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Postprint of AIA Image Enhancement Method Based on Blind Deconvolution

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Abstract

Solar images contain physical activity phenomena of various scales, brightness levels, and structures. Due to factors such as the highly dynamic activities of the solar corona and sensor equipment limitations, the imaging quality of solar images is often compromised. Based on the characteristics of data captured by the Atmospheric Imaging Assembly (AIA) of the Solar Dynamics Observatory (SDO) across different wavelengths—including large dynamic range, high noise, and relatively blurred structures—this paper proposes an effective SDO/AIA image enhancement method based on blind deconvolution. First, the SDO/AIA images undergo denoising and dynamic range reduction processing. Then, based on the distribution assumption of the image power spectrum, the power spectrum of the point spread function (PSF) is estimated from the original image. Subsequently, a phase extraction algorithm is employed to recover the phase of the PSF, followed by deconvolution to obtain a higher-quality target image. Finally, quantitative and qualitative analyses of the enhancement results are performed through contour slice analysis, power spectrum analysis, and PSF analysis. Experimental results demonstrate that, compared with existing image enhancement methods, the proposed method effectively enhances the detailed structures of solar coronal images while simultaneously restoring structures that were unidentifiable in the original image due to blurring.

Full Text

AIA Image Enhancement Method Based on Blind Deconvolution

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Abstract: Solar images exhibit diverse physical phenomena across various scales, brightness levels, and structures. However, the high dynamic activity of the solar corona and sensor limitations result in poor imaging quality. Addressing the characteristics of SDO/AIA data—namely large dynamic range, significant noise, and relatively blurred structures—this paper proposes an effective blind deconvolution-based enhancement method for SDO/AIA images. The approach first denoises the images and reduces their dynamic range. Based on power spectrum distribution assumptions, the point spread function (PSF) power spectrum is estimated from the original image, followed by phase retrieval to recover the PSF phase. High-quality target images are then obtained through deconvolution. Finally, both quantitative and qualitative analyses are performed using contour slice analysis, power spectrum analysis, and PSF evaluation. Experimental results demonstrate that compared to existing methods, the proposed approach effectively enhances fine structural details in solar coronal images while restoring structures that were unidentifiable due to blur in the original images.

Keywords: solar image; SDO/AIA; power spectrum; blind deconvolution; phase retrieval

To investigate the highly dynamic structures of the solar corona, researchers have continuously pursued improvements in temporal and spatial resolution. Due to rapid changes in coronal structure density, position, and shape within seconds, combined with the large dynamic range, telescope observations suffer from blurred edges and substantial noise, making visualization challenging. Several effective enhancement algorithms have been developed for solar coronal images. Histogram-based methods can process different images using specified histogram distributions [1] or apply Gaussian filtering followed by independent equalization of each partition, such as Brightness Preserving Dynamic Histogram Equalization (BPDHE) [2]. These methods effectively improve overall contrast, but the typically square neighborhood shape of histograms introduces severe artifacts that affect coronal loop structures. Additionally, they amplify low-contrast noise, further blurring details, and cause loss of effective structures between regions of different brightness.

The Exposure Fusion Framework (EFF) [3] addresses the problem of excessive or insufficient contrast that arises with histogram equalization. The Multi-deviation Fusion method (MF) [4] combines multiple classical enhancement algorithms to leverage their respective strengths, simultaneously improving detail enhancement, contrast, and subjective visual quality. Most of these methods employ logarithmic transformation in preprocessing to reduce computational complexity. However, logarithmic transformation suppresses gradient magnitude variations in bright regions, potentially causing loss of fine structural details.

Retinex-based methods can compress dynamic range while enhancing edges and maintaining color stability. The Robust Retinex Model (rR) algorithm [5] improves noise robustness by using an alternating direction minimization method based on Lagrange multipliers instead of logarithmic transformation, effectively solving optimization problems and preserving structural details and edge stability. These methods, however, only provide visualization enhancements and cannot effectively address the blur of precise structures caused by coronal dynamics, telescope jitter, CCD undersampling, and stray light.

With advances in digital image processing, blind deconvolution algorithms provide a scientific theoretical basis for recovering structural accuracy and authenticity. Paolo G et al. [6] estimated theoretically-derived PSFs for different SDO/AIA bands based on telescope design theory. However, besides sensor equipment, image blur also results from solar activity displacement and shape changes. Therefore, theoretically estimated PSFs cannot effectively deconvolve clear images. When observing solar coronal structures with the SDO/AIA space telescope, the imaging blur caused by coronal displacement, shape changes, CCD undersampling, and stray light can be modeled as:

$$B(x) = I(x) * k(x) + n(x)$$

where $*$ denotes convolution, $B(x)$ represents the observed blurred image (i.e., SDO/AIA images), $I(x)$ denotes the latent clear image, $k(x)$ is the unknown PSF, and $n(x)$ is the noise term, independently and identically distributed at each pixel.

Blind deconvolution algorithms can be broadly categorized into two classes based on their solution methods. The first class introduces additional constraints to alternately iterate between target image and PSF estimation, completing blind deconvolution based on maximum a posteriori (MAP) estimation. These methods provide some noise suppression but involve multiple iterations between target image and PSF estimation, making the process computationally expensive and heavily dependent on prior characteristics of the clear image and PSF. For SDO/AIA images, obtaining statistical prior information about clear images is difficult. The second class first estimates the blur kernel and then deconvolves to obtain a clear image. These methods primarily include saliency edge-based [7] and power spectrum-based approaches [8-9]. Edge-based methods estimate blur kernels from salient edges, but their effectiveness largely depends on edge selection and is more suitable for motion blur estimation. SDO/AIA images have blurred structures, making edge selection challenging. Power spectrum-based methods directly recover the PSF power spectrum from the input image' s power spectrum and then use phase retrieval algorithms to solve for the PSF phase.

Therefore, this paper investigates a single-frame blind deconvolution algorithm that estimates the PSF using the power spectrum of blurred images for enhancing solar SDO/AIA images. The method first preprocesses the data (including denoising and grayscale transformation), estimates the PSF power spectrum from AIA images, and then uses a phase retrieval algorithm to recover the PSF. To improve noise robustness, a weight parameter is introduced to relax the hard constraint of using the PSF power spectrum for phase estimation. The algorithm is solved multiple times with random initialization to avoid local minima. The L_2 norm distance between all possible solutions is computed. If the distance between potential solutions is smaller, the PSF is considered closer to the true solution. Finally, this PSF is used in Equation (1) to deconvolve the target image. To further reduce noise effects, the image to be enhanced is divided into four adjacent local sub-images. The PSF for each sub-image is estimated using the above method, and the four PSFs are normalized and averaged to obtain the PSF for restoring the entire image. Experimental analysis employs contour slice curves, power spectrum analysis, PSF analysis, and comparison with other advanced enhancement algorithms for objective evaluation of reconstructed target image details. Validation against The High-Resolution Coronal Imager (Hi-C) image power spectrum assumptions and fine structure enhancement effects shows that the proposed method achieves good enhancement and restoration results for SDO/AIA structures in the 193 Å, 211 Å, and 171 Å bands with robustness to noise. Additionally, since the method does not involve repeated reconstruction of the target image, it offers advantages in restoration speed.

1 SDO/AIA Data

The primary objective of the Solar Dynamics Observatory' s Atmospheric Imaging Assembly (SDO/AIA) [10] is to understand the mechanisms of solar energy storage and release, determining how and why the Sun changes. By studying plasma interactions in the solar atmosphere, it enhances our understanding of how solar activity affects Earth's atmosphere and societal production. SDO/AIA consists of four telescopes providing simultaneous full-disk images in ten wavelength bands, including seven extreme ultraviolet bands (94 Å, 131 Å, 171 Å, 193 Å, 211 Å, 304 Å, 335 Å), two ultraviolet bands (1600 Å, 1700 Å), and one visible band (4500 Å). It observes the solar transition region and corona up to 0.5 solar radii, with a spatial resolution of 1.5 arcsec, temporal resolution of 12 seconds, and a field of view of 41\$×\$41 arcmin, launched on February 11, 2010.

The High-Resolution Coronal Imager (Hi-C) [11-12] provides finer coronal structures with high spatial resolution (0.3–0.4 arcsec) and high temporal resolution (5 seconds) for solar active region images, representing the highest resolution solar coronal images currently available. It has enabled the discovery of small-scale coronal features and transition region phenomena, further validating their potential interconnections.

As shown in Table 1 , while Hi-C offers higher spatiotemporal resolution, its small field of view and short observation duration prevent stable long-term coronal monitoring. In contrast, SDO/AIA provides large field-of-view, long-term full-disk observations, albeit with lower image quality than Hi-C. Therefore, enhancing SDO/AIA images is particularly important.

Table 1. Comparison of SDO/AIA and Hi-C Data Characteristics

Data Properties	SDO/AIA	Hi-C
Data Acquisition	2010.02.11–now	18:52:10–18:57:49
Field of view (arcmin)	41×41	6.66×7.03
Image size (pixel)	3880×4096	4096×4096
Spatial Resolution (arcsec)	1.5	0.3–0.4
Temporal Resolution (s)	12	5
Channel (Å)	94, 131, 171, 193, 211, 304, 335, 1600, 1700, 4500	193

This work employs SDO/AIA data including: a 193 Å partial image observing hot flare plasma and the corona at 18:53:32 on July 11, 2012; a 211 Å partial image of an active region corona at 23:40:11 on February 2, 2014 (both captured by the same telescope); and a 171 Å partial image of a quiet region corona at 10:13:11 on October 4, 2014 (captured by a different telescope). For the 193 Å band experiment, Hi-C images from active region 11520 at 18:53:27 on July 11, 2012, are used as clear image power spectrum assumption validation and experimental comparison. Additional comparison includes deconvolution results using PSFs estimated in reference [3]. Data preprocessing involves logarithmic transformation to reduce the high dynamic range of SDO/AIA data, followed by median filtering for denoising, which removes noise without smoothing transitions and effectively preserves image structures.

2 Blind Deconvolution Algorithm Theory

The proposed method comprises three components: natural image power spectrum assumption modeling, Hi-C power spectrum analysis, and AIA image PSF estimation.

3.1 Natural Image Power Spectrum Assumption Model

Amit et al. [8] demonstrated that clear images have isotropic power spectra (or autocorrelation). During blurring, mid- and high-frequency components are attenuated. When computing autocorrelation after applying differential filtering in different directions to blurred images, maximum loss occurs when the blur direction aligns with the differential direction. The direction with the minimum absolute energy sum can thus be considered the blur direction. Based on these conclusions, we apply Fourier central projection transforms to both clear and blurred images at different angles (θ) to obtain one-dimensional slices corresponding to different projection angles. After one-dimensional differential filtering of these slices, their autocorrelation yields:

$$I * d_\theta \approx c(\theta)\mathcal{R}\{\delta\}$$

$$B * d_\theta \approx \mathcal{R}\{k\} * c(\theta)\mathcal{R}\{\delta\}$$

where d_θ is a one-dimensional differential filter, $c(\theta)$ represents a multiplicative factor varying with angle, $\mathcal{R}$ denotes autocorrelation computation, $\mathcal{P}$ denotes the projection operator, and δ is the impulse function:

$$\delta(x,y) = \begin{cases} 1 & \text{if } x = 0, y = 0 \\ 0 & \text{otherwise} \end{cases}$$

3.2 Hi-C Power Spectrum Analysis

Figure 1 [Figure 1: see original paper] illustrates the power spectrum characteristics of Hi-C images. A local sub-image from Hi-C(a) is shown in (b), with its directional power spectrum cross-sections plotted in (c). Dividing the values of the four curves in (c) yields result (d). Observation of (c) reveals that the power spectrum computed from the clear image (a) using Equation (2) is not an exact δ function. Figure (d) shows that dividing power spectra at different angles yields different constants, with $c(\theta)$ varying as projection angle changes. This demonstrates that the Hi-C power spectrum of clear solar images exhibits multiplicative factor variations with θ, validating the reliability of Equations (2) and (3) for AIA image PSF estimation. Multiple spikes in the figure result from zero values in divisors.

To avoid increasing total image energy, the filter d_θ has zero mean. During $\mathcal{R}\{B * d_\theta\}$ computation, this causes the mean of $\mathcal{R}\{k\}$ to be missing (zero), while the actual image power spectrum is not zero. Therefore, parameter m_θ is introduced to replace zero values, i.e., $\mathcal{R}\{B * d_\theta\} = \mathcal{R}\{k\} + c(\theta)$. From Equation (3), we obtain:

$$\mathcal{R}\{k\} = \mathcal{R}\{B * d_\theta\} - m_\theta$$

3.3 PSF Estimation

Equation (4) is an underdetermined system. Additional constraints are required to successfully recover $\mathcal{R}\{k\}$ and $c(\theta)$.

3.3.1 Constraint Estimation Three assumptions about the PSF [13] enable equivalent computation of Equation (4):

1. During camera exposure, photons accumulate on the sensor with non-negative energy, making the PSF non-negative ($k \geq 0$). Consequently, $\mathcal{R}\{k\}$ is non-negative for all θ, yielding $\mathcal{R}\{B * d_\theta\} \geq c(\theta)$.
2. Camera movement during exposure is finite, making the blur process compactly supported. Thus, for each angle' s projection autocorrelation, there

exists θ_s such that $\mathcal{R}\{k\} = 0$ when $\theta \geq \theta_s$, satisfying:

$$\mathcal{R}\{B * d_\theta\} = \begin{cases} c(\theta) + \mathcal{R}\{k\} & \text{if } \theta < \theta_s \\ c(\theta) & \text{otherwise} \end{cases}$$

3. Theoretically, blur does not affect the total number of photons reaching the sensor, implying $\int k(x)dx = 1$ and consequently $\int \mathcal{R}\{k\}dx = 1$. From Equation (4):

$$\int \mathcal{R}\{B * d_\theta\}dx = \int c(\theta)dx + \int \mathcal{R}\{k\}dx = \int c(\theta)dx + 1$$

This normalizes the blur kernel k.

In summary, computing Equation (4) is equivalent to:

$$\mathcal{R}\{k\} = \arg\min_x \|\mathcal{R}\{B * d_\theta\} - (x + c(\theta))\|_2^2$$

3.3.2 Support Range Estimation The PSF support range $s(\theta)$ and $c(\theta)$ are estimated through Expectation-Maximization (EM) iteration between PSF estimation and $c(\theta)$ estimation. Each EM iteration refines the PSF, enabling more accurate estimation and effectively suppressing ringing and artifacts in blind restoration.

1. Initialize $c(\theta)^0$, then update as $c(\theta)^{i+1}$;
2. Use $c(\theta)^i$ to estimate $s(\theta)^i$, then iterate the current PSF k^{i+1} satisfying maximum expectation via phase retrieval (Algorithm 2);
3. Update $c(\theta)^{i+1}$ based on step (2) for the $(i+1)$-th iteration;
4. Repeat steps (2) and (3) until $\max |\mathcal{R}\{k^{i+1}\} - \mathcal{R}\{k^i\}| < 0.1$.

Figure 2 [Figure 2: see original paper] shows the support domain $s(\theta)$ iteration process (a) and the recovered one-dimensional PSF autocorrelation (b). In (a), the blue curve represents the initialized $s(\theta)$, updated through EM iteration to $s(\theta)$ (red curve). The final $s(\theta)$ (green curve) upon meeting termination conditions provides the support domain values for the horizontal axis in (b).

Algorithm 1 (Solving for $\mathcal{R}\{k\}$):

Input: Blurred image B
Step 1. T denotes the number of cropped sub-images, $t = 1$
Step 2. Initialize $c(\theta)^0$
Step 3. Outer loop begins, set iteration count $i = 1$
Step 4. Inner loop begins:
Step 4.1. Using given $c(\theta)^i$, compute blur kernel power spectrum $\mathcal{R}\{k\}$ via Equation (5) ($\mathcal{F}$ denotes Fourier transform)
Step 4.2. Compute blur kernel k via Algorithm 2
Step 4.3. EM iteration updates $c(\theta)^i$

Step 5. Inner loop ends when $\max|\mathcal{R}\{k^{i+1}\} - \mathcal{R}\{k^i\}| \leq 0.1$
Step 6. Outer loop ends when $t = T$ (where T represents the number of cropped sub-images)

Figure 3 [Figure 3: see original paper] illustrates the algorithm workflow: original image (a) undergoes denoising and logarithmic transformation to produce (b); one-dimensional autocorrelation of (b) is computed (c); support domain $s(\theta)$ is iteratively derived (d); this $s(\theta)$ calibrates the one-dimensional PSF power spectrum (e), which is restored to two-dimensional power spectrum (f); phase extraction algorithm computes the phase to recover the PSF (g); final non-blind deconvolution yields the target image (h).

3.4 PSF Phase Recovery

After obtaining $\mathcal{R}\{k\}$, a phase retrieval algorithm recovers the phase component $\varphi(\omega)$ of blur kernel k to obtain the final PSF. Phase retrieval is an underdetermined algorithm whose solution suffers from trivial ambiguities, often converging to trivial solutions or local minima. The classic Error-Reduction (ER) algorithm reduces error during iteration but frequently stagnates by setting signals violating constraints to zero. The Hybrid Input-Output (HIO) algorithm [14] improved this by introducing small perturbations to escape stagnation and accelerate convergence. Luke [15] proposed the Relaxed Averaged Alternating Reflection (RAAR) algorithm for faster, more stable convergence. However, RAAR treats the input power spectrum as a hard constraint, requiring the recovered signal to perfectly match the input power spectrum. This causes oscillations and poor robustness when the input contains noise. SDO/AIA images have complex noise that cannot be completely eliminated during preprocessing. Therefore, this algorithm relaxes the hard constraint on PSF power spectrum (via weight parameter α) to improve noise robustness. Random phase initialization with multiple repetitions avoids local minima. Additionally, the HIO perturbation method (term β in Algorithm 2) helps escape stagnation. Finally, L_2 distances between all possible solutions are computed to find the optimal solution.

Algorithm 2 (Solving for k):

Input: $\mathcal{R}\{k\}$, PSF size s
Output: k
Step 1. Outer loop $t = 1$
Step 1.1. Randomly initialize phase $\varphi(\omega) \in [-\pi, \pi]$
Step 1.2. Compute $G = \mathcal{F}^{-1}\{\rho(\omega)e^{i\varphi(\omega)}\}$
Step 1.3. Inner loop $m = 1$
Step 1.3.1. Apply Fourier domain constraint (relaxing amplitude $\rho(\omega)$ by factor α):

$$G' = \mathcal{F}^{-1}\{\alpha\rho(\omega) + (1-\alpha)\mathcal{F}\{G\}\}$$

Step 1.3.2. Apply spatial domain constraint (PSF non-negativity and support constraints):

$$G = \begin{cases} \beta G' + (1-\beta)G & \text{if } x \in \Omega \\ G' & \text{otherwise} \end{cases}$$

where $\Omega = \{x : |x| \leq s_0, x \notin \text{support region}\}$. To ensure stable, rapid convergence during m iterations, the HIO algorithm' s β setting is adopted: $\beta = 1 + e^{3-m/700}$. In this experiment, when $m = 0$, $\beta = 0.75$ gives G a small perturbation to escape stagnation.
Step 1.4. Inner loop ends when $m = M$
Step 1.5. Recover $k = G$
Step 2. Outer loop ends when $t = N$. Compute L_2 distances between all solutions pairwise to obtain the optimal solution k.

Algorithm 2 employs a dual-loop structure. The outer loop prevents local minima—solutions converge more easily to the global minimum when initialization is closer to the true value. Multiple random phase initializations produce N solutions; the solution with minimum L_2 norm distance is considered optimal. The inner loop ensures stable, rapid convergence by alternately applying frequency-domain (amplitude) and spatial-domain (PSF non-negativity and support) constraints. When $G \in \Omega$, assigning a small perturbation value helps escape stagnation. Literature [15] indicates that gradually increasing β toward 1 guides stable convergence. Thus, this algorithm dynamically sets β as a value approaching 1 through inner loop iterations.

As shown in Equation (1), solving for the target clear image given blur kernel k and blurred image B is called non-blind deconvolution. This experiment uses the alternating minimization method from literature [16], specifically the half-quadratic splitting approach, to solve for the target image I.

3 Experimental Results and Analysis

To evaluate the method' s effectiveness and accuracy, we enhanced images from three AIA bands (193 Å, 211 Å, 171 Å) across different regions. All AIA images are displayed logarithmically. In Figure 4 [Figure 4: see original paper], enhanced images from the three bands show sharper details, with previously blurred structures between coronal loops well separated and clearer boundaries. As shown by the estimated PSF sizes in the third column, the PSFs for 193 Å and 211 Å bands are larger than for 171 Å, indicating greater blur in the former two bands. Since 193 Å and 211 Å images primarily capture active regions, their larger dynamic range and coronal loop motion relative to the telescope cause higher blur. In the power spectrum plots (fourth column), enhanced images from all three bands show improved mid-frequency components compared to original AIA images. Enhanced mid-frequency components manifest as sharper structural boundaries and recovery of previously unobserved details lost to blur.

Figure 4 [Figure 4: see original paper]. Enhancement images of AIA in different bands

For detailed comparison of structural enhancement, Figure 5 [Figure 5: see original paper] introduces contour slice plots. Reference [6] estimated PSFs for different AIA bands based on telescope theory and applied them to all images in a band, which is inaccurate as it only considers telescope equipment and ignores other blur sources, yielding suboptimal results (second column). In Figure 5, we enhance different regions separately for each band and compare our estimated PSFs with those from reference [6]. For the two partial images in the 193 Å band, our estimated PSFs have similar sizes but different shapes. Structures A and B show well-separated coronal loops, as demonstrated in contour slice plots. Similarly, in 211 Å and 171 Å enhanced images, the blur directions of structures C, D, and E align with PSF shapes. Different regions exhibit varying solar activity, with uncontrollable changes in coronal loop positions and shapes causing mutual interference, necessitating region-specific PSF estimation.

Figure 5. Detail enhancement images of different bands and regions

Figure 6 [Figure 6: see original paper] presents comparisons with higher-resolution Hi-C images to evaluate enhancement accuracy. For comparison convenience, images (a) and (b) are magnified and log-transformed. Energy maps show that AIA images have similar colors in detail regions with obvious blur, making structures nearly invisible. Enhanced images resemble Hi-C images. Power spectrum plots (d) reveal that AIA images have almost no high-frequency details and weak mid-frequency components. Enhanced images show improved mid- and high-frequency components, slightly weaker than Hi-C but with mid-frequency slightly higher than Hi-C in some regions. Detail maps (e) demonstrate that our method not only separates relatively blurred coronal loop structures but also better preserves edges of existing loops, with sharper edges than Hi-C, explaining the slightly higher mid-frequency curve. Structures A, B, and C were unresolvable due to blur but remain stable and accurately recovered after enhancement, as confirmed by comparison with Hi-C. The contour slice plot (f) for structure A shows that a single coronal loop in AIA is successfully separated into two loops matching Hi-C.

Figure 6 [Figure 6: see original paper]. Detail comparison with Hi-C

Figure 7 [Figure 7: see original paper] compares results from the classic histogram-based BPDHE algorithm and state-of-the-art EFF, MF, and rR algorithms. The first row shows that BPDHE causes local over-enhancement and detail blur, while our algorithm provides better detail enhancement with stable edge structures. The second row displays histograms for each algorithm, with MF showing the best visualization quality. Compared to other methods, our algorithm restores finer details while ensuring contrast and brightness enhancement. Table 2 lists standard deviation and entropy measurements for different algorithms—effective indicators of contrast and brightness information, where larger values indicate richer information. Lightness Order Error (LOE) objectively measures brightness distortion, with smaller values indicating better brightness. SSIM (structural similarity) assesses restoration quality by evaluating brightness, contrast, and structure, with values closer to 1 indicating better quality. All methods are compared against Hi-C images for SSIM calculation. Although our algorithm has longer runtime, it provides more accurate detail structure enhancement.

Figure 7 [Figure 7: see original paper]. Comparison of different enhancement algorithms

Table 2. Image Enhancement Measurement Parameters

Method	Standard Deviation	Entropy	Running Time(s) (400$×$400)	LOE	SSIM
BPDHE					
EFF					
MF					
rR					
Ours					

This paper proposes a blind deconvolution-based method for enhancing solar AIA image quality. The PSF estimation model based on image power spectrum characteristics estimates the PSF from AIA images, which is then used to deconvolve enhanced images. The method' s accuracy is evaluated through contour slice analysis, effectiveness via power spectrum analysis, and rationality through regional PSF analysis. Experimental results demonstrate that the proposed method achieves excellent enhancement for SDO/AIA 193 Å, 171 Å, and 211 Å band images, particularly for texture details and edge structures. The algorithm also exhibits noise suppression benefits, thanks to the relaxed design of the PSF phase estimation process, enabling accurate recovery of new details. This is facilitated by relatively low noise and rich, distinct coronal structures in these three bands, allowing accurate blur kernel estimation.

Compared to other enhancement methods, the proposed approach has poorer real-time performance, primarily due to time-consuming PSF estimation and deconvolution optimization iterations. Future work will focus on improving computational performance and adopting faster, more effective optimization methods. For other AIA bands (94 Å, 131 Å, 335 Å) that also observe the corona, high noise, numerous outliers, and relatively blurred structures limit enhancement effectiveness. Future research will investigate better denoising algorithms and more robust deconvolution methods for effective enhancement of these bands.

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