Postprint of Single-Input Aperture Field Phase Retrieval Method for Reflector Antennas Based on Adversarial Neural Networks

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Abstract

Microwave holography measurement technology is widely used in the surface measurement of reflector antennas. Among these techniques, phase retrieval methods are extensively applied to the surface profile calibration of radio telescopes because they do not require additional specialized equipment. This method involves obtaining the approximate aperture field phase through an iterative process between the aperture field and far-field data, typically utilizing specific inversion algorithms based on antenna far-field intensity data.

To improve computational efficiency, a model based on the Conditional Generative Adversarial Network (CGAN) method was designed using deep learning technology to solve the problem of reflector antenna aperture field phase retrieval under a single input of far-field amplitude. The phase retrieval method based on this model abandons the dependence on prior knowledge and the time-consuming iterative processes characteristic of traditional methods. In the original CGAN loss function, Mean Square Error (MSE) and Structural Similarity Index Measure (SSIM) loss functions were incorporated to optimize network training and improve phase retrieval accuracy.

Verification demonstrates that the CGAN network is robust against Poisson noise and can be used as a denoising tool during the phase retrieval process. The CGAN framework not only enhances phase retrieval accuracy and reduces computational complexity but also contributes to solving phase retrieval problems in Fourier imaging systems; furthermore, this method can be applied to phase error measurements in other fields.

Full Text

Preamble

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Single-Input Aperture Field Phase Retrieval Method for Reflector Antennas Based on Adversarial Neural Networks

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Abstract: To address the issues of low efficiency and susceptibility to local optima in traditional phase retrieval methods for reflector antennas, this paper proposes a single-input aperture field phase retrieval method based on an Adversarial Neural Network (ANN). By integrating a Generative Adversarial Network (GAN) with a Convolutional Neural Network (CNN), the proposed method establishes a mapping relationship between the single-amplitude far-field pattern and the aperture field phase. Specifically, the generator network utilizes an encoder-decoder structure with residual blocks to extract deep features from the far-field pattern, while the discriminator network employs a multi-layer convolutional structure to distinguish between the predicted phase and the ground truth. To improve the accuracy of phase reconstruction, a composite loss function combining pixel-level loss and adversarial loss is designed. Simulation results demonstrate that the proposed method can accurately reconstruct the aperture field phase from a single far-field amplitude measurement, significantly reducing the time required for phase retrieval compared to iterative algorithms. Furthermore, the method exhibits robust performance under different signal-to-noise ratios, providing an efficient and reliable solution for the surface error diagnosis of large reflector antennas.

Key words: reflector antenna; phase retrieval; adversarial neural network; deep learning; aperture field

1 Introduction

Large reflector

摘要

Surface shape calibration for radio telescopes widely employs phase retrieval methods. This approach typically involves an iterative process using inversion algorithms to recover the approximate aperture field phase from the antenna' s far-field intensity data. To improve computational efficiency, this study utilizes deep learning techniques to design a model based on the Conditional Generative Adversarial Network (CGAN) framework. This model is specifically designed to solve the phase retrieval problem of reflector antenna aperture fields using only a single far-field amplitude input.

Unlike traditional methods, this CGAN-based phase retrieval approach eliminates the dependence on prior knowledge and the time-consuming iterative process. To optimize network training and enhance phase recovery accuracy, the original CGAN loss function was modified by incorporating Mean Square Error (MSE) and Structural Similarity Index Measure (SSIM) loss components. Validation results demonstrate that the CGAN network is robust against Poisson noise, suggesting its potential as a denoising tool during the phase retrieval process. The CGAN framework not only improves recovery precision and reduces computational complexity but also provides a viable solution for phase retrieval in Fourier imaging systems and phase error measurements in other fields.

Keywords: techniques: phase retrieval, methods: numerical, methods: data analysis
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1 引言

Introduction

In the architecture of communication systems, the antenna of a radio telescope plays a vital role. The aperture efficiency of an antenna is significantly affected by the precision of its reflective surface shape. Due to manufacturing tolerances and structural deformations caused by environmental loads such as gravity, the antenna surface deviates from an ideal paraboloid, leading to a reduction in efficiency. To maintain antenna performance, it is necessary to calibrate the precision of the reflective surface, measure surface deviations, and readjust the panel positions to improve the surface accuracy [?]. As radio telescope designs continue to advance, antenna diameters are increasing and operating frequencies are rising, imposing even stricter requirements on surface precision. Therefore, accurate measurement and calibration of the antenna surface are essential for maintaining and enhancing electrical performance. Industrial measurement systems were first introduced to the field of antenna measurement in the 1980s [?]. Depending on the type of sensors employed, these systems utilize various techniques such as the theodolite method and photogrammetry. The theodolite method uses high-precision electronic theodolites to achieve non-contact measurement of the antenna based on spatial angle measurement technology.

However, as the measurement aperture area increases, more markers must be manually set, which increases the time and labor required for measurement. Photogrammetry uses one or several high-precision measurement cameras to perform rapid, non-contact measurements based on the principle of close-range photogrammetry. This method also requires the manual placement of a large number of markers, the quantity of which increases significantly with the aperture area, thus requiring more time. Since the 1980s, a series of medium and large-scale millimeter-wave and sub-millimeter-wave radio telescopes have been put into operation. The precision of the aforementioned traditional measurement methods has approached its limit. Consequently, the application of microwave holography in measuring antenna surface precision has become increasingly common. This technique is based on the Fourier transform relationship between the aperture field distribution of the radio telescope antenna and its far-field radiation pattern. Depending on the method of phase acquisition, microwave holography can be divided into two main categories: phase-coherent holography and phase-retrieval holography. [Figure 1: see original paper] shows a schematic diagram of phase-coherent holography. This technique can accurately measure the complex far-field radiation pattern of a radio telescope by observing strong radio sources or geostationary satellites [**?**]. During this measurement process, the satellite beacon signal received by a reference antenna is fed into the reference channel of the holographic receiver, while the signal received by the antenna under test (AUT) serves as the measurement signal. During testing, the reference antenna remains fixed and continuously pointed at the satellite, while the AUT adjusts its azimuth or elevation angles. Using an amplitude-phase receiver, the amplitude and phase data of the antenna are recorded at various positions to obtain the far-field amplitude and phase patterns of the AUT. Through the Fourier transform, the aperture field distribution can be derived from these data, including the electric field amplitude and phase information at each point on the antenna aperture. Based on the analysis of the aperture field phase, the deviation between the antenna surface and the ideal geometric shape can be determined. Phase-retrieval holography does not require the phase of the antenna radiation field; instead, it utilizes the radio telescope' s receiver for measurement. After obtaining the far-field amplitude data, phase information is recovered through iterative algorithms.

Iterative phase-retrieval algorithms using a single amplitude input originated from the GS (Gerchberg-Saxton) algorithm proposed by Gerchberg in 1972, which can inversely derive the phase distribution of the antenna aperture field. However, the convergence of this algorithm is sensitive to the choice of initial values and relies on certain prior knowledge [**?**]. Following the GS algorithm, modified GS algorithms based on multiple amplitudes, such as the Misell algorithm, were developed to reduce dependency on initial value selection. The Misell algorithm uses multiple far-field amplitude distributions and a preset initial phase value to gradually approach the true phase through multiple iterations. When processing phase-retrieval problems, the Misell algorithm can flexibly adjust gradients to reduce the possibility of falling into local minima [?]. This method has demonstrated good results in the surface precision testing of the 64 m antenna at the Usuda Deep Space Center (UDSC) in Japan and the 13.7 m antenna at the Qinghai Station of the Purple Mountain Observatory [?]. Nevertheless, the choice of initial values still significantly impacts the performance of the Misell algorithm; inappropriate initial values can lead to slow convergence or entrapment in local minima. Furthermore, the Misell algorithm needs to process multiple far-field amplitude distributions during the iterative process, which increases the complexity of data processing [?].

With the development of artificial intelligence, deep learning has been widely applied to phase retrieval. In 2021, Tong et al. developed the 1FPRNetV1 (Fourier Phase Retrieval Network version 1), which can achieve phase retrieval through a single far-field diffraction pattern. Compared to the GSF (Gerchberg-Saxton-Fienup) algorithm, its phase recovery is more accurate and faster [?], providing inspiration for the approach in this paper. The Conditional Generative Adversarial Network (CGAN), an improvement of the Generative Adversarial Network (GAN), introduces conditions to replace noise, resulting in superior network stability while retaining the advantages of GANs. This model has garnered significant attention in the field of neural networks and continues to be improved [?]. In 2018, Tang utilized a GAN generator to expand datasets for automatic modulation classification in wireless networks, thereby improving classification accuracy [?]. In 2024, Zou et al. used GANs to address issues arising from increasing communication rates and complex communication scenarios, such as complex channel generation, high-dimensional channel estimation, and insufficient acquisition of actual signals. Their results suggested that GANs can break through the bottlenecks of traditional communication technologies, proving that GANs possess excellent nonlinear fitting capabilities and play a significant role in data generation and processing [?].

To address the sensitivity to initial values in the GS algorithm—a common single-input phase-retrieval method—this paper proposes an aperture field phase-retrieval framework based on CGAN, utilizing deep learning concepts. Deep learning is employed to learn the input-output relationship between the far-field amplitude and the aperture field phase, thereby achieving data-driven aperture field phase retrieval. Ultimately, a convolutional network can be used to recover the aperture field phase of a reflector antenna from a single far-field amplitude input. Compared to traditional methods, this approach can rapidly recover the aperture field phase and avoid reliance on prior knowledge. Additionally, in the iterative process of the GS algorithm, each update step depends on the result of the previous step. If noise exists in the input data, it can accumulate and amplify during iterations, causing the final recovered phase distribution to deviate from the true value. In contrast, the end-to-end training method of deep learning optimizes directly from input data to output results. This optimization approach can better utilize the information within the data and reduce the accumulation of errors from intermediate steps.

2.1 单输入相位恢复迭代算法原理

Single-input phase retrieval iterative algorithms approximate the aperture field phase distribution step-by-step using only a single far-field intensity map. The Gerchberg-Saxton (GS) algorithm is one of the most representative methods among single-input phase retrieval iterative algorithms, and it is widely used in the field of phase retrieval due to its simplicity and effectiveness.

As shown in [Figure 2: see original paper], the GS algorithm is a phase retrieval method based on iterative principles. Its core concept involves repeatedly iterating between the far-field and the aperture field under the condition of a known far-field intensity distribution until the operation finally converges. The iterative process includes the Fast Fourier Transform (FFT) and the inverse Fast Fourier Transform (iFFT). In the k-th iteration, the far-field distribution is calculated from the aperture field via FFT, as shown in the following equation:

Where (u, v) represent the transverse and longitudinal coordinates of the antenna far-field, and (x, y) represent the transverse and longitudinal coordinates of the antenna aperture plane. $T_{far}(u, v)$ denotes the antenna far-field distribution, $T_{ap}(x, y)$ denotes the aperture field distribution, $\phi(u, v)$ represents the far-field phase, A represents the far-field amplitude, and $\mathcal{F}\{T_{ap}(x, y)\}$ represents the Fourier transform of the aperture field. After the Fourier transform of the aperture field, the phase of the resulting far-field T_{far} is retained, and a new antenna far-field is formed using the measured far-field amplitude I. Then, the antenna aperture field T'_{ap} is calculated via inverse Fourier transform as follows:

In the equation, $\mathcal{F}^{-1}\{T_{far}(u, v)\}$ represents the inverse Fourier transform of the far-field. The Root Mean Square (RMS) error between the far-field amplitude calculated from each Fourier transform and the actual measured amplitude is determined by:

If the difference between two consecutive RMS values is less than 10^{-8}, the iteration stops; otherwise, the iteration continues until the convergence condition is met.

$$T_{far}(u, v) = \mathcal{F}\{T_{ap}(x, y)\} = A \exp[i\phi(u, v)]; \tag{1}$$

$$T'_{ap}(x, y) = \mathcal{F}^{-1}\{T_{far}(u, v)\} = \mathcal{F}^{-1}\{I \exp[i\phi(u, v)]\}; \tag{2}$$

$$RMS_{far} = \sqrt{\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}[|T_{far}(i, j)| - |T_{far\_real}(i, j)|]^2}{M \times N}}; \tag{3}$$

$$RMS_{far}(k) - RMS_{far}(k-1) < 10^{-8}; \tag{4}$$

In the equations, $|T_{far}|$ is the far-field amplitude obtained during the iteration process, and $|T_{far\_real}|$ is the observed far-field amplitude. The objective function of the algorithm, namely the RMS of the aperture field phase, can be defined as:

Where $M \times N$ is the number of data points in the far-field. Here, ϕ_{iter} is the aperture field phase obtained during the iteration process, and ϕ_{set} is the target aperture field phase. This iterative algorithm requires multiple iterations to achieve good convergence and obtain high-precision reconstruction results.

Furthermore, the results of the GS algorithm depend partly on the initial values required during the iterative optimization process. when using random phases or zero values as the initial solution, the GS algorithm generally requires many iterations to converge and may even stagnate due to encountering local minima. Therefore, the computational speed and convergence of iterative algorithms are critical issues. Deep learning-based methods, through their powerful nonlinear mapping capabilities, multi-layer abstract representations, automatic feature extraction, and end-to-end learning, provide a new approach to solving nonlinear relationships. These methods can also address the computational speed and convergence challenges faced in phase retrieval.

[Figure 2: see original paper] GS iterative algorithm schematic diagram

2.2 基于条件生成对抗网络的口径场相位恢复

To address the phase retrieval problem, a neural network model can be employed to map the nonlinear relationship between far-field amplitudes and aperture field phases. By leveraging the ability of convolutional layers to capture local data features, the model achieves complex mapping between inputs and outputs through nonlinear activation functions. As illustrated in [Figure 3: see original paper], the network model establishes a direct connection between far-field amplitude and aperture field phase recovery, thereby bypassing the issues of repetitive iterations and the sensitivity to initial value selection inherent in the Gerchberg-Saxton (GS) algorithm.

Regarding network training, a numerical simulation method commonly used in antenna holographic measurement is adopted to rapidly generate the training dataset. In this approach, the aperture field phase is modeled using polynomials to simulate realistic antenna phase distributions. This phase is then combined with a Gaussian illumination function to construct the aperture field. The corresponding far-field is efficiently obtained via the Fourier transform, and the resulting pairs of aperture field phases and far-field amplitudes constitute the dataset. The workflow for training the Conditional Generative Adversarial Network (cGAN) is shown in [Figure 4: see original paper]. The training process for this phase retrieval method consists of two primary stages: dataset generation and model training.

3 条件生成对抗网络（CGAN）的构建

Generative Adversarial Networks (GANs) possess exceptional nonlinear fitting capabilities and play a significant role in fields such as data generation and data processing.

When applying Conditional Generative Adversarial Networks (CGAN) to the field of phase retrieval, it is necessary to introduce conditional constraints. By incorporating additional information as conditions for the model, the data generation process can be guided. This conditional information can consist of data from different modalities; in this paper, it is defined as the far-field magnitude. This network adds the condition to the input layer, thereby transforming the original unsupervised adversarial network into a supervised one. Referencing the U-Net (Convolutional Networks for Biomedical Image Segmentation) architecture, we design a CGAN framework based on an encoder-decoder structure [**?**, **?**]. [Figure 5: see original paper] illustrates the construction of the CGAN network proposed in this paper. In this architecture, the generator network takes either the far-field magnitude or a random initial value as input. The discriminator network evaluates the input y, where y represents the value fed into the discriminator, and P represents the probability that the input image is a real image.

[Figure 3: see original paper] Schematic diagram of aperture field phase recovery based on the network and the GS algorithm.

$$\mathrm{RMS}_{ap} = \sqrt{\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}[\phi_{ap}(i,j) - \phi_{ap\_real}(i,j)]^2}{M \times N}} \tag{5}$$

As shown in Fig. 3, the process involves using the GS algorithm for recovering the near-field phase. The initial near-field phase and amplitude are processed via an Inverse Fourier Transform (iFFT) and a Fourier Transform (FFT). The far-field amplitude and phase obtained from the Fourier Transform are then substituted with actual values to iteratively refine the near-field amplitude and phase.

3.1 应用于相位恢复的生成器网络构建

The generator network consists of six downsampling layers designed to reduce the spatial dimensions of the feature maps while increasing the number of channels, followed by five upsampling layers and one output layer for image reconstruction. Each downsampling layer is composed of a 2D convolutional layer with a 3×3 kernel, a stride of 2, and a padding of 1. Following the convolution, a LeakyReLU (Leaky Rectified Linear Unit) activation function is applied in-place to the input tensor. A batch normalization layer is then integrated to normalize the resulting feature maps. A forward propagation interface is defined to manage the batch normalization process. For image reconstruction, upsampling is employed to restore the image to its original dimensions. This is achieved using transposed convolutional layers with a 3×3 kernel, a stride of 2, and a padding of 1. Similarly, these layers utilize the LeakyReLU activation function applied in-place, followed by a batch normalization layer to normalize the output feature maps. The forward propagation interface defines the transformation from input to output: the input is first upsampled and then passed through the batch normalization layer, with the optional application of Dropout during specific training phases to enhance the model' s generalization capabilities.

The final output layer is a transposed convolutional layer that transforms the upsampled feature maps into the final output. This layer reduces the number of channels to one and adjusts the image dimensions accordingly. Finally, a tanh activation function is applied to normalize the output values to the range of $[-1, 1]$.

3.2 应用于相位恢复的判别器网络构建

The discriminator network consists of two downsampling modules and an output layer. Initially, a downsampling module is employed, taking the concatenated real and generated images as input. A second downsampling module further extracts features, followed by a convolutional layer to adjust the number of feature map channels, after which batch normalization and LeakyReLU activation functions are applied. By adjusting the number of convolutional kernels, the multi-channel feature maps are converted into a single-channel map, and a Sigmoid function is used to output a value between 0 and 1. During each step of the upsampling process, the output of the current layer is combined with the feature maps from the corresponding previous downsampling layer by calling the appropriate upsampling layers. This feature fusion helps the network integrate previously extracted details into the currently generated image.

[Figure 4: see original paper]

Before each optimization step, the gradients in the optimizers for both the generator and discriminator networks must be cleared to prevent gradient accumulation. The phase produced by the generator and its corresponding label are input into the discriminator to obtain the discriminator' s output regarding the generated phase. This output reflects the discriminator' s judgment on the "authenticity" of the generated phase. The total loss of the generator is then calculated by integrating the various loss terms. Backpropagation is performed on this total loss to calculate the gradients for all trainable parameters in the generator, which are subsequently used to update the weights.

Fig. 4 The network training workflow of CGAN

4 实验与分析

To evaluate the performance of the Conditional Generative Adversarial Network (CGAN) in phase retrieval tasks, this study focuses on three key metrics: recovery accuracy, stability, and computational efficiency. We employ the Structural Similarity Index (SSIM) and Root Mean Square Error (RMSE) to quantitatively assess the quality of the phase reconstruction. Higher SSIM values and lower RMSE values indicate superior recovery precision.

The dataset generation process involves constructing the aperture field and calculating the corresponding far-field distributions via Fourier transform. To evaluate the network' s robustness against noise, we introduce synthetic noise to the far-field amplitudes within the test set. These noisy inputs are then processed by the pre-trained network to recover the aperture field phase, and the results are compared against those obtained from the noise-free test set.

Furthermore, this network-based phase recovery method is compared with the Gerchberg-Saxton (GS) algorithm, a traditional iterative approach utilizing a single amplitude input. This comparison aims to demonstrate that the proposed CGAN framework achieves more accurate and rapid recovery of the aperture field phase than the conventional GS algorithm.

4.1 构建数据集

During the network training process, the numerical simulation methods typically employed in phase-retrieval holographic measurements were used to construct the necessary training dataset. Deformations on the antenna surface lead to minute variations in the electromagnetic wave propagation path, which in turn induce optical path differences (OPD). The phase distribution of the aperture field is directly proportional to the optical path difference of the reflecting surface, and their relationship is expressed as:

$$\phi = \frac{2\pi}{\lambda}\Delta L \tag{6}$$

where ΔL represents the optical path difference, ϕ denotes the aperture field phase, and λ is the wavelength. The above equation transforms the geometric deformation problem of the antenna surface into a relationship involving the optical path difference and the corresponding phase variations.

In this study, the Nanshan 26 m Cassegrain antenna in Urumqi was selected as the model. In engineering practice, the equivalent paraboloid theory is frequently applied to approximate and simplify the performance evaluation of Cassegrain antennas.

分析，26 m 天线的主要参数如表 1．卡塞格伦反射

The main reflector of a reflector antenna is a circular paraboloid. The surface error distribution of the reflector can be described using Zernike polynomials, which represent the resulting optical path length error distribution:

$$\phi = \frac{2\pi}{\lambda}\Delta L \tag{6}$$

$$\Delta L(r', \theta') = \sum [a_i Z_i(r', \theta')] \tag{7}$$

where r' is the radial coordinate of surface S, θ' is the angular coordinate, and a_i is the coefficient of the i-th Zernike polynomial. The expressions for

Zernike polynomials in polar and Cartesian coordinates are shown in . As a set of orthogonal functions, Zernike polynomials are commonly used for wavefront analysis and the description of antenna surface shapes.

Using Zernike polynomials to simulate the optical path length error distribution allows for an accurate and efficient characterization of the surface. These polynomials correspond to the Seidel aberration coefficients commonly found in optical design (such as defocus, astigmatism, and coma), making them well-suited for describing how reflector antennas compensate for effects caused by structural deformation. By combining Zernike polynomial simulations of the actual antenna phase distribution, the aperture field phase is formed. This aperture field phase is then integrated with a Gaussian illumination function to construct the aperture field model. Through the Fourier transform, far-field data can be rapidly calculated.

The aperture field phase and its corresponding far-field amplitude are paired to construct the dataset for network training. For reflector antennas, according to the equivalent antenna principle, the aperture field amplitude is typically maximum at the center and decays uniformly toward the edges. Generally, the aperture field amplitude distribution is described by a Gaussian illumination function, while the aperture field phase is represented by a third-order, 10-term Zernike polynomial.

Data Generation and Training Process

The workflow for the proposed method is as follows: 1. **Start Dataset Manufacturing**: Generate pairings of aperture field phases and far-field amplitudes. 2. **Split Dataset**: Divide the data into a training set and a test set. 3. **Model Training**: Perform a grid search to optimize hyperparameters and train the model using the training data. 4. **Obtain Results**: Use the trained model to recover the near-field phase from the test set.

[Figure 5: see original paper] illustrates the structure of the Conditional Generative Adversarial Network (CGAN) used in this study. The network takes the far-field amplitude (y^*) as input and outputs the recovered phase. The generator G attempts to produce a phase map that matches the true phase (x^*), while the discriminator D evaluates the authenticity of the generated phase given the input amplitude.

provides the main parameters of the 26-meter antenna at Nanshan, Urumqi, which serves as the basis for our simulations.

The main parameters of the 26-meter antenna in Nanshan of Urumqi | Parameter | Value | | :–| :–| | Aperture diameter / m | 26 | | Secondary face diameter / m | 3 | | Edge taper / dB | -12 | | Wavelength / cm | 1.3 | | Focal length ratio | 0.32 |

Zernike polynomial expression (The specific polynomial terms are omitted here as per the source text structure, but they represent the standard orthogonal basis for the circular aperture.)

According to Equation (6), the aperture field phase can be represented by a third-order, 10-term Zernike expansion, providing a robust mathematical framework for phase recovery using deep learning.

4.2 损失函数分析

Zernike polynomials are expressed as follows, and the aperture field distribution can be represented as: We implemented the proposed CGAN (Conditional Generative Adversarial Network) framework using the PyTorch library. The far-field amplitude and the near-field phase distribution are utilized as the input and the theoretical output of the training network, respectively. During the training process, the loss function significantly influences the performance of phase recovery. The adversarial loss function for the Generative Adversarial Network is defined as:

Utilizing the Fourier transform relationship between the far-field and the aperture field, the far-field amplitude is obtained. This method acquires the dataset based on the Fourier transform, thereby avoiding the high computational cost associated with performing complex direct integration of data in the far field. This approach enables the rapid acquisition of the aperture field phase and far-field amplitude, significantly enhancing computational efficiency.

In the numerical simulations, 10,000 sets of arrays, each consisting of 10 random numbers ranging from 0 to 1, were set as Zernike coefficients. These were combined with corresponding Zernike polynomials to form new arrays to generate the aperture field phase, from which the far-field amplitude was subsequently derived. The dataset used to train the proposed network consists of 10,000 pairs of constructed aperture field phases and calculated far-field amplitude images. Among these, 9,500 pairs serve as the training dataset, while the remaining 500 sets are used as the test dataset. Both the far-field intensity images and the aperture field phase images are represented as 8-bit grayscale images. To facilitate network training, min-max normalization [19] was applied to the dataset. The aforementioned data preparation process was implemented using Python on the PyCharm platform.

$\mathbb{E}_{x\sim P_{data}(x)}$ represents the expectation of sampling noise from the real data distribution, while $\mathbb{E}_{z\sim P_z(z)}$ represents the expectation of sampling data from the input noise distribution. $D(x|y)$ denotes the log-probability of the discriminator correctly identifying real data under given conditions, and $1 - D(G(z|y))$ denotes the complement of the log-probability of the discriminator identifying generated data under given conditions. Mean Square Error (MSE) is the most commonly used error metric in regression loss functions, and its definition is shown in the following equation:

where R and G represent the recovered phase image and the ground truth phase image, respectively, and N is the total number of pixels in the image. In the context of phase recovery, since MSE is a global metric, the MSE loss function may encounter obstacles when recovering fine phase details. The Structural Similarity Index Measure (SSIM) is a quality metric ranging from 0 to 1 used to evaluate the structural similarity between two images, which largely compensates for the weaknesses of MSE. Its definition is:

where μ_R and σ_R are the mean and standard deviation of the recovered phase image, respectively; μ_G and σ_G are the mean and standard deviation of the ground truth phase image; and σ_{RG} represents the covariance. Additionally, very small constant parameters C_1 and C_2 are required to ensure numerical stability.

The three basic loss functions are combined to pursue better phase recovery performance. The definition of the applied total loss function is: where the coefficients represent the weights of the corresponding loss functions. To balance the loss ratios, these weights are set to 2, 1, and 16, respectively. The Adam optimizer is used to optimize the loss function. The learning rate is reduced by observing the trend of the validation loss until the losses for both the training and test datasets converge stably, at which point the training process is terminated.

4.3 网络训练结果分析

Network training was conducted on a cloud computer equipped with dual RTX 3080 (20 GB) GPUs and a 12-vCPU Intel (R) Xeon (R) Platinum 8352V CPU. In this study, the training process was terminated once the loss functions for both the training and test datasets reached stable convergence, resulting in a total training time of 12 hours. To characterize the network learning process, the relationship between the training and validation loss curves of the CGAN and the number of epochs is shown in [Figure 6: see original paper] (a). The loss curves converge at approximately 60 epochs. The validation loss values are close to the training loss values, indicating that the CGAN model fits the validation dataset well. For the normalized test dataset, the box plot in [Figure 6: see original paper] (b) shows that the corresponding phase retrieval Root Mean Square Error (RMSE) is concentrated at 0.0054, while the Structural Similarity Index Measure (SSIM) is concentrated at 0.9981. Since far-field intensity images are often affected by various types of noise, representative Poisson noise was added to the 500 intensity images used as the test set. The network model was then tested under different noise levels with Signal-to-Noise Ratios (SNR) ranging from 25 to 26 dB. The average SSIM and RMSE for phase retrieval are shown in [Figure 6: see original paper] (c). The SSIM remains concentrated at 0.9940 and the RMSE at 0.0077, both of which represent high performance levels. This demonstrates that the CGAN can still achieve effective phase retrieval when processing Poisson noise.

A batch of test sets was designed to verify the network' s performance in recovering the aperture field phase under ideal (noise-free) conditions. To construct the aperture field phase, four groups of ten random numbers ranging from 0 to 1 were set as Zernike coefficients, as shown in . The test set generation method was identical to the dataset construction method described previously, yielding four groups of far-field amplitudes, as shown in [Figure 7: see original paper] (a), and aperture field phases, as shown in [Figure 7: see original paper] (c).

These four groups of far-field amplitudes were input into the network, and the resulting aperture field phases output by the network are shown in [Figure 7: see original paper] (d). Through the CGAN training process, the phase retrieval results for the test dataset were obtained. Compared with the ground truth phases, the network successfully recovered the global contours and most features of the aperture field phase.

Additionally, another batch of test sets was established using the Zernike coefficients from , with Poisson noise added to the far-field amplitudes. Under the influence of Poisson noise, the reconstructed far-field intensities are shown in [Figure 7: see original paper] (b), where the centers of the far-field intensity images are severely corrupted. The ground truth phases and the phases recovered by the CGAN are shown in [Figure 7: see original paper] (c) and [Figure 7: see original paper] (e), respectively. It can be observed that even when using far-field amplitudes corrupted by Poisson noise as input, the network still recovers the global contours and most features of the aperture field phase.

To investigate the mechanism by which noise affects the phase retrieval of the CGAN network, Poisson noise with SNRs ranging from 10 to 60 dB was added to the four test sets mentioned above. [Figure 8: see original paper] illustrates the relationship between the SNR of the antenna far-field and the RMSE of the recovered aperture field phase. As shown in the figure, a higher SNR in the antenna far-field corresponds to a smaller RMSE in the measurement error, indicating that the aperture field phase recovered by the CGAN is closer to the ground truth phase. The experimental data reveal that when the SNR is below 30 dB, the RMSE of the recovered phase decreases rapidly as the SNR increases. Upon entering the 30–40 dB transition range, the error decay curve flattens, suggesting that the improvement in retrieval accuracy provided by the SNR is limited within this range. When the SNR exceeds 40 dB, the change in RMSE becomes negligible and tends to stabilize, indicating that further increasing the SNR under high-SNR conditions has an almost negligible effect on improving retrieval accuracy.

The added noise can be regarded as a form of interference to the network. During the training process, the vast number of parameters in the deep learning architecture are adjusted through optimization to minimize prediction error. The depth and complexity of the network enable it to capture high-level features and patterns within the input data. The collective action of these numerous parameters and nonlinear network layers provides the network with a certain degree of fault tolerance. This characteristic allows the network to maintain high performance and accuracy even in the presence of noise interference. Consequently, the model exhibits strong robustness, enabling it to resist noise interference to a certain extent and maintain stable outputs. The loss functions used include the SSIM loss:

$$L_{SSIM}(R,G) = \frac{(2\mu_R\mu_G + c_1)(2\sigma_{RG} + c_2)}{(\mu_R^2 + \mu_G^2 + c_1)(\sigma_R^2 + \sigma_G^2 + c_2)}$$

The total loss is defined as:

$$L = W_{BCE}L_{BCE} + W_{SSIM}(1 - L_{SSIM}) + W_{MSE}L_{MSE}$$

where W_{BCE}, W_{SSIM}, and W_{MSE} are weighting coefficients. [Figure 6: see original paper] shows the training results of the CGAN, and lists the Zernike coefficients required for the test sets.

4.4 CGAN 恢复相位法与 GS 算法的对比

Both the Conditional Generative Adversarial Network (CGAN) phase recovery method and the Gerchberg-Saxton (GS) algorithm utilize only a single far-field intensity image. To compare the effectiveness of these two methods in recovering the aperture field phase, four groups of ten random numbers ranging from -1 to 1 were set as Zernike coefficients. This process followed the same procedure as the dataset generation, and the specific Zernike coefficients required are listed in Table 4 .

[Figure 7: see original paper] Fig. 7 Network recovery performance on test sets. Phase recovery was performed using the CGAN and the GS algorithm, each taking a single far-field intensity image as input. The original phase images, along with the phases recovered by CGAN and GS, are shown in Figure 9 [Figure 9: see original paper] (a), (b), and (c), respectively.

Although both methods utilize only a single far-field amplitude, the GS algorithm fails to accurately recover the aperture field phase information, whereas the CGAN achieves precise recovery. Among the phase images recovered by the GS algorithm (Fig. 9 (c)), group (III) exhibits the highest recovery accuracy. To further illustrate the performance of these two phase recovery algorithms, Figure 10 [Figure 10: see original paper] (a) and (b) display the horizontal and vertical cross-sectional profiles for group (III), respectively. It is clear from these profiles that the phase recovered by the CGAN network is very close to the ground truth, while the GS recovery profile deviates significantly. All aforementioned calculations were performed on a laptop equipped with an Intel Core i5-11400H CPU and 16 GB of RAM. As shown in Figure 11 [Figure 11: see original paper], the GS algorithm generally requires multiple iterations before the Root Mean Square Error (RMSE) of the far-field amplitude converges. For the four groups of examples mentioned above, the GS algorithm took an average of 12.1608 s to converge. In contrast, the CGAN network took an average of only 0.0508 s from model loading to decoding completion, demonstrating a significant advantage in terms of operational efficiency.

The experimental results indicate that the proposed CGAN has successfully learned the mapping between the input far-field intensity images and the output aperture field phase images. After learning from the training dataset, a separate test set was established. By using only a single far-field intensity image as the network input, quantitative phase recovery was obtained via CGAN. Observation of the recovered phase contours, as well as the RMSE and Structural Similarity Index (SSIM) values, shows that the CGAN exhibits excellent phase recovery performance, proving the accuracy and feasibility of the model. Furthermore, a comparison of the phase recovery performance between the CGAN and the GS algorithm on a batch of test data shows that the GS algorithm cannot accurately recover the phase in numerical simulations. Additionally, the GS algorithm is time-consuming due to the high number of iterations required for convergence, whereas the CGAN completes the phase recovery rapidly.

[Figure 8: see original paper] Fig. 8 The impact of far-field signal-to-noise ratio on the RMSE of recovered phase.

Table 4 The Zernike coefficients required for simulating near-field phase.

[Figure 9: see original paper] Fig. 9 Comparison chart of near-field phase recovery between the GS algorithm and the CGAN model.

[Figure 10: see original paper] Fig. 10 Cross-sectional comparison chart of near-field phase recovery between the GS algorithm and the CGAN model.

The proposed method demonstrates robustness and can effectively perform denoising during the phase recovery process. This approach has broad application prospects and can provide critical support for the rapid surface calibration of ultra-large aperture antennas.

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[Figure 11: see original paper] Fig. 11 RMSE of far-field amplitude using the

GS algorithm.

5 结论

Adversarial Neural Network-Based Phase Retrieval from Single Far-Field Data for Reflector Antennas

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ABSTRACT

Microwave holographic measurement technology is widely utilized in the surface measurement of telescopes, among which the phase recovery method is extensively applied in the surface calibration of radio telescopes due to its elimination of the need for additional specialized equipment.

The algorithmic model proposed in this paper successfully achieves the precise recovery of aperture field phases. This method inherits the advantages of phase retrieval holography; namely, it does not rely on a reference signal and requires only the far-field amplitude as input to obtain phase information. The network demonstrates superior phase reconstruction performance using only a single far-field intensity image.

In numerical simulation experiments, this method achieves both quantitative and qualitative phase recovery. Compared to the Gerchberg-Saxton (GS) algorithm for single-input phase retrieval, the proposed approach exhibits higher precision and faster computational speeds. Furthermore, it eliminates the dependency on prior knowledge such as aperture field amplitude distributions and the selection of initial values. The Conditional Generative Adversarial Network (CGAN) used for aperture field phase recovery also demonstrates significant robustness against Poisson noise.

[Figure 1: see original paper]

As shown in the comparative analysis, the CGAN-based approach outperforms traditional iterative methods. Figure (a) and (b) illustrate the phase recovery results compared to the ground truth and the GS algorithm across different pixel positions. The Root Mean Square Error (RMSE) of the far-field amplitude across different iterations for four test groups (Group I, II, III, and IV) further confirms the stability and convergence efficiency of the proposed neural network model.

This method typically employs inversion algorithms to iteratively obtain an approximate near-field phase from far-field intensity data of the antenna. To enhance computational efficiency, this paper adopts deep learning techniques and designs a model based on the Conditional Generative Adversarial Network (CGAN) approach to address the issue of near-field phase recovery for reflector antennas under single-input far-field amplitude conditions. The phase recovery method proposed by this model dispenses with the traditional reliance on prior knowledge and the time-consuming iterative process. The original CGAN loss function has been augmented by incorporating Mean Squared Error (MSE) and Structural Similarity Index (SSIM) loss functions to optimize network training and improve the precision of phase recovery. Validation has shown that the CGAN network is robust against Poisson noise and can serve as a denoising tool in the phase recovery process. The CGAN framework not only enhances the precision of phase recovery and reduces computational complexity but also contributes to solving phase recovery issues in Fourier imaging systems. Moreover, this method can be extended to phase error measurement in other fields.

Key words techniques: phase retrieval, methods: numerical, methods: data analysis

Note: Figure translations are in progress. See original paper for figures.