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A Novel Phase Enhancement Method for Low-Angle Estimation Based on Supervised DNN Learning

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ABSTRACT In low-altitude target situation, the multi-path signals cause the amplitude-phase distortion of direct signal from targets and degrade the performance of existing methods. Hence, in this paper, we propose a phase enhancement method for low-angle estimation using supervised deep neural network (DNN) to mitigate the phase distortion, thus to improve direction of arrival (DOA) estimation accuracy. The mapping relationship between the original phase difference distribution of the received signal and desired phase difference distribution is learned by DNN during training. The phase of test data is enhanced by trained DNN, and the enhanced phase is used for DOA estimation. We explain the significance of enhancing phase instead of amplitude by discussing the sensitivity of amplitude and phase on DOA estimation. Moreover, we prove the effectiveness and superiority of the proposed method by simulation experiments. The results demonstrate that the proposed technique has a better performance in terms of estimation error and goodness of fit (GoF) than the physics-driven DOA estimation methods and state-of-the-art methods including feature reversal and the support vector regression (SVR).

INDEX TERMS Phase enhancement, supervised deep neural network, DOA estimation.

I. INTRODUCTION

When radar tracks a low-angle target over a severe terrain environment, the distribution feature of received signal is not only determined by the direct signal, but also the multi-path signals including specular reflection signal and the diffuse reflection signals. Generally, the effect of multi-path signal can be regarded as an amplitude and phase perturbation on direct signal [1], [2]. Because that the characteristics of the far-field plane wave of direct signal become blurred in the multi-path environment, the performance of existing far-field plane wave based super resolution methods such as digital beam forming (DBF), multiple signal classification (MUSIC) [3] and maximum likelihood (ML) [4] method degrades. And it is sensitive to the size of unknown perturbation. Hence, the feature of the far-field plane wave that recovers the direct signal is the only way to improve the performance of physics-drive methods.

In order to improve the performance of DOA estimation, neural network based methods [5]–[8] are introduced into the field of array signal processing. In [5], the problem of DOA estimation is modeled as classification task. The whole of spatial domain is divided into several bins, each bin represents a class. Obviously, on the one hand, the size of bin determines the resolution; on the other hand, the problem of model mismatch exists. Recently, two new neural networks [6]–[8] are used for solving DOA estimation. In [6], a new method called feature reversal is introduced. The method utilizes an unsupervised auto-encoder network to learn the latent distribution feature of corresponding DOA. The advantage of feature reversal is that it has a small computation load and high accuracy compared with MUSIC. In [7] and [8], a regression strategy is adopted and an end-to-end SVR network is established to predict DOA. The SVR based methods also show a higher accuracy than DBF and MUSIC. In spite of the great achievements above, there is no paper discussing the feature selection during training and fundamental origins of error in DOA estimation. And we will discuss it in this paper.

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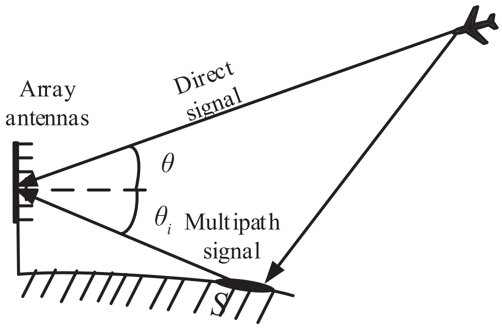

FIGURE 1. Signal model.

Different from unsupervised feature reversal in [6] and supervised end-to-end learning SVR-based method in [7] and [8], a supervised feature-to-feature learning-based method is presented in this paper to reduce the influence of phase error in term of DOA estimation, and improve the DOA estimation accuracy. Compared with existing methods, this paper has the following innovations. First, different from [6]–[8], we only train phase feature to improve the DOA estimation accuracy. That is, instead of training amplitude feature and phase features together or training real part feature and imaginary part features together, we train phase feature only in this paper. And we explain the importance of phase feature on DOA estimation by analyzing the sensitivity of amplitude feature and phase feature on DOA estimation, principle of DBF method and data integration. Second, an feature-to-feature learning based phase enhancement framework is established to reduce the negative influence of feature perturbation, and thus to improve estimation accuracy.

The paper is organized as follows. In section II, we review the signal model and discuss the feature selection problem. In section III, the structure of proposed method is introduced. Simulation experiments demonstrate the predominance of proposed method is better than existing DBF, MUSIC, ML, feature reversal and SVR based methods in terms of estimation accuracy and GoF in section IV. In section V, the performance of proposed method is validated by real data. Section VI gives the conclusion of this paper.

Notations: Vectors are defined by boldface small letters, while matrices are noted by boldface capital letters; superscripts $(\cdot)^T$ and $(\cdot)^H$ represent conjugate, transpose and Hermitian operator, respectively. Additionally, $j = \sqrt{-1}$ represents the imaginary unit, $\|\cdot\|$ denotes l_2 norm.

II. SYSTEM OVERVIEW AND FEATURE SELECTION

We consider an uniform linear array (ULA) of M isotropic elements with L snapshots. The inter-element spacing d equals to half of wavelength. The received vector is

$$\boldsymbol{x}(t) = (\boldsymbol{a}(\theta) + \sum_{i=1}^{n} \gamma_i \boldsymbol{a}(\theta_i))s(t) + \boldsymbol{n}(t), \quad t = 1, \cdots, L \tag{1}$$

with

$$\boldsymbol{a}(\theta) = [1, e^{-j\phi}, e^{-j2\phi}, \cdots, e^{-j(M-1)\phi}]^T \tag{2}$$

where θ is the DOA of direct signal we need to estimate. θ_i denotes the DOA of reflected signal. γ_i is the decay factor. n represents the number of unknown multi-path signals. $\phi = \pi \sin\theta$ is the phase difference of adjacent elements. $s(t)$ is complex echo signal. $\boldsymbol{n}(t)$ is the additive complex Gaussian white noise with zero mean and variance σ^2. Analyzing the term $(\boldsymbol{a}(\theta) + \sum_{i=1}^{n} \gamma_i \boldsymbol{a}(\theta_i))$ in expression (1), the term $\sum_{i=1}^{n} \gamma_i \boldsymbol{a}(\theta_i)$ actually causes the amplitude and phase perturbation on $\boldsymbol{a}(\theta)$. So, the signal model can be rewritten as follows

$$\boldsymbol{x}(t) = \boldsymbol{\Gamma} \odot \boldsymbol{a}(\theta)s(t) + \boldsymbol{n}(t) \tag{3}$$

with

$$\boldsymbol{\Gamma} = [\tau_1, \tau_2, \cdots, \tau_M]^T \tag{4}$$

Owing to the existence of perturbation term $\boldsymbol{\Gamma}$, the amplitude and phase distribution of $\boldsymbol{a}(\theta)$ is distorted. This is the reason why the existing super resolution methods such as MUSIC, ML and DBF methods may be failed to work. In order to mitigate the negative influence of $\boldsymbol{\Gamma}$ on DOA estimation, we propose a new phase enhancement method using DNN. The purpose of recovering the performance of physics-driven methods is achieved through recovering the desired phase distribution by DNN. In order to explain the importance of phase information rather than amplitude on DOA estimation accuracy, the sensitivity of phase and amplitude information on DOA estimation, principle of DBF method and data integration principle of planar array are analyzed here.

A. SENSITIVITY ANALYSIS

Considering single far-filed source, the array configuration is $M = 21, L = 2M, d = 0.5\ m$, signal-to-noise ratio (SNR) is 0 dB, the percentage of the amplitude and phase error is 5% to 25% in 200 Monte-Carlo experiments. The relationship between root-mean-square error (RMSE) and error size is shown in Fig. 2.

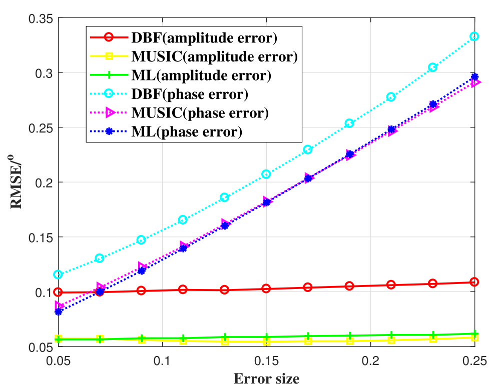

FIGURE 2. Relationship curve between RMSE and error size.

According to the statistical results shown in Fig. 2, we can see that the phase error causes a larger estimation error for all physics-driven methods compared with amplitude error. For

MUSIC method, 15% amplitude error causes 0.06° RMSE of angle, but 15% phase error causes 0.18° RMSE of angle. Moreover, the estimation error increases sharply with the increase of the phase error, and the amplitude error has less influence on the estimation error. Hence, we can draw the conclusion that all physics-driven methods on the DOA estimation are more sensitive to phase feature instead of amplitude feature. In other words, reducing the phase error is an effective way to improve DOA estimation accuracy. Training phase feature instead of amplitude feature can effectively reduce learning complexity. In addition, we can observe that different DOA has unique phase difference distribution from Fig. 3. The signal source data $s(t)$ does not affect the phase difference distribution of the received data. And the phase difference distribution has linearity. Hence, during the supervised feature-to-feature learning system, the label phase distribution can be calculated by label DOA.

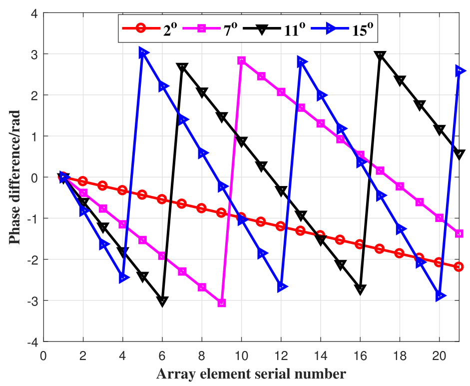

FIGURE 3. Phase difference distribution when $\theta = 2°, 7°, 11°, 15°$.

B. ESTIMATION ANALYSIS

The estimation expression of DBF method is shown as follows

$$\begin{aligned}\hat{\theta} &= \arg_{\theta} \max \frac{1}{L} \boldsymbol{a}^{H}(\theta)\boldsymbol{X}\boldsymbol{X}^{H}\boldsymbol{a}(\theta) \\ &= \arg_{\theta} \max \boldsymbol{a}^{H}(\theta)\hat{\boldsymbol{R}}\boldsymbol{a}(\theta)\end{aligned} \tag{5}$$

According to formulations (5), we can observe that for DBF algorithm, the projection vector $\boldsymbol{a}(\theta)$ is determined by the angle θ, and the θ determines the phase of $\boldsymbol{a}(\theta)$. Hence, the phase of $\boldsymbol{X}$ or $\hat{\boldsymbol{R}}$ must be accurate so that the DOA can be accurately estimated. Hence, the argument that phase information is more important than amplitude is proved, and we must get a more accurate phase through DNN approach.

C. DATA INTEGRATION

Assume that the size of VHF radar with uniform planar array is $M \times k$, the radar usually is used to estimate azimuth and elevation of targets. In order to improve the SNR in a certain dimension, data column and row synthesis operator is taken for azimuth estimation and elevation estimation. The data row synthesis operator can be depicted as Fig. 4.

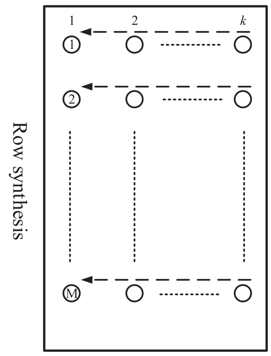

FIGURE 4. Row data synthesis operator.

Owing to the fact that the signal type we considered is far-field plane wave, the array elements of each column keep the same distribution of phase difference. Hence, the synthesized data, denoted by $\boldsymbol{y}(t)$, can be expressed as

$$\boldsymbol{y}(t) = k\boldsymbol{\Gamma} \odot \boldsymbol{a}(\theta)s(t) + \sum_{p=1}^{k} \boldsymbol{n}_p(t) \approx k\boldsymbol{x}(t) \tag{6}$$

$\boldsymbol{n}_p$ is independent of each other, so it cannot to be integrated. Hence, the synthesized amplitude $\boldsymbol{y}(t)$ is k times stronger than single column $\boldsymbol{x}(t)$. We can conclude that the phase of received data determines the amplitude of synthesized data, that is, the SNR.

III. PROPOSED METHOD

The scheme of proposed method can be described as Fig. 5. In the training stage, the original noisy sampled covariance matrix and corresponding clean sampled covariance matrix are used. The phase difference distribution feature are extracted and feed into the defined DNN and training. A 4-layer DNN architecture is shown in Fig. 6. As we observe, the architecture of DNN is determined once the number of layers and the number of neurons of each layer determined. Considering the mapping relationship between input data and output data is unknown, optimizing the architecture of DNN is necessary. Here, $\boldsymbol{W}^p$ and $\boldsymbol{b}^p$ ($p \in 1, 2, 3, 4$) denote the parameter of the DNN, that is, the weight and bias of p^{th} layer.

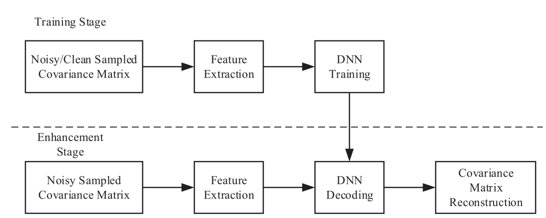

FIGURE 5. Framework of phase enhancement.

After DNN learning, the phase of noisy sampled covariance matrix is enhanced during the enhancement stage. The output of DNN, that is, the enhanced phase, is used for

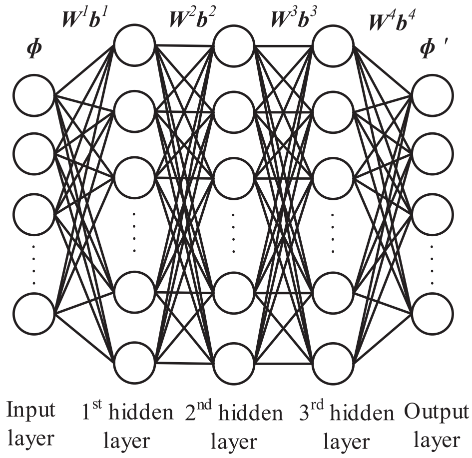

FIGURE 6. Example of 4-layer DNN architecture.

reconstructing a new sampled covariance matrix with original amplitude and DOA estimation.

A. PREPROCESSING

Assuming that the labeled training dataset phase information is denoted as $\{\mathbf{\Phi}_1; \hat{\mathbf{\Phi}}_1\}$, where $\mathbf{\Phi}_1$ and $\hat{\mathbf{\Phi}}_1$ represent the input data and corresponding known output data, respectively. And the size of $\mathbf{\Phi}_1$ and $\hat{\mathbf{\Phi}}_1$ is $Q \times N$, where Q and N represent the number of samples and the length of features, respectively. In order to keep neurons active and preserve the distribution of features, $\mathbf{\Phi}_1$ should be normalized in each dimension before inputting DNN. We adopt the Gaussian normalization, which can be formulated as follows

$$\overline{\mathbf{\Phi}}_1 = \frac{\mathbf{\Phi}_1 - \boldsymbol{\mu}_1}{\boldsymbol{\sigma}_1} \tag{7}$$

where $\boldsymbol{\mu}_1$ and $\boldsymbol{\sigma}_1$ denote the means and standard deviations of the $\mathbf{\Phi}_1$, respectively. Hence, the supervised DNN is trained by the normalized input dataset $\overline{\mathbf{\Phi}}_1$ and corresponding known output data $\hat{\mathbf{\Phi}}_1$ during the training process.

B. FORWARD PROPAGATION

Assuming that the p^{th} input is the $\boldsymbol{x}^p$, then the output $\boldsymbol{h}^p$ can be expressed as follows

$$\boldsymbol{h}^p = f(\boldsymbol{W}^p\boldsymbol{x}^p + \boldsymbol{b}^p) \tag{8}$$

where $f(\cdot)$ is an activation function. In order to prevent the problem of gradient vanishing and keep the sparsity of neuron, we adopt the Rectified Linear Unit (ReLU) function [9]. The function can be expressed as follows

$$f(z) = \max(z, 0) \tag{9}$$

where z is denoted as the argument of the function. In order to make data distribution between the output of 3^{th} hidden layer and the unnormalized label data match, a linear mapping layer is followed. The output vector $\boldsymbol{\phi}_1'$ can be formulated as follows

$$\boldsymbol{\phi}_1' = \boldsymbol{W}^4\boldsymbol{x}_4 + \boldsymbol{b}^4 \tag{10}$$

C. BACK PROPAGATION

We adopt the mean square error (MSE) between the DNN output and unnormalized label data as the objective function. The parameters of the network are optimized to minimize the MSE. The error Back Propagation (BP) [10] strategy is used for fine-tuning by Adaptive Moment (AdaM) [11] estimation method. The minimization problem is formulated as follows

$$\begin{aligned}(\boldsymbol{W}, \boldsymbol{b}) &= \min_{\boldsymbol{W},\boldsymbol{b}} \mathcal{L}oss_1 \\ \mathcal{L}oss_1 &= \frac{1}{N}\|\boldsymbol{\phi}_1' - \hat{\boldsymbol{\phi}}_1\|^2\end{aligned} \tag{11}$$

In order to accelerate the convergence of the training stage, the total training dataset is randomly divided into several batches, and the batch size is D. The formula (11) can be rewritten as

$$(\boldsymbol{W}, \boldsymbol{b}) = \min_{\boldsymbol{W},\boldsymbol{b}} \frac{1}{D}\sum_{i=1}^{D} \mathcal{L}oss_i \tag{12}$$

where $\mathcal{L}oss_i$ represents the MSE of i_{th} batch of data.

The updating formulas for $\boldsymbol{W}$ and $\boldsymbol{b}$ can be expressed as follows

$$\begin{aligned}\boldsymbol{W} &= \boldsymbol{W} - \alpha\frac{v^c_{d\boldsymbol{W}}}{\sqrt{s^c_{d\boldsymbol{W}}} + \epsilon} \\ \boldsymbol{b} &= \boldsymbol{b} - \alpha\frac{v^c_{d\boldsymbol{b}}}{\sqrt{s^c_{d\boldsymbol{b}}} + \epsilon}\end{aligned} \tag{13}$$

with

$$\begin{aligned}v^c_{d\boldsymbol{W}} &= \frac{v_{d\boldsymbol{W}}}{1-\beta_1} \\ v^c_{d\boldsymbol{b}} &= \frac{v_{d\boldsymbol{b}}}{1-\beta_1} \\ s^c_{d\boldsymbol{W}} &= \frac{s_{d\boldsymbol{W}}}{1-\beta_2} \\ s^c_{d\boldsymbol{b}} &= \frac{s_{d\boldsymbol{b}}}{1-\beta_2}\end{aligned} \tag{14}$$

$$\begin{aligned}v_{d\boldsymbol{W}} &= \beta_1 v_{d\boldsymbol{W}} + (1-\beta_1)d\boldsymbol{W} \\ v_{d\boldsymbol{b}} &= \beta_1 v_{d\boldsymbol{b}} + (1-\beta_1)d\boldsymbol{b} \\ s_{d\boldsymbol{W}} &= \beta_2 s_{d\boldsymbol{W}} + (1-\beta_2)d\boldsymbol{W} \\ s_{d\boldsymbol{b}} &= \beta_2 s_{d\boldsymbol{b}} + (1-\beta_2)d\boldsymbol{b}\end{aligned} \tag{15}$$

where β_1 and β_2 denote exponential decay rates for the moment estimates, α is learning rate. And the Initial values of $v_{d\boldsymbol{W}}, v_{d\boldsymbol{b}}, s_{d\boldsymbol{W}}$ and $s_{d\boldsymbol{b}}$ are both 0.

The DNN training and enhancement procedure can be summarized as follows

1) Initialize the network parameters $\boldsymbol{W}^k$ and $\boldsymbol{b}^k$

2) Normalize the training dataset in each dimension by (7), and obtain the parameters $\boldsymbol{\mu}_1$ and $\boldsymbol{\sigma}_1$.

3) Divide $\overline{\mathbf{\Phi}}_1$ into several batches randomly. And perform a forward propagation.

4) According to the error of the output layer, apply BP strategy and AdaM method to fine-tune the network parameters $\boldsymbol{W}^k$ and $\boldsymbol{b}^k$.

5) Repeat 2) to 4) until the error of objective function converges by learning and adjusting the network architecture.

6) Fix the architecture and parameters of DNN during the enhancement stage, input the phase of noisy covariance matrix and get the corresponding enhanced phase.

7) Reconstruct sampled covariance matrix and accomplish DOA estimation with DBF, MUSIC and ML.

IV. SIMULATION

In this section, we conduct numerical experiments to validate the performance of the proposed method, and compare it with existing methods. All the experiments were performed on a computer with Intel i7-7820 CPU 2.90 GHz. The data processing was completed on MATLAB 2017a. In order to prevent the problem of over-fitting, a strategy of "dropout" [12]' is used at each nonlinear layer, the dropout ratio is 0.8. First of all, the process of determining the architecture of DNN is discussed. Here, we introduce the GoF. Its expression can be written as follows

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - y_i')^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}, R^2 \leq 1 \tag{16}$$

where y_i' and y_i are label data and given data, $\bar{y}$ represents the means of label data. We can see that when y_i is close to y_i', the value of R^2 is approximately 1. Hence, for a given training dataset, we can obtain an optimal network architecture by calculating the GoF of neural networks with different architecture. The closer the value of GoF is to 1, the better performance of network is.

A. NETWORK ARCHITECTURE ANALYSIS

We evaluate nine network architectures, where the number of network layers is 1, 2, and 3, and the number of neurons is 600, 800 and 1000. The simulation conditions are as follows

- θ is uniformly sampled from 1.5° to 2.5° during the training. And θ is randomly (different from training dataset) sampled from 1.5° to 2.5° in test dataset. Computer simulation generates 20000 batches of data for training and 2000 batches of data for test.
- The amplitude of $\tau_i \sim U(-0.2, 0.2)$, the phase of $\tau_i \sim U(-20°, 20°)$.
- The SNR is -5 dB, $M = 24, L = 48, \lambda = 1m, d = 0.5\lambda$.

The average training loss of different network architecture is shown in Fig. 7. In Fig. 7, the x-axis and y-axis represent the number of step and train loss. As shown in the nine curves, the optimal number of layers of the network structure is 3 and each layer contains 1000 neurons. In order to shows the performance of different network architecture, the GoF of test dataset is calculated. And the result is shown in table 1.

We can observe that when the architecture of DNN is 3 layers and contains 1000 neurons of each layer, the GoF is maximum. So, the architecture of DNN is determined.

B. RMSE VERSUS SNR

In this subsection, we compare the statistical performance of proposed method with classic physics-driven DBF, MUSIC, ML methods and latest data-driven feature reversal, SVR-based methods in GoF and RMSE under different SNR. The only difference between the simulation conditions of this subsection IV-B and IV-A is that the range of SNR in IV-B is −5 dB to 5 dB.

Fig. 8 depicts the relationship curve between RMSE and SNR. We can observe that the proposed method shows more superior estimation accuracy over MUSIC, ML, DBF, feature reversal and SVR based methods. After enhancing the phase feature, the performance of existing physics-driven methods such as MUSIC, DBF and ML are significantly improved. This means that applying DNN to enhance phase feature of received data can improve DOA estimation accuracy effectively, which is consistent with our theoretical analysis in section II.

In order to demonstrate that the phase error occurred on each antenna has been mitigated through DNN training, a comparison about phase difference distribution of original received data and enhanced data is shown in Fig. 9. As we

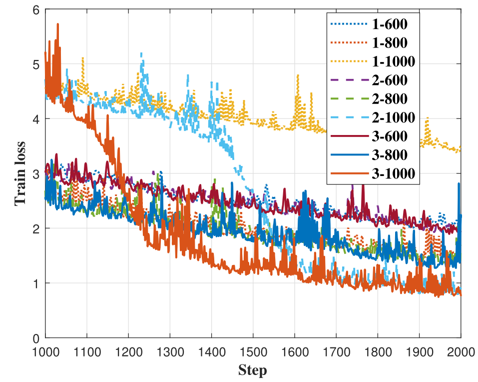

FIGURE 7. Convergence analysis of different network architecture.

TABLE 1. Network architecture analysis.

R^2 neurons / layers	600	800	1000
1	0.9204	0.9198	0.9215
2	0.9481	0.9487	0.9474
3	0.9462	0.9581	**0.9641**

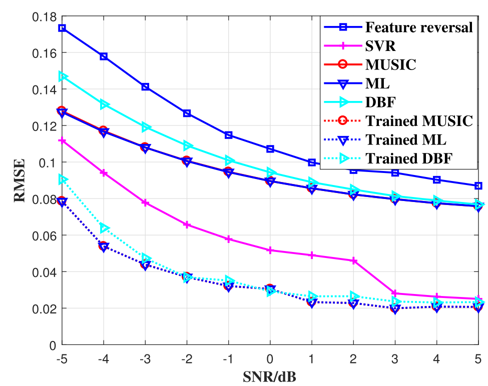

FIGURE 8. Relationship curve between RMSE and SNR.

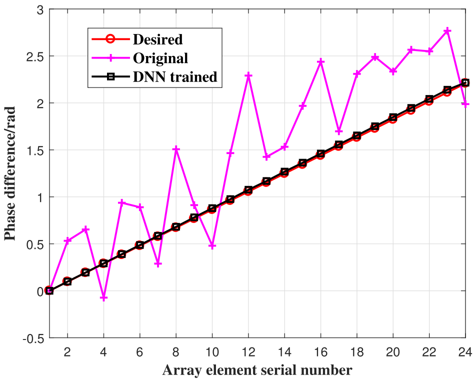

FIGURE 9. Phase difference comparison.

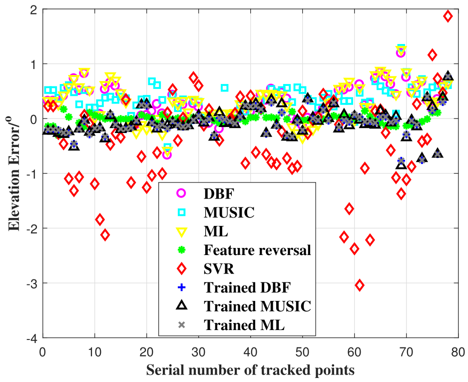

FIGURE 11. Phase difference comparison.

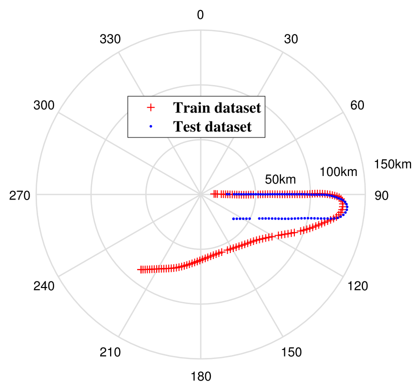

FIGURE 10. Flight path of target in train dataset and test dataset.

TABLE 2. Statistical result.

Approach	RMSE(°)	GoF
DBF	0.43	0.95
MUSIC	0.44	0.95
ML	0.45	0.94
Feature reversal	1.19	0.87
SVR	1.05	0.88
Trained DBF	**0.25**	**0.97**
Trained MUSIC	**0.26**	**0.97**
Trained ML	**0.25**	**0.97**

can observe, the phase distortion has been mitigated through DNN training. The DOA estimation error of the enhanced data is only 0.03°, which is completely acceptable. Hence, enhancing phase to improve the DOA estimation accuracy is viable.

V. VALIDATION WITH REAL DATA

The proposed phase enhancement method is also validated with real data sampled from a 21-element VHF array radar. The radar's 3 dB beamwidth is about 5°. The original data are processed by pulse compression, moving target indication (MTI) and constant false alarm rate (CFAR) to detect targets and form flight paths for detected targets. In order to ensure the training dataset and test dataset are mutually exclusive, one flight path is used to collect data to train the DNN, and a different flight path is used to collect data to test. The path of target in the train dataset and the test dataset were depicted in Fig. 10. The real elevation information in training dataset can be computed by collecting ADS-B launched by targets.

Fig. 11 shows the error of DOA estimation. Owing to existence of irregular reflected signal from ground, the phase distribution is severely distorted. We can see that the results of elevation that error of classic MUSIC, DBF and ML methods fluctuates around the real value. Through enhancing phase feature with our proposed method, the DBF, MUSIC and ML methods have smaller error. Also, ours outperforms feature reversal and SVR based methods in performance.

In table 2, we calculate the results of DOA estimation in terms of RMSE and GoF. We can see that through DNN training, the angular error of DBF, MUSIC and ML methods is reduced to about 0.25°, and the GoF is increased to 97%. Moreover, after DNN training, the performance of DBF, MUSIC and ML algorithms are approximately equal. Since MUSIC involves eigenvalue decomposition, ML has matrix inversion operation. MUSIC method and ML method have much larger computational complexity than DBF method. Therefore, after phase enhancement, super-resolution algorithms such as MUSIC and ML are no longer needed, and the DBF method can perform super-resolution estimation. Considering the training process is off-line, phase enhancement process is pure real operation and DBF method can achieve super-resolution DOA estimation, the computation complexity of proposed method is lower.

As we know, the lower the elevation angle of the target, the more complex the ground reflection signals, the more severe the phase distortion of the direct signal. When the target elevation angle is the smallest (about 3.86°), the phase distribution before and after DNN enhancement is shown in Fig. 12. And the corresponding spatial spectrum of DBF and MUSIC method is shown in Fig. 13. We can clearly see that the unknown phase distortion has been mitigated through phase enhancement with DNN. The spectral peak at desired angle is shaper than before. Therefore, the proposed method is more robust than existing methods. The validity

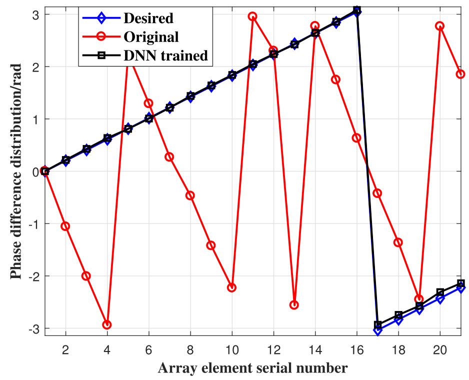

FIGURE 12. Phase difference comparison when θ is 3.86°.

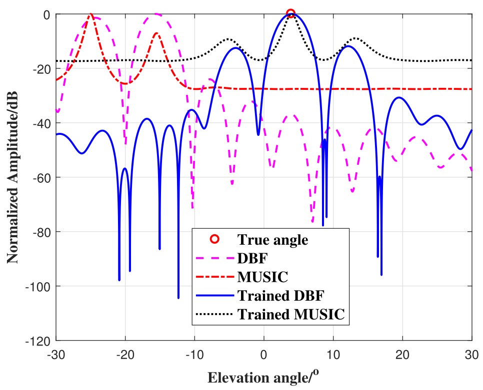

FIGURE 13. Spatial Spectrum comparison when θ is 3.86°.

and feasibility of the proposed method has been verified by real data.

VI. CONCLUSION

In this paper, a novel phase enhancement method for low-angle estimation using supervised DNN is proposed. We analyze the effect of unknown multi-path signals. The unknown multi-path signals severely distort the phase feature distribution of desired signal. Through phase enhancement with DNN, the distortion is effectively mitigated, and the DOA estimation accuracy is improved. Experimental results and real data results show the validity and feasibility of proposed method.

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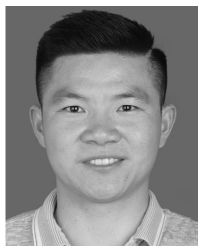

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