# Modulation Recognition Based on Constellation Diagram for M-QAM Signals

Chou Zhendong[1], Jiang Weining[1], Xiang Changbo[1], Li Min[2]
[1]The 41st Institute of China Electronics Technology Group Corporation, Qingdao 266555, China
[2]University of Electronic Science and Technology of China, Chengdu 610054, China

***Abstract —*** *This paper proposed a modulation recognition algorithm for M-QAM signals by the constellation diagram which does not require the prior information. Firstly, this scheme estimates the modulation parameters. Secondly, it reconstructs the received signals' constellation and uses k-means cluster algorithm to compute the number of the signal constellation points which are as a recognition feature used for classification. The experimental simulation results proves that this method is effective for M-QAM signals, and the correct recognition ratio reaches 100% under the condition that the SNR is higher than 15dB. So it has relatively preferable practical value.*

***Keywords—*** *modulation recognition, clustering, constellation, K-means clustering algorithm, M-QAM.*

## I. INTRODUCTION

Signal modulation recognition is an important part in the Communication Signal Analysis filed. It has broad application prospects and occupies an important position in the field of reconnaissance, communications confrontation, and electronic warfare. It is one of the key technologies for software radio. With the increase of communicational service, M-QAM has a high bandwidth ratio, and QAM is a better choice. Therefore, the identification of signals is very necessary [3].

Practically, in this paper, the author starts from the modulation identification methods of statistical pattern recognition, by signal preprocessing and feature extraction by classifying, and adjudging modulation schemes of signal. Recognition method of M-QAM signals including 16QAM, 32QAM and 64QAM is researched with feature extraction of the signal constellation. This scheme does not require the prior information about baud rate and carry frequency of the received signals, but it directly estimates these parameters, computing the number of the signal constellation points by blind clustering algorithm. Consequently, the modulation type is identified [1].

## II. M-QAM MODULATION SIGNAL CONSTELLATION CLUSTERING FEATURES

Any kind of digital amplitude phase modulated signals can be represented with a unique constellation diagram. By this correspondent relationship, the constellation diagram can be used for the identification of modulation method. The identification process includes symbol sequence matches with constellation graph, constellation point counting, reconstruction of the constellation diagram match, clustering, shape normalization, the size and location normalization, shape modeling, selection of the mesh size, and shape classification of maximum likelihood estimation, etc.

The ISI (Inter-symbol interference) caused by multi-path effects has great impact on the shape of the constellation diagram in modulation method of QAM (Quadrature Amplitude Modulation). Therefore, before the signal identification, firstly, using blind equalization technique to overcome channel multipath effects and the system synchronization error. Secondly, k-means clustering on the signal, normalized the constellation diagram, and thereby completed the reconstruction of the constellation diagram. Finally, it matches with the ideal constellation diagram model, to achieve the M-QAM modulation method identification.

QAM is a frequent use of digital communication techniques in digital modulation. It is dual-baseband digital signals on the two mutually orthogonal to the same frequency carrier suppressed carrier double sideband modulation, and using the modulated signals within the same bandwidth spectrum orthogonal nature to achieve a dual-way parallel transmission of digital information. The QAM signal recognition can be mainly divided into three categories. First, modulation classification methods use maximum likelihood ratio. The second one are commonly used identification methods based on statistical moment feature. The third recognition methods are based on transform domain feature. According to searching signal amplitude's probability distribution function (Estimated approximate by Histogram) Fourier transform spectrum's first zero position for category QAM signals, we look upon QAM signal constellation as a graphical with grid-like distribution, constellation point uniformly distributing in the plane with the same intervals. Therefore, the dual-dimensional histogram can be transformed by rotating. The QAM constellation is shown in Fig. 1.

Clustering is a data set which is divided into several groups that cause the similarity within the group is greater than different groups. To achieve such a division needs a similarity measure, which input two vectors, and returned the value which reflects the similarity between these two vectors [4]. Since most of

**978-1-4799-0759-5 /13/$31.00 ©2013 IEEE**

the similarity measure is very sensitive to the elements' value range of the input vectors, each input variable must be normalized, and its value belongs to interval [0, 1].

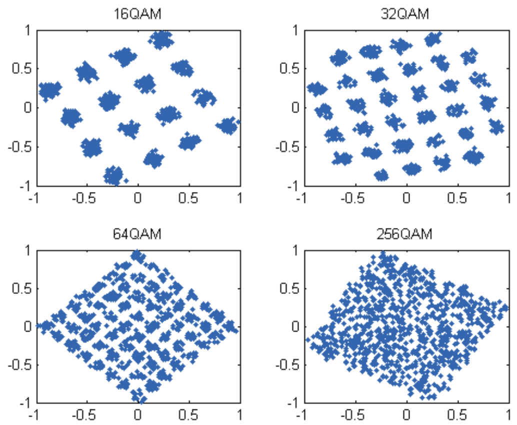


**Fig. 1. QAM signal constellation.**

From the M-QAM signal constellation, we know that constellation point is very obvious clustering, and this feature can be used for identification of QAM signals. In the present QAM signal recognition, identification M-ary is generally up to 64, which can also be seen from the constellation. In the 256QAM constellation map, constellation points are too much. Even signal has high SNR and large number of symbols in the case, it is still difficult to achieve the desired effect of cluster identification. Therefore, the signal identification for 16QAM, 32QAM and 64QAM is mainly achieved.

## III. BASED ON M-QAM CONSTELLATION DIAGRAM CLUSTERING RECOGNITION

After using blind equalization techniques to overcome channel's multipath effects and system synchronization error, intuitive performance of the signal constellation of data points gathered in the respective modulated state. Continue processing of output signals from equalizer can identify the type of modulation of the signal.

M-QAM signal identification methods are currently mainly based on wavelet transform modulus sequence recognition, those based on the recognition of the magnitude's statistical moments, those based on the recognition of the log-likelihood function, etc. These methods either need to know the baud rate of the sender or be sensitive to frequency offset or have to get the modulation interval from the sender, in short, all these must get more of prior parameter info. However, in non-collaborative communication, frequency offset, baud rate, and prior knowledge are unknown, so these identification methods have not too high practical value, but the proposed method does not require prior knowledge to complete the M-QAM signal identification.

Designed in this paper based on the k-means clustering, QAM constellation diagram identification is achieved through the identification of the signal constellation cluster characteristics, so it need to restore the signal constellation diagram, but the quality of restored constellation diagram, directly affect the level of signal recognition rate. Since the constellation map recovery is achieved in the baseband signal, in non-cooperative communication, under the premise of advance unknown with the offset, the baud rate, and the timing error. Firstly, it need estimate these parameters from the received signal then process them and identify. This method is implemented in Fig. 2. It can be seen from the figure, estimating the received signal's frequency offset for one thing; carrying out the baud rate estimation and timing error estimate, thereby estimating the frequency offset and symbol rate, and timing information, to achieve carrier synchronization and symbol synchronization, and then recover the signal constellation diagram.

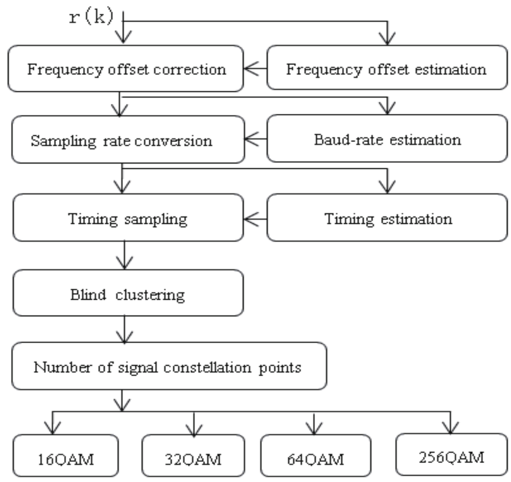


**Fig. 2. Signal identification of QAM constellation.**

After acquire signal constellation diagram, the rest of the work need an identifier analysis through cluster and automatically determine the specific number of points in the constellation diagram, where use k-means clustering algorithm, the algorithm is a typical representative of partition clustering algorithms, in real terms, the algorithm based on the average of the objects in the cluster. Partition-based clustering requires to enumerate all possible division in order to achieve global optimal. The algorithm can use effective range of the data according to pre-specified, in accordance with the minimum mean square error criteria to get the final clustering points and the position of the cluster center. Algorithm [2] input objects of data and the number of clusters $k$, to obtain the minimum of the square error criterion $k$ clusters. Algorithm is shown as follows:

1) Set the initial category center and the number of categories. Arbitrarily select $k$ objects from the entire sample $n$ as initial cluster center $m_i (i=1,2,...2k)$.

2) Partition the data according to the category center. Use the (1) to calculate the distance from each of the data set $p$ to the center of $k$ clusters $d(p,m_i)$.

3) Recalculate the center the category in the current category partition. Find the minimum $d(p,m_i)$ of each object $p$, put this $p$ into the cluster the same with $m_i$.

4) Partition category in the gained category center. After traversing all the objects, use (2) to recalculate the value of $m_i$, as the new cluster center.

5) Re-assign the entire data object set to the most similar cluster. This process is repeated until gain a minimum value of the squared error criterion. If two consecutive category partition results are same, stop the algorithm. Otherwise, loop 2 to 5.

$$d(i,j)=\sqrt{(x_{i1}-x_{j1})^2+(x_{i2}-x_{j2})^2+...+(x_{in}-x_{jn})^2} \quad (1)$$

In (1), $i=(x_{i1},x_{i2},...,x_{in})$ and $j=(j_{i1},j_{i2},...,j_{in})$ are two n-dimensional data objects.

$$m_k=\sum_{i=1}^{N}\frac{x_i}{N} \quad (2)$$

In (2), $m_k$ represents the cluster center in $k$ clusters, $N$ represents the number of data objects of the $k$ clusters.

Squared error criterion attempt to make clustering results as independent and compact as possible, in the other word, the similarity of the objects within the cluster is as high as possible. Defined as (3), $E$ represents the sum of all the square errors of the object, $p$ represents the space object, and $m_i$ represents the average value of the cluster $C_i$.

$$E=\sum_{i=1}^{K}\sum_{p\in C_i}\left|p-m_i\right|^2 \quad (3)$$

## IV. FIGURES SIMULATION AND EXPERIMENT RESULTS OF M-QAM SIGNAL IDENTIFICATION

### *A. Recognition Rate under the Gaussian Channel Environment*

Fig. 3 shows the 16QAM, 32QAM and 64QAM signal recognition of the computer simulation results, the SNR range used in simulation is 0dB ~ 30dB, normalized baud rate set 1.0 or 0.5, shaping filter roll-off factor α set 0.35,0.6,0.8 respectively. Simulate each signal with every modulate parameter (including the carrier frequency, roll-off factor, signal to noise ratio) 100 times. Testing the effect on SNR for signal identification. Simulation result shows that the signal can get a higher recognition ratio in a condition of SNR is10dB.

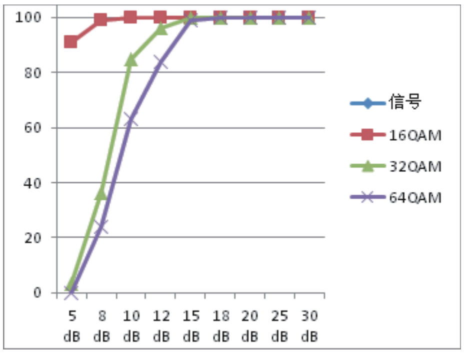


**Fig. 3. Signal recognition of the computer simulation results under the Gaussian channel environment.**

### *B. Recognition rate under the Multipath channel environment*

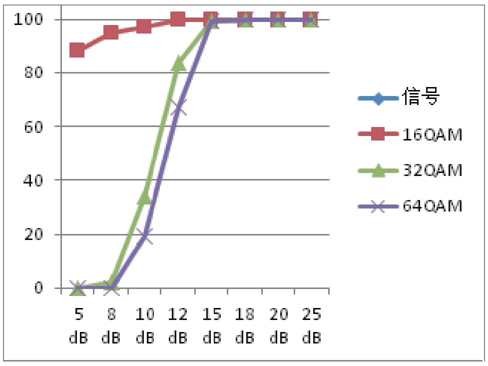


**Fig. 4. Signal recognition of the computer simulation results under the multipath channel environment.**

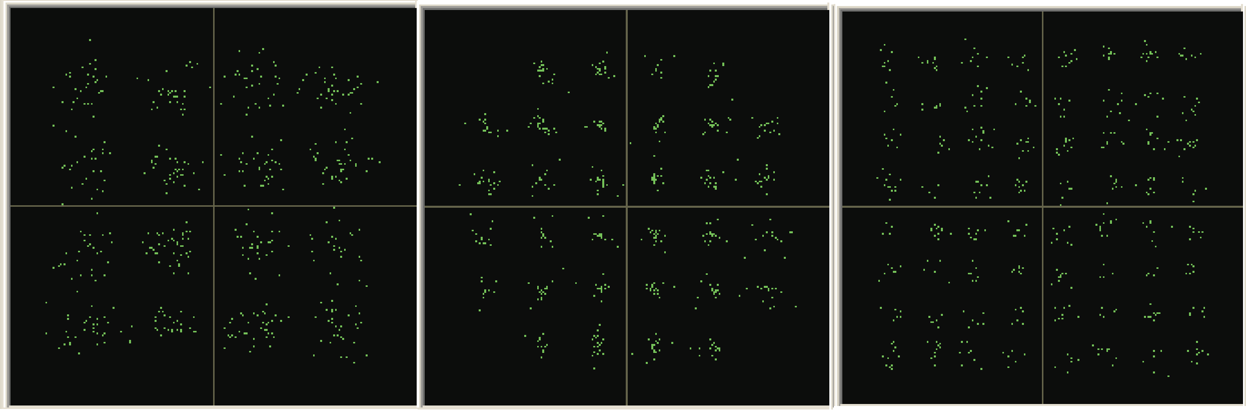

**Fig. 5. 16QAM, 32QAM, 64QAM signal correct recognition ratio reaches 100% with SNR 15dB.**

In simulation, select a dual-diameter radio channel, channel impulse response is delayed of the raised cosine pulse function.

$$h(t) = \left(0.2c(t, 0.11) + 0.4c(t - 2.5, 0.11)\right) w_{6T} \tag{4}$$

In (4), $c(t,a)$ represents a single pulse, $a$ is the Rolloff factor, $w_{6T}$ is rectangular window with 6T wide. Oversampling the received signal with four times baud rate.

Fig.4 shows the simulation with the same signal set, to test the effect on SNR for signal identification. The result indicates that it can also achieve a high recognition rate in the case of the SNR is higher than 15dB.

In the experiment, we found that 16QAM signals can achieve 100% recognition rate, when SNR equals 10dB. However, 32QAM and 64QAM signals only have 63% and 81% recognition rate respectively even the SNR equals 25dB. From the recognition results (see Table 1), it can be seen, identifying QAM signal use constellation, which is more sensitive to noise. When SNR equals 5dB, the recognition rate of 16QAM, 32QAM and 64QAM signals respectively drop to 89%, 5% and 3%. Moreover, the constellation points of 32QAM and 64QAM signal were more than 16QAM obviously, using k-means clustering method to cluster, increase the points lead to an elevated recognition rate. Might as well, comparing the recognition rate of 32QAM and 64QAM signals, we can see, the recognition rate of 64QAM signal is higher than 32QAM. The constellation diagram of 32QAM signal is a cross-shaped, however, that of the 64QAM is a square, when fewer symbols, the symbols estimate error rate of 32QAM signal is greater than 64QAM, which leading to the reconstructed constellation fuzzy, sequentially the recognition rate of 32QAM is lower than 64QAM.

Experimental results show that this method is experimentally approved effective for M-QAM signals, and the correct recognition ratio reaches 100% under the condition that the SNR is higher than 15dB( i.e. Fig.5). However, as Fig. 6 shown, only when the SNR must be higher than 30dB, the recognition ratio can reaches 100% which uses Genetic Algorithm and Hierarchical Clustering identification method [6], and which also need 20-25dB to reaches 100% [7][8].

**Table 1. QAM Signal Recognition Rate (%)**

| SNR / Signals | 5 dB | 8 dB | 10 dB | 12 dB | 15 dB | 18 dB | 20 dB |
|---|---|---|---|---|---|---|---|
| 16 QAM | 91 | 98 | 100 | 100 | 100 | 100 | 100 |
| 32 QAM | 3 | 24 | 57 | 63 | 97 | 100 | 100 |
| 64 QAM | 1 | 36 | 66 | 81 | 99 | 100 | 100 |

## V. CONCLUSION

In this paper, the author presents an identification method based on constellation for QAM signals, the K-means clustering algorithm used is simple and easy to implement, and it can determine the specific constellation points in the constellation map in the better way. Experimental results show that the algorithm when SNR is greater 15dB, the QAM signal recognition rate can reach 100%, which has a high application value. Since the algorithm is more sensitive to noise, identification of the constellation normally require a higher signal to noise ratio, and high-level QAM signal transmission also requires a higher signal to noise ratio, Therefore, identification of QAM signals mainly in case of signal recognition with high SNR, and pre-process signal with low-pass filter, reducing the timing phase dithering caused by noise.

## REFERENCES

[1] ZHAN Y F, CAO Z G. Modulation classification of M-QAM signals[J]. Journal of China Institute of

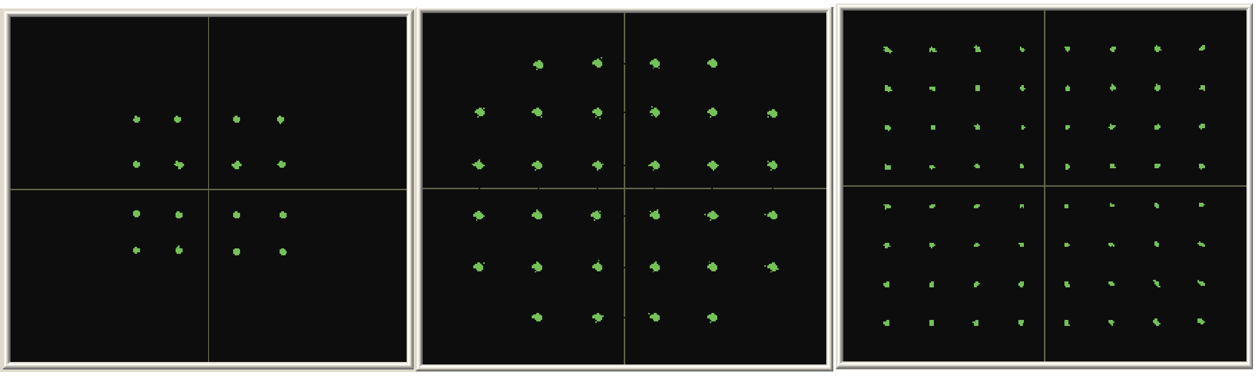

**Fig. 6. 16QAM, 32QAM, 64QAM signal correct recognition ratio reaches 100% with SNR 30dB.**

Communications, 2004,25(2): 68-74.
[2] HUANG T, LIU S H. Research of clustering algorithm based on K-means[J]. Computer Technology and Development, 2011, 21(7):54-57.
[3] HOU J, WANG H K. MQAM recognition based on research of constellation clustering[J]. Radio Communications Technology, 2009, 35(3):35-38.
[4] WANG J X, SONG H. Digital modulation recognition based on constellation diagram[J]. Journal of China Institute of Communications, 2004, .25(6):166-173
[5] ZHANG D P, CHEN Y F. The recognition of QAM signal based on constellation diagram[J]. Communication Countermeasures, 2006, 1(1):8-11.
[6] AHMADI N. Modulation classification of QAM and PSK from their constellation using genetic algorithm and hierarchical clustering[C]. IEEE ICITA Cairns, 2008:98-103.
[7] BRADLEY P, FAYYAD U M. Refining initial points for KM clustering[R]. MS Technical Report MSR-TR-98-36, 1998.
[8] MOBASSERI B G. Digital modulation classification using constellation shape[J]. Signal Processing, 2000, 80(2):251-277.

## AUTHOR BIOGRAPHY

Chou Zhendong was born in 1987. His research interests include digital signal processing, software radio and parallel image processing.

Jiang Weining was born in 1971. Now he is a senior engineer. His research interests include digital signal processing, software radio and signal recognition.

Xiang Changbo was born in1978. He received PhD from Changchun Institute of Optics, Fine Mechanics and Physics, Chinese Academy of Sciences in 2008. Now he is an engineer in The 41st Institute of CECT, China. His research interests include software radio, image processing.

Li Min. His research interests include digital signal processing and software radio.