Reinforcement Learning for Astronomical Image Processing

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Abstract

Image enhancement is a necesary aspect of image capture, which machine learning has in recent years greatly assisted (Fang, Pang, and Yi 2020). In this paper we propose to study a specific method of reinforcement learning improving image enhancement with a focus on astronomical photos; in doing so, we will investigate several techniques that have been attempted in other domains in recent years, and select one that we expect to have an improvement over non-learning algorithms currently in use.

Introduction

While humanity has looked to the skies for as long as it has existed, our current knowledge of the universe outside of earth is a relatively recent phenomina. Photography in particular has only been applied to astronomy since the late 1800s (Gill 1887), although once applied, it greatly improved the knowledge gained and shared from astronomy. An article from 1923 explains that longer camera exposures made visible "objects too faint to be seen with the eye even when aided by the most powerful telescope" (Stokley Jr 1923). The ability of modern cameras to record faint detail is what enables scientific advancement in cosmology and astrophysics.

However, modern photography is more complicated than in the past - images need to be processed, which may involve a variety of steps using non-learning algorithms such as debayering (also known as demosaicing) (Kwan et al. 2018), noise-reduction (Seybold et al. 2014), high-dynamice-range (Gao et al. 2020), contrast enhancement, and overexposure correction (DONG 2011). These traditional algorithms are very powerful, but may require manual input to produce a photograph that is aesthetic, or useful. Recent research using machine learning have shown that it is possible to improve upon these algorithms, even in their basic functionality, with some algorithms acting as replacements and others as additional components to existing algorithms (Fang, Pang, and Yi 2020).

(Yu et al. 2018)

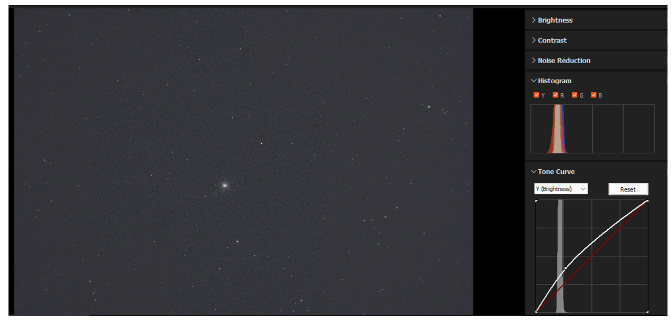

Figure 1: Example of activities available when manually photo editing. Shown is Sony Photo Editor.

Background

Before examing what reinforcement learning has been doing, it is good to understand what types of editing may happen with a photograph. Someone using a photo editor may, for example, adjust the contrast and brightness of an image (see figure 1). There are usually more complex features available, such as adjusting the brightness mapping of the photo as a whole, or even of each color in the photo - known as a Tone Curve or Light Curve.

Someone may adjust these features to produce a photo that has adequate brightness, shows a full dynamics range (i.e., the shadows are dark and the highlights bright), has proper color balance, and does not show excessive noise. Alternatively, a machine might learn how to use the parameters to produce as good or better a photo, or modify the photo in another fashion that accomplishes the same goals. The greatest difficulty with these edits is ensuring that no information is lost in the image - a problem exacerbated when the image is intended for scientific use, as is common in astronomical photos, as seen in figure 2.

Reinforcement Learning Photo Editing

Several reinforcement algorithms examined for this problem were ReLLIE (Zhang et al. 2021), DeepExposure (Yu et al. 2018), PixelRL (Furuta, Inoue, and Yamasaki 2019), and RSE-RL (Bajaj, Yang, and Wang 2023).

ReLLIE (Zhang et al. 2021) modifies photos by applying various light curves, which may be high-order polynomials, which the machine learns to either select from or build. This is similar to having a person edit a photo, since no human will try to edit each pixel individually; the process used in this method is fairly understandable, at least so far as the process that edited a particular photo. A similar method is explored in a paper titled “Unpaired Image Enhancement Featuring Reinforcement-Learning-Controlled Image Editing Software” (Kosugi and Yamasaki 2020), with the caveat that the focus is improving images produced by a GAN rather than using reinforcement learning as the primary editing tool.

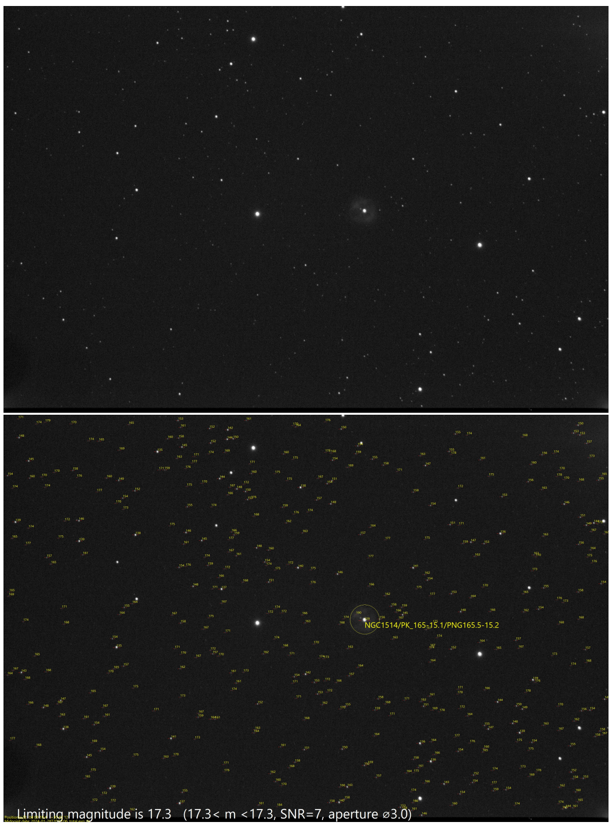

Figure 2: An example of the type of detail present in astronomical photographs. Photos by the author.

DeepExposure (Yu et al. 2018) operates similarly to high-dynamic-range - several images are taken of an object at various brightnesses, and then an algorithm selects the best part of each photo and splices them together to build a composite image. However, where high-dynamic-range may use a preset exposure (image brightness) values and analytical algorithm to splice images, DeepExposure uses intelligent selection of exposures and splicing. A somewhat similar process is used in a paper “Image Enhancement Using Adaptive RegionGuided Multi-Step Exposure Fusion Based on Reinforcement Learning” (Xi et al. 2023) - an image is encoded through one neural network, and then split and decoded through several different neural networks - and the outputs spliced - to artificially produce a similar effect.

PixelRL (Furuta, Inoue, and Yamasaki 2019) is perhaps the most computationally-challenging algorithm investigated - it utilizes an agent at each pixel (for a 9 mega-pixel image, this equates to 9 million agents) which modifies its pixel value based on the actions and status of the agents and pixels around it, thus working at a lower level than other reinforcement learning methods. The applications of this algorithms are fairly broad and may include denoising, high-dynamic-range, and other operations.

RSE-RL (Recursive Self Enhancing Reinforcement Learning) (Bajaj, Yang, and Wang 2023) operates by recursively (hence the name) improving an imave through a series of auto-encoders, the goal being to produce fewer artifacts in the improved image than are often found in other learning algorithms (such as guided neural networks).

Proposal

This project proposes to apply reinforcement learning to improve the processing of astronomical photos. In order to do this, a method similar to ReLLIE or Deep Exposure will be used; advantages of doing this method are: a reasonably high chance of success, working with understandable processes (the machine is learning how to use existing photo editing algorithms to improve the final result), a “normal” amount of computation required as opposed to the other methods investigated, and a straight-forward approach to understand how reinforcement learning works (i.e. it will not be as difficult to debug). The possibility that the results will not be drastically better than the current status quo is an excepted risk for this project.

Datasets

Dataset needs for this project are a sufficient number of images to learn processing over, and some means of measuring the goodness (SNR, etc.) of an image. As seen in the background for this project (figure 1, most tools can produce a histogram for an image to measure how "good" it is; in this case, a weighted model using the histogram, a measurement of the noise floor (often visible on histograms), and metric capturing the amount of data that has been clipped (too bright) should be enough to start this project. Images can be taken by the author using his own equipment, found in online repositories such as the galaxy10 repository (Leung 2023), or in legacy sky surveys such as the Mayall z-band Legacy Survey (NOIRLab 2024). While the purpose of this project is different than the purpose the mentioned datasets were created for, they should provide sufficient astronomical image data to produce meaningful results.

Timeline

The planned timeline is shown here:

2/15-3/1	Code learning algorithms, determine dataflow
3/1-3/10	Create datasets
3/10-4/5	Initial testing and tuning
4/5-4/19	Refine model and results
4/19-5/11	Prepare and give final presentation and report

Conclusion

In this paper we have proposed to apply reinforcement learning to enhance images, as would be done in a post-processing effort. In doing so we have proposed a fairly straightforward and simple method which provides an improved chance of success over other more complicated methods that were researched.

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