Improving Image Quality of the Solar Disk Imager (SDI) of the Lyα Solar Telescope (LST) Onboard the ASO-S Mission postprint

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Abstract

The in-flight calibration and performance of the Solar Disk Imager (SDI), which is a pivotal instrument of the Lyα Solar Telescope onboard the Advanced Space-based Solar Observatory mission, suggested a much lower spatial resolution than expected. In this paper, we developed the SDI point-spread function (PSF) and Image Bivariate Optimization Algorithm (SPIBOA) to improve the quality of SDI images. The bivariate optimization method smartly combines deep learning with optical system modeling. Despite the lack of information about the real image taken by SDI and the optical system function, this algorithm effectively estimates the PSF of the SDI imaging system directly from a large sample of observational data. We use the estimated PSF to conduct deconvolution correction to observed SDI images, and the resulting images show that the spatial resolution after correction has increased by a factor of more than three with respect to the observed ones. Meanwhile, our method also significantly reduces the inherent noise in the observed SDI images. The SPIBOA has now been successfully integrated into the routine SDI data processing, providing important support for the scientific studies based on the data. The development and application of SPIBOA also paves new ways to identify astronomical telescope systems and enhance observational image quality. Some essential factors and precautions in applying the SPIBOA method are also discussed.

Full Text

Preamble

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Abstract

The in-flight calibration and performance of the Solar Disk Imager (SDI), a pivotal instrument of the Lyα Solar Telescope onboard the Advanced Space-based Solar Observatory mission, revealed a much lower spatial resolution than expected. In this paper, we developed the SDI point-spread function (PSF) and Image Bivariate Optimization Algorithm (SPIBOA) to improve the quality of SDI images. This bivariate optimization method smartly combines deep learning with optical system modeling. Despite the lack of information about the real image taken by SDI and the optical system function, this algorithm effectively estimates the PSF of the SDI imaging system directly from a large sample of observational data. We use the estimated PSF to conduct deconvolution correction on observed SDI images, and the resulting images show that the spatial resolution after correction has increased by a factor of more than three relative to the observed ones. Meanwhile, our method also significantly reduces the inherent noise in the observed SDI images. The SPIBOA has now been successfully integrated into the routine SDI data processing pipeline, providing important support for scientific studies based on the data. The development and application of SPIBOA also paves new ways to identify issues in astronomical telescope systems and enhance observational image quality. Some essential factors and precautions in applying the SPIBOA method are also discussed.

Key words: techniques: image processing –Sun: chromosphere –Sun: flares –methods: numerical

1. Introduction

The Advanced Space-based Solar Observatory (ASO-S; Gan et al. 2019, 2023), launched on 2022 October 9, is the first comprehensive Chinese space observatory dedicated to solar observations. The Lyα Solar Telescope (LST), characterized by its unique observations in the Hydrogen Lyα line (121.6 nm)—the most intensive line in the ultraviolet (UV) band of the solar spectrum—from disk center to inner corona up to 2.5 solar radii, is one of the three payloads onboard the ASO-S mission and was described in detail in Li et al. (2019) and Chen et al. (2019). Here, we provide a brief introduction to the LST payload, which is essential for readers to understand the study in this paper.

The LST payload comprises three instruments:

1. **White-light Solar Telescope (WST).** With an aperture of 130 mm, the WST works in the 360.0 $\pm$ 1.9 nm wave band to observe white-light flares on the Sun with a field of view (FOV) up to 1.2 solar radii. The highest cadence of WST is 1–2 s in burst mode.
2. **Dual-channel Solar Corona Imager (SCI).** Featuring an aperture of 60 mm, the SCI works in both the Hydrogen Lyα (SCIUV: 122.2 $\pm$ 3.9 nm) and the visible (SCIWL: 704.1 $\pm$ 31.3 nm) wave bands to capture coronal mass ejections (CMEs) and other activities within the inner corona up to 2.5 solar radii.
3. **Solar Disk Imager (SDI).** The SDI has an aperture of 68 mm and works in the Lyα wave band similar to SCIUV but with a slightly different central wavelength and width (120.8 $\pm$ 4.5 nm). It is used to observe various activities on the solar disk with the same FOV as the WST.

The in-flight calibration and performance of the LST have been successfully completed and presented in Chen et al. (2024). Readers are referred to it for detailed information.

SDI was proposed to image the Sun with a spatial resolution of 1 .2 and a cadence as high as 4 s in burst mode and a lower cadence (say 60 s) in routine mode depending on available telemetry (Chen et al. 2019; Li et al. 2019). As outlined in Chen et al. (2024), in-flight observations revealed a much lower resolution than expected, measured to be approximately 9 .5 based on first-light images captured on 2022 October 26. One potential cause suggested is wavefront errors in the entrance Lyα filter, which could lead to defocusing and subsequent image blurring. However, it is important to note that other factors can also contribute to such low measured spatial resolution, including, but not limited to, aberrations and imperfections in the optical components of the instrument. Determining the exact causes of the lower resolution is beyond the scope of this paper.

SDI images sometimes exhibit horseshoe-like bright structures, as illustrated in the white rectangular area of Figure 1. These structures, together with the low spatial resolution, significantly affect research efforts related to the scientific objectives of LST, including the evolution and eruption characteristics of flares and filaments/prominences, source regions of CMEs in the Lyα line, the parameters and triggering mechanisms of solar flares, and potential wave phenomena in the Lyα line on the solar disk (Feng et al. 2019; Li et al. 2019). Therefore, it is crucial to mitigate or eliminate these structures and enhance image quality (in terms of spatial resolution, noise reduction, etc.) through various algorithms. A comparison of SDI images with those captured by the Atmospheric Imaging Assembly (AIA; Lemen et al. 2012) on the Solar Dynamics Observatory (Pesnell et al. 2012) in the 304 and 1600 Å channels, as shown in Figure 2, reveals that the sharp, bright structures in the AIA images appear diffused and blurred in the SDI images, further emphasizing the necessity to improve SDI image quality.

One promising algorithm to enhance image quality relies on deep learning techniques (LeCun et al. 2015), which have experienced rapid advancements in recent years and found widespread applications in astronomical adaptive optics. In this paper, we leverage deep learning techniques and in-flight observational data, taking into account the optical design of the SDI, to estimate the wavefront aberration of the SDI imaging system, and subsequently apply the results to observational data to improve image quality. The reconstructed images exhibit significant quality improvement compared to the original ones, demonstrating the feasibility of our proposed method.

This paper is organized as follows. Section 2 introduces the development and application of adaptive optics and wavefront sensing technologies based on deep learning. We describe our basic methodology and estimate the point-spread function (PSF) of the SDI imaging system in Section 3, and delineate our experiment and analysis in Section 4. In Sections 5 and 6, we present our discussions and conclusions, respectively.

2. Deep Learning for Adaptive Optics and Wavefront Sensing

As a core technology of artificial intelligence, deep learning has made significant advances in many fields, including computer vision, natural language processing, bioinformatics, and drug discovery (LeCun et al. 2015). Deep learning, powered by artificial neural networks, excels at processing complicated data through its ability to learn sophisticated multi-level representations and abstractions. These multiple layers of nonlinear transformations, also known as deep neural networks (DNNs), enable the extraction of intricate patterns from data.

Improving the accuracy and sensitivity of wavefront sensors in adaptive optics systems through deep learning not only represents a developmental trend in the field but may also establish a novel domain within its applications, enhancing wavefront detection accuracy and expanding the capability of wavefront sensors to handle complex scenarios.

Deep learning technology was first applied to astronomical adaptive optics in the early 1990s, marking a significant development in the field. Angel et al. (1990) successfully used artificial neural networks to correct piston and tip/tilt aberrations in the Multiple Mirror Telescope (MMT), mitigating the effects of turbulence and tilt between mirrors. Sandler et al. (1991) further applied neural network wavefront detection on a 1.5 m single-mirror telescope at the Phillips Laboratory of the United States Air Force. This technique was later extended to the Hubble Space Telescope (Barrett & Sandler 1993) for estimating static aberrations, demonstrating its adaptability to complex applications and its emergence in a novel application domain.

Recent advancements in deep learning adaptive optics have led to significant breakthroughs, improving observation accuracy, extending range, enhancing cost-effectiveness, and broadening applicability, ultimately strengthening astronomical observations. Notably, Nishizaki et al. (2019) introduced a machine learning-based wavefront sensor that streamlines optical hardware and image processing, demonstrating the ability to estimate Zernike coefficients directly from single images using convolutional neural networks (CNNs). They also demonstrated that the sensor could be trained to estimate wavefront distortions from both point and extended sources. Niu et al. (2020) explored deep learning algorithms for interferometric wavefront detection, accurately extracting phase distribution and analyzing distortions under general conditions. Their method has been experimentally validated for higher measurement accuracy, faster computation, and excellent performance in noisy conditions. Wang et al. (2021) proposed a deep learning-based method for wavefront sensing and aberration correction in atmospheric turbulence. They successfully recovered the wavefront distortion phase from distorted images and corrected them using spatial light modulators, significantly improving image quality and resolution, and providing a new solution for adaptive optical systems. Furthermore, de Bruijne et al. (2022) investigated deep learning wavefront sensing for extended sources, integrating blind deconvolution with deep learning to process Shack-Hartmann sensor images, which enhances precision and reliability in complicated application scenarios and wavefront distortions. Lastly, Ge et al. (2023) presented a target-independent dynamic wavefront sensing method, which employed a distorted grating and deep learning to enable real-time detection and correction of aberrations across various and dynamic environments.

Recent research in wavefront sensing using deep learning, as mentioned above, has yielded significant achievements and wide-ranging practical applications. These studies not only introduce innovative methods and technologies but also confirm their practicality and efficacy through experimental validation. These findings are pivotal for advancing astronomical adaptive optics and wavefront sensing technologies and offer invaluable insights for our research to enhance the quality of SDI observational images through wavefront aberration correction.

3. Instrumental Point-spread Function Estimate

This section outlines the fundamental approach and method for applying deep learning techniques in our study, along with the process for estimating the instrumental point-spread function (PSF). To mitigate the risk of unpredictable nonlinear distortions, we chose to keep the SDI optical imaging system within the linear convolution domain. By employing a structured approach, we apply a bivariate optimization strategy to simultaneously estimate both the true SDI image I_{ref} and the PSF, which are unknowns in our calculations. We translated the PSF estimation into a wavefront estimation of the imaging system so as to effectively leverage the optical parameter information from the SDI imaging system.

Unlike the deep learning-based methods for imaging system estimation reviewed in Section 2, we do not use CNN for direct wavefront prediction. Instead, we utilize CNN to apply nonlinear transformations to high-quality observational images with similar characteristics, such as those from the AIA 304 Å channel, to generate ideal SDI reference images that comply with the linear constraints of the optical system. The CNN used in this study, denoted with $N(I_{304}, \Theta_N)$, is a standard multi-layer CNN with an input layer consisting of 1–64 convolutional kernels, which transform the input image I_{304} into 64 feature maps. $N(I_{304}, \Theta_N)$ contains 72 hidden layers with a width of 64. The output layer uses 64–1 convolutional kernel to transform the 64 feature maps into the output image I_{ref}. The algorithmic process for estimating the PSF of the SDI imaging system is illustrated in Figure 3.

The objective of the optimization is to iteratively refine the parameter Θ_N of the convolutional neural network $N(I_{304}, \Theta_N)$ and the value of the wavefront to minimize the error defined by Equation (1), ensuring that the convolution of the ideal SDI image I_{ref} with the system' s PSF aligns with the actual observational data I_{SDI}, thereby enabling an accurate estimation of the PSF.

$$e = \|I_{\mathrm{SDI}} - I_{\mathrm{ref}} \otimes \mathrm{psf}\|^2 \quad (1)$$

The ideal SDI image I_{ref} is output by the neural network $N(I_{304}, \Theta_N)$ (Equation (2)):

$$I_{\mathrm{ref}} = N(I_{304}, \Theta_N) \quad (2)$$

The system' s PSF is calculated from the generalized pupil function defined by Equation (3):

$$\mathrm{psf} = \left|\mathcal{F}\left(A \cdot e^{j \cdot \mathrm{wavefront}}\right)\right|^2 \quad (3)$$

The Θ_N in these equations denotes the parameters of the CNN, while wavefront refers to the wavefront aberration, identified as the variable to be optimized and highlighted in the red square in Figure 3. The term A stands for the aperture transmission, which equals 1 inside the aperture and 0 outside, assuming uniform transmission. The function $\mathcal{F}$ denotes the Fourier transform, while the symbol $\otimes$ signifies the convolution operator.

Figure 3 depicts the processing steps of the SPIBOA (SDI PSF and Image Bivariate Optimization Algorithm). The algorithm' s detailed procedure is as follows: (1) Data Preprocessing: coalign the images of SDI and AIA, and suppress noise in the SDI observational images. (2) Initialize I_{ref} with the AIA 304 Å image I_{304} and the wavefront with data gleaned from pre-launch (on-ground) tests of the SDI flight model. (3) Calculate the error using Equation (1). (4) By propagating the error e backwards, the stochastic optimization algorithm Adam (Kingma & Ba 2014) is utilized to update the optimization targets, namely I_{ref} and wavefront. (5) If e is less than the predefined threshold, terminate the iteration and output the PSF. Otherwise, continue iterating and return to step (4).

SPIBOA accepts SDI and AIA 304 Å observational images with aligned FOV and suppressed thermal noise as input. It employs the Adam algorithm to jointly refine the wavefront aberration (wavefront) and the parameters of the CNN (Θ_N). By minimizing the error defined in Equation (1), SPIBOA derives an estimate of the ideal SDI image (I_{ref}) and the wavefront aberration (wavefront). Subsequently, it computes the PSF of the SDI observational system using Equation (3). This PSF is then utilized for the deconvolution of observed SDI images to enhance their quality.

Figure 4 depicts the intermediary results of the SPIBOA training procedure. Panel (a) displays I_{SDI} from the training dataset, while panel (b) shows the result of the convolution between I_{ref} and PSF. Panel (c) presents the I_{ref} generated by the CNN $N(I_{304}, \Theta_N)$, and panel (d) gives the initial value of I_{ref}, namely I_{304}.

The resemblance between panels (b) and (a) suggests that the optimal solution derived by SPIBOA aligns with the SDI imaging model. Panels (e) and (f) present a test sample that was excluded from the training phase, together with its deconvolution outcomes, thereby implying the generalization capability of SPIBOA. Panel (g) presents the wavefront optimized by SPIBOA, whereas panel (h) displays the PSF derived from this wavefront based on Equation (3). This PSF is consistent with the anomalous 'horseshoe' structure depicted in Figure 1, suggesting that the estimation of the PSF is reasonable.

4. Experiment and Analysis

We use the PSF derived from SPIBOA to make deconvolution corrections to actual SDI observational images utilizing the Richardson-Lucy iteration algorithm (Richardson 1972), and present the results in Figure 5. Panels (a) and (b) in Figure 5 show the full-disk images of the Sun before and after correction, respectively, while panels (c) and (d) provide comparisons of subareas (corresponding to the red-boxed regions), revealing enhanced clarity and effective noise reduction in the corrected images. Figure 5(e) displays the PSF estimated by SPIBOA, which closely matches the distinctive 'horseshoe' pattern observed in the SDI images, indicating a reasonable and accurate estimation. Figure 5(f) shows the power spectral density profiles of the images in panels (c) and (d), which demonstrate a significant increase in high-frequency energy in the corrected image compared to the observed image, quantitatively validating the improvements in clarity and contrast.

To quantitatively assess the effect of image correction, we employed a series of flare images with varying intensities to measure the resolution improvement after correction. We use the Spatial Image Resolution Assessment by Fourier Analysis (SIRAF) technique (Brostrøm & Mølhave 2022) to conduct the resolution evaluation of SDI images. Our quantitative analysis indicates an enhancement in spatial resolution by a factor of more than three after correction, as outlined in Table 1. The table provides basic information on four flares, including the estimated spatial resolution before and after correction, as well as the factor of improvement in spatial resolution.

Figures 6–8 present resolution comparisons of SDI images before and after correction for the GOES X1.0 flare of 2024 May 8 in Table 1. Figure 6 displays the full-disk images before and after correction. In Figures 7 and 8, panel (a) shows the windowed images of 800 by 800 pixels, starting at [1600, 1600] in image coordinates, which are used for resolution estimations, panel (b) displays the FFT-transformed images, whereas panel (c) displays the corresponding spectral amplitude profiles. Following the SIRAF guidelines, a Hanning window is applied to the windowed images to effectively mitigate spectral leakage.

The corrected images, consistent with the results shown in Figure 5, demonstrate a significant improvement in clarity and contrast, which is due to the fact that the Fourier spectrum of the images before correction was concentrated in the low frequencies, while the mid- to high-frequency energy is noticeably increased after correction. This change can be easily seen by comparing panels (b) in Figures 7 and 8. The spectral amplitude profiles presented in panels (c) of Figures 7 and 8 reveal that the normalized cutoff frequency, which was below 0.05 before correction, rises to approximately 0.15 after correction. This substantial increase quantitatively confirms a more than threefold improvement in spatial resolution.

Figure 9 compares the corrected SDI images with AIA 304 Å and AIA 1600 Å images. The structural features in the areas marked by squares and circles demonstrate that the spatial resolution of the corrected images has significantly improved. Moreover, these features are well consistent with those in the AIA 304 Å and AIA 1600 Å images, further validating the effectiveness and rationale of the SPIBOA method.

5. Discussion

As shown above, the SPIBOA procedure significantly improves the quality of SDI images. In this section, we discuss some important factors, tailored strategies, essential considerations, and precautions for the practical application of the procedure.

5.1. The Essential Elements for the Implementation of SPIBOA

1. Prior Constraints. Utilizing the design and manufacturing parameters of the SDI optical system as fundamental constraints, we determine the equivalent aperture of the imaging system and then deduce the PSF of the optical system by refining the wavefront aberration corresponding to this aperture. This approach promotes the efficiency of the optimization procedure and also guarantees that the results conform more closely to the inherent physical constraints of the optical system. More specifically, the SDI has an aperture of 68 mm and works in the 121.6 nm wave band, corresponding to a diffraction limit of 0 .183. The designed pixel resolution is approximately 0 .5 with an FOV of 40 and an image dimension of 4608 × 4608 pixels. Such a configuration indicates that the digital imaging process is undersampled. Therefore, to accurately estimate the wavefront aberration across the entire aperture, it is imperative to magnify the observed image by a factor of 2.73, equivalent to 0.5 divided by 0.183.

2. Initial Value Selection. The choice of initial values is crucial for optimization problems. Taking into account the structural similarity and comparable pixel resolution between SDI and AIA 304 Å images (AIA 304 Å image has a pixel resolution of 0 .6, whereas the designed resolution of SDI is 0 .5), together with the fact that they both capture full-disk images of the Sun, we select AIA 304 Å images that are temporally close to the SDI observations as the initial values for I_{ref}. We subsequently utilize the prowess of CNNs to generate ideal SDI images under optimal imaging conditions. The advantage of this method is its ability to exploit the sophisticated nonlinear fitting capabilities of DNNs, thereby minimizing any potential nonlinear discrepancies between AIA 304 Å and actual SDI images. The alignment is achieved through linear constraints, which enables a more accurate estimation of the PSF. During the process, we utilize data obtained from ground-based tests as the initial value of the wavefront.

3. Data Samples. An extensive and diverse dataset is indispensable for training deep learning models. Over the past two years, SDI has accumulated a vast cube of observational data, from which we carefully curated a balanced selection that encompasses data from various regions, including solar limb, quiet regions, active regions, and flare regions ranging from C to X class. Each of these categories is paired with corresponding AIA 304 Å images. The balanced training dataset is crucial for optimizing our model, which has a ratio of 1:1:1:2 for solar limb, quiet regions, active regions, and flare regions.

4. Preprocessing. For the purpose of improving the accuracy of the optimization process and accelerating the training phase, it is necessary to coalign the observed SDI images with the AIA 304 Å images within the same FOV. Additionally, it is important to mitigate the adverse effects of cosmic rays and thermal noise, which can interfere with image quality and optimization accuracy.

5.2. Important Considerations and Precautions

1. Image correction is fundamentally a deconvolution process in linear system theory, equivalent to inverse filtering in the frequency domain. However, so-called "ringing" artifacts are often introduced due to model inaccuracies and information loss. These artifacts arise from the loss of high-frequency image information during degradation, which is particularly noticeable in high-frequency image areas. Severe loss of image information results in steep changes in the corresponding inverse filter, which leads to oscillations of the resulting image in areas with sharp intensity changes. Notably, ringing is especially prominent in regions of SDI images with abrupt intensity changes, such as rapid brightening or intense flares. Figure 10 compares the flare region of the observed SDI image on 2024 May 8 with the corrected image. The corrected image (right panel) exhibits typical ringing artifacts, characterized by darker areas with intensity discontinuities within high-contrast regions.

2. The SPIBOA training program incorporates a wide variety of image samples from a broad temporal range and diverse locations on the Sun into a cohesive training structure, so as to produce a PSF that effectively captures the average impact of linear distortions across the entire FOV. However, the current version of SPIBOA does not address the temporal variations or spatial inconsistencies that are inherent in the SDI imaging system, which may also introduce inaccuracy. This likely explains the varying improvement factors in spatial resolution after applying SPIBOA corrections to the flares listed in Table 1, which occurred at different locations on the Sun. Additionally, SPIBOA currently lacks the ability to provide a precise, quantitative assessment of these potential errors.

6. Conclusion

This paper concentrates on correcting LST/SDI observational data to enhance image quality, with the specific goals of estimating the PSF of the SDI imaging system and performing deconvolution corrections on observed SDI images, despite the unknown real SDI image and optical system function. By leveraging a large sample of observational data and employing deep learning techniques, we introduce a bivariate optimization-based imaging model estimation algorithm called SPIBOA.

The outcomes of our research are encouraging and demonstrate a substantial enhancement in the spatial resolution of corrected images. Analysis of sample data has shown an average resolution improvement of over three times, accompanied by a notable decrease in noise levels. We have successfully developed and implemented the SDI data correction software package based on the SPI-BOA algorithm, which is currently used to process routine SDI observational data. Furthermore, it incorporates parallel algorithms, which enable efficient and prompt processing of observational data on a single computing node.

We plan to continue our efforts in the future to conduct comprehensive long-term evaluations and enhancements related to the topics discussed in Section 5.2. Additionally, we will be attentive to addressing any emerging challenges. This ongoing commitment will ensure strong support for the scientific utilization of SDI observational data, promoting scientific outputs and advancing reliability in our research endeavors.

The successful deployment of the SDI data correction software package makes it feasible to extend this technique to the other two instruments of the LST payload, namely the WST and SCI, when required. It also pioneers innovative methods for identifying and rectifying issues within the optical systems of astronomical telescopes. Furthermore, it may pave the way for improvements and refinements in astrophysical data and research.

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