Neurocomputing 202 (2016) 49–66

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Development of robust neighbor embedding based super-resolution scheme

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ARTICLE INFO

Article history:
Received 3 August 2015
Received in revised form
3 March 2016
Accepted 16 April 2016
Communicated by Jiwen Lu
Available online 6 May 2016

Keywords:
Super-resolution
Histogram matching
Global neighborhood selection
Locally linear embedding
Robust principal component analysis
Robust locally linear embedding

ABSTRACT

In this paper, we propose a robust neighbor embedding super-resolution (RNESR) scheme to generate a super-resolution (SR) image from a single low-resolution (LR) image. It utilizes histogram matching for selection of best training pair of images. This helps to learn co-occurrence prior to high-resolution (HR) image reconstruction. The global neighborhood size is computed from local neighborhood size, which avoids the over-fitting and under-fitting problem during neighbor embedding. Robust locally linear embedding (RLLE) is used in place of locally linear embedding (LLE) to generate HR image. To validate the scheme, exhaustive simulation has been carried out on standard images. Comparative analysis with respect to different measures like peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), and feature similarity index (FSIM) reveals that the RNESR scheme generates high-quality SR image from a LR image as compared to existing schemes.

1. Introduction

Image analysis is an important direction of research in the field of image processing and computer vision. Image resolution plays a significant role during image analysis. The higher the resolution of an image, the more accurate is its analysis. However, during image acquisition due to some unfavorable conditions we get a low-resolution (LR) image with loss of information. Hence, achieving high-resolution (HR) image from a low-resolution image becomes a necessity. To our favor, there exists a technique called super-resolution (SR) to achieve HR images from corresponding LR ones. SR uses one or multiple LR images to produce a HR image with high spatial resolution. Due to loss of missing frequency components, there is a possibility of information loss in a SR image during the process of conversion. Hence, the major challenge in SR process is to enhance the quality of the LR image by preserving the missing high-frequency components. The primary task of SR process is to produce an image having alias free, up-sampled, and high spatial frequency from a LR image [1]. Over the past years, the SR algorithms have been extensively used in computer vision applications like remote sensing, astronomical imaging, medical imaging, and video surveillance. SR is broadly divided into two categories namely, reconstruction-based SR and recognition-based SR. Reconstruction-based SR refers to generation of HR image from a degraded LR image through traditional upscaling methods [2]. Recognition-based SR utilizes learning algorithms as it identifies pre-configured patterns hidden in LR images. Hence, recognition based SR is also known as learning based SR and it has been widely used in detection, recognition, and identification.

This paper proposes a robust learning based SR algorithm to generate a HR image from a single LR image. The scheme utilizes neighbor embedding approach and suitably named as robust neighbor embedding based super-resolution (RNESR). RNESR is trained using known LR–HR image pairs to generate the information with respect to local geometry and neighborhood. Further, it uses histogram matching to select the best LR–HR image pairs for training. Subsequently, the scheme is validated using LR images selected from training pairs as well as images not used during training to generate their corresponding HR image. The proposed RNESR scheme is simulated along with other competent schemes are also simulated, and results are compared with respect to peak signal-to-noise ratio (PSNR), structural similarity index (SSIM) [3], and feature similarity index (FSIM) [4]. It is observed that RNESR scheme outperforms others with respect to qualitative and quantitative parameters.

The rest of the paper is organized as follows. Section 2 presents the related work. The proposed RNESR algorithm is described detail in Section 3. The experimental results and discussion are

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http://dx.doi.org/10.1016/j.neucom.2016.04.013
0925-2312/

presented in Section 4. Finally, Section 5 deals with the concluding remarks.

2. Related work

Existing single image SR approaches can be classified into two general classes, including frequency-domain methods and spatial-domain methods. Furthermore, the spatial domain-based approaches can be classified into three categories containing interpolation-based methods [5,6], reconstruction-based techniques [7,8], and learning-based approach. The proposed scheme is based on learning based scheme. An exhaustive literature on learning based approaches discussed below. Basically, the learning based SR can be categorized into two categories comprising example-based and sparse representation based. The goal of learning based SR is to generate a mapping relationship between HR and LR image patches by learning the co-occurrence prior. Numerous learning based algorithms have been recently proposed for single image SR with different evaluation criteria.

2.1. Example-based SR

In one of the pioneer works, Freeman et al. [9] have introduced an approach to learn the relationship between LR patches and its corresponding HR counterparts using Markov random field model and loopy belief propagation (EBSR). However, due to incompatibility between the predicted HR patches and its neighboring patches the yielded results are not stable and pleasant. Later on, a number of neighbors embedding based SR [10–13] techniques have been proposed to eradicate this problem. Chang et al. [10] have used first order and second order luminance gradient features and manifold learning scheme for HR image generation (SRNE). The training patch generation being uniform, do not generalize the output image formation. Fan and Yeung [14] have proposed a neighbor embedding based SR, where training patches based on primitive edge information is used (NEVPM). In addition, the residual errors have been associated with the reconstructed image to compensate the information loss during the local averaging. Chan and Zhang [15] have used histogram selection for better training set generation and enhanced the SR process by edge based features. Chan et al. [11] have proposed a novel feature selection for neighbor embedding SR to preserve edges and used phase congruency to generate edge training patches (NeedFS). Zhang et al. [16] have introduced an example-based SR using clustering and partially supervised neighbor embedding to enhance the quality of complicated texture structure in the image. Guo et al. [17] have presented fields of experts (FoE) model to combine both global and local constraints. They have used a statistical learning approach called maximum a posteriori (MAP) estimation to combine the global parametric constraint with a patch-based local non-parametric constraint. Gao et al. [18] have proposed an extended Robust-*SL*0 algorithm to find out the neighbors and an optimal reconstruction weight. They have further proposed a method to project the original HR and LR patch onto the jointly learning unified feature subspace [19]. Bevilacqua et al. [20] have introduced a new algorithm based on external dictionary and non-negative embedding. They have used the iterative back-projection (IBP) to refine the LR image patches and a joint *K*-means clustering (JKC) technique to optimize the dictionary. In addition, they have used ridge regression technique to determine the neighborhoods off-line for precomputed projections to map LR patches with the HR patches. Considering the computational speed, a fast example-based SR technique has been proposed by Timofte et al. [21], where they combine sparse learned dictionaries with neighbor embedding technique. Lu et al. [22] have proposed an approach by incorporating the locally linear embedding (LLE) with the traditional sparse coding objective function to overcome the issues in preserving the local geometric structure. Zhang et al. [23] have employed the learning of multi-scale self-similarities between a LR image and the image itself. In their work, non-local mean method has been used to learn the similarity within the same scale and formulated a non-local prior regularization. The scheme results blurred images due to the fixed number of neighborhood in *k*-nearest neighbor (KNN) search. Zhu et al. [24] have proposed a non-local neighbor embedding based SR to overcome the smoothing problem in the image. They have introduced fields of experts (FoE) features and non-local self-similar constraints to suppress the undesirable artifacts. Li et al. [25] have introduced a neighbor embedding approach using nonlinear mappings and kernel trick. They mapped the original HR and LR into high-dimensional spaces using two non-linear mapping, where the unified feature subspace is generated by linear projection matrices. Chen and Qi [26] have solved the issues of learning and improper estimation of nonlinear high-dimensional feature data. Hence, to obtain the global and local structures of data, they have projected the high dimensional data into kernel principal component analysis (KPCA) subspace and modified locality preserving projection (MLPP) subspace. By this method, they have achieved better performance in neighbor search and embedding weight estimation.

2.2. Sparse representation based SR

In addition to the neighbor embedding based technique, sparsity-based prior and emerging regularization technique has drawn a considerable attention of many researchers recently. Dong et al. [27] have proposed a scheme based on the centralized sparse representation model that estimates representation error using non-local self-similar patches. They have further proposed an approach for image model using low-rank method with simultaneous sparse coding in patch space [28]. This method achieved the strategies of iterative regularization and deterministic annealing for noisy and incomplete data during image restoration. Yang et al. [29] have suggested a sparse representation based SR, where they have adaptively selected the sparse embedding weights when the dictionary is over-complete (SCSR). They have further adopted a dual-geometry neighbor embedding (DGNE) method and explored the geometric structure in both feature and spatial domain to reconstruct the HR image [30]. They have considered multi-view features of the patches. Their spatial neighbors are sparsely coded through a tensor simultaneous orthogonal matching pursuit (OMP) algorithm. Chen and Qi [31] have used low-rank matrix recovery (LRMR) and neighbor embedding method, where weights are amended through low-rank decomposition for better HR patch reconstruction. Jiang et al. [32] have proposed a graph constrained least square regression method using learning projection matrix. They have further suggested a scheme for face image SR using multilayer locality constrained iterative neighbor embedding [33]. Li et al. [34] have introduced a dual-sparsity regularized sparse representation (DSRSR) approach, where the row non-local similarity prior to regularization. Sajjad et al. [35] have suggested an image super-resolution using an over-complete dictionary. In their approach, a vector of common sparse representation between LR and corresponding HR image patches have been multiplied with the learned dictionary. The sparse representation based SR needs a large data set to train the dictionary and the cost is computationally high.

A comparison among different example-based schemes is presented in Table 1 with respect to different aspects. From the literature, it is observed that neighbor embedding technique is a promising method for super-resolution. However, locally linear