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A NEW IMAGE RESOLUTION TECHNIQUE USING NEIGHBOR EMBEDDING

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***Abstract*:-** Neighbor-embedding-based ((NE) algorithms for super resolution (SR) have carried out two independent processes to synthesize high resolution (HR) image patches. In our paper we propose a sparse Neighbor selection scheme for SR reconstruction We first predetermine a larger number of neighbors as potential candidates and develop an extended Robust-SL0 algorithm to simultaneously find the neighbors and to solve the reconstruction weights. Recognizing that the nearest neighbor (k-NN) for reconstruction should have similar local geometric structures based on clustering, we employ a local statistical feature, namely histograms of oriented gradients (HoG) of low-resolution (LR) image patches, to perform such clustering. By conveying local structural information of HoG in the synthesis stage, the -NN of each LRinput patch is adaptively chosen from their associated subset, which significantly improves the speed of synthesizing the HR image while preserving the quality of reconstruction. Experimental results suggest that the proposed method can achieve competitive

Keywords: Histograms of oriented gradients (HoG),neighbor embedding (NE), sparse representation, super-resolution(SR).

1. INTRODUCTION

Super-resolution is class of techniques which exploits information from successive image frames and/or training images to enhance the resolution of input images. The application of super-resolution includes video/image enhancement, image printing, video surveillance etc

Generally, current super-resolution algorithms can be divided into two categories: reconstruction-based super-resolution algorithms which utilize successive low-resolution (LR) input image frames and recover the high-frequency component of one or several of the input images, and learning-based super-resolution algorithms which infer high resolution (HR) images from input LR images according to a training set of known HR images. Image super-resolution (SR) reconstruction is the process of generating an image at a higher spatial resolution by using one or more low-resolution (LR) inputs from a scene. By super-resolving an LR image, more robust performance can be achieved in many applications such as computer vision, medical imaging, video surveillance, and entertainment .Over more than two decades, many methods for SR reconstruction have been proposed, which can broadly be grouped into three categories: interpolation-based methods , multi image-based methods , and example-learning-based methods. The focus of this paper is the example-learning-based method because methods of this kind exhibit stronger SR capability when a larger magnification ratio(e.g., a factor of more than double) is performed. Example-learning-based SR approaches, also called "image hallucination", assume that high-frequency details lost in an LR image can be predicted from a training data set. There are two main types: coding-based methods and regression-based methods. The coding-based methods first prepare the counterparts or co-occurrence dictionaries of LR–HR image patch pairs for learning. Next, the relation between the LR image patches in the test data set and the training data set is estimated to synthesize the desired HR image patches. The representative works include –nearest neighbors (k -NN) learning methods and sparse coding methods . Proposed an example-learning-based SR method by employing an occurrence relation that the LR–HR image patch pairs share with the same sparse representation with respect to their own dictionaries .Recently, presented a unified image restoration framework by integrating adaptive sparse domain selection and adaptive regularization, which performs well on image denoising, deblurring, and SR reconstruction. By considering both the local sparsity and the nonlocal sparsity constraints, they presented a sparse representation model for image restoration. Another class of methods is the regression-based methods, which directly estimate the HR pixels via a set of learned mapping functions. In this paper, we focus on the NE-based methods .In contrast to , the NE-based SR algorithms can represent more patterns even if a relatively smaller training data set is available and thus show a much stronger generalization ability for a variety of images. Nonetheless, the limitation of the NE-based method is twofold: 1) The LR–HR feature mappings cannot be established well because features in a high-dimensional space cannot be represented perfectly in a low-dimensional space, leading to some ambiguity between LR–HR patch pairs; and 2) the strictly fixed neighborhood size usually ends up with blurring effects, due to over or under-fitting.

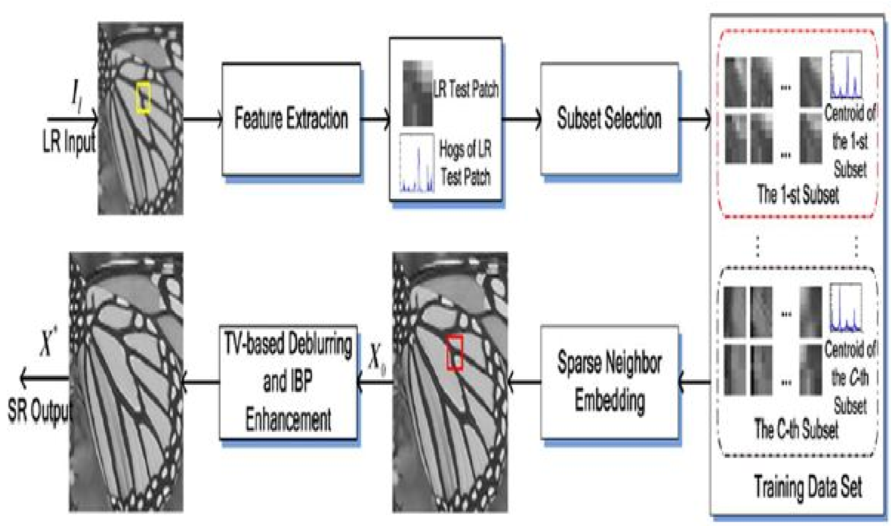

Figure. 1.Reconstruction framework of the proposed method.

The reconstruction framework of the proposed method is illustrated in Fig. 1. As shown, the reconstruction process takes place in the following stages: 1) Both the HoG and the first and second-order gradient features are extracted in a raster-scan order from the up scaled version of the LR input by using the bicubic (BI) interpolation with a factor of 2; 2) subset selection that the HoG feature of each LR input matches the centroids of clusters is performed to find a medium-scale subset close to theLR input for synthesis process; 3) SpNE is applied to synthesize the HR image patch of the LR input, in which searching neighbors and estimating weights are simultaneously conducted; and4) after constructing all the HR patches and obtaining the initial HR image, the total-variation-based (TV) deblurring and the iterative back-projection (IBP) algorithm are sequential performed to obtain the final HR outcome.

2.PROPOSED METHOD

This paper focuses on the NE-based methods. In contrast to, the NE-based SR algorithms can represent more patterns even if a relatively smaller training data set is available and thus show a much stronger generalization ability for a variety of images. The limitation of the NE-based method is twofold:

1. The LR–HR feature mappings cannot be established well because features in a high-dimensional space cannot be represented perfectly in a low-dimensional space, leading to some ambiguity between LR–HR patch pairs.
2. The strictly fixed neighbor hood size usually ends up with blurring effects, due to over- or under-fitting.

NE-based SR methods use the Euclidean distance metric to search a fixed number of neighbours for linear embedding. Due to blurring, down sampling, and noisy data, this simple tactic for neighbour selection cannot perform well for image SR problems because the neighbor search and minimum reconstruction error are separated into two independent processes. Moreover, neighbor search is often manipulated within the whole training data set, leading to a computationally intensive process. To reduce these problems and to further improve the NE-based algorithm for SR reconstruction, we propose a sparse-NE-based (SpNE) method that takes the following factors into account. To target the problems in the NE-based SR algorithm, we first exploit the HoG feature to characterize the local geometric structure of LR image patches and divide the whole training data set into a set of medium-scale subsets to accelerate the SR process. To overcome the limitation of previous NE methods that use the Euclidean distance metric to search neighbours and to improve the quality of reconstruction, we develop a SpNS scheme by using a variation of sparse representation with –norm.

1. Representation of LR Image Patch With HoG

   In order to represent a variety of image patterns, example-learning-based SR methods often collect a large number of samples for learning. The approach is to search the -NN of a given sample within asubset close to the input. To achieve the objective, we can use low-level but efficient features to characterize the local structure of image patches and perform clustering on them.

We choose HoG rather than other low-level features, such as pixel intensities, gradient information or a combination of both, because pixel intensities exhibit their variance to intensity difference between image patches, whereas gradient features are sensitive to noise.

To extract the HoG, a gradient detection operator is first conducted on the input image in the horizontal and vertical directions. Once achieved, the gradients of each pixel can be represented by a vector, $\bar{p}i = \{dx_{i,} dy_i \}$ where dx_i and dy_i denote the horizontal and vertical derivatives of the pixel point, respectively. For the gradient direction that falls into the range of in the radian form, we can transform it. Next, the discrete directions should be determined. We specify the orientation bins evenly spaced over at intervals of 5 and round the continuous angle of each pixel to a discrete value, i.e., downward or upward. We then take a weighted vote on the discrete direction and accumulate these votes into a set of orientation bins within the 3 3 local spatial regions called "cells". Finally, the number of pixels falling into the same bin is calculated for edge orientation histograms. By linking the edge orientation histograms of each cell in an LR image patch of size 6 6 and by normalizing the patch to the unit -norm, a 144-dimensional HoG feature is constructed.

2. Clustering on HoG

HoG can characterize the local geometry structure of LR image patches well. With HoG, we can segment the image patch pairs in the training data set into a set of subsets. Specifically, all training samples comprise a union of such clusters as follows: where and denote the matrices of the training data set and by stacking the features of LR and HR image patches in column form and represents the number of clusters. Correspondingly, and denote the data matrices consisting of the features of LR and HR image patches in the cluster, respectively. To accomplish clustering, we make use of a version of the standard -means clustering algorithm, which is relatively fast and can successfully partition the training samples into satisfying subsets. We can divide the training data set into the prefix number of clusters by minimizing the inter cluster variance such that where is the mean vector.

3. Sparse Neighborhood Selection

The neighbourhood selection differs from the original NE-based algorithm in that there exists an extra constraint term. To solve this, we can divide the whole index set of into two index sets. We can divide the optimization problem into two parts. The additional term provides a smoother approximation of the minimum. We can use a gradient descent algorithm to obtain the solution vector by decaying with a factor in each iteration. For example-learning-based SR approaches, patch wise synthesis is adopted to estimate all HR patches, and averaging fusion is applied to sequentially merge these estimated HR patches into a whole HR image. However, the local averaging process would result in blurred details and unwanted artifacts. To obtain a local optimal solution of SR, we employ the TV-based regularization for image deblurring and use the IBP algorithm to further enhance the deblurring result by imposing the global reconstruction constraint that the HR image should meet the LR input via the degradation process.

In our experiments, we download the software for from the author's homepage, and 61 HR images are used to prepare our training data set. To mimic the real imaging system, all the training images are blurred by a 9 9 Gaussian filter with standard deviation 1.1 and down sampled by a decimation factor of 3 to produce the corresponding LR training images. Since the human visual system is more sensitive to the luminance channel than the chrominance channels, we transform RGB values into YCbCr color space and only carry out the SR process on this part. We directly magnify the chrominance (Cb and Cr) channels to the desired size with the BI interpolation. For a fair comparison, we use the same feature representation of the LR and HR image patches as .One-hundred-thousand image patches are randomly extracted from the training image pairs to build the training data set. To avoid uninformative image patches affecting the learning efficiency, we exclude the patches whose norms are close to zero from the training data set, which results in 99 918 training pairs being available for learning. To segment the whole training data set into subsets, we perform -means clustering on the HoG feature. As a tradeoff between the processing speed and reconstruction quality, 40 clusters are constructed in all the experiments. In the synthesis phase, all the LR test images are degraded in the same manner as in the training phase. For the methods, only the neighborhood size is determined. In addition to this parameter, the proposed method requires another major parameter to probe the potential neighbors beyond the neighborhood size . We experimentally tune this with . The initial deviation value is set to the double maximum absolute values of the pseudo inverse solution

3. CONCLUSION

In this paper, we have presented an improved NE-based algorithm for image SR reconstruction by combining the sparse neighbor search and subset selection based on HoG clustering. To accelerate the speed of SR reconstruction, we first employ clustering on HoG features to partition the training data set into a set of subsets. Second, to surmount the drawback of the –NN criterion with Euclidean distance metric, we develop a novel neighbor selection scheme by introducing a variation of the Robust-SL0 algorithm. Competitive experimental results validate the efficiency of this scheme. However, one challenging problem that remains is how to establish optimal subsets. This problem can be mitigated by cluster validity analysis to determine a more rational number of subsets. Furthermore, for complicated image structures, such as textural regions, the proposed method does not perform well. In future work, we will further investigate texture similarity. In addition, constructing a more reliable sparse representation model for the SR problem, such as group sparse representation via structural clustering and self-adaptive dictionary learning, is expected to improve the performance of example-learning-based image SR.

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