Deep Learning based Super-Resolution Imaging

Wei Wang
Department of Electrical Engineering
Stanford University
Email: wwang23@stanford.edu

Qiaojing Yan
Department of Electrical Engineering
Stanford University
Email: qiaojing@stanford.edu

***Abstract*—We propose a deep learning based method for super-resolution image reconstruction under the impact of noise. We will implement two different deep learning methods, simple convolutional neural networks and generative adversarial networks, and evaluate and compare their performance with the basic super-resolution imaging taught in class with/wo additive Gaussian noise.**

I. Introduction

A. *Super-Resolution image reconstruction*

Super-resolution is playing an important role in many image processing applications such as satellite imaging, medical imaging, biometric recognition, and high dynamic range imaging. Existence of the-state-of-the-art techniques in super resolution has introduced a high impact into many image processing applications [1]. Generally, image super-resolution algorithms can be categorized into four types prediction models, edge based methods, image statistical methods and patch based (or example-based) methods [2].

B. *Convolutional Neural Networks (CNN)*

CNN is a type of feed-forward artificial neural network in which the connectivity pattern between its neurons is inspired by the organization of the animal visual cortex. And it has recently been widely used in image processing systems from face recognition [3], image classification to object detection [5].

II. Proposed model

A. *Simple Convolutional Neural Networks*

Dong et al. [2] first resize the low-resolution image by 2x and then used three layer convolutional neural networks to transform the scaled low-resolution image to a higher resolution image. The loss function is the difference between the original high-resolution image and the image produced by neural network. They compared the PSNR of their method with traditonal interpolation method such as bicubic and found out that convolutional neural networks produce better results.

B. *Generative Adversarial Network*

Ledig et al. [6] used generative adversarial network to produce super-resolution image. Their model consists of a generative network and a discrimitive network. The generative network produces super-resolution image from a low-resolution image. The super-solution image and the original high-resolution image are fed into the discrimitive network, which try to decide which one is the original image. Using the adversarial training, the generative model was trained to produce super-resolution images that are very similar to original images.

III. Evaluation

We plan to use PSNR as our primary evaluation method. We will first downsample a set of high-resolution images to low-resolution and feed them into the neural network. Then the PSNR between the output image and the original image will be calculated.

IV. Milestones

A. *Milestone 1*

We first want to familiar ourselves with the set up of the problem and the basic processing pipeline. We'll try to train a simple convolutional neural network to perform the task and compute the average PSNR score.

B. *Milestone 2*

Our next step would be to use generative adversarial network to train a generator that can improve image resolution. We'll try different architectures and tune the parameters to optimize the model and compute the PSNR score.

C. *Milestone 3*

We want to explore the possibility of using generative adversarial network to process images that both have low resolution and also noise. We'll add gaussian noise to original image and train the neural network. This is an interesting task because the neural network needs to discern between feature and noise and enhance the features while reducing the noises.

V. Conclusions

References

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