Automatic Modulation Classification Method for Multiple Antenna System Based on Convolutional Neural Network

Juan Wang [1], Yu Wang [1], Wenmei Li [1], Fumiyuki Adachi [1], and Haris Gacanin [1]

[1]Affiliation not available

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Abstract

In order to transmit communication signals of different properties, quickly, effectively, and accurately, various different modulation styles can be adopted. Accurate recognition of signal modulation is required at the receive side. Automatic modulation recognition (AMR) is a key technique to identify various styles of modulation of signals received in wireless channels. It can be used in many kinds of communication systems, including single antenna system and multiple antenna system. In this paper, we propose a convolutional neural networks (CNN) aided AMR method for multiple antenna system. Compared with the high order cumulants (HOC) and artificial neural networks (ANN) aided traditional AMR classification method, both with two specific combination strategies, such as relative majority voting method and arithmetic mean method, the proposed AMR with arithmetic mean method has the best classification performance. The experimental results obtained verify that the CNN, one of the representative algorithms of deep learning, has a strong ability to exploit dominant features and classify the modulation styles.

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Juan Wang[†], Yu Wang[†], Wenmei Li[†,‡], Guan Gui[†], Haris Gacanin[††], and Fumiyuki Adachi[*]

[†]College of Telecommunications and Information Engineering, NJUPT, Nanjing ~~210003~~, China
[‡]School of Geographic and Biologic Information, NJUPT, Nanjing 2~~10023~~, China
[††] ~~Electrical Engineering~~ and Information Technology, RWTH Aachen University, Aachen ~~55-52062~~, Germany
[*] Research Organization of Electrical Communication, Tohoku University, Sendai ~~980-8577~~, Japan
E-mails: {1219012920, guiguan}@njupt.edu.cn, haris@ieee.org, adachi@ecei.tohoku.ac.jp

***Abstract*—In order to transmit communication signals of different properties, quickly, effectively, and accurately, various different modulation styles can be adopted. Accurate recognition of signal modulation is required at the receive side. Automatic modulation recognition (AMR) is a key technique to identify various styles of modulation of signals received in wireless channels. It can be used in many kinds of communication systems, including single antenna system and multiple antenna system. In this paper, we propose a convolutional neural networks (CNN) aided AMR method for multiple antenna system. Compared with the high order cumulants (HOC) and artificial neural networks (ANN) aided traditional AMR classification method, both with two specific combination strategies, such as relative majority voting method and arithmetic mean method, the proposed AMR with arithmetic mean method has the best classification performance. The experimental results obtained verify that the CNN, one of the representative algorithms of deep learning, has a strong ability to exploit dominant features and classify the modulation styles.**

***Index Terms*—Convolutional neural network, signal recognition, multiple antenna system, deep learning, cooperative decision.**

I. Introduction

Automatic modulation recognition (AMR) ~~refers to recognize the actual modulation style of the signal received~~ to ensure that the signal can be demodulated correctly ~~and the information sent can be accurately recovered, which~~ is the basis of various applications~~, especially in~~ cognitive radio (CR), spectrum sensing, ~~etc~~ [1]–[6]. ~~The role of the AMR is of importance to communication in both the particular military and civil fields [7].~~ AMR ~~need to be versatile, including being able~~ to recognize as many modulation ~~styles~~ as possible~~, being able to function~~ with ~~limited~~ knowledge of the channel or target communication system~~, and being able to be used in multiple styles of communication systems~~ including single ~~antenna~~ ~~system~~ [8] and multiple antenna ~~system~~ [9]–[13].

Until now, many AMR method have been proposed. High-precision decision theory (DT) and easy-to-implement pattern recognition (PR) are the two basic ~~styles of these~~ methods [10]. Although DT-based method ~~can have high accuracy, it not only need to be based on signal model matching and accurate channel statement information (CSI) [14]. but also~~ has higher computational complexity. More PR-based methods are adopted~~, no need for such complicated processing and breaking away from the limitations of prior information, generally~~ consisting of signal preprocessing, feature exploitation and classification recognition. Among these sub-systems, artificial feature extraction covers circulatory stationary analysis [15], high-order statistics (HOS)~~, etc, and circulatory stationary analysis, and classification identification includes~~ k-nearest neighbor (KNN), support vector machines (SVM) and traditional artificial neural networks (ANN) [9]–[13]. ~~In the background of the additive white Gaussian noise (AWGN),~~ HOS is a popular option in single antenna and multiple antenna systems because of its powerful ability ~~of~~ suppress interference [10]. A~~MR research for single antenna system has been widely carried out. In recent years, the multiple antenna system has been widely concerned, in which multiple transmitting and receiving antennas are capable of improving transmission quality of signals as well as enhancing utilization efficiency of spectrum, accordingly satisfying the increasing data rate needs of current and future wireless systems [15].~~

The applications of deep learning (DL) in wireless communications ~~are increasingly widespread~~ [16]–[20], such as beamforming [21], non-orthogonal multiple access (NOMA) [22], network traffic prediction [23]–[27], internet of things [28]–[31], and AMC [32]–[35]. The DL-based AMR methods are mainly designed for single antenna system, ~~but is~~ not suitable for multiple antenna system because ~~the receiver receives mixed signals~~ from all transmitting antennas. Few studies have been conducted ~~on the introduction of~~ DL, not only ~~restrict~~ to convolutional neural network (CNN) [33] and long short-term memory (LSTM) [36], into AMR in multiple ~~systems~~. ~~In this thesis, we~~ propose a convolutional neural networks (CNN) aided AMR method for multiple antenna system, where CNN is trained according to the signals received by all antennas. Following this ~~part~~, the given decision maker collaboratively determines the modulation style according to

the identification results of each antenna obtained by CNN. ~~Here~~, two ~~kinds~~ of combination strategies~~,~~ the relative majority voting method and ~~the~~ arithmetic mean method, are adopted. ~~Comparison result shows that the classification performance of proposed AMR method is better than that of~~ the HOC and ANN aided AMR ~~method in [12], [37]~~. Moreover, the arithmetic mean method is always better than the relative majority voting method in the two proposed combination strategy.

~~The rest of this paper is organized as below. In Section II, we introduce the system model and dataset generation. In Section III, we present the proposed CNN based AMC method for multi-antenna system. Section IV provides simulation results to evaluate the proposed method. In Section V, we conclude this paper and point out some future work.~~

II. System Model and Dataset Generation

A. System Model

The multiple antenna system, which utilizes the air separation transmitting and receiving antenna arrays, has become the key technology of many innovative communications in recent years. Multiple antenna systems transmit multiple signal streams through different signal paths in space, known as space division multiplexing (SDM), and provide the possibility to improve link reliability. Since there are multiple paths between the transmitting antenna array and the receiving antenna array, each receiver receives a mixed signal symbol from all transmitters, so it is no longer applicable in a single antenna system.

The multiple antenna system consists of N_t transmit antennas and N_r receive antennas. Consider a time-invariant Rayleigh fading channel whose channel matrix $\boldsymbol{H}$ is given by $N_r \times N_t$ complex matrix. In the case of complete synchronization, in the total observed N samples, the sample vector $\boldsymbol{r}_k = [r_k(1), r_k(2), \cdots, r_k(N_r)]^T$, $k \in [1, N]$ of the k-th received signal can be given by

$$\boldsymbol{r}_k = \boldsymbol{H}\boldsymbol{s}_k + \boldsymbol{w}_k, \tag{1}$$

where $\boldsymbol{s}_k = [s_k(1), s_k(2), \cdots, s_k(N_t)]^T$, $k \in [1, N]$ is the k-th transmitted signal symbol vector. $\boldsymbol{w}_k = [w_k(1), w_k(2), \cdots, w_k(N_t)]^T$, $k \in [1, N]$ is the observed additive noise from the k-th signal sample. It is assumed that the transmitted symbol vectors are independent and identically distributed, and each modulation symbol has the same probability, and furthermore, the additive noise is AWGN with zero mean and one variance, i.e. $w_k \in N(0, I_{N_r \times N_r})$.

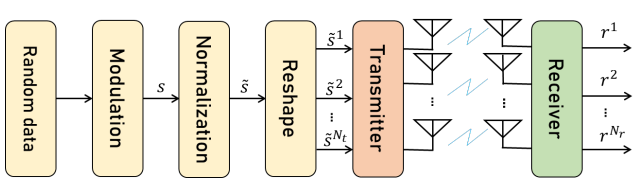


Fig. 1. Data set formation process for multiple antenna system.

B. Dataset Generation

Fig. 1 shows the specific data set formation process, where $\boldsymbol{s}$ is a data sequence with dimension is $1 \times N$ formed by modulation of randomly generated data. The normalization is to speed up convergence and make the signals of different modulation styles have better differentiation. After reshaping, $\tilde{\boldsymbol{s}}^i = [\tilde{s}_1(i), \tilde{s}_2(i), \cdots, \tilde{s}_{N/N_t}(i)]^T$, $i \in [1, N_t]$, represents N/N_t signals of the i-th transmitting antenna. Accordingly, $\boldsymbol{r}^j = [r_1(j), r_2(j), \cdots, r_{N/N_t}(j)]$, $j \in [1, N_t]$ represents N/N_t complex-value baseband signal at the j-th receiving antenna after passing through wireless channel. The real part and imaginary part of $\boldsymbol{r}^j$ will be set as a set of training sample of the j-th antenna.

III. The Proposed AMC Method

The classification decision is to find the candidate modulation style that provides the maximum likelihood value, which can be calculated by

$$\hat{m}_n^j = \arg \max_{n \in [1, |\mathcal{M}|]} P(m_n | r^j), \ j \in [1, N_r], \tag{2}$$

where $P^j = \{P(m_n|r^j)\}_{n=1}^{|\mathcal{M}|}$ is the received antenna N_r probability distribution function (PDF).$\hat{m}_n^j$ and m_n represents the predicted modulation type and the real modulation type, respectively. Here, the modulation signal types are set as $\mathcal{M} = \{BPSK, QPSK, 8PSK, 16QAM\}$ [32], and the number of its internal modulation styles is expressed in $|\mathcal{M}|$.

Fig. 2 shows the structure of proposed AMC method, containing a designed CNN and a specific decision maker. The testing process can be divided into two stages. First, the signals r^j received by each antenna are input into the trained CNN to extract the effective features and give the predicted PDFs $\{P^j\}_{j=1}^{N_r}$. It is important to note that the CNN here is the central training, which means to train CNN together according to the received signals of all the receiving antennas, rather than to train their own CNN separately with the received signals of each antenna. Then, the specific decision maker will decide whether to receive the PDFs or the sub-results of each receiving antenna according to the selected decision rule, and jointly give the final prediction style.

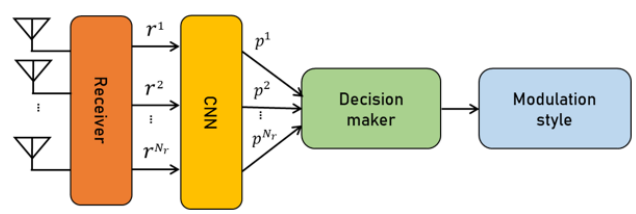


Fig. 2. Architecture of proposed AMR method.

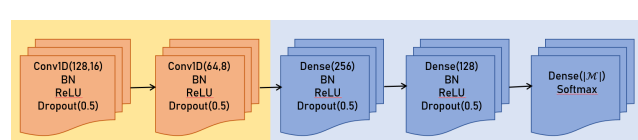


Fig. 3. The framework of CNN.

A. CNN Structure

As shown in Fig. 3, the CNN has five layers with two convolutional (i.e. conv1D) layers and three full connected (i.e. Dense) layers. Batch normalization (BN) allows for faster convergence and shorter overall training time. To prevent overtraining the network from leading to overfitting, we set dropout $= 0.5$. Based on our training dataset and CNN, the final optimization function, i.e. structural risk minimization (SRM), can be described as

$$L\left(f_{CNN}, \theta; \{s_i, l_i\}_{i=1}^{S}\right) = \min\left[-\frac{1}{S}\sum_{i=1}^{S}\log(f_{CNN}(\theta; s_i)) + \lambda J(f_{CNN}, \theta)\right] \tag{3}$$

where $\{s_i, l_i\}_{i=1}^{S}$ represents the combination of training dataset containing S training samples and their corresponding one-hot coded-labels; f_{CNN} and θ are the mapping function and parameters of the CNN, respectively. $\min\left[-1/S\sum_{i=1}^{S} l_i \log(f_{CNN}(\theta; s_i))\right]$ represents empirical risk minimization (ERM) for the classification problem. $J(f_{CNN}, \theta)$ is a function of the complexity of the model, and $\lambda \geq 0$ is a coefficient used to weigh empirical risk and the complexity of model. Adaptive moment estimation (ADAM) is selected as the optimizer [10].

B. Combination Strategy

The specific decision maker jointly determines the modulation style according to the PDFs of the receiving antenna N_r. The PDF here is the product of the signal samples to be tested obtained by designed CNN. Especially, the joint decision is because the proposed AMR method is based on two combination strategies, namely relative majority voting method and arithmetic mean method. It is obvious from relative majority voting method that the modulation style with the most predicted sub-result will be determined as the final classification result. It is important to note that if more than one category wins the highest vote, one category is randomly selected to be the final category. The arithmetic mean method is the arithmetic mean of the PDFs of the receiving antenna and the final decision result depends on the one with the highest probability of the modulation style. The detailed description of relative majority voting method and arithmetic mean method is listed in **Algorithm 1**.

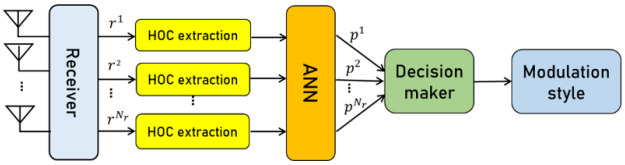


Fig. 4. Architecture of HOC and ANN aided traditional AMR method.

C. Traditional HOC and ANN aided AMR Methods

Different modulation styles have different cumulative values, so the classification of modulation styles can be realized. Swami and Sadler suggest to classify M-PAM, M-PSK, and M-QAM modulation by charactering the fourth-order cumulants of complex signals [38]. Here, we use a traditional AMR based on ANN and HOC [12], [37] to make a comparison, whose architecture is shown in Fig. 4. Traditional AMR also uses central training and cooperative decision to be fair. In addition, ANN is a classifier having three fully-connected whose parameters are consistent with the fully-connected layer of proposed AMR.

Algorithm 1 The proposed AMR based on two combination strategy.

Require: Test sample $\{\boldsymbol{r}^j\}_{j=1}^{N_r}$ and the trained CNN;
Ensure: The predicted modulation type;
1: for $j = 1 : N_r$:
Give the $\hat{m}^j$ by (2) and
$\boldsymbol{P}^j = [P(m_1|r_j), P(m_1|r_j), \cdots, P(m_{|\mathcal{M}|}|r_j)]$
end
2: if choosing relative majority voting method,
$\hat{M} = \frac{1}{N_r}\sum_{j=1}^{N_r}\hat{m}_n^j$;
$\hat{m}_n^{voting} = \arg\max_{n\in[1,|\mathcal{M}|]}\hat{M}(n)$;
end
3: if choosing arithmetic mean method,
$\hat{P} = 1/N_r\sum_{j=1}^{N_r}P_j$;
$\hat{m}_n^{averaging} = \arg\max_{n\in[1,|\mathcal{M}|]}\hat{P}(n)$;
end
4: **return** The predicted modulation type $\hat{m}^{Voting}$ or $\hat{m}^{Averaging}$.

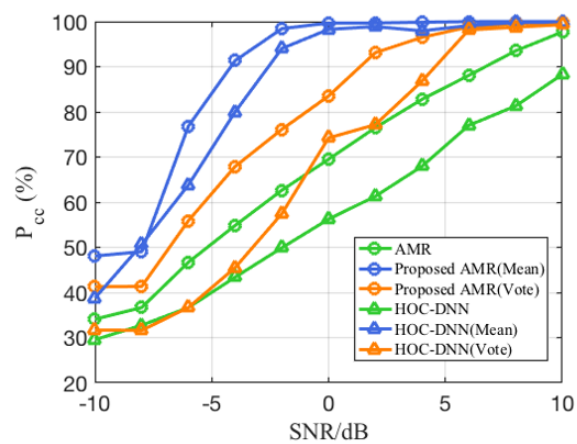
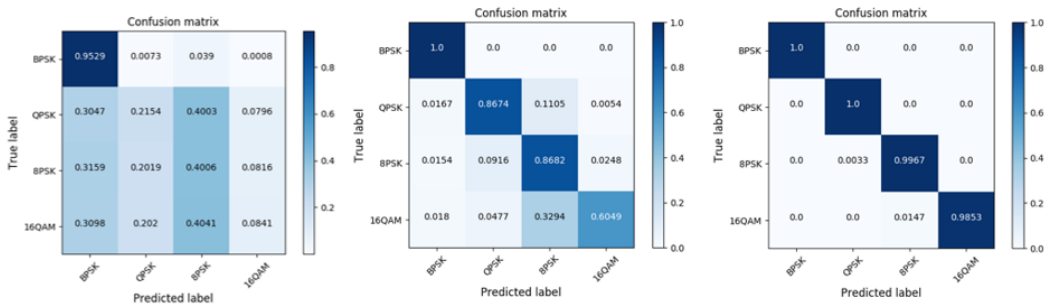


Fig. 5. The performance of classification of proposed AMR method and the HOC and ANN aided traditional AMR methods with two specific combination strategies.

IV. Simulation Results

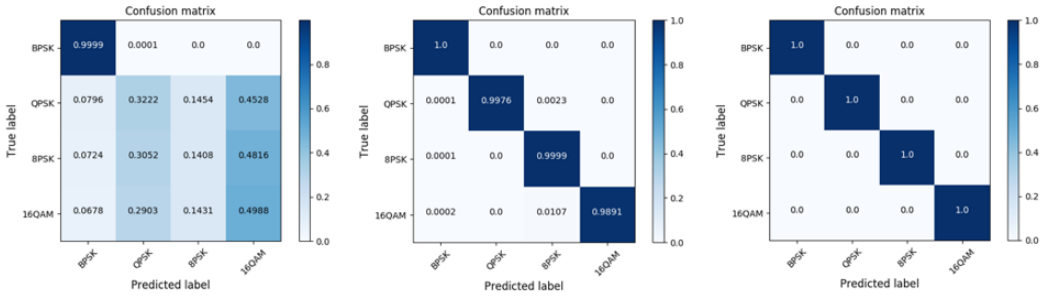
In this section, we demonstrate that the proposed AMR method for multiple antenna system has better classification performance through simulation. For each modulation style, 20,000 samples are prepared per signal-to-noise ratio (SNR) for training CNN network, the training set and validation set reasonably divided according to 7 : 3, and 10,000 samples are prepared per SNR for testing to obtain the correct classification probability P_{cc} at snr dB.

$$P_{cc} = \frac{S_{correct}^{snr}}{S_{test}} \times 100\% \tag{4}$$



$snr = -8$ dB $snr = 0$ dB $snr = 8$ dB

(a) voting method



$snr = -8$ dB $snr = 0$ dB $snr = 8$ dB

(b) averaging method

Fig. 6. Confusion matrices of CNN using (a) relative majority voting method and (b) arithmetic mean method when $snr \in \{-8, 0, 8\}$ dB.

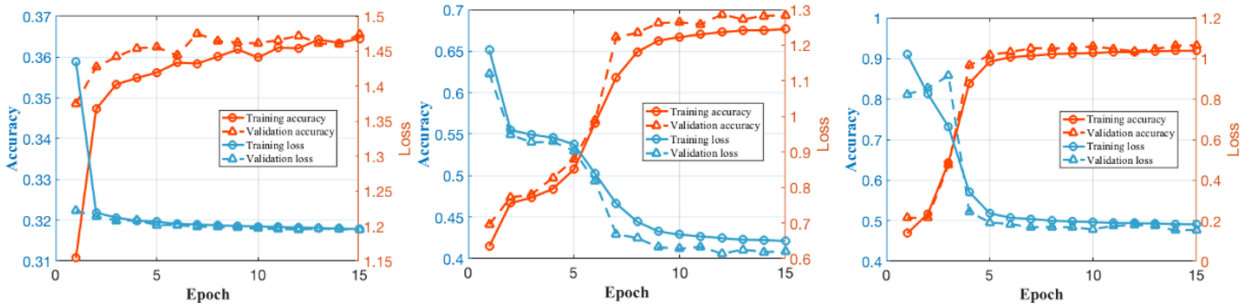


Fig. 7. The loss and accuracy curves of training validation.

where S_{test} and $S_{correct}^{snr}$ represent the number of samples of each modulation style and the correct number of classification of all modulation styles at snr dB, respectively. The performance of classification of proposed AMR method and the HOC and ANN aided traditional AMR methods with two specific combination strategies under different SNR are showed in Fig. 5. Here, we design $N_r = 4$ and $N_t = 1$. AMR in 5 represents the average probability of correct classification of four received antennas. It is obvious that the arithmetic mean method is always better than the relative majority voting method in both proposed AMR method and the HOC and ANN aided traditional AMR methods. In condition, through the comparison of the two AMR methods, the classification performance of proposed AMR has been greatly improved in two kinds of combination strategies.

Furthermore, we provide six confusion matrices of proposed AMR method using relative majority voting method and arithmetic mean method when $snr \in \{-8, 0, 8\}$ dB in Fig. 6 respectively, which helps to analyze the performance of our algorithm in detail. We can see that proposed AMR using arithmetic mean method can almost accurately identity BPSK modulation even when $snr = -8$ dB, and it can completely identity four modulation styles when $snr = 8$ dB, which is also better than the relative majority voting method. The accuracy and loss curves of training and validation are also provided in Fig. 7 to prove that we do not overtrain the network just to get the desired results and lead to overfitting.

V. Conclusion

In this paper, we have proposed CNN aided AMR method for multiple antenna system. Our approach adopted two combination strategies: relative majority voting method and arithmetic mean method. Experimental results show that the arithmetic mean method has better classification performance than the relative majority voting method. Comparing with the HOC and ANN aided traditional AMR methods with the same two combination strategies under the same fully-connected layer parameters, the proposed AMR method with the arithmetic mean method has best classification performance, which shows that CNN has the advantage of dominant feature exploitation and high recognition accuracy, compared with the traditional artificial feature designing methods. In future work, we plan to propose more advanced method by using transfer learning and federated learning algorithms.

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