ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 11, November 2016

Structure-Modulated Sparse Representation to Improve the Performance of Sparsity-Based Image Super-Resolution

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ABSTRACT: The resolution of images is limited by the image acquisition devices, the optics, the hardware storage and other constraints in digital imaging systems. However, high-resolution (HR) images or videos are usually desired for subsequent image processing and analysis in most real applications. As an effective way to solve this problem, super-resolution (SR) techniques aim to reconstruct HR images from the observed LR images. The super-resolution reconstruction increases high-frequency components and removes the undesirable effects, *e.g.*, the resolution degradation, blur and noise. Many SR techniques have been proposed over the last three decades. Early SR studies mainly focus on exploring the shift and aliasing properties of the Fourier transform. Although these approaches are computationally efficient, they have limited abilities to model the complicated image degradation and various image priors. Due to these drawbacks of frequency domain approaches, the spatial domain approaches are very popular recently for their flexibility to model all kinds of image degradations. In this paper, we propose a joint super-resolution framework of structure-modulated sparse representations to improve the performance of sparsity-based image super-resolution. The proposed algorithm formulates the constrained optimization problem for high-resolution image recovery. The multistep magnification scheme with the ridge regression is first used to exploit the multiscale redundancy for the initial estimation of the high-resolution image. Finally, the numerical solution is provided to solve the super-resolution problem of model parameter estimation and sparse representation.

KEYWORDS: Super-resolution, ridge regression, sparse representation, dictionary learning, gradient histogram.

I. INTRODUCTION

Super-resolution imaging (SR) is a class of techniques that enhance the resolution of an imaging system. In most digital imaging applications, high resolution images or videos are usually desired for later image processing and analysis. The desire for high image resolution stems from two principal application areas: improvement of pictorial information for human interpretation; and helping representation for automatic machine perception. Image resolution describes the details contained in an image, the higher the resolution, the more image details. The resolution of a digital image can be classified in many different ways: pixel resolution spatial resolution, spectral resolution, temporal resolution, and radiometric resolution. SR reconstruction has been one of the most active research areas since the seminal work by Tsai and Huang in 1984. Many techniques have been proposed over the last two decades representing approaches from frequency domain to spatial domain, and from signal processing perspective to machine learning perspective. Early works on super-resolution mainly followed the theory by exploring the shift and aliasing properties of the Fourier transform. However, these frequency domain approaches are very restricted in the image observation model they can handle, and real problems are much more complicated. Researchers nowadays most commonly address the problem mainly in the spatial domain, for its flexibility to model all kinds of image degradations.

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II. RELATED WORK

The example learning-based methods exploit the information from training images or example images to learn the mapping between the LR and HR image patches for super-resolution reconstruction. Recently, numerous SR methods have appeared to estimate the relationship between the LR and HR image patches with promising results. Some typical methods usually need a large and representative database of the LR and HR image pairs to encompass various images as much as possible that leads to a heavy computational load in the mapping learning process. Glasner *et al.* implies that if the structural patterns of the input LR image do not appear in a general image database, the mapping learned from the database may not be able to restore the faithful high-frequency details in the HR image. Yang *et al.* employed sparse dictionary learning on the LR and HR image patches from a general image database, and then utilized sparse representations of the LR input to generate the output HR image. Dong *et al.*] proposed a deep learning method that learns an end-to-end mapping between the LR and HR images for single image super-resolution. Michaeli and Irani exploited the inherent recurrence property of small natural image patches to estimate the optimal blur kernel for blind super-resolution. Timofte *et al.* introduced the anchored neighborhood regression (ANR) that learns sparse dictionaries and regressors anchored to the dictionary atoms for fast super-resolution. Subsequently, they proposed an improved variant of ANR that achieves substantially less complexity and better performance. Similarly, Perez-Pellitero *et al.* presented an improved training strategy for SR linear regressors and an inverse-search approach for the speedup of the regression-based SR method. In this paper, we mainly focus on the study of the example learning-based SR methods with multiple image priors for further improvements of single image super-resolution. The optimized example learning-based SR method will build a suitable training set and make full use of image priors to reduce edge halos, blurring and aliasing artifacts effectively.
The task of single image super-resolution is to recover a HR image from an input LR image. For an observed image $\mathbf{y}$, the problem of image super-resolution is generally modeled as $\mathbf{y} = \mathbf{Hx} + \upsilon$.
where the degradation matrix $\mathbf{H}$ is a composite operator of blurring and down-sampling, $\mathbf{x}$ is the original image, and υ is the noise term. In the past decades, many works have been reported on single image super-resolution. Due to the ill-posed nature of the SR inverse problem, the regularization is introduced to eliminate the uncertainty of recovery. Several regularization-based techniques have been extensively studied in the recent literatures. The typical regularization models include the total variation (TV), the nonlocal similarity and the sparsity-based regularization. The TV regularization was introduced in image processing and successfully applied to inverse problems. Since its piecewise constant assumption, the TV regularization tends to over-smooth the images. To recover solutions which have discontinuities or are spatially inhomogeneous, the sparsity-based regularization has appeared and attracted great attention for image super-resolution problems in recent years.

III. EXISTING SYSTEM

In real world scenarios, the low-resolution (LR) images are generally captured in many imaging applications, such as surveillance video, consumer photographs remote sensing, magnetic resonance (MR) imaging and video standard conversion.
The resolution of images is limited by the image acquisition devices, the optics, the hardware storage and other constraints in digital imaging systems. However, high-resolution (HR) images or videos are usually desired for subsequent image processing and analysis in most real applications. As an effective way to solve this problem, super-resolution (SR) techniques aim to reconstruct HR images from the observed LR images. The super-resolution reconstruction increases high-frequency components and removes the undesirable effects, e.g., the resolution degradation, blur and noise. Recently, numerous SR methods have appeared to estimate the relationship between the LR and HR image patches with promising results. Some typical methods usually need a large and representative database of the LR and HR image pairs.

IV. PROPOSED SYSTEM

We propose a novel joint framework of the structure-modulated sparse representation (SMSR) for single image super-resolution. The multi-scale similarity redundancy is investigated and exploited for the initial estimation of the target HR image. The image gradient histogram of a LR input is incorporated as a gradient regularization term of the image sparse representation model. The proposed SMSR algorithm employs the gradient prior and non locally centralized

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sparsity to design the constrained optimization problem for dictionary training and HR image reconstruction. The main contributions of our work can be summarized as follows:
The multi-step magnification scheme with the ridge regression is proposed to initialize the target HR image for the solution of image SR problem;
The novel sparsity-based super-resolution model is proposed with the combination of multiple image priors on the structural self-similarity, the gradient histogram and the nonlocal sparsity;
The gradient histogram preservation (GHP) is theoretically deduced for image SR reconstruction and also incorporated as the regularization term for the sparse modeling of HR image recovery.

V. SYSTEM ARCHITECTURE

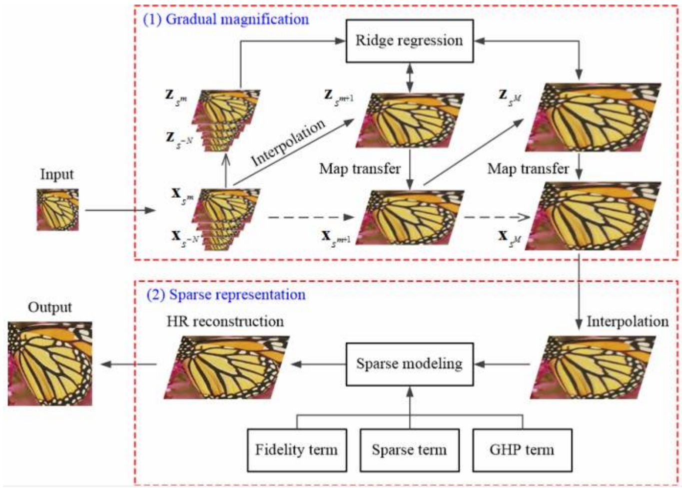

Fig. 1. Overview of the proposed SMSR method.

The subgraphs with the solid boxes denote the specific techniques. The subgraph with the dashed box is the algorithm modules: gradual magnification, and sparse representation.
The flowchart of our proposed SMSR method is shown
in Fig. 1. Given an input LR image, our goal is to produce
a suitable HR image such that its underlying high-frequency details are recovered while preserving the intrinsic geometrical structures of original HR image. In brief, our SMSR algorithm consists of two stages: the gradual magnification and the structured sparse representation.

VI. IMPLEMENTATION

A. PREPROCESSING

Create LR image by down sampling method. Firstly, for an input LR image y, the HR database Dx and its corresponding LR database Dz are separately built for the gradual magnification. Then, the LR image $z_s m$ at the m-th is estimated from the HR image $x_s m-1$.

B. RIDGE REGRESSION

The ridge regression is applied to both each query patch of $z_s m$ and its k_n nearest patches, which are found from the LR database Dz by the approximate nearest-neighbor (ANN) searches. Therefore the corresponding HR image $x_s m$ is reconstructed from the fitted coefficients and its k_n HR nearest patches in the HR database Dx.

C. GRADIENT HISTOGRAM PRESERVATION

An image texture is a set of metrics calculated in image processing designed to quantify the perceived texture of an image. Image texture gives us information about the spatial arrangement of color or intensities in an image or selected region of an image.

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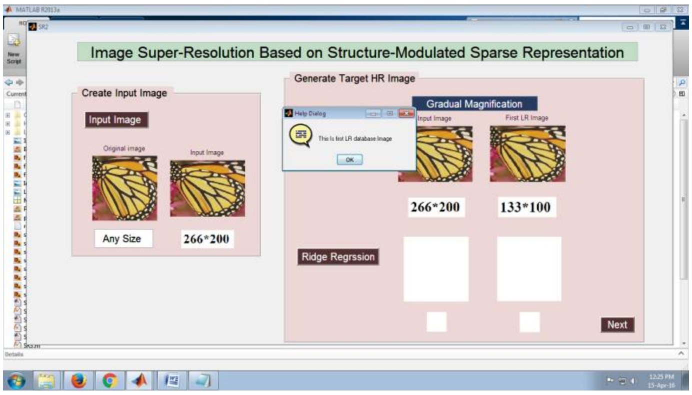
D. GRADIENT HISTOGRAM PRESERVATION (GHP)

A novel gradient histogram preservation (GHP) algorithm is developed to enhance the texture structures. Target HR image enhanced or sharped by gradient histogram preservation.

VII. SIMULATION RESULTS



VIII. CONCLUSION

In this paper, we implemented a method to the single super-resolution difficulty with an SMSR system. Due to the fact that there is abundant similarity redundancy each inside the equal scale and throughout the exclusive scales, the multi-scale magnification scheme with the ridge regression is first used to compute the initial estimation of the target HR snapshot. Then the sparse modeling of single image tremendous-decision is designed with a gradient regularization time period that preserves the gradient histogram of the target HR photograph. One more centralized sparse constraint

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that exploits the snapshot neighborhood and nonlocal redundancy is also integrated to give a boost to the performance of the picture sparse illustration. To approximate the worldwide optimization result, which is nonconvex and hard to resolve straight, an alternating minimization procedure with an iteratively reweighted regularization parameter is used to clear up the constitution-confined optimization predicament of single photo tremendous-decision. The sparse coefficients of the estimated HR photograph are extra corrected via an efficient iterative shrinkage perform. Now we have performed huge experiments on photograph super-resolution and evaluated the results of each the proposed algorithm and the well known SR methods.

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