

Postprint of Neural Network Wavefront Reconstruction Method Based on Multi-feature Fusion

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Abstract

The Shack-Hartmann Wavefront Sensor (SH-WFS) is widely used in adaptive optics systems. To fully utilize the information contained in SH-WFS images, a neural network wavefront reconstruction method based on multi-feature fusion, Moment-U-Net, is proposed. In addition to the centroid offsets used in traditional wavefront reconstruction methods, this method introduces spot intensity and second-order moment features to characterize the shape information of the spots, enabling high-precision wavefront reconstruction. Moment-U-Net adopts U-Net as the backbone architecture. By introducing the dense connection module DenseBlock (Dense Convolutional Block) and the channel attention mechanism SEBlock (Squeeze-and-Excitation Block), the model can effectively extract high-order aberration features during the training process. The model is trained using large-scale atmospheric phase and wavefront image data generated through simulation and exhibits good convergence. Validated using simulated atmospheric turbulence of varying intensities, the root mean square error of Moment-U-Net wavefront reconstruction can reach 0.010-0.025 μm . Furthermore, this method maintains high reconstruction accuracy for faint stars, with a reconstruction error below 0.070 μm at 8 mag. The validation results demonstrate that Moment-U-Net not only possesses extremely high wavefront reconstruction accuracy but also exhibits high generalization capability across different turbulence intensities and magnitudes, showing the potential to enhance the correction capabilities of adaptive optics systems in practical observations.

Full Text

Neural Network Wavefront Reconstruction Method Based on Multi-Feature Fusion

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Abstract

The Shack-Hartmann Wavefront Sensor (SH-WFS) is widely utilized in adaptive optics systems. To fully exploit the information contained within SH-WFS images, a neural network wavefront reconstruction method based on multi-feature fusion, termed Moment-U-Net, is proposed. In addition to the centroid offsets used in traditional wavefront reconstruction methods, this approach introduces spot intensity and second-order moment features to characterize the morphological information of the focal spots. Moment-U-Net adopts U-Net as its backbone architecture and incorporates DenseBlocks and SEBlocks (Squeeze-and-Excitation Blocks) to enhance feature extraction. The model demonstrates excellent convergence when trained using large-scale simulated atmospheric phase and wavefront image data. Validation tests with simulated atmospheric turbulence of varying intensities show that Moment-U-Net achieves root mean square error (RMSE) values ranging from $0.010 \mu\text{m}$ to $0.025 \mu\text{m}$. Furthermore, the method maintains high reconstruction accuracy for faint stars, with errors remaining below $0.070 \mu\text{m}$ at a magnitude of 8 mag. Experimental results demonstrate that Moment-U-Net possesses high reconstruction precision and strong generalization capabilities across different turbulence intensities and stellar magnitudes, highlighting its potential for practical astronomical observations.

Key words: atmospheres: atmospheric turbulence; waves: wavefront sensor; adaptive optics

1 Introduction

Adaptive Optics (AO) systems are widely utilized in astronomical observations of the Sun, galaxies, exoplanets, and circumstellar disks. By providing real-time correction of wavefront perturbations caused by atmospheric turbulence, these systems enable ground-based telescopes to achieve observation images approaching the diffraction limit. In the field of direct exoplanet imaging [?], the requirement to detect faint planets located at distances of less than $1''$ from their host stars places even more stringent demands on the performance of adaptive optics. Currently, international instruments dedicated to exoplanet imaging, such as GPI (Gemini Planet Imager) and SPHERE (Spectro-Polarimetric High-contrast Exoplanet REsearch) at the VLT, are equipped with Extreme Adaptive Optics (Extreme AO) systems [?], which can achieve correction performance with a Strehl Ratio exceeding 0.9.

The Shack-Hartmann Wavefront Sensor (SH-WFS) is the most commonly utilized wavefront sensing instrument. It employs a microlens array to focus the

incident beam onto a two-dimensional camera, forming an array of focal spots [?]. By measuring the displacement of the centroid position of these spots relative to reference positions, the local wavefront slope can be determined. The precision of wavefront sensing directly determines the correction capability of an AO system. While increasing the number of sub-apertures can improve sensing precision, it reduces the light intensity received by each sub-aperture, thereby lowering the limiting magnitude. Consequently, optimizing wavefront reconstruction algorithms to improve the reconstruction accuracy of the SH-WFS has become a critical research topic.

Traditional SH-WFS reconstruction algorithms, such as modal and zonal methods, typically utilize only the centroid displacement of the focal spots while ignoring information regarding spot intensity, shape, and structure. Effectively utilizing the full information contained within these focal spots is key to improving accuracy. Recent studies have explored incorporating spot intensity [?], second-order moments [?, ?], and compressed sensing [?] to enhance performance. Furthermore, deep learning architectures such as ResNet [?] and Transformers [?] have been applied to map spot images directly to wavefront aberrations.

In this paper, we propose a deep learning-based wavefront reconstruction model named Moment-U-Net. This model utilizes six dimensions of information—spot displacement, intensity, and second-order moments—to perform wavefront reconstruction. By using extracted features rather than full images as input, the model reduces computational requirements while fully extracting morphological information.

2 Methodology

2.1 Wavefront Data Simulation

We utilized the HCIPy [?] package to construct an atmospheric turbulence model and a wavefront sensor model. Using Monte Carlo numerical simulation methods, we generated atmospheric phase screens and corresponding wavefront images. The phase screens were generated based on the algorithm proposed by Assémat et al. [?]. Simulations considered three turbulence intensities with Fried parameters (r_0) of 20.2 cm, 14.4 cm, and 10.1 cm. The SH-WFS utilized a 16×16 sub-aperture array. A total of 40,000 sets of data were generated for training and validation.

[Figure 1: see original paper]

2.2 Feature Extraction

For each sub-aperture focal spot, we extracted the intensity, centroid displacement, and second-order moment information. The total intensity I_{total} is:

$$I_{total} = \iint_{\Omega} I(x, y) dx dy \quad (??)$$

The centroid displacements Δx and Δy are:

$$\Delta x = x_c - x_{ref}, \quad \Delta y = y_c - y_{ref} \quad (??)$$

The second-order moments, representing spot shape, are calculated as:

$$M_{xx} = \frac{\iint_{\Omega} I(x, y)(x - x_c)^2 dx dy}{\iint_{\Omega} I(x, y)} \quad (??)$$

$$M_{yy} = \frac{\iint_{\Omega} I(x, y)(y - y_c)^2 dx dy}{\iint_{\Omega} I(x, y)} \quad (??)$$

$$M_{xy} = \frac{\iint_{\Omega} I(x, y)(x - x_c)(y - y_c) dx dy}{\iint_{\Omega} I(x, y)} \quad (??)$$

These six features form a $16 \times 16 \times 6$ matrix used as the network input.

[Figure 2: see original paper]

2.3 Moment-U-Net Model Design

Moment-U-Net is built upon the U-Net [?] architecture, enhanced with DenseBlocks [?] and SEBlocks [?]. The encoder-decoder structure captures multi-scale features, while skip connections fuse low-level and high-level information.

[Figure 3: see original paper]

The DenseBlock facilitates feature reuse and mitigates vanishing gradients. The SEBlock (Squeeze-and-Excitation Block) introduces a channel attention mechanism to adaptively recalibrate channel-wise feature responses.

[Figure 4: see original paper]

2.4 Model Training

The model was trained using the AdamW optimizer and RMSE loss function. The training set consisted of 32,000 groups, with 8,000 groups used for validation. The model converged within 60 epochs, achieving a minimum validation loss of $RMSE = 0.013$.

[Figure 5: see original paper]

3 Results and Analysis

3.1 Benchmark Testing

We compared Moment-U-Net against a version without second-order moments (similar to ISNet [?]) and the traditional Zernike modal method.

[Figure 6: see original paper]

Results show that Moment-U-Net achieves the lowest RMSE across all turbulence intensities. Under strong turbulence, the inclusion of second-order moments significantly improves stability and accuracy compared to traditional methods.

[Figure 7: see original paper]

3.2 Performance under Natural Guide Stars

Performance was evaluated for guide stars from 3 to 8 mag. Even at 8 mag, the reconstruction error remains approximately $0.070 \mu\text{m}$, demonstrating robustness to photon noise and low SNR conditions.

[Figure 8: see original paper]

4 Discussion

4.1 Principle Analysis

The high precision of Moment-U-Net stems from its multi-feature fusion. Second-order moments provide wavefront curvature information, which complements the slope information from centroids. Additionally, the neural network can adaptively handle non-linearities at the edges of the sensor and identify low-SNR spots.

4.2 Waffle Mode Reconstruction

The “waffle mode” is a checkerboard phase error that traditional slope-based methods struggle to detect because adjacent slopes cancel out. By incorporating spot shape information via second-order moments, Moment-U-Net can effectively reconstruct waffle-mode distortions.

[Figure 9: see original paper]

4.3 Third-Order Moment Extension

We further explored adding third-order moments ($M_{30}, M_{03}, M_{21}, M_{12}$) to capture high-order asymmetries like coma and trefoil.

$$M_{30} = \frac{\iint_{\Omega} I(x, y)(x - x_c)^3 dx dy}{\iint_{\Omega} I(x, y)} \quad (??)$$

This increased the input features to 10. While accuracy improved by 9.2% (RMSE decreased to $0.0131 \mu\text{m}$), computational time increased by 45.6%.

[Figure 10: see original paper] [Figure 11: see original paper]

5 Conclusion

This paper proposed Moment-U-Net, a multi-feature fusion neural network for wavefront reconstruction. By integrating spot intensity, centroid displacement, and second-order moments, the model achieves high-precision reconstruction (RMSE $\approx 0.010 \mu\text{m}$) and demonstrates strong robustness against atmospheric turbulence and photon noise. The method effectively addresses the waffle mode and shows potential for improving the limiting magnitude and correction performance of practical adaptive optics systems.

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

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