Unsupervised Image Denoising using Deep Learning

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New York University - Fall 2018

1 Introduction

Previous models exist which have been used to denoise images. However, these models require the use clean images for training the model. In this approach, unclean images will be used to denoise images. Without observing the clean targets, the network will learn to generate a clean image as long as the underlying image is the same in both - inputs and targets [1].

$$Supervised: \sum_i L(f(noisy_i|\theta), clean_i)$$

$$Unsupervised: \sum_i L(f(noisy_{1,i}|\theta), noisy_{2,i})$$

The image denoiser could have applications in a plethora of domains, including military and healthcare, where access to clean target images is not available.

2 Problem Statement and Goal

2.1 Problem Formulation

The objective is to apply synthetic noise on the image dataset, train the model, recover the images using the model, and observe the recovery loss. This process will be repeated for different noise inputs like Gaussian noise, Poisson noise, Textual noise, Bernoulli noise and random-valued impulse noise.

2.2 Goal

The goal is to achieve similar level of performance in terms of recovery loss as in the Noise2Noise paper [1].

3 Dataset and Proposed Method

3.1 Dataset

Three datasets will be used for each each noise implementation - the BSD300, the Kodak dataset, and the Set14 dataset.

3.2 Proposed Method

We plan to generate noisy target images (from different noise distributions) and train the network to generate the underlying clean image. We plan on using a U-Network [3] for all the tasks, except for the one involving Additive Gaussian Noise, for which we will use the RED30 Network [2] consisting of 15 convolutional and deconvolutional layers. The final architecture may vary depending upon the complexity, training time and loss.

In the Noise2Noise paper [1], NVidia Tesla P100 GPUs were used for training the models. In order to get faster training time with a single GPU, we will be using cropped images.

4 Evaluation Criteria

Loss function: Peak signal-to-noise ratio (PSNR)

$$L_0 Loss: \frac{1}{N} \sum_i \lim_{p \to 0} \sqrt[p]{(y_i)^p}$$

$$L_1 Loss: \frac{1}{N} \sum_i |y - y_i|$$

$$L_2 Loss : \frac{1}{N}\sum_i \sqrt{(y-y_i)^2}$$

Initially - L2 loss will be used to clean images from Gaussian and Poisson noise, L1 loss will be used to clean images from Textual noise and L0 loss will be used to clean images from Random-values impulse noise. Final choice may change depending on the results.

5 Timeline

5.1 Milestone

Working model of Image denoising, comparing results with clean target training. Objective is to produce clean images based on Noise2Noise paper.

5.2 Final

Robust model which is able to denoise images with varying levels of noise. Objective is to observe the effect of varying levels of noise on image recovery.

References

[1] Jaakko Lehtinen, Jacob Munkberg, Jon Hasselgren, Samuli Laine, Tero Karras, Miika Aittala, and Timo Aila. Noise2noise: Learning image restoration without clean data. *CoRR*, abs/1803.04189, 2018.

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