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Single image super resolution based on sparse domain selection

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ABSTRACT

Single image super-resolution (SR) aims to form a high-resolution (HR) image from an input low-resolution (LR) image. The sparse coding-based example learning methods typically assume that the low-resolution and high-resolution features share the same representation coefficients over their own dictionaries. The assumption is a strong constraint which limits the flexibility to model the complexity of feature space and the mapping among them. To solve the problem, this paper proposes a novel single image super-resolution method utilizing sparse domain selection. In the training phase, the efficient mapping between LR and HR coefficients is established by searching the sparse domain among feature spaces spanned by LR–HR dictionaries. Then this mapping and learning HR dictionary are optimized jointly through minimizing the sparse representation error and sparse domain mapping error. During the reconstruction phase, the learned mapping from the input LR feature is applied to the desired HR feature to achieve accurate and stable SR recovery. Experimental results indicate that the proposed approach is more capable of modeling the relationships from feature of LR to those of HR, thus improves the quality of reconstruction image.

1. Introduction

Single image super-resolution (SR) aims to restore a visually pleasing high-resolution (HR) image from a single low-resolution (LR) input. Existing single image SR methods can be divided into three categories: interpolation-based [1,2] methods, reconstruction-based [3–7] methods and example learning-based [8–12] methods. Interpolation-based methods are simple, fast, and can be parallelized computing. Instead of using interpolation based techniques which are taken for granted by exiting methods, Wang and Yuan [13] propose an expansion model learned from a set of training images. Although these methods are efficient for real-time applications, the quality of the reconstructed images is unsatisfactory in many cases. Reconstruction-based methods use priori to solve the problem. They can reconstruct the high frequency texture and suppress false contours, but the results are not satisfactory in a higher magnification. Example learning-based methods apply machine learning theory to solve the image super-resolution problem. Wang and Li [14] explore the definition of energy function from another aspect, matrix decomposition of low-rank representation. The energy function for resizing is then inferred from the sparse one. Wang and Yuan [15] propose a novel learning based method for seam carving by incorporating the learned boundary of the important content and the region of interest (ROI) is learned on a set of training images at first. Thus, the desirable regions can be preserved in the target image and the structural consistency of the input image is naturally maintained. The algorithm is usually divided into training phase and reconstruction phase. In training phase, the methods learn the mapping model from LR images to corresponding HR images on the training dataset, and apply the model in the LR images as input in the reconstruction phase. The characteristics of nearly all the example learning-based methods can be summarized into three key aspects: (i) an efficient representation of image features for reconstruction, (ii) compactly as well as adaptively built LR and HR dictionaries, and (iii) an accurate mapping from LR feature space to HR one, which can reveal the underlying relationship between them. Typical example learning-based methods differ in one or more aspects above. The example learning-based method usually can be categorized into two types: regression-based and sparse coding-based methods. The regression-based methods directly establish mapping models between LR image and its corresponding HR image. Ridge regression based methods [16] utilize the nearest neighbors which were calculated by the correlation with the dictionary atoms rather than the Euclidean distance. Support vector regression (SVR) [25,26,27] based methods [17] use the optimal kernel to find the relationship between LR and HR images by formulating the kernel problem as a convex optimization. Neural network based methods

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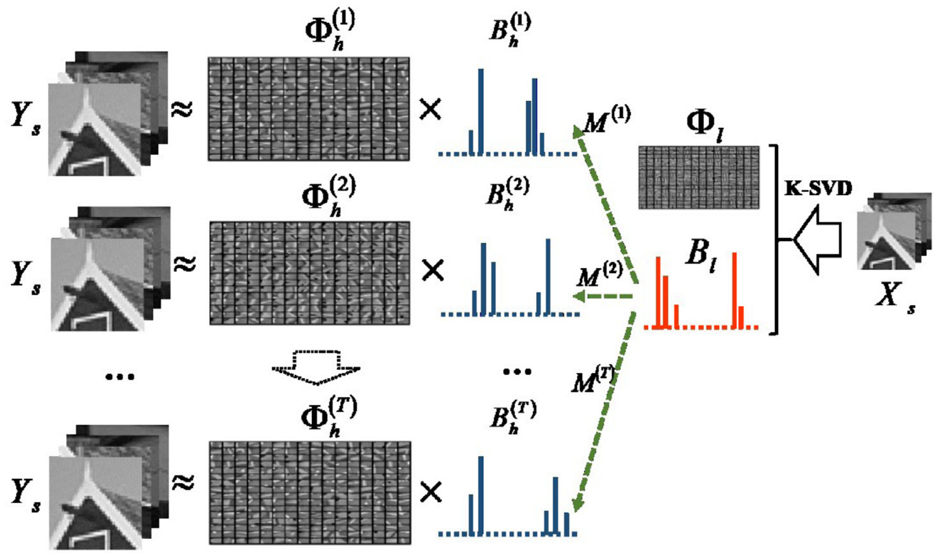

Fig. 1. Training phase of sparse domain selection based method.

[18] consider the mapping as a deep convolution neural network (CNN) and obtained great reconstruction quality.

In learning-based methods, we are concerned about the sparse coding-based example learning methods, which utilize the concept of neighborhood or dictionary, establish the mapping model between LR feature and corresponding HR feature. In particular, Chang et al. [9] assume that small image patches in the LR and HR images form manifolds with similar local geometry in two distinct feature spaces. Because of using fixed K neighbors for SR reconstruction, these methods [9,19] often result in blurring effects. As natural image patches could be sparsely represented by an over-complete dictionary of atoms. Yang et al. [10] improve the SR reconstruction efficiency by jointly learning a compact LR–HR dictionary pair for sparse reconstruction. They make the same assumption as Chang's method that LR–HR feature spaces share the same coefficients regarding to their nearest neighbors or jointly learned dictionaries. Huang and Wang [20] use dual learning method to mapping and reconstruction on the public feature space, which significantly improve the quality of reconstruction image by the statistics of natural images priori knowledge and self-similarity of image. Zeyde et al. [11] improve SR efficiency utilizing principal component analysis (PCA) dimensionality reduction and orthogonal matching pursuit (OMP) [12] for sparse representation. Wang et al. [19] propose a semi-coupled dictionary learning (SCDL) model to solve the SR reconstruction problem. In SCDL, not fully coupled dictionary integrated with the relaxation of “same sparse representation” gives the cross-style mapping more flexibility. Nevertheless, in accordance with the object function of SCDL, there will be information exchange between two learned dictionaries in the training stage, which results in jaggy textures in reconstructed image. These methods above usually assume that the LR and HR features share the same representation coefficients over their own dictionaries. This assumption limits the flexibility and accuracy for complex mapping modeling to a certain extent, resulting in ringing effect and artifacts on the edge of reconstruction image.

To solve this problem, we propose a sparse domain selection (SDS) based single image super-resolution method, assuming that LR feature and the corresponding HR feature have specific coefficient mapping relationship over their own dictionary. By learning the mapping model between LR features and HR features, we obtain a more accurate relationship and then get a better reconstruction quality.

The remainder of this paper is organized as follows: Section 2 presents our SDS-based SR algorithm. And the experimental results are described in Section 3. Finally, we conclude our paper in Section 4.

2. Sparse domain selection based SR recovery

As we know that sparse domain has been taken as a pleasing image modeling technique, and natural images are intrinsically sparse in some domains. Sparse property also is one of the important visual perceptual characteristics. Hence, this paper utilizes the sparse domain as the feature representation space. In this section, we first describe the problem formulation of sparse domain selection after constructing LR–HR feature spaces for training. Then optimization details are presented for the proposed model. Finally, we present how to restore a desired HR output during reconstruction phase. Our algorithm has the same framework with learning-based method, which is divided into training phase and reconstruction phase.

2.1. Training phase

The training phase is described in Fig. 1. We first extract features of LR–HR training pairs. In order to improve learning efficiency, PCA is used to reduce the dimensionalities of each space. LR and HR dictionaries are learned separately in the proposed scheme to improve both the flexibility of learned mapping and accuracy of reconstructed outputs. By applying K-SVD [21] method, we obtain the LR dictionary and sparse coefficients of LR features. The mapping is established by searching the sparse domain among feature spaces spanned by LR and HR dictionaries. Then we alternately optimize learning HR dictionary and mapping. The feasible domain where we pursue the desired sparse coding coefficient of HR feature space is noted as sparse domain in the paper.

2.1.1. Training set construction

It starts by collecting several images as HR examples that have complex textures and geometry edges. Let $I_Y^S = \{i_Y^1, \ldots, i_Y^p, \ldots, i_Y^{N_S}\}$ be the HR examples, i_Y^p denotes the pth HR image, N_s is the number of HR images. We downsample the HR images by a factor of 3, and then utilize bi-cubic interpolation method to get original size LR images, denoted by $I_X^S = \{i_X^1, \ldots, i_X^p, \ldots, i_X^{N_S}\}$, i_X^p denotes the pth

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