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Retrieving back Super Resolution Image through Iterations

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Abstract: **Morphological operators are well known tool that can extract structure from image, which are used in image denoising, image segmentation and image fusion. In this paper we model a non linear regularization method based on multi scale morphology for edge preserving super resolution (SR) image reconstruction. We formulate SR reconstruction problem from low resolution (LR) image as a deblurring and denoising and then solve the inverse problem using Bregman iterations. The proposed algorithm can suppress inherent noise generated during low-resolution image formation as well as during SR image estimation efficiently. Experimental results show the effectiveness of the proposed method and reconstruction method for SR image.**

Keywords: **morphological operators, Bregman iteration, deblurring, denoising, edge preserving, sub gradients.**

1. INTRODUCTION

It is always desirable to generate a Super Resolution (SR) image as it shows more intricate details. However, available sensors have limitation in respect to their maximum resolution. Thus our basic goal is to develop an algorithm to enhance the spatial resolution of images captured by an image sensor with a fixed resolution. This process is called the super resolution (SR) method and has remained an active research topic for the last two decades. A number of fundamental assumptions are made about image formation and quality, which in turn lead to different SR algorithms. These assumptions include the type of motion, the type of blurring, and also the type of noise. It is also important whether to produce the very best HR image possible or an acceptable HR image as quickly as possible. Moreover, SR algorithms may vary depending on whether only a single low-resolution (LR) image is available (single frame SR) or multiple LR images are available (multi frame SR).Also, SR image reconstruction algorithms work either: 1) in the frequency domain or 2) in the spatial domain. In this paper, we focus only on spatial domain approach for multi frame SR image reconstruction.

Among spatial domain multi frame SR image reconstruction algorithms, representative works include non uniform interpolation-based approaches .The advantage of these approaches is that their computational cost is relatively low, which makes them suitable for real-time applications. The first successful edge preserving regularization method for denoising and deblurring is the total variance (TV) method [1]. Another interesting algorithm, proposed by Farsiu et al. [2], employs bilinear total variation (BTV) regularization. Bregman iteration for fast SR image reconstruction with TV regularization. However, even though all these regularization terms for SR image reconstruction lead to a stable solution, their performance depends on optimization technique as well as regularization term. For example, with gradient descent optimization technique, BTV[2], which gives better result than TV [1] regularization. On the other hand, based on TV regularization, Marquina and Osher [3] obtained superior result by employing Bregman iteration. So we envisage that even better results would be obtained by combining Bregman iteration and a more sophisticated regularization method that can suppress noise in LR images and ringing artifacts occurred during capturing the details of the HR image. We propose a new regularizing method based on multiscale morphologic operators and filters which are nonlinear in nature. Morphological operators and filters are well known tools that can extract structures from images [4].They are used in image denoising [5], [6], image segmentation [7] and image fusion [8] successfully. Since proposed morphologic regularization term uses non differentiable max and min operators, we develop an algorithm based on Bregman iterations and the forward–backward operator splitting using sub gradients. It is seen that the results produced by the proposed regularization are less affected by a fore mentioned noise evolved during the iterative process.

The rest of this paper is organized as follows. Section II Low Resolution (LR) image formation model and inverse reconstruction of High Resolution (HR) image from multiple LR images. We introduce proposed multiscale morphological operator regularizing method in Section III. In Section IV, we review Bregman iteration and develop an algorithm for SR image reconstruction with proposed morphological operators. Section V presents the results and compares our results with those of some existing regularization methods for SR image reconstruction. Finally, some concluding remarks are made in Section VI.

II. LOW RESOLUTION (LR) IMAGE FORMATION MODEL AND INVERSE RECONSTRUCTION OF HIGH RESOLUTION (HR) IMAGE FROM MULTIPLE LR IMAGES

The observed images of a scene are usually degraded by blurring due to atmospheric turbulence and inappropriate camera settings. The LR images are further degraded because of down sampling by a factor determined by the intrinsic camera parameters. The relationship between the LR images and the HR image can be formulated as

$$Y_k = DF_k H_k X + e_k \qquad \forall k = 1,2 \dots K \qquad (1)$$

where Yk , X, and ek represent lexicographically ordered column vectors of the kth LR image of size M, HR image of size N and additive noise, respectively. Fk is a geometric warp matrix and Hk is the blurring matrix of size N×N incorporating camera lens/CCD blurring as well as atmospheric blurring. D is the down sampling matrix of size M × N and k is the index of the LR images. Assuming that the LR images are taken under the same environmental condition and using same sensor, Hk becomes the same for all k and may be denoted simply by H. As a result, the LR images are related to the HR image as

$$Y_k = DF_k HX + e_k \qquad \forall k = 1,2 \dots K \ (2)$$

Since under our assumption, D and H are the same for all LR images, we avoid down sampling and then up sampling at each iteration of iterative reconstruction algorithm by merging the up sampled and shifted-back LR images Yk together. After applying up sampling and reverse shifting, Yk will be aligned with HR image X. Suppose Yk denotes the up sampled and reverse-shifted kth LR image obtained through reverse effect of DFK of (2). That means $Y_{k+} = {F_k}^{-1} D^T Y_k$

Where is the up sampling operator matrix of size N × M and is an N × N matrix that shifts back (reverse effect of Fk) the image. Thus from (2) we can write

$${F_k}^{-1} D^T Y_{k+} = {F_k}^{-1} D^T D F_k H X + {F_k}^{-1} D^T e_k$$

$$Y_{k+} = R_k H X + e_k \qquad \forall k = 1,2 \dots K$$

Where $R_k = {F_k}^{-1} D^T D F_k$ captures the contribution of pixels of the blurred image HX from which the LR image Yk is generated. In our formulation, we have chosen purely integer valued translational shifts with respect to the HR grid. In that case, Fk has only 0 and 1 entries. Since D is just a down sample matrix applied on Fk , Rk has only 0 and 1 entries. For a more general formulation, if we incorporate rotational shifts as well in our motion model and/or if we use bilinear interpolation for non integer translational shift, Rk has real entries in the range [0, 1] and we may call it a weight matrix. However, in this paper we assume a purely integer-valued translational shift and Rk is called an index matrix.

$$Y = \sum_{1}^{k} Y_{k+} \quad \text{and} \quad R = \sum_{1}^{k} R_k$$

Then the relation between the HR and LR images can be rewritten as

$$Y = RHX + e \qquad (3)$$

Now, we get Y as a blurred image of actual HR image X except that some pixel values may be missing if we take fewer LR images, and index matrix R keeps track of those missing values.

A. ERROR-BASED ESTIMATION OF THE SR IMAGE:

Since number of unknowns (pixels in the HR grid) in X is usually very large, a solution of (3) to obtain X by inversion of RH may not be feasible. Instead, we estimate an HR image Xˆ, which when degraded minimizes ρ(R H X, Y), i.e., Xˆ =arg min X ρ(R H X, Y) , where the dissimilarity measure ρ defined

as$\rho(U,V) = 1/p\|RHX - Y_{k+}\|_2^2$, $(1 \le p \le 2)$

here we choose p = 2; then the estimated HR image satisfies (3)in the least-squares sense

Xˆ=arg min X $[\|RHX - Y_{k+}\|_2^2]$ (4)

When K < N/M, the SR image reconstruction (4) becomes an ill-posed problem and, therefore, it becomes necessary to impose regularization to obtain a stable solution.

B. REGULARIZATION FOR THE SR RECONSTRUCTION ALGORITHM:

Regularization has already been used in conjunction with iterative methods for the restoration of noisy degraded images, in order to solve an ill-posed problem and prevent over fitting. To obtain a stable solution of (4),suppose that a regularization operator ϒ(X) in corporating prior knowledge is imposed on the estimated HR image X.Then the SR image reconstruction can simply be formulated as

Xˆ=arg min $\{\gamma(X) : \|RHX - Y_{k+}\|_2^2 < \eta\}$ (5)

Where η is a scalar constant depending on the noise variance in the LR images. Now the constrained minimization problem of (5) may be reformulated as a unconstrained minimization problem as

Xˆ=arg min $X\{\frac{1}{2}\|RHX - Y_{k+}\|_2^2 + \mu\gamma(X)\}$ (6)

X where μ is the regularization parameter that controls the emphasis between the data error term (first term) and the regularization term (second term). Choosing regularization parameter μ for optimum solution of (6) is a nontrivial task. For example, a large value of μ may not satisfy the constraint in (5) as the data error term is less emphasized; on the other hand, a small value of μ may amplify unwanted ringing artifacts as the smoothness criteria get less importance. . In this paper, we define ϒ(X) based on morphologic filters that preserve structures and suppress noise. It is well known that morphological opening and closing remove bright and dark noise, respectively, without affecting the edge sharpness.

III. MORPHOLOGICAL OPERATORS REGULARIZING

Let B be a disk of unit size with origin at its center and sB be a disk structuring element (SE) of size s. Then the morphological dilation Ds (X) of an image X of size m ×n at scale s is defined as

$$D_s(X) = \begin{pmatrix} max_{r\epsilon(sB)(1)}\{x_r\} \\ max_{r\epsilon(sB)(2)}\{x_r\} \\ \vdots \\ max_{r\epsilon(sB)(mn)}\{x_r\} \end{pmatrix} \quad (7)$$

Where is a set of pixels covered under SE sB translated to the i -th pixel xi. Similarly, the morphological erosion Es(X) at scale s is defined as

$$E_s(X) = \begin{pmatrix} min_{r\epsilon(sB)(1)}\{x_r\} \\ min_{r\epsilon(sB)(2)}\{x_r\} \\ \vdots \\ min_{r\epsilon(sB)(mn)}\{x_r\} \end{pmatrix} \quad (8)$$

Morphological opening Os (X) and closing Cs (X) by SE sB are defined as follows:

$$\text{Os (X)} = \text{Ds (Es(X))} \quad (9)$$

$$\text{Cs (X)} = \text{Es(Ds (X))} \quad (10)$$

In multiscale morphological image analysis, we have seen that the difference between the sth scale closing and opening extracts noise particles and image artifacts in scale s and may be used for denoising purposes. So in this paper, we propose the regularization function based on multiscale morphology as

$$\gamma(X) = \sum_{s=1}^{s} \propto^s 1^t \,[\text{Cs (X)} - \text{Os (X)}] \quad (11)$$

Where 1 is a column vector consisting of all 1s and α is the weighting coefficient. To give more emphasis on the small scale for noise removal, the value of α is chosen from the interval 0 < α < 1. Therefore, with the proposed regularization term, the SR reconstruction problem (5) is reduced to

$$\hat{X}=\min X\{ \sum_{s=1}^{s} \propto^s 1^t \,[\text{Cs (X)} - \text{Os (X)}]: \|RHX - Y_{k+}\|_2^2 < \eta\}$$

IV. SUBGRADIENT METHODS AND BREGMAN ITERATION

Marquina and Osher formulated a model for SR based on a constrained variational model that uses

the total variation of the signal as a regularizing functional. In this section, we develop an algorithm based on Bregman iterations and the proposed morphologic regularization for the SR image reconstruction problem. We present the proposed SR image reconstruction algorithm for a small amount of noise by using Bregman iteration and operator splitting as shown in Algorithm 1. Fill Unknown(**Y**) in the initialization step of the above algorithm fills the unknown pixels in **Y** by the corresponding known neighboring pixels. The parameter η is a predefined threshold chosen depending on variance of noise in LR images and

Algorithm: proposed iterative algorithm for SR image reconstruction

Initialize Y(0)=n=0,X(0)=fill unknown(Y_{k+});

While ($\left\|RHXX^{(n)} - Y_{k+}\right\|_2^2 < \eta$)

$$U^{(n+1)} = X^{(n)} - \gamma H^T R^T \left(RHX^{(n)} - Y^n\right)$$

$$X^{(n+1)} = U^{(n+1)} - \mu' \frac{\delta\gamma(X)}{\delta X}$$

$$Y^{(n+1)} = Y^{(n)} + \left(Y_{k+} - RHX^{(n+1)}\right)$$

n=n+1

end

DIFFERENT IMAGES	TOTAL VARIANCE(TV) METHOD		BILINEAR TOTAL VARIANCE (BTV) METHOD		PROPOSED METHOD	
	MSE	PSNR	MSE	PSNR	MSE	PSNR
CAMERAMAN.JPG	3.1668	43.1586	6.6543	39.9338	1.8233	82.3123
PEPPERS.JPG	1.57832	50.5431	1.3588	46.8331	1.0692	75.0203
MANDRILL.JPG	11.4987	37.5583	20.7093	35.0031	1.0869	74.9095

Significantly small for noise-free LR images. So we iterate until constraint in (5) is satisfied.

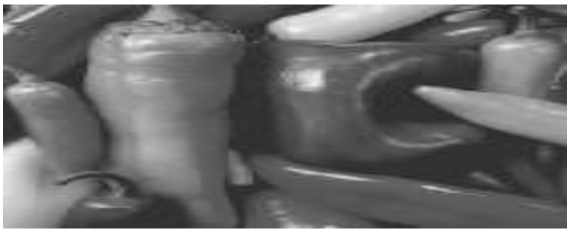
V. RESULTS

In this section, we study and analyze the performance of the proposed method as well as that of some other existing SR reconstruction methods.

By considering the different input images like cameraman, mandrell, peppers etc and applying total variance method such as bicubic method on our input image, image will be transformed and the transformed image is shown below. By applying bilinear total variance method such as bilinear method on our input image, image will be transformed in to new image as shown below and by our proposed method super resolution image reconstruction using Bregman iterations using morphological operations such as dilation, erosion, opening and closing and by using stationary wavelets on our input, image will be reconstructed and reconstructed super resolution image has decrease in mean square error and increase in peak signal to noise ratio when compared to other methods is as shown in the table and below figures.

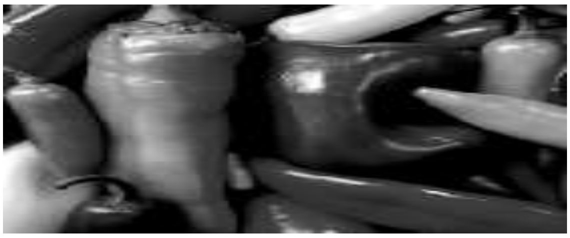
INPUT IMAGE

TV

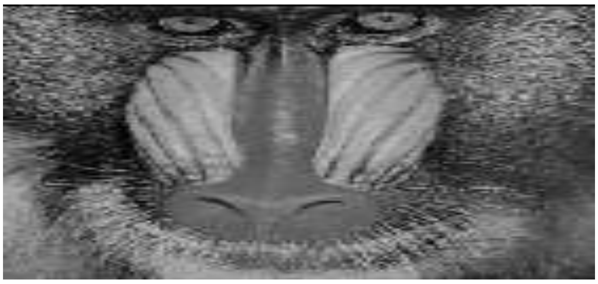


BTV

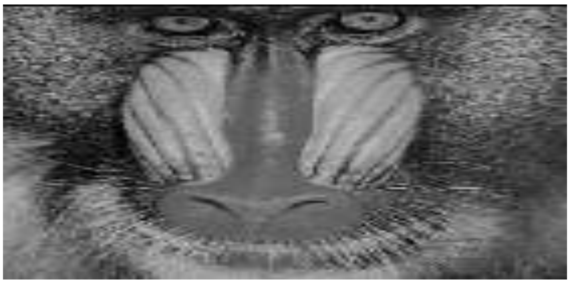
PROPOSED



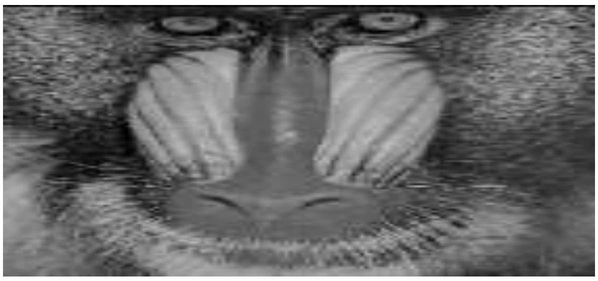
INPUT IMAGE



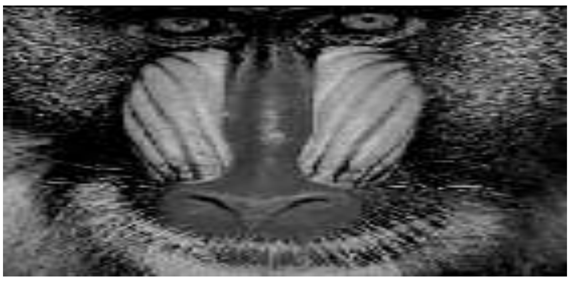
TV



BTV



PROPOSED



INPUT IMAGE

TV

BTV

PROPOSED

VI. CONCLUSION

In this paper, we have presented an edge-preserving SR image reconstruction problem as a deblurring problem with a new robust morphologic regularization method. Then we put forward two major contributions. First, we proposed a morphologic regularization function based on multiscale opening and closing, which could remove noise efficiently while preserving edge information. Secondly, we employed Bregman iteration method to solve the inverse problem for SR reconstruction with the proposed morphologic regularization. It is well known that multiscale morphological filtering can reduce noise efficiently, so we have built up successfully a regularization method based on multiscale morphology. Our experimental section shows that it works quite well, in fact better than existing methods. Nonlinearity of the regularization function is handled in a linear fashion during optimization by means of the sub gradient and proximal map concept.

We also showed that, if there is impulse noise with random values or salt-and-pepper noise in LR images, they can be handled efficiently using our two-step SR reconstruction algorithm. It first detects the noisy pixels (note: it does not substitute their values) and then, by considering those detected pixels as unknown pixels, reconstructs SR image using only those pixels which are not corrupted by noise. The morphologic regularization method proposed here was tested only on SR reconstruction problem, but one can easily extend this method to other ill-posed problems as well. Also, one can extend this regularization method to be adaptive by choosing SE of different shapes and sizes depending on the local statistics of neighboring pixels.

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