ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 8, August 2015

Multi view Neighbour Embedding High Resolution Image Restoration Using Spatial Image Tensors

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ABSTRACT: Neighbors embedding (NE) technology have established its potency in single image super resolution (SISR). However, image patches don't strictly follow the similar structure within the low-resolution and high-resolution areas, consequently resulting in a bias to the image restoration. during this paper, considering that patches area unit a collection of information with multiview characteristics and abstraction organization, we tend to advance a dual-geometric neighbor embedding (DGNE) approach for SISR. In DGNE, multiview options and native abstraction neighbors of patches area unit explored to search out a feature-spatial manifold embedding for pictures. we tend to adopt a geometrically motivated assumption that for every patch there exists a little neighborhood within which solely the patches that come back from a similar feature-spatial manifold can lie or so in an exceedingly low-dimensional affine topological space developed by distributed neighbors. so as to search out the distributed neighbors, a tensor coinciding orthogonal matching pursuit formula is advanced to comprehend a joint distributed committal to writing of feature-spatial image tensors. Some experiments area unit performed on realizing a 3X amplification of natural pictures, and therefore the recovered results prove its potency and superiority to its counterparts.

KEYWORDS: color image; dual-geometric neighbor embedding; a tensor coinciding orthogonal matching pursuit formula; 3X amplification;

I. INTRODUCTION

In the last decade, there have increasing interests in synthesizing a replacement high-resolution (HR) image by victimization one low-resolution (LR) image and a collection of examples, together with k-nearest neighbors synthesis algorithms, distributed committal to writing algorithms, distributed regression algorithms self-similarity learning algorithms and then on. one amongst the representative works is that the Neighbors Embedding (NE) methodology that generates unit of time patches via regionally Linear Embedding (LLE). LLE could be a well-known manifold learning methodology whose goal is to search out a low-dimensional embedding that best preserves the native pure mathematics of information.

Each information is assumed to be linearly delineated by its k nearest neighbors in an exceedingly native region, and therefore the low-dimensional embedding is calculated by the closest neighbors and their weights. In Chang's methodology, the authors assumed that LR patches and unit of time patches type manifolds with similar native pure mathematics in 2 distinct areas. Then LLE is introduced to estimate unit of time patches by weightily combining k candidate unit of time patches designated from the coaching examples. Compare to the normal interpolation-based Single Image Super-Resolution (SISR) approaches, the NE-based SISR methodology and its variants have shown higher generalization capability for a range of pictures.

The preservation of native pure mathematics of information within the embedding area is incredibly difficult for the inherent ill-posed characteristic of SISR. Most of obtainable NE-based SISR strategies believe that victimization first-

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ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

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Vol. 3, Issue 8, August 2015

order and second-order gradients as LR options will higher preserve the native pure mathematics of unit of time patches. However, patches from real-world pictures area unit thus various that patches can be multiple manifolds or subspaces of probably totally different dimensions, and consequently manifolds is also terribly near one another and have capricious dimensions and curvature. Therefore, image patches don't strictly follow the similar structure in an exceedingly single LR feature area and unit of time image area, that results in associate degree inaccurate LLE and a bias to the image restoration.

Depicts the match of manifold structure of image patches within the LR-to-HR mapping.Some works are planned to beat the match of manifold structure of image patches within the LR-to-HR mapping. as an example, paper conferred a projection matrix learning approach to preserve the intrinsic geometric manifold structure of unit of time image patches, by employing a regionally swish constraint as a previous data of reconstruction. Paper planned associate degree improved embedding methodology for face hallucination by incorporating the position previous of face and native pure mathematics of unit of time patch manifold, however it's restricted by the position previous of face, thus it couldn't be directly transferred to natural pictures.

It is documented that the willy-nilly generated image patches area unit thus various that they're going to be multiple manifolds. If the manifolds area unit near one another, like 2 manifolds M1 and money supply in Fig.1, then the k nearest neighbors of a picture patch p belongs to M1, can come back from another manifold, M2. once k nearest neighbors area unit accustomed synthesize the unit of time patch, it'll cause a plain bias to the reconstruction, as a result of solely the neighbors in M1 span a 1D topological space round the patch [28]. Fig.2(a) shows associate degree LR image patch pLR and its 5 neighbors _NB1 LR, . . . NB5 LR_ found by the first-order and second-order gradients in Chang's methodology, and therefore the second line shows the 5 corresponding unit of time patches of the LR neighbors. Fig.2(b) indicates the unit of time image patch and its 5 neighbors _NB1 unit of time, . . . NB5 hormone-replacement therapy found within the unit of time area, to boot, the PSNR by victimization unit of time neighbors from (a) and (b) severally area unit calculated, from that we are able to see that the 5 unit of time neighbors in Fig.2(a) and Fig.2(b) area unit terribly various, that verifies the inconsistency of the manifold structure in associate degree LR-HR mapping.In order to beat this match of manifold structure, several modifications on NE-based SISR strategies are planned, which might be classified into 2 categories.

A. Improved Neighbors Embedding And Neighbor Choice

Su et al. [21] addressed the neighborhood issue in SISR and indicated that the brightness worth will higher reveal the manifold structure of unit of time patches. Fan et al. advanced a good learnt image primitive model by analyzing the native structure in an exceedingly Mid-frequency (MF)-to-High-frequency (HF) mapping. In [23], Chan et al. used feature choice to boost the recovery accuracy of LR patches. In terribly recent works, coupled constraints based mostly joint learning is advanced for higher embedding [16], associate degreed an accommodative distributed embedding is conferred in [24].

B. Existing System:

Compression-then-Encryption (CTE) paradigm meets the wants in several secure transmission eventualities, the order of applying the compression and secret writing must be reversed in another things. because the content owner, Alice is often curious about protective the privacy of the image information through secret writing. however, Alice has no incentive to compress her information, and hence, won't use her restricted procedure resources to run a compression formula before encrypting the info. this is often very true once Alice uses a resource-deprived mobile device. In distinction, the channel supplier Charlie has associate degree predominate interest in press all the network traffic thus on maximize the network utilization. it's thus a lot of desired if the compression task are often delegated by Charlie, World Health Organization usually has overabundant procedure resources.

Disadvantages :

1. the present ETC systems still fall considerably short within the compression performance, compared with the progressive lossless/lossy image and video coders that need unencrypted inputs.

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ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

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Vol. 3, Issue 8, August 2015

2. the first focus of this work is on the sensible style of a try of image secret writing and compression schemes, in such how that press the encrypted pictures is sort of equally economical as press their original, unencrypted counterparts..

II. LITERATURE SURVEY

C. Super-resolution image reconstruction:

A new approach toward increasing abstraction resolution is needed to beat the constraints of the sensors and optics producing technology. One promising approach is to use signal process techniques to get associate degree high-resolution (HR) image (or sequence) from determined multiple low-resolution (LR) pictures. Such a resolution sweetening approach has been one amongst the foremost active analysis areas, and it's referred to as super resolution (SR) (or HR) image reconstruction or just resolution sweetening. during this article, we tend to use the term "SR image reconstruction" to consult with a proof process approach toward resolution sweetening as a result of the term "super" in "super resolution" represents fine the characteristics of the technique overcoming the inherent resolution limitation of LR imaging systems. the main advantage of the signal process approach is that it should price less and therefore the existing LR imaging systems are often still utilised. The SR image reconstruction is established to be helpful in several sensible cases wherever multiple frames of a similar scene are often obtained, together with medical imaging, satellite imaging, and video applications. The goal of this text is to introduce the construct of SR algorithms to readers World Health Organization area unit unacquainted this space and to produce a review for consultants. to the present purpose, we tend to gift the technical review of varied existing SR methodologies that area unit usually utilized. Before presenting the review of existing SR algorithms, we tend to 1st model the LR image acquisition method.

D. Novel Example-Based Methodology For Super-Resolution And Denoising Of Medical Pictures :

In this paper, we tend to propose a unique example-based methodology for denoising and super-resolution of medical pictures. the target is to estimate a high-resolution image from one droning low-resolution image, with the assistance of a given info of high and low-resolution image patch pairs. Denoising and super-resolution during this paper is performed on every image patch. for every given input low-resolution patch, its high-resolution version is calculable supported finding a plus distributed linear illustration of the input patch over the low-resolution patches from the info, wherever the coefficients of the illustration powerfully rely on the similarity between the input patch and therefore the sample patches within the info. downside|the matter} of finding the plus distributed linear illustration is sculpturesque as a plus quadratic programming problem. The planned methodology is particularly helpful for the case of noise-corrupted and low-resolution image. Experimental results show that the planned methodology outperforms alternative progressive super-resolution strategies whereas effectively removing noise.

E. Image Hallucination With Primal Sketch Priors :

We propose a theorem approach to image hallucination. Given a generic low resolution image, we tend to perceive a high resolution image employing a set of coaching pictures. Our work is galvanized by recent progress on natural image statistics that the priors of image primitives are often well delineated by examples. Specifically, primal sketch priors (e.g., edges, ridges and corners) area unit made and accustomed enhance the standard of the hallucinated high resolution image. Moreover, a contour smoothness constraint enforces consistency of primitives within the hallucinated image by a Markov-chain based mostly illation formula. A reconstruction constraint is additionally applied to any improve the standard of the hallucinated image. Experiments demonstrate that our approach will perceive top quality super-resolution pictures.

F. Super-Resolution Through Neighbor Embedding :

In this paper, we tend to propose a unique methodology for determination single-image super-resolution issues. Given a low-resolution image as input, we tend to recover its high-resolution counterpart employing a set of coaching examples. whereas this formulation resembles alternative learning-based strategies for super-resolution, our

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ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

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methodology has been galvanized by recent manifold teaming strategies, notably regionally linear embedding (LLE). Specifically, tiny image patches within the lowand high-resolution pictures type manifolds with similar native pure mathematics in 2 distinct feature areas. As in LLE, native pure mathematics is characterised by however a feature vector such as a patch are often reconstructed by its neighbors within the feature area. Besides victimization the coaching image pairs to estimate the high-resolution embedding, we tend to additionally enforce native compatibility and smoothness constraints between patches within the target high-resolution image through overlapping. Experiments show that our methodology is incredibly versatile and offers smart empirical results.

G. On Single Image Scale-Up Victimization Sparse-Representations:

This paper deals with the one image scale-up downside victimization sparse-representation modeling. The goal is to recover an inspired image from its blurred and down-scaled droning version. Since this downside is extremely ill-posed, a previous is required so as to regularize it. The literature offers numerous ways in which to handle this downside, starting from straightforward linear space-invariant interpolation schemes (e.g., bicubic interpolation), to spatially-adaptive and non-linear filters of varied kinds. we tend to embark from a recently-proposed successful formula by principle et. al. [1,2], and equally assume a neighborhood Sparse-Land model on image patches, serving as regularization. many vital modifications to the above-named resolution area unit introduced, and area unit shown to guide to improved results. These modifications embrace a serious simplification of the general method each in terms of the procedure quality and therefore the formula design, employing a totally different coaching approach for the dictionary-pair, and introducing the power to control while not a training-set by boot-strapping the scale-up task from the given low-resolution image. we tend to demonstrate the results on true pictures, showing each visual and PSNR enhancements.

H. Single-Image Super-Resolution Reconstruction Via Learned Geometric Dictionaries And Clustered Distributed Committal To Writing:

Recently, single image super-resolution reconstruction (SISR) via distributed committal to writing has attracted increasing interest. during this paper, we tend to planned a multiple-geometric-dictionaries-based clustered distributed committal to writing theme for SISR. Firstly, an outsized range of high-resolution (HR) image patches area unit willy-nilly extracted from a collection of example coaching pictures and clustered into many teams of “geometric patches,” from that the corresponding “geometric dictionaries” area unit learned to any sparsely code every native patch in an exceedingly low-resolution image. A cluster aggregation is performed on the unit of time patches recovered by totally different dictionaries, followed by a resulting patch aggregation to estimate the unit of time image. Considering that there area unit usually several repetitive image structures in a picture, we tend to add a self-similarity constraint on the recovered image in patch aggregation to reveal new options and details. Finally, the unit of time residual image is calculable by the planned recovery methodology and paid to higher preserve the refined details of the pictures. Some experiments take a look at the planned methodology on natural pictures, and therefore the results show that the planned methodology outperforms its counterparts in each visual fidelity and numerical measures.

I. Multitask Lexicon Learning And Distributed Illustration Based Mostly Single-Image Super-Resolution Reconstruction:

Recent researches have shown that the distributed illustration based mostly technology will cause state of art super-resolution image reconstruction (SRIR) result. It depends on the concept that the low-resolution (LR) image patches are often considered down sampled version of high-resolution (HR) pictures, whose patches area unit assumed to own a sparser presentation with relation to a lexicon of example patches. so as to avoid an outsized coaching patches info and procure additional correct recovery of unit of time pictures, during this paper we tend to introduce the construct of examples-aided redundant lexicon learning into the single-image super-resolution reconstruction, and propose a multiple dictionaries learning theme galvanized by multitask learning. Compact redundant dictionaries area unit learned from samples classified by K-means cluster so as to produce every sample a additional applicable lexicon for image reconstruction. Compared with the offered SRIR strategies, the planned methodology has the subsequent characteristics: (1) introducing the instance patches-aided lexicon learning within the distributed illustration based mostly SRIR, so as to scale back the intensive computation quality brought by huge lexicon, (2) victimization the multitask learning and previous from unit of time image examples to reconstruct similar unit of time pictures to get higher reconstruction result and (3) adopting the offline dictionaries learning and on-line reconstruction, creating a fast

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 8, August 2015

reconstruction attainable. Some experiments area unit taken on testing the planned methodology on some natural pictures, and therefore the results show that alittle set of willy-nilly chosen raw patches from coaching pictures and little range of atoms will manufacture smart reconstruction result. each the visual result and therefore the numerical tips prove its superiority to some start-of-art SRIR strategies.

J. Joint Learning For Single-Image Super-Resolution Via A Coupled Constraint:

The neighbor-embedding (NE) formula for single-image super-resolution (SR) reconstruction assumes that the feature areas of low-resolution (LR) and high-resolution (HR) patches area unit regionally isometric. However, this is often not true for SR due to one-to-many mappings between LR and unit of time patches. to beat or a minimum of to scale back the matter for NE-based SR reconstruction, we tend to apply a joint learning technique to coach 2 projection matrices at the same time and to map the initial LR and unit of time feature areas onto a unified feature topological space. after, the k -nearest neighbor choice of the input LR image patches is conducted within the unified feature topological space to estimate the reconstruction weights. To handle an outsized range of samples, joint learning regionally exploits a coupled constraint by linking the LR-HR counterparts along side the K-nearest grouping patch pairs. so as to refine any the initial SR estimate, we tend to impose a world reconstruction constraint on the SR outcome supported the most a posteriori framework. Preliminary experiments recommend that the planned formula outperforms NE-related baselines.

III. PROPOSED SYSTEM

To achieve higher compression ratios, lossy compression of encrypted information was additionally studied. Zhang et. Al planned a ascendible lossy committal to writing framework of encrypted pictures via a multi-resolution construction. in an exceedingly compressive sensing (CS) mechanism was utilised to compress encrypted pictures resulted from linear secret writing. A changed basis pursuit formula will then be applied to estimate the initial image from the compressed and encrypted information. Another CS-based approach for encrypting compressed pictures was rumored.

1. extremely economical compression of the encrypted information has then been complete by a context-adaptive arithmetic committal to writing approach.
2. among the planned framework, the image secret writing has been achieved via• prediction error cluster and random permutation.

K. Dual-Geometric Neighbor Embedding (Dgne) With Distributed Tensor:

In this section, we tend to 1st exploit multiview options to improvethe preservation of the neighborhood relationship between LR and unit of time patches. Then the dual-geometric structure is explored within the manifold learning, to formulate a Dual-Geometric Neighbor Embedding (DGNE) via T-SOMP formula, that is mathematically developed very well.

L. Multiview Options:

Each image patch are often properly characterised by multiple visual options, and multiple views area unit gift and complementary to every alternative. A read of patches refers to a sort of feature that summarizes a particular characteristic of the info. for example, Chang's formula utilized the first-order and second-order gradient because the LR options. Su et al.indicated that gradient options couldn't reveal the info structure, whereas the brightness worth of pictures will higher categorical patches structure. Chan et al.proposed a norm feature for characterizing image patches. during this section, a multiview options set of image patches is outlined. For the pel Z33 in an exceedingly 5×5 patch in Fig, the primary set of options consists by first-order gradients:

$$f_1 = \nabla_x = Z_{34} - Z_{32}, \quad f_2 = \nabla_y = Z_{43} - Z_{23} \qquad (1)$$

which describes the variation round the pel in horizontaland vertical severally. The second-order gradients of Z33 area unit outlined as,

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ISSN (Print): 2320-9798

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Vol. 3, Issue 8, August 2015

$$f_3=\nabla_x^2=Z_{35}-2Z_{33}+Z_{31},\quad f_4=\nabla_y^2=Z_{53}-2Z_{33}+Z_{13} \quad (2)$$

which describes the convexo-convex and therefore the dished characteristicaround Z33. to boot, 2 new options area unit outlined, i.e., pel Deviation (PD) and mathematician Gradient (LG) options,

$$f_5 = 9Z_{33} - \sum_{i=2,3,4\, j=2,3,4} Z_{ij},$$
$$f_6 = 4Z_{33} - Z_{43} - Z_{23} - Z_{34} - Z_{32} \quad (3)$$

The two options take the discrepancies of various directionsand characteristics of patches into consideration. that the options will describe the variation of pixels in an exceedingly native window, and therefore the variation on the cross direction severally. The Pd feature will distinguish swish patches from patches with textures and edges, and therefore the LG feature will capture the elaborated data within the horizontal and vertical directions. The filters that extract these multiview options area unit shown in Fig..The options of all the pixels in a picture patch area unit vectorizedto formulate multiple feature vectors fi (i = one, . . . ,6)

M. Background On Distributed Tensor:

In the neighbors embedding, the neighbors choice additionally includes a outstanding influence on the embedding result. within the following section we tend to advance a Tensor-Simultaneous Orthogonal Matching Pursuit (T-SOMP) formula for distributed neighborsselection. thus during this section we tend to 1st build a propaedeutic introduction on distributed tensors. Given a tensor Y ∈ _I1×I2....×IN ,its n-mode vectors area unit obtained by fixing each index however the one within the mode n. The n-mode evolution matrix Y(n) ∈In×I1 I2...In−1 In+1...INis outlined by transcription all the n-mode vectors as columns of a matrix. Then the n-mode product ofa tensor with a matrix Z = Y×nA ∈I1×I2...In−1.×J×In+1...INis outlined by,

$$z_{i_1 i_2 \dots i_{n-1} j i_{n+1} \dots i_N} = \sum_{i_n=1}^{I_n} y_{i_1 i_2 \dots i_N} a_{j i_n} \quad (4)$$

with ik = one, 2, . . . , Ik (k _= n) and j = one, 2, . . . , J ., the authors indicated the link between the Tucker model and a mathematician illustration. Given Y _I1×I2....×'IN , y = vec Y and x = vec X, the subsequent 2 representations area unit equivalent,

$$\underline{\mathbf{Y}} = \underline{\mathbf{X}} \times_1 \mathbf{D}_1 \times_2 \mathbf{D}_2 \dots \times_N \mathbf{D}_N \quad (5)$$
$$\mathbf{y} = (\mathbf{D}_N \otimes \mathbf{D}_{N-1} \otimes \dots \otimes \mathbf{D}_1)\,\mathbf{x} \quad (6)$$

where vec $\underline{\mathbf{Y}} \equiv \mathrm{vec}(\mathbf{Y}_{(1)}) \in \Re^I \left(I = \prod_{n=1}^N I_n\right)$, i.e., by stacking all the 1-mode vectors [30], [31]. supported this equivalence, we are saying that the tensor Y I1×I2....×IN includes a distributed illustration with relation to the n-mode dictionaries $\mathbf{D} = \mathbf{D}^{N} \otimes \mathbf{D}^{N-1} \otimes \cdots \otimes \mathbf{D}^{1}$ If its vectorized version admits a k-sparse illustration over the mathematician lexicon it's constant Tucker illustration with a distributed core tensor X, i.e. with solely k nonzero entries.

N. Dual-Geometric Neighbor Embedding With Distributed Tensor:

Several existing works have indicated that there area unit usually several repetitive image structures (or self-similarity) in a picture, particularly in an exceedingly native region. associate degree example is shown within the Baraba image in Fig., wherever patches in these 2 regions area unit similar. Considering this similarity among the native neighbors, we tend to outline a neighborhood neighborhood of patches and construct a dual-geometric neighbor

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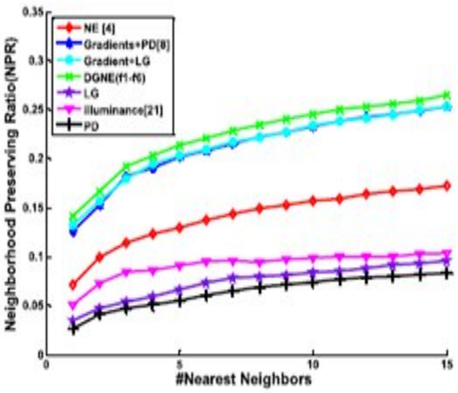
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 8, August 2015

embedding approach for SISR. Assume a √p×√p patch p targeted at the (i, j) –th pel of the initial LR image, and denote the amount of multiview options as R. In our methodology, the multiple options fi (i = one, . . . , 6) of p and its abstraction neighbors area unit at the same time used for locating a distributed embedding.



SUMMARY OF PSNR (dB), SSIM AND FSIM RESULTS OF EIGHT TEST IMAGES FOR 3X MAGNIFICATION BY DIFFERENT METHODS. FOR EACH IMAGE, WE HAVE THREE ROWS: PSNR, SSIM AND FSIM

Image	BI	[4]	[11]	[12]	[7]	[13]	SGNE	DGNE
Butter-fly	23.07	25.06	23.93	25.63	27.08	26.78	26.18	**27.06**
	0.787	0.860	0.819	0.884	0.903	**0.904**	0.881	0.890
	0.780	0.863	0.803	0.846	0.884	**0.885**	0.864	0.863
Parrots	27.21	28.47	28.09	27.73	29.48	**30.01**	29.39	29.98
	0.863	0.882	0.881	0.885	0.906	**0.914**	0.902	0.909
	0.902	0.921	0.917	0.921	0.944	**0.944**	0.935	0.940
Bike	22.16	23.22	22.78	23.13	24.34	24.14	23.93	**24.49**
	0.656	0.715	0.702	0.762	0.784	0.793	0.761	**0.793**
	0.768	0.806	0.798	0.825	0.849	**0.859**	0.837	0.854
Flower	26.66	27.75	27.44	27.37	28.76	**29.05**	28.54	29.01
	0.750	0.794	0.787	0.825	0.838	**0.850**	0.826	0.846
	0.825	0.856	0.852	0.848	0.881	**0.895**	0.881	0.887
Girl	32.08	32.56	32.65	31.57	33.07	33.48	33.20	**33.55**
	0.778	0.789	0.798	0.807	0.817	0.823	0.812	**0.827**
	0.867	0.883	0.889	0.882	0.906	0.917	0.906	**0.919**
Hat	28.59	29.98	29.17	29.14	30.97	30.71	30.51	**30.82**
	0.809	0.839	0.827	0.856	0.873	**0.868**	0.854	0.861
	0.836	0.876	0.858	0.880	0.895	**0.905**	0.894	0.900
Leaves	22.35	24.20	23.36	23.81	25.99	26.05	25.44	**26.09**
	0.754	0.844	0.803	0.877	0.892	**0.903**	0.880	0.892
	0.767	0.860	0.800	0.858	0.883	**0.893**	0.871	0.873
Plants	30.22	31.82	31.03	31.34	32.69	33.14	32.56	**33.23**
	0.842	0.879	0.868	0.885	0.902	**0.911**	0.896	0.909
	0.872	0.907	0.892	0.910	0.919	**0.928**	0.918	0.925
Aver-age	26.54	27.88	27.31	27.46	29.05	29.17	28.72	**29.28**
	0.780	0.825	0.810	0.848	0.864	0.871	0.851	**0.866**
	0.827	0.871	0.851	0.871	0.895	0.903	0.888	**0.895**

In the feature domain, we first choose the closest neighbors subsets {*FNB*1, . . . , *FNBR*} in multiviews space via the Euclidean distance metric. Then these subsets are combined to form a set of candidate neighbors {*FNB* = U*FNBi*} (|*FNB*| = *d)* in the feature domain. Similarly in the spatial domain we select the closest neighbors subsets {*SNB*1, . . . , *SNBR*} for *R* views, and form a set of candidate spatial neighbors {*SNB* = U*SNBi* } (|*SNB*| = *m)* in the feature domain. This feature-spatial manifold can be analyzed via a tensor form of images. In our method, instead of utilizing vector stacking strategy that simply concatenates different feature vectors, a feature-spatial image tensor is constructed. Because manifolds may have arbitrary curvature in different regions, we automatically select a few neighbors for patches via tensor sparse representation.

O. Images Patches have Multiview and Heterogeneous Representations:

It is well known that partial representation of patches only allows finding neighbors in a specific type of LR feature space, where image patches do not strictly follow the similar structure to that of HR patches.. In many real-world scenarios, each object can be described by multiple sets of features, where each feature describes a view of the same set of underlying objects. One feature that summarizes a patch can be considered as a view of the image patch, and finding multiview representation that describes the patch character heterogeneously and integrating them into a unified representation for subsequent processing, is a promising brand in image processing. Therefore, a comprehensive and mutliview representation of patches will help to better reveal the underlying manifold structure. In order to find better embedding manifold, the complementary information of distinct features can be well explored, to reveal different physical meanings and statistical properties of patches.

P. Images Patches Are a Collection of Data With Spatial Organization:

Images patches are not only a set of samples but also data with some spatial organization. Some researchers have indicated that a local area in a natural image can be viewed as a stationary process, which can be well modeled by Autoregressive (AR) models. There are often many repetitive image structures (or self-similarity) in an image. When images are divided into small patches, the patches are self-similar in a local region, that is, an image patch is often similar to its neighbor patches centered around it. Consequently, these similar patches will have the similar neighbors in the manifold embedding and neighbor search. Although this self-similar characteristic has been frequently used in other SISR approches, it is rarely explored in available NE based SISR methods. Summarily, image patches have inherent geometric structure in both the underlying multiview features domain and the spatial domain. In order to find a low-dimensional embedding that well preserves the local geometry of image patches, in this paper we explore this dual-geometric structure in the feature patial domain, to advance a new Dual-Geometric Neighbor Embedding (DGNE) approach for SISR. In DGNE, multiview features and local spatial neighbors of patches are explored to find a feature-spatial manifold embedding for images. We use the geometrically motivated assumption that for each patch there exists

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 8, August 2015

a small neighborhood in which only the patches that come from the same feature-spatial manifold, will lie approximately in a low-dimensional affine subspace.

IV. CONCLUSIONS

In this paper, we propose a novel Dual-Geometric Neighbor Embedding (DGNE) approach by exploring the geometric structure in both the feature domain and spatial domain. Multiview features of image patches and their spatial neighbors are jointly sparsely coded, via a tensor-simultaneous orthogonal matching pursuit algorithm. DGNE is characteristic of simple principle for it does not introduce any additional regularizers in the restoration, which is different with most of the state-of-the-art SISR approaches. Moreover, it is also characteristic of feasible realization for advancing a tensor- SOMP to automatically select embedded neighbors. Some experiments are taken on some benchmark images, and the recovered results indicate that DGNE is comparable to some state-of-the-art SISR approaches without additional regularizers. Moreover, both the multiview feature and local spatial neighbors of patches can help to find more accurate embedding. Too large a spatial neighbor region will degrade the recovery results, while the number of neighbors in the feature domain and the number of maximum iterations in T-SOMP have less influences on the restoration. In DGNE, the degration way of test images is the same with that of training dictionary pairs, which is a limitation of the proposed method. In future work, we will further take more efforts on breaking this limitation and regularizing the recovery process, to achieve accurate amplification of very low-resolution images.

REFERENCES

1. S. C. Park, M. K. Park, and M. G. Kang, "Super-resolution image reconstruction: A technical overview," IEEE Signal Process. Mag., vol. 20, no. 3, pp. 21–36, May 2003.
2. W. T. Freeman, T. R. Jones, and E. C. Pasztor, "Example-based super-resolution," IEEE Comput. Graph. Appl., vol. 22, no. 2, pp. 56–65, Mar./Apr. 2002.
3. J. Sun, N.-N. Zheng, H. Tao, and H.-Y. Shum, "Image hallucination with primal sketch priors," in Proc. IEEE Comput. Soc. Conf. CVPR, Jun. 2003, pp. 729–736.
4. H. Chang, D.-Y. Yeung, and Y. Xiong, "Super-resolution through neighbor embedding," in Proc. IEEE Comput. Soc. Conf. CVPR, Jun./Jul. 2004, pp. 1–6.
5. A. Eftekhari, H. A. Moghaddam, and M. Babaie-Zadeh, "k/K-nearest neighborhood criterion for improving locally linear embedding," in Proc. 6th Int. Conf. CGIV, Aug. 2009, pp. 392–397.
6. K. Zhang, X. Gao, D. Tao, and X. Li, "Single image super-resolution with sparse neighbor embedding," IEEE Trans. Image Process., vol. 21, no. 7, pp. 3194–3205, Jul. 2012.
7. R. Zeyde, M. Elad, and M. Protter, "On single image scale-up using sparse-representations," in Proc. 7th Int. Conf. Curves Surfaces, Jun. 2010, pp. 711–730.
8. J. Yang, J. Wright, T. S. Huang, and Y. Ma, "Image super-resolution via sparse representation," IEEE Trans. Image Process., vol. 19, no. 11, pp. 2861–2873, Nov. 2010.
9. S. Yang, M. Wang, Y. Chen, and Y. Sun, "Single-image super-resolution reconstruction via learned geometric dictionaries and clustered sparse coding," IEEE Trans. Image Process., vol. 21, no. 9, pp. 4016–4028, Sep. 2012.
10. A. Marquinaand and S. J. Osher, "Image super-resolution by TV-regularization and Bregman iteration," J. Sci. Comput., vol. 37, no. 3, pp. 367–382, Dec. 2008.