

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 SRCNN combined with De-blurring. This paper focus super resolution of a de-focussed 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.

Index Terms— 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]. 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]

In order to deblur a degraded image, its 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. 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.

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

II. 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.

III. PROPOSED ARCHITECTURE

To focus on super-resolving high quality image from LR one with degradation, we deployed a cascading scheme, where a de-blurring module followed by an SR module. A detailed description of architecture design as follows

A. 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

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. 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 $p \times p$, compensation factor α

Output: blur kernel h

$A = \text{ComputeProjectionAngleSet}(p)$

$\{R(P \theta (D \theta v))\} = \text{ComputeProjectionsAutocorrelation}(v, A, p, \alpha)$

$\{s \theta\} = \text{InitialSupportEstimation}(\{R(P \theta (D \theta v))\}, A)$

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for i from 1 to N outer do
  |H|2 = EstimatePowerSpectrum({R(P θ (D θ v))}, {s θ })
  h = RetrievePhase(|H|, p)
  {s θ } = ReEstimateSupport(h, A)

```

B. SRCNN Module

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

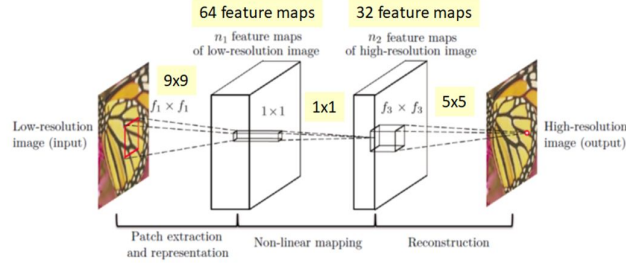


Fig 1: SRCNN Network

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 $F_1(Y)$.

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

size of W_1 : $c * f_1 * f_1 * n_1$

size of B_1 : 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, $c=1$, $f_1=9$, $n_1=64$.

Non-Linear Mapping

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

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.

Reconstruction

After mapping, we need to reconstruct the image. Hence, we do once again.

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

Size of W_3 : $n_2 * f_3 * f_3 * c$

Size of B_3 : c

Loss Function

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

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

IV. EXPERIMENTS & RESULTS

We performed extensive experiments on three publicly available data-sets. 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 [11], MSE [11]and SSIM [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	BI CUBIC			SRCNN			AFTER DE BLURRING			PROPOSED		
	PSNR	MSE	SSIM	PSNR	MSE	SSIM	PSNR	MSE	SSIM	PSNR	MSE	SSIM
SET5												
BABY	34.25	73.27	.934	36.25	46.16	.954	37.07	38.29	.976	42.50	10.95	.989
BIRD	32.97	98.40	.953	36.54	43.10	.969	34.56	68.31	.965	40.09	19.07	.989
BUTTERFLY	24.75	653.06	.878	30.38	178.64	.951	27.33	360.41	.936	33.46	87.82	.982
HEAD	30.88	159.21	.80	31.64	133	.82	37.44	35.15	.961	40.63	16.84	.975

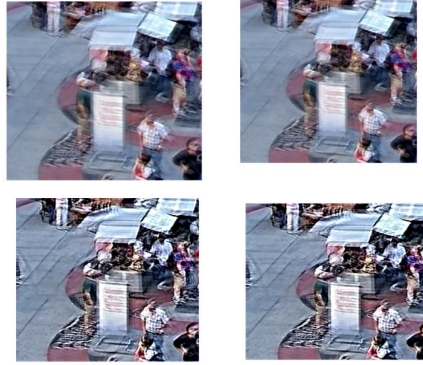


Fig 2. Blurred test case I for experimentation and result

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

DATA SET	BICUBIC			SRCNN			AFTER DEBLURRING			PROPOSED		
	PSNR	MSE	SSIM	PSNR	MSE	SSIM	PSNR	MSE	SSIM	PSNR	MSE	SSIM
SET14												
Baboon	22.05	1152.6	.632	23.03	969.7	.709	30.27	182.9	.889	32.44	111	.936
Barbara	25.88	502.5	.808	26.57	429.16	.950	29.46	220.56	.924	31.90	125.8	.952
Bridge	25.84	495.85	.782	27.47	348.89	.856	30.94	156.87	.918	34.62	67.26	.964
Comic	23.63	844.54	.829	28.67	264.72	.899	27.96	311.64	.92	31.92	125.22	.967
Flower	27.24	367.56	.869	29.60	210.95	.859	30.66	167.43	.94	35.94	49.67	.975
Foreman	32.01	121.8	.938	36.14	47.36	.962	33.60	85.02	.971	40.21	18.55	.991
Lena	31.35	142.67	.845	33.10	95.35	.868	35.41	56.09	.971	41.08	15.20	.986
Peppe	31.44	139	.83	32.83	102.77	.84	34.99	61.71	.97	39.49	22.07	.986



Fig 3. Blurred test case II for experimentation and result

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