CS 7180 Milestone 2

Nalin Gupta NUID: 001726854
Christopher Botica NUID: 001726854
Tyler Brown NUID: 001684955

1 Introduction and Related Work

Images taken in low-light conditions are often too dark, noisy, and distorted to be used in industrial purposes. We propose a deep-learning model that processes low-light images to improve image brightness and increase their overall quality. The problem with imaging in low-light conditions is challenging due to low-photon count and low Signal-to-Noise (SNR) ratio. These yield very dark and noisy images. The most common technique to overcome this problem is long exposure shot. However, this method yields blurry images with the slightest camera shake or object motion[1]. Common post-processing techniques brighten the image at the expense of image quality. Being able to "see in the dark" provides a number of real-world benefits such as photography, computer vision, and social networking.

In the past, the problem of enhancing low light images has been tackled via noise reduction. This noise becomes dominant especially in low-light images due to low SNR. Remez et. al. proposed a deep CNN for noise reduction under the assumption that this low-light noise belongs to a Poisson distribution [2]. They used images from ImageNet [3] as their ground truth data and added synthetic Poisson noise to simulate corrupted images. Even though their model outperform the state-of-the art de-noiser "BM3D", it does not scale well to real world images, due to their underlying assumptions. Furthermore, their model only denoises images but does not brighten them. Motivated by these downfalls, Chen et. al., proposed an end-to-end CNN, "See-in-the-Dark" (SID), which brightens extremely low light images and removes noise without making any underlying assumptions [1]. However these advances come with the added expense of collecting large amounts of low light and bright light images. In the absence of a true vs noisy image dataset, the team captured scenes using various exposure times to generate true (bright light) and corrupted (low light) image pairs called "See-in-the-Dark Dataset" (SID Dataset [1]). Furthermore, their model is camera specific and not easily generalizable.

We propose a transferable CNN for image brightening and denoising. Instead of training our model on actual true (bright light) and corrupted (low light) image pairs, we use images from the publicly available "MIT-Adobe FiveK Dataset" dataset as our baseline and corrupt these by simulating low-light conditions. We train our CNN on the synthetic data to obtain our initial model parameters. Then, using these, and a small fraction of the real image pairs from the SID Dataset, we adopt a transfer learning [4] approach to update our model parameters. We then use this model to test on our SID Dataset. In addition, we aim to test various transfer learning approaches, such as the traditional transfer learning and zero shot learning [5, 6, 7].

The novelty of our approach stems from the idea of "more for less". Our model drastically reduces the overhead costs of data collection by synthesizing readily available training data (MIT-Adobe FiveK). This is particularly beneficial in domains where collecting images pairs is expensive/time consuming.

[1] https://github.com/cchen156/Learning-to-See-in-the-Dark

32nd Conference on Neural Information Processing Systems (NeurIPS 2018), Montréal, Canada.

2 Model

We first collect 5,000 images in raw format from the MIT-Adobe dataset, taken with SLR cameras by a set of different photographers in different scenarios. We made sure that these photographs cover a broad range of scenes, subjects, and lighting conditions. Considering these images as the ground truth (i.e., images taken in normal light conditions), we corrupt them to simulate images taken in low-light conditions. These distorted images and original images consist of our training inputs to our first model. In order to simulate the distortion created by taking pictures in poor light conditions, we emulate the traditional image processing pipeline for correcting such images, only in reverse.

As illustrated in Figure 1, the traditional pipeline takes a corrupted image, and applies the following sequence of modules: Reduce Black Level, Denoising, White Balance, and Gamma Correction. The Black Level refers to refers to the level of brightness at the darkest parts of the image, and is reduced by subtracting the minimum pixel value. Denoising is reduced using common algorithms such as BM3D. White Balance refers to the color balance in the image (i.e., white should be true white) and is corrected by re-balancing the intensities of each color RGB. Finally, Gamma Correction controls the overall brightness of the image. We synthetically generate corrupted images by applying the reverse of this pipeline. Gamma Distortion: decrease the brightness of the image, White Imbalance: skew the color-space by multiplying each level of RGB by a random weight, Poisson Noise: add Poisson noise to the image, Black Level: add a negative bias to the pixel values (i.e., random black level).

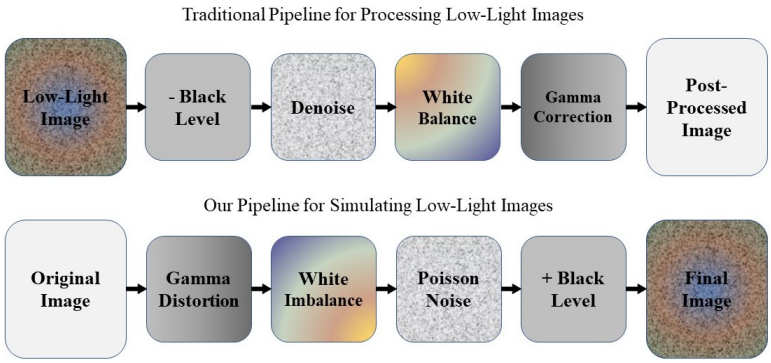


Figure 1: Top: Traditional Pipeline for processing low-light images. Bottom: Our pipeline to simulate low-light images based on the traditional, only in reverse.

Our model is based on the one developed for SID, with the addition of 2 fully-connected layers. Note that we may increase this if training runtime permits. Using the transfer learning approach, we will first train our model on the MIT dataset, then erase the learned weights from the last two fully-connected layers, and retrain on the SID dataset. This is highlighted in our model framework in Figure 2.

2.1 Low Light Image Simulation

TODO: some theory, maybe Chris?

2.2 Replicating their Model

We tried to replicate their model to using other readily available data such as CIFAR10 [8] and ImageNet [3]. The CIFAR10 ad ImageNet data is augmented to simulate properties of the images used by Chen et. al. (2018) [1]. The CIFAR10 and ImageNet datasets are distinctly different because they are not *raw* images. This means the dimensionality of CIFAR10 is $32 \times 32 \times 3$ rather than a raw image which could be $512 \times 512 \times 4$. We not only need to simulate images but also account for the *change in dimensionality* across image types.

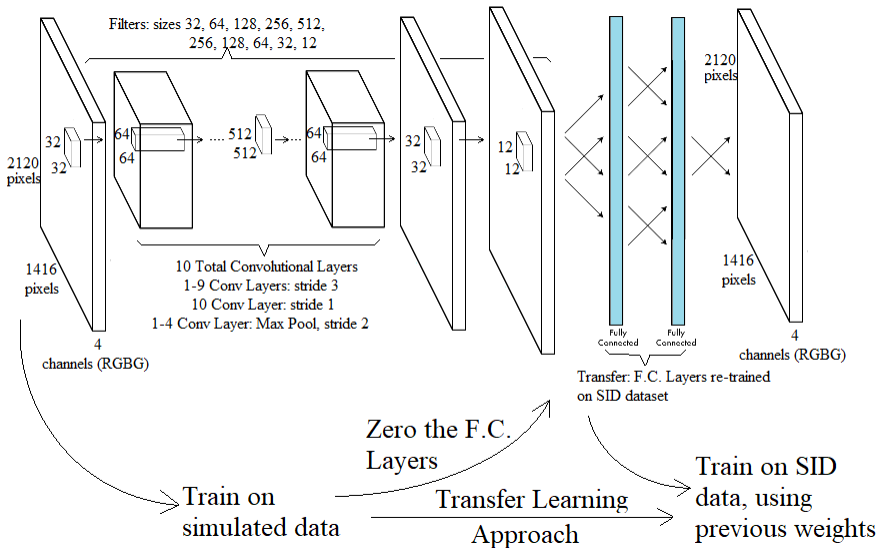
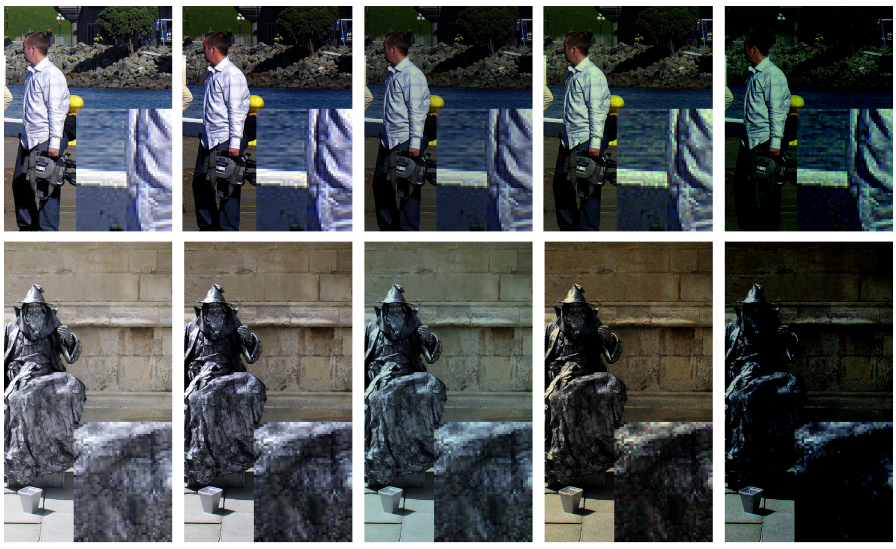


Figure 2: Our proposed model framework

3 Experiment

We first collect 5,000 images in raw format from the MIT-Adobe dataset, taken with SLR cameras by a set of different photographers in different scenarios. We then run these images through our pipeline to generate our simulated low-light images. An example of two of such images is represented in Figure 3. We train our first model on these simulated images, and then transfer to a fraction of the Sid dataset (500 images). We use the SID Model as our baseline and our performance measure will be achieving a Peak Signal-to-Noise Ratio (PSNR) greater or equal to the baseline.



(a) (b) (c) (d) (e)

Figure 3: Simulating two low-light images via our pipeline: (a) Original image, (b) Gamma Distortion, (c) White Imbalance, (d) Poisson Noise addition, (e) Black Level, final low-light simulation

As part of Milestone 1, we used the GitHub repository provided by Chen et. al. [1], we were gather and run to run their code but ran into limitations with computational resources. Chen et. al. [1] used a separate model for each of the two cameras. They specified a minimum of 64GB of GPU RAM for the Sony model and 128 GB of GPU RAM for the Fuji model. We decided to try replicating the less

resource intensive Sony model. The hardware requirements for the Sony model are nontrivial so we have explored several options.

Using AWSEducate did not work for us. We were unable to create roles with IAM authentication so it's really hard or impossible to move data from a S3 Bucket to an EC2 Instance. We tried to create a $p3.8xlarge$ instance but these instances are not allowed even though they are listed. Using regular AWS does work but is costly. Ran a single AWS EC2 $p3.8xlarge$ instance with 32 CPU, 244 GB of Memory, 4 Tesla V100 GPUs, and 64 GPU Memory. This costs $12.24 an hour. This is the amount of GPU Memory requested by the paper authors as a minimum amount.

Given these initial facts, we then tried to estimate run time requirements for the Sony model. We trained the Sony model for 90 minutes using an AWS $p3.8xlarge$ instance. We were able to complete ≈ 12 training epochs. Figure 4 contains an example test image/labelled image pairing. We then tried to use the training parameters to test the model but could not get this to work without modifying the script provided by Chen et. al. [1]. The model parameters were available to download, we used these parameters to run against test data for 30 minutes. Figure 5 contains example output from this test run. Both Figure 4 and Figure 5 are pictures of a similar yellow bike. We can see a qualitative improvement across the three renderings of the same predicted test image in Figure 5.

Additional time was required to extract the Sony dataset which decompressed to about 115GB of image files. We estimate that replicating the Chen et. al. [1] training parameters for *only* the Sony model takes approximately 500 hours or $ 6,120. We will either require more resources or have to work on just a subset of this problem. We are currently looking for additional resources and would appreciate any help in this matter.

3.1 Low Light Image Simulation

TODO: Nalin script

3.2 Model Replication

We tried replicating their model and writing a model in parallel to replicate their functionality. We also tried using the CIFAR10 and ImageNet datasets as input. The primary issue when replicating their model related to dimensionality. The RGB images in CIFAR10 and ImageNet have $m \times n \times 3$ dimensions. Raw images have $m \times n \times 4$ dimensions.

We were able to confirm that output dimensions from Chen et. al. [1] follow the pattern $2m \times 2n \times 3$ irrespective of the image size or type used. During our experiment, we focused our debugging efforts on understanding whether the dimensionality of a raw image as an input generated incompatible dimensions with the target vector after model output. This error resulted in our replicated model not being able to compute the cost function.

In terms of techniques used, their model is mostly written in a higher level Tensorflow contribution module called "slim". The "slim" contribution module does not appear to have any documentation and requires one to read the module code embedded within Tensorflow. We initially tried writing a model in parallel using Keras but found that moving from Keras objects back down to lower level Tensorflow for some blocks within forward propagation to not be documented well. We then rewrote the Chen et. al. [1] model using only low level Tensorflow code. This approach has the disadvantage of requiring the dimensions of all weight matrices to be specified and initialized in a separate function we called 'initialize_parameters()'.

These efforts allowed us to understand the dimensionality of both models at each of the 10 blocks within their forward propagation. We also experimented with pooling in regards to window size. We also experimented with strides for convolutional layers with each block. We also added up to three additional blocks with different parameters in an attempt to get the output dimensions to match the dimensionality of our input image.

At this point, we have not been able to use RGB images, having $m \times n \times 3$ dimensions, to work with Chen et. al. [1] model. It is important for us to develop this capability in order to qualitatively

verify that we are correctly augmenting image data. We are unable to generate images in raw format because it would require us to know proprietary information about how a camera generated an image.

In order to generate output for this milestone, we modified images from Chen et. al. [1], such that

$$X = g(y_{train})$$
$$Y = y_{train}$$

where function g is an application of artificial noise to a clean image in y_{train} which is then trained against a corresponding image where g has not been applied.

4 Appendix

Figure 4: Example Training Data

(a) Input (b) Output

Figure 5: Example Test Data

References

[1] Chen Chen, Qifeng Chen, Jia Xu, and Vladlen Koltun. Learning to see in the dark. *arXiv preprint arXiv:1805.01934*, 2018.

[2] Tal Remez, Or Litany, Raja Giryes, and Alex M Bronstein. Deep convolutional denoising of low-light images. *arXiv preprint arXiv:1701.01687*, 2017.

[3] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei. ImageNet: A Large-Scale Hierarchical Image Database. In *CVPR09*, 2009.

[4] Ian Goodfellow, Yoshua Bengio, and Aaron Courville. *Deep Learning*. MIT Press, 2016. `http://www.deeplearningbook.org`.

[5] Hugo Larochelle and Y Bengio. Classification using discriminative restricted boltzmann machines. pages 536–543, 01 2008.

[6] Mark Palatucci, Dean Pomerleau, Geoffrey Hinton, and Tom M. Mitchell. Zero-shot learning with semantic output codes. In *Proceedings of the 22Nd International Conference on Neural Information Processing Systems*, NIPS'09, pages 1410–1418, USA, 2009. Curran Associates Inc.

[7] Richard Socher, Milind Ganjoo, Hamsa Sridhar, Osbert Bastani, Christopher D. Manning, and Andrew Y. Ng. Zero-shot learning through cross-modal transfer, 2013.

[8] Alex Krizhevsky, Vinod Nair, and Geoffrey Hinton. Cifar-10 (canadian institute for advanced research).