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Deep Learning in Digital Modulation Recognition Using High Order Cumulants

WENWU XIE[1], SHENG HU[1], CHAO YU[1,2], PENG ZHU[1], XIN PENG[1], AND JINGCHENG OUYANG[1]

[1]School of Information Science and Engineering, Hunan Institute of Science and Technology, Yueyang 414006, China
[2]Department of Information and Communication Engineering, Hoseo University, Asan 31066, South Korea

Corresponding author: Peng Zhu (jianchongren@sina.com)

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ABSTRACT By considering the different cumulant combinations of the 2FSK, 4FSK, 2PSK, 4PSK, 2ASK, and 4ASK, this paper established new identification parameters to achieve the recognition of those digital modulations. The deep neural network (DNN) was also employed to improve the recognition rate, which was designed to classify the signal based on the distinct feature of each signal type that was extracted with high order cumulants. The extensive simulations demonstrated the exceptional classification performance for new key features based on high order cumulants. The overall success rate of the proposed algorithm was over 99% at the signal to noise ratio (SNR) of -5 dB and 100% at the SNR of -2 dB. The results of the experiments also showed the robustness of the proposed method for a variety of conditions, such as frequency offset, multi-path, and so on.

INDEX TERMS Modulation recognition, high order cumulants, deep learning, wireless communications.

I. INTRODUCTION

The automatic modulation recognition has become more and more important as the number and complexity of digital modulation formats increased. For the poor versatility and high complexity of the conventional approaches, there is an emerging need for the quick discrimination of the signal type which is capable of intelligent modems. In general, the automatic modulation classification systems are designed based on one of these two approaches [1]: the decision theoretic (DT) approaches or the pattern recognition (PR) approaches. The DT methods use probabilistic hypothesis testing arguments to formulate the recognition problems. Because of the complex computations and lack of robustness against the model mismatches, the DT approaches are not efficient for the recognition of the different types of digital signals. The PR approaches are easy to implement. And the researchers should take their focus on the key feature extraction and the selection of classification criteria. In the feature extraction part, the high-order cumulants have been took extensive attention for its better anti-noise and anti-interference. The digital modulation recognition algorithm based on high-order statistics (HOS) proposed by Swami A was the most representative and influential [2], which employed the fourth-order cumulant of the ideal synchronized and power normalized signals as the classification feature to classify the BPSK, QPSK, 4PAM and 16QAM signals. It also discussed the influence of signal-to-noise ratio (SNR) and sample number on the recognition performance.

Chen et al. completed BPSK, 4PSK and 8PSK recognition based on fourth-order cumulant and estimated the unknown parameters of the signal [3]; Wang *et al.* realized the classification of digital modulation signals 2ASK, 4ASK, 8ASK, 4PSK and 8PSK based on the fourth-order, sixth-order cumulant and support vector machine methods [4]. Sun *et al.* compared the recognition performance of the fourth-order and sixth-order cumulants to the MPSK signal, and proved that the anti-interference performance of the sixth-order cumulant was better than that of forth-order [5]. As the respective order cumulants are completely equal, the recognition of

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the MFSK signals became hardly. So employing the cyclic spectrum was introduced to construct the feature parameters by Fehske *et al.* they also employed the neural network classifier to realize the recognition of the modulated signal [27]. However, for the BPSK, QPSK and 16QAM, the identification was difficult as the cyclic spectrum of that were similar. Furthermore, there are still other research outcomes on the modulation recognition [6]–[15]. With the development of the machine learning (ML) [16], it is widely applied to the wireless communication [17]–[26], such as channel automatic detection and estimation, Nonorthogonal Multiple Access (NOMA), massive multi-input multi-output (MIMO), Physical layer and so on. Under this background, some papers applied the ML into modulation recognition [27]–[31]. Take the paper [27] for example, it uses the cyclic spectrum to construct the feature parameters and uses the neural network classifier to realize the recognition of the modulated signal. However, the cyclic spectrum characteristics of BPSK, QPSK, and 16QAM are similar, and identification is difficult. These modulation recognition methods based on ML generally use more than two steps to realize the modulation recognition, whose complexity is too high. This paper proposed a new approach, which only needs one step to realize the modulation recognition.

Based on the sixth-order cumulant of the extracted signal, a new feature parameter is constructed to use as the feature input of the neural network. The simulation results show the good recognition performance and robustness under low SNR condition that the effects of frequency offset and multipath are considered.

II. DEEP LEARNING FOR MODULATION RECOGNITION

A. HIGH ORDER STATISTICS

1) DEFINITIONS

For a zero-mean complex stationary random process $X(t)$, the second-order moment can be defined in two different ways depending on placement of conjugation

$$C_{20} = Cum(X, X) = M_{20} \tag{1}$$

$$C_{21} = Cum(X, X^*) = M_{21} \tag{2}$$

Similarly, the forth-order cumulants can be written in three ways. Thus, forth-order can be defined as

$$C_{40} = Cum(X, X, X, X) = M_{40} - 3M_{20}^2 \tag{3}$$

$$C_{41} = Cum(X, X, X, X^*) = M_{41} - 3M_{20}M_{21} \tag{4}$$

$$C_{42} = Cum(X, X, X^*, X^*) = M_{42} - |M_{20}|^2 - 2M_{21}^2 \tag{5}$$

And the sixth-order defined as

$$C_{60} = M_{60} - 15M_{40}M_{20} + 30M_{20}^3 \tag{6}$$

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

where M_{pq} is the pth order mixing moment of the zero-mean complex stationary random process $X(t)$, expressed as $M_{pq} = E\{X(t)^{p-q}X^*(t)_q\}$ and $p > q$.

2) THEORETICAL VALUES

Here, we consider the theoretical values of each order cumulant for various signal (2ASK, 4ASK, 2PSK, 4PSK, 2FSK and 4FSK), and assume that the symbols are equiprobable. When the carrier frequency information is known at the receiving end and the timing synchronization is reached, the signal to be identified is down-converted, and the expression of the k-th sampled complex signal sequence is obtained as follows,

$$s_k = x_k + n_k = \sqrt{P}e^{j\theta_c}a_k + n_k \quad k = 1, 2, \ldots, N \tag{8}$$

where P represents average power; θ_c represents carrier phase deviation caused by wireless channel; x_k represents the transmitted symbol sequence; and n_k represents zero-mean and σ^2 variance additive complex Gaussian white noise sequence (AWGN).

According to (1) to (8), these theoretical cumulants for various modulation signals can be derived, which are listed in the Tab.1, where the $\Delta = 2\sigma^4 + 4P\sigma^2$, $\Lambda = P^2 + 3\sigma^2 P$, $P' = P^2 + \sigma^2$ and $\Gamma = 2P^2 + 3\sigma^2 P$.

While estimating the C_{21}, the noise power σ^2 can be estimated at the same time, and then the noise power can be delimited. Therefore, the Tab.1 can be rewritten as Tab.2.

TABLE 1. Theoretical cumulants using traditional method.

Modulation format	C_{20}	C_{21}	C_{40}	C_{41}	C_{42}	C_{60}
2ASK	$Pe^{j2\theta_c}$	P'	$-P^2e^{j4\theta_c}$	$-\Lambda e^{j4\theta_c}$	$-P^2-\Delta$	$4P^3e^{j4\theta_c}$
4ASK	$Pe^{j2\theta_c}$	P'	$-P^2e^{j4\theta_c}$	$-\Lambda e^{j4\theta_c}$	$-P^2-\Delta$	$4.63P^3e^{j4\theta_c}$
2PSK	$Pe^{j2\theta_c}$	P'	$-2P^2e^{j4\theta_c}$	$-\Gamma e^{j4\theta_c}$	$-2P^2-\Delta$	$16P^3e^{j4\theta_c}$
4PSK	0	P'	$-P^2e^{j4\theta_c}$	0	$-P^2-\Delta$	0
2FSK	0	P'	0	0	$-P^2-\Delta$	0
4FSK	0	P'	0	0	$-P^2-\Delta$	0

TABLE 2. Theoretical cumulants using modified method.

Modulation format	C_{20}	C_{21}	C_{40}	C_{41}	C_{42}	C_{60}
2ASK	$Pe^{j2\theta_c}$	P	$-P^2e^{j4\theta_c}$	$-P^2e^{j4\theta_c}$	$-P^2$	$4P^3e^{j4\theta_c}$
4ASK	$Pe^{j2\theta_c}$	P	$-P^2e^{j4\theta_c}$	$-P^2e^{j4\theta_c}$	$-P^2$	$4.63P^3e^{j4\theta_c}$
2PSK	$Pe^{j2\theta_c}$	P	$-2P^2e^{j4\theta_c}$	$-2P^2e^{j4\theta_c}$	$-2P^2$	$16P^3e^{j4\theta_c}$
4PSK	0	P	$-P^2e^{j4\theta_c}$	0	$-P^2$	0
2FSK	0	P	0	0	$-P^2$	0
4FSK	0	P	0	0	$-P^2$	0

3) KEY FEATURES EXTRACTION

When extracting the feature parameters to recognize the digital signal, two mainly rules to be considered as following, I). phase jittering effecting on the cumulant value, which can be diminished by using the absolute value of the cumulant value; II) signal amplitude effecting on the cumulant value, which can be removed by using the ratio value.

If these features' value mentioned are applied in Tab.2, these six modulation formats can't be classified. The reason is that the 2ASK and 4ASK have the similar feature value, and the 2FSK and 4FSK have the same feature value. To classify these modulation formats, these features need some modifications. Firstly, modulation signals is processed as following,

$$\widehat{s}_k = s_k - E[s_k] \tag{9}$$

By using the modified modulation signal of (9) to update the theoretical cumulants for MASK modulation signals, which are shown in the Tab.3. From the features' value, the 2ASK and 4ASK can be classified by C_{60} easily.

In order to recognize the 2FSK and 4FSK, modulation signals s_k is modified as following,

$$\widehat{s}_k = s_k e^{-j\cdot\Delta w\cdot l/(2f_s)} \tag{10}$$

By using the modified modulation signal of (10) to update the theoretical cumulants for MFSK modulation signals, which are shown in the Tab.4. From the features' value, the 2FSK and 4FSK can be classified by C_{40} easily.

TABLE 3. Theoretical cumulants for MASK.

Modulation format	C_{20}	C_{40}	C_{60}
2ASK	$0.5Pe^{j2\theta_c}$	$-0.5P^2e^{j4\theta_c}$	$2P^3e^{j6\theta_c}$
4ASK	$0.357Pe^{j2\theta_c}$	$-0.1735P^2e^{j4\theta_c}$	$0.379P^3e^{j6\theta_c}$

TABLE 4. Theoretical cumulants for MFSK.

Modulation format	C_{20}	C_{40}	C_{41}
2FSK	$0.5Pe^{j2\theta_c}$	$-0.25P^2e^{j4\theta_c}$	$-P^2e^{j2\theta_c}$
4FSK	$0.25Pe^{j2\theta_c}$	$-0.0625P^2e^{j4\theta_c}$	$-0.5P^2e^{j2\theta_c}$

From the knowledge of the Tab.2–4, it can obtain the flow diagram of modulation format classification as shown in Fig.1, and the least number of features is five, such as $|C_{42}|$ (from Tab.2), $|C_{40}/C_{42}|$ (from Tab.2), $|C_{41}/C_{42}|$ (from Tab.2), $|C_{40}/C_{42}|$ (from Tab.4) and $|C_{60}|$ (from Tab.3). If the five features are applied in modulation classification, these modulation types can be classified clearly, as shown in Fig.2 at high SNR scenario (eg. SNR = 15dB). However, at the low SNR scenario, the discrimination is not very clear. Take SNR = −2dB for an example, as shown in Fig.3, especially, the 4FSK and 2FSK can't be classified. In order to solve lower detection precision at the low SNR scenario by using traditional approach, the next section the DL approach is proposed for modulation classification.

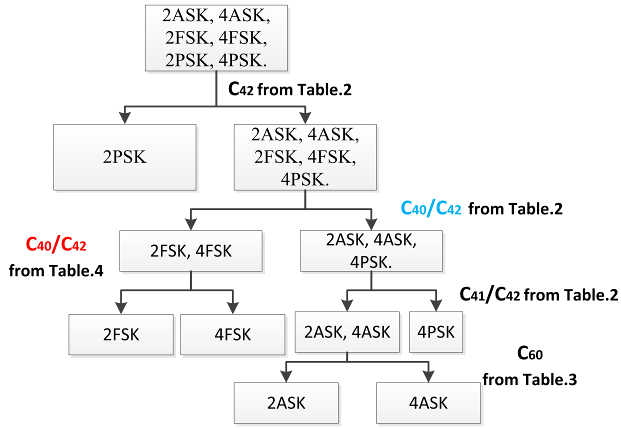

FIGURE 1. The flow diagram of modulation format classification.

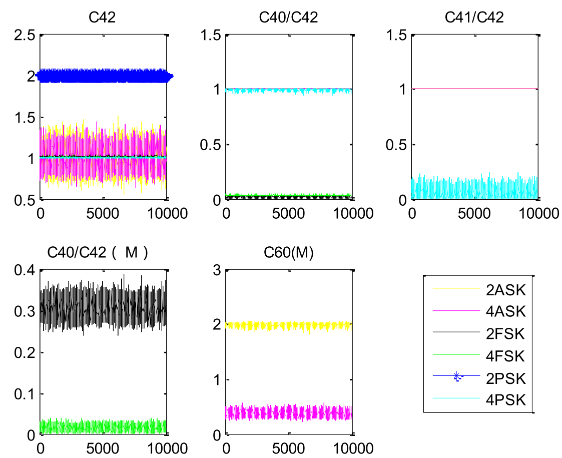

FIGURE 2. The feature for modulation classification (SNR = 15dB).

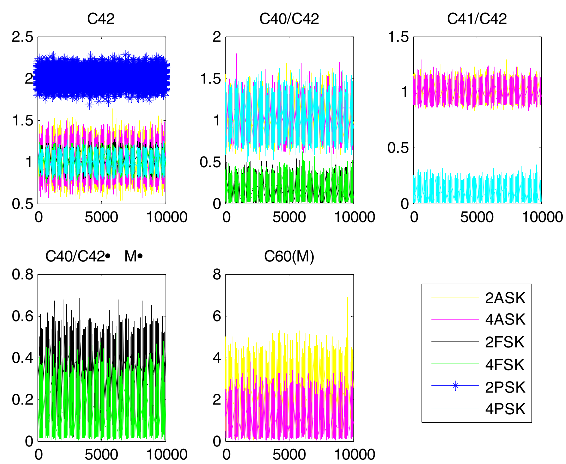

FIGURE 3. The feature for modulation classification (@SNR = −2dB).

B. BASIC IDEAL OF DEEP LEARNING

Deep Learning (DL) have achieved success in the fields of image recognition, speech recognition, natural language processing and so on. A comprehensive introduction to deep learning and machine learning can be found in [16].

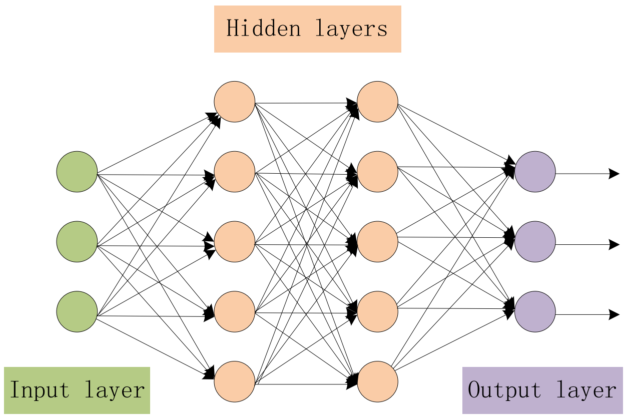

FIGURE 4. The structure of Deep Neural Network (DNN) model.

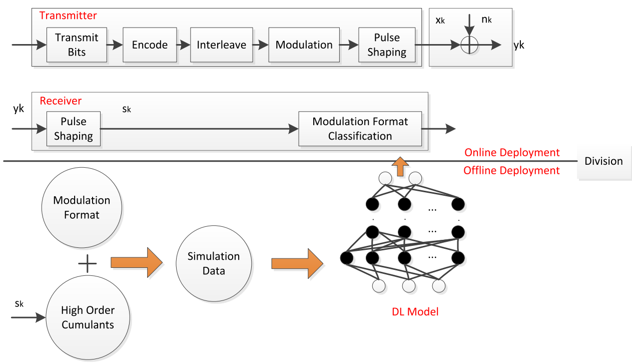

FIGURE 5. The architecture of the modulation classification with DL.

The structure of Deep Neural Network (DNN) model is shown in Fig 4. Generally speaking, the DNN is deeper versions of a single perceptron by adding the number of hidden layers and neurons between the input and output layers in order to improve the ability of representation or recognition. Each layer of the network consists of multiple neurons, the weighted sum of neurons of its preceding layer is fed into an activation function $f(\cdot)$, usually a Sigmoid function or a Rule function, to obtain an output y. Hence, the output of the network Z is a cascade of nonlinear transformation of input data X, mathematically expressed as

$$Z = f(X, W) = f^{L-1}(f^{L-2}(\cdots f^{1}(X))) \tag{11}$$

The data set of the neural network can be expressed as $\{(x_i, y_i)\}_{i=1}^{N}$, where N is the number of samples; x_i is the input variable of the ith sample; and $y_i \in \{1, 2, \ldots, C\}$ is the label or output variable of the corresponding sample and C is the number of the total type. We adopt one-hot label for the output value, and the corresponding output vectors of each modulation mode are 2ASK (100000), 4ASK (010000), 2FSK (001000), 4FSK (000100), 2PSK (000010) and 4PSK (000001).

C. SYSTEM ARCHITECTURE

The architecture of the modulation classification with DL is illustrated in Fig.5. We consider AWGN channel, then the received signal can be expressed as equation (8). Our architecture is divided into two parts: online deployment and offline deployment. The main work of the offline part is training and obtains the optimal neural network configuration, which is used in the online part to classify the real received data. With the different modulation format, the training data can be obtained by simulation. Secondly, the high order cumulant can be extracted from the training data. The input of DL model is the high order cumulant and the true modulation format.

III. SIMULATION RESULTS

This paper has conducted several experiments to demonstrate the performance of the DL methods for modulation classification. A DNN model is trained based on simulation data by using offline deployment, and is compared with the traditional methods and other AI methods in term of recognition accuracy. In the following experiments, the proposed feature based on DL is proved to be more robust than the traditional methods and other AI methods. In the following simulation, the DNN model is configured four layers: one input layer, two hidden layers and one output layer. the related parameters are configured as following: (1) the numbers of neurons in each layer are 5,13,6,6, respectively; (2) the activation function used by the two hidden layers is Rule function, and the activation function used by the output layer is Softmax function; (3) The cross entropy function is used as the loss function of the model in classification task. The loss error of the model is shown in the Fig.6.

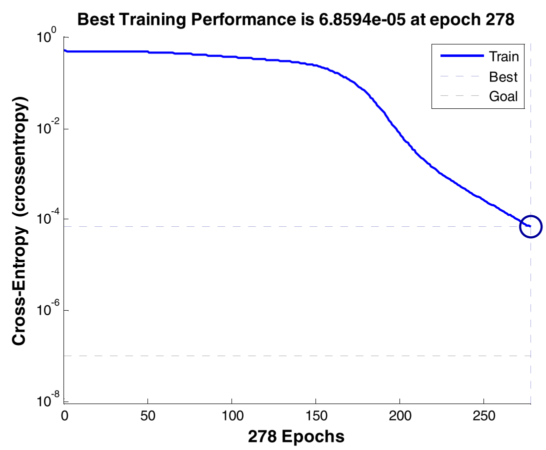

FIGURE 6. The training performance of the NN.

In our simulation, six modulation types-2ASK, 4ASK, 2FSK, 4FSK, 2PSK and 4PSK are considered. The results are presented in Tab.5-7. The results in Tab.5 represent the performance evaluation for recognition accuracy by using traditional method-the decision-theoretic approach, and the results in Tab.6-7 represent the performance by using DNN with traditional features and modified features, respectively. It is clear that all modulation types have been correctly classified with 100% success rate with the proposed feature and DNN (Tab.7, the confusion matrix of the other

TABLE 5. Recognition accuracy by using traditional method.

	recognition accuracy (%) SNR = -2dB (Total Accuracy: 72.91%)					
	2ASK	4ASK	2FSK	4FSK	2PSK	4PSK
2ASK	58.99	41.00	0	0	0.01	0
4ASK	51.74	48.26	0	0	0	0
2FSK	0	0	92.22	7.78	0	0
4FSK	0	0	60.74	39.26	0	0.02
2PSK	0	0	0	0	100	0
4PSK	0	1.0	0	0	0.25	98.75

TABLE 6. Recoginition accuracy with features in Table. I.

	recognition accuracy (%) SNR = -2dB (Total Accuracy: 87.58%)					
	2ASK	4ASK	2FSK	4FSK	2PSK	4PSK
2ASK	61.65	38.35	0	0	0	0
4ASK	44.4	55.6	0	0	0	0
2FSK	0	0	97.72	2.28	0	0
4FSK	0	0	1.82	98.16	0	0.02
2PSK	0	0	0	0	100	0
4PSK	0	0	0	0.07	0	99.93

TABLE 7. Recoginition accuracy with features in TABLE.III-IV (proposed).

	recognition accuracy (%) SNR = -2dB (Total Accuracy: 100%)					
	2ASK	4ASK	2FSK	4FSK	2PSK	4PSK
2ASK	100	0	0	0	0	0
4ASK	0	100	0	0	0	0
2FSK	0	0	100	0	0	0
4FSK	0	0	0	100	0	0
2PSK	0	0	0	0	100	0
4PSK	0	0	0	0	0	100

SNR is added in the APPENDIX). The results obtained from the DNN approach are better than those obtained by the decision-theoretic approach. Therefore, direct comparisons of these three approaches can be made. In the decision-theoretic approach, the overall success rate is about 72.91% at the SNR of -2dB, and the overall success rate is about 87.58% for the DNN approach with general features at the SNR of -2dB, while the overall success rate is 100% for the DNN approach with proposed features at the SNR of -2dB.

A. PERFORMANCE COMPARISON

As mentioned in [6], direct comparison with other works is difficult in signal type classification. This is mainly because there is no single unified data set available. Tab. 8 shows the comparison among the important previous papers and the hybrid proposed system. Since the QAM modulation type can be acted as hybrid modulation type with PSK and ASK, this paper did not consider the QAM modulation set. In comparison with other works, the proposed recognizer has many advantages. This system includes a variety of digital signal types. It discloses great generalization ability for classifying the considered digital signal types. The proposed classifier has a success rate of 100% at the SNR $= -2$ dB. The performance of the classifier is higher than 99% for SNR > -5dB. In addition, this performance has been achieved with few samples. Results imply that our chosen features manifest efficient properties in signal representation.

TABLE 8. Comparative study of different works.

Ref	Consider modulation signal	SNR (dB)	Recognition accuracy (%)
[15]	ASK4, ASK8, PSK2, PSK4, PSK8, QAM8, QAM16, QAM32, QAM64	0	98
[30]	ASK2, ASK4, PSK2, PSK4, FSK2, FSK4, QAM16	8	93
Proposed	ASK2, ASK4, FSK2, FSK4, PSK2, PSK4	-2	100
		-5	99.5

TABLE 9. Recognition accuracy (10 PPM FO) with features in TABLE.I.

	recognition accuracy (%) SNR = -2dB (Total Accuracy: 87.5271%)					
	2ASK	4ASK	2FSK	4FSK	2PSK	4PSK
2ASK	62.38	37.62	0	0	0.01	0
4ASK	43.91	56.09	0	0	0	0
2FSK	0	0	97.43	2.57	0	0
4FSK	0	0	2.97	96.94	0	0.09
2PSK	0	0	0	0	100	0
4PSK	0	0	0	0.14	0	99.86

B. FREQUENCY OFFSET EFFECT

Here, we see how performance is degraded by frequency offset, whose value is configured as 10 ppm. The results are presented in Tab. 9-10. Compared with no frequency offset results shown in Tab.6-7, it is shown that the 10 ppm frequency offset effects a little performance loss for some certain modulation type classification. Therefore, our proposed approach is robust for frequency offset.

C. MULTIPATH EFFECT

If the symbol sequence is passed through a finite-impulse response with Rayleigh fading channel, the related features will be changed. And the results are presented in Tab. 11-12 with multi-path channel, which shows that the multi-path doesn't degrade the performance of the modulation type classification.

TABLE 10. Recognition accuracy (10 PPM FO) with features in TABLE.III-IV.

	recognition accuracy (%) SNR = -2dB (Total Accuracy: 100%)					
	2ASK	4ASK	2FSK	4FSK	2PSK	4PSK
2ASK	100	0	0	0	0	0
4ASK	0	100	0	0	0	0
2FSK	0	0	100	0	0	0
4FSK	0	0	0	100	0	0
2PSK	0	0	0	0	100	0
4PSK	0	0	0	0	0	100

TABLE 11. Recognition accuracy with features in Table. I.

	recognition accuracy (%) SNR = -2dB (Total Accuracy: 90.66%)					
	2ASK	4ASK	2FSK	4FSK	2PSK	4PSK
2ASK	66.3	33.7	0	0	0	0
4ASK	31.14	68.86	0	0	0	0
2FSK	0	0	99.75	0.02	0	0.23
4FSK	0	0	0.04	98.16	0	0
2PSK	0	0	0	0	100	0
4PSK	0	0	0.22	0.07	0	99.78

TABLE 12. Recognition accuracy with features in TABLE.III-IV.

	recognition accuracy (%) SNR = -2dB (Total Accuracy: 100%)					
	2ASK	4ASK	2FSK	4FSK	2PSK	4PSK
2ASK	100	0	0	0	0	0
4ASK	0	100	0	0	0	0
2FSK	0	0	100	0	0	0
4FSK	0	0	0	100	0	0
2PSK	0	0	0	0	100	0
4PSK	0	0	0	0	0	100

IV. CONCLUSION

Higher order cumulants are less affected by noise and have better anti-interference, but is unable to fully identify the digital modulation formats. We use different cumulant combinations to establish new identification parameters to achieve digital modulation signal recognition that considered 2FSK, 4FSK, 2PSK, 4PSK, 2ASK, 4ASK. In order to improve the recognition rate better, this paper also combines the DNN algorithm. Distinct feature of each signal type was extracted using high order cumulant, and the DNN was designed to classify signal based on these features. Extensive simulations demonstrated exceptional classification performance for new key feature based on high order cumulants. The overall success rate in the DNN algorithm is over 99% at the SNR of -5dB and 100% at the SNR of -2dB.

APPENDIX

The confusion matrixes of the other SNR are listed as following,

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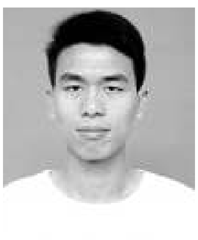
WENWU XIE was born in Jingzhou, Hubei, China, in 1979. He received the B.S., M.S., and Ph.D. degrees in communication engineering from Huazhong Normal University, in 2004, 2007, and 2017, respectively. From 2007 to 2009, he was a Communication Algorithm Engineer with Spreadtrum Communication Co. Ltd. Since 2012, he has been an Algorithm Manager with Mediatek Co. Ltd. Since 2017, he has been a Lecturer with HNIST. He holds two patents. His research interests include communication algorithm, such as channel estimation, equalizer, and encoding/decoding.



SHENG HU was born in Yongzhou, Hunan, China, in 1994. He received the B.S. degree in communication engineering from HNIST, in 2017, where he is currently pursuing the master's degree. His major research interests include NOMA and signal processing.

CHAO YU was born in Yueyang, Hunan, China, in 1986. He received the B.S. degrees in communication engineering from Guilin Electronic Technology University, in 2009 and 2012, respectively. He is currently pursuing the Ph.D. degree with Hoseo University, South Korea. Since 2012, he has been a Teacher with HNIST. His research interests include MIMO-NOMA physical layer security cooperative communications mmWave communications and so on.

PENG ZHU was born in Yueyang, Hunan, China, in 1990. He received the Ph.D. degree in space physics from Wuhan University. His major research interests include signal processing and communication techniques.

XIN PENG received the B.S. degree in communication engineering and the M.S. and Ph.D. degrees in computer science from Hunan University, Changsha, China, in 2003, 2008, and 2011, respectively. He was a Visiting Researcher with Auburn University, USA, in 2014. His main research interests include the Internet of Things, CPS, and cloud computing. His research work is sponsored by the National Natural Science Foundation of China, the Natural Science Foundation of Hunan Province, the 13th Five-Year Plan of Education Science Program of Hunan Province, and the Key Research Foundation of Education Bureau of Hunan Province.

JINGCHENG OUYANG was born in 1967. He received the Ph.D. degree from the College of Computer Science and Electronic Engineering, Hunan University, China, where he is currently an Associate Professor. His current research interests include peer-to-peer networks, information retrieval, and safety research.

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