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A transductive graphical model for single image super-resolution

Peitao Cheng [a], Yuanying Qiu [a,b], Ke Zhao [a], Xiumei Wang [c,*]

[a] School of Mechano-Electronic Engineering, Xidian University, Xi'an 710071, China
[b] Key Laboratory of Ministry of Education for Electronic Equipment Structure Design, Xidian University, Xi'an 710071, China
[c] VIPS Lab, School of Electronic Engineering, Xidian University, Xi'an 710071, China

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ABSTRACT

The image super-resolution technique plays a critical role in many applications, such as digital entertainments and medical diagnosis. Recently, the super-resolution method has been focused on the neighbor embedding techniques. However, these neighbor embedding based methods cannot produce sparse neighbor weights. Furthermore, these methods would not reach minor reconstructing errors only based on low-resolution patch information, which will result in high computational complexity and large construction errors. This paper presents a novel super-resolution method that incorporates iterative adaptation into neighbor selection and optimizes the model with high-resolution patches. In particular, the proposed model establishes a transductive probabilistic graphical model in light of both the low-resolution and high-resolution patches. The weights of the low-resolution neighbor patches can be treated as priori information of the construction weights for the target high-resolution image. The quality of the desired image is greatly improved in the proposed super-resolution method. Finally, the effectiveness of the proposed algorithm is demonstrated with a variety of experiment results.

1. Introduction

In computer vision and pattern recognition, image super-resolution (SR) is of great importance and has been extensively studied. Existing methods for image super-resolution can be divided into three general categories, i.e., interpolation-based, regularization-based and learning-based methods [1,2]. The interpolation-based methods assume that an image is piecewise smooth in local structure and use the smooth kernel function to approximate the discrete image [3,4]. These kinds of methods are simple to be implemented with high speed. However, these methods may lead to losing the high frequency information, i.e., the detail information. The regularization-based method can solve the super-resolution computation problem, i.e., ill-posed inverse problem [5–8]. By incorporating the global and local regularization priors of the low-resolution (LR) image, an effective single image SR method is proposed by Zhang et al. [9]. But the optimal hyper-parameter cannot be computed directly. Although the former two kinds can obtain a higher-resolution (HR) image from a set of LR images, they may be not suit for dealing a single image super-resolution problem. The last one belongs to the single image super-resolution methods [10–13], which is also the focus of this paper.

The learning-based super-resolution method is also referred to as example-based super-resolution method, which has drawn much attention in recent years. Freeman et al. proposed an image super-solution model based on the Markov network, in which the LR and HR patches are considered as the nodes [10]. Just like other network models, the super-resolution results will be sensitive to the selection of nodes, i.e., training samples. However, the algorithm is weak in generalization. To utilize the couple neighbor relationship of LR patches and HR patches, the manifold learning based super-resolution methods have been proposed. This category can catch the local geometric structure of images, which makes the output HR image remain more detailed information. The super-resolution through neighbor embedding (NESR) is a representative of the manifold based models, where the neighbor patches are embedded in the way similar to locally linear embedding (LLE) [14–16]. LLE is a well known manifold learning method for dimensionality reduction, which obtains the nonlinear embedding structure with the locally linear technique. Various extension methods have been proposed in the following years. Fan et al. proposed an image super-resolution model combining neighbor embedding with primal sketch prior [15]. Bevilacqua et al. also proposed a neighbor embedding SR technique replacing LLE with nonnegative matrix factorization, where the weights of linear approximation are computed with nonnegative matrix factorization [16].

* Corresponding author. Tel.: +86 29 88202262.
E-mail address: wangxm@xidian.edu.cn (X. Wang).

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Jia et al. established a framework connecting the source image space and corresponding target image space, and the framework is successively used in image SR [17]. By utilizing the self-similarities across different scales, Zhang et al. proposed a reliable SR reconstruction algorithm [18]. Another representative branch of learning-based super-resolution methods is sparse representation learning (SRSR). Yang et al. proposed a sparse coding based super-resolution method which can adaptively choose the relevant reconstruction neighbor patches in two training dictionaries [19]. Furthermore, using patch-wise sparse recovery, they proposed a coupled dictionary training method for single image super-resolution [20]. In order to use the supervised information, Gao et al. proposed a sparse neighbor selection scheme for SR reconstruction [21].

As mentioned above, the learning-based super-resolution methods can be summarized as two kinds. One is l_2-constrained least square super-resolution method, such as NESR. Another is l_1-regularized least square super-resolution method, such as SRSR. In fact, the former method is established based on the K-nearest neighbor search (KNN), the most popular neighbor search technique. KNN is famous for its high search speed. However, the reconstruction error of the method will be also restricted. As we known, the KNN method cannot promise the minimum reconstruction error. The latter, sparse representation-based super-resolution method, is superior in reconstructing high resolution image. Aiming at addressing the above question, we combine the high speed of KNN with the performance of sparse representation.

Recently, a fast and efficient neighbor searching method named iterative nearest neighbors (INN) is proposed [22]. Through synthesizing the power of SR and computational simplicity of KNN, INN obtains a sparse neighbor representation of a sample. Inspired by INN, we propose a novel image super-resolution method based on the iterative neighbor embedding. In the proposed SR method, the neighbors are iteratively selected with continuously compensating for the reconstruction error. The weights of neighbor patches obtained by INN are considered as the priori information. Furthermore, we design a probabilistic graphic model to describe the relationship between the LH and HR patch pairs. Then a maximum joint likelihood framework is adopted to solve the probabilistic model, in which the weights and HR image patches are alternatively optimized. Therefore, the weights are determined not only by the LR dictionary, but by LR and HR dictionaries. The proposed method has the capability to handle the HR and LR patches simultaneously. The contributions of this paper are summarized as follows: (1) it utilizes a sparse representation for a patch from iterative selecting neighbors; (2) it considers the LR image and aims HR image from a generative model view; and (3) the neighbor weights of HR image are determined based on the LR and HR patches.

The rest of this paper is organized as follows. Section 2 briefly reviews the original NE-based SR method. Section 3 introduces the proposed SR method and gives its implementation details. Section 4 presents the experimental results on nine popular images. The final section gives the conclusions.

2. Single image super-resolution based on neighbor embedding

In this section, we review some previous work on the super-resolution based on neighbor embedding which was first introduced by Chang et al. [14]. Let X be the inputting low-resolution image and Y be the desired high-resolution image. In the NE-based super-resolution methods, images are dealt with small patches with overlap. Images X and Ycan be represented as $\{x_i\}_{i=1}^{N} \in R^{D\times N}$ and $\{y_i\}_{i=1}^{N} \in R^{D\times N}$ respectively, where N is the number of patches in one image. Before NE search, the high-resolution (HR) dictionary and low-resolution (LR) dictionary would be joint trained first. We define $X^{Dic} = \{x_j^{Dic}\}_{j=1}^{M} \in R^{d\times M}$ as the LR dictionary and $Y^{Dic} = \{y_j^{Dic}\}_{j=1}^{M} \in R^{D\times M}$ as HR dictionary. Table 1 lists the notations will be appeared in the following sections.

Table 1
Remarks of some notations.

X	Low-resolution image	Y	High-resolution image
x_i	Low-resolution patch	y_i	High-resolution patch
X^{Dic}	Low-resolution dictionary	Y^{Dic}	High-resolution dictionary
$N_L(i)$	K-nearest neighbor of x_i	$N_H(i)$	K-nearest neighbor of y_i
$w(i)$	The weight vector of $N_L(i)$	T_i	The indices of neighbors of x_i in the dictionary
$q_1(x_i)$	The nearest neighbor of x_i	λ	The adaptive parameter for INN search

The NE-based super-resolution method is similar to LLE. The super-resolution algorithm can be divided into three steps:

(1) Given the LR patch x_i, we search the K-nearest neighbor patches in the LR dictionary. The set of K-nearest neighbor patches is denoted as $N_L(i) = \{x_j^{Dic}, j \in T_i\}$ where T_i is the indices $T_i \subset \{1, 2, \ldots, M\}$;
(2) Reconstruct the LR patch x_i with neighbor set $N_L(i)$ and obtain the reconstruction weight vector $w(i)$,

$$\arg\min_{w(i)} \left\{ \varepsilon(i) = \left\| x_i - \sum_{j=1}^{M} x(j) w(j) \right\|_2^2 \right\}$$
$$s.t. \quad \|w(i)\|_0 = k, w(i)^T 1 = 1. \tag{1}$$

In the equation, the weight value is zero if the patch is not the neighbor of LR patch x_i.
(3) According to the indices T_i, we find the $N_H(i) = \{y_j^{Dic}, j \in T_i\}$ in the LR dictionary, and compute the corresponding HR patch y_i with the indices T_i and $w(i)$,

$$y_i = \sum_{j=1}^{M} x(j) w(j) \tag{2}$$

3. Proposed work

3.1. Iterative nearest neighbor based super-resolution methods

The key step in NE-based SR method is searching K-nearest neighbors and corresponding weights. Follow the process of INN, we will first show how to iteratively determine the neighbors for a LR patch. The detail steps are presented as follows:

(1) for a LR patch x_i, search the nearest neighbor point $q_1(x_i)$, initialize $\bar{x}_i$ with x_i;
(2) update $\bar{x}_i$ with the diversity between $\bar{x}_i$ and $q_1(x_i)$, i.e., $\bar{x}_i = \bar{x}_i + \lambda(\bar{x}_i - q_1(x_i))$;
(3) find the nearest neighbor of $\bar{x}_i$ and denote it with $q_2(x_i)$;
(4) repeat step (2) and step (3) until convergence;
(5) then $x_i = \sum_{j \in N(i)} w_j q_j(x_i)$;

where $N(i)$ denotes the set of K-nearest neighbor patches for x_i, and λ in (2) is the adaptive parameter. Tracing the source, the idea of iterative selection is inspired by the feedback loop. It minimizes the reconstruction error by compensating the residual continuously in each stage, and the convergence of the process and the sparse of weights have been proved in Ref. [22].