Research on Influencing Factors of Digital Signal Modulation Recognition

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***Abstract*—In the real environment, modulation recognition has low classification recognition rate under low SNR and is affected by many factors such as symbol rate, frequency offset and adjacent channel crosstalk. Based on the combination of high-order cumulants and instantaneous features, this paper firstly analyzes the performance of modulation signal recognition in Gaussian environment. Then through the experimental verification, symbol rate, frequency offset, adjacent channel crosstalk has an impact on the accuracy of modulation recognition. The experimental results show that the ratio of symbol rate and sampling rate has a significant impact on the recognition results, while frequency offset and adjacent channel crosstalk have little impact on the recognition rate.**

***Index Terms*—pattern recognition, digital modulation, higher order statistics, multiple signal classification, machine learning.**

I. INTRODUCTION

Wireless signal recognition mainly includes modulation recognition and wireless technology recognition, which has broad application prospects in military and civil fields, including signal reconnaissance and interception, anti-interference and equipment recognition [1]. At present, the modulation recognition algorithms of communication signals are divided into decision theory recognition method based on likelihood function and statistical pattern recognition method based on feature extraction [2]. Because modulation classification mainly distinguishes signal modulation types in the case of unknown modulation parameters, there are many research results of modulation recognition based on feature extraction.

Since the Gaussian white noise is higher than the second-order cumulant constant to zero [3], the modulation recognition method based on the high-order cumulant [4]-[6] has good anti-noise performance, and has received extensive attention in the field of modulation recognition. Literature [7]-[12] uses high-order cumulants to distinguish common digitally modulated signals. In [7], the fourth-order statistic (HOS) is applied to blind channel estimation and pattern recognition. In the case of known channel information, the QPSK recognition rate is about 90%, and the 64QAM recognition rate is about 80%. Literature [8] uses four-order, eighth-order cumulants to distinguish between MASK, MPSK, and MQAM signals. Literature [9]-[10] uses two to eight-order cumulants to identify multiple digitally modulated signals such as MASK, MPSK, MQAM, and MAPSK with Gaussian noise only. Among them, the literature [10] verified the correctness and rationality of the characteristic parameters through simulation experiments without considering the carrier phase deviation. In [11], the high-order cumulants and instantaneous parameters are combined to extract four characteristic parameters. The decision tree decision method is used to realize the noise-only 2ASK, 4ASK, BPSK, QPSK, 2FSK, 4FSK, 16QAM seven-type signals. Modulation recognition, when the SNR is 5dB, the recognition rate of each signal reaches 95%. In [12], based on high-order cumulant and depth learning, 11 kinds of modulated signals such as MASK, MPSK, MFSK, MQAM and OFDM are classified and recognized. In the Gaussian white noise environment, when the SNR is -1dB, the correct recognition rate is 72%. When the SNR is 20 dB, the correct recognition rate reaches 100%. Literature [13] is based on the instantaneous characteristics of digitally modulated signals and the second, third and fourth-order cumulants, combined with artificial neural networks, in the presence of additive white Gaussian noise with a signal-to-noise ratio of 8 dB, MASK, MPSK, MQAM signals The recognition rate is over 95%.

In the above published literature, modulation recognition is carried out in the additive white Gaussian noise environment. In the actual communication, blind signal processing needs to complete carrier frequency estimation, modulation type recognition, symbol rate estimation, symbol synchronization, etc. In reference [14] , based on the sixth order cumulant and depth learning algorithm, the influence of frequency offset and multipath effect on modulation recognition is considered. When SNR = -2dB, the recognition rate of 2ASK, 4ASK, 2FSK, 4FSK, 2PSK, 2PSK and 4PSK are all 100%. When the frequency offset is 10ppm, the recognition result of some specific modulation types is very little affected, while the multi-path effect will not reduce the recognition ability. In this paper, based on the statistical pattern recognition method of feature extraction, the instantaneous feature [15] and high-order cumulant are selected to extract the feature parameters to realize the hybrid modulation recognition algorithm, and the decision tree and neural network [16]-[17] classifier are constructed for simulation verification. Firstly, 10 kinds of modulation signals, such as MFSK, MPSK, MQAM, are identified under Gaussian condition, and the effectiveness of the algorithm is verified. Then, the influences of the ratio of symbol rate and sampling rate, frequency offset, crosstalk of adjacent channels on the accuracy of modulation recognition are analyzed.

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II. Characteristic Parameters and Algorithm Analysis

In modulation recognition based on statistical pattern, feature extraction is an important part and the basis of the subsequent classification decision. In the existing research, modulation recognition technology based on instantaneous information has a low recognition rate in the case of low SNR, while modulation recognition technology based on high-order cumulant has a bad effect on intra class classification of signals, and some signals cannot be completely distinguished. In order to solve the problem of single feature, this paper uses the method of high-order cumulant and instantaneous feature to realize modulation recognition and classification.

A. Definition of Higher Order Cumulants

The k-high order cumulant of the signal is [18]:

$$C_{kx}\left(\tau_1,\tau_2,\ldots,\tau_{k-1}\right)= Cum\left(x(t),x(t+\tau_1),,x(t+\tau_{k-1})\right) \quad (1)$$

$X(\mathrm{t})$ is a zero-mean complex stationary stochastic process whose p order mixing moment is defined as [19]:

$$M_{pq}=E\left[X(n)^{p-q}X^*(n)^q\right] \quad (2)$$

Where $*$ represents a complex conjugate, p represents an order $(p<q)$, and q is the number of sequences to which the conjugate is taken. The cumulative amount of signal order can be defined as:

$$C_{20}=Cum(X,X)=M_{20} \quad (3)$$

$$C_{21}=Cum\left(X,X^*\right)=M_{21} \quad (4)$$

$$C_{41}=M_{41}-3M_{20}M_{21}(1) \quad (5)$$

$$C_{42}=M_{42}-\left|M_{20}\right|^2-2M_{21}^2 \quad (6)$$

$$C_{63}=M_{63}-6M_{41}M_{20}- 9M_{21}M_{42}+18M_{21}M_{20}^2+12M_{21}^3 \quad (7)$$

$$C_{80}=M_{80}-28M_{60}M_{20}- 35M_{40}^2+420M_{40}M_{20}^2-630M_{20}^4 \quad (8)$$

Assume that the transmitted symbols are independently and identically distributed, and the signal energy is E. According to the calculation method of the higher-order cumulant theoretical value in [20], the theoretical values of the cumulative quantities of MFSK, MPSK, and MQAM are shown in Table I:

Table I. Theoretical Value of Each Order of Different Modulation Modes

Modulated signal	$\lvert C_{41}\rvert$	$\lvert C_{42}\rvert$	$\lvert C_{63}\rvert$	$\lvert C_{80}\rvert$
MSK	0	E^2	$4E^3$	0
2FSK	0	E^2	$4E^3$	0
4FSK	0	E^2	$4E^3$	0
BPSK	$2E^2$	$2E^2$	$13E^3$	$272E^4$
QPSK	0	E^2	$4E^3$	$34E^4$
8PSK	0	E^2	$4E^3$	E^4
8QAM	$0.89E^2$	E^2	$5.33E^3$	$54.15E^4$
16QAM	0	$0.68E^2$	$2.08E^3$	$13.98E^4$
32QAM	0	$0.69E^2$	$2.11E^3$	$1.99E^4$
64QAM	0	$0.62E^2$	$1.80E^3$	$11.50E^4$

B. Feature Parameter Extraction

In order to eliminate the influence of the average power E of the signal, according to the difference of the cumulative quantities of the different modulation modes in Table I, the following three characteristic parameters are constructed:

$$Fx_1=\frac{\left|C_{41}\right|}{\left|C_{42}\right|} \quad (9)$$

$$Fx_2=\frac{\left|C_{63}\right|^2}{\left|C_{42}\right|^3} \quad (10)$$

$$Fx_3=\frac{\left|C_{80}\right|}{\left|C_{42}\right|^2} \quad (11)$$

According to Table I, the theoretical values of each characteristic parameter can be obtained as shown in Table II:

Table II. Theoretical Value of Each Characteristic Parameter

Modulation type	Characteristic Parameters		
	Fx_1	Fx_2	Fx_3
MSK	0	16	0
2FSK	0	16	0
4FSK	0	16	0
BPSK	1	21.12	68
QPSK	0	16	34
8PSK	0	16	1
8QAM	0.89	28.44	54.15
16QAM	0	13.76	30.23
32QAM	0	13.55	4.19
64QAM	0	13.59	29.92

It can be seen from Table II that the high-order cumulant cannot handle MFSK and MQAM signal class recognition well. This paper extracts the following four instantaneous characteristic parameters [21]-[22] to deal with intra-class signal identification.

1. Zero-center normalized instantaneous amplitude on the non-weak signal segment. Logarithm of the second-order origin moment:

$$Fx_4=\lg\left[\frac{1}{N_s}\sum_{n=0}^{N_s-1}A_{cn}{}^2(n)\right] \quad (12)$$

Where N_s is the number of points on the non-weak signal segment among all sampled data points, and $A_{cn}(n)$

is the instantaneous amplitude normalized by the center.

2. Recursive zero-center normalized on the non-weak signal segment. Logarithm of the instantaneous magnitude absolute value of the origin moment:

$$Fx_5 = \lg\left[\frac{1}{N_s}\sum_{n=0}^{N_s-1}\left|A_{sn}(n)\right|\right] \tag{13}$$

Where $A_{sn}(n)$ is the recursive normalized instantaneous magnitude.

3. Zero-center normalized instantaneous frequency absolute value of the origin moment on the non-weak signal segment:

$$Fx_6 = \lg\left[\frac{1}{N_s}\sum_{n=0}^{N_s-1}\left|f_{cn}(n)\right|\right] \tag{14}$$

Where $f_{cn}(n)$ is the instantaneous frequency normalized to zero center. This parameter is mainly used to identify 2FSK and 4FSK signals.

4. The second order amplitude moment of the MQAM signal [23]:

$$Fx_7 = M_{2,MQAM}^{2n} = \frac{M-1}{3} \tag{15}$$

Fx_4, Fx_5, and Fx_7 resolve the intra-class identification of the MQAM signal, and Fx_6 separates the MFSK signal.

C. Classifier Design

Machine learning can find the relationship between the feature parameters adaptively, and adjust them constantly, then get the optimal classification method. In this paper, the decision tree and neural network classifier, which are common and easy to implement in engineering, are selected for modulation signal classification and recognition.

The neural network can simulate the biological nervous system to judge the input object, and has good adaptability [24]. Common neural network classifiers mainly include BP neural network, radial basis neural network, adaptive resonant neural network and wavelet neural network. The neural network has a good ability to learn and store information, which helps to improve recognition performance in pattern recognition. In this paper, a 3-layer backpropagation BP neural network is selected. The 7 nodes of the input layer correspond to 7 characteristic parameters, and the 10 nodes of the output layer correspond to 10 signal modulation types, and the number of hidden layer nodes is 20.

Decision tree is a classification algorithm for supervised learning, also called decision tree. The algorithm implementation includes two stages of learning and prediction [25]-[26]. The main idea is to simplify the decomposition of complex problems, and to enter the next layer by comparing the thresholds of each layer. The algorithm is simple, and can make feasible and effective results for large data sources in a relatively short time. Before using the decision tree classifier, you need to set the relevant parameters of the decision tree, mainly including the maximum number of categories, the depth of the decision tree, the minimum number of samples of nodes, etc. in this paper, the specific parameters of the decision tree classifier are set, as shown in Table III:

TABLE III. DECISION TREE CLASSIFIER SPECIFIC PARAMETERS

Parameter name	Parameter meaning	Value
Max Categories	The largest category of decision tree node splitting	4
Max Depth	Possible maximum depth of the decision tree	10
Min Sample Count	The smallest sample size of the decision tree node	5
Truncate Pruned Tree	If set to true, the trimmed branch will be completely removed.	True
Regression Accuracy	Stop condition of regression decision tree training	0

D. Decision tree learning process

The implementation of decision tree algorithm includes two stages: learning and prediction. Fig.1 shows the learning process of decision tree, which is a recursive implementation process.

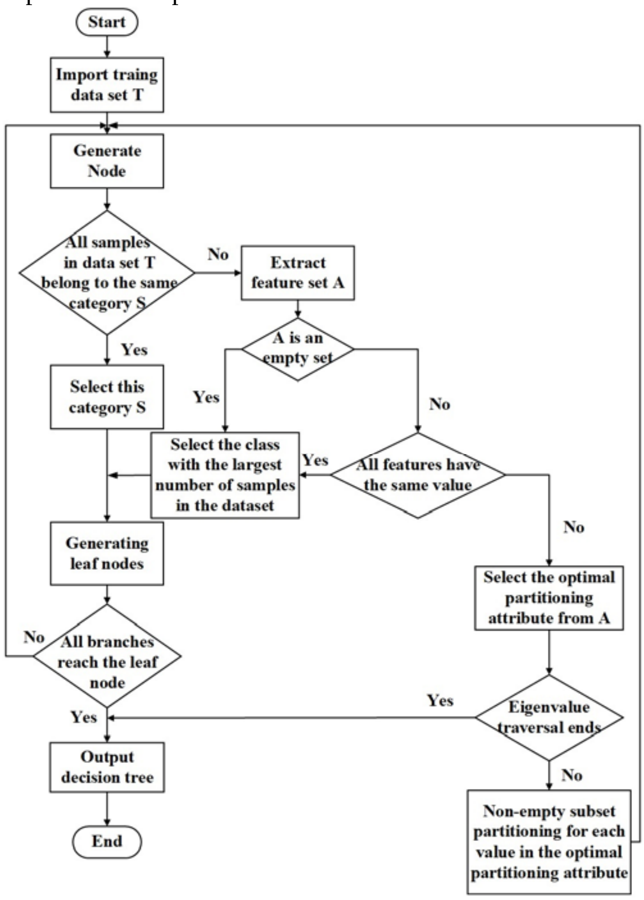

Figure 1. Decision tree learning process

It can be seen from Fig.1 that after importing the training data set, a node is generated first, and then whether the data in the training sample belongs to the same category is determined. If it belongs to the same category, the node is marked as this category. Otherwise, the judgment needs to be continued. Then judge the feature attribute set. If the attribute set is empty or has only one attribute, mark the class with the largest number of samples as the leaf node. Otherwise, select the best attribute in the attribute set to divide the class.

III. EXPERIMENTAL RESULTS AND ANALYSIS

In this paper, the modulation signal set is to be identified: {MSK, 2FSK, 4FSK, BPSK, QPSK, 8PSK, 8QAM, 16QAM, 32QAM, 64QAM}. There are two sources of experimental data required: one is to generate a digital modulated signal set under the MATLAB platform.

Simulation conditions: Assuming training signal set baud rate 8000, verify signal set baud rate are 7000, 8000, 9000, 11000, unit: baud. Samples Per Symbol is 8, Sample Rates calculated according to baud rate, Modulation Order, and Samples Per Symbol. The signal data length is 16384, the signal-to-noise ratio varies from 0dB to 29dB, and the step size is 1. The noise is A. The second is to generate signals through the Agilent E4432B RF digital signal generator and receive them after the actual channel. The carrier frequency of the signal is set to 500MHz, and the acquisition symbol rate is 24ksps and 65ksps respectively. The signal is processed by down-conversion in the receiving process to obtain the complex baseband signal. Because the actual acquisition signal and the simulation signal recognition results are basically the same, this paper only describes the experimental results analysis of the simulation signal.

A. Simulation Research on Recognition Performance of Each Modulation Signal under AWGN

The simulation experiment is carried out by using MATLAB software to verify the validity of the proposed method. The symbol rate of the signal set is 8000, which only contains Gaussian white noise. It can be seen from Fig.2 that the modulation recognition accuracy of the basic neural network classifier is 97.45% at SNR = 0 dB and the modulation recognition accuracy based on the decision tree classifier is 97.8%. At SNR > 4 dB, the correct rate of modulation recognition based on neural network classifier and decision tree classifier is 100%. In the literature [5], the correct recognition rate reaches 100% at SNR = 20dB.

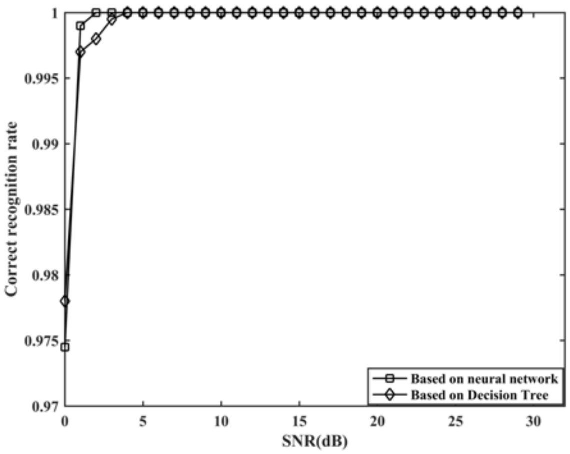

Figure 2. The relationship between correct recognition rate and SNR under Gaussian channel

It can be seen from Fig.3 and Fig.4 that for noise-only MQAM, MFSK and BPSK signals, the recognition rate using the decision tree and the neural network classifier is 100%. QPSK and 8PSK signals, when SNR = 0 dB, are identified by decision tree classifier, and the recognition rates are 91% and 86% respectively. With the neural network classifier, the recognition rates are 81% and 91% respectively. The signal-to-noise ratio increases and the recognition rate increases. When SNR > 3 dB, the recognition rate of QPSK and 8PSK signals reaches 100%. At low SNR, the recognition rate of each modulated signal is higher. However, the literature [2] can effectively identify all signals when the signal-to-noise ratio is greater than 20dB; in [4], when the SNR=5dB, the recognition rate of each signal reaches 95%; in the literature [3], when the signal-to-noise ratio is greater than -3dB, the signal The recognition rate can reach more than 90%. Therefore, under the low SNR, the correct recognition rate of the method used in this paper is higher than that in the literature [2], [4], which is lower than the literature [3]; thus the low SNR of the proposed method in Gaussian channel environment is verified. It has a good recognition result.

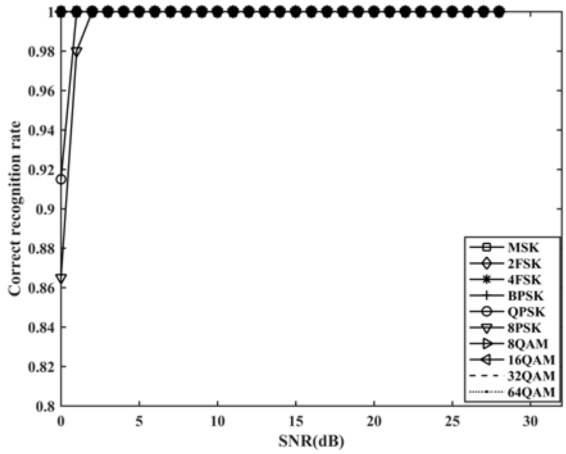

Figure 3. Correct recognition rate of each modulation signal based on decision tree

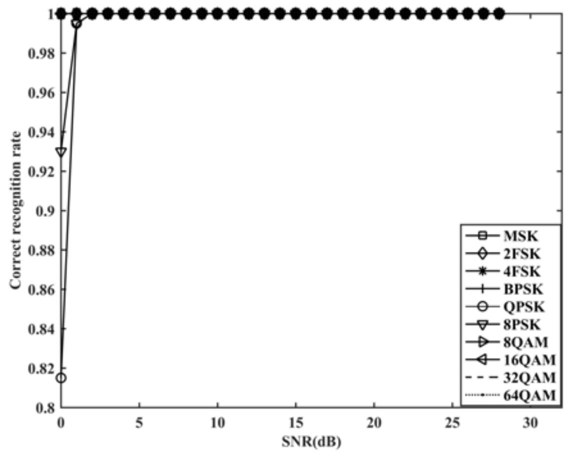

Figure 4. Correct recognition rate of each modulated signal based on neural network

B. The effect of Baud Rate on the correct rate of modulation recognition

Consider the effect of the baud rate on the correct rate of modulation recognition. The training signal set baud rate is 8000, and the verification signal set baud rate is 7000, 8000, 9000, 11000, and the unit is: baud. It contains only Gaussian white noise.

From Table IV, when SNR = 0dB, the baud rate is 8000, the baud rate is 8000, and the recognition rate is over 97%. When the baud rate is reduced to 7000, the recognition rate is reduced to about 78%, and the recognition rate is significantly reduced. When the baud rate is increased to 9000 and 11000, the recognition rate is 98% and 97%, respectively. Compared with the baud rate of 8000, the result is almost unchanged.

TABLE IV. RECOGNITION RESULTS AT DIFFERENT SYMBOL RATES

Classifier	Baud rate (baud)	Recognition rate(%)			
		0dB	5dB	10dB	20dB
Decision tree	7000	78.2	80	80	80

	8000	97.8	100	100	100
	9000	98	100	100	100
	11000	97.25	100	100	100
Neural Networks	7000	79	80	80	80
	8000	97.45	100	100	100
	9000	98.05	100	100	100
	11000	97.45	100	100	100

It can be seen from Fig. 5 and Fig. 6 that when the baud rate is reduced, the MSK and QPSK signal recognition rates are both 0; 8PSK signals, SNR = 0 dB, the recognition rates of the decision tree classifier and the neural network classifier are 82% and 90%, respectively. The signal recognition rate is still 100%.

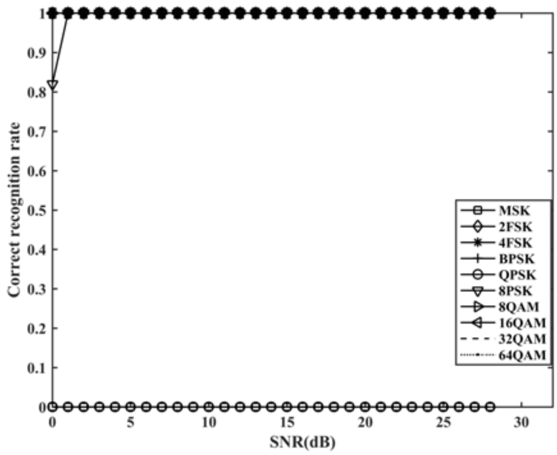

Figure 5. The verification set symbol rate is 7000, based on the decision tree's modulation recognition rate

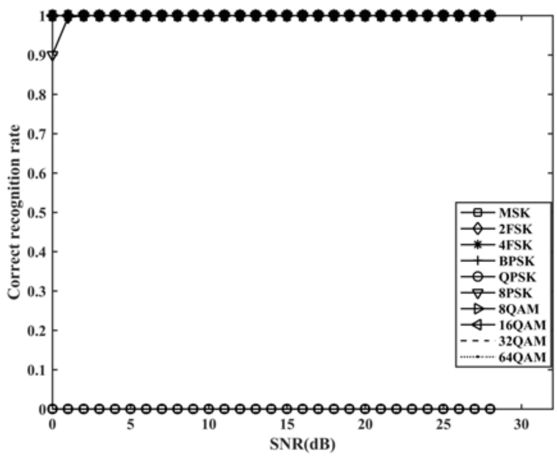

Figure 6. The verification set symbol rate is 7000, based on the neural network-based modulation recognition rate

C. The effect of frequency offset on the correct rate of modulation recognition

Simulation conditions: There is frequency offset and noise, the symbol rate is 8000, and the frequency offset is 2.5%, 5% and 10% of the symbol rate, respectively.

Fig. 7 is a spectrum diagram of a QPSK signal with frequency offset, where the frequency offset is 5% of the symbol rate.

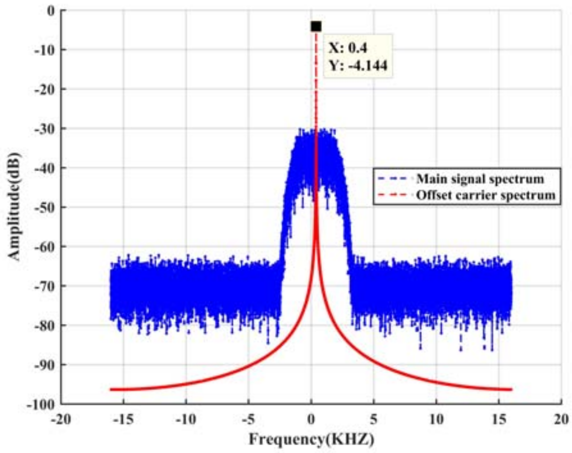

Figure 7. QPSK signal spectrum

As can be seen from Table V, the frequency offset is added. Compared with the noise only, the correct recognition rate of the modulated signal is significantly reduced at a low SNR, and different frequency offsets have different effects on the correct recognition rate.

TABLE V. RECOGNITION RESULTS AT DIFFERENT FREQUENCY OFFSETS

Classifier	**Frequency offset is X% of baud rate**	**Recognition rate(%)**					
		0dB	**5dB**	**10dB**	**15dB**	**20dB**	**25dB**
Decision tree	0	97.8	1	1	1	1	1
	2.5	89.85	90.05	90.05	90	99.8	99.95
	5	89.9	90.05	89.95	90.1	99.95	99.95
	10	90.15	90.05	90	90.5	97.75	99.9
Neural Networks	0	97.45	1	1	1	1	1
	2.5	92.2	97.1	99.25	1	1	1
	5	93.1	99.8	1	1	1	1
	10	99.15	1	1	99.85	99	99.95

As can be seen from Fig.8, in addition to the 8PSK signal, the recognition rate of other signals is 100%. As can be seen from Fig.9 and Fig.10, the recognition rate of the QPSK signal is also affected as the frequency offset increases, but the recognition rate of the QPSK signal is always better than the 8PSK signal.

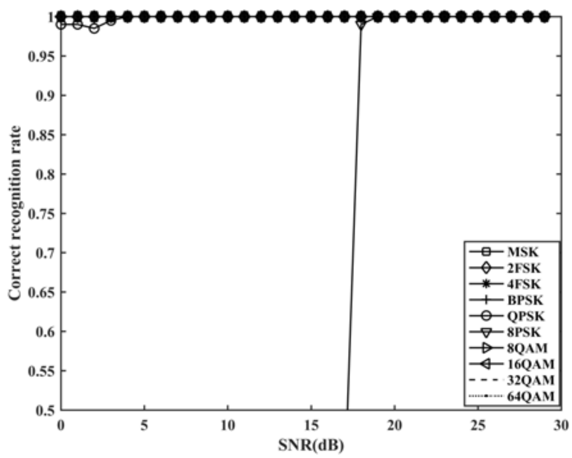

Figure 8. Based on the decision tree, the frequency offset is 2.5% of the baud rate

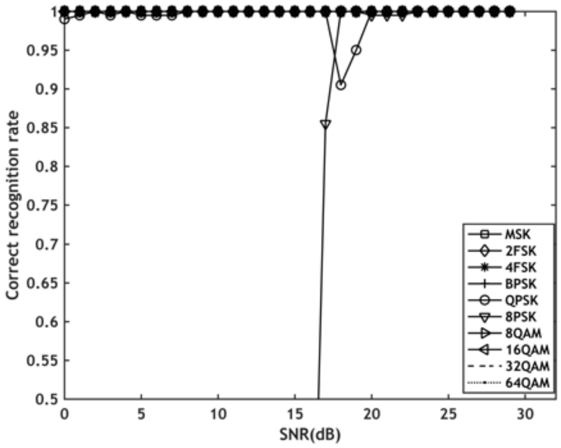

Figure 9.Based on the decision tree, the frequency offset is 5% of the baud rate

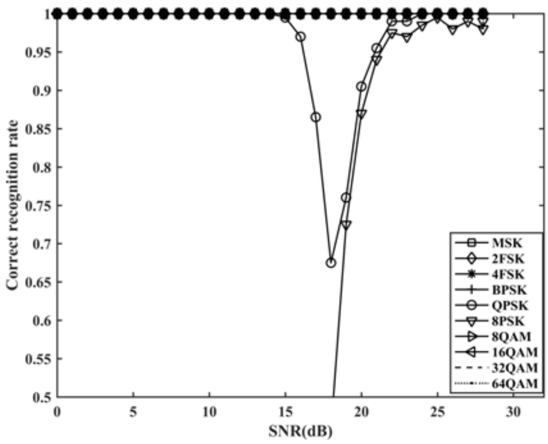

Figure 10. Based on the decision tree, the frequency offset is 10% of the baud rate

As can be seen from Fig.11, Fig.12, and Fig.13, in addition to the QPSK and 8PSK signals, the recognition rate of other signals is 100%. And with the increase of frequency offset, the recognition rate of QPSK and 8PSK signals also increases. When the frequency offset is 10% of the symbol rate, the recognition rate of QPSK and 8PSK signals is more than 85%.

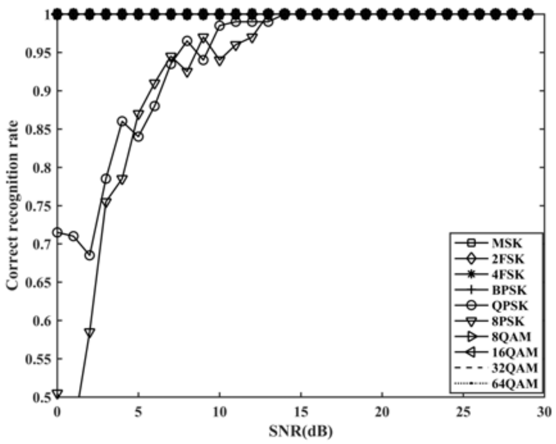

Figure 11. Based on the neural network, the frequency offset is 2.5% of the baud rate

In summary, the QPSK and 8PSK recognition rates are susceptible to frequency offset, and the MFSK and MQAM signal ratios are poorer than the frequency offset, which is related to the phase-carrying information of the MPSK signals.

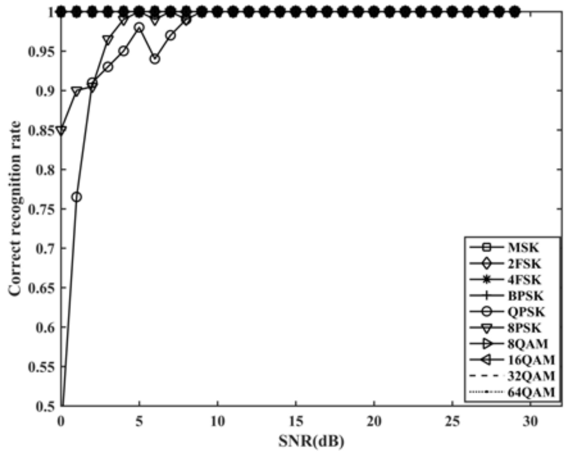

Figure 12. Based on the neural network, the frequency offset is 5% of the baud rate.

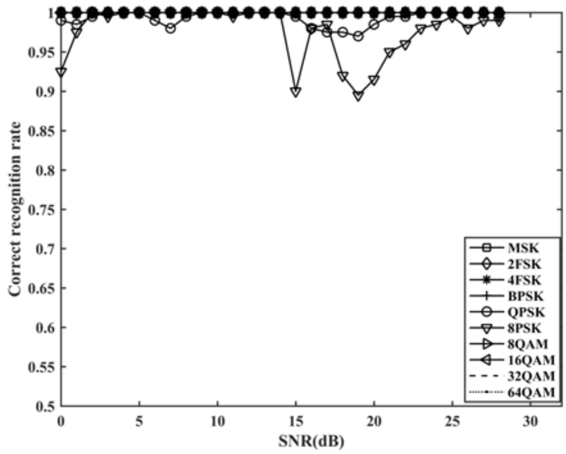

Figure 13. Based on the neural network, the frequency offset is 10% of the baud rate.

D. Influence of adjacent channel interference on the correct rate of modulation recognition

The actual blind signal is simulated by adding frequency offset, adjacent channel signal and noise to the simulated signal. Fig.14 and Fig.14 shows the recognition rate of each modulated signal when the frequency offset is 5% of the symbol rate and the adjacent channel signal gain is 4.

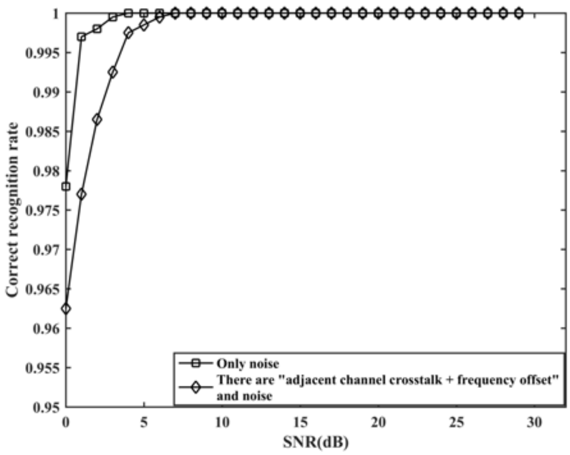

Figure 14. Based on the decision tree, there is "adjacent channel signal interference + frequency offset" and the modulation recognition rate of noise

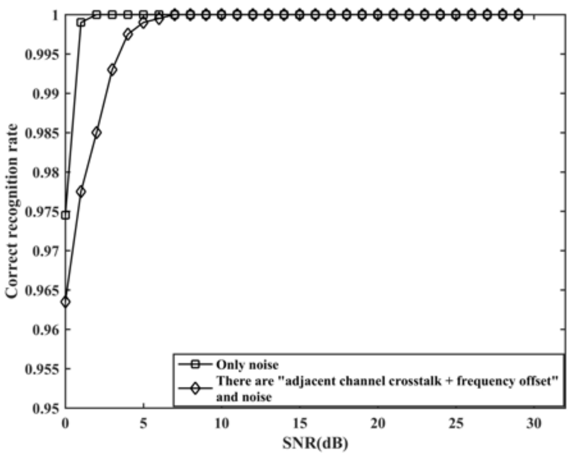

Figure 15. Based on the neural network, there is "adjacent channel signal interference + frequency offset" and the modulation recognition rate of noise

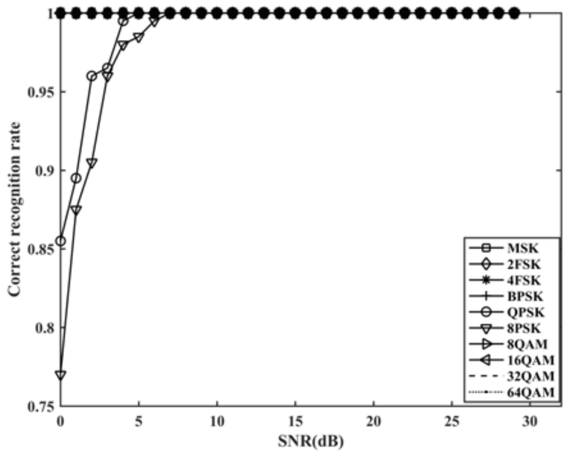

Figure 16. Based on the decision tree, there are "adjacent channel signal interference + frequency offset" and noise modulation signal recognition rate

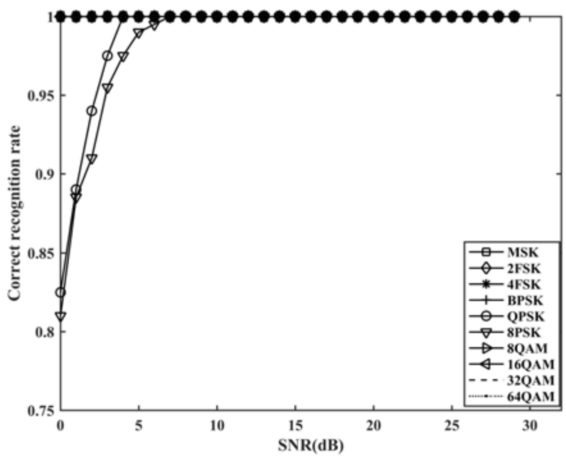

Figure 17. Based on the neural network, there are "adjacent channel signal interference + frequency offset" and the recognition rate of each modulated signal of noise

As can be seen from Fig.18 and Fig.19, when there is "adjacent channel signal crosstalk + frequency offset" and noise, when SNR = 0 dB, the QPSK recognition rate reaches 80% or more, the 8PSK signal recognition rate reaches 75% or more, and the SNR increases as the SNR increases. The rate increases. At SNR > 5 dB, the QPSK recognition rate reaches 100%; in SNR > 7 dB, the 8PSK signal recognition rate reaches 100%. Compared with noise only, the recognition rate of QPSK and 8PSK signals is slightly lower at low SNR.

IV. Conclusion

In this paper, high-order cumulant and instantaneous feature are combined to extract feature parameters. Decision tree and neural network classifier are used to identify MFSK, MPSK and MQAM signals. The effects of noise, baud rate, frequency offset and adjacent channel crosstalk on the modulation recognition accuracy of MFSK, MPSK and MQAM signals are analyzed. The simulation results show that increasing the baud rate has little effect on the modulation recognition results, while decreasing the baud rate has great effect on the modulation recognition results. And the recognition algorithm used in this paper can achieve a high recognition rate under the conditions of noise only, frequency offset and noise, and the presence of "adjacent channel crosstalk + frequency offset" and noise, and the recognition rate has been improved when the signal-to-noise ratio is low. It is proved that it is feasible to select higher-order cumulant and instantaneous feature to extract feature parameters under non ideal conditions, which provides reference for signal modulation type recognition in practical engineering. However, in the real environment, the modulation types are far more than these, and the signals are mostly co channel and multi signal aliasing, which is also a problem to be studied in the future.

V. References

[1] T. Liu, Y. Guan, Y. Lin, "Research on modulation recognition with ensemble learning," EURASIP Journal on Wireless Communications and Networking, vol. 179, no. 1, 2017. doi:10.1186/s13638-017-0949-5.

[2] L. Zhang, "Research on modulation recognition algorithm based on high-order cumulant," Journal of Information Engineering University, vol. 18, no. 4, pp. 403-408, 2017. doi:10.3969/j.issn.1671-0673.2017.04.005.

[3] J. J. Guo, H. D. Yin, L. Jiang, "Recognition of digital modulation signals via high-order cumulants," Communications Technology, vol. 47, no. 11, pp. 1255-1260, 2014. doi:10.3969/j.issn.1002-0802.2014.11.004.

[4] A. Swami and B. Sadler, "Modulation classification via hierarchical agglomerative cluster analysis," In First IEEE Signal Processing Workshop on Signal Processing Advances in Wireless Communications, pp. 141-144, 1997. doi:10.1109/spawc.1997.630180.

[5] C. M. Spooner, "On the utility of sixth-order cyclic cumulants for RF signal classification," In Conference Record of Thirty-Fifth Asilomar Conference on Signals, Systems and Computers, vol. 1, pp. 890-897, 2001. doi:10.1109/acssc.2001.987051.

[6] O. A. Dobre, Y. Barness, and W. Su, "Higher-order cyclic cumulants for high order modulation classification," In IEEE Military Communications Conference, vol. 1, pp. 112-117, 2003. doi:10.1109/milcom.2003.1290087.

[7] H. Wu, M. Saquib, and Z. Yun, "Novel Automatic Modulation Classification Using Cumulant Features for Communications via Multipath Channels," IEEE Transactions on Wireless Communications, vol. 7, no. 8, pp. 3098-3105, 2008. doi:10.1109/twc.2008.070015.

[8] L. Liu and J. Xu, "A Novel Modulation Classification Method Based on High Order Cumulants," In 2006 International Conference on Wireless Communications, Networking and Mobile Computing, pp. 1-5, 2006. doi:10.1109/wicom.2006.157.

[9] Y. Q.Zhang , "Digital Signal Modulation Recognition Based on Higher Order Cumulants," Information & Communications, vol. 2, pp. 27-30, 2016.

[10] Li Y., Guo X. G., Zhao X., "Study on Modulation Recognition Based on Higher-Order Cumulants," Journal of Southwest University of Science and Technology (Natural Science Edition), vol. 33, no. 3, pp. 64-68, 2018.

[11] Hu X., Liu H. L., Zhang J. C., "Algorithm of Modulation Identification Based on Higher Order Cumulant and Instantaneous Characteristics," World Science and Technology Research and Development, vol. 33, no. 6, pp. 1002-1005, 2011. doi:10.16507/j.issn.1006-6055.2011.06.017.
[12] Yuan L.F., Ning S.G., He Y.G, Lyu M., Lu J., "Modulation recognition method based on high-order cumulant feature learning," Systems Engineering and Electronics, vol. 41, no. 9, pp. 2122-2131. doi:10.3969/j.issn.1001-506X.2019.09.28.
[13] W. Juanping, H. Yingzheng, Z. Jinmei, and W. Huakui, "Automatic Modulation Recognition of Digital Communication Signals," presented at the international conference on pervasive computing, 2010, pp. 590-593. doi:10.1109/PCSPA.2010.148.
[14] W. Xie, S. Hu, C. Yu, P. Zhu, X. Peng, and J. Ouyang, "Deep Learning in Digital Modulation Recognition Using High Order Cumulants," IEEE Access, vol. 7, pp. 63760-63766, 2019. doi:10.1109/access.2019.2916833.
[15] E. E. Azzouz and A. K. Nandi, "Automatic identification of digital modulation types," Signal Processing, vol. 47, no. 1, pp. 55-69, 1995. doi.10.1016/0165-1684(95)00099-2.
[16] 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, 1998. doi:10.1109/26.664294.
[17] G. P. Zhang, "Neural networks for classification: a survey," systems man and cybernetics, vol. 30, no. 4, pp. 451-462, 2000. doi:10.1109/5326.897072.
[18] A. E. Shermeh and R. Ghazalian, "Recognition of communication signal types using genetic algorithm and support vector machines based on the higher order statistics," Digital Signal Processing, vol. 20, no. 6, pp. 1748-1757, 2010. doi: 10.1016/j.dsp.2010.03.003.
[19] Flohberger, M., Gappmair, W., & Koudelka, O., "Modulation classifier for signals used in satellite communications," In 2010 5th Advanced Satellite Multimedia Systems Conference and the 11th Signal Processing for Space Communications Workshop, pp. 198-202, 2010. doi:10.1109/asms-spsc.2010.5586892.
[20] A. Swami and B. M. Sadler, "Hierarchical digital modulation classification using cumulants," IEEE Transactions on Communications, vol. 48, no. 3, pp. 416-429, 2000. doi:10.1109/26.837045.
[21] A. K. Nandi and E. E. Azzouz, "Automatic analogue modulation recognition," Signal Processing, vol. 46, no. 2, pp. 211-222, 1995. doi:10.1016/0165-1684(95)00083-P.
[22] H. U. Youqiang, J. Liu, and X. Tan, "Digital modulation recognition based on instantaneous information," The Journal of China Universities of Posts and Telecommunications, vol. 17, no. 3, pp. 52-90, 2010. doi:10.1016/S1005-8885(09)60471-4.
[23] L. I. Qiuna, "Modulation Classification Method of MQAM Signals Based on Amplitude Statistical Moment," Computer Simulation, 2009. doi:10.16182/j.cnki.joss.2009.15.035.
[24] Y. Ettefagh, M. H. Moghaddam, and S. Eghbalian, "An adaptive neural network approach for automatic modulation recognition," presented at the conference on information sciences and systems, 2017, pp. 1-5. doi:10.1109/ciss.2017.7926153.
[25] S. K. Murthy, "Automatic Construction of Decision Trees from Data: A Multi-Disciplinary Survey," Data Mining and Knowledge Discovery, vol. 2, no. 4, pp. 345-389, 1998. doi:10.1023/A:1009744630224.
[26] Maimon, O., & Rokach, L., "Decision trees," Data mining and knowledge discovery handbook. Springer, Boston, MA, 2005, pp. 165-192. doi:10.1007/978-0-387-09823-4.