CSC2529 Computational Imaging Project Proposal

Jiachen Xu*[1], Bingjie Shen†[1], and Jingtao Zhou‡[1]

[1]Department of Computer Science, University of Toronto, Canada

1 Background and Motivation

Recent advancements in machine learning have witnessed the great potential of neural networks in image manipulation tasks such as denoising, superresolution, and inpainting. Most solutions generally require ground-truth images in training, where the trained models approximate the original image using patterns observed from other images in the entire image set. This pipeline is ideal for general-purpose images but sets barriers to recovering images in a specific field where no ground-truth images are available. In this project, we intend to leverage both the newest technologies in neural networks and traditional rule-based methods to form a pipeline that can recover images without training data.

2 Related Works

Ulyanov et al. [1] proposed a powerful and effective method for imaging processing called Deep Image Prior (DIP). DIP makes use of a deep convolutional neural network to perform different tasks, such as denoising, inpainting, super-resolution, and so on. Different from other neural network based denoising methods, DIP itself is a non-training process that requires zero training data and validation data. The whole process treats CNN as the regularizer and thus is an optimization problem in general. Depending on the fact that noise is more reluctant for the CNN to learn since "the parametrization offers high impedance to noise and low impedance to signal.", we can use proper methods of early stopping to prevent the network from overfitting. The parameters will be approaching a clear image in the process of optimizing.

At the same time, many extensions can be made based on the idea of DIP. Bredell et al. [2] came up with an idea that uses Wiener deconvolution to guide DIP for better performance on image deblurring. The intuition behind this is that deconvolution is better at reproducing high-frequency artifacts and DIP is the opposite. Combining these two tools indeed produces better performance and stability. We may want to extend this idea and use different methods of denoising and deblurring to compare the results.

3 Project Overview and Goals

In our project, we want to investigate the mechanism and effectiveness of DIP, as well as potential improvements.

Task1:

The first aspect of DIP that we're interested in improving is the corrupted input image. We want to investigate the following question: if we manually denoise/deblur the image before training it with deep neural networks, will the result be better? To obtain the answer, we plan to utilize different image denoising/deblurring methods as a preprocessing unit for the corrupted input image to the DIP and compare the final results.

Task2:

Apart from that, we are also interested in working on the early stop point: When is the best time to stop? Is there a theoretical optimal stop point that can be calculated? Or is it purely empirical? In the experimental setup, we plan to gather a variety of images and add the same noise to them. Then, we train each image with DIP and monitor for the best early stop point. We will then compare and see if they all have similar optimal early stop points.

*jiachen.xu@cs.toronto.edu
†bingjie.shen@mail.utoronto.ca
‡jingtao.zhou@mail.utoronto.ca

4 Timeline

1. Writing project proposal - 11/16
2. Configure and run DIP - 11/19
3. Finish task 1 - 11/26
4. Finish task 2 - 12/03
5. Project Report Due - 12/08

References

[1] Dmitry Ulyanov, Andrea Vedaldi, and Victor Lempitsky. Deep image prior. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 9446–9454, 2018.

[2] Gustav Bredell, Ertunc Erdil, Bruno Weber, and Ender Konukoglu. Wiener guided dip for unsupervised blind image deconvolution. *arXiv preprint arXiv:2112.10271*, 2021.