**CSC420 Project Proposal for Super resolution**

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1. What is the problem exactly and what are you going to achieve?

A crucial problem in image processing is recovering a high resolution image from a given small and obscured image. This process to enhance and upscale an image is called super resolution. Traditional ways like weighted average neighborhoods or bilinear/bicubic interpolation methods don’t perform very well since missing data cannot be recovered by further processing. With rapid development of deep learning, deep learning based SR models have been actively explored. In this project, we are going to implement an algorithm to produce a high resolution image given low resolution input by using a neural network to add details to the input image.

1. How is this problem relevant to this course?

The image up-sampling that we learnt in the lecture gives us a basic idea for the super resolution task. The earliest methods of super resolution are using various interpolations to fill in the missing information due to magnification. At the same time, to produce a high resolution image, the high-resolution image model must be inverted. And the inversion can be enhanced by adding some regularization.[1] Moreover, the basic concepts, such as blurring, will help us to do super resolution easier.

1. What others have tried to solve this problem?

The traditional method to solve super resolution problems is super resolution reconstruction (SRR), which discretized continuous high-resolution images by using a zero-order hold interpolation. Patti and Altunbasak have tried to optimize the traditional method through using higher interpolation and adding regularization in the inversion. In recent years, a variety of deep learning methods have been applied to SR tasks. In 2015, Chao Dong and some of his researchers proposed a deep learning method for single image super-resolution(SR) using deep convolutional networks(SRCNN). They trained a neural network to learn a mapping between low and high-resolution images, output high resolution images which match the original one best. However SRCNN minimizes square difference, the structural information about the content of an image is ignored.

Recent SR approaches use Generative Adversarial Nets(GAN) (e.g. SRGAN) . It is a perceptual driven method and it’s good at adding texture details to high resolution output. GAN consists of two models: a discriminator and a generator. Both networks are trained simultaneously and get better over time. Compared to SRCNN, it uses adversarial loss to enhance images.

In 2016, Google published RAISR(Rapid and Accurate Image Super Resolution), which produces results that are faster than the currently available super-resolution methods and faster. And it is able to avoid aliasing artifacts.

In general, the family of SR algorithms using deep learning techniques differ from each other in the following aspects: different types of network architectures, different types of loss functions and different types of learning principles.

1. What approaches are you going to try and why do you think these approaches might work?

We will be mainly implementing the algorithm based on the proposed paper “Image Super-Resolution Using Deep Convolutional Networks” by Chao Dong’s team. One of the most challenging problems in super resolution is finding the missing details in the upscaled image. Since it is hard to get these details from the input image, using a neural network to hallucinate details becomes a good choice. We can train the neural network with a dataset which collects high-resolution images and downscaling them (or using an existing super resolution dataset). The neural network can help us to upscale a low resolution image to a higher resolution image by mapping between missing pixels in the input image and high-resolution images.

However, the SRCNN uses MSE as the loss function which cares only about pixelwise intensity difference. We may design our own network architecture and add more details on loss functions to get a better measure of perceptual image quality. In addition, we consider different datasets for training and testing purposes.

1. What steps are you going to take to achieve your goals in this project?

* Implement our deep learning algorithm based on the idea of SRCNN
* Research and choose a proper dataset (e.g.DIV2K)
* Use the dataset to train the neural network model, compare and validate the results
* To get better image quality, refining the loss function and learning principle

**References:**

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3. C. Ledig et al., "Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, 2017, pp. 105-114, doi: 10.1109/CVPR.2017.19.
4. Y. Romano, J. Isidoro and P. Milanfar, "RAISR: Rapid and Accurate Image Super Resolution," in IEEE Transactions on Computational Imaging, vol. 3, no. 1, pp. 110-125, March 2017, doi: 10.1109/TCI.2016.2629284.
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