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

EE367 Project Proposal

Raina Song

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Motivation

Astrophotography inspires both scientific discovery and public fascination, yet a gap exists between amateur and professional image quality. Professionals benefit from high-end equipment and dark-sky observatories, while hobbyists face limitations. To bridge this gap, we are developing an automated image processing pipeline that improves astrophotography images by resolving common issues: removing star trails, reducing noise, and improving non-uniformed background to enhance signal-to-noise ratio (SNR) for hobbyist astrophotography setups.

Related Work

Many researchers have explored classical methods for low-light and astrophotography image restoration. Wiener and Richardson-Lucy deconvolution can effectively remove light trails [1]. However, in astrophotography, variations in the blur kernel caused by exposure time, tripod motion, and atmospheric conditions make determining the Point Spread Function (PSF) challenging. To address similar issues, other fields have used ADMM-based blind deconvolution and denoising techniques from low-photon fluorescence imaging [2]. Additionally, methods for extracting light streaks have been successfully applied to estimate the PSF in low-light conditions [3]. Background removal in astrophotography has been approached through various techniques, including background subtraction, wavelet-based denoising, and filtering. For instance, [4] combines Gaussian filtering, background subtraction, histogram equalization, and Otsu's thresholding to address non-uniform backgrounds in astronomical images.

Recently, neural network-based approaches have gained attention in low-light and astrophotography image enhancement due to the availability of larger datasets and advancements in deep learning. [5] introduced a multi-stage progressive image restoration network for denoising, deblurring, and dehazing. Each stage refines an intermediate output that is then passed to the next stage, helping to manage the complexity of the restoration task. [6] improved this model by incorporating MLPs that operate along spatial and channel dimensions, allowing the network to capture both local and global context effectively. These methods produce high-quality low-light image restoration results but are not specifically designed for astrophotography, which has unique sparsity characteristics. To address astrophotography-specific challenges, [7] proposed a deep learning approach that integrates band-dependent PSF information into the deconvolution process. This method extends the Deep Wiener Deconvolution Network by applying Wiener deconvolution separately to each color band. For motion blur correction, [8] estimated motion blur kernel parameters using hyper-Laplacian priors for blur angle and an ensemble neural network for blur length, enabling robust deblurring of star images.

Although these approaches show promising results, there is no dedicated imaging pipeline designed specifically for DSLR astrophotography, particularly at the amateur level. Developing such a pipeline could make astrophotography more accessible to a broader audience.

Project Overview

Our goal is to build an automated pipeline to enhance astrophotography images taken with amateur DSLR cameras. This pipeline will address common issues such as star trails caused by camera or Earth movement, non-uniform backgrounds from light pollution or sensor inconsistencies, and noise from dark current and shot noise. We are comparing two approaches: a classical signal processing method and a neural network (NN)-based method. By evaluating their strengths and weaknesses, we aim to develop a more efficient image processing workflow.

Our dataset contains over 50 images captured with amateur-grade DSLR cameras over the past few years. These images were mostly captured with 10mm-25mm focal lengths, ISO settings of 400–800, and shutter speeds of 10–15 seconds. We will use these images as the starting point for analysing and exploring both classical and NN-based methods, and at the end we will capture new images to further validate our pipelines.

For the classical method, we plan to apply Richardson-Lucy deconvolution by estimating multiple blur PSFs that are common in the sample images to remove star trails caused by camera movement or slight earth movement (short star trails). Then we will clean the non-uniform background by doing wavelet-based denoising. For noise reduction, we will apply an ADMM-based blind deconvolution with a sparsity prior. For the NN-based method, we will use the multi-stage progressive image restoration method as the base and incorporate a blur kernel estimator with a deconvolution stage using predicted blur kernels to remove star trails. As we explore both methods, we will assess their limitations and iteratively improve their performance.

Milestones, Timelines & Goals

2/17 - 2/23: Find astrophotography datasets and simulate star trails, non-uniform background, and noise. Start with classical signal processing methods.
2/24 - 3/2: Develop the NN-based approach.
3/3 - 3/9: Finish pipeline development and capture real data to test and compare two methods.
3/10 - 3/12: Final project presentation and report preparation.

References

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