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Super Resolution Blind Reconstruction of Low Resolution Images using Wavelets based Fusion

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***Abstract*—**Crucial information barely visible to the human eye is often embedded in a series of low resolution images taken of the same scene. Super resolution reconstruction is the process of combining several low resolution images into a single higher resolution image. The ideal algorithm should be fast, and should add sharpness and details, both at edges and in regions without adding artifacts. In this paper we propose a super resolution blind reconstruction technique for linearly degraded images. In our proposed technique the algorithm is divided into three parts an image registration, wavelets based fusion and an image restoration. In this paper three low resolution images are considered which may sub pixels shifted, rotated, blurred or noisy, the sub pixel shifted images are registered using affine transformation model; A wavelet based fusion is performed and the noise is removed using soft thresolding. Our proposed technique reduces blocking artifacts and also smoothens the edges and it is also able to restore high frequency details in an image. Our technique is efficient and computationally fast having clear perspective of real time implementation.

***Keywords*—**Affine Transforms, Denoiseing, DWT, Fusion, Image registration.

I. Introduction

DURING the process of imagery, many factors including the motion between the earth and the platform, atmosphere disturbance, out of focus, non-ideal sampling and so on, all make the images blurred and degraded [13]. Super resolution technology is the signal processing based methods in software it can remove the blur caused by the imaging system as well as recover spatial frequency information beyond the diffraction limit of the optical system [1] [2].The field of super resolution has seen a tremendous growth in interest over the past decade. High resolution images are crucial in several applications including medical imaging and diagnosis, military surveillances, satellite and astronomical imaging and remote sensing. Constraints due to factors such as technology, cost, size, weight, and quality prevent the use of sensors with the desired resolution in image capture devices and consequently necessitate the design of super resolution algorithm to achieve the desired image resolution.

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Super resolution refers to the reconstruction of a high resolution image from a set of blurred and noisy low resolution images which are sub-pixel shifted from each other. Each low resolution image contains new information about the scene and super resolution aims at combining these to give a higher resolution image. Super resolution image reconstruction algorithms investigate the relative sub pixel motion information between multiple low resolution images and increase the spatial resolution by fusing them into a single frame. By fusion of several shifted low resolution images onto a finer grid, the sampling rate of the sensor can be increased in software and a resolution up to the diffraction limit of the optics can be achieved.

The organization of the paper is as follows: Section II discusses about the existing super resolution methods, in section III we provide a brief outline of the super resolution problem statement, section IV provides the steps involved in the super resolution reconstruction, section V provides the computer simulation results, finally in section VI consists of conclusion.

II. Exiting Super Resolution Methods

The methods developed so far can be divided into three different categories: (1) frequency domain reconstruction (2) Iterative (3) Bayesian Method. Frequency domain reconstruction method was first proposed by Tsai and Huang [4]. In this method, the data is first transformed to the frequency domain where it is then combined. This data is then transformed back into the spatial domain where the new image will have a higher resolution than the original frames. A high resolution image can also be reconstructed using a POCS algorithm, where the estimated reconstruction is successively obtained on different convex sets. The POCS method was originally developed by Tekalp, Ozkan, and Sezan [5]. The method proposed by Michal Irani and Schmuel Peleg [7] falls into the class of iterative algorithms. The main feature of the Irani and Peleg method is that it iteratively uses the current best guess for the SR image to create LR images and then compare the simulated LR images to the original LR images. These difference images (found by subtracting real LR - simulated LR) are then used to improve the initial guess by "back projecting" each value in the difference image onto the SR image. The Bayesian method was developed by Cheeseman [17] at NASA for SR reconstruction of planetary images. The name comes from Bayes theory, this method relies largely on the statistical knowledge that pixel to pixel differences are very small, and can be modeled with a probability distribution function. The Bayesian method seeks to find the solution possessing the maximum probability (i.e. the most likely surface given the observed values and the observation conditions).

III. Super Resolution Problem Formulation

Super resolution reconstruction is proved to be useful in many practical cases such as remote sensing, in case of remote sensing a large amount of remote sensing images of the earth with multi-platform, multi-sensor, multi-phase, multi-spectral can be obtained. In these data, there are considerable image data of the same area. But limited by the manufacturing process of the imagery equipment, these images are the under sampled of the same scene. The problem is formally described as

$$g_i = DB_iW_if[x_i] + n_i \tag{1}$$

Where
f - is the unknown high resolution
g_i - is the i th low resolution image
D_i - is the down Sampling operator
Wi - represents wrapping,
B_i - represents Blur and
η_i - represents the noise.
i =1…h

The super Resolution observation model is show in Fig. 1 below, a real world scene is seen to be wrapped at the camera lens due to the relative motion between the scene and the camera. The images are often degraded by both optical and motion blur. They are discretized or down sampled resulting in a aliased, blurred and noisy low resolution image. The objective is to obtain a high resolution image from a set of low resolution images.

IV. Super Resolution Blind Reconstruction Using Wavelet Based Fusion

In our earlier research [1] [2], In order to recover the original image, technique called blind deconvolution and zonal filters are applied to remove the blur, noise and increase the spatial resolution contained in it, the images are restored blindly i.e. without the knowledge of the true image or the noise .This type of restoration is called blind image restoration we have seen that blind deconvlution is an inverse problem with insufficient data. It is therefore desirable to exploit the extra information available in multiple frames in the super resolution problem. Among the many techniques available for blind deconvlution, few extend directly and easily to multiframe case. In [1][2] we have used the iterative blind deconvlution algorithm, but this algorithm relies on the assumption of prior knowledge, or alternatively, trial and error estimation . The goal of super resolution image reconstruction is to obtain an estimate of the source image from its blurred noisy observations, exploiting the known complementary of different low resolution images.

One of the main objectives of this research was the development of algorithms based on wavelets for super resolution with the capability of simultaneous noise reduction. The possibility of achieving simultaneous noise reduction by the use of wavelets coefficient thresholding provided an added incentive to delve deeper in this direction.

The ideal algorithm should be fast, and should add sharpness and detail, both at edges and in regions without adding artifacts. In this paper we propose a technique to yield a super resolved image from three low resolution input images; our algorithm is divided into three stages: registration, wavelet based fusion and restoration. Image registration is extremely essential for super resolution reconstruction. Our registration technique is based on affine transformation. An affine transformation is an important class of linear 2-D geometric transformations which maps variables (*e.g.* pixel intensity values located at position x_1, y_1 in an input image) into new variables (*e.g.* x_2, y_2 in an output image) by applying a linear combination of translation, rotation, scaling and/or shearing operations. The aligned images are then fused using wavelet transform.

The fusion technique should ensure that all important spatial and spectral information in the input image is transferred into the fused image, without introducing artifacts or inconsistencies, which may damage the quality of the fused image and distract or mislead the human observer. The importance of image fusion lies in the fact that each observation image contains complementary information. When this information is integrated with that of another observation, an image with maximum amount of information is obtained. Wavelet transform fusion is more formally defined by considering the wavelet transforms ω of the two or more registered input images $I_1(x, y)$,$I_2(x, y)$ and $I_3(x, y)$ together with the fusion rule . Then, the inverse wavelet transform ω^{-1} is computed, and the fused image I(x, y) is reconstructed

$$I(x,y) = \omega^{-1}(\phi(\omega(I_1(x,y)), \omega(I_2(x,y)), \omega(I_3(x,y)))) \tag{2}$$

Wavelet transform is more compact, and able to provide directional information in the low-low, high-low, low-high, and high-high bands, and contains unique information at different resolutions. Image fusion based on wavelet transform can provide better performance than those based on other multi scale methods.

A. Steps Involved in Fusion of Images in DWT Domain

As shown in Fig. 2, the approach to image fusion in DWT (Discrete Wavelet Transform) domain is as follows. By applying the Discrete Wavelet Transform(DWT) on a 2-D signal such as an image, we have reached to four outputs, i.e., Approximation(LL), Horizontal Details(LH), Vertical Details(HL) and Diagonal details(HH) of the original image. The wavelet transform can be performed for multiple levels. The next level of decomposition is performed using only the LL image. The result is four sub-images, each of size equal to half the LL image size. This process could be continuing to reach the required level. In order to obtain the fused image inverse wavelet transform is performed.

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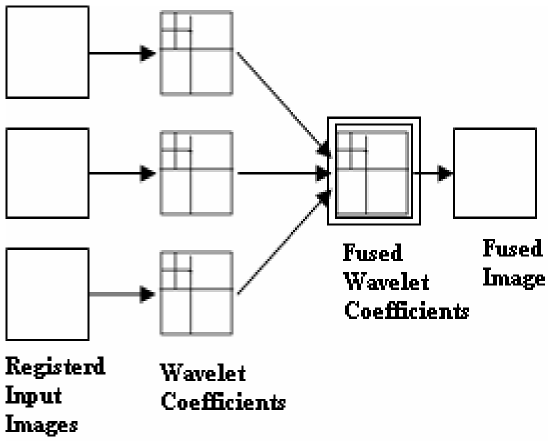

Fig. 2 Fusion of Low resolution images

B. The Algorithm for the Proposed Method is as Follows

Step 1: Three input color images are considered which may be sub pixel shifted, blurred or noisy.

Step2: The input images are registered using affine transformation.

Step 3: The registered low resolution images are decomposed into approximation and detail coefficients using 2-Level wavelet transform.

Step 4: The above steps are repeated for R, G and B bands of the low resolution images.

Step 5: In each sub band, individual pixels or groups of pixels of the wavelet transform of the two images are compared using criterion that serves as a measure such as absolute values of pixel values, maximum absolute gray value of the group of pixels being compared, and the variance.

Step 6: A fused wavelet transform is created by taking pixels from that wavelet transform that shows greater activity at the pixel location.

Step 7: The inverse wavelet transform is the fused image.

Step 8: The fused image is then denoised using soft thresholding which results in a super resolved image.

V. Results

We have considered Trees image and multispectral image of size 256x 256 as test images. The low resolution input images are shifted, rotated and blurred or noisy instances of the same scene. The images are first registered using affine transformation than they are fused using wavelet transforms and the noise present in it is removed using the denoiseing techniques such as soft thresolding. For measuring the performance of the reconstructed image the improvement in signal to noise ratio (ISNR) is calculated and compared with techniques such as blind deconvolution and zonal filters. The proposed wavelet based fusion for super resolution reconstruction is superior to the conventional techniques such as blind deconvolution and interpolation in terms of the ISNR The blur is measured using blurred signal to noise ratio (BSNR), Considering all the test images the ISNR for our techniques resultant images is on an average better by a factor 5 to 6 dB as compared to existing methods.

A. Restoration Performance

1) Blurred Signal- to-Noise Ratio (BSNR)

The degradation modeled by blurring and additive noise is referred in terms of BSNR

$$\text{BSNR}=10\log_{10}\frac{\left[\frac{1}{N^2}\right]\sum_{i,j} g(i,j)^2}{\sigma^2} \tag{3}$$

where g(i, j) is the noise free blurred image and σ is noise variance .

2) Improvement in Signal-to-Noise Ratio (ISNR)

For the purpose of objectively testing the performance of the restored image, Improvement in signal to noise ratio (ISNR) is used as the criteria which is defined by

$$\text{ISNR}=10\log_{10}\frac{\sum_{i,j} f(i,j)-y(i,j)^2}{\sum_{i,j} f(i,j)-g(i,j)^2} \tag{4}$$

Where j and i are the total number of pixels in the horizontal and vertical dimensions of the image; f(i, j), y(i, j) and g(i, j) are the original, degraded and the restored image.

B. Plot of ISNR for Various Bit Rates (BR)

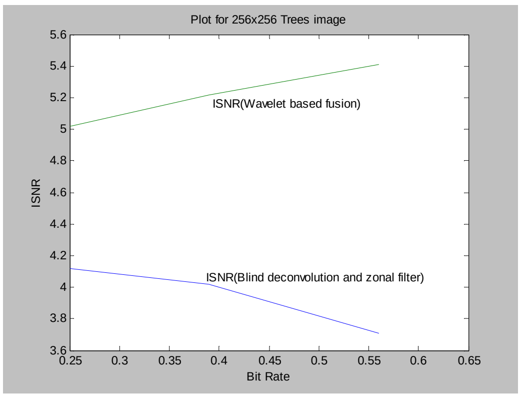

Fig. 5 Plot of ISNR's for Trees Image

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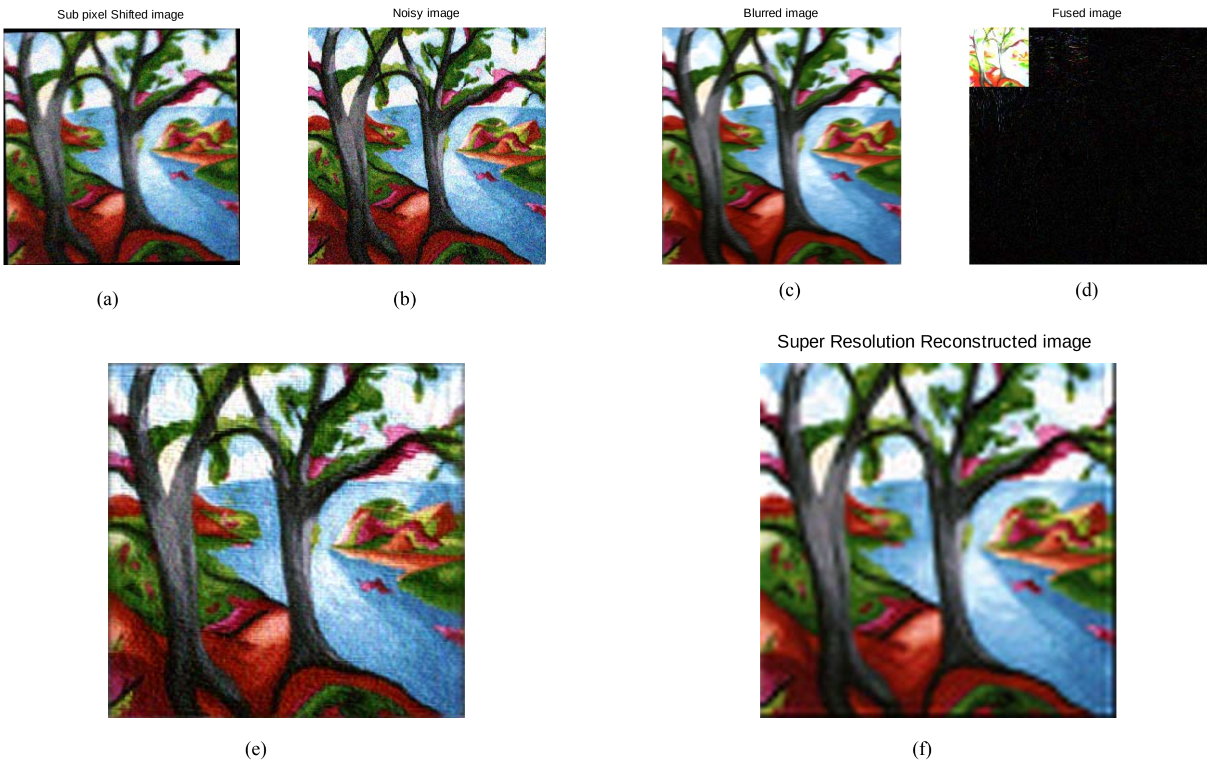

Fig .3 (a) Sub pixel shifted low resolution image (b) Noisy low resolution image (c) Blurred low resolution images with a BSNR of 40 db (d) Wavelet decomposed fused image (e) Super resolution blind reconstruction using zonal filter and blind deconvolution (f) Super resolution blind reconstruction using wavelet based fusion with an ISNR of 5.56 db at 0.56 bit rate

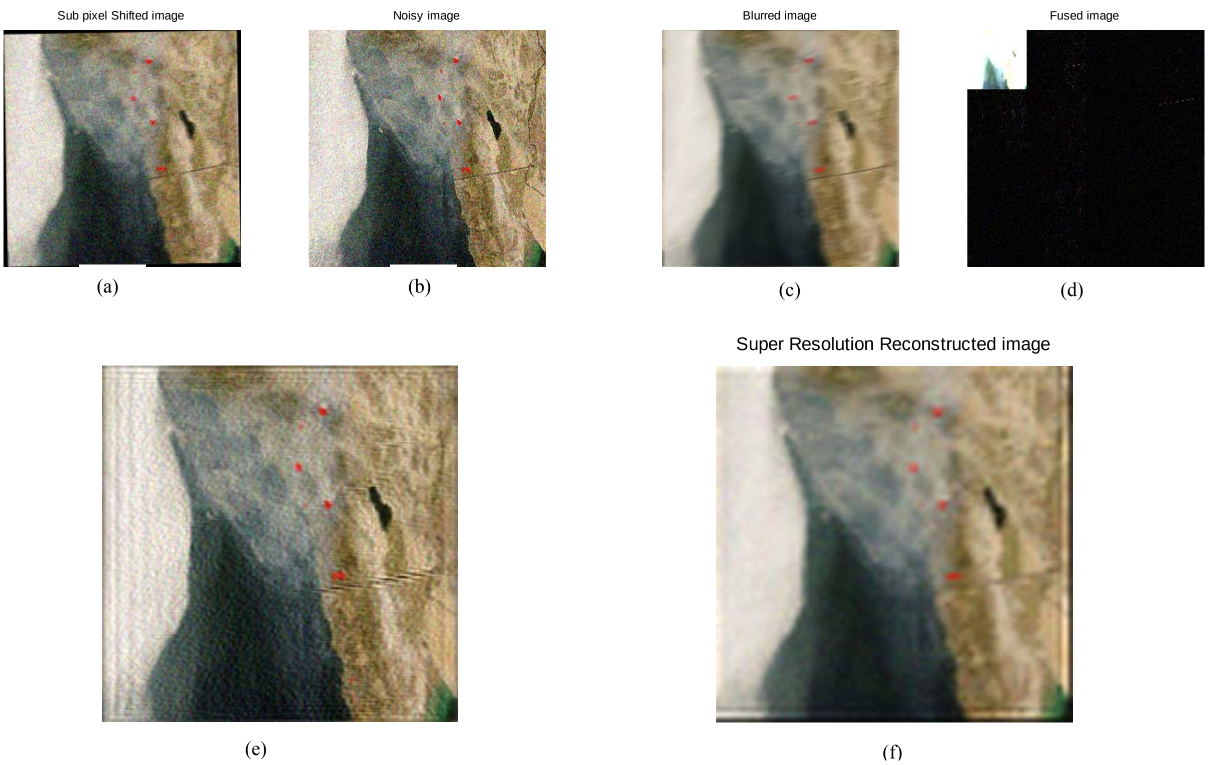

Fig .4 (a) Sub pixel shifted low resolution image (b) Noisy low resolution image (c) Blurred low resolution images with a BSNR of 40 db (d) Wavelet decomposed fused image (e) Super resolution blind reconstruction using zonal filter and blind deconvolution (f) Super resolution blind reconstruction using wavelet based fusion with an ISNR of 4.556 db at 0.56 bit rate

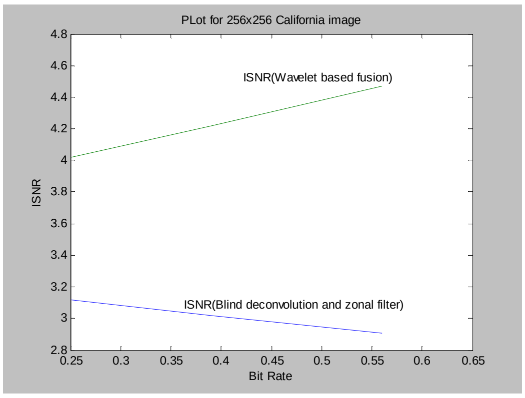

Fig. 6 Plot of ISNR's for California fire Image

VI. Conclusion

Super resolution techniques have proved to be useful in many different applications in terms of quality and computational complexity. Most of the existing super resolution methods attempt to increase the resolving power by means of bilinear interpolation, which only adds pixels but does not improve the resolving power. But in our proposed method we are reconstructing an unknown image from multiple low resolution images as well as improving the resolving power with techniques such as wavelet based fusion and soft thresolding. The efficacy of the proposed technique is evidenced by the presented simulation results.

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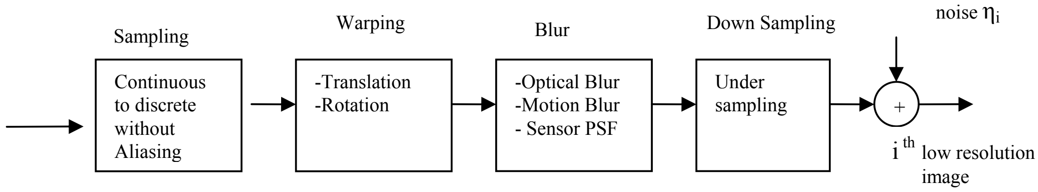

Fig. 1 Super Resolution observation Model