Deep Learning Based Signal Detection in Dual Mode Generalized Spatial Modulation

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Abstract—This paper proposes a kind of deep learning (DL) based signal detection in dual mode generalized spatial modulation (DM-GSM) system, which aims to balance the detection performance and the complexity. Specifically, two neural networks, deep neural network (DNN) and convolutional neural network (CNN), are utilized to gain the mapping relationship among the received symbols, the channel matrix, and the transmitted bits. After offline training, the trained network is deployed for the online signal detection according to the input feature vector. Simulation results illustrate that the proposed DL detection can obtain the approximate performance of maximum likelihood (ML) detection at lower complexity and can provide better robustness compared with the conventional detection algorithms in the presence of various noise deviating from the standard Gaussian distribution.

Keywords—*Dual mode generalized spatial modulation (DM-GSM), deep neural network (DNN), convolutional neural network (CNN), signal detection.*

I. INTRODUCTION

As an emerging multi-antenna technology, spatial modulation (SM) [1] utilizes the transmit antenna indexes and the constellation symbols to transmit information bits, which effectively solves the antenna synchronization and interference problems in multiple-input multiple-output (MMO) system. Considering the large transmit antenna number in the SM system, the case that there is only one transmit antenna activated in each timeslot may result in resource waste. Generalized spatial modulation (GSM) scheme overcomes the limitations of SM by conveying multiple data streams simultaneously on multiple active transmit antennas [2]. Compared with the conventional SM technology, the GSM scheme offers significant improvement in spectral efficiency and transmission rate. Recently, a dual mode GSM (DM-GSM) scheme was presented in [3] to optimize the system performance effectively, which divides all the transmit antennas into two groups using index bits and transmits two distinguishable constellation modulation symbols on the corresponding antenna groups simultaneously.

For GSM and DM-GSM systems, various signal detection methods have been presented. The maximum likelihood (ML) [4] detection obtains the optimal detection performance in GSM and DM-GSM systems, but its complexity grows exponentially as the active antennas increase. To reduce the detection complexity, sub-optimal linear detection algorithms, such as the minimum mean square error (MMSE) detection and the zero-forcing (ZF) detection, were proposed [5]. Although the complexity of linear detectors is decreased compared with the ML detection, their performance loss is also significant. With the intensive exploration of artificial intelligence, the deep learning (DL) technique has displayed enormous potential for signal detection in wireless communications [6]. A small deep neural network (DNN) structure was introduced in [7] to detect the transmitted symbols of the GSM system, which reduces the learning parameters and attains nearly optimum ML detection performance at low complexity. The convolutional neural network (CNN) owning the characteristics of partial connectivity and shared weights in the convolutional layer has been widely deployed in wireless fields. A DL based signal detector for dual mode orthogonal frequency division multiplexing with index modulation (DM-OFDM-IM) was presented in [8] to detect the index bits and the modulation bits by utilizing CNN and DNN individually, decreasing the complexity while enhancing the detection performance.

In this paper, we design a signal detection scheme based on DNN and CNN respectively in the DM-GSM system, called DNN-DM and CNN-DM. The proposed CNN-DM offers a superior bit error rate (BER) performance than the DNN-DM. Specifically, the mapping relationship among the received signal, the channel matrix, and the transmitted bits can be simplified by the neural network model. Through simulation, we find that the proposed DL detection leverages the powerful learning ability of the neural network to offer a better tradeoff between complexity and detection ability and outperforms the traditional ZF and MMSE detection schemes under the condition of perfect and imperfect channel state information (CSI). Meanwhile, the proposed CNN-DM achieves a superior BER performance over the ML detection in the presence of noise that deviates from the standard Gaussian distribution.

The rest of this paper is introduced in the following. The DM-GSM system model and the ML detection are illustrated in Section II. In Section III, the DNN-DM and CNN-DM schemes in the DM-GSM system are proposed. In Section IV, the system BER performance and the detection complexity are analyzed. The conclusions are offered in Section V.
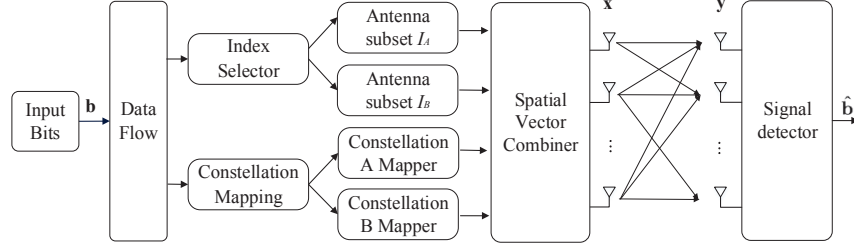
Fig. 1. DM-GSM system model.

II. SYSTEM MODEL

Fig. 1 depicts the DM-GSM system, which is developed on the basis of the GSM system. In each time slot, the input bit sequence **b** is separated into index bits and modulation bits. The index bits are input into the index selector to select two transmit antenna subsets I_A and I_B, where the antennas in the corresponding subset transmit the signal generated by the modulation bits and modulated with constellation mode A and B, respectively. The modulated signal set with constellation A is represented by M_A, the modulated signal set with constellation B is defined as M_B, and m_A and m_B represent the constellation points in M_A and M_B, respectively.

Suppose that the DM-GSM system has N_t and N_r antennas at the transmitter and the receiver, respectively. The antenna subset I_A contains p_1 active antennas and I_B has p_2 active antennas. The active antennas at the transmitter of each time slot is $N_p = p_1 + p_2$. The total number of transmitted bits at each time slot is $b_t = b_1 + b_2$, where the index bits $b_1 = \left\lfloor \log_2 \left(\dfrac{N_t!}{(N_t - N_p)! N_p!} \right) \right\rfloor$ and the modulation bits $b_2 = p_1 \log_2 m_A + p_2 \log_2 m_B$.

To introduce the DM-GSM system in detail, we take $(N_t, N_p, m_A, m_B) = (4, 2, 4, 4)$ as an example. With the above system setting, we have the index bits $b_1 = 2$, the modulation bits $b_2 = 4$, and the total transmitted bits per time slot $b_t = 6$. Assuming that the transmitted bit sequence is [0 1 1 0 1 1], and the first two bits [0 1] are the antenna index bits. It is shown in Table I that the system activates the second and fourth antennas. The following four bits [1 0 1 1] are the modulation bits, where the bit groups [1 0] and [1 1] are mapped by the constellation sets M_A and M_B, respectively.

The DM-GSM transmitter generates the signal vector as $\mathbf{x} = [\cdots 0, s_A^1, 0, \cdots, 0, s_B^1, 0, \cdots, 0, s_A^{p_1}, 0, \cdots, 0, s_B^{p_2}, 0, \cdots]^T \in \mathbb{C}^{N_t \times 1}$ with N_p nonzero elements, $s_A^i \in M_A$ and $s_B^i \in M_B$ represent the symbols in constellation set A and B transmitted by the ith transmit antenna, respectively. Thus, the received vector $\mathbf{y} \in \mathbb{C}^{N_r \times 1}$ is represented as

$$\mathbf{y} = \mathbf{Hx} + \mathbf{n} , \qquad (1)$$

where $\mathbf{H} \in \mathbb{C}^{N_r \times N_t}$ indicates the channel matrix, whose elements obey the complex Gaussian distribution $\mathcal{CN}(0,1)$, and $\mathbf{n} \in \mathbb{C}^{N_r \times 1}$ represents the complex additive white Gaussian noise.

TABLE I. A MAPPING TABLE FOR $N_T = 4$ AND $N_P = 2$

Index Bits	Antenna Set	Symbol
00	(1,3)	[s_A 0 s_B 0]
01	(2,4)	[0 s_A 0 s_B]
10	(3,2)	[0 s_B s_A 0]
11	(4,1)	[s_B 0 0 s_A]

The ML detection algorithm makes the optimal detection by traversing all the possible active antenna subsets $\{I_A, I_B\}$ and constellation symbol sets $\{s_A^i, s_B^i\}$. Therefore, the estimated transmit vector can be calculated with ML detection as

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x} \in \chi} \|\mathbf{y} - \mathbf{Hx}\|_F^2 , \qquad (2)$$

where χ denotes all the available signal sets in the DM-GSM scheme generated by two different constellations M_A and M_B for a given active antenna combination. Due to the exponential growth of the complexity of ML detection with N_t, the ML detector is difficult to be taken in practice.

III. PROPOESD DL BASED SIGNAL DETECTION IN DM-GSM SYSTEM

To investigate the typical DL based signal detection in the DM-GSM system, we design and compare two signal detection schemes based on DNN and CNN, DNN-DM and CNN-DM, where CNN is more suitable for feature extraction. In the following, we respectively present the structure of DNN-DM and CNN-DM, and provide the training procedure.

A. Structure of DNN-DM

We assume the perfect CSI is known at the receiver side. The received complex symbols are transformed into a real-value signal for the neural network process. The real and imaginary parts of the receiving signal vector **y** and the channel matrix **H** are fed into the DNN respectively.
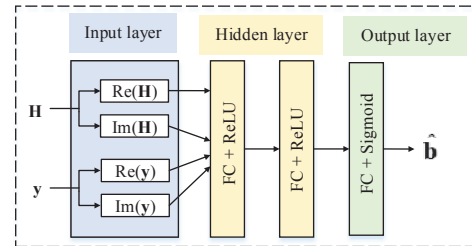

Fig. 2. Structure of DNN-DM.

The DNN framework for the DM-GSM signal detection is illustrated in Fig. 2, which mainly involves an input layer, two hidden layers, and an output layer. The input layer includes $2(N_r+N_rN_t)$ neurons and the number of neurons in the hidden layers is Q_1 and Q_2, respectively. The rectified linear unit (ReLU) activation function $f_{\text{ReLU}}(x) = \max(0, x)$ is applied to the input and hidden layers. The output layer maps the variables to the values in [0, 1] by taking a sigmoid activation function, denoted as $f_{Sigmoid}(x) = 1/(1+e^{-x})$. The output of the DNN architecture is denoted as

$$\hat{\mathbf{b}} = f_\theta(\mathbf{y}, \mathbf{H}) , \tag{3}$$

where $f_\theta(.)$ denotes the DNN mapping function with training parameter θ.
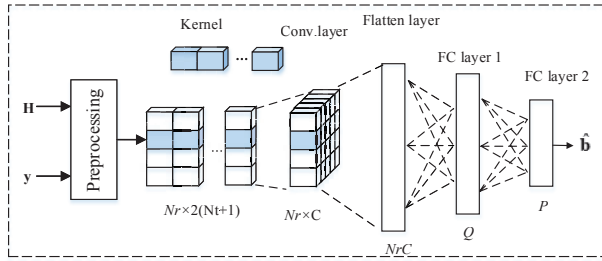
B. Structure of CNN-DM

Fig. 3. Structure of CNN-DM.

Fig. 3 shows the proposed CNN-DM detection framework. The CNN contains a two-dimensional convolutional layer, a Flatten layer, and two fully connected (FC) layers. The convolutional layer owns the characteristics of partial connectivity and shared weights, which significantly decreases the number of network parameters to be learned. For the CNN-DM detection scheme, its signal preprocessing is depicted as follows.

Firstly, the received signal vector and the channel matrix are reshaped into a two-dimensional matrix $\mathbf{Z}$. The channel coefficient and the received signal for the kth receive antenna are stored in the column vector $\mathbf{z}_k$, which can be represented as

$$z_k[2i+1] = \begin{cases} \text{Re}(h_{k,i}), 0 \le i \le N_t \\ \text{Re}(y_k), \quad i = 2N_t \end{cases}, \tag{4}$$

$$z_k[2i+2] = \begin{cases} \text{Im}(h_{k,i}), 0 \le i \le N_t \\ \text{Im}(y_k), \quad i = 2N_t \end{cases}, \tag{5}$$

where $h_{k,i}$ represents the element in the kth row and the ith column of $\mathbf{H}$, y_k is the signal received by the kth antenna. The matrix $\mathbf{Z} = [\mathbf{z}_1, \mathbf{z}_2, \cdots, \mathbf{z}_{N_r}]^T$ with dimension $N_r \times 2(N_t+1)$ is taken as the input of the CNN to fully extract the characteristic information among the transmitted symbols.

Secondly, the pre-processed two-dimensional data matrix $\mathbf{Z}$ is used as the input of the convolutional layer. The convolutional kernel is $\mathbf{v}_c = [v_c^1, v_c^2, \cdots, v_c^{2(N_t+1)}] \in \mathbb{R}^{1 \times 2(N_t+1)}$ $(c = 1, 2, \cdots, C)$, where C represents the quantity of convolutional kernels and v_c^i

indicates the ith element of the cth convolutional kernel. At the convolutional layer, the ReLU function is adopted. The output of the convolutional layer is presented as $\mathbf{D} \in \mathbb{R}^{N_r \times C}$, where the element of the nth row and the cth column of $\mathbf{D}$ is given by

$$d_{n,c} = f_{\text{Relu}}\left(\sum_{i=1}^{2(N_t+1)} z_{n,i} \times v_c^i + b_c \right) , \tag{6}$$

where $z_{n,i}$ denotes the element at the nth row and the ith column of the input matrix $\mathbf{Z}$ of the convolutional layer and b_c indicates the bias of the cth convolutional kernel.

Then, the flatten layer converts the two-dimensional matrix $\mathbf{D}$ output by the convolutional layer into a one-dimensional array $\mathbf{d}_F \in \mathbb{R}^{N_r C \times 1}$. Followed by the flatten layer, two FC layers are adopted in the CNN. The first FC layer utilizes the ReLU activation function and the output layer adopts the Sigmoid activation function for classification. The output of the CNN-DM detector can be expressed as

$$\hat{\mathbf{b}} = f_{Sigmoid}(\mathbf{W}_2 f_{\text{Relu}}(\mathbf{W}_1 \mathbf{D}_F + \mathbf{b}_1) + \mathbf{b}_2) , \tag{7}$$

where $\mathbf{W}_1$, $\mathbf{b}_1$ and $\mathbf{W}_2$, $\mathbf{b}_2$ represent the weights and biases of the first and the second FC layers, respectively.

C. Training Procedure

Before using a neural network for signal detection, the network needs to be trained offline according to the randomly generated data samples. In the training stage, based on the generated data samples of the DM-GSM system, the pre-processed vector is considered as the input feature vector of the signal detection network, and the actual transmitted bit sequence is the corresponding label vector.

To determine the optimal model, it is necessary to continuously adjust the parameters to reduce the losses, which means reducing the discrepancies between the transmitted symbols and the estimated ones. Therefore, we employ the binary cross-entropy loss function to optimize the training parameters, which is calculated as

$$L = -\frac{1}{N} \sum_{i=1}^{N} [y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)] \tag{8}$$

where y_i is the transmitted binary bit 0 or 1, $\hat{y}_i$ is the estimated bit, and N indicates the total number of transmitted bits. The training and test datasets contain 4×10^5 and 1×10^5 symbols, respectively. We take the Adam optimization algorithm to update the network weights with a learning rate $\eta = 0.0005$, which supports large datasets and high-dimensional parameters.

IV. SIMULATION RESULTS

To verify the effectiveness of the proposed DNN-DM and CNN-DM algorithms, we also make comparison with the optimum ML detection, the ZF detection, and the MMSE detection in BER performance and detection complexity. We take $(N_t, N_p, N_r)=(4, 2, 2)$ as an example, and the two constellation modulation modes are both set as BPSK. Flat Rayleigh fading channel is deployed in the simulation, and the noise obeys independent and identically distributed (i.i.d) Gaussian distribution. The two hidden layers of DNN comprise 256 and 128 nodes, respectively, and the hyperparameters of

CNN are set as C=128 and Q=128. In the training process, the training signal-to-noise ratio (SNR) is 20dB.

A. BER Performance

The BER performance of the DM-GSM system with different detection schemes under the perfect CSI is given in Fig. 4. It is shown that the proposed DNN-DM and CNN-DM algorithms achieve the suboptimal performance close to the optimal ML detection and are much better than the MMSE detector and ZF detector by 6 dB and 8.5 dB for BER of 10^{-2}. Meanwhile, the CNN-DM scheme gets superior BER performance to the DNN-DM scheme. In addition, we also compare the system BER performance with different detection schemes under the imperfect CSI in Fig. 5, where the imperfect CSI model in [6] is adopted and the covariance of the CSI estimation error σ_e^2 varies with the average SNR $\bar{\gamma}$ with $\sigma_e^2 = (1+\bar{\gamma})^{-1}$. Similar to the BER performance trend under perfect CSI, the proposed deep learning-based detection has better robustness under the imperfect CSI. At the BER of 10^{-2}, the proposed DNN-DM and CNN-DM obtain about 6.5 dB and 9.0 dB gains over the MMSE and ZF detectors.
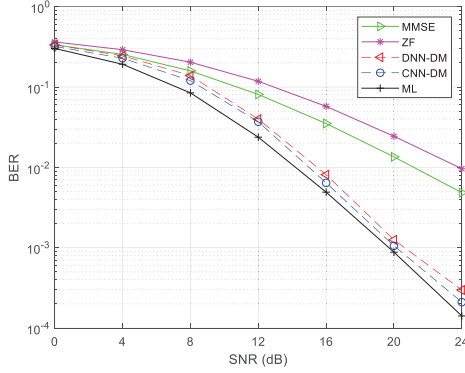

Fig. 4.   BER performance of DM-GSM system with different detection schemes under perfect CSI.
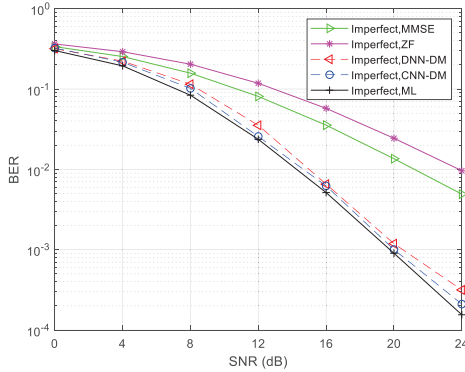

Fig. 5.   BER performance of DM-GSM system with different detection schemes under imperfect CSI.

For the practical communication system, it is hard to ensure the independent noise at the receive antennas because of the limited antenna space. Therefore, we further consider the case

of correlated noise with the correlation matrix in [9], where the noise correlation matrix $\mathbf{N}_c$ is expressed as $\mathbf{N}_c = \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}$, $\rho\,(0 \le \rho < 1)$ denoting the noise correlation coefficient and the correlated noise can be written as $\mathbf{n}_c = \mathbf{N}_c\mathbf{n}$. Fig. 6 depicts the BER performance of the DNN-DM and CNN-DM schemes under the influence of correlated noise with ρ=0.2. The results indicate that the CNN-DM scheme obtains superior BER performance than the DNN-DM scheme in dealing with the correlated noise. In the case of high noise correlation, CNN can fully extract signal features to recover transmitted signal.
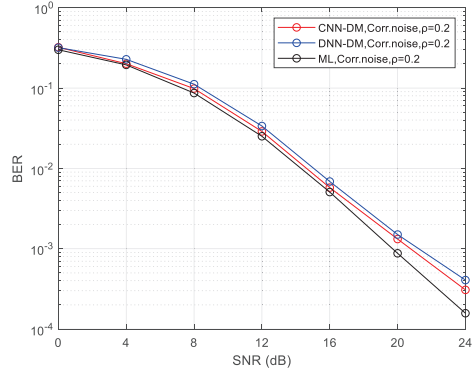

Fig. 6.   BER performance of DM-GSM system with DNN-DM, CNN-DM, and ML detection in the presence of correlated noise.
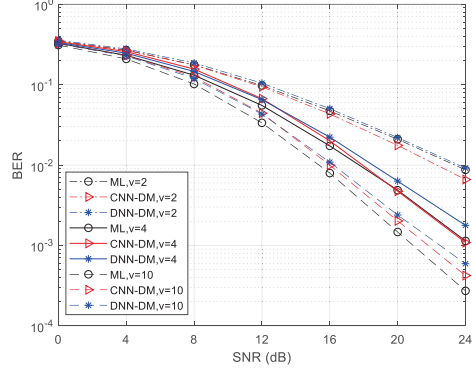

Fig. 7.   BER performance of DM-GSM system with DNN-DM, CNN-DM, and ML detection under t-distributed noise.

Furthermore, we also contemplate the condition that the noise does not obey the Gaussian distribution. We take into account the case where the noise obeys a *t*-distribution [10] with the degree of freedom *v*. The larger v is, the closer the *t*-distribution is to the standard Gaussian distribution. Fig. 7 gives the BER performance of the proposed DNN-DM, CNN-DM, and ML detection algorithms, where the noise obeys the *t*-distribution with v =2, 4, and 10. It shows that the proposed CNN-DM obtains better BER performance versus ML and DNN-DM detection schemes at higher SNR. When the parameter *v* becomes smaller, the performance of the ML detection decreases due to the larger deviation from the

Gaussian distribution. In the case of non-Gaussian noise, the CNN-DM provides better BER performance than the DNN-DM scheme. This is because the two-dimensional convolutional layer is employed to extract the features in the received symbols.

B. Computational Complexity

The computational complexity of the proposed DNN-DM, CNN-DM, and the conventional detectors is analyzed with the required number of floating-point operations (flops) as a metric, such as the real number addition and the real number multiplication in [11]. Table II provides the complexity of the different detection schemes in the DM-GSM system. Different with the traditional detection schemes, the complexity of the proposed DL detection is affected by the amount of neurons and the variation of the transmit antennas has less impact on the complexity of the CNN-DM and DNN-DM algorithms. As the transmit antenna, active antenna and receive antenna are 16, 4, and 8, and 8QAM is employed, the proposed CNN-DM scheme requires 3.3×10^5 flops and the ML detection scheme requires 1.8×10^7 flops, which confirms that the CNN-DM can decrease the detection complexity effectively.

TABLE II.   COMPUTATIONAL COMPLEXITY OF THE DETECTOR

Detector	Complexity(flops)
CNN-DM	$N_r C(2Q + 4N_t + 5) + 2QP + Q + 3P$
DNN-DM	$Q_1(4N_r N_t + 4N_r + 1) + Q_2(2Q_1 + 2P + 1) + P$
ML	$2^h m_A^{P_1} m_B^{P_2}(8N_p N_r + 4N_p - 1)$
ZF	$2^h(12N_r N_p^2 + 7N_p^2 + 6N_r N_p + 4N_p^3 - 2N_p)$
MMSE	$2^h(12N_r N_p^2 + 7N_p^2 + 6N_r N_p + 4N_p^3)$

V. CONCLUSION

In this paper, two signal detectors based on DNN and CNN in the DM-GSM system are proposed to explore the mapping relationship among the received symbols, the channel matrix, and the transmitted bits, and balance the detection performance and the complexity. Simulation results indicate that the proposed CNN-DM achieves excellent BER performance close to the ML detection at lower complexity, while obtaining better BER performance than the DNN-DM, ZF detector and MMSE detector. Furthermore, the CNN-DM scheme has better robustness compared with the conventional detection algorithms under non-standard Gaussian noise distribution. In the future, we will continuously optimize the overall structure of the system, such as improving the system detection performance through antenna selection algorithms.

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