MAP-MRF based Simultaneous Image Registration, Interpolation and Restoration for Super Resolution Image Reconstruction

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Abstract:- Super-resolution (SR) is the process of combining a sequence of low resolution images in- order to producea higher resolution images. The goal of super resolution, as its name suggests, is to increase the resolutionof an image. Reduction of noise and blur in the super resolution process is a challenge task in reconstruction.Resolution of registered image depends on accurate feature extraction and matching. These factors reduce the quality of the image. In this paper we presented a novel approach for simultaneous image registration, interpolation and restoration is proposed with the help of affine transformation,RANdomSAmple Consensus, New Edge Directed Interpolation and MAP-MRF.The performance of the proposed is verified with quality metrics such as PSNR,SSIM and MSE values with existing methods.The results show that the proposed method generates high quality images.

***Index Terms* - SIFT (Scale Invariant Feature Transform),PCA-SIFT (Principal Component Analysis Scale Invariant Feature Transform), SURF (Speeded up Robust Features),POCS (Projections Onto Convex Sets), RANSAC (RANdomSAmple Consensus) ASIFT (Affine Scale Invariant Feature Transform).**

I. INTRODUCTION

Super resolution used to enhance the high quality (high resolution) images from a set of low quality images (low resolution images). Usually there is always a need for better quality images. However, the hardware for HR images is expensive and can be hard to obtain. The resolution of digital photographs is limited by the optics of the imaging device [2].In conventional cameras; the resolution depends on CCD sensor density, which may not be sufficiently high[3]. As the image-capturing environment is not ideal, many distortions are also present in the low-resolution images [4] .They may have blurred, noisy, aliased low resolution captures of the scene. Therefore, a new approach is required to increase the resolution of the image. It is possible to obtain an HR image from multiple low-resolution (LR) images by using the signal processing technique called super resolution. There are three major steps in super resolution i.e., image registration, interpolation and restoration. Accurate image registration is an important factor in super resolution performance. The demand for accuracy in image registration is increasing because of the super resolution applicability in various fields. There is a great deal of the image registration research in the literature. There are several super resolution reconstruction methods are used to improve resolution of a images, Tsai and Huang were the first to consider the problem of obtaining a high-quality image from several lower quality and translation ally displaced images in 1984 [5]. Their data set consisted of terrestrial photographs taken by Landsat satellites. Super resolution is a process of increase the quality of image. Now a day's Image restoration plays a major role. It is a well defined process of visually increase the quality of image and focus on clipping of unwanted effects which accomplished during the image capturing. For instance, de-blurring, de-noising methods are used to cancel or minimize those effects. Neither of these methods is able to increase the spatial resolution of the images [6, 7] Nevertheless, without image restoration and interpolation one cannot understand the concept of super resolution. In this study, an image super-resolution (SR) reconstruction approach SIRIR is proposed. The proposed method consists of three stages namely, sub pixel shift for feature extraction and worst feature elimination by modified ASIFT algorithm with perceptive transformation , extracted feature interpolation by New Edge directed interpolation to Sharpening the edges further Markov random field regularization and MAP is used for de noising and de blurring.

The rest of the paper is organized as follows. Section 2 presents methods and materials for super resolution reconstruction. Section 3 presents the image observation model of the SR problem. In Section 4 formulation of our proposed method is presented. Section 5 presents complete algorithm of our approach Finally Experimental results of proposed method is compared with other methods are provided in section 6 and section 7 concludes this paper.

II. RELATED WORK

According to method of Jianjun Zhu and others [12], high resolution image is constructed using pixel value of the corresponding area can be calculated by using the gray function and also proves that the visual feeling of image can be improved. A. Geetha Devi and others [13] proposed a SR algorithm based on fusion and blind deconvolution method to remove noise and blur. But no attention is given to the motion estimation model of LR images. According to the early work of Hongyan Zhang and others [14] , for reconstruction of multiangle remote sensing The registration of the non flat areas is still a challenge task, so more robust motion estimation methods are needed. Prof.Netra M Lokhande and others [15] showed the quality metrics of various super resolution algorithm based on the various parameter and conclude the fast robust SR method provide the best results. According to Hengyu LI and Jiqing Chen [16], super-resolution image reconstruction algorithm based on SURF (Speeded up Robust Features) and POCS (Projections Onto Convex Sets). And use RANSAC (RANdomSAmple Consensus) algorithm to kick out fault feature to improve the accuracy of image registration. But no concentration is given for interpolation errors. According to early work of EsmaeilFaramarzi and others [17] , unified blind method for multi-image super-resolution (MISR or SR), single-image blur deconvolution (SIBD), and multi-image blur deconvolution (MIBD) of low-resolution (LR) images degraded by linear space-invariant (LSI) blur, aliasing, and additive white Gaussian noise (AWGN). And also proves blur estimation is done in filter domain rather than pixel domain for better performance. According to SapanNaik [18], reconstruction can be done by combining wavelet domain and spatial domain. They proposed iterative Algorithm and it use back projection to minimize reconstruction error. The drawback of the method is they are not concentrated on the errors during registration and interpolation process. According to early work Mathew K and others [19], the wavelet-based techniques offer high accuracy in numerical differentiation and a flexible implementation of physical boundary conditions. Wavelet transform helps in attaining a good reconstruction after decompression. According to Budi Setiyono and others [20], PBIM is used to register an image and proves that estimation of translational motion is needed to improve registration accuracy. According to the work of Liyakathunisa and C.N .Ravi Kumar [21] Multiframe fusion is needed to obtain a single noise free image. And they use DCT and zonal filtering for De noising The drawback of this method is no attention is given for registration errors. According to Liangpei Zhang and others [23], a block-based local spatially adaptive reconstruction algorithm is proposed. To reduce the large computation load and realize the local spatially adaptive process of the prior model and regularization parameter and also proves that the edge is preserved during restoration process. S. DerinBabacan and others [24], proposed Variational Bayesian SR using unknown HR image to reduce the propagation of errors between the estimates of the various unknown. According to Stefanos P. Belekos and others [25] MAP approach is utilized for image prior model, and they applied it for both stationary and non stationary forms of digital video SR and also proves that it provides good result when compared to other method. Examining most of the papers [18-25] most of the techniques proposed by the authors attempt to reduce the effect of estimation errors and noise in restoration process. They do not attempt to correct the errors in the registration and interpolation process.(such as motion blur, artifacts, edge preserving etc.,).

III. OBSERVATION MODEL

Even though Super resolution of an image can be obtained through various steps the first and foremost process is to formulate an observational model from the desired High Resolution Image. So we start by modeling a problem to get the Low Resolution image from the High Resolution image. Figure [1] shows the commonly used observational model in the literature[1,3]

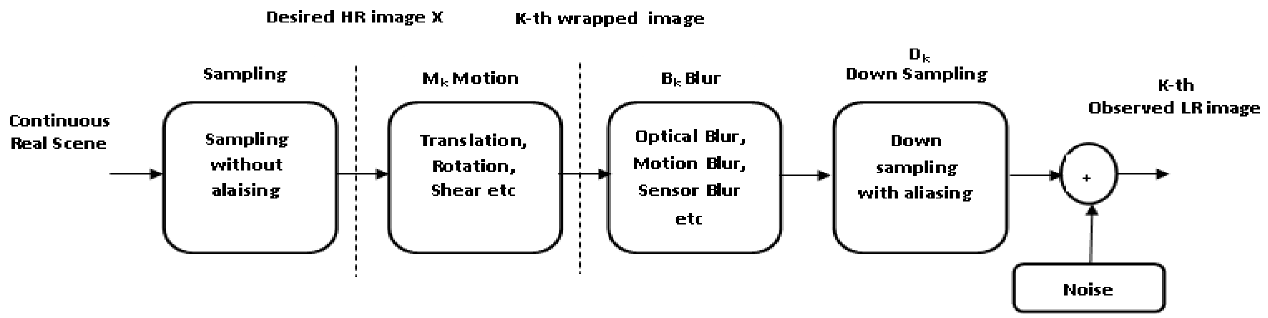

Fig. 1. Observational model

Assuming that the size of the desired HR image is W×H whereW and H are its width and height respectively. The HR image can be rewritten in lexicographical order as the vector z where $z = [x_1, x_2, \ldots x_N]^T$where N= W x H.

The vector xis a degraded image that is sampled from the continuous real world scene capture by a camera. These images are blurred because of several camera limitations. Thefinite sensor size results in sensor blur,the finite aperture size causes optical blur, the insufficient shutter speed causes motion blur[10]. The blurred images are further down sampledby the sensor into pixels. The spatial resolution of the acquired images is limited by the sensordensity which can lead to aliasing effect. Further assuming that each observed images is contaminated by Gaussian noise. Therefore, the final images are warped, blurred, down sampled and noisy versions of the real scenedescribed by the vector x.

Let $y_k$denotes the kth LR image represented as$y_k = [y_{k,1}, y_{k,2}, \ldots y_{k,M}]^T$, where $k = 1,2, \ldots, p$, with p being number of LR images.

The observational model can be defined by the equation

$$y_{k=} D_k B_k M_k x + n_k \text{ for } 1 \le k \le p$$

Where p is number of LR images. Here$D_k$is decimation sub sampling matrix,B_k is the linear space variant blur matrix,M_k is a matrix representing the motion model and $n_k$is white Gaussian noise being encountered inthe observation model.

IV. PROPOSED APPROACH:

Existing super resolution methods attempt to reduce the effect of estimation errors and noise in restoration process. They do not attempt to correct the errors in the registration and interpolation process.(Such as motion blur, artifacts, edge preserving etc.). In this proposed method we deal with noise and blurring related problem in edges region to preserve edges by Simultaneous Image Registration, Interpolation and Restoration approach (SIRIR).The proposed super resolution reconstruction methods have three stages of operation that is registration, interpolation and restoration. Our aim is to enhance the resolution of the image in every steps of the super resolution scheme. The observed low resolution image is needed to be registered first and then interpolate the image in the high resolution grid and finally the image is restored from noise and blur. Description of the proposed approach is as follows

4.1 ***Image Registration***

Image registration needs to obtain correspondence between the images such as key points detection and feature matching. Resolution of registered image depends on accurate feature extraction and matching. Image registration is a challenging task in super resolution. The point image registration algorithm most commonly use SIFT based feature extraction. Although SIFT feature is ineffective for multi-angle image matching, especially when there is a severe deformation between scenes, this algorithms is basically failure. In 2009, Morel et al analyzed the efficiency of SIFT in case of the affine variation and proposed the Affine scale invariant feature transform (ASIFT) algorithm based on the set of image transform, which simulate the transformation of the target at different angles through discrete affine sampling. ASIFT concentrate on translation rotation and scaling changes it does not concentrate on perspective distortion. Our aim is to combine both affine and perspective sampling for image registration to enhance the resolution of the image.

Steps for Registration

Step 1: Input low resolution image.

Step 2: generate the image y1 and y2 by perform affine sampling and perspective sampling of the reference image respectively.

Step 3: Perform feature point extraction and matching using SIFT

Step 4: Eliminate the mismatched feature points using RANSAC algorithm.

4.2 ***Interpolation***

Image interpolation relates to methods of constructing newimage detail from a discrete set of known points resultingin a high-resolution image. After registration our next set is to interpolate the image into high resolution grid. Even though the false feature are eliminated during registration the registered image is suffered from artifacts. In order to preserve the edge we go for two step interpolation process to preserve the edges

Steps for Interpolation

Step 1: Interpolate the unknown pixel from four neighboring pixels using fourth order linear predication.

Step 2: estimate the coefficient vector with auto covariance matrix.

Step 3: The high-resolution covariance are then replaced by the low-resolution covariance with dual geometric property

Step4: interpolate the pixel again with sixth order linear predication with the window rotated by π/2.

4.3 ***Restoration***

The image restoration or reconstruction is the final step and very important step in super resolution process. It removes blurring effect (and also the noise present in the image. Even though The geometric dual interpolation preserve the edges still the images suffer from noising and blurring because of enlargement of the image so we go for restoration process.

Steps for Restoration:

Step1: Formulate the parameter estimation using ML (maximum like hood) optimality criterion.

Step 2: Reconstruct the image using MRF prior by formulating the MAP estimate of z

V. COMPLETE ALGORITHM OF PROPOSED METHOD

1. Input Observed Low Resolution Image.
2. Obtain image1 by Perform affine distortion using latitude θ and longitude Ø angle sampling for images.
3. Obtain image 2 by performing perspective transformation of the observed image.
4. Apply tilt t=1/cos(θ) to the image1 after performing image rotation with angle Ø.
5. Perform affine transformation for low resolution image1 using the equation
$$A = \lambda \begin{bmatrix} \cos\psi & -\sin\psi \\ \sin\psi & \cos\psi \end{bmatrix} \begin{bmatrix} t & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \cos\phi & -\sin\phi \\ \sin\phi & \cos\phi \end{bmatrix}$$
whereλ is the scale factor ψ is the angle between the camera and the optical axis.
6. Perform perspective transformation for the image2 using the equation
$$P = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(-\varphi) & -\sin(-\varphi) \\ 0 & \sin(-\varphi) & \cos(-\varphi) \end{bmatrix} \times \begin{bmatrix} \cos(-k) & -\sin(-k) & 0 \\ sin(-k) & \cos(-k) & 0 \\ 0 & 0 & 1 \end{bmatrix}$$
7. Extract match and combine the feature vectors using affine scale invariant feature transform.

8. Transformational matrix is chosen as the objective function to eliminate the mismatched feature points such that $\begin{cases} u=a_1x+a_2y+t_1 \\ v=a_3x+a_4y+t_2 \end{cases}$ where I (x,y) and C (u,v) represent a feature point of reference image I and collected image C, respectively.
   // Even though the false feature are eliminated during registration the registered image is suffered from artifacts. In order to preserve the edge we go for two step interpolation process to preserve the edges.
9. Interpolate the unknown pixel from four neighboring pixels using fourth order linear predication i.e.,

$$y_{2i+1,2j+1} = \sum_{k=0}^{1}\sum_{l=0}^{1} \propto_{2k+l} Y_{2(i+k),2(j+l)}$$

10. Obtain the optimal coefficient vector set $\propto = R_{yy}^{-1} r_y$. where $\propto = [\propto_0, \dots, \propto_3], R_{yy} = [R_{kl}]$ and $r_y = [r_0, \dots r_3]$
11. Results obtained from step 6 is interpolated to the HR window using sixth order linear prediction i.e.,$y_{2i+1,2j} = \sum_{k=0}^{1}\sum_{l=-1}^{1} \propto_{2k+l} Y_{2(i+k),2(j+l)}$
   // even though The geometric dual interpolation preserve the edges still the images suffer from noising and blurring because of enlargement of the image so we go for restoration process.
12. Formulate the parameter estimation using ML(maximum likehood) optimality criterion $\hat{\theta} = \arg\max_{\theta} P(Z = z|\, \theta)$ where z is the high resolution field and Z is random field over arbitrary $N \times N$ lattice of site L.
13. Reconstruct the image using MRF prior by formulating the MAP estimate of z as $\hat{z} = \arg\max_{z} P\left(z \mid y_1, y_2, \dots, y_p\right)$

VI. EXPERIMENTAL RESULTS

We evaluate the performance of our approach with other registration and interpolation methods such as SIFT,PCASIFT,SURF,ASIFT and Bilinear, Bi-cubic,NN ,EDI respectively by MAP-MRF Reconstruction. The result is compared with quality metrics of an image (i.e. SSIM, MSE, PSNR) and it shows that our approach produce better resolution. The performance measure for the reconstructed image is done on three quality metrics, (i) peak signal to noise ratio (PSNR). (Table.2 shows the PSNR comparison of methods, Fig.2 shows the PSNR Comparison Chart of the Methods) (ii) Mean Square Error (MSE) (Table.1 shows the MSE comparison of methods, Fig.1 shows the MSE Comparison Chart of the Methods) (iii) Structured similarity index measure (SSIM) (Table.3 shows the SSIM comparison of methods, Fig.3 shows the SSIM Comparison Chart of the Methods).

(i) Peak signal to noise ratio:

$$PSNR = 10\, log_{10}\left(\frac{max^2}{MSE}\right)$$

Where max is the maximum pixel value of reconstructed image.

(ii) Mean Square Error:

$$MSE = \frac{1}{pq}\sum_{i=1}^{p}\sum_{j=1}^{q}\left(x_{ij} - y_{ij}\right)^2$$

Where p denotes number of rows, q denotes number of columns, X_{ij} denotes pixel density value of the original image and Y_{ij} denotes pixel density value of the reconstructed image.

(iii) Structured similarity index measure:

SSIM is designed by modelling any image distortion as combination of three factors that are loss of correlation,luminance distortion and contrast distortion. The SSIM is defined as:

$$SSIM = l(x,y), c(x,y), s(x,y)$$

	MAP- MRF RESTORATION (MSE)				
	Bilinear Interpolation	Bicubic Interpolation	NN method	B-Spline	New Edge Directed Interpolation
SIFT	82.3932	137.466	96.2937	160.073	0.006459
SURF	138.149	168.883	138.603	180.551	0.013641
PCA-SIFT	96.8941	131.141	105.187	145.649	0.010473
ASIFT	160.644	182.257	156.681	190.543	0.018255
Proposed	190.707	202.476	185.841	208.516	0.025621

Table 1 .MSE Comparison

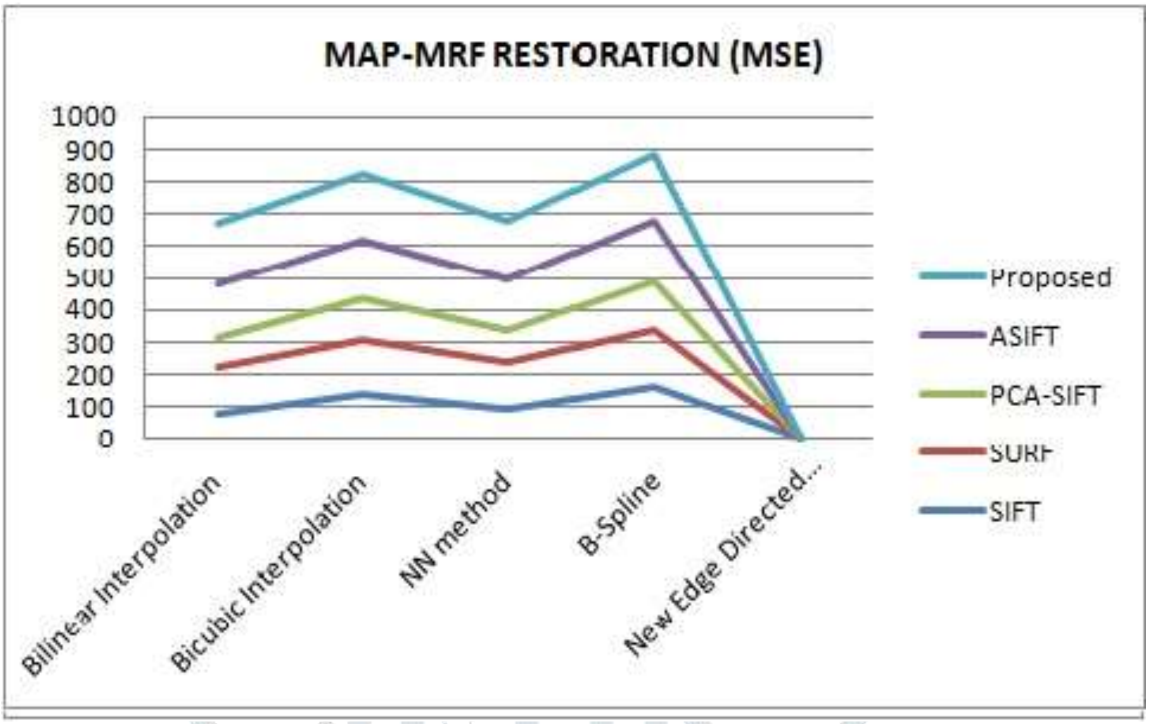

Fig .2. MSE Comparison Chart

	MAP - MRF RESTORATION (PSNR)				
	Bilinear Interpolation	Bicubic Interpolation	NN method	B-Spline	New Edge Directed Interpolation
SIFT	28.9719	26.7489	28.2948	26.0876	70.0291
SURF	26.7273	25.8549	26.7131	25.5648	66.7824
PCA-SIFT	28.2678	26.9534	27.9112	26.4977	67.9301
ASIFT	26.0722	25.524	26.1807	25.3309	65.5171
Proposed	25.3271	25.0671	25.4394	24.9394	64.0449

Table 2 .PSNR Comparison

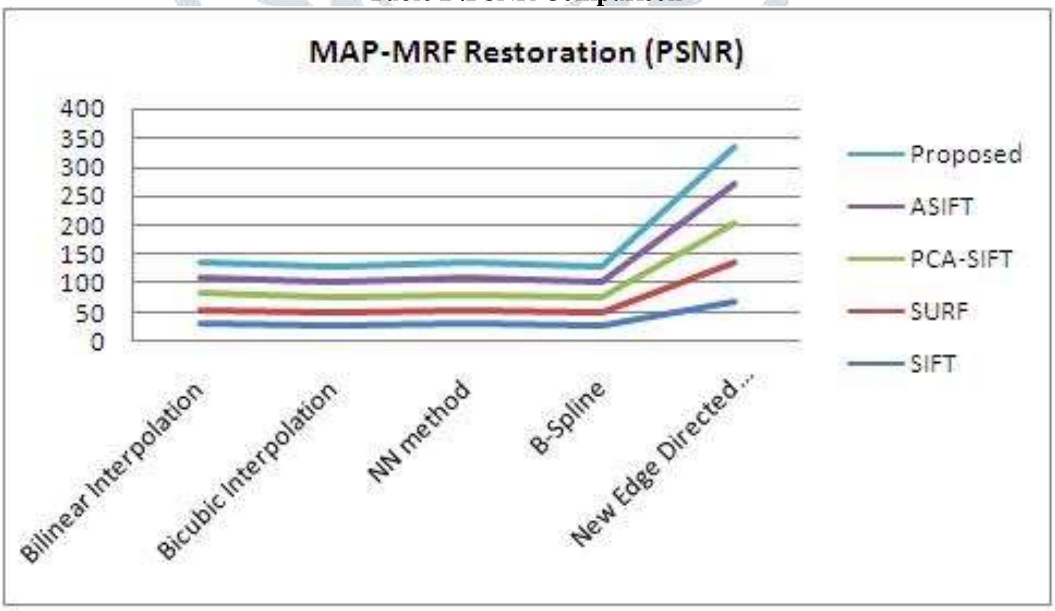

Fig .3. PSNR Comparison Chart

	MAP - MRF RESTORATION (SSIM)				
	Bilinear Interpolation	Bicubic Interpolation	NN method	B-Spline	New Edge Directed Interpolation
SIFT	0.413909	0.344839	0.358375	0.32534	0.0932214
SURF	0.342987	0.287273	0.300971	0.26605	0.152013
PCA-SIFT	0.355622	0.302703	0.311462	0.28552	0.107716
ASIFT	0.322694	0.264232	0.280613	0.24271	0.190499
Proposed	0.303258	0.236998	0.258265	0.21472	0.230997

Table 3 .SSIM Comparison

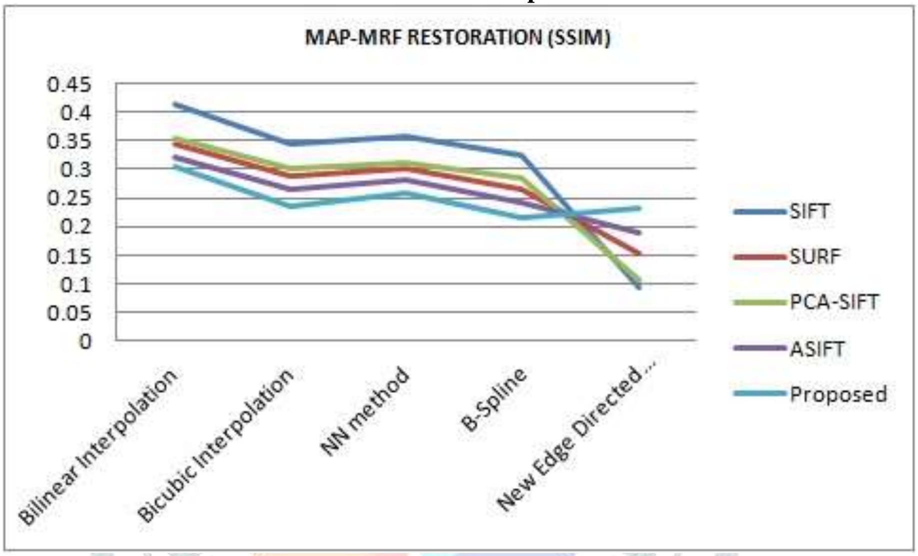

Fig .4. SSIM Comparison Chart

Fig.5: Images Obtained using Proposed Method

VII. CONCLUSION

In this paper, we propose a novel approach for simultaneous image registration, interpolation and restoration process to improve the resolution of the image. We performs more than twenty comparison with the image registration and interpolation techniques such as SIFT,PCASIFT,SURF,ASIFT and interpolation techniques Bilinear, Bi-cubic, NN, New edge directed interpolation with MAP-MRF restoration. The results showed that simultaneous methods such as ASIFT – RANSAC,NEDI and MAP-MRF produce a high resolution based on the quality metrics SSIM,PSNR&MSE.The advantage of proposed method is that it preserves edges even after interpolation which results in increase of visual quality of the image.

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