



Application of Region Growing Algorithm in Hartmann Wavefront Reconstruction

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Abstract

The Shack-Hartmann wavefront sensor measures wavefront slopes by analyzing the displacement of focal spots formed by a microlens array. Based on these slope measurements, wavefront reconstruction can be achieved by solving the difference equations that relate slope to phase. A wavefront reconstruction algorithm based on the region-growing method is proposed. Numerical simulations are conducted to compare its performance with the Southwell method for reconstructing various simulated wavefronts. The noise resistance of the algorithms was analyzed by introducing additive white Gaussian noise, and experimental results further validated the effectiveness of the proposed method. The findings indicate that the region-growing-based reconstruction algorithm achieves a lower Root-Mean-Square (RMS) error value compared to the Southwell method, with a computational time reduced to less than 2% of that required by the Southwell method. Moreover, under high-noise conditions, the proposed algorithm maintains

superior accuracy and demonstrates strong robustness. It efficiently processes wavefront slope data, providing both theoretical and experimental support for enhancing wavefront reconstruction speed in adaptive optical systems.

Keywords: adaptive optics, wavefront reconstruction, region growing algorithm, shack-hartmann wavefront sensor.

1 Introduction

Atmospheric turbulence induces wavefront distortion during laser propagation, significantly degrading beam quality [1]. As an active wavefront aberration compensation technique, adaptive optics employs real-time feedback mechanisms to dynamically correct wavefront distortions with high precision [2]. The wavefront sensor, a critical component of adaptive optical systems, is primarily used to acquire wavefront information from received beams [3]. The Shack-Hartmann wavefront sensor (SHWFS) is widely adopted in adaptive optics and related fields due to its simple structure, strong resistance to environmental noise, and high measurement accuracy, with ongoing efforts to further improve its reconstruction precision [4]. The SHWFS utilizes a microlens array to partition incident light into subapertures.



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By measuring focal spot displacements, it obtains local wavefront slopes, which are then integrated through wavefront reconstruction algorithms to achieve accurate characterization of the incident wavefront [5].

As a critical link between Shack-Hartmann sensor measurements and adaptive optics compensation, wavefront reconstruction algorithms are primarily categorized into two types: modal methods based on orthogonal basis function expansions and zonal methods based on discrete integration [6], both of which have been employed in practical adaptive optics systems [7]. Modal methods employ orthogonal basis functions such as Legendre polynomials and Zernike polynomials to represent the wavefront. By solving for the polynomial coefficients using measured slope data, a complete wavefront can be reconstructed [8]. Among these, Zernike polynomials are the most widely applied modal approach due to their direct correspondence with classical Seidel aberrations, enabling quantitative characterization of various wavefront distortions [9]. Zonal methods include three classical reconstruction models: the Hudgin model [10], Fried model [11], and Southwell model [12]. These methods exhibit strong locality, higher spatial resolution, and adaptability to arbitrarily shaped apertures. Notably, the Southwell method positions measurement points and reconstructed phase points at identical locations, with each reconstructed phase point incorporating differential phase measurements in both x- and y-directions. This configuration yields superior reconstruction accuracy, making the Southwell method the preferred choice for zonal wavefront reconstruction [4].

The zonal method faces the challenge of optimal integration path selection, as failure to reconstruct the integration along the optimal path will lead to propagation and accumulation of noise along the integration direction, thereby reducing wavefront reconstruction accuracy. Additionally, the zonal method exhibits high computational complexity and significant resource consumption, which has motivated the development of faster reconstruction approaches [13]. Although optimization algorithms, including Fourier-based modal approaches, can enhance the computational accuracy and speed of wavefront reconstruction [14], slope measurement errors cannot be fully eliminated. Therefore, a trade-off among noise immunity, accuracy, and computational complexity is inevitable. In the context of wireless optical communication systems, where real-time

compensation of atmospheric turbulence-induced wavefront distortion is critical to link performance, a wavefront slope integration reconstruction algorithm based on a region-growing approach is proposed, which initiates from a known starting point and progressively utilizes gradient information from adjacent points to achieve complete wavefront reconstruction. Research demonstrates that this algorithm can efficiently process wavefront slope data, exhibiting lower RMS values, faster reconstruction times, and superior noise resistance compared to the Southwell method.

2 Theoretical Analysis

2.1 Shack-Hartmann Wavefront Sensor

The Shack-Hartmann wavefront sensor (SH-WFS) consists primarily of a microlens array and a charge-coupled device (CCD) camera positioned at the focal plane of the microlenses, as illustrated in Figure 1. The microlens array typically comprises hundreds of microlenses with identical apertures and focal lengths, arranged in a specific tightly-packed configuration. This arrangement ensures uniform segmentation and effective sampling of the incident optical field [7].

Under ideal conditions where the incident wavefront is a perfect plane wave, each microlens focuses the incoming light onto the CCD target surface, forming a regular array of circular spots as shown in Figure 1. However, when wavefront distortion occurs, the subaperture wavefront deviates from the ideal planar state and becomes tilted. This tilt causes the focal spot array on the CCD to shift from its nominal position, resulting in the star-shaped spot displacement pattern illustrated in Figure 1.

Assuming the displacement of each deviated spot relative to the preset reference point is σx and σy along the x-axis and y-axis directions respectively, the following mathematical relationship can be derived based on geometric optics principles and wavefront sensing theory:

$$S^x = \sigma x / f, \quad S^y = \sigma y / f \quad (1)$$

where f is the focal length of the microlens. The quantities S^x and S^y are the wavefront slopes at each subaperture.

2.2 Discretization and Notation Convention

In the SHWFS, the wavefront is spatially sampled by the microlens array. To bridge the continuous

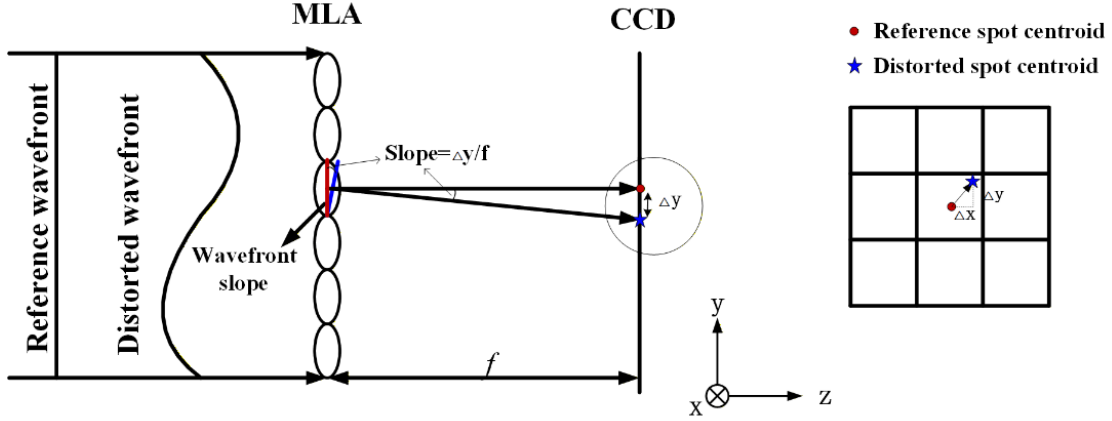


Figure 1. Schematic diagram of the measurement principle of a Shack-Hartmann wavefront sensor.

physical quantities and the discrete computational model used throughout this paper, we define the following notation, where the microlens array consists of $M \times N$ microlenses arranged on a rectangular grid with uniform pitch h (units: meters); integer indices $i = 1, \dots, M$ and $j = 1, \dots, N$ label individual microlenses, the integer indices (i, j) serve as discrete coordinates, and the corresponding physical spatial coordinates of microlens (x'_i, y'_j) are $x'_i = i \cdot h$ and $y'_j = j \cdot h$; $\phi(i, j)$ denotes the discrete wavefront phase to be reconstructed at microlens (i, j) ; the discretized slopes $S^x(i, j)$ and $S^y(i, j)$ from Eq. (1); for simulation purposes, dimensionless coordinates are identified with the integer microlens indices i and j , so that a coordinate difference of 32 corresponds to a physical displacement of $32 \cdot h$ from the origin.

2.3 Wavefront reconstruction from discrete slope measurements

Given the discrete slope measurements $S^x(i, j)$ and $S^y(i, j)$ on the $M \times N$ microlens grid defined in Section 2.2, the wavefront phase $\phi(i, j)$ can be recovered by path integration. Summing the slope data along a path from a starting microlens (i_0, j_0) to an arbitrary microlens (i, j) , an approach also adopted in recent wavefront sensing studies [15], yields

$$\phi(i, j) = \sum_c [S^x(i_c, j_c) \cdot \Delta x' + S^y(i_c, j_c) \cdot \Delta y'] + \phi(i_0, j_0) \quad (2)$$

where C denotes a path of adjacent microlenses connecting (i_0, j_0) to (i, j) , and $\Delta x' = x'_{p+1} - x'_p = h$, $\Delta y' = y'_{q+1} - y'_q = h$ are the physical spacings between adjacent microlenses along the path. The term $\phi(i_0, j_0)$ is the phase at the starting microlens.

The relationship between the measured slopes and the unknown phase values is established by

finite-difference approximations of the phase gradient. The classic Southwell method places the phase reconstruction points and the slope measurement points at the same grid locations, yielding the following set of equations

$$\frac{S^x(i+1, j) + S^x(i, j)}{2} = \frac{\phi(i+1, j) - \phi(i, j)}{h}, \quad (3)$$

$$i = 1, \dots, M-1; j = 1, \dots, N$$

$$\frac{S^y(i, j+1) + S^y(i, j)}{2} = \frac{\phi(i, j+1) - \phi(i, j)}{h}, \quad (4)$$

$$i = 1, \dots, M; j = 1, \dots, N-1$$

The left-hand sides of Eq. (3) represent the phase gradient averaged between adjacent microlenses; the right-hand sides are finite-difference approximations of the phase derivative. Together they form a system of linear equations relating the measured quantities S^x, S^y to the unknown $\phi(i, j)$.

The conventional numerical approach to solving Eqs. (3) and (4) is an iterative method [12]: starting from an initial seed point, the phase values at all grid points are repeatedly updated by applying the Southwell difference relations. In the next section, we present a non-iterative region-growing algorithm that reconstructs the wavefront by path integration: starting from an adaptively chosen seed point, it computes the phase of each neighbor directly from the local slope data and propagates outward, processing each grid point exactly once.

2.4 Wavefront Reconstruction Using Region Growing Algorithm

The zonal wavefront reconstruction method typically relies on local gradient information. The Region Growing Algorithm starts from a known initial point

and progressively reconstructs the entire wavefront by utilizing slope data from eight adjacent points. This approach is particularly suitable for processing wavefront slope measurements, as it sequentially calculates the wavefront values of neighboring points based on known reference points [16]. For complex wavefront shapes, the Region Growing Algorithm can better handle local variations and discontinuities during reconstruction. Through this propagation method, local wavefront features can be processed with higher precision, especially when dealing with sudden phase changes or irregular wavefront profiles.

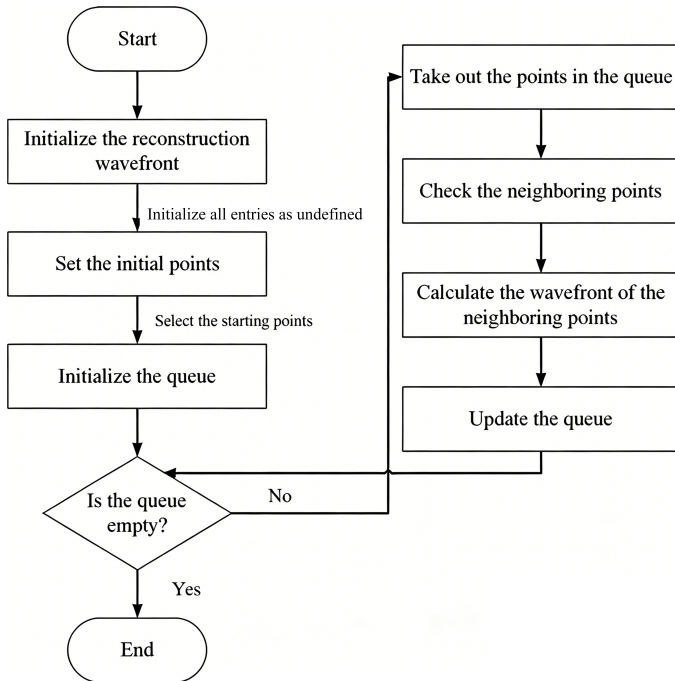


Figure 2. Flowchart of wavefront reconstruction using the region-growing algorithm.

As shown in Figure 2, the algorithm first initializes the reconstructed wavefront matrix by setting the wavefront value of the starting point to zero. The starting point is then added to the processing queue to initiate the growing procedure. The algorithm retrieves a point from the queue as the current processing point and systematically examines its eight neighboring points in all directions. For each neighbor that lies within the matrix boundaries and has not been previously visited, the corresponding wavefront value is computed based on gradient information and the point is added to the queue. This process continues until the queue is empty and the wavefront values for all points have been computed.

Algorithm Steps for Region-Growing Wavefront Reconstruction

Step 1: Initialize the phase matrix.

Create an $M \times N$ matrix ϕ to store the reconstructed phase values. Initialize all entries as undefined, indicating that no phase value has been assigned yet

$$\phi(i, j) = \text{undefined}, \quad \forall i, j \quad (5)$$

Step 2: Select the starting point adaptively.

Compute the full-field gradient magnitude as $G(i, j) = \sqrt{S^x(i, j)^2 + S^y(i, j)^2}$. Apply a small averaging window (e.g., 3×3) to obtain the local average gradient magnitude. The center point of the window with the smallest average magnitude is selected as the starting point $(i_{\text{start}}, j_{\text{start}})$. This adaptive strategy ensures that integration begins in the region of minimal phase variation. Set its initial value to zero

$$\phi(i_{\text{start}}, j_{\text{start}}) = 0 \quad (6)$$

Step 3: Initialize the processing queue.

Place the coordinates of the starting point into a queue Q that holds all points pending for processing

$$Q = \{(i_{\text{start}}, j_{\text{start}})\} \quad (7)$$

Step 4: Check queue status.

If Q is empty, terminate the algorithm. Otherwise, proceed to Step 5.

Step 5: Dequeue the current point.

Remove the first point (i, j) from Q .

Step 6: Neighboring Point Inspection.

Examine the eight adjacent points $(i + \Delta i, j + \Delta j)$ where $\Delta i, \Delta j \in \{-1, 0, 1\}$ and are not simultaneously zero. A neighbor is valid if

$$1 \leq i + \Delta i \leq M, \quad 1 \leq j + \Delta j \leq N, \quad \phi(i + \Delta i, j + \Delta j) = \text{undefined} \quad (8)$$

Step 7: Compute the phase at valid neighbors.

For each valid neighbor, compute its phase value from the known $\phi(i, j)$ and the local slope data.

Right-direction at $(\Delta i = 0, \Delta j = 1)$:

$$\phi(i, j + 1) = \phi(i, j) + S^y(i, j) \cdot h \quad (9)$$

Left-direction at ($\Delta i = 0, \Delta j = -1$):

$$\phi(i, j-1) = \phi(i, j) - S^y(i, j-1) \cdot h \quad (10)$$

Down-direction at ($\Delta i = 1, \Delta j = 0$):

$$\phi(i+1, j) = \phi(i, j) + S^x(i, j) \cdot h \quad (11)$$

Up-direction at ($\Delta i = -1, \Delta j = 0$):

$$\phi(i-1, j) = \phi(i, j) - S^x(i-1, j) \cdot h \quad (12)$$

Bottom-right at ($\Delta i = 1, \Delta j = 1$):

$$\phi(i+1, j+1) = \phi(i, j) + S^x(i, j) \cdot h + S^y(i, j) \cdot h \quad (13)$$

Top-right at ($\Delta i = -1, \Delta j = 1$):

$$\phi(i-1, j+1) = \phi(i, j) - S^x(i-1, j) \cdot h + S^y(i, j) \cdot h \quad (14)$$

Bottom-left at ($\Delta i = 1, \Delta j = -1$):

$$\phi(i+1, j-1) = \phi(i, j) + S^x(i, j) \cdot h - S^y(i, j-1) \cdot h \quad (15)$$

Top-left at ($\Delta i = -1, \Delta j = -1$):

$$\phi(i-1, j-1) = \phi(i, j) - S^x(i-1, j) \cdot h - S^y(i, j-1) \cdot h \quad (16)$$

Step 8. Update the queue.

Add each neighbor whose phase has just been computed to queue Q .

Step 9. Return to Step 4 to process the next point in the queue.

Step 10. Termination.

When the queue is empty, the matrix ϕ stores the fully reconstructed wavefront over the $M \times N$ grid.

3 Simulation Study

To validate the feasibility of the proposed method, this section conducts MATLAB simulations of wavefront aberration detection and reconstruction based on the principles of Shack-Hartmann Wavefront Sensor (SHWFS). The simulation parameters are listed in Table 1.

Table 1. Simulation parameters.

Parameters	Numerical value
Wavelength	632 nm
CCD resolution	2048 × 2048
Pixel size	10 μm
Microlens array size	64 × 64
Focal length of microlenses	10 mm
Pixels per sub-aperture	32
Full Well Capacity	10,000 e ⁻
Readout Noise	3.0 e ⁻
Dark Current	0.5 e ⁻ /px
Gain	1 DN/e ⁻

3.1 Simple Wavefront Reconstruction

In this study, the Southwell method is implemented by solving the sparse linear system derived from Eqs. (3) and (4) using a standard least-squares solver in MATLAB R2023a. This approach directly minimizes the residual of the finite-difference equations, providing a robust and unique solution for the overdetermined system without requiring iterative updating with relaxation factors. All algorithms are executed under the same software environment to guarantee a fair and reproducible comparison.

Based on the Gaussian phase formula

$$\phi(i, j) = A \cdot \exp \left(- \left(\frac{(i - i_0)^2}{2\sigma_i^2} + \frac{(j - j_0)^2}{2\sigma_j^2} \right) \right) \quad (17)$$

where $A = 30$ rad is the peak phase at the center of the Gaussian profile. The variables i and j are the dimensionless microlens indices defined in Section 2.2, obtained by normalizing the physical coordinates by the microlens pitch h ; i_0 and j_0 denote the center of the phase profile on the microlens grid. Because i and j are dimensionless, the standard deviations $\sigma_i = \sigma_j = 1/\sqrt{2} \approx 0.707$ (variances $\sigma_i^2 = \sigma_j^2 = 0.5$) are also dimensionless. For the 64×64 microlens array, the maximum distance from the center to the edge is approximately 32 microlens units. With $\sigma_i = 1/\sqrt{2}$, the phase at the boundary is $\exp(-32^2/(2 \times 0.5)) \approx 0$, confirming that the Gaussian phase effectively decays to near-zero at the sensor edges, ensuring proper boundary conditions for the reconstruction algorithm.

A Gaussian phase distribution was simulated as shown in Figure 3(a). This phase profile was input into the Shack-Hartmann wavefront sensor

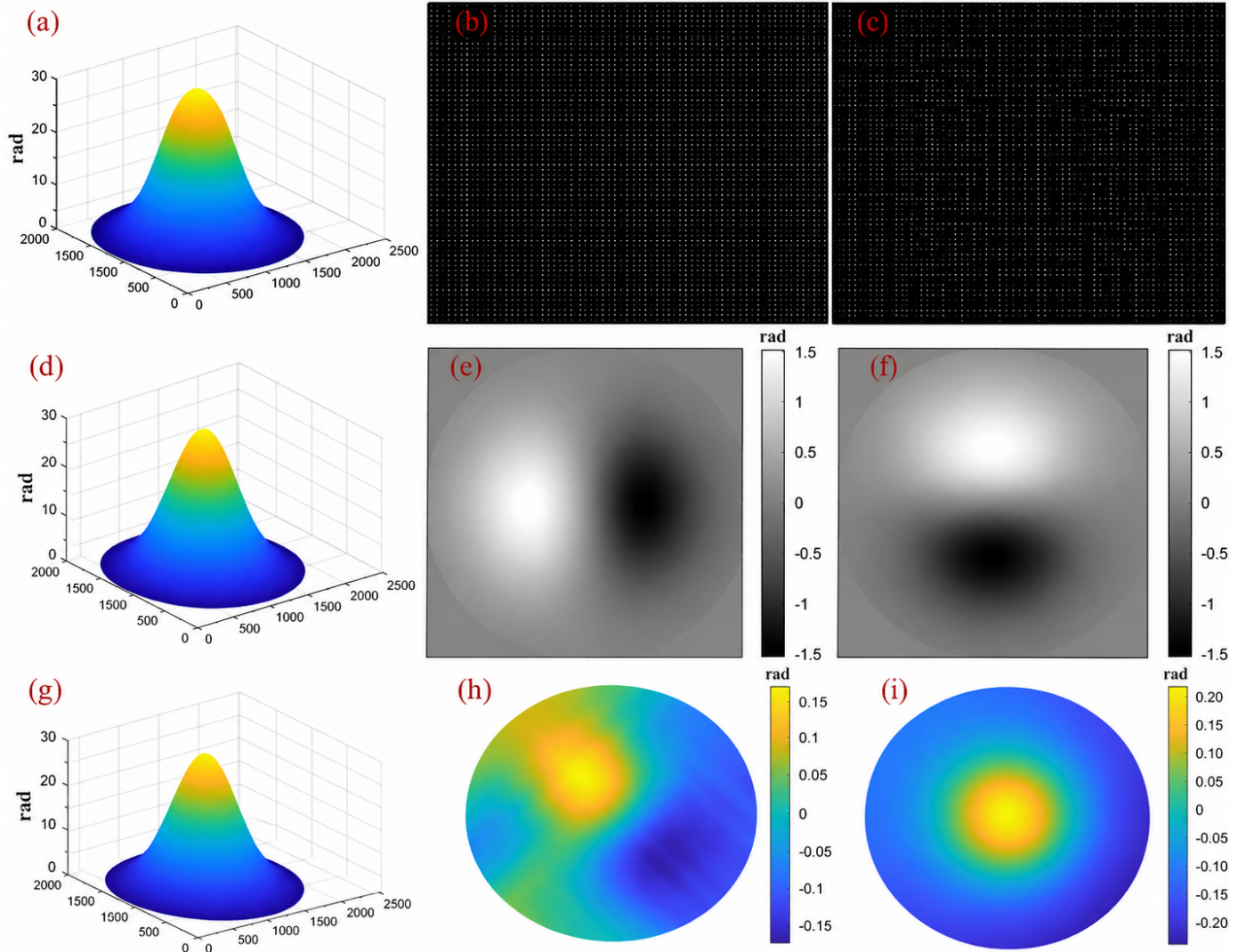


Figure 3. Reconstruction of Gaussian wavefront (a) Simulated Phase (b) Reference Spot Array (c) Displaced Spot Array from Hartmann Sensor (d) Wavefront Reconstruction Using Region-Growing Algorithm (e) X-direction Slope Field (f) Y-direction Slope Field (g) Wavefront Reconstruction Using Southwell Method (h) Error in wavefront reconstruction using regional growth algorithm (i) Error in wavefront reconstruction using Southwell method.

simulation system, generating a displaced spot array modulated by the Gaussian phase (Figure 3(c)). A reference spot array modulated by a plane wave was also obtained. Following the demodulation principle of Shack-Hartmann wavefront sensing, the displacements ($\Delta X, \Delta Y$) of each spot relative to its reference position in X and Y directions were obtained by subtracting reference spots from displaced spots. Following Eq. (1), the demodulated slope information in the X and Y directions is presented in Figures 3(e) and (f), respectively. Using these extracted slopes and our proposed method, we successfully reconstructed the wavefront, with results shown in Figure 3(d). To quantitatively evaluate the reconstruction accuracy, we computed the deviation between simulated and reconstructed phases using MATLAB's RMS function. The deviation map (Figure 3(h)) shows an RMS error

of 0.10943λ , with a reconstruction time of 0.0358 s. For comparison, the Southwell method achieved an RMS error of 0.1216λ (Figure 3(i)) with a computation time of 72.992 s.

Furthermore, this paper numerically investigates the impact of starting point selection on the accuracy of wavefront reconstruction, with the results illustrated in Figure 4. The horizontal axis represents the position of the starting point, expressed in diagonal coordinates. For instance, "1" corresponds to the starting point at (1,1), while "32" denotes the central point at (32,32). The total number of microlenses is 64×64 . The results demonstrate that the choice of the starting point has a measurable influence on the reconstruction accuracy. When the seed point is set at the center (i.e., at coordinate 32 in the figure), the RMS value

of the reconstructed wavefront is 0.10943λ . In contrast, when the adaptive starting point strategy is applied, the selected point is located at coordinate 16 (i.e., the central point located at (16, 16)), yielding a lower RMS value of 0.0908λ . Additionally, the results indicate that when the starting point is selected beyond coordinate 38, the RMS value of the reconstructed wavefront exceeds 0.1233λ , which is inferior to that achieved by the Southwell method.

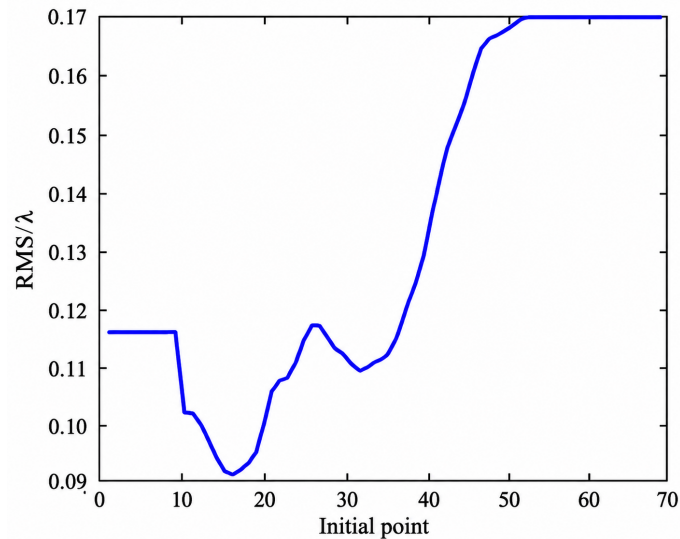


Figure 4. Effect of Starting Point Selection on Wavefront Reconstruction Accuracy.

Figure 4 illustrates the influence of starting point location on the reconstruction accuracy of a Gaussian wavefront. This phenomenon can be qualitatively explained from the perspective of error accumulation in path integration. The gradient of a Gaussian wavefront increases from the center outward. If the growth begins from a region with a large gradient, measurement noise or computational errors propagate toward regions with smaller gradients and become amplified. Moreover, because the region-growing algorithm processes neighbors in a fixed directional sequence, the integration path is inherently asymmetric: even geometrically symmetric starting points, such as (1,1) and (64,64), accumulate errors differently depending on their position relative to the traversal order. Conversely, starting from the region with the smallest gradient magnitude—i.e., the adaptive starting point—effectively suppresses error accumulation and minimizes the path-dependent bias. The adaptive starting point strategy therefore enhances the robustness of the algorithm by optimizing both the starting location and the subsequent growth direction.

3.2 Complex Wavefront Reconstruction

As shown in Figure 5, this set of simulations employed standard Zernike polynomials to simulate complex aberrations. The Zernike polynomial terms selected were the 4th, 5th, 7th, 8th, 9th, 10th, and 11th orders, with corresponding coefficients of 1.3, 1.5, 2.1, 4.9, 3.2, 6.1, and 2.8 rad, respectively, as detailed in Table 2. The phase map generated using these standard Zernike polynomials is presented in Figure 5(a). The simulation produced a displaced spot array, as illustrated in Figure 5(c). The demodulated slope information in the X and Y directions is shown in Figures 5(e) and (f), respectively. The reconstructed wavefront using the proposed method is displayed in Figure 5(d), achieving an RMS deviation of 0.0536λ with a reconstruction time of 0.03968 s. In comparison, the wavefront reconstructed using the Southwell method yielded an RMS deviation of 0.2778λ and required a significantly longer computation time of 75.9859 s.

Table 2. Zernike polynomial terms and coefficients used to generate the complex wavefront.

Term Index	Polynomial Name	Coefficient/rad
4	Pri Astigmatism-A	1.3
5	Focus	1.5
7	Pri Trefoil-A	2.1
8	Pri Coma-A	4.9
9	Pri Coma-B	3.2
10	Pri Trefoil-B	6.1
11	Pri Tetrafoil-A	2.8

3.3 Noise Robustness Analysis

To verify the noise robustness of the proposed algorithm, additive Gaussian white noise with a standard deviation of $\sigma = 0.4$ rad was added to the wavefront shown in Figure 6(a), i.e., the noise follows a normal distribution with a mean of 0 and a standard deviation of 0.4 rad. The resulting displaced spot array is presented in Figure 6(c), from which the slope information in the X and Y directions was derived (Figures 6(e) and (f), respectively). The reconstructed wavefront is displayed in Figure 6(d). The proposed algorithm achieved a wavefront reconstruction with an RMS deviation of 0.054λ and a computation time of 0.3489 s. In comparison, the Southwell method yielded an RMS deviation of 0.07368λ with a significantly longer reconstruction time of 75.4143 s.

These results demonstrate that our algorithm provides superior reconstruction performance compared to the

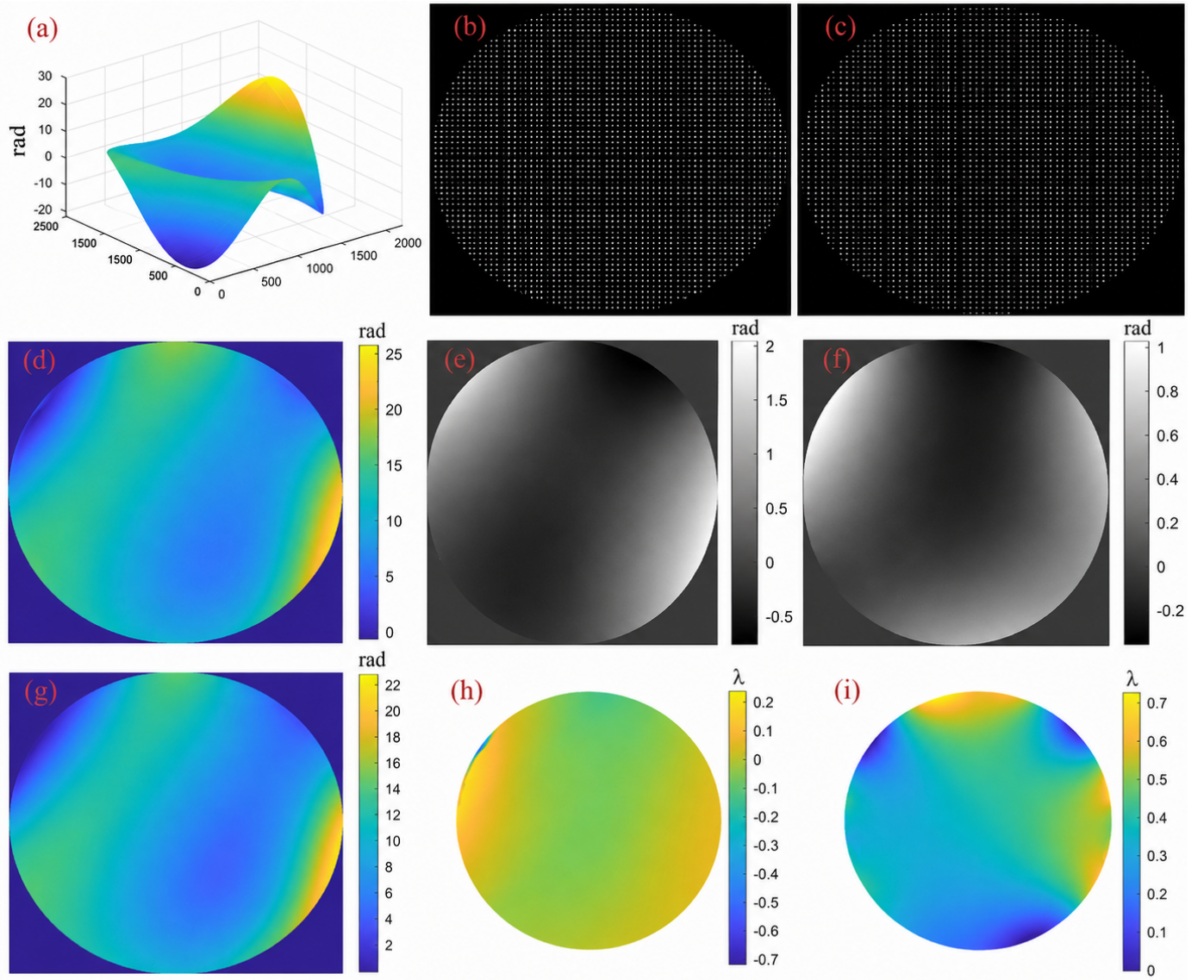


Figure 5. Reconstruction of complex wavefront with multiple Zernike coefficients (a) Simulated Phase (b) Reference Spot Array (c) Displaced Spot Array from Hartmann Sensor (d) Wavefront Reconstruction Using Region-Growing Algorithm (e) X-direction Slope Field (f) Y-direction Slope Field (g) Wavefront Reconstruction Using Southwell Method (h) Error in wavefront reconstruction using regional growth algorithm (i) Error in wavefront reconstruction using Southwell method.

Southwell approach under noisy conditions.

Figure 7 presents the trend of RMS values of the reconstructed wavefronts versus different noise levels when the wavefront shown in Figure 6(a) is subjected to white noise in the range of $\sigma = 0 - 0.6$ rad and reconstructed using both the Southwell method and the proposed algorithm in this paper. It can be observed from Figure 7 that when the noise level exceeds $\sigma = 0.2$ rad, the proposed method achieves smaller root mean square errors, indicating that the proposed method exhibits superior reconstruction performance under high noise levels.

Subsequently, additional noise was introduced at the detector side to further validate the robustness

of the proposed regional growth-based wavefront integration reconstruction method. The results are presented in Figure 8. Figure 8(a) displays the original simulated wavefront phase. Figure 8(b) shows the spot array after adding noise, where noise based on a typical camera model (key parameters are listed in Table 1) has been introduced at the detector end, including a mean dark current ($0.5 \text{ e}^-/\text{px}$) and readout noise (standard deviation of 3.0 e^-). Figure 8(c) presents the wavefront reconstructed using the regional growth method proposed in this study. The root mean square (RMS) deviation between the reconstructed wavefront and the simulated wavefront was calculated to be 0.0127λ . The results demonstrate that the proposed method maintains good wavefront reconstruction

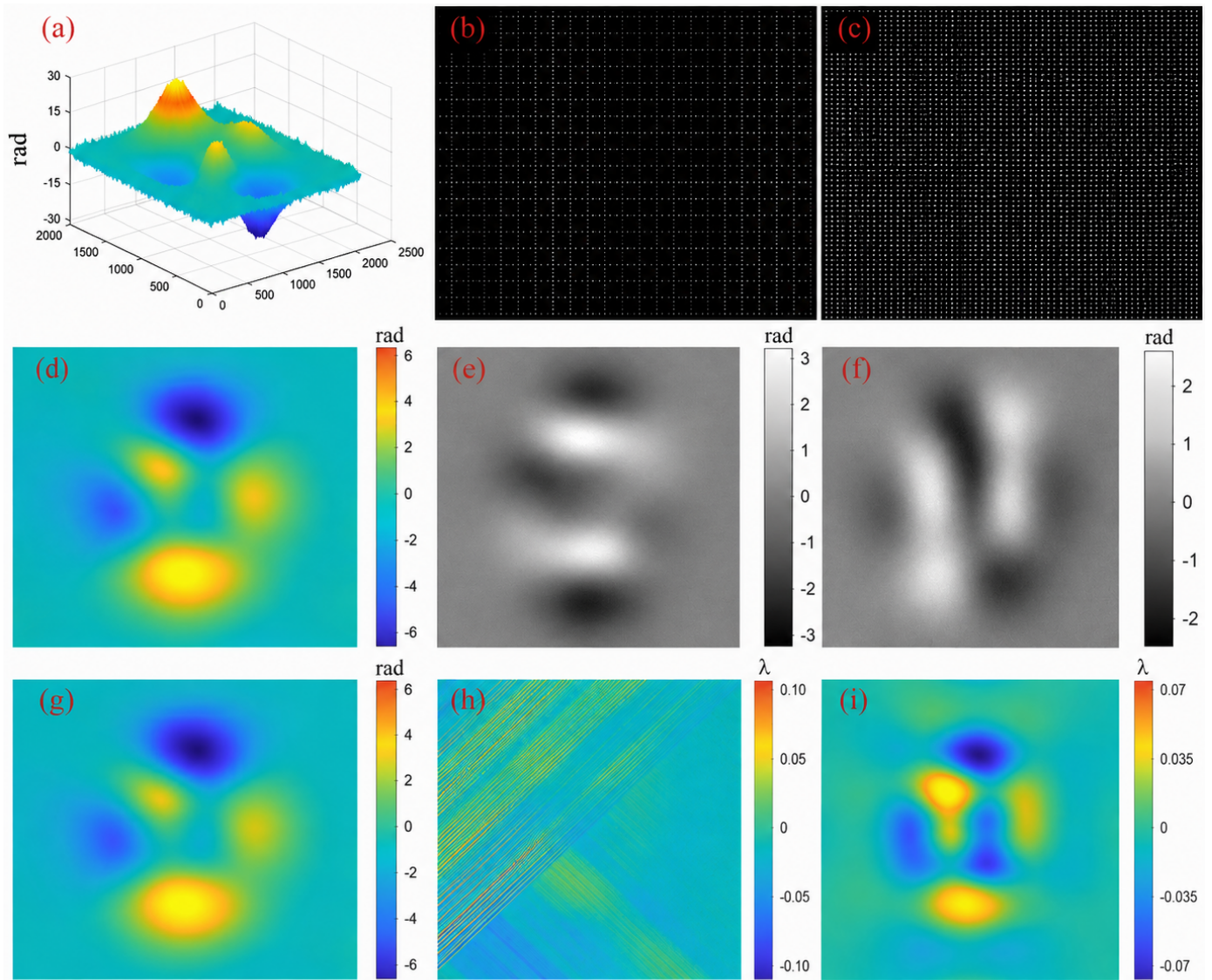


Figure 6. Wavefront reconstruction with additive white noise. (a) Simulated Phase with Additive White Gaussian Noise (b) Reference Spot Array (c) Displaced Spot Array from Hartmann Sensor (d) Wavefront Reconstruction Using Region-Growing Algorithm (e) X-direction Slope Field (Noisy) (f) Y-direction Slope Field (Noisy) (g) Wavefront Reconstruction Using Southwell Method (h) Error in wavefront reconstruction using regional growth algorithm (i) Error in wavefront reconstruction using Southwell method.

capability even under noisy conditions.

Beyond additive wavefront noise, the practical performance of SHWFS reconstruction is critically affected by centroid extraction errors arising from CCD readout noise, photon shot noise, and background non-uniformity. The camera noise model adopted in this study (dark current of $0.5 \text{ e}^-/\text{px}$ and readout noise of 3.0 e^-) partially accounts for these effects. In more extreme scenarios, such as spot overlap or pixel saturation, the proposed region-growing algorithm exhibits inherent robustness. Since it employs an eight-neighbor integration strategy, a spurious slope spike caused by an erroneous single

centroid only affects the local growth path originating from that particular point. Furthermore, the adaptive seed-point selection strategy, which initializes the growth from the region with the minimal gradient magnitude, effectively prevents large-scale error propagation across the entire aperture. This localized error-confinement mechanism provides the proposed algorithm with superior resilience against centroid extraction inaccuracies compared to the global iterative smoothing nature of the Southwell method.

3.4 Turbulent Wavefront Reconstruction

To evaluate the performance of the proposed algorithm under simulated real atmospheric

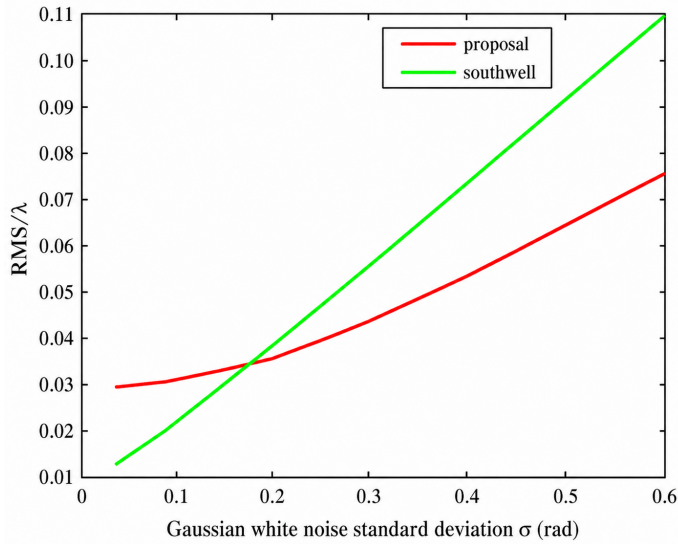


Figure 7. Trend of RMSE in reconstructed wavefront versus varying noise levels.

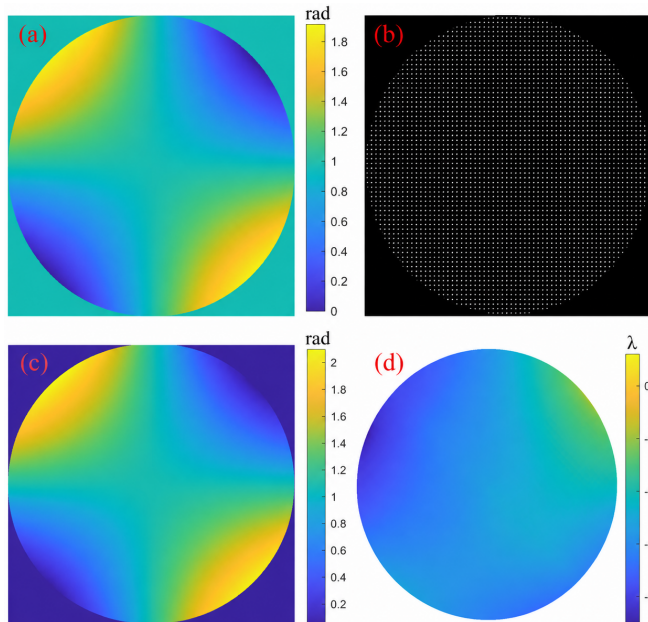


Figure 8. Robustness of the regional growth-based wavefront reconstruction method. (a) Simulated Phase (b) Displaced Spot Array from Hartmann Sensor (c) Wavefront Reconstruction Using Region-Growing Algorithm (d) Error in wavefront reconstruction using regional growth algorithm.

turbulence conditions, a simulation experiment based on a Kolmogorov turbulence phase screen was conducted. The simulated turbulent wavefront phase is shown in Figure 9(a). This phase was loaded into the Shack-Hartmann wavefront sensor simulation model. The resulting reference spot array and the turbulence-modulated spot array are displayed in Figures 9(b) and (c), respectively. After demodulation, the obtained wavefront slope

distributions in the X and Y directions are presented in Figures 9(e) and (f).

Based on the aforementioned slope data, wavefront reconstruction was performed using the proposed region-growing algorithm. The result is shown in Figure 9(d). The RMS deviation between the reconstructed wavefront and the ideal turbulent phase is 0.0539λ , and the reconstruction process took only 0.008 seconds. For comparison, the traditional Southwell method was used to reconstruct the same set of slope data. The result is shown in Figure 9(g), with a reconstruction RMS deviation of 0.0803λ and a computation time of 13.6935 seconds. The results indicate that under simulated turbulence conditions, the reconstruction error of the proposed algorithm is approximately 32.9% lower than that of the Southwell method, while its computation time is only about 0.058% of the latter's (corresponding to a speed increase of approximately 1712 times). This demonstrates a significant balance between accuracy and efficiency.

To quantitatively assess the algorithm's capability for reconstructing complex turbulent wavefronts in modal space, we performed a Zernike Fringe polynomial decomposition (up to the 36th order) on the ideal wavefront and the two reconstructed wavefronts, as detailed in Table 3. By calculating the absolute deviation of each coefficient from the ideal value (see Figure 10), it was found that for 20 out of the 36 analyzed terms, the deviation of the proposed method was lower than that of the Southwell method. The advantage was particularly evident in terms with large aberration amplitudes (e.g., Z1, Z4, Z8) and several high-order aberrations (e.g., Z17, Z19, Z26). The root mean square error (RMS) of the coefficient deviation sequences for the two methods are 0.089λ for the proposed method and 0.112λ for the Southwell method, respectively. This further demonstrates that the proposed algorithm achieves superior overall reconstruction accuracy in the Zernike modal space and better preserves high-order spatial frequency information. In contrast, the Southwell method exhibits coefficient attenuation in some high-order terms due to the global iterative smoothing effect.

4 Experimental Verification

To verify the effectiveness of the algorithm, we constructed an experimental setup as shown in Figure 11. A He-Ne laser emitted a laser beam that sequentially passed through two lens systems for collimation to make it as close to a parallel beam as

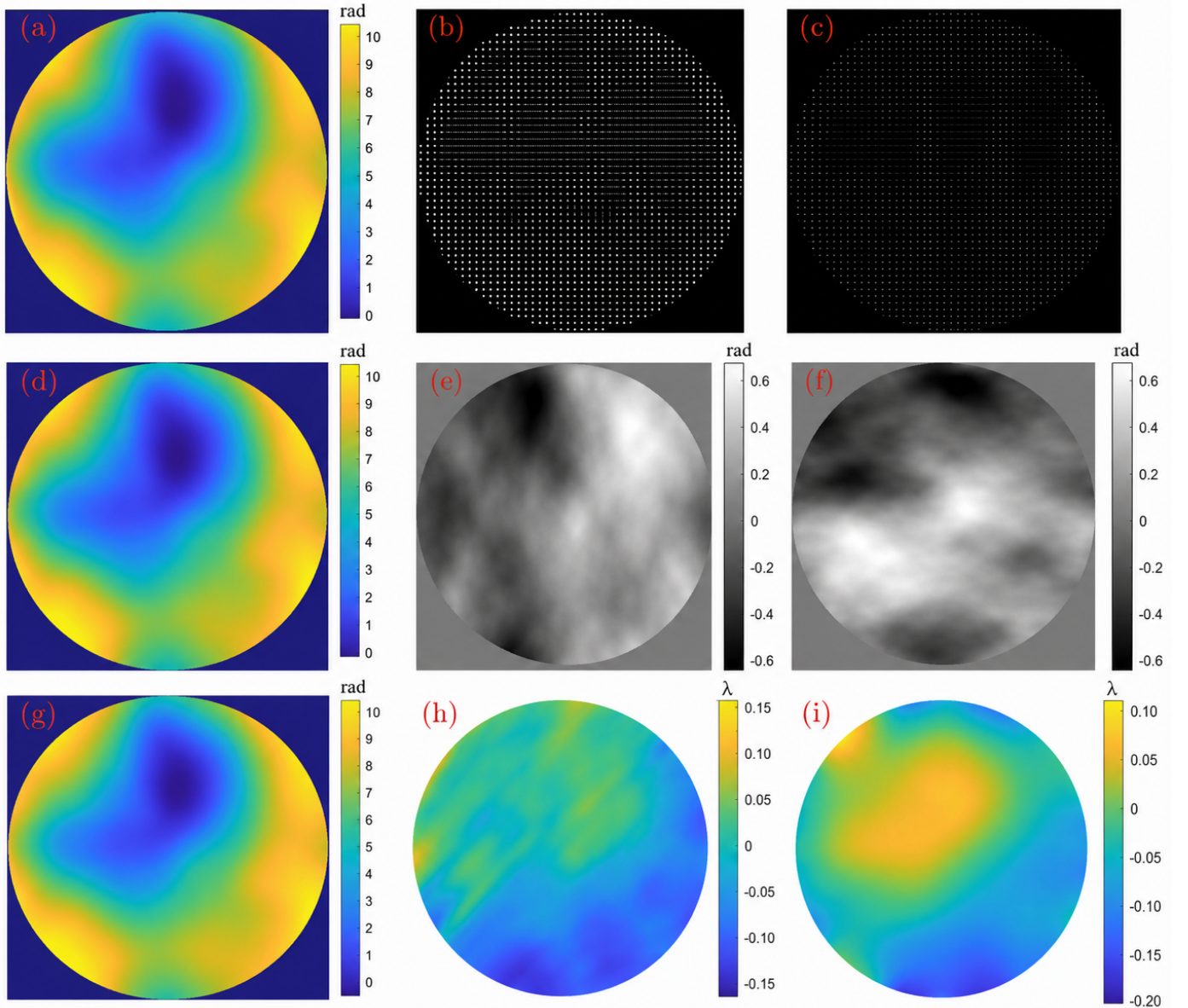


Figure 9. Reconstruction of turbulence wavefront (a) Simulated Kolmogorov Phase (b) Reference Spot Array (c) Displaced Spot Array from Hartmann Sensor (d) Wavefront Reconstruction Using Region-Growing Algorithm (e) X-direction Slope Field (f) Y-direction Slope Field (g) Wavefront Reconstruction Using Southwell Method (h) Error in wavefront reconstruction using regional growth algorithm (i) Error in wavefront reconstruction using Southwell method.

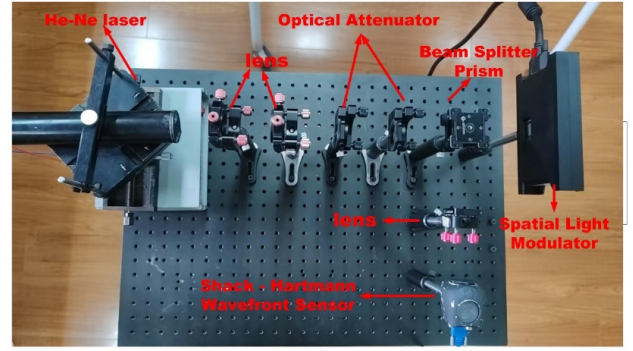
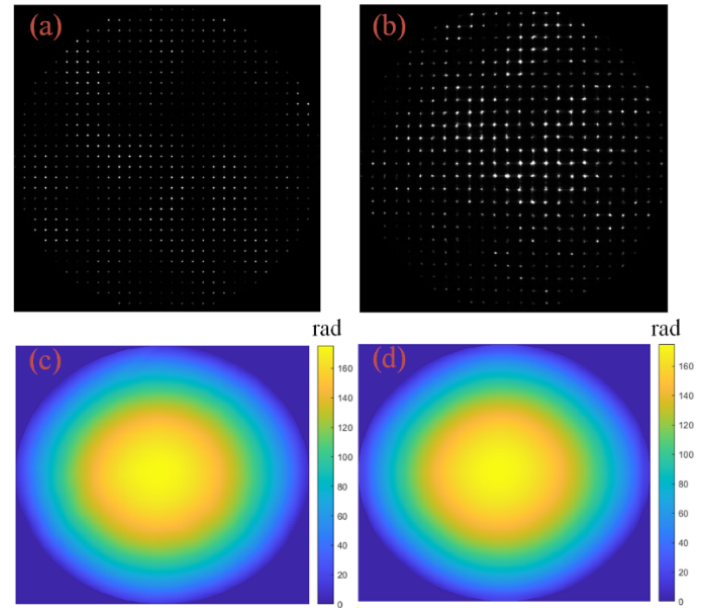
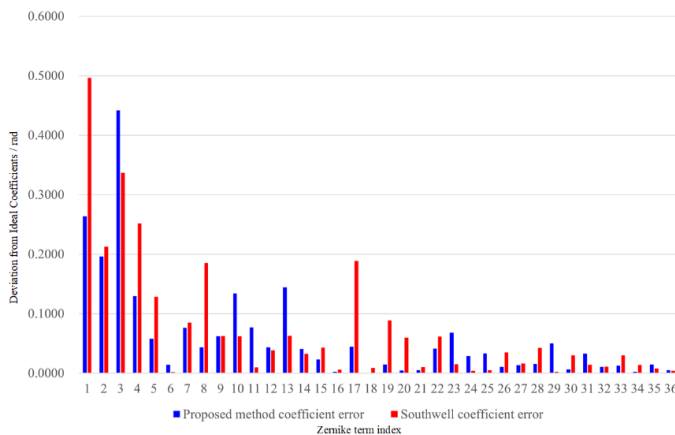
possible. Subsequently, the laser beam passed through two attenuators, effectively reducing the beam intensity. The intensity-adjusted laser beam was then incident on a spatial light modulator without loaded phase information and was reflected. The reflected wavefront was then reflected again by a beam splitter, focused by a focusing lens, and precisely incident into the wavefront sensor, thereby obtaining a reference spot array without phase information. Subsequently, the wavefront was modulated via a spatial light modulator, yielding a modulated spot array pattern. The corresponding slope data was then acquired through demodulation, and finally, the modulated wavefront was reconstructed using a wavefront

reconstruction algorithm. A Shack-Hartmann wavefront sensor (Thorlabs, WFS40-7AR) with a 73×73 microlens array and a 2048×2048 pixel CMOS camera (pixel size: $5.5 \mu\text{m}$) was used. The wavefront was modulated by a spatial light modulator (HDSLM80R) with a resolution of 1920×1200 pixels and a pixel pitch of $8 \mu\text{m}$.

During the experiment, the reference spot array, Figure 12(a), is first acquired by loading a zero-phase mask (i.e., no phase modulation) onto the spatial light modulator (SLM). The laser beam reflected from the SLM under this condition preserves its original planar wavefront, serving as the baseline. Subsequently, the

Table 3. Zernike FRINGE polynomial decomposition of the reconstructed wavefronts.

Term Index	Ideal Phase Coefficient/rad	RGA Coefficient/rad	Southwell Coefficient/rad
1	5.9895	6.2531	6.4859
2	0.7502	0.9462	0.9627
3	1.8959	2.3378	2.2326
4	3.211	3.3405	3.463
5	1.6158	1.5578	1.4876
6	0.2996	0.3136	0.2979
7	-1.1296	-1.0535	-1.2147
8	-2.3203	-2.3637	-2.5052
9	-0.6298	-0.6917	-0.6923
10	1.2266	1.3608	1.1647
11	-0.5921	-0.669	-0.5823
12	-0.5257	-0.4825	-0.5643
13	-0.7275	-0.8718	-0.7903
14	0.4001	0.3595	0.4323
15	0.4428	0.466	0.4856
16	-0.0556	-0.0578	-0.0495
17	-2.0308	-2.0755	-1.8421
18	-0.0586	-0.0592	-0.0677
19	-1.1596	-1.1744	-1.2484
20	0.7548	0.7594	0.8145
21	0.1443	0.1396	0.1546
22	0.7824	0.8236	0.8438
23	-0.2151	-0.1468	-0.2302
24	0.0021	0.031	0.0062
25	0.0518	0.0185	0.047
26	0.2721	0.2615	0.307
27	0.2499	0.2634	0.2661
28	0.5833	0.5987	0.6258
29	0.2188	0.1685	0.221
30	0.4114	0.4049	0.4416
31	-0.1706	-0.1377	-0.185
32	-0.0144	-0.0038	-0.0255
33	-0.3959	-0.4083	-0.4258
34	0.0755	0.0734	0.0892
35	0.1079	0.1224	0.1158
36	-0.0392	-0.0345	-0.0431

**Figure 11.** Schematic of the experimental setup.**Figure 12.** Experimental results of wavefront reconstruction (a) Reference Spot Array (b) Displaced Spot Array from Hartmann Sensor (c) Wavefront Reconstruction Using Region-Growing Algorithm (d) Wavefront Reconstruction Using Southwell Method.**Figure 10.** Absolute deviation of each order coefficient from the ideal values.

zero-phase mask is removed, and the target phase pattern (e.g., Gaussian phase or a combination of Zernike aberrations) is loaded onto the active area of the SLM. The reflected beam now carries the imposed phase distortions, and the corresponding modulated spot arrays, Figure 12(b) and Figure 13(a), are captured by the SHWFS. The slope data are then extracted by subtracting the reference centroid positions from the modulated ones.

Figures 12(a) and (b) present the reference spot array pattern and the modulated spot array pattern, respectively. The reference pattern was acquired without any phase modulation applied to the spatial light modulator, whereas the modulated pattern was obtained after introducing a Gaussian phase

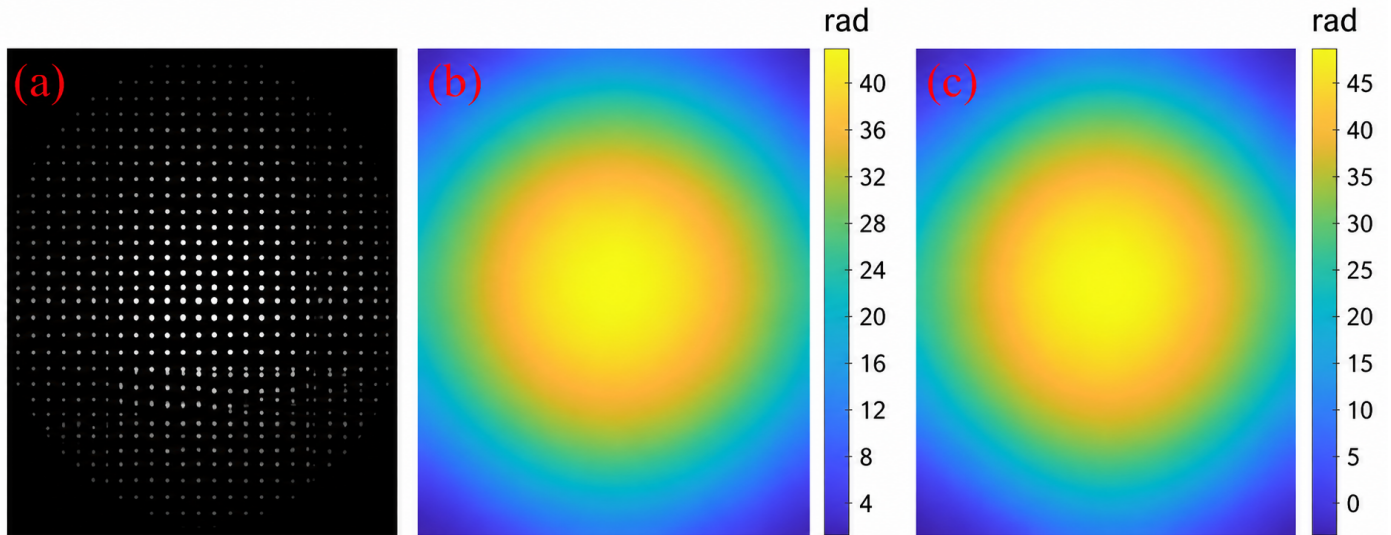


Figure 13. Experimental results of wavefront reconstruction (a) Displaced Spot Array from Hartmann Sensor (b) Wavefront Reconstruction Using Region-Growing Algorithm (c) Wavefront Reconstruction Using Southwell Method.

modulation. The corresponding slope information was extracted from both patterns through demodulation. The wavefront was then reconstructed using the proposed regional growth-based method, as shown in Figure 12(c), with a reconstruction time of 1.398 seconds. For comparison, the wavefront reconstructed using the Southwell method is also presented in Figure 12(d), which required 70.338 seconds. The root mean square (RMS) deviation between the wavefronts obtained by the two methods was calculated to be 0.233λ . The results demonstrate that the proposed method performs effectively in experimental conditions and achieves a reconstruction speed 50.3 times faster than that of the Southwell method.

Subsequently, we introduced tilt in the X and Y directions as well as astigmatism to the Gaussian phase on the spatial light modulator, resulting in the spot array shown in Figure 13(a). After demodulation to extract the slope information, the wavefront was reconstructed using the region-growing algorithm (the coordinates of the adaptive starting point are (15, 15)), yielding the result presented in Figure 13(b) with a processing time of 0.9187 s. For comparison, the Southwell method was also applied to reconstruct the wavefront, as depicted in Figure 13(c), which required 87.1979 s. The RMS deviation between the wavefronts obtained by the two methods was 0.4295λ , and the proposed method achieved a reconstruction speed approximately 94.9 times faster than that of the Southwell method, further demonstrating the

effectiveness of the proposed algorithm.

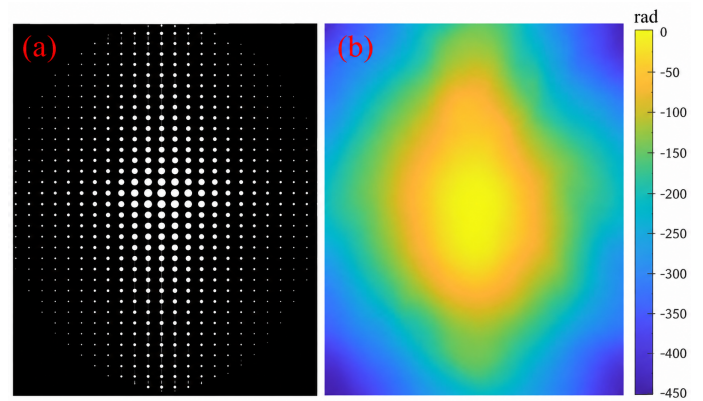


Figure 14. Experimental results of wavefront reconstruction (a) Displaced Spot Array from Hartmann Sensor (b) Wavefront Reconstruction Using Region-Growing Algorithm.

To controllably simulate the distortion effect of atmospheric turbulence on an optical wavefront in experiments, a discrete phase screen conforming to the classical Kolmogorov turbulence statistics was generated using the power spectral inversion method and loaded onto a Spatial Light Modulator to physically emulate the turbulent wavefront. This method is based on the Kolmogorov turbulence refractive-index fluctuation power spectrum. By applying random complex amplitude modulation to the target power spectrum and performing an inverse fast Fourier transform (IFFT), a turbulent phase distribution $\phi(x, y)$ satisfying isotropic and stationary

random characteristics was inversely derived. Weak atmospheric turbulence conditions were selected for the experiment, with the refractive-index structure constant set to $C_n^2 \sim 10^{-14} - 10^{-13} \text{ m}^{-2/3}$, ensuring that turbulence introduces only phase distortion. The generated discrete phase screen grid was matched one-to-one with the SLM pixel array. After phase quantization and normalization, it was converted into grayscale drive signals recognizable by the SLM and loaded onto the effective working area of the SLM, resulting in the spot array shown in Figure 14(a). The slope information was extracted through demodulation, and the wavefront shown in Figure 14(b) was reconstructed using a region-growing algorithm.

As a comparison, the same wavefront was also reconstructed using the Southwell method in this work. The relative deviation between the wavefronts obtained by our method and the Southwell method was calculated, yielding an RMS value of 0.3653λ . This result confirms that the proposed method achieves an accuracy comparable to that of the Southwell method. The reconstructed wavefront was decomposed into Zernike polynomials, and the resulting coefficients are presented in Figure 15. The results demonstrate that this method can effectively detect and reconstruct the complex, localized distortions induced by turbulence.

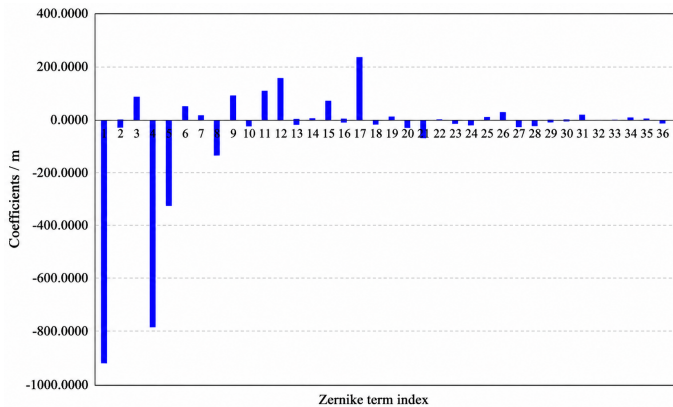


Figure 15. Zernike FRINGE polynomial decomposition of the reconstructed wavefronts.

It should be noted that, in the above experimental validations, the reconstructed wavefront is compared primarily with the Southwell method rather than directly with the theoretical phase pattern loaded onto the SLM. This is because, in practical experiments, the absolute ground-truth phase at the sensor plane is difficult to obtain accurately due to inherent phase calibration errors of the SLM, pixelation discretization effects, and uncorrelated low-frequency

vibrations in the optical path. These factors introduce non-negligible deviations between the nominal loading values and the actual physical phase modulation. Therefore, following the common practice in comparative studies of wavefront reconstruction algorithms, we adopt the deviation between the results of the proposed method and the well-established Southwell method as the primary experimental metric. The rigorous validation against the absolute ground truth has already been extensively performed in the simulation section (Section 3), where the exact input phase is precisely known and free from experimental uncertainties. For the turbulence simulation experiment in particular, the Zernike FRINGE decomposition presented in Figure 15 provides a modal-domain comparison between the reconstructed wavefront and the theoretical coefficients of the loaded Kolmogorov phase screen, further confirming that the proposed algorithm successfully recovers the dominant aberration modes.

5 Conclusions

This paper commenced by introducing the fundamental principles of wavefront detection using the Shack-Hartmann wavefront sensor, followed by the discrete zonal reconstruction model based on the Southwell difference equations. A novel wavefront reconstruction algorithm based on the region-growing method was subsequently proposed. Numerical simulations were conducted to emulate the process of wavefront aberration detection with SHWFS, and the proposed algorithm was applied to reconstruct various wavefront types. Comparative analyses with the iterative Southwell method were carried out in terms of both reconstruction accuracy and computational time, while the noise resistance of the algorithm was also evaluated. Finally, an experimental platform was established to further validate the effectiveness of the proposed algorithm. The research demonstrates that:

- (1) The region-growing-based wavefront reconstruction algorithm effectively recovers the wavefront. Utilizing a breadth-first search strategy, each point is processed only once (and not updated after computation). This single-pass traversal mechanism significantly enhances computational efficiency and yields faster solution speed.
- (2) The proposed algorithm is essentially a path-based integration method, relying solely on the values of previously computed neighboring points and local gradients. This approach strictly confines

the propagation of measurement or computational errors to subsequent points along the growth path, thereby preventing contamination across the entire wavefront field. This mechanism effectively mitigates the global error diffusion inherent in the Southwell method, better preserving local features and high-frequency components of the wavefront. As a result, under high-noise conditions, the proposed algorithm achieves a lower root mean square error compared to the Southwell method.

The consistency between experimental and simulation results provides a solid foundation for further exploration of wavefront reconstruction algorithms in adaptive optical systems, offering both theoretical insights and empirical evidence.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

Xizheng Ke served as an Editor-in-Chief of the *Optical Wireless Communication* at the time of manuscript submission. To ensure the integrity of the peer-review process, Xizheng Ke was not involved in the editorial handling, peer review, or decision-making process for this manuscript, which was handled independently by another editor. The remaining authors declare no conflicts of interest.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

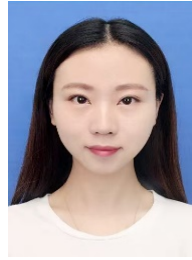
Not applicable.

References

- [1] Xizheng, K., Jiali, W., & Shangjun, Y. (2021). Research progress and prospect of atmospheric turbulence for wireless optical communication. *Chinese journal of radio science*, 36(3), 323-339. [CrossRef]
- [2] Wenhan, J. (2018). Overview of adaptive optics development. *Opto-Electronic Engineering*, 45(3), 170489-1. [CrossRef]
- [3] Platt, B. C., & Shack, R. (2001). History and principles of Shack-Hartmann wavefront sensing. *Journal of refractive surgery*, 17(5), S573-S577. [CrossRef]
- [4] Li, G., Li, Y., Liu, K., Ma, X., & Wang, H. (2013). Improving wavefront reconstruction accuracy by using integration equations with higher-order truncation errors in the Southwell geometry. *Journal of the Optical Society of America A*, 30(7), 1448-1459. [CrossRef]
- [5] Poyneer, L. A., Gavel, D. T., & Brase, J. M. (2002). Fast wave-front reconstruction in large adaptive optics systems with use of the Fourier transform. *Journal of the Optical Society of America A*, 19(10), 2100-2111. [CrossRef]
- [6] Dai, G. M. (1996). Modal wave-front reconstruction with Zernike polynomials and Karhunen-Loève functions. *Journal of the Optical Society of America A*, 13(6), 1218-1225. [CrossRef]
- [7] Liang, J., Williams, D. R., & Miller, D. T. (1997). Supernormal vision and high-resolution retinal imaging through adaptive optics. *Journal of the Optical Society of America A*, 14(11), 2884-2892. [CrossRef]
- [8] Duan, H. F., Yang, Z. P., & Wang, S. Q. (2002). Model wavefront reconstruction of Shack-Hartmann sensor on arbitrary area and wavefront expression by Zernike polynomials. *Chinese Journal of Lasers*, 29(6), 517-520. <https://www.opticsjournal.net/Articles/OJ327ae222f01aec44/Abstract>
- [9] Jingyuan, L., Xiwen, L., Chenghu, K., & Xizheng, K. (2024). Surface characterization using Zernike polynomials. *Opto-Electronic Engineering*, 51(11), 240163-1. [CrossRef]
- [10] Hudgin, R. H. (1977). Wave-front reconstruction for compensated imaging. *Journal of the Optical Society of America*, 67(3), 375-378. [CrossRef]
- [11] Fried, D. L. (1977). Least-square fitting a wave-front distortion estimate to an array of phase-difference measurements. *Journal of the Optical Society of America*, 67(3), 370-375. [CrossRef]
- [12] Southwell, W. H. (1980). Wave-front estimation from wave-front slope measurements. *Journal of the Optical Society of America*, 70(8), 998-1006. [CrossRef]
- [13] Hao, C., Ling, W., Ende, L., Yi, H., Jinsheng, Y., Xiqi, L., ... & Yudong, Z. (2021). A B-spline based fast wavefront reconstruction algorithm. *Opto-Electronic Engineering*, 48(2), 200160-1. [CrossRef]
- [14] Poyneer, L. A., & Véran, J. P. (2005). Optimal modal Fourier-transform wavefront control. *Journal of the Optical Society of America A*, 22(8), 1515-1526. [CrossRef]
- [15] Guan, H., Zhao, W., Yang, K., Zhao, C., Wang, S., Liu, S., ... & Yang, P. (2025). Improving wavefront

reconstruction performance with a binary phase hybrid Shack-Hartmann wavefront sensor. *Optics Express*, 33(5), 9756-9774. [[CrossRef](#)]

- [16] Pathak, B., & Boruah, B. R. (2014). Improved wavefront reconstruction algorithm for Shack-Hartmann type wavefront sensors. *Journal of Optics*, 16(5), 055403. [[CrossRef](#)]



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