CS 7180 Milestone 2

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1 Introduction

We are trying to make it more cost effective for AI to see in the dark. Chen et. al. (2018) [1] successfully demonstrated that a neural network could process dark images into light images. Their model requires a specially curated dataset by a professional photographer, and substantial processing resources. Our group is trying to replicate Chen et. al. (2018) functionality using data augmentation on existing datasets. Our goal is to make the Chen et. al. (2018) more cost efficient and generalizable across domains.

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.

This is a hard problem because simulating natural phenomena using augmented data is not easy. In other words, "[i]mitation is possible because distinct physical systems can be organized to exhibit nearly identical behavior" [2]. Identifying this identical behavior using statistical distributions of image properties such as distortion, and lighting.

2 Related Work

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 [3]. They used images from ImageNet [4] 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.

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

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

3 Method/Model

4 Experiment

5 Discussion

References

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

[2] Herbert A. Simon. *The Sciences of the Artificial (3rd Ed.)*. MIT Press, Cambridge, MA, USA, 1996.

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

[4] 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.