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Example-based super-resolution via social images

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ABSTRACT

A novel image patch based example-based super-resolution algorithm is proposed for benefitting from social image data. The proposed algorithm is designed based on matrix-value operator learning techniques where the image patches are understood as the matrices and the single-image super-resolution is treated as a problem of learning a matrix-value operator. Taking advantage of the matrix trick, the proposed algorithm is so fast that it could be trained on social image data. To our knowledge, the proposed algorithm is the fastest single-image super-resolution algorithm when both training and test time are considered. Experimental results have shown the efficiency and the competitive performance of the proposed algorithm to most of state-of-the-art single-image super-resolution algorithms.

1. Introduction

Social images from online social platforms, for example, Flickr or YouTube, provide not only a new opportunity but also a challenge for various image processing tasks such as example-based super-resolution [1], visual query suggestion [2,3], saliency detection [4,5], ranking [6–8], and image classification [9–11] because a large amount of training images are available. The big size of training set means more information, however, it is also a huge burden during using all of these training samples. In this paper, we focus on the problem of example-based super-resolution with the help of a large amount of social image data, especially the problem of efficiently super-resolving with the help of a big size of training set.

1.1. Brief review of example-based super-resolution

Example-based super-resolution [1], also named as single-image super-resolution, is a problem of enhancing the resolution of some low-resolution images with the help of a set of training image pairs. Each of training image pairs consists of a low-resolution image and its corresponding high-resolution image. By learning on these training image pairs, the priori defining the relation between a low-resolution image and its high-resolution counterpart could be found. When a low-resolution image is observed, the learned priori could be applied on it for generating high-resolution estimation. The process of example-based super-resolution is summarized in Fig. 1.

Traditional example-based super-resolution algorithms could be generally divided into two categories according to the different ways of obtaining priori from training set. The first one belongs to implicit priori based algorithms where the priori is directly represented by the given training set. Most *K*-nearest neighbor based algorithms, such as Chang et al. [12], Tang et al. [13] and Gao et al. [14], belong to this category. It is clear that the implicit priori makes the learning process be omitted, but the *K*-nearest neighbor searching makes the price of recovering high-resolution estimation more expensive. The second one is explicit priori based algorithms. Dictionary [15–17] and regression function are two popular methods to represent the learned priori. Dictionary based algorithms such as Yang et al. [18], Lu et al. [19] focus on representing the priori between low- and high-resolution training images with the low- and high-resolution dictionary pair. Similarly, the priori on the relation between low- and high-resolution images is represented by a regression function which is learned by supervised or semi-supervised learning methods [20], such as, Ni and Nquyen [21], Kim and Kwon [22], and Tang et al. [23]. Generally, the training time of these explicit priori based algorithms is extremely long when the size of training set is big. Therefore, both of these traditional example-based super-resolution algorithms are not suitable for applying on a big size training set.

1.2. Motivation and our contributions

Two basic motivations make us focusing on the problem of super-resolution with the help of social images. Firstly, social images cover many image categories which could serve as a training set for super-resolving almost all kind of natural images. Secondly, huge training set

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is changing the framework of example-based image processing. For example, Burger et al. [24] have shown that simple image denoising algorithm is competitive when big training set is available. Therefore, we discuss the problem of efficiently super-resolving natural images based on social images in this paper.

To benefit from a huge social image set, the computational complexity of an example-based super-resolution must be sufficiently low. However, the computational complexity of the traditional example-based super-resolution algorithms is too high to apply on a huge training set. To relieve the computational burden, a novel matrix-value operator based super-resolution algorithm is proposed based on the work [25]. Comparing with the work [25], more theoretical analysis and experiments are reported in this paper. Two main contributions of the novel algorithm can be summarized as follows:

- *Low computational complexity*. The computational complexity of the proposed super-resolution algorithm is only $O(N)$ where N is the number of training samples. The linear computational complexity makes the novel algorithm suitable for dealing with large training set.
- *Novel model for example-based super-resolution*. The proposed algorithm is designed based on representing images as matrices. And then, a novel matrix-value operator based learning model is introduced into example-based super-resolution. The novel learning model enables the computational and memory complexities of the proposed algorithm heavily reduced.

The rest of this paper is organized as follows. Main algorithm is introduced in Section 2. Some comments and theoretical analysis on the main algorithm are reported in Section 3. Experimental results are shown in Section 4.

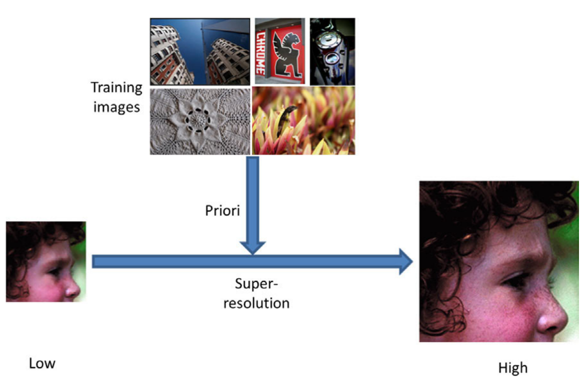

Fig. 1. The process of example-based super-resolution.

2. Main algorithm

Our algorithm is designed based on the idea of representing an image patch as a matrix. And then, the matrix-value operators are used to explicitly represent the relation between low- and high-resolution image patches. Taking advantage of operator learning techniques, our matrix-based super-resolution algorithm is fast enough for applying on a huge training set. The flowchart of our algorithm is summarized in Fig. 2.

Denote the matrix space as $R^{d \times d}$, where $d > 0$ is an integer. Let low-resolution image patch space X and high-resolution image patch space Y be the subsets of $R^{d \times d}$ where d means the size of an image patch. Denote the training set

$$S_n = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\} \subseteq X \times Y, \tag{1}$$

where (x_i, y_i) is a pair of low- and high-resolution image patches, and n is the number of training pairs. The matrix-value operator $\mathcal{A} : X \mapsto Y$ is used to represent the super-resolution priori containing the training set S_n.

Least square operator regression model is used to learn the optimal matrix-value operator $\hat{\mathcal{A}}$ from the training set S_n:

$$\hat{\mathcal{A}} = \underset{\mathcal{A}}{\operatorname{argmin}} \sum_{i=1}^{n} \|y_i - \mathcal{A}x_i\|_F^2, \tag{2}$$

where $\|\cdot\|_F$ is Frobenius norm. By restricting the matrix-value operator $\mathcal{A}$ be Hilbert–Schmidt operator, the least square operator regression model (2) could be thought in Hilbert–Schmidt operator space, that is,

$$\begin{aligned}
\hat{\mathcal{A}} &= \underset{\mathcal{A}}{\operatorname{argmin}} \sum_{i=1}^{n} \|y_i - \mathcal{A}x_i\|_F^2 \\
&= \underset{\mathcal{A}}{\operatorname{argmin}} \sum_{i=1}^{n} \langle y_i, y_i \rangle_F - 2\langle y_i, \mathcal{A}x_i \rangle_F + \langle \mathcal{A}x_i, \mathcal{A}x_i \rangle_F \\
&= \underset{\mathcal{A}}{\operatorname{argmin}} \sum_{i=1}^{n} \|y_i y_i^T\|_{HS} - 2\langle y_i x_i^T, \mathcal{A} \rangle_{HS} + \langle x_i x_i^T, \mathcal{A}^* \mathcal{A} \rangle_{HS},
\end{aligned} \tag{3}$$

where x^T is the transpose of the matrix x, $\langle \cdot, \cdot \rangle_F$ is the Frobenius inner on the matrix space, $\|\cdot\|_{HS}$ is the Hilbert–Schmidt norm on Hilbert–Schmidt operator space, the $\langle \cdot, \cdot \rangle_{HS}$ is the Hilbert–Schmidt inner on Hilbert–Schmidt operator space, and $\mathcal{A}^*$ is the adjoint operator of $\mathcal{A}$.

Denoting $F(\mathcal{A}) = \sum_{i=1}^{n} \|y_i y_i^T\|_{HS} - 2\langle y_i x_i^T, \mathcal{A} \rangle_{HS} + \langle x_i x_i^T, \mathcal{A}^* \mathcal{A} \rangle_{HS}$, the optimal operator $\hat{\mathcal{A}}$ satisfies the necessary conditions of the minimum, that is,

$$\frac{\partial}{\partial \mathcal{A}} F(\hat{\mathcal{A}}) = 0. \tag{4}$$

Because $F(\mathcal{A}) = \sum_{i=1}^{n} \|y_i y_i^T\|_{HS} - 2\langle y_i x_i^T, \mathcal{A} \rangle_{HS} + \langle x_i x_i^T, \mathcal{A}^* \mathcal{A} \rangle_{HS}$, there exists

$$\frac{\partial}{\partial \mathcal{A}} \left(\sum_{i=1}^{n} \|y_i y_i^T\|_{HS} - 2\langle y_i x_i^T, \mathcal{A} \rangle_{HS} + \langle x_i x_i^T, \mathcal{A}^* \mathcal{A} \rangle_{HS} \right) = 0$$

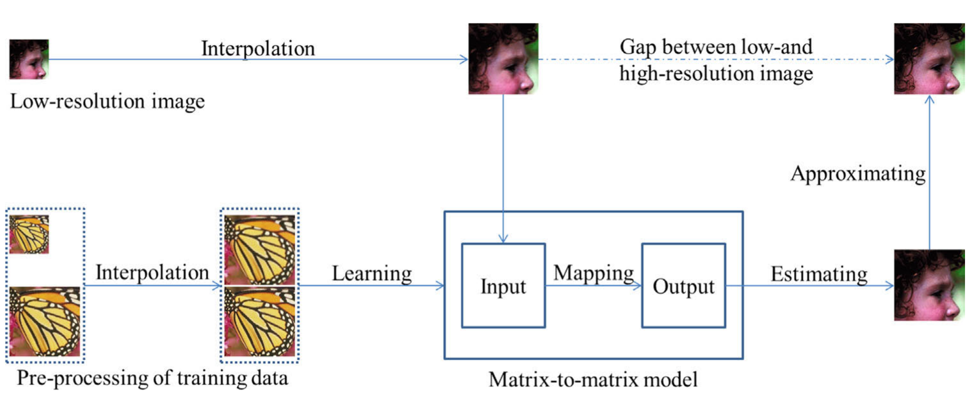

Fig. 2. The flowchart of the matrix-based super-resolution algorithm.