A Deep Neural Network Method For Automatic Modulation Recognition In OFDM With Index Modulation

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***Abstract*—Automatic modulation recognition (AMR) plays an indispensable role in many fields, such as cognitive radio, spectrum sensing, non-cooperative link adaptation, and other civilian and military fields. OFDM-IM is an innovative OFDM-based scheme which has better bit error performance than classical OFDM scheme especially in high mobility cases. Different from OFDM, the modulation parameters include both M-ary signal constellations and indices of the subcarriers in OFDM-IM scheme. In this paper, we studied a deep neural network (DNN) based AMR method in orthogonal frequency division multiplexing with index modulation (OFDM-IM) scheme.**

***Index Terms*—automatic modulation recognition (AMR), machine learning, deep neural network, OFDM, index modulation**

I. Introduction

Orthogonal frequency division multiplexing with index modulation (OFDM-IM) is an innovative transmission scheme which is based on OFDM. OFDM-IM scheme have better performance in high mobility scenarios by exploiting subcarrier indices to carry part of the information [1]. In OFDM-IM scheme, all information bits will be divided into two parts, index selecting bits and constellation modulation bits. In an OFDM-IM frame, all of the subcarriers will be divided into several subblocks. In every subblock, subcarriers will be in one of two states, active or silent. The indices of active subcarriers will be determined by index selecting bits and constellation modulation bits will be systematically mapped into these active subcarriers.

AMR is a method to determine modulation parameters from received signal. With the development of modern communications system, the AMR algorithm plays an indispensable role in plenty of civilian and military applications such as spectrum sensing and management, electromagnetic countermeasure, etc. In general, AMR methods can be classified in two classes: likelihood-based (LB) methods and feature-based (FB) methods respectively [2].

The main principle of LB methods is exploiting probabilistic and statistical hypothesis testing. In [3–7], several likelihood functions were proposed as a LB-AMR method. Though LB methods could have optimal performance, it is hard to implement due to its high computational complexities. Usually, there are two main steps in FB methods, feature extraction and classification. Features for AMR have been studied in many papers including higher order statistics (cumulants [8, 9], statistics [10, 11]), transform domain features (wavelet transforms [12, 13], short-time Fourier transform [14]), etc. Many classification algorithms also have been widely used in AMR such as support vector machine (SVM) [9, 13], minimum distance classifier (MDC) [15], multilayer perceptron (MLP) [16, 17], etc.

In lately years, with the rise of machine learning technique, many researchers have made a lot of breakthroughs in wireless communication [18–23]. Machine learning could extend AMR as a powerful classifier. In [21], the author proposed an DNN based AMR method which employs a kind of time-frequency transformation as feature extractor and exploits convolutional neural network (CNN) as classifier. Machine learning could also be an end-to-end AMR method which units feature extraction step and classification step. In [22], the author proposed a recurrent neural network (RNN) based AMR method which takes N timesteps time domain amplitude and phase vector as input. The method also was verified on a standard dataset [24]. In [23], the author proposed a convolution neural network model for AMR which could extract features automatically.

With the rapid development of modern communication technology, the new wireless communication scheme brings us new AMR challenge. Different from conventional AMR problem, the modulation parameters in OFDM-IM scheme includes both M-ary signal constellations and indices of the subcarriers in OFDM-IM scheme. Hence, the AMR in OFDM-IM scheme is to identify both modulation type M and the number K of active subcarriers in each subblock. In [25], a LB based AMR method was proposed for OFDM-IM scheme and it is the first paper that study on this problem. In this paper, we extend FB based AMR method for OFDM-IM scheme and proposed a practical DNN based method to solve this problem.

II. PROBLEM STATEMENT

A. System Model

The structure of OFDM-IM transmitter is shown in Fig. 2. There are N_c subcarriers in every OFDM-IM frame. These subcarriers will be divided into G subblocks and N subcarriers in each subblock, i.e., $N_c = N * G$. In every subblock, the number of active subcarriers K keeps in fix. Only K

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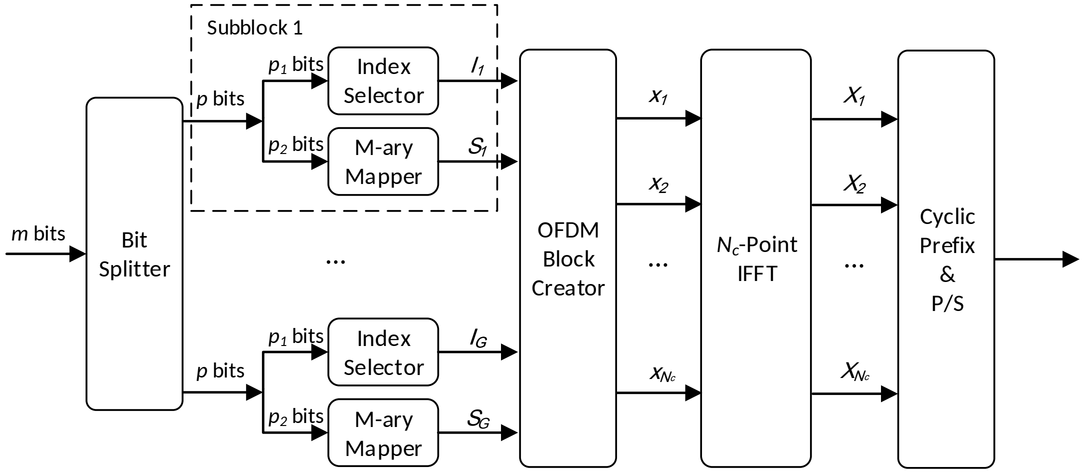

Fig. 1. Structure of the OFDM-IM transmitter

subcarriers will be used to transmit signal in each subblock. The rest $N-K$ subcarriers keeps in silent.

Correspondingly the incoming L-bits into OFDM-IM transmitter will be also divided into G groups with each containing P-bits, i.e., $L = P * G$. In every subblock, the P-bits will be divided into P_1-bits and P_2-bits further. The P_1-bits will be used to determine which subcarriers should be active. Hence, $P_1 = \lfloor log_2 C(N,K) \rfloor$ in which $C(N,K)$ denotes the binomial coefficient and $\lfloor . \rfloor$ represents floor operator. The P_2-bits will be mapped into M-ary QAM or PSK constellation symbols on K active subcarriers. Obviously, $P_2 = K * log_2 M$.

For every subblock g, the indices of K active subcarriers are given by

$$I_g = \{i_{g,1}, i_{g,2}, ..., i_{g,K}\} \tag{1}$$

where $i_{g,k} \in [1,2,...,N]$ for $g = 1,2,...,G$. The modulated symbols which created by M-ary mapper is given by

$$S_g = \{s_{g,1}, s_{g,2}, ..., s_{g,K}\} \tag{2}$$

where $s_{g,k} \in \mathcal{S}$, $k = 1,2,...,K$ and $\mathcal{S}$ denotes the set of the M-ary complex signal constellation. Then, the OFDM block creator will take in I_g and S_g from every subblock for $g \in \{1,2,...,G\}$ and create the frequency domain (FD) signal

$$\mathbf{x}_{FD} = \{x_1, x_2, ..., x_{Nc}\}$$

in which

$$x_{(g-1)*N+n} = \begin{cases} s_{g,k} & \text{, if } n = i_{g,k} \\ 0 & \text{, others} \end{cases}$$

where $g = 1,2,...,G$, $n = 1,2,...,N$ and $x_{(g-1)*N+n}$ stands for the n-th subcarrier in g-th subblock.

After that, the same procedures as the classical OFDM like IFFT, adding cyclic prefix (CP), parallel to series (PS) conversion will be applied. The FD signal will be transformed into time domain (TD) signal

$$X_{TD} = \frac{N_c}{\sqrt{GK}} IFFT\{\mathbf{x}_{FD}\} = \frac{1}{\sqrt{GK}} F^H_{N_c} \mathbf{x}_{FD}$$

where $F^H_{N_c}$ is the discrete Fourier transform (DFT) matrix with $F^H_{N_c} * F_{N_c} = N_c * I_{N_c}$ and $N_c/\sqrt{GK}$ stands for the normalization factor since only GK of N_c subcarriers are mapped to M-ary constellation symbol. After adding CP and PS conversion, the equivalent FD received signals is given by:

$$\mathbf{y_{FD}} = \frac{N_c}{\sqrt{GK}} \mathbf{x_{FD}} \mathbf{h} + \mathbf{w}$$

where $\mathbf{y_{FD}}$ is the FD received signal, $\mathbf{h}$ is the channel fading coefficient, $\mathbf{w}$ is the additive white gaussian noise (AWGN) with $\mathbf{w} \sim \mathcal{CN}(0, \sigma_f^2)$.

B. Problem Formulation

The aim of AMR in OFDM-IM scheme is identifying the combinated modulation parameter (K, M) in different cases including AWGN channel or fading channel. We assume that the candidate set of K is $\mathcal{K} = \{1,2,...,N\}$ and the candidate set $\mathcal{M}$ of M includes various modulation type. The distribution of K and M should be random and equally. The number G of subblocks and the number N of subcarriers per subblock is assumed known.

The probability of correct classification (PCC) will be employed to assess the performance. The PCC is defined by $p(H = \widehat{H})$ where $H = (K, M)$ and $\widehat{H} = (\widehat{K}, \widehat{M})$ are the true and estimated combinated modulation parameter separately.

III. DNN-Based AMR Method

We proposed an end-to-end DNN-Based AMR method to recognize the parameters in OFDM-IM scheme.

A. Architecture of Proposed DNN Architecture

The structure of proposed DNN model is shown in Fig. 1. The input y_{FD} is the in-phase and quadrature (I/Q) samples of one OFDM-IM frame which is a 2D vector with the size of $N_c \times 2$. The output is the estimated modulation parameter combination $(\widehat{K}, \widehat{M})$. The whole network could be divided into two sub-networks. The sub-network in the right region is used to estimate the modulation type $\widehat{M}$ and we call it

M-network. M-network consists of 3 stacked convolutional layers for feature extraction and 3 stacked dense layers for classification. This structure is proved to be a kind of effective model for modulation types recognition [18]. The sub-network in the left region is used to estimate the number $\widehat{K}$ of active subcarriers and we call it K-network. The K-network takes both y_{FD} and the estimated $\widehat{M}$ from M-network as input and give the final estimated $\widehat{K}$.

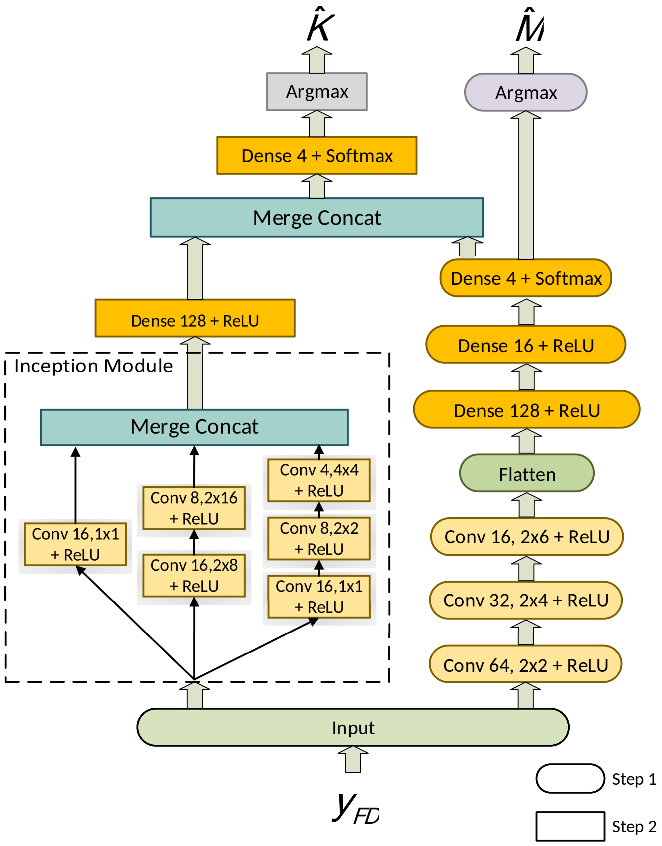

Fig. 2. Structure of the OFDM-IM transmitter. The text 'Conv 64 2,2 + ReLU' means this layer is convolution layer with the kernel number is 64 and the kernel size is 2 × 2 and the activation function is ReLU. The text 'Dense 128 + Softmax' represents there are 128 nodes in this layer and the activation is Softmax.

Generally speaking, DNN is a deeper feedforward neural network (FNN) with various network structures in different layers. We could describe our DNN model with a mapping function

$$(\widehat{K}, \widehat{M}) = f(y_{FD}; \theta)$$

where $f(.)$ is the network structure and θ denotes the network parameter. The L-layers network structure $f(.)$ can also be described as L iterative processing steps :

$$r_l = f_l(r_{l-1}; \theta_l), \qquad l = 1, ..., L \tag{3}$$

where $f_l(.)$, θ_l, r_{l-1}, r_l are the network structure, network parameters, input vectors, output vectors in l-th layer respectively.

In our model, the convolutional layers are performed as a higher-level feature extractor. Convolutional layer can be described as

$$\begin{aligned} r_l^f(i,j) &= f_{cnn}(r_{l-1}; \theta_l) \\ &= \sum_{p=0}^{m-1} \sum_{q=0}^{n-1} W_{m-p,n-q}^f r_{l-1}(i-p, j-q) \end{aligned} \tag{4}$$

where $W_f \in \mathbb{R}^{m \times n}$ is the f-th convolutional kernel which is a trainable vector parameter, $r_{l-1}(i,j) \in \mathbb{R}^{I \times J}$ is the input vector. It should be noted that $r_{l-1}(i,j) = 0$ in calculation when $i \notin [1, I]$ or $j \notin [1, J]$.

The flatten layer is used to transfer a 2D vector to a 1D vector. The dense layer is performed as a multiple classifier in our model and takes extracted higher-level information from flatten layer as input. The l-th dense layer can be described as

$$f_l(r_{l-1}; \theta_l) = W_l r_{l-1} + b_l \tag{5}$$

where $W_l \in \mathbb{R}^{N_l \times N_{l-1}}$, $b_l \in \mathbb{R}^{N_l}$, and N_l is the output size of l-th layer.

The activation function $\sigma(.)$ will be applied after convolutional layer or dense layer. Rectified linear unit (ReLU) and softmax are choosed in our model which can be described as

$$\sigma_{ReLU}(x_i) = max(0, x_i) \tag{6}$$

$$\sigma_{softmax}(x_i) = \frac{e^{x_i}}{\sum_j e^{x_j}} \tag{7}$$

In K-network, the Inception module is selected as feature extractor instead of stacked convolutional layers. The main idea of the Inception architecture [26] is built from convolutional layers with different kernel size and make a combination of all those layers with their output filterbanks concatenated into a single output vector forming the input of the next stage.

B. Model Training and Testing

To training and evaluating the performance of our proposed model, we use MATLAB for simulations and generate signal dataset. The half of the signal dataset will be randomly selected to train model. The rest will be equally divided into two parts to test and validate separately. We train the CNN by using 880000 samples and 440000 samples for validation and testing. The construction, training and prediction of our proposed model are implemented in Keras [27] running on top of TensorFlow [28] on an NVIDA Cuda [29] enabled GeForce GTX Titan GPU. The adaptive moment estimation (Adam) [30] algorithm is employed as the training algorithm.

As shown in the Fig. 2, there are two steps in the training process in our model. In the first step, the M-network will be trained. In the second step, the output of the M-network will be part of the input of K estimate sub-network. The parameters in M-network will keep in fix and parameters in K-network will be trained in step 2.

IV. Simulation and Results

We compared the performance among our DNN based method and several other different methods including simple CNN method and FNN method in this section. The simple CNN applied the M-network architecture for both K and M recognition and trained separately. The FNN model is formed by four stacked hidden-layer which contains 256, 128, 64, 4 nodes separately. The PCC is used to assess the performance of AMR algorithm. In this simulation, $\mathcal{M}$ includes BPSK, QPSK, 8PSK and 16QAM which is $\mathcal{M} = \{2, 4, 8, 16\}$.

As shown in Fig. 3, we compared our proposed DNN method with a simple CNN method and FNN method in AWGN channel. In this simulation, the number of subcarriers in one OFDM-IM frame N_c is 128 and keeps fix. The length of each subblock is N = 4 or 8, and the number of subblocks in each OFDM-IM frame is G = 32 or 16 correspondingly. The result shows that out proposed DNN method has the best performance among these three models. The FNN model has the worst performance which is lower 70% than PCC of DNN and Simple CNN in high SNR (SNR >= 10 dB). Besides, our proposed DNN method consistently outperform Simple CNN method by 10% average better performance when SNR in [-4dB, 4dB].

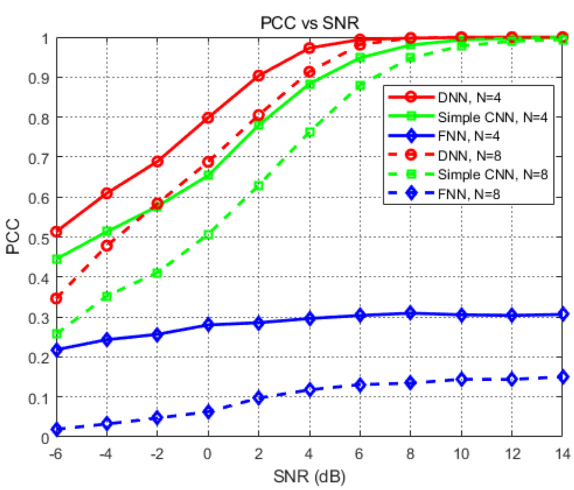

Fig. 3. The PCC curves with AWGN channel at N = 4 and N = 8.

Fig. 4 shows the training history about these three networks. It shows how training loss and validate loss changes with varying training epochs. We exploited cross entropy loss as our training loss function. According to training history graph, the loss of our proposed DNN method has the minimum convergence value.

In Fig. 5, we provide a performance analysis of the PCC for varying K when $N = 4$. It shows that our model has better performance with decreasing K when SNR is low.

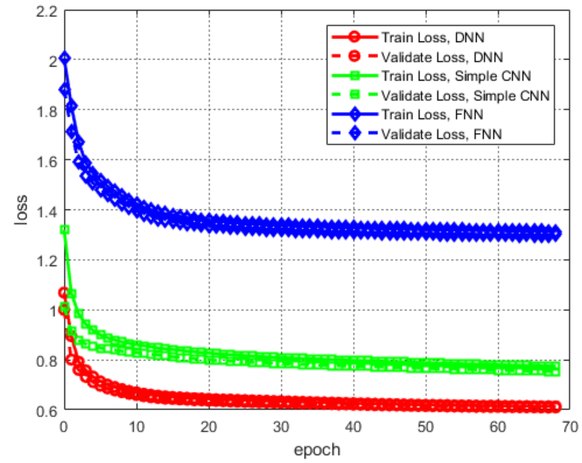

Fig. 4. Training History

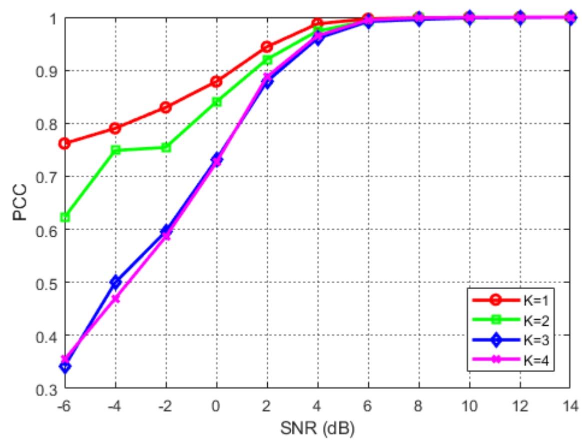

Fig. 5. The PCC curves for varying K with proposed DNN method when N = 4

V. Conclusions

Different from classical wireless communication scheme, the modulation parameters in OFDM-IM scheme includes not only the signal constellation, but also the number of active subcarriers. In this paper, we extend FB based AMR method for OFDM-IM scheme and proposed a practical DNN based method to recognize parameters in OFDM-IM. The PCC simulations show that our proposed DNN-based method is effective for AMR in OFDM-IM, and has almost 100% the recognition accuracy when SNR is above 6dB. Through the analytical comparison with several models, our proposed model has the best performance in different cases.

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