2017 9th IEEE International Conference on Communication Software and Networks

Constellation Based Signal Modulation Recognition for MQAM

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***Abstract*—QAM modulation signal has been widely used in wireless communication system. This paper presents a method of identifying MQAM signals, which is effective even in high-order QAM modulation signals. Owing to different types of modulation signals mapping to different constellations, we propose a constellation-based algorithm. In this paper, we use subtractive clustering algorithm which automatically calculate the center of the constellation, and then according to the number of center points, we can recognize modulation signals. From the simulation results, the method can effective recognize MQAM signals, including: 4QAM, 16QAM, 32QAM, 64QAM, 128QAM, 256QAM. When SNR≥5dB, 99% of 4QAM and 16QAM can be correctly recognized, in addition, for high-order QAM signals 128QAM and 256QAM etc., we have a highly recognition rate when SNR≥15dB.**

Keywords-automatic modulation recognition; MQAM; constellation diagram; subtractive clustering algorithm

I. INTRODUCTION

Signal modulation recognition is an important component in the field of blind signal analysis. It is widely used in civil and military fields, such as radio resource management, spectrum monitoring, electronic warfare, electronic reconnaissance, signal detection etc. At present, the most attractive applications are software radio and some reconfigurable communication systems. The automatic recognition of signal modulation type is the prerequisite and basis for its follow-up work. Only the correct recognition of the signal modulation model, can we further estimate the relevant communication parameters and then real-time reconstruction software radio receiver and achieve automatic reception. With the increasing degree tension of spectrum resources, the modulation method with high spectral resource utilization rate has become a hot-topic in research and application field. Because of their high spectrum efficiency, higher order Quadrature Amplitude Modulation (32QAM, 64 QAM, 128 QAM, 256 QAM etc.) have been widely used in satellite communications and microwave communications. Therefore, it is necessary to research the automatic modulation recognition of QAM signals.

This paper is organized as follow: the related work is presented in Section II and the recognition algorithm based on constellation diagram subtractive clustering is discussed in Section III. In Section IV, we give the simulation results. Finally, we conclude in Section V.

II. RELATED WORKS

Some relevant works have been addressed in other papers, in which various recognition methods have been proposed, and many attractive results are shown. For example:

The most common method is the pattern recognition based method. Such as, A. K. Nandi and E. E. Azzouz extracted some parameters on time domain and frequency domain [1], which is the basis for many later algorithms. However, with the development of wireless communication, the method cannot be applied to recognize high-order QAM modulation signals. E. H. Jayatunga and O. A. Dobre extract high order cumulants from modulation signals [2]. However, this method is effective for low-order QAM (such as 4QAM, 16QAM), and cannot effectively recognize the high-order QAM signal. Yang Liu and Zhang Lin et al. combine higher-order cumulants with hierarchical thinking [3], but their method requires higher signal-to-noise ratio and computational complexity.

In addition, Konstantinos Maliatsos and Stavroula Vassakicaiyong pose a method based on the wavelet transform [4], but this method is effective for inter-class recognition and cannot be effectively recognize higher-order QAM. Li Bing and Chen shuang-shuang used the generalized dimension based on the morphological covering method [5], but this method is mainly used for inter-class recognition, and the algorithm has highly computational complexity. C. S. Long, C. Y. Hwang and Huijian Li used the method based on maximum likelihood estimation [6]-[8]; however, due to the complexity of the method based on maximum likelihood estimation, it cannot be widely used.

There are also many recognition methods based on constellation diagram. Negar Ahmadi and Reza Berangi combine genetic algorithms with hierarchical clustering algorithms [9]. The core of this algorithm is to cluster the constellation points, which using genetic algorithms to reduce the number of points. Although this method reduced the number of clustering algorithm, its additional genetic algorithm actually increases the computational complexity. Chou Zhendong and Jiang Weining used K-means clustering to cluster constellation points [10], but K-means clustering method needs to calculate the number of clustering center points for each hypothesis leading to the increasing of computational complexity. Xu Zhinan and Bai Wenle used subtractive clustering algorithm to cluster the constellation points [11], but the clustering algorithm was used to cluster the amplitude of the signals. In low SNR, recognition accuracy rate rapid decline.

III. CONSTELLATION DIAGRAM CLUSTERING RECOGNITION

A. *Signal Model*

Signals are interfered by noise in the channel could be expressed as follow:

$$r(t) = s(t) + n(t) \tag{1}$$

where n(t) is additive white Gaussian noise and s(t) is modulated signal depends on modulation type.

MQAM signal models s(t) can be expressed as follow:

$$\begin{aligned} s_k(t) = {} & a_i g(t - nT_B) * \cos(2\pi f_c t + \varphi_0) \\ & + b_j g(t - nT_B) \sin(2\pi f_c t + \varphi_0) \end{aligned} \tag{2}$$

where, a_i and b_j are the magnitude of In-phase and Quadrature signal respectively. $a_i=\pm(2i-1)$, $b_j=\pm(2j-1)$, $i=1,2,\ldots,L_i$, $j=1,2,\ldots,L_j$. g(t) is baseband pulse with unit energy, T_b is symbols duration, f_c is carrier frequency, φ_0 is initial phase of carrier.

B. *Subtractive Clustering Algorithm*

Different types of digital modulation signals have their specific constellation. According to this feather, we can convert the modulation recognition to constellation diagram identification. The process of signal recognition method based on constellation diagram concluding: symbol sequence match constellation point, count the number of constellation point, and rebuild the constellation diagram, cluster constellation diagram. Finally, according to the number of Clustering center, we can judge the modulation type.

Clustering algorithm is a method of data classification, its main purpose is to find several similar clusters in all data, and find the center point of each clusters. There are many kinds of clustering algorithms. Many modulation recognition algorithms are based on K-means. However, the number of center points of the K-means algorithm cannot be adapted in the calculation process. It must be calculated for each hypothetical center point, and then find the optimal hypothesis, which resulted in the time redundancy of algorithm. Therefore, in this paper, we use subtractive clustering algorithm whose number of cluster centers is adaptive in the process of calculation. Only one cluster calculation, can we draw the number of cluster center for each received signal, thus it greatly reducing computational complexity.

Subtractive clustering algorithm is proposed by Chiu. Consider the n data points in N-dimensional space (X_1, X_2, … , X_N), assuming that the data points are normalized to a hypercube space. Each data point is possible as a cluster center; the density function at the data point x_i is defined as:

$$P_i = \sum_{j=1}^{N} \exp(-\alpha \| x_i - x_j \|^2) \tag{3}$$

where $\alpha=\gamma/r_a^2$ is a positive constant that affects the curvature of the exponential function; r_a is a positive number that is the radius of the effective neighborhood of the cluster center. r_a defines a neighborhood of the data point x_i, and the data points outside the radius contribute little to the density of the point. Obviously, if a data point has multiple neighboring data points, the data point has a higher density value. After calculating the density of each data point, select the data point with the highest density as the first cluster center, that is, find only one cluster center at a time. In order to find a new cluster center, we need to modify the density of each data point, that is, the density of each data point minus a certain density value:

$$P_i = P_i - P_k^* \cdot \xi \tag{4}$$

$$\xi = \exp(-\beta \| x_i - x_k^* \|^2) \tag{5}$$

$$\beta = \gamma / r_b^2 \tag{6}$$

$$r_b = \eta \cdot r_a \tag{7}$$

where P_k^* is the density of kth clustering center; x_i is the data point to be corrected; x_k^* is kth clustering center; r_b is a positive constant denotes the neighborhood whose density is significantly attenuated; η donates inhibitory factor which is a positive constant larger than 1. Generally, $1.25 \le \eta \le 1.5$, it can avoid one clustering center close to others. Combined with the above equations can be drawn:

$$P_i = \sum_{j=1}^{N} \exp(-\alpha \| x_i - x_j \|^2) - P_k^* \cdot \exp(-\beta \| x_i - x_k^* \|^2) \tag{8}$$

After correcting the density value of each data point, the data with the maximum density is selected as the cluster center, and then the density of all data points is corrected again. The process is iterated until all effective clustering centers are found. The termination condition can be expressed as follow:

$$P_k^* < \varepsilon \cdot P_1^* \tag{9}$$

P_1^* is the density value of the first clustering center, $0<\varepsilon\le 1$.

C. *Algorithm Procedure*

The algorithm procedure in this paper is shown in Figure 1:

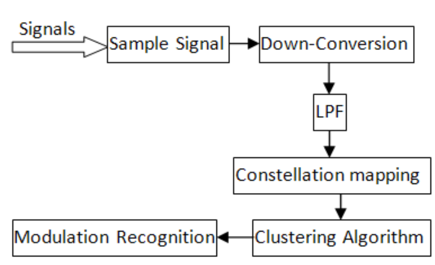

Figure 1. Steps of the algorithm

1. The receiver receives the signal and then down-conversion, low-pass filter is the role of filtering out-bands noise.

2. The received signal mapping constellation diagram.

3. Adopt subtraction clustering algorithm to cluster the constellation points of the signal, and then calculate the number of cluster centers, and finally combine cluster center points with the threshold to recognition the modulation.

Different modulation signals have different constellation diagram, we can calculate the number of cluster center points by subtractive clustering algorithm. This article is mainly on MQAM signals recognition, such as: 4QAM, 16QAM, 32QAM, 64QAM, 128QAM, 256QAM. Theoretically, the clustering center points of these signals are: 4,16,32,64,128,256. However, because of channel noise, the number of clustering centers will fluctuate up and down close to the theoretical value. We set some threshold to recognize modulation signals. Assuming the number of clustering centers is N, the classification decision method is shown in Figure 2.

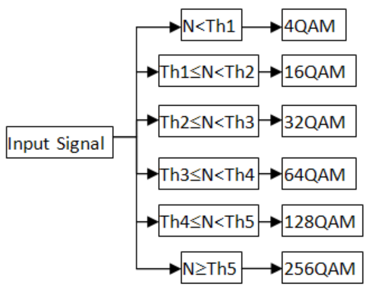

Figure 2. The method of classification decision

IV. SIMULATIONS

According to the algorithm in this paper, simulation process and results presented as follows:

First of all, simulate the constellation diagram of each signal, simulation conditions are as follows: simulation 4QAM, 16QAM, 32QAM, 64QAM, 128QAM, 256QAM signals, carrier frequency fc = 15MHz, sampling rate f_s = 60MHz, symbol rate 3MHz, Gaussian white noise is added. Subtractive clustering is used to process the constellation, and the number of cluster center points can be obtained directly from the calculation result. Then, the modulation mode can be recognized according to the number of cluster center points. As shown in Figure 3, 32QAM, 64QAM, 128QAM, 256QAM interference by the Gaussian noise, the signal constellation and cluster centers:

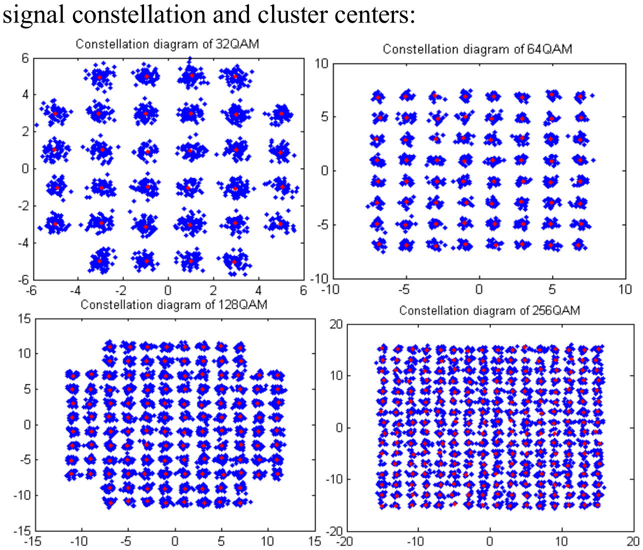

Figure 3. The constellation diagram of MQAM signals

As shown in Figure 3, different modulation methods have their corresponding specific constellation diagram, and each constellation can calculate the corresponding cluster center. Thus, according to the number of cluster center point, we can distinguish the modulation signals.

The number of clustering center points by changing the signal-to-noise ratio shown in Figure 4. SNR range [0dB, 30dB].

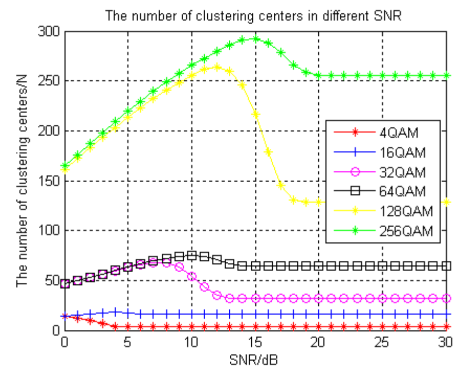

Figure 4. The number of center points under different SNR

According to the simulation results, we choose Th1 = 14, Th2 = 25, Th3 = 50, Th4 = 100, Th5 = 200. Then according to the classification decision method, we can recognize the modulation signals.

Select the appropriate threshold, the correct recognition rate shown in Figure 5:

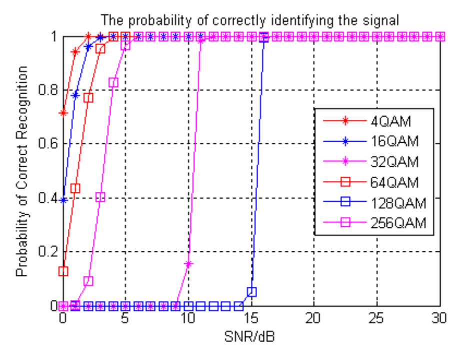

Figure 5. The correct recognition rate of MQAM signals.

V. CONCLUSION

In this paper, we propose a method based on constellation diagram clustering for effectively identifying MQAM signals, including 4QAM, 16QAM, 32QAM, 64QAM, 128QAM, 256QAM or even higher order QAM modulation signals. In this paper, we do not need any prior knowledge, so it is suitable for some non-cooperative communication signals. Simulation results show that our algorithm can effectively identify the MQAM signal even in the case of low signal to noise ratio. The correct recognition rate for the low-order QAM signal such as: 4QAM, 16QAM, when SNR 5dB, 99% modulation signals could be correctly recognized. For high-order QAM modulation signal, even 128QAM, 256QAM with a high correct recognition rate in the condition of SNR≥15dB.

The algorithm in this paper compared with others similar algorithms, the comparison results shown in Table I:

TABLE I. COMPARING RESULTS

	the number of center points	Number of execute algorithms	99% Recognition rate (64QAM)
Algorithm 1	Adaptive	1	5dB
Algorithm 2	Not adaptive	K	15dB
Algorithm 3	Adaptive	1	13dB

In order to read the table, the meaning of each symbol is as follows:

Algorithm 1: the algorithm proposed in this paper.

Algorithm 2: the K-means clustering algorithm is used to cluster the constellation.

Algorithm 3: the subtractive clustering algorithm is used to signal amplitude.

K: assume the number of categories of signals to be identified.

From the comparison results, we can conclude that the algorithm proposed in this paper can automatic adapt to the number of clustering centers without clustering for each hypothesis. In addition, considering from the correct recognition, with 64QAM as an example, our algorithm has higher recognition efficiency at low SNR.

ACKNOWLEDGMENT

I would like to express my gratitude to all those who helped me during the writing of this paper. I gratefully acknowledge the help of my supervisor Professor Li Yubai, who has offered me valuable suggestions in the academic studies. Without his consistent and illuminating instruction, this thesis could not have reached its present form.

REFERENCES

[1] A.K.Nandi and E.E.Azzouz, "Algorithms for Automatic Modulation Recognition of Communication Signals." IEEE Transactions on Communications, vol.46, No.4, pp.431-436, April 1998.

[2] E.H.Jayatunga and O.A.Dobre, "A Robust Higher-order Cyclic Cumulants Feature-based Vector for QAM Classification." 2014 9th International Symposium on Communication Systems, Networks & Digital Sign (CSNDSP), pp.417-421, July 2014.

[3] Yang Liu, Zhang Lin and Zhang Zhongpei, "High Order QAM Signals Recognition Based on Layered Modulation", 2009 International Conference on Communications, Circuits and Systems, pp.73-76, July 2009.

[4] Konstantinos Maliatsos, Stavroula Vassaki and Philip Constantinou, "Inter-Class and Intra-Class Modulation Recognition Using the Wavelet Transform", Personal, Indoor and Mobile Radio Communications, 2007. IEEE 18th International Symposium, pp.1-5, September 2007.

[5] Li Bing, Chen shuang-shuang, Dong Jun and Han Hui, "Generalized dimension of Modulation Signals Using Morphological Covering Method", 2015 8th International Conference on Intelligent Computation Technology and Automation (ICICTA), pp.433-435, June 2015.

[6] C.Y. Hwang and A. Polydoros, "Advanced methods for digital quadrature and offset modulation classification." MILCOM 91 - Conference record, vol. 2, pp. 841-845, November 1991.

[7] C. Long, K. Chugg and A. Polydoros, "Further results in likelihood classification of QAM signals." Military Communications Conference, 1994. MILCOM '94. Conference Record, 1994 IEEE, vol. 1, pp. 57-61, October 1994.

[8] Huijian Li, Qian Wang and Xiao Yan, "Modulation Classification for QAM Signals Based on Log-likelihood estimation in NCA environments." 2013 International Conference on Computational Problem-Solving (ICCP), pp.437-440, October 2013.

[9] Negar Ahmadi and Reza Berangi, "Modulation Classification of QAM and PSK from their Constellation using Genetic Algorithm and Hierarchical Clustering", 2008 3rd International Conference on Information and Communication Technologies: From Theory to Applications, pp.1-5, April 2008.

[10] Chou Zhendong, Jiang Weining, Xiang Changbo, Li Min, "Modulation Recognition Based on Constellation Diagram for M-QAM Signals", 2013 IEEE 11th International Conference on Electronic Measurement & Instruments, vol.1, pp.70-74, August 2013

[11] Xu Zhinan, Bai Wenle, "A Novel Blind Recognition Algorithm for Modulated M-QAM Signals", 2009 WRI International Conference on Communications and Mobile Computing, vol.1, pp.461-465, January 2009.