International Journal of Signal Processing, Image Processing and Pattern Recognition
Vol.7, No.1 (2014), pp.283-298
http://dx.doi.org/10.14257/ijsip.2014.7.1.27

An Improved Super Resolution Image Reconstruction using SVD based Fusion and Blind Deconvolution techniques

A. Geetha Devi[1], T. Madhu[2] and K. Lal Kishore[3]

[1]Dept., of ECE, PVP Siddhartha Institute of Technology, Vijayawada, India
[2]Swarnandra Institute of Engg., &Tech., Narasapuram, India
[3]Jawaharlal Nehru Technological University, Ananthapur, Andhra Pradesh, India
[1]geetha.agd@gmail.com, [2]tennetimadhu@yahoo.com

Abstract

The High resolution (HR) images can be obtained from a set of noisy and blurred low resolution (LR) observations by applying the Super Resolution (SR) technique. In this paper a new SR algorithm that uses Singular Value Decomposition (SVD) based Fusion and Blind deconvolution techniques is proposed. The algorithm significantly improves the resolution and eliminates the noise and blur associated with low resolution images, when compared with the other existing methods.

Keywords: *Super Resolution, Image Fusion, Image registration, Blind Deconvolution*

1. Introduction

The quality of image information determines the efficiency and effectiveness of applications such as medical imaging, remote sensing, HDTV (High Definition Television), Video Surveillance, Video conferencing *etc*. Hence, high resolution images are required to improve the efficacy of these systems. Although High Precision optics and sensors will produce high resolution images, their cost is very high. Hence, efforts are made to improve the resolution of images acquired from low precision, low cost image acquisition equipment by using signal processing techniques and is known as the Super Resolution(SR) image reconstruction technique. Hence, Super Resolution is the method of obtaining High Resolution [HR] images from a set of noisy and blurred low resolution observations. The generalized block diagram of the super resolution image reconstruction is depicted in Figure 1.

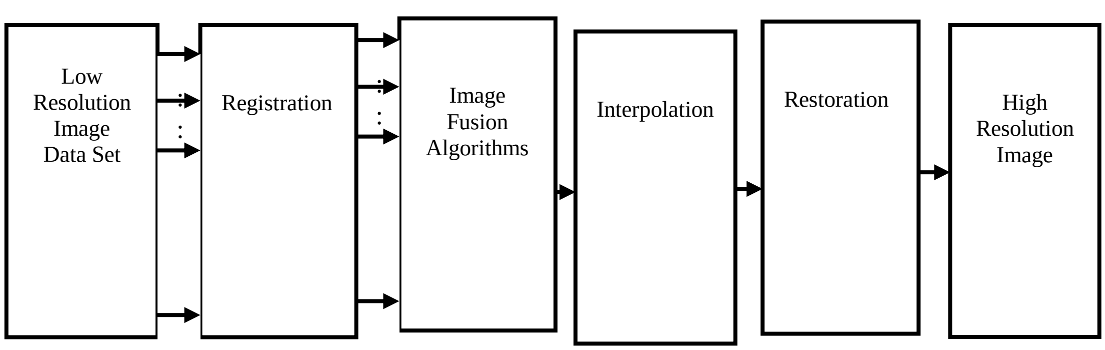


Figure 1. The Generalized Block Diagram of Super Resolution

ISSN: 2005-4254 IJSIP

SR image reconstruction can be achieved by using either a single image or a set of multiple images. Single image SR techniques require a large amount of training data for the learning methods, where as the multiple image SR Methods deal with the inverse problem [1]. In multiple SR reconstruction technique, the low resolution (LR) images are obtained with a low resolution camera or sensor operated from different viewpoints, at different times or with the use of cameras having different resolution. The low resolution observations can be formulated as

$$y_{c,i} = DHF_{c,i}X_c + N_{c,i} \qquad c = \mathrm{R,G,B} \;\&\; i = 1,2,3 \ldots\ldots\ldots\ldots \mathrm{N}. \qquad \ldots(1)$$

Where N is the number of low resolution observations made, *Xc* is the c^{th} colour component of unknown High resolution image, $y_{c,i}$ is the i^{th} Low resolution image of the *Xc*, D is the down sampling matrix, H is the point spread function of the blur operator, $F_{c,i}$ is the warping matrix and $N_{c,i}$ is the additive noise. The LR images so obtained must be brought onto a common geometrical plane to improve the resolution and the process is known as image registration [2]. Image registration techniques such as point based, feature based and area based image registration techniques are studied [3]. Feature based image registration & analysis is found to be more suitable for medical imaging applications [9]. A new method of super resolution using SIFT based registration is applied to medical images with improved results [10] and is used in our proposed method.

Further, as more pixel details will be available in a number of low resolution images due to the sub pixel shift among them, all the registered LR images are to be fused into a single HR grid and interpolated to improve the resolution of the image[13]

Various fusion algorithms such as averaging method, Principle component analysis (PCA) and wavelet based Fusion [13], scale Invariant-wavelet Transform [4], Laplacian pyramid [5], Filter Subtract decimate(FSD)pyramid, Ratio of low pass Pyramid and Morphological difference Pyramid fusion methods and Radon Transform fusion [4]are implemented and explained in section II. The SVD (Singular Value Decomposition) technique is mainly utilized in facial feature extraction and recognition [6] and is used in many SR reconstruction problems for effective identification of features in LR images when compared to other fusion algorithms. Hence SVD based fusion is utilized in the proposed algorithm.

The resolution of an image can be improved by using image interpolation techniques such as nearest neighborhood, bilinear, Bicubic and spline interpolation. Bicubic interpolation is the standard used in many commercial image editing software due to its better job in obtaining good quality of resolution than its counterparts and hence is used in the proposed algorithm [14].Next, during the restoration process, most of the methods make use of prior information about noise and blur [7]. However, it may not be possible all the times to get prior information of the image condition/surroundings. Hence in this paper, blind deconvolution method of restoration which restores the image without any prior information about noise and blur is used [8]. The proposed method is compared with the other available methods using different comparison metrics like mean, standard deviation, entropy, PSNR, correlation coefficient and Universal Image Quality Index (UIQI).

2. SR Methods based on the Type of Fusion

The SR algorithms realized in this paper are differentiated only at the stage of Image fusion. The various techniques employed are discussed in this section.

2.1. Average Fusion Based SR:

In this SR reconstruction technique utilises the simple average based fusion. Averaging fusion comes under arithmetic fusion algorithms which are very simple and effective in nature. The fused image is obtained as an arithmetic combination of the corresponding pixel intensities in the input images and is expressed as

$$I_{fused}(x,y)=K_1 I_1(x,y) + K_2 I_2(x,y) + C \qquad ...(2)$$

Where I_{fused} is the resultant fused image, I_1 & I_2 are the input images to be fused and K_1, K_2 & C are constants. For simple averaging method K_1 & K_2 are ½ and C=0. It is computationally efficient than any other fusion algorithms but does not provide enviable performance since there is a loss of contrast during the averaging process. It produces reasonable image quality in the places where the input information is similar but the quality falls abruptly when the input information is different.

2.2. Principle Component Analysis (PCA) Fusion Based SR:

The name of the method itself defends the method of fusion employed in this algorithm. It is the PCA which is a variable reduction procedure and is suitable for the development of smaller number of variables from the obtained measures on a number of observed variables. These variables are called the principle components, those account for most of the variance in the observed variables *i.e.*, most of the information lies in the observed variables. The variance captured by the principle components will give the same result as the original with all observed variables.PCA can identify the strongest patterns in the image and thus helps in reducing the complexity by reducing the variables and also removes the noise in the dataset.

The fusion algorithm using PCA is explained in the following steps in detail for two observed LR images

1. Read the Two LR images I_1 and I_2
2. Compute the size of the images. If size is same go to step3 else fusion is not possible.
3. Calculate the mean (m_x)and the covariance matrix (C_x)using

$$m_x=E[X] \;\&\; C_x= E[(X-m_x)(X- m_x)^T] \qquad ...(3)$$

4. Compute the Eigen vectors and Eigen values.
5. Eigen vectors corresponding to largest eigen value is obtained *i.e.*, v(1) &v(2)
6. Normalized Eigen vectors for both the images p1 and p2 are computed *i.e.*, $p1=v(1)/\sum v$ & $p2=v(2)/\sum v$
7. For each pixel (i,j) compute $F(i,j)=p1(I_1(i,j))+p2(I_2(i,j))$

   Where F (i,j) is the fused image pixel at(i,j).

2.3. Discrete Wavelet Transform (DWT) Fusion based SR:

The wavelet transform is a powerful tool in the area of image fusion and is used to represent the local frequency content of the image. The two dimensional DWT can be obtained by applying the wavelet transform across rows and columns of the image and is given by

$$f(x,y)=\sum_{i,j} A_{l0}(j,k)\phi_{i,j,k}(x,y)+\sum_{s=H,V,D}\sum_{l=l0}^{\infty}\sum_{j,k} D_l^s[j,k]\psi_{i,j,k}^s(x,y) \quad ...(4)$$

Where A_{l0} is approximation coefficient

$\phi_{i,j,k}(x,y)$ is the scaling function

$D_l^s[j,k]$ is detail coefficients

$\psi_{i,j,k}^s$ is set of wavelet function.

The coefficients of wavelet transform for an image can be calculated by using a series of LPF, HPF and down samples across the rows and columns. The representation of wavelet transform is shown in the Figure 2. The wavelet based fusion can be obtained using the following steps and is depicted in the Figure 3.

1. Apply wavelet transform on both the input low resolution images.
2. Fuse the images at each transform level
3. Take the inverse DWT to get the fused image in spatial domain.

2.4. Scale Invariant DWT(SIDWT) Fusion Based SR:

The conventional DWT encounters many problems during the fusion process *i.e.*, it directs to unstable and flickering results during the fusion process. The fusion process should not be dependent on the location of the objects in the image and it must offer stable and consistent output with original input sequence. SIDWT conquers this disadvantage by considering the maximum selection rule of the maximum of approximation wavelet coefficient of SIDWT.

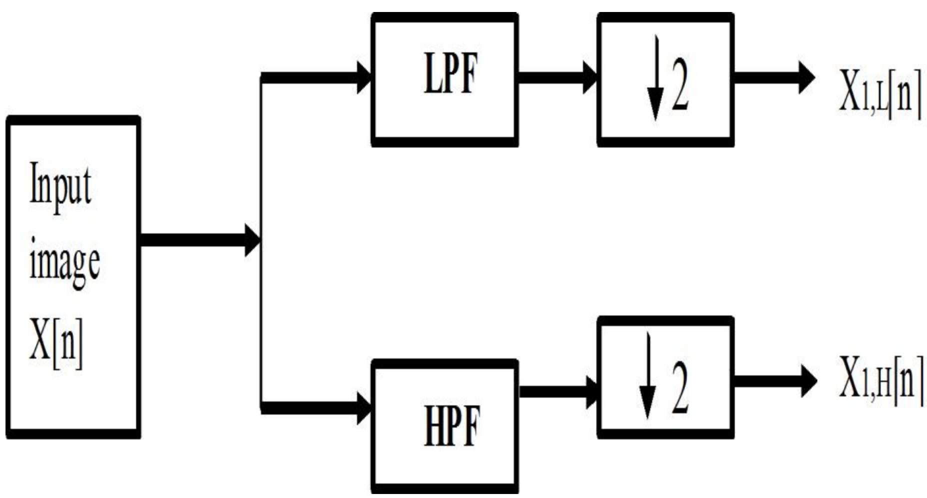


Figure 2. Wavelet Transform of an Image

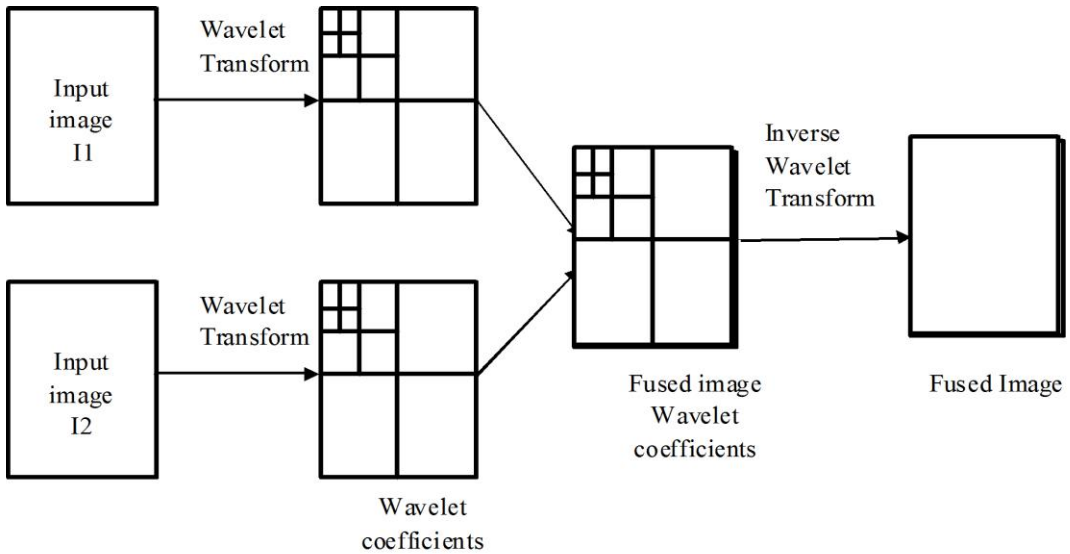


Figure 3. Wavelet based Fusion of Two LR Images

2.5. Radon Transform Fusion based SR:

The Radon transform is used to represent an image with lines into a domain of parameters where each line in the image give a peak, located at the corresponding line parameters. The radon transform of an image I(x,y) is given in the plane (ρ,θ) as

$$g(\rho,\theta) = R(I(x,y)) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} I(x,y)\delta(x\cos\theta + y\sin\theta - \rho)dxdy \quad ...(5)$$

where δ(.) is 2-D impulse function, ρ is the perpendicular distance from the origin and θ is the angle formed by the distance vector.

The steps to be followed for image fusion in Radon space are

1. Compute the Radon transform of the input registered images.
2. Take the average in radon space
3. Get the fused image by applying the inverse radon transform

2.6. Image Pyramid Approaches:

An image pyramid is a stack of low pass and high pass copies of an image and each copy represents the image information at different scales. Each level in an image pyramid is a factor of two smaller than its predecessor. As the level increases it comprises lower frequencies. The basic image pyramid is Gaussian image pyramid and is a set of low pass filtered versions of the actual image such that the consecutive levels correspond to lower frequencies. The low pass filtering is done using convolution with a Gaussian filter kernel and is given by

$$\Re[I(i,j)] = \sum_{x=1}^{5}\sum_{y=1}^{5} w[x,y]I[2i+x,2j+y] \quad ...(6)$$

$G_0 = I$ and $G_{i+1} = \Re(G_i)$

where $\Re$ is the reduction function, w(x,y)is the weighting function and I is the input image and G_i is i^{th} level of the image pyramid. The reduction function $\Re$ is a filtering followed by elimination of unnecessary pixels and the dimensions for the w(x,y) the weighting function is 5×5 and the reduction factor is 4.There is a corresponding expansion operator which will reconstruct the low pass filtered image by interpolating between pixels in the reduced image.

2.6.1. Laplacian Pyramid Fusion based SR:

The Laplacian pyramid is a decomposition of the original image into a hierarchy of images such that each level corresponds to a different bond of image frequencies. This can be carried out by the difference of levels in the Gaussian pyramid. For image I the Laplacian pyramid L(I) is given by

$$L_i = G_i - E(G_{i+1}) \qquad \text{...(7)}$$

Where Li is the i^{th} level of Laplacian pyramid G_i is the i^{th} level of Gaussian pyramid and the E is the expansion operator of Gaussian pyramid. The image fusion algorithm using the Laplacian pyramid is achieved by the following steps.

1. Represent the input images to be fused using the Laplacian pyramids.
2. Select a strength measure to decide the source and pixels that contribute at each sample location. For example local area sum as a measure of strength or maximum high pass component selection.
3. Add the selected components to get the fused image.

2.6.2. Contrast Pyramid/Ratio Pyramid Fusion based SR:

This scheme takes the ratio of the low pass images at successive levels of the Gaussian pyramid since contrast is the ratio of difference between luminance at a certain location in the image plane. These levels differ in sample density, it is necessary to interpolate new values of low frequency image before it can divide he higher frequency image. In this case the fusion rule is to select at each pixel location (i,j) at the pyramid level L, the pixel value from the largest deviation from unity of the input images.

2.6.3. Filter- Subtract- Decimate Pyramid (FSD) Fusion based SR:

This is analogous to Laplacian fusion, the only difference is using FSD pyramid in place of Laplacian Pyramids. In Laplacian pyramid, the difference image L_i at level i is obtained by subtracting an image up sampled and then low-pass filtered at level i+1 from the Gaussian image G_i at level i, while in FSD pyramid, this difference image is acquired directly from the Gaussian image G_i at level i subtracted by the low-pass filtered image of G_i. As a result, FSD pyramid fusion technique is computationally more proficient than the Laplacian pyramid method by skipping an up sampling step.

2.6.4. Morphological(MOD) Difference Pyramid Fusion based SR:

The filtering techniques applied in the above stated image pyramids change the features of shape and the exact position of the objects in the image. This problem can be solved using morphological filters to eliminate the image details without any undesirable effects. A morphological pyramid is obtained by applying morphological filters to the Gaussian pyramid at each level and taking the difference between two successive levels. The morphological filters comprised of a number of basic transformations like closing and opening. The opening operator is a combination of two other operators, erosion followed by dilation, by the same input structural element. The Structuring element is a matrix used to define a neighbourhood shape and size for morphological operations. It consists of 0's and 1's and may have a random shape and size depending on the input image. A morphological filer is used for noise removal and image smoothing similar to a low-pass filter, but it will not change nature and locations of objects in the image. Therefore the morphological pyramid fusion is the same as the Laplacian pyramid fusion except replacing the Laplacian pyramid with the morphological pyramid.

3. Proposed Algorithm: SVD Fusion Based SR

The estimate of high resolution image can be obtained by applying the inverse operation on the low resolution observations. The various segments of the proposed algorithm, as shown in Figure 2, are explained using two images and can be extended to any number. The flow of the algorithm comprises of four steps. Automatic feature based registration using Scale Invariant feature transform (SIFT) algorithm, SVD (Singular Value decomposition) fusion and Bicubic interpolation followed by Blind deconvolution restoration.

3.1. Automatic Feature Based Registration Using SIFT:

Registration is the process of bringing all the shifted versions of low resolution images into a single plane with respect to a reference image. Feature based registration comprises of feature detection, feature matching, optimum transformation and up-sampling and provides better results in many applications. Features of the image are the distinct and prominent objects like edges, lines and contours which can be detected either manually or automatically. These points are called control points. The location and scale of the control points has to be determined by a detailed model. SIFT (scale Invariant Feature Transform) model is used for the automatic registration [11]. In SIFT algorithm the control points are called SIFT keys. These SIFT keys are obtained using the Difference of the Gaussian (DoG) by comparing a pixel to its 26 neighbours at the current three adjoining scales and based on the image gradient directions each key point location is given one or more orientations. The feature matching is establishing the correspondence between the detected features of the image. The regular approach is to build local descriptors around the feature point and then match the descriptors. This is a very important step since the amount of accuracy in the correct match’s identification decides the precision of the transformation in the next step. Euclidian distance matching, invariant moment and nearest neighbour based matching are the usual methods of feature matching. RANdom Sampling Consensus(RANSAC) is a strong feature estimator and is proposed in the year 1981 by Fischeler and Bolles [6]. It classifies the matching features into inliers and outliers. Inliers are the features that hold on to the model while the outliers won’t. The RANSAC algorithm starts by randomly selecting the set of corresponding points. For each possible set of four key points in the reference image and their corresponding match in the target image a mapping transform is found. Then a transformation matrix is estimated as

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = T \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \qquad ...(8)$$

Where (x,y)↔(x’,y’) are the coordinates of the matching point in the reference and targeted images and T is the transformation matrix. The symmetric transfer error d[(x,y),T^{-}

$^{1}(x',y')]^{2}$ +d[(x'y'),T(x,y)]^{2} is calculated for every matching point, and the inliers that are less than the threshold value are counted. Here d[(x,y),(x',y')]is the Euclidean distance between pixel points with coordinates(x,y) and(x',y'). Then the same procedure is applied to the rest of the key points in the reference image and the spatial coordinates of transformed key points are compared with the coordinates of the respective key points in the target image. This allows a number of key point pairs that fit the model within a certain tolerance to be identified. The model that supports the maximum number of key point pairs (consensus set) within a transform model is considered as optimal. After finding the optimal value, the model will transform the target image into the reference image, so that the corresponding points in both the images are spatially coincident.

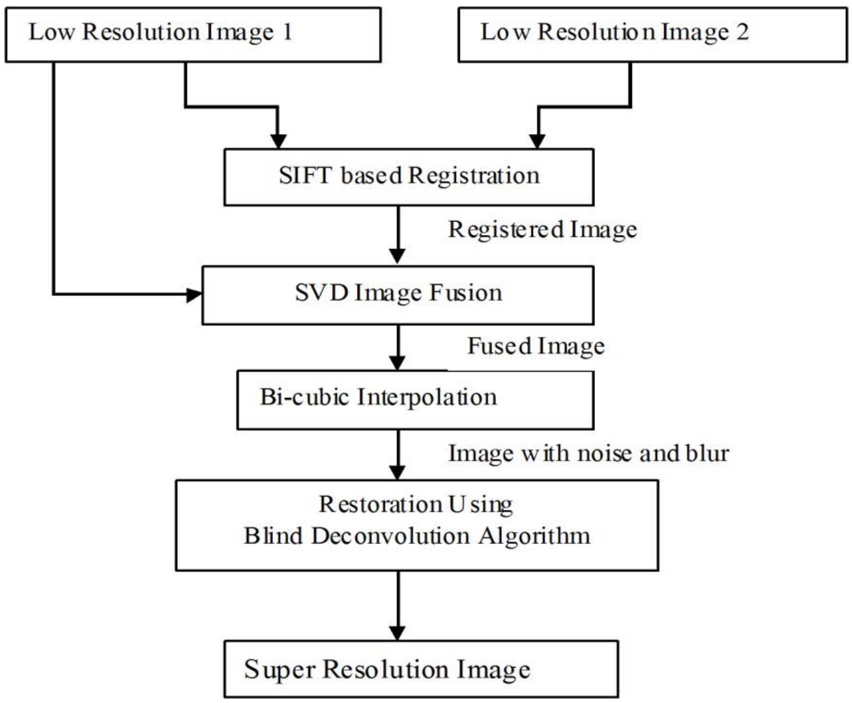


Figure 4. The Block Diagram of the Proposed Super Resolution Algorithm

3.2. Singular Value Decomposition (SVD) Fusion:

Image fusion is the process of integrating the information contained in all the low resolution observations into a single image. The Singular Value decomposition fusion gives better results in applications like signal processing, pattern recognition and data compression applications [6].

The SVD of any matrix L of dimension m×n is represented by

$$L=USV^{T} \quad ...(9)$$

Where the matrices U and V are orthogonal to each other. The columns of the m×n matrix U are the eigen vales of the LL^{T} and is known as left singular vector matrix and the columns of the m×n matrix V^{T} are the eigen vales of the $L^{T}L$ and is called the right singular vector matrix. The diagonal elements of the n×n matrix S are the singular values of the matrix L. It represents the intensity information of 'L'. The gray scale representation of any image is a two dimensional matrix which can be decomposed in to SVD. The inspiration is the fact that the highest singular value has greatest amount of input information in it and the change of highest value of SVD lies at the upper left corner of the S matrix.

The SVD fusion of the two images L_1 and L_2 are represented respectively as

$$L_1=U_1S_1V_1^T \quad ...(10)$$

$$L_2=U_2S_2V_2^T \quad ...(11)$$

For the colour images the decomposition is performed in each colour plane separately. Let the maximum values of S_1 and S_2 are $\beta1_{max}$ and $\beta2_{max}$ respectively. Then if $\beta1_{max} > \beta2_{max}$ then S_1 is used in the reconstruction of the fused image otherwise S_2 is used.

$$L_{fused}=U_2\, S_{max}V_2^T \quad ...(12)$$

Where $S_{max} = S_{1;}$ if $\beta1_{max} > \beta2_{max}$
$=S_{2;}$ if $\beta2_{max} > \beta1_{max}$

The fused image L_{fused} is passed through the interpolation step. When more than two images are available for registration the approach can be extended to multiple images. When $\beta2_{max} > \beta1_{max}$ the reference image will not come into picture at all. But in most of the images $\beta1_{max} > \beta2_{max}$, which forms a fused image of original and reference images.

3.3. Bicubic Interpolation:

The resolution of the image is improved by preserving the finer details of the fused LR images during interpolation. Bicubic Interpolation determines the grey level value from the weighted average of the 16 closest pixels to the specified input coordinates, and assigns that value to the output coordinates. The image is slightly sharper than that produced by Bilinear Interpolation, and it does not have the disjointed appearance produced by Nearest Neighbour Interpolation.

The intensity of the pixel is computed by considering its sixteen nearest neighbours as

$$x(p,q)=\sum_{i=0}^{3}\sum_{j=0}^{3}a_{ij}\,p^i q^j \quad ...(13)$$

Where the sixteen coefficients a_{ij} are determined from sixteen neighbours. Solving the sixteen equations provides a surface x(p, q) on unit square which is continuous and with continuous derivatives. Bicubic interpolation on a random sized regular grid can then be achieved by patching all such cubic surfaces, making sure that the derivatives match on the boundaries. If the derivatives are not known then they are typically approximated from the function values at points neighbouring the corners of unit square [12].

3.4. Blind De-Convolution Restoration:

Blind deconvolution Technique has been employed for the reduction of noise. The blind deconvolution includes Maximum Likelihood Algorithm and optimization strategy for obtaining the estimation of Point Spread Function (PSF). In many situations the Point Spread Function is known explicitly prior to the image restoration process. Here, the recovery of the original image is a classical linear image restoration problem and can be attempted by using techniques like inverse filtering, wiener filtering and least square filtering. However there are many situations in which PSF is not known. Then the original image should be identified directly from the observed image using partial or no information about the original image and

PSF. In such cases blind deconvolution technique permits the recovery of the original image and can be performed iteratively. If there is a presence of additive noise the exact blind deconvolution of the observed scene is not possible, and only an approximation can be obtained.

4. Results and Discussion

Two sets of low resolution data sets have been acquired for the execution of the algorithm as shown in the Figure 1.

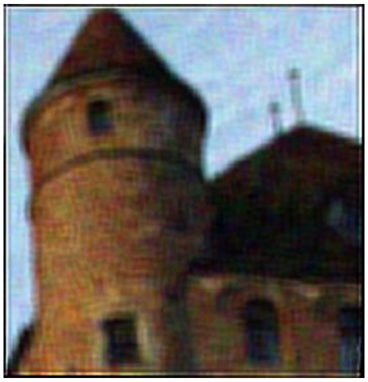
Figure 5. Low Resolution Dataset-1& 2

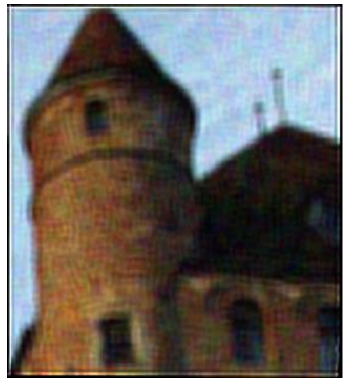
Various methods of fusion have been used to obtain the Super resolution algorithm. In all the methods Scale invariant Feature transformation method of registration has been applied, ten types of Fusion algorithms namely Simple averaging method, Discrete wavelet Transform(DWT), Scale Invariant-DWT, Laplacian Pyramid (LAP), Filter Subtract Decimate (FSD) pyramid, Morphological(MOD) difference pyramid, Principal Component Analysis(PCA), Ratio of low pass pyramid(RAT), Radon Transform and Singular Value Decomposition(SVD) Fusion techniques have been implemented. The resolution of the images has been increased by bi-cubic interpolation method and all are restored using Blind deconvolution algorithm.

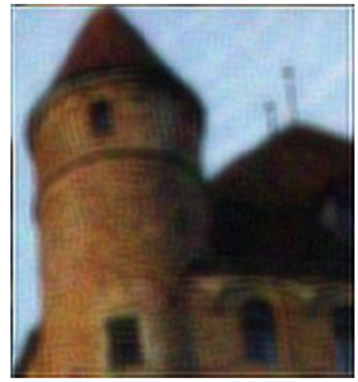
All the algorithms are compared by measuring the Mean, Standard Deviation and Entropy. These parameters do not require any ground truth image, Whereas other parameters like PSNR (Peak Signal To Noise Ratio), Correlation Coefficient and Universal Image Quality Index (UIQI) are used to find out the image quality with reference to a ground truth image. The Table 1 exemplifies the different parameters of the data set-1 without applying to blind deconvolution algorithm, whereas the Table-2 illustrates the parameters of the data set-1 with restoration. Table-3 lists the values of data set-2 without restoration and Table-4 presents the results of Dataset-2 with restoration. From all the results, SVD fusion based SR gives better results in both the types of comparisons and for both the data sets and the blur component has been almost removed from the image when compared with all the other methods.

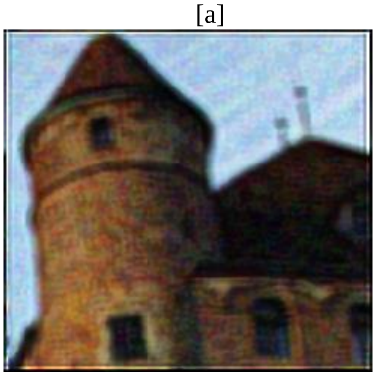
5. Conclusions

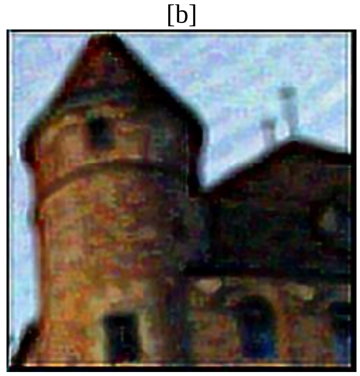
Several Super Resolution reconstruction algorithms are implemented and presented. SVD Fusion based SR algorithm is giving better results, by significantly removing the noise and blur, with an enhanced PSNR value around 11 dB and UIQI value around 0.022. This technique can be efficiently implemented in critical applications like medical imaging, facial recognition, bio-metrics and remote sensing to extract the finer details of the image.

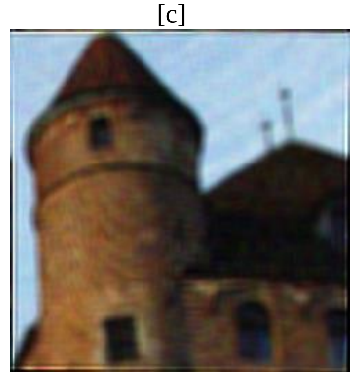

[a]

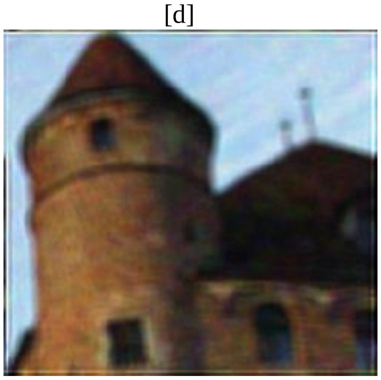

[b]

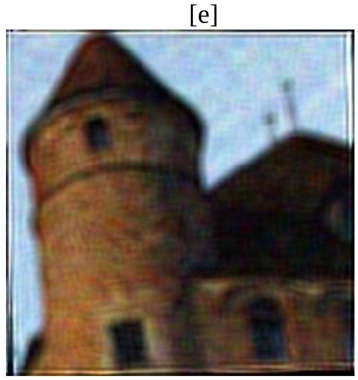

[c]

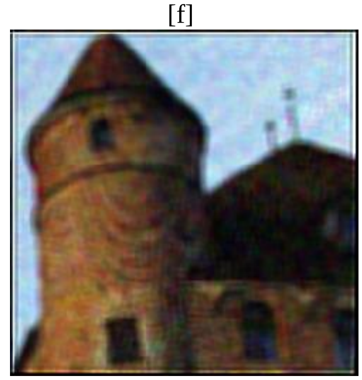

[d]


[e]


[f]


[g]


[h]


[i]

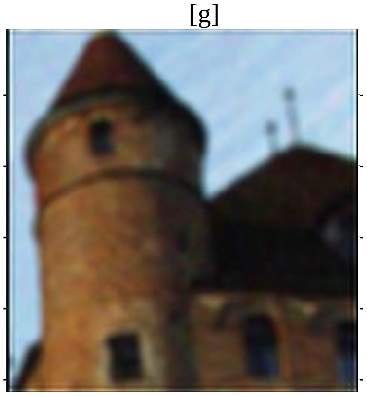

[j]

Figure.6. Super Resolution Images of Data set-1
[a]-Restored image in Simple average Fusion based SR
[b]- Restored image in DWT Fusion based SR
[c]- Restored image in FSD Fusion based SR
[d]- Restored image in LAP Fusion based SR
[e]- Restored image in MOD Fusion based SR
[f]- Restored image in PCA Fusion based SR
[g]- Restored image in RAT Fusion based SR
[h]- Restored image in SIDWT Fusion based SR
[i]- Restored image in SVD Fusion based SR
[j]- Restored image in Radon Transform Fusion based SR

Figure.7. Super Resolution Images of Data set-2
[a]-Restored image in Simple average Fusion based SR
[b]- Restored image in DWT Fusion based SR
[c]- Restored image in FSD Fusion based SR
[d]- Restored image in LAP Fusion based SR
[e]- Restored image in MOD Fusion based SR
[f]- Restored image in PCA Fusion based SR
[g]- Restored image in RAT Fusion based SR
[h]- Restored image in SIDWT Fusion based SR
[i]- Restored image in SVD Fusion based SR
[j]- Restored image in Radon Transform Fusion based SR

Table 2. Comparison Parameters with Restoration for Dataset-1

S.No.	Applied Method	Parameters without reference image			Parameters with reference image		
		Mean	Standard Deviation	Entropy	PSNR	UIQI	Correlation Coefficient
1	Average Fusion Based SR	89.5407	74.69	7.5695	39.3015	0.5023	0.6001
2	Discrete Wavelet transform (DWT) Fusion based SR	90.2269	70.1639	7.6587	36.9755	0.5666	0.5904
3	Filter Subtract Decimate (FSD) pyramid fusion based SR	89.8869	66.0597	7.5267	35.4476	0.5783	0.5904
4	Morphological(MOD) difference pyramid fusion based SR	90.1549	76.4695	7.4144	30.6839	0.5135	0.5244
5	Principle Component Analysis(PCA) Fusion based SR	89.5098	69.4095	7.5273	37.0485	0.5766	0.5831
6	Ratio of low pass pyramid(RAT)/ contrast pyramid Fusion based SR	89.8869	75.5924	7.6767	39.1988	0.8440	0.8465
7	Laplacian Pyramid(LAP) Fusion based SR	90.1549	70.5148	7.6311	39.18	0.5994	0.6044
8	**Singular Value Decomposition (SVD) Fusion based SR**	**91.7402**	**78.4092**	**7.6977**	**37.0416**	**0.5742**	**0.5747**
9	Radon Transform Fusion Based SR	89.8869	71.0852	7.6523	39.1988	0.8926	0.9002
10	Scale Invariant wavelet Transform (SIDWT) Fusion based SR	89.8869	70.3709	7.6206	39.2593	0.5722	0.5747

S.No.	Applied Method	Parameters without reference image			Parameters with reference image		
		Mean	Standard Deviation	Entropy	PSNR	UIQI	Correlation Coefficient
1	Average Fusion Based SR	92.2390	75.8437	7.6523	41.2792	0.9010	0.9037
2	Discrete Wavelet transform (DWT) Fusion based SR	90.7875.	76.1694	7.6911	40.0478	0.9067	0.9089
3	Filter Subtract Decimate pyramid fusion based SR	88.4104	71.0852	7.6467	39.1988	0.8926	0.9002
4	Morphological difference pyramid fusion based SR	77.4141	78.0397	7.4452	40.0839	0.8973	0.8986
5	Principle Component Analysis Fusion based SR	90.6773	71.0852	7.6401	40.0026	0.9571	0.9654
6	Ratio of low pass pyramid (RAT) /contrast pyramid Fusion based SR	89.8869	75.5924	7.6767	39.1988	0.8440	0.8465
7	Laplacian Pyramid (LAP) Fusion based SR	93.18	77.0935	7.6972	40.0839	0.9784	0.9866
8	**Singular Value Decomposition (SVD) Fusion based SR**	**92.6740**	**73.1122**	**7.6731**	**52.7251**	**0.9777**	**0.9884**
9	Radon Transform Fusion Based SR	89.8869	71.0852	7.6523	39.1988	0.8926	0.9002
10	Scale Invariant wavelet Transform Fusion based SR	92.9259	76.0672	7.6837	51.1915	0.8755	0.8767

Table 3. Comparison Parameters without Restoration for Dataset-2

S.No.	Applied Method	Parameters without reference image			Parameters with reference image		
		Mean	Standard Deviation	Entropy	PSNR	UIQI	Correlation Coefficient
1	Average Fusion Based SR	91.7763	40.0496	7.3080	28.2824	0.339	0.3404
2	Discrete Wavelet transform (DWT) Fusion based SR	88.8771	50.4574	7.4550	28.2824	0.2463	0.2500
3	Filter Subtract Decimate (FSD) pyramid fusion based SR	89.1663	47.4949	7.4643	28.3097	0.2603	0.2621
4	Morphological difference (MOD) pyramid fusion based SR	77.9099	51.9818	7.2823	28.2730	0.1693	0.1730
5	Principle Component Analysis (PCA) Fusion based SR	90.5735	44.7564	7.3833	29.8310	0.3282	0.3306
6	Ratio of low pass pyramid(RAT) /contrast pyramid Fusion based SR	100.53	50.1140	7.5410	29.3520	0.2649	0.2670
7	Laplacian Pyramid(LAP) Fusion based SR	89.6935	51.0313	7.4006	28.8011	0.2552	0.2570
8	**Singular Value Decomposition (SVD) Fusion based SR**	**96.5034**	**53.7698**	**7.5141**	**29.9424**	**0.3756**	**0.3769**
9	Radon Transform Fusion Based SR	89.8443	48.5416	7.3728	28.5370	0.2525	0.2539
10	Scale Invariant wavelet Tranform (SIDWT) Fusion based SR	89.6453	38.3261	7.2577	24.3683	0.3019	0.3169

Table 4. Comparison Parameters with Restoration for Dataset-2

S.No	Applied Method	Parameters without reference image			Parameters with reference image		
		Mean	Standard Deviation	Entropy	PSNR	UIQI	Correlation Coefficient
1	Average Fusion Based SR	91.7529	41.6443	7.3728	31.8146	0.3846	0.3921
2	Discrete Wavelet transform (DWT) Fusion based SR	89.8444	48.5416	7.4179	28.5370	0.2525	0.2539
3	Filter Subtract Decimate (FSD) pyramid fusion based SR	89.8445	48.5416	7.4585	28.5372	0.2525	0.2539
4	Morphological(MOD) difference pyramid fusion based SR	89.7260	56.2984	7.1947	26.8309	0.1985	0.2019
5	Principle Component Analysis(PCA) Fusion based SR	90.5029	47.0241	7.4625	31.0314	0.3908	0.3927
6	Ratio of low pass pyramid(RAT) /contrast pyramid Fusion based SR	89.8400	53.83	7.5464	28.5370	0.2271	0.2289
7	Laplacian Pyramid(LAP) Fusion based SR	89.7260	48.5416	7.3868	26.8309	0.2403	0.2417
8	**Singular Value Decomposition (SVD) Fusion based SR**	**95.7784**	**57.6277**	**7.5693**	**48.4745**	**0.3982**	**0.3992**
9	Radon Transform Fusion Based SR	89.8443	48.5416	7.3728	28.5370	0.2525	0.2539
10	Scale Invariant wavelet Transform (SIDWT) Fusion based SR	89.8444	54.0632	7.4480	48.4011	0.1988	0.2022

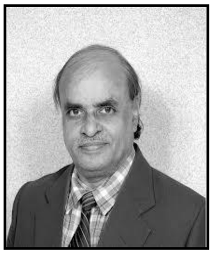
References

[1] S. Cheol Park, M. Kyu Park and M. Gi Kang, "Super Resolution Image Reconstruction: A Technical Overview", IEEE Signal processing magazine, vol. 20, no. 3, **(2003)** May, pp. 21-36.
[2] M. Irani and S. Peleg, "Improving resolution by image registration CHIP: Graph. Models Image Processing", vol. 53, no. 3, **(1991)** May, pp. 231-239.
[3] L. Brown Gottesfeld, "Survey of Image Registration techniques", ACM Computing Surveys, vol. 24, no. 4, **(1992)**, pp. 325-376.
[4] M. Deshmukh and U. Bhosale, "Image Fusion and Image Quality Assessment of Fused Images", International Journal of Image Processing (IJIP), vol. 4, no. 5, **(2010)**, pp. 484-508.
[5] P. Burt and E. Adelson, "Laplacian pyramid as a compact image code", IEEE Transactions on Communications, vol. 31, no. 4, **(1983)**.
[6] H. Nasir, V. Stankovic and S. Marshall, "Singular Value decomposition based Fusion for super resolution Image Reconstuction Signal Processing", Image Communication, vol. 27, **(2012)**, pp. 180-191.
[7] R. Hardie, "A Fast Image Super-Resolution Algorithm Using an Adaptive Wiener Filter", IEEE Transactions on Image Processing, vol. 16, no. 12, **(2007)** December.
[8] F. Sroubek, G. Cristóbal and J. Flusser, "A Unified Approach to Superresolution and Multichannel Blind Deconvolution", IEEE Transactions on Image Processing, vol. 16, no. 9, **(2007)** September.
[9] K. S. Arun and K. S. Sarath, "An Automatic Feature Based Registration Algorithm for Medical Images", International Conference on Advances in Recent Technologies in Communication and Computing, IEEE Computer Society, **(2010)**.
[10] H. Nasir, V. Stankovic and S. Marshall, "Image registration for super resolution using scale invariant", Feature transform, belief propagation and random sampling consensus 18th European Signal Processing Conference (EUSIPCO-2010), Aalborg, Denmark, **(2010)** August 23-27.
[11] Z. Yuan. P. Yan and S. Li, "Super resolution based on scale invariant feature transform", Proc. Int. Conf. Audio, Language and Image Processing, 2008. ICALIP 2008, **(2008)** July 7-9, pp. 1550-1554.
[12] D. Lancaster, "A Review of Some Image Pixel Interpolation Algorithms", www.tinaja.com/glib/pixintpl.pdf.
[13] T. Stathaki, "Image Fusion: Algorithms and Applications", First edition ,Academic Press is an imprint of Elsevier, **(2008)**.
[14] R. C. Gonzalez and R. E. Woods, "Digital Image Processing", 3rd Edition, PHI, **(2011)**.

Authors

A. Geetha Devi is presently working as an Associate Professor in PVP Siddhartha Institute of Technology, Vijayawada, India. She received her M.Tech Degree from Pondicherry Engineering College, Pondicherry, India. Presently, she is pursuing her Ph.D. from Jawaharlal Nehru Technical University, Hyderabad, India under the guidance of Dr. T. Madhu and Dr. K. Lalkishore. Her research area is Image and Video Processing.

Dr. T. Madhu is currently working as a Principal at Swarnandhra Institute of Technology, Narasapuram, India. He received the Ph.D. degree from Osmania University, Hyderabad, India. He has 22 years of teaching experience. He guided several B.Tech and M.Tech theses. He has been guiding PhD students in the area of GPS, Image processing and Embedded systems. He published many papers in various National and International Journals.



Dr. K. Lal Kishore is currently Vice Chancellor of Jawaharlal Nehru Technical University, Anathapur, India. He guided several PhD students in the area of VLSI and Image processing. He has more than 100 publications in various National and International Journals and he is author of many books. His research interests are in VLSI and Image Processing.