



# Developing an Image Processing Pipeline for DSLR Astrophotography Using Classical and Deep Learning Methods

Raina Song, Yifei Deng

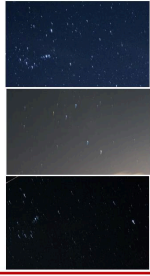
Department of Electrical Engineering, Stanford University

## Motivation

Amateur astrophotography with DSLR cameras faces several challenges that degrade image quality compared to professional setups. Key issues include:

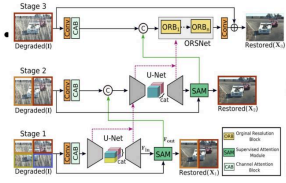
- **Star Trails:** Caused by camera movement or Earth's rotation, leading to streaked stars instead of sharp points.
- **Non-Uniform Backgrounds:** Resulting from light pollution or sensor inconsistencies, reducing contrast and making faint details harder to see.
- **High Noise:** Introduced by dark current and shot noise, obscuring fine astronomical details.

We are developing an automated image processing pipeline, and comparing classical signal processing methods with neural network-based approaches.



## Related Work

- A non-linear blur model has been proposed to model light streaks in low-light conditions, but this may fail with large saturated regions [1].
- With non-iterative thinning and Richardson-Lucy algorithm, one can extract deblur kernel and then deblurring it [2].



Light streak patch detection:

$$\begin{aligned} |\hat{I}(\omega)|^2 &\propto \|\omega\|^{-\beta} \\ |\hat{I}(\omega)|^2 |\hat{L}(\omega)| &\approx C \\ B &= K * I + N \\ |\hat{B}(\omega)|^2 |\hat{L}(\omega)| &\approx |\hat{I}(\omega)|^2 |\hat{K}(\omega)|^2 |\hat{L}(\omega)| \approx C |\hat{K}(\omega)|^2 \\ B \otimes B * L &\approx C (K \otimes K) \\ d(P, B) &= \min_C \|B \otimes B * L - C(P \otimes P)\|^2 \end{aligned} \quad [1]$$

## References

- [1] Hu Z, Cho et al., Deblurring Low-Light Images with Light Streaks, IEEE, 2014
- [2] Su, Shao et al., Richardson-Lucy deblurring for the star scene under a thinning motion path, Satellite Data Compression, Communications, and Processing XI, 2015
- [3] Zamir, Arora et al. Multi-Stage Progressive Image Restoration, CVPR, 2021
- [4] Zamir, Arora et al. Restormer: Efficient Transformer for High-Resolution Image Restoration. CVPR, 2022.

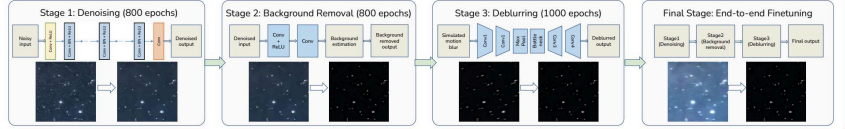
## Methods

### Classical Method:

- Step 1: Background gradient removal (morphological opening rolling-ball)
- Step 2: PSF motion blur kernel estimation (local patch extraction)
- Step 3: Richardson-Lucy deblurring
- Step 4: Non-local Means denoising
- Step 5: Star Mask + Boosting



### Neural Network Method:



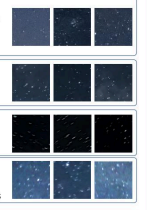
### Dataset Pipeline:

- Stage 1 Denoising (train/val split (80/20)):**
- Extract 200 random 256x256 patches from raw images (without star trails)
  - Apply non-local means denoising

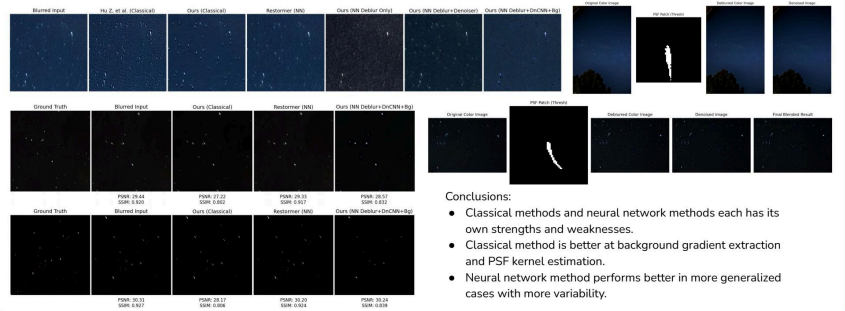
- Stage 2 Background Removal:**
- Use Stage1 target as input and remove background via Gaussian blur subtraction

- Stage 3: Star Trail Simulation**
- Use Stage2 target as input
  - Apply random star trails with curvatures

- Stage 4: "All-in-One" Degradation**
- Use Stage2 input as clean reference
  - Apply noise, partial background & star trails



## Experimental Results



### Conclusions:

- Classical methods and neural network methods each has its own strengths and weaknesses.
- Classical method is better at background gradient extraction and PSF kernel estimation.
- Neural network method performs better in more generalized cases with more variability.