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GUI based Multi-frame Super-Resolution Reconstruction and Image Quality Metrics of Different Gray Scale Images

Abstract

High Resolution images can be reconstructed from several blurred, noisy and aliased low resolution images using a computational process know as super resolution reconstruction. Multi-frame super resolution reconstruction is the process of combining several low resolution images into a single higher resolution image. Super resolution reconstruction consists of registration, restoration and interpolation phases, once the low resolution image are registered with respect to a reference frame then restoration is performed to remove the blur and noise from the images, finally the images are interpolated using bilinear interpolation.

Image super-resolution creates an enhanced high resolution image using multiple low-resolution images of the same scene. A typical image formation model introduces major three parameters i.e. blurring, aliasing, and added noise. Super-resolution is designed to jointly reduce or remove all these three parameters. While the first super-resolution algorithm appeared over 20 years ago, only recently people explored the performance of these algorithms. However, these papers have explored only objective MSE performance. In this paper, we use subjective testing to explore the visual quality of images enhanced with super-resolution. Experimental results in this paper show that the proposed approach has succeeded in obtaining a high-resolution image with a better PSNR value and good visual quality.

Keywords: *Super-resolution; reconstruction; bilinear interpolation; blurring; aliasing*.

1. INTRODUCTION

In many imaging applications, High Resolution (HR) images or a magnified portion of images are required. Super-Resolution (SR) is the technique to reconstruct a HR image using a multiple low quality low resolution (LR) images obtained from a same scene with sub-pixel shifts. The hardware solution to increase spatial resolution is by increasing the pixel size, but it is expensive. Super Resolution is the inexpensive solution to increase spatial resolution. Super-Resolution techniques are being applied to variety of fields. HR image can offer more details that may be critical in various applications. Medical imaging, satellite imagery, surveillance, forensics, video enhancement and restoration are some of the application areas. In SR, the sub-pixel shifted LR images can be obtained from one camera with several captures or from multiple cameras located in different position.

If we use low resolution images which is shifted by integer pixel units then no new information is available and the resulting reconstructed image is simply a zoomed version of a single low resolution image and does not yield higher resolution, but if the LR images are with different sub-pixel shifts then each image add new information and this information can be exploited to obtain a super resolved image.

2. OBSERVATION MODEL

The first step to comprehensively analyze the SR image reconstruction problem is to formulate an observation model that relates the original HR image to the observed LR images. A dynamic scene with continuous intensity distribution X is to be warped at the camera lens because of the relative motion between the scene and camera. The images are blurred both by atmospheric turbulence and camera lens by continuous point spread functions $H_k = H_k^{atm} H_k^{cam}$. Then, they are discretized at the CCD resulting in a digitized noisy frame X. The forward relationship from the HR image to a degraded LR image is given by(1) and Fig.1 shows the difference between the zoomed image and HR image obtain from SR.

$$\underline{Y}_k = D_k H_k F_k \underline{X} + V_k \qquad k = 1,2,\ldots\ldots\ldots,N \qquad (1)$$

Where X is the unknown high resolution image, Y_k is the k^{th} LR image and N is the number of available LR images. D_k is the down sampling operator, H_k represents the blur, F_k represents warping, and V_k represents noise [1].

Two steps are involved in the process of SR: Registration and Interpolation.

Registration: The samples of LR images are mapped onto the common HR grid. From the available set of LR images we can arbitrarily choose one LR image as the reference image and the relative motions between the successive LR images w.r.t the reference image is estimated and used for aligning the sample points in each frame onto a HR grid. The Fig.2 shows that after registering all the LR samples on HR grid the samples distribute non-uniformly [5].

In this paper pure translational motion is considered and it is assumed that the motion parameters are been estimated already using a suitable registration technique. The blur is usually assumed to be shift-invariant [2]. This property allows interchanging the blurring and warping operators in (2)

$$\underline{Y}_k = D_k F_k H_k \underline{X} + V_k \qquad k = 1,2,\ldots\ldots\ldots,N \quad (2)$$

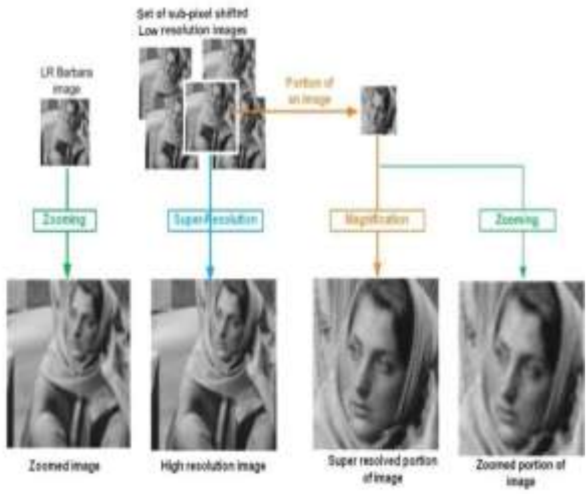

Fig.1. Difference between the zoomed image and the HR image obtained from SR and also the magnified portion of the image. Interpolation: *This step estimates missing pixels on HR gird. The paper mainly focuses on this step using bilinear interpolation.*

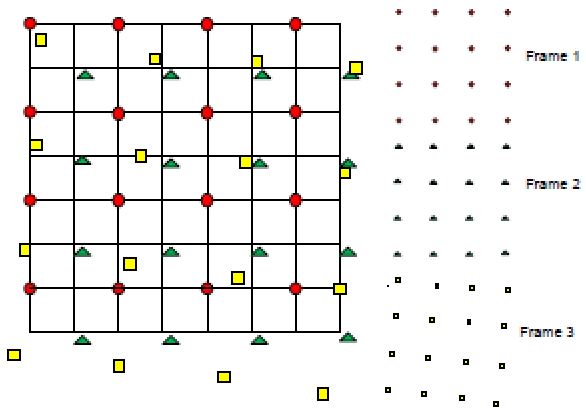

Fig.2.The left image is registered LR data on high resolution grid. The displacement is translational and rotational. The right image contains three LR frames and the frame1 is chosen as reference frame and the frame2 is translated and frame 3 is translated and rotated from the reference frame.

3. SUPER-RESOLUTION ALGORITHMS

The two reconstructions based Multi-frame SR algorithms will be compared using different image quality measures discussed in section IV. First algorithm to be compared is Robust Super resolution in [4] enhanced in [3] and the second being the Fast and Robust Super Resolution.

3.1 Robust Super-resolution

In this section, an iterative solution for the super-resolution problem is explained. It is desired to produce a high resolution result which is similar to low-resolution frames, so a cost function is needed which compares the similarity of low and high resolution frames. The L1 norm cost function is used instead of the common L2 norm cost function, as including the effects of outliers in this comparison is not desirable [3.4]. In the underdetermined super-resolution cases ($N < r^2$ in which N is the number of non-redundant low-resolution frames and r is the resolution enhancement factor), certain pixel locations will have no estimate at all. For these cases, it is essential for the estimator to have an extra term, called regularization term, to remove outliers. Adding a regularization term is needed for efficiently calculating missing data (i.e. interpolation).

Regularization is a useful tool even in the square and over-determined cases ($N = r^2$ and $N > r^2$ respectively) as it can help the algorithm to remove artifacts from the final answer. The following expression formulates our minimization criteria [3]:

$$\hat{\underline{X}} = \underset{\underline{X}}{ArgMin} \left[\sum_{k=1}^{N} \| D_k H_k F_k \underline{X} - \underline{Y}_k \|_1 + \lambda \sum_{l=0}^{P} \sum_{m=0}^{P} \alpha^{m+l} \| \underline{X} - S_x^l S_y^m \underline{X} \|_1 \right] \tag{3}$$

λ is a scalar for properly weighting the first term (similarity cost) against the second term (regularization cost). S_x^l is the operator corresponding to shifting X by *l* pixels in horizontal direction and operator S_y^m shifts X by m pixels in vertical direction, presenting several scales of derivatives. Scalar weight α, $0 < \alpha < 1$, is applied to give a spatially decaying effect to the summation of the regularization term.

3.2 Fast Robust Super-resolution

Fast and robust super-resolution algorithm uses the L1 norm, both for the regularization and the data fusion terms. Whereas the former is responsible for edge preservation, the latter seeks robustness with respect to motion error, blur, outliers, and other kinds of errors not explicitly modeled in the fused images.

In this method, resolution enhancement is broken into two consecutive steps:

1) Non-iterative data fusion

2) Iterative de-blurring - interpolation.

Registration followed by median operation results in blurred HR image$\hat{\underline{Z}} = H\,\hat{\underline{X}}$. The goal of the de-blurring interpolation step is finding the de-blurred HR frame$\hat{\underline{X}}$. The following expression formulates our minimization criterion for obtaining $\hat{\underline{X}}$ from $\hat{\underline{Z}}$.

$$\hat{\underline{X}} = \underset{\underline{X}}{ArgMin} \left[\| H\underline{X} - \hat{\underline{Z}} \|_1 + \lambda' \underbrace{\sum_{l=-P}^{P} \sum_{m=0}^{P}}_{l+m>=0} \alpha^{|m|+|l|} \| \underline{X} - S_x^l S_y^m \underline{X} \|_1 \right] \tag{4}$$

Where matrix *A* is a diagonal matrix with diagonal values equal to the square root of the number of measurements that contributed to make each element of $\hat{\underline{Z}}$ (in the square case *A* is the identity matrix). So, the undefined pixels of $\hat{\underline{Z}}$, have no effect on the HR estimates$\hat{\underline{X}}$. On the other hand, those pixels of $\hat{\underline{Z}}$ which have been produced from numerous measurements have a stronger effect in the estimation of the HR frame $\hat{\underline{X}}$

Decimation and warping matrices (D and F) and summation of measurements are not present anymore which makes implementation of (4) much faster than (3).

4. IMAGE QUALITY ASSESSMENT

In this paper, the quality of a super-resolved image is shown as compared to its initial estimate of HR image in Fig.7 and Fig.8. Therefore, similarity measures are used as indicators of quality. Three different measures 1) the PSNR, 2) the Structural SIMilarity Measure (SSIM), 3) Mean Square Error (MSE) and 4) Standard Deviation (SD), are used to compare the results.

4.1 Peak Signal-to-Noise Ratio (PSNR)

The PSNR is most commonly used as a measure of quality of reconstruction in image compression etc. It is most easily defined via the mean squared error (MSE) which for two rn x n monochrome images I and K where one of the images is considered a noisy approximation of the other is defined as:

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2$$

The PSNR is defined as

$$PSNR = 20 * \log_{10}\frac{255}{RMSE}$$

where RMSE is the Root-Mean-Square-Error between the two images. The closer the images, the bigger the PSNR will be.

4.2 Structural SIMilarity Measure (SSIM)

The Structural SIMilarity Measure takes into account contrast, luminance and structure to determine similarity between two images. The measure was designed to better represent what is perceived by the HVS. It is defined as:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C1)(2\sigma_{xy} + C2)}{(\mu_x^2 + \mu_y^2 + C1)(\sigma_x^2 + \sigma_y^2 + C2)}$$

Where

$$\sigma_{xy} = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu_x)(y_i - \mu_y)$$

x and y are sub images of X and Y, μ_x μ_y σ_x, σ_y are the weighted means and standard deviations inside these windows, C1 is set to C1= $(0.01* 255)^2$ and C2= $(0.03 * 255)^2$. The mean SSIM (MSSIM) is then simply the mean of the SSIMs for each window. A value of MSSIM of 1 indicates perfect similarity.

5. ROBUST SUPER-RESOLUTION IMPLEMENTATION

In this section, combining the above ideas presented a solution for the robust super-resolution problem is proposed. The proposed robust solution of the super-resolution problem as shown in (4) is that we use steepest descent to find the solution to this minimization problem

$$\hat{\underline{X}}_{n+1} = \hat{\underline{X}}_n - \beta\Big\{\sum_{k=1}^{N} F_k^T H_k^T D_k^T sign(D_k H_k F_k \hat{\underline{X}}_n - \underline{Y}_k) + \lambda \underbrace{\sum_{l=-P}^{P}\sum_{m=0}^{P}}_{l+m\geq 0} \alpha^{|m|+|l|}[I - S_y^{-m} S_x^{-l}] sign(\hat{\underline{X}}_n - S_x^l S_y^m \hat{\underline{X}}_n)\Big\} \tag{5}$$

Where β is a scalar defining the step size in the direction of the gradient S_x^{-l} and S_y^{-m} define the transposes of matrices S_x^{l} and S_y^{m} respectively and have a shifting effect in the opposite directions as S_x^{l} and S_y^{m} .

The Block Diagram as shown in Fig.3. is the representation of (5). There, each LR measurement is compared to the warped, blurred, and decimated current estimate of HR frame X_n. Block G_k represents the gradient back projection operator that compares the k^{th} LR image to the estimate of the HR image in the n^{th} steepest descent iteration. Block $R_{m,l}$ represents the gradient of regularization term, where the HR estimate in the n^{th} steepest descent iteration is compared to its shifted version (*l* pixel shift in horizontal and m pixel shift in vertical directions).

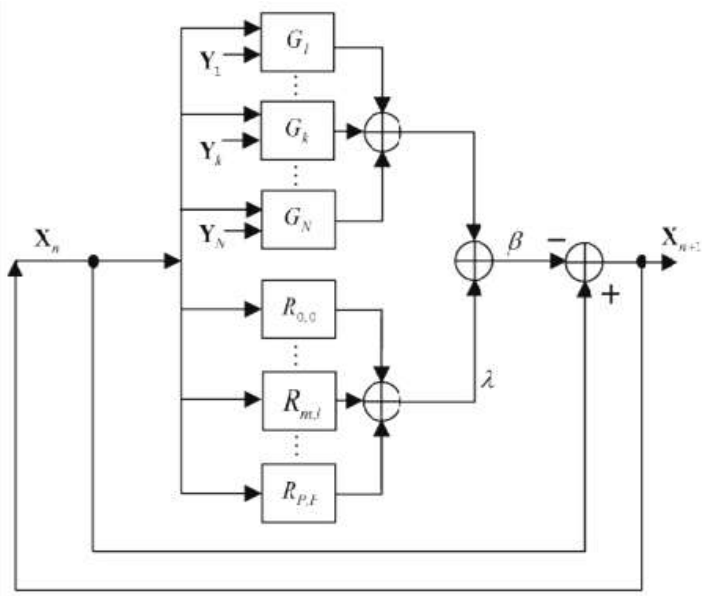

Fig.3. Block Diagram representation of (5).

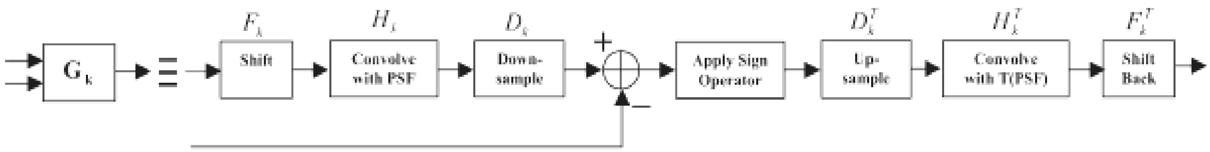

Fig.4. Block diagram representation of similarity cost derivative.

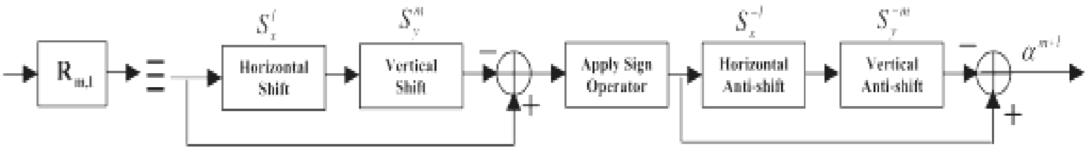

Fig.5. Block diagram representation of regularization cost derivative.

Details of the blocks G_k and $R_{m,l}$ are defined in Fig.4.and Fig.5. Block T(PSF) in Fig.4. replaces the matrix H_k^T with a simple convolution. Function T flips the columns of PSF kernel in the left-right direction (that is, about the vertical axis), and then flips the rows of PSF kernel in the up-down direction (that is, about the horizontal axis). The D_k^T up sampling block in Fig.4. can be easily implemented by filling r – 1 zeros both in vertical and horizontal directions around each pixel as shown in Fig.6. Finally the F_k^T shift back block in Fig.4. is implemented by inverting the translational motion in the reverse direction. The robust super-resolution approach developed in this paper has an advantage over other methods proposed in [4] with respect to computational aspects.

6. FLOW CHART OF PROPOSED METHOD

The flow chart depicted in Fig.7.is the implementation of the proposed method i.e. Robust Super-resolution. A brief idea about the implementation of the proposed method as per the flow chart is as below: Firstly we find out by how much amount each frame is shifted in x and y directions with respect

to base frame. Let D be an array which stores x and y shifts of

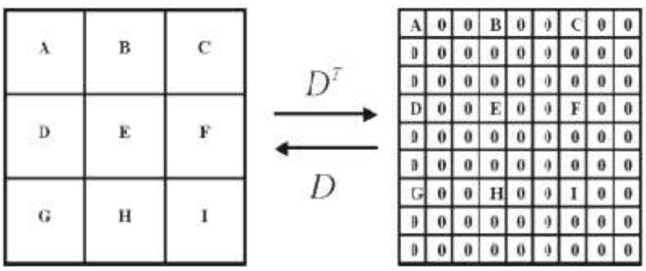

Fig.6. Effect of up sampling D^T matrix on a 3 x 3 image and down sampling matrix D on the corresponding 9 x 9 up sampled image (resolution enhancement factor of three).

Every frame with respect to base frame. To calculate this we have used classical Lucas Kanade Pyramidal Optical Flow Algorithm. The parameters which are used to reconstruct HR frame are 1) PSF – Point Spread Function 2) PSF Var – Variance of this Point Spread Function 3) Res Factor Resolution Factor (by default 2). 4) Number of iterations: How many times Gradient Back Projection and Gradient Regularization to be carried out. The very first step is to find out the frames which have equal displacement in x and y direction. If the displacement in x direction is {2,3} and displacement in y direction is {2,3}then the motion vector combinations are {2,2},{2,3},{3,2},{3,3}.If there are 'n' no of frames and if 6 frames are found out of n which are having x= = 2 and y= =2 then mean (median) is calculated for those 6 frames. This frame Z calculated is the initial estimate of HR frame. The 'A' variable stores the number of frames obtained with same displacement value and their median pixel value is stored at respective position in Z. Frame Z is used as an HR frame for gradient regularization and gradient back projection. Suppose GREG is equal to the output of gradient regularization Z and GBack is the output of gradient back projection Z. For gradient regularization and gradient back projection the above block diagram shown in Fig.3. is referred. The following calculations are carried out for given number of iterations. Iterations are defined by the program where no of iterations are 10 to 20.

Hence HR = Z and i < iterations, GREG is equal to Gradient Regularization HR and GBack is equal to Gradient Back projection HR where HR = HR – β (GBack + λ GREG).The HR calculated is the final output i.e. reconstructed high resolution frame.

7. RESULTS AND CONCLUSION

The proposed flow chart for robust super-resolution is shown in Fig.11.and is implemented in MATLAB and GUI is developed for multi- frame super-resolution. A MATLAB based program is developed and implemented for different test vectors and also different image quality assessment parameters such as PSNR, MSE, SD, and SSIM are calculated. The results of 4 test vectors are shown in Fig.7.,Fig.8, Fig.9 and Fig.10. below. Table.1 shows the results of all test vectors.

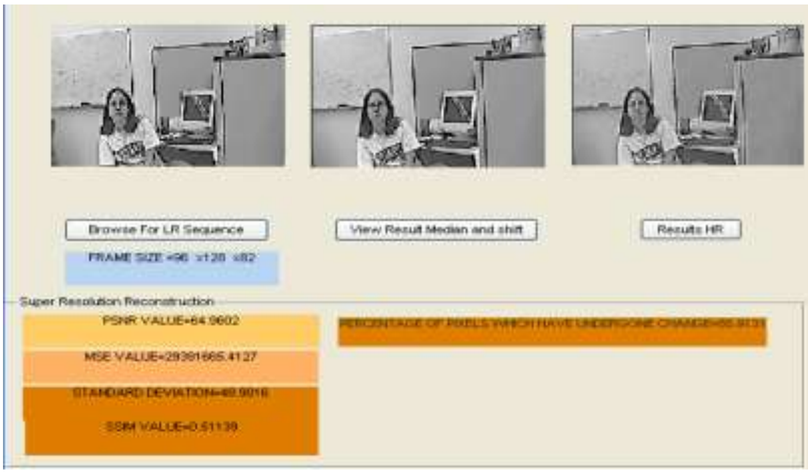

Fig.7. GUI wit HR result and different calculated image quality parameter for Emily test vector

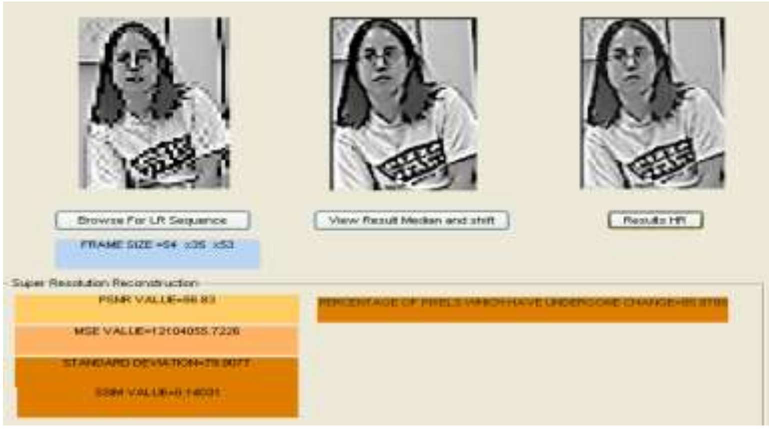

Fig.8. GUI wit HR result and different calculated image quality parameter for Emily_small test vector

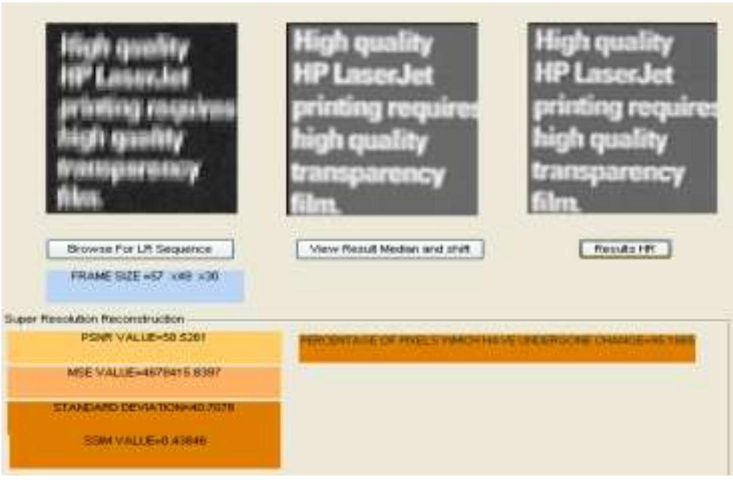

Fig.9. GUI wit HR result and different calculated image quality parameter for Printer text test vector

Fig.10. GUI wit HR result and different calculated image quality parameter for disk test vector

Test Vector	% Change in pixel values	Image Quality Parameters			
		PSNR	MSE	SD	SSIM
Emily.	85.91	64.96	23.39×10^{6}	48.9	0.511
Emily_ small	95.97	56.83	12.10×10^{6}	79.9	0.14
Printer Text.	95.16	58.52	46.78	40.7	0.438
Disk	95.62	57.86	44.1	42.5	0.411

Table.1 -Results showing different test vectors and their image quality parameters and % change in pixel values

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