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Blind Channel Identification Aided Generalized Automatic Modulation Recognition Based on Deep Learning

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ABSTRACT Automatic modulation recognition (AMR) plays an important role in cognitive radio (CR), which relies on AMR responding to changes in the surrounding environment and then adjust strategies simultaneously. Deep learning based reliable AMR method have been developed in recent years. However, all of their AMR training models are considered in a specialized channel rather than generalized channel. Hence, these AMR methods are hard to be applied in general scenarios. In this paper, we propose a blind channel identification (BCI) aided generalized AMR (GenAMR) method based on deep learning which is conducted by two independent convolutional neural networks (CNNs). The first CNN is trained on in-phase and quadrature (IQ) sampling signals, which is utilized to distinguish channel categories like BCI behaviors. The second CNN is trained by line of sight (LOS) model and non-line of sight (NLOS) model, respectively. Simulation results confirm that our proposed generalized AMR method is significantly better than conventional method.

INDEX TERMS Automatic modulation recognition (AMR), deep learning, convolutional neural network (CNN), in-phase and quadrature (IQ) samples, blind channel identification.

I. INTRODUCTION

Modulation identification techniques have many potential applications in the field of wireless communications, typically in cognitive radio systems [1], [2]. Generally speaking, the communication receiver desires to implement a universal receiver to accurately receive the signal. In the design of general-purpose receiver, recognition of the modulation signal is considered one of most important techniques. When modulation mode of the signal is recognized, the information of frequency and bandwidth can be accurately estimated, which help us demodulating and decoding. Furthermore, with the increased complexity of today's wireless communication environment, the electromagnetic signal space is more complex. While the amount of information transmitted becomes larger, the signal changes faster. Therefore, high-efficient automatic modulation recognition (AMR) method for different modulation signals (e.g., two frequency shift keying (2FSK), quadrature phase shift keying (QPSK), quadrature amplitude modulation (QAM)) is truly required to develop.

In the last decade, many interesting AMR methods have been proposed [3]–[6]. In general, those methods can be classified into two categories: maximum likelihood theory method [7] and statistical-based pattern recognition method. Hence, statistical-based pattern recognition method can distinguish the signals by extracting characteristic parameters from the received signals while does not depend on certain assumptions. This advantage makes a large number of researchers pay attention to this method. The statistical-based pattern recognition system, as shown in Fig. 1, can be divided into two subsystems: feature extraction and pattern classification. The function of the feature extraction system is to extract the defined feature parameters in the received

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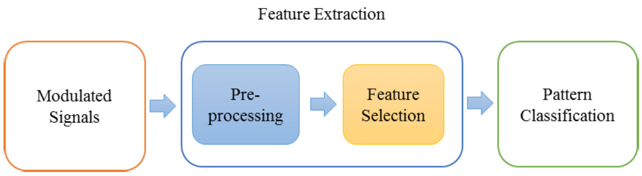

FIGURE 1. Framework of a statistical-based pattern recognition system.

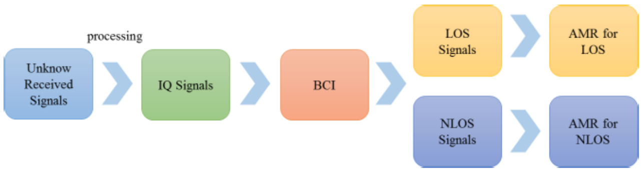

FIGURE 2. Architecture of our proposed BCI aided GenAMR.

signal and reduce the dimension of the mode representation such as instantaneous features [8], Fourier transform, wavelet transform [9], higher order cumulants (HOC) [10]. Pattern classification system can identify modulation of the signal using artificial neural architecture (ANN) [11], support vector machine (SVM) [12], and decision tree [13].

In recent years, deep learning has been widely applied in physical layer wireless communications [14]–[17]. Many methods are proposed that achieve better classification performance. There are some scholars proposing AMR based on CNN to identify multiple modulation signals. The authors proposed different AMR systems to classify QAM and PSK modulation signals for various channels [18]. Wang *et al.* proposes a network architecture containing two CNNs to achieve higher classification accuracy as well [19].

Both of the previous methods just identify the modulation signals with the same channel. However, a huge drawback exists. When we use the mixed signals under LOS and NLOS channels, these AMR systems seem to be incapable and is difficult to achieve the previous high accuracy. One deep learning-based algorithm containing two CNN networks proposed in this paper can solve such problem. The former CNN identifies the channel categories of signals, while the latter is responsible for classifying the signals under the same channel.

The reminder of the rest paper is organized as follows. Section II introduces the system model and CNN model, respectively. In Section III, we propose the BCI based generalized AMR based on deep learning. In Section IV, experiments are conducted to evaluate the proposed method. Finally, we conclude this paper in Section V.

II. SYSTEM MODEL AND DATASET

A. SYSTEM MODEL

In this work, the goal of AMR is to classify the modulation patterns of unknown signals, including 2FSK, DQPSK, 16QAM, 4PAM, MSK, GMSK. Our proposed AMR system consists of two CNNs, and the system model is shown in Fig. 2. After the unknown signal reaches, the former CNN classifies the signal containing the IQ samples to distinguish whether going through LOS or NLOS channel, which is called as BCI. In the latter CNN, we train the modulation recognition based LOS and NLOS channel, respectively. After distinguishing the channel category, the corresponding CNN-based AMR system can be selected to identify its modulation mode accurately.

B. DATASET

To test the algorithm presented in this paper, we created two separate datasets, one for training and one for testing. Each data set contains data for both channel categories. The random input signals in each channel category are first divided into in-phase and quadrature samples and the IQ sampling [20] points are 256, so the matrix of each signal is 2×256. In addition, one of the following modulation modes, i.e., 2FSK, DQPSK, 16QAM, 4PAM, MSK, GMSK, are considered, respectively, and the signal-to-noise ratios (SNRs) range from 0∼12 dB with the interval of 2 dB. The amount of samples for each modulation mode is 2000. Besides, training set and testing set are set to 1:1, each the set has 24,000 samples.

C. CNN MODEL

Actually, the CNN architecture [21] is a neural network containing multiple hidden layers, each of which has several two-dimensional planes consisting of several neurons. Besides, all of neurons are assumed independently. Its input data can be considered a two-dimensional image, and the feature extraction module is embedded in the CNN architecture. The basic architecture of CNN is shown in the Fig. 3.

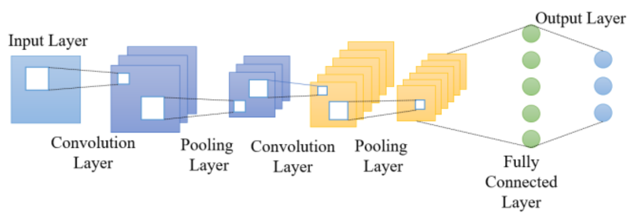

FIGURE 3. Basic architecture of CNN.

As is shown in the Fig. 3, the basic composition of CNN architecture can be divided into five parts: input layer, convolution layer, down-sampling layer, fully connected layer and the output layer. The detailed description of each part is explained as below.

Input Layer: The input raw data set can be directly input to the input layer. One image is actually inputted by its pixel value into the input layer.

Convolutional Layer: Also known as the up-sampling layer that is to extract features from the input data. Each convolutional layer has its own convolutional kernel and different convolutional kernels extract different features from the input data. The number of extracted features grows as the number of convolutional kernels included in the up-sampling layer increases.

Down-Sampling Layer: Also called as the pooling layer. Its main function is to finish the second extraction of the feature data followed by the convolution layer. Under normal conditions, the CNN architecture contains at least two convolutional layers and two down-sampling layers respectively. With the more layers of the architecture are set, extracting features from input data are more likely to help obvious classification.

Fully Connected Layer: All the feature maps are connected together as input. In general, the nodes of the neurons in the later layer are connected to the nodes of the neurons in the previous layer, but the nodes in each layer are disconnected. This layer integrates and normalizes the abstracted features of the previous convolutions in order to yield a probability for various conditions.

Output Layer: The number of neurons in this layer is set according to the required conditions. If the classification is required, the number of neurons is generally related to the number of categories to be classified.

TABLE 1. Layers of former CNN and activation functions and output dimensions of every layer.

Layer	Output dimensions
Input	2×256×1
Conc2D (filters 128, size 1×8) + BN + PReLU	2×249×128
Dropout (0.4)	/
Conc2D (filters 64, size 1×4) + BN + PReLU	2×249×64
Dropout (0.4)	/
Flatten	31488
Dense + BN + PReLU	256
Dropout (0.4)	/
Dense + BN + PReLU	128
Dropout (0.4)	/
Dense + BN + PReLU	64
Dropout (0.4)	/
Dense + SoftMax	channel modes

III. OUR PROPOSED BCI AIDED GenAMR ALGORITHM

A. FORMER CNN FOR BCI

We use the former CNN to implement one two-class problem of bind channel identification (BCI). The structure is shown in Table 1. It consists of two parts such as two convolutional layers and four fully connected layers. The first convolutional layer is composed of 128 filters, each of which is a 1×8 convolution kernel. In addition, the second convolutional layer containing 64 filters whose convolution kernel is 1×4. Totally, the last three layers of the network shown in the table are fully connected layers. Neurons in the first fully connected layer is connected to neurons in the second convolutional layer one by one. Based on the same strategy, one connection exists between each neuron in the second fully connected layer and each neuron of the first fully connected layer. Therefore, the fourth fully connected layer that is the output layer can get the output of the entire network.

After above network layers, we also add a batch normalization (BN) layer [22] and an activation function layer. The power of the BN is to choose a large learning rate, which achieve fast training speed as well as fast convergence. Since each layer of the network causes changes in the distribution of the data, hence pre-processing step is required at the input layers. The input data $x^{(k)}$ is normalized via

$$\hat{x}^{(k)} = \frac{x^{(k)} - E\left[x^{(k)}\right]}{\sqrt{Var\left[x^{(k)}\right]}} \tag{1}$$

and then send it to the next layer of the network. Hence, the normalization stage can affect the characteristics learned from the former network layer. The features learned by the network layer will be destroyed resulting in the normalization being forced directly. So we need to make some improvements to the above method, such as transforming, refactoring and introducing parameters that can be learned as

$$y^{(k)} = \gamma^{(k)}\hat{x}^{(k)} + \beta^{(k)} \tag{2}$$

Each neuron $x^{(k)}$ will have such a pair of parameters γ and β, they are defined as:

$$\gamma^{(k)} = \sqrt{Var\left[x^{(k)}\right]} \tag{3}$$

$$\beta^{(k)} = E\left[x^{(k)}\right] \tag{4}$$

In this way, we can recover the features learned from a certain layer of the original layer. Therefore, we can introduce the parameters that can be learned so that our network can recover the distribution of features in the original network. Finally, our activation function uses parametric rectified linear unit (PReLU), which is distributed after each convolutional layer and fully connected layer. In recent years, the ReLU [23] algorithm becomes more and more popular because it converges faster than other activation functions. What's more, it also has a low computational complexity and is suitable for backward propagation. As an upgraded version of it, PReLU has an excellent performance.

B. LATTER CNN FOR GenAMR

The latter CNN used to identify the six modulation modes under the specified channel conditions, thus we need to train the AMR models under LOS and NLOS channel conditions respectively. This work has been done in GenAMR system. As is shown in Table 2, This CNN contains two layers of convolutional layers and three layers of fully connected layers. The number of convolution kernels in the convolutional layer is 128 and 64 respectively, while the number of neurons in the fully connected layer is 256, 128 and 6 respectively. In addition, the activation function what we use is PReLU and the drop layer [19] is added to prevent overfitting problems. Finally, Softmax is utilized as an activation function of the output layer in order to predict the probability of each classification result.

TABLE 2. Layers of latter CNN and activation functions and output dimensions of every layer.

Layer	Output dimensions
Input	2×256×1
Conc2D (filters 128, size 1×8) + PReLU	2×249×128
Dropout (0.6)	/
Conc2D (filters 64, size 1×4) + PReLU	2×249×64
Dropout (0.6)	/
Flatten	31488
Dense + PReLU	256
Dropout (0.6)	/
Dense + PReLU	128
Dropout (0.6)	/
Dense + SoftMax	Modulation modes

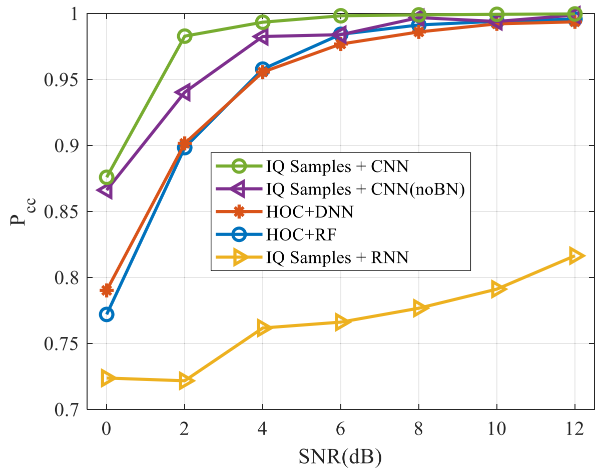

FIGURE 4. Test accuracy of different networks in various SNRs.

C. AMR AND BCI AIDED GenAMR

Our data set has two attributes, one of which is modulation mode divided into 2FSK, DQPSK, 16QAM, 4PAM, MSK, GMSK. The other is channel category including LOS and NLOS. Furthermore, we need to prepare two labels (y_{mod} and y_{cha}) for the data set. Firstly, we ignore the y_{cha} of the data set and randomly assign it to the LOS or NLOS channel label with equal probability, and pass it to the traditional AMR system. So we could simulate the situation that because of ignoring the channel category of the input signals, the training model of AMR can only be randomly selected. Then, we use the data set with the correct y_{mod} and y_{cha} as the input of the BCI-AMR system, which consists of the former CNN for blind channel identification (BCI) and the latter CNN for generalized automatic modulation recognition (GenAMR).

D. IMPLEMENTATION PLATFORM

All training and testing data sets are randomly generated by Matlab software. The entire system is trained and tested on the GPU, which contains four NVIDA GeForce GTX1080Ti. The deep learning algorithm framework we use is the Keras library with tensorflow as the backend.

IV. EXPERIMENT RESULTS

A. FORMER CNN PERFORMANCE COMPARISONS

In this paper, the first CNN we trained is used to identify the channel type of the unknown input signal sampled by IQ. We have adopted 5 deep learning or machine learning algorithms to compare the classification accuracy. They are CNN, CNN without BN layer, RNN, HOC feature extraction followed by Deep Neural Network (DNN) and HOC feature extraction followed by the Random Forest (RF) classification algorithm. The experimental results of blind channel identification are shown in the Fig. 4. As the SNR increases, the accuracy of each algorithm performs well obviously observed in the figure. The correct classification probability under high SNR condition can reach over 99% with CNN. It is a pleasure for us to observe that CNN is superior to other traditional algorithms under all SNR conditions. In addition, RNN (LSTM) did not achieve great performance, and classification is even not good. It is preliminarily determined that because of random characteristics of the channel and no

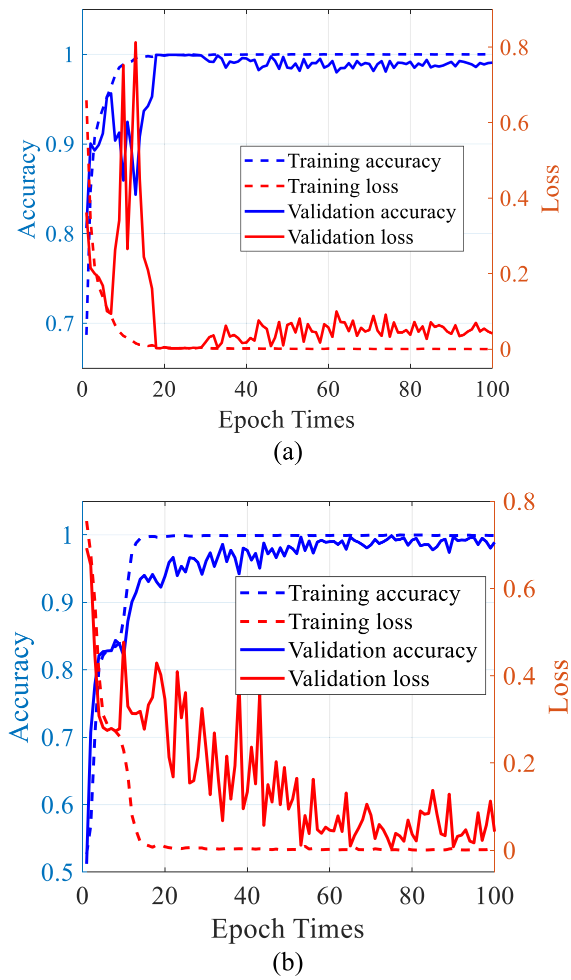

FIGURE 5. Training/validation curves of accuracy and loss. The x-axis denotes the training epoch. (a) CNN; (b) CNN without BN.

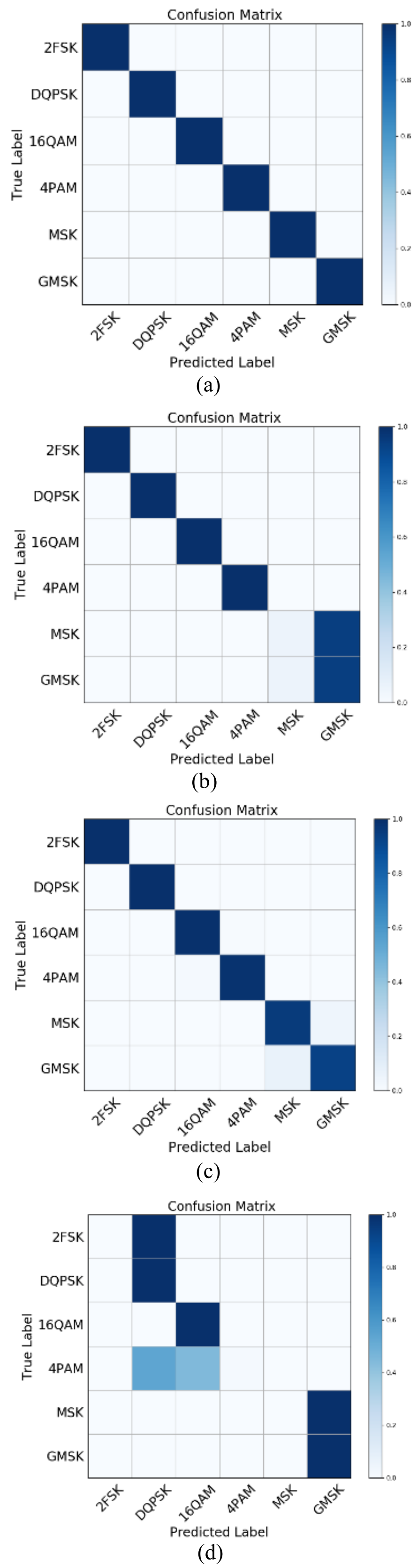

FIGURE 6. Confusion matrix of the modulated signals passing GenAMR system: (a) LOS signals pass LOS AMR; (b) LOS signals pass NLOS AMR; (c) NLOS signals pass NLOS AMR; (d) NLOS signals pass LOS AMR.

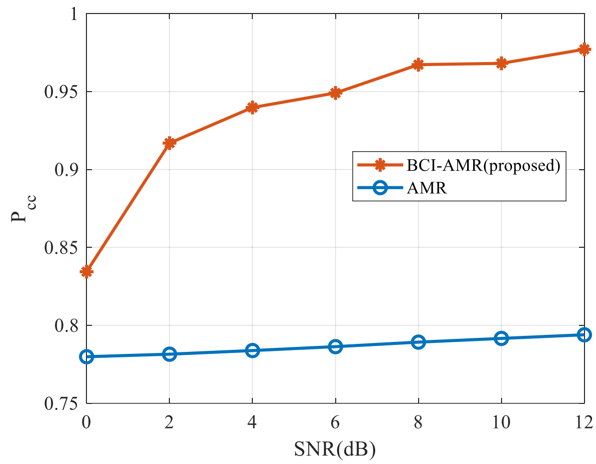

FIGURE 7. Test accuracy of different AMR systems in various SNRs.

temporal correlation, the continuous input of samples hard to improve the accuracy.

With previous comparison of accuracy, we can see that results of CNN and CNN without BN are quite similar because of great performance. The difference is whether the BN layer is added or not after each network layer. In total, the curves of training/validation loss/accuracy in a complete CNN with or without BN layers training process are plotted in Fig. 5. From the curves we obviously see that due to absence of the BN layers, the accuracy and loss fluctuate violently. Curves are hardly to obtain stable. However, after adding the BN layers, the accuracy and loss curves converge quickly and smoothly. Therefore, the training and validation curves are basically similar.

B. BCI AIDED GenAMR PERFORMANCE COMPARISONS

Firstly, we tested the accuracy of the modulated signals in GenAMR system. Fig. 6 illustrates that the confusion matrix of LOS signals and NLOS signals with different AMR systems when SNR is 12 dB. It is obvious that LOS signals passing the AMR system for NLOS and NLOS signals passing the AMR system for LOS have no ability to recognize modulations precisely, especially the latter one. Above all, classifying the modulated signals without understanding their channel modes is terrible.

Then, the correct classification probabilities under the conditions of 0-12 dB with AMR and BCI-AMR are plotted in Fig. 7. It can be seen that the correct classification probabilities of AMR system increase slowly with SNR range from 0 dB to 12 dB. Because of lacking channel identification for unknown signals, the accuracy is always less than 80%. Conversely, the BCI aided GenAMR proposed in this paper obtains ideal classification result, who reaches 95% or more with large SNRs (greater than 4 dB). While this system has a low Modulation recognition accuracy under low SNR conditions (0-2 dB), which is caused by poor channel classification. Generally, BCI-AMR system's Modulation recognition

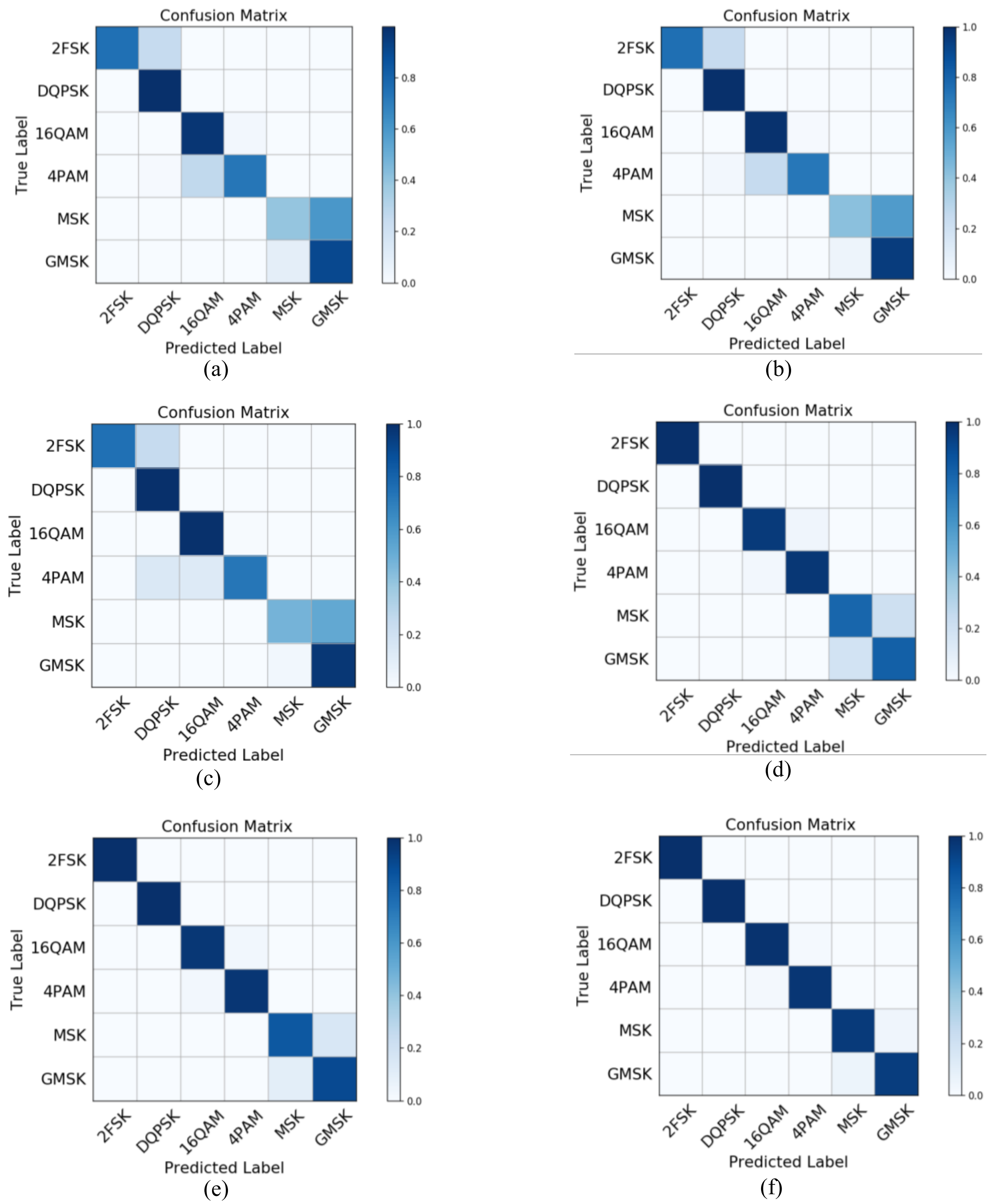

FIGURE 8. **Confusion matrix of different AMR systems. (a) SNR=0 dB in AMR; (b) SNR=6 dB in AMR; (c) SNR=12 dB in AMR; (d) SNR=0 dB in BCI-AMR; (e) SNR=6 dB in BCI-AMR; (f) SNR=12 dB in BCI-AMR.**

accuracy is much better than AMR system, no matter what the environment is.

In order to further investigate the correct recognition probabilities of the two systems, we visualized the confusion matrix of two AMRs at the region of SNR = 0 dB, 6 dB and 12 dB in Fig. 8. Each column of the confusion matrix represents a prediction label, and the total number of each column representing the number of data predicted to be a modulation. Each row representing the true label of the data, and the total number of data for each row representing the number of its true modulation category.

Comparing the prediction label accuracy of the two AMR systems, the traditional AMR system often misjudges 2FSK as DQPSK, MSK as GMSK at all SNRs. However, the difference between this two AMR system is very obvious. The predicted label of the BCI system is basically consistent with the true label and the label prediction accuracy rate is 98% when SNR is greater than 6 dB.

V. CONCLUSION

In this paper, we have proposed a BCI aided GenAMR based on deep learning with two CNNs. This BCI-AMR system can obtain correct recognition probabilities in identifying modulation modes because of the double CNN architecture. Moreover, the former CNN classifies the unknown signals sampled by IQ into certain channel categories. After that, the latter CNN obtains the channel information by modulation recognition of the signals. Finally, our research implies that the proposed BCI aided GenAMR can replace conventional AMR in many applications. In future work, we will focus on the robustness of CNN-based classifiers in the larger range of SNR, and further improvement of recognition efficiency in many applications [24]–[29].

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