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)

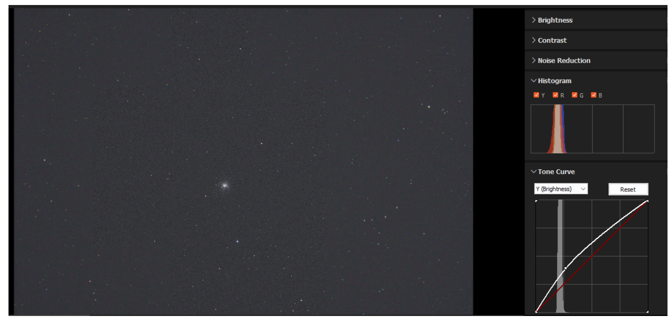

Figure 1: Example of activities available when manually photo editing. Shown is Sony Photo Editor.

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,

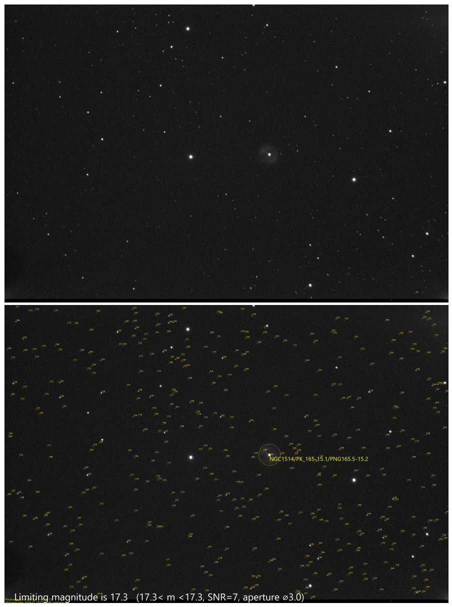

Figure 2: An example of the type of detail present in astronomical photographs. Photos by the author.

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 2020a), with the caveat that the focus is improving images produced by a GAN rather than using reinforcement learning as the primary editing tool.

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.

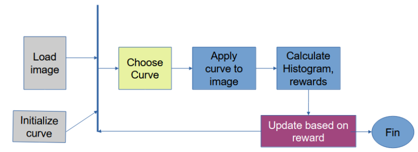

Figure 3: Example of the flow during a single episode. This process would be done many times during an epoch.

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).

Progress

Datasets

Initial testing has used two datasets for this training - one created by the author, and one a small set of sample images from the European Space Agency (ESA 2019).

Methodology

The most difficult part of this project currently is producing a useable reward and state space. At the time of writing, the state space is the median of the “perceived” histogram - perceiving meaning a log_2 transform is used to adjust the brightness scale to better match the human eye’s nonlinear light response. This means that there are more shades between black and the grey midpoint than between the grey midpoint and white on the histogram; additionally, catching minute improvements in images that start very dark means that appropriate rewards can be given when learning has just started.

An example of the process during a single episode is shown in figure 3.

Each training episode executes until either the reward has reached its maximum allowed value, or 20 iterations have been done (multiplying the curves together eventually leads to numerical issues, so the allowed iterations is limited to account for this limitation in the environment at the time of writing). Rewards are determined by checking for several criteria - the mean being within a certain value, the standard deviation being within a certain value, and the Wasserstein distance - the distance for the image’s histogram from the histogram of a known “good” image (Kosugi and Yamasaki 2020b) - being within a certain value. Additional smaller rewards are given for improving the standard deviation and mean - although negative rewards are also given for going the wrong direction.

Initial Results

At the moment, this project has been testing Q-learning to improve test images. Initial results are shown in figure 4.

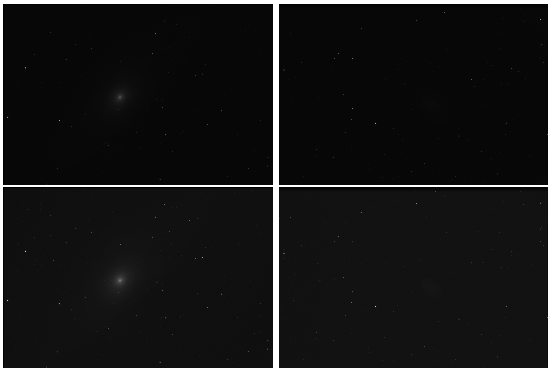

Figure 4: Example input (top) and output (bottom) images. Clearly there is room for improvement.

The area that involves the most work in this situation is how to adequately represent the image histogram to provide states that are useable for image manipulation. At the moment, the median of the histogram is used with an 8-bit image assumption, which provides 256 possible states; however, initial testing revealed that only about 20 of those states (near the lowest part of the histagram) are used consistently, which means the remainder do not represent useful information for learning. This was initially remedied by taking the histogram of the "percieved" image, i.e. the image with the brightness adjusted by a log_2 function. Clearly there is more to be done to provide sufficient rewards and states for reinforcement learning to succeed in this scenario. Ideas being explored include adding a standard-deviation dimension - since the median and mean quantify images by brightness, this would add a quantification for contrast.

Another perceived problem with the current process is that the curves, being multiplied by each new addition over time, eventually start to become polynomial functions - i.e., a cube root multiplied by itself three times is a line, and multipled nine times is a cubic function. For initial testing a limit of 10 iterations per episode was used to account for this defect; it may be useful to increase this amount when more actions are included, but a different curve multiplication/addition architecture will be needed at that point to ensure the action space does not become excessive.

Future Directions

Some ideas being explored - beyond updates to the environment described above - such as using an actor-critic network. Once the environment has developed in a way that it can be treated as a Gym environment, there are many available libraries that become useful for reinforcement learning, greatly improving the potential for this project.

Timeline

The planned timeline is shown here - some of these steps have already been done:

2/15-3/1	Code learning algorithms, determine dataflow
3/1-3/10	Find datasets
3/18	Midterm Presentation
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

Initial results for this project leave something to be desired - which is understandable, since the project has not progressed all that far at the time of writing. Initial work hints at the method being feasible, and future work should provide better results and analysis of what works. Additionally, as the enviromnet is developed, it should become possible to use other libraries that are not currently being explored.

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