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Image Super-Resolution based on the Dual-Dictionary Learning and Sparse Representation Method

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***Abstract* — Learning based image super-resolution method is used to reconstruct high-frequency (HF) details from the prior model trained by a set of high-(HR) and low-resolution (LR) image patches. In this paper, newly proposed novel image super-resolution method via dual-dictionary learning and sparse representation, which consists of the main dictionary learning and the residual dictionary learning, to recover MHF and RHF respectively.The experimental results on test images validate that by employing the proposed method, more image details can be recovered and much better results can be achieved than the state-of-the-art algorithms in terms of both PSNR and visual perception.**

***Keywords*—Learning-based, High resolution, Low Resolution, RHF.**

I. INTRODUCTION

Super resolution is the process of recovering a high resolution image than what is afforded by the physical sensor through post processing, making use of one or more low resolution observations [1].Single image super resolution SR means only one observed image is available. Single image super resolution (SR) has been studied in recent years due to its practical uses. Single image SR aims at synthesizing the high resolution (HR) version using the information collected from training image data or from the input low resolution (LR) image itself. These SR approaches are typically referred to as example or learning-based SR methods. In example-based SR approaches, for an input LR image a typical search for its similar patches from training LR image data, and the corresponding HR versions are used to synthesize the final SR output. The learning-based methods aims at modeling the relationship between the images with different resolutions by observing particular image priors, and these models are used to predict the SR output. For example, Yang et al. [2] proposed to learn sparse image representation for SR. In this paper, Yang et al. [3] and Michael Image super-resolution deals with

The problem of reconstructing a high-resolution (HR) image from one or several of its low-resolution (LR) . In this Paper, focus on single image super-resolution, which can be formulated as follows:

Newly proposed a novel image super-resolution method via dual-dictionary learning and sparse representation, which consists of the main dictionary learning and the residual dictionary learning, to recover MHF and RHF respectively.

II. BACKGROUND

Super-resolution image reconstruction is an important digital image processing technique, which can improve the visual effects of images or serve as a pre-processing technique. Because of its impressive reconstruction results, sparse representation based super-resolution image reconstruction has become the focus of recent research. To alleviate the high computational complexity of the traditional sparse representation schemes, this study presents a fast sub-dictionary-based super-resolution reconstruction method. For each small input image block, a sub-dictionary is adaptively selected and thus the high-dimensional redundant dictionary-based sparse representation vector is replaced by a low-dimensional sub-dictionary based representation vector, the computational complexity is therefore reduced. Experimental results estimated that the proposed method can enhance the visual effects of images with a significantly low computational complexity.

III. PREVIOUS WORK

M. Elad. et al [1]. introduced Sparse methods based on an over complete dictionary for solving a number of image analysis problems. This group of methods is generative and models an image by linearly combining a set of dictionary atoms. The generative nature is directly applicable for example image restoration problems like denoising , image compression , inpainting and texture seperation , super-resolution and many more [1]. Some of the attractive properties of the sparse methods are their robustness to noise, closeness to data and simplicity in both implementation and interpretation [1]. Roman Zeyde et al[2]. proposed Single-Image Scale-Up Algorithm. Such work would assume that there is no blur involved, so that the inversion process is purely an interpolation task. Alternatively, if there is a blur, the recovery performance would be measured with respect to the blurred high-resolution image. The rational of such work is that once the image has been scaled-up in the best possible way, a deblurring stage should be used to get the final outcome. The scaled-down images are typically blurred prior to sub-sampling, a separate treatment of the sampling and blur is necessarily suboptimal, compared to a joint treatment, as done .Privious work is done on the image scale up problem, but in the Interpolation scheme, the additive noise in the resulting high-resolution image is remain and off-the-shelf deblurring algorithms may perform poorly. Since this problem is highly ill-posed, a prior is needed in order to regularize it. For solving this problem the Authors proposed the Single-

Image Scale-Up Algorithm. The proposed algorithm performs visually much better than bicubic interpolation. The implementation of the proposed algorithm is much faster (by an order of magnitude) than Yang et. al. implementation, using optimized K-SVD and OMP implementations. The image scale up problem solved by using the proposed algorithm.In previous work the sparse representation models (SRM) have shown promising results in image .superresolution[3]. The SRM based super-resolution has a close relationship with the compressive sensing (CS) theory. Weisheng Dong et al. [3]proposed a nonlocal autoregressive model (NARM) is proposed and taken as the data fidelity term in SRM.The NARM-induced sampling matrix is less coherent with the representation dictionary, and consequently makes SRM more effective for image interpolation method. Author proposed the concept of nonlocal autoregressive model (NARM), which refers to modeling a given pixel as the linear combination of its nonlocal neighboring pixels. The NARM can be viewed as a natural extension of the commonly used autoregressive model, which approximates a pixel as the linear combination of its local neighbors. The NARM method reflects the image self-similarity, and it constrains the image local structure (i.e., the local patch) by using the nonlocal redundancy. For solving the SRM problem Author proposed the new method NRM .The sparse coding models with image. The extensive experimental results demonstrate that the proposed NARM-based image interpolation method can effectively reconstruct the edge structures and suppress the jaggy/ringing artifacts, achieving the best image interpolation results. The proposed NARM-based image interpolation method can effectively reconstruct the edge structures and suppress the jaggy/ringing artifacts, achieving the best image interpolation results. The NARM method may fail to faithfully reconstruct the grass region in image *Cameraman* and the fence region in image *Fence* regions. So future work on that.Adnan Saeed et al[4] proposed knowledge-based regression model (SCPM) to reconstruct a spatially continuous plantar pressure image from a small number of pressure sensors. This model makes use of high resolution pressure data collected clinically to train a per subject regression function. SCPM is shown to outperform all other tested interpolation methods for $K < 60$ sensors, with less than 1/3 of the error for $K = 10$ sensors. According to previous work the sparse placement makes reconstruction of the full plantar pressure image extremely challenging, and because the size, number, and placement of sensors substantially vary from study to study, it is almost impossible to compare research outcomes among studies for solving this problem with a knowledge-based regression model that can reconstruct the plantar pressure distribution from a small number (less than 10) of well-placed pressure sensors. The existing heuristic of placing pressure sensors in key areas works because the anatomical structure of each subject's foot restricts the pressure distribution space. Future work is on determination of the effect of different walking surfaces and styles on model error and finds another solution. Sven Wanner et al [5] proposed a novel local data term tailored to the continuous structure of light field .The proposed method can locally obtain robust results very fast, without having to quantize the disparity space into discrete disparity values. The local results can further be integrated into globally consistent depth maps using state-of-the-art labeling schemes based on convex relaxation methods. In this way, Author obtains an accurate geometry estimate with sub pixel precision matching, which can leverage to simultaneously address the problems of spatial and angular super-resolution. Following state-of-the-art spatial super resolution research in computer vision Author formulate a variation inverse problem whose solution is the synthesized super-resolved (SR) novel view. As Authors work in a continuous setting and for the first time correctly .Take into account foreshortening effects caused by the scene geometry. All optimization problems are solved with state-of-the-art convex relaxation techniques. The proposed approach does not use the full 4D light field information around a ray to obtain the local Estimate only work on two different 2D cuts through this space. Future working is on the Experiments on new benchmark data sets tailored to the light field paradigm show state-of-the-art results, which surpass a traditional stereo-based method in both accuracy as well as speed.

IV. EXISTING METHODOLOGY

The discriminative Image Patches method is based on a dictionary of image patches, which denote dictionary atoms. To each atom associate a label atom that used for building the segmentation image. The procedure for building the dictionary is illustrated in Figure 1 and the segmentation procedure is shown in Figure 2. Basically the segmentation is performed by finding the nearest dictionary atom to an image patch. The associated label atom is used for inferring the label probability to the image region covered by the image patch. Patches are overlapping so several label atoms are added to the same pixel. A good dictionary is characterized by modeling the image patches well and containing atoms that are unique for a given texture. There is a different line of work on the image scale-up problem that strive to separate the treatment of the deblurring and the up-sampling problems [2]. Such work would assume that there is no blur involved, so that the inversion process is purely an interpolation task. Alternatively, if there is a blur, the recovery of such method work performance would be measured with respect to the blurred high-resolution image. The scaled-down images are typically blurred prior to sub-sampling, a separate treatment of the sampling and blur is necessarily suboptimal, compared to a joint treatment in the previous work. After whatever interpolation method, the additive noise in the resulting high-resolution image cannot be assumed as homogeneous, implying that off-the-shelf deploring algorithms may perform poorly.In order to avoid the complexities caused by the different resolutions between $\mathbf{z}l$ and $\mathbf{y}h$, and in order to simplify the overall recovery algorithm, it is assumed after that the image $\mathbf{z}l$ is scaled-up by a simple interpolation operator $\mathbf{Q} : R^{Nl} \rightarrow R^{Nh}$ (e.g. bicubic interpolation) that fills-in the missing rows/columns, returning to the size of $\mathbf{y}h$. This decision will not badly influence the computational

complexity of the algorithm, and in fact, the eventual scale-up algorithm proposed is much faster than the one proposed method .The scaled-up image shall be denoted by $\mathbf{y}l$ and it satisfiesthe relation$\mathbf{y}l = \mathbf{Qz}l = \mathbf{Q}(\mathbf{SHy}h + \mathbf{v}) = \mathbf{QSHy}h + \mathbf{Qv} = \mathbf{L}all\mathbf{y}h + \tilde{\mathbf{v}}$. (2) The goal is to process $\mathbf{y}l \in R^{Nh}$ and produce a result $\hat{\mathbf{y}}h \in R^{Nh}$, which will get as close as possible to the original high-resolution image, $\mathbf{y}h \in R^{Nh}$. Author proposed method operates on patches extracted from $\mathbf{y}l$, aiming to estimate the corresponding patch from $\mathbf{y}h$. Let $\mathbf{p}k\,h = \mathbf{R}k\mathbf{y}h \in R^{n}$ be a high resolution image patch of size$\sqrt{n} \times \sqrt{n}$, extracted by the operator $\mathbf{R}k : R^{Nh} \rightarrow R^{n}$ from the image $\mathbf{y}h$ in location k. It is assumed that the locations to consider$\{k\}$ are only those centered around true pixels in the low-resolution image $\mathbf{y}l$(as opposed to filled-in pixels due to the interpolation). This set of samples is referred to hereafter as the set Ω.A nonlocal autoregressive model (NARM) is proposed and taken as the data fidelity term in SRM [3]. The NARM-induced sampling matrix is less coherent with the representation dictionary, and consequently makes SRM more effective for image interpolation. Author proposed the concept of nonlocal autoregressive model (NARM), which refers to modeling a given pixel as the linear combination of its nonlocal neighboring pixels. The NARM can be viewed as a natural extension of the commonly used autoregressive model, which approximates a pixel as the linear combination of its local neighbors. The NARM reflects the image self-

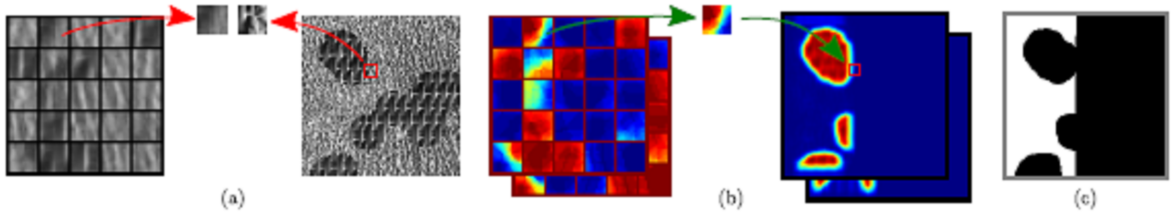

Fig.1 Method illustration of the construction of the dictionary. (a) is the intensity dictionary and (b) is the label dictionary[1].

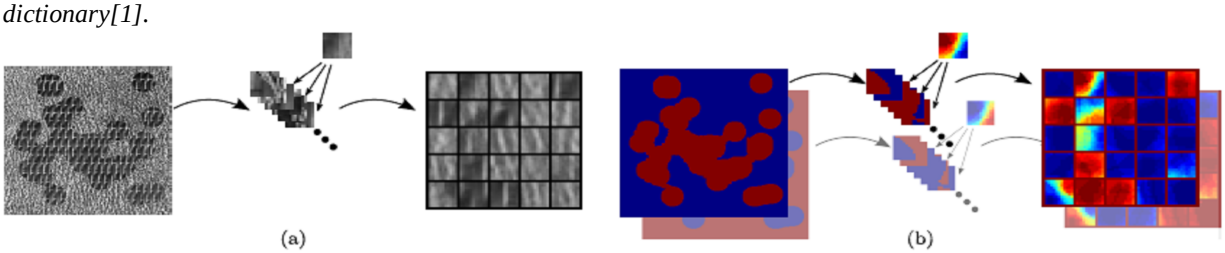

Fig.2 Method illustration of the labeling. In (a) an image patch is extracted and the most similar dictionary atom is found. In (b) the corresponding label atom is added to the label probability image in a window covering the same spatial area as in the intensity image.(c) is found as the label image with the highest energy (the black and white part)[1]

similarity, and it constrains the image local structure (i.e., the local patch) by using the nonlocal redundancy. On the other hand, the NARM can act as a kernel, and can be embedded into the data fidelity term of the conventional SRM model. This shows that the embedding of NARM kernels makes the sampling matrix more incoherent with the dictionary , which consequently enhances the effectiveness of SRM in image reconstruction according to the CS theory.By introducing and embedding NARM into SRM, the image interpolation problem can be generalized to the conventional SRM based image restoration problem. In addition to the sparsely prior of representation coefficients, also assume that the nonlocal similar patches have similar coding coefficients. This further improves much the stability and accuracy of sparse coding. The variable splitting and Augmented Lagrange Multiplier (ALM) techniques are adopted to effectively solve the proposed NARM based SRM model. Our experimental results on benchmark test images clearly demonstrate that the proposed NARM method outperforms much the classical bi-cubic interpolator the representative edge-guided interpolators and the recently developed SRM based image interpolation methods in term of PSNR, SSIM and FSIM measures, as well as visual perception quality

The proposed method of the knowledge-based regression model [4] that can reconstruct the plantar pressure distribution from a small number (less than 10) of well-placed pressure sensors. Regression model, the Sparse-sensing Continuous plantar Pressure Model (SCPM), is trained from a small set of high-resolution plantar pressure data taken from the subject walking. The trained regression model can then reconstruct a full plantar-pressure image from a small number of sensors at arbitrary, but known locations. The locations do not need to be chosen ahead of time, conferring on this system natural fault tolerance.

The variation inverse problem is based on the synthesized super-resolved (SR) novels view[5] .The proposed method can locally obtain robust results very fast, without having to quantize the disparity space into discrete disparity values. The local results can further be integrated into globally consistent depth maps using state-of-the-art labeling schemes based on convex relaxation methods.

V. Analysis And Discussion

A good dictionary is characterized by modeling the image patches well and containing atoms that are unique for a given texture. The image patched method provides the flexibility and robustness to noise. The Sparse representation model algorithm performs visually much better than bicubic interpolation. and the implementation of the proposed algorithm is much faster (by an order of magnitude) than Yang et. al. implementation, using optimized K-SVD and OMP implementations. This algorithm produces less visual artifacts compared with bicubic interpolation. The NARM proposed method to the luminance channel since human visual system is more sensitive to luminance changes, and apply the bicubic interpolator to chromatic channels. To evaluate the quality of interpolated images, the PSNR and two perceptual quality metrics SSIM and FSIM are computed to compare the competing interpolation algorithms. For color images, Author only report the PSNR, SSIM and FSIM measures for the luminance channel. Knowledge-based regression model (SCPM) to reconstruct a spatially continuous plantar pressure image from a small number of pressure sensors. Location of pressure sensors. Rnd, Pk, and GC stand for sensor locations randomly scattered, on peak pressures, and on Gaussian centers. SCPM has the potential to become an important tool bridging medical need and technological capability and can ultimately improve the quality of life for many people suffering from foot problems. SCPM Model has some error such as per-frame basis, Gaussian parameters change with amplitude.

VI. Proposed Methodology

The proposed method based on the dual-Dictionary learning and sparse representation method.The proposed method consist of a two stage

i)Dictionary learning stage

ii)Image synthesis stage

The dictionary learning stage that trains dual dictionaries,namely main dictionary(MD) and residual dictionary(RD) as described in fig.1 and image synthesis stage as described in fig.2

set of patches extracted from the high resolution image *HHF* directly, and $\mathbf{p}_l^k$ mean those patches

built by first extracting patches from filtered images obtained by filtering *HLF* with certain high-pass filters egg Laplacian high-pass filters, and then reducing the dimensions by Principal Component Analysis (PCA) algorithm.

3) Next, the K-SVD dictionary training methods is applied to the set of patches $\mathbf{p}_l^k$ .Finally, the residual dictionary method will be trained in the following steps.

i) With the main dictionary and *HLF*, the HR main high-frequency image denoted by *HMHF* is form By virtue of image reconstruction m ethod which will be

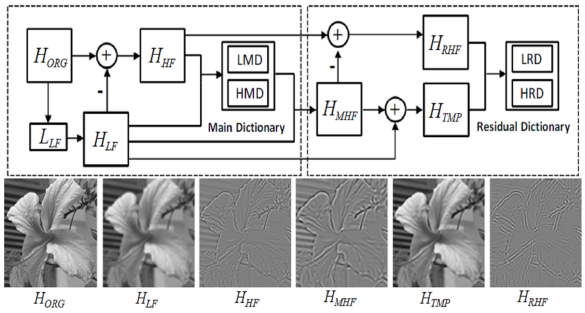

Fig.3 Illustration of dictionary lerning stage.

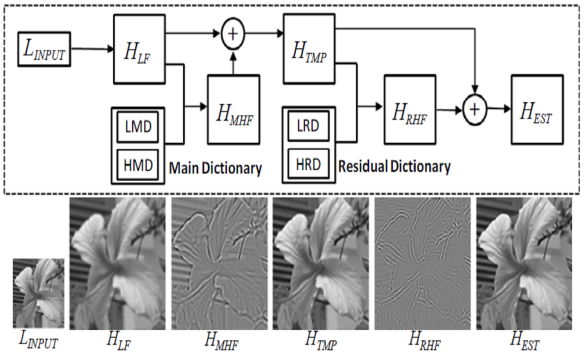

Fig.4 Illustration of image synthesis stage

Introduced in the next subsection. Utilizing *HMHF*, the HR temporary image denoted by *HTMP* which contains more details than *HLF* and the HR residual high-frequency image denoted by *HRHF* are

frequency image *HHF* is generated by subtracting *HLF* om *HORG*.

2)Then, in next stapes MD will be built, which is actually a combination of two coupled sub-dictionaries: low-frequency main dictionary (LMD) and high-frequency main dictionary (HMD). With *HLF* and *HHF*, local patches are extracted forming the training data $TD = \{\mathbf{p}_h^k, \mathbf{p}_l^k\}_k$ $\mathbf{p}_h^k$ is the

and down sampled to yield a corresponding LR low-frequency image denoted by *LLF*. By applying bicubic interpolation on *LLF*, a HR low-frequency image is obtained , denoted by *HLF* in Fig.3, which is of the same size as *HORG*. Then, real HR high-

1)The dictionary learning stage starts with collecting a set of training HR images. As illustrated in Fig. 1, a HR training image denoted by *HORG*, is first blurred generated, as shown in Fig. 3. Thus, RD can be form with the input of *HTMP* and *HRHF* using the same dictionary learning method as MD.

2) To begin with, an input LR image denoted by *LINPUT* is interpolated by bicubic method to produce a HR low-frequency image denoted by *HLF*. Combining *HLF* and MD, the HR main high-frequency image denoted by *HMHF* is generated employing the image reconstruction method in [2]. Concretely, *HLF* is filtered with the same high-pass filters and PCA projection as the training stag, and then is decomposed into overlapped patches $\{\mathbf{p}_l^k\}_k$. The OMP algorithm is applied to generate $\{\mathbf{p}_l^k\}_k$ $\mathbf{p}l$, and the sparse representation vectors $\{\mathbf{d}_n\}^k$ $\mathbf{q}$ is built by allocating L atoms to their representation. The representation vectors $\{\mathbf{q}^n\}_k$ $\mathbf{q}$ are multiplied by HMD, reconstructing high-resolution patches by $\{\hat{\mathbf{p}}_h^k\}_k = \{\mathbf{HMD} \cdot \mathbf{q}^k\}_k$. $\mathbf{R}k$ denotes the operator which extracts a patch from the high resolution image in location *k*. The HR main high-frequency image denoted by *HMHF* is generated by solving the following minimization problem:

$$H_{MHF} = \arg\min_{H_{MHF}} \sum_k \left\| \mathbf{R}_k H_{MHF} - \hat{\mathbf{p}}_h^k \right\|_2^2,$$

Which has a closed-form Least-Square Solution?

$$H_{MHF} = [\sum_k \mathbf{R}_k^T \mathbf{R}_k]^{-1} \sum_k \mathbf{R}_k^T \hat{\mathbf{p}}_h^k .$$

Fig.5 Dictionary training and performance test image

3) Then, the HR temporary image denoted by *HTMP* containing more details than *HLF* is built by adding *HLF* to *HMHF*. Next, by making use of *HTMP* and RD,

VII.Possible Outcomes And Result

The proposed method compare with on some other interpolation methods such as bicubic interpolation method and sparse representation method [1]. The blurring operator is 5×5 Gaussian filter with standard deviation of 1, and the decimation operator is direct down sampling with scale factor 2. The proposed method performs visually much better than bicubic interpolation, having less visual artifacts and producing sharper results. Compared with [3], the

Proposed algorithm provides more image details with improved PSNR.

Conclusion

The newly proposed method a novel image super-resolution approach via dual-dictionary learning and sparse representation, which can reconstruct lost high-frequency details by a two layer progressive

way utilizing distinct dictionaries. Experimental results show that the proposed method is able to remove some restrictions of frequency spectrum suffered by traditional example-based methods which lead to missing much image details, and achieve better results in terms of both PSNR and visual perception.

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