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Deep Learning-Based Automatic Modulation Recognition Method in the Presence of Phase Offset

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ABSTRACT Automatic modulation recognition (AMR) plays an important role in various communications systems. It has the ability of adaptive modulation and can adapt to various complex environments. Automatic modulation recognition is also widely used in orthogonal frequency division multiplexing (OFDM) systems. However, because the recognition accuracy of traditional methods to extract the features of OFDM signals is very limited. In order to solve these problems, many deep learning based AMR methods have been proposed to improve the recognition performance. However, most of these AMR methods neglect the harmful effect by carrier phase offset (PO) which often appears in realistic communications systems. Hence it is required to consider the PO effect for designing the OFDM system. Unlike conventional methods, we propose a convolutional neural network (CNN) based AMR method for considering PO in the OFDM system. The proposed method is used to eliminate the PO to achieve the high classification accuracy. Experiment results are provided to confirm the proposed method when comparing to conventional methods.

INDEX TERMS Deep learning, convolutional neural network, automatic modulation recognition, phase offset.

I. INTRODUCTION

Blind signal recognition is considered as one of important techniques in many military and civilian applications [1]–[8], such as adaptive modulator, spectrum sensing and non-cooperative signal detection. Automatic modulation recognition (AMR) is a key step to realize the recognition technique and hence many AMR methods have been proposed in last decades. Generally speaking, these traditional AMR methods can be developed based on two types, i.e., likelihood function and feature extraction [9]. For one thing, the likelihood-based AMR method is formulated as a hypothesis testing problem [10] and hence it is necessary

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to design a correct likelihood function to find a likelihood for each modulation type within hypothesis pool. However, the likelihood-based AMR methods require accurate channel estimation of wireless channels. For another, the feature extraction based AMR methods are formulated as a pattern recognition problem and it can be realized by pre-processing, feature extraction, and classifier design. However, these feature extraction-based AMR methods are considered as instantaneous realization scenarios, such as instantaneous features, wavelet transform-based features, high-order statistics-based features, cyclic spectrum analysis-based features, and so on. To classify the modulation types by extracted features [11], [12], they usually adopt various classifiers, such as high-order cumulants (HOC), support vector machine (SVM), decision tree (DT), k -nearest neighbor (KNN) and

multilayer perception (MLP). According to aforementioned discussion, one may find that here traditional AMR methods require instantaneous information and real-time computational computing. Hence it is hard to apply these AMR methods in the next-generation heterogeneous communication systems [13]–[19].

Recently, deep learning (DL) has been attracted a lot of attentions due to its powerful ability to combine the offline training and online deployment [20]. In the perspective of data analysis, DL is expert in automatic feature extraction from big data, instead of the complex and difficult design of manmade features [21], [22]. Motivated by the advances, DL has been successfully applied in network traffic prediction [23]–[25], wireless communications [26]–[31], and internet of things [25], [32]–[36].

Motivated by widespread applications, many DL-based AMR methods have been proposed to recognize different modulation signals in different systems. Among these DL methods, convolutional neural network (CNN) has been considered one of most effective methods due to excellence performance for extracting signal feature information in signal. CNN-based AMR methods have been proposed for various wireless communications systems due to their reliable performance [41]–[43]. For example, Gu *et al.* [37] proposed a blind channel identification aided generalized AMR method based on two independent convolutional neural networks (CNNs). Hong *et al.* [38] proposed a decision theory based AMR method for orthogonal frequency division multiplexing (OFDM) system. Note that OFDM technique can combat channel multipath fading by multi-carrier transmission and hence support high-speed parallel transmission by frequency division multiplexing [39]. In addition, because all of subcarriers are orthogonal, each sub-channel can overlap each other, which improves the frequency band utilization rate and is suitable for high-speed data transmission services. In the frequency domain, a given channel is divided into many orthogonal sub-channels. On each sub-channel, a sub-carrier is used for modulation, and each sub-carrier is transmitted in parallel, so as to effectively suppress inter-symbol interference (ISI) caused by time dispersion of wireless channels [40].

However, these methods do not consider PO problem which is strongly deteriorate to signal detection at the receiver. A simple example of constellation diagrams of binary phase shift keying (BPSK) signal in two PO cases is shown in Fig. 1. PO is a very harmful factor in many multi-carrier communication systems [45] and radar signal systems [46]–[52].

In view of the excellent performance of CNN in the famous ImageNet large scale visual recognition challenge (ILSVRC) [53], this paper introduces CNN into AMR to complete the classification task. Among the two methods of AMR, the method of decision theory requires obtaining prior information and using probability theory and hypothesis testing theory to identify modulation types. This method is complex in calculation but simple in classification. Statistical pattern recognition can reflect the difference between the

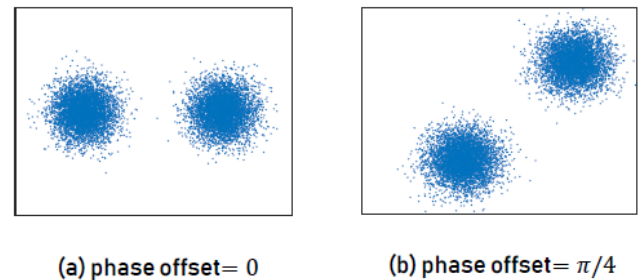


FIGURE 1. Example of constellation diagrams of BPSK signal in two phase offset cases.

two, by extracting the characteristics of different modulation methods, and no prior knowledge is required. In addition, an appropriate classifier should be designed for modulation recognition according to the extracted features. At present, the latter method is the most important and effective one. In this paper, we propose a CNN-based AMR method by considering the PO effect. At first, our proposed CNN is trained by in-phase and quadrature (IQ) components of the received signal containing received signals at different SNRs by considering PO effects. We conduct the experiments to validate the proposed CNN-based AMR method. Several typical results show that our proposed can achieve comparable performance of the ideal CNN-AMR method without PO.

The rest of this paper is organized as follows. Section II introduces problem formulations including system model, signal model, dataset training and CNN architecture. Section III presents our proposed CNN-based AMR method. Section IV conducts experiments and evaluates our proposed method in different modulations. Finally, Section V concludes our work.

II. PROBLEM FORMULATION

A. SYSTEM MODEL

In this paper, a typical AMR-aided OFDM system is considered. The system model is shown in Fig. 2. In the whole system model, OFDM transmitter serves as the sending terminal. Firstly, the data stream through the modulator is converted in series and parallel, and the frequency domain signal is converted into a time-domain signal by means of inverse fast Fourier transformation (IFFT) for modulation. In addition, a cyclic prefix (CP) is added to reduce the inter-symbol interference (ISI) between sub-channels. Finally, the parallel data stream is converted into serial data stream and the output is OFDM signal.

Then, the generated OFDM signal is sent to receiver, passing through channel and adding additive white Gaussian noise (AWGN). The signal needs to be pre-processed and signal-to-noise ratio (SNR) estimation is conducted. In this paper, a non-cooperative communication system is considered. That is to say, receiver cannot get any prior information about received signal, including modulation types. Hence, CNN-based AMR is introduced into the correct recognition of modulation types of received signals. After recognized signal modulation type, then it can be demodulated. Next,

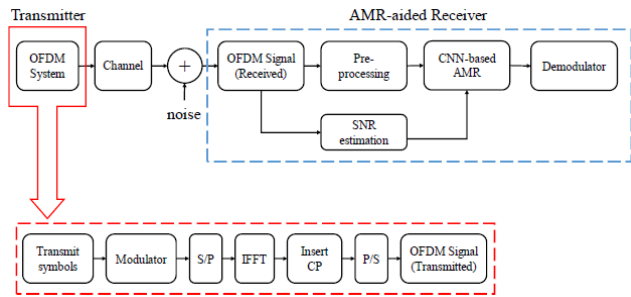


FIGURE 2. Framework of the proposed CNN-based AMR system.

we briefly introduce the signal model and corresponding dataset generation for neural network training.

B. SIGNAL MODEL AND DATASET GENERATION

Here, single input single output (SISO) system is considered and its received signal model is given as

$$r_n = \alpha e^{j\varphi_c} s_n + w_n, \quad (1)$$

where φ_c denotes the PO and its range is usually set as $\varphi_c \in [0, \pi]$. w_n stands for additive white Gaussian noise (AWGN), i.e., $w_n \sim CN(0, 1)$. $\{r_n\}_{n=0}^{N-1}$ refers to the discrete time complex signal sequence sampled by Nyquist criterion. s_n denotes one symbol in modulation signal, and $\{s_n\}_{n=0}^{N-1}$ has unit energy for fair comparison of different modulation types. α represents channel attenuation factor, and it is constant, when considering a time invariant system. Besides, non-ideal synchronization problem is considered in order to make simulation closer to actual communication. In this paper, PO is the main influence of non-ideal synchronization to be considered. PO mainly results of propagation delay and initial carrier phase and assuming that PO obeys uniform distribution, i.e., $\varphi_c \sim U(0, \theta)$, $0 \leq \theta \leq \pi$. It is noted that PO is constant at the same observation phase. IQ samples are applied to train the former CNN. Through OFDM modulation, the i -th sampling data we obtained can be represented by a complex vector as

$$s_i = [s_0, s_1, \dots, s_n, \dots, s_{N-1}], \quad (2)$$

where n represents the number of sample points. At the same time, s_n represents the value of the Nyquist sampling point, which is a complex number. s_n can be expressed as

$$s_i = \text{Re}_n + j\text{Im}_n, \quad (3)$$

where Re_n represents the real part of the n -th sampling point and Im_n represents its imaginary part of the signal s_n . They are the in-phase and orthogonal components of the signal respectively. It also represents the I's and Q's in the IQ sample. It is worth noting that \mathbf{R}_{IQ} is a real matrix with dimensionality $2 \times N$ and it is the input of neural network.

III. THE PROPOSED DL-BASED AMR METHOD

A. CNN FOR AMR METHOD

In this section, a DL-based AMR method is proposed for uncooperative OFDM systems. The core of this method is

CNN because of its excellent performance in feature extraction. It has been widely used in many fields, especially in the field of image processing.

A simple CNN model consists of an input layer, an output layer, a pooling layer, a fully connected layer, and an output layer. The convolutional layer is mainly used to extract the features of the input data and has been processed in the next step. The pooling layer can be used to improve accuracy by ignoring changes between the relative positions of the data. On the other hand, the pooling layer can reduce the feature dimension to avoid overfitting to a certain extent. The fully connected layer functions as a classifier in the entire CNN model. It uses the results of the previous layers to classify the input data to achieve the function of the CNN model. In this paper, modulation modes used by the received OFDM signal are classified through the fully connected layer, so as to effectively identify and facilitate subsequent demodulation work.

Every layer in CNN except the input layer needs a suitable activation function. More commonly used are rectified linear unit (ReLU) activation function and parametric rectified Linear Unit (PReLU) activation function. As the name suggests, PReLU is ReLU with parameters. ReLU and PReLU activation function formulas are as follows:

$$\text{ReLU}(x) = \begin{cases} x & x > 0 \\ 0 & x \leq 0, \end{cases} \quad (4)$$

$$\text{PReLU}(x) = \begin{cases} x & x > 0 \\ ax & x \leq 0 \end{cases}, \quad (5)$$

The sparse model implemented by PReLU can better mine related features and fit the training data. In addition, compared to other activation functions, PReLU has the following advantages: For linear functions, PReLU has a better effect, especially in deep neural networks. For non-linear functions, PReLU does not have a Vanishing Gradient Problem because the gradient of the non-negative interval is constant, so that the convergence speed of the model is maintained in a stable state.

Softmax regression model is a generalization of logistic regression model on multi-classification problems. It is applicable to multi-classification problems where the categories are mutually exclusive.

Suppose there is an array E , e^i represents the i -th element in E , then the softmax value of the e^i element is:

$$S_i = \frac{e^i}{\sum_j e^j}, \quad (6)$$

The Softmax activation function maps the output of multiple neurons into the (0, 1) interval. It can be seen as the probability that the current output belongs to each classification, thereby completing the multi-classification task.

B. THE PROPOSED DL-BASED AMR METHOD

As shown in Fig. 3, the proposed DL-based AMR method is mainly implemented by CNN, which includes two convolutional layers and three fully connected layers. There

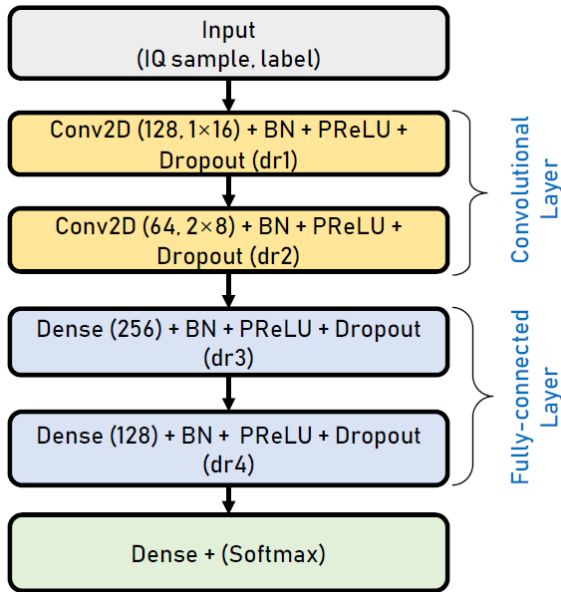


FIGURE 3. CNN structure design in the proposed CNN-based AMR method.

are 128 convolution kernels in the first convolution layer, and the size of each convolution kernel is 1×16 . The second convolution layer contains 64 convolution kernels, each of which is 2×8 in size. The number of neurons in the three fully connected layers is 256, 128, and n , where n represents the number of modulation modes. The PReLU function is used for all layers except the last layer, and the softmax function is used for the last layer to implement a multi-classification problem.

From Fig. 3, it can also be intuitively seen that each layer except the last layer has a batch normalization (BN) layer and a dropout layer. The BN layer has been widely used in major networks, which has the effect of accelerating the speed of network convergence and improving training stability. It essentially solves the gradient problem in the process of backpropagation. That is, the BN layer forcibly pulls the input distribution of the relevant data back to a relatively standard normal distribution with a mean of 0 and a variance of 1. The input value of the non-linear transformation function is made to fall into a region that is more sensitive to the input, thereby avoiding the problem of gradient disappearance.

When a complex feedforward neural network is trained on a small data set, it is easy to cause overfitting. To prevent overfitting, a certain neuron will stop working with a certain probability during forward propagation. The performance of neural networks can be improved by preventing the common response of feature detectors. This also makes the model more general, because the model does not rely too much on some local features.

C. ALGORITHM DESCRIPTION

The algorithm description of the proposed CNN-based AMR method is shown in Algorithm 1. Known test samples $\{x^j, y^j\}_{j=1}^{N_r}$, where x^j is the data of the j -th sample, and y^j is the

Algorithm 1 Algorithm of the Proposed CNN-Based AMR Method

Require: Test sample $\{x^j, y^j\}_{j=1}^{N_r}$ and the trained CNN;
 Ensure: The probability of correct classification;

- 1: for $j = 1 : N_r$:
 Give the $P^j = x^j \nabla W$;
 end
- 2: if $P^j = y^j$,
 $\hat{P} = \hat{P} + 1$;
 end
- 3: $P_{pcc} = \frac{1}{N_r} \hat{P}$;
- 4: return The probability of correct classification P_{pcc} .

label value of the j -th sample, that is, the modulation type. Traverse N_r samples and calculate the predicted label of the j -th sample as P^j . Where W is the weight of the neural network, and ∇ represents the calculation of the data from input to output. By comparing the values of the predicted label and the actual label, the number of samples with accurate prediction \hat{P} is calculated. Finally, the probability of correct classification of the proposed CNN-based AMR method P_{pcc} is obtained.

D. DATASET GENERATION AND DATA TRAINING

For the AMR problem, we generate two data sets with different modulation modes. Dataset 1 consists of three modulation modes, which are BPSK, quadrature phase shift keying (QPSK), and eight phase shift keying (8PSK). Dataset 2 contains BPSK, QPSK, 8PSK, and sixteen quadrature amplitude modulation (16QAM). In our experiments, the OFDM system with 16 sub-carriers, 6 symbols of each sub-carrier, CP of length 2 and 256-point FFT is considered. Taking BPSK modulation as an example, an initial signal is first generated. Then perform BPSK modulation, add subcarriers, and use inverse fast Fourier transform (IFFT) to convert the frequency domain signals into time domain signals. After that, the cyclic prefix and phase offset are added in turn. Finally, the received OFDM signal is obtained through Gaussian white noise.

A large number of OFDM signals obtained through different modulation methods are sent to our proposed CNN-based AMR model for training, and finally the weight values of each neuron in the model are obtained. Then use the test data to verify our proposed model. By comparing the recognition accuracy, we can intuitively find that our proposed method has a high accuracy, which will be introduced in detail in the next section.

IV. EXPERIMENT RESULTS AND DISCUSSIONS

In this section, we perform several sets of comparative experiments to verify the performance of DL-based AMR in non-cooperative OFDM systems. Traditional AMR methods are mostly composed of feature extraction and classifier. In this paper we consider the use of artificial features, which are mainly composed of the HOC feature and the

TABLE 1. Experiment parameters and setting.

Parameter	Value
Style of the training	Training IQ samples at each SNR = i dB, where $i \in \{-10, -5, \dots, 20\}$
The number of training	20,000 samples/type/SNR
The number of testing	20,000 samples/type/SNR
Batch size	500
Epochs	500
Optimize	Stochastic gradient descent (SGD)
Dropout (dr1-dr2-dr3-dr4)	0.6-0.6-0.6-0.6

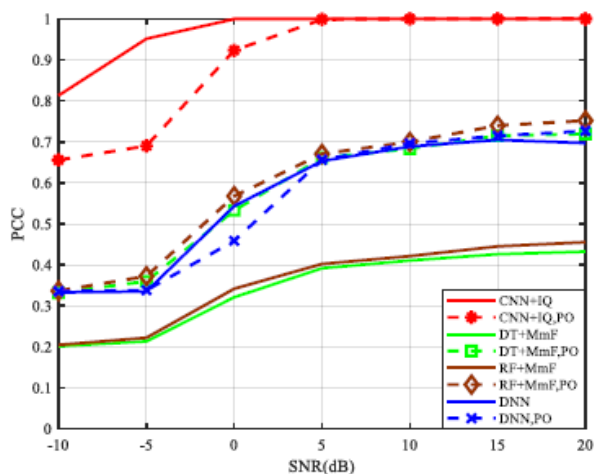


FIGURE 4. Performance evaluations of these AMR methods in dataset 1: {BPSK, QPSK, 8PSK}.

instantaneous feature of the signal. In the classifier section, we use decision tree (DT) and random forest (RF) in traditional classification algorithms. The other two neural network based methods are CNN and Deep Neural Network(DNN). In addition, we also consider the difference in performance between the proposed method and the traditional method when the signal has a phase offset. Simulation parameters and setting are listed in Table 1. The simulation requires powerful computing resources, so it is conducted on the platform with one Intel i7-8750H CPU and one NVIDIA GTX 1080Ti GPU. The implementation of neural networks relies on Keras 2.2.2 with Tensorflow 1.10 and Python 3.6.5 as the backend. Moreover, Matlab R2018a is applied to build our datasets.

In the simulation experiments, we prepare two datasets. Dataset 1: {BPSK, QPSK, 8PSK} and dataset 2: {BPSK, QPSK, 8PSK, 16QAM}. The robustness of the proposed method is analyzed by performance comparison on different data sets. All data samples range from -10 dB to 20 dB with the interval of 5 dB. The total dataset consists of $20,000$ samples at each signal-to-noise ratio, which are divided into training samples and test samples by $7:3$. 70% of the data is used for training the model, and 30% of the data is used for testing the model to evaluate the recognition accuracy of the proposed method. In addition, Stochastic gradient descent (SGD) is chosen to detect the loss value to prevent overfitting.

Fig. 4 shows the probability of correct classification (PCC) of the proposed DL aided AMR method in dataset1. It can be seen intuitively that the performance of our proposed method is better than the traditional method based on feature

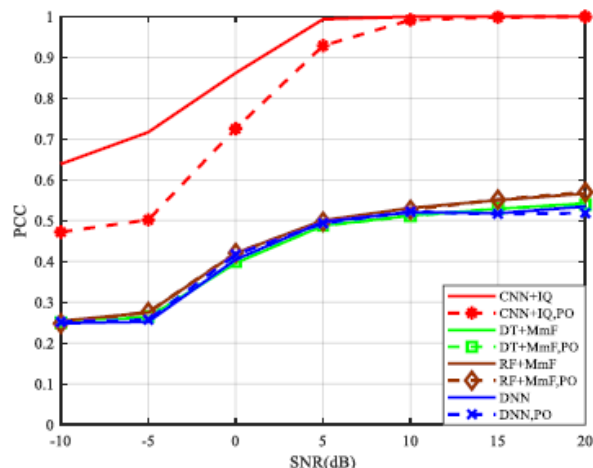


FIGURE 5. Performance evaluations of these AMR methods in dataset 2: {BPSK, QPSK, 8PSK, 16QAM}.

extraction with or without phase offset. In the case of no phase offset, when the SNR is 0 dB, the recognition accuracy is as high as 100% . Although the accuracy is slightly lower in the case of phase offset, almost no error recognition can be achieved when $SNR = 5$ dB. On the other hand, the PCC of the traditional method can only reach 70% under the high SNR. In Fig. 4, the curve trends of the traditional methods based on DT and RF are very similar, but the performance of the RF-based method is slightly better than that based on DT. This is because RF is composed of multiple DTs. When classifying and deciding, it will comprehensively consider the decisions of multiple DTs to give an overall decision. So the performance is better than DT to a certain extent. By comparing the CNN-based method and the DNN-based method, the superior performance of the proposed method can also be found intuitively. Because compared to DNN, CNN will first use the convolution layer to extract features of the signal. Then use the extracted features to recognize modulations. Taking into account the characteristics of the signal will help improving the accuracy of recognition.

In dataset 2, PCC of the proposed method is compared with the other three methods as shown in Fig. 5. Compared with curves in dataset 1, when the SNR is less than 5 dB, the recognition accuracy based on dataset 2 will be lower, and it is no exception when considering phase deviation. It can be seen that the introduction of $16QAM$ has caused some confusion to the original three modulation methods, so the recognition accuracy is lower. But when SNR gradually increases to 5 dB, the PCC of proposed method can also reach 100% . When SNR is 10 dB, it can be recognized without error considering the phase offset. Therefore, combining the PCC of the proposed method and other traditional methods, we can find that the proposed DL aided method has high recognition accuracy and good robustness under different datasets.

V. CONCLUSION

In this paper, we have proposed a DL aided automatic modulation recognition method in the presence of phase offset in OFDM systems. This method is mainly implemented

using CNN and training on IQ samples. It can accurately recognize four modulation modes: BPSK, QPSK, 8PSK, and 16QAM. Through comparative experiments, it is found that its recognition performance is far superior to the traditional feature extraction based methods. At the same time, the proposed method shows good robustness for different datasets. Although the introduction of phase offset will make the recognition accuracy slightly decrease at low SNRs, but with the gradual increase of SNRs, effective recognition can be achieved eventually. In future work, we plan to consider CNN aided AMR methods in multiple input multiple output systems (MIMO). More importantly, we try to further validate our proposed model using actual modulated signals instead of the ideal signals generated by Matlab.

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