Image Super Resolution Using Direction Lifting Schemes

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Submitted By
Chirag Garg
(Roll No. 601203007)

Under the supervision of
Dr. Singara Singh Kasana
Assistant Professor

SCHOOL OF MATHEMATICS AND COMPUTER APPLICATIONS
THAPAR UNIVERSITY
PATIALA –147004

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CERTIFICATE

I hereby certify that the matter presented in this dissertation titled as **"Image Super Resolution Using Direction Lifting Schemes"** in the partial fulfillment of the requirements for the award of degree of M. Tech. (Computer Science and Applications) submitted in School of Mathematics and Computer Applications, Thapar University, Patiala is my authentic work carried out under the supervision of **Dr. Singara Singh Kasana** and refers other researcher's work duly listed in the reference section.

The matter presented in this dissertation has not been submitted for award of any other degree of this or any other university.

(Chirag Garg)
601203007

This is to certify that the above statement made by the candidate is correct and true to the best of my knowledge.

(Dr. Singara Singh Kasana)
Assistant Professor

Countersigned by:

(Dr. Rajesh Kumar)
Head, SMCA
Thapar University
Patiala

(Dr. S. K. Mohpatra)
Dean (Academic Affairs)
Thapar University
Patiala

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Chirag Garg
601203007
M. Tech. (*CSA*)
SMCA

ABSTRACT

Now a day, Image super resolution is in great demand as of its use in various applications such as high definition television broadcasting, video conferencing, medical imaging and satellite imaging. To achieve super resolution one has to design the appropriate equipment so that the resolution of a particular image can be enhanced to a large extent. But due to various influencing parameters such as cost, speed and storage requirements, it is not easy to achieve high resolution up to a large extent by using the digital equipment like camera. In order to meet the customers and researchers demands for the high resolution image, designing of an image super resolution algorithm is necessary. Image super resolution is the process of constructing a high resolution image of a given low-resolution image or from a set of low resolution images for compensating the losses by increasing the number of high frequency components followed by the enhancement of edges. Our main aim is to develop an image super resolution algorithm by lowering the computational complexity and decreasing the cost.

In this work, various super resolution algorithms are proposed which produces better super resolved images. In this dissertation, there are total five chapters. In Chapter 1, introduction related to super image resolution is discussed. In Chapter 2, literature survey related to image super resolution and direction lifting schemes is discussed. In Chapter 3, an image super resolution approach is proposed using the interpolation and star polygon direction lifting scheme. In Chapter 4, image super resolution based on direction lifting, SWT and mid-point algorithm is proposed followed by the proposed approach using fusion of images in Chapter 5. Chapter 6 concludes the dissertation and the future scope is discussed.

LIST OF PUBLICATIONS

Papers Published

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4. C. Garg and S. S. Kasana, “Image super resolution using fusion of images,” IBM Journal of Research and Development.

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ABBREVIATIONS

ADL	Adaptive Direction Lifting
BMP	Bitmap
2-D	Two Dimensional
DASR	Demirel Anbarjafari Super Resolution
DCT	Discrete Cosine Transforms
DWT	Discrete Wavelet Transforms
HH	High-high
HL	High-low
HMM	Hidden Markov Model
ICBI	Iterative Curvature Based Interpolation
IDWT	Inverse Discrete Wavelet Transform
JPEG	Joint Photographic Experts Group
LL	Low-low
LH	Low-high
MEDI	Modified Edge Directed Interpolation
MRF	Markov Random Field
MSE	Mean Square Error
NEDI	New Edge Directed Interpolation
SWT	Stationary Wavelet Transform
WAL	Weighted Adaptive Lifting

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Today, image processing is being immensely used in large number of applications like video conferencing, medical imaging, satellite imaging, weather forecasting, pattern recognition, face detection, astronomy, microscopy, law enforcement, high definition television broadcasting *etc.* (Yi-bo *et al.,* 2007; Atkins *et al.*, 2001; Lehmann *et al.,* 1999). During the last few decades, the field of image processing has exhibited high growth rate while improving the cost effectiveness, speed and high memory requirements. The concept of image processing is very old as firstly it was required to transmit the digital images over cables. Today, the technology has shown such growth that one using a system can manipulate a captured image according to the requirements. The hardware requirements for image processing basically include a capturing device, a processing device and a display device. A high resolution image is always preferred over a low resolution image to be used in the application area of image processing. Using a super resolution image, one is capable of extracting various features which further help in better classification of regions of the image, accurate pattern recognition and identification of non-uniformity in medical imaging. So, obtaining a super resolved image from a low resolution image by algorithmic approach is the main concern because using the equipment for getting a super resolution image will affect the cost very badly and acquisition device may not be affordable everywhere. So, image super resolution is of great importance in various practical applications and therefore to develop the algorithm for image super resolution to obtain a super resolution image while reducing the cost and memory requirements is necessary.

1.2 Image Resolution

Image resolution, the term basically applied to the raster images of digital types and film images refers to the details a particular image holds. Resolution if considered in terms of digital cameras is the capability of the camera to identify the very smallest detail in the image. So technically, image resolution refers to the smallest measurable detail in the image. Some people confuse resolution and pixel terms, but they are meaningful in their own terms. Basically, the resolution and the pixel size are dependent on each other. The smaller the pixel size the higher will be the resolution and vice versa. In Optics, Modulus Transfer function (MTF) is used to measure the resolution of the device in which the response of the system is measured using different spatial frequencies. The term resolution can be categorized into five different types:

- *Pixel Resolution*
  An image is a collection of a number of intensity value pixels which provides information about the features of the image. Resolution and pixel size are closely related terms. Smaller the pixel size, larger is the resolution. Resolution basically accounts for the number of pixels in the image. Pixel resolution can be calculated by using two numbers; first is the width of the image in number of pixels and second is the height of the image in number of pixels.

- *Spatial Resolution*
  Spatial resolution which does not depend only on the number of pixels also depends on the system which creates the image. So technically, spatial resolution is measurement of how closely the information can be resolved in a particular image. Higher spatial resolution results in better acquisition of sharp details and transitions of colours present in the image. The image is said to be suffering from artifacts if it is not spatially correlated.

- *Brightness Resolution* Brightness resolution is termed as the colour range of an image in which brightness of each pixel is defined by a bit or set of bits depending on whether the image is grey scale or colour. Brightness resolution basically depends upon the number of bits per pixel (bpp) in an image. Higher the number of bits, high is the brightness resolution and hence the large image size. In case of monochromatic image, each pixel is represented by 8 bits. For colour images, the number of bits per pixel increases to a number 24 corresponding to red, green and blue components.

- *Temporal Resolution*

  Temporal resolution refers to the total number of frames captured per second. Less smearing due to the movements is there where the number of frames is extremely large. For a pleasing view, the number of frames per second must be 30 frames per second or more. The concept of temporal resolution can be mainly seen in the application areas like videos, movies and moving cameras.

- *Spectral Resolution*

  In sensors, spectral resolution refers to the smallest resolvable wavelength difference and is defined as how much spectral resolvable the sensor is. Multispectral images have high spectral resolution because they resolve finer wavelength difference using which the colour may be reproduced.

- *Radiometric Resolution*

  Difference in the intensity of the pixels can be better studied using the radiometric resolution. It can be defined in terms of number of bits. Here, 8 bits represent 256 levels. Higher the value of the radiometric resolution better will be the difference in the intensity of the pixels.

1.3 Need of Super Resolution

Now a day, the need of image super resolution is in great need due to its increasing use in high definition television broadcasting, video conferencing, medical imaging and satellite imaging. Due to various influencing parameters such as cost, speed and storage requirements, it is not easy to achieve high resolution up to a large extent by using the digital equipment like camera. It needs a large number of sensors to generate a super resolution image. Large number of sensors results in super resolution image but with a very high price not affordable by the customer whereas small number of sensors results in the low resolution image. In order to meet the customers and researchers demands for the high resolution image, designing of an image super resolution algorithm is necessary.

The implementation of image super resolution algorithms may cost less and utilization of existing systems can also be made. The direct technique to increase spatial resolution is to decrease the pixel size as it is inversely proportional to the spatial resolution. But pixel size reduction can lead to the shot noise effect, so there must be a limit on the pixel size reduction. High capacitance may be the other option for increasing spatial resolution but difficulty lies in the speed up process of charge transfer rate. The high cost of the sensors and various devices is the main limitations. So, new approach is needed to overcome the above said limitations.

The most reliable technique for the image super resolution is the post-acquisition technique which can be implemented to obtain better super resolution images from one or more low resolution images. The implementation of these techniques result in super resolution image with reduced cost and the negligible hardware requirements but the computational cost will be the only concern left to be dealt with.

1.4 Image Super Resolution

As the image obtained from camera suffers from various noising and blurring artifacts because of the loss of the high frequency details in the image. This loss results in poor edge formation and bad texture in the images. Image super resolution is the process of constructing a high resolution image of a given low-resolution image or from a set of low resolution images for compensating the losses by increasing the number of high frequency components followed by the enhancement of edges. Interpolation is used in image super resolution technique to generate the non-existing samples in the high resolution image. In super resolution image, the pixel density of an image is high as compared to the low resolution version which provides more details and can be useful in various applications. Using super resolution technique, it becomes easy to distinguish a particular object from its low resolution version. Therefore, super resolution results in high quality image by increasing the number of high frequency components and minimizing the blurring effects in high resolution images.

The efficiency of any image super resolution technique is dependent on two factors:

(i) *Quality of the super resolution image*

The visual quality of the super resolution image obtained after applying the super resolution algorithm is defined in terms of Peak signal to Noise Ratio (PSNR). Higher PSNR value results in better super resolved image.

(ii) *Computational complexity of the image super resolution*

Computational complexity of an image super resolution algorithm refers to the total time elapsed by the algorithm to generate a super resolved image. Lesser the computational complexity of the algorithm better will be the super resolution algorithm.

Various algorithms for transforming the low resolution image to a high resolution image have been developed. Main method for implementing super resolution as discussed in the previous section is to increase the pixel density, but the increase in the pixel density results in the shot noise in the image which is undesirable. So other approaches are to be followed for compensating the loss. Another approach is to use the interpolation technique for the image super resolution. The conventional interpolation methods are nearest, bilinear and bicubic (Lehmann *et al.,* 1999). The implementation of these methods results in the blurred image which is due to the loss of high frequency components which are basically the details to be provided by an image. The conventional interpolation techniques cannot be termed as the super resolution techniques as these don't result in super resolved images. Recently, many approaches have been developed for single frame image super resolution in which the super resolution image is obtained on the basis of single low resolution image. These techniques are based on the statistical analysis of the pixels and wavelet transforms. One method for increasing the high frequency components is to apply the wavelet transforms followed by the interpolation process.

As better image super resolution can be achieved by increasing the number of high frequency components, more number of high frequency components can be introduced in the image using the Discrete Wavelet transforms (DWT) (Shensa, 1992) and lifting schemes (Sweldons, 1997). These are the techniques for image compression which can also be used for increasing the details which help in better super resolution of a low resolution image. The implementation of conventional lifting scheme increases the number of high frequency components in the image which further helps in better super resolution to the former. Similarly, the direction lifting schemes can be used to increase the number of high frequency components as direction lifting schemes result in better compaction and therefore results in better image super resolution.

1.5 Lifting Scheme

Storage requirements are increasing day by day which are influencing the lives of human beings. Besides the storage requirements, transmission speed is another main factor while transmitting data over the internet. Image compression reduces the size of the image while preserving the information and details of the original image as much as possible without causing of artifacts in the reconstructed image. It is basically performed on the data irrespective of whether it is image, audio, video or any other file format to reduce these requirements. Therefore, the only way to improve these requirements is to compress the images such that they can be transmitted and then decompressed on the receiver side to gain the original data.

The wavelet transforms as proposed by Antonini *et al.* (1992) are the methods used for the image compression which ensures perfect reconstruction of the images (Sifuzzaman *et al*., 2009) but the memory requirements as compared to the lifting scheme (Daubechies and Sweldens, 1998) are very high. Lifting scheme was introduced by Sweldons (1997) which does not include the Fourier transforms but performs discrete wavelet transform while preserving the possible details and information which guarantees perfect reconstruction. The main advantages which make lifting scheme possible over wavelet transforms include perfect reconstruction; speed up by a factor of two, fast algorithm implementation and less storage needed. The conventional lifting scheme termed over here results in large number of high frequency components as compared to the methods listed in the previous section which further enhances image super resolution. The lifting scheme results in efficient image super resolution as the computational time complexities are also very less and it also reduces the memory requirements.

In conventional lifting scheme, original long-length wavelet filters are decomposed into short length operators which include predict and update to perform the convolution on the even and odd data which is extracted from the odd and even positions in the original image

Basically the pixel direction estimation is done in conventional lifting scheme either horizontally or vertically as shown in Figure 1.1.

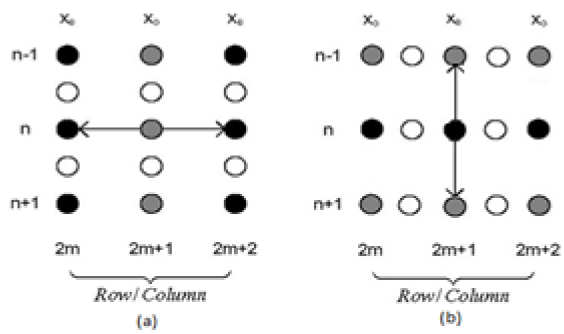


Figure 1.1 (a) Horizontal Direction Prediction (b) Vertical Direction Prediction in Conventional Lifting Scheme

Let us consider a 2-D signal $X[m,n]$. Following steps are carried in conventional lifting scheme:

1) Splitting

In this step, the original data is divided into even and odd samples $X_e[2m,n]$ and $X_o[2m+1,n]$.

2) Prediction

The odd samples are predicted from the even samples. The predictor P can be given as

$$P(X_e)[m,n] = \sum_i p_i X_e[m+i,n]. \qquad \ldots(1.1)$$

where p_i are high pass filter coefficients. The prediction residual $z[m,n]$ is computed as

$$z[m,n] = X_o[m,n] + P(X_e)[m,n]. \qquad \ldots(1.2)$$

Now, the odd samples can be recovered by

$$X_o[m,n] = z[m,n] - P(X_e)[m,n]. \qquad \ldots(1.3)$$

3) Update

In this Lifting Step, the even samples $X_e[m, n]$ are updated based on the predicted odd samples $X_o[m, n]$ in the prediction step. The updater U is computed as

$$U(z)[m, n] = \sum_j u_j z[m + j, n]. \quad \ldots (1.4)$$

On the basis of which $x_e[m, n]$ is replaced with coarse approximation as given by

$$c[m, n] = X_e[m, n] + U(z)[m, n]. \quad \ldots (1.5)$$

4) Normalization

The outputs of the lifting are normalized in this step. This step is basically performed to normalize the energy of scaling and wavelet functions.

Direction Lifting Schemes for image compression further increase the number of high frequency components as compared to the conventional lifting scheme which results in sharper image as desired in which the details are well preserved. The computational complexities are also reduced. Direction lifting schemes for image compression also includes other directions for prediction rather than horizontal and vertical directions unlike in conventional lifting scheme. In Edge Orientation Estimator lifting scheme, a span of three directions is considered for the prediction purpose on the basis of which update is to be made. Basically, the surrounding pixels of a pixel are considered for estimating the direction. There are a total number of 8 pixels which are used for estimating the direction. In ADL lifting scheme, a full span of nine directions is considered by which the predicting and updating signals can be derived even at the fractional pixel precision level to achieve high directional resolution still maintaining perfect reconstruction followed by the sub pixel interpolation. The sub pixel interpolation is needed to find the intensity of the fractional pixels considered for the lifting process. In WAL direction lifting scheme, the concept of improved weighted lifting is introduced which maintains the consistency between the prediction and update steps as much as possible and preserves the perfect reconstruction. The concept of direction adaptive interpolation is also introduced in WAL which improves the orientation property of the interpolated image. In quincunx directional lifting scheme, the properties of quincunx subsampling are considered because of which high quality for image features and the compression performance is achieved.

All these directional lifting schemes result in super resolution image with better visual effects and low computational complexities. This is achieved by increasing the number of high frequency components which further decrease the blur and noise introduced in the low resolution image taken by the camera.

1.6 Quality Parameters

For the analysis purpose, the quality parameter PSNR is taken into consideration for checking the quality of the image obtained after decompression which is of great importance for the analysis. PSNR is written as

$$PSNR = 10log_{10}\frac{255}{MSE} \qquad ...(1.6)$$

where MSE is the mean square error and is defined as

$$MSE = \sum_{m=1}^{h}\sum_{n=1}^{w}\frac{(X(m,n)-Y(m,n))^2}{m\times n} \qquad ...(1.7)$$

where m is the number of rows and n is the number of columns. Here $X(m,n)$ represents the original image and $Y(m,n)$ represents the reconstructed image.

1.7 Contribution of the Dissertation

Image super resolution is the process of obtaining a super resolution image from one or more low resolution by extracting the details from the low resolution image. Most of the approaches developed for the image super resolution take into consideration the multiple images of the low resolution images followed by the construction of super resolved image from the set of low resolution images. But in this dissertation, the main focus lies on the construction of a high resolution image from single low resolution image. For this particular to put into practice we make the use of the star polygon lifting which is also proposed in the Thesis, the direction lifting schemes, the stationary wavelet transform and the midpoint algorithm. The problem of image super resolution arises in a various set of applications where high resolution is very great demand. A common problem arises in satellite imaging and medical imaging where the details are highly needed for the analysis purpose and super resolution image is of great importance. A very efficient method while reducing the memory requirements, speed and cost factors is to download the low resolution image on the client's machine and run an image super resolution algorithm to enhance the resolution.

To make the low resolution image a super resolution image, we are proposing some methods for the image super resolution based on direction lifting schemes. The main focus is to increase the high frequency components which compensates for the loss incurred in the image and removes the blur in the image. The contributions of the dissertation, in summary are:

- First, an image super resolution algorithm is proposed in which star polygon adaptive direction lifting scheme is used along with interpolation. The star polygon direction lifting scheme is used to increase the number of high frequency components in the image. The input low resolution image is firstly decomposed into subbands using the star polygon adaptive direction lifting scheme followed by the interpolation process. The interpolated subbands are then subjected to inverse star direction lifting scheme which results in a super resolution image. Thus, we propose a method for image super resolution which is of low complexity in terms of time and memory requirements are also reduced to half.
- Further image super resolution approach based on the direction lifting schemes is proposed in which SWT and mid-point algorithm are also used. This super resolution approach produces even better results as compared to the previous discussed approach. Here edge enhancement in the low resolution image is also performed by applying the SWT and finally the error image is back projected using the mid-point algorithm. The back projecting of the error image results in the increase in number of high frequency components which results in better image super resolution.
- Finally image super resolution is achieved by the fusion of the images obtained by the conventional interpolation method, SWT and the mid-point algorithm. The fusion of the images results in super resolution image which is better in terms of visibility as compared to the former. The computational complexity of the proposed approach is bearable.

We have performed various experiments to validate the usefulness of different proposed methods.

1.8 Organization of the Thesis

We address the problem of single image super resolution in this Thesis. Here, we develop several methods for image super resolution using the direction lifting schemes which are the schemes for image compression. We also develop a method for image super resolution in which the direction lifting schemes along with the Stationary wavelet transforms (SWT) and mid-point algorithm along with the back projecting of the error. Further, we develop a method for image super resolution in which the final super resolved image is obtained by the fusion of the images as generated by the conventional interpolation methods, SWT and the mid-point algorithm. The dissertation is organized as follows.

In Chapter 2, current literature on image super resolution is specified which generally includes the method for single image super resolution.

Image super resolution using the star polygon adaptive lifting scheme (SPADL) and interpolation of subbands is discussed in Chapter 3. In this chapter, we show that the star polygon lifting scheme leads to increase in the number of high frequency components which further compensates for the loss and blur in the image.

In Chapter 4, Image super resolution scheme based on the direction lifting scheme, SWT and midpoint algorithm is discussed which leads to the edge enhancement and therefore leads to better visual effects followed by the image super resolution as discussed in Chapter 5 in which the images obtained by the conventional interpolation method, the SWT based method and using the midpoint algorithm method are fused together to produce a super resolved image.

The dissertation concludes in chapter 6 where we summarize our work and also discuss some issues for further research in the area of image super resolution.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

In this chapter, the literature review of image super resolution techniques and direction lifting schemes is discussed. Section 2.2 includes brief description of the existing image super resolution techniques used for image super resolution. In Section 2.3 literature review related to various existing direction lifting schemes is discussed in brief.

2.2 Single Image Super-resolution

In this section, we review the literature on the image super resolution techniques for single image super resolution. Image super resolution is the process of generating the super resolution image from a low resolution image and a set of low resolution images. Single image super resolution refers to the generation of super resolution image from single low resolution image. Most of the methods include the statistical methods for the single image super resolution while other methods include the learning of appropriate features from an image based to increase the high frequency details in the low resolution image which further results in super resolved image.

The concept of image super resolution was first given by Tsai and Huang (1984) to improve the resolution of images in satellite imaging. In satellite imaging, during the course of orbit various images of a particular are taken in a sequence and are considered for super resolution. Here the authors used continuous and discrete Fourier transforms to obtain a super resolution image. In this the shifting and aliasing properties of the system relating the equations of discrete Fourier transform to continuous Fourier transform. The equations are then used to reconstruct the original image and this is achieved by applying inverse Fourier transform. Main limitation of this was that the images considered for the super resolution were noise free. A new approach as an extension to this was proposed by Kim *et al.* (1990) in which weighted least squares algorithm was used for image super resolution. Blur and noise was also reduced from the low resolution image. Other transforms like discrete cosine transforms have been used by researchers to perform image super resolution as discussed by Rhee and Kang (1999). The most efficient approach for image super resolution is the interpolation approach in terms of computational complexity and size. Conventional super resolution methods on smoothing and interpolation techniques have been used for various applications of image processing. The use of Gaussian, Weiner and median filters results in smoothing of the image. Conventional interpolation methods such as nearest, bilinear and bicubic (Hou and Andrews, 1978; Keys, 1981) produce the blurred image because of the smoothing performed in discontinuous regions. Ringing artifacts are the disadvantage as produced by the bicubic interpolation because of the nature of overshooting sharp discontinuities.

All above said limitations are resolved by an edge preserving non-linear image expansion technique proposed by Schultz and Stevenson (1994) using the Bayesian estimation technique. Some researchers preferred the analytic continuation of the signal because the methods proposed by them deal with the missing high frequency components which further results in spectral extension. Harris (1964) proposed a method for increasing the number of high frequency components in which using the finite portion of the spectrum of the object entire spectrum can be generated using the analytic continuation of the signal. It works very well in the noise free environment but a little noise in the environment in the given portion of the spectrum results in high unreliability. An extension to this method for obtaining the entire spectrum of the object using the finite considered spectrum was proposed by Gerchberg (1974). Here, both the frequency and time domains are used alternatively as in alternate projections as mentioned in Jain (2001) to carry out extrapolation which results in error reduction.

Papoulis (1975) proposed the dual of the above proposed method in which an iterative procedure is used to generate the band-limited spectrum from the finite spectrum of the object. It was shown that by limiting the number of iterations the aliasing effect and the noise by aliasing can be determined. Many methods based on the learning are proposed for single image super resolution where the learning is performed using a large set of images in the database. In order to produce a super resolution image, the best features from the low resolution image are extracted from a set of training images. In the method proposed by Papoulis *et al.* (2001), the super resolution image is generated by low resolution and high resolution versions of some portions of the image. As our work in dissertation is related to the geometrical and statistical analysis of image data with the use of various interpolation techniques, we will now review some methods in which the statistical and geometrical analysis of data is made.

A number of edge detected image super resolution algorithms have also been proposed keeping in view that super resolution images are obtained when the pixel values are interpolated based on the edges in the original image. In some proposed approaches, geometric properties of the image are used to find the accurate model to find the intensity values of unknown pixels (Jensen and Anastassiou, 1995; Allebach and Wong, 1996; Morse and Schwartzwald, 1998; Alagazi *et al.*, 1991). The main problem here lies in the actual estimation of the edges and details in the image being used for the image super resolution as poor edge estimation results in poor visual quality of the image. The methods (Morse and Schwartzwald, 1998; Alagazi *et al.,* 1991) make use of isophote based methods which are highly efficient while interpolating sharp edges. But this results in blurred image which degrades the performance. This problem was solved by Wang and Ward (2001) by adapting to the edge enhancement techniques while performing image super resolution. Some methods make the use of the gradient operators for determining the edge orientation in the input image (Battiato *et al.,* 2002; Battiato *et al.,* 2007; Battiato *et al.,* 2008). These methods reduced the problem of blur and the noise from the image by determining the edge orientation but they suffer from the problem of edge map and gradient operator as these are not well adaptable to the image. Other edge directed interpolation methods for better image super resolution without the use of edge maps and gradient operators make the use of geometrical and statistical method to generate a super resolved image with better visual quality (Li X. and

Orchard, 2001; Chen *et al.,* 2003; Li and Nguyen, 2008; Asuni and Giachetti, 2008; Chen *et al.*, 2005).

Piao *et al.* (2007) enhanced the image resolution by using Inter-Subband correlation in wavelet domain. Sharpness of the reconstructed image was improved by Carey *et al.* (1999) by preserving the regularity in image interpolation. Li and Orchard (2001) proposed a new edge-directed interpolation (NEDI) approach in which interpolation was performed based on edge regions. NEDI makes use of simple linear prediction for the estimation of unknown pixels. Second order locally stationary Gaussian process is used as model for the image. Compared to conventional methods such as the nearest, bilinear or bicubic methods of interpolation, the NEDI method enhances the interpolated edges by preserving the sharpness and continuity of the edges present in the image. In this method, four nearest neighboring pixels along the diagonal edges are considered. As all the unknown pixels are not estimated from the original image, it leads to degradation in the quality of the output image obtained. Due to the large kernel size as defined in the NEDI method, the visual quality and Peak Signal to Noise Ratio (PSNR) of the super resolution image is reduced. After that the Markov random field (MRF) model-based method by Chen *et al.* (2003) was proposed which models the image with MRF and extends the estimation of edges in a number of directions greater than the number of directions in NEDI. The number of possible directions is estimated by increasing the number of neighboring pixels in the kernel. The MRF model-based method results in preserving the visual quality of the interpolated edges and also maintains the fidelity of the interpolated image, thus enhancing the PSNR level. The more accurate the MRF model, the better the efficiency of the MRF model-based method. But the computational complexity of this model becomes high. However, both the NEDI and MRF models are optimally equal statistically but MRF model's complexity is computationally high. But NEDI in comparison to the MRF model relies on a very simple model is thus less computationally expensive. Therefore, a lot of research has been performed to enhance the performance of the NEDI method. An extension to the NEDI algorithm was proposed as improved new edge-directed interpolation (iNEDI) method by Asuni and Giachetti (2008) which modifies the NEDI method by varying the size of the training window which is dependent on edge size and hence achieves better PSNR performance. However, the computational cost is high and the performance is highly dependent on the chosen parameters, which are also image dependent. Regarding the computational cost, there are fast algorithms that integrate the advantages of the isophote-based methods and edge enhancement techniques, which can achieve high quality interpolated images (Chen *et al.*, 2005; Giachetti and Asuni, 2008). However, not all these methods are statistically optimized, thus they degrade the continuity and sharpness of the interpolated edges. The iterative curvature-based interpolation (ICBI) method by Giachetti and Asuni (2008) considers the effects of the curvature continuity, curvature enhancement, and isophote contour. By properly weighting these three effects, the ICBI method produces perceptually pleasant images and significantly reduces the computational cost. However, similar to the iNEDI method, the performance depends on the chosen parameters. Further modified edge-directed interpolation (MEDI) by Tam *et al.* (2011) is proposed in which a different training window to mitigate the interpolation error propagation problem. Li and Nguyen (2008) used a similar training window in improved edge-directed interpolation (IEDI) independently. While the enlarged training window eliminates the error propagation problem, it also inevitability increases the interpolation error due to the worsened covariance mismatch problem.

After that wavelet based statistical signal processing came into being which was implemented using hidden markov models (HMM) was proposed by Kinebuchi *et al.* (2001). Zhao *et al.* (2003) proposed a wavelet domain image super resolution approach which produced better results as compared to existing techniques Zhao *et al.* (2003). Tezimal and Vlachos (2005) used cycle spinning for the image resolution enhancement which produces better results . Gholamreza and Hasan (2010) proposed an image super resolution method based on the interpolation of the high frequency subbands and input image using discrete wavelet transform (DWT). This technique uses DWT to decompose an image into different subband images and the high-frequency subband images excluding the low-frequency subband image are interpolated along with the low resolution image. Further all these subbands are combined to generate a super resolution image and this is achieved using the inverse DWT transform. This technique shows the superiority over conventional image resolution enhancement techniques. An extension to this algorithm was proposed by Gholamreza and Hasan (2011) in which the authors proposed an image resolution enhancement technique based on interpolation of the high frequency subband images obtained by discrete wavelet transform (DWT) (Shensa, 1992) and the input image. The edges are further enhanced by introducing an intermediate stage by using stationary wavelet transform (SWT). DWT is applied on the input image to decompose an input image into different subbands. Then the high frequency subbands are interpolated along with the interpolation of the input image. The SWT is used to modify the estimated high frequency subbands by using the high frequency subbands as obtained through SWT. Then inverse DWT (IDWT) is applied on all these combined subbands to generate a new high resolution image. The quantitative and visual results obtained outperform the results obtained by conventional and other existing super resolution techniques.

2.3 Direction Lifting Schemes

Storage requirements are increasing day by day which are influencing the lives of human beings. Besides the storage requirements, transmission speed is another main factor while transmitting data over the internet. Image compression reduces the size of the image while preserving the information and details of the original image as much as possible without causing of artifacts in the reconstructed image. It is basically performed on the data irrespective of whether it is image, audio, video or any other file format to reduce these requirements. Therefore, the only way to improve these requirements is to compress the images such that they can be transmitted and then decompressed on the receiver side to gain the original data.

The wavelet transforms as proposed by Antonini *et al.* (1992) are the methods used for the image compression which ensures perfect reconstruction of the images (Sifuzzaman *et al.*, 2009) but the memory requirements as compared to the lifting scheme (Daubechies I. and Sweldens, 1998) are very high. Lifting scheme was introduced by Sweldons (1997) which does not include the Fourier transforms but performs discrete wavelet transform while preserving the possible details and information which guarantees perfect reconstruction. The main advantages which make lifting scheme possible over wavelet transforms include perfect reconstruction; speed up by a factor of two, fast algorithm implementation and less storage needed.

Direction lifting schemes for image compression also includes other directions for prediction rather than horizontal and vertical directions unlike in conventional lifting scheme. In Edge Orientation Estimator lifting scheme proposed by Gerik and Cetin (2006), a span of three directions is considered for the prediction purpose on the basis of which update is to be made. The two dimensional structure used is similar to Daubechies 5/3 wavelet. Here an edge orientation estimator is used to predict the value of the next polyphase component using the 2-D prediction filter. The prediction domain with diagonal gradient is allowed to rotate $\pm 45_{\circ}$ in regions. The gradient estimator is computationally inexpensive because only additional costs of six subtractions per lifting instructions and no multiplications are required, only addition and subtraction operations.

In ADL lifting scheme proposed by Ding *et al.* (2007), a full span of nine directions is considered by which the predicting and updating signals can be derived even at the fractional pixel precision level to achieve high directional resolution still maintaining perfect reconstruction. Instead of alternately applying horizontal and vertical lifting as in case of conventional lifting scheme, high pixel correlation direction is used for lifting based prediction in local windows. Hence, it adapts far better to the image orientation features in local windows. The ADL transform is basically achieved by existing 1-D wavelets and can be mapped to the global wavelet transform. To enhance the ADL performance, a rate-distortion optimized directional segmentation scheme is also proposed to form and code a hierarchical image partition adapting to local features. Sub pixel Interpolation is the operation performed to find the intensity of the fractional pixels used for the direction prediction. The ADL method produces the images with enhanced quality and rich orientation feature. In WAL lifting scheme (Liu and Nagan, 2008), the concept of improved weighted lifting is introduced which maintains the consistency between the predict and update steps as much as possible and preserves the perfect reconstruction The concept of direction adaptive interpolation is also introduced in WAL which improves the orientation property of the interpolated image. In quincunx directional lifting scheme (Chang *et al.*, 2005), the properties of quincunx subsampling are considered because of which high quality for image features and the compression performance is achieved.

CHAPTER 3

IMAGE SUPER RESOLUTION USING STAR POLYGON LIFTING SCHEME

3.1 Introduction

In this chapter, a star polygon adaptive direction lifting scheme (SPADL) is proposed in which the prediction and update steps of the lifting scheme are performed using the directions given by geometrical star polygon. Further image super resolution approach is proposed on using the SPADL scheme and the interpolation of subbands. Then the input image and sub-bands excluding the low frequency sub-bands are interpolated and inverse SPADL scheme is applied to obtain a super resolution image. PSNR is the main factor taken into consideration for determining the quality of the reconstructed image.

There are many lifting schemes which take into consideration the non-horizontal and non-vertical prediction directions. These schemes provide better compaction for images having edges which are neither horizontal nor vertical. But there is still a scope of other directions of prediction which can represent edges more efficiently in high frequency subbands. Keeping this in mind, a separable SPADL scheme is proposed in which the adaptive wavelet filters are combined with the properties of the star to make the prediction and update of the pixels. In this scheme, 7 directions are taken into consideration to predict and update the pixels of an image to get the wavelet coefficients. Based on these 7 directions the operations for performing the prediction and update are applied on the image which results in the formation of the subbands. The subbands are interpolated independently and then subjected to inverse direction lifting scheme to obtain a super resolution image.

3.2 Proposed SPADL scheme

Image data is a 2 dimensional set of pixels with a positive intensity value. In SPADL, a 2-D data X considered of even samples X_e and odd samples X_o are given by:

$$X_e = \{X[l_e], l_e \in \Pi_e \; where \; \Pi_e = \{(m,n) \in \Pi | m \; even\}$$
$$X_o = \{X[l_o], l_o \in \Pi_o \; where \; \Pi_o = \{(m,n) \in \Pi | m \; odd\} \qquad \ldots(3.1)$$

In Figure 3.1, the odd pixels are of grey color and the corresponding even pixels are of white color. The prediction of odd pixel $X_0(m,n)$ is done on the basis of the direction given by the even pixels $X_e(m,n)$. Here only those even pixels are considered for the direction estimation which lies on the boundary of star by placing one vertex of star on the odd pixel considered for prediction.

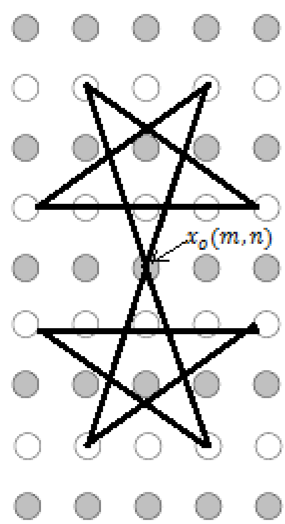


Figure 3.1 Direction prediction for $\boldsymbol{X_0(m,n)}$ based on star

In prediction, the odd samples are predicted from even samples. The predictor P can be given as

$$P(X_e)[m,n] = \sum_i p_i \times X_e[m+i,n]. \qquad \ldots(3.2)$$

where p_i are high pass filter coefficients.

The even pixels $X_e[m+i,n]$ used in the predictor P are estimated based on the direction $d \in D$ where D a domain of seven directions is given by Fig. 3.

$$D = \{d_1, d_2, d_3, d_4, d_5, d_6, d_7\}$$

The value of each direction in D is calculated based on the difference of pixels lying in that direction.

Then the direction for Predict P is given by

$$d = \min(d_i \in D) \;\; for\ i = 1,2 \ldots\ldots 7$$

Where d_i is given as

$$\begin{cases} X_e(2m-1, 2n+i-3) - X_e(2m-1, 2n+3-i) \\ \quad for\ i = 1,2 \ldots\ldots 5 \\ X_e\left(2m-1, 2n+\left\lceil {}^{i}/_{6} - 1 \right\rceil\right) - X_e\left(2m-1, 2n+\left\lceil 1 - {}^{i}/_{6} \right\rceil\right) \\ \quad for\ i = 6\ and\ 7 \end{cases} \qquad \ldots(3.3)$$

Similarly the update is made on the even pixel. The update step is performed using the directions as estimated below in Figure 3.2.

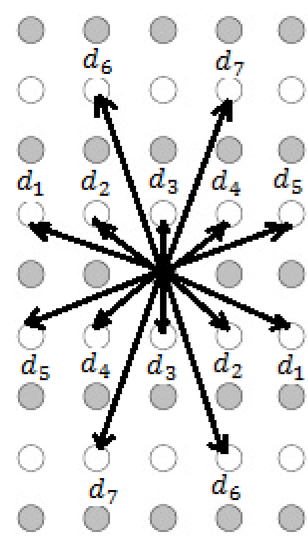


Figure 3.2 Span of 7 directions for the prediction and update step

The pixels by which the update is to be made are specified by the direction given by the star. Firstly, the process defined above is applied column-wise after which the prediction and update is performed row-wise. In inverse SPADL scheme, the row-wise lifting is performed followed by the column wise lifting scheme.

The prediction and update step complete one lifting step while performing column and row lifting. Forward SPADL scheme when applied on input image will therefore result in the formation of four subbands and the inverse on these bands will result in the formation of the original image.

3.3 Proposed Super Resolution Approach Based on Interpolation and SPADL scheme

In this section, SPADL for super resolution has been applied on the image to decompose the image into subbands namely low-low subband (LL), low-high subband (LH), high-low subband (HL) and high-high subband (HH). The main reason for the loss is due to the smoothing while performing the interpolation of the image. This loss is due to the edges region also called as high frequency components. Therefore, SPADL is applied over here to overcome this problem.

Various techniques used for dividing the images into subbands have been used earlier. Table 3.1 shows the average wavelet coefficient value of the subbands of various images using existing lifting schemes and proposed lifting scheme.

Table 3.1 Average wavelet coefficient value of each subband of various images by using various techniques

Images / Techniques	Lena				Baboon				Pepper			
	LL	**LH**	**HL**	**HH**	**LL**	**LH**	**HL**	**HH**	**LL**	**LH**	**HL**	**HH**
DWT	250.32	3.64	5.23	2.25	275.5	16.1	10.92	5.43	299.64	5.18	5.47	5.89
Conventional lifting scheme	126.04	3.38	2.59	2.64	138.9	7.74	13.13	5.60	150.89	4.55	4.47	10.10
Edge orientation estimator scheme	126.09	4.06	3.18	3.43	139.0	14.5	14.95	13.76	150.83	7.16	5.74	7.36
Proposed SPADL Scheme	126.13	5.28	3.94	4.24	139.0	18.4	17.84	18.26	150.73	7.80	6.26	7.51

From this table one can infer that the proposed SPADL scheme produces the high frequency subbands with large value as compared to the subband values generated by other techniques. The values of the high frequency subbands must be high as to compensate the loss due to interpolation.

In the proposed approach, the subbands are generated using the SPADL scheme. The low-frequency components present in the LL subband which are a result of low pass filtering of an image contains less information as compared to the original input image. The high-frequency components present in the LH, HL and HH subbands therefore will increase the quality of super resolution image obtained after reconstruction.

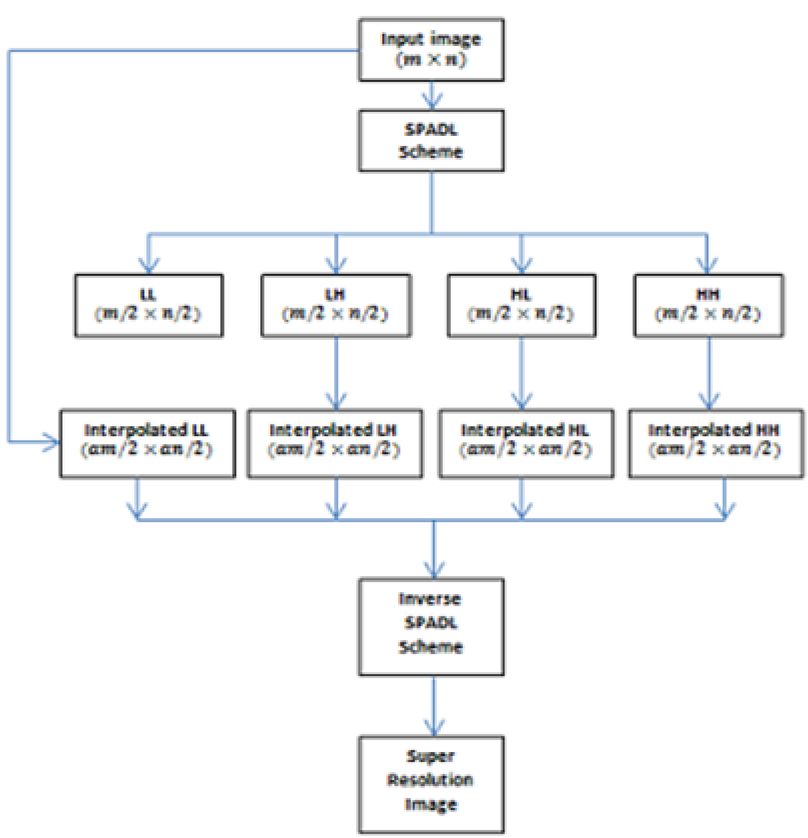


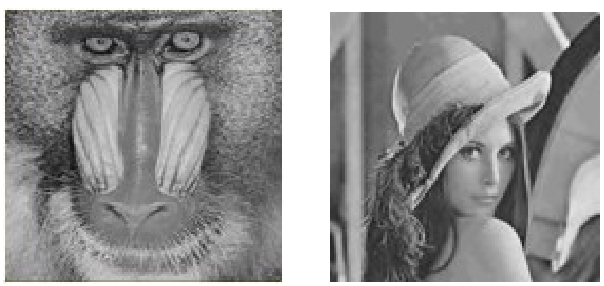
Figure 3.3 Flow chart of the proposed approach.

The input image and high-frequency subbands are interpolated by some factor and then by applying the inverse SPADL scheme, the super resolution image with sharp edge regions is obtained. This type of results obtained all because of the separate interpolation of each subband and interpolation of the input image. Figure 3.3 shows the proposed scheme for image super resolution. The input image is firstly divided into four subbands using the SPADL scheme. Then the input image and the high frequency subbands are interpolated and after interpolation it is subjected to inverse SPADL scheme to obtain the super resolution image. The interpolation is performed with a factor α.

Therefore, the proposed approach implemented on input image using the SPADL scheme results into subband formation followed by the interpolation of the input image and the subbands, and finally resulted in super resolution image by applying the inverse SPADL scheme on the interpolated images.

3.4 Experimental Results

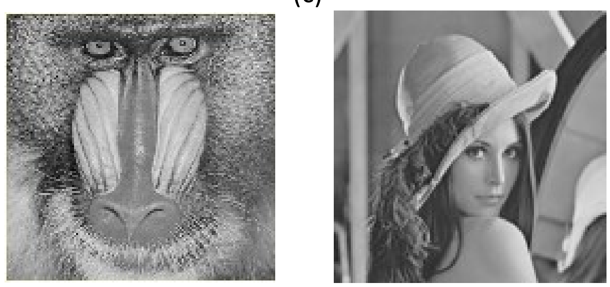
Proposed SPADL scheme and the image super resolution approach have been implemented in MATLAB. Test images considered in this work are Lena, Baboon, Elaine and Pepper. The input image is divided into four subbands using the newly proposed SPADL scheme and the high frequency subbands and the input image are subjected to interpolation and using the inverse SPADL scheme the reconstruction of image is done.



(a)

(b)

(c)

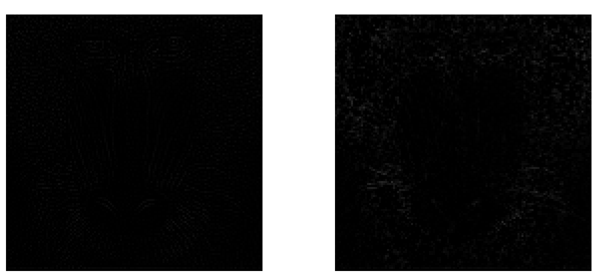


(d)

Figure 3.4 (a) Original low resolution mages (b) Bicubic interpolated images (c) DASR super resolution images (d) Super resolution images obtained from proposed approach

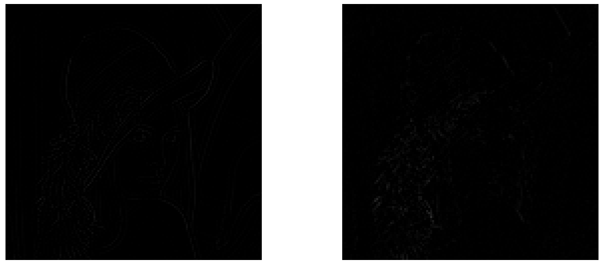
Various images of Lena and Baboon are shown in Figure 3.4 which are obtained by applying the existing approaches and our proposed algorithm. From the figure it can be seen that the results obtained by the proposed approach are of high quality and high resolution.

Figure 3.5 shows the error image of Lena and Baboon between the original high-resolution image with the image obtained through the proposed approach, and the error image obtained by using bicubic interpolation method. The proposed approach preserves the high-frequency details more than the conventional interpolation techniques.



(i) (ii)

(a)



(i) (ii)

(b)

Figure 3.5 Error image of (a) Baboon between the original images and (i) proposed approach (ii) bicubic interpolated image (b) Lena between the original image and (i) proposed approach (ii) bicubic interpolated image.

Table 3.2 compares the PSNR performance of the proposed approach using DB9/7 and 5/3 wavelet functions with bicubic interpolation with various existing resolution enhancement techniques: nearest, bilinear, bicubic, WZP (DB9/7), WZP (Haar), NEDI, HMM, HMT SR, WZP-CS, WZP-CS-ER, regularity- preserving image interpolation and DASR image super resolution technique. The image resolution enhancement comparison is done basically on the image of input size 128 × 128 which results in output the image of size 512 × 512 with better visual quality.

Table 3.2 PSNR results for resolution enhancement from 128 × 128 to 512 × 512 of the proposed approach compared with other existing approaches

Images Approaches	**Baboon**	**Lena**	**Eliane**	**Peppers**
Bilinear	20.51	26.34	25.38	25.16
Bicubic	20.61	26.86	28.93	25.66
WZP(db9/7)	21.47	28.84	30.44	29.57
WZP(haar)	18.02	26.67	28.06	23.80
Carey *et al.* (1999)	21.47	28.81	30.42	29.57
NEDI (Li *et*	21.18	28.81	29.97	28.52

***al.*, 2001)**				
HMM (Kinebuchi *et al.*, 2001)	21.47	28.86	30.46	29.58
HMT SR (Zhao *et al.*, 2003)	21.49	28.87	30.51	29.60
WZP-CS (Temizel *et al., 2005)*	21.54	29.27	30.78	29.87
WZP-CS-ER (Temizel *et al., 2005)*	21.56	29.36	30.89	30.05
DASR haar +bicubic (Anbarjafari *et al.*, 2010)	18.06	27.07	27.94	23.84
DASR db9/7+bicubic (Anbarjafari *et al.*, 2010)	23.29	34.79	32.73	32.19
SPADL 5/3 + bicubic	22.01	32.63	30.16	29.45
SPADL 9/7 + bicubic	24.10	35.42	33.52	33.07

For example, in the Lena image, the PSNR of proposed approach using the db.9/7 wavelet function is 6.06 dB higher than the PSNR obtained by using WZP-CS-ER and 8.56 dB higher than the PSNR obtained by using the bicubic interpolation.

Table 2 indicates that the proposed approach outperforms the existing image resolution enhancement techniques. In Figure 3.6, the curves show the PSNR curve for different images taken into consideration. Greater PSNR defines the super resolution quality of the image obtained after implementation.

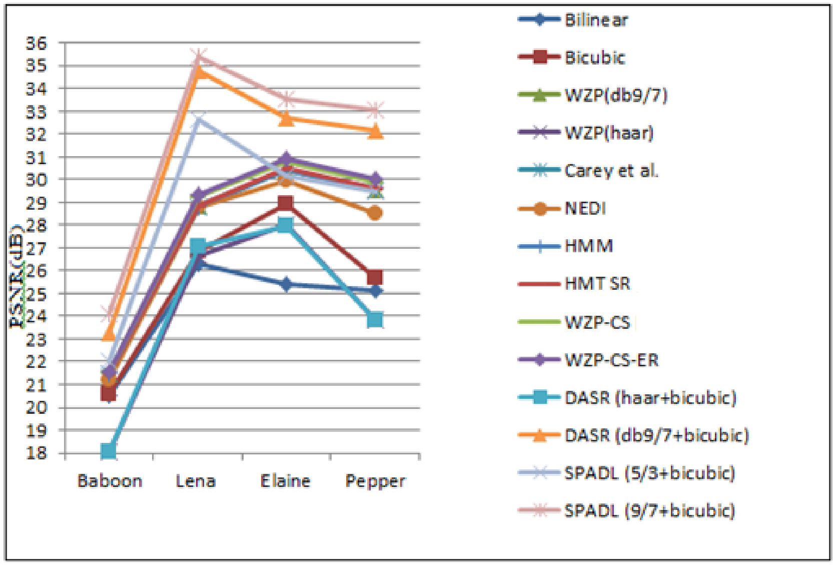


Figure 3.6 Comparison of PSNR for different images obtained using existing techniques and the proposed approach.

The PSNR curve in Figure 3.6 shows that the proposed approach when applied for DB. 9/7 outperforms the existing schemes.

3.5 Conclusion

In this chapter, a new direction lifting scheme is proposed in which the star polygon is used for the direction estimation. Further a new image super resolution approach is proposed which is based on the interpolation of the high-frequency subband images obtained by using the SPADL scheme and the input image. The image super resolution approach uses SPADL scheme for decomposing an image into subbands and reconstruction of image using the low resolution image and high frequency subbands obtained after interpolation. The proposed approach has been performed on various images and the experimental results show that the images are of superior quality as in comparison to the conventional and state-of-art image resolution approaches in terms of PSNR.

CHAPTER 4

DIRECTINAL LIFTING BASED IMAGE SUPER RESOLUTION USING STATIONARY WAVELET TRANSFORM AND MID-POINT ALGORITHM

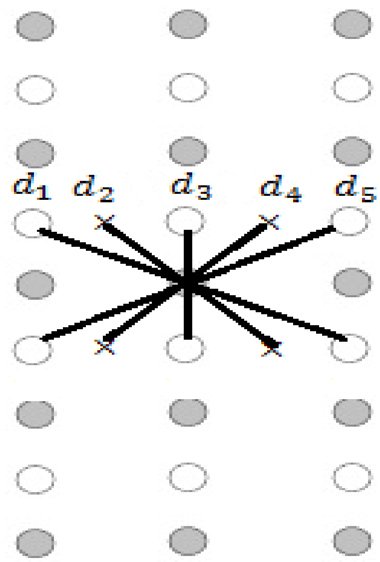
4.1 Introduction

In this chapter, an approach for image super resolution based on the direction lifting scheme is proposed which also takes into consideration the Stationary wavelet transform (SWT) for edge enhancement. The input image is interpolated using the general interpolation method and then divided into subbands using directional lifting scheme. The subbands are the fused with the bands obtained by applying SWT on the input image. The image thus formed is de-noised using filters and further is used to back project the error image obtained using the mid-point algorithm.

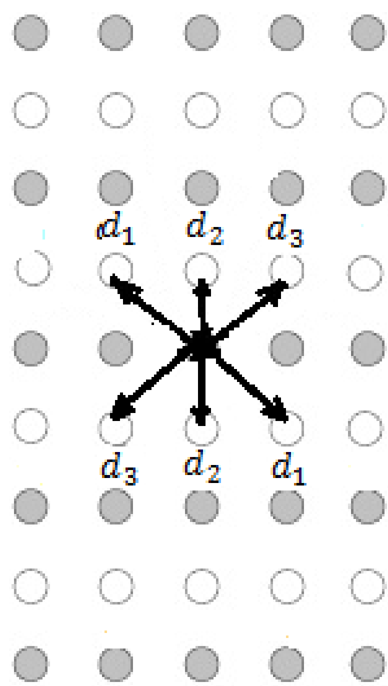
4.2 Direction Lifting Schemes

There are many lifting schemes which take into consideration the non-horizontal and non-vertical prediction directions (Ding *et al.,* 2007; Liu and Nagan, 2008; Chang *et al.*, 2005). These schemes provide better compaction for images having edges which are neither horizontal nor vertical. But there is still a scope of other directions of prediction which can represent edges more efficiently in high frequency subbands. Keeping this in mind, various directions other than the horizontal and the vertical directions are also taken into consideration for the prediction and the update step.

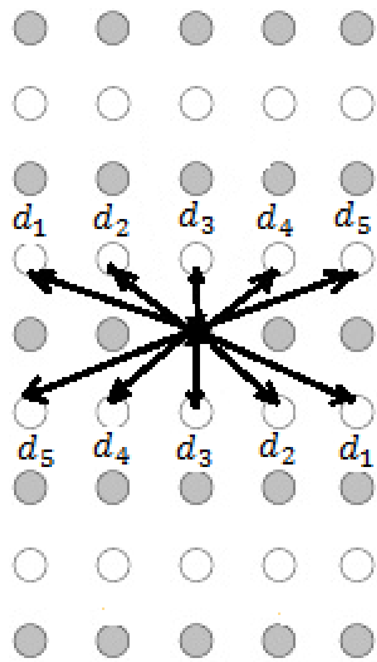
Figure 4.1 shows various ways of considering the directions for the estimation purpose. Figure 4.1(a) shows the three directional lifting scheme for the estimation purpose while the direction estimation in Figure 4.1(b) shows the estimation even at the fractional pixel precision level. Figure 4.1(c) shows the five directional estimation lifting scheme which takes into consideration a span of five pixels for the estimation purpose.



(a)



(b)



(c)

Figure 4.1 (a) Fractional Pixel Estimation (b) 3-Directional Estimation (c) 5-Directional Estimation.

In prediction, the odd samples are predicted from even samples. The predictor P can be given as

$$P(X_e)[m,n] = \sum_i p_i \times X_e[m+i,n]. \qquad \ldots \text{ (4.1)}$$

where p_i are high pass filter coefficients.

The even pixels $X_e[m+i,n]$ used in the predictor P are estimated based on the direction $d \in D$ where D a domain of directions is given by Fig. 1(a)-(c).

$$D = \{d_1, d_2, d_3, \ldots \ldots\}$$

The value of each direction in D is calculated based on the difference of pixels lying in that direction.

Then the direction for Predict P is given by

$$d = \min(d_i \in D) \; for \; i = 1,2 \ldots ..$$

where d_i is given as

$$\begin{cases} X_e(2m-1,2n+i-3) - X_e(2m-1,2n+3-i) \\ for\ i = 1,2 \ldots \ldots \end{cases} \quad \ldots (4.2)$$

4.3 Mid-point Algorithm

In mid-point algorithm, the input image is super resolved using (8)-(10).

$$F(2*\mathrm{i}-1, 2*\mathrm{j}-1) = I(\mathrm{i},\mathrm{j}). \quad \ldots\ (4.3)$$

where I is the original image and F is the super resolved image. Intermediate pixels are calculated using the mean of the surrounding pixels in the vertical and horizontal directions respectively. The equations for calculating these for an image of size $m \times m$ are as given as under

$$F(2*\mathrm{i}-1, 2*\mathrm{j}) = \frac{(F(\mathrm{i}, 2*\mathrm{j}-1) + F(\mathrm{i}, 2*\mathrm{j}+1))}{2} \quad \ldots (4.4)$$

$$F(2*\mathrm{i}, \mathrm{j}) = (F(2*\mathrm{i}-1, \mathrm{j}) + I(2*\mathrm{i}+1, \mathrm{j}))/2 \quad \ldots (4.5)$$

$$\text{where } \mathrm{i},\mathrm{j} = 1,2,3, \ldots \ldots m$$

By applying (9) and (10) on the input image the values of intermediate pixels are obtained by using which super resolution image of double size is obtained.

4.4 Proposed Approach

As discussed in Section 1, high frequency components play an important role in image super resolution approach. Various techniques used for dividing the images into subbands have been used earlier. In Table 4.1**,** average wavelet coefficient values of the subbands of various images using existing lifting schemes are compared.

Table 4.1 Average wavelet coefficient value of each subband of Lena and Baboon images by using various techniques

Images / **Techniques**	**Lena**				**Baboon**			
	LL	**LH**	**HL**	**HH**	**LL**	**LH**	**HL**	**HH**
DWT	250.32	3.64	5.23	2.25	275.53	16.1	10.92	5.43

Conventional lifting scheme	126.04	3.38	2.59	2.64	138.94	7.74	13.13	5.60
Edge orientation estimator scheme	126.09	4.06	3.18	3.43	139.04	14.5	14.95	13.76

From this table, one can infer that the direction lifting scheme produces the high frequency subbands with large value as compared to the subband values generated by DWT and conventional lifting scheme. The values of the high frequency subbands must be high as to compensate the loss due to interpolation.

On the basis of this observation, an approach for the image super resolution has been proposed in this chapter using direction lifting scheme, SWT algorithm and the mid-point algorithm and is illustrated by a flow chart diagram in Figure 4.2.

The proposed approach mainly aims at increasing the high frequency components in the image by smoothing the image as obtained by applying the general interpolation methods and directional lifting schemes on the input image. This high frequency component adjustment leads to edge enhancement which further helps in better image super resolution. At last, the error in the image is also back propagated.

Firstly as shown in Figure 4.2 the input image is subjected to interpolation using the general interpolation scheme either bicubic or linear. The interpolated image is then divided in to subbands using the directional lifting scheme which could be either one directional, three directional, five directional or fractional precision directional as shown in Figure 4.1. Parallel to that the input image is subjected to SWT and midpoint algorithm. The mid-point algorithm results in image of double size and the bands generated by SWT are of same size as that of the input image.

The bands generated by SWT are then fused with the subbands generated by using the directional lifting scheme. The subbands after the fusion process are subjected to the inverse directional lifting scheme. The image obtained is then passed through the Gaussian filters which results in the smooth image. Then the smooth image is used for finding out the error image which is to be back projected for obtaining a super resolution image. In the error back projecting process, the image generated using the mid-point algorithm is used along with the image obtained after applying the inverse directional lifting scheme.

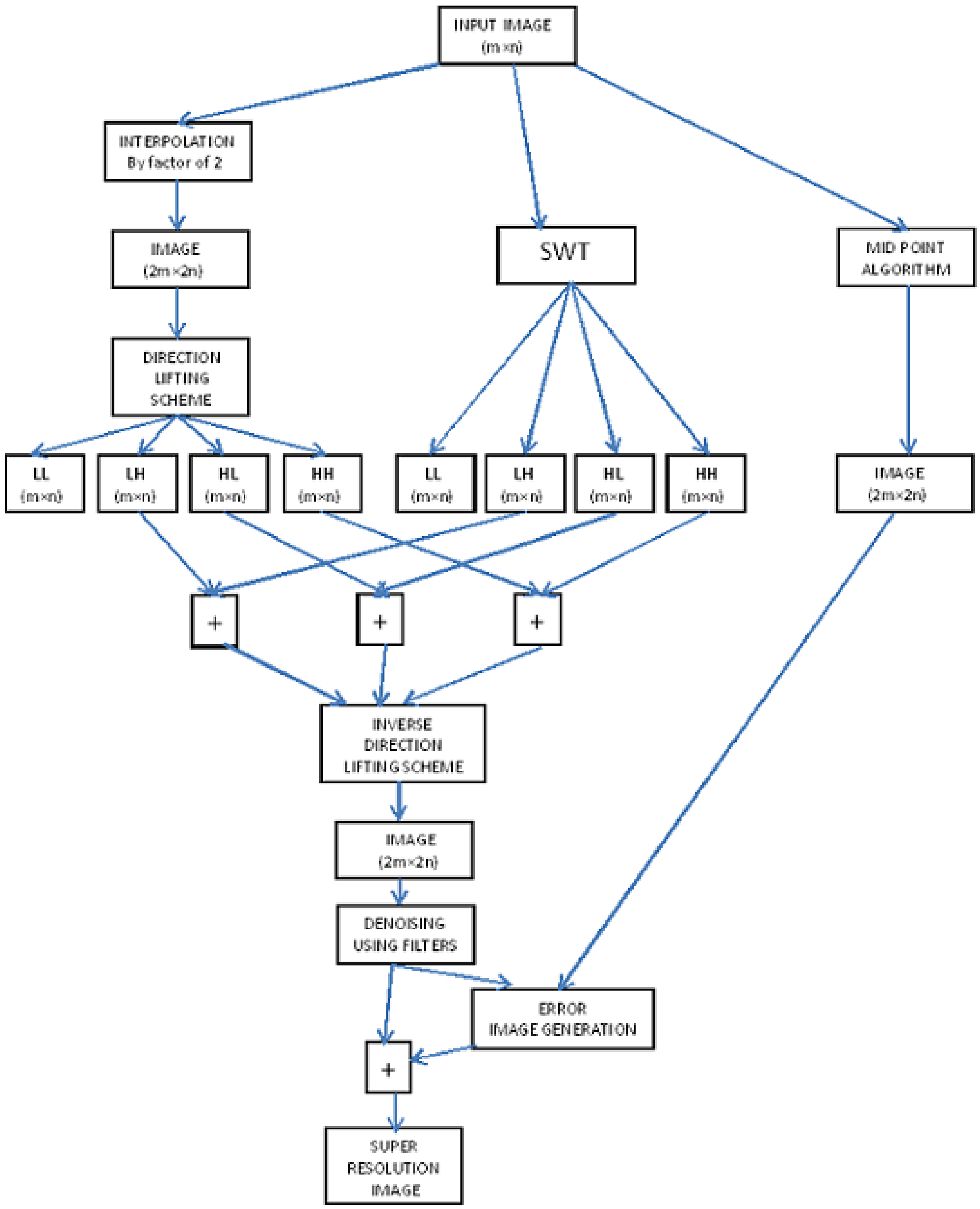


Figure 4.2 Flowchart of the proposed algorithm

The proposed approach finally results in the super resolution image with the enhancement of the edges in the super resolved image by increasing the number of high frequency components in the resultant image. Back projecting of error further smoothens the image by compensating the loss incurred during the process.

4.5 Experimental Results

The proposed approach is implemented in MATLAB. Test images considered in this work are Lena, Baboon, Pepper, Boat, Bridge, Airplane, Aerial and Couple, each of size 512×512. The input image is firstly interpolated using the interpolation and then divided into four subbands using the directional lifting scheme and the subbands are then fused with the bands produced using the SWT to increase the high frequency components and the finally the inverse direction lifting scheme is performed to get super resolution image. Then, smoothing of the super resolution image is performed using Gaussian filters. Finally, the error is back projected with the help of the image as obtained by the mid-point algorithm.

Various images of Lena, Baboon, Aerial and Airplane are shown in Figure 4.3 which are obtained by applying proposed approach. From this figure, it can be seen that the results obtained by the proposed approach are of good visual quality and high resolution.

(a)

(b)

Figure 4.3 (a) Original images of Lena, Baboon, Aerial and Airplane (b) Super resolution images of Lena, Baboon, Aerial and Airplane.

Proposed approach is compared with existing super resolution approaches and this comparison is shown in Table 4.2. For proposed approach, bilinear and bicubic interpolation are considered in this comparison.

Proposed approach provides better PSNR than other existing approaches. Maximum PSNR improvement is 2.39 dB in case of Aerial image and minimum PSNR improvement is 0.8 dB in case of Boat image.

Table 4.2. PSNR (in dB) comparison of various existing schemes and the proposed approach

Schemes / Images	Bicubic	Bilinear	Nearest	NEDI[6]	Naik *et al.* [32]	Proposed approach +bicubic+ 1direction Lifting Scheme	Proposed approach +bilinear+ 1direction Lifting Scheme
Lena	30.70	30.76	28.82	30.42	29.31	31.20	31.19
Baboon	22.12	22.39	21.12	22.60	21.58	22.81	22.87
Pepper	27.57	27.66	26.14	26.10	27.51	28.31	28.43
Bridge	23.99	24.26	22.67	24.25	22.80	24.74	24.87
Boat	26.93	27.10	26.51	26.96	25.34	27.51	27.31
Aerial	24.28	24.36	22.62	24.80	24.23	24.95	25.01
Airplane	26.58	26.45	25.10	26.65	26.18	27.18	27.31
Couple	26.76	26.91	25.29	26.78	25.35	27.52	27.55

We have also compared the performance of different lifting scheme using bilinear and bicubic interpolations in the proposed approach. This comparison is shown in Table 4.3.

Table 4.3 PSNR (in dB) comparison of the proposed approach using different directional lifting schemes

Schemes / Images	Proposed approach +bicubic+ 3direction Lifting Scheme	Proposed approach +bilinear+ 3direction Lifting Scheme	Proposed approach +bicubic+ 5direction Lifting Scheme	Proposed approach +bilinear+ 5direction Lifting Scheme	Proposed approach +bicubic+ 3directional fractional Lifting Scheme	Proposed approach +bilinear+ 3directional fractional Lifting Scheme
Lena	31.1	31.21	30.80	30.89	31.21	31.23
Baboon	22.44	22.58	22.23	22.33	22.54	22.56
Pepper	28.66	28.73	28.45	28.56	28.78	28.83
Bridge	24.46	24.64	24.44	24.52	24.52	24.55
Boat	27.14	27.15	27.01	27.08	27.12	27.19
Aerial	24.78	24.82	24.66	24.70	24.86	24.71
Airplane	27.36	27.41	27.19	27.20	27.19	27.18
Couple	27.11	27.05	27.02	27.05	27.13	27.15

From this table, one can infer that the directional lifting scheme in which prediction is performed at fractional precision level provides higher PSNR and hence better visual quality.

4.6 Conclusion

In this chapter, a new approach for image super resolution is proposed in which both the SWT and the mid-point algorithm are used for edge enhancement to increase the high frequency components in the image. For smoothing purpose, the Gaussian filters are used. The image super resolution approach uses the directional lifting scheme for decomposing an image into subbands and reconstruction of image using the low resolution image and high frequency subbands obtained after fusion with the bands obtained by using SWT. The proposed approach has been performed on various images and the experimental results show that the images are of superior quality as in comparison to the conventional and state-of-art image resolution approaches in terms of PSNR values.

CHAPTER 5

IMAGE SUPER RESOLUTION USING FUSION OF IMAGES

5.1 Introduction

In this chapter, an approach for image super resolution based on the fusion of images is proposed. The input image is interpolated and then subjected to direction lifting scheme to decompose it into subbands. Also the bands of the input image are obtained by applying SWT on it. SWT transform is applied on the image to enhance the edges present in the image. The bands formed after applying SWT and direction lifting scheme are fused to obtain the image. Second image for the fusion process is obtained using the conventional interpolation method. Third image is obtained by applying the mid-point algorithm which helps in preserving the average intensity of the image. All produced images are fused together to generate a super resolution image. The information from the images is fused such that the number of high frequency components present in the images is increased to a higher value which results in better image super resolution.

5.2 Proposed Method

The proposed approach aims at increasing the number of high frequency components in the image which thereby reduces the loss incurred and results in better image super resolution. The proposed approach deals with increasing the number of high frequency components by fusion of images as obtained by the direction lifting scheme and SWT, the conventional interpolation method and the mid-point algorithm.

The first image is obtained by using the conventional interpolation method either bilinear or bicubic as shown in Figure 5.1. The input image is firstly subjected to conventional interpolation method and then subbands are generated by applying the direction lifting scheme on the input image.

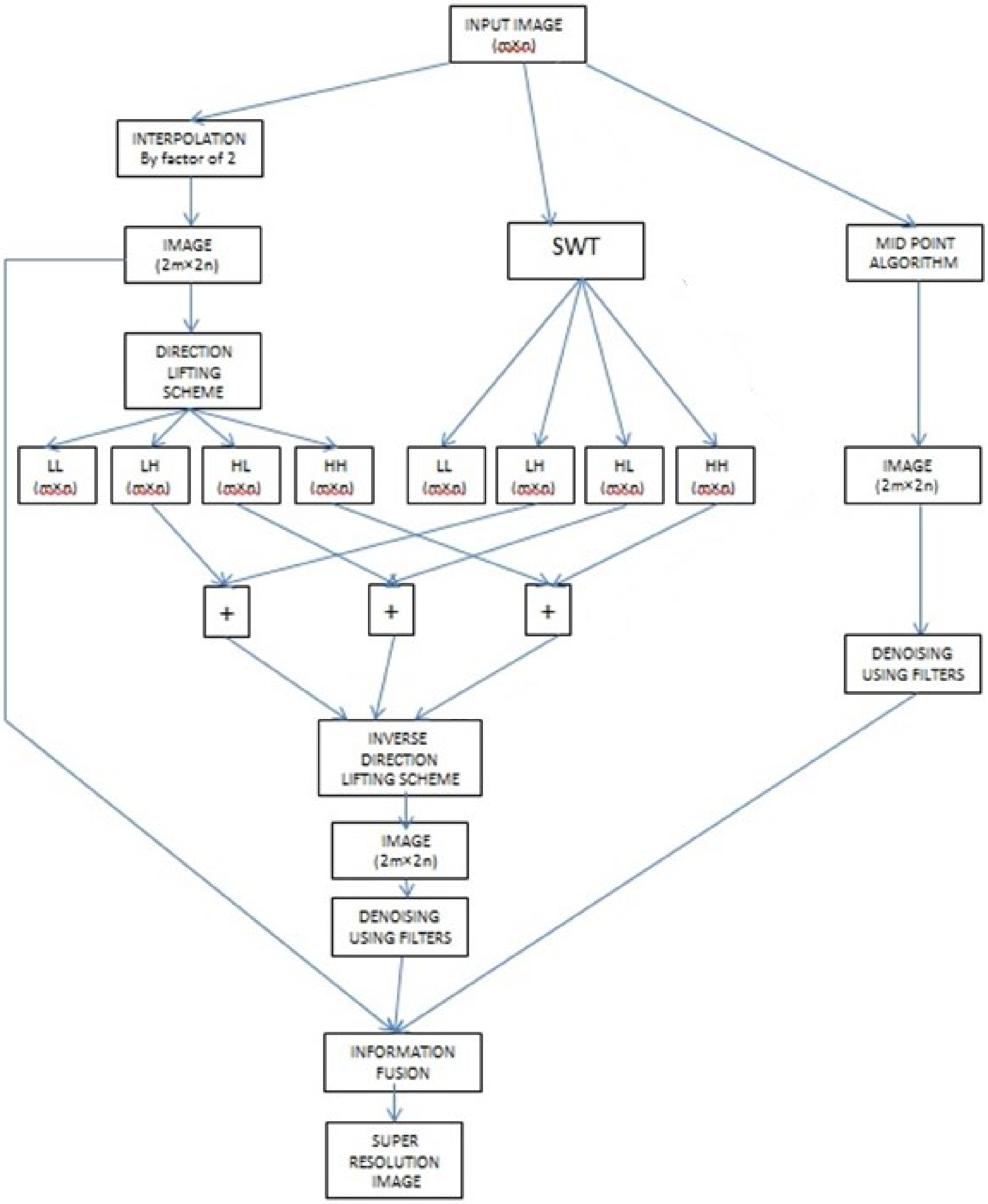


Figure 5.1 Flow Chart of Proposed Approach

Parallel to this the input image is subjected to SWT and the bands of same size as that of input image are generated. Then the subbands obtained by using the direction lifting scheme and the bands obtained by applying SWT are fused together and then these fused bands are subjected to inverse direction lifting scheme which is used to generate the first image for an image super resolution. The second image for fusion of images is obtained using the mid-point algorithm. The mid-point algorithm helps in preserving the average intensity value of pixels of the image. The third image used for fusion of images is as obtained by applying the conventional interpolation method on the input image. Then all the three images are fused together to obtain a super resolved image.

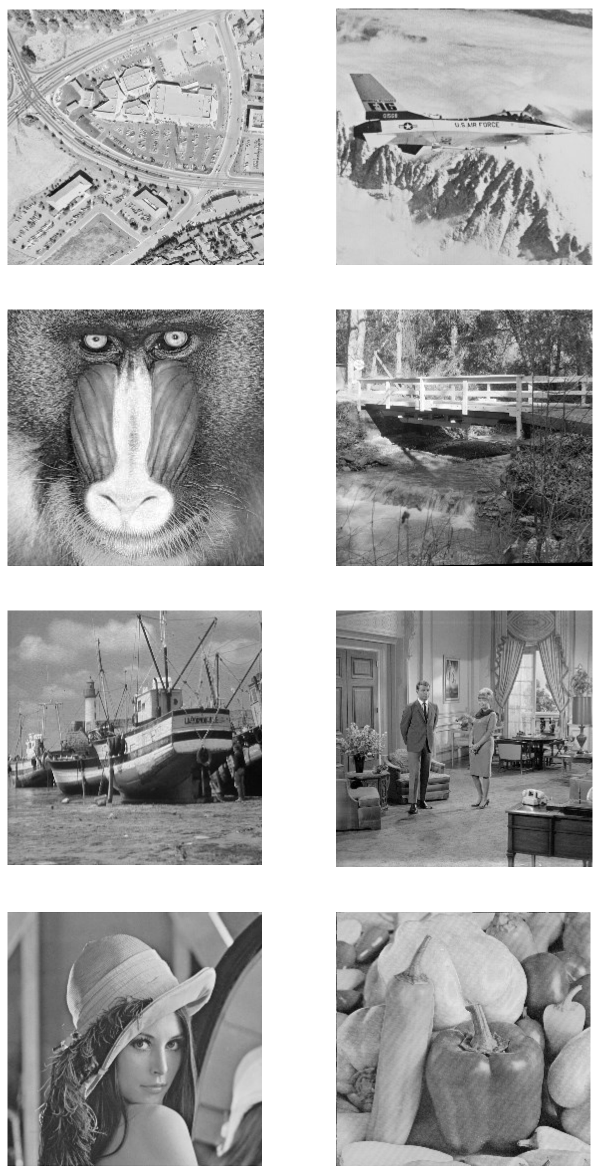
Figure 5.1 shows the flow chart diagram of the entire process followed in this approach. As shown in the flow chart diagram, the conventional interpolation method and SWT are applied on the input image parallel to each other. The SWT and direction lifting on the interpolated image result in the formation of LL, LH, HL and HH bands. The bands generated by both the schemes are fused together and subjected to inverse direction lifting scheme. Then the image obtained using inverse direction lifting scheme is de-noised using filters. The third image as shown in Figure 5.1 is generated using the mid-point algorithm. The mid-point algorithm helps in preserving the average intensity value of the image. The images are then fused together to produce a super resolution image with best visual quality.

5.3 Experimental Results

The proposed approach is implemented in MATLAB. Test images considered in this work are uncompressed Lena, Baboon, Pepper, Boat, Bridge, Airplane, Aerial and Couple images each of size 256×256.

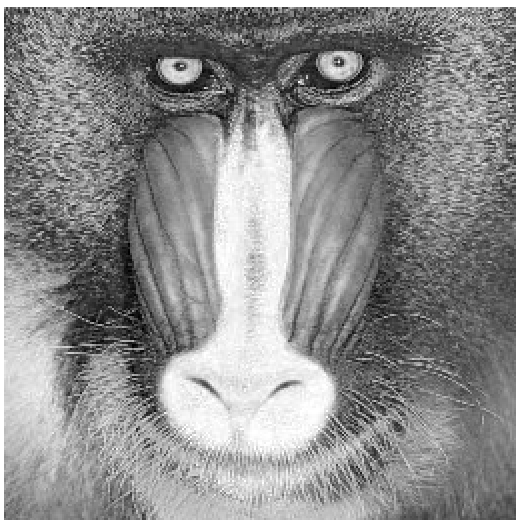
The input image is firstly interpolated using the conventional interpolation method and then divided into four subbands using the directional lifting scheme and the subbands are then fused with the bands produced using the SWT to increase the high frequency components and the finally the inverse direction lifting scheme is performed to get super resolution image. This particular process leads to the generation of first image used for image super resolution in this approach. Then, smoothing of the super resolution image is performed using Gaussian filters. Second image for the fusion purpose is generated via the conventional interpolation method which produces the output image of the double size as that of the input image. The third image is generated via the mid-point algorithm which helps in preserving the average pixel intensity value of the image.

Various images of Lena, Baboon, Aerial, Airplane, Boat, Bridge, Pepper and Couple are shown in Figure 5.2 which is obtained by applying proposed approach. From these images, it can be seen that the results obtained by the proposed approach are of good visual quality.



(a)


F16
U.S. AIR FORCE



(b)

Figure 4.3 (a) Original images of Lena, Baboon, Aerial, Airplane, Boat, Bridge, Pepper and Couple (b) Super resolution images of Lena, Baboon, Aerial, Airplane, Boat, Bridge, Pepper and Couple.

Proposed approach is compared with existing super resolution approaches and this comparison is shown in Table 5.1. For comparison purpose, the proposed approach, bilinear and bicubic interpolation are considered in this comparison.

Table 5.1 PSNR(in dB) Comparison of various existing schemes and the proposed approach

Schemes / **Images**	**Bicubic**	**Bilinear**	**Nearest**	**NEDI[6]**	**Naik *et al.* [32]**	**Proposed approach +bicubic+ 1direction Lifting Scheme**	**Proposed approach +bilinear+ 1direction Lifting Scheme**
Lena	30.70	30.76	28.82	30.42	29.31	33.03	32.63
Baboon	22.12	22.39	21.12	22.60	21.58	23.27	23.33
Pepper	27.57	27.66	26.14	26.10	27.51	29.27	28.95
Bridge	23.99	24.26	22.67	24.25	22.80	25.6	25.42
Boat	26.93	27.10	26.51	26.96	25.34	28.65	28.45
Aerial	24.28	24.36	22.62	24.80	24.23	26.52	26
Airplane	26.58	26.45	25.10	26.65	26.18	27.79	27.68

Couple	26.76	26.91	25.29	26.78	25.35	28.6	28.33

Above given table shows the PSNR values of images obtained after implementing different super resolution schemes on different images. This table shows that the proposed algorithm shows better results as compared to other existing algorithms for image super resolution. The improvement is satisfactory for every image considered for test purpose.

We have also compared the performance of different lifting scheme using bilinear and bicubic interpolations in the proposed approach. This comparison is shown in Table 5.2.

Table 5.2 PSNR (in dB) comparison of the proposed approach using different directional lifting schemes

Schemes / Images	**Proposed approach +bicubic+ 3direction Lifting Scheme**	**Proposed approach +bilinear+ 3direction Lifting Scheme**	**Proposed approach +bicubic+ 5direction Lifting Scheme**	**Proposed approach +bilinear+ 5direction Lifting Scheme**	**Proposed approach +bicubic+ 3directional fractional Lifting Scheme**	**Proposed approach +bilinear+ 3directional fractional Lifting Scheme**
Lena	32.95	32.8	32.84	32.71	33.00	32.97
Baboon	23.21	23.23	23.14	23.2	23.30	23.50
Pepper	29.28	29.33	29.2	29.25	29.42	29.65
Bridge	25.56	25.53	25.48	25.52	25.51	25.65
Boat	28.6	28.49	28.48	28.43	28.71	28.82
Aerial	26.5	26.4	26.38	26.22	26.56	26.64
Airplane	28.23	28.15	28.22	28.07	28.43	28.39
Couple	28.38	28.34	28.34	28.3	28.45	28.44

From this table, one can infer that the directional lifting scheme in which prediction is performed at fractional precision level provides higher PSNR and hence better visual quality.

5.4 Conclusion

In this chapter, a new approach for image super resolution is proposed in which the images obtained from the corresponding direction lifting scheme and SWT, the mid-point algorithm and the conventional interpolation method are fused together to obtain a super resolution image. SWT along with the direction lifting scheme is used to enhance the edges in the image considered for image super resolution. For smoothing purpose, the Gaussian filters are used. The image super resolution approach uses the directional lifting scheme to decompose an image into subbands and reconstruction of image using the low resolution image and high frequency subbands obtained after fusion with the bands obtained by using SWT. Further the image obtained by applying the inverse direction lifting scheme is fused with the images obtained from mid-point algorithm and conventional interpolation method The proposed approach has been performed on various images and the experimental results show that the images are of superior quality as compared to the conventional and state-of-art image resolution approaches in terms of PSNR values.

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

In this dissertation, various super resolution approaches for digital images are proposed. First, an image super resolution approach using our proposed SPADL scheme and the conventional interpolation method is proposed. The super resolution image obtained using this proposed method produces better results as compared to various existing approaches. Further another super resolution approach is proposed using direction lifting scheme, SWT and mid-point algorithm which produces super resolution image of better quality as compared to the images obtained using existing approaches. In addition to this, an image super resolution approach based on fusion of images obtained by using direction lifting scheme, SWT and mid-point algorithm is proposed. This approach produces ever much better results as compared to the results obtained by using our proposed approaches. It can be concluded that by increasing the values of high frequency components of an image, results in better super resolution images. All the approaches proposed in dissertation result in increase of values of high frequency components and hence better are the quality of super resolved image. PSNR is the quality factor taken into consideration for checking the quality of the image obtained after applying image super resolution algorithm.

6.2 Future Scope

In future, some other method using some other scheme could be developed such that the visibility and PSNR of the image are well maintained after applying the super resolution image. The following future direction can be

- It can be extended for video files and medical images *etc*.
- More neighboring pixels can be considered to increase the values of high frequency components in the image.

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