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Image Quality Improvement by Multi-Scale Dictionary Method

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***Abstract* – This paper presents the comparison of different techniques of Super-Resolution (SR). Multi dictionary technique is compared with SR in the frequency domain and Interpolation-restoration.This paper shows how multiscale dictionary gives high quality SR images than the other two techniques. Frequency domain technique fails to presence of outliers due to motion errors, inaccurate blur models, noise, moving objects, motion blur etc. Interpolation restoration fails to do intensive computation due to large number of unknowns. Multiscale dictionary overcome this problem by integrating local and non-local priors, and gives better outliers and intensive computation.**

***Keyword* - Muti-Scale Dictionary, Frequency Domain, Interpolation Restoration.**

I. INTRODUCTION

The approach of this paper is based on the fundamental idea that the High Resolution image could be generated from any of the possible Low resolution images. Different types of Image super resolution technique is introduced and shows the results that how multiscale dictionary method is better than frequency domain and interpolation restoration methods.Interpolation restoration forward approaches are intuitive, simple and computationally effcient [1,3] assuming simple observation models. However, the step-by-step forward approach does not guarantee optimality of the estimation. The interpolation step is suboptimal without considering the noise and blurring effects. Frequency domain techniques assumes a noise-free and global translation model with known parameters. These approaches are computationally effcient, but limited in their abilities to handle more complicated image, degradation models and include various image priors as proper regularization.

The Multiscale dictionary SR method introduces the following features.

A jointly learn multi-scale dictionary by using image patches at different scale by giving LR input and recover missing details by sparsely representing the expected HR image from the learnt multi scale dictionary, which is able to capture the syperfluous of similar patches at different scales.

Steering Kernel Regression (SKR) captures the local information of an image. Non Local Means adds non-local prior regularization to obtain a sturdy SR result.These two terms are added into reconstruction based SR method to maintain smother and sharp edges.

Comparision is shown that how multiscale dictionary is better than the frequency domain and interpolation restoration method. Multiscale dictionary result appears to be noiseless, leading to photo-realistic results..Literature survey is briefly reviewed in section II .Section III explains the super resolution in frequency domain..In section IV interpolation-restoration: non-iterative approaches. Section V explains multi-dictionary method. Section VI demonstrates the experimental result

II. LITERATURE SURVEY

Edge directed prior methods [2,4] are popular for the reconstruction-based methods which impose some priors during the reconstruction process to obtain a reliable estimate. Fattal [5] enforced an edge statistics prior on the reconstructed HR image to generate sharper edges and suppress noticeable artifacts. This edge directed prior methods preserves sharper edges and suppress noticeable artifacts, but this method fails to recover visual details. This drawback is overcome by example based SR approaches which exceeds the reconstruction-based methods in recovering plausible details by learning the correspondences between LR image patches (or pixels) and HR image patches (or pixels) from a training database consisting of LR and HR patch pairs. Representative approaches include k-nearest neighbor (k-NN) learning (e.g., [7]), manifold learning (e.g., [6, 9]), sparse coding (e.g., [11]), and regression-based (e.g., [15]) methods.

Sperresolution is a class of techniques that enhance the resolution of an imaging system.A novel single images Super-Resolution (SR) method is given which by integrates example and reconstruction based SR methods. Multi dictionary technique which is the overcome of reconstruction and example based SR, which store high resolution (HR) image from low resolution (LR) image. Multi-dictionary technique, which is a SR method that integrates local and non local priors.

III. SUPER-RESOLUTION IN THE FREQUENCY DOMAIN

The pioneering work for super-resolution traces back to Tsai and Huang [4], in which the authors related the high resolution image with multiple shifted low-resolution images by a frequency domain formulation. It is based on the shift and aliasing properties of the Continuous and Discrete Fourier Transforms.

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Let x(t_1,t_2) denote a continuous high resolution scene. The global translations yield *K* shifted images,

$$x_k(t_1,t_2) = x(t_1 + \Delta k_1, t_2 + \Delta k_2) \text{ with k =1,2..K}$$

Where $\Delta k_1, \Delta k_2$ are arbitrary known as shifts. The continuous Fourier transform (CFT) of the scene is given by $X(u_1,u_2)$ and those of the translated scenes by $X_K(u_1,u_2)$. Then by the shifting prope- r ties of the CFT is used. The shifted images are im-pulse sampled with the sampling period *T*1 and *T*2 to yield observed low resolution image.

$$y_k[n_{1,}n_2] = x_k(n_1T_1 + \Delta k_1, n_2T_2 + \Delta k_2)$$

The CFTs of the shifted images are related with their DFTs by the aliasing property. Then the matrix form is given by

$$y = \Phi x \quad (1)$$

where *Y* is a $K \times 1$ column vector with the k^{th}element being the DFT coefficient $Y_k[r_1,r_2]$, X is a $N_1N_2{\times}1$ column vector containing the samples of the unknown CFT coefficients of , $X(t_1,t_2)$ and ϕ is a $K{\times}N_1N_2$ matrix relating *Y* and *X*. Eqn. 1defines a set of linear equations from which we intend to solve *X* and then use the inverse DFT to obtain the reconstructed image.

The frequency domain SR theory of these works did not go beyond as what was initially proposed. These approaches are computationally efficient, but limited in their abilities to handle more complicated image degradation models and include various image priors as proper regularization.

IV. Interpolation Resto-Ration: Non-Iterative Approaches

A non-iterative forward model for SR recons-truction is in the spatial domain. Assume H_K is Linearly Spatial Invariant (LSI) and is the same for all *K* frames, and denote it as *H*. F_k considers only simple motion models such as translation and rotation, then computing *H* and F_k we get

$$Y_K = D_KF_KHX + V_K = D_KF_KZ, k = 1, 2,..K \quad (2)$$

which motivates a forward non-iterative methods based on interpolation and restoration. There are 3 stages for this methods.

1) Low resolution image registration
2) Non uniform interpolation to get *Z*
3) De-blurring and noise removal to get *X*.

The low resolution frames are first aligned by some image registration algorithm [10] to subpixel accuracy. These aligned low resolution frames are then put on a high resolution image grid, where nonuniform interpolation methods are used to fill in those missing pixels on the HR image grid to get *Z*. At last, *Z* is de-blurred by any classical deconvolutional algorithm with noise removal to achieve *X*.

These interpolation-restoration forward approaches are intuitive, simple and computationally efficient [8,13], assuming simple observation models. However, the step-by-step forward approach does not guarantee optimality of the estimation. The registration error can easily propagate to the later processing. Also, the interpolation step is suboptimal without considering the noise and blurring effects. Moreover, without HR image prior as proper regularization, the interpolation based approaches need special treatment of limited observations in order to reduce aliasing.

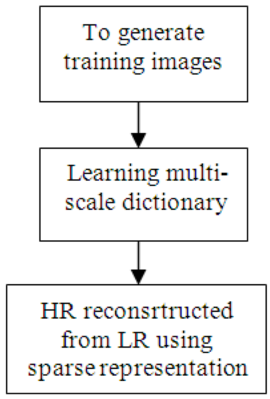
V. Multi-Scale Dictionary Method

Multi-scale dictionary-based hallucination is based upon the following two observations.

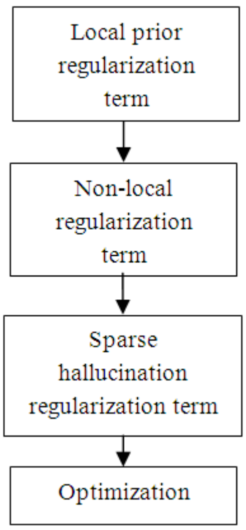
The local structures in a natural image usually tend to repeat themselves many times, both within the same scale and across different scales. Therefore, details missing in a local structure at a smaller scale can be estimated from its similar patches at a larger scale.

The next is that different images prefer different patch sizes for optimal representation. For instance, the major edges prefer a larger scale while the sophisticated details tend to a smaller one. Therefore, it is important to jointly represent an image at different scales. Considering the above cues a multi-scale dictionary representation [8] (originally used in image/video denoising) to example-based hallucination is introduced.

The following shows the block diagram of how to create multi-dictionary.



Next shows the block diagram of the recombination of single image SR model



Mathematically, it is defined as

$$X^* = \min_X \left\{ \begin{matrix} E(X|Y) + \alpha_1 E_{local}(X) + \alpha_2 E_{non-local}(X) \\ + \alpha_3 E_{sparse}(X) \end{matrix} \right\} \quad (3)$$

Where $E(X|Y) = \|(X * B)\downarrow - Y\|_2^2$ is the recostruction term to ensure that the reconstructed HR image is consistent with the LR input via back-projection. The second term E_{local} (X) is the local prior regularization, which indicates that each HR pixel should be perfectly estimated from a small local area around it. The third term $E_{non\text{-}local}$(X)is the non-local prior that assumes that each HR pixel can be predicted by weighting average of a large neighborhood. The last sparse hallucination regularization term requires that the estimated HR image has a sparse representation over a multi-scale dictionary learnt from the LR input itself.

VI. EXPERIMENTAL RESULTS

Original, blurred, down sampled and noisy images are given as a input image and then our technique is applied and we get HR image from LR image.

Fig.1.a Original, blurred, down sampled and noisy input image of parrot

Fig.1.b parrot LR to HR image

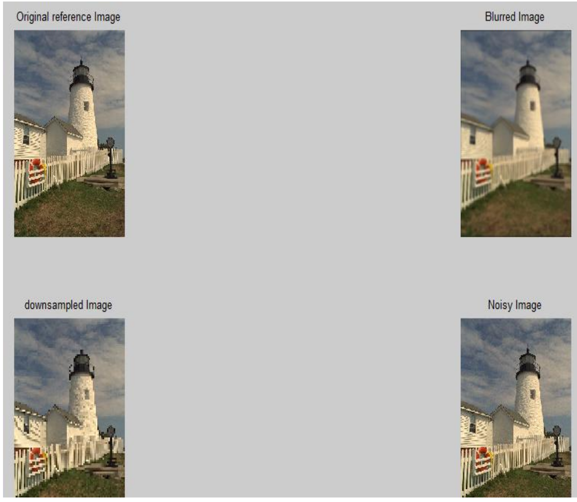


Fig.2.a Original, blurred, downsampled and noisy input image of Light House

Fig.2.b Light House LR to HR image

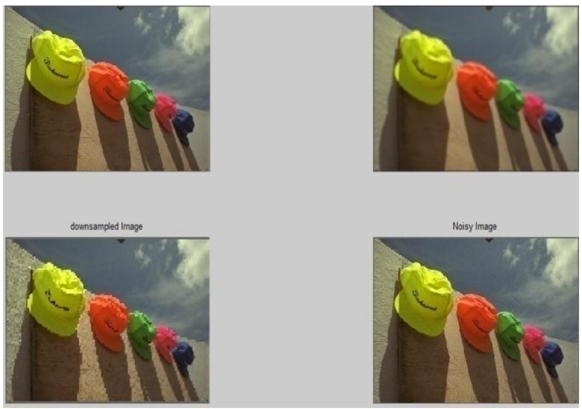


Fig.3.a. Original, blurred, downsampled and noisy input image of Caps

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Fig.3.b. Caps LR to HR image

Table No.1 PSNR values of all three fig.

PSNR	Parrots	Light House	Caps
Multi-scale dictionary	24.1124	24.0809	24.1389
Frequency domain	22.4115	22.3153	22.4215
Interpolation-Restoration	23.118	23.0910	23.1682

Table No.2 SSIM values of all three fig.

SSIM	Parrots	Light House	Caps
Multi-scale dictionary	0.9687	0.9715	0.9621
Frequency domain	0.9421	0.9542	0.9436
Interpolation-Restoration	0.9562	0.9600	0.9589

In the above figure the above method is rested on parrot, light house, caps and compare SR results obtained from the dictionaries at different scales with Suoer-Resolution in the frequency domain and Inter polation-Restoration method. This method works on ten database images out of which the result of parrot, light house, caps images are shown here. It is observed that the reconstructed HR images obtained from the multi-scale dictionary shown in Figure 1b, 2b and 3.b are better in terms of quantitative and visual quality than that obtained from the single-scale dictionary.

VII. Conclusion

The example-based method estimates the high frequency details by jointly learning a multi-scale dictionary from a given LR image and produces expected details by sparse representation over the learnt multi-scale dictionary. The reconstruction-based method produces sharper edges and suppresses unwanted artifacts by taking local and non-local priors as regularization terms. A unified SR framework consists of the reconstruction constraint term, local and non-local regularization terms, and sparse hallucination regularization term. It is observed that this method can produce sharper edges and more faithful details in comparison to the other state-of-the-art super-resolution in the frequency domain, interpolation-restoration: non- iterative approaches SR approaches.

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