Development of Image Super-resolution Algorithms

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Development of Image Super-resolution Algorithms

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by

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under the supervision of

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dedicated to my Parents and Brother...

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Professor

May , 2013

Certificate

This is to certify that the work in the thesis entitled *Development of Image Super-resolution Algorithms* by *Mayank Agrawal*, bearing roll number 211CS1066, is a record of an original research work carried out by him under my supervision and guidance in partial fulfillment of the requirements for the award of the degree of *Master of Technology* in *Computer Science and Engineering*. Neither this thesis nor any part of it has been submitted for any degree or academic award elsewhere.

Ratnakar Dash

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Mayank Agrawal

Abstract

This thesis addresses the problem of image super-resolution from a low resolution image. Spatial resoltuion of images are restricted by the size of CMOS sensors. Spatial resolution can be increased by increasing no of COMS sensors resuling in decrease in size of CMOS sensors which cause shot noise. In this thesis attempts have been made to enhance the spatial resolution of different images. Two schemes are proposed for this purpose. The basic idea behind both the techniques is to utilize the high frequency subband images derived using lifting wavelet transform. In the first scheme the high frequency subband images are interpolated using surface fitting. In another scheme lifting wavelet transform and stationary wavelet transform are used along with surface fitting interpolation to increase the spatial resolution in the frequency domain.

Each technique is studied separately, and experiments are conducted to evaluate their performances. The visual, blind image quality index, visual image fidelity index as well as the peak signal to noise ratio (PSNR in dB) of high resolution images are compared with competent recent schemes. Experimental results demonstrate that the proposed approaches are very effective in increasing resolution and compare favorably to state-of-the-art super-resolution algorithms.

***Keywords*:** Image super-resolution, Spatial Resolution, Discrete Wavelet Transform, Complex Wavelet Transform, lifting wavelet Transform, Blind Image Quality Index, Visual Image Fidelity.

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Chapter 1

Inroduction

Out of all five senses vision is most advanced, so it is not surprised that images play the single most important role in human perception. Human vision system is limited to visual band of electromagnetic (EM) spectrum, while imaging machines cover almost the entire EM spectrum, ranging from gamma to radio waves. They can operate on images generated by source that humans are not accustomed to associate with images. These include electron microscopy, computer generated images.

Digital image processing works same as the human vision system. It involves the process of acquiring, analyzing and manipulating images using digital computers. There are various physical devices to capture digital images like camera, satellite, magnetic resonance imaging machine and microscope etc. The area of application of digital image processing is very vast. The simplest way to develop the extent of image processing is to categorize the images according to their source. There are various fields that use digital image processing [1].

1. **Gamma-ray Imaging**

   Nuclear medicine and astronomical observation are areas use most of the gamma ray imaging. The principal of positron emission tomography is same as with X-ray tomography. Gamma rays detected and converted to image using principles of tomography.

2. **X-ray imaging**

   X-rays are being used in medical and astronomy. The digital X-ray images are captured by digitizing the X-ray films. Angiography and computerized axial tomography (CAT) are other medical areas that use X-ray Imaging.

3. **Ultraviolet Band Imaging**

   Ultraviolet Imaging is used in lithography, industrial inspection, microscopy, lasers, biological imaging and astronomical observation.

4. **Visible and Infrared Bands Imaging**

   The application area for this imaging is very broad. It ranges from micro-inspection and material characterization to pharmaceutical. This spectrum images also applied in various security, identity detection, recognition and surveillance application and remote sensing.

5. **Microwave Band Imaging**

   Microwave band imaging is used in RADAR. Radar uses antenna and computer processing to generate image.

6. **Radio Imaging**

   The main application area of radio wave imaging is in medical and astronomy. In medical radio wave are used in magnetic resonance imaging (MRI).

Due to the increase in demand and performance of personal computing digital image processing is widely being used in many applications. Digital image process has advantage in term of cost, speed and flexibility. The objective is to extract information from the scene is being viewed. Digital image processing can be classified in following subareas on the basis of nature of application [1].

(i) Image Enhancement

(ii) Image Restoration

(iii) Image Compression

(iv) Image Segmentation

(v) Image Understanding

A digital can be represented by function of two dimensional variables and mathematically can be represented as

$$I = f(x, y) \tag{1.1}$$

where I is an image, x and y are spatial coordinates, and f is the amplitude of any pair of coordinates (x,y) and is called as intensity or grey level of the image at that point. When values of coordinates (x,y) and amplitude f all are finite and discrete quantities, the image is called digital Image. A digital image is composed of finite number of elements, each of which has particular location and value. These elements are called *picture elements*, *image elements*,*pels* and *pixels*.

The rest of the chapter is organized as follows. The introduction of digital image super-resolution and its applications are given in Section 1.1. Some of the existing litratures are reviewed in Section 1.2. The research motivation and its objective are formally stated in Section 1.3. Finally Section 1.4 outline the layout of thesis.

1.1 Digital Image Super-resolution

There are several image processing application requires high resolution images for processing and analysis. The desire for high resolution images came from two principal application areas: improvement of pictorial information for human interpretation; and helping representation for automatic machine perception. Image resolution describes the amount of information contained by images. Lower resolution less would be the amount of information, higher resolution more would be amount of information in images. Resolution of a digital image can be classified in many ways: *pixel resolution*, *spatial resolution*, *spectral resolution*, *temporal* *resolution*, and *radiometric resolution*. In this thesis concentration is given mainly in *spatial resolution*.

spatial resolution: A digital image is made from small picture elements called pixels. Spatial resolution refers to the pixel density in an image and measures in pixels per unit area. Figure 1.1 shows a classic test target to determine the spatial resolution of an imaging system.

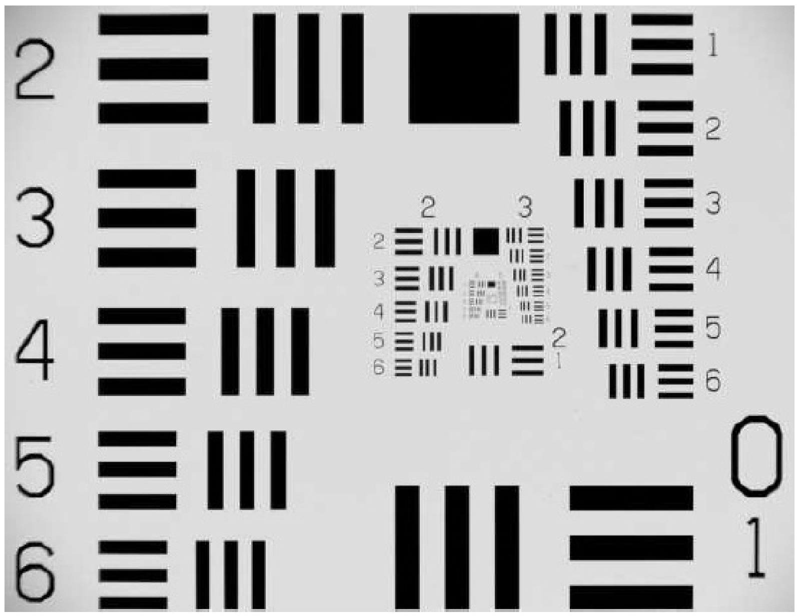


Figure 1.1: The 1951 USAF resolution test target, a classic test target used to determine spatial resolution of imaging sensors and imaging systems.

The spatial resolution of an image is limited by the image sensors or the image acquisition devices. The modern image acquisition devices are using charge-coupled device (CCD) or complementary metal oxide semiconductor (CMOS) as active pixel sensor. These sensors are arranged in two dimensional arrays to capture two dimensional image signals. The number of sensors per unit area or the sensor size determines the number of pixels in image. One way to increase the resolution of the imaging device is to increase the sensor density by reducing the size of sensors. When the size of sensors is reduced beyond a limit it causes shot noise in the captured images as reducing the size of sensor also reduces the amount of light incident on it. Increment in the number of sensors in imaging device/system also increases the hardware cost. Therefore there is limitation with the hardware that restricts the spatial resolution of the image.

While spatial resolution is limited by sensor size, the image details (high frequency bands) are also limited by the optics due to lens blurs (associated with the sensor point spread function (PSF)), lens aberration effects, aperture diffractions and optical blurring due to motion. Constructing imaging chips and optical components to capture very high-resolution images is prohibitively expensive and not practical in most real applications, e.g., widely used surveillance cameras and cell phone built-in cameras. In some other scenarios such as satellite imagery, it is difficult to use high resolution sensors due to physical constraints. Another way to address this problem is to accept the image degradations and use image processing to post process the captured images, to trade of computational cost with the hardware cost. These techniques are specifically referred as super-resolution (SR) reconstruction.

The idea of super-resolution (SR) techniques is to construct a high-resolution (HR) images from several input low-resolution (LR) images, thereby increasing the high frequency components and removing the degradations caused by limitations of low-resolution imaging device/system. The SR technique combines non redundant information contained in multiple low-resolution frames to get a high-resolution image. If there is no additional information provided, the quality of the single image interpolation is very much limited due to the ill-posed nature of the problem, and the lost frequency components cannot be recovered. The broad classification of SR techniques is based on use of single low-resolution and multiple low-resolution images to generate a large size image. Section 1.2 gives a brief review of different SR techniques.

For the purpose of measuring the performance of the techniques quantitative and qualitative metrics is used. For quantitative performance comparison peak signal to noise ratio ($PSNR$ in dB) is often used which is defined

$$PSNR(dB) = 10\log_{10}\left(\frac{255^2}{MSE}\right) \tag{1.2}$$

where MSE is defined as

$$MSE = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}\Big(f(x,y) - \hat{f(x,y)}\Big) \tag{1.3}$$

For the qualitative performance comparison of results *blind imagequality index* ($BIQI$) [2] and *visual image fidelity* (VIF) [3] index is used. Blind image quality index is subjected to human perception of a image without any knowledge of reference image. BIQI also called *no reference image quality index*. It takes single image as input and gives index value between 1-100. Higher the values of BIQI better would be the correlation of image to real world.

Visual image fidelity (VIF) index is subjected to human perception with the prior knowledge of the image. This metric is the ratio of information measure of test image to the information measure of the reference image and can be given as

$$VIF = \frac{I(test)}{I(refrence)} \tag{1.4}$$

This metric takes reference and test image as input and generate index value between 0-1. If the metric value is 1, it shows the perfect test image.

1.1.1 Application areas of SR Imaging

The need for high resolution is common in computer vision application for better performance in pattern recognition and analysis of images. High resolution is of importance in medical imaging for diagnosis. Many applications require zooming of a specific area of interest in the image where in high resolution becomes essential. SR images are being used in many areas such as:

(i) Remote sensing [4]: several images of the same area are provided, and an improved resolution image can be sought.

(ii) Surveillance video [5, 6]: frame freeze and zoom/focus region of interest (ROI) in video for human perception (e.g. look at the license plate in the image), resolution enhancement for automatic target recognition (e.g. try to recognize a criminal's face).

(iii) Video standard conversion, e.g. from NTSC video signal to HDTV signal.

(iv) Medical imaging (CT, MRI, Ultrasound etc) [7, 8]: several images limited in resolution quality can be acquired, and SR technique can be applied to enhance the resolution.

1.2 Litreture Review on SR Techniques

Although wide variety of super-resolution literature is available, it is still an open topic to investigate. Following subsections describe some of the existing basic image super-resolution schemes.

1.2.1 SR via Sparse Representation [9]

Jianchao Yang *et al.* considered the sparse signal representation of an image. Based on previous research on image statistics the image patches can be well-represented as a sparse linear combination of elements from an appropriately chosen over-complete dictionary. Motivated by this, they proposed a sparse representation for each patch of the low-resolution input. The coefficients of this representation are used to generate the high-resolution output. Theoretical results from compressed sensing suggest that the sparse representation can be correctly recovered from the down-sampled signals under mild conditions.

Similarity of sparse representations between the low-resolution and high-resolution image patch pair with respect to their own dictionaries is enforced, by jointly training two dictionaries for the low and high-resolution image patches. So, the sparse representation of a low-resolution image patch is being applied with the high-resolution image patch dictionary to generate a high-resolution image patch. They showed the effectiveness of such a sparsity prior for both general image super-resolution (SR) and the special case of face hallucination. This algorithm can handle SR with noisy inputs in a more unified framework because the local sparse modeling is naturally robust to noise.

1.2.2 Nonlinear Mapping of Coherent Features [10]

Xiao Zeng and Hua Huang presented a regression based method that can successfully recognize the identity given all these difficulties. They built a radial basis function in subspace by canonical correlation analysis to nonlinear regression models from the specific nonfrontal low resolution image to frontal high resolution features.

1.2.3 Geometric Grouplets [11]

A. Maalouf and M. C. Larabi proposed the idea of generating a super-resolution (SR) image from a single multi-valued low-resolution (LR) input image. This problem approaches from the perspective of image geometry-oriented interpolation. They computed the grouplet transform to obtain geometry of the LR image. Geometric grouplets is constructed by orthogonal multiscale grouping with weighted Haar lifting to points grouped by association fields.

To preserve the sharpness of edges and textures SR image is synthesised by an adaptive directional interpolation using the extracted geometric information. This method showed imporovements over existing geometrically driven interpolation techniques on a subjective scale, and in many cases with an improvement in psychovisual color difference.

1.2.4 Remotely Sensed image by Hopefield Neural Network [12]

J Tatem Andrew *et al.* used their idea of super-resolution for target identification in remotely sensed images. Fuzzy classification improves the accuracy of land cover target identification make robust and better for spatial representation of land cover. The Hopfield neural network converges to a minimum of an energy function, defined as a goal and several constraints. The energy minimum represents a best guess map of the spatial distribution of class components in each pixel.

They used two goal functions to make the output of a neuron similar to that of its neighboring neurons. The first goal function aims to increase the output of center neuron to 1. The second goal function aims to decrease the output of the center neuron to 0. They showed that, by using a Hopfield neural network, more accurate measures of land cover targets can be obtained compared with those determined using the proportion images alone.

By the results, the Hopfield neural network used in this way represents a simple, robust, and efficient technique, and suggest that it is a useful tool for identifying land cover targets from remotely sensed imagery at the subpixel scale.

1.2.5 Neural Network based Optimal Recovery Theory [13]

Yizhen Huang and Yangjing Long proposed a optimal recovery based neural-network Super Resolution algorithm. This method evaluated on classical SR test images with both generic and specialized training sets, and compared with other state-of-the-art methods.

Motivated by the idea that back propagation neural network are capable of learning complex nonlinear function they proposed a neural network approach that produces better results in high-frequency regions. They integrated an optimal recovery based approach with in a neural network framework and, if so, two different branches of algorithms complement each other to offer a better algorithm. Using this algorithm in a two-pass way generates visual results that are very similar regardless of the initial interpolation step, and more times of iteration only waste the computing resource but yield negligible performance gain.

1.2.6 Gaussion Process Regression [14]

He He and Wan-Chi Siu addressed the problem of producing a high-resolution image from a single low-resolution image without any external training set. They proposed a framework for both magnification and deblurring using only the original low-resolution image and its blurred version. In This method, each pixel is predicted by its neighbors through the Gaussian process regression.

They showed that, by using a proper covariance function, the Gaussian process regression can perform soft clustering of pixels based on their local structures. This algorithm can extract adequate information contained in a single low-resolution image to generate a high-resolution image with sharp edges. Compared to other edge-directed and example-based super-resolution algorithms this algorithm is superior in quality and performance.

1.2.7 Learning-based SR with a combining of both global and local constraints [15]

K. Guo *et al.* proposed a statistical learning method for SR with both global and local constraints. More specifically, they introduced a mixture model into maximum a posteriori (MAP) estimation, which combines a global parametric constraint with a patch-based local non-parametric constraint.

The global parametric constraint guarantees the super-resolved global image to agree with the sparse property of natural images, and the local non-parametric constraint is used to infer the residues between the image derived from the global constraint and the ground truth high-resolution (HR) image.

They compared it with traditional patch-based learning methods without the global constraint, and showed that this method can not only preserve global image structure, but also restore the local details more effectively.

1.2.8 Interpolation based SR using Multisurface Fitting [16]

Fei Zhou *et al.* proposed a interpolation-based method of image super-resolution reconstruction. They used the idea of multisurface fitting to take advantage of spatial structure information. Each site of low-resolution pixels is fitted with one surface, and the final estimation is made by fusing the multisampling values on these surfaces in the maximum a posteriori fashion. Figure 1.2 shows the flow chart of interpolation based SR using Multisurface Fitting.

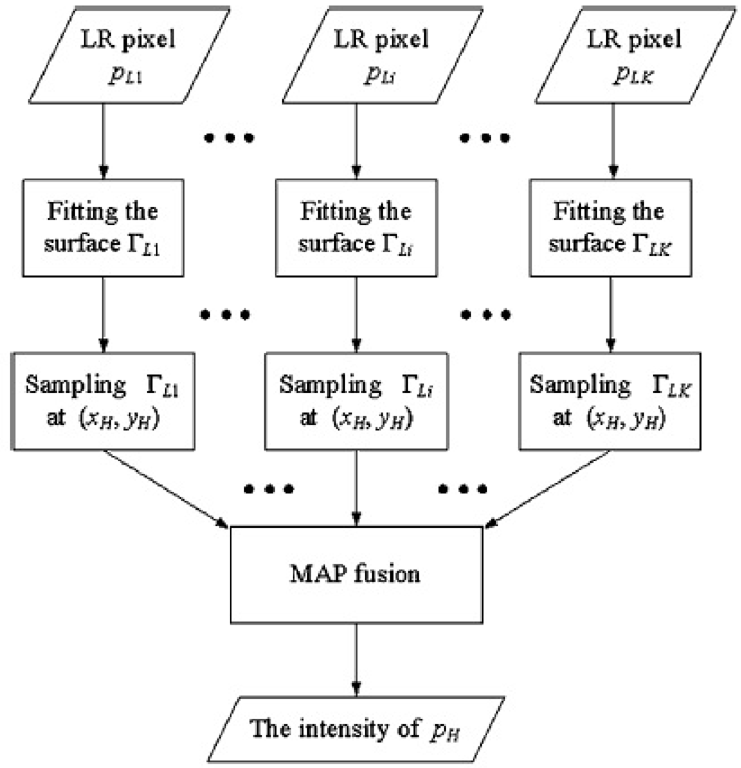


Figure 1.2: Flow chart of Multisurface Fitting

For the final values of high intensity pixels they used maximum a posteriori estimation on sampled surface constructed using Taylor series. They showed that, this method reconstructs high-resolution images, that preserve image details effectively without any hypothesis on image prior. They extended this method to a more general noise model.

1.2.9 SR Based on Interpolation of Wavelet Domain High Frequency Subbands and the Spatial Domain Input Image [17]

Gholamreza Anbarjafari and Hasan Demirel proposed a super-resolution technique based on interpolation of the high-frequency subband images obtained by discrete wavelet transform (DWT) and the input image. They used DWT to decompose an image into different subband images. Then the high-frequency subband images and the input low-resolution image have been interpolated, followed by combining all these images to generate a new super-resolved image by using inverse DWT. Figure 1.3 shows the block diagram of the method proposed by Gholamreza Anbarjafari and Hasan Demirel.

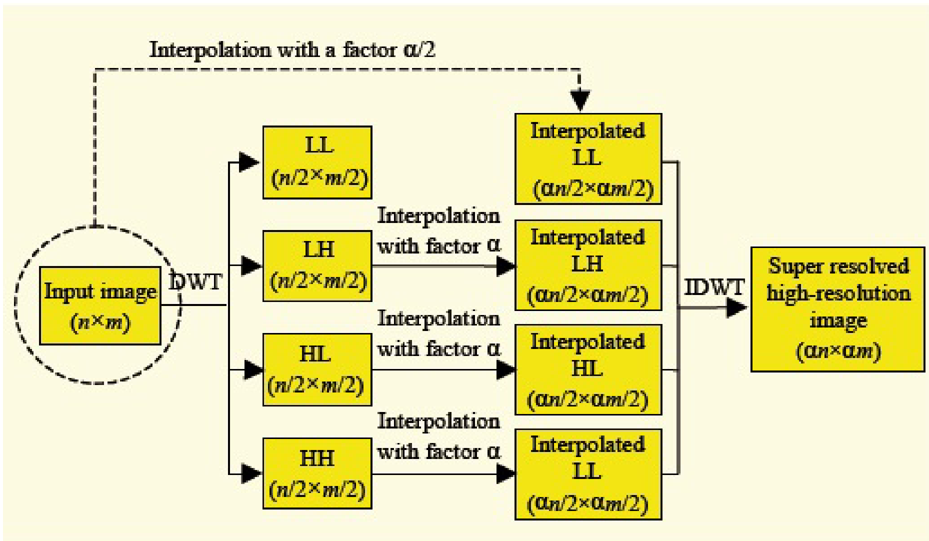


Figure 1.3: Block Diagram of method proposed by Gholamreza Anbarjafari and Hasan Demirel

1.2.10 SR by Complex Wavelet Transform [18]

Gholamreza Anbarjafari and Hasan Demirel proposed a technique to enhance to resolution of satellite images based on interpolation of high-frequency subband images obtained by dual-tree complex wavelet transform (DT-CWT). This method uses DT-CWT to decompose an input low-resolution satellite image into different subband images and interpolates input images followed by combining all these images to generate high-resolution images by using inverse DT-CWT. Figure 1.4 shows the diagram of the method.

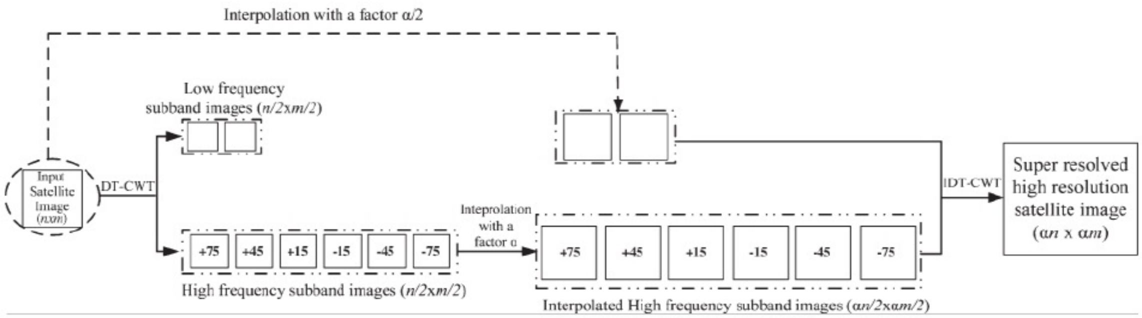


Figure 1.4: Block diagram of DT-CWT SR

1.2.11 IMAGE Resolution Enhancement by Using Discrete and Stationary Wavelet Decomposition [19]

Gholamreza Anbarjafari and Hasan Demirel proposed a image resolution enhancement technique based on interpolation of the high frequency subband images obtained by discrete wavelet transform (DWT) and the input image. The edges are enhanced by introducing an intermediate stage by using stationary wavelet transform (SWT). DWT is applied in order to decompose an input image into different subbands. Then the high frequency subbands as well as the input image are interpolated. The estimated high frequency subbands are being modified by using high frequency subband obtained through SWT. Then all these subbands are combined to generate a new high resolution image by using inverse DWT (IDWT). Figure 1.5 shows block diagram of this method.

1.3 Motivation

Keeping the research directions a step forward, it has been realised that there exists enough scope to new research work. The previous work used different wavelet transforms (DWT,CWT) to enhance the resolution. This motivated us to use lifting wavelet transform for enhancement of resolution of images. In this work, an effort has been made to propose new SR methods for images. In particular,

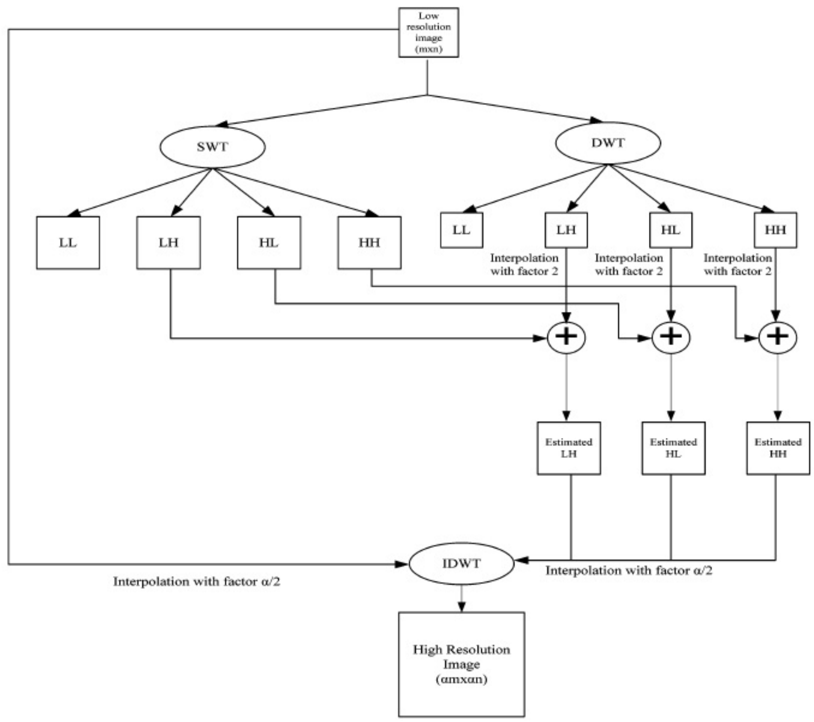


Figure 1.5: Block Diagram of DWT SWT SR

the objectives are narrowed to —

(i) To decompose the low resolution images in its high-frequency subband images.

(ii) To generate the high resolution image using an interpolation technique.

1.4 Thesis Layout

Rest of the thesis is organised as follows —

Chapter 2: Image Resolution enhancement using Lifting Wavelet Transform (LWT) This chapter, proposes method to enhance the resolution of images. A introduction of Lifting wavelet transform has been discussed. The application of LWT to generate the high frequency components is described. These high frequency components are utilized to generate the high resolution images using surface fitting interpolation.

Chapter 3: Image Super Resolution by Lifting (LWT) and Stationary Wavelet Transform (SWT) In this chapter, we proposed another scheme to enhance the resolution of images. The application of LWT and SWT to generate the high frequency components is described. These high frequency components are utilized to generate the high resolution images using surface fitting interpolation..

Chapter 4: Conclusion and Future Work This chapter provides conclusions made out of proposed scheme along with future work.

Chapter 2

Image Resolution enhancement using Lifting Wavelet Transform

This chapter proposes a super-resolution technique interpolating wavelet domain high frequency subband images obtained by lifting wavelet transform. Wavelets are tools to represent data and general functions. The fundamental property of wavelets is that they allow efficient and computationally fast representations. The wavelet transform, decomposes an image into its frequency subbands. However lifting wavelet transform has been utilized here to generate high-frequency subbands.

2.1 Proposed SR Technique

2.1.1 Lifting Wavelet Transform (LWT)

The basic idea behind lifting scheme is, to start with a very simple or trivial multiresolution analysis, and gradually work one's way up to a multiresolution analysis with particular properties. The lifting scheme allows one to custom-design the filters, needed in the transform algorithms, to the situation at hand [20]. The lifting scheme builds a new wavelet, with improved properties, by adding a new basis function [21]. The properties of wavelets results in fact that for compressing, estimating and recovering functions wavelets is optimal bases. The lifting scheme insures to a fast in-place calculation of the wavelet transform, i.e. an implementation that does not require auxiliary memory. The LWT has advantage over DWT such as the transform can be modified locally while preserving invertibility. Following section describes the proposed scheme in details.

2.1.2 Surface fitting

The idea of surface fitting is proposed by Fei Zhou, Wenming Yang, and Qingmin Liao [16]. It uses two dimensional taylor series to preserve the high frequency details. In two dimensional taylor series first order derivatives preserves edges and second order derivatives preserves curves. The estimated prior is fused by using MAP estimation to generate intensity of high resolution pixel. Block diagram of this interpolation is shown in Chapter 1. This interpolation is used for interpolation of high-frequency subband images.

The wavelet domain frequency components of input low-resolution input images are generated by decomposing it. The decomposition of input low-resolution images is done by one level two dimensional lifting wavelet transform with biorthogonal (bior1.5) liftwave. LWT uses sampling hence the generated frequency components less in size that is half of input low-resolution input image. These frequency components contain three high frequency components and one low frequency component. The high frequency components are the horizontal, vertical and diagonal detail coefficients of low-resolution input images. These high frequency components are interpolated with factor β by using surface fitting [16].

The low frequency component of low-resolution generated by low pass filtering of low-resolution input image. This low frequency component contains less information of the image. Instead of low frequency component we used low-resolution input image. The input low-resolution is interpolated by factor $\beta/2$ using surface fitting. Input low-resolution image is interpolated by factor $\beta/2$ to equal the size to interpolated high frequency subband images. The interpolated high frequency components and input image is given to inverse lifting wavelet transform (ILWT) to generate high-resolution output image. Figure 2.1 shows block diagram of proposed technique.

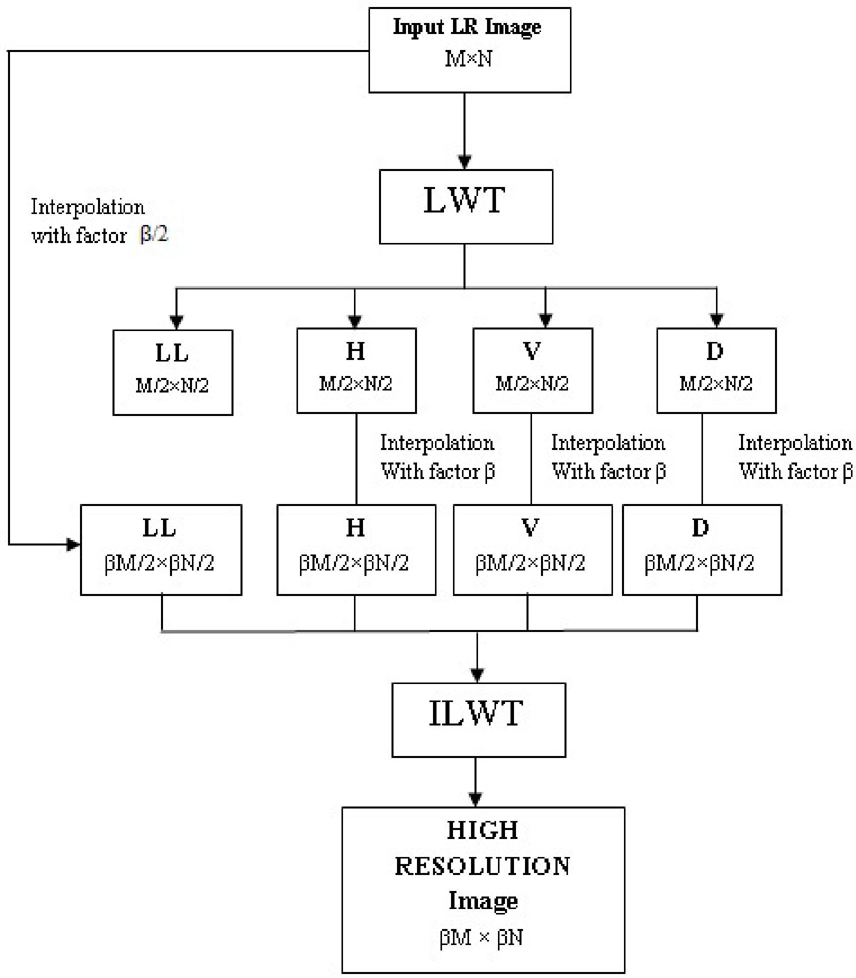


Figure 2.1: Illustrated Diagram of proposed method.

2.2 Results and Discussion

The proposed method is tested on various standard images taken from USC-SIPI image database [22]. All the computations are done in MATLAB on Intel n-series architecture with Core 2 Duo processer. Various metrics have been used including PSNR, BIQI and VIF for the comparison of results of proposed technique to other conventional and state-of-the-art techniques. Different experiments are conducted to show the efficiency of the proposed schemes.

(A) **Experiment with Miscellaneous Images**

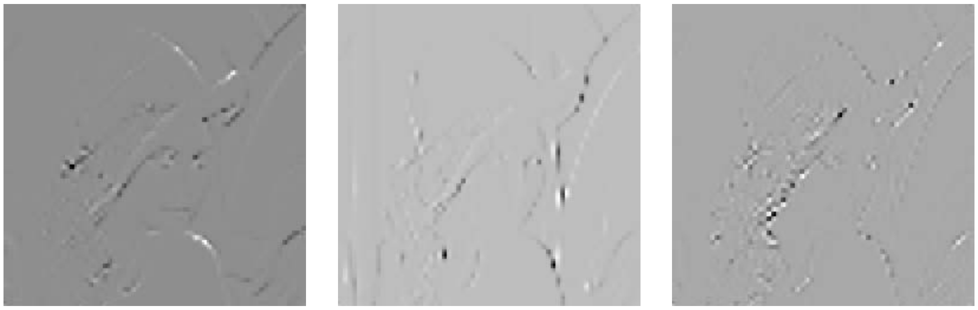
In this section we analyze the performance of the proposed algorithm on miscellaneous images. All the input low-resolution images interpolated with factor 4. The resolution of input image was 128×128. These input images are interpolated to the size of 512×512.

For quantitative comparison of results peak signal to noise ratio ($PSNR$) is used. The quantitative comparison of proposed technique with other methods is shown in Table 2.1. The comparison shows that the proposed method gives better results. Figure 2.2 shows the interpolated high frequency subband images of the low-resolution *Lena* image.

Table 2.1: PSNR (dB) Results for Resolution Enhancement from 128×128 to 512×512

Techniques/Images	*Baboon*	*Peppers*	*Elaine*	*Lena*
Bilinear	20.51	25.16	25.38	26.34
Bicubic	20.61	25.66	28.93	28.86
WZP(db.9/7)	21.47	29.57	30.44	28.84
Regularity preserving interpolation [23]	21.47	29.57	30.42	28.81
NEDI [24]	21.18	28.52	29.97	28.81
HMM SR [25]	21.49	29.60	30.51	28.88
WZP-CS [26]	21.54	29.87	30.78	29.27
DWT SR [17]	23.29	32.19	32.73	34.74
CWT SR [18]	23.12	31.03	33.05	33.74
LWT SR	30.96	36.09	28.17	30.61

Table 2.2 shows BIQI values of proposed technique with DWT. Higher BIQI index is obtained with the proposed method and are more subjected to human perception with no reference image.



(a) (b) (c)

Figure 2.2: (a)interpolated Horizontal details coefficients. (b)interpolated Vertical details coefficients. (c)interpolated Diagonal details coefficients.

Table 2.2: BIQI index for Resolution Enhancement from 128×128 to 512×512

Techniques/Images	*Babbon*	*Elaine*	*Peppers*	*Lena*
Bicubic	47.64	43.98	38.69	41.68
DWT(db.9/7) [17]	41.99	33.91	30.87	20.74
Proposed Method	68.18	46.68	39.34	43.97

Table 2.3 shows the comparison of VIF of results. The VIF indexes show that the outputs of proposed technique are higher in quality.

Table 2.3: VIF index for Resolution Enhancement from 128×128 to 512×512

Techniques/Images	*Baboon*	*Elaine*	*Peppers*	*Lena*
DWT(db.9/7) [17]	0.40	0.25	0.29	0.38
Proposed Method	0.69	0.79	0.73	0.72

The results of proposed technique are also compared visually with the results of state-of-the-art techniques. The visual results shows that the results of proposed technique are good from DWT. Figure 2.3 shows the comparison of visual results of proposed technique with the results of DWT SR [17] technique.

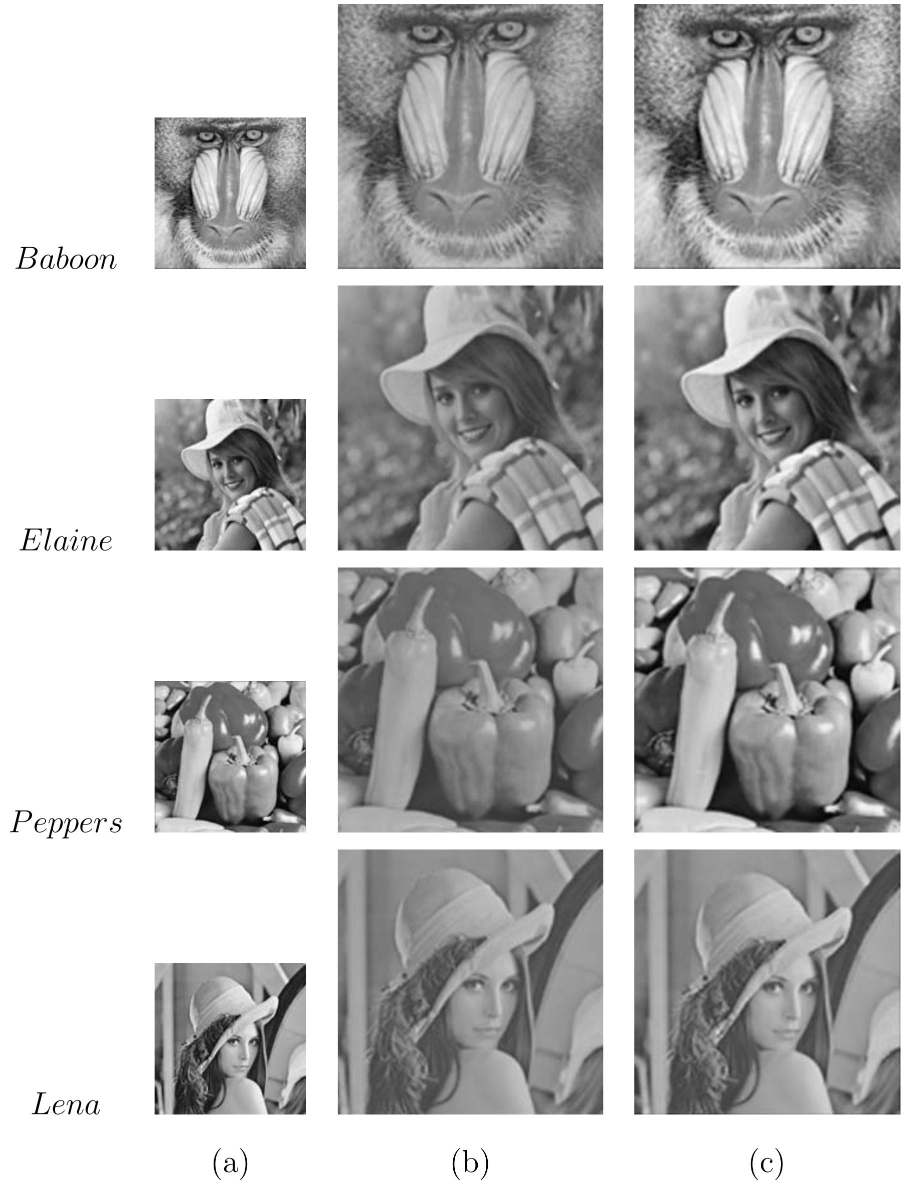
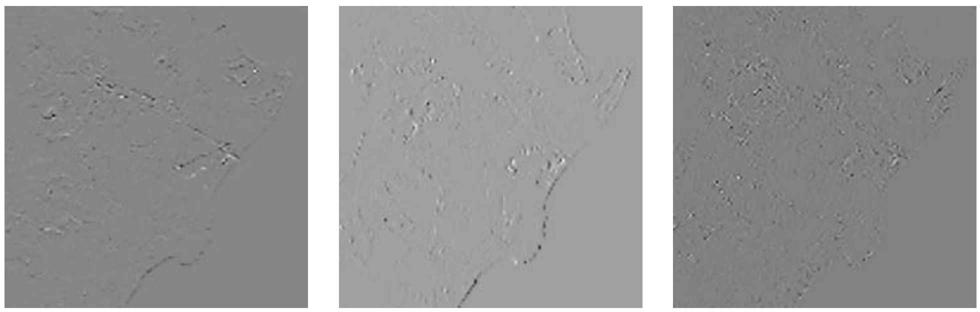


Figure 2.3: (a) input images of resolution 128×128. (b) DWT SR outputs of resolution 512×512. (c) Proposed method outputs 512×512.

(B) Experiment on Satellite and Texture Images

To evaluate the efficiency of the proposed technique in different applications it is tested on satellite and texture images. This technique is applied to interpolate all low resolution input satellite images with factor of 4. Figure 2.4 shows the interpolated high frequency subband images of the low-resolution image $input1$.



(a) (b) (c)

Figure 2.4: (a)interpolated Horizontal details coefficients. (b)interpolated Vertical details coefficients. (c)interpolated Diagonal details coefficients.

The resolution of input satellite images are 256×256. The resolution of output images are 1024×1024 in spatial resolution. The quantitative comparison of results is shown in Table 2.4. The PSNR values of results of proposed technique are compared with that of conventional and DWT SR technique.

Table 2.4: PSNR (dB) Results for Resolution Enhancement from 256×256 to 1024×1024

Techniques/Images	$Image1$	$Image2$	$Image3$	$Image4$	$Image5$
Nearest Neighbour	25.24	24.23	27.20	28.34	29.56
Bilinear	25.51	24.45	27.75	28.61	26.66
Bicubic	25.74	24.79	28.34	28.99	29.93
DWT(db.9/7) [17]	27.62	25.69	30.72	29.01	30.16
Proposed Method	30.35	28.56	32.98	33.59	31.10

Figure 3.3 shows the comparison of visual results of proposed technique with the results of DWT SR technique. The visual results show that the results of proposed technique are good in quality form DWT SR. The outputs of proposed method are sharper than that of DWT SR. Figure 3.3 (a) is showing low resolution input images, (b) is showing the visual results of DWT SR and (c) is showing the visual results of proposed technique.

Table 2.5 is showing the comparison of BIQI indexes of the outputs of proposed technique with that of DWT SR. This comparison shows that the outputs of proposed method are good in quality than that of bicubic and DWT SR. The outputs of proposed method are more subjective to human perception without any reference image.

Table 2.5: BIQI Results for Resolution Enhancement from 256×256 to 1024×1024

Techniques/Images	$Image$ 1	$Image$ 2	$Image$ 3	$Image$ 4	$Image$ 5
Bicubic	44.15	68.79	74.73	47.94	51.03
DWT(db.9/7) [17]	50.84	73.87	79.23	50.47	62.53
Proposed Method	54.99	75.03	86.43	53.75	62.04

For the quality index with reference image VIF is calculated and is shown in Table 2.6. The outputs of proposed technique are good in quality and are more similar to reference images.

Table 2.6: VIF for Resolution Enhancement from 256×256 to 1024×1024

Techniques/Images	$Image$ 1	$Image$ 2	$Image$ 3	$Image$ 4	$Image$ 5
DWT(db.9/7) [17]	0.053	0.083	0.09	0.17	0.67
Proposed Method	0.53	0.44	0.55	0.56	0.49

Figure 2.6 shows the interpolated high frequency subband images of the low-resolution image $Texture$ 2.

The proposed method is applied to generate high resolution texture image with interpolation factor of 4. The input low resolution image are of size

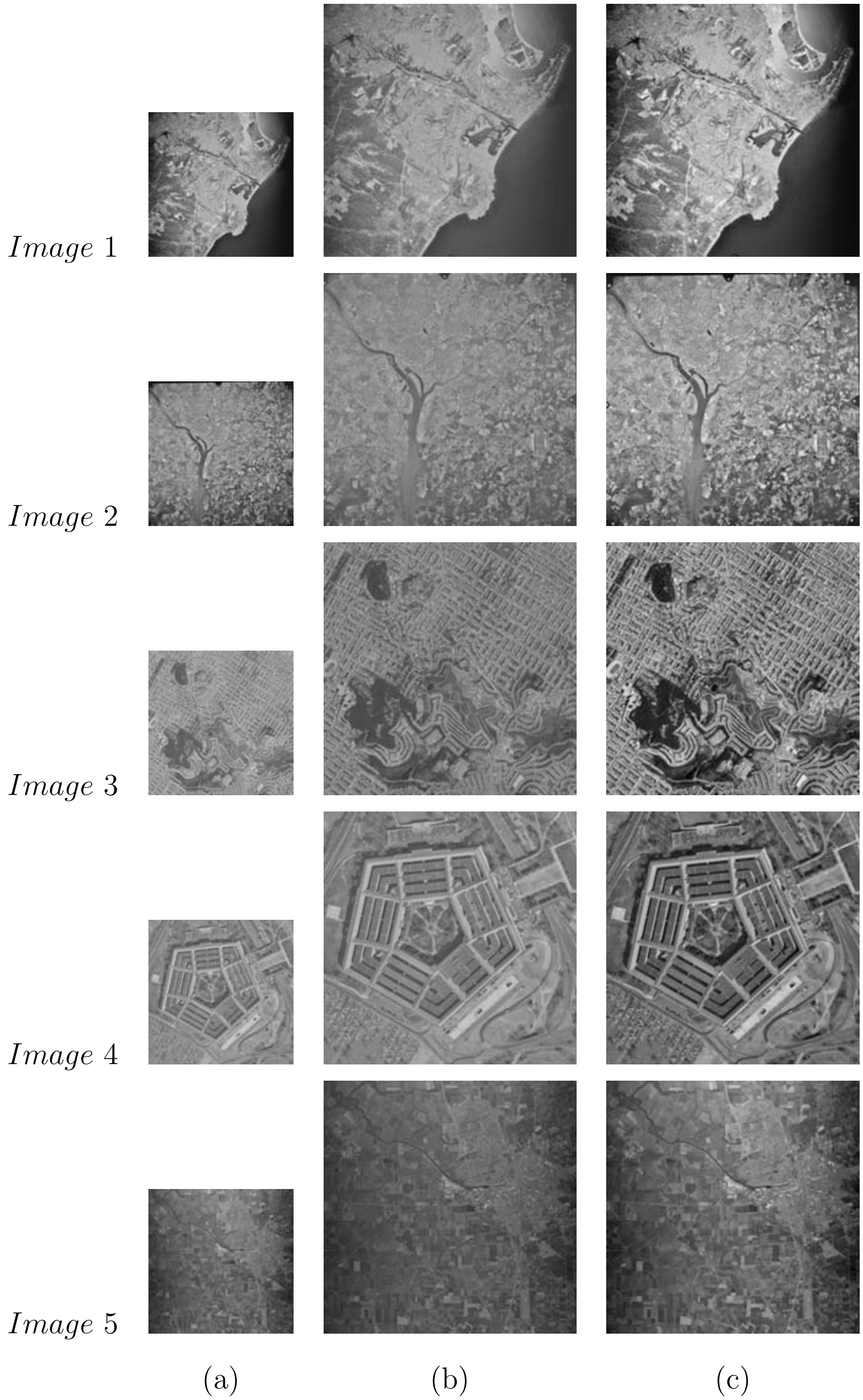
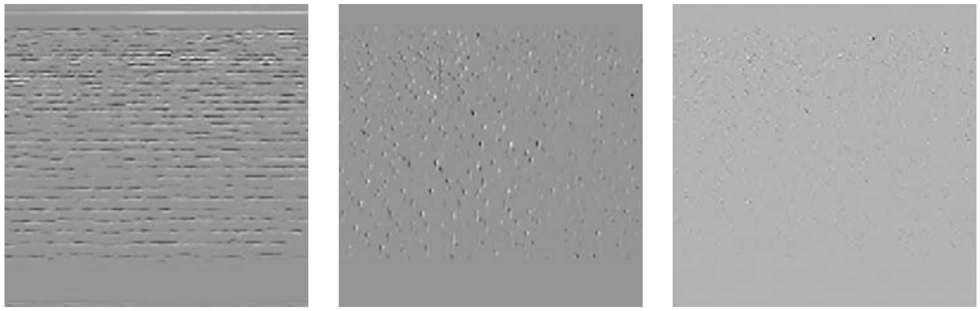


Figure 2.5: (a) input images of resolution 256×256. (b) DWT SR outputs of resolution 1024×1024. (c) Proposed method outputs 1024×1024.



(a) (b) (c)

Figure 2.6: (a)interpolated Horizontal details coefficients. (b)interpolated Vertical details coefficients. (c)interpolated Diagonal details coefficients.

256×256. The generated high resolution images are of size 1024×1024. The quantitative comparison of results is done by comparing PSNR values of the outputs of proposed technique to that of conventional and DWT SR. Table 2.7 shows the comparison of PSNR values.

Table 2.7: PSNR (dB) Results for Resolution Enhancement from 256×256 to 1024×1024

Techniques/Images	*Texture* 1	*Texture* 2	*Texture* 3	*Texture* 4
Nearest Neighbour	25.99	25.98	29.06	23.22
Bilinear	26.12	27.57	29.27	23.24
Bicubic	26.57	28.29	30.24	23.67
DWT(db.9/7) [17]	29.76	28.73	34.35	23.24
Proposed Method	36.53	26.08	34.93	24.15

The visual results of proposed technique and the results of DWT SR technique Figure 2.7. The outputs of proposed method are sharper than that of DWT SR. Figure 2.7 (a) shows low resolution input images, (b) is showing the visual results of DWT SR and (c) shows the visual results of proposed technique.

The comparison of BIQI index of outputs of proposed technique for texture images with that of DWT SR is shown Table 2.8. The outputs of proposed

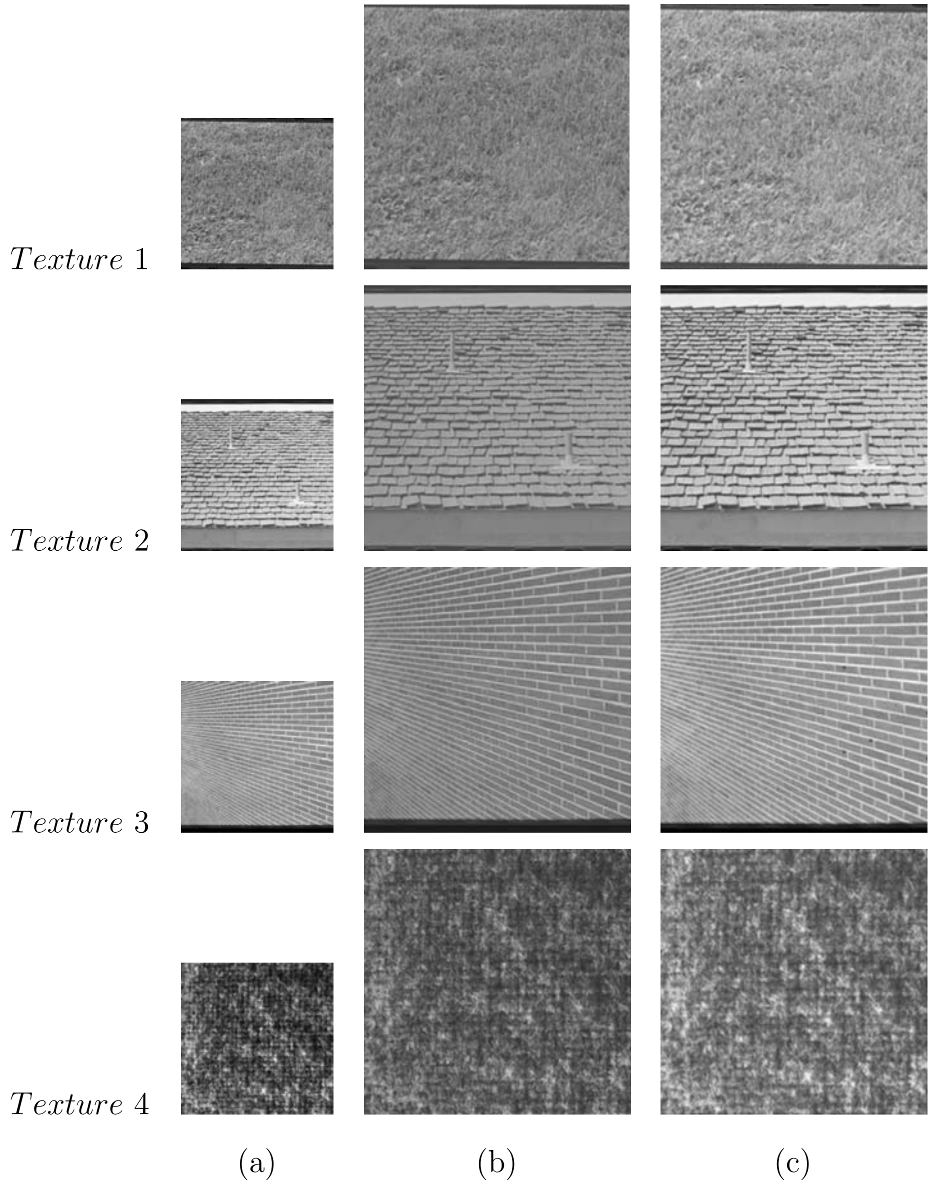


Figure 2.7: (a) input images of resolution 256×256. (b) DWT SR outputs of resolution 1024×1024. (c) Proposed method outputs 1024×1024.

method are more subjective to human perception without any reference image.

Table 2.8: BIQI Results for Resolution Enhancement from 256×256 to 1024×1024

Techniques/Images	$Texture$ 1	$Texture$ 2	$Texture$ 3	$Texture$ 4
Bicubic	63.83	34.54	32.30	82.60
DWT(db.9/7) [17]	43.92	42.52	44.15	67.49
Proposed Method	71.06	72.12	83.46	83.46

2.3 Summary

In this chapter a super resolution technique based on lifting wavelet transform. The proposed method for resolution enhancement of image gives good qualitative, quantitative and visual results than that of some conventional and state-of-the-art methods. This method is applied for the interpolation of miscellaneous, satellite and texture images. It has been observed that the proposed technique can be utilized to increase the spatial resolution of satellite as well as texture images.

Chapter 3

Image Super Resolution by Lifting (LWT) and Stationary Wavelet Transform (SWT)

This chapter proposes another technique for image super resolution using lifting wavelet transform and stationary wavelet transform. Lifting wavelet transform is discussed in chapter 2.The Stationary wavelet transform (SWT) is a wavelet transform algorithm designed to overcome the lack of translation-invariance of the discrete wavelet transform (DWT). Translation-invariance is achieved by removing the downsamplers and upsamplers in the DWT and upsampling the filter coefficients by a factor of $2^{(j-1)}$ in the j^{th} level of the algorithm.

The idea is to enhance edges, by adding the high-frequency subbands generated using stationary wavelet transform to the high-frequency subbands generated using lifting wavelet transform at intermediate stage. In this chapter, we try to improve the DWT SWT [19] method for super-resolution. Following section discuess the details of the proposed scheme.

3.1 Proposed Scheme

The input low resolution input image is decomposed into different frequency subbands by lifting wavelet transform using Cohen-Daubechies-Feauveau 4.4 (cdf4.4) as liftwave. Four frequency sabbands are generated by LWT, out of which three are high-frequency and one is low-frequency subband. In stationary wavelet transform biorthogonal 5.5 (bior5.5) is used as filter to generate various frequency subbands. High-frequency subbands contain horizontal, vertical and diagonal detail coefficients of input image.

These high-frequency subbands initially interpolated with factor of 2 using surface fitting. These-interpolated high frequency subbands are adjusted by adding high-frequency subbands generated using SWT. Initial interpolation of high-frequency subbands generated using LWT is required because LWT uses sampling that generates frequency subbands half of the size of input image while SWT generates same size frequency subbands. These adjusted high frequency subbands further interpolated using surface fitting [16] by a factor of γ. The low resloution input image is used instead low-frequency subbands to generate high-frequency subbands. Low-resolution input image is interpolated by factor of γ using surface fitting. The interpolated input image and high frequency subbands are combined using inverse lifting wavelet transform. The high resolution image is 2γ times to the size of low resolution input image. Figure 3.1 shows the block diagram of the method.

3.2 Experiments and Results

In this section experiments and results of the proposed method are discussed. This technique is applied on various images taken from USC-SIPI image database [22]. This technique is applied on miscellaneous images like *Lena*, *Elaine*, *Babbon* and *Peppers*. Performance of proposed technique is compared to various conventional and state-of-the-art methods. Various performance metrics are compared here as discussed in chapter 1.

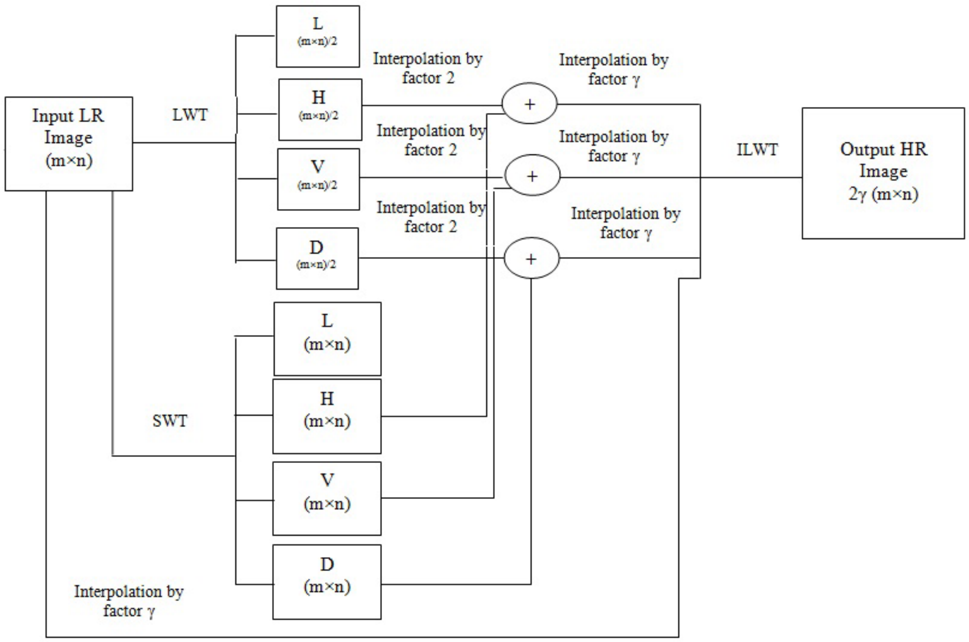


Figure 3.1: Block diagram of proposed technique

The resolution of all input image is enhanced by a factor of 4. The resolution of input images was 128×128. The resolution of generated output images is 512×512. The high frequency components of *Lena* image are generated using one level two dimensional stationary wavelet transform is shown in Figure 3.2.

(a) (b) (c)

Figure 3.2: (a)interpolated Horizontal details coefficients. (b)interpolated Vertical details coefficients. (c)interpolated Diagonal details coefficients.

Figure 3.3 shows the comparison of visual results of proposed technique with the results of DWT SR technique. The visual results show that the results of proposed technique are good in quality from DWT SR. The outputs of proposed method are sharper than that of DWT SR. Figure 3.3 (a) shows low resolution input images,(b) shows the visual results of DWT SR and (c) shows the visual results of proposed technique.

Figure 3.3: (a) input images of resolution 256×256. (b) DWT SR outputs of resolution 1024×1024. (c) Proposed method outputs 1024×1024.

The PSNR comparison of results is shown in Table 3.1. Higher the PSNR values better will be the result of proposed SR technique.

Quality of results is tested by using BIQI and VIF metrics as discussed in

Table 3.1: PSNR (dB) Results for Resolution Enhancement from 128×128 to 512×512

Techniques/Images	*Baboon*	*Peppers*	*Elaine*	*Lena*
Bilinear	20.51	25.16	25.38	26.34
Bicubic	20.61	25.66	28.93	28.86
WZP(db.9/7)	21.47	29.57	30.44	28.84
Regularity preserving interpolation [23]	21.47	29.57	30.42	28.81
NEDI [24]	21.18	28.52	29.97	28.81
HMM SR [25]	21.49	29.60	30.51	28.88
WZP-CS [26]	21.54	29.87	30.78	29.27
DWT SR [17]	23.29	32.19	32.73	34.74
CWT SR [18]	23.12	31.03	33.05	33.74
DWT and SWT SR [19]	23.87	33.06	35.01	34.82
LWT and SWT SR	28.92	36.10	34.95	34.91

chapter 1. The compariosion of BIQI and VIF of results of proposed and DWT SR is shown in Table 3.2.

Table 3.2: BIQI and VIF indexs for Resolution Enhancement from 128×128 to 512×512

Index Techniques/Images	BIQI DWT SWT	BIQI LWT SWT	VIF DWT SWT	VIF LWT SWT
Baboon	46.09	55.67	0.17	0.49
Elaine	34.02	49.06	0.19	0.72
Peppers	34.37	39.64	0.19	0.83
Lena	38.21	48.67	0.15	0.57

3.3 Summary

In this Chapter a super-resolution technique based on LWT and SWT has been proposed. High-frequency subbands of input image are generated by LWT and adjusted by adding the high-frequency subbands of input image generated using SWT. These adjusted high-frequency subbands are interpolated and high resolution image is generated by inverse lifting wavelet transform.

Chapter 4

Conclusions and Future Work

Increasing spatial resolution becomes a mandatory requirement in many applications. The resolution of image can be enhanced by increasing sensors in two dimensional matrixes. Increasing sensors increases the hardware cost. The size of sensors reduces as the number of CMOS sensors increase. Beyond a limit it causes shot noise in images. This problem gives way to develop techniques to increase the resolution of images. Although several schemes have been developed for super-resolution still there are scopes to improve the results. Two contributions are made in this regard. The idea behind both the techniques is to generate the high frequency sub-band images using LWT and later they are interpolated using surface fitting.

In the first contribution, lifting wavelet transform has been used to enhance the resolution of low resolution images. Qualitative quantitative and visual performance analysis have been made on Standard, Satellite and Texture images. It has been observed that the suggested technique prodces good results for satellite images.

Stationary wavelet transform has been used with lifting wavelet transform in second technique proposed for super resolution. This technique has been applied only on miscellaneous images. Qualitative quantitative and visual performance analysis have been made by using PSNR for quantitative and BIQI and VIF for qualitative perfofmance analysis. This suggested technique produces good results compared to the existing schemes.

Scope for Further Research

This thesis has opened several research directions which have scope of further investigation. This proposed can be extended to color image. The computational complexity can be improve by parallel implementation to increase response time. This technique can be extended to super-resolution of videos and can be used for color videos.

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Dissemination of Work

Communicated

Journals

1. **Mayank Agrawal**, and Ratnakar Dash. *Image Resolution Enhancement based on Interpolation of High-Frequency sub-bands Generated using Lifting Wavelet Transform of Satellite Images*, Preprint submitted to Optik Elsevier

Conferences

1. **Mayank Agrawal**, Ratnakar Dash. *Image Super-resolution by Interpolating High Frequency Sub-bands of Image using Surface Fitting.* Manuscript submitted to International Conference on Contemporary Computing Noida, India, Aug 2013.

2. **Mayank Agrawal**, Ratnakar Dash. *Image Resolution enhancement using lifting wavelet Transform and Stationary wavelet Transform* Manuscript submitted to I International Conference on Image Information Processing Shimla, India, Dec 2013.