Super Resolution Image Reconstruction Using Wavelet Lifting Schemes

Sanwta Ram Dogiwal[1], Y.S. Shishodia[2], Abhay Upadhyaya[3]
[1]Department of Information Technology, [2]Department of Computer Science
[1]Swami Keshvanand Institute of Technology Management & Gramothan, Jaipur
[2]JaganNath University, Jaipur, [3]University of Rajasthan, Jaipur
Email- [1]dogiwal@gmail.com

Abstract: **The main objective of the super resolution images is to enhance the quality of the multiple lower resolution images. Super Resolution image is constructed by using raw images. An Image with improved resolution is always desirable for various applications like satellite, medical etc. to enhance the qualitative features are the images. In this paper, Super Resolution Image Reconstruction (SRIR) is proposed for improving the resolution of lower resolution images. Proposed approach is described as follows. Initially, Some low resolution images of same scene which are usually translated, rotated and blurred are used to form a super resolution image. Then, the image registration operation translated, orients, scaled and rotated images in the similar way to that of source image. Next, Lifting Wavelet Transform (LWT) with Daubechies4 coefficients are applied to color components of each image due to its less memory allocation compared to other wavelet techniques. Further, Set Portioning in Hierarchical Trees (SPIHT) technique is appliedfor image compression as it possess lossless compression, fast encoding/decoding, and adaptive nature. The three low resolution images are fused by spatial image fusion method. The noise is removed by dual tree Discrete Wavelet Transform (DWT) and blurring is reduced by blind deconvolution. Finally, the samples are interpolated to original samples to obtain a super resolution image. The structural similarity for each intermediate image is compared to the source image to observe high structural similarity by objective analysis. Gabor transform is also implemented for image enhancement and edge detection.**

Keywords: **Super Resolution, Wavelets Lifting Scheme, Daubechies, Image Registration, SPIHT, Gabor transform, Image enhancement.**

1. INTRODUCTION

Images processing is very important for various applications in office automation, bio-medical, remote sensing, scientific application, criminology, astronomy and space application, military application. When processing images for these applications, uncertainty in the measurement may include in form of noise, blur, contrast, rotation etc. Therefore, to remove these degradation Super Resolution technology are being used[1]. Image restoration technique is super resolution imaging. This is simply a method of increasing pixel resolution synthetically. A direct method for increasing the pixel resolution may be sensor manufacturing technique. However, increasing chip size or packing more sensor in a single chip leads to an increasing in capacitance, which make it difficult to speed up the charger transfer rate. Thus using image restoration technique to obtain a high-resolution image from many observed low resolution images has become a promising solution to the problem. The main aim of Super Resolution (SR) is to enhance the spatial resolution of multiple lower resolution images. HR means pixel density within the image is high and indicates more details about original image. Super resolution technique is an efficient lossy and low cost technology. In this paper we are using Wavelet Transform (WT) technique to get an HR image from Low Resolution (LR) images by involving image blurring, decimation, registration, deblurring, denoising and interpolation operation[2]. The Gabor filter [3] representation of images captures the pattern corresponding to spatial frequency, spatial frequency location, and orientation.

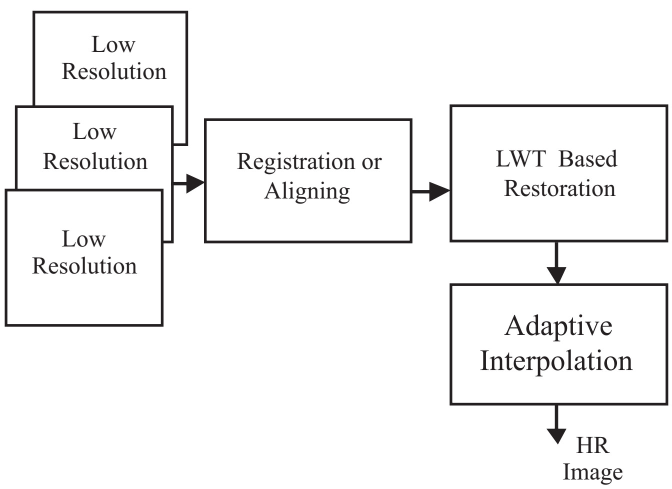

Fig 1: The Super Resolution Image Reconstruction Model

This paper uses both super resolution and Gabor wavelet to perform edge detection on low resolution images. The proposed approach initially reconstructs a higher quality image by wavelet schemes and then performs Gabor transform based on edge detection.

The flow of the topics as follows: In section 2 we provide a brief review of the image reconstructions. In section 3 we provide the mathematical model for super resolution in context of low resolution images, section 4 presents the wavelet transform, is discussed. In section 5 the proposed method for super resolution image reconstruction from low resolution images is discussed, in section 6 discussed the performance parameters for enhanced images, in section 7 provided the results and finally in section 8 consists of conclusion and future scope.

2. RELATED WORK

Image enhancement is to improve the interpretability or perception of information in images to provide better input for other automated image processing steps. The image acquired from natural environment with high dynamic range includes both dark and bright regions. Due to exceed in dynamic range of human eyes sensing, those image are difficult to perceive by human eyes. Image enhancement is a common approach to improve the quality of those images in terms of human visual perception.

Hu, Yi [3] et al proposed a a new approach has been proposed to estimate these parameters in an effective way. The local image is modeled as a non-stationary signal and the technique of Short Time Fourier Transform (STFT) is applied to it. Besides, to avoid the multi-step processing and inter-dependency, we extend the theory of probability in mathematics to get the orientation and frequency simultaneously. Experimental results show that our method can improve both the image quality and the accuracy of fingerprint recognition.

A. G. Ananth [4] et al proposed a detailed study of the lifting compression scheme for satellite imageries has been carried out. A comparison between the performance of the lifting scheme and SPHIT technique has been made in the context of satellite imageries.

C. N. R. Kumar [5] et al proposed a novel approach an efficient lifting wavelet based denoising with adaptive interpolation for super resolution reconstruction. Under this frame work, the digitized low resolution mammographic images are decomposed into many levels to obtain different frequency bands. We use Daubechies (D4) lifting schemes to decompose low resolution mammogram images into multilevel scale and wavelet coefficients. Our proposed lifting wavelet transform based restoration and adaptive interpolation preserves the edges as well as smoothens the image without introducing artifacts. The proposed algorithm avoids the application of iterative method, reduces the complexity of calculation and applies to large dimension low-resolution images.

Sapan Naik [6] et al proposed a super resolution algorithm which takes three shifted and noisy low resolution images and generated high resolution images using lifting wavelet transform based on denoising, filtering and interpolation algorithms

3. SUPER RESOLUTION

We consider the several low resolution images for SRIR. Low resolution means the lesser details of image. In digital technology, digital devices produce the noisy, rotated and blurred images [7]. Whenever an image is converted from one from to another, such as digitizing, transmitting or scanning, some form of degradation occurs at the output. Secondly, no imaging system, however accurate it is, can produce an exact ideal image. The images are not sampled according to the frequency range criterion by these imaging systems. Before processing, let us mention the term super-resolved image we mean the enhancement in spatial resolution only and not that of gray level. And the enhancement in image quality by enhancing spatial resolution is possible if and only if LR images were sampled at a rate lower than the Nyquist rate. Secondly, the SR methodologies work only when we have multiple LR images of the same scene that are different from one another because of motion or blurring or any another physical reason.

We have presented preliminary concept of some mathematical treatments that are frequently used in image reconstruction. The problem has been stated by capture a low resolution frame f observed that images $\{y_m\}_{m=1}^{f}$, each frame size F_1xF_2 are decimated, noisy and blurred versions of a high quality image z of size I_1xI_2 , $I_1=qF_1$ and $I_2=qF_2$the blurred matrix, and noise vector, the image construction model is expressed as shown in equation (1).

$$Y_F = H_F DZ + \eta_F \quad \text{where } F = 1\ldots\ldots f \tag{1}$$

Here D is the decimation matrix of size $F_1F_2xq^2F_1F_2$, H is the PSF of size $F_1F_2xF_1F_2$, ηFis F_1F_2x1 noise vectors and f is the number of low resolution observations. The f vector equations from different low images to a single vector matrix are representing by equation (2).

$$\begin{bmatrix} Y_1 \\ . \\ . \\ . \\ Y_2 \end{bmatrix} = \begin{bmatrix} DH_1 \\ . \\ . \\ . \\ DH_f \end{bmatrix} Z + \begin{bmatrix} \eta_1 \\ . \\ . \\ . \\ \eta_f \end{bmatrix} \tag{2}$$

4. WAVELET TRANSFORM

Fourier transformation is very useful in representation and analysis of stationary signal in witch the frequency components do not change with time. However, in case of non-stationary signal, where frequency components change with time, sometime it becomes a necessary to know not only which frequency components are present but also where they present. Above transforms are not good. Images are usually non-stationary two-dimensional signal.

The term wavelet means small wave. These small waves are generated from bigger one through scaling and translation. There are various types of wavelets. some of them are Haar wavelets, Mexican hat wavelets, Modulated Gaussian wavelets, Meyer wavelets, Doubechies wavelets[4]. First one of above is the simplest to understand and implement, while the last one is the most effective as it satisfies various requirement of wavelets such as compact support, orthogonally condition and regularity conditions.

A. Lifting Scheme

The lifting scheme [4] is a process for reconstruction of images. In this scheme, wavelet transform decomposes into a set of levels. In the forward lifting scheme, each level divides the value of level into an odd half and even half for further processing. The forward wavelet transform as three step lifting scheme is as below in fig.2

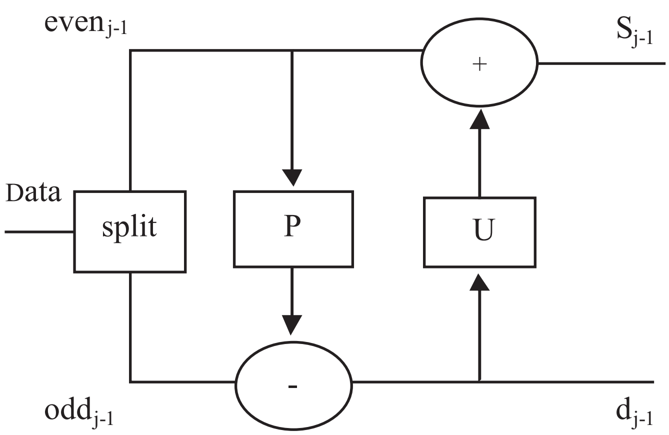

Fig 2: The three step lifting scheme

In above figure, the predict step P compute the wavelet transforms. In split step sort the entries into the even and odd entries. Generally prediction procedure step p compute d_{j-1} = odd_{j-1} – p($even_{j-1}$). Update U for given entry, the prediction is made for the next entry has the small values and difference is stored. Updates are $S_{j-1}[n] = S_j[2n] + d_{j-1}[n]/2$ and $S_{j-1} = even_{j-1} + U(d_{j-1})$.This is known as high pass filter. Update procedure step U calculates the scaling function, for results in a smoother version of the data for low pass filter.

A. Lifting Scheme of the Daubechies4 Wavelet Transforms

The two steps for Lifting Scheme wavelet transform[6] are update and predict. Here a new step is included named normalization. Input data in the split step are separated as even and odd elements. The even elements are kept in S_0 to $S_{half-1}$the first half of an N elements. The odd elements inS_{half}toS_{n-1} the second half of an N elements. The nature of the coefficients are labeled by 'L', 'H' etc, where 'L' stand for low frequency, 'H' for high frequency. and 'HH' represent the higher frequencyand 'LL' refers to lower frequency components, as similar LH represent the horizental high frequency components,HL represents the vertical high frequency components and HHrepresent the diagonal higher frequency component

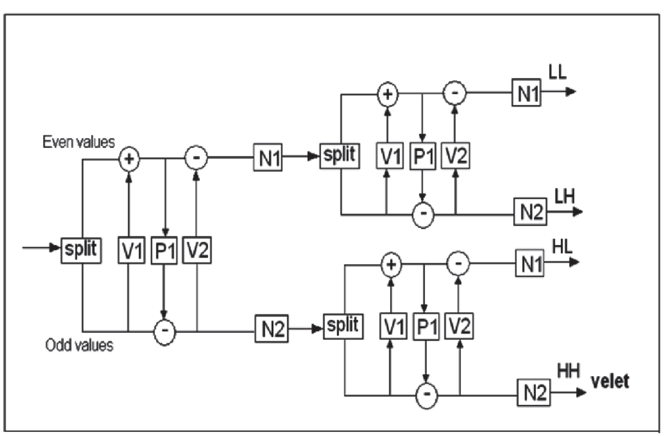

Fig 3: Two stages Daubechies4 forward lifting wavelet transform

The forward steps are:

Update1 (UI): for P = 0 to hf-1

S[P] = S[P]+√3S[hf+P]

Predict (PI): S[hf] = S[hf] – $\frac{\sqrt{3}}{4}$S[0]-$\frac{\sqrt{3}-2}{4}$S[hf-1]

For P = 1 to hf-1

S[hf +P] = S[hf + P]-$\frac{\sqrt{3}}{4}$S[P]-$\frac{\sqrt{3}-2}{4}$S [P-1]

Update2 (U2):

For P = 0 to hf-2

S[P] = S[P]-S[hf+P+1]

S[hf-1] = S[hf-1]-S[hf]

Normalize (P): for P = 0 to hf-1

S[P] = $\frac{\sqrt{3}-1}{\sqrt{2}}$S[P]

S[P+hf] = $\frac{\sqrt{3}+1}{\sqrt{2}}$S[P+hf]

The backward transform, the subtraction and addition operation are interchanged.

A. Gabor Filters

The Gabor filter is generated from two dimensional Gabor function or multichannel texture analysis, the band pass filters, known as the 2-D Gabor filters[3],. Gabor filters are used to detect the non periodic placement of the oriented segments composing the textures[6].

The impulse response G(x,y) of the 2D complex Gabor filter can be expressed as by equation (3).

$$G(x,y) = g(x',y')e^{[j2\pi(Ux+Vy)]} \quad (3)$$

Where $j=\sqrt{-1}$, (x',y')=(xcos+ysin,-xsin+ycos) represents coordinates of (x,y) rotated by an angle , and (U,V) signifies the centralspatial frequency of the filter.

The spatial frequency G(u,v) of the Gabor filter G(x,y) is represented as shown in equation (4).

$$G(u,v) = \exp[-2\pi^2\sigma^2[(u'-U')^2\lambda^2 + (v'-V')^2]] \quad (4)$$

wheredenotes the aspect ratio and represents the scale parameter. (*u'*,*v'*)=(*u*cos+*v*sin, -*u*sin+*v*cos) denotes frequency coordinates of (*u*,*v*) rotated by an angle , and (*U'*,*V'*) is a similar rotation of the center frequency (*U*,*V*).

5. PROPOSED SUPER RESOLUTION RECONSTRUCTION

The growing requirement for high resolution images resulted in the need for super resolution image reconstruction. Our goal in creating a super resolution image is to consider different types of same scene image of low resolution as inputs and combine them to generate a high resolution image through a series of steps. The implementation consists of taking either a source image for developing low resolution images like blurred, noisy and rotated versions or directly considering the different versions of same scene low resolution images based on availability.

Reconstruction Algorithm using Wavelet Lifting Scheme and SPHIT[5]. This working algorithm is the way of our work. This is the step by step procedure that how we implement the images and how we evaluate the working parameters. The algorithm followed in order to fulfill the aim of our work, as follows:

Step 1: Consider the source image Orig_I[i,j] and Resize as (256x256). Where i=1…255, j=1…255.

Step 2: Produce the following images from source image Orig_I[i,j].

(a) Noise image : Add the random noise
X[i,j]=.05*randn(256,256).*255 + Orig_I[i,j].

(b) Rotated image :
Y[i,j]=imrotate(Orig_I[i,j],15,'bicubic','crop');
Here imrotate() is the MATLAB command, Rotate with 15 digree, bicubic interpolation can produce pixel values outside the original range, crop can maintain the size of image should be same as image Orig_I[i,j].

(c) Bluerred image
ZZ[i,j]=imfilter(Orig_I[i,j], hblur,'conv');
Here imfilter is the MATLAB filter command and hblur=[1 2 2 2 2 2 1] now hblur=hblur/sum(hblur); and conv can perform multidimensional filtering using convolution.

Step 3: Obtained the Registered image using the Noise, Rotated and Bluerred images: IR[ij]=Register_f(Orig_I[i,j].

Here images are initially preprocessed, i.e. registered by FFT scheme and Register_f() is the MATLAB program for image registration.

Step 4: After registration of image, we obtain reconstruction image I[i,j] as folowing:

(a) The registered images are decomposed by Daubechies Db4 forward lifting wavelet lifting scheme.
(b) Decomposed images are encoded by SPHIT scheme.
(c) Apply the fusion rule to decomposed three low resolution images obtains the average fused image.
(d) Apply the inverse lifting scheme for final fused image.
(e) Decoded the fused image by DSPHIT.

Step 5: Apply De-noising and Deblurring on inage I[i,j].

Step 7: Apply Interpolation for final super resolution image I[ij]=imresize(I[512 512],'bilinear'); Here imresize() is the MATLAB command, resize the resultant image as 512x512 and 'bilinear' produce the bilinear interpolation, the output pixel value is a weighted average of pixel in the nearest 2-by-2 neighborhood.

Step 8: Obtained the edge detection image using Gabor transform.

Step9 . Calculate the RMSE, PSNR and SSIM between source image orig_I[i,j] and reconstructed image I[i,j]

6. PERFORMANCE MEASUREMENT OF SUPER RESOLUTION

In this section, the image quality metrics such as PSNR, MSE and SSIM Index [4] used for analyzing and comparing results are discussed. The simulation results have been calculated and compared using the mean square error (MSE), the peak signal to noise ratio (PSNR) and Structural Similarity Index Measure (SSIM) measures that have been explained as shown in equation (5), (6), (7).

Peak Signal to Noise Ratio (PSNR) :

PSNR is defined as an expression for ratio between maximum possible value of a signal and the value of corrupting noise that affects the quality of its representation. The PSNR is widely used as a measure to find quality of reconstruction in digital images. The original data in this case is the signal, and the noise is the error introduced by compression. PSNR is expressed in logarithmic terms because of large and wide dynamic range of signals. Different noise removal algorithms can be compared to find whether a particular algorithm produces better result or not. PSNR is defined through mean square error (MSE)

$$MSE = \frac{\sum[f(i,j)-F(i,j)]^2}{N^2} \tag{5}$$

Where f (i,j) is the source image and F(i,J) is the reconstructed image, containing N xN pixels, and for 8bits representations.

$$PSNR = 20 log_{10}\left(\frac{max}{RMSE}\right) \tag{6}$$

Where RMSE is the root of MSE, max represents the highest possible value of pixel i.e. 255 in the case of gray scale image.

Structural Similarity Index Measure (SSIM):

The SSIM index is a complete reference metric. It measures the image quality by taking an initial distortion-free or uncompressed image as reference. The main reason behind the designing of SSIM is to advance on traditional methods like PSNR and MSE. SSIM is a new standard for quality evaluation, based on the assumption that the Hue, Saturation and Value (HSV) are highly suitable for extracting structural information. It takes into consideration the luminance, contrast and the structural information of the image and is found to be an excellent measure in comparison to PSNR and MSE. In use, SSIM index alone is sufficient enough to assess the overall image quality. SSIM index is normally used for quality assessment. SSIM is defined as:

$$SSIM(x, y) = ((2\mu_x \mu_y + c'_1)(2\sigma_{xy} + c'_2))/((2\mu_x + \mu_y + c'_1)(\sigma_x^2 + \sigma_y^2 + c'_2))$$

SSIM Index = mean of SSIM. (7)

Where μ_x , μ_y are the average of x and y respectively, σ_x^2 , σ_y^2 are the variance of x and y respectively, σ_{xy} is the covariance of x and y. c'_1, c'_2 are the constants.

7. RESULTS

In simulation, Interpolation is performed in order to increase the size of the image. The constructed image is the super resolution image with increase the intensity of pixels.

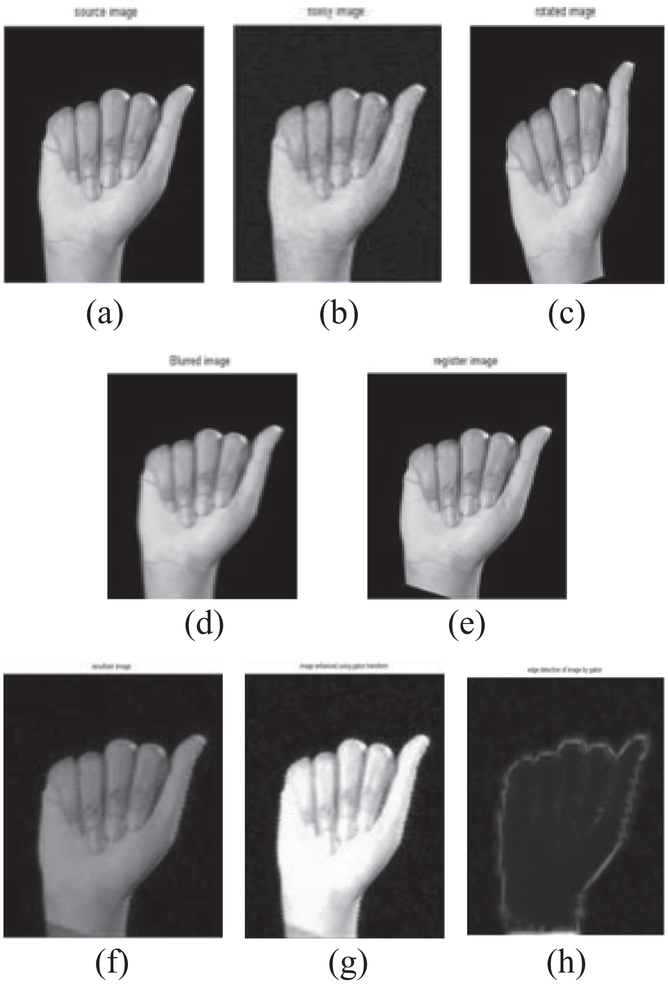

Fig 4: (a) Source image (512 512), (b) Noisy image (256 256), (c) Rotated image (256 256), (d) Blurred image (256 256), (e) registered image (256 256), (f) SRR image (512 512) after image fusion, (g) Enhancement image (512 512) of the resolution image by Gabor filter, (h) Edge detection of the image (512 512) by gabor filter.

From the Fig 4(a) represents the low resolution source image (512, 512), Fig4(b) is the rotated version of source image by an angle of 15 degrees. It was noted that rotation was checked for different angles and results coalesce.Fig4(c) represents the noisy image derived from source image by adding an random noise. Fig 4(d) is the blurred version of source image developed by convolution with an impulse response of [1 2 2 2 2 2 2 2 2 2 2 1] The results were verified for many impulse responses. The images were Pre-processed in image registration with arguments such that it applies to only translational, rotational and scaled images. By overlaying with reference images provided, the orientation of rotated image aligns similar to that of reference image. Fig 4(e) represents the registered image from noise, blurred and rotated images. Fig 4(f) represents the super resolution reconstructed images after reducing blur by blind deconvolution and iterative blind deconvolution respectively and are interpolated to twice the samples with the increase in the image size. Fig 4(g) is the enhancement image of the super resolution image using gabor transform. Fig 4(h) edge detection using gabor features.

Table 1: RMSE, PSNR and SSIM Index comparison of our proposed approach with other approaches

Denoising Methods	RMSE	PSNR(db)	SSIM Index
Separable DWT (S-DWT)	8.5656	27.096	0.53291
Real Dual-Tree DWT (RD-DWT)	10.322	27.855	0.60505
Complex Dual-Tree DWT (CD-DWT)	10.059	28.08	0.63758
Adaptive Dual-Tree DWT (AD-DWT)	5.6877	33.066	0.75905
Proposed method	3.9271	36.283	0.88377

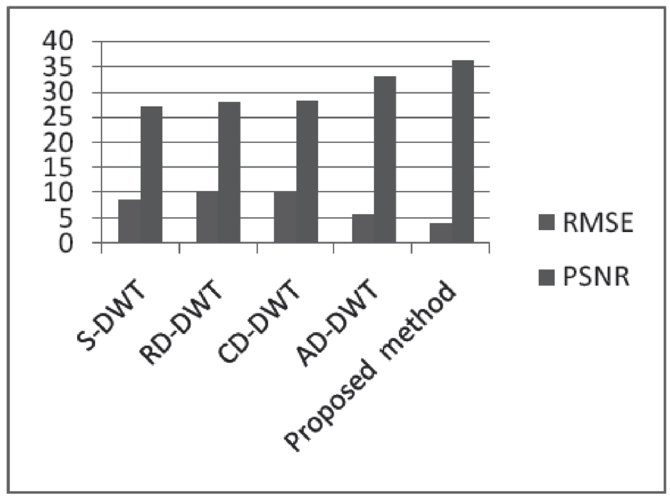

Fig 5: Comparison graph of RMSE and PSNR Results of our proposed approch with other approaches

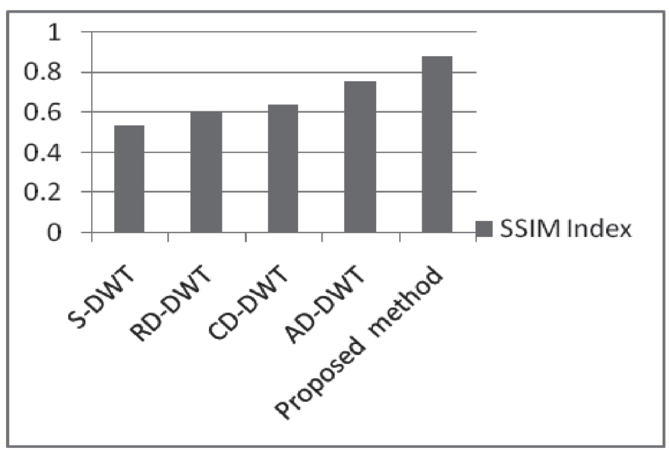

Fig 6: Comparison graph of SSIM Index Results of our proposed approach with other approaches

Table 1 presents the results of the proposed approach with other approaches with respect to RMSE, PSNR and SSIM index values. Experimental results show that proposed approach outperforms other methods. Proposed approach produces the 36.283 PSNR value, which is much higher as compared to other methods which gives 27.096, 27.855, 28.08 and 33.066 PSNR values for Separable DWT, Real Dual-Tree DWT (RD-DWT), Complex Dual-Tree DWT (CD-DWT), Adaptive Dual-Tree DWT (AD-DWT) respectively as shown in Table 1. Similarly, proposed approach gives 0.88377 SSIM index value, which is much higher as compared to other methods those are 0.53291, 0.60505, 0.63758, and 0.75905 SSIM index for Separable DWT, Real Dual-Tree DWT (RD-DWT), Complex Dual-Tree DWT (CD-DWT), Adaptive Dual-Tree DWT (AD-DWT) respectively as shown in Table 1. Figure 5 and 6 presents the graphical representation of various methods with respect to RMSE, PSNR values and SSIM index values respectively.

it can be observed from the Table 1, and figure 5, 6 that output is a super resolution version of input image with higher perceptual quality judging from the values are MSE, PSNR and SSIM in reference to input image. We achieved acceptable results under all environments and with different varieties of input images i.e. noisy, blurred and rotated images. Image fusion is applied and improved MSE values are noted. However some blur and noise component is observed in the image. Denoising is performed by Dual tree DWT based algorithm and Blur component is suppressed by Blind Deconvolution. This algorithm is providing the better edge detection by performing the image enhancement of the super resolution image constructed from the noisy, rotate, blur image.

8. CONCLUSION

Super resolution images enhance the quality of the multiple lower resolution images like noisy, blurred and rotated. Super resolution images increase the recognition rate in various applications like health domain, security applications etc. This paper proposed a technique for improving quality of lower resolution images namely Super Resolution Image Reconstruction (SRIR). Proposed method is based on wavelet transformation technique with Daubechies4 coefficient. Experiments are performed with various input images like noisy, blurred and rotated images. Experimental results show that proposed method for construction of super resolution image performs well for super resolution image construction. In addition, Gabor transform is applied to enhance the quality of the image. It is due to the fact that Gabor transform proves better results for edge detection. In future, work can be performed on the creating the super resolution images with the implementation of the neural networks.

REFERENCES

[1] Zhang Haiyang, "Image Preprocessing Methods in Face Recognition," Symposium on Photonics and Optoelectronics (SOPO), pp.1-4, 2011.

[2] Liyakathunisa, C.N.Ravi Kumar,"A Novel and Efficient Lifting Scheme based Super Resolution Reconstruction for Early Detection of Cancer in Low resolution Mammmmogram Images", International Journal of Biometrics and Bioinformatics, Vol. 5, Issue 2, 2011.

[3] Hu, Yi, et al. "Low quality fingerprint image enhancement based on Gabor filter." Advanced Computer Control (ICACC), 2010 2nd International Conference on. Vol. 2. IEEE, 2010.

[4] A. G. Ananth, “Comparison of SPIHT and Lifting Scheme Image CompressionTechniques for Satellite Imageries,” International Journal of Computer Applications, vol. 25, no. 3, pp. 7–12, 2011.

[5] A. Morales and S. Agili, “Implementing the SPIHT Algorithm in MATLAB”,InProceedings of ASEE/WFEO International Colloquium, 2003.

[6] Sapan naik, Viral borisagar, “ A novel Suoer resolution Algorithm Using Interpolation and LWT Based denoising Method”, International journal of Image Processing, Col. 6, Issue 4, 2012.

[7] Jayaraman, S., Esakkirajan, S. and Veerakumar, T. Digital Image Processing,Tata McGraw Hill Education Private Limited, India, 2009.

◆ ◆ ◆