Literature Review

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Abstract

Astronomical imaging has made stupendous progress through the years with more and more sophisticated techniques being introduced with every new telescope launch. The rise in computation power enabled astronomers to increase the number of observations and resulted in flooding of information that could be processed as quickly as it could be seen by the human eye. The data albeit abundant, is computationally expensive to process and remains dormant in the archives globally. One such example being the Hubble Legacy Archive where there are hundreds and thousands of snapshots taken by the Hubble Space telescope which lie unprocessed in the database but can be of astronomical significance. This document summarizes a brief study of generative adversarial networks and convolutional neural networks and different techniques belonging to the disciplines that can be applied to astronomical images to make them usable for astronomical inspection.

1 Introduction

Hubble Legacy Archive or HLA is a project which endeavours to complement the Hubble Space Telescope by augmenting the HST Data Archive and providing superior browsing and searching capabilities. A large amount of raw images remain unprocessed in the HLA, never seen by a human eye. These raw images are typically low resolution, black and white and unfit to work with in today's day and age. It takes hundreds of hours to process them.

2 Hubble Legacy Archive

In the past decade, astronomical research was extensively performed using large catalogs which were search-able. This was made possible due to advances in computer technology and databases. The biggest challenge that is faced today is to convert this large unstructured database into a comprehensive catalog. Advances in relational databases technology has made it efficient to create and store and search large catalogs.

Sloan Digital Sky Survey or SDSS, was one such catalog. It uniformly observed the regions of the sky in a certain filter band at regular intervals of time. The HST however, has targeted only particular sources.

The Hubble Space Telescope (often referred to as HST or Hubble) is a space telescope that was launched into low Earth orbit in 1990 and remains in operation. It was not the first space telescope, but it is one of the largest and most versatile, well known both as a vital research tool and as a public relations boon for astronomy.

The Hubble Space Telescope archive was an archive for the Hubble Space Telescope which was launched in low Earth orbit back in 1990. It is an important tool for research and is the one of the biggest and most versatile telescopes which is active today.

The Hubble Legacy Archive (HLA) endeavours to create calibrated science data from the Hubble Space Telescope archive and make them accessible via user-friendly and Virtual Observatory (VO) compatible interfaces.

3 Image Colorization

3.1 Hint Based Colorization

Automated colorization of gray scale images has been researched extensively throughout the machine learning community and is more specifically studied by those who indulge in the discipline of computer vision. Apart from being visually fascinating, it has many other applications ranging from restoration to enhancement for better interpretability.

Levin et al. (2004) proposed using colorization hints from the user in a quadratic cost function which imposed that neighboring pixels in space-time with similar intensities should have similar colours. This was a simple but effective method but only had hints which were provided in form of imprecise

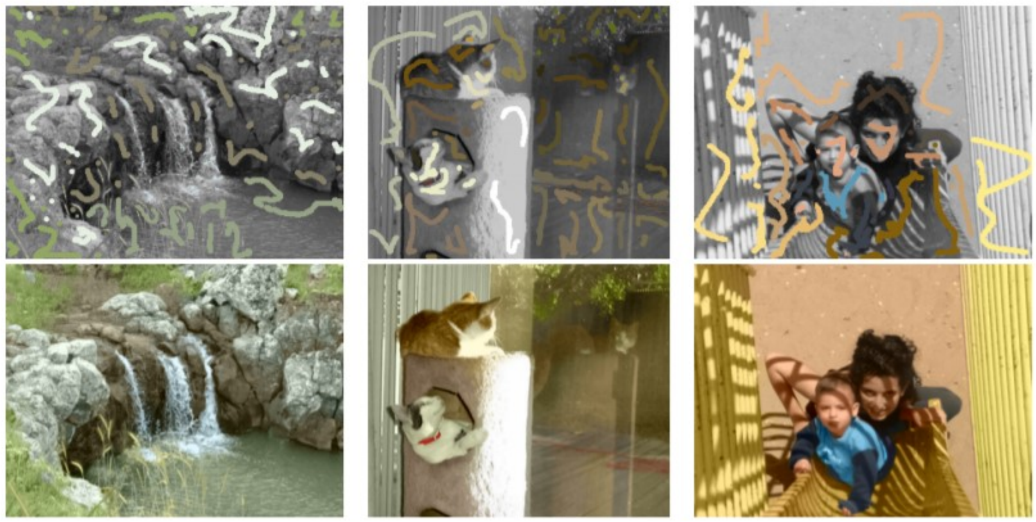

Figure 1: Example of Scribble based colorization (Levin et al., 2004)

colored scribbles on the grayscale input image. But with no additional information about the image, the method was able to efficiently generate high quality colorizations. Huang et al. (2005) addressed the color bleeding issue faced in this approach and solved it using adaptive edge detection. Yatziv and Sapiro (2006) used luminescence based weighting for hints to boost efficiency. Qu et al. (2006) extended the original cost function to enforce color continuity over similar textures along with intensities.

Welsh et al. (2002) had proposed another approach that reduced the burden on the user by only requiring a full color example of an image with similar composition. It matched the texture and luminescence between the example and the target grayscale image and received realistic results as long as the example image was sufficiently similar.

Regardless of the scribble based or example based approach, the algorithms still needed sufficient human assistance in form of hand drawn or colorized images.

3.2 Deep Colorization

Owing to recent advances, the Convolutional Neural Networks are a de facto standard for solving image classification problems and their popularity continues to rise with continual improvements. CNNs are peculiar in their ability to learn and differentiate colors, patterns and shapes within an image and their ability to associate them with different classes.

Cheng et al. (2016) proposed a per pixel training for neural networks using DAISY (Tola et al., 2008), and semantic (Long et al., 2015) features to predict the chrominance value for each pixel, that used bilateral filtering to smooth out accidental image artifacts. With a large enough dataset, this method proved to be superior to the example based techniques even with a simple Euclidean loss function against the ground truth values.

Finally, Dahl (2016) successfully implemented a system to automatically colorize black & white images using several ImageNet-trained layers from VGG-16 Simonyan and Zisserman (2015) and integrating them with auto-encoders that contained residual connections. These residual connections merged the outputs produced by the encoding VGG16 layers and the decoding portion of the network in the later stages. He et al. (2015) showed that deeper neural networks can be trained by reformulating layers to learn residual function with reference to layer inputs. Using this *Residual Connections*, He et al. (2015) created the *ResNets* that went as deep as 152 layers and won the 2015 ImageNet Challenge.

3.3 Generative Adversarial Networks

Goodfellow et al. (2014) introduced the adversarial framework that provides an approach to training a neural network which uses the generative distribution of $p_g(x)$ over the input data x.

Since it's inception in 2015, many extended works of GAN have been proposed over years including DCGAN (Radford et al., 2016), Conditional-GAN (Mirza and Osindero, 2014), iGAN (Zhu et al., 2018), Pix2Pix (Isola et al., 2018).

Radford et al. (2016) applied the adversarial framework for training convolutional neural networks as generative models for images, demonstrating the viability of *deep convolutional generative adversarial networks*.

DCGAN is the standard architecture to generate images from random noise. Instead of generating images from random noise, Conditional-GAN (Mirza and Osindero, 2014) uses a condition to generate output image. For e.g. a grayscale image is the condition for colorization of image. Pix2Pix (Isola et al., 2018) is a Conditional-GAN with images as the conditions. Besides learning the mapping from input image to output image, it can also learn a separate loss function to train this mapping. Pix2Pix is considered to be the state of the art architecture for image-image translation problems like colorization.

4 Image Upscaling

The principle objective of Super Resolution imaging is to reconstruct a low resolution image into a high-resolution one based on a set of low-resolution images to rectify the limitations that existed while the procurement of the original low-resolution images. This is to insure better visualization and recognition for either scientific or non-scientific purposes.

4.1 Frequency-domain-based SR image approach

TSAI (1984) proposed the frequency domain SR method, where SR computation was considered for the noise free low resolution images. They transformed the low resolution images into Discrete Fourier transform (DFT) and further combined it as per the relationship between the aliased DFT coefficient of the observed low resolution image and that of unknown high resolution image. Then the output is transformed back into the spatial domain where a higher resolution is now achieved. While Frequency-domain-based SR extrapolates high frequeny information from the low resolution images and is thus useful, however they fall short in real world applications.

4.2 The interpolation based SR image approach

The interpolation-based SR approach constructs a high resolution image by casting all the low resolution images to the reference image and then combining all the information available from every image available. The method consists of the following three stages (i) the registration stage for aligning the low-resolution input images, (ii) the interpolation stage for producing a higher-resolution image, and (iii) the deblurring stage for enhancing the reconstructed high-resolution image produced in the step ii).

However, as each low resolution image adds a few new details before finally deblurring them, this method cannot be used if only a single reference image is available.

4.3 Regularization-based SR image approach

Most known Bayesian-based SR approaches are maximum likelihood (ML) estimation approach and maximum a posterior (MAP) estimation approach. While (Tom and Katsaggelos, 1996) proposed the first ML estimation based SR approach with the aim to find the ML estimation of high resolution image, some proposed a MAP estimation approach. MAP SR tries to takes into consideration the prior image model to reflect the expectation of the unknown high resolution image.

4.4 Super Resolution - Generative Adversarial Networks (SR-GAN)

The Genrative Adversarial Network (Goodfellow et al., 2014), has two neural networks, the Generator and the Discriminator. These networks compete with each other in a zero-sum game. (Ledig et al., 2017) introduced SRGAN in 2017, which used a SRResNet to upscale images with an upscaling factor of 4x. SRGAN is currently the state of the art on public benchmark datasets.

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