IJCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Volume-4, Special Issue-3, May 2016 E-ISSN: 2347-2693

Image Super Resolution In View of Sparse Representation

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Available online at: www.ijcseonline.org

Abstract—Sparse representation has attracted it interests in the field of image resolution. On small images with certain constraints the sparsity based methods enforce sparse coding. For the observed low resolution images it has certain limitations on small scale and different scales for image sparse representation. In this paper a joint super resolution framework has been proposed to improve sparsity based image performances. The algorithm proposed here optimizes the problem for high resolution image recovery. Both the ridge regression and the gradient histogram is incorporated to solve the problem.

Keywords— super resolution, ridge regression, sparse representation, gradient histogram.

I. INTRODUCTION

The low resolution images are usually captured in imaging applications like magnetic resonance(MR) imaging , photographs and video standard conversions. The image resolution may be limited by the device acquisition, hardware storage or by the other constraints in digital imaging sequence. To solve this, SR technique reconstructs the HR images from LR images. These undesirable effects are removed and high frequency components are increased. For example the degradation blur and noise in the images are cleared.

Tsai and Huang [2] researched the image super resolution problem. The early studies about SR have limitations of about complicated image degradation and various images. Image priors. The SR approaches [3] have 2 categories based on LR image input. One groups static super resolution classified in frequency domain methods [2], the non-uniform interpolation method, statistical methods [4][5]and Projection onto convex sets(POCS). POCS is good for any constraints or priors incorporation. For POCS solutions are mainly depend on initial values. Other group is dynamic super resolution [6][1], the HR frames that are previously reconstructed are used to estimate new HR frame. Single image super resolution is divided into interpolation based methods, reconstruction based methods and example learning based methods [9].Reconstruction based

Method model incorporate constraints or prior knowledge for a regularized cost functions. To improve the performance of SR images, combinations of multiple image priors are may be beneficial. It recovers the sharp edges also.

To learn mapping between LR and HR images for super resolution reconstruction the example learning based methods are used. Some methods need large database of LR and HR image pairs, which leads to a heavy load in mapping learning process.

The novel joint framework of the structure modulated sparse modulation (SMSR) is used for single image super resolution has been proposed. The image gradient histogram is incorporated has gradient term.

For HR image reconstruction the SMSR algorithm employs the gradient prior problem for dictionary training and reconstruction of HR images

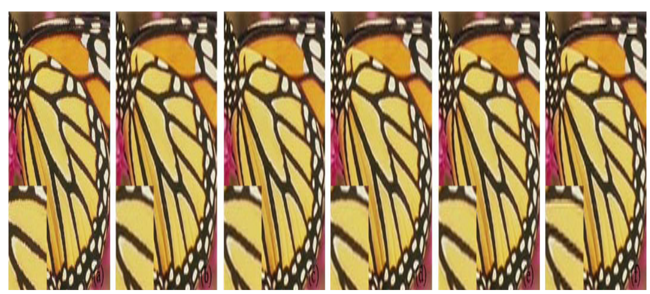

Fig. 1. Visual comparisons of the super-resolution results of the NCSR method with the different interpolations for the *'Butterfly'* image (the scaling factor 3). From left to right: (a) Ground truth, (b) the oracle interpolation, (c) SMSR1,(d) the bicubic interpolation, (e) the bilinear interpolation, and (f) the nearest neighbor interpolation.

II. RELATED WORK

Single image SR is used to recover HR image from a given input LR image. To overcome SR inverse problem, regularization is introduce to eliminate uncertainty. The nonlocal similarity, the total variations(TV)[7] and the sparsity based regularization are the typical regularization models. For inverse problems the TV regularization method was introduced and implemented successfully. Thus it over smooth the images. The sparsity based regularizations attracted image super resolution problems and solves discontinuities which are spatially inhomogeneous factors .

A critical issue dictionary && is present in the sparse representation model. The analytical dictionary and learning dictionary are two categories for dictionary selection. DCT, wavelets, curvelets and counterlets are generally the analytical dictionaries and these are efficient and highly structured. Better characterization of image features and the performance improvements can be obtained from the learning dictionaries.

Sparse coding with adaptive dictionary learning has become the focus for its high efficiency for signal modeling. Kernel ridge regression (KRR) has been adopted by Kim and Kwon. It is used to learn a map from input LR images to target HR images. The coupled dictionaries trained from LR and HR image patch pairs are proposed by the Yang. Dong has proposed adaptive sparse domain selection (ASDS) model for SR image recovery. Further they proposed NCSR model (nonlocally centralized sparse representation) with very high performance. Bicubic interpolation can be seen in NCSR method that has better performance than nearest neighbor interpolation or bilinear interpolation. But in the reconstructed HR images still it undergoes with blurred textures and smooth edges because it ignores geometry constraints and it takes heavy advantage of redundancy. But still the NCSR method has great benefits because this method does not consider gradient histogram preservations in which that improve the super resolution of the image.

III PROPOSED SMSR ALGORITHM

A. Overview of the SMSR model

As shown in below fig.2 the proposed SMSR has an input LR image, main goal is to produce a correct HR image such that its underlying high frequency details are recovered while preserving the intrinsic geometrical structures of original HR image. SMSR algorithm consists of two stages that is gradual magnification and the structured sparse representation.

To generate the initial value the target HR image and the estimated HR image may be blurred and downsampled to achieve the same size of image by bicubic interpolation method.

Next, here we have iteration method to solve the problem of the image sparse representation begins with dictionary learning. Dictionary learning adopts a multi class and multi level training framework which is the same as that of the NCSR method according to the estimated image signal deviation, the reference histogram of gradients is estimated after compute reference histogram of gradients is estimated. After computing the transform function, the HR image is successively updated by the gradient histogram preservation regularization, the data fidelity constraint and the nonlocal means. After that, the HR image is sparsely coded over the trained dictionaries. Each element of the sparse coefficients is further updated with its nonlocal means by the shrinkage operator. The iteration proceeds until the convergence condition is reached. Finally, the target HR image $\mathbf{x}_H$ is reconstructed by gathering the small image patches with the weighted averaging method.

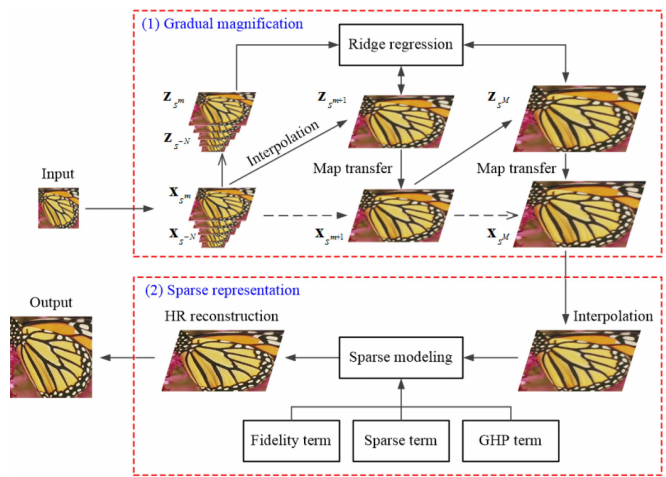

Fig. 2. Overview of the proposed SMSR method. The subgraphs with the solid boxes denote the specific techniques. The subgraph with the dashed box is the algorithm modules: gradual magnification, and sparse representation.

B. Gradual Magnification with Ridge Regression

A LR image available for SR reconstruction, we need to build a training set of the LR and HR image pairs to restore the high-frequency details lost in the LR input. Since there is the self-similarity redundancy both within the same scale and across different scales, the input LR image and its degraded versions can be used to construct the LR and HR image pairs. Considering the different sizes of the LR and HR images, the LR input $\mathbf{y}$ is enlarged to the same size of the HR image $\mathbf{x}$ by the bicubic interpolation, whereas it is also a blurred and downsampled version of the HR image $\mathbf{x}$. Therefore, the correspondence between the LR and HR images at the same scale is established as follows:

$$\mathbf{z} = (\mathbf{y}) \uparrow s = ((\mathbf{x} * \mathbf{G}) \downarrow s) \uparrow s = \mathbf{E}_s\mathbf{x},$$

C. Structured Sparse Representations

1. SR model: image gradients conveying abundant

semantic features are crucial to the subjective visual image quality. Therefore, the histogram of image gradients can be used as a feature descriptor to constrain new image SR model. Besides that the gradual magnification is used as a preprocessing process for structured sparse representation, we propose the gradient histogram preservation regularization for single image SR modeling. That is, the gradient histogram of the reconstructed HR image should be close to that of the original HR image, which is estimated from the given LR image. Fig.3 shows the flowchart of the proposed sparse representation of image SR model.

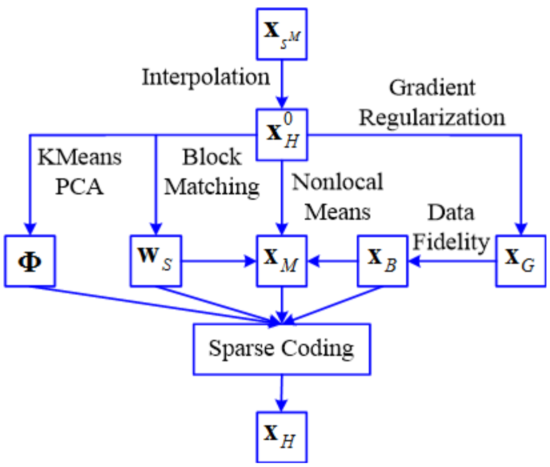

Fig 3.The flowchart of our sparse representation of single image SR model.

2. Reference Histogram of Gradients: To solve the sparse coding problem in (10), we first need to know the reference histogram of gradients that is assumed to be the gradient histogram of the original HR image **x**. As there is only one LR input **y** available, we use the gradient histogram of **y** to infer that of the original HR image **x**. Different from the GHP for image denoising, we have extended the GHP regularization and provided the theoretical deduction for image super-resolution as follows. Let **z** denote the upsampled version of the LR image **y** that has the same size as the HR image **x**. For the observation model of image SR problem.

$$\mathbf{z} = \mathbf{B} * \mathbf{x}, \quad (13)$$

where **B** is a blurring operator. Thus we have

$$\nabla \mathbf{z} = \mathbf{B} * \nabla \mathbf{x} = b_0 \nabla \mathbf{x} + {}_i b_i \nabla \mathbf{x}_i,$$

where b_0 and b_i denotes the center coefficient and its surrounding neighbors of the blur kernel **B**, respectively. Assume that each pixel in the gradient image $\nabla\mathbf{x}$ can be regarded as the value of a scalar random variable. The normalized histogram of $\nabla\mathbf{x}$ is seen as a discrete approximation of the probability density function (PDF) of the random variable x.

3. Numerical Solution: The mentioned above problem of image super-resolution is non-convex and is hard to solve exactly in a reasonable time. In our algorithm, we propose an alternating minimization method to solve the image SR problem in (10) so that the constrained optimization is carried out with some variables fixed in cyclical fashion. First, the multi step magnification scheme is used to enlarge the input LR image **y** to get the HR image $\mathbf{x}_{sM}$ at the M-th scale. Then the initial value of the target HR image is acquired by downsampling $\mathbf{x}_{sM}$ with the bicubic interpolation method. Next, the iterative solution process starts with dictionary learning like that of the NCSR method.

V CONCLUSION

An SMSR method is used as a solution to the single image super resolution problem. Here to compute the initial estimation of target HR image multiscale magnification scheme is used with ridge regression, then with the gradient regularization single image super resolution is designed. Local and nonlocal redundancy has also been incorporated that improves the sparse representation performance. The SMSR algorithm produces sharper edges and suppress aliasing artifacts and outperforms other methods in most cases.

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