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A new hybrid algorithm for co-phasing segmented active optical system based on phase diversity

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ABSTRACT

In order to reach its diffraction limited performance, the co-phase errors of segmented mirror synthetic aperture optics (SAO) systems must be accurately measured and corrected. A new hybrid algorithm based on phase diversity is proposed for co-phasing the segmented mirrors. It utilizes an improved adaptive genetic algorithm to determine the global initial aberration coefficients, and then uses an iterative linear correction algorithm to obtain the linear estimator of coefficients under small residual phase after initial alignment of the system. The numerical simulation results demonstrate that the proposed method is highly sensitive and noise tolerant. It can fulfill the requirements for the phasing of segmented mirror telescopes and retrieving the unknown object for the system.

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1. Introduction

Segmented mirror synthetic aperture optics (SAO) systems can meet the demands of the next generation space telescopes being lighter, larger and foldable [1]. Segmented primary mirror stitches serials of sub-mirrors together to reach the optimal capabilities of a monolithic one. This kind of space telescopes can be folded for launch and deploy autonomously after reaching orbit. However, only if co-phasing of the segmented mirrors is achieved, can it provide a high quality image equivalent to that of a monolithic mirror. Co-phasing a segmented mirror is to remove the misalignments, including relative piston aberrations between segments and tip/tilt aberrations of each segment.

Many methods are proposed for co-phasing the segmented mirror to obtain nearly diffraction limited performance from the total aperture, such as curvature sensing [2], modified Hartmann–Shack wavefront sensing (WFS) [3], phase retrieval based on PSF data sets [4], modified peak ratio technique [5], Michelson interferometry [6] and phase diversity WFS [7–10] etc. PD WFS outstands in the development of segmented active optical systems where traditional wavefront reconstruction like using Shack–Hartmann wavefront sensing tends to break down at the mirror segment edges. Additionally, this approach requires no new instrumentation be added to the already complicated optical system and is considerably sensitive to both relative piston and tip/tilt aberrations for continuous and discontinuous input distorted wavefront.

This paper presents a new hybrid algorithm based on phase diversity aimed at massive sub-apertures of segmented primary mirror. The number of variables needing to be solved from the non-linear optimization problem increases triply as that of sub-mirrors, which slows down the convergence speed significantly. Since genetic algorithm (GA) [11–13] is a global probability search method, by taking advantage of which global initial value of Zernike aberration coefficients can be obtained. After initial alignment by active segmented primary mirror analog system, linearization the expression of the OTFs in each diversity plane can be processed under the small residual aberrations. This hybrid algorithm can avoid converging to local optima, reduce the computational complexity, improve the convergence speed and provide higher calculation accuracy.

2. Basic theory

2.1. Theoretical analysis of co-phase errors impact on segmented space telescope

The generalized pupil function of the segmented primary mirror is given by Eq. (1):

$$P(\varepsilon,\eta)=\sum_{n=1}^{N}P_n(\varepsilon,\eta)=\sum_{n=1}^{N}p_n(\varepsilon,\eta)\,\exp\left[i\varphi_n(\varepsilon,\eta)\right] \tag{1}$$

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where, (ε, η) is the coordinate of pupil plane, n is the index of sub-aperture. P_n donates complex pupil function of nth segmented sub-mirror, p_n and φ_n are its amplitude and phase separately. The shape function of sub-aperture in the pupil plane p_n is given by formula (2):

$$p_n(\varepsilon, \eta) = \begin{cases} 1 & \text{inside the sub-aperture} \\ 0 & \text{outside the sub-aperture} \end{cases} \tag{2}$$

In case to simply the situation, just like Keck [14], all the sub-apertures are assumed to have the same shape and are perfect without high-order aberrations except co-phasing errors, namely pistons and tip–tilts. Thus the generalized pupil can be rewritten as function (3):

$$P(\varepsilon, \eta) = \sum_{n=1}^{N} p_n(\varepsilon, \eta) \exp\left[i\frac{2\pi}{\lambda}(e_n + T_{xn} + T_{yn})\right] \tag{3}$$

where, e_n and T_{xn}, T_{yn} represent piston and tip–tilts errors respectively.

Using the principles of Fourier optics, corresponding incoherent point spread function (PSF) of the image plane $s(u, v)$ can be gained by Eq. (4):

$$s(u, v) = \left|h(u, v)\right|^2 = \left|\Im\left\{\sum_{n=1}^{N} p_n(\varepsilon, \eta) \exp\left[i\frac{2\pi}{\lambda}(e_n + T_{xn} + T_{yn})\right]\right\}\right|^2 \tag{4}$$

where, (u, v) are position vector in the image plane, $h(u, v)$ donates coherent impulse response function and $\Im\{\}$ is the Fourier transform operator. According to paper [15], $h(u, v)$ is given by formula (5):

$$h(u, v) = \sum_{n=1}^{N} [\Im\{\exp[jkf_n(\varepsilon, \eta)]\} * \Pi(u, v)] \times \exp[jk(\alpha_n - \lambda u \varepsilon_n - \lambda v \eta_n) \tag{5}$$

among which, $\Pi(u, v)$ is Fourier transform of sub-aperture's pupil function, wave number is $k = 2\pi/\lambda$, α_n and $f_n(\varepsilon, \eta)$ denotes the pistons and the remaining tip–tilts aberration of the nth sub-aperture respectively.

Above equations reveal relevant physical significance, coupled with the relative offsets of pupil centers in different sub-apertures, co-phase errors affect the far-field image of system directly and $\Pi(u, v)$ reflects the impact of sub-aperture pupil.

Thus it can be seen that, in segmented extremely large telescope, how to co-phase its segmented primary mirror to achieve the ultimate resolution is an unavoidable problem. The key issue to solve the problem depends on whether the pistons among the segments and their tip–tilts can be measured and corrected with very high accuracy.

2.2. Theoretical derivation of PD cost function

The PD reconstructed algorithm not only can be used to detect the continuous wavefront aberration caused by atmospheric turbulence or surface error of optical elements, but also is very sensitive to the discontinuous aberrations such as relative piston errors between segments and tip/tilt aberrations of each segment. The major issue is to detect the phase distortion or aberration coefficients in an incoming wavefront by one image recorded in the focal plane and the other one recorded in an out-of-focus plane of the optical system simultaneously under circumstance that both object distribution and optical transfer function of atmosphere-telescope synthetic system are unknown.

Based on least-square approach, a cost function is presented by Eq. (6) in frequency domain to fit the data such that the total RMS difference between the images observed in the different channels and those assumed by the imaging mode:

$$L[I_k; o, \{e_j, T_{xj}, T_{yj}\}] = \sum_{k=1}^{K}\sum_{f_u, f_v}[I_k(f_u, f_v) - O(f_u, f_v)S_k(f_u, f_v)]^2 \tag{6}$$

where, (f_u, f_v) is the coordinate in frequency domain, I_k and O represent the Fourier transforms of the kth image intensity and object distribution respectively, S_k is the optical transfer function (OTF) of the kth image plane and K is the total images number.

In order to eliminate the dependence of the cost function L on object frequency spectrum O in the optimization process, the partial differential of L with respect to O is set to equal zero, then the following formula (7) can be obtained:

$$O = \frac{\sum_{k=1}^{K} I_k S_k^*}{\sum_{k=1}^{K} \left|S_k\right|^2 + \gamma} \tag{7}$$

Thus the cost function L is solved for simplification as Eq. (8):

$$L = \sum_{f\in\chi}\sum_{k}\left|I_k\right|^2 - \sum_{f\in\chi}\frac{\left|\sum_k I_k S_k^*\right|^2}{\sum_k \left|S_k\right|^2 + \gamma} \tag{8}$$

among which, γ is the regularized coefficient which guarantees the existence and uniqueness of solutions. Then the problem of estimating phase distribution or aberration coefficients of the wavefront is transferred to optimize the functional L, namely to find the coefficient set for which the cost function [Eq. (8)], is a minimum.

2.3. Search algorithms to optimize the PD cost function

Many search algorithms have been proposed to optimize the PD cost function, such as conjugate gradient method, quasi-Newton method, neural network algorithm and genetic algorithm. The gradient of cost function needs to be deduced while using conjugate gradient method or quasi-Newton algorithm, which adds the calculation complexity and is prone to converge to local optima. Neural network optimization algorithm has to process highly cumbersome network training to massive images. Genetic algorithm (GA) is a global probability search method, it only needs the information of cost function and do not need to deduce its gradient, which simplify the calculation procedure and has a better global convergence. However, GA is also very complex and has a quite limited usage in real-time correction algorithms.

Thus this paper presents a new hybrid algorithm, which uses improved adaptive GA to obtain the global initial coefficients of distorted phase by utilizing smaller population size and fewer evolution generations and then linearizes OTF under small residual phase aberrations to decrease the calculation complex and increase the convergence speed.

2.3.1. Improved adaptive GA

The flow chart of improved adaptive GA based on PD is shown in Fig. 1.

For special note, the increase in number of sub-mirrors will lead to massive variables needed to be optimized. Therefore multi-point crossover and mutation are applied to accelerate the convergence rate. Meanwhile, due to priori knowledge, when piston errors between segments approach $\lambda/2$, it is prone to fall into local extreme around the negative value of piston errors. In order to solve this problem, piston errors of the best individual among each new

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