Image Super Resolution Using Deep Convolution Neural Network

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ABSTRACT –
We propose a deep learning method for single image super-resolution (SR). Super Resolution (SR) is an image reconstruction process in which the resolution of an image is improved. It searches for creating a high- quality image from combining one or more low quality images. Our method directly learns an end-to-end mapping between the low/high resolution images. The mapping is represented as a deep convolutional neural network (CNN) that takes the low-resolution image as the input and outputs the high resolution one. We further show that traditional sparse-coding-based SR methods can also be viewed as a deep convolutional network. But unlike traditional methods that handle each component separately, our method jointly optimizes all layers. Our deep CNN has a lightweight structure, yet demonstrates state of-the-art restoration quality, and achieves fast speed for practical on-line usage. Key Words: Super resolution, Deep convolutional neural networks, Reconstruction, Interpolation, Regression, PSNR

Keywords: SRCNN, PSNR, Low resolution (LR), High resolution (HR), Image resolution, Max pooling and Averagepooling

I. INTRODUCTION

Super Resolution image reconstruction is a promisingtechnique of digital imaging which attempts to reconstruct HR imagery by fusing the partial information contained within a number of under-sampled low-resolution (LR) images of that scene during the image reconstruction process. Super-resolution image reconstruction involves up- sampling of under sampled images thereby filtering out distortions such as noise and blur. In comparison to various image enhancement techniques, super- resolution imagereconstruction technique not only improves the quality of under- sampled, low-resolution images by increasing their spatial resolution but also attempts to filter out distortions.

Aim and Scope

The main aim of our project is to convert low resolutionimage to high resolution image in which it undergoes through various functions like peak signal to noise ratio (PSNR), mean square error(MSE), structure similarly index(SSIM) and SRCNN methods. Single image super resolution has fundamental low-level vision problems. The SISR aims torecover the High-Resolution images from a single Low- Resolution image.

Goals and Objectives

The main task of this project is to get Super Resolution image from different downgraded images like bicubic or unknown downgrading with scale 4. In this project, we will use a deep residual network for single image super-resolution (SR). The method directly learns an end-to-end mapping between the low-resolution image and highresolution image. The mapping is represented as a deep convolutional neural network (CNN) that takes the low-resolution image as the input and outputs the high resolution one. In this project, we will use a known downgrade function and follow a supervised learning .

II. METHODOLOGY

Images resampled with the bi-cubic interpolation will be having very smoother surface and have very few interpolation artifacts. So, we need to choose a Bi-cubic Interpolated image as an input and is sent to three convolution layers for further

processing.

1. **Convolution layer 1:** In this layer patch extraction will be performed. Patch extraction is a process of selecting the patch i.e. set of pixels in the image. SRCNN technique will perform patch extraction than to select an entire image to make the process much easier.

2. **Convolution layer 2:** In this layer non-linear mapping is performed. Rectified linear unit (RELU) is used. This RELU is a form of activation function which returns 0 if it receives a negative input. The function is as: f(x)=max(0,x). Padding and pooling operations are performed in the second layer because after patch extraction loss of informationmay happen at the border of images.

3. **Convolution layer 3:**In this layer reconstruction of image is performed. We need to rebuild the image which isconsidered as output. This image will have high PSNR values and noise will be completely erased. easier. The machine learning makes it easier through its wide range of algorithms. The algorithms are taken here in order to choose the high précised output for the user.

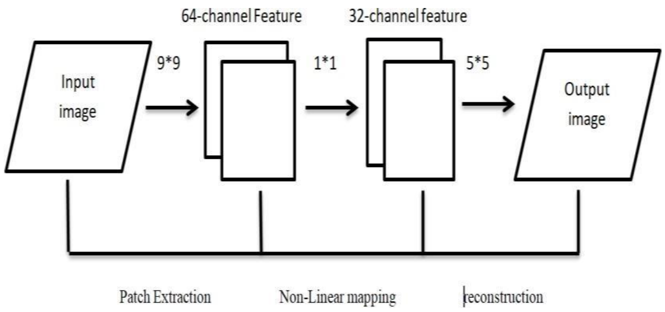

Fig 1: System architecture of SRCNN

III. LITERATURE SURVEY

1) Chao Dong, Chen Change Loy, Kaiming He and Xiaoou Tang, Fellow, "Image Super-Resolution Using Deep Convolutional Networks", IEEE, 2015. In this paper, Authors have presented a description of deep learning. In recent time deep learning techniques are predominantly used for single image super resolution (SR). end-to-end mapping among low and high-resolution images taught by SRCNN approach. It required extra pre or post- processing and after then the optimization. By using proper structure, greater performance than the state-of-the-art methods isachieved by SRCNN.

Yancong Wei, Qiangqiang Yua, Huanfeng Shen, Liangpei Zhang, "A Universal Remote Sensing Image Quality Improvement Method with Deep Learning", IEEE,2016.

In this paper, Author establishes deep learning approach CNN for comprehensive quality getting better tasks of remote sensing images, and research showed that it can get done satisfying performance when train on datasets with in time disintegration form. Thus, in the field of remote sensing data processing, we can give the impression of being forward to further applications with the ability of deep learning techniques. Besides, for all images included in this paper, ethereal components were not restored, which should be challenged in further analysis. SRCNN improves result of single frame super resolution compare with old used techniques.

IV. EXISTED SYSTEM

Super Resolution (SR) is the way toward improving picture quality by expanding pixel densities in a Low Resolution (LR) picture and get a High Resolution (HR) picture as a yield. There are numerous SR procedures proposed in most recent couple of decades. The mainstream insertion strategies, for example, Bilinear, Bicubic, Lanczos, B-Spline interjection techniques canbuild pixel-thickness however these procedures are not allaround ok in extraction of edge antiques. Insertion systemperforms well in smooth locale. The SSI-filtration strategy is fundamentally a high recurrence picture filtration method which can remove the high recurrence parts for example the edge ancient rarities.

V. PROPOSED SYSTEM

We approach another calculation which can improve the SRCNN technique by changing the preprocessing of Bicubic interjection with SSI-filtration. We additionally study and look at the super goals strategies, for example, change procedure with SSI filtration system, SRCNN learning based strategy and proposed calculation with theassistance of Peak-Signal-to Noise Ratio (PSNR). Wepresent a fully convolutional neural network for imagesuper resolution. The network directly learns an end-to-end mapping between low- and high-resolution images,with little pre/post processing beyond the optimization.We establish a relationship between our deep learning- based SR method and the traditional sparse-coding based SR methods. This relationship provides a guidance for thedesign of the network structure. We demonstrate that

deep learning is useful in the classical computer vision problem of super-resolution, and can achieve good quality and speed.

MODELING AND ANALYSIS

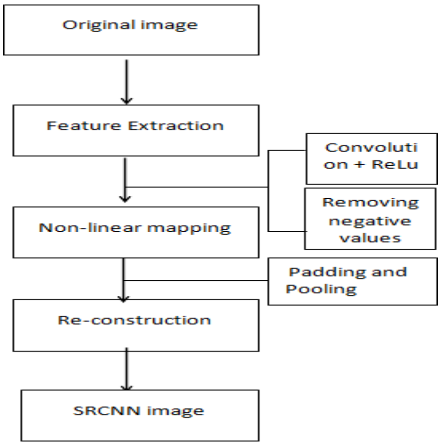

Fig 2: Flow of the model

VI. RESULTS

Original Image

Degraded Image

SRCNN Image

Table 1. PSNR and MSE (Mean Squared Error) Values of images

In this process PSNR values of the SRCNN image is increased as the increase in PSNR values will result into better quality of the image. In the above figure first convolution layer will perform 64 9*9 filters, second layer will perform max pooling and average pooling using kernel operations and finally output will be the same as original image which is more better in high resolution with good quality of texture.

VII. CONCLUSION

We have presented a novel deep learning approach for single image super resolution (SR). We show that conventional sparse-coding-based SR methods can be reformulated into a deep convolutional neural network. The proposed approach, SRCNN, learns an end-to-end mapping between low and high-resolution images, with little extra pre/post processing beyond the optimization. With a lightweight structure, the SRCNN has achieved superior performance than the state-of-the-art methods. We conjecture that additional performance can be further gained by exploring more filters and different training strategies. Besides, the proposed structure, with its advantages of simplicity and robustness, could be applied to other low-level vision problems, such as image deblurring or simultaneous SR+ denoising. One could also investigate a network to cope with different upscaling factors.