Single image super resolution of blurred natural images using blur kernel estimation combined with super resolution convolution neural network

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Abstract—Image De-blurring and super-resolution (SR) are computer vision tasks aiming to restore image detail and spatial scale, respectively. Despite the significant improvement in image quality resulting from improvement in optical sensors and general electronics, camera shake blur significantly undermines the quality of hand-held photographs. We evaluated the state-of-the-art super-resolution convolution neural network (SR-CNN) architecture and proposed a new architecture for SR application inspired by SR-CNN combined with De-blurring. This paper focus super resolution of a de-focused and motion blurred natural images. Unlike most de-blurring methods that attempt to solve an inverse problem through a variational formulation, deblurring method applied in this work directly estimates the blur kernel by modeling statistical irregularities in the power spectrum of blurred natural images. Extensive experiments indicate that the proposed method not only generates remarkably clear HR images, but also achieves compelling results in PSNR, MSE and SSIM quantitatively.

Keywords-component; Image super-resolution, de-blurring, deep learning, convolution neural networks.

I. INTRODUCTION

Single image super resolution (SISR) is a well defined problem in computer vision area. It tries to reconstruct a high resolution image from a single low resolution image. It has been a very attractive research topic over the last two decades [1] [2] [3]. Early SISR methods include interpolation such as bicubic interpolation and Lanczos resampling[4], more powerful methods utilizing statistical image priors[4, 5] or internal patch recurrence. Since SISR can restore some high frequency details, it has been applied to many practical applications such as medical imaging, satellite imaging and face identification where rich details are greatly desired. But in many applications images are of poor quality since it suffers from degradation like (i) optical blur (ii) image sampling by the CCD array (iii)motion blur. Motion blur in particular introduces significant image degradation.[7]

Image Restoration refers to the construction of the original image given its degraded version, when the phenomenon responsible for the degradation is known. In order to deblur a degraded image, it important to know the characteristics of the blurring process [7]. De-blurring method is used to produce the highest quality image by removing the blur from the degraded image as much as possible. Estimating the blur kernel of an image is the first step towards its de-blurring. The state-of-the-art non-uniform deblurring methods can generate clear output, but fail to enlarge the spatial resolution. On the other hand, the existing advanced SR methods are hardly capable of processing blurry LR images well, to address these issues, we have used blur kernel estimation method proposed by Goldstein and Fattal et al, which estimates the kernel by modeling statistical irregularities exhibited in the power spectrum of blurred images, After de-blurring, SRCNN applied for the image spatial resolution enhancement.

In view of the discussions above, this paper focus to generate a high resolution image from a blurred low resolution image that is as close as possible to an ideal image.

The rest of the paper is arranged as follows. Section II describes related work of image super resolution of blurred
images, In Section II architecture of proposed methodology. In Section IV, shown data set details and results.

II. PROPOSED METHODOLOGY-DEBLURRING COMBINED WITH SRCNN TO GENERATE A HIGH RESOLUTION IMAGE FROM A BLURRED LOW RESOLUTION IMAGE

A. Aim
Generate super-resolving high quality image from LR one with degradation.

B. Design
Deployed a cascading scheme, where a de-blurring module followed by an SR module. A detailed description of architecture design as follows

1) De-blurring module
Despite the significant improvement in image quality resulting from improvement in optical sensors and general electronics, camera shake blur significantly undermines the quality of hand-held photographs. Estimating the blur kernel of an image is the first step towards its deblurring. In this work, we have used blur kernel estimation method proposed by Goldstein and Fattal et al [3] which estimates the blur kernel by modeling statistical irregularities exhibited in the power spectrum of blurred images, which described as follows

   a) Numerical Algorithm for Blur Kernel Estimation[2.3]

   Goldstein and Fattal et al [3] described a method which extracts a set of statistics from the input image after properly whitening its spectrum, and uses them to recover the blur. The algorithm is based on a model that derived for modeling the power spectra of natural images. This model accounts for the presence of strong and long edges in the image and makes it possible to recover the blur in such scenarios. The first step computes the 1D auto correlation of the projections of the whitened image for a set of angles and an initial support of the projections is then estimated. This process estimates the power spectrum of the kernel then recovers a kernel using a phase retrieval algorithm, and re estimates the kernel support.

   Algorithm 1: Kernel estimation from blurry image. [2]

   Input : blurred image v, approximate kernel size p × p, compensation factor α
   Output: blur kernel h

   A = ComputeProjectionAngleSet(p)
   \{R(P_θ (D_θ v))\} = ComputeProjectionsAutocorrelation(v, A, p, α)
   \{s_θ \} = InitialSupportEstimation(\{R(P_θ (D_θ v))\}, A)
   for i from 1 to N_out do
     |H|² = EstimatePowerSpectrum(\{R(P_θ (D_θ v))\}, \{s_θ \})
     h = RetrievePhase(|H|, p)
     \{s_θ \} = ReEstimateSupport(h, A)

   2) SRCNN Module(Super resolution Convolution Neural Network)

   In SRCNN, network have 3 sections, patch extraction and representation, non-linear mapping, and reconstruction as shown in the figure below:

   Figure 1. SRCNN Network

   a) Patch Extraction and Representation

   It is important to know that the low-resolution input is first upscale to the desired size using bi-cubic interpolation before inputting to SRCNN network.

   X: Ground truth high resolution image
   Y: Bi-cubic up sampled version of low resolution image.
And the first layer performs a standard convolution with Relu to get $F_1(Y)$.

$$F_1(Y) = \max(0, W_1 \cdot Y + B_1) \quad (1)$$

size of $W_1$ : $c \cdot f_1 \cdot f_1 \cdot n_1$

size of $B$ : $n_1$

where $c$ is number of channels of the image, $f_1$ is the filter size, and $n_1$ is the number of filters, $B_1$ is the $n_1$-dimensional bias vector which is used for increasing the degree of freedom by 1.

In this case, $c=1$, $f_1=9$, $n_1=64$.

b) Non-Linear Mapping

$$F_2(Y) = \max(0, W_2 \cdot F_1(Y) + B_2) \quad (2)$$

The second layer

Size of $W_2$ : $n_1 \times 1 \times 1 \times n_2$

Size of $B_2$ : $n_2$

It is a mapping of $n_1$-dimensional vector to $n_2$-dimensional vector. When $n_1 > n_2$

In this case, $n_2=32$.

Here, it is used for mapping low-resolution vector to high-resolution vector.

c) Reconstruction

After mapping, we need to reconstruct the image.

Hence, we do once again.

$$F(Y) = W_3 \cdot F_2(Y) + B_3 \quad (3)$$

Size of $W_3$ : $n_2 \cdot f_3 \cdot f_3 \cdot c$

Size of $B_3$ : $c$

d) Loss Function

$$L(\Theta) = \frac{1}{m} \sum_{i=1}^{m} \|F(Y_i; \Theta) - X_i\|^2 \quad (4)$$

For SRCNN, the loss function $L$ is the average of mean square error(MSE) for the training samples.

III. RELATED WORK

Several methods have been proposed in the past to generate a high resolution image from a blurred low resolution image using deep learning methods and blur kernel estimation methods. Kai Zhang et al[1] described a method for super-resolution of blurred images in which degradation model defined by Maximum A Posteriori (MAP) probability and followed by deep neural network. Amit Goldstein et al[2] proposed a method for recovering the blur kernel in motion-blurred images based on statistical irregularities their power spectrum exhibits and the blur kernel is then recovered using a phase retrieval but it not operated on small images where these statistics are unreliable. Jeremy Anger et al [3] detailed the model presented in [2] and able to estimate complex motion blur kernels from slightly noisy images through a detailed anatomy of the Goldstein and Fattal method. In [4] Fatma Albluwi et al proposed a deep learning approach that simultaneously addresses deblurring and super-resolution from blurred low resolution images using convolution neural network with four layers and but not addressed blur kernel estimation. Dongyang Zhang et al [5] performed super-resolution from single image that combines gradient and motion blur kernel prior in a coherent frame-work and on an average, result was better. In [6], Linyang et al presented a method in which the original image modeled as Markov Random field and the blurred image as degraded version of the original MRF. and estimated a relationship between degraded pixels in blurred image and corresponding pixels in original image.

Currently, learning methods are widely used to model a mapping from LR to HR patches. In [7], Chao Dong et al presented a fully convolutional neural network for image super-resolution and established a relationship with sparse coding. Nidhi B et al [8] described different deblurring algorithms. Khizar Hayat et al, Haopeng Zhang et al [9,10] described super resolution using deep neural network. In recent years, CNNs have shown powerful ability to learn highly non-linear transformations. Due to their powerful
learning ability, the CNN based methods are widely used for SISR tasks and have achieved remarkable progress.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

An extensive experiments on three publicly available data-sets are performed. The training data-set composed of 91 images by Fatma Albluwi et al. [4]. The test data-sets are denoted “Set5” [4], “Set14” [4] and blur data-set [2, 3] by Amit Goldstein et al., Jeremy Anger et al. to evaluate the performance and efficiency of our proposed methodology in terms of the standard PSNR (Peak Signal to Noise Ratio) [11], MSE(Mean Squared Error)[11] and SSIM(Structural Similarity Index) [11] metrics. Table I & Table II, shows results of our proposed method and its comparison with other state of art methods. Figure 2 & Figure 3 shows visual comparison of our proposed method with other methods for motion blurred and out focused images.

TABLE I. PSNR/MSE/SSIM VALUES ON DATASET SET5. RED COLOR INDICATES BEST PERFORMANCE AND YELLOW COLOR INDICATES SECOND BEST PERFORMANCE

| DATASET | BICUBIC | SRCNN | AFTER DEBLURRING | PROPOSED |
|---------|---------|-------|------------------|----------|
| SETS    | PSNR    | MSE   | SSIM            | PSNR     | MSE  | SSIM   | PSNR    | MSE   | SSIM   |
| BABY    | 34.29   | 73.2  | 934             | 59.3     | 974  | 27.08  | 89.29   | 978   | 10.95  | .989   |
| BIRD    | 23.36   | 98.4  | 953             | 36.54    | 960  | 34.54  | 68.31   | 962   | 40.49  | .989   |
| BUTTERFLY | 24.75   | 853   | 46.4            | 178.64   | 951  | 24.89  | 89.61   | 908   | 33.46  | .982   |
| HEAD    | 30.88   | 139.2 | 80              | 31.64    | 131  | .82    | 37.48   | 85.15 | .981   | 48.83  | .975   |

TABLE II. PSNR/MSE/SSIM VALUES ON DATASET SET14. RED COLOR INDICATES BEST PERFORMANCE AND BLUE COLOR INDICATES SECOND BEST PERFORMANCE

| DATASET | BICUBIC | SRCNN | AFTER DEBLURRING | PROPOSED |
|---------|---------|-------|------------------|----------|
| SET14   | PSNR    | MSE   | SSIM            | PSNR     | MSE  | SSIM   | PSNR    | MSE   | SSIM   |
| Baboon  | 22.85   | 115.6 | .632            | 23.83    | 969.7| .709   | 30.27   | 182.9 | .899   |
| Barbara | 45.80   | 502.5 | .808            | 26.57    | 428.1| .956   | 29.46   | 228.5 | .924   |
| Bridge  | 25.84   | 495.8 | .782            | 27.47    | 348.8| .856   | 30.94   | 156.8 | .918   |
| Comic   | 23.63   | 844.5 | .828            | 28.67    | 264.7| .909   | 27.96   | 311.6 | .92    |
| Flower  | 27.24   | 367.5 | .859            | 29.68    | 219.9| .859   | 29.66   | 167.4 | .94    |
| Foreman | 32.01   | 121.8 | .938            | 36.14    | 47.36| .962   | 33.60   | 50.02 | .971   |
| Lena    | 31.55   | 142.6 | .845            | 33.18    | 95.3 | .968   | 35.41   | 54.09 | .971   |
| Pepper  | 31.44   | 139.8 | .83             | 32.83    | 183.7| .84    | 34.59   | 61.71 | .97    |

Figure 2. Blurred test case I for experimentation and result

Figure 3. Blurred test case I for experimentation and result
V. CONCLUSION

This paper proposed a novel method to generate HR image from a blurred LR image using deep neural network. Here we have highlighted some limitations of SR-CNN and to overcome these limitations, proposed and implemented a methodology which combined de-blurring module and SR-CNN module. In this work two types of blurred images are considered namely motion blur and de-focused, and obtained considerably better results in terms of PSNR, MSE and SSIM compared to other state of art methods.

VI. ABBREVIATIONS USED

SR --- Super resolution  
SISR -- SInle image super resolution  
LR – Low resolution image  
HR – High resolution image  
SR-CNN – Single image super resolution convolution neural networks  
PSNR—Peak signal to noised ratio  
MSE—Mean squared error  
SSIM—Structured similarity index

VII. DECLARATIONS

1) Availability of data and materials

The test data-sets are denoted “Set5” [4], “Set14” [4] are available from+ kaggle which is common evaluation dataset for Super Resolution of images, contains various images of buildings to animal faces. Blur data set by Amit Goldstein et al. [2]. The training data-set composed of 91 images by Fatma Albluwi et al. [4].

2) Competing interests

The authors declare that they have no competing interests” in this section.

3) Funding

Not applicable

4) Authors’ contributions

PP designed and coded proposed methodology under the guidance of V K. Manuscript prepared by PP, read and approved by VK.

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