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Combining sparse representation and local rank constraint for single image super resolution

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ABSTRACT

Sparse representation based reconstruction methods are efficient for single image super resolution. They generally consist of the code stage and the linear combination stage. However, the simple linear combination has not considered the image edge constraint information of image, and hence the classical sparse representation based methods reconstruct the image with the unwanted edge artifacts and the unsharp edges. In this paper, considering that the local rank is able to extract better edge information than other edge operator, we propose a new single image super resolution method by combining the sparse representation and the local rank constraint information. In our method, we first learn the local rank of the HR image via the traditional sparse representation model, and then use it as the edge constraint to restrict the image edges during the linear combination stage to reconstruct the HR image. Furthermore, we propose a nonlocal and global optimization model to further improve the HR image quality. Compared with many state-of-art methods, extensive experimental results validate that the proposed method can obtain the less edge artifacts and sharper edges.

1. Introduction

High resolution (HR) images are needed in many practical applications, such as medical image analysis, computer vision, remote sensing and so on. The direct way to get the HR images is to increase the number of pixels per unit area or reduce the pixel size by sensor manufacturing techniques [23]. However, these methods are constrained by the physical limitations of imaging systems [16]. In order to overcome the physical limitations, various single image super resolution (SISR) methods have been proposed to obtain the HR image from its low resolution (LR) observation.

The classical SISR methods can be mainly divided into three categories: the interpolation based methods [13] and [18], the reconstruction based methods [3] and [11] and the example based methods [12] and [6]. Although the interpolation based methods are easy to perform, the reconstructed HR images tend to be blurry with jagged artifacts and ringing. The reconstruction based methods can introduce some prior knowledge into the reconstruction process, but the HR results may be over smoothing or lacking some important details because of a large magnification factor or failing to model the visual complexity of the real image. In this paper, we focus on the example based methods because these methods are of stronger capability of SISR as the magnification factor becomes larger and are able to obtain the HR image which fuses the high-frequency information from all the example HR images and the LR images.

The example based methods [12] and [6], which assume that the high-frequency details lost in LR image can be obtained by learning the relationship between a set of LR example patches and their corresponding HR patches, have become an active area

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of research. Freeman et al. [12] proposed the example based method to obtain the HR image by employing the pairs of LR and HR patches directly in a Markov network. Chang et al. [6] further proposed a neighbor embedding based method with the assumption that the LR image and its corresponding HR vision have similar local geometry. To improve neighbor embedding based method, other neighbor embedding based methods have been proposed in [4] and [5]. Nevertheless, the effect of these methods mainly depends on a large supporting image database [31]. Recently, to alleviate this weakness, Yang et al. [31] proposed the sparse representation based SISR method which generally consists of the code stage and the linear combination stage. In this work, the joint dictionary training framework is first proposed for training the couple HR and LR dictionaries. Under this framework, Zeyde et al. [32] introduced the sparse-land model into sparse representation for better SISR results. In order to preserve the difference between image patch contents, Yang et al. [27] and [29] employed the cluster technology to learn multiple dictionaries in the code stage. Except for the sparse prior [27,29,31,32] and [19], other image priors, such as the structural similarity [22] and [28], the nonlocal self-similarity [8–10,17,30] and [34], are studied in the code stage. In order to improve the stability of the recovery results, [15] and [24] proposed the coefficient mapping methods, [20,26] and [35] attempted to capture more image information, such as edges and texture, in the code stage. A drawback of the above mentioned methods is that they fail to consider the edge constraint information of image in the linear combination stage. Thus the reconstructed image has unwanted edge artifacts and unsharp edges.

Recently, local rank transform, as a useful tool for describing the data distribution characteristics, is usually used in statistical analysis [7], object detection [14], image denoising [1] and stereo matching [2]. In this paper, considering that local rank can extract better edge information and is insensitive to noise than other edge operator [21], we develop the local rank edge constraint and introduce it into the linear combination stage for SISR task. By combining this edge constraint and the sparse representation, we propose a new SISR method, which can better reconstruct HR image with less edge artifacts and sharp edges. First, the local rank edge information of the HR image is learned by the sparse representation model, and then it is used as the edge constraint to restrict the image edges during the linear combination stage. Second, we propose a nonlocal and global optimization model to further improve the image quality. The contributions of this paper can be summarized as follows:

1) We classify the training image patches into different patterns to learn the local rank of HR image.
2) We constrain the local rank of the HR image patch as close as possible to the reconstructed local rank by the energy minimization model to reconstruct the HR image.
3) We propose a new weight calculation method for non-local self-similarity in the nonlocal and global optimization model.

The rest of this paper is organized as follows. In Section 2, we give a brief overview of the sparse representation based single image super resolution and local rank transform. The proposed method is presented in Section 3. Experimental results are provided in Section 4. Section 5 concludes this paper.

2. Brief overview of sparse representation based SISR and local rank transform

2.1. Sparse representation for SISR

The LR image can be seen as a blurred and down-sampled version of the HR image. This observation model can be formulated as follows:

$$Y = SHX + E, \tag{1}$$

where Y represents the LR image, S is the down-sampling operator, H is the blurring filter, E is the noise and X is the HR image. Since there are many HR images satisfying the reconstruction constraint for a given LR image, the process of recovering X from Y is ill-posed. An effective way to deal with this problem is sparse representation.

Sparse representation has become an important tool for single image super resolution. The SISR problem via sparse representation consists of the code stage and the linear combination stage. The code stage is formulated as follows:

$$\min_{\alpha} \left\{ \left\| \tilde{y} - \tilde{D}\alpha \right\|_2^2 + \lambda \|\alpha\|_1 \right\}, \tag{2}$$

where $\tilde{y} = [\begin{smallmatrix} Fy \\ \beta w \end{smallmatrix}]$ and $\tilde{D} = [\begin{smallmatrix} FD_l \\ \beta PD_h \end{smallmatrix}]$, D_h and D_l are HR dictionary and LR dictionary respectively, F is a feature extraction operator, y is the input LR image patch, P extracts the region of overlap between the current target patch and previously reconstructed image patch, α is the sparse coefficients matrix and w contains the values of the previously reconstructed HR image on the overlap. The parameter β controls the tradeoff between matching the LR input and finding a HR patch that is compatible with its neighbors.

In the linear combination stage, the ith image patch vector $x_i \in \mathbb{R}^n$, which is extracted from the HR image X, can be represented as a sparse linear combination in the HR dictionary $D_h \in \mathbb{R}^{n\times K}$:

$$x_i \approx D_h\alpha_i, \quad \alpha_i \in \mathbb{R}^K, \ \|\alpha_i\|_0 \ll K, \tag{3}$$

where α_i is the sparse coefficient vector which is computed by the input LR image patch and the LR dictionary.

2.2. Local rank transform

Let x be an element of set S, the rank of x with respect to S is defined as the number of elements less than x: $lr(x) = r(x; S)$. The local rank of S is: $LRT(S) = \{r(x; N(x)) | x \in S\}$, where $N(x)$ is the neighborhood of x.