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Design and Optimization of Intelligent Antenna System Based on Convolutional Neural Network

Ting-Ting Sun
Huaibei Vocational and Technical College
Huaibei 235000, P. R. China
13965862272@163.com

Fei Li*
Huaibei Vocational and Technical College
Huaibei 235000, P. R. China
lf2024123@126.com

Qin Zhang
Dongseo University
Busan 47011, South Korea
qp9406@163.com

*Corresponding author: Fei Li
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Abstract. *As the key communication technologies rapidly growing, the number of smart antennas configured in communication systems is increasing. As a key part of wireless communication, smart antenna system has always been the focus of research in the field of communication. In this article, a design and optimization method of smart antenna system on the ground of Convolutional Neural Network (CNN) is suggested to address the issues of large computation and slow convergence of current smart antenna system design algorithms. Firstly, CNN is adopted to estimate the signal arrival direction of the smart antenna in wireless communication, and only some elements of the upper or lower triangle of the correlation matrix are considered as the input of the network, which effectively reduces the calculation amount. Secondly, the antenna array signal data set is constructed, and binary multiple labels are used to define labels for data set samples. Then, the convolution characteristics of CNN in deep learning are adopted to capture the statistical characteristics of the receiving and transmitting channels, and relied on the above optimized calculation model, the optimal outcome of the antenna array signal at both the sending and receiving ends is obtained by multi-channel method, so as to realize the signal separation of different users. The experimental outcome indicates that compared with the comparison method, the suggested optimization method has lower NMSE and computation time consumption, which proves the effectiveness of the suggested optimization method.*
Keywords: Smart antenna; Convolutional neural network; Binary multi-label; Deep learning; Computational model

1. **Introduction.** Smart antenna is a significant research topic in today's mobile communication system, and it is also one of the key technologies to further increase the system capacity to achieve Space Division Multiple Access (SDMA) [1]. Smart antenna in mobile communications is mainly used for base stations in wireless cellular systems in the near future. It absorbs the advantages of the original multi-access mode and can reuse space

resources more effectively. The function of smart antenna is mainly manifested in that it can adaptively judge the signal direction and number, track the expected signal, and then beamforming through the downlink will generate the maximum gain in the expected signal direction and minimize the interference square gain, thus suppressing the interference signal [2, 3, 4]. Because the smart antenna often receives multi-path signals, and the number of signal sources may be more than the number of antenna array elements. The complexity of the channel puts forward higher requirements for the selection and judgment of the arrival direction of the signal, which is also the technical key to the practical application of the uplink [5, 6]. Therefore, the design and optimization of smart antenna system is urgent. In an environment where users are densely distributed, multi-user concurrency will greatly increase the interference in the space. Smart antenna needs technical means, such as neural network, to reduce interference and improve the experience of users close to the coverage edge.

1.1. **Related work.** Sung et al. [7] offered a microstrip antenna with reconfigurable direction pattern by changing the current distribution on and off the antenna surface by controlling the PIN diode. Song et al. [8] suggested an incremental antenna structure where each iteration selects an antenna to be added to the desired antenna subset. Salucci et al. [9] designed an antenna optimization structure based on norm and improved the antenna design algorithm based on the channel capacity maximization criterion. Khatami et al. [10] suggested a generalized bit plane matching tracking transmit antenna scheme, but this scheme requires the number of selected antennas to be equal to the number of users, which has limitations. Chen et al. [11] proposed a Monte Carlo tree search method based on self-supervised learning to address large-scale antenna optimization problems. Caccami et al. [12] adopted decision tree and multi-layer perceptron algorithm as the design method of transmitting antenna. Ding et al. [13] designed a transmitting antenna optimization algorithm relied on the criterion of maximizing the total power of the user's received signal, reducing the algorithm complexity. Zhu et al. [14] studied the joint distribution mechanism of 3D beamforming and power distribution in smart antenna systems, which assumes that users obey uniform distribution.

Artificial intelligence technology has brought new ideas to solve the difficulties encountered in the optimization of smart antenna, and more and more communication scholars have begun to study the application of deep learning technology to the design of smart antenna. Machine learning algorithms, such as artificial neural network (ANN) and support vector machine (SVM), are used to assist the optimization problem in antenna design. This method can alleviate the calculation pressure brought by full-wave simulation and accelerate the system design process. By training the model to predict the antenna performance, the expensive and time-consuming electromagnetic simulation times are reduced. Zhang et al. [15] offered a structure and design method of a smart antenna receiver based on deep learning, which uses autoencoders and decoders for data target detection. Enriconi et al. [16] suggested to use radial basis function neural network to optimize the signal arrival algorithm of smart antennas in wireless communication, but the calculation amount was large. Xu et al. [17] proposed a design scheme of smart antenna system based on BP neural network, and designed the structure model of smart antenna system composed of microwave connector antenna and neural network, but the signal processing time was relatively long. Al-sadoon et al. [18] modeled the antenna system in a Multi Measurement Vector (MMV) model and then used the Bayesian network model to achieve a high-performance smart antenna system. Zhong et al. [19] adopted deep learning technology to seek alternative algorithm for antenna polarization code decoding in flat fading channels, and achieved coding gain in fading channels. Ullah et al. [20] designed an antenna design scheme relied on deep Convolutional Neural Network (CNN). CNN was adopted to train and learn antenna array signals without optimizing the antenna calculation model. Although the prediction accuracy was improved, the calculation time was long.

1.2. **Contribution.** Existing optimization methods for smart antenna systems, despite their high resolution, are generally large in computation and slow in convergence, making it tough to achieve effective signal selection in environments that require high-speed real-time processing. To deal with the above issues, this article suggests a smart antenna system design and optimization method relied on CNN. Firstly, the CNN is adopted to estimate the signal arrival direction of the smart antenna in wireless communication, using the symmetric nature of the signal correlation array, and only considering some elements of the upper or lower triangle in the correlation array as the inputs to the network, which effectively reduces the amount of computation. Secondly, the antenna array element signal data set is constructed, the channel matrix is obtained, the samples of the data set are preprocessed, and the label is defined for the samples of the data set by using the multi-label method. Then, a two-channel convolutional neural network model is used to select the antenna array signals for both transceivers and receivers, and the training model is iteratively updated by the acquired data set, and the optimal results are obtained based on the above optimized computational model to realize the signal separation of different users. The experimental results show that the proposed optimization method improves the NMSE and computation time consumption indexes compared with the comparison method, which illustrates the effectiveness of CNN optimization of smart antenna system.

2. Theoretical analysis.

2.1. **Theory of smart antenna.** Smart antenna, also known as adaptive array antenna, is an antenna system that can automatically adjust its radiation pattern according to the changes in wireless communication environment. Smart antenna is a new type of antenna, according to the feedback information of the desired user, selectively cover the main flap to the desired user, and use the side flap to exclude the interference signal, so as to save the channel resources and eliminate interference [21]. The workflow of the smart antenna system is shown in Figure 1, which receives the feedback information from the desired user and obtains the transmit power estimation and the direction of arrival of the signal wave from this information. On this basis, the uplink beam is fitted to enhance the concentration of coverage.

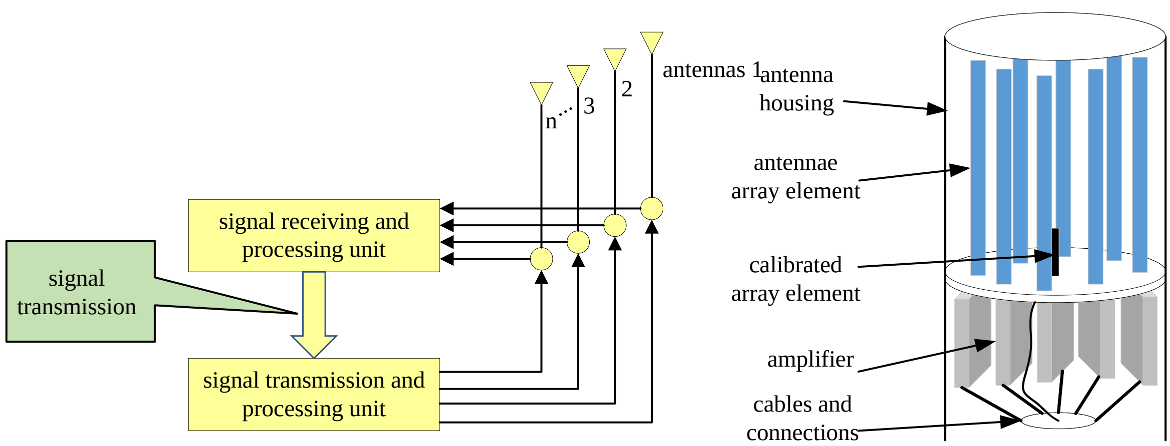

Figure 1. The structure of the smart antenna

Let the number of array elements of an equally spaced linear array be M, the spacing of the array elements be d, the first array element be the reference array element, and the angle between the incident direction of the signal $s(l)$ and the normal direction of the antenna array be Θ. The time difference between signal $s(l)$ arriving at the j-th array element and arriving at the reference array element is as follows.

$$\phi_j(\Theta) = (j-1)\frac{a}{d}\sin\Theta \tag{1}$$

where d is the speed of light. If the carrier frequency is f, the induced signal of $s(l)$ at the j-th array element can be expressed as below.

$$x_i(l) = v(l)\, e^{j2\pi f\left[l-\phi_i(\Theta)\right]} = x_1(l)\, e^{-j2\pi\phi_i(\Theta)} \tag{2}$$

Represent the signal $s(l)$ induced on the antenna array as a vector as follows.

$$X(l) = [x_1(l)\; x_2(l)\; \ldots\; x_M(l)]^T = \beta(\Theta)\, x_1(l) \tag{3}$$

where $\beta(\Theta)$ is called the bootstrap vector and can be expressed as below.

$$\beta(\Theta) = \begin{bmatrix} 1 & e^{-j\frac{2\pi}{\lambda}c\sin\Theta} & \ldots & e^{-j(M-1)\frac{2\pi}{\lambda}} \end{bmatrix} \tag{4}$$

where λ is the carrier wavelength.

2.2. **Convolutional neural network.** A CNN consists of one or more convolutional layers and a fully connected layer at the top (which can also be pooled to reduce the number of parameters and dimensionality). The local connectivity and weight sharing make convolutional networks very useful in image processing and speech processing [22], as indicated in Figure 2. Each convolutional and pooling layer in a CNN is followed by a nonlinear activation function.

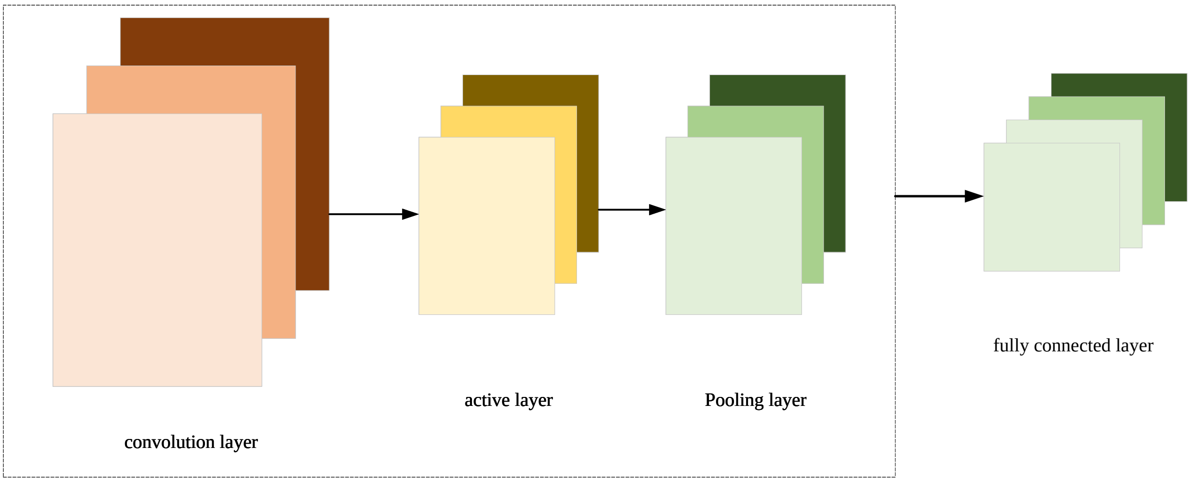

Figure 2. Network structure of CNN

In a CNN, the convolutional level convolves the input using a learnable filter and then obtains the mapping; then a nonlinear activation function is operated, usually using a function such as the Relu function; and then a pooling level is used to further compress the representation and reduce the number of parameters, commonly known as maximum pooling and average pooling, which are used as inputs to the convolutional level for processing. The fully-connected layer outputs the outcome of the model at the end [23].

3. **Computational model of smart antenna based on CNN.** Intending to the current smart antenna computational model with large computational capacity and slow convergence speed, this article utilizes CNN to estimate the signal arrival direction of smart antenna in wireless communication. To reduce the input using the symmetric nature of the signal correlation array, only the upper or lower triangular elements of the correlation array are considered as the input to the network, which effectively reduces the amount of computation.

The N antenna units are equally spaced d to form a linear antenna array. The signal is pre-processed and fed into a four-layer network (convolutional, pooling, activation, and fully connected levels), and then post-processed to obtain an estimate of the direction of incidence of the signal. The first input antenna signal matrix passes through two channels. The more complex one consists of three serial convolutional levels, which are responsible for providing a large-area view of the signal matrix features. The other simpler channel consists of one 3×3 convolutional level, which is responsible for providing high-resolution features of the channel state information matrix. The features extracted from these two channels are then concatenated and the activation function on the activation level is a Gaussian activation function [24] as indicated below.

$$G(x) = \exp\left(-x^2/\delta^2\right) \tag{5}$$

where δ is the width of the Gaussian function. Let there be L ($L < N$) narrowband signals from space, and the signals received by an equally spaced line antenna array are as below.

$$x_n(s) \;=\; \sum_{l=1}^{L} t_l(s)\, e^{-j(n-1)2\pi\frac{c}{\lambda}\sin\vartheta_l} \;+\; m_n(s) \tag{6}$$

where t_l and ϑ_l are the l-th incident signal and its Boda angle, λ is the carrier wavelength, $m_n(s)$ is the zero-mean Gaussian white noise of the nth array element, and c is the antenna array element spacing. The matrix form of Equation (6) is indicated below.

$$X(s_0) = B\,T(s) + N(s) \tag{7}$$

where B is the $N \times L$–signal oriented matrix, i.e.,$B = \left[b(\vartheta_1),\, b(\vartheta_2),\, \ldots,\, b(\vartheta_L)\right]$, where $b(\vartheta_l)$ is computed as follows:

$$b(\vartheta_l) = \left[\,1,\; e^{-j2\pi\frac{c}{\lambda}\sin\vartheta_l},\; e^{-j4\pi\frac{c}{\lambda}\sin\vartheta_l},\; \ldots,\; e^{-j(M-1)2\pi\frac{c}{\lambda}\sin\vartheta_l}\,\right]. \tag{8}$$

The issue of predicting the arrival direction of space signals is essentially to solve the problem of mapping the antenna output signal space $\{X(s) = [x_1(s), x_2(s), \ldots, x_N(s)]^T\}$ to the signal direction space $\{\vartheta = [\vartheta_1, \vartheta_2, \ldots, \vartheta_L]\}$. The correlation array of the received signals needs to be calculated:

$$R = \mathbb{E}\{X(s)X(s)^H\} = B\,\mathbb{E}\left[T(s)S(T)^H\right] B^H + \mathbb{E}\left[M(s)M(s)^H\right]. \tag{9}$$

The $N \times N$–dimensional correlation matrix is obtained, where $\mathbb{E}(\cdot)$ denotes the statistical average and H denotes the conjugate transpose. Since the correlation matrix contains all the information of the antenna incident signal, and R is Hermitian so that $R(i,j)$ and $R(j,i)$ have the same information, and the diagonal elements do not contain signal direction information, only the upper triangular elements are considered, forming the vector

$$r = [\,R_{12}, R_{13}, \ldots, R_{1N}, R_{23}, R_{24}, \ldots, R_{N-1,N}\,]. \tag{10}$$

Considering that the antenna may receive an undesirable narrow-band signal, each complex element in r is split into its real and imaginary parts, forming a new vector r'

of twice the length. The normalized vector $W = \frac{r'}{\|r'\|}$ is used as the input to the network, where $\|\cdot\|$ denotes the Euclidean norm. As the data propagates from the input layer to the activation level, a Gaussian activation function is applied:

$$G_{kl} = \exp\left(-\frac{\sum_{s=1}^{S}\left(W_{ks} - C_{ls}\right)^2}{\delta^2}\right), \tag{11}$$

where C_{ls} is the s–th component of the l–th desired signal vector, $l = 1, 2, \ldots, L$, $k = 1, 2, \ldots, K$, and δ is the width of the Gaussian function.

Fully connected levels alone do not yield an angle estimate and must be combined to produce the final output:

$$\vartheta = G^T V, \tag{12}$$

where ϑ is the network's output antenna signal angle vector and V is the weight vector of the fully connected layer.

4. Design and optimization of smart antenna system based on CNN.

4.1. Modeling of smart antenna system. The essence of smart antenna optimization is to realize the signal separation of different users by selecting the array signals at the transmitter side while selecting the array signals at the receiver side. Most of the optimization methods of transmitter–receiver smart antenna system in the existing research is to fix one side to carry out antenna array signal tampering before transferring to the other side, which is still unilateral processing in essence, and this method not only leads to the increase of computation, but also cuts off the antenna signal correlation between the transmitter and receiver to a certain extent. The entire model of the optimized smart antenna system is indicated in Figure 3.

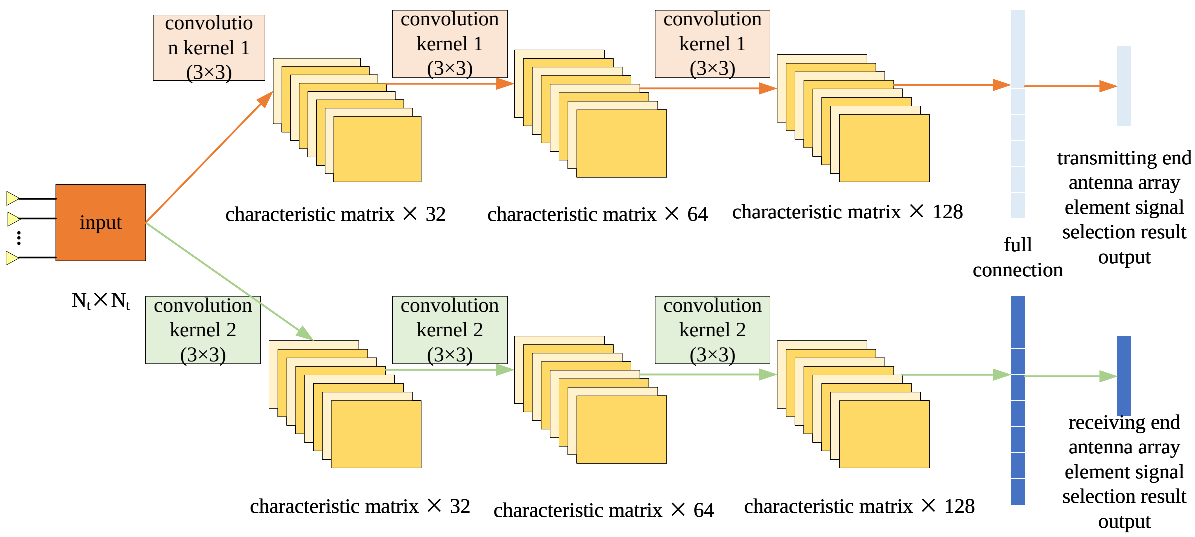

Figure 3. CNN-based optimization model for smart antenna systems

Focusing on the above issues, this section proposes a CNN-based design and optimization method for the transmitter-smart antenna system, which uses the convolutional characteristics of CNN in deep learning to capture the statistical characteristics of the channel at the receiver and the transmitter, and obtains the antenna array signal results of the transmitter and receiver at the same time based on the optimized computational model mentioned above by using the multi-channel method, so as to ensure the communication connection between the transmitter and the receiver.

Assume that the transceiver and receiver ends of the antenna are configured with M_s and M_t array elements, and the number of RF links at the transmitter and receiver ends are L_s and L_t. Based on the channel capacity maximization criterion [?], L_t received signals need to be selected from M_t array elements at the receiver end, and L_s transmitted signals need to be selected out of M_s array elements at the transmitter end. Between the transmitter and receiver side is a flat Rayleigh fading channel, denoted by the random channel matrix $\mathbf{H}$. Assuming that both the transmitting and receiving elements of the antenna are used for communication, the signal received at the receiving end can be expressed as follows.

$$y = Hx + m \tag{13}$$

where x is an M_s-dimensional independent identically distributed transmit signal satisfying $E[x^H x] = \mu$ and m is a complex noise vector with M_t dimensions, mean 0 and variance δ_m^2.

The channel matrix H is defined as below.

$$\mathbf{H} = \begin{bmatrix} h_{11} & h_{12} & \cdots & h_{1M_s} \\ h_{21} & h_{22} & \cdots & h_{2M_s} \\ \vdots & \vdots & \ddots & \vdots \\ h_{M_t1} & h_{M_t2} & \cdots & h_{M_tM_s} \end{bmatrix} \tag{14}$$

Assuming that the receiver knows the perfect channel state information and the transmitter performs equal power allocation, the channel capacity of the antenna system of $M_t \times M_s$ is expressed as follows.

$$D_t \;=\; \log_2\!\left[\det\!\left(J_{M_t} + \tfrac{\gamma_R}{M_s}\, H_{ch} H_{ch}^H\right)\right] \;-\; \log_2\!\left[\det\!\left(J_{M_e} + \tfrac{\eta_E}{N_t}\, G\, G^H\right)\right] \tag{15}$$

where H_{ch} is defined as the selected channel matrix and L_s and L_t are the number of selected signals at the transmitter and receiver, respectively.“‘

4.2. **Smart antenna dataset construction.** For smart antenna systems, the number of array element signals will increase exponentially, and if the definition method of multi-categorized labels is used, it will increase the computational complexity of the neural network. Therefore, in this section, we introduce the definition method of binary multi-label [26], where each array element signal corresponds to one label, assuming that there is a transmitter with M_s transmitting signals, and the best antenna L_s is selected for signal transmission, there will be L_s labels in the data set for each data sample of the Channel State Information (CSI), where the selected signals are labeled as 1, and the unselected signals are marked as 0.

Firstly, after obtaining the channel matrix $H \in \mathbb{Z}^{M_t \times M_s}$ of the smart antenna system, we take the modulus value of its elements to form $C \in \mathbb{Z}^{M_t \times M_s}$ as the feature matrix of the data set. We then obtain the optimal antenna array subset $t \in \{t_1, t_2, \ldots, t_l\}$ based on the original CSI data samples as in Section 3. The M channel state information samples form the training dataset, denoted by $\left[(H^1, G^1), (H^2, G^2), \ldots, (H^N, G^N)\right]$.

Next, before model construction and prediction, we extract and normalize the feature vectors of each antenna array element signal sample. The specific steps are as follows.

(1) Real-valued vector generation. Generate a real-valued vector $c^m = [\, c_1^m,\, c_2^m,\, \ldots,\, c_M^m \,]$ of size $1 \times M$, where $M = M_s \times (M_t + M_e)$. This vector is formed by the absolute values of the channel matrix elements:

$$c^m \;=\; \left[\, |h_{11}^m|, \ldots, |h_{1M_s}^m| \mid |h_{21}^m|, \ldots, |h_{M_sM_s}^m| \mid \cdots \mid |g_{11}^m|, \ldots, |g_{1M_s}^m| \mid |g_{21}^m|, \ldots, |g_{2M_s}^m| \mid \ldots \right]. \tag{16}$$

(2) Extraction of feature vectors. From each of the N antenna array element signal samples, extract the feature vectors $c^1, c^2, \ldots, c^N$.

(3) Normalization. Normalize each eigenvector by

$$s_j^m = \frac{c_j^m - E(c^m)}{\max(c^m) - \min(c^m)}, \quad j = 1, 2, \ldots, M, \tag{17}$$

where c_j^m is the j-th element of the feature vector c^m and $E(\cdot)$ denotes the mean value.

Then define a multi-label vector t^n for the antenna array element set $y = [y_1, y_2, \ldots, y_n]$, where n is the total number of array elements at the transmitter or receiver, and each element in the multi-label vector y represents whether the array element is selected or not. The optimal antenna array element set is mapped to the corresponding label vectors, and the label vector at the transmitter side is denoted as $y^s \in \mathbb{R}^{1\times M_s}$ and the label vector at the receiver side is denoted as $y^t \in \mathbb{R}^{1\times M_t}$. Finally, the feature matrix C and the label vectors are generated several times to form the sample data set.

4.3. **CNN-based smart antenna system design and optimization.** The entire network consists of two channels to extract different features of the input matrix, and has three parts: the input layer, the feature extraction layer and the output layer. The input layer is an input matrix D of $M_t \times M_s \times 1$. Starting from this layer, the next structure transforms the matrix of the previous layer into the input matrix of the next layer until the last fully connected layer. The feature extraction consists of three convolutional levels. The input matrix C is filtered by the first layer 3×3 to get 32 feature matrices, then by the second layer to get 64 feature matrices, and finally by the third layer to get 128 feature matrices. The antenna channel characteristics can be obtained through the multi-layer convolution operation. The feature matrices obtained from the convolutional levels are fed into the respective channel classification layers to make the final decision, and the final outputs are mapped into signal combinations to obtain the antenna array selection results at both the transmitting and receiving ends.

The output of each level of the convolutional level is de-linearized by the Relu activation function, and the output nodes of the fully connected level are finally input to the Sigmoid activation function, which is calculated as below.

$$f(x) = \frac{1}{1 + e^{-x}} \tag{18}$$

After the sigmoid activation function, the output node return value is in the range of $[0, 1]$, and a suitable probability threshold is set according to the number of labels, i.e., nodes larger than the probability threshold are determined as 1, and nodes smaller than the probability threshold are determined as 0, so as to obtain the output vector of predicted labels at the transmitter side, $\hat{y}^s \in \mathbb{R}^{1\times M_s}$, and the vector of predicted labels at the receiver side, $\hat{y}^t \in \mathbb{R}^{1\times M_t}$. The output vector of predicted labels at the receiver side is the vector of predicted labels at the receiver side.

In the training process of the model, the loss function is constructed to calculate the error between the predicted value and the real value, and the parameters of the model are updated by minimizing the loss function to improve the performance of the optimization model. Since the network structure designed this time contains two channels to get the prediction of the antenna array elements at the transmitter and receiver ends respectively, we will calculate the loss function of the two channels separately, and the loss function of the channel at the transmitter end of the antenna will be calculated as follows for the transmitter channel of the antenna:

$$L_s(y^s, \hat{y}^s) \;=\; -\sum_{j=1}^{M_s}\big(y_j^s \log y_j^s + (1-y_j^s)\log(1-y_j^s)\big) \tag{19}$$

The loss function for the receiver channel is as follows:

$$L_t(y^t, \hat{y}^t) \;=\; -\sum_{j=1}^{M_t}\big(y_j^t \log y_j^t + (1-y_j^t)\log(1-y_j^t)\big) \tag{20}$$

Therefore, the total loss function used in the model of this paper is expressed as below.

$$L(y^s, \hat{y}^s, y^t, \hat{y}^t) \;=\; L_s(y^s, \hat{y}^s) \;+\; L_t(y^t, \hat{y}^t) \tag{21}$$

5. System performance testing and analysis.

5.1. Comparison of classification performance. For the goal of verifying the performance of the CNN-based designed and optimized smart antenna system, simulation experiments are conducted in this paper based on `Python 3.8`. The hardware parameters used are 2.60 GHz Intel Core i5-9300H processor, 16 GB RAM, and Windows 10 operating system. The CNN network is constructed using the deep-learning framework TensorFlow [27] and the smart antenna system was trained in the PyCharm compiler. The antenna has the number of transmitter array elements $M_s = 20$, and the number of receiver array elements $M_t = 16$, $L_s = 8$, and $L_t = 4$; the initial learning rate is set to 0.5.

This article synthesizes the NMSE [28] for the smart antenna system (CSAN) optimized in this paper, and the existing optimization methods DLOS [15] and DCNN [20] are used for the comparison experiments. Figure 4 demonstrates the comparison results of NMSE with different models. From Figure 4, it can be seen that with the gradual increase of SNR, the NMSE values of all algorithms decrease. The NMSE performance of the CSAN algorithm is significantly better than that of the DLOS method at any SNR. It is worth noting that the NMSE performance of the CSAN algorithm is better than that of the DCNN algorithm when the SNR is higher than 5 dB [28]; however, the NMSE performance of the DCNN method is better when the SNR is lower than 5 dB. In the DCNN algorithm, a DNN model needs to be trained with a specific SNR value; therefore, the algorithm performs well only around the specific SNR used for model training. Unlike DLOS, the proposed CSAN algorithm does not need to use a large amount of data to train the antenna array elements, and predicts the direction of arrival of the signals from the antenna array elements by three-layer convolution, which effectively reduces the computation amount of the antenna.

Then the method of this paper (CSAN) and DLOS, DCNN simulation comparison of the size of the computational volume; respectively choose two and three desired signal cases, compare the processing time of these two methods after a number of simulation comparisons to obtain a set of average processing time as indicated in Table 1. It is obvious that CSAN is better than DLOS and DCNN and has faster processing speed. This is due to the fact that the training and working of the network are separated, and the network can work directly after training, and its processing time is mainly used in obtaining some elements of the signal correlation array, and the input of the elements can directly generate the direction estimation, and the output of the weights is already completed in the training. The DLOS algorithm has to decompose the signal correlation array and analyze the power spectrum before outputting the direction estimation, which increases the complexity of the hardware implementation. Although the DCNN method is based on CNN for the antenna system design, it does not optimize the direction of

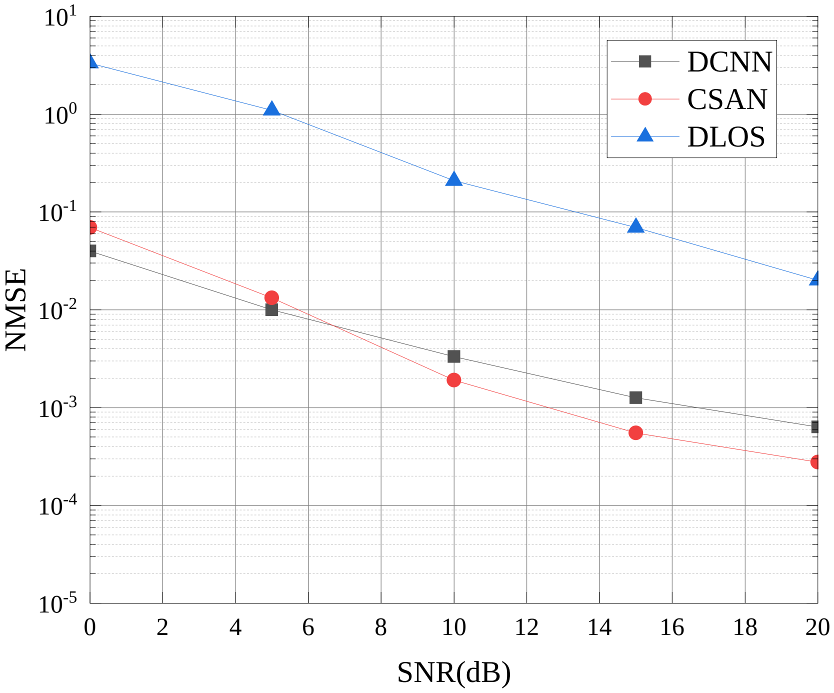

Figure 4. NMSE comparison of different smart antenna optimization methods

arrival of the signal of the smart antenna system, so the computational time consumption is higher than that of the CSAN.

Table 1. Comparison of computation time for different optimization methods

Method	DLOS		DCNN		CSAN	
Desired Signal Number	2	3	2	3	2	3
Average time /s	0.623	0.815	0.217	0.192	0.041	0.021

5.2. **Convergence analysis.** In order to study the convergence of CSAN for optimized smart antenna system, experiments are carried out on signals with different SNR values and the variation of NMSE values of the CSAN method is observed. The results are shown in Fig. 5. When the SNR value increases, the NMSE value of the CSAN method will decrease accordingly. When the number of iterations is 30, there is a large decrease in the NMSE, and then there is a small fluctuation when it reaches 40, indicating that the optimized smart antenna system in this paper is more stable. In addition, for all SNR values, the CSAN method can converge within 80 iterations.

Figure 6 compares the variation of the loss function of the CNN when performing the signal selection of the antenna transceiver array elements, and the image reflects the gap between the predicted value and the true value using the CNN. From the figure, it can be seen that as the number of iterations of the model increases, the gap between the predicted and true values of both the antenna transceiver and the antenna transceiver are decreasing, and by calculating the loss function in each round, the model performs backpropagation to update the parameters and reduce the loss to achieve the purpose of further learning. From the simulation results, it can be seen that with the increase of the number of model iterations, the CNN-based smart antenna system optimization method proposed in this section can achieve better feature learning ability at both the transceiver and receiver ends, which verifies that the model has better robustness in the selection of transceiver array element signals.

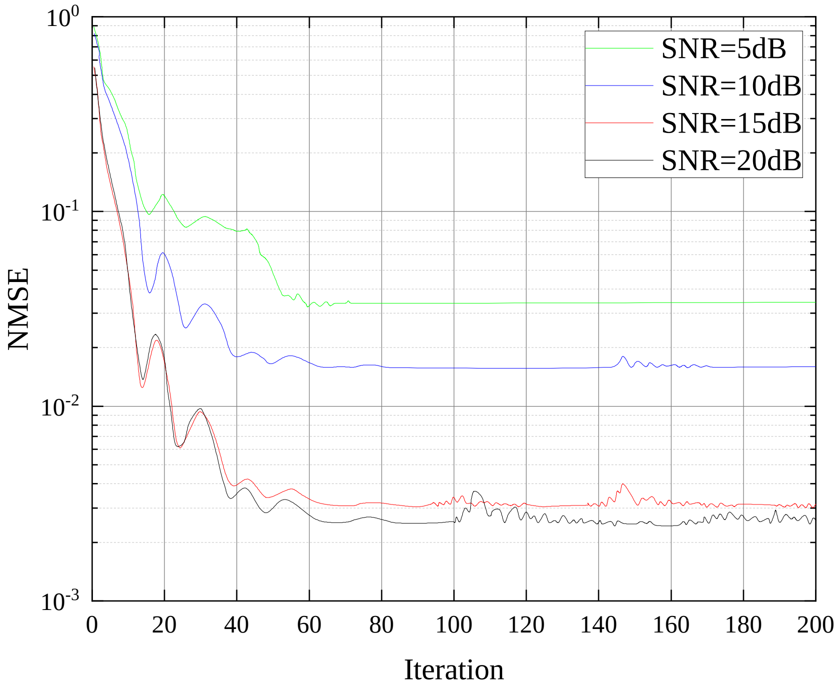

Figure 5. The convergence of CSAN

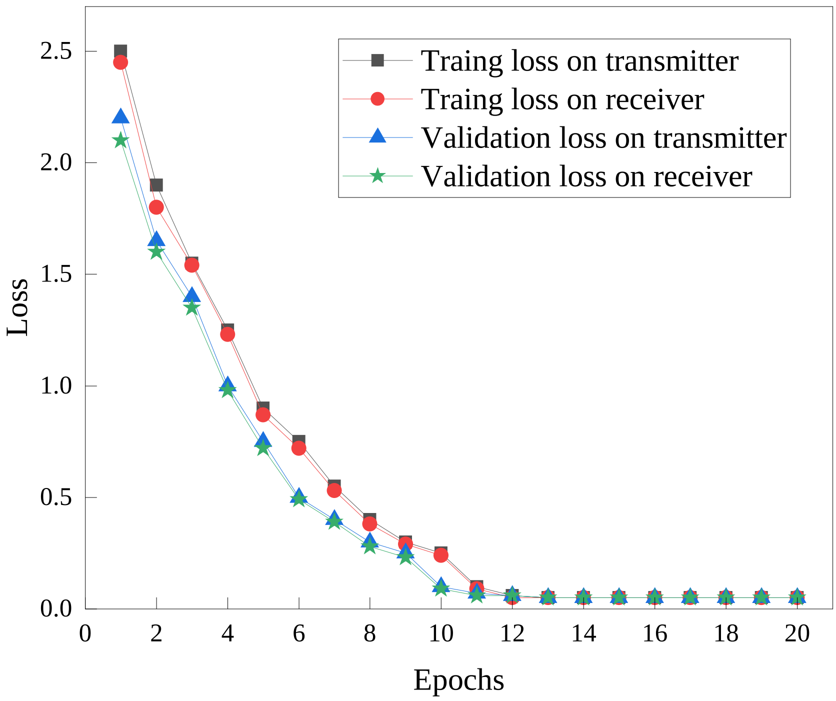

Figure 6. Variation of loss function for CSAN

6. **Conclusion.** Focusing on the current smart antenna system optimization methods with large computational volume and slow convergence speed, this paper proposes a smart antenna system design and optimization method relied on CNN. Firstly, CNN is utilized to estimate the signal arrival direction of the smart antenna in wireless communication, which effectively reduces the computational amount. Secondly, we construct the antenna array element signal dataset, obtain the channel matrix, preprocess it to get the samples as the dataset, and define the labels for the dataset samples by using the multi-label

method. Then, we use the convolutional characteristics of CNN in deep learning to capture the statistical characteristics of the channels at the receiving end and the transmitting end, select the array element signals for both the transmitting and receiving ends of the antenna, and iteratively update the training model through the acquired data set to finally obtain the optimal antenna array element signal model. The experimental results show that the proposed method has low NMSE and computation time consumption, and can be better applied to the optimization of smart antenna system.

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