Single Image Super Resolution

Project report for IITB EE610 Image Processing 2021

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***Abstract*— Image Super Resolution refers to enhancing a low-quality image to a high-quality image. It is very important for applications such as Surveillance, Medical Treatment, Media. Lots of development has been made in recent years in this area with the help of Machine learning methods. In this paper, we try to implement Single-Image Super Resolution using SRCNN on BSD300, BSD100 CIFAR-10 datasets. We have provided the model with images in different formats such as blurred, /2 down sampled and /4 down sampled. Further we have compared the outputs to find out what method can yield a better result.**

I. INTRODUCTION

Image Super Resolution in one of the most common image restoration issue that has been getting attention over the years. The purpose of Image Super-Resolution (ISR) is to generate a higher resolution image from lower resolution images i.e., recover information lost during processing or not available. High resolution image has high pixel density & thereby provide more information about the original scene. The need for high resolution is common in computer vision applications for better performance in pattern recognition and analysis of images. High resolution is also of importance in medical imaging for diagnosis. Many applications require zooming of a specific area of interest in the image wherein high resolution becomes essential, e.g., surveillance, forensic and satellite imaging applications. However, high resolution images are not always available. This is since the setup for high resolution imaging proves expensive and also it may not always be feasible due to the inherent limitations of the sensor, optics manufacturing technology. These problems can be overcome through the use of image processing algorithms, which are relatively inexpensive, giving rise to concept of super-resolution. It provides an advantage as it may cost less and the existing low resolution imaging systems can still be utilized Here, we have used the CIFAR-10,BSD300, BSD100 datasets for training our model. The CIFAR-10 dataset consists of 60000 32x32 color images in 10 classes, with 6000 images per class. There are 5000 training images. We tested our model with SET5 dataset. The training batches contain the images in random order, but some training batches may contain more images from one class than another. Between them, the training batches contain exactly 5000 images from each class and BSD300 dataset on another type of model with a blurring the input and BSD100 dataset on other model with a scale factor of 2. These modules, our proposed model is efficient at separating the noise and texture of the single image.

II. BACKGROUND AND PRIOR WORK

Single Image Super-Resolution: Super-resolution is based on the idea that a combination of low resolution (noisy) sequence of images of a scene can be used to generate a high-resolution image or image sequence. Thus, it attempts to reconstruct the original scene image with high resolution given a set of observed images at lower resolution. The general approach considers the low-resolution images as resulting from resampling of a high-resolution image. The goal is then to recover the high-resolution image which when resampled based on the input images and the imaging model, will produce the low resolution observed images. Thus, the accuracy of imaging model is vital for super-resolution and an incorrect modeling, say of motion, can actually degrade the image further. The observed images could be taken from one or multiple cameras or could be frames of a video sequence. These images need to be mapped to a common reference frame. This process is registration. The super-resolution procedure can then be applied to a region of interest in the aligned composite image. The key to successful super-resolution consists of accurate alignment i.e., registration and formulation of an appropriate forward image model. The figure 1 below shows the stages in super-resolution process.

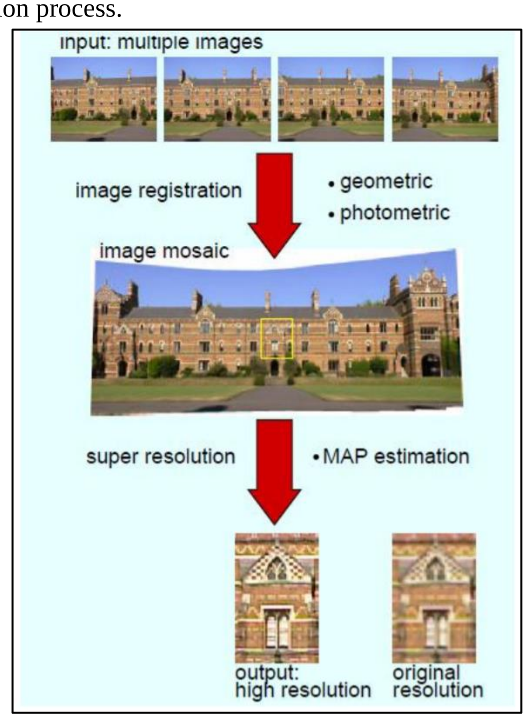


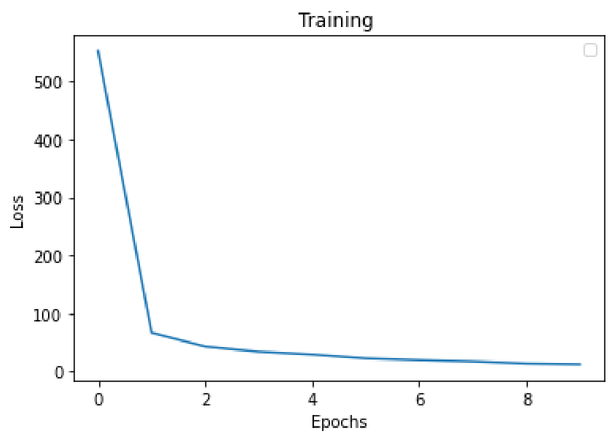
Figure 1: Stages in Super-resolution

III. DATA AND METHODOLOGY

We started with studying the methods used by various sources, and started our work by importing the relevant models.
We downloaded the CIFAR-10, BSD300, BSD100 datasets as it contains lots of images for training the model. We used different datasets on three different models and tested our model with SET5 dataset.
For Training the Model, we tried 3 different approaches

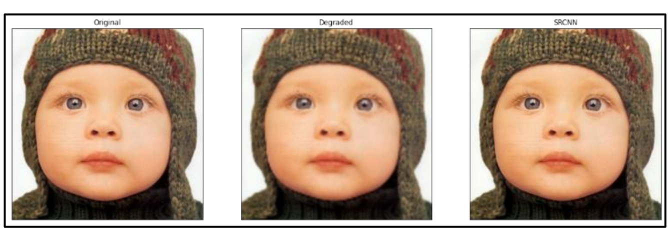
1. Linear Down-Sampling: In order to obtain low resolution image, here we down-sampled the images by 4
2. Bicubic Down-Sampling: we down-sampled images by 2
3. Blurred Image: We blurred the image using gaussian kernel of window size=13.

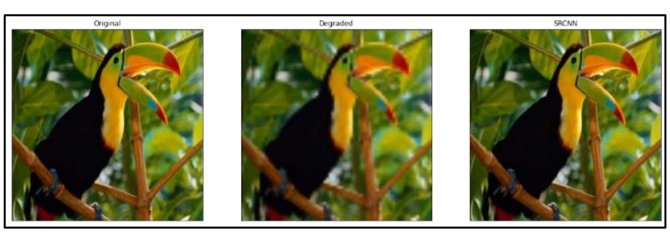
The images were now basically divided into 2, the original image which could be provided as Target to the Model and the degraded image as the Input to the Model. We used sequential layer of 2D convolution as our model, with internal nodes having ReLu and the final node having Linear activation. We then compiled the model with Adam Optimizer, selected the Type of Loss as Mean Square Error. We ran the model with different batch sizes and for different count of epochs and found that the accuracy increased for with the increase in number of Epochs.



IV. EXPERIMENTS AND RESULTS

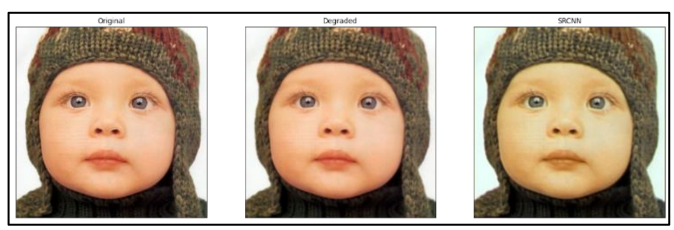
A) LINEAR: Accuracy = 0.89





B) BLURRED: Accuracy = 0.87

C) Bicubic: Accuracy = 0.73



On, subjecting our model with different type of input we found that our model worked better on down-sampled by 4 images refer (A), with accuracy of approx. 0.89. Even though we were able to achieve accuracy close to 0.87 using Blurred images the subjective quality of the images was not at par with Linear input and finally for down-sampled images we were able to achieve accuracy close to 0.73 but the subjective quality was much better than expected.

V. CONCLUSION AND FUTURE WORK

In this paper, we propose a model to solve the image super resolution that is robust to noisy and LR image. We present a architecture with parallel modules to handle the noise and texture effectively at the same time. In future work we hope that the use of our framework will solve a variety of image restore operations. In the real world, multiple degradation factors occur arbitrarily. Therefore, we also plan to investigate to solve the various unknown degradation with the single model. This is one of the ultimate issues to be solved urgently in image processing.

Contribution:

Group Contribution: Detailed discussion for selection, implementation, understanding of the project.
Sasi Kiran - Development of Main Code for the Project and Presentation
Ankit - Coding and Video Presentation
Devendra - Coding and Report
Ronak - project/dataset selection, implementation activities

References:

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