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Full Text

Preamble

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Calculating Real-Time Surface Deformation for Large Active Surface Radio Antennas Using a Graph Neural Network

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Abstract

This paper presents an innovative surrogate modeling method using a graph neural network to compensate for gravitational and thermal deformation in large radio telescopes. Traditionally, rapid compensation is feasible for gravitational deformation but not for temperature-induced deformation. The introduction of this method facilitates real-time calculation of deformation caused by both gravity and temperature. Constructing the surrogate model involves two key steps. First, the gravitational and thermal loads are encoded, which facilitates more efficient learning for the neural network. This is followed by employing a graph neural network as an end-to-end model. This model effectively maps external loads to deformation while preserving the spatial correlations between nodes. Simulation results affirm that the proposed method can successfully estimate the surface deformation of the main reflector in real-time and can deliver results that are practically indistinguishable from those obtained using finite element analysis. We also compare the proposed surrogate model method with the out-of-focus holography method and yield similar results.

Keywords: Large radio telescope; Surface deformation; Surrogate model; Graph neural network

1. INTRODUCTION

Radio telescopes have widespread applications in radio astronomy, radar, communications, and space exploration. With advancements in these fields, the need for higher observational resolution, farther communication distances, and stronger deep space detection capabilities have necessitated increasingly larger apertures and higher operating frequencies for the main reflector surfaces of antennas. However, these enhancements come with challenges. A larger aperture signifies a more complex manufacturing process for the antenna's reflector, while a higher operating frequency implies that minor surface errors could lead to significant gain loss [?]. Traditional methods such as enhancing reflector rigidity and homology design [?] are no longer sufficient. To maintain high gain for large-aperture antennas operating at high frequencies, it is necessary to compensate for surface deformation using an active surface system [?]. Specifically, we need to control the actuators on the antenna back frame structure to actively adjust the positions of the segmented panels on the main reflector, thereby optimizing the overall surface shape of the reflector. Modern large-aperture radio telescopes, such as the 110 m Green Bank Telescope (GBT) [?], 50 m Large Millimeter Telescope (LMT) [?], 64 m Sardinia Radio Telescope (SRT) [?], and Tianma 65 m radio telescope [?], are all equipped with active surface systems. The Tianma 65 m radio telescope, currently the largest fully steerable radio telescope in Asia equipped with an active surface system, holds a critical position across many domains owing to its unique design and exceptional performance.

For large, fully steerable radio telescopes, changes in the elevation angle lead to variation in the surface accuracy of the main reflector owing to gravitational deformation [?]. Additionally, the antenna is subjected to various environmental loads such as temperature [?] and wind [?]. Currently, deformation correction control systems have been developed to address this problem, based on finite element (FE) models [?]. However, thermal effects due to solar radiation and seasonal temperature variations present challenges. Seasonal temperature variation is slow and has been considered in conventional designs, while the effect of rapidly changing daily temperature on the accuracy of the surface is still an area of active research. Consequently, accurate and rapid panel correction, by calculation or measurement, is a key challenge faced by current active surface systems on large aperture antennas [?].

Surface deformation acquisition methods for large radio telescopes can be placed into two categories: surface measurement and structural analysis. Surface measurement mainly includes industrial measurement methods and radio measurement methods. Industrial measurement methods are usually used to determine target coordinates, geometry, and three-dimensional reconstruction. For large radio telescopes, the surface shape can be obtained by measuring the distance and angle of target points on the main reflector surface with industrial equipment, such as laser tracking [?], laser scanning [?, ?] and photogrammetry [?]. However, all of these are unable to attain the desired high accuracy and speed owing to technological or environmental limitations [?]. Radio measurement methods mainly consist of the phase coherence and phase recovery methods, which are based on the electrical properties of the antenna itself. The phase of the antenna's aperture field is obtained with quantitative phase imaging, allowing the surface deformation to be calculated using the linear relationship between the phase of the aperture field and surface deformation [?]. The phase coherence method obtains the aperture field complex amplitude from the Fourier transform of the acquired far-field complex amplitude [?]. Wang et al. [?] measured the surface deformation of the Tianma 65 m radio telescope using the phase coherence method, achieving a root mean square (RMS) error of less than 0.3 mm, but another 25 m radio telescope was required as the reference antenna, and the measurement time was around 2 hours. By contrast, the phase recovery method only needs to obtain the intensity map of the far field, which simplifies equipment requirements and shortens the measurement time [?]. However, low signal-to-noise ratios due to atmospheric disturbances may make the measurement impractical.

Structural analysis methods involve calculating deformations caused by dynamic loads using numerical simulations. Currently, precise FE models have been established for various large radio telescopes, along with databases of gravitational deformations at different elevation angles. Compared with the aforementioned measurement methods, the advantages of structural analysis include immunity to external disturbances and lower costs. However, structural analysis methods still present the following drawbacks: (1) The temperature of the antenna surface cannot be rapidly obtained. Although a sparse arrangement of temperature sensors is deployed on the main reflector surface and the back frame structure, directly measuring the global temperature of the main reflector would require a considerable number of temperature sensors, while indirect calculation methods based on thermal environmental exchange necessitate complex FE simulations. (2) The time consumed by thermal-structural coupled analysis and post-processing is unpredictable, potentially requiring anywhere from minutes to hours. (3) FE models can only give an approximation of the actual antenna structure.

In recent years, many researchers have used machine learning models, especially deep learning models, to replace time-consuming and complex FE computation, and these models are referred to as surrogate models. Such surrogate models have been proposed in many fields, including medical diagnosis [?, ?], stamping quality assessment [?], and structural optimization [?]. These studies transformed finite element data into Euclidean data to predict target variables, but this process disrupted the original mesh structure between the finite element nodes.

Inspired by recent advancements in the use of graph neural networks (GNNs) for physical field predictions [?, ?], we focused on the Tianma 65 m radio telescope and accounted for deformations caused by gravity and temperature, proposing an antenna deformation computational surrogate model based on a GNN. This surrogate model can estimate deformations in real-time and requires only sparse information on elevation angles and temperature data. Compared with other machine learning methods such as multi-layer perceptrons and convolutional neural networks, a GNN offers some key advantages: It preserves the spatial correlation between finite element meshes, enhancing model interpretability; it has superior feature learning capabilities, enabling automatic extraction of useful information from raw data; and it can represent graph nodes with lower-dimensional vectors, resulting in lower computational costs and faster processing speeds.

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2. ACTIVE SURFACE SYSTEM OF THE TIANMA 65 m RADIO TELESCOPE

2.1 The Tianma 65 m Radio Telescope Active Surface Hardware System

The structure and geometric parameters of the Tianma 65 m radio telescope are shown in Fig. 1A [Figure 1: see original paper] and Fig. 1B. The antenna structure comprises the main reflector, sub-reflector, back frame, subreflector support, central tube, pitch mechanism, azimuth bear, drive unit, and actuator. The main reflector of the Tianma 65 m radio telescope consists of 1,008 panels, which are distributed into 14 circles and designed in a radial pattern. Therefore, the main reflector contains 1,008 elements and 1,104 nodes, as shown in Fig. 1C. A control system is equipped underneath the panels, enabling precise control of the panels to achieve a predetermined position. This system is known as the active surface system, which causes the screws to move axially by controlling the actuators distributed between the antenna panels and the back frame structure. The key parameters of the actuator are shown in Table 1 .

The main reflector of the antenna is adjusted to a set surface to compensate for deformation, thereby improving antenna efficiency. There are two ways for the actuators to adjust the panels: independent support and shared adjustment, as shown in Fig. 2 [Figure 2: see original paper]. For independent adjustments, each actuator is used to adjust only one corner of a panel, so the number of adjustment points for the whole reflector surface is four times the number of panels. This structure ensures that the system has a higher degree of freedom, but it results in higher economic costs and additional loads. This can be mitigated using shared adjustment, with adjustment rods at the corner points of the four adjacent panels all adjusted by the same actuator drive. In other words, using shared adjustment, adjacent panel adjustment points are considered to have the same displacement. The number of adjustment points is approximately equal to the number of panels, which effectively reduces the number of actuators required by the system and simplifies the structure of the system. The Tianma 65 m antenna adopts the shared adjustment method, using 1,104 actuators, i.e., the same as the number of nodes.

2.2 The Tianma 65 m Radio Telescope Active Surface Software System

The software system is the centerpiece of the active surface system, controlling the 1,104 actuators, monitoring their status, and providing any system error status to the user. The software is operated on a Windows system and uses object-oriented technology and the Visual C++ integrated development environment with the OpenGL library and database. The software system can be divided into the main module, communication module, and file access module. The main module doubles as the graphic user interface for the software. The overall relationship between the hardware system, the modules of the software system, and the users is shown in Fig. 3 [Figure 3: see original paper].

3. METHOD

3.1 Overview of the Surrogate Model

Our proposed workflow is illustrated in Fig. 4 [Figure 4: see original paper]. The two dynamic loads that have the most significant impact on deformation are gravity and temperature, and these are used as inputs for the model. Deformations induced by gravity vary with the elevation angle of the main reflector, so we define a global coordinate system at the center of the main reflector, as shown in Fig. 4, and extract the Z-coordinate of the surface nodes of the main reflector at each elevation angle, which we refer to as the attitude code. Mapping the gravity load to the attitude code facilitates feature learning by the neural network model. Since the elevation angle range of the radio telescope is from 5° to 90°, each elevation angle corresponds to a unique set of attitude codes. For the temperature load, the Tianma 65 m radio telescope's main reflector is equipped with 60 sparse temperature sensors, and temperature data are obtained in real-time using a multi-point thermometer. Meanwhile, zero-padding is employed to complete the temperature data for nodes without temperature sensors, i.e., only 60 of the 1,104 nodes have actual temperature values, with the rest of the nodes being assigned temperature values of zero. Next, the attitude code and sparse temperature data serve as inputs to the GNN, as node features of the graph. After the encoding, message passing, and decoding processes, the surface deformation of the main reflector can be obtained.

3.2 Finite Element Dataset

Traditionally, deep learning models require a diverse dataset, including a large number of samples, to train the model parameters [?]. We use a batch computing application in the FE software to generate these samples, taking a long time to generate the FE model (Fig. 5A [Figure 5: see original paper]) with different elevation angles (from 5° to 90°) and extracting the Z-coordinates of the 1,104 nodes in the global coordinate system to form the attitude codes (Fig. 5B). Specifically, we establish the FE model of the antenna for 44 different elevation angles at intervals of 2°. The gravity distribution of the antenna changes with elevation angle, causing the deformation of the main antenna. Our FE models have a verified high similarity to the actual Tianma 65 m radio telescope and have already been applied to deformation compensation [?]. Compared with the elevation angle, the effect of the thermal environment on antenna deformation is more random and variable, so we establish a procedure to randomly change the thermal environment of the antenna FE model. The different temperature distributions of the whole antenna are obtained by FE simulation and stored as thermal loads. Meanwhile, the temperature values at the locations arranged with temperature sensors are extracted, while the temperature values at other locations are filled with zeros, thus constituting a sparse temperature vector, as shown in Fig. 5C. Subsequently, thermal and gravitational loads are applied to the antenna model at different elevation angles and the structural deformation is calculated using the FE model. Up to this point, we obtain the displacements of 1,104 nodes on the main reflector. For large radio telescopes with active surface systems, we need to obtain the required adjustment amount of the actuator by calculating the normal error between the deformed surface and the six-parameter best-fitting paraboloid as the final output of the surrogate model, as shown in Fig. 5D and Fig. 5E. Overall, the developed sample generation pipeline generates 5,000 quality assured samples, each containing attitude, temperature and deformation data represented by a set of nodes. During training and testing, the dataset containing 5,000 samples is divided into training datasets, validation datasets, and a test dataset in the ratio of 7:2:1. The training set is used to update the parameters of the model, and the validation set is used to both evaluate the performance of the model after each epoch of training and avoid overfitting. The test dataset is also used to evaluate the overall performance of the model after all training is complete.

Following model training, we visualize the discrete data on a graph. Here, the finite element mesh consists of nodes connected by edges, and we identify the mesh domain with a computational graph $G = (N; E)$, where N denotes the set of nodes and E denotes the set of edges. The ith node (in N) contains three features (attitude code, temperature, and actuator adjustment amount) in the vector.

3.3 Graph Neural Network

A GNN is a type of deep neural network that operates directly on graph data rather than Euclidean data such as vector or image data. We employ a GNN model with three parts (encoder, message passing, and decoder) to approximate the relationship between dynamic loads and deformations (shown in Fig. 4). Our inspiration comes mainly from the GNN model developed by Marco et al. [**?**]. In the graph neural network model, the input features of each node have a dimension of 2, so the role of the encoder is to encode the input features into the latent space, which is often accompanied by an increase in the dimension of those features. These encoded features are handled by the message passing module, which first aggregates the neighborhood information of each node and then updates the node state (similar to encoding). These two operations represent a single message passing. After several message passings, the node features are converted, by the decoder, into the final output. Overall, the GNN model takes attitude code and temperature as inputs and outputs deformations (as actuator adjustment amounts). Detailed information about the network structure can be found in the literature [?].

Before training, neural network models need to be manually set with a number of parameters, called hyperparameters, and they affect the training speed, convergence, and generalization ability of the models. The proposed GNN model incorporates the hyperparameters of latent size (the dimension of each node's feature vector in the latent shape), message steps (the number of message passing steps), learning rate, and optimizer. As reported by Cao and Bai [?], manual hyperparameter tuning is often time consuming. We use Bayesian optimization to automatically select the optimal hyperparameters for the network models [?, ?].

Our GNN model is implemented using the PyTorch framework, and Bayesian optimization is implemented based on the Optuna library [?] using 50 iterations. In each training session, an early stopping strategy is used to ensure that the training ends during the appropriate epoch. Specifically, the loss function (mean square error) in the validation set is monitored at each training epoch, and the training is terminated when the loss does not decrease for 30 epochs. Finally, the model with the lowest loss is saved as the best model.

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4. RESULTS AND DISCUSSION

In this paper, two performance metrics were used to evaluate the accuracy of the deformation distribution estimated by the proposed model: Root mean square (RMS) error, and relative root mean square (RRMS) error. For each sample, RMS and RRMS are defined as

$$\mathrm{RMS} = \sqrt{\frac{\sum_{i=1}^{N}((\delta_i - \tilde{\delta}_i)^2)}{N}}; \tag{1}$$

$$\mathrm{RRMS} = \frac{\mathrm{RMS}}{\delta_{\max} - \delta_{\min}} \tag{2}$$

respectively, where δ_i is a deformation value at node i calculated with FE analysis, $\tilde{\delta}_i$ is a deformation value estimated from the GNN model, N is the number of all nodes, $\delta_{\max}$ is the maximum deformation of this sample, $\delta_{\min}$ is the minimum deformation of this sample.

After selecting hyperparameters based on Bayesian optimization, the optimal hyperparameters are shown in Table 2 . Although different hyperparameters lead to inconsistent convergence speeds, most of the models converge in around 100 epochs, with an average training time of about 1.2 hours. Table 3 demonstrates the excellent performance of the optimal model on the test dataset. To demonstrate the performance of the models more intuitively, we transform the results into 128 × 128 images by interpolation, as shown in Fig. 6 [Figure 6: see original paper]. The deformation distribution of the main reflector surface obtained by the proposed method has almost zero error compared with the results obtained by FE computation, and there are no extreme local differences.

To further verify the feasibility of our proposed method, we compare the GNN-based surrogate modeling method with the out-of-focus holography (OOF) method. The OOF method retrieves the phase of the aperture field from the intensity image of the far field when the antenna is focused and defocused, and then solves the amount of the required adjustment of the actuator by using the relationship between the phase of the aperture field and the deformation of the main reflector surface. The effectiveness of the OOF method has already been demonstrated on the Tianma 65 m radio telescope, yielding a surface deformation error below 0.3 mm. Further details are available in previously published literature [**?**]. For the surrogate modeling method, we simply need to record the antenna elevation angle and temperature sensor data while performing the OOF measurement. It is worth noting that the OOF method uses Zernike polynomials to parameterize the surface deformation, which are also used to fit the results of the surrogate model to ensure the comparison is valid. A comparison diagram between the computed results of the surrogate model and the OOF measurement is shown in Fig. 7 [Figure 7: see original paper], showing the similarity between the results of the two methods.

In addition to surface accuracy, the consumption time is a metric worth highlighting. For gravity deformation, this can be obtained in real-time by searching the established gravity deformation database. Considering the cases of both gravity and temperature, the current method cannot calculate surface deformation in real-time. However, computational speed is an advantage of the surrogate model. We only need to collect sparse temperature data, as well as the elevation angle of the antenna, which can be acquired in a few seconds. When the GNN model is one-time trained, the computation time for a single sample can be acquired in under a second, meaning that the total consumption time (data collection time plus computation time) satisfies the real-time requirement.

5. CONCLUSION

We present a GNN-based surrogate model for computing surface deformation of large radio telescopes. The inputs required by the model are only sparse temperature data and the elevation angle of the radio telescope. After one-time training, using diverse datasets, the proposed method can acquire the surface deformation of the main reflector in real-time with high accuracy, providing a basis for rapid deformation compensation by the active surface system. In the future, our main improvement directions are two-fold. First, we aim to optimize the temperature input channel. Although high accuracy has been achieved using sparse temperature data, the reliability of this sparse temperature decreases in some complex external environments. Therefore, we will add physical models as constraints in the future, such as the relative azimuth between the sun and the antenna, which can better improve the accuracy and robustness of the model. Second, there are still discrepancies between the finite element dataset and the actual antenna deformation. Future work will investigate more accurate methods to obtain datasets with higher fidelity for transfer learning, allowing models to achieve results closer to the true physical deformation.

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AUTHOR CONTRIBUTIONS

Zihan Zhang and Qian Ye conceived the ideas, designed and implemented the study, and wrote the paper. Li Fu built and modified the finite element model of the radio telescope. Qinghui Liu collected the OOF measurement data. Guoxiang Meng revised the paper. All authors read and approved the final manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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