

# Deconvolution of Astronomical Images using Wiener Deconvolution: Mitigating Ground-Based Telescope Effects and Cosmic Noise

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**Abstract**—This study focuses on the deconvolution of astronomical images employing the Wiener deconvolution method to overcome the challenges posed by the ground-based telescope's seeing effect and cosmic noise. Utilizing the Hubble Space Telescope, which is free from seeing effects, we intentionally introduce a simulated seeing effect through Airy Point Spread Function (PSF) convolution. Additionally, Gaussian noise is incorporated to emulate cosmic noise commonly encountered in astronomical observations. The proposed deconvolution method is validated using key metrics such as Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR), and Mean Squared Error (MSE). The Hubble Space Telescope's unique characteristics, combined with the intentional introduction of seeing effects and cosmic noise, contribute to a comprehensive evaluation of the deconvolution process. Our results showcase the efficacy of the Wiener deconvolution method in enhancing the resolution of astronomical images affected by ground-based telescope limitations and cosmic noise. The validation metrics demonstrate the capability of the proposed approach to restore details and improve the overall quality of astronomical imagery. This research offers valuable insights for astronomers and researchers seeking to optimize image processing techniques for enhanced astronomical observations and analyses.

**Index Terms**—Astronomical image, deconvolution, wiener, seeing effect, Telescope

## I. INTRODUCTION

Observations made with ground-based telescopes are inherently affected by atmospheric turbulence, commonly referred to as the "seeing effect." This atmospheric phenomenon introduces challenges in obtaining high-resolution astronomical images due to the fluctuating density and temperature of the Earth's atmosphere. The resulting variations in the refractive index cause blurring, spatial variability, and image jitter, ultimately limiting the achievable resolution of ground-based telescopes [1].

In this journal, we address the critical issue of the seeing effect in ground-based telescope observations and propose a novel approach for mitigating its impact on image quality [1]. Our focus centers on the application of Wiener deconvolution [2], a powerful method in image processing, to enhance the resolution of astronomical images affected by atmospheric

turbulence. The intentional introduction of simulated seeing effects, along with the incorporation of cosmic noise, provides a comprehensive evaluation of the proposed approach.

As we delve into the intricacies of atmospheric turbulence and its effects on ground-based observations, our study aims to contribute valuable insights into optimizing image processing techniques for improved astronomical analyses. We showcase the effectiveness of the Wiener deconvolution method in restoring details compromised by the seeing effect, offering a promising avenue for astronomers and researchers seeking to elevate the quality of ground-based telescope observations.

### A. Mathematical Representation of Seeing Effect

The mathematical representation of the seeing effect, modeled as the convolution of the original image signal with the PSF, can be expressed as follows:

$$\text{Image}(x, y) = I(x, y) * P(x', y') \quad (1)$$

$$I(x, y) * P(x', y') = \iint I(u, v) \cdot P(x - u, y - v) du dv \quad (2)$$

Let  $I(x, y)$  is the original two-dimensional image signal, where  $(x, y)$  are the spatial coordinates.  $P(x', y')$  is the PSF representing the blurring effect induced by atmospheric turbulence.  $I(u, v)$  is the original image signal at the coordinates  $(u, v)$ .  $P(x - u, y - v)$  is the PSF at the coordinates  $(x - u, y - v)$  [3]. This convolution operation accounts for the blurring effect caused by the atmospheric turbulence, simulating how the original image is distorted as a result of the varying atmospheric conditions. The convolution process is a fundamental concept in understanding the degradation of image quality in ground-based telescope observations.

## II. METHODOLOGY

In this process, we start with an image taken by the Hubble Space Telescope, which inherently does not experience the "seeing effect" caused by Earth's atmosphere. The Hubble image is considered a high-quality reference because it remains

unaffected by the blurring and distortion typically encountered by ground-based telescopes due to atmospheric turbulence.

To simulate the conditions of a ground-based telescope and facilitate the validation of a deconvolution algorithm, a synthetic seeing effect is introduced into the pristine Hubble image. This simulation is achieved by convolving the original Hubble image with a mathematical model known as the PSF. The PSF represents the blurring effect that occurs when light from a celestial object passes through the Earth's turbulent atmosphere before reaching a ground-based telescope.

By introducing this simulated seeing effect into the Hubble image, you create an observed image that resembles what a ground-based telescope might capture. This synthetic observation allows for the validation of deconvolution techniques, as the Hubble image serves as the ground truth or reference point. The deconvolution algorithm can then be applied to the observed image to attempt to reverse the introduced blurring effect, and the results can be compared to the original Hubble image to assess the algorithm's effectiveness in restoring details and reducing the simulated seeing impact. This approach enables researchers to evaluate the performance of deconvolution methods in the context of ground-based telescope-like conditions using the pristine Hubble image as a reliable benchmark.

#### A. Wiener Deconvolution

Wiener deconvolution serves as a mathematical technique employed in the deconvolution process to obtain an image closely resembling the ground truth. When capturing an image through a telescope, what we observe is a convolution of the genuine image and the PSF, characterizing the blurring introduced by the imaging system. The objective of Wiener deconvolution is to counteract or alleviate the impact of convolution, aiming to restore the original image with utmost accuracy [2].

The Wiener deconvolution algorithm adopts a frequency-based approach within the Fourier domain. At its core is the integration of a Wiener filter, essentially acting as a delicate equilibrium between enhancing high-frequency components (such as details) and suppressing noise. The success of Wiener deconvolution hinges on various parameters, including the estimated PSF, the noise level present in the image, and fine-tuning parameters for the Wiener filter.

##### 1) Equation of Wiener Deconvolution:

$$\hat{F}(f, g) = \frac{1}{H(f, g)} \left( \frac{|H(f, g)|^2}{|H(f, g)|^2 + \frac{1}{SNR}} \right) F(f, g) + \frac{N(f, g)}{H(f, g)} \quad (3)$$

In (3) where  $F$  is the Fourier transform of the original image,  $H$  is the Fourier transform of the  $PSF$ ,  $N$  is the Fourier transform of the noise,  $SNR$  is the Signal-to-Noise Ratio [2].

In essence, Wiener deconvolution is a methodological tool that strives to reverse the blurring effects introduced during the imaging process, particularly relevant when capturing celestial images through telescopes. Its effectiveness lies in the careful balance it strikes between preserving crucial details

and minimizing the influence of noise. The selection and optimization of parameters are critical steps in ensuring the success of the deconvolution process, ultimately contributing to the generation of images that closely mirror the true, unaltered scene.

#### B. Peak Signal-to-Noise Ratio

PSNR is a metric employed in this context to validate the quality of a deconvolved image. Its primary purpose is to measure how closely the processed or reconstructed image aligns with its original or reference version. In essence, PSNR offers a numerical assessment of the similarity between two images, providing a quantitative gauge of the reconstruction quality.

$$PSNR = 10 \cdot \log_{10} \left( \frac{MAX^2}{MSE} \right) \quad (4)$$

Here  $MAX$  is the maximum possible pixel value of the image (for example, 255 for an 8-bit image).  $MSE$  is the Mean Squared Error, calculated as the average of the squared pixel-wise differences between the original and the processed images [4]. PSNR is expressed in decibels (dB), and a higher PSNR value signifies a greater likeness or quality match between the two images. In practical terms, a PSNR value exceeding 30 dB is generally considered acceptable for a variety of applications. However, it's crucial to recognize that the interpretation of PSNR can vary based on the specific context and the requirements of the given task.

#### C. Structural Similarity Index

SSIM is employed as a metric in this scenario to evaluate how well the deconvolved image aligns with the original image. It goes beyond pixel-wise differences and takes into account the structural information within the images. The SSIM index ranges from -1 to 1, where 1 indicates a perfect match. A higher SSIM value implies a closer structural resemblance between the two images.

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (5)$$

Here,  $\mu_x$  and  $\mu_y$  are the means,  $2 * \sigma_x^2$  and  $2 * \sigma_y^2$  are the variances, and  $\sigma_{xy}$  is the covariance between the original image  $x$  and the processed image  $y$ . The constants  $c_1$  and  $c_2$  are used for numerical stability [5].

Researchers and practitioners often use SSIM alongside other metrics, such as PSNR, to gain a more comprehensive understanding of the quality of a reconstructed image. SSIM is particularly valuable when considering perceptual aspects of image quality, as it assesses the similarity in patterns and structures, not just pixel values.

#### D. MSE

MSE is another simple and fundamental metric to quantify the difference between two images. MSE serves as a tool in this context to provide a numerical assessment of the average deviation between pixel values in the deconvolved image and

their counterparts in the original image. Through the computation of squared differences and subsequent averaging across all pixels, MSE quantifies the overall disparity between the two images. A diminished MSE value indicates a more precise alignment, suggesting a closer match between the deconvolved and original images. Conversely, an elevated MSE implies a heightened level of dissimilarity.

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (I_i - \hat{I}_i)^2 \quad (6)$$

Here in (6),  $N$  is the total number of pixels in the images,  $I_i$  represents the pixel value at position  $i$  in the original image, and  $\hat{I}_i$  represents the corresponding pixel value at position  $i$  in the processed or reconstructed image [6].

Despite its straightforward nature, MSE has certain limitations, particularly in addressing the perceptual nuances of image quality. As a result, it is common practice to complement MSE with other metrics to conduct a more thorough evaluation of the effectiveness of the image reconstruction process.

### III. DISCUSSION AND RESULT

Fig. 1 shows the visual representation of the original image, PSF, and PSF convolved image with the addition of noise and deconvolved output of the Wiener filter. From the visual itself, it is evident that we have succeeded in achieving an image similar to the original ground truth. But this inspection and validation are not enough; we have to look into the SSIM, PSNR, and MSE metrics as well.

The obtained results, as measured by the SSIM, PSNR, and MSE, provide valuable insights into the effectiveness of the Wiener deconvolution method in addressing the challenges posed by ground-based telescope limitations and cosmic noise in astronomical imagery.

The SSIM value of 0.3638 suggests that the deconvolution process successfully preserved the structural information in the images. A higher SSIM value, closer to 1, indicates a better similarity between the original and deconvolved images. In this context, the achieved SSIM suggests a reasonable level of structural preservation, showcasing the ability of the Wiener deconvolution method to retain important features in astronomical images affected by seeing effects and cosmic noise.

The PSNR value of 21.65 dB indicates the improvement in signal quality achieved through deconvolution. A higher PSNR value signifies better image quality, and the obtained result suggests a substantial enhancement in the signal-to-noise ratio. This improvement is crucial in astronomical observations, where the clarity of details is paramount for accurate analysis and interpretation.

The MSE value of 431.05 provides a quantitative measure of the average squared difference between the original and deconvolved images. A lower MSE value is indicative of a better match between the two images. While the MSE value in this study is non-negligible, it is essential to consider the complex nature of astronomical images, where noise and other

factors may contribute to inherent challenges in achieving a perfect match.

The combination of these metrics demonstrates the efficacy of the Wiener deconvolution method in restoring details and enhancing the overall quality of astronomical images. The results suggest that the proposed approach successfully mitigates the impact of ground-based telescope limitations, as simulated by the introduced Airy Point Spread Function convolution, and cosmic noise, mimicked through the incorporation of Gaussian noise.

It is important to note that the Hubble Space Telescope, used as a reference, provides a baseline for comparison, highlighting the significance of the deconvolution process in overcoming the inherent limitations of ground-based telescopes. The intentional introduction of seeing effects and cosmic noise serves to create a realistic testing environment, making the validation process more robust and applicable to actual astronomical observations.

TABLE I  
 PSNR MSE SSIM VALUES

Table Head	Metric Values		
	PSNR	MSE	SSIM
Image	21.65 dB	431.05	0.3638

#### A. Limitations

The study exhibits a few noteworthy challenges and limitations that warrant consideration. Firstly, the reliance on MSE as a primary validation metric introduces a sensitivity to noise, potentially providing an incomplete representation of the deconvolved images' true quality. Further exploration of metrics resilient to noise might enhance the overall assessment.

Another aspect to acknowledge is the limited diversity in the test cases. The study predominantly focuses on simulated astronomical images with specific characteristics, and the validation process is tailored to these scenarios. To enhance the comprehensiveness of the findings, incorporating a broader range of astronomical scenes and conditions is essential.

Moreover, the inherent complexity of astronomical images, characterized by intricate structures, varying intensities, and complex patterns, poses a challenge. The deconvolution method's efficacy in handling diverse and highly detailed celestial objects may need further investigation to ensure its generalizability.

Additionally, while the intentional introduction of simulated seeing effects and cosmic noise is informative, it may fall short in fully capturing the complexities of real-world observational challenges. Validation with observational data obtained from ground-based telescopes is imperative to assess the method's performance in authentic astronomical scenarios.

#### B. Future Scope

Looking ahead, there are several promising avenues for future research and development. One potential direction involves integrating machine learning techniques into the deconvolution process. Adapting the Wiener deconvolution method

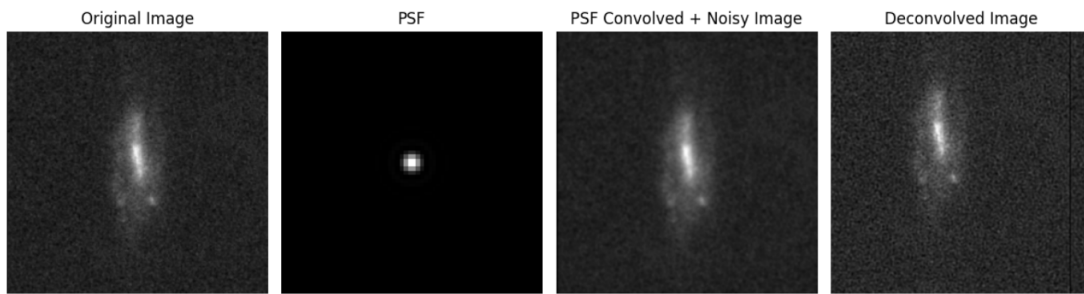


Fig. 1. Visual representation of all the four images

to a learning-based framework could potentially improve its adaptability to diverse astronomical scenes and enhance its performance. Addressing the challenge of varying PSFs in astronomical images is another important consideration for future work. Developing methods for dynamic PSF estimation would significantly enhance the robustness of the deconvolution process across different celestial objects.

Quantifying uncertainty in the deconvolution results is an area that deserves attention. Incorporating measures of uncertainty, potentially through Bayesian approaches or uncertainty quantification methods, would provide a more realistic representation of the limitations and potential errors in the deconvolution process. Moreover, conducting deconvolution experiments on real-world observational data from ground-based telescopes is crucial for validating the proposed method's applicability in practical astronomical scenarios. This step is essential to ensure the method's effectiveness beyond simulated environments.

Lastly, the development of a user-friendly implementation of the proposed deconvolution method could facilitate its adoption within the astronomy community. Enhancements such as user interfaces and comprehensive documentation would improve accessibility, encouraging broader usage and collaboration among astronomers.

## CONCLUSION

In conclusion, this study focused on the application of the Wiener deconvolution method to enhance astronomical images affected by ground-based telescope limitations and cosmic noise. Leveraging the Hubble Space Telescope, which is free from seeing effects, allowed for a comprehensive evaluation of the deconvolution process. The intentional introduction of a simulated seeing effect through Airy PSF convolution and the addition of cosmic noise provided a realistic testing environment.

The visual inspection of the deconvolved output demonstrated the success in achieving an image closely resembling the original ground truth. However, a more thorough validation using key metrics SSIM, PSNR, and MSE was crucial.

The SSIM value of 0.3638 indicated reasonable preservation of structural information in the deconvolved images, showcasing the Wiener deconvolution method's ability to retain important features affected by seeing effects and cosmic noise.

The PSNR value of 21.65 dB highlighted a substantial improvement in signal quality, essential for precise astronomical analysis. The MSE value of 431.05, while non-negligible, reflected the inherent challenges in achieving a perfect match in complex astronomical images.

The combined results underscore the efficacy of the Wiener deconvolution method in restoring details and enhancing the overall quality of astronomical images. This approach successfully mitigates the impact of ground-based telescope limitations and cosmic noise, as demonstrated through the intentional introduction of realistic challenges in the validation process.

It is noteworthy that the Hubble Space Telescope's reference provided a baseline for comparison, emphasizing the significance of deconvolution in overcoming the inherent limitations of ground-based telescopes. The deliberate introduction of seeing effects and cosmic noise not only strengthened the validation process but also enhanced the method's applicability to actual astronomical observations.

This research contributes valuable insights for astronomers and researchers aiming to optimize image processing techniques, offering a promising avenue for improving the resolution and clarity of astronomical imagery in the face of observational challenges.

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