Edge-Directed Single Image Super-Resolution via Cross-Resolution Sharpening Function Learning

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Abstract. Edge-directed single image super-resolution methods have been paid more attentions due to their sharp edge preserving in the recovered high-resolution image. Their core is the high-resolution gradient estimation. In this paper, we propose a novel cross-resolution gradient sharpening function learning to obtain the high-resolution gradient. The main idea of **cross-resolution learning** is to learn a sharpening function from low-resolution, and use it in high-resolution. Specifically, a blurred low-resolution image is first constructed by performing bicubic down-sampling and up-sampling operations sequentially. The gradient sharpening function considered as a linear transform is learned from blurred low-resolution gradient to the input low-resolution image gradient. After that, the high-resolution gradient is estimated by applying the learned gradient sharpening function to the initial blurred gradient obtained from the bicubic up-sampled of the low-resolution image. Finally, edge-directed single image super-resolution reconstruction is performed to obtain the sharpened high-resolution image. Extensive experiments demonstrate the effectiveness of our method in comparison with the state-of-the-art approaches.

Keywords: Super-resolution · Gradient magnitude transformation · Linear transformation function

1 Introduction

Single image super-resolution is to estimate a high-resolution image from a given low-resolution image, and it can be used for various computer vision applications. The classical methods, such as interpolation based methods, often produce undesired artifacts in the high-resolution image, especially along the salient edges. To preserve local sharp edge structures in the recovered high-resolution image, in

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this paper, we propose a new cross-resolution sharpening method. In the following, we first briefly review the related work.

The single image super-resolution that related to our work can be mainly divided into two categories[1], i.e., learning based methods and reconstruction based methods (including edge-directed methods).

The learning based super-resolution methods [1–5] want to learn the corresponding relationship between low-resolution and high-resolution images from a training set. After that, they apply it to other low-resolution images for reconstructing the high-resolution images. These methods are based on offline training set, therefore, the training sample selection may affect the high-solution image reconstruction, and the computational cost of these methods may not be cheap. In [5], the correspondence between low-resolution and high-resolution patches is learned from the scale (resolution) space of the input image. The core idea is to use the cross-resolution similarity to reconstruct the high-resolution image. Motivated by this idea, in our method, the sharpening function is also learned by utilization of the cross-resolution similarity.

The reconstruction based super-resolution methods [6–17] recover the high-resolution image from low-resolution image by considering a reconstruction constraint. In [6–8], they consider the relationship between low-resolution and high-resolution image, and think that the down-sampling image of high-resolution should be close to the low-resolution image. However, it can take some undesired artifacts along salient edges. Compared with the above methods, in [9–16], their methods recover the high-resolution image from low-resolution image by enforcing gradient profile prior, and the enforced edge knowledge has the ability to produce sharp edges better. Especially in [10] and [12], their methods are the scaling sharpening and self-interpolation sharpening, and work well on points of edges. However, in [10], the corresponding point extraction may be prone to error, which further influences the final results. Following these methods, we also want to produce sharp edges in the recovered high-resolution image.

Motivated by Sun et al. [10] and Wang et al. [12], we propose a novel cross-resolution gradient sharpening function learning method to restore a high-resolution image. The main process is summarized in Fig. 1. Our main idea is to learn a sharpening function from low-resolution, and use it in high-resolution. The main contributions are highlighted as follows:

– Our cross-resolution gradient sharpening function learning method makes the transformation relationship, which is learnt from the low-resolution image, applied to super-resolution reconstruction directly. This method uses the similarity between different scales on the image itself (this self-similarity has been successfully applied to learning based methods for super-resolution). The advantage of the similarity is to avoid the offline training process, therefore, it can disaffiliate the dependence on an offline database.

[1] Note that, the interpolation based methods can also be regarded as single image super-resolution method. However, they are not very related to our work, thereby, we do not review them in detail in this paper.

– Our method, unlike the edge directed methods proposed by Sun, never needs to find the points on the edges and the corresponding relationship. First, we have advantages on running time, because we reduce the step of finding the edge points and their corresponding relationship. Second, our method can avoid the risk of error location of edge points in high-resolution image recovering.

The remainder of this paper is organized as follows. We introduce an edge-directed single-image super-resolution framework in Section 2. We indicate that the main difference from edge-directed super-resolution methods is in the estimation on the sharp gradient (or gradient magnitude). The cross-resolution gradient sharpening method is presented in Section 3. The implementation details of the proposed super-resolution algorithm are listed in Section 4. The experimental results are presented in Section 5. Finally, conclusion and future work are given in Section 6.

2 Edge-Directed Single-Image Super-Resolution

In edge-directed single image super-resolution framework, the high-resolution image I_h is recovered from the input low-resolution image I_l and the estimated high-resolution gradient $\widehat{\nabla I_h}$:

$$\begin{aligned} I_h^\star &= \arg\min_{I_h} E(I_h|I_l, \widehat{\nabla I_h}) \\ &= \arg\min_{I_h} \|[I_h \otimes g]_{\downarrow(\beta)} - I_l\|_2^2 + \alpha \|\nabla I_h - \widehat{\nabla I_h}\|_2^2, \end{aligned} \tag{1}$$

where $\otimes$ is the convolution operation with the blurry kernel g, $[\cdot]_{\downarrow(\beta)}$ is the down-sampling operation with factor β. The core behind the edge-directed single image super-resolution is the estimation of the high-resolution gradient $\widehat{\nabla I_h}$.

As presented in [12], the high-resolution gradient $\widehat{\nabla I_h}$ can be estimated uniformly by transforming the blurred gradient ∇I_h^u, given by

$$\widehat{\nabla I_h} = \mathrm{Tran}(\nabla I_h^u), \tag{2}$$

where Tran(.) is a transformation function, and I_h^u is the bicubic up-sampled high-resolution image. As discussed in [12], the transformation function proposed in [10] is the scaling function, which is offline learned from an image dataset.

The method of Sun et al. [10] is the scaling sharpening. They obtain a corresponding relationship between an up-sample image and a high-resolution image by offline training some samples, and use the corresponding relationship to reconstruct the high-resolution image. But this method requires to train in advance. Moreover, the corresponding point extraction may be prone to error, which can influence the final results.

In practical application, the gradient direction changes a little under the variation of scales. Hence, we only consider the gradient magnitudes, and Eqn. (2) is simplified as (please refer to [12] for details)

$$\widehat{G_h} = \mathrm{Tran}(G_h^u), \tag{3}$$

where $\widehat{G_h}$ and G_h^u are the gradient magnitudes of $\widehat{\nabla I_h}$ and ∇I_h^u, respectively. The finally sharpened gradient field $\widehat{\nabla I_h}$ is obtained by

$$\widehat{\nabla I_h} = \widehat{G_h} \cdot \theta_h^u \ . \tag{4}$$

where θ_h^u is the gradient direction of ∇I_h^u. In the following, we only consider the sharpening process of the gradient magnitudes G_h.

3 Cross-Resolution Gradient Magnitude Sharpening

To estimate a sharp high-resolution image I_h, our objective is in conformity with Sun's. However, our method considers the corresponding relationship of all points in different scales on the high-resolution image I_h and the low-resolution image I_l rather than offline training some samples, and uses the corresponding relationship to reconstruct the high-resolution image. Specifically, we want to learn the linear transformation function T_l on low-resolution, and then apply it on the high-resolution. We name it as cross-resolution sharpening function learning.

As shown in Fig. 1, we have the low-resolution gradient magnitude in Fig. 1(a), and want to reconstruct the high-resolution gradient magnitude in Fig. 1(e). The up-sampled gradient magnitude in Fig. 1(d) is used to estimate the high-resolution gradient magnitude in Fig. 1(e). In this process, we need to know the corresponding relationship T_h between the up-sampled gradient magnitude and the high-resolution gradient magnitude. Therefore, how to estimate the T_h is the key for high-resolution gradient magnitude reconstruction.

In our method, we first down-sample the low-resolution gradient magnitude G_l (see Fig. 1(a)) to G_{ll} (see Fig. 1(b)), and up-sample the gradient magnitude G_{ll} to G_l^u (see Fig. 1(c)). Here, we assume that the gradient magnitude transformation (the details about transformation will be described in the following subsection) from G_l^u to G_l is similar to the gradient magnitude transformation from G_h^u to $\widehat{G_h}$. That is, the transformation T_l is assumed to be similar to the transformation T_h.

Hence, we first calculate the linear transformation coefficient T_l from the low-resolution gradient magnitude. Then, we obtain T_h from T_l. Meanwhile, the high-resolution gradient is obtained by applying T_h to the gradient magnitude shown in Fig. 1(d). In the following, we describe each step in detail.

3.1 Construction of T_l

The blurred low-resolution image is obtained by performing down-sampling and up-sampling operations sequentially, given by

$$I_l^u = [[I_l]_{\downarrow(\beta)}]_{\uparrow(\beta)}, \tag{5}$$

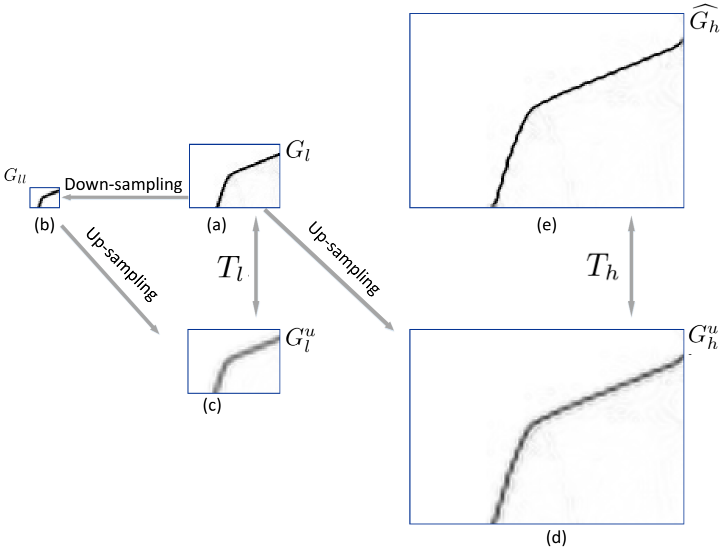

Fig. 1. Example of gradient magnitude sharpening with up-sampling scale factor of 3. (a) Input low-resolution gradient magnitude. (b) Bicubic down-sampled version of (a). (c) Bicubic up-sampled version of (b). (d) Bicubic up-sampled version of (a). (e) Output high-resolution one. T_l and T_h are the linear transformation functions.

and the gradient magnitude of a blurred low-resolution image I_l^u is G_l^u. The low-resolution sharpening function is defined as a linear transformation function, given by

$$G_l = T_l \odot G_l^u \tag{6}$$

where G_l is the gradient magnitude of the input low-resolution image I_l, and T_l is the low-resolution sharpening parameter with the same size of the input low-resolution image. The operation $\odot$ is the element-wise multiplication operation, satisfying that $(G_l)_{ij} = (T_l)_{ij}(G_l^u)_{ij}$, in which $()_{ij}$ is the ij-th element of the image. In this work, the parameter T_l can be obtained by

$$T_l = G_l \oslash (G_l^u + \eta) \tag{7}$$

where $\oslash$ is element-wise dividing operation, and $\eta = 10^{-4}$ is a small positive value to prevent dividing zero.

3.2 High-Resolution Gradient Construction

The purpose of T_h is to make blurred high-resolution gradient sharp. Hence, it can be obtained from low-resolution sharpening function T_l. In this work, the high-resolution gradient sharpening function is constructed by up-sampling the low-resolution sharpening function T_l directly, given by

$$T_h = [T_l]_{\uparrow(\beta)}. \tag{8}$$

After T_h is obtained, the high-resolution gradient magnitude $\widehat{G_h}$ is calculated by

$$\widehat{G_h} = T_h \odot G_h^u \tag{9}$$

where G_h^u is the gradient magnitudes of the up-sampled image I_h^u. Combining $\widehat{G_h}$ with the gradient direction θ_h^u, we obtain the high-resolution gradient $\widehat{\nabla I_h}$ by Eqn. (4).

4 Implementation

The proposed super-resolution algorithm is listed as follow:

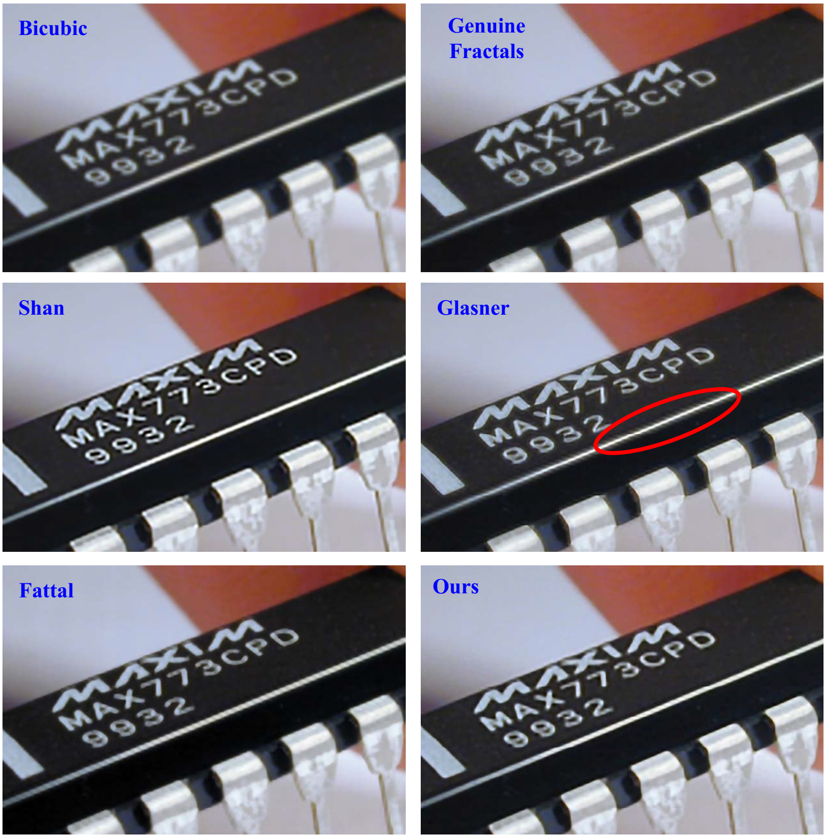

Fig. 2. Comparisons with the state-of-the-art approaches. All the results of high-resolution image experiments are obtained by the Bicubic, the commercial product Genuine Fractals, Shan [17], Glasner [5], Fattal [16] and ours.

Step_1: Initialing the high-resolution image I_h^{init}.
Step_2: Constructing the high-resolution gradient by four sub-steps.
2.1: Calculating the low-resolution sharpening function T_l by Eqn. (7).
2.2: Calculating the high-resolution sharpening function T_h by Eqn. (8).
2.3: Calculating the high-resolution gradient magnitude $\widehat{G_h}$ by Eqn. (9).
2.4: Calculating the high-resolution gradient $\widehat{\nabla I_h}$ by Eqn. (4).
Step_3: Obtaining the high-resolution gradient $I_h^{\star}$ by optimizing Eqn. (1).
It is worth noting that the initial high-resolution image I_h^{init} and the optimization of Eqn. (1) are the same as the method of Wang [12].

5 Experiments and Analysis

In this section, we use extensive experiments to evaluate our method. First, we make comparisons of our method with several state-of-the-art methods. Then, representative methods from two categories, namely edge-directed reconstruction based and large-scale based, are evaluated to compare with ours. In our experiments, for each color image, we first transform it from RGB to YIQ. We only consider the Y (intensity) channel, which is up-sampled by our algorithm. The I and Q chromatic channels have low-frequency information, and they are interpolated by the bicubic method. Finally, we combine the three channels to form the high-resolution image. The visual comparisons are used to evaluate our method.

5.1 Comparisons with the State-of-the-Art Approaches

The visual comparisons of our method with four state-of-the-art approaches and one commercial product Genuine Fractals are shown in Fig. 2. Our results are

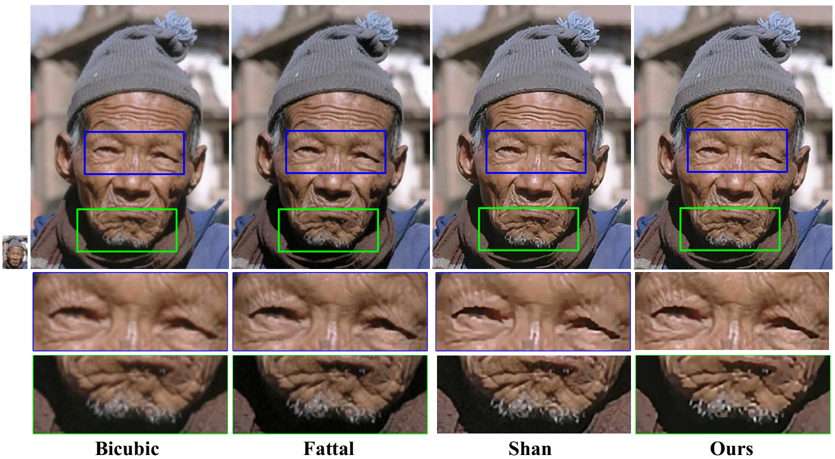

Fig. 3. Comparison on Large-scale factor (X8). From left to right are the results of bicubic, Fattal [16], Shan [17] and ours. The second and third row are the local details for each method.

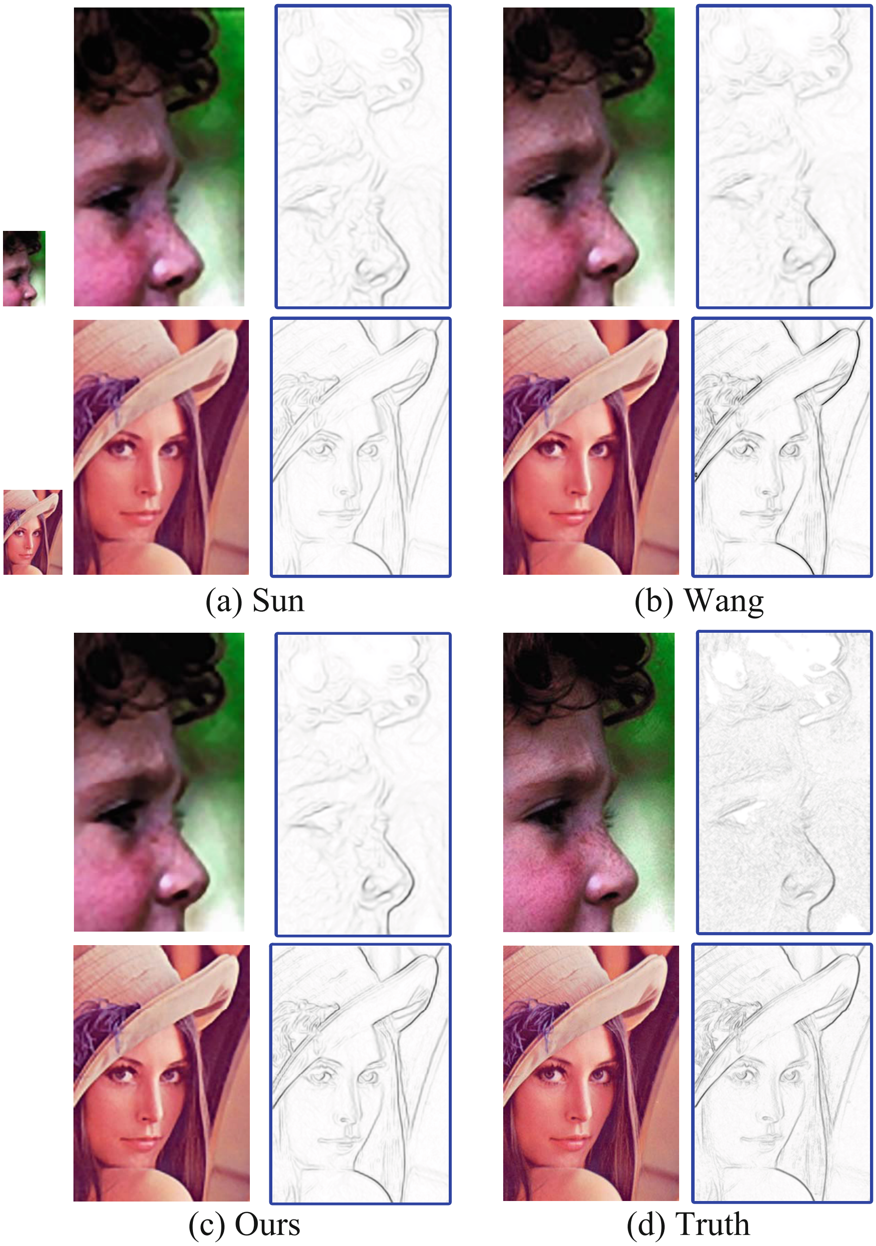

Fig. 4. Comparisons with the edge-directed approaches. The input low-resolution image are the small image in the left. The resluts of Sun [10] (a), Wang [12] (b), Ours (c) and the ground truth (d). We also present the gradient magnitude of the up-sampled images.

more sharp in comparison with Genuine Fractals and the bicubic interpolation. For example, the numbers and letters look very fuzzy, as shown in Fig. 2. On the edge aspects, the results of Glasner contain small artifacts along salient edges(see the red ellipse in Fig. 2). Moreover, in comparison to Shan and Fattal's results, our result is more natural, as we can see in Fig. 2.

5.2 Large-Scale Comparison

Fig. 3 illustrates the comparative results of our method with bicubic, Fattal et al. [16] and Shan et al. [17]. As shown in the Fig. 3, we can see our results contain more local details than the others. On the edge aspects, Shan's results are significantly blurred in comparison with ours. In addition, our method can generate sharper edges reliably than the Bicubic method, for example, in the aspect of the corner of eyes, our results is more sharp as shown in Fig. 3.

5.3 Comparisons with Edge-Directed Reconstruction Method

Fig. 4 shows the comparison of our method with some other edge-directed approaches, namely, Sun et al. [10] and Wang et al. [12]. To compare more fully, we also present gradient magnitude of the up-sampled images. we can see our results are better than those of Sun et al. [10] and Wang et al. [12] in the aspect of the sharpness along the salient edges. On the other hand, our results can look more natural, as compared with Sun et al. [10]. However, our results miss some local details, as compared with the ground truth.

6 Conclusion and Discussion

A cross-resolution sharpening function learning method is proposed for high-resolution image restoring. In this method, the linear transformation function on different resolution is estimated for high-resolution gradient construction. The extensive experimental results demonstrate the effectiveness of our method. In the future, we plan to propose other sharpening functions, which can preserve sharp edge better than the linear model used in this work.

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