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DOA Robust Estimation of Echo Signals Based on Deep Learning Networks With Multiple Type Illuminators of Opportunity

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ABSTRACT Traditional DOA estimation algorithms have poor adaptability to antenna errors. To enhance the direction of arrival (DOA) estimation performance for moving target echo signals in the environment of multiple type illuminators of opportunity, a DOA estimation framework leveraging deep learning networks (DLN) is proposed. In the proposed framework, the DLN is divided into two main components, including linear classification networks (LCN) and convolutional neural networks (CCN). The LCN is utilized to identify the spatial subregion of received signals and divide the signals from each subregion into corresponding output modules. Then, the output of the LCN after matrix transformations will be input into multiple parallel CNNs, where DOA estimations are carried out. Extensive simulation studies are conducted, demonstrating that our proposed method has excellent estimation performance and strong universality with high estimation accuracy even under large antenna defects.

INDEX TERMS Convolutional neural networks, deep learning networks, direction of arrival estimation, illuminator of opportunity, linear classification networks.

I. INTRODUCTION

In the moving target detection, illuminators of opportunity are fundamental and important for observation data information, which may be realized by heterogeneous radiation sources, such as FM radio, communication base stations, digital TV, and satellites. Unfortunately, due to a fact that radiation sources may result in complicated electromagnetic environments, it is difficult to carry out target detections in such an environment. Therefore, some scholars have begun to study the target detection technology under complicated electromagnetic environments [1]–[3]. Direction of arrival (DOA) estimation is one of technologies in the moving target detection. The basic idea behind the DOA estimation is to estimate the wave direction by using the measurement data received by the sensor array arranged in a certain way. Obviously, the position parameters of the moving target could be more precisely estimated with both DOA estimations and the time delay difference considered compared to only relying on either of them. However, DOA estimations in the moving target detection is very challenging because of complicated electromagnetic environments. Therefore, in this paper, we focus on studying DOA estimations in the moving target detection under multiple illuminators of opportunity.

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Recently, more and more scholars have participated in the research on the DOA estimation and made great progress [4]–[6]. One of representative work is the MUSIC algorithm and the corresponding improved methods, like ROOT-MUSIC [7]. In addition, rotation invariant subspace based methods have also been proposed to address DOA estimation problems [8], [9]. in [10] DOA estimation was performed using the MUSIC method and the ESPRIT method, and the performance of the MUSIC and ESPRIT algorithms were compared according to the required calculation time and estimated DOA resolution. although the ESPRIT algorithms can effectively avoid a large number of calculations, such as spectral peak search, and improve the parameter estimation efficiency, this method cannot always possess preferable performance, which has a slightly worse estimation accuracy than the MUSIC algorithm. Notably, traditional DOA estimation methods have to depend on the strong assumptions of specific antenna array types or the antenna array geometry, making these method unable to adapt to general cases. For example, the methods introduced in [11]–[13], are merely applicable in particular antenna array patterns and may not be able to achieve good performance in other cases and correct the errors caused by unsuitable antenna array patterns. To overcome these problems, some scholars have proposed some methods that do not need to correct array errors [14], [15].

Deep learning technologies and artificial neural network have been used in array signal processing and array antenna technologies [16]. The DOA estimation method based on multilayer perception have been proven to be able to realize high resolution in DOA estimations [17], [18]. In [19], the authors proposed a DOA estimation method based on radial basis neural network (RBFNN) for uncorrelated and related signals, which have proven that can greatly reduces the CPU time for DOA estimations, but there is some decrease in estimation accuracy Furthermore, to enhance the positioning accuracy of the RBFNN method, DOA estimation methods based on back propagation (BP) neural network were proposed, in which the particle weight algorithm (PSO) was used to optimize the weight and threshold [20]. In addition, the convolutional neural networks are used for sound source DOA estimation [21]–[23], when there are sufficient training samples, good estimation performance can be obtained by using convolutional neural networks. The authors in [24] proposed a DOA estimation method based on deep neural networks (DNN), which can achieve a higher estimation accuracy compared to the methods based on support vector machine (SVM). Unfortunately, this method is applicable only when the signal angle is in the range of $\theta \in [-60, 60]$. Apparently, existing traditional DOA estimation methods are designed for particular antenna array patterns and are not applicable in general cases. While deep learning based methods are used for DOA estimations, the network generalization burden is very large and input data can not be fully utilized, resulting in low accuracy of the estimation performance.

Thus, in this paper a deep learning networks (DLN) framework is proposed for DOA estimation, consisting of two main components, a linear classifier networks (LCN) and a convolutional neural networks (CNN). The LCN is leveraged to conduct preliminary classification, in which the output units of the LCN are comprised of P groups. Each group of output units represents a spatial subregion of a certain angular range. The signals are processed by LCN and output into different units. Then the CNN is responsible for DOA estimations in each subregion. The main innovative contributions of the proposed method are summarized as follows:

- A novel DOA estimation method using deep learning networks (DLN) is put forward consisting of linear classification networks (LCN) and convolutional neural networks (CCNs).
- The LCN is employed to simplify the burden of CNN and improve estimation performance. Additionally, $L1$ regularization terms are deployed in LCN to address the overfitting issue. CNNs are applied to perform DOA estimations, where CNNs take fully advantages of the connection between the real and imaginary signals for the DOA estimation performance improvement.
- The parameters in neural networks and deep learning are optimized by extensive simulation studies.

The rest of this paper is organized as follows. The system model and signal model are presented in Section II. The preprocessing of received signals is expressed in Section III. The DLN framework and DOA estimation method are introduced in Section IV. The DLN training precess is described in Section V. Section VI shows the numerical examples to verify the estimation performance. Finally, Section VII concludes the main work of this paper.

II. SYSTEM MODEL AND SIGNAL MODEL

A. SYSTEM MODEL

As shown in Fig. 1, a receiver will receive two types of signals through two channels, a surveillance channel and a reference channel. One is echo signals which is generated by the irradiation of illuminators of opportunity from a moving target. Another one is direct waves from multiple type illuminators of opportunity directly. Echo signals and direct waves are received on a surveillance channel and a reference channel, respectively. Since the position of the illuminator of opportunity is known, we are only concerned with the condition of the surveillance channel. In practice, on a surveillance channel, the receiver will receive not only echo signals, but also direct wave signals and multipath signals.

As the power of direct wave interference signals and multipath interferenc signals are much stronger than echo signals, echo signals may be submerged in the interference. Therefore, we need to suppress the direct path interference (DPI) and the multiple path interference (MPI) on the surveillance channel. Since the current research on suppression technology is quite mature, many existing DOA estimation methods are based on the assumption that interference signals could be effectively suppressed [25]. Without loss of generality, in this

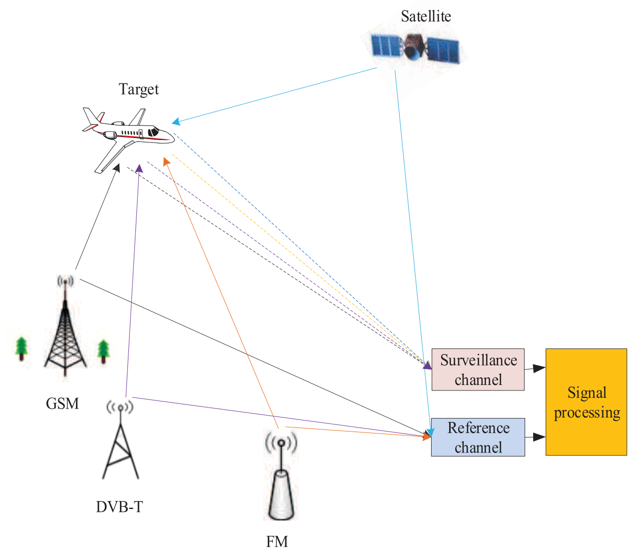

FIGURE 1. System model.

paper it is assumed that interference signals are suppressed with the method introduced in [26].

B. SIGNAL MODEL

An array antenna composed of antenna elements receives echo signals. These echo signals are a mixed signal composed of independent illuminator of opportunity reflected by the target. After DPI and MPI suppression, the received signal can be expressed as

$$x(t) = \sum_{k=1}^{K} a(\theta_k)s_k(t)+n(t), \tag{1}$$

where $s_k(t)$ represents various illuminators of opportunity signal components in the echo signals, $a(\theta_k)$ represents the array responding function, and θ_k is the angular information of the echo signal of each illuminator of opportunity. Since the propagation path of the echo signal is from the target to the observation antenna, the incident angle $\theta_1 = \theta_2 = \ldots = \theta_k = \theta$, and $n(t)$ stands for zero mean Gaussian noise.

After the received signal being sampled, it can be expressed as follows

$$x(t_q) = \sum_{k=1}^{K} a(\theta)s_k(t_q)+n(t_q), \quad for\ q = 1, \cdots, Q, \tag{2}$$

where t_q represents sampling time.

In actual scenarios, due to the influence of various error factors, the preset array responding function often cannot accurately correspond to the actual antenna. e is used as the error parameter, then the model of the signal can be expressed as

$$x(t_q) = \sum_{k=1}^{K} a(\theta, e)s_k(t_q)+n(t_q), \quad for\ q = 1, \cdots, Q, \tag{3}$$

where $a(\theta, e)$ represents the array responding function containing the error parameter and $\|a(\theta, e)\|_2 = 1$, $\|\bullet\|_2$ is the l_2 norm.

III. PREPROCESSING OF RECEIVED SIGNALS

In the DOA estimation, the signal without additional processing is usually not directly sent to the neural network for training [27], but the covariance matrix of the signal is used as the input of the neural network [19], [24]. The covariance matrix of the received signal is expressed as

$$R_{xx} = E[x(t_q)x^H(t_q)] = ASA^H + R_N, \tag{4}$$

where $E[\bullet]$ and $(\bullet)^H$ represent the expectation and conjugate transformation, A is the array response function, and S and R_N are the signal covariance matrix and noise matrix, which can be expressed as following

$$S = E[s(t)s^H(t)], \tag{5}$$
$$R_N = E[n(t)n^H(t)]. \tag{6}$$

The noise obeys zero mean Gaussian distribution, so the noise matrix also expressed as

$$R_N = \sigma^2 I, \tag{7}$$

where σ represent the noise variance, and the covariance matrix is rewritten as

$$R_{xx} = E[x(t_q)x^H(t_q)] = ASA^H + \sigma^2 I, \tag{8}$$

where R_{xx} is a symmetric matrix, so we are only interested in the upper triangle part of the covariance matrix. The normalized elements of upper triangle part can be expressed as

$$\bar{r} = E[R_{1,2}R_{1,3}\ldots R_{1,M}R_{2,3}\ldots R_{2,M}\ldots R_{M-1,M}]^T, \tag{9}$$
$$r = E[Real\left\{\bar{r}^T\right\}, \quad Imag\left\{\bar{r}^T\right\}]^T/\|\bar{r}\|_2, \tag{10}$$

where $R_{i,j}$ represents the element in the i-th row and the j-th column in the covariance matrix, and $Real\{\bullet\}$ and $Imag\{\bullet\}$ are the real part and the imaginary part, respectively.

IV. FRAMEWORK OF DEEP LEARNING NETWORKS

In this section, a DLN DOA estimation framework is proposed to address the DOA estimation problem, which consists of a LCN and a CNN. The angular space where signals may exist is divided into P regions, and the function of the LCN is to divide the received signals into corresponding regions. Each region is adopted a CNN. The output of the LCN will be input to the corresponding multiple CNNs after matrix transformation, and the DOA estimation after performing a spectral peak search operation on the output of the CNN. The design of the entire DLN framework is shown in Fig. 2.

A. LINEAR CLASSIFICATION NETWORKS

The autoencoder can extract the key information by reducing the dimension of the data, and obtain accurate results when the network structure is relatively simple [28]. The purpose of introducing a LCN is to divide the received signal into the

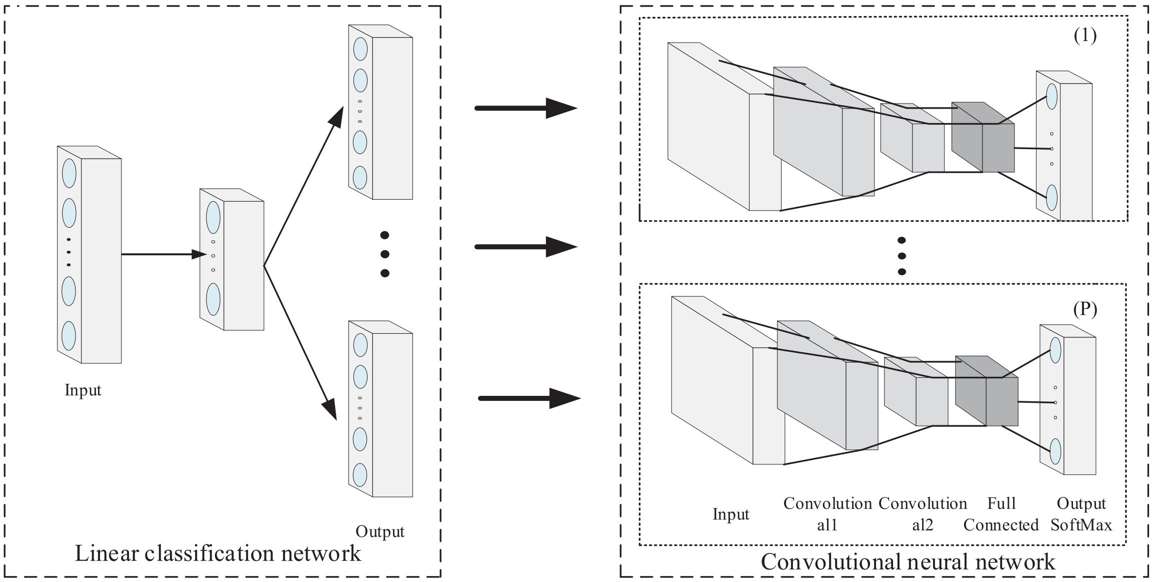

FIGURE 2. Framework of deep learning networks.

spatial subregion where it comes from, the form of input data will not be changed during this process, so we consider using autoencoder networks to build this LCN.

An autoencoder networks consists of an encoder and a decoder, where the encoder compresses the input vector to a lower dimension to extract the principal components from the original input, and then the decoder restores it to its original size. Different from general autoencoder networks, the output dimension and input dimension of the LCN are different. This is because we want to output the input vector at different decoders, each decoder corresponds to a spatial subregion. Therefore, the output dimension of the LCN is P times the input dimension.

Although there are only unidirectional signals in the scene, the design principle of the auto-encoder network is to recover the signals from different regions at different decoders. Based on this design principle, we think the network should have superimposed properties. And we expect that no matter what the input signal is, there will be a decoder with the same output as the input signal, so the network should also be homogeneous. For the above considerations, the classification network should be the LCN.

For the LCN, the effect of one hidden layer is the same as that of multiple hidden layers. Therefore, the LCN has only three layers of structures, namely the input layer, the hidden layer and the output layer. The input of the LCN is the real and imaginary parts of the upper triangular elements of the normalized covariance matrix. The input layer and the hidden layer are fully connected, the connection between the hidden layer and the output layer as

$$f = Wc + b, \tag{11}$$

where c represents the neuron of the previous network layer, W represents the weight matrix, b is the amount of paranoia, f stands for the neuron that the current network. In order to avoid overfitting, $L1$ regularization term can be added as a penalty term.

B. INTELLIGENT INFORMATION REPRESENTATION

Each decoder output can be connected into a one-dimensional matrix. The decoder output corresponding to the subregion where the echo signal exists is $\tilde{r}$. In view of $\tilde{r} = \bar{r}$, the elements in matrix $\tilde{r}$ are composed of the upper triangular elements of the covariance matrix R_{xx} under ideal conditions. Therefore, it can be transformed into the covariance matrix R_{xx} through an inverse transformation. Considering that the CNN may not be able to identify complex terms, it is necessary to separate the real and imaginary part of the signal into two matrices, which the real matrix $\bar{R}$ and the imaginary matrix $\tilde{R}$ are shown as

$$\bar{R} = \begin{bmatrix} \bar{R}_{1,1} & \cdots & \bar{R}_{1,M} \\ \vdots & \ddots & \vdots \\ \bar{R}_{M,1} & \cdots & \bar{R}_{M,M} \end{bmatrix}, \tag{12}$$

$$\tilde{R} = \begin{bmatrix} \tilde{R}_{1,1} & \cdots & \tilde{R}_{1,M} \\ \vdots & \ddots & \vdots \\ \tilde{R}_{M,1} & \cdots & \tilde{R}_{M,M} \end{bmatrix}, \tag{13}$$

where $\bar{R} = Real\left\{\bar{r}^T\right\}$ and $\tilde{R} = Imag\left\{\bar{r}^T\right\}$. Since the covariance matrix is symmetrical, all elements in the real matrix $\bar{R}$ and imaginary matrix $\tilde{R}$ can be restored from the output of decoders.

C. ESTIMATOR BASED ON CONVOLUTIONAL NEURAL NETWORKS

For many neural networks, there is no special relationship between the input neurons of the neural network, and the input neurons are not given a special connection during the network processing. Therefore, the relationship between the real and imaginary elements in the one-dimensional matrix $\tilde{r}$ is not used by these neural networks, but in fact there is a one-to-one correspondence between the real and imaginary elements. For example, the element in the i-th row and j-th column of the covariance matrix R_{xx} is R_{ij}, which can satisfy the following

$$R_{ij} = \bar{R}_{ij} + j\tilde{R}_{ij}, \tag{14}$$

where $\bar{R}_{ij}$ and $\tilde{R}_{ij}$ represent the real and imaginary parts of R_{ij}, respectively.

CNN can take advantage of the connection between $\bar{R}_{ij}$ and $\tilde{R}_{ij}$ instead of ignoring this relationship like many other neural networks [29]. The real matrix $\bar{R}$ and the imaginary matrix $\tilde{R}$ are sent to the convolutional neural network together, the elements in $\bar{R}$ and the elements in $\tilde{R}$ will be fused in the first convolution layer. It should be noted that the CNN treats the matrix elements in the same position in $\bar{R}$ and $\tilde{R}$ in the same way. Therefore, we believe that the features extracted by the CNN can better explain the relationship between the received signals and the more accurate estimation results can be obtained.

The input of the CNN is the real matrix $\bar{R}$ and the imaginary matrix $\tilde{R}$, and its dimensions are $M \times M$. The structure of the CNN includes convolutional layer, pooling layer, and fully connected layer. The settings of each layer are as follows:

The real and imaginary matrix corresponding to the p-th decoder can be used as the input of the p-th CNN classifier. The input data first passes through a convolution layer. The structure of the convolution layer h is as follows

$$h = \sigma(W * V + b), \tag{15}$$

where V represents the input data, W is the trained convolution kernel, b represents the offset, and $\sigma(\bullet)$ stands for the activation function. The convolution kernel is trained by the stochastic gradient descent method. This paper uses the hyperbolic tangent function $tanh(x)$ as the activation function, which is shown as

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}, \tag{16}$$

where $x = W * V + b$.

After the input data passes through the convolutional layer, a pooling operation is needed to reduce the network overhead. Since the input of the CNN is a matrix of $M \times M$ dimensions, and M is the number of antenna elements. It is generally not too large, so only one or two pooling operations are required. There are two types of pooling, which are maximum pooling and average pooling. Because the scale of the input matrix is small and the angle range to be estimated is wide, we choose the average pooling method to process the data in order to make full use of useful information.

The input of this layer is a new vector composed of all the feature maps output by the convolution layer, and the connection mode is fully connected. The goal is to integrate the local features extracted by the convolutional layer into a high-level feature. Local vision is integrated in dense layers, resulting in a feature based on global vision.

The output layer neurons of the CNN represent the angle of the horizontal space. Each CNN is responsible for the DOA estimation of a subregion. The number of neurons in the output layer is related to the range of angles contained in the subregion. Each neuron represents an angular grid in horizontal space, and all the output layer neurons of each CNN to form a one-dimensional matrix $y_i^T i = 1, 2, \ldots, P$ to determine whether a signal exists in the corresponding subregion by concatenating the outputs of P convolutional neural networks into a one-dimensional matrix in the same way. It should be noted that multiple CNNs work in parallel to obtain estimation results.

When the echo signals come from only one direction, using the SoftMax as the activation function in the output layer can greatly improve the training speed. In order not to destroy the mode of CNN estimators working in parallel, an activation function must be added after each CNN, instead of only adding an activation function after CNN. SoftMax can be expressed as

$$y_i = \frac{e^{z_i}}{\sum_{j=1}^{J} e^{z_j}} for i = 1, 2, \cdots, J, \tag{17}$$

where z_i represents the value of the i-th output neuron when no activation function is added, J is the number of neurons in the output layer of each convolutional neural network, and y_i stands for the final output value of the neurons in the output layer. However, using SoftMax directly will also cause a negative impact. CNN estimator without softMax function may cause training to fail to converge. To solve this problem, the SoftMax function must be modified as

$$y_i^p = \omega^{(p)} \frac{e^{z_i p)}}{\sum_{j=1}^{J} e^{z_j (p)}} for\ i = 1, 2, \cdots, J p = 1, 2, \cdots, P, \tag{18}$$

$$\omega^{(p)} = \frac{\left\| \tilde{r}^{(p)} \right\|_1}{\sum_{i=1}^{P} \left\| \tilde{r}^{(i)} \right\|_1} for\ p = 1, 2, \cdots, P, \tag{19}$$

where $(\bullet)^{(p)}$ represents the p-th CNN estimator, $\tilde{r}^{(i)}$ represents the output of the p-th decoder in the LCN, and $\omega^{(p)}$ is the proportion of the output of the p-th decoder among all decoder outputs. The introduction of weighting factor ω can effectively alleviate the side effects of the SoftMax function.

After getting the outputs of all CNN estimators, we connect the outputs of all CNN estimators in order to estimate the direction of the signal. Only the grid nodes that are expected to be close to the true signal direction are taken as positive numbers, and all other grid nodes are taken as zero, and then the spectrum peak search is performed to obtain the DOA estimation result.

Algorithm 1 The Procedure of DOA Estimation Based on LCN-CNN

1: Calculate the covariance matrix R_{xx} of the received signal $x(t)$;
2: Extract the upper triangular elements of R_{xx}, separate the real and imaginary parts of each element to form a one-dimensional matrix r;
3: Send r to the LCN and pass through a linear network layer: $h = \sigma(W * r + b)$;
4: The compressed data h is restored to $\tilde{r}^{(p)}$ by P decoders through a linear network layer;
5: Calculate the proportion of the output of the p-th decoder among all decoder outputs: $\omega^{(p)} = \frac{\|\tilde{r}^{(p)}\|_1}{\sum_{i=1}^{P} \|\tilde{r}^{(i)}\|_1}$;
6: $\tilde{r}^{(p)}$ is restored into a covariance matrix through matrix transformation, and constitutes a real matrix $\bar{R}^{(p)}$ and an imaginary pmatrix $\tilde{R}^{(p)}$;
7: P CNNs work in parallel, the real matrix $\bar{R}^{(p)}$ and the imaginary matrix $\tilde{R}^{(p)}$ are sent to a CNN together and passed through the convolutional layer, and activation function is $\sigma(x)=\frac{e^x-e^{-x}}{e^x+e^{-x}}$;
8: $\bar{R}^{(p)}$ and $\tilde{R}^{(p)}$ pass through the first convolution layer, and the output results are superimposed as $R^{(p)}$;
9: $R^{(p)}$ is sent to a average pooling layer, and the output of the pooling layer is then passed through m convolutional layers as shown in 7;
10: The output of the last convolutional layer passes through the fully connected layer and the output layer, and the output of the CNN is $z^{(p)}$;
11: The outputs of the output layers of the P CNNs pass the weighted SoftMax $y_i{}^p = \omega^{(p)} \frac{e^{z_i{}^{(p)}}}{\sum_{j=1}^{J} e^{z_j{}^{(p)}}}$;
12: Concatenate all outputs $y_i{}^p$ to form a one-dimensional matrix y;
13: Perform spectral peak search on y to get the result of DOA estimation;
14: End.

In summary, the proposed DLN framework includes LCN and CNNs. The upper triangular element of the covariance matrix of the received signal is represented by a one-dimensional matrix r, which is input into the linear neural network. The LCN will initially classify the signals and divide the signals into corresponding subspace regions. The output of the LCN undergoes matrix transformation to form a real matrix $\bar{R}$ and an imaginary matrix $\tilde{R}$, which are input to the CNN estimator for DOA estimation. The procedure of DOA estimation based on LCN-CNN is summarized in Algorithm 1.

V. TRAINING OF DEEP LEARNING NETWORKS

A. TRAINING OF LINEAR CLASSIFICATION NETWORKS

During the DLN training, the input r of the LCN is the upper triangular element of the received signal covariance matrix. If there is an echo signal in the spatial subregion corresponding to the decoder, the expected output of the decoder is r. If there is no echo signal in the spatial subregion corresponding to the decoder, the values of the neurons in the output layer of the decoder are all 0. Our proposed solution divides the 180-degree horizontal space into 9 regions, and each decoder corresponds to 20 degree spatial angle range. Since the signal may come from any angle in the half-plane, theoretically there should be an infinite number of types of training signals, and the direction of arrival $\theta \in [0, 180]$ is a continuous variable. It is unrealistic to send an infinite number of signals to the DLN for training. Therefore, the training set we constructed only contains signals with an integer direction of arrival, and the noise is set to zero mean Gaussian noise. Each set of training data is randomly shuffled the order, and then slice it and send it to the LCN for training.

The parameters of network training are set as follows: the training signals are FM, DVB-T, GPS and GSM, the power ratio of these illuminators of opportunity signals is set as 1: 0.8: 0.025: 0.025, the signal-to-noise ratio (SNR) is 10dB, and the number of antenna elements is 10, the training step is 0.001, the number of training is 400, and the evaluation criterion is the root mean square error (RMSE) between the network output and the label and the RMSE with the progress of LCN training is shown in Fig. 3.

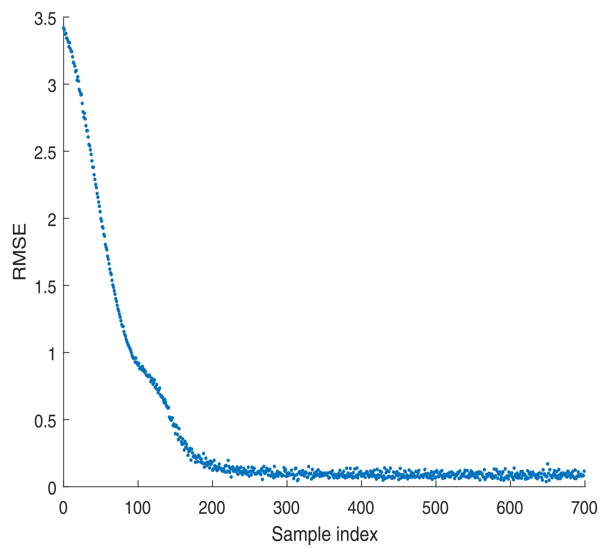

FIGURE 3. Training of linear classification networks.

B. TRAINING OF CONVOLUTIONAL NEURAL NETWORKS

The training of the CNN estimator after the LCN training completed, so when training the CNNs, the parameters of the

LCN have been fixed. Therefore, a LCN can be considered as a preprocessing process, which divides the signal into the spatial subregion to belongs, resulting in each CNN performing DOA estimation on the signal in only one spatial subregion, reducing the generalization burden of CNNs.

The data received by the CNN estimator is the output of the self-encoder, and the output is the signal distribution in the horizontal space. There are 180 output units in the P CNN estimator. The value of each unit represents whether there is an incoming wave in the angular direction. Training rule of the label as follows: if the signal's arrival angle $\theta = \theta_k$, then only the value of the neuron in the k-th output layer is positive, and the values of the other output layer neurons are 0. (If θ_k is not an integer, for example, there is a signal at an angle of 20.5, then the output of the 20th neuron is 21.5-20 = 0.5, the output of the 21st neuron is 22-21.5 = 0.5, and the value of other neurons is 0).

When training the CNN estimator, the input data needs to pass through the LCN before entering the CNN estimator. Therefore, during the training process, the input data of the CNN estimator and the input data of the LCN are the same, the expected output of the CNN estimator is not same as the expected output of the LCN. The evaluation criterion is the RMSE between the CNN output and the expected output.When the number of neurons in each network layer is not optimized, the change of RMSE with the progress of CNN training is shown in Fig. 4.

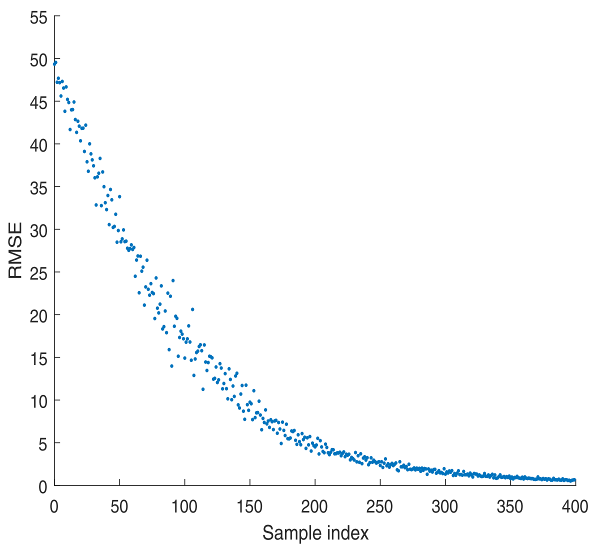

FIGURE 4. Training of convolutional neural networks.

VI. SIMULATION RESULTS AND ANALYSIS

A. ESTIMATION PERFORMANCE WITH DIFFERENT SNR

In order to verify the effectiveness of the proposed method, the simulation experiment using MATLAB and the four types illuminators of opportunity including FM, DVB-T, GPS and GSM are considered. In the application scenario of the proposed method, the SNR is usually lower than 10dB. We have designed an experiment to evaluate the estimation effect of the DLN under different SNRs. The testing signals are FM signals, DVB-T signals, GPS signals and GSM signals, the power ratio of these external radiation source signals is 1: 0.8: 0.025: 0.025, the DOA of the test signal is 12.5, the number of tests is 3000, the SNR region is $[-10\text{dB}, 10\text{dB}]$, and the interval is 2. The performance of the proposed method with different SNRs in Fig. 5. Form Fig. 5, it can be seen that the estimation performance tends to stabilize when the SNR more than 4, which meets the needs of the DOA estimation scenario.

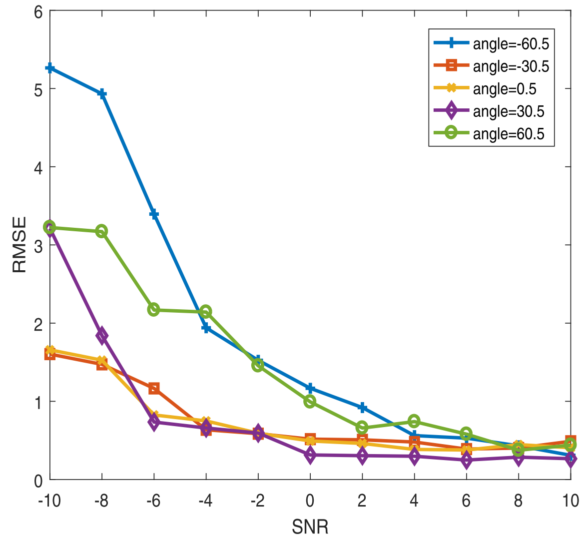

FIGURE 5. Performance of proposed method with different SNRs.

B. OPTIMIZATION OF THE NUMBER OF NEURONS

In order to optimize the network structure and pursue a faster training speed and training effect, it is necessary to optimize the structure of the DLN and the number of neurons in each network layer. In the proposed DLN, the LCN has only one hidden layer, and the network structure is relatively simple. Therefore, its optimization is not described in detail in this section. We are interested in the optimization of CNN estimators. According to the application scenario, we proposed a reasonable network architecture, and then selected several different situations to optimize the number of neurons. In view of the dimensions of the input covariance matrix are relatively small, the size and step size of the convolution kernel are set to 2 without adjustment. Therefore, it is necessary to optimize the number of convolution kernels of convolution layer 1, the number of convolution kernels of convolution layer 2, and the number of features of the fully connected layer.

We selected several groups of neurons for comparison, and the estimation performance with different numbers of neurons is shown in Tab. 1. In Tab. 1, Conv1 represents the convolution layer 1, and Conv2 represents the convolution

TABLE 1. Estimation performance with different numbers of neurons.

Group	Conv1	Conv2	Fullc	Times	Size	RMSE
1	8	16	32	700	1800	0.93771
2	16	32	64	700	1800	0.51687
3	32	64	128	700	1800	0.22017
4	64	128	256	700	1800	0.34673
5	128	256	512	700	1800	0.58008

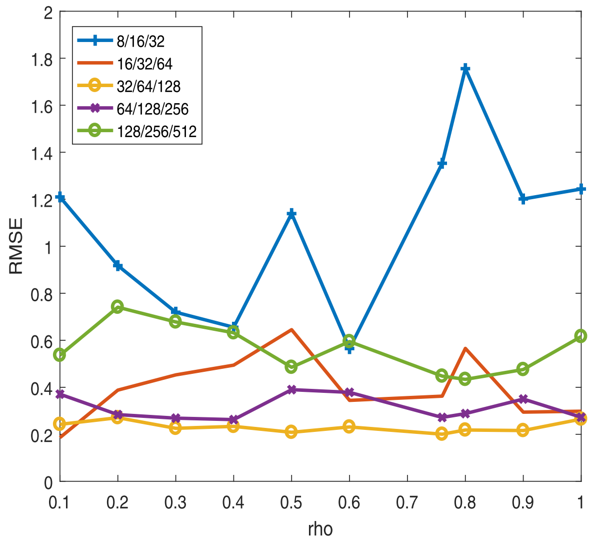

FIGURE 6. Estimation performance of different schemes with different array defects.

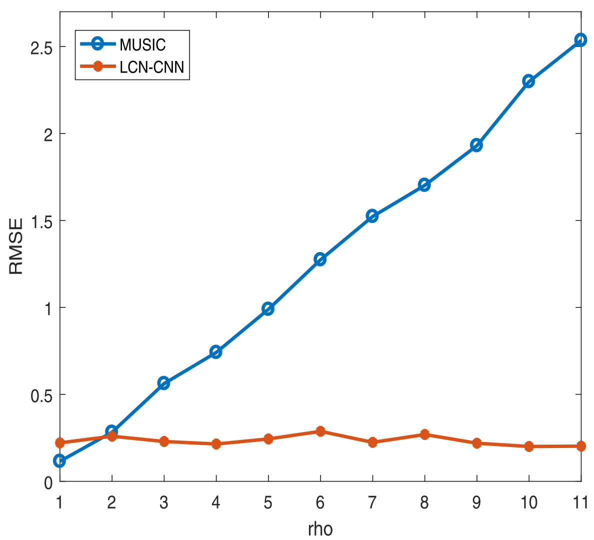

FIGURE 7. Estimation performance comparison with mixed error.

layer 2, the Fullc is the fully connected layer. Each sample set has 1800 signals, which are obtained by sampling 180 signals with integer angles 10 times respectively. Each training has a total of 700 sample sets, and the RMSE in the table is the average RMSE of 2000 times network training. The test signal is a mixed signal with an arrival angle of 32.5 degrees and SNR is 5dB. From tab. 1, it can be seen that the test results

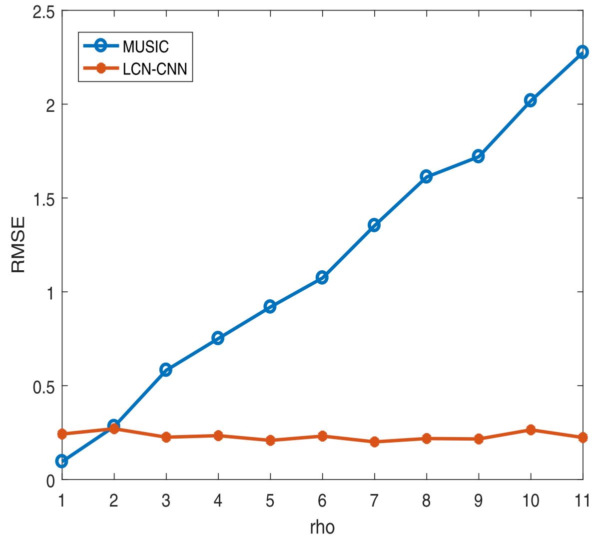

FIGURE 8. Estimation performance comparison with amplitude and phase errors.

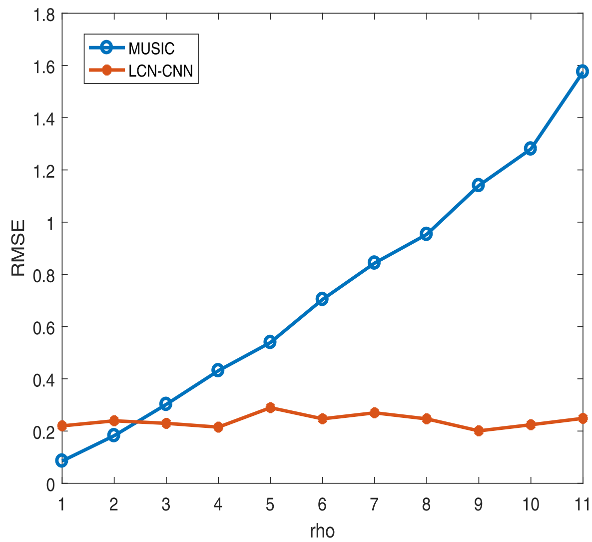

FIGURE 9. Estimation performance comparison with sensor position error.

are best when the number of neurons is 32/64/128. It should be noted that the training set only contains signals with integer arrival angles, so the samples are insufficient. In this case, when the network model is too complicated, overfitting will occur, so the neurons in group 4 and group 5 are more than in group 3, but the estimated performance is worse than group 3.

C. ADAPTABILITY OF DPN TO ARRAY DEFECTS

The previous experiments were designed on the premise that array defects did not exist, and the difference in the number of neurons may lead to different adaptability to different array defects. In order to illustrate the effect of the number of neurons on the adaptability of the neural network, we preset the

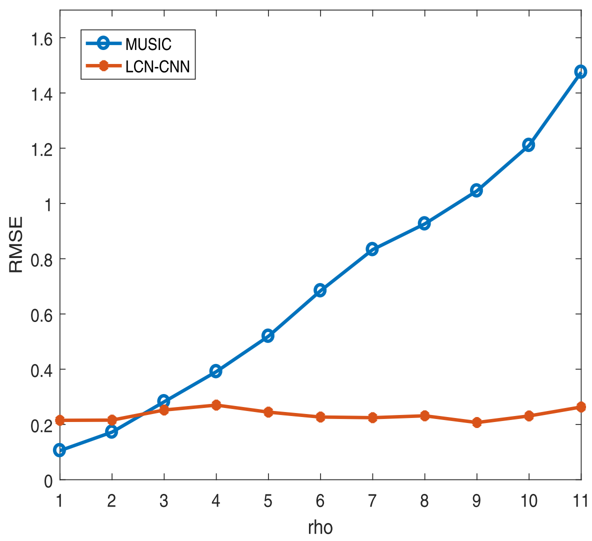

FIGURE 10. Estimation performance comparison with mutual coupling.

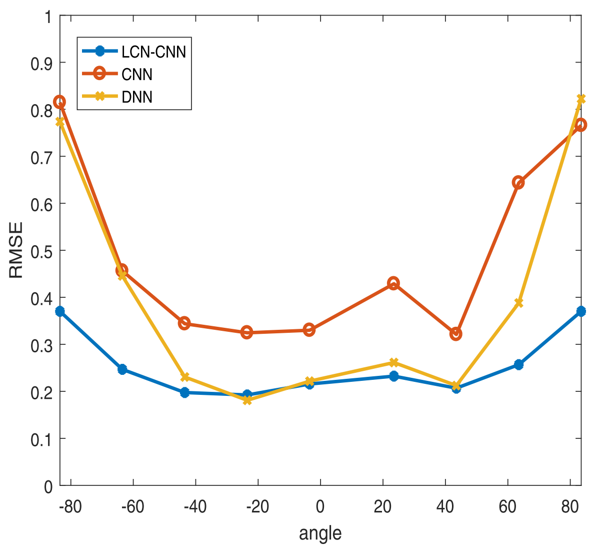

FIGURE 11. Performance comparison of different estimation methods.

basic values of amplitude error, phase error, sensor position error, and mutual coupling, and define a multiplicative variable rho as the coefficient of these errors. Therefore, when rho takes different values, it means that the antenna array defects are different. Estimation performance of different schemes with different array defects in Fig. 6. From Fig. 6, it can be seen that when the number of neurons is 32/64/128, both the accuracy of the estimation and the stability of the estimation are stronger than other schemes. We compared the proposed method with the method based on MUSIC algorithm with different array defects in Fig. 7, Fig. 8, Fig. 9, and Fig. 10. From Fig. 7 to Fig. 10, we can see that the proposed method can achieve good performance with different antenna array defects.

D. ESTIMATION PERFORMANCE COMPARISON

In order to evaluate the performance of the proposed method, the proposed method is compared with the CNN method without LCN and the DNN method in [24]. The angles of the mixed echo signals are taken $[-83.5, -63.5, -43.5, -23.5, -3.5, 23.5, 43.5, 63.5, 83.5,]$, and performance comparison of different estimation methods in Fig. 11. Form Fig. 11, it can be seen that both the proposed method and the DNN method have better estimation performance than the CNN method. When $\|\theta\|_1$ is small, the estimation performance of the proposed method and the DNN method are close. However, when $\|\theta\|_1$ is large, the estimation performance of proposed method is much better than the DNN method. Although the angle $\|\theta\|_1$ is large, the effect of proposed DOA estimation is still good. In addition, compared with the DNN method which can only detect signals in the range of 120 degrees, the proposed method can estimate DOA on signals in the half-plane.

VII. CONCLUSION

In this paper, a novel and robust DOA estimation method is proposed for echo signals with multiple illuminators of opportunity using linear classification networks and convolutional neural networks. Linear classification networks (LCNs) are utilized to identify the spatial subregion of received signals. Then, based on the output of LCNs, the corresponding convolutional neural networks (CCNs) are adopted to perform DOA estimations. With the help of powerful neural networks, the proposed method has better adaptability to various antenna array defects compared with traditional methods, such as MUSIC algorithm. Extensive simulation studies are conducted to show that the proposed method has better estimation performance compared to other methods based on neural network.

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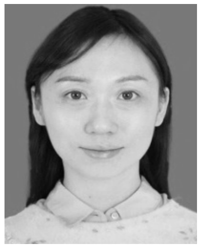

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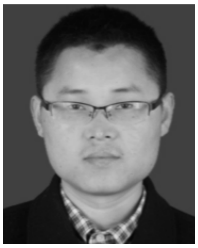

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