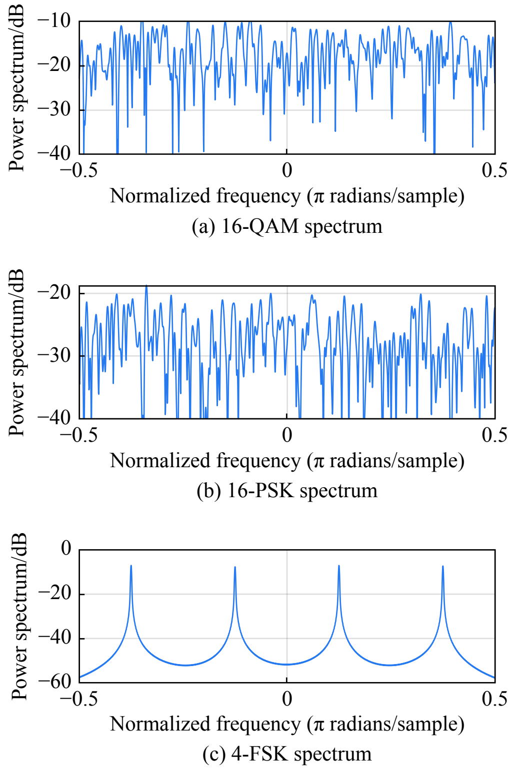


Fig. 2 Baseband frequency spectrum of 16PSK, 16QAM, and 4FSK in the spectrum analyzer

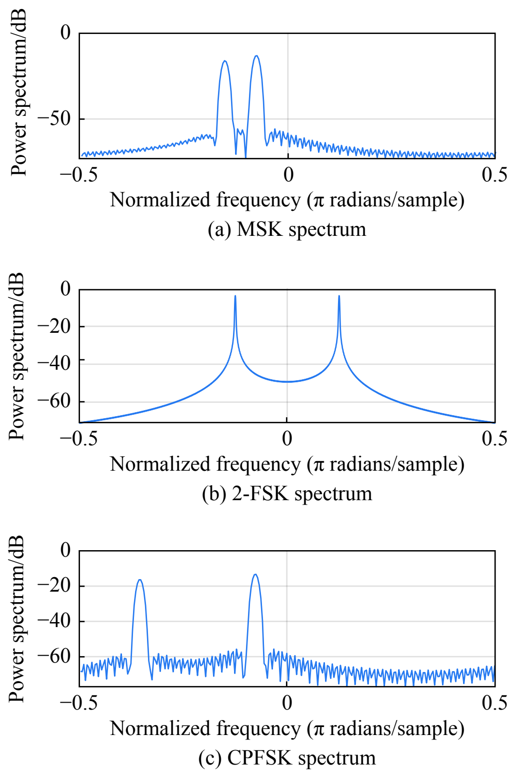


Fig. 3 Baseband regular-shape frequency spectrum of MSK, 2FSK, and CPFSK in the spectrum analyzer

$$\text{Modulation} = \begin{cases} \text{MSK}, \ d = T_b \\ \text{FSK}, \ d > T_b \end{cases} \tag{1}$$

d is the frequency difference between detected peaks in the modulation spectrum and T_b is the time interval of a bit in the modulated data frame.

3.3 Using I-Q diagram

In this step, the last and accomplishing part of the algorithm is performed. We use k-center and k-means algorithms to extract the I-Q diagram of the signal in low SNRs [39]. An example of using this method for QAM modulation with SNR equal to 8 dB is shown in Fig. 4. In this figure, blue and red dots denote the symbols of the I-Q constellation diagram of the received signal, and the estimation results of symbols centers using k-center and k-means algorithms, respectively. Considering the estimated centers as a constellation is an appropriate benchmark for modulations classification.

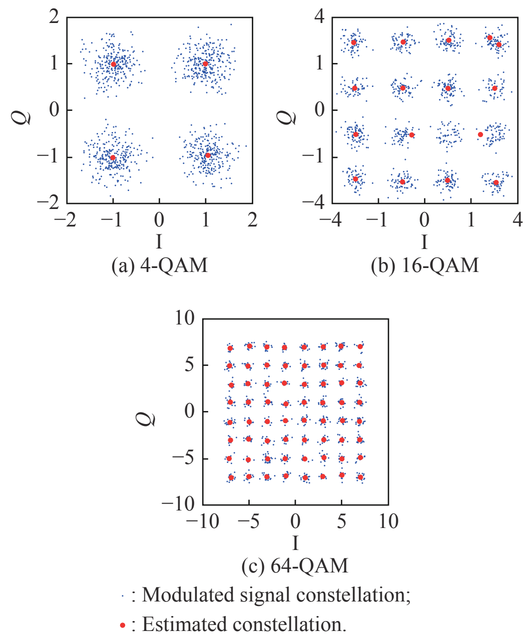


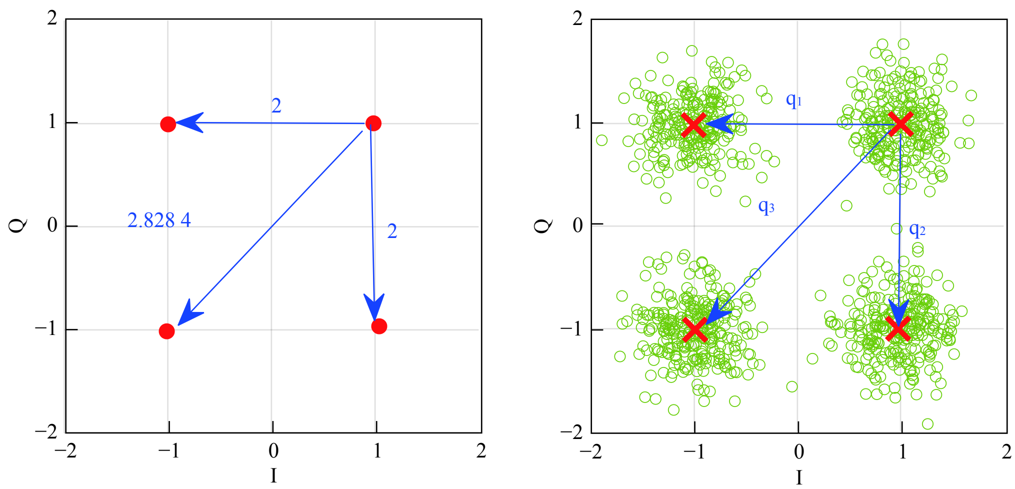
Fig. 4 Performance of the data classification using k-means and k-center with SNR=8 dB

In our method, the Euclidean distances between estimated symbols in I-Q diagrams are measured from a specific coordinate in a noiseless condition. Then, the measured results are saved and recorded as sequences in a data base. This procedure is done for all types of considered modulations in the proposed method, as reported in Table 1. In the following, the specific coordinate, saved sequences, and recorded data base are called reference coordinate, reference sequences, and I-Q features bank information, respectively. This bank information used as modulated signals is received. In the case of noisy channel, the centers of I-Q diagram of the received signal are estimated using k-means and k-center algorithms.

In the next step, a maximum-likelihood based algorithm is used to measure distances between calculated centers. Like the noiseless situation, in noisy channel, the distances are measured from the mentioned reference coordinates in the I-Q constellation diagram. Then the measured distances are stored in other sequences as I-Q features of the received signal. Finally, a search-based algorithm compares the sequences of the I-Q features of the received signal with the bank information presented in Table 2. In other words, the comparison is done by correlating between the reference sequence which is named d and saved in the I-Q features bank information and the extracted I-Q features of the received signals. For example, Fig. 5(a) shows how the reference sequence from the coordinate (1, 1) is measured by the proposed method. The reference sequence in the noiseless condition recorded in data base is S= {2 2 2.82} for 4-QAM modulation. Fig. 5(b) shows how the sequence, S'= {$q1$ $q2$ $q3$} where qi (i=1, 2, 3) is the estimated Euclidean distance between estimated symbols in I-Q diagram, for 4-QAM received modulated signal in a noisy channel is measured from reference coordinate (1,1). Fig. 5 identifies the I-Q diagram of the received signal, estimated centers of the I-Q diagram, and S'. If the correlation search-based algorithm results in a correlation value more than a threshold, it means that S and S' are matched adequately. Thus, the algorithm detects 4-QAM modulation.

Table 2 Reference sequences for each modulation that are extracted and saved in an I-Q features bank information

Modulation type	Sequence length	Reference coordinate	Reference sequence
64-QAM	64	(1,1)	d={0.0 2.0 2.0 2.0 2.0 2.82 2.82 2.82 2.82 4.0 4.0 4.0 4.0 4.47 4.47 4.47 4.47 4.47 4.47 4.47 4.47 5.65 5.65 5.65 5.65 6.0 6.0 6.0 6.0 6.36 6.32 6.32 6.32 6.32 6.32 6.32 6.32 7.21 7.21 7.21 7.21 7.21 7.21 7.21 7.21 8.0 8.0 8.24 8.24 8.24 8.24 8.48 8.48 8.48 8.48 8.94 8.94 8.94 8.94 10.0 10.0 10.0 10.0 11.31};
32-QAM	32	(−3, −5)	d={0.0 2.0 2.0 2.8 2.82 4.0 4.0 4.47 4.47 4.47 5.65 6.0 6.0 6.32 6.32 6.32 7.21 7.21 8.0 8.24 8.24 8.24 8.48 8.94 8.94 10.0 10.0 10.0 10.19 10.77 11.31 11.66};
16-QAM	16	(3,3)	d = {0.0 2.0 2.0 2.82 4.0 4.0 4.47 4.47 5.65 6.00 6.32 6.32 6.0 8.48 7.21 7.21}
8-QAM	8	(3,3)	d={2.0 2.82 4.0 4.47 4.47 5.65 6.32 7.21}
4-QAM	4	(1,1)	d={0 2.0 2.0 2.82}
4-FSK	Variable	(0,0)	Sequence with any elements ={1, 1, 1, 1, 1,⋯}
2-FSK	Variable	(0,0)	Sequence with any elements ={1, 1, 1, 1, 1,⋯}
MSK	Variable	(0,0)	Sequence with any elements ={1, 1, 1, 1, 1,⋯}
4-PSK	4	(0,0)	d ={0.0 1.41 1.41 2.0}
8-PSK	8	(0,0)	d={0.0 0.76 0.76 1.41 1.41 1.84 1.84 2.0}
16-PSK	16	(0,0)	d={0 0.39 0.39 0.76 0.76 1.11 1.11 1.41 1.41 1.66 1.66 1.84 1.84 1.96 1.96 2.0}



(a) 4-QAM for scale (b) 4-QAM+AWGN

● : 4-QAM symbols center; ○ : Recieved 4-QAM signal; × : Estimated center.

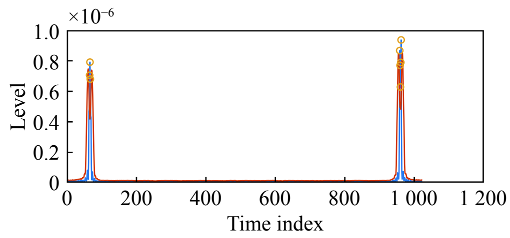
Fig. 5 Symbol centers of 4-QAM constellation

4. Simulation results

In this section, simulation results are presented.

4.1 Frequency spectrum analysis simulation results

As an example, frequency spectrum analysis is simulated for MSK, 2-FSK, and 4-FSK modulated signals. Consequently, according to (1), signals with two detected peaks belong to MSK or 2-FSK and signals with four detected peaks belong to 4-FSK. Results of spectrum analysis and extraction of the peaks of power spectral density for 2-FSK and 4-FSK are shown in Fig. 6. It is clear that spectrum analyzer can detect spectrum features well. As a result, this step's output is an effective part of the fingerprint criterion in the proposed algorithm.



(a) Spectrum analyzing of 2-FSK modulation signal

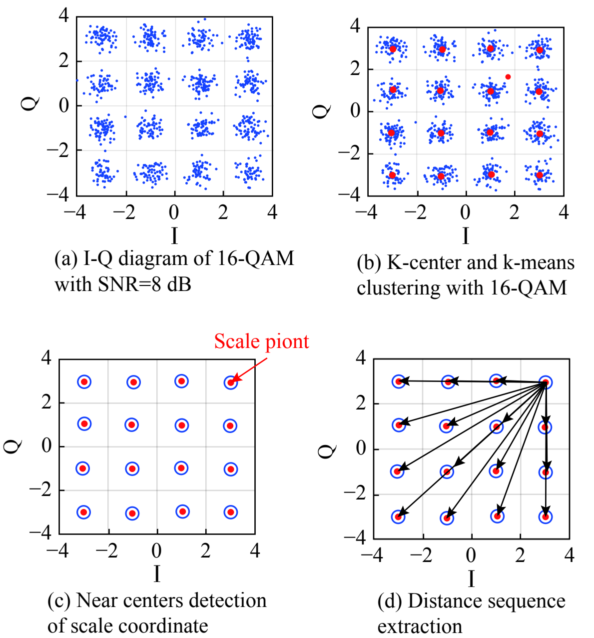
(b) Spectrum analyzing of 4-FSK modulation signal

—— : Received signal; —— : Threshold implementation;
○ : Frequency peaks detection.

Fig. 6 Spectrum analysis and extraction of the peaks of power spectral density for 2-FSK and 4-FSK

4.2 I-Q diagram features extraction simulation results

As shown in Fig. 1, after the frequency analysis and the peaks detection, we applied k-means and k-center clustering algorithms to the I-Q diagram of the received signal to estimate centers of symbols. In the next step, the sequence of distances between symbols is generated and then compared to the I-Q diagram of features bank information presented in Table 1. As previously stated, a correlation search-based algorithm generates correlation of measured sequence with sequences in the data base. Finally, if the maximum correlation value is larger than or equal to a threshold, the algorithm determines the type of the modulation and its order. For instance, Fig. 7 indicates I-Q diagram features extraction for 16-QAM modulation at SNR=5 dB. Fig. 7(a) is the I-Q diagram plotting, Fig. 7(b) shows centers estimating of symbols, Fig. 7(c) shows distances sequence generating, and Fig. 7(d) presents the comparison distances sequence with the I-Q diagram features bank information in Table 1. At the first step, I-Q diagram is plotted (blue spots in Fig. 7(a)), then the center of each cluster or symbol is estimated (red spots in Fig. 7(b)). Next, at the third step the distances sequence is constructed (blue rings around red spots in Fig. 7(c)), and finally the generated sequence is compared to the reference sequences (black arrows in data base in Fig.7(d)). Finally, the comparison can determine the type of modulation and its order.



(a) I-Q diagram of 16-QAM with SNR=8 dB

(b) K-center and k-means clustering with 16-QAM

(c) Near centers detection of scale coordinate

(d) Distance sequence extraction

· : I-Q diagram; • : Center of symbols; ○ : Near center.

Fig. 7 I-Q diagram features extraction for 16-QAM modulated signal

5. Proposed algorithm results

In this section, comparison results are presented in two parts. The first part is dedicated to presenting the success rate of the proposed algorithm in classification of the modulations, and the second part is focused on comparing the performance of the proposed method with recent published modulation classifiers.

5.1 Success rate

One of the important criteria of modulation classifiers is the success rate. The success rate presents the reliability of the classification. Different modulated signals have different features in their signaling, I-Q constellation diagram, and geometrical construction. In this situation, difficulty of features extraction is not equal in all types of modulations, and it depends on the SNR levels. In other words, there is a trade-off between difficulty of features extraction and SNR levels. Moreover, the required SNR to achieve a specific success rate is different in each modulation. In other words, different modulations need different SNRs to obtain any success rate.

In this section, in order to evaluate the proposed algorithm we aim at success rate levels of 99% and 80%. Fig. 8 shows the success rates of classification named Ps in terms of SNR. These curves are analyzed in Table 3. In addition, the number of symbols and the number of iterations are set as 10^3 and 10^5, respectively, where the number of symbols indicates the number of symbols that we receive from the modulated signal, and the number of iterations is the number of the proposed algorithm repetition to classify modulated signals. Additionally, equivalent symbol number provides similar conditions in the modulated signals sampling. The large number of repetitions (iterations), 10^5 for any classification, can improve the reliability of the classifier results. Iteration does not have any influences on the success rate, but it can improve the reliability and the preciseness of the achieved success rate.

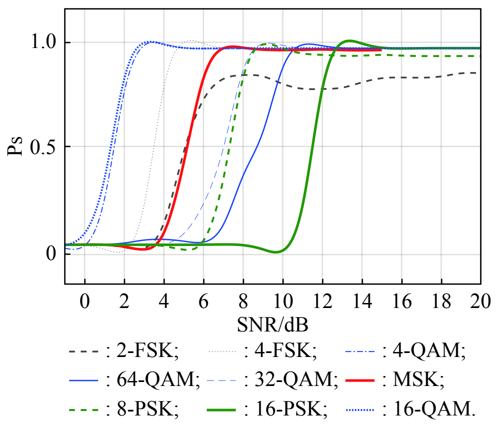


Fig. 8 Success rate of proposed algorithm in terms of SNR for different modulations

Table 3 Different SNRs for the proposed algorithm at 99% and 80% success rates

Modulation type	SNR/dB (99% success rate)	SNR/dB (80% success rate)	Symbol	Iteration
64-QAM	11	10	10^3	10^5
32-QAM	9	8	10^3	10^5
16-QAM	3	2	10^3	10^5
4-QAM	3	2	10^3	10^5
4-FSK	5	4	10^3	10^5
2-FSK	7	6	10^3	10^5
MSK	7	6	10^3	10^5
8-PSK	9	8	10^3	10^5
16-PSK	13	12	10^3	10^5

As Table 3 shows, the proposed method achieves a 99% success rate at SNR as low as 3 dB for 4-QAM and 16-QAM modulations. In QAM modulation classification, from 4th order to 64th order, the required SNR for a 99% success rate increases from 3 dB to 11 dB.

Moreover, the worst case for a 99% success rate is for the 16-PSK modulation that is not detectable at SNRs below 13 dB. For a 99% success rate, 8-PSK and both 2-FSK and MSK modulations are detected at SNR=9 dB and SNR =7 dB, respectively. Success rate results show that higher orders of modulations would need higher SNRs to achieve the same success rates, except in FSK modulation that 4FSK can be detected with about a 2 dB lower SNR than 2FSK.

As a result, in this section we fix two success rate levels in order to evaluate the proposed algorithm. We also report the required SNRs to achieve these success rates for any modulation categories of QAM, PSK, FSK, and MSK. It is shown that the required SNRs are different for the sake of different difficulties in features extraction.

5.2 Performance comparison with previous AMCs

In Table 4, we compare the proposed classifier with other algorithms in AMC approaches, modulation set, SNR, success rate, complexity, advantages, and disadvantages. Since our criterion for AMC performance is near 99%, we compare the proposed algorithm with the algorithms that report their success rates near 99%. Thus, results in Table 4 are provided according to whatever are reported in literature.

The first column of Table 4 indicates the names of algorithms and their references. In the next column, the AMC approaches of all algorithm are informed. For more evidence, we try to compare the proposed algorithm with both of the LB and FB approaches. For instance, the ALRT, HLRT, and Quasi-HLRT reported in [5] used LB approaches to AMC. Additionally, the FB based algorithms that are compared with the proposed algorithm are reported in [5,11,26,27,29,34–36]. The third column demonstrates the modulation set that any algorithm can recognize.

Most current methods identify a limited set of modulation types, whereas the set of modulations considered in this paper are OFDM, M-QAM, M-PSK, M-FSK, where M is the order of them, and MSK types in total. The modulation set of the compared algorithms can be seen in Table 4.

In addition, Table 4 describes the complexity of the proposed algorithm against others. Complexity clearly means the volume of mathematics and the number of steps required to recognize modulation types. In this paper, our algorithm has a low complexity computation in comparison with current methods since we use triple low complexity processes in features extraction. This algorithm first involves spectral analysing. Spectral-based features can be calculated simply and instantaneously, so it can improve the recognition accuracy for different modulation schemes at low SNR.

This paper's AMC algorithm benefits k-means and k-center techniques. They are simple classifiers and are defined as a nonparametric approach that does not require information about data distributions [47]. Thus, utilizing a cascade of k-center and k-means algorithms can lead to the achievement of much higher accuracy in determining the type of the modulation and also reduce the complexity of the process [20]. Furthermore, in the third process, implementing correlation-based function is not complicate at all. According to what was described previously, using I-Q diagram is based on features information bank prepared and saved as sequences in a data base. Therefore, the algorithm only correlates the achieved I-Q diagram of the received signal with what was saved in the database. As a result, there is no complicated process in the last process of the proposed algorithm. Consequently, our algorithm has low complexity in terms of implementation.

Table 4 Performance comparison of the proposed algorithm with other automatic classifiers

Algorithm classification	AMC	Modulation set	Complexity	Success rate/%	SNR for 16QAM/dB	Advantage	Disadvantage
Proposed algorithm: FPMC	FB	OFDM, 2FSK, 4FSK, MSK, 4QAM, 16QAM, 2QAM, 64QAM, 8PSK, 16PSK	Low	99	3	Low SNR Wide modulation set Recognition of higher-order QAM	–
ALRT [5], L=1, ηA=1 L=likelihood ratio; ηA= average likelihood ratio	LB	BPSK, QPSK, 16QAM, 32QAM, 64QAM	High	99	7	Maximum probability of classification	Multidimensional integration Impractical [48]
HLRT [5], μ, H not specified μH= hybrid likelihood ratio	LB	BPSK, QPSK, 8PSK, 16PSK, 16QAM, 64QAM	High	99	9	Treated as deterministic known Overcome to nested Constellation	Un-conditional PDF
Quasi-HLRT [5], threshold = 1	LB	16QAM, 32QAM, 64QAM	Low	99	19	Low-complexity Enhanced performance	Require high SNR Disabled in high-order QAM
Cumulant-based [11], Nm=2, μH=−0.68 Nm=Number of modulation	FB	2ASK, 2FSK, 4FSK, 8FSK, BPSK, QPSK, MSK	Low	99	9	Low SNR Robust in phase and frequency	Sub-optimal performance [37]
AMC with ELM [29]	FB	BPSK, QPSK, 8-PSK, 16-QAM, 64-QAM, 4-ASK	Low	99	7	High accuracy Low SNR levels Robustness	Impractical Limited modulation set
GPOS [37], symbol length 4096	FB	BPSK, QPSK, 8-PSK, 16-QAM, 64-QAM	Low	99	15	Accelerate the feature process Satisfactory performance Stronger robustness	Limited modulation set
[26]	FB	BPSK, QPSK, 16QAM, 64QAM	Low	98	11	Good performance	Disable in high-order QAM
AMC with HMLN [36]	FB	BPSK, QPSK, 16QAM, LFM, SF, 2FSK, 4FSK	Low	99.26	30	Wide modulation set	Requires high SNR
[27]	FB	4ASK, 8ASK, 16ASK, 2PSK, 4PSk, 8PSK, 16PSK, 4FSK8FSK, 6FSK, 8QAM, 16QAM, MSK, OOK	Low	100	20	Reduced complexity	Large set of modulations Need high SNR Need many features
[34]	FB	4QAM, 16QAM, 32QAM, 64QAM, 128QAM, 256QAM	Low	100	15	Enhanced recognition Higher-order QAM	Require high SNR
[35]	FB	16QAM, 32QAM, 64QAM	Low	100	15	Enhanced performance Without prio information	Need high SNR Disable in high-order QAM

The low computational complexity was reached in [11] by statistical features. The authors in [29] stated that the low complexity of their algorithm is due to the reduction of dimension. It also occurs because of programming at high SNR scenarios. It can reduce the computational complexity without any performance loss. Subsequently, benefiting from instantaneous autocorrelation in [37] resulted a less complex method.

Similarly, other FB methods can obtain suboptimal solutions with a low computational complexity and do not depend on prior information. For example, in [36], the advantage of the instantaneous autocorrelation is having less complexity compared to the high-order cyclo-stationarity approach. The features subset selection using PCA in [27] is used to reduce the complexity of the used neural network through the selection of the best features.

In [34], the subtractive clustering algorithm, in which the number of cluster centers was adaptive, was used. This idea greatly reduced computational complexity. Also, k-means clustering in [35] is applied, which needs to calculate the number of clustering centerpoints. It can lead to simpler I-Q diagram features extraction. Using GP to reduce the computational time in k-means clustering techniques was done in [26].

The complexities of LB methods are presented in Table 4. Although LB methods can theoretically achieve the optimal solution, they have a high complexity. For prime instance, ALRT [5] experiences a high computational complexity in the case that unknown parameters are increased. In addition, due to un-conditional PDF in HLRT [5], it has a high computational complexity. To achieve less complexity in the LB method a sub-optimal algorithm namely Quasi-HLRT [5] is used by the aid of observation conditional PDF.

Next, according to what were reported in literature, the success rates and their required SNRs are stated in the fifth and the sixth columns of Table 4. As can be seen, in FB-AMC, the algorithm of extreme learning machine (ELM) needs SNR=7 dB to achieve a success rate of 0.99 while the proposed method needs SNR=3 dB.

The AMC with ELM method uses an ELM as a classifier, which has a faster learning process and a better performance than conventional machine learning methods. Additionally, a method for classifying the electromagnetic signals of a radar or communication system according to their modulation characteristics has been presented in [36]. It identifies 16-QAM with a success rate of 99.26% and SNR=30 dB. In addition, in [36] a method based on genetic algorithm has been proposed that it needs SNR=15 dB for a success rate of 99%. The SNR=15 dB was reported in [34,35] for the success rate 100%. One more example, a good performance was reached by [26] with SNR=11 dB for a success rate near 99%.

More importantly, the success rate and the SNRs for the LB-AMCs are informed in Table 3. The SNR=7 dB and the success rate 99% were attained by ALRT while HALRT could reach the same success with SNR=9 dB. However, the Quasi-HLRT having a low computational complexity reached a 99% success rate of recognition with SNR=19 dB. From these results it can be understood that the proposed algorithm with SNR=3 dB leads to a 4 dB processing gain in comparison with the best previously published results in ELM [29] with SNR=7 dB.

For more clearance in this paper, we summarized advantages and disadvantages of compared methods in the last two columns of Table 4 based on what were reported in their references. What can be reasoned about the preference of the proposed algorithm are low complexity, low SNR, wide range of modulation set, and enhanced recognition at higher-order QAM.

6. Conclusions

In this paper, a new automatic modulation detection and classification algorithm has been proposed based on a set of unique properties of modulations. At first, normality test of the received signal is used for OFDM detection. Then the separation between FSK and MSK modulations from PSK and QAM modulations is performed using primitive spectrum analysis. The next steps include the analysis of the spectrum, the estimation of the I-Q constellation diagram of the received signal using k-means and k-center methods, the extraction of the geometric properties (Table 2), and then the calculation of the correlation of the received signal with the data recorded in the database that is saved in the memory of the algorithm to recognize the type of modulation. The simulation results show a high success rate of the proposed algorithm. SNR range is also compared to the previously proposed methods. For example, it can be understood that the proposed algorithm with SNR=3 dB leads to a 4 dB processing gain in comparison with the best previously published results in ELM [29] with SNR=7 dB. In this paper, our algorithm has a low computation complexity in comparison with current methods since we use triple low complexity processes in features extraction. What can be reasoned about the preference of the proposed algorithm are low complexity, low SNR, wide range of modulation set, and enhanced recognition at higher-order QAM.

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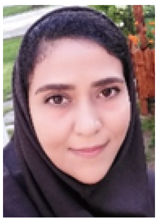

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