“Technique for Reconstructing Super Resolution Image using Low Resolution Natural Color Image”

By

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For the Degree of

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In
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Submitted To

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Thesis Titled

"Technique for Reconstructing Super Resolution Image using Low Resolution Natural Color Image"

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Under Guidance of

Dr. Dattatraya S. Bormane

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Declaration

I hereby declare that the thesis entitled "Technique for Reconstructing Super Resolution Image using Low Resolution Natural Color Image" completed and written by me has not formed the basis for the award of any degree or diploma or similar titles of this or any other university or examining body.

Date: 5/6/2008

Place: Pune

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Certificate

This is to certify that the thesis entitled "Technique for Reconstructing Super Resolution Image using Low Resolution Natural Color Image" which is being submitted herewith for the award of the degree of Doctor of Philosophy in Computer Engineering of Bharati Vidyapeeth University, Pune is the result of the original research completed by Mrs. Varsha Hemant Patil under my supervision and guidance. And to the best of my knowledge and belief the work embodied in this thesis has not formed earlier the basis for award of any degree or similar title of this or any other university or examining body.

5/6/08

Date: 5/6/08 Dr. Dattatraya S. Bormane

Place: Pune Research Guide

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Abstract

High resolution image along with a pleasant look, tenders additional detail to viewer that are essential for the analysis in many applications such as medical image analysis and diagnoses. In high resolution image pixel density is high. One of the ways to increase resolution of image is to opt for high end camera which is often not a practical option. As the cost for high-precision optics and sensors may not be reasonably priced for general-purpose applications.

Mostly, the resolution of image depends on the resolution of image acquisition device. The current technology to obtain high resolution images mainly depends on sensor manufacturing technology that attempts to increase the number of pixels per unit area by reducing the pixel size and by reducing interpixel distance. But as the pixel size decreases, the image quality is degraded due to aggregation of shot noise. Thus signal processing approach is proposed by researchers for reconstruction of super resolution image.

The signal processing approach that reconstructs high resolution image using low resolution image(s) is known as super resolution image reconstruction. Crucial information barely visible to the human eye is often embedded in a low resolution image(s). Super resolution enables the extraction of this information by reconstructing an image at higher resolution than is present in any of the individual low resolution image(s).

The process of super resolution includes upsampling the image, thereby increasing the pixel density, and processing one or more low-resolution images assist in enriching the information. Methods for digital image resolution enhancement have been the subject of research over the past decade. Today, super resolution image reconstruction is one of the most spotlighted research areas, because it can overcome the inherent resolution limitation of the imaging system, improve the

performance of digital image processing applications and existing imaging systems can still be used. Wide set of applications demand high resolution images.

A lot of research is currently being in progress for developing efficient super resolution imaging techniques viz, reconstruction based, learning based and wavelet based.

The scope of this research work is to study these super resolution imaging techniques spanning over almost two decades of research, from the presenting concept of super resolution imaging by Tsai and Huang in the late 80's to the work under research till 2007 and suggest a novel technique to achieve the super resolution imaging by retaining the originality of an image along with good visual quality.

In the super resolution process, preservation of originality of image plays crucial role. In this research work, wavelet is used to decompose image into structurally correlated subimages and then super resolving each by using appropriate kernel on the basis of the nature of the subimage. Subsequently the super resolved subimages are used so as to reconstruct super resolution image.

The algorithm is developed, implemented, and tested over the set of natural and synthetic images, and conclusions are drawn. The results reveal that the technique have overcome the problems of blur and checker board effect; the edges are well preserved and the originality of images is preserved well. Peak signal to noise ratio is used as quality measure using novel suggested quality measure framework for super resolution imaging. It is noticed that the higher PSNR is observed for the developed technique than the existing methods in use.

Notation and Abbreviations

Abbreviation / Symbol	Description
ω	Angular frequency
⊗	Correlations operations
*	Convolution operator
2D	Two-dimensional
AD	Average Difference
CCD	Charge Coupled Device
CG	Conjugate Gradient
CLS	Constrained Least Square
CMY	Cyan, Magenta, Yellow
CMYK	Cyan, Magenta, Yellow, Black
CWT	Continuous Wavelet Transform
DCT	Discrete Cosine Transform
DFD	Depth From Focus
DFT	Discrete Fourier Transform
dpi	Dots per inch
DSCQS	Double Stimulus Continuous Quality Scale
DWT	Discrete Wavelet Transform
FGW	First Generation Wavelet
HDTV	High Definition Television
HIS	Hue, Saturation and Intensity
HMT	Hidden Markov Tree
HR	High Resolution
HVS	Human Visual System
IBP	Iterative Back Projection
LLE	Local Linear Embedding
LR	Low Resolution
MAP	Maximum a Posteriori
MD	Maximum Difference

ML	Maximum Likelihood
MOS	Mean Option Score
MPL	Maximum Pseudo Likelihood
MRF	Markov Random Field
MSE	Mean Square Error
MTF	Modulation Transfer Function
NAE	Normalized Absolute Error
NC	Normalized Convolution
NK	Normalized Cross-correlation
NTSC	United States National Television Systems Committee
PDF	Probability Density Function
POCS	Projection Onto Convex Set
Ppi	Pixels per inch
PSF	Point Spread Function
PSNR	Peak Signal to Noise Ratio
PWS	Partition Based Weighted Sum
QMF	Quadrature Mirror Filter
RGB	Red, Green, and Blue
ROI	Region of Interest
SAR	Synthetic Aperture Radar
SC	Structural Content
SFT	Short Fourier Transforms
SGW	Second Generation Wavelet
SNR	Signal to Noise Ratio
SR	Super Resolution
SSIM	Structural Similarity Index Measure
STFT	Short-Time Fourier Transform
VQ	Vector Quantization
WT	Wavelet Transforms

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Chapter 1

Introduction

The chapter covers brief discussion on the super resolution imaging, need for super resolution imaging, study of existing techniques in use with their pros and cons, motivation and objectives of research work. Application areas of super resolution imaging are listed as well. The chapter concludes with organization of the thesis.

1.1 Introduction

Image processing is quite a mature field and has applications in diverse areas. The most significant and one of the desired features of all image processing applications is good quality of image. The quality of an image can be more appropriately evaluated on its spatial resolution. High resolution (HR) image along with a pleasing look, offers more details to viewer that are vital for the analysis in many applications such as medical image analysis and diagnoses. High resolution means pixel density within image is high. Primarily, the resolution of image depends on the resolution of image acquisition device. The current technology to obtain high resolution images mainly depends on sensor manufacturing technology that attempts to increase the number of pixels per unit area by reducing the pixel size and interpixel distance. But as the pixel size and interpixel distance decreases, the image quality is degraded due to decrease in amount of light available and aggregation of shot noise [1]. Moreover the cost for high-precision optics and sensors may not be affordable for general-purpose applications. Thus there is room to improve the resolution of the captured image using software approach.

A resolution enhancement approach using signal processing technique has been a great concern in many areas, and it is called super resolution (SR) (or HR) image reconstruction or simply resolution enhancement [1,3,6]. The process of super resolution includes upsampling the image, thereby increasing the pixel density, and processing one or more low-resolution images assist in enriching the information. Methods for digital image resolution enhancement have been the subject of research over the past decade. Today, super resolution image reconstruction is one of the most spotlighted research areas, because it can overcome the inherent resolution limitation of the imaging system, improve the performance of digital image processing applications and existing imaging systems can still be used. The research is confined at improving the spatial resolution of an image and avoiding drawbacks of existing techniques that are currently in use.

1.2 Motivation

The super resolution means the quality of the image to the extent of the maximum capability of the technology referring it. Human visual system has the limitation capturing the details of an image, but artificial eye can see beyond it to capture the miniature details. The naked human eye cannot see the matter beyond certain limit. For example, naked human eye can not see molecular structure of the matter. But it is possible to see molecular structure with the help of intelligent computational and analytical power. The image capturing devices have their hardware limitations to reach to the perfection [1]. And the applications demand more and more details for accurate analysis; therefore there is a need to develop a technique for improving the resolution.

Super resolution image reconstruction can overcome the inherent resolution limitation of the imaging system and provide a high resolution image to improve the performance of image processing applications. Offering the high resolution image in medical imaging adds precision to the diagnosis process and that may be decisive[96,105]. Consequently there is need to develop the novel technique that improves the resolution of image.

Today communication through web has become inseparable part of human lives. Many times pictorial information has to be accessed for study and analysis. The original image, if used for transmission takes more space, bandwidth and time. To save storage space, bandwidth and time for transmission, one solution is to transmit low resolution image by down-sampling it and then reconstructing the high resolution image at receivers end. Use of existing techniques to down-sample the image before transmission and reconstruction of high resolution image suffers from loss of information. If an efficient super-resolution technique is available, low-resolution image can be transmitted and at the receiver end super-resolution image can be reconstructed; it saves the storage space, bandwidth and time required for communication[107]. Thus there is need to develop a novel technique to reconstruct the high resolution image using single image that minimizes the loss.

Recently desktop video conferencing has become popular in distant learning education programs. It is apparent that the quality of the frames is often poor due to limitations of low cost sensor devices, processing time of the frames and bandwidth available for transmission. Although quality of the frames is not important but good quality adds to effective interaction that is important for an impact of distant education programs, especially when figures and documents are presented. Therefore super resolution imaging is one of the solutions to improve the quality of picture frames with minimum response time.

Recently, the sensor networks are being used to collect secured information from remote sites. To collect the pictorial information, image capturing devices are part of these networks. Considering the low cost and low power consumption requirements, preference is given to low resolution image capturing devices. Researchers are working towards improving the life span of such devices by reducing the power consumption. Low cost and low power devices have limitations over the resolution that in turn affects the quality of image. Thus there is need to develop a cost effective technique that offers an image comparable to high cost sensor network devices.

In the process of tele-diagnosis, it is necessary to take digital photographs from remote patients, which can improve diagnosis efficiency and accuracy. There are limitations such as digital camera, such as integrated circuit technology, bandwidth availability, and cost. And due to these limitations, desired high resolution images are difficult to obtain. In order to improve resolution of an image, the low resolution image can be collected and used to reconstruct the desired high resolution image using super resolution imaging technique[104].

The high resolution image is in demand for various applications. The objective of research work is to develop the novel algorithm to reconstruct the super resolution image which overcomes the limitations of current techniques in use and satisfies the need for different applications as discussed.

1.3 Applications

High resolution images are expected to enhance the capability of detection and identification of details in the image, improve performance of pattern recognition algorithms, as well as the performance of automatic classification algorithms in computerized systems. Super resolution imaging has wide set of applications such as face recognition, Iris recognition, Network aware applications[100], video conferencing, High Definition Television (HDTV), reproduction of photographs, biomedical Imaging[109], telemedicine, medical imaging, military, space research, and satellite imaging among many others.

1.4 Current Techniques in Use

One of the ways to increase resolution of image is to opt for high end camera which is often not a pragmatic option. The smoothing and interpolation are the well-known software approaches for enhancing the visual quality of the still image. Smoothing is usually achieved by applying various spatial filters such as Gaussian, Wiener, and median. The filtering of an image results in adding low frequency components and loosing the focus from high frequency components. Human eye is more sensitive to low frequency components than high frequency components. The results of the filtering apparently show enhancement in the visual quality of the image, but at the cost of loss of information.

Interpolation is a technique used for increasing the number of pixels in a digital image. The high resolution image is obtained by estimating pixel value at a location in between existing pixels. Interpolation technique converts the discrete data into a continuous function. For two dimensional data such as an image, the interpolation converts the discrete matrix into continuous function of two variables. The high resolution image is obtained by estimating the pixels in between original data based on this continuous function constructed.

It is one of the techniques used in digital camera to increase (or decrease) the number of pixels in a digital image and to produce a higher (or lower) resolution image than the sensor captured one. Usually all image editing softwares support one or more methods of interpolation. Commonly used interpolation methods are nearest neighbor, bilinear, and bicubic interpolation [65,66,67].

Researchers have claimed that these methods suffer from several types of the most noticeable visual degradations, and the zigzagging artifact [65,80,81]. Zigzagging artifact is a major problem of Bilinear and Bicubic interpolation. Zigzagging artifact, also known as jaggies, are commonly observed as a stair casing of image edges or as moiré patterns in areas having fine textures. Since edges are crucial to image perception, zigzagging is one of the most annoying visual artifacts.

Nearest neighbor interpolation method makes the pixels bigger. The value of a new pixel in the image is the value of the nearest pixel of the original image [81]. It is not suitable to super resolve the images because it increases the width of edges unnecessarily. The bilinear interpolation method calculates the value of a new pixel based on a weighted average of the 4 pixels in the nearest 2 x 2 neighborhood of the pixel in the original image [81]. The averaging produces relatively smooth edges than nearest neighbor interpolation. In Bicubic interpolation method the value of a new pixel is determined based on a weighted average of the 16 pixels in the nearest 4 x 4 neighborhood of the pixel in the original image [81]. It produces smoother edges than bilinear interpolation.

Interpolation methods usually give better performance than simple smoothing methods. However, both methods are based on generic smoothness priors and are indiscriminate since they smooth edges as well as regions with little variations, causing blurring problems and checkerboard effect [33]. In brief, currently used interpolation and smoothing techniques are inadequate to reconstruct high resolution image from low resolution image[101]. So the recent research trend is confined to reconstruct high resolution image from low resolution image(s).

1.5 Objectives of Research Work

Efficient representation of visual information lies at the heart of many image processing applications. Efficient representation refers to the ability to capture significantly correct information from available information. In super resolution imaging, the significant information calculation from available information is nothing but estimation of the intermediate pixels based on available data.

The resolution enhancement techniques that are currently in use suffer from many drawbacks. Therefore considering demand of high resolution images, there is need to develop a novel technique to satisfy this demand overcoming the limitations of existing techniques.

The thorough investigation has shown that the techniques currently in use and under development suffer from loss of high frequency components of image. The objective of this research work is to develop novel algorithm that can avoid loss of high frequency components while super resolving the image. From last decade, wavelet transform plays an important role in image processing applications. It separates the signal based on frequency bands. Recently few of the researchers have suggested the use of wavelet for super resolution image reconstruction [46-54]. The wavelet transform helps to separate the image components according to frequency bands. In this research work, a new technique is developed that processes these separated frequency components independently. Decomposition and independent processing avoids loss of high frequency components and undesired addition of low frequency components as well. As the separated components are processed independently, one can develop parallel implementation of the same to save processing time[93].

The prime objective of the research work is to develop novel technique for reconstructing super-resolution image from low-resolution natural color image. The thesis presents an innovating state-of-the-art super resolution image enhancement technique based on wavelet. The images used in this work include many popular images like Cheetah, Lena, Woman, Barbara, Mandrill, Butterfly, Aaishvarya, and Bird among many others. Additionally real images have been captured with camera and few synthetic images are used for testing the technique. Objectives of the research work are:

- Various image resolution enhancement techniques currently in use are studied, and their merits and demerits are discussed,
- Various sources and literature about super resolution is studied and their limitations and scope are discussed,
- Wavelet and wavelet transforms confined to image processing are studied, and further the properties of few popular wavelet families are listed,
- Different visual quality performance measures that are commonly used in image processing are studied, and their comparative analysis

towards suitability for super resolution imaging performance measure has been discussed,

- Comparative analysis of important properties of the popular wavelet families are discussed and proper wavelet transform is selected for the super resolution algorithm,
- The correlation among pixels in natural images is studied in detail and conclusions are drawn about structural properties. Further, for the color images suitable color model is selected for the processing,
- Wavelet transform is used for decomposition of image. Nature of each individual components of the wavelet is studied; the algorithm is designed, implemented and tested for individual component independently according to its nature to improve the resolution. Qualitative and quantitative measures of few sample images are presented and the conclusions are drawn,
- The new framework for super resolution performance measure has been suggested[108], and
- The novel algorithm for reconstructing the super resolution image from low resolution natural color image is presented. Further the algorithm is implemented and tested over the set of different frequency and different resolution images. Images used are standard, synthetic as well as real captured images. The both qualitative and quantitative measures of performance are examined for the test images. And comparisons are made with techniques currently in use.

1.6 Organization of Thesis

The research work reported in this thesis is focused on a technique for reconstructing super resolution image from low resolution natural color image using wavelet transform. The detailed discussion on current techniques in use and the techniques under research for the same is presented as well. The highlights of the research work presented are,

- Use of the wavelet transform for preprocessing of image,

- Independent technique to process each individual decomposed component of wavelet based on its nature,
- Suggestion of a suitable super resolution quality measurement framework and
- Novel algorithm for reconstructing super resolution image from low resolution natural color image using wavelet transform.

The work reported in this thesis has been organized into seven chapters. The content of each chapter is presented briefly in following paragraphs.

Chapter one includes brief discussion on super resolution imaging, motivation behind the work, briefs of existing methods in use along with their pros and cons, and the objectives of research work. Application areas of super resolution imaging are listed as well. The chapter ends with organization of thesis.

Chapter two includes model of the digital image acquisition system with its limitations, image representation, color models, the generalized model of super resolution process, and existing techniques in use along with their limitations. Literature survey of current trends and techniques for topic under research are presented. The shortcomings and discrepancies among methods are identified and mentioned.

Chapter three includes the basic theory of wavelets and wavelet transform. From last few decades, the wavelet transform has been proposed as a flexible tool for the multiresolution decomposition of continuous time signals. Many popular wavelets with characteristics are discussed in details in this chapter.

Chapter four includes survey of classic image quality assessment techniques. The criteria for image quality measurements are mentioned in detail for Mean Option Score(MOS), Double Stimulus Continuous Quality Scene(DSCQS), Mean Square Error (MSE), Root Mean Square Error, Signal to Noise Ratio, Peak Signal to Noise Ratio, Normalized Absolute Error, Maximum Difference, Structural Contents and Average Difference.

Suitability of these measures towards super resolution imaging is discussed in brief.

Chapter five includes discussion on the selection of wavelet to decompose the image, structural properties of natural images, decomposition of color image and a new framework for the performance measure of super resolution imaging. Algorithm for super resolving subbands of wavelet and algorithm for reconstruction of super resolution image from low resolution natural color image is presented.

Chapter six includes results of the algorithm as super resolved images. The images include the wide variety of natural and synthetic colored and gray images. Along with super resolved images the PSNR is displayed.

Chapter seven includes summary of research work. The core aim of chapter is to presents conclusions drawn. Chapter ends with future scope that identifies some future research directions.

Chapter 2

Literature Survey

The chapter includes the digital image acquisition model with its limitations, image representation, color models, and existing techniques in use along with their pros and cons. Literature survey of current trends and techniques for topic under research are presented. The shortcomings and discrepancies among methods are identified and mentioned.

2.1 Digital Image Acquisition System

Digital image acquisition is the process of digital image creation. A digital image may be created directly from a physical scene with digital camera or similar device. Alternatively, it may be obtained from another image in an analog medium, such as photographs, photographic film, or printed paper and obtaining their digitized version by a scanner or similar device. Also many technical images can be acquired with tomography equipment, side-looking radar, or radio telescopes. A digital image can also be computed from a geometric model or mathematical formula as well.

A typical image acquisition system consists of image formation system that has a detector, and a recorder [80]. Consider an electro-optical system such as the television camera. It contains an optical system that focuses an image on a photoelectric device, which is scanned for transmission or recording of the image. Similarly, an ordinary camera uses lens to converge an image that is detected and recorded on a photosensitive film. A generalized image observation model for such systems is shown in figure 2.1.

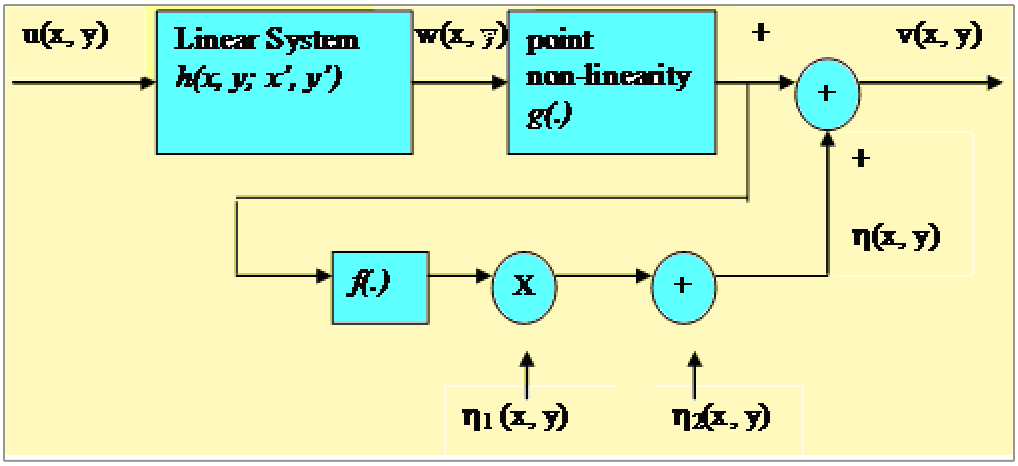


Figure 2.1 Image Observation Model

In this model, $u(x, y)$ represents an object (the original image), $v(x, y)$ is the observed image and $w(x,y)$ is output of linear system.

The block diagram includes the linear system that is defined by impulse response $h(x,y; x',y')$ and nonlinear system shown in model represents the characteristics of the detector or recording mechanisms. The output of image observation model is given as:

$$v(x, y) = g[w(x, y)] + \eta(x, y) \tag{2.1}$$

$w(x,y)$ is output of linear system that is obtained by process of convolution of an original image and impluse response of linear system. It is given as :

$$w(x, y) = \int \int_{-\infty}^{\infty} h(x, y; x', y')u(x', y')dx'dy' \tag{2.2}$$

For space invariant systems,

$$h(x, y; x', y') = h(x-x', y-y' ;0, 0)) \approx h(x-x', y-y') \tag{2.3}$$

The additive noise $(\eta(x, y))$ has an image-dependent random component $f[g(w)]\eta_1$, and an image independent random component η_2. The functions $f(.)$ and $g(.)$ are nonlinear functions that represent the characteristics of the detector or recording mechanisms.

$$\eta(x, y) = f [g(w(x, y))] \eta_1(x, y) + \eta_2(x, y) \tag{2.4}$$

Practically, in real world model, while recording a digital image, there is a natural loss of spatial resolution caused by the optical distortions, motion blur and noise. Consequently, the recorded image suffers from blur, noise, and aliasing effects. Therefore, there is need to study these problems, their causes and develop possible solutions to minimize them. The real world model of digital image capturing process [6] is shown in figure 2.2.

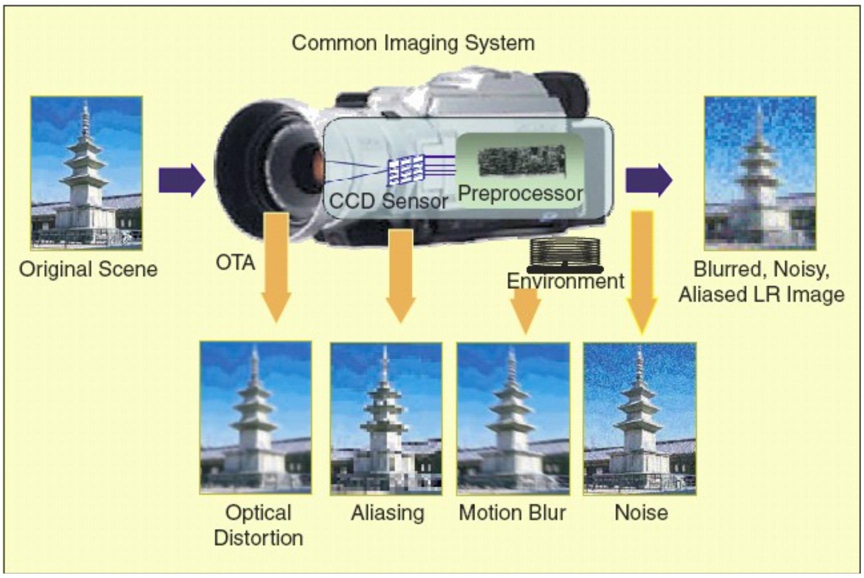


Figure 2.2 Real World Image Formation Model

2.2 Limitations of Existing Image Capturing Systems

It is observed that, in real world model, the process of recording a digital image captured by camera or digitized version suffers from few problems: Optical distortion, Motion Blur, Aliasing effect and Noise [6,80].

Optical Distortion

If the capturing system is ideal then the system can detect and record all frequency components of input scene so that there would not be any loss of information. The ideal system has the impulse response is that infinitesimally thin Dirac delta function having an infinite pass band. Since no system is ideal having its own diffraction limit, there is loss of some information. This is known as optical distortion. The optical distortion is one of the causes for loss of spatial resolution. The resolution of optical system is defined in terms of modulation transfer function (MTF) that is ratio of magnitude of Fourier transform of output and input signal. It is very difficult to overcome the limitations of diffraction limit of the system so as to capture nearly ideal image of the scene. There is need to find alternative way to overcome this limitation.

Blur

One of the degradations in low resolution image is the sensor related blur that appears as a consequence of the low resolution point spread function of the camera. Blurring can also arise due to relative motion between camera and the scene during exposure. Now a days the softwares are available to remove blur by processing the image. Atmospheric turbulence is one of the problems occurring due to the random variation in diffraction index of medium between object and that degrades quality of image. Such degradation occurs in imaging of astronomical objects. Image blur also occurs in image acquisition while digitizing the image using device like scanner in which the pixels are integrated over scanning aperture.

Aliasing

If charge coupled device (CCD) array used for image acquisition is not sufficiently dense; so as to meet the Nyquist criterion, the resulting images will be degraded by aliasing. Since the optics of the imaging system will serve to effectively band limit the image on the detector array, it is possible to acquire an image that is free of aliasing. However, this requires the appropriate combination of optics and detector array. Generally, a broad instantaneous field of view is desired which requires optics with a short focal length. To prevent aliasing in this case requires a dense detector array, which may be very costly or simply unavailable. Thus, many imaging systems are designed to allow some level of aliasing during image acquisition; this is particularly true for staring infrared imagers because of fabrication complexities. Visual CCD cameras also suffer from under sampling.

Aliasing artifacts in images are visually very unpleasant. Therefore, most imaging devices apply a low-pass filter before sampling. This removes all aliasing from the image that leads to blurred image. Actually, all the image information above half the sampling frequency is removed. Super-resolution (SR) techniques aim at estimating a high resolution image with reduced aliasing from a sequence of low-resolution images. Few researchers have developed technique for estimating a unaliased high-resolution image from the aliased images acquired from such an imaging system[9-16].

Noise

Noise is unwanted signal distributed over the image. Generally, noise occurs within sensor during transmission or due to insufficient sensor density. Quality enhancement algorithms are available that are used to eliminate noise and improve visual quality of image.

In addition to above problems, all imaging systems have an upper limit on resolution. Resolution is an important parameter that defines quality of an image. The reasons limiting resolution are:

- Diffraction of light limits resolution to the wavelength of the illuminating light.
- Lenses in optical imaging systems truncate the image spectrum in the frequency domain.
- Sampling of images limits the maximum spatial frequency to a fraction of the sampling rate.

Objective of this research work is confined to increase spatial resolution of an image. The most direct solution to increase spatial resolution is to reduce the pixel size in order to pack more photo-detectors and increase the number of pixels per unit area by sensor manufacturing techniques [1]. As the pixel size decreases, however, the amount of light available decreases and reduced inter pixel distance generates shot noise that degrades the image quality severely. There exists the limitation on the pixel size reduction. The optimally limited pixel size is estimated at about 50 μm^2 for a 0.35 μm CMOS process

[1,57]. The current image sensor technology has almost reached this level.

Another approach for enhancing the spatial resolution is to increase the chip size, which leads to an increase in capacitance [1]. Since large capacitance makes it difficult to speed up a charge transfer rate, this approach is not considered to be effective. The high cost for high precision optics and image sensors is also an important concern in many commercial applications regarding high resolution imaging. Therefore, a new signal processing approach toward increasing spatial resolution is aim of this research work.

2.2.1 Image Resolution

Resolution of an image in its simplest form is defined as the smallest discernible or measurable details in a visual presentation. Image resolution has three different categories: spatial resolution, brightness resolution and temporal resolution.

Spatial Resolution

Spatial resolution refers to number of pixels per unit area and is measured using pixels per inch (ppi). High spatial resolution means pixel density within image is high. The resolution of the display device is often expressed in terms of dots per inch (dpi) and it refers to the size of the individual spots created by the device.

Brightness Resolution

Brightness resolution refers to the number of brightness levels that can be recorded at any given pixel. For monochrome images, each pixel in the image is represented using a byte and has a numerical value between 0 and 255. For color images, pixel is defined by three color bytes one per color channel. This scheme can be expanded as 16 bits for each color.

Temporal Resolution

Temporal Resolution refers to the number of frames captured per second and is also commonly known as the frame rate. It is related to the amount of perceptible motion between the frames.

The main objective of this research work to improve spatial resolution of an image.

2.3 Image Representation

The digital image is represented as two-dimensional array of picture elements having M rows and N columns. $M \times N$ defines the resolution of the image. Every sampled picture element is known as pixel in digital image processing. Each pixel is identified with unique positional tuple (x, y). In other words, image is stored as a two dimensional signal. It is represented by function f (x, y), where x and y are spatial co-ordinates of a pixel and the value of function f at any pair of co-ordinate (x, y) is called as intensity of a pixel or gray level of a pixel of the image at that point in gray images. For color images the function f maps the color information associated with the pixel at (x, y).

Different techniques are used to represent the digital image. The basic techniques used to represent the digital images are: Indexed image, Binary image, Intensity image and Color image.

2.4 Color Image

In today's multimedia era color images have significant impact on human lives. There are various techniques of representation of color in color images that have been developed and used in various applications. The color associated with a single picture element is constituted by intermixes of various color components. The color models are developed to support the idea of color image representation. Color model is a specification of a co-ordinate system and a sub space within that system, where a single point represents each color. Most color models in use today, are oriented either towards hardware or towards applications, where color manipulation is the goal. In terms of digital image processing the hardware oriented models most commonly used in practice are RGB (Red, Green, Blue); the CMY (Cyan, Magenta, Yellow);

the CMYK (Cyan, Magenta, Yellow, Black); and the HSI (Hue, Saturation and Intensity) [80,81,82].

2.4.1 Red, Green, Blue Color Model

In the RGB model, each color appears in its primitive spectral component of red, green, and blue. These are the primary colors of light. This model is based on Cartesian coordinate system. The RGB is referred as 'true color' or "full color" image. The number of bits used to represent each pixel in RGB space is called the pixel depth. In color image representation each pixel has three-color values red, green, and blue. The color of each pixel is determined by the triplet (R, G, B). In graphical file formats, RGB images are stored using 24-bits 8 bits per color for each pixel. This yields a potential of sixteen million different colors. The actual number of colors in a 24-bit RGB image is 2^{24} = 16,777,216. The RGB color model, use predominantly for light emitting systems (for example Televisions and Computer monitors).

2.4.2 CMY and CMYK Color Models

Cyan, Magenta, and Yellow are the secondary colors of light but are primary colors of color pigments. Since these are colors of the color pigments the original colors of light are not reflected. For example when a surface is coated with Cyan pigment and is illuminated with white light; red light is not reflected from the surface. That is Cyan subtract from red light from reflected white light, which it self is composed of equal red, green, and blue light. CMY color values are computed from the primary colors values. Equal amount of pigment primaries Cyan, Magenta, and Yellow should produce black and it gives rise to CMYK color model. The CMY color model, use for light-absorbing systems [80,81,82].

2.4.3 HSI Color Model

Hue, Saturation and Intensity are calculated from the primary colors (RGB). Hue is the color attribute that describes the pure color (pure Yellow, Orange, or Red), where saturation gives a measure of the degree to which the pure color is diluted by white light. The intensity is the most useful descriptor of monochromatic images. HIS color model; decouples the intensity components from the color carrying information in color image [81].

2.4.4 Color Space and Human Perception

The use of color in image processing algorithm is motivated due to two key factors [80,81,82]

i) The color is powerful component, that often simplifies object identification and extraction of the scenes;
ii) The human visual perception can identify thousands of color shades and intensities, compared to about only few shades of gray color.

The color image processing is divided into two major areas: full color and pseudo color image processing. Basically the colors that humans and some other animals perceive are determined by the nature of the light reflected from the object. The human eye has two types of cells playing major role in object perception; Rod cell and Cone cell. Detail experimental evidence has established that the six to seven million cone cells in the human eye can be divided into three major sensing categories corresponding roughly to red, green and blue. Approximately sixty-five percent of all cones are sensitive to red light, thirty-three percent are sensitive to green light and two percent are sensitive to blue light. Wavelength of red light is 700 nm, green light is 546.1 nm and blue light is 435.8 nm.

The characteristics used to distinguish one color from another are brightness, hue, and saturation. Brightness embodies chromatic notation of intensity. Hue is an attribute associated with the dominant wavelength by an observer. Saturation refers to the relative purity or the amount of the white light mixed with a hue. Degree of saturation is inversely proportional to the amount of white light added. Hue and saturation taken together are called chromaticity and therefore a color may be characterized by its brightness and chromaticity.

RGB color model is ideal for image color generation, but when it is used for color description; its scope is much limited. The HSI model is an ideal tool for developing image-processing algorithm based on color descriptions that are natural and intuitive to human eye.

For color image processing, the selection of proper color model is extremely crucial. Red, green and blue color components of pixel are correlated with visual appearance, therefore even though RGB is most common storage format for images; it is not used for processing. If it is used, high visual distortion is introduced. Thus, it necessitates the conversion of RGB colors into another colors representation, which doesn't have the correlation among the components.

2.4.5 YUV and YC_rC_b Color Representation

United States National Television Systems Committee (NTSC) mandated color encoding for color televisions. It uses YUV color encoding, where Y is luminance, U is the difference (R – Y), and V is difference (B – Y). U and V represent color information (chrominance) [81]. YCrCb is subset of YUV. The luminance Y and chrominance U (R – Y) and V (V – Y) are calculated with the equations

$$Y = 0.299 \times Red + 0.587\times Green + 0.114 \times Blue \qquad (2.5)$$

$$R - Y = 0.701 \times Red - 0.587 \times Green - 0.114 \times Blue \qquad (2.6)$$

$$B - Y = -0.299 \times Red - 0.587 \times Green + 0.886 \times Blue \qquad (2.7)$$

The Red, Green and Blue values are assumed to be the fractions in the range of 0.0 to 1.0. Notice that the luminance equation will always produce a value of Y in the range of 0.0 to 1.0. However, the value of color difference (R – Y) produces values in the range from – 0.701 to +0.701, and the value of color difference (B – Y) produces values in the range from – 0.886 to +0.886. These ranges are not ideal for digital representation, so they are both remapped into the range of values –0.5 to +0.5 [82]. This gives

$$Cr = 0.500 \times Red - 0.419 \times Green - 0.081 \times Blue \quad (2.8)$$

$$Cb = -0.169 \times Red - 0.331 \times Green - 0.5 \times Blue \quad (2.9)$$

These values are converted to an 8-bit binary encoding using the equations:

$$Y = round\ (219 \times Y + 16)$$

$$Cr = round\ (224 \times 0.713 \times (R - Y) + 128)$$

$$Cb = round\ (224 \times 0.564 \times (B - Y) + 128)$$

The Red, Green and Blue values are assumed to be in the range of 0 to 255. The luminance equation will produce a value of Y in the range of 0 to 255. Human eyes are more sensitive to the change in brightness of color. It is proved that YCrCb color space do not have correlation among the spaces hence this is correct choice of color space for the color image processing. The equations used to convert the basic colors RGB into YCrCb are given by

$$Y = 0.299 \times Red + 0.587 \times Green + 0.114 \times Blue \quad (2.10)$$

$$Cr = 0.701 \times Red - 0.587 \times Green - 0.114 \times Blue \quad (2.11)$$

$$Cb = -0.299 \times Red - 0.587 \times Green + 0.886 \times Blue \quad (2.12)$$

After the color image processing, the components YCrCb are remapped to RGB color components to display the image, using the equations

$$Xr = Y + Cr \quad (2.13)$$

$$Xg = Y - 0.509 \times Cr - 0.194 \times Cb \quad (2.14)$$

$$Xb = Y + Cb \quad (2.15)$$

2.5 Super Resolution

In today's modern era, multimedia has tremendous impact on human lives. It becomes inseparable part of our day-to-day activities. Image is one of the most important media contributing to multimedia. The significant feature of all image processing applications is good quality of image. The resolution of image is the principal factor in determining the quality of an image. The resolution is nothing but number of pixels per unit area. With the development of image processing applications, there is a big demand for high resolution (HR) images. The high resolution images not only give users a pleasing picture but also offer minute additional details that may be important for the analysis of image in many applications. Initial technology to obtain high resolution images mainly depends on sensor manufacturing technology. Sensor manufacturing technology has its own limitations. The cost for high precision optics and sensors may not be affordable for general purpose commercial applications such sensor networks. Recently researchers have started paying attention towards the enhancement of image resolution. Super Resolution is a process to increase the resolution of an image beyond the resolving power of the imaging system. Hence super resolution allows overcoming the limitations of the imaging system without the need for additional hardware.

This thesis presents an algorithm to reconstruct the high resolution image that can take care of low frequency as well as high frequency image with optimum time and cost.

2.5.1 The Super Resolution Process

Super Resolution is a process of reconstructing high resolution image from available information. The low frequency components in an image represent smoothness in image whereas high frequency components provide details in image. The basic idea is to reconstruct super resolution image by restoring the appropriate frequency components those are lost by the image capturing process.

The super resolution approaches suggested by researchers in literature reconstruct the high resolution image using low resolution images of same scene or low resolution images of similar scenes or a low resolution image. The generalized block diagram of super resolution process is shown in fig 2.3. Most of the multiframe super resolution image reconstruction methods consist of three basic components [6]: i) motion compensation (registration), ii) interpolation, and iii) blur and noise removal, if any (restoration).

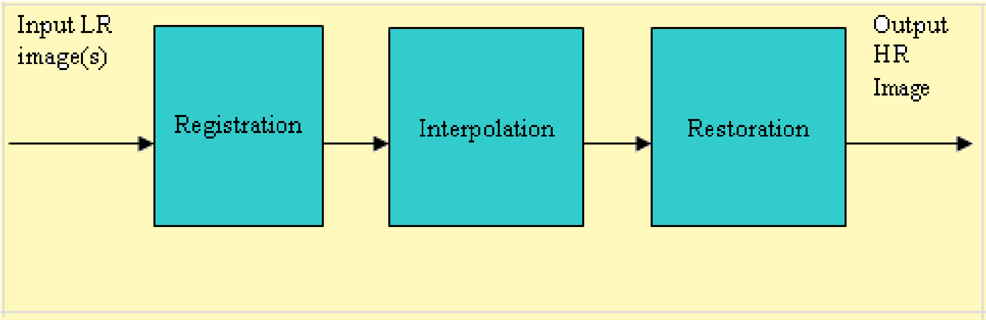


Fig
ure 2.3 The Super Resolution Process

Registration is basically preprocessing of the input information. Image registration is to align the different images as precisely as possible by estimating the motion between them. All the frames in the low-resolution observed image sequence are geometrically registered to a fixed reference frame, resulting in a composite image of non-uniformly-spaced samples. These nonuniformly spaced sample points are then interpolated and resampled on a regularly spaced high resolution sampling lattice. Restoration is used to remove noise and blur, if exists in the resultant image.

2.6 Resolution Enhancement Techniques in Use

High resolution images are expected to enhance the capability of detection and identification of details in image. It is observed that the demand of higher resolution can not be fully satisfied by current imaging devices. Hence softwares techniques are developed and are in use to fulfill these demands by enhancing resolution of captured image. Smoothing and interpolation are the commonly used approaches for still image resolution enhancement. Smoothing is usually achieved by applying the various spatial filters such as Gaussian, Weiner, and Median. Most of the recent digital cameras use interpolation to produce higher resolution image.

2.6.1 Interpolation

The interpolation is used to enhance the resolution of image and it has two basic steps. First step involves transforming a discrete matrix into continuous image or to transform a discrete matrix into two dimensional continuous functions. Secondly, resample this continuous function as per need (up-sample or down-sample). In other words, for image resampling, the interpolation step reconstructs the two dimensional continuous signal from discrete samples. Mathematically this can be represented as convolution of discrete image samples with continuous two dimensional impulse response of a reconstruction filter. The reconstruction filter used defines the type of interpolation. Generally, the symmetrical and separable interpolation kernels are used to reduce the computational complexity.

$$h(x,y)= h(x).\ h(y) \tag{2.16}$$

In case of ideal interpolation the Sinc function is impulse response of reconstruction filter. In ideal interpolation technique the results are obtained in spatial domain by the convolution of discrete signal with Sinc function. In frequency domain, the result is obtained by multiplication of rectangular function and continuous spectrum of the image. Ideally, if a Nyquist criterion is satisfied, original image can be reconstructed perfectly from discrete samples avoiding smoothing and loss of high frequency components. The Sinc function has infinite impulse response and is not suitable for local interpolation with finite impulse response. Practically, it is impossible to implement system with infinite impulse response. Hence truncation of infinite impulse response is suggested. Different windows are used to truncate or approximate the Sinc function. Truncation of ideal interpolator produces ringing effect in frequency domain as considerable amount of energy is discarded. Literature [65,66,67] reveals that different practical interpolation techniques are suggested but commonly used interpolation techniques are Nearest neighbor, Bilinear and Bicubic techniques.

Nearest Neighbor Interpolation

The nearest neighbor interpolation is one of the simplest techniques used to enhance resolution of the image. This technique is based on assumption that there exists redundancy among pixel densities. In this technique, value of new pixel is computed from closest pixels in original image. The pixel replication is a special case of nearest neighbor method [81]. Pixel replication is applicable when there is need to increase size of an image integer number of times. Duplicating each column doubles the size of image horizontally and further duplicating each row double the image size vertically. In other words, in nearest neighbor method the output image is obtained by convolution of image with rectangular function in spatial domain or multiplication of frequency domain representation of image with Sinc function. Amplitudes of side lobes of Sinc function are significant and number of side lobes is infinite and hence this method suffers from distortion. The rectangular function is given as:

$$\begin{aligned} h(x) &= 1 \qquad 0 \le |x| < 0.5 \\ &= 0 \qquad 0.5 \le |x| \end{aligned} \tag{2.17}$$

Linear Interpolation

Linear interpolation is developed to minimize the problem of replication method. Linear interpolation is first order hold where a straight line is first fitted in between pixels along a row. Then the pixels along each column are interpolated along a straight line. In the spatial domain, it is equivalent to convolving of sampled input with triangular function.

$$\begin{aligned} h(x) &= 1 - |x| \qquad 0 \le |x| < 1 \\ &= 0 \qquad 1 \le |x| \end{aligned} \tag{2.18}$$

It is equivalent to the multiplication of frequency domain representation of image and Fourier transform of above rectangular function that is square of Sinc function. This improves performance in stop band due to low amplitude side lobes as compared to replication technique. It does not mean that response is ideal. Even though the amplitude of side-lobes is low, it is still considerable. Hence limitations of linear interpolation include attenuation of high frequency components and aliasing of data beyond the cutoff point into low frequencies. In passband, the signal is attenuated and it results in image smoothing.

The linear interpolation is referred as bilinear interpolation when value of new pixel is computed using weighted average of four pixels in nearest 2 x 2 neighborhood of original image. Similarly, the linear interpolation is called as bicubic interpolation when value of new pixel is computed using weighted average of 16 pixels in nearest 4 x 4 neighborhood of original image. The performance of bicubic interpolation is better than bilinear. Edges in bicubic interpolation are less smooth than that of bilinear and pixel replication. But it has more computational complexity.

Different interpolation and smoothing methods are suggested to enhance the image resolution. These traditional interpolation techniques mix up the values of neighboring pixels and thus mix up different information across whole image. Thus loosing important part of possible final resolution enhancement provided by whole resolution enhancement method.

These resolution enhancement techniques are not suitable for super resolution image reconstruction as proper care of high frequency components is not taken. Hence there is lot of scope for developing a new technique for super resolution imaging taking care of all frequency spectrums properly.

2.7 Image Quality Measures

Researchers have suggested number of techniques to reconstruct the super resolution image in last two decades such as, Mean Opinion Score (MOS), Double stimulus Continuous quality Scale (DSCQS), Mean Square Error (MSE), Signal to Noise Ratio (SNR), Peak Signal to Noise Ratio (PSNR), Normalized Cross-correlation (NK), Average Difference (AD), Maximum Difference (MD), Structural Content (SC), and Normalized

Absolute Error (NAE) among few more. These measures are discussed in chapter four. These measures are not appropriate for measuring the quality of super resolution imaging as reference image is not available. In this research work, a new framework for measuring quality of super resolution image using PSNR is suggested.

2.8 Super Resolution Design Criteria

The super resolution imaging is useful for a variety of applications and each application imposes different design criteria such as: time, cost, color consideration, number of images used and quality. These constraints vary according to application demands. Real time applications impose stiff constraints regarding time. If special purpose hardware is required for the application then it adds to the expenses. The best cost/benefit ratio is to be achieved. When more than one shifted low resolution images are available, super resolution image can be reconstructed by incorporating more details from them. There is tradeoff between the amount of prior information and number of images required to produce better quality results.

Often single low resolution image is available and it should be exploited appropriately to get super resolution image. For web based applications, a low resolution image can be transmitted so that less bandwidth is needed for transmission with fast transfer. The super resolution image can be then reconstructed at receivers end.

Quality is one of the most important criteria. Resolution augmentation in medical imaging is important for visualization and early diagnosis. Super resolution based medical imaging can play major role in providing the same and assist physician for faster and accurate diagnosis. Objective is to balance good tradeoff between bandwidth and signal to noise ratio and tradeoff between cost and quality.

It is needed to extend SR algorithm to real world color imaging system with a careful consideration that reflects inter-correlationship between color components in the reconstruction procedure.

Adding features like robustness, less memory requirement, good computational efficiency, color consideration and automatic selection of parameters should be design criteria of super resolution algorithm.

2.9 Literature Survey

The rapid growth of digital image processing applications including desktop publishing, multimedia, videoconferencing, High Definition Television (HDTV), and medical image analysis has increased the need of very high resolution images.

Interpolation methodologies have been presented over the years for reconstructing higher resolution image. These methods have one common goal to enhance the quality of image by increasing resolution of image so that it can help to improve quality of frames during communication in video conferencing and HDTV, and correct diagnoses in medical applications. Recently the active research is going on to develop the effective technique for the perfection to match the technology advances.

Tsai and Huang [2] first proposed the super-resolution idea in year 1984. They first derived a system equation that describes the relationship between low resolution images and a desired high resolution image by using the relative motion between low resolution images. They used the frequency domain approach to demonstrate the ability of reconstructing a single improved resolution image from several down-sampled noise-free versions of it. Several extensions to the basic Tsai-Huang method have been proposed in literature. However, contrary to the naive frequency domain description of this early work, it is seen that, in general, super resolution is a computationally complex and numerically ill-posed problem [8].

The differences among the several proposed works are subject to what type of reconstruction method is employed, which observation model is assumed, in which particular domain (spatial or frequency) the algorithm is applied, what kind of methods is used to capture low resolution images, and so on. The technical report by S. Borman and R.L. Stevenson in [3] provides a comprehensive and complete overview on the super resolution image reconstruction algorithms until around 1998. They have defined Super-resolution as recovery of spatial frequency information beyond the diffraction limit of the optical system as well as removal of blur caused by the imaging system such as out of focus blur, motion blur, non-ideal sampling, etc.

Super-resolution restoration from a still image is a well recognized example of an ill-posed inverse problem. Such problems may be approached using regularization methods, which constrain the feasible solution space by employing a-priori knowledge. This may be achieved in two complimentary ways; firstly, obtain additional novel observation data and second, constrain the feasible solution space with a-priori assumptions on the form of the solution. Both techniques feature in modern super-resolution restoration methods which utilize image sequences which provide additional spatio-temporal observation constraints (typically in the form of novel data arising from sub-pixel motion) and various a-priori constraints on the super-resolution image (e.g. local smoothness, edge preservation, positivity, energy boundedness, etc.). The use of non-linear a-priori constraints provides the potential for bandwidth extension beyond the diffraction limit of the optical system.

Authors claim that among two frequency domain and spatial domain approaches, frequency domain approaches are, to a greater or lesser extent, unable to accommodate general scene observation models including spatially varying degradations, non-global relative camera/scene motion, general a-priori constraints or general noise models. Whereas spatial domain formulations can accommodate all these and provide enormous flexibility in the range of degradations and observation models which may be represented and are thus the methods of choice. Spatial domain observation models facilitate inclusion of additional data in the observation equation with the effect of reducing the feasible solution space.

Further authors have put forth three critical factors affecting super-resolution restoration. Firstly, reliable subpixel motion information is essential. Poor motion estimates are more detrimental to restoration than a lack of motion information. Secondly, observation models must accurately describe the imaging system and its degradations. Thirdly, restoration methods must provide the maximum potential for inclusion of a-priori information.

In super resolution image reconstruction process, registration is first and the most important step. The accuracy of registration is based on motion estimation and hence accurate knowledge of relative scene locations sensed by each pixel in observed images is necessary for super resolution. Irani and Peleg suggested an iterative back propagation (IBP) super resolution reconstruction approach of improving the resolution in their paper titled "Improving resolution by image registration" [4]. The high resolution image is estimated by back propagating the error (difference) between simulated low resolution images. Initially the high resolution image is guessed and low resolution images are constructed from it. Further, these are compared with low resolution images constructed from input image. The difference is calculated and used to improve initial guess by back projecting each value in difference image into its respective field in original guess image. This process is repeatedly used to minimize error function. The authors have concluded that in given technique original high resolution frequencies are not fully restored because the blurring function is low pass filter that filters out the high frequency information.

Authors further put forth that this problem can be avoided with use of more than one high resolution images that give same low resolution images after imaging process. However, this leads to several possible solutions and algorithm may converge to one of them or may oscillate among some of them. Choice of initial guess does not influence the performance of algorithm. A good choice of initial guess is average of low resolution images. Average image is constructed by registering the low resolution images over fixed finer grid. Another issue raised for given algorithm is selection of the proper back projecting kernel that affects the characteristics of the solution reached when there are several solutions. For color images, it is suggested to convert image into YIQ domain, apply iterative super resolution algorithm only to Y component, and use simpler process for I and Q components.

Researchers M. Irani and S. Peleg, in paper "Motion analysis for image enhancement: resolution, occlusion, and transparency" [5] have described methods for enhancing image sequences using the motion information computed by a multiple motions analysis method. The multiple moving objects are first detected and tracked using both a large spatial region and a large temporal region without assuming any temporal motion constancy. This paper has discussed in brief the approaches used for segmenting the image plane into different moving objects, computing their motion and tracking them throughout image sequence. Authors have described algorithm for image enhancement using the computed motion information. The techniques for improving resolution of tracked objects, occluded segments of tracked objects and transparent moving objects are presented in paper as well. It is concluded that quality of high resolution image is a function of good motion estimation and segmentation of tracked objects.

S. Park, M. Park and M. Kang in article titled "Super-Resolution Image Reconstruction: a Technical Overview" [6] have presented concepts of super resolution technology along with review of super resolution algorithms until around 2003 and issues to improve performance of super resolution algorithms. The author has discussed limitations of sensor manufacturing technique in details and has supported signal processing approach to obtain high resolution image(s) using low resolution image(s). Major advantage of signal processing approach is that it costs less and existing low resolution image capturing devices can still be used. Authors believe that a resolution enhancement approach has been a great concern in many areas, and it is referred as super-resolution imaging also known as super resolution image reconstruction or simply resolution enhancement. For multiple image based techniques, low resolution images are sub sampled as well as shifted with subpixel precision. If low resolution images are shifted by integer shift, then each image contains same information, and thus there is no new information that can be used to reconstruct a high resolution image. Most of the multiple image based super resolution approaches include registration, interpolation and/or restoration as phases of overall process.

Further, the authors have classified super resolution techniques as-Nonlinear interpolation approach, Frequency domain approach, Deterministic & Stochastic regularization approach and The Projection onto Convex Sets (POCS) approach.

In non-uniform interpolation approach, the steps registration, non-uniform interpolation and restoration are performed successively. With the relative motion information estimated, the high resolution image on non-uniformly spaced sample is obtained. Then the direct or iterative reconstruction procedure is followed to produce uniformly spaced sampling points. Finally, restoration is applied to remove blur and noise. It is noticed that the accuracy of the resultant high resolution image depends on set of low resolution images and precision of motion estimation. Authors claim that the restoration step ignores the errors occurred during interpolation; that do not guarantee optimality of solution.

The frequency domain approach makes explicit use of the aliasing that exists in each low resolution image to reconstruct a high resolution image. The frequency domain approach is based on the following three principles: i) the shifting property of the Fourier transform, ii) the aliasing relationship between the continuous Fourier transform (CFT) of an original high resolution image and the discrete Fourier transform

(DFT) of observed low resolution images, iii) and the assumption that an original high resolution image is band-limited. Theoretical simplicity is major advantage of the frequency domain approach. That is, relationship between low resolution and high resolution image is clearly demonstrated in the frequency domain. However, it is observed that due to the lack of data correlation in the frequency domain, it is also difficult to apply the spatial domain priori knowledge for regularization. This problem of frequency domain approach using Fourier transform can be overcome up to certain extend with use of latest mathematical tool, the wavelet.

Authors have discussed the regularization approach for super resolution image reconstruction. Authors says that the super resolution image reconstruction approach is ill posed problem because of less number of low resolution images and ill conditioned blur operators. Approaches used to minimize the inversion of ill posed problem are called as regularization. Authors have discussed two regularization approaches: Deterministic and stochastic those are used for super resolution image reconstruction.

Deterministic approach analyzes the deterministic relationship between the lower-resolution and the corresponding higher resolution images. Robustness and flexibility in modeling noise characteristics and a priori knowledge about the solution are the major advantages of the stochastic super resolution approach. Assuming that the noise process is white Gaussian, Maximum Posteriori Estimation (MAE) with convex energy functions in the priors ensures the uniqueness of the solution. Therefore, efficient gradient descent methods can be used to estimate the high resolution image. It is also possible to estimate the motion information and the high resolution image simultaneously.

Typically Constrained Least Squares (CLS) and Maximum a Posteriori (MAP) super resolution image reconstruction methods are employed. The projection onto convex sets (POCS) method describes an alternative iterative approach to incorporate prior knowledge about the solution into the reconstruction process. With the estimates of registration parameters, this algorithm simultaneously solves the restoration and interpolation problem to estimate the super resolution image. The advantage of POCS is that it is simple, and it utilizes the powerful spatial domain observation model. It also allows a convenient inclusion of a priori information. These methods have the disadvantages of no uniqueness of solution, slow convergence, and a high computational cost. The maximum likelihood -projection onto convex sets (ML-POCS) hybrid reconstruction approach finds super resolution estimates by minimizing the ML (or MAP) cost functional while constraining the solution within certain sets. The advantage of the hybrid approach is that all a priori knowledge is effectively combined, and it ensures a single optimal solution in contrast to the POCS approach.

Iterative back-projection (IBP) super resolution reconstruction approach is similar to the back projection used in tomography. In this approach, the high resolution image is estimated by back projecting the error (difference) between simulated low resolution images via imaging blur and the observed low resolution images. This process is repeated iteratively to minimize the energy of the error. The advantage of IBP is that it is understood intuitively and easily. However, this method has no unique solution due to the ill-posed nature of the inverse problem, and it has some difficulty in choosing the back propagation kernel. In contrast to the POCS and regularized approach, it is difficult to apply a priori constraints.

Further few issues in super resolution are presented by authors: registration error, blind super resolution image reconstruction, computational efficiency, color super resolution and compression issue.

Registration is important step in super resolution image reconstruction, as accurate registration is necessary for success of super resolution process. If any error occurs during registration, it should be overcome in reconstruction phase. In article, solutions to overcome registration error up to certain limit are discussed in brief.

In most of the super resolution image reconstruction algorithms, one of the problems is blurring. This problem can be minimized, if it is known during reconstruction. However, in practical situations, blur process is unknown or it is known within set of problems. Therefore, authors have suggested that it is necessary to incorporate the blur identification in reconstruction process.

Most of the super resolution imaging algorithms model imaging process to represent the low resolution image as degraded version of high resolution image due to various parameters such as blur, noise, motion etc. Further, the aim is to estimate the high resolution image from observed low resolution image(s). This inverse procedure in super resolution image reconstruction requires a large computational load. To apply the super resolution algorithm to practical situations, it is important to develop an efficient algorithm that reduces the computational cost. Authors state that the interpolation based approach and adaptive filtering approach can be appropriate to real time implementation.

It is needed to extend current super resolution algorithm to real world color imaging system with a careful consideration that reflects the characteristics of color. The important problem in color super resolution is to analyze the characteristics of a color filter array and color interpolation procedure and further take into account inter-correlationship between color components in the reconstruction procedure.

The use of compressed low resolution video data results in challenging super resolution problem. The application of the super resolution algorithm to compression system is also needed since images are routinely compressed prior to transmission and storage. The super resolution algorithm must account for the structure of the compression system. It is important to analyze and model the compression error caused by quantization since a simple Gaussian noise model is not acceptable especially when a significant amount of compression is employed.

Ur & Gross [7] presented spatial domain algorithm in paper titled "Improved resolution from sub-pixel shifted pictures". Assuming a known 2D translation, a fine sample grid image is created from the input images, using interpolation, and the camera blur is canceled using deblurring technique. The paper concentrates on a special super-resolution case, where the blur is space invariant and is same for all the measured images; the geometric warps between the measured images are pure translations; and the additive noise is white. These assumptions are valid in cases where the same camera with slight vibrations obtains the images, such as in many video scenes. The method assumed uniform blur function over all the images, and identical on different images. They were also restricted to global 2D translation. In time domain, researchers have used Papoulis-Brown generalized sampling theorem [73-74] to obtain an improved resolution picture from an ensemble of spatially shifted pictures. However, these shifts are assumed to be known by the authors, which in practical may not be a feasible solution. This super resolution method requires fewer low resolution images and computational load. The restoration process then uses a convolution method to remove blurs. The disadvantage is that the resulting high resolution image is not optimal and only one blurring model can be applied for all low resolution images.

The researchers Sina Farsiu, Robinson, Elad, and Milanfar, in article titled "Advances and Challenges in Super-Resolution" [8] have reviewed a variety of Super-Resolution methods proposed in the last 20 years, and provided some insight into, and a summary of, recent contributions to the general Super-Resolution problem. A detailed study of several very important aspects of Super-Resolution such as robustness, treatment of color, and dynamic operation modes is presented. Authors have formulated super resolution as an inverse problem, wherein the source of information (high-resolution image) is estimated from the observed data (low-resolution image or images). Solving an inverse problem in general requires first constructing a forward model. The most common forward model for the problem of Super-Resolution is linear in form: $Y(t) = M(t) X(t) + V(t)$ where Y is the measured data (single or collection of images), M represents the imaging system, X is the unknown high-resolution image or images, V is the random noise inherent to any imaging system, and t represents the time of image acquisition. Here the image is represented in the form of vector.

Authors have concluded that an inherent difficulty with inverse problems is the challenge of inverting the forward model without amplifying the effect of noise in the measured data. In the linear model, this results from the very high, possibly infinite and condition number for the model matrix M. Solving the inverse problem, as the name suggests, requires inverting the effects of the system matrix M. At best, this system matrix is ill conditioned, presenting the challenge of inverting the matrix in a numerically stable fashion.

Aliasing artifacts in images are visually very disturbing. Therefore, most imaging devices apply a low-pass filter before sampling. This removes all aliasing from the image, but it also creates a blurred image. Actually, all the image information above half the sampling frequency is removed. In the paper Authors P. Vanwalle, Sbaiz, Vetterlia and Susstruk in “Super Resolution from Highly Under Sampled Images” [9], have presented a new method for the reconstruction of a high resolution image from a set of highly undersampled and thus aliased images. Authors have used the information in the entire frequency spectrum, including the aliased part, to create a sharp, high resolution image. The unknown relative shifts between the images are computed using a subspace projection approach. The projection has been decomposed into multiple projections onto smaller subspaces. Once the offset is known, the original signal is reconstructed as the solution of a set of linear equations in unknown basis components. A high resolution image is reconstructed from registered low resolution images. This allows for a considerable reduction of the overall computational complexity of the algorithm. A high resolution image is then reconstructed from the registered low resolution images.

It is further emphasized by authors that if the signal is sampled at lower frequency the sampled signal is aliased, and the original signal can not be reconstructed. However, all the frequency content is still present in the sampled signal. It would therefore be interesting to use all this frequency information to reconstruct the signal.

Based of their study authors have drawn few conclusions and have extended their work in [10] to exploit aliasing. Often aliasing, caused by under-sampling of a signal, is considered as a nuisance and is avoided. To avoid the effect aliasing, an anti-aliasing low-pass filter is often placed in front of the actual sampling operation, such that the sampled signal is not aliased. However, in super-resolution signal reconstruction, aliased components contain valuable high-frequency information that can be used to recover a higher resolution reconstruction. In paper "Super Resolution from Unregistered and Totally Aliased Signals Using Subspace Methods" [10], by Patrick Vandewalle, L Sbaiz, J Vandewalle and M Vetterli have studied methods to reconstruct a signal, including its high-frequency information, from multiple aliased sampled signals with relative offsets. When multiple copies are available, they have used the information that is inherently present in the aliasing to reconstruct a higher resolution signal. These different copies have unknown relative offsets; this is a nonlinear problem in the offsets and the signal coefficients. They are not easily separable in the set of equations describing the super-resolution problem. The offsets are unknown and are computed first. For the estimation of those offsets, they have explicitly used the information available in the aliased part of the spectrum and do not need extra measurements. They perform joint registration and reconstruction from multiple unregistered sets of samples.

Further authors have discussed practical issues related to technique proposed. For given technique, no sampling kernel was considered. Signal is sampled using Dirac function. Although this is not very much realistic, it is approximately obtained to make analysis simple. For one-dimensional signal, it is easy to calculate relative offset required. The image is two-dimensional, hence to use this technique for image, number of offsets increase, and hence in turn the computational complexity becomes a critical issue.

The accuracy of results is based on the estimation of offset. To calculate this offset iterative method is used. This method calculates approximate offset and takes more time. For relative offset it is needed to estimate the first offset. This first offset could be obtained from another registration method that does not use aliasing. In super resolution imaging it is observed that shift is generally very small. This approximation of offset may introduce the error. To calculate this offset the main limitation of these methods is their computational complexity. They are therefore mainly applicable in domains that do not require real-time reconstruction.

Maria Teresa Merino and Jorge Nunez in “Super-Resolution of Remotely Sensed Images with Variable-Pixel Linear Reconstruction”[11] present a method known as Super-Resolution Variable-Pixel Linear Reconstruction (SRVPLR) proposed by Hook [69]. The technique is useful for not only astronomical but also satellite remotely sensed images. Authors have concluded that the suggested algorithm for super resolution imaging is difficult to use for object recognition in satellite remotely sensed images that usually have a large dimension as well as high distortion and observation effects. In satellite imaging, automatic registration is very difficult as subpixel accuracy is complex and image is highly distorted. Authors have put forth that it is preferable to use simple super resolution algorithm that performs only proper interpolation. Further authors have pointed out drawbacks of interpolation techniques. The method fulfills the additional requirements of being computationally fast and versatile with the desired type of images. The algorithm preserves photometry, can weight input images according to the statistical significance of each pixel, and removes the effect of geometric distortion on both image shape and photometry.

Patrick Vandewalle, Sabine Susstrunk and Martin Vetterli "A Frequency Domain Approach to Registration of Aliased Images with Application to Super-resolution" [12] have proposed a frequency domain technique to reconstruct high resolution image from set of aliased images. Authors have defined high resolution image as image with more resolving power. Adding high frequency typically based on known specific image model can increase the resolving power of image. Authors have mentioned that for super resolution imaging two major challenges are to be handled. First, the difference between low resolution images is to be known precisely. This difference can have many origins: camera motion, change of focus or combination of these two. The camera motion can be calculated by using process of motion estimation. However, in high resolution it is difficult to find the effect of change of focus. Author strongly claimed that an error in motion estimation translates most directly into degradation of resulting high resolution image. Further authors claim that the result obtained by interpolating one of the low resolution images is better solution than high resolution image obtained from set of low resolution images using incorrect motion estimation. The artifacts due to bad motion estimation are visually very noticeable. The second challenge is to apply information obtained from different registered images to reconstruction of sharp high resolution image.

Authors have discussed image registration algorithm in frequency domain method. In algorithm authors have used four low resolution images that are necessarily under-sampled otherwise the algorithm is not able to reconstruct better image. For the registration, authors have discussed plain motion estimation algorithm. Authors claim that their algorithm estimates shift and rotation parameter better than other methods in particular when strong directionality is present in image. It is observed that most of the natural image has strong frequency directionality. If directions are not present, the registration performance decreases and results are slightly worst.

One of the important limitations of algorithm discussed while concluding is that the proposed algorithm works properly if captured images possess aliasing. Now a day's most of the digital cameras manufacturers design optical system of their cameras to remove the aliasing. Optical low pass filter is applied to image before it is captured to ensure that aliasing cannot occur. Hence, the algorithm presented can not perform better than regular interpolations that use single image.

Manjunath Joshi and Subhasis Choudhari in paper titled "Simultaneous estimation of super resolved depth map and intensity field using photometric cue"[13] have proposed regularization based technique to obtain the super resolution scene that simultaneously enhances the surface gradients and albeto representing the object shape and reflectance. Researchers traditionally use the motion cue to super-resolve the image. However, such methods being inherently a 2-D dense feature matching technique, it does not consider the 3-D structure of the scene being imaged, albeit such information is inherently available from the disparity map. Since the structure of an object is embedded in the images in various forms, e.g., texture, shading, etc., it limits the quality of the super-resolved image and its applicability for subsequent use in 3-D computer vision problems. To explore a structure preserving super-resolution technique, authors have investigated the usefulness of the photometric cue instead of the motion cue for super-resolving a scene. Since there is no relative motion between the camera and the scene, the super-resolution technique based on the differential spatiotemporal sampling of the plenoptic function is no longer valid. The sampled plenoptic function is sampled by taking the photographs of same scene with different light source positions. The plenoptic function is decomposed into a number of sub-functions and a generalized upsampling process with the prior-based regularization is used. The problem is stated as- given a set of observations of a static scene taken with different light source positions, obtain a super-resolved image not only for a particular light source direction but also for an arbitrary illuminant pattern. In addition, obtain the super-resolved depth map of the scene and the albeto simultaneously. Naturally, the proposed method is only applicable to indoor scenes where the ambient illumination can be controlled.

In the technique proposed the 3-D shape preservation is used as a constraint while super-resolving a scene. Given the observations under different illuminant positions, method combines these observations to obtain the super-resolved image and the spatially enhanced scene structure simultaneously. The use of shape cue in the form of photometric measurements, instead of the motion cue, eliminates the need for image registration with sub-pixel accuracy. Authors have modeled the high-resolution image, the structure, and the albeto of the surface as separate Markov random fields and super-resolve them using a suitable regularization scheme. The approach avoids the correspondence and wrapping problem inherent in current super resolution techniques that involve the motion cue in low resolution observations.

In paper “Simultaneous Estimation of Super-Resolved Scene and Depth Map from Low Resolution Defocused Observations” [14] authors Deepu Ranjan and Subhasis Choudhari have extended scope of super resolution to techniques from intensity domain to depth estimates to include high resolution depth information in a scene in addition to recovering intensity values. It is observed that one of the degradations in a low resolution image is the sensor related blur, which appears because of the low resolution point spread function of the camera. Blurring can also arise due to relative motion between the camera and the scene. In the case of real aperture imaging, the blur at a point is a function of the depth of the scene at that point. Thus, blur is a natural cue in a low resolution image formed by a real-aperture camera. Authors have exploited this blur to recover the depth map through the depth from defocus formulation; and propose how the depth map can be estimated at a higher resolution than one that can be normally extracted from such observations. They have concluded that it is indeed possible to super resolve both intensity and depth maps using the depth related defocus as natural cue.

In the single image restoration theory, three major and distinct approaches are extensive used in order to get practical restoration algorithms: Maximum Likelihood (ML) estimator, maximum a posteriori (MAP) probability estimator, and projection onto convex sets (POCS) approaches. Researchers Elad and Feuer in “Restoration of a single super-resolution image from several blurred, noisy and undersampled measured images” [15] have proposed a unified methodology for super-resolution restoration from several geometrically warped, blurred, noisy, and down-sampled measured images. It is achieved by combining maximum likelihood (ML), MAP, and projection onto convex sets (POCS) approaches. Typically, super resolution restoration methods assume that motion exists between the measured images and authors have challenged this issue whether the motion is necessary for super resolution. Theoretical analysis to show that super resolution restoration is possible even without motion between measurements. The proposed approach is single image restoration using single image. The proposed method is general that assumes explicit knowledge of linear space and time invariant blur, additive Gaussian noise, the different measured resolutions and smooth motion characteristics.

Most of the super resolution reconstruction methods assume that exposure time is fixed for all observations, which are not necessarily true. In reality, cameras have limited dynamic range and nonlinear response to the quality of light received, and exposure time might be adjusted automatically or manually to capture the desired portion of the scene’s dynamic range. The authors Bahedir Gunturk & Gevrekci in research letter "High Resolution Image Reconstruction from Multiple Differently Exposed Images"[16] have proposed a Bayesian super resolution algorithm based on an imaging model that includes camera response function, exposure time, sensor noise and quantization error in addition to spatial blurring and sampling. The basic principle of multiframe super resolution imaging is modeling imaging process between an unknown high resolution image and multiple low resolution observations and then solves this inverse problem to get high resolution image based on assumptions.

Major drawback of this approach is if assumptions are wrong, false information may be added in high resolution image. In this letter, authors have made efforts towards minimizing this error by modeling the imaging process considering exposure time along with sensor noise and quantization error as independent random variables with Gaussian distributions. It is assumed that there is no correlation among noise values at different pixel locations. The means of sensor noise and quantization error are assumed zero.

The algorithm starts with an initial guess obtained by interpolating one of the low resolution images. This reference image is updated iteratively. Each of iterations includes simple image operations: warping, convolution, sampling and scaling. For registration, spatial registration parameters are estimated using feature based method. The feature points are extracted and are matched using normalized cross correlation. After spatial registration, exposure time is estimated using least-squares estimation. The outliers are eliminted and homographies are estimated. This estimate is further fine tuned. It is noticed that this registration approach may fail when the exposure time difference is significant.

Reconstruction of super resolution image from low resolution images outliers is major problem that degrading the performance of super resolution algorithms. Authors Marcelo Victor Wust Zibetti and Joceli Mayer in paper titled "Outlier Robust and Edge Preserving Simultaneous Super resolution" [17] have proposed algorithm to reconstruct high resolution image using set of low resolution images. During reconstruction of high resolution images, there is need to estimate the motion and compensate it. Author says that during process of compensations the error may get included. These errors represent new information. This new information can be divided into two types: Firstly, small differences in the motion compensated image, which can be due to small errors in the estimated motion parameters, or due to limitations of the discretized operator in modeling the continuous motion, or even due to other temporal variations than the motion.

Secondly, large errors, assumed to be outliers. In the context of motion, an outlier is often a region that has been occluded, an object that suddenly appears in one of the images, or a region that undergoes unexpected motion. New pixels coming from outside of the image boundaries due to a translational motion are also considered outliers. Outliers degrade the performance of the super resolution algorithms. Their influence needs to be minimized either using a detection and elimination procedure. Authors have proposed a new approach that reduces the effect of outliers even without outlier's detection and removal. They simulate super resolution image by estimating entire sequence of high resolution images in one process.

Super resolution reconstruction consists of combining multiple low-resolution images of the same scene or object to form a higher resolution image. The signal processing involved is divided into two steps. The first step registers (aligns) the images, i.e., estimates the motion of pixels from one image to the others. The second step fuses the multiple (aligned) low resolution images into a higher resolution one.

One of the major issues regarding super resolution algorithms is their dependence on an accurate registration. If the displacement between images is inaccurately estimated, a super resolution algorithm may lead to image degradation instead of image improvement. This degradation is usually called registration error noise and it depends on the characteristics of both the registration algorithm and the images being processed. Recognizing the importance of the registration errors to super resolution imaging, some recent works have proposed super resolution algorithms, which are designed for robustness to such errors [6]. Researchers, Guilherme Holsbach Costa, and José Carlos Moreira Bermudez in paper titled "Statistical Analysis of the LMS Algorithm Applied to Super-Resolution Image Reconstruction" [18] have proposed different registration algorithms for super resolution image reconstruction.

It is important to determine how sensitive a given super resolution algorithm is to the motion estimation errors caused by different registration algorithms. The work in this paper is a contribution to the quantification of the sensitivity of super resolution methods to errors in the image registration process. The application of interest is the real-time super resolution algorithm of image sequences, for which fast and accurate registration tends to be more important for performance than in the case of still images. A deterministic model for its stochastic behavior is proposed. The new model permits the determination of the mean square high-resolution estimation error for a given level of registration error.

Interpolation, often used for image magnification, is sensitive to noise or non-robust to blocking artifacts or of high computational cost and hence has limited usability. Wenze Sohao, Zhihui Wei in "Efficient Image Magnification and Applications to Super Resolution Reconstruction" [19] have proposed an alternative magnification approach utilizing filtering based implementation scheme and novel regularization through coupling bilateral filtering with digital total variation model. The image magnification is formulated as inverse problem in terms of low resolution image, high resolution image and noise. The regularization theory is exploited to solve this ill-posed problem imposing some kind of a priori constraints such as locations of sharp edges, fine textures etc. The problem is further extended to super resolution reconstruction, as super resolution reconstruction and image magnification are mathematically consistent. The proposed model is simple, fast and robust and is put forth for super resolution reconstruction, which leads to new super resolution algorithm.

Nguyen et al. and Milanfar in “A computationally efficient super-resolution image reconstruction algorithm” [20] proposed a multichannel super resolution problem. Conceptually, super resolution, multichannel, and multisensor data fusion are very similar problems. The goal is to combine information about the same scene from different sources. In super resolution, in particular, the low resolution frames typically represent different “looks” at the same scene from slightly different directions. Each frame contributes new information used to interpolate subpixel values. To get different looks at the same scene, some relative scene motions must be recorded from frame to frame. If these scene motions are known or can be estimated within subpixel accuracy, super resolution is possible.

Authors model each low resolution frame as a noisy, uniformly down-sampled version of the high resolution image, which has been shifted and blurred. In this paper, authors consider only shifts of integral multiples of one high resolution pixel. A nonintegral shift is replaced with the nearest integral shift. If all possible combinations of subpixel horizontal and vertical shifts are available, the above linear system is square and reduces to essentially a deblurring problem. For each frame, the relative motions between that frame and a reference frame is approximated by a single motion vector. In the case where the scene motions are controlled, the motion vectors are known.

The proposed approach is an efficient and robust algorithm for image super resolution. The contributions in this work are twofold. First, robust approach for super resolution reconstruction employs Tikhonov regularization. To automatically calculate the regularization parameter, authors adopt the generalized cross-validation criterion to our underdetermined systems. Although generalized cross-validation is a well-known technique for parameter estimation for over determined least squares problems, the derivation for underdetermined problems is new. Secondly, to accelerate conjugate gradient (CG) convergence, authors proposed circulant-type preconditioners. These preconditioners can be easily constructed, operations involving these preconditioners can be done efficiently by FFTs, and most importantly, the number of CG iterations is dramatically reduced. In practice, it is observed that preconditioned CG takes at most the number of iterations of unpreconditioned CG, leading to significant improvement in runtime.

Experimentally it is observed that, algorithm stops after five preconditioned CG iterations because results obtained thereafter are not significantly different visually. By these experiments, authors have demonstrated that with the use of appropriate preconditioners, image super resolution is computationally much more tractable.

Reconstructing a high resolution image from several low resolution images using super resolution techniques becomes complicated when the scenes contain multiple independently moving objects. When scenes contain multiple independently moving objects, the estimated motion vectors are prone to be inaccurate around the motion boundaries and occlusion regions, which results in artifacts in the reconstructed high resolution image. To address this challenge, researchers Huanfeng, Zhang, Huang and Pingxiang, proposed a joint MAP formulation combining motion estimation, segmentation, and super resolution together in paper [21] titled, "A MAP Approach for Joint Motion Estimation, Segmentation & Super resolution". The formulation is solved by a cyclic coordinate decent process that treats the motion fields, segmentation fields, and high resolution image as unknowns and estimates them jointly using the available data.

A novel joint estimation approach for motion estimation, segmentation, and super resolution reconstruction to deal with the multiple moving objects problem is based on the following recognitions: The desired high resolution image and motion estimates are interdependent. Accurate subpixel motion estimates are critical for super resolution image reconstruction. On the other hand, a high-quality high resolution image can also facilitate accurate motion estimates. Motion estimation and segmentation are also interdependent. The success of motion segmentation is closely related to the accuracy of the motion field, and vice versa. Motion segmentation can benefit the super resolution result, especially for scenes containing multiple independent moving objects. As motion estimation, segmentation and super resolution reconstruction are mutually interdependent and influence each other, an ideal approach is addressing them simultaneously. In algorithm, all the three processes are judiciously integrated within a MAP framework. The motion fields and segmentation fields are iteratively updated along with the high resolution image in a cyclic optimization procedure. The algorithm reinforces the interdependence among the motion estimates, segmentation map and high resolution image in a mutually beneficial manner. In particular, it can suppress the artifacts around motion boundaries and occlusion regions without the need of interaction. The advantage of this algorithm is that the motion estimates, segmentation maps and high resolution image can benefit each other.

When high resolution image is obtained from set of randomly positioned low resolution images then the common space invariant blur is introduced. To minimize this blur, the researchers Tuan Pham, Vliet & Schutte [22], in “Robust Fusion of Irregularly sampled Data Using Adaptive Normalized Convolution” have proposed the super resolution fusion as a separate step after image registration and before deblurring. They have presented a novel algorithm for image fusion from irregularly sampled data based on framework of Normalized Convolution (NC). The NC is a technique for local signal modeling on a set of basis function. Use of polynomial basis function makes the traditional NC equivalent to local Taylor series expansion. Authors say that the choice of polynomial order depends on specific application. If processing speed is more important than accuracy then NC with constant basis is sufficient. This locally flat model does not model the edges and ridges very well. The first order NC with three bases can model the edges; the second order NC with six bases can further model ridges and blobs. In short, if order of NC increases, accuracy increases that requires more computation time.

In paper, authors have proposed first order NC for super resolution fusion. A full first order NC requires nine convolutions and produces three output images: interfolded image and two directional derivative for x and y dimensions. The author says that the NC better interpolates uncertain data but it requires signal certainly known in advance. In proposed technique, robust certainty is assigned to each neighboring sample before local polynomial expansion around pixel. The robust certainty being Gaussian functions of the residual error, it assigns the local weight to potential outlier. The robust certainty changes as window of analysis moves. If residual error is less than standard deviation of input noise, the certainty is extremely low.

In short, in proposed technique initially low resolution images are registered, adjusting then their weight factors followed by performing robust adaptive NC is performed and finally super resolution image is constructed using deblurring function. In NC, the local signal is approximated through a projection onto a subspace. The method performs a robust polynomial fit over an adaptive neighborhood. Each sample carries own certainty or is automatically assigned a robust certainty based on intensity difference against the central pixel in analysis window. Novelty of method lies in the adaptability that extends along local orientation to gather more samples of the same modality for a better analysis. The applicability function also contracts in the normal orientation to prevent smoothing across lines and edges. The robust sample certainty minimizes the smoothing of sharp corners and tiny details because samples from other intensity distributions are effectively ignored in local analysis.

Researchers Bo-Won Jean, Park & Yang in paper [23] have discussed drawbacks of existing resolution enhancement techniques and the drawbacks associated such as blurred edges and annoying artifacts. Solutions provided by different researchers to minimize this problem are discussed in paper as well. They have presented a resolution enhancement algorithm titled "Resolution Enhancement by Prediction of High Frequency Image Based on the Laplacian Pyramid" for predicting high frequency image based on Laplacian / Gaussian pyramid structure. The Gaussian pyramid is a set of low resolution images obtained by low pass filtering and then decimation (smooth image). The Laplacian pyramid is defined by difference image between two Gaussian images. Laplacian images contain high frequency image components such as edge details.

High frequency image is estimated by utilizing the characteristics of Laplacian images. In Laplacian Images, the normalized histogram of the Laplacian images is fitted to the Laplacian Probability Density Function (pdf) and the parameter of Laplacian pdf is estimated based on Laplacian image pyramid. In addition, a control function is employed to remove overshoot artifacts in reconstructed image. The proposed algorithm is tested over RGB color images. The RGB image is converted to YUV format, only Y component is processed by proposed algorithm, and the components U and V are interpolated using bilinear interpolation.

Since the human visual system is sensitive to luminance components and relatively insensitive to color components, magnifying U and V components by a simple bilinear interpolation method has not influence on image quality much. Results are compared with interpolation. The computational cost and PSNR are the parameters considered for comparison. Proposed method shows better results than conventional approaches in terms of connectivity, sharpness at edges and smoothness in uniform region.

Due to physical limitations of sensor and imperfect observation conditions, the captured images represent only degraded versions of original scenes. Mainly high frequency information is suppressed, degraded or missing. The fusion low resolution images are effective means of breaking of sensor limitations and removing a degradation introduced by atmospheric turbulence, sensor motion and other factors. To construct the high resolution image from such low resolution images is more complicated task. In paper titled “Resolution Enhancement via Probabilistic Deconvolution of Multiple Degraded Images”, authors F. Sroubek & J Flusser [24] present a maximum a posteriori (MAP) solution to the problem of obtaining a high resolution image from set of degraded low resolution images of the same scene. Authors claim that in most of the super resolution algorithms, prior knowledge of blurring function is necessary for reconstruction. The main feature of proposed fusion technique is that that no prior knowledge of blurring function is required. In this paper, they present stochastic fusion method that performs multi channel blind convolution and the super resolution simultaneously. The proposed method mainly focuses on accurate identification of a subpixel shift and the formation of different methodologies to find super resolution solution. Further authors claim that this approach provides the high quality fused image fully comparable to the ideal one. Further, they claim that solving the super resolution and blind convolution simultaneously is a pioneering step in the field of image reconstruction.

Registration being a very important step in ensuring success of super resolution, accurate motion estimation is key factor. Many existing super resolution algorithms assume the displacement is known a priori that is known image formation model or try to estimate the registration parameters by assuming a translational motion model or through an iterative two phase estimation procedure. Y. He, K. Yap, L. Chen & L. Chau, in paper “Joint Image Registration and Super Resolution Using Nonlinear Least Squares Method” [25], present a new algorithm to integrate image registration into super resolution by fusing multiple blurred low resolution images to render a high resolution image. The registration and high resolution reconstruction is handled jointly. It is an iterative scheme based on nonlinear least squares method to estimation of motion shift and high resolution image progressively. Unlike traditional two stage super resolution methods, the image registration estimated from the high resolution image iteratively instead of low resolution images. Conventional Super resolution methods assume that the estimated motion errors by existing registration method are negligible or the displacement is known a priori. This assumption, however, is not practical as the performance of existing registration algorithms is still less than perfect. In this regard, the proposed framework for joint registration and reconstruction is beneficial. Results demonstrate that method is effective in performing image super resolution.

Cohen, Avrin and Dinstein in paper titled “Polyphase Back Projection Filtering for Resolution Enhancement of Image Sequences” [26], have proposed a method for resolution enhancement of image sequence by polyphase back projection filtering. The work is extension of super resolution image sequence restoration algorithm proposed by Avrin and Dinstein [68]. The first super resolution images are initiated by interpolation of the first low resolution image. The imaging system is simulated for every super resolution image at a time, and the error between the simulated image and the corresponding low resolution image is calculated. This error is back projected to the corresponding super resolution image for resolution enhancement. The imaging system Point Spread Function and back projection filter are estimated with a resolution higher than that of the super resolution image and filtering is done by polyphase version of these filters. The polyphase filters have embedded subpixel displacements corresponding to translation parameters between the super resolution image and low resolution one. The use of polyphase filters allows exploitations of the observed data without any smoothing and /or interpolation operations. In addition, known modeling of the PSF by an analytical function is necessary.

Authors Balaji N, Kenneth E in paper titled “A Computationally Efficient Super Resolution Algorithm for Video Processing using Partition Filters” [27], propose a computationally efficient super resolution algorithm to produce high-resolution video from low-resolution video using partition-based weighted sum (PWS) filters. First, subpixel motion parameters are estimated from the low resolution video frames. These are used to position the observed low resolution pixels into a high-resolution grid. Finally, PWS filters are employed to simultaneously perform nonuniform interpolation (to fully populate the high resolution grid) and perform deconvolution of the system point spread function. Unlike traditional methods, PWS filters are then employed to perform nonuniform interpolation and image restoration simultaneously. The PWS filters operate with a moving window on the high resolution grid. At each window location, the output is formed using a weighted sum of the pixels present in the high resolution grid that are spanned by the window. The weights used at each window location depend on the configuration of missing pixels on the high resolution grid within the span of the window and the intensity structure of the present pixels. The intensity structure is classified using vector quantization (VQ). The PWS may be viewed as a spatially adaptive Wiener filter and it has been shown to be an effective way to treat the non-stationary commonly found in images. The proposed PWS filter training and implementation methodology makes it suitable for video processing. With the proposed algorithm, the bulk of the filter training is done offline. For the case of translational motion, minimal computations are required per frame to obtain all the needed filter weights. In quantitative experimental results, the proposed method generally outperformed the benchmark methods and has one of the lowest computational complexities.

Authors believe that, in addition to super resolution image enhancement, the proposed technique is a very useful tool for addressing the general problem of nonuniform interpolation. The primary novel contribution of this paper is the innovative PWS filter training and implementation methodology for super resolution enhancement of video. Authors have presented a detailed computational analysis, quantitative comparisons with several benchmark techniques, and apply and evaluate the method with rotational motion as well as translational motion.

The study report of literature for theoretical aspects and a set of super resolution imaging techniques, which are reconstruction based [1-27] is presented till now. These reconstruction based approaches seek to create an high resolution image estimate that, when put through the image observation model, produces simulated low resolution frames that closely match the observed frames and is consistent with certain a priori assumptions.

Another technique that is popularly used for super resolution image reconstruction is Learning Based Approach that is neural network based. These use a learning scheme to capture the high-frequency details by determining the correspondence between low resolution and high resolution training images. In this technique either set of images or an image is used to reconstruct the super resolution image. Once the network is trained, the high resolution image is reconstructed from captured low resolution image. Detailed survey of these techniques is presented further with their pros and cons.

The super resolution problem is said to be ill posed one. To obtain desired resolution image requires reasonable assumptions about nature of true image. Approach presented by authors in [28] addresses ill posed nature of super resolution by assuming that similar neighbors remain similar across the scales. Hence, structure of image can be learned locally from available image samples across the scale.

In [28] the authors Frank M. Candocia, and Jose C. Principe, in paper titled “Super-Resolution of Images Based on Local Correlations” have developed an adaptive two-step paradigm for the super resolution of optical images. The procedure locally projects image samples onto a family of kernels that are learned from image data. First, an unsupervised feature extraction is performed on local neighborhood information from a training image. These features are then used to cluster the neighborhoods into disjoint sets for which an optimal mapping relating homologous neighborhoods across scales can be learned in a supervised manner. A super-resolved image is obtained through the convolution of a low-resolution test image with the established family of kernels.

The results of proposed approach are nearly accurate under assumption that given a class of images, there is much similar local structure among images and that this similarity holds across the scales. The fundamental problem here is to decide similarity of local information and capture similarity across the scale. The solution to the problem is discussed by author. When new image is presented, the kernel that best reconstructs each local image region is selected automatically and output is reconstructed. In this technique, it is assumed the clusters are similar in some scenes. Nevertheless, practically this assumption is not fully correct and hence the establishment of kernel may not be proper. Hence each cluster neighborhood transforms into its corresponding to high resolution neighborhood may be wrong.

Super resolution imaging is defined as creation of high resolution view of pixel based image through interpolating original pixels. Natural images are highly redundant on a pixel by pixel, such as lines and textures. Greater super resolution can be achieved by taking advantage of these local features inherent in natural images. Local group of pixels in natural images has much less variability than they would have in randomly generated images. Such regularities can be used to reconstruct high resolution image accurately. However, identifying these regularities is difficult task.

To discover and learn these statistically significant features of natural images, the authors Olcay Kursun and Oleg Favorov have used SINBAD (Set of Interacting Back propagating Dendrites) to reconstruct high resolution image in paper titled “Single frame super resolution by a

Cortex based mechanism using high level visual features in natural images" [29]. Single frame super resolution task involves interpolating between the pixels in the original single frame image to generate higher resolution view where the challenge is to prevent blurring or loss of lines, edges and fine textural details in enlarged image. They have achieved super resolution through interpolating the original pixels for creation of high resolution view of pixel based image. SINBAD method allows inferring missing pixel values better and authors have explained how it can be used to reconstruct super resolution image using single low resolution image. The standard interpolation techniques are insensitive to the lines or textures in the images. The results show that SINBAD interpolation is visually significantly better by filling the reconstructed image with realistic fine spatial details, such as sharp lines and edges. However, for some images it is observed that few lines and edges are broken down into separate segments in reconstructed image.

Standard pixel interpolation methods, such as pixel replication and cubic-spine interpolation, introduce artifacts or blur edges. Researchers W. T. Freeman, T. R. Jones, and E. C. Pasztor, in paper titled "Example based Super resolution" [30] refer the methods that achieve high resolution enlargement of pixel based images as the super resolution algorithms. Many applications such as in graphics or image processing could benefit from resolution independence, including IBR, texture mapping, enlarging consumer photographs, and converting NTSC video content to high-definition television. Authors have proposed example based, training based, single image, and one pass super resolution algorithm. Their algorithm requires only nearest neighbor search training set for a vector derived from each patch of local image data. Authors have discussed basic three techniques to improve resolution of image:

1. Sharpening by amplifying existing image details. This is the change in the spatial frequency amplitude spectrum of an image associated with image sharpening. Existing high frequencies in the image are

amplified. This is often useful to do, provided noise is not amplified.

2. Aggregating from multiple frames. Extracting a single high-resolution frame from a sequence of low-resolution video images, adds value and is referred as super-resolution.
3. Single-frame super-resolution- the goal is to estimate missing high-resolution detail that is not present in the original image.

Authors strongly suggest that one should use one of these methods wherever applicable as per needs and availability of input low resolution image(s). Authors have been exploring a learning-based approach for enlarging images [70, 71, and 72]. In a training set, the algorithm learns the fine details that correspond to different image regions seen at a low-resolution and then uses those learned relationships to predict fine details in other images. The training set is generated from collection of high resolution images by degrading them. Using cubic-spine interpolation high resolution images are obtained. The difference between original high resolution image and interpolated image is only saved for training set. They also save high resolution patch corresponding to every possible low-resolution image patch. Even restricting to plausible image information, there is a huge amount of information to store, so authors suggest that one must preprocess the images to remove variability and make the training sets as generally applicable as possible.

Authors believe that the highest spatial-frequency components of the low-resolution image are most important in predicting the extra details and that the relationship between high- and low-resolution image patches is essentially independent of local image contrast. Authors put forth that if local image information alone were sufficient to predict the missing high-resolution details, the training set patches by themselves can be used for super-resolution. Authors worked on this principle and noticed that their approach does not work properly. Further, in their research work, they have used it globally instead of locally and better results are achieved.

Author says that the missing high frequency details can be estimated from single low resolution image for constructing high resolution image. They have explored two different approaches to exploit neighborhood relationships in super-resolution algorithms. The first uses a Markov network to probabilistically model the relationships between high- and low-resolution patches and between neighboring high-resolution patches. It uses an iterative algorithm, which usually converges quickly. The second approach is a one-pass algorithm that uses the same local relationship information as the Markov network. It is a fast, approximate solution to the Markov network. Major steps involved are- construct high-resolution image using conventional interpolation from low resolution image and predict the missing image details based on patches.

The algorithm works best when the data's resolution or noise degradations match those of the images to which it is applied. Numerically, the root-mean squared error from the true high frequencies tends to be approximately the same as for the original cubic-spine interpolation. Unfortunately, this metric has only a loose correlation with perceived image quality.

Defining Super-resolution as the process of producing a high spatial resolution image than what is not afforded by the physical sensor through post processing, making use of one or more low resolution observations, authors C V Jijji & S. Chaudhari [31] in paper titled "Single Frame Image Super Resolution through Contourlet Learning" have proposed a learning based, single frame super resolution reconstruction technique. The technique uses contourlet transform that is capable of capturing the smoothness along the contours making use of directional decomposition. The basic theme of paper is to reconstruct the super resolution image using single low resolution image using database of several high resolution images. The single frame image super resolution problem arises in several practical situations. In many biometric databases, a large number of images of similar contents, shape, and size are available. If one encounters a poor quality of image, it can be enhanced using the knowledge of the properties of the database images.

Authors have used the contourlet transform to learn the best features from high resolution image database while upsampling the image. The contourlet transform is an extension of the Cartesian wavelet transform in two dimensions using multiscale and directional filter banks. The contourlet expansion of images consists of basis images oriented at various directions in multiple scales, with flexible aspect ratios. Thus, the contourlet transform retains the multiscale and time-frequency localization properties of wavelets. In addition, it also offers a high degree of directionality.

Authors have said that when an image is interpolated, a region without any edges does not suffer from any degradation. However, if it contains edges, they are blurred during the upsampling process. This is major problem of existing interpolation techniques. The algorithm learns the mapping of a low resolution edge to its high resolution representation locally from the training data set during upsampling. Since wavelets are known to capture the high-frequency details very well locally, they propose to use wavelets to learn this mapping.

In the single-frame super-resolution algorithm proposed in [32], authors of [31] have used a wavelet-based learning technique where the high resolution edge primitives are learned from the high resolution data set locally with the assumption that a primitive edge element in the high resolution image is localized to an 8×8 pixel area, and the corresponding edge elements over a 4×4 pixel area in the low resolution image. Each local region is learned independently from the high resolution data. Authors have extended this research work in [31]. They have used contourlet transform. The contourlet coefficients at finer scales of the unknown high resolution image are learned locally from a set of high resolution arbitrary set of training images, the inverse contourlet transform of which covers the super resolution image.

Paper titled “Super Resolution through Neighbor Embedding” by authors Hong Chang, Dit Yan Yeng [33] propose a novel method for solving single-image super-resolution problems. Given a low-resolution image as input, method recovers its high resolution counterpart using a set of training examples. The focus of this paper is on generating a high-resolution image from a single low-resolution image, with the help of a set of one or more training images from scenes of the same or different types; and the technique is referred as the single-image super-resolution problem. The single-image super-resolution problem arises in a number of real-world applications. A common application occurs when one wants to increase the resolution of an image while enlarging it using digital imaging software (such as Adobe Photoshop). Another application is found in web pages with images. To shorten the response time of browsing such web pages, images are often shown in low-resolution forms (as the so-called “thumbnail images”). An enlarged, higher resolution image is only shown if the user clicks on the corresponding thumbnail. However, this approach still requires the high-resolution image to be stored on the web server and downloaded to the user’s client machine on demand. To save storage space and communication bandwidth (hence download time), it would be desirable if the low-resolution image is downloaded and then enlarged on the user’s machine. Yet another application arises in the restoration of old, historic photographs, sometimes known as image inpainting. Besides reverting deteriorations in the photographs, it is sometimes beneficial for enlarging them with increased resolution for display purposes.

In proposed approach, a feature vector corresponding to patch is reconstructed by its neighbors in the feature space. For each patch in the low-resolution image, algorithm first computes the reconstruction weights of its neighbors in feature vector set by minimizing the local reconstruction error. The high-resolution embedding is then estimated from the training image pairs by preserving local geometry. Finally, authors enforce local compatibility and smoothness constraints between adjacent patches in the target high-resolution image through overlapping.

As in local linear embedding (LLE), local geometry is characterized by how a feature vector corresponding to a patch can be reconstructed by its neighbors in the feature space. Besides using, the training image pairs to estimate the high-resolution embedding, authors also enforce local compatibility and smoothness constraints between patches in the target high-resolution image through overlapping. The approach is based on assumption that the high dimension data points whose corresponding low dimensional data points are neighbors will still be neighbors in high dimension space. However, in super resolution, this is not true. If low dimension patches are in neighborhood, their corresponding high resolution patches are not in neighborhood any more and vice versa. This is neighborhood issue associated with single image super resolution algorithms. Authors have concluded with few future research directions. In order to increase neighborhood preservation, there are two possible ways. One is two select a good feature to represent image patch that can preserve neighborhood better. In addition, the other is to select a good reconstruction function given some high resolution neighbor patches.

Liming Zhang and Fengzhi Pan have proposed “A New Method of Images Super Resolution Restoration by Neural Network” [34] for generating an image that has higher resolution than that of the original one. The proposed super resolution restoration scheme is based on neural network. They assume that the low resolution image is obtained from high resolution image by low pass filtering and down sampling. Under these assumptions, they have discussed relationship between low and high resolution images mathematically. They construct high resolution image and corrections are made by residual error restoration.

Authors have presented results to put forth that they are better than interpolation. As the multi-frame interpolation consume tremendous time and storage, they are difficult to use in real time. Hence, authors have proposed a single image based super resolution scheme combining intra-frame interpolation and linear restoration of residual errors by neural networks. It is concluded that the proposed technique has short training time, good generalization and small computation consumption and hence can be easily implemented on real time. The system trained with only one image, can be used to magnify other images accurately.

This method may work and may provide correct results if assumptions are correct and original high resolution image are available to estimate the residual error. If high resolution original image is not available then proposed algorithm cannot work.

David Chapel and Zisserman [35] in “Super Resolution from Multiple Views Using Learnt image models” have discussed objective of super resolution restoration. The super resolution restoration aim at solving problem: given a set of observed images, estimate an image at higher resolution than is present in any of the individual images. The observed images are regarded as degraded observations of a real, high resolution texture. These degradations typically include geometric warping, optical blur, spatial sampling and noise. Given several such observations, a maximum likelihood (ML) estimate of a super resolution image may be obtained such that, when projected back into the images via a generative imaging model, it minimizes the difference between the actual and predicted observation.

The author has discussed the learning image model and this learning image model is used for super resolution imaging from set of images. In paper, it is demonstrated that restoration of far higher quality than that determined by classical maximum likelihood estimation can be achieved by either constraining the solution to lie on a restricted subspace or by using the subspace to define a spatially varying prior.

This subspace can be learnt from image examples. The proposed technique is applied to both real and synthetic images of text and faces and it is claimed that quality of results based on face space model may be improved by using large set of printing images.

They have explored the learning constrained models and priors from training images and applying those to super resolution restoration. Authors have used classes of scenes where the intensity distribution of neighbors is not spatially homogeneous. The constrained model is a subspace, which is computed using principle component analysis of a set of registered face images. This subspace is used to define spatially varying prior within a MAP estimator. Novelty of this method is that the low resolution images need not be at same resolutions. Results are demonstrated using real face images.

The quality of an image can be evaluated on its spatial frequency resolution. Image interpolation and super resolution are the ways to respectively produce high spatial and high spatial frequency resolution of image especially for a single down sampled image. Some algorithms have been proposed in the literature [1-27], where a high resolution image is reconstructed by combining multiple low resolution images and incorporating with some constraints for the specific purpose. The paper [36] considers hyper-resolution for a single gray-level or color image without any constraint. Furthermore, hyper-resolution of a noisy image is also performed; generally, the procedure for processing noisy images that is, noise removal, interpolation, and then super-resolution; whereas the proposed scheme is dealing with interpolation and noise removal simultaneously.

Min Cheng Pan in paper "Improving a Single Down-sampled Image Using Probability Filtering Based Interpolation and Improved Poisson Maximum a Posteriori Super Resolution" [36], have presented technique for super resolving a single down sampled image. The approach uses interpolation and smoothing simultaneously by exploiting probability filter coupled with a pyramidal decomposition, thereby extending the conventional applications of probability filter originally designed for noise removal. Later, the improved Poisson Maximum a Posteriori (MAP) super resolution is performed to reconstruct high spatial frequency spectrum of interpolated image. Further author has suggested exploiting the inter-correlation among the colors to significantly improve performance as it would extend adaptive capability by incorporating image characteristics.

Rajaram, Gupta, Petrovic and Huang [37] in "Learning Based Nonparametric Image super resolution" have presented a novel learning based framework for zooming and recognizing images of digits. Authors have presented approach that can handle image restoration with super resolution. The author says that there are two basic research approaches used to reconstruct image in time domain: Iterative and learning based. In iterative approach, initially guess the high resolution frame and is refined in each iteration. The principle idea of machine learning approach is to use set of high resolution images and their corresponding low resolution frames to build the compatibility model. The images are stored as patches or coefficients of other feature representations. In principal component analysis (PCA) based technique, the relation between low resolution and high resolution patches has been defined. Then nonparametric modeling was used to estimate missing details. The authors strongly say that the learning based approach can be made more powerful and robust if images are restricted to specific type.

The work presented in paper has two unique features: partial messages and restoration super resolution recognition loop. The reconstruction algorithm is built on notation of partial message propagation. They propose that any given image patch is only partially influenced by its neighbors, depending on spatial orientations.

Proposed method is not example-based method, which means that reconstructed image is not limited to one of the candidate from training set. The reconstructed high resolution image may be similar to few patches of training image. The proposed algorithm is based on the assumption that training set includes various kinds of blurs. These blur images are used as training set to train the network.

The crucial feature of this work is an iterative loop that alternates between super-resolution and restoration stages. A machine-learning-based framework has been used for restoration, which also models spatial zooming. Image segmentation is done by a column-variance estimation-based “dissection” algorithm. Initially, the compatibility functions are learned by nonparametric kernel density estimation, using random samples from the training data. Next, algorithm solves the inference problem by using an extended version of the nonparametric belief propagation algorithm, in which it introduces the notion of partial messages.

Finally, algorithm recognizes the super-resolved and restored images. The resulting confidence scores are used to sample from the training set to better learn the compatibility functions. Images are obtained from vehicle registration plates, which are blurred using an unknown kernel. The image is modeled as an undirected graphical model over image patches in which the compatibility functions is represented as nonparametric kernel densities. A machine learning based framework is used for restoration that models spatial zooming. Results demonstrate significant improvement in recognition performance for synthetic images and digits in license plate.

The richness of real world images would be difficult to capture analytically. This motivates researchers to use a learning based approach where the parameters of the super resolved image can be learned from the most zoomed observations and hence, can be used to estimate zoomed entire scene. Authors M Joshi, S Choudhari and R Panuganti in paper [38] titled “A Learning Based Method for Image Super Resolution From zoomed Observations” propose use of the homogeneous MRF to model the high resolution field for learning purposes. However, the learning of MRF parameters is computationally tedious job. The estimates of MRF parameters are obtained using a maximum Pseudo likelihood (MPL) estimator in order to reduce the computations. Algorithm learns the field parameters on the fly instead of assuming them to be known. Often learning based methods use observations at the same resolution. Authors use observations at arbitrary levels of resolution (scale) and these scale factors are estimated while super resolving the entire scene. The super resolved image of the entire scene is generated although only part of the observed scene has multiple observations.

Efficiency of proposed technique has been demonstrated with results. First order MRF is used to model the intensity process. Metropolis-Hasting algorithm is used to set initial values of parameters as unity. The convergence of algorithm was observed for most of the cases in 1000 iterations. Using initial parameter set super resolved scene is obtained. The results are compared with bilinearly interpolated results. It is noticed that both images are quite blurred near periphery. The zoom factor two is found quite well. For zoom factor four, one needs to reconstruct 16 pixels for each observed pixel near periphery, which is difficult task. Again, the comparative results where the prior term uses a second order neighborhood show that there is no perceptual improvement with an additional order introduced in prior term. It is suggested that the improvement is gradual as the order of the MRF parameterization is increased. Ideally, one requires a large number of cliques to learn the prior. However, the computation goes up drastically while learning the scene prior. Hence, authors refrain from using a neighborhood structure beyond a second order.

Fuzzy classification techniques have been developed recently to estimate the class composition of image pixels, but their output provides no indication of how these classes are distributed spatially within the instantaneous field of view represented by the pixel. As such, while the accuracy of land cover target identification has been improved using fuzzy classification, it remains for robust techniques that provide better spatial representation of land cover to be developed. Such techniques could provide more accurate land cover metrics for determining social or environmental policy. Andrew J. Tatem, Hugh G. Lewis, Peter M. Atkinson, and Mark S. Nixon, in paper, “Super-Resolution Target Identification from Remotely Sensed Images Using a Hopfield Neural Network” [39] have investigated the use of a Hopfield neural network to map the spatial distribution of classes more reliably using prior information of pixel composition determined from fuzzy classification. An approach has been adopted that used the output from a fuzzy classification to constrain a Hopfield neural network formulated as an energy minimization tool. The network converges to a minimum of an energy function, defined as a goal and several constraints. Extracting the spatial distribution of target class components within each pixel was, therefore, is formulated as a constraint satisfaction problem with an optimal solution determined by the minimum of the energy function. This energy minimum represents a “best guess” map of the spatial distribution of class components in each pixel.

The technique is applied to both synthetic and simulated Landsat TM imagery, and the resultant maps provided an accurate and improved representation of the land covers studied, with root mean square errors (RMSEs) for Landsat imagery of the order of 0.09 pixels in the new fine resolution image recorded. As such, authors show how, 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. The Hopfield neural network used in this way represents a simple, robust, and efficient technique, and results suggest that it is a useful tool for identifying land cover targets from remotely sensed imagery at the subpixel scale.

Super-resolution has been considered as an inverse problem, which needs to recover the lost information due to under sampling. To tackle this ill-posed problem, researchers have proposed various methods, which take use of the learning capability of neural networks to learn the mapping between the high-resolution and the low resolution images. Authors Shuangteng Zhang, Yihong Lu in paper in “Image Resolution Enhancement Using a Hopfield Neural Network” [40], have presented a neural network based single-frame super-resolution technique. In this technique, an observation model, which closely follows the physical image acquisition process, is established. And based on the model; a cost function is created and minimized by using a Hopfield neural network to enhance the resolution of the under sampled images. An effective way to solve ill-posed optimization problems is to minimize some cost function with regularization, which is usually a smoothing constraint. This technique takes into consideration both PSF (Point Spread Function) blurring and additive noise. Hopfield type neural networks have demonstrated great potential for solving optimization problems. A Hopfield neural network is used to minimize the cost function. The Hopfield neural network is a single-layer feedback neural network, consisting of N interconnected neurons with connecting weights. This single-frame super-resolution technique takes into consideration both blurring and additive noise and generates high-resolution images with more preserved or restored image details.

Outliers are defined as data points whose distributions do not follow as assumed model. One of the major issues of super resolution techniques is their dependence on an accurate modeling of super resolution problem. Authors Guilherme Holsbach Costa and José Carlos Moreira Bermudez in paper titled “Informed Choice of the LMS parameters in Super Resolution Video Reconstruction Applications” [41] have discussed effect and solution for it. The paper addresses the design of the least mean square algorithm applied to super resolution reconstruction. Based on statistical model for the algorithm behavior, authors have proposed a design strategy to reduce effect of outliers. They have proposed a strategy for the choice of the parameters of the choosing the step size and the number of algorithm iterations per time sample in order to minimize the effects of outliers in the reconstructed image sequence. Authors have studied the effect of these two parameters on the algorithm performance and have shown that reducing the step size does not always slow down the algorithm or lead to better steady state estimations. But this conclusion contradicts with the typical least mean square behavior.

Most of the learning based single image super resolution algorithms search the database for estimating respective high resolution patch for each low resolution patch. These methods need a good database of images and search through it which takes considerable amount of time. Authors Heng Lain, in paper “Variational Local Structure Estimation for Image Super Resolution” [42] has tried to overcome these limitations by suggesting an algorithm for single image super resolution that does not use training images or database of images. Algorithm estimates each low resolution pixel value as a linear combination of neighboring pixel values and uses local structure to construct filter for interpolation. Drawback of algorithm is that interpolation adaptive filter design used is based on estimated local structure of an image. The resulting filter reflects both local pixel variance and global image information. This approach is still based assumption that pixel structure has relations in all directions. It leads to smoothing effect as specific directional structure is not exploited to good extent.

Author has further put forth that super resolution is an important but difficult problem in image or video processing. Reconstruction of high resolution image becomes easy if extra information is available through video sequence or set of training images. The problem is substantially more difficult if only single low resolution image is available. Author has proposed a new adaptive linear interpolation for single image super resolution problem. With only one image it is generally difficult to interpolate the missing pixel with little prior information about image. Traditionally bilinear or bicubic interpolation methods are used that work under assumption that images are smooth for most of the part.

Dirk Robinson & Milanfar in “Statistical Performance Analysis of Super Resolution” [43], have analyzed the performance bounds for super resolution algorithms combining set of low resolution images performing joint task of registering and fusing the low resolution data sets. This analysis measures the performance limits from statistical first principle using Cramer-Rao(CR) inequalities. The analysis offers insight into the fundamental super resolution performance bottlenecks as they relate to other associated problems such as registration, reconstruction and image restoration. The analysis shows that there is no single bound which applies to all super resolution operating scenario as others have done in the past. Instead, they have shown that super resolution performance depends on a complex relationship between measurement SNR, the number of observed frames, and set of relative motion between frames, image contents, and imaging systems PSF.

The authors instead have presented problem in the Fourier domain that facilitates numerical analysis of the CR bound. Authors have proved that degradation in super resolution performance can be substantial when image motion must be estimated from the data, as opposed to being known a priori. This degradation occurs most severely along edges within image. The analysis presented focuses on the case of image sequences containing simple translational motion. It is showed that when the motion vectors are uniformly random, the performance bounds exhibit a threshold number of frames, above which reasonable performance may be expected with high probability.

In [44] the paper titled “Multi-Objective Super Resolution: Concept and Examples”, the authors Deepu Ranjan, S Chaudhari, M Joshi have addressed various issues related to motion estimation and modeling. Authors have looked at the possibility of capturing multiple observations of a scene with different types of cues in which each frame does contain some additional information, although there is no relative positional shift among them. Further authors have expanded the scope of super resolution technique to include recovering intensity values. In this way, they get not only an super resolution image but also the structural information of a scene at higher resolution. Authors have named their algorithm the multi-objective technique in which they have recovered various high resolution structural (physical properties) of a surface besides the super resolving the intensity field. They have fed back extracted structural information to the super resolution algorithm whereby such information is used to generate the super resolution image in an alternated iterative way. The structural information is embedded within observations and, through the two formulations of DFD (depth from focus) and shape from shading (SFS) problems they generate super resolution image and structure. The DFD method avoids correspondence and wrapping problem inherent in current super resolution techniques involving the motion cues a more natural depth related focus as a natural cue in real aperture imaging.

In “Limits on super-resolution and how to break them,” [45] authors S. Baker and T. Kanade, have presented limits on super resolution and techniques to break them. The paper is in to parts. In first half of paper authors have showed that the super resolution reconstruction constraints provide less and less useful information as magnification factor increases. The major cause is the spatial averaging over the photo sensitive area is nonzero. In order to be able to capture nonzero number of photons of light, authors have derived a sequence of analytical results to support these conclusions. It is claimed that any smoothness prior leads to overly smooth results with very little high frequency contents.

In second half authors have proposed a super resolution algorithm that uses a different kind of constraints, in additional to the reconstruction constraints the algorithm attempts to identify local features in low resolution images and then enhances there resolution appropriately. They have developed a super-resolution algorithm by modifying the prior term in the cost to include the results of a set of recognition decisions, and call it recognition-based super resolution or hallucination. They have introduced the notion of a recognition-based prior as a prior that is a function of a collection of recognition decisions. Their prior enforces the condition that the gradient in the super-resolved image should be equal to the gradient in the best matching training image. The algorithm learns a recognition based prior for specific classes of objects, scenes or images. Algorithm has been applied to super resolution, both for faces and text, claiming that it has obtained significantly better results both qualitatively and in terms of RMS pixel error than traditional reconstruction based super resolution algorithms using standard smoothness priors. After investigating how much and from where the information comes from when that information is, author puts forth two conclusions: firstly, information content is fundamentally limited by the dynamic range of images; secondly, strong class based priors can provide far more information than the simple smoothness priors that are used in existing super resolution algorithm.

Recently researchers have started using wavelet for super resolution image reconstruction. Though researchers have used wavelet in either registration phase or for interpolation, popularly they have used wavelet for noise removal in multiframe based super resolution imaging. Wavelet has also been used widely in single frame super resolution algorithms. In these algorithms the assumption is low resolution is low pass filter output of wavelet transform of original high resolution scene.

In paper titled “Simultaneous Noise Filtering and Super Resolution with Second Generation Wavelets” by authors Mahesh Chappalli and N K Bose [46] have defined the term super resolution as algorithm that produces the high resolution image by combining the information from the captured low resolution images. Authors say that due to various factors like, imperfections in acquisition device, limited resolution of physical sensing elements, motion and medium turbulence, the low resolution frames are blurred and noisy. Hence super resolution algorithms commonly include the noise filtering and deblurring modules.

In this paper they propose the wavelet coefficient thresholding for reducing spatial denoising. The choice of the threshold plays crucial role in super resolution algorithm. Thresholding of wavelet coefficients reduces the noise in reconstruction but that may create significant blurring in reconstructed image.

The choice of the optimum threshold involves the tradeoff between noise filtering and blurring introduced by thresholding. Generally higher level of PSNR and lower value of mean square error are expected to be indicators for better visual quality. However, it is known that PSNR does not match human visual system; that is, higher PSNR does not always imply better visual quality. It is observed that HVS is more sensitive to blurring than to the noise. Image quality means Q, is more sensitive to blur than PSNR and hence Q is one of the factors to find optimum threshold. Results show that threshold increases from zero there is initially significant improvement in image quality due to noise reduction. But as threshold increases, effect of blur introduced due to threshold starts dominating quality of reconstructed image.

It is observed that the high frequency components are considered as noise for visual quality point of view and hence the used method of thresholding to remove the noise. But in reality in all images we can not consider high frequency components present as noise only. These may be original representations of image or scene. And hence the proposed technique may remove important details of scene. The super resolution reconstruction of image the preserving originality of image is more important than visual quality.

In paper “Wavelet Domain HMT Based Image Super resolution” by authors Shubin Zhao, Hua Han and Silong Peng [47], image super resolution algorithm using wavelet domain Hidden Markov tree model (HMT) domain has been proposed. In this paper single image is used to reconstruct the super resolution image under the assumption that low resolution image is noise free. By introducing HMT model, image super resolution is formulated as constrained optimization problem.

Wavelet-domain HMT models the dependencies of multiscale wavelet Coefficients through the state probabilities of wavelet coefficients, whose distribution densities can be approximated by the Gaussian mixture. Because wavelet-domain HMT accurately characterizes the statistics of real-world images, that reasonably specify it as the prior distribution and then formulate the image super-resolution problem as a constrained optimization problem. The experimental results show that the reconstructed high resolution image exhibits visual artifacts in the neighborhood of discontinuities, including ringing and sawtooth effects, Gibbs phenomena. Authors have used the "cycle spinning" technique to suppress such artifacts. Initially the low resolution image is magnified two times using bicubic spine interpolation. So, through different sampling it obtains four small images of the same size as the original low resolution image. Then, using the algorithm reconstructs four high resolution images from these four small images. Finally, after registration, averaging these four high resolution images gives a high resolution image in which almost all visual artifacts are removed.

Authors Choong boon, Onur Guleryuz, Toshiro and Y Suzuki in paper "Sparse Super resolution reconstruction of video from mobile devices in digital TV broadcast applications PS-2006-0117" [48] have discussed efficient use of super resolution technique in video communication, digital TV broadcasting application using mobile device and proposed the wavelet based sparse super resolution reconstruction technique. They say that multi-frame super resolution technique is not suitable for use in digital TV broadcasting application because of need of buffers, extensive memory operations (more delay) and accurate motion estimation. They provide a novel technique to construct super resolution image using single low resolution frame so that required delay is negligible, no need of buffer, less extensive memory operations and motion estimation. In this paper the approximate component of original image is only used to reconstruct the super resolution image at destination. From the low frequency component they have proposed estimation of missing high frequency subband of wavelet transform. They claim that estimation procedure proposed in the paper guess high frequency subbands accurately. Also the results obtained are better than simple inverse. Results are presented in paper with subjective and objective performance measures.

The new technique for reconstruction of super resolution image that includes image registration and wavelet based interpolation is proposed by authors N K Bose and S Lertrattanapanich in paper titled " Advances in Wavelet Super resolution"[49]. Author says that considerable progress has been reported in the task of reconstruction of functions from their sample at nonuniformly distributed locations. Currently, most of the researchers propose the reconstruction of high resolution image from multiple aliased low resolution noisy and blurred frames. Feasibility of these motivates research into deployment of other transform method, particularly, the wavelet transform. In paper author has discussed multi-resolution analysis for 2D signal (image) and wavelet based interpolation of 2D nonuniformly sample data. Multiple shifted low resolution images are first registered and then the wavelet based interpolation is used to get high resolution image.

In [50], the paper "Application of Wavelet-based POCS Super resolution for Cardiovascular MRI Image Enhancement", authors have presented image super resolution method to enhance the spatial resolution MRI heart image from temporal sequence. In this paper author says that because of time limit to scan the MRI image it is difficult to capture the high resolution image even though the facility is available. To scan the high resolution MRI image, more time is required. When non stationary objects such as beating heart is scanned, it introduces the motion artifacts in image thus limiting the spatial resolution of cardiovascular images. And hence there is need to scan low resolution MRI image and reconstruct the high resolution image.

In paper, the wavelet based projection onto convex set super resolution algorithm is discussed. It starts with initial guess of the high resolution source image, projects it into the simulated measurement space, and updates the guess according to the simulation error. A convex set is defined which represents certain tight constraints on the solution image. The POCS yields progressively improved super resolved construction with assured convergence. Further they say that wavelet approach to super resolution image reconstruction has been developed in recent years. The high frequency information contained in wavelet coefficients of neighboring frames can be extracted and fused. The results of proposed method presented in paper have been compared with cubic spine interpolation and concluded that the results show better visual quality than that of interpolation.

In paper "A Second-Generation Wavelet Framework for Super-Resolution with Noise Filtering" [51], authors N. K. Bose, Mahesh B. Chappalli, have presented use of second generation wavelets (SGW) to attend super resolution with noise filtering for captured sequence of low resolution frames without any assumption on grid structure. Authors have discussed in brief the first generation wavelets (FGW) & SGW and importance of SGW their properties and use in signal processing. In this paper the super resolution algorithm using SGW with hard and soft thresholding is discussed in details. Image sequence super-resolution (high resolution) can be viewed in the context of the conversion of the high-resolution non uniformly sampled raster (irregular grid or non uniform sampling lattice) generated from an acquired sequence of low-resolution frames to the desired uniformly sampled high resolution grid. Second-generation wavelets (SGWs) can not only deal with bounded domains and arbitrary boundary conditions, but also irregular sampling intervals, which are at the heart of a sequence of low-resolution images from which image super-resolution is desired.

Authors claim that due lifting technique used for implementation of wavelet, the algorithm is computationally efficient. SGW surface has been defined on irregularly sampled reconstruction grid. In proposed algorithm, the detail coefficient values are point on high resolution grid can be computed either by ignoring the irregularity of the grid and assigning value of closed irregular print or by resampling the wavelet and simultaneously for the noise reduction the thresholding of a coefficient is implemented. The simulated results are presented with PSNR as measuring parameter and comparison is made with interpolation techniques. Authors claim that choice of mother wavelet and scaling function which makes the SGW super resolution potentially more suitable in multimedia applications.

The process of image registration with respect to a reference frame results in a grid with irregularly spaced sampling points. Hence, the super resolution algorithm needs to handle irregular sampling most algorithms employ some means of approximating the irregularly sampled grid with a regularly sampled one. This induces some error in the process of super resolution which is reflected in the output image quality. The ability of second generation wavelets to adapt to irregular sampling intervals rendered them an ideal for use in super resolution algorithms. The additional property of handling arbitrary boundaries eliminates the need to assume and impose assumptions like the zero, periodic and Neumann boundary conditions and enhances the probability of obtaining better results from a super resolution algorithm based on second generation wavelets. The possibility of achieving simultaneous noise reduction by the use of wavelet coefficient thresholding provided an added incentive to delve deeper in this direction.

Second generation wavelet based super resolution algorithms is presented in paper [52] by M. El-Sayed Wahed titled “Image enhancement using second generation wavelet super resolution”. A framework for achieving image sequence super resolution simultaneously with noise filtering has been developed based on SGWs coupled with wavelet coefficient thresholding. The main advantages of the developed procedures are the adaptation to non-uniform sampling lattices, the absence of a priori assumptions on boundary conditions, independence from proper choice of mother wavelets and scaling functions, and the speed of implementation provided by the lifting technique. These advantages coupled with the improved performance in terms of visual quality of the reconstructed high resolution images make SGWSR algorithms potentially natural and suitable choices for multimedia applications.

A wavelet based super resolution algorithm has been presented in [53], a paper titled "A New Super resolution Reconstruction Algorithm Based on Wavelet Fusion" by S.E. Khamy, Hadhaud, Dessouky, Salam, and Abd El-Samie. The super resolution ill-posed problem has been solved in four consecutive steps: a registration step, a multi channel maximum entropy restoration step, a wavelet based image fusion step and finally a maximum entropy image interpolation step. The technique uses wavelet for image fusion. The wavelet packet decomposition is calculated for each observation to obtain the multi-resolution levels of the images to be fused. In transform domain the coefficients in all resolution levels whose absolute values are larger are chosen between the available observations. This is maximum frequency rule. The maximum entropy interpolation gives high resolution image. The algorithm achieves good PSNR and is computationally fast.

Much work has been reported the use of wavelet in super resolution imaging for denoising, deblurring and reconstruction. A common feature of all these is the assumption that the low resolution image to be enhanced is the low pass filtered subband of a decimated wavelet transformed high resolution image. The high frequency wavelet coefficients are estimated by low resolution image and the high resolution image is obtained by applying the inverse wavelet transform. Researchers H.C. Liu, Y Feng, and G Y Sun, have presented their single image based super resolution algorithm in paper "Wavelet Domain Image Super Resolution Reconstruction Based on Image Pyramid and Cycle Spinning" [54]. The algorithm consists of three steps: firstly, the predictive high resolution images are obtained by a low resolution image based on Laplacian pyramid; secondly, the discrete wavelet transform is used for predictive high resolution image to obtain high frequency wavelet coefficients and finally a high resolution image is obtained by the inverse wavelet transform. The proposed method avoids the number of iterative operations and makes the super resolution reconstruction possible of large dimension image less time consuming. Cycle spinning is used to reduce the ringing effect.

Researchers Karl S. Ni and Truong Q. Nguyen in “Image Super resolution Using Support Vector Regression” [89] have done a thorough investigation of the application of support vector regression (SVR) to the super resolution problem is conducted through various frameworks. The SVR problem is enhanced by finding the optimal kernel by formulating the kernel learning problem in SVR form as a convex optimization problem, specifically a semi-definite programming (SDP) problem. An additional constraint is added to reduce the SDP to a quadratically constrained quadratic programming (QCQP) problem. After this optimization, investigation of the relevancy of SVR to super resolution proceeds with the possibility of using a single and general support vector regression for all image content, and the results are impressive for small training sets. This idea is improved upon by observing structural properties in the discrete cosine transform (DCT) domain to aid in learning the regression. Further improvement involves a combination of classification and SVR-based techniques, extending works in resolution synthesis. This method, termed kernel resolution synthesis, uses specific regressors for isolated image content to describe the domain through a partitioned look of the vector space, thereby yielding good results.

2.10 Overview of Literature Survey

A number of super resolution techniques have been suggested over the years. Since its conception in 1984 by Tsai and Haung, the topic has received huge interest due to its potential to increase performance of existing camera system without the need of dedicated hardware. Literature survey reveals that proposed super resolution algorithms can be categorized into three major classes: Reconstruction based super resolution, Learning based super resolution, and Wavelet based super resolution. The super resolution process can be generalized into three important phases: the preprocessing, the reconstruction, and the post processing. Though a wide variety of super resolution approaches are proposed, most of them suffer from drawbacks.

It is observed that there is scope to develop the efficient technique for super resolution using wavelet by exploiting structural properties of natural images and also a necessity to develop an efficient technique to satisfy todays demand of high resolution images.

Chapter 3

Wavelet Transform

This chapter includes the basic theory of wavelets and wavelet transform. From last few decades, the wavelet transform has been proposed as a flexible tool for the multiresolution decomposition of continuous time signals. Many popular wavelets with characteristics are discussed in details in this chapter.

3.1 Introduction

The information is represented by the signal. This signal representation may be one dimensional or multidimensional. For example audio information is represented by single dimensional signal and image information is represented by two-dimensional signal. Signal can be represented in time domain or in frequency domain. Different mathematical tools are available to convert the signal from time domain to frequency domain and vice versa. Various operations are carried out over the signal, such that, the signal information becomes appropriate for the particular application. Signal processing is based on transforming a signal in the manner that it is more useful to the application. For example, it is easy to measure the time (period) of a signal in time domain representation, but it is difficult to find frequency of a complex signal. It is easy to measure the frequency of a signal in frequency domain representation but it is difficult to find time of a signal. The wavelet transform is one of the transforms used for signal transformation. This chapter includes the detail discussion on wavelet, many popular wavelets with characteristics and wavelet packets tree.

3.2 Wavelet

The concept of wavelets has been discussed in the literature for a very long time. It is based on fundamental ideas, which were first expressed more than a century ago in a variety of forms. However, it is only recently that significant progress has been made in the application of wavelet to practical problem in signal processing. The wavelet transform has been proposed as a flexible tool for the multiresolution decomposition of continuous time signals. Significant practical applications of wavelets have been found in signal and image processing.

In 1909, Haar replaced the sine and cosine functions of the Fourier transforms with another orthonormal basis, now commonly known as the Haar basis.

Daubechies introduced the concept of compactly supported wavelets and theory of frames. She also saw the connection between the wavelet theory, and theory of subband decomposition which was independently being pursued by the digital signal processing community of electrical engineers. Mallat introduced the concept of multiresolution, which is intimately related to multi-rate digital filter used for subband decomposition.

The signal is defined by a function of one variable or many variables. Any function is represented with the help of basis function. An impulse is used as the basis function in the time domain. Any function can be represented in time as a summation of various scaled and shifted impulses. Similarly the sine function is used as the basis in the frequency domain. However these two-basis functions have their individual weaknesses: an impulse is not localized in the frequency domain, and is thus a poor basis function to represent frequency information. Likewise a sine wave is not localized in the time domain [80]. In order to represent complex signals efficiently, a basis function should be localized in both time and frequency domains. The support of such a basis function should be variable, so that a narrow version of the function can be used to represent the high frequency components of a signal while wide version of the function can be used to represent the low frequency components. Wavelets satisfy the conditions to be qualified as the basis functions.

Sinusoidal wave is one of the popular waves, which extend from $-\infty$ to $+\infty$. Sinusoidal signals are smooth and predictable; it is the basis function of Fourier analysis. Fourier analysis consists of breaking up a signal into sine and cosine waves of various frequencies. A wavelet is waveform of limited duration that has an average value of zero [84]. Wavelets are localized waves and they extend not from $-\infty$ to $+\infty$ but only for a finite time duration, as shown in figure 3.1.

The wavelet as shown in figure 3.1 is a mother wavelet (*h(t)*).The mother wavelet and its scaled daughter functions are used as a basis for a new transform. Unfortunately, if *h(t)* is centered around t = 0, with extension between – T and + T, no matter how many daughter wavelets we use, it will not be possible to properly represent any point at t >T of a signal *s(t)*.

Please note that the wave transform did not have this problem, as the wave function was defined for every value of t. For the case using a localized wave or wavelet, it must be possible to shift the center location of the function. In other words, it must include a shift parameter, b, and the daughter wavelets should be defined as

$$h_{ab}(t) = \frac{1}{\sqrt{a}} h\left(\frac{t-b}{a}\right) \tag{3.1}$$

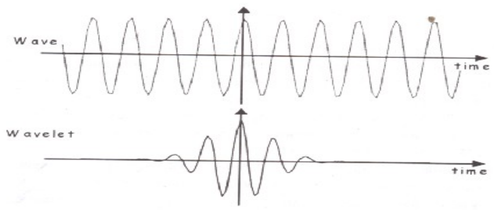


Figure 3.1 the Wave and Wavelet

The reason for choosing the factor in the above equation is to keep the energy of the daughter wavelets constant.

Thus, the wavelet transform has to be a two-dimensional transformation with the dimension being *a*, the scale parameter, and *b*, the shift parameter. The wavelet transform maps 1-D time signals to 2–D scale (frequency) and shift parameter signals.

It is observed that for periodic functions, Fourier analysis is ideal. However, wavelet transforms are not restricted to only the periodic function, but for any function, provided it is admissible. In many cases of signal processing, one can choose the signal itself or a theoretical model as the mother wavelet. The advantage of doing this is that only few wavelet transform coefficients are then required to represent the signal. Wavelets tend to be irregular and asymmetric. The original wave is known as Mother Wavelet. Wavelet analysis consists of breaking up of signal into shifted and scaled versions of the original (mother) wavelet.

3.3 Properties of Wavelet

In this section, the properties of wavelet like Localized in time and frequency, Admissibility, Vanishing Moments, Compact support, Orthogonal, bi-orthogonal and symmetry have been discussed in brief [85-87].

Localized In Time and Frequency

Daughter wavelet is given as

$$h_{ab}(t) = \frac{1}{\sqrt{a}} h \frac{(t - b)}{a} \tag{3.2}$$

The Fourier Transform of $h_{ab}(t)$

$$H_{ab}(\omega) = F.T.\left\{ \frac{1}{\sqrt{a}} h \frac{(t - b)}{a} \right\}$$

$$H_{ab}(\omega) = \sqrt{a}\, H(a\omega)\, e^{-jwb} \tag{3.3}$$

The equation 3.2 and 3.3 shows that $h_{ab}(t)$ and $H_{ab}(\omega)$ has a finite length. It means that $h_{ab}(t)$ is localized in time and $H_{ab}(\omega)$ is localized in frequency and hence the mother wavelet h(t) is localized in time and frequency.

Admissibility

Mother wavelet is said to be admissible if it has finite energy or mother wavelet must be square integrable.

$$\|h\|^2 = \int_{-\infty}^{\infty} |h(t)|^2 \, dt < +\infty \tag{3.4}$$

This satisfies the following admissibility condition

$$C_H = \int_{-\infty}^{\infty} \frac{|H(\omega)|^2}{\omega} d\omega < \infty \tag{3.5}$$

For a band-limited mother wavelet h (t), the admissibility condition is equivalent to imposing the condition that the function has zero mean.

$$\int_{-\infty}^{\infty} h(t)\, dt = 0 \quad or\ H(\omega) \Big/_{\omega = 0} = 0 \tag{3.6}$$

Since mother wavelet is admissible the properties of linearity scaling and time shifting is applicable for CWT.

Vanishing Moments

To measure the local regularity of the signal, it is not important to use wavelet with narrow frequency support, but vanishing moments are crucial. If the wavelet has the n vanishing moment, then we show that the wavelet transform can be interpreted as a multi-scale differential operator of order n. A wavelet has n vanishing moments if and only if its scaling function can generate polynomials of degree smaller than or equal to n. While this property is used to describe the approximating power of scaling functions, in the wavelet case it has a "dual" usage, e.g. the possibility to characterize the order of isolated singularities. The number of vanishing moments is entirely determined by the coefficients h[n] of the filter h which is featured in the scaling equation [83]. The wavelet h(t) has n vanishing moments, if

$$\int_{-\infty}^{+\infty} t^k \, h(t)\, dt = 0, \quad for \quad 0 \le k \le n \tag{3.7}$$

Compact Support

If the impulse response of the filters h1 and h2 has a finite support, then the scaling functions have the same support, and the wavelets are compactly supported. If the supports of the scaling functions are respectively [N1, N2] and [M1, M2], then the corresponding wavelets have support [(N1-M2+1)/2, (N2-M1+1)/2] and [(M1-N2+1)/2, (M2-N1+1)].

Orthogonal

The orthogonal transform is useful tools for signal processing. Many filters have to be design so far to be applied to the transform domain. Suppose there is set of continuous functions {h0(t), h1(t), h2(t), …} of t. These functions, real or complex, are said to be orthogonal functions in the interval [t0, t0+T] [83], if

$$\int_{x_0}^{x_0+X} h_i(t)\, h_j(t)\, dt = \begin{cases} \text{k} & \text{if i = j} \\ 0 & \text{otherwise} \end{cases} \tag{3.8}$$

When k = 1 the set is called orthonormal.

Bi-Orthogonal

In a wavelet transform the separate filter for analysis and synthesis can be used. Let us consider h1 and g1 is low pass and high pass filter used for analysis and h2 and g2 are low pass and high pas filters used for synthesis [80-87], then the condition for perfect reconstruction is

$$H_1^*(\omega+\pi)H_2(\omega)+G_1^*(\omega+\pi)G_2(\omega)=0 \tag{3.9}$$

$$H_1^*(\omega)H_2(\omega)+G_1^*(\omega)G_2(\omega)=2 \tag{3.10}$$

As the filter pairs (h1, g1) and (h2, g2) create basis for the representation of the any signal s[n] ε L2(Z), then the resulting wavelet and scaling functions represents bi-orthogonal Riesz bases in L2(Z).

Symmetry

Symmetric scaling functions and wavelets are important because they are used to build bases of regular wavelets over an interval, rather than the real axis. If the filters h1 and h2 have and odd length and are symmetric with respect to 0, then the scaling functions have an even length and are symmetric, and the wavelets are also symmetric. If the filters have an even length and are symmetric with respect to n=1/2, then the scaling functions are symmetric with respect to n=1/2, while the wavelets are antisymmetric. Daubechies has proved that, for a wavelet to be symmetric or antisymmetric, its filter must have a linear complex phase, and the only symmetric compactly supported conjugate mirror filter is the Haar filter, which corresponds to a discontinuous wavelet with one vanishing moment. Besides the Haar wavelet, there is no symmetric compactly supported orthogonal wavelet.

3.4 Wavelet Families

In this section, most of the known families of mother wavelets, which have proven to be useful in a variety of signal processing applications, are discussed with their characteristics.

Haar Wavelet

This is the simplest of all wavelets. This wavelet is discontinuous and resembles a step function. It is also referred as 'db$_1$' and it is defined as

$$h(t) = \begin{cases} 1 & 0 \leq t \leq 1/2 \\ -1 & 1/2 \leq t \leq 1 \\ 0 & \text{otherwise} \end{cases} \quad (3.11)$$

The Haar wavelet has the shortest support among all orthogonal wavelets; it is not adapted to approximately smooth functions because it has only one vanishing moment.

Daubechie Wavelets

Ingrid Daubechies invented compactly supported orthogonal wavelets, and makes discrete wavelet analysis practical. The names of the Daubechies family wavelets are written db$_N$, where N is the order. The db$_1$ wavelet is same as Haar wavelet. Daubechies wavelets are extremely important, because it can be shown that they have the minimum support size for given number of N. Daubechies constructed her wavelets from the finite response of the conjugate mirror filter. These wavelets have no explicit expression except for db$_1$, which is Haar wavelet. However, the square modulus of the transfer function of h is explicit, and fairly simple [83].

$$P(y) = \sum_{k=0}^{N-1} C_k^{N-1+k} y^k \quad (3.12)$$

where C_k^{N-1+k} *denotes the binomial coefficients*.

Then $$|m_0(\omega)|^2 = \left(\cos^2\left(\frac{\omega}{2}\right)\right)^N P\left(\sin^2\left(\frac{\omega}{2}\right)\right) \quad (3.13)$$

where $m_0(\omega) = \frac{1}{\sqrt{2}} \sum_{k=0}^{2N-1} h_k e^{-ik\omega}$

General characteristics of Daubechies wavelet are:

- The supporting length of wavelet function ϕ and scaling function ψ is 2N – 1.
- The number of vanishing moments of ψ is N.
- The analysis is orthogonal.
- Filter length is 2N.
- Discrete wavelet transforms and continuous wavelet transform is possible.
- Order of N is 1, 2 ---- 48.
- It doesn't have explicit expression.
- It is asymmetrical.
- It has arbitrary regularity.
- It is compactly supported orthogonal.
- Exact reconstruction is possible.
- It is implemented using FIR filter.
- Fast algorithm is possible.

Coiflet Wavelets

These mother wavelets built by Daubechies at the request of Coifman. It is also orthogonal wavelet; it is compactly supported wavelets with highest, number of vanishing moments for both phi and psi for given support width. These wavelets are written as coifN, where N is the order. The function psi has 2N moments equal to zero and, what is more unusual, the function phi has 2N – 1 moment equal to zero. The two functions have a support of length 6N – 1. The CoifN psi and phi are much more symmetrical than the DbNS with respect to the support length [83-84].

General characteristics of Coiflet wavelets are:

- The supporting length of wavelet function ϕ and scaling function ψ is 6N – 1.
- The number of vanishing moments of ψ is 2N and ϕ is 2N – 1.
- The analysis is orthogonal.

- Filter length is 6N.
- Discrete wavelet transforms and continuous wavelet transform is possible.
- Order of N is 1, 2, ----5.
- It doesn't have explicit expression.
- It is nearly symmetrical.
- It is arbitrary regular.
- It is compactly supported orthogonal.
- Exact reconstruction is possible.
- It is implemented by using FIR filters.
- Fast algorithm is possible.

Biorthogonal Wavelets

It is compactly supported Biorthogonal wavelets for which symmetry and exact reconstruction are possible with FIR filters. Biorthogonal wavelets written as bior N_r,N_d, where N_r, is order of wavelet, which is used for reconstruction and N_d, is order of wavelet, which is used for decomposition. Two wavelets, instead of just one, are introduced:

- One, $\tilde{\psi}$, is used in the analysis, and the coefficients of a signal s are:

$$\tilde{C}_{j,k} = \int s(x)\tilde{\psi}_{j,k}(x)dx \qquad (3.14)$$

- The other ψ, is used in the synthesis

$$s = \sum_{j,k} \tilde{C}_{j,k}\, \psi_{j,k} \qquad (3.15)$$

General characteristics of Biorthogonal wavelets are:

- The supporting width of wavelet $2N_r + 1$ for reconstruction and $2N_d + 1$ for decomposition.
- The number of vanishing moments of ψ is N_r.
- The analysis is not orthogonal.

- Filter length is max $(2N_r, 2N_d) + 2$.
- Discrete wavelet transforms and continuous wavelet transform is possible.
- It doesn't have explicit expression except for splines.
- It is symmetrical.
- It is arbitrary regular.
- Exact reconstruction is possible.
- It is implemented by using FIR filters.
- Fast algorithm is possible.

3.5 The Discrete Wavelet Transforms

Calculating wavelet coefficients at every possible scale is a fair amount of work, and it generates huge amount of data. If only a subset of scale, and positions the data are selected then the size of the data may be reduced significantly. It turns out, rather remarkably, that if scales and positions base on the power of two are selected (so called dyadic scales and positions), then the analysis will be much more efficient and accurate. And such analysis is possible from the discrete wavelet transform. In the case of Continuous Wavelet Transform the scaling 'a' and delay 'b' are assumed to be continuous in value and hence in a result of continuous wavelet transform redundancy of signal is present. This redundancy can be reduced by discretizing the transform parameter (a, b).

$$a = a_0^j, \quad a_0 \neq 1, \; j \in z \tag{3.16}$$

Where a_0 is constant but not equal to one, and m is any positive integer. Parameter b is also chosen as power of two.

$$b = k.a_0^j = k.a \qquad \text{where} \qquad k \in z$$

If $a_0 = 2$, $a = 2^j$ and $b = k\,2^j$

The Discrete Wavelet Transform of continuous time signal is given by the equation.

$$C(a,b) = \int_R s(t)\,\psi_{ab}(t)\,dt \qquad (3.17)$$

Where $\psi_{ab}(t) = \frac{1}{\sqrt{|a|}}\frac{\psi\,(t-b)}{a}$ and $a = 2^j$, $b = k\,2^j$, $(j,k) \in Z^2$

In 1998, Ingrid Daubechies and Mallet [83] discovered that the wavelet transform could be implemented with a specially designed Finite Impulse Response (FIR) filter pair. The filter banks are in effect a fast way of implementing the Discrete Wavelet Transform for orthogonal wavelets the filter banks are a set of Quadrature Mirror Filters [84].

The analysis bank has two filters low pass and high pass. These filters separate the input signal into low and high frequency banks. This process is called as wavelet decomposition. The low frequency components of the signal are known as approximations and high frequency components are known as details. When one performs the filtering operation on real digital signal, then it winds up with twice as much data as one started with [83]. Using down sampling after the filtering solves this problem. Figure 3.2 shows one-stage Discrete Wavelet Transform of signal 'S'.

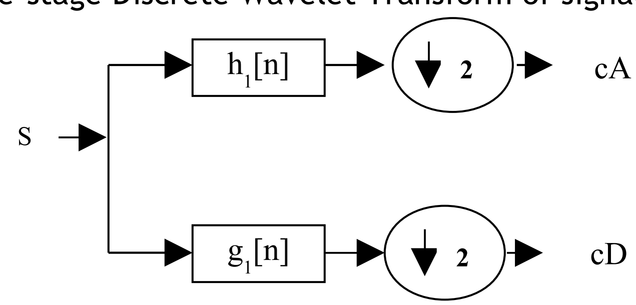


Figure 3.2 one-stage Discrete Wavelet Transform of signal S

Where $h_1[n]$ and $g_1[n]$ are the impulse response of low pass and high pass filter, and cD and cA are detail coefficients and approximate coefficients of signal S.

It is observed that the actual length of the detail and approximation coefficients vectors are slightly more than half of the length of the original signal, because filtering process is implemented by convolving the signal with filter.

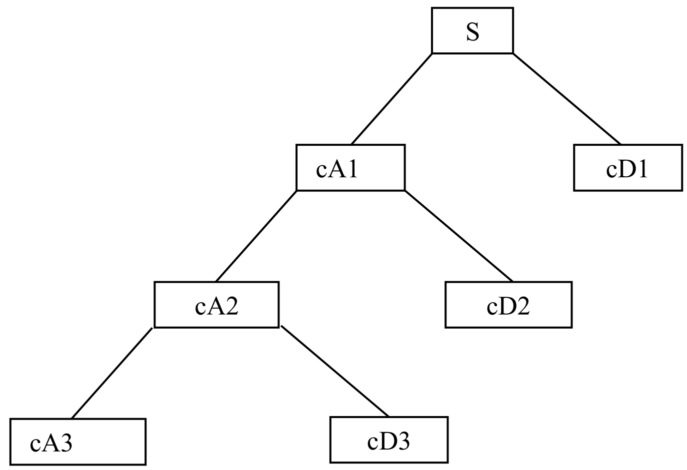


Figure 3.3 Three level decomposition tree

The decomposition process can be iterated, with successive approximations being decomposed in turn, so that one signal is broken down into many lower resolution components. This is called the wavelet decomposition tree as shown in figure 3.3.

The wavelet reconstruction process is just reversed to the decomposition process. It consists of up sampling and filtering as shown in figure 3.4.

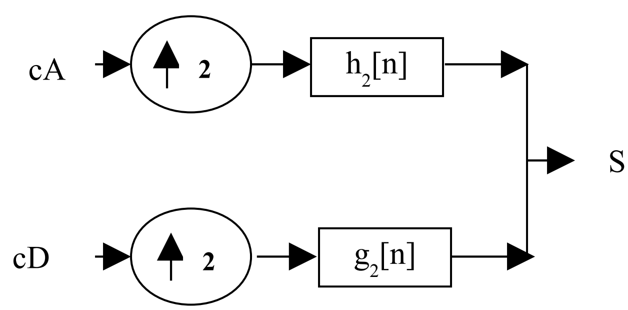


Figure 3.4 Signal reconstruction process

Where $h_2[n]$ and $g_2[n]$ are the impulse response of low pass and high pass filter, and cD and cA are detail coefficients and approximate coefficients of signal S.

3.6 Two Dimensional DWT

Two dimensional wavelet transform is applicable to analyze the two-dimensional signal such as image. A two-dimensional wavelet transform is readily computed by combining the one-dimensional basis transform for both the dimensions (horizontal and vertical). In two dimensional wavelet transform the process breaks the original band into four sub-bands: one tuned for low frequency (approximation), one tuned for vertical high frequency (vertical details), one tuned for horizontal high frequency (horizontal detail), and one tuned for both orientations of diagonal high frequency (diagonal details). This kind of two-dimensional DWT leads to decomposition of approximation coefficients at level j in four components: the approximation at level j+1 and the details in three orientations (horizontal, vertical and diagonal). The figure 3.5 shows the basic decomposition steps.

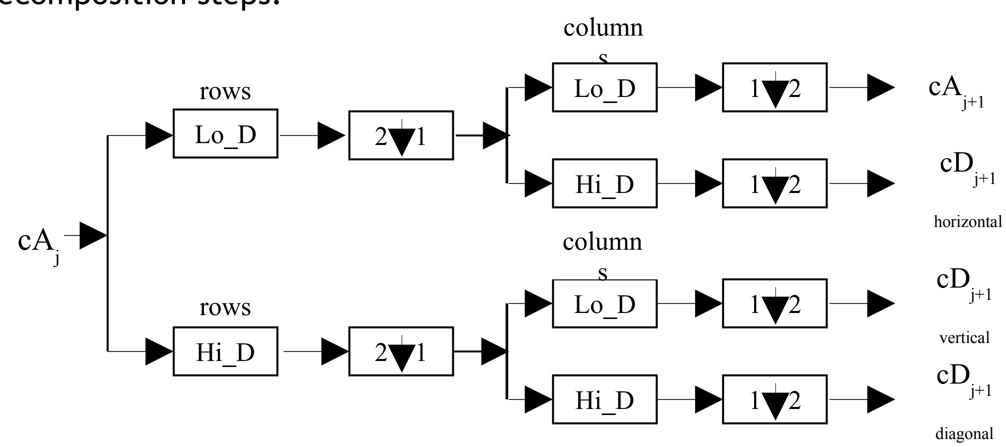


Figure 3.5 Two-Dimensional DWT Decomposition

The decomposition phase has two filters: low pass and high pass. These filters separate the input signal into low and high frequency components. The two-dimensional signal first filtered row wise, and down sampled by the amount of two. Then, the procedure is repeated for the column components of two-dimensional signals. This process is called as wavelet decomposition of two-dimensional signal. The low frequency components of row and column of two-dimensional signals are known as approximations, low frequency components of row and high frequency components of column of two-dimensional signal are known as horizontal details, high frequency components of row and low frequency components of column of two-dimensional signal are known as vertical details, and high frequency components of row and high frequency components of column of two-dimensional signal are known as diagonal.

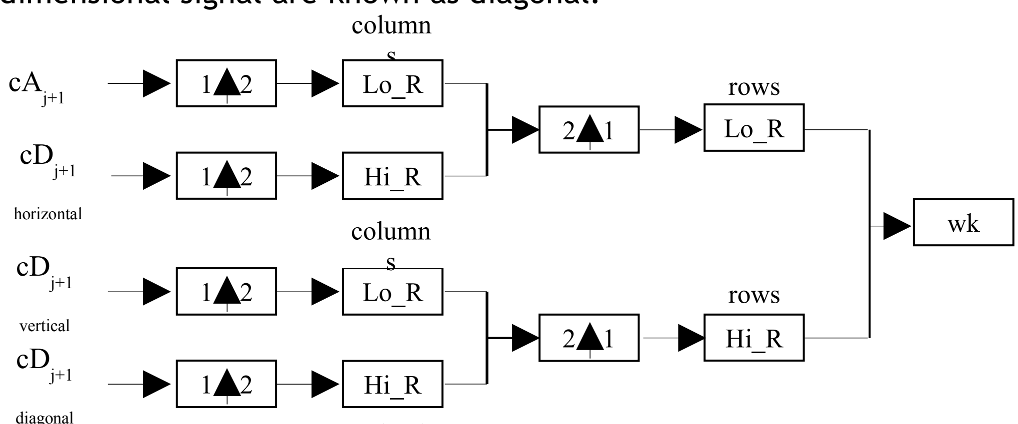


Figure 3.6 The basic reconstruction steps

In reconstruction stage the approximate and detail components are first up sampled with the factor of two, and the row components, and column components are separately filtered with the reconstruction low pass, and high pass filters. Sum of the filtered components are again up sampled with the factor of two, and again filtered with low pass and high pass filters. The filtered components when added reconstruct the original signal.

3.7 Wavelet Packet

The weakness of wavelet transform is that it fails to capture high frequency components of an image, and hence, another transform method must be employed. Coifman, Meyer and Wickerhauser developed the technique, which was based on the wavelet transform and known as wavelet packets. Wavelet packets are better able to represent the high frequency information [84-87].

Wavelet packets represent a generalization of multi-resolution decomposition. In wavelet, the decomposition is applied recursively to the coarse scale approximation, whereas in the wavelet packets decomposition, the recursive procedure is applied to the coarse scale approximation along with horizontal detail, vertical detail, and diagonal detail, which leads to a complete binary tree. Wavelet packets is an extension of the octave band wavelet decomposition to a full tree decomposition by allowing the low pass filtering, high pass filtering and down sampling procedure to be iterated on approximate and details. High pass branches in the tree, add more flexibility in frequency resolution. Tree structure of wavelet packets decomposition up to third level is shown in figure 3.7.

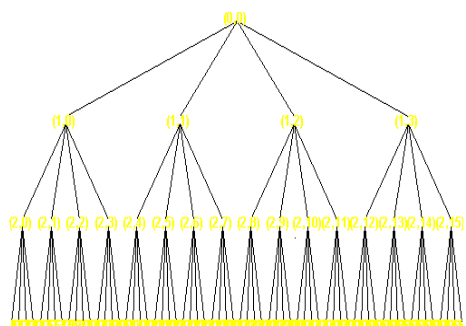


Figure 3.7 The tree structure of wavelet packets decomposition up to third level

The original signal is decomposed at first level to generate four successors as approximation, horizontal detail, vertical detail, and diagonal detail. Further, these successors are decomposed at second level to generate total sixteen successors. Similar process is carried out at third level also to yield total sixty-four successors as leaves of the tree. Decomposition process includes low pass, high pass filtering for rows of two-dimensional signal followed by down sampling with amount of two. Then, the procedure is repeated for the column components of two-dimensional signals.

Chapter 4

Performance Measures

This chapter aims to present a study of image quality assessment measures. Even though many efforts have been made towards development of both qualitative and quantitative measures, defining the appropriate quality measures for super resolution imaging is unnoticed. This chapter presents discussion on suitability of conventional performance measures for super resolution imaging.

4.1 Introduction

Imaging and video devices have limitations over spatial and temporal resolution. The spatial resolution is number of pixels per unit area and temporal resolution is number of frames per second. The spatial resolution defines quality of still image whereas the temporal resolution defines the quality of video. Researchers have developed a variety of super resolution algorithms in last decade for both spatial as well as temporal resolution. Key objective of super resolution imaging is to enhance the quality of image/video. To evaluate performance of super resolution imaging technique, a suitable performance measure is required. Most of the researchers have used peak signal to noise ratio (PSNR) as measure for super resolution image quality assessment. However, they also claim that PSNR is not suitable for SR techniques performance measurement due to absence of real reference [11-44]. It noticed that there is mismatch between PSNR and the quality observed by visual inspection. An image that looks better may not necessarily have higher PSNR. Therefore, it is necessary to inspect the results visually, and the high frequency images should be shown to highlight the difference.

Popularly there are two approaches that are used for image quality assessment: subjective and objective measures. Subjective quality measure is based on human visual system and objective measure criteria involve numerical calculations that are based on computable distortion measures. This chapter is devoted for discussion on suitability of these performance measures for super resolution imaging.

4.2 Image Quality Measures

Wide set of quality measures are used to assess visual quality of image. These are broadly categorized into:

- Subjective quality measures and
- Objective quality measures

4.2.1 Subjective Measures

The subjective criteria are based on group of human examiners assessing the image quality. In subjective criteria the group of human experts examine original image, and reconstructed image; and they assign grades. On the basis of these assigned grades, quality of reconstructed image is assessed. Mean Opinion Score (MOS) is one of the subjective evaluations of image quality measure. The MOS values are obtained from an experiment involving the group of persons. The testing methodology is the double stimulus impairment scale method. The double stimulus impairment scale method uses references and test conditions, which are arranged in pairs such that the first in the pair is unimpaired reference, the second are the same sequence impaired. The original source image is used as the reference condition. The assessor is asked to note on the second, keeping in mind the first and five-grade impairment scales are assigned as described in ITU-BT Rec. 500 [75]. The method uses five grade impairment with proper description: 5-imperceptible, 4-perceptible, 3-slightly annoying, 2-annoying, 1-very annoying. MOS for each test condition and test image are calculated.

$$MOS = \sum_{i=1}^{5} i.P(i) \tag{4.1}$$

Where 'i' is the grade and P(i) is the grade probability.

Another method for evaluation of the quality based is Double Stimulus Continuous Quality Scale (DSCQS) [75], which presents two images to viewers: original image and processed image. Viewers evaluated image quality of both images using grading scale of five intervals (1-Excellent, 2-Good, 3-Fair, 4-Poor, 5-Bad). Though subjective evaluation is usually too convenient, it is more expensive, and measurements are to be processed very carefully [75-79]. This method has some difficulties:

- Human judgment vary from time to time and person to person
- Human judgment may be significantly get affected by the presence of the system, which introduces errors or artifacts.

As Human Intervention is involved in subjective criteria of image quality assessment, it is prone to improper interpretation. Hence objective criteria are preferred over the subjective criteria for quality of image assessment. However, their conveniences may lead their use in few applications.

4.2.2 Objective Measures

In the process of super resolution image reconstruction, the noise may get introduced due to inaccurate image fusion or improper prediction. The noise is referred as an error in image processing, and it degrades the quality of image. There are many objective quality measures that have been developed for image quality evaluation in last few years. These criteria involve computations to calculate various parameters contributing to quality assessment of an image. These are based on numerical measures of image quality and computable distortion measures [76]. They are discrete, providing some degree of closeness between the digital images by exploiting the differences in the statistical distributions of pixels. The few common objective quality measures are discussed here.

- Mean Square Error (MSE)
- Signal to Noise Ratio (SNR)
- Peak Signal to Noise Ratio (PSNR)
- Normalized Cross-correlation (NK)
- Average Difference (AD)
- Maximum Difference (MD)
- Structural Content (SC)
- Normalized Absolute Error (NAE)

Mean Square Error (MSE)

It is measured as the average of square of error introduced in a processed image. It is defined by the equation

$$MSE = \left[\frac{1}{MN} \sum_{r=0}^{M-1} \sum_{c=0}^{N-1} \left\{ f(r,c) - \hat{f}(r,c) \right\}^2 \right] \qquad (4.2)$$

where M × N is size of image, $f(r,c)$ and $\hat{f}(r,c)$ denotes the row element r, and column element c of original image and the reconstructed image respectively.

Root Mean Square (RMSE)

The root mean square error is one of the image quality measures and is calculated from MSE. It is given by the equation

$$RMSE = \left[\frac{1}{MN} \sum_{r=0}^{M-1} \sum_{c=0}^{N-1} \left\{ f(r,c) - \hat{f}(r,c) \right\}^2 \right]^{\frac{1}{2}} \qquad (4.3)$$

Signal to Noise Ratio (SNR)

Signal to Noise Ratio is defined as ratio of signal power to noise power. It is given by the equation

$$SNR. = 10\log\left(\frac{\sum_{r=0}^{M-1}\sum_{c=0}^{N-1}\left\{f^2(r,c)\right\}}{\sum_{r=0}^{M-1}\sum_{c=0}^{N-1}\left\{f(r,c)-\hat{f}(r,c)\right\}^2}\right) \tag{4.4}$$

Peak Signal to Noise Ratio (PSNR)

Peak Signal to Noise Ratio is defined as ratio of maximum signal power to noise power. It is given by the equation

$$PSNR = 20\,log\left(\frac{2^n - 1}{RMSE}\right) \tag{4.5}$$

where n is number of bits used for the intensity of pixel. For n = 8

$$PSNR = 20\log\left(\frac{255}{RMSE}\right) \tag{4.6}$$

Normalized Cross-Correlation (NK)

Normalized Cross-correlation is obtained by the given equation

$$NK = \left(\frac{\sum_{r=0}^{M-1}\sum_{c=0}^{N-1} f(r,c)\,.\,\hat{f}(r,c)}{\sum_{r=0}^{M-1}\sum_{c=0}^{N-1} f^2(r,c)}\right) \tag{4.7}$$

Average Difference (AD)

Average Difference is obtained by the given equation

$$AD = \sum_{r=0}^{M-1}\sum_{c=0}^{N-1} f(r,c) - \hat{f}(r,c)/MN \tag{4.8}$$

Maximum Difference (MD)

Maximum Difference is obtained by the given equation

$$MD = max\left(\left|f(r,c) - \hat{f}(r,c)\right|\right) \tag{4.9}$$

Structural Content (SC)

Structural Content is obtained by the given equation

$$SC = \left(\frac{\sum_{r=0}^{M-1} \sum_{c=0}^{N-1} f^2(r,c)}{\sum_{r=0}^{M-1} \sum_{c=0}^{N-1} \hat{f}^2(r,c)} \right) \qquad (4.10)$$

Normalized Absolute Error (NAE)

Normalized Absolute Error is obtained by the given equation

$$NAE = \sum_{r=0}^{M-1} \sum_{c=0}^{N-1} \left| f(r,c) - \hat{f}(r,c) \right| / \sum_{r=0}^{M-1} \sum_{c=0}^{N-1} \left| f(r,c) \right| \qquad (4.11)$$

The Mean Square Error and Peak Signal to Noise Ratio are most commonly used objective quality measures in image quality evaluation. They are simple to calculate, have clear physical meanings and mathematically suitable in the context of optimization. For color images, the Mean Square Error is calculated for each color and their average is used to generate the Peak Signal to Noise Ratio. If the value of MSE is low, it indicates that noise introduced is low and it is desirable as it results in good quality of processed image. If the value of PSNR is high, it indicates that noise introduced due to processing is low and it is desirable as it results in good quality of processed image.

4.3 Performance Measures for Super Resolution Imaging

For super resolution image, quality is measure of preservation of originality of scene. When image is captured, the originality of scene is lost and the distortions are added due to limitation over point spread function of capturing device. To remove distortions, different algorithms are offered in digital image processing.

The subjective measure involves human factor and is not recommended for quality assessments due to variance of results. It requires set of two images for comparison; the original and the processed one. It is difficult to quantitatively assess the super resolution technique as the true high resolution image is not available for reference. Hence, the subjective measures are not appropriate for accessing super resolution image quality.

The objective measures are based on numerical computations. For these calculations this measure also requires two images; the original image *f(r,c)* and $\hat{f}(r,c)$ the processed image. The prime requirement for computations is that these two should have same spatial resolution; their sizes must match. For super resolution imaging, the processed image is the reconstructed high resolution image and the source is/are the low resolution image(s). Variation in the sizes puts constraint on these calculations. Still few researchers have suggested use of MSE, SNR and PSNR for assessment of quality in super resolution imaging techniques.

To quantify the technique, often researchers decimate captured image generally by a factor at two using interpolation. The decimated low resolution image is used as the input and original undecimated image is considered as true reference.

Most of the super resolution algorithm's performance is measured against interpolation. It should be noted that there is a positive bias in the calculations of these parameters in favor of the interpolation. This is due to the fact that these parameters are calculated using the same high resolution reference from which the low resolution image is made.

For reconstruction based multiframe super resolution technique, more than two low resolution images of the scene are to be used as input. Often these images are decimated, shifted and noisy versions created from single captured high resolution image.

In brief, the performance calculations in super resolution imaging algorithm, *f(r,c)* is original image and it is shifted and/or rotated and downsampled to generate set of low resolution input images. From these low resolution images, the super resolution image $\hat{f}(r,c)$ is reconstructed.

Based on $f(r,c)$ and $\hat{f}(r,c)$ objective quality measures are calculated. The techniques used to generate low resolution images from high resolution image and the techniques used to generate high resolution from low resolution images are not reversible.

Hence, the technique recommended by researchers is not suitable to measure the quality of super resolution image. In this research work a novel quality measurement frame work for super resolution imaging is proposed in chapter five.

Chapter 5

Reconstruction of Super Resolution Image

This chapter covers the selection of wavelet transform, structural property of natural images, preprocessing input image, processing based on image nature, the novel super resolution image reconstruction technique, and framework for SR image quality measure.

5.1 Introduction

The spatial resolution represents the number of pixels per unit area in an image and it is the key factor in determining the quality of an image. With the development of image processing applications, there is a big demand for high resolution images. High resolution images not only give the viewer a pleasing picture but also offer additional details which are many times important for the analysis in applications such as medical imaging. The current technology to obtain high resolution images mainly depends on sensor manufacturing technology.

A signal processing approach that tries to satisfy these demands is super resolution image reconstruction. The key feature is that it can overcome the inherent resolution limitation of the imaging system and improve the performance of digital image processing applications. At present interpolation is being used to satisfy these needs up to some extent. The study of interpolation has been presented in chapter two.

Super Resolution is a process that creates a high-resolution image from one or more low-resolution images. The fundamental idea is to restore high frequency information that is lost during the image capturing process. Literature survey reveals that the wide set of the super resolution imaging techniques have been suggested by researchers. These approaches can be broadly categorized into three classes:

- Reconstruction Based Super Resolution ,
- Learning Based Super Resolution, and
- Wavelet Based Super Resolution

Accuracy of reconstruction based approach is largely dependent on registration process which in turn depends on accurate motion estimation. Pros and cons of this approach have been discussed in chapter two. For learning based approach, its accuracy mostly relies on set of training images. Pros and cons of learning based approach are listed in chapter two.

Recently, the wavelet based techniques have been suggested for super resolution image reconstruction. Most of them use wavelet coefficient thresholding for reducing the noise and blur that is introduced by registration process. The choice of optimal thresholding involves tradeoff between noise filtering and blurring. Wavelet based super resolution imaging has been discussed in chapter two along with its pros and cons.

Through study reveals that there is need for better super resolution technique that overcomes drawbacks of existing techniques in use. And there is call for technique that avoids the limitations of the approaches suggested in literature by various researchers as well. Wavelet transform decomposes image into different frequency subbands, these can be processed independently and then used for super resolution image reconstruction.

This chapter covers selection of wavelet transform and its use in image decomposition. The chapter continues with the details of processing of these sub images along with results and the novel super resolution algorithm.

5.2 Selection of Wavelet Transform

Major class of super resolution methods utilizes frequency domain formulation of super resolution problem. The spatial domain image is transformed to frequency domain using Fourier transform. The Fourier transform suffers from a serious drawback and the drawback is that while transforming the image to frequency domain, time domain information is lost. Looking into frequency transform of the image it is difficult to tell at what position particular event took place. Researchers in [6] have been strongly put forth this issue with respect to super resolution imaging. It is asserted that due to lack of data correlation in frequency domain, it is difficult to apply the spatial domain prior knowledge for regularization in super resolution imaging. This problem has been overcome in wavelet transform. In wavelet transform, finite wave is used as a basis function that is localized in time domain as well as frequency domain.

Haar described the first wavelet basis in 1910; in 1986 many researchers performed pioneering work in wavelets, particularly in multi-resolution and fast wavelet transforms [84-88]. The researchers have developed a wide set of wavelets. The major wavelets are Daubechies Wavelet, Coiflets Wavelet, Biorthogonal Wavelet, Symlets Wavelet, Morlet Wavelet, and Mayer Wavelet. These wavelets are used for interdomain transform of signals. Wavelet transform is a two-dimensional time-frequency signal analysis method.

Wavelet Transform represents an image as a sum of wavelet functions (wavelets) with different locations and scales. Any decomposition of an image using wavelet involves a pair of waveforms, one to represent the high frequencies corresponding to the detail parts of an image (wavelet function), and another for the low frequencies or smooth parts of an image (scaling function).

Important properties of wavelet are: compact support (leads to efficient implementation), symmetry (useful in avoiding dephasing in image processing), orthogonality (allows fast algorithm), regularity, vanishing moment, phase linearity, time frequency localization and degree of smoothness (related to filter order or filter length) [88]. These properties of most of the well-known wavelets are discussed in detail in chapter three.

The wavelets are implemented by using different ordered quadratic filters. Filter length is determined by filter order, the relationship between filter order and filter length is different for different wavelet families. Higher filter order gives wide function in the time domain with higher degree of smoothness those results in blurring of an image and more computational cost. Filter with lower order has a better time localization and preserves important edge information with minimum time complexity.

A major disadvantage of Daubechies and Coiflet wavelets is their asymmetry, which can cause artifacts at borders of the wavelet sub-band. Symmetry is one of the important properties of the wavelet transform. It can be achieved in wavelet by losing either compact support or orthogonality. Haar wavelet is the only wavelet, which is orthogonal, compactly supported and symmetric. Mayer wavelet family is non-compactly supported but symmetric and orthogonal. For this wavelet, Discrete Wavelet Transform is possible without Fast Wavelet Transform; its support width is infinite. The use of Mayer wavelet adds computational burden, and does not provide efficient implementation.

For good visual quality, wavelet must support symmetry and compact properties. If both symmetry and compact support are required in wavelets, then one should relax the orthogonality condition and allow non-orthogonal wavelet functions. Bi-orthogonal wavelets are compactly supported and symmetric [84, 87]. Considering the time complexity, effect of blur, edge preservation and symmetry at border, Biorthogonal wavelet bior2.2 is used in this research work for preprocessing of the image.

In [51] authors have discussed second generation wavelet (SGW) framework in super resolution for noise filtering. Paper covers details of first generation and second generation wavelets. The first generation wavelets (FGW) are dilates and translates of chosen mother wavelet, imply regular sampling of data that are defined on infinite domains and have difficulties in dealing with boundaries. Daubechies and Coiflets are examples of first generation wavelets.

SGW replace the dialations and translations with entire spatial domain lifting scheme based on operation of splitting, predication and updating. They are suitable for use in multi-dimensions. SGW are generalization of Biorthogonal wavelets. SGW can not only deal with bounded domain and arbitrary boundary conditions but also in irregular sampling intervals. Therefore, SGW are used in this research work to decompose the image for reconstruction of super resolution image.

5.3 Structural Property of Natural Images

Super resolution image reconstruction yields the high resolution image with the help of low resolution image(s). As such no technique has been yet suitable that uses set of low resolution images and reconstructs the super resolution image. Generally, interpolation methods such as nearest neighbor, bilinear and bicubic are used to improve resolution of image. The interpolation techniques are based on assumption that there exists interpixel redundancy and interpixel correlation in all directions. These assumptions are not fully true and hence results of interpolation show loss in high frequency information and introduces blurring effect. However, most of the natural images have correlation among neighboring pixels but in specific direction. In other words, the natural images are often comprised of directional structure [55, 56].

Natural images are highly redundant on pixel by pixel scale due to local dependencies among the pixels such as lines and textures [29]. Taking the advantage of these local features that are inherent in natural images, the algorithm is developed to reconstruct super resolution image from low resolution image; these regularities are exploited well. However, it is difficult task to extract these regularities. But use of wavelet makes it possible and easy to extract these regularities and use them for further processing.

The super resolution approach suggested by researchers in literature use low resolution images of same scene or low resolution images of similar scenes or single low resolution image [9-54]. The main objective of these approaches is to recover the lost information mostly; high frequency components from the set of observed low resolution image(s) and reconstruct the super resolution image.

Few researchers have suggested technique to extract high frequency components from aliased information and used them for reconstructing high resolution image [10,12]. Major difficulty is that, now a day's most of the digital cameras use optical low pass filter that avoids aliasing [88].

Since natural image has directional correlation it is possible to add the detail information by using the prediction technique and to reconstruct high resolution image from single low resolution image. For the correct prediction, the wavelet transform is used to decompose the image and the new value of the pixel is predicted according to the nature of the image.

The wavelet transform is used to decorrelate the image data. A pair of approximately designed quadrature mirror filter efficiently implements the wavelet transform. The low and high pass filters are applied to the image in both horizontal and vertical directions and then the filter outputs are subsampled by factor of two. It generates four different horizontal and vertical frequency outputs. These outputs are defined as approximate, horizontal, vertical and diagonal components.

Approximate component contains low frequency horizontal and vertical components of the image. Most of the natural images have maximum low frequency components and less number of high frequency components. But these high frequency components have significant effect in super resolution image. In this research, equal weightage is given to both low frequency and high frequency components.

Consequently, results are not affected from blurring problem which is main limitation of existing techniques in use.

The experimental results of wavelet decomposition for few test images are examined for standard, real natural and synthetic images and few of them are displayed in figure 5.1 to figure 5.12.

Figure 5.1 Barbara Image

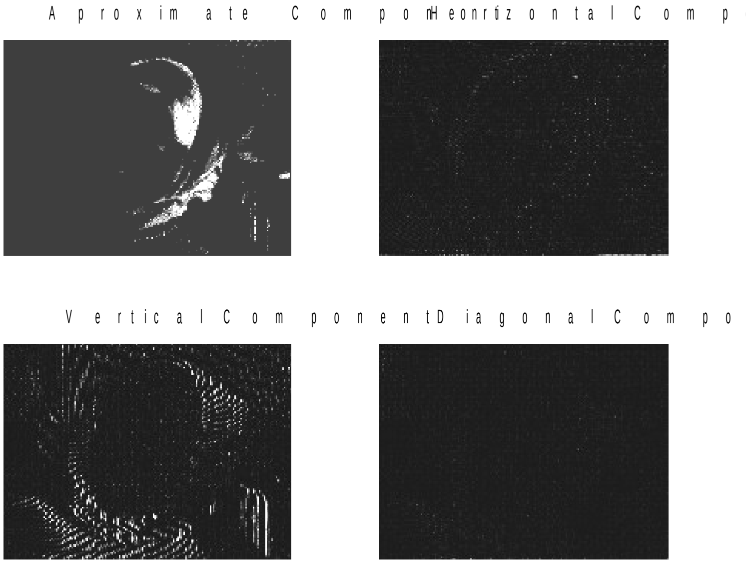


Figure 5.2 Wavelet Decomposition of barbara Image

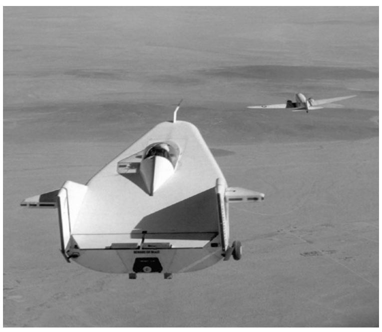


Figure 5.3 Plane Image

Figure 5.4 Decomposition of Plane Image

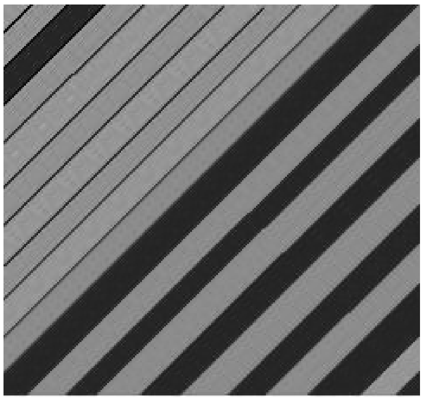


Figure 5.5 Decomposition of Diagonal Image

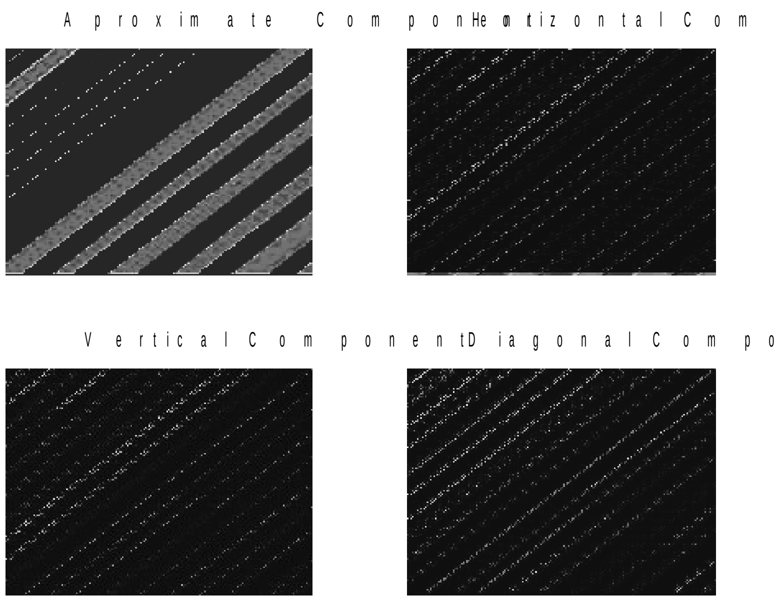


Figure 5.6 Decomposition of diagonal Image

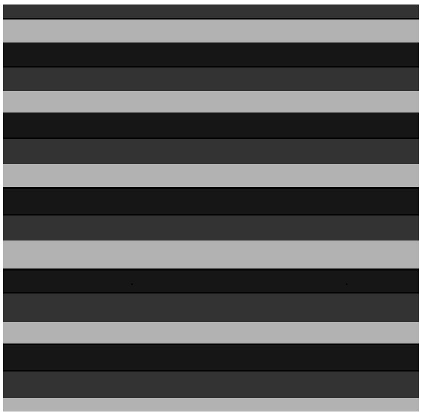


Figure 5.7 Horizontal Image

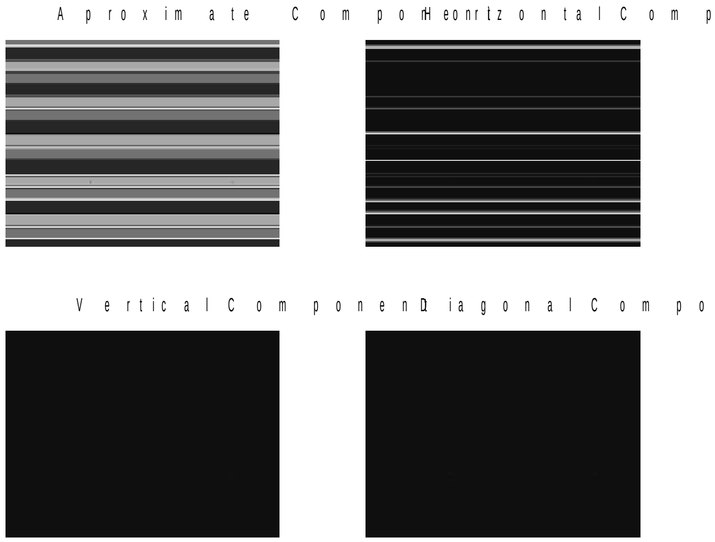


Figure 5.8 Decomposition of Horizontal Image

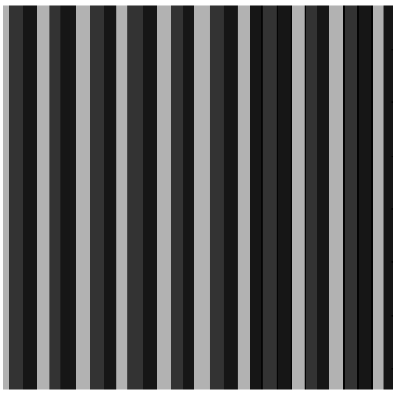


Figure 5.9 Vertical Image

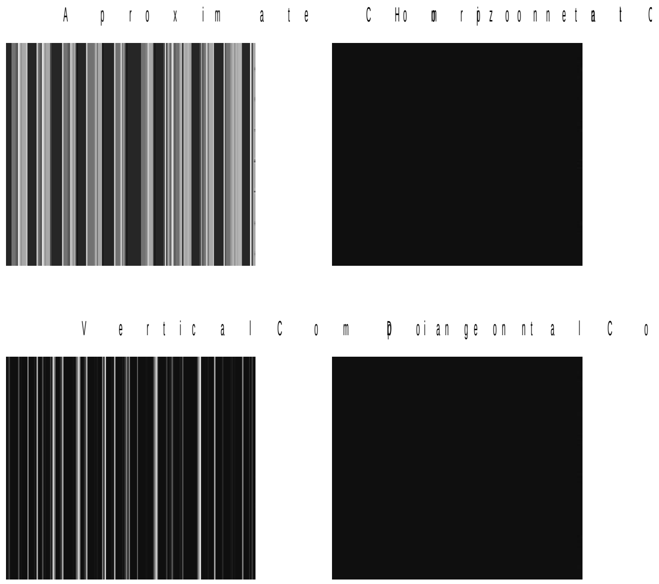


Figure 5.10 Decomposition of Vertical Image

Figure 5.11 Natural Plant Image

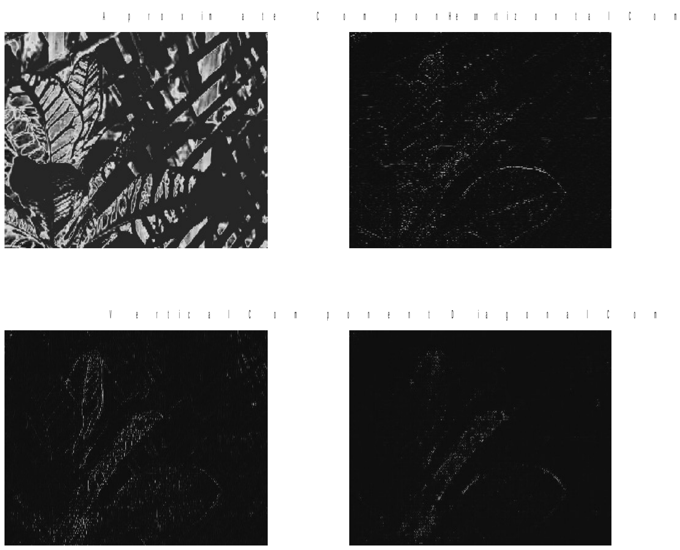


Figure 5.12 Decomposition of Natural Plant Image

Experimental results of wavelet decomposition have four components: approximate, horizontal, vertical and diagonal (fig. 5.1 to 5.12). From results it is observed that approximate component has low frequency horizontal and low frequency vertical components and it looks like smooth image with less fine structure.

From results it is also observed that the horizontal component includes high frequency vertical and low frequency horizontal components. The horizontal component includes horizontal lines those are present in original scene.

Results demonstrate that the vertical component includes high frequency horizontal and low frequency vertical components. The vertical component has vertical lines those are present in original scene.

It is also noticed that the diagonal component has high frequency vertical and high frequency horizontal components. The diagonal components includes diagonal lines those are present in original scene.

5.4 Decomposition of Color Image

In today's multimedia era, color images have significant impact on human lives. The full color image with high resolution provides more information present in image that is useful for pleasing view as well as for better analysis. Most of the applications demand for high resolution color images.

The objective of this research work is to improve the spatial resolution of color natural image. The color associated with single picture element (pixel) is constituted by intermixture of various color components. The color models are developed to support idea of color image representation. Various popular used color schemes are RGB, CMY, CMYK and HIS. Most of the color image capturing devices use RGB model; these are primary colors of light. The RGB is referred as true color or full color image. The number of bits used to represent each pixel in RGB space is called as pixel depth or color resolution. For monochrome images it is referred as brightness resolution. Core objective of the research work is to improve spatial resolution, not to improve color or brightness resolution.

RGB color model is ideal for image color generation but when it is used for color description its scope is much limited. It is important to note that human perception is very sensitive to small change in one of the colors when other colors are fixed. Therefore, individual components of RGB color image can not be processed independently. For color image super resolution algorithm, the selection of proper color model is extremely crucial because in super resolution algorithm the prediction of data must be nearly correct.

Human eye is very sensitive to certain artifacts in color images which can only be avoided by processing all of the color channels together [8]. As human eye is less sensitive to chrominance channel resolution, if RGB model is directly used for the processing the high visual distortion is introduced. Most of the researchers have suggested conversion of RGB model to YCrCb components representation. Here Y is luminance and Cr & Cb are red and blue chrominance respectively. It is proved that YCrCb color space do not have correlation among the spaces. As a result, YCrCb components can be processed independently.

It is well-accepted that edge and color information are important distinction features for image analysis. It is also noticed that human vision system (HVS) has an ability to accommodate itself to the whole color circumstance just as it can adjust itself to different light conditions. For this reason, two colors could be regarded as the same in one image, but as different in another. Moreover, HSV is not sensitive to color difference in texture. So the local spatial distribution of colors is also important.

The YCrCb color space is widely used for digital video. In this format, luminance information is stored as a single component (Y), and chrominance information is stored as two color-difference components

(Cb and Cr). Cb represents the difference between the blue component and a reference value. Cr represents the difference between the red component and a reference value. In the human visual system, changes in color Cr and Cb components are less detectable, and perceptual changes in luminance seem more important. It is observed that most of the energy is concentrated in luminance component and little energy in chrominance components. Hence the conversion of RGB to YCrCb surely takes care of all these issues.

Some researchers have given more importance to Y and less importance to Cr and Cb [4,33]. It is also observed that human eye is less sensitive to chrominance channel resolution than luminance channel resolution. Objective of this research work is not to improve the resolution of specific color component but to improve spatial resolution of overall image by taking into consideration all the color components. Thus, in this research work, equal weightage is given to all the three components Y, Cr and Cb.

In this research work, RGB components are converted into YCrCb and then each of these is decomposed using the wavelet transform. The results of few sample images are shown in figures 5.13 to 5.24.

Figure 5.13 Tulip Image

In figures, prominence of the particular color component is highlighted with crimson color.

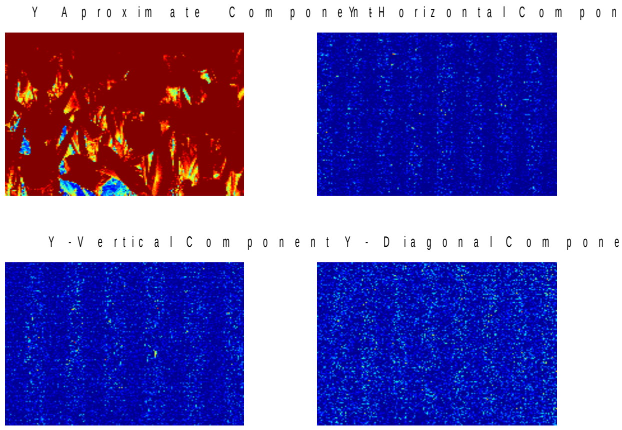


Figure 5.14 Decomposition of Y component for Tulip Color Image

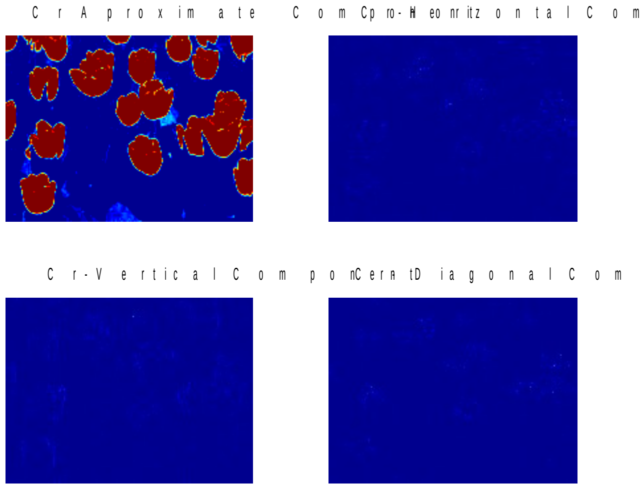


Figure 5.15 Decomposition of Cr component for Tulip Color Image

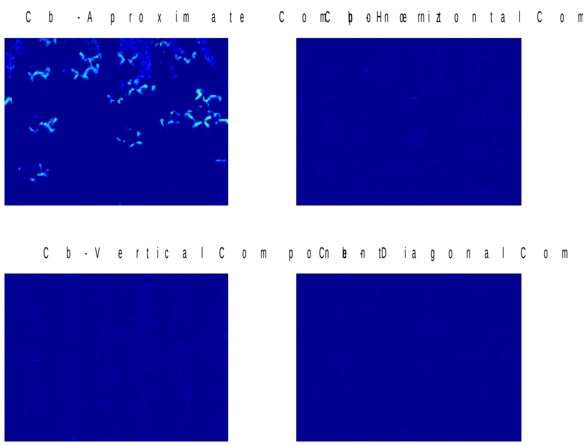


Figure 5.16 Decomposition of Cb components for Tulip Color Image

Figure 5.17 Jelly Fish Image

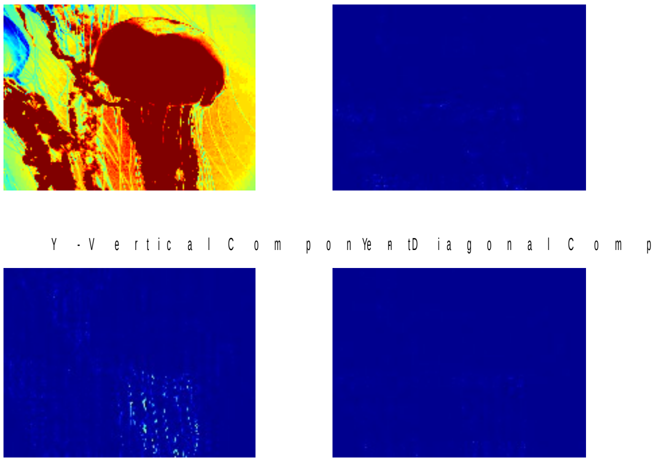


Figure 5.18 Decomposition of Y component for Jelly Fish Color Image

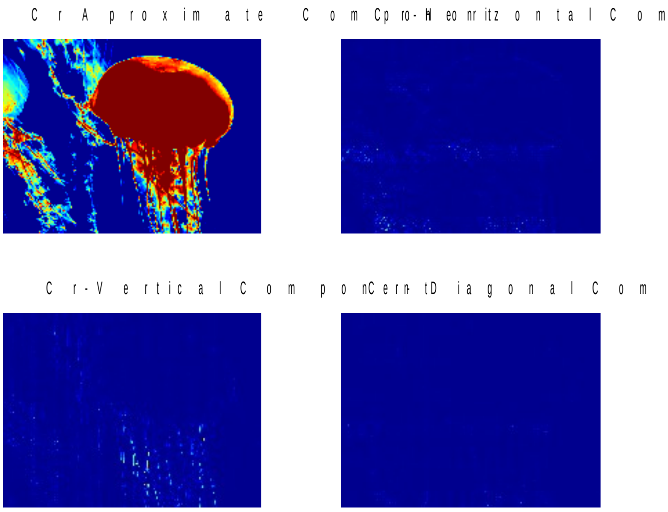


Figure 5.19 Decomposition of Cr component for Jelly Fish Color Image

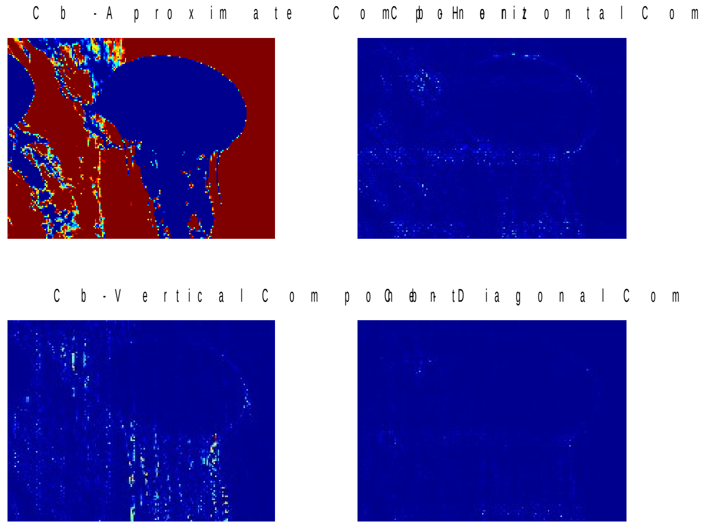


Figure 5.20 Decomposition of Cb component for Jelly Fish Color Image

Figure 5.21 Gajanan Maharaj Image

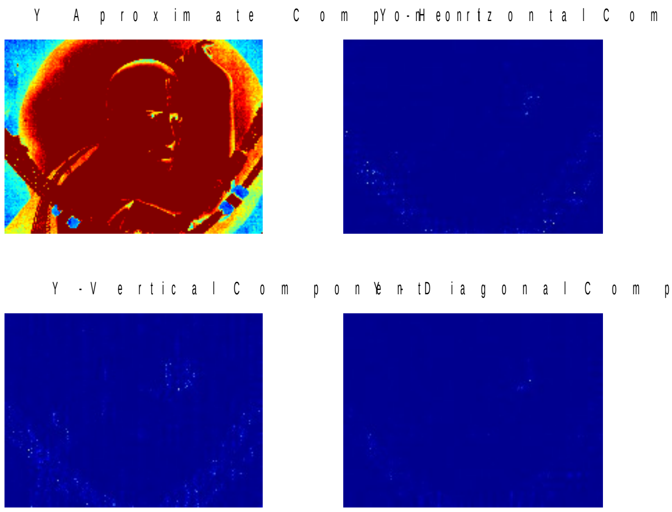


Figure 5.22 Decomposition of Y component for Gajanan Image

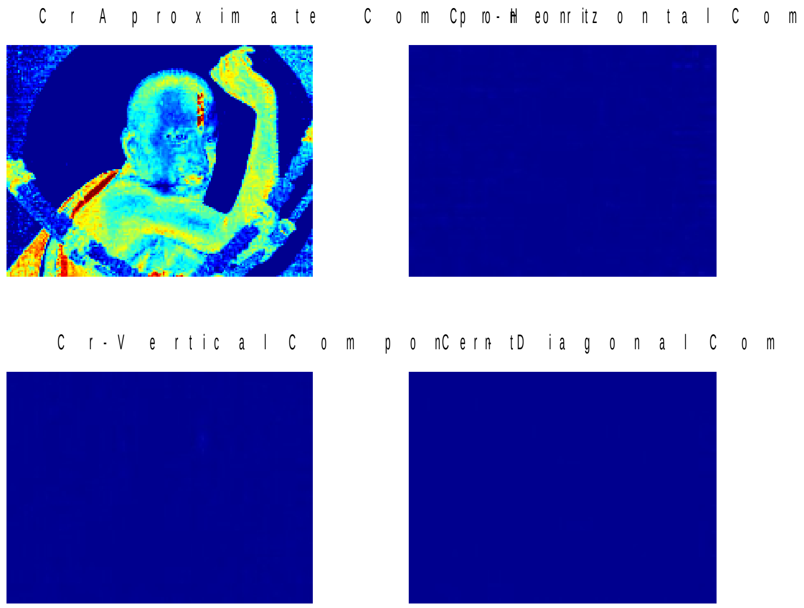


Figure 5.23 Decomposition of Cr component for Gajanan Image

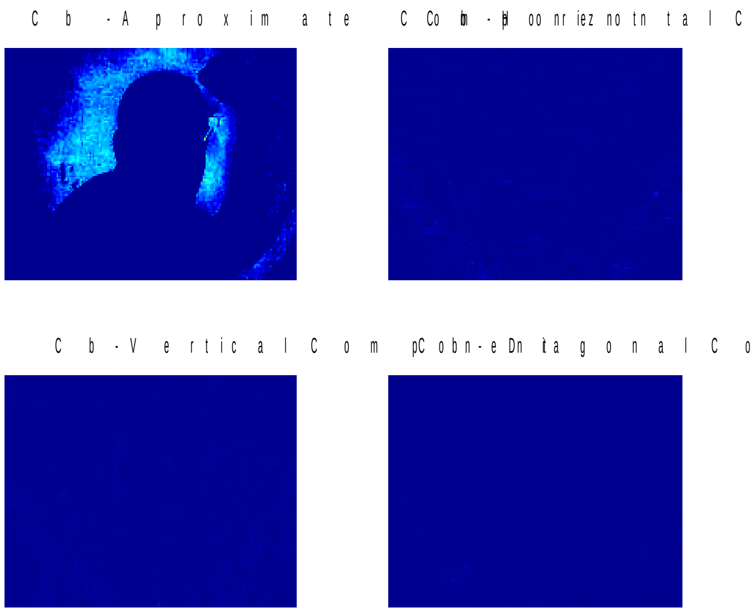


Figure 5.24 Decomposition of Cb component for Gajanan Image

From results of wavelet decomposition and further color separation, it is observed that wavelet is suitable transform and YCrCb is suitable color model for structural decomposition of image so as to take its advantage while super resolving the image.

5.5 Super Resolving Subbands of Wavelet

Aim of super resolution reconstruction is to get super resolution image using low resolution image(s). In most of the applications, the correct set of shifted and/or rotated low resolution images is not available. This research is devoted to develop technique to reconstruct the high resolution image from low resolution image. Researchers have claimed that it is difficult to incorporate additional details in high resolution image with the help of single low resolution image [6]. But they also discuss the about limitations and scope of super resolution image reconstruction that uses set of low resolution images. This problem in details has been put forth in chapter two. Consequently, no technique has yet been standardized as super resolution method that uses set of low resolution images.

At present, interpolation is in use for reconstructing high resolution image from low resolution image. Interpolation technique is based on the assumption that there exists interpixel redundancy and interpixel correlation in all directions. As this assumption is not fully true, results of interpolation are poor. However most of the natural images do have correlation among pixels but it is in specific direction. Natural images contain intrinsic geometrical structure that is key feature in visual information. Natural image signals are highly structured, there pixels exhibit strong dependency especially when are proximate. Taking advantage of these features, the super resolution algorithm is developed in this research work.

Wavelets are good at isolating the discontinuities at edge points and can capture directional information. It can decompose a digital image into frequency sub-images, each represented with proportional frequency resolution clearly classifying the neighborhood structure. Use of wavelet transform helps separating and the processing of frequency band signals independently. It helps in avoiding elimination of high frequency components and helps in minimizing blurring effect.

Conventionally color image is stored in RGB format. In this work this RGB format is converted into YCrCb format. Each of these YCrCb components is decomposed using wavelet transform bior2.2. Decomposition of each yields four subbands viz, approximate, Horizontal, Vertical and Diagonal. Each of these is processed independently. Initially each of these components is upsampled using zero interlacing and then values of newly added pixels are estimated. The estimation is based on structural relationship among pixels of image. Mathematically estimation process is defined as equation,

$$Z = S \times K \qquad (5.1)$$

Where Z is high resolution subimage matrix to be computed,

S is low resolution subimage with zero interlacing and

K is the kernel that is defined to predict the original contents of subimage without losing high frequency components.

5.5.1 Super Resolving Approximate Subimage

Approximate component includes low frequency vertical and low frequency horizontal signals. Visual quality of the image is mainly defined by approximate component. This approximate component must be processed such that unnecessary addition of high frequency components should be avoided and avoid losing visual quality of image as well. Therefore the kernel associated with processing of approximate component is defined so as to estimate correct value of newly added pixels. It is observed that most of the natural images are smooth. Synthetic images have smooth background, due to which maximum energy of scene is concentrated in approximate component for most of the natural and synthetic images. From the results of decomposition (Fig 5.25 to Fig 5.27) it is observed that values of pixels in approximate component have correlation with all directional neighboring pixels. Hence the kernel is defined so as to estimate value of newly added pixels by averaging of neighboring pixels. This kernel performs two dimensional low pass filtering operation over S to calculate the Z image of equation 5.1. Here S is low resolution subimage to reconstruct super resolved Z and K_A is Kernel.

Approximate subimage processing is represented using equation 5.2 as-

$$\mathbf{Z_A = S_A \times K_A} \qquad \mathbf{(5.2)}$$

To estimate the super resolved approximate subimage $\mathbf{Z_A}$ from low resolution approximate subimage $\mathbf{S_A}$ the algorithm is as:

1. $\mathbf{S_A}$ is zero interlaced columnwise to yield matrix say $\mathbf{S_{AC}}$
2. Multiply $\mathbf{S_{AC}}$ with kernel $\mathbf{K_A}$ to compute newly added columns to yield $\mathbf{Z_{AC}}$
3. Take transpose of $\mathbf{Z_{AC}}$ that is, get $\mathbf{[Z_{AC}]^T}$
4. $\mathbf{S_A = [Z_{AC}]^T}$
5. $\mathbf{S_A}$ is zero interlaced columnwise to yield matrix say $\mathbf{S_{AR}}$
6. Multiply $\mathbf{S_{AR}}$ with kernel $\mathbf{K_A}$ to compute newly added columns to yield $\mathbf{Z_{AR}}$
7. $Z_A = [Z_{AR}]^T$

Sample kernel of size 4 x 4 is as,

$$K_A = \frac{1}{2}\begin{pmatrix} 2 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 2 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 2 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 2 & 2 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \qquad (5.3)$$

Let us consider the image of size 4 x 4. Its approximate subimage is $\mathbf{S_A}$ of size 4 x 4 is,

$$\mathbf{S_A} = \begin{pmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{pmatrix}$$

Applying algorithm Using kernel K_A we get super resolved Z_A as

$$Z_A = \begin{pmatrix} a_{11} & A & a_{12} & B & a_{13} & C & a_{14} & D \\ A_1 & A_2 & B_1 & B_2 & C_1 & C_2 & D_1 & D_2 \\ a_{21} & E & a_{22} & F & a_{23} & G & a_{24} & H \\ E_1 & E_2 & F_1 & F_2 & G_1 & G_2 & H_1 & H_2 \\ a_{31} & I & a_{32} & J & a_{33} & K & a_{34} & L \\ I_1 & I_2 & J_1 & J_2 & K_1 & K_2 & L_1 & L_2 \\ a_{41} & M & a_{42} & N & a_{43} & O & a_{44} & P \\ M_1 & M_2 & N_1 & N_2 & O_1 & O_2 & P_1 & P_2 \end{pmatrix}$$

Where

$A = (a_{11} + a_{12}) / 2$, $B = (a_{12} + a_{13})/2$, $C = (a_{13} + a_{14})/2$ and $D = a_{14}$

$E = (a_{21} + a_{22}) / 2$, $F = (a_{22} + a_{23})/2$, $G = (a_{23} + a_{24})/2$ and $H = a_{24}$

$I = (a_{31} + a_{32}) / 2$, $J = (a_{32} + a_{33})/2$, $K = (a_{33} + a_{34})/2$ and $L = a_{34}$

$M = (a_{41} + a_{42})/ 2$, $N = (a_{42} + a_{43})/2$, $O = (a_{43} + a_{44})/2$ and $P = a_{44}$

$A_1 = (a_{11} + a_{21})/2$, $A_2 = (A + E)/2$, $B_1 = (a_{12} + a_{22})/2$ and $B2 = (B + F)/2$

$C_1 = (a_{13} + a_{23})/2$, $C_2 = (C + G)/2$, $E_1 = (a_{21} + a_{31})/2$ and $E2 = (E + I)/2$

$F_1 = (a_{22} + a_{32})/2$, $F_2 = (F + J)/2$, $G_1 = (a_{23} + a_{33})/2$ and $G2 = (G + K)/2$

$H_1 = (a_{24} + a_{34})/2$, $H_2 = (H + L)/2$, $I_1 = (a_{31} + a_{41})/2$ and $I_2 = (I + M)/2$

$J_1 = (a_{32} + a_{42})/2$, $J_2 = (J + N)/2$, $K_1 = (a_{33} + a_{43})/2$ and $K_2 = (K + O)/2$

$L_1 = (a_{34} + a_{44})/2$, $L_2 = (L + P)/2$, $M_1 = a_{41}$ and $M_2 = M$

$N_1 = a_{42}$, $N_2 = N$, $O_1 = a_{43}$, $O_2 = O$, $P_1 = a_{44}$, $P_2 = P$.

The above algorithm is implemented and tested over set of natural and synthetic images. The objective measures are preferred to measure quality of processed image. The mean square error (MSE), signal to noise ratio (SNR), peak signal to noise ratio (PSNR), structural content (SC), and average difference (AD) are the objective measures used and few results are listed in table 5.1.

Table 5.1 Objective measures for reconstructed approximate subimage

SR NO	Image	Type	Resolution	RMSE	SNR (dB)	PSNR (dB)	SC	AD
1	Horizontal	Bmp	189 x 181	29.75	30.93	42.96	0.964	3.22
2	Vertical	Bmp	261 x 265	32.90	28.54	40.95	0.953	1.66
3	Flowers	Jpg	1482 x 984	10.42	38.39	63.94	0.944	0.022
4	Mandate	Jpg	298 x 298	18.43	44.80	52.54	0.959	0.280
5	Mandrill	Bmp	512 x 512	16.42	42.44	54.84	0.940	0.180
6	Woman	Bmp	499 x 512	07.20	63.04	71.32	0.980	0.140
7	Kids	Jpg	512 x 644	05.14	62.49	78.06	0.995	0.069
8	Lena	Bmp	800 x 600	06.12	61.28	74.51	0.991	0.006
9	Peppers	Png	800 x 600	05.64	57.80	76.20	0.993	0.033
10	Matlogo	Bmp	920 x 880	09.16	57.18	66.52	0.996	0.068
11	Text	Bmp	500 x 432	07.36	70.66	70.89	0.970	0.001
12	Budha	Jpg	768 x 1024	05.70	56.51	75.87	0.980	0.051
13	Tulip	Jpg	1472 x 978	07.55	52.92	70.34	0.980	0.070
14	Jellyfish	Bmp	1588x 1098	05.98	60.25	75.05	0.996	0.049

For testing of algorithm, the original image is treated as a super resolution image. This image is decomposed using wavelet and the approximate subimage is used as reference. Now the original high resolution is down sampled by two using neatest neighbor method to generate low resolution input image. It is decomposed using wavelet transform, its approximate subimage is processed using novel algorithm developed and the high resolution approximate image is reconstructed. Resultant reconstructed image and reference are used for computing objective measures.

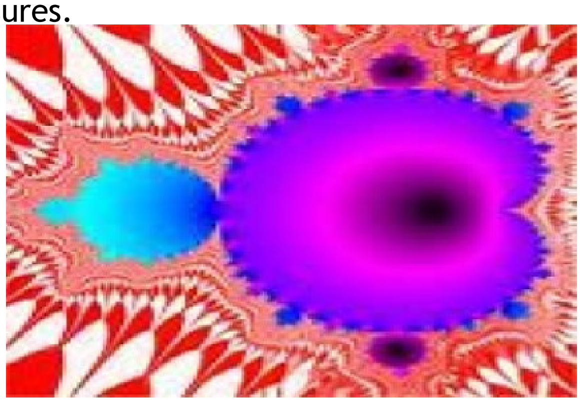


Figure 5.27 Approximate subimage of mandate image

RMSE =18.4302 SNR=44.8004 PSNR

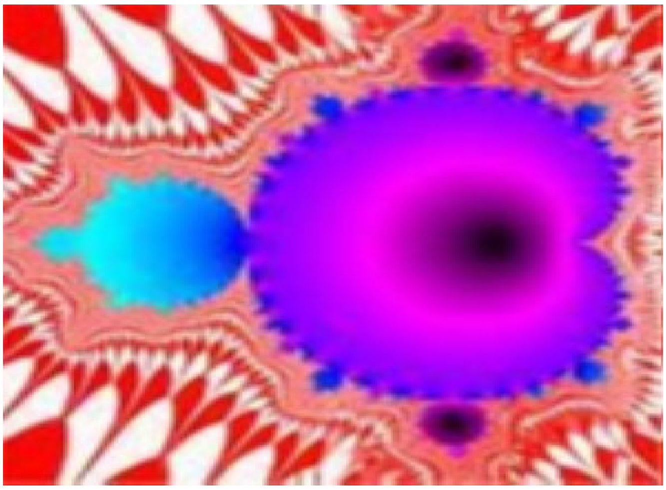


Figure 5.26 Approximate super resolved subimage of mandate image

RMSE =7.3632 SNR=70.6675 PSNR

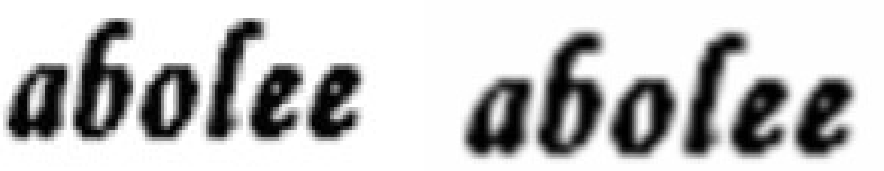


Figure 5.27 Approximate Original and super resolved subimages of text image

5.5.2 Super Resolving Horizontal Subimage

Horizontal component includes low frequency horizontal and high frequency vertical signals. Visual quality of the image is mainly defined by approximate component but it does not mean that horizontal component does not have effect on quality or originality of image. As such the detail component has significant impact from information point of view. Thus it is very important to process this component carefully so that originality of scene is not affected. Existing techniques do not take care of this issue. These techniques process all frequency components simultaneously and treat them equally. In this research work, horizontal component is processed independently. The horizontal component includes horizontal lines those are present in original scene.

The horizontal component should be processed such that these horizontal components are not widened unnecessarily while super resolving them. Therefore the kernel associated with processing of horizontal component is defined to estimate correct value of newly added pixels. It is observed that most of the natural images are smooth. These images have smooth background and they include fine details in the form of lines and curves as well. From the results of decomposition (Fig 5.29, 5.30) it is observed that values of pixels in horizontal component has correlation with neighboring pixels in horizontal direction. Hence the kernel is defined so as to estimate value of newly added pixels by considering horizontal neighbors only. The process of super resolving horizontal subimage is defined by equation 5.4 and the kernel K_H is defined in equation 5.5.

$$\mathbf{Z_H = S_H \times K_H} \qquad \textbf{(5.4)}$$

To estimate the super resolved horizontal subimage Z_H from low resolution horizontal subimage S_H the algorithm is as,

1. $\mathbf{S_H}$ is zero interlaced columnwise to yield matrix say S_{HC}
2. Multiply $\mathbf{S_{HC}}$ with kernel $\mathbf{K_H}$ to compute newly added columns to yield $\mathbf{Z_{HC}}$
3. $\mathbf{Z_{HC}}$ is zero interlaced rowwise to yield matrix say $\mathbf{Z_H}$

Sample kernel of size 4 x 4 is given as,

$$K_H = \frac{1}{2}\begin{pmatrix} 2 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 2 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 2 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 2 & 2 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \tag{5.5}$$

Let us consider the image of size 4 x 4. Its horizontal subimage is **S_H** of size 4 x 4 is given below,

$$\mathbf{S_H} = \begin{pmatrix} h_{11} & h_{12} & h_{13} & h_{14} \\ h_{21} & h_{22} & h_{23} & h_{24} \\ h_{31} & h_{32} & h_{33} & h_{34} \\ h_{41} & h_{42} & h_{43} & h_{44} \end{pmatrix}$$

Applying algorithm using kernel K_H we get super resolved horizontal subimage Z_H as

$$\mathbf{Z_H} = \begin{pmatrix} h_{11} & A & h_{12} & B & h_{13} & C & h_{14} & D \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ h_{21} & E & h_{22} & F & h_{23} & G & h_{24} & H \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ h_{31} & I & h_{32} & J & h_{33} & K & h_{34} & L \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ h_{41} & M & h_{42} & N & h_{43} & O & h_{44} & P \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

Where

$A = (h_{11} + h_{12}) / 2$, $B = (h_{12} + h_{13})/2$, $C = (h_{13} + h_{14})/2$ and $D = h_{14}$

$E = (h_{21} + h_{22}) / 2$, $F = (h_{22} + h_{23})/2$, $G = (h_{23} + h_{24})/2$ and $H = h_{24}$

I= $(h_{31} + h_{32}) / 2$, J = $(h_{32} + h_{33})/2$, K = $(h_{33} + h_{34})/2$ and L = h_{34}

M= $(h_{41} + h_{42}) / 2$, N = $(h_{42} + h_{43})/2$, O = $(h_{43} + h_{44})/2$ and P = h_{44}

The above algorithm is implemented and tested over set of natural and synthetic images. The objective measures are preferred to measure quality of processed image. The mean square error (MSE), signal to noise ratio (SNR), peak signal to noise ratio (PSNR), structural correlation (SC), and average difference (AD) are the objective measures used and few results are listed in table 5.2.

Table 5.2 Objective measures for reconstructed horizontal subimage

SR NO	Image	Type	Resolution	RMSE	SNR (dB)	PSNR (dB)	SC	AD
1	Horizontal	Bmp	189 x 181	12.89	5.67	59.69	0.66	5.07
2	Vertical	Bmp	261 x 265	10.16	-5.83	64.45	0.018	0.50
3	Flowers	Jpg	1482 x 984	2.57	- 4.08	91.91	0.13	0.76
4	Mandate	Jpg	298 x 298	3.61	- 4.1	85.12	0.063	0.89
5	Mandrill	Bmp	512 x 512	12.06	- 4.78	61.02	0.08	2.86
6	Woman	Bmp	499 x 512	1.3	- 4.06	104.13	0.13	0.37
7	Kids	Jpg	512 x 644	1.14	- 4.70	108.16	0.06	0.21
8	Lena	Bmp	800 x 600	0.71	- 4.9	117.47	0.631	0.117
9	Peppers	Png	800 x 600	0.96	- 4.81	111.56	0.032	0.16
10	Matlogo	Bmp	920 x 880	2.46	- 5.63	92.80	0.058	0.32
11	Text	Bmp	500 x 432	0.21	- 5.31	141.87	0.0049	0.0109
12	Budha	Jpg	768 x 1024	1.34	- 4.76	104.83	0.024	0.19
13	Tulip	Jpg	1472 x 978	2.29	- 3.70	94.17	0.139	0.71
14	Jellyfish	Bmp	1588 x 1098	0.63	- 5.1	119.75	0.019	0.070

For testing of algorithm, the original image is treated as a super resolution image. This image is decomposed using wavelet and the horizontal subimage is used as reference. Now the original high resolution is down sampled by two using neatest neighbor method to generate low resolution input image. It is decomposed using wavelet transform, its horizontal subimage is processed using novel algorithm developed and the high resolution horizontal image is reconstructed. Resultant reconstructed image and reference are used for computing obj

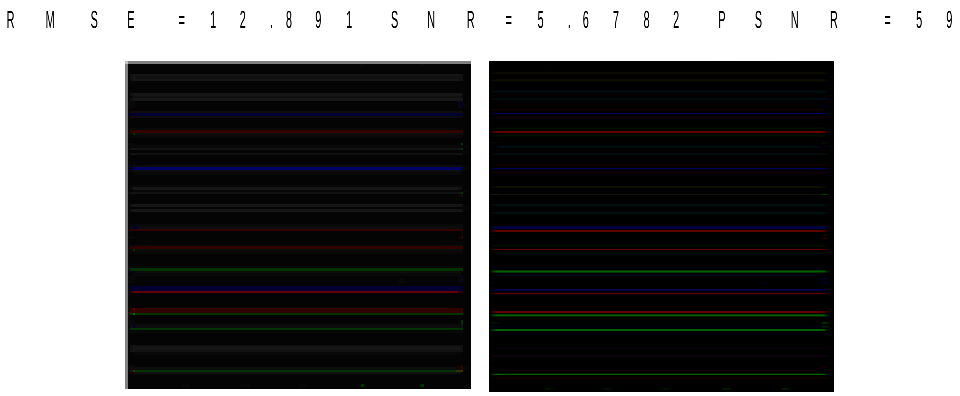


Figure 5.28 Horizontal original & super resolved subimages

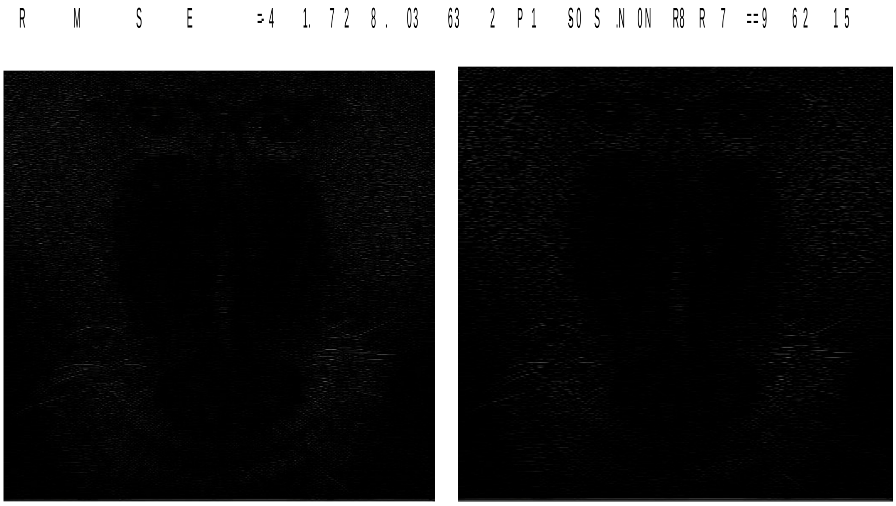


Figure 5.29 Horizontal original & super resolved subimages of Mandrill

5.5.3 Super Resolving Vertical Subimage

Vertical component includes low frequency vertical and high frequency horizontal signals. Visual quality of the image is mainly defined by approximate component but it does not mean that vertical component do not have effect on quality or originality of image. As such the detail component has significant impact from information point of view. Thus it is very important to process this component carefully so that originality of scene is not affected. Existing techniques do not take care of this issue. These techniques process all frequency components simultaneously and treat them equally. In this research work vertical component is processed independently. The vertical component includes vertical lines those are present in original scene.

The vertical component should be processed such that these vertical components are not widened unnecessarily while super resolving them. Therefore the kernel associated with processing of vertical component is defined to estimate correct value of newly added pixels.

It is observed that most of the natural images are smooth. These images have smooth background and they include fine details in the form of lines and curves as well. From the results of decomposition (Fig 5.30, 5.31) it is observed that values of pixels in vertical component has correlation with neighboring pixels in vertical direction. Hence the kernel is defined so as to estimate value of newly added pixels by considering vertical neighbors only. The process of super resolving vertical subimage is defined by equation 5.6 and the kernel K_V is defined in equation 5.7.

$$\mathbf{Z_V = S_V \times K_V} \qquad (5.6)$$

To estimate the super resolved vertical subimage $\mathbf{Z_V}$ from low resolution vertical subimage $\mathbf{S_V}$ the algorithm is:

1. Take transpose of S_V to get $[S_V]^T$
2. $[S_V]^T$ is zero interlaced columnwise to yield matrix say S_{VC}
3. Multiply $\mathbf{S_{VC}}$ with kernel $\mathbf{K_V}$ to compute newly added columns to yield $\mathbf{Z_{VC}}$
4. Take transpose of $\mathbf{[Z_{VC}]^T}$
5. $\mathbf{[Z_{VC}]^T}$ is zero interlaced rowwise to yield matrix say $\mathbf{Z_V}$

Sample kernel of size 4 x 4 is given as,

$$K_V = \frac{1}{2}\begin{pmatrix} 2 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 2 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 2 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 2 & 2 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \qquad (5.7)$$

Let us consider the image of size 4 x 4. Its vertical subimage is $\mathbf{S_V}$ of size 4 x 4 is:

$$\mathbf{S_V} = \begin{pmatrix} V_{11} & V_{12} & V_{13} & V_{14} \\ V_{21} & V_{22} & V_{23} & V_{24} \\ V_{31} & V_{32} & V_{33} & V_{34} \\ V_{41} & V_{42} & V_{43} & V_{44} \end{pmatrix}$$

Applying algorithm with kernel K_V we get super resolved vertical subimage Z_V as

$$[Z_V]^T = \begin{pmatrix} v_{11} & A & v_{21} & B & v_{31} & C & v_{41} & D \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ V_{12} & E & v_{22} & F & v_{32} & G & v_{42} & H \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ V_{13} & I & v_{23} & J & v_{33} & K & v_{43} & L \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ V_{14} & M & v_{24} & N & v_{34} & O & v_{44} & P \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

Where

$A = (v_{11} + v_{21}) / 2$, $B = (v_{31} + v_{21})/2$, $C = (v_{31} + v_{41})/2$ and $D = v_{41}$

$E = (v_{12} + v_{22}) / 2$, $F = (v_{22} + v_{32})/2$, $G = (v_{32} + v_{42})/2$ and $H = v_{42}$

$I = (v_{13} + v_{23}) / 2$, $J = (v_{23} + v_{33})/2$, $K = (v_{33} + v_{43})/2$ and $L = v_{43}$

$M = (v_{14} + v_{24}) / 2$, $N = (v_{24} + v_{34})/2$, $O = (v_{34} + v_{44})/2$ and $P = v_{44}$

The above algorithm is implemented and tested over set of natural and synthetic images. The objective measures are preferred to measure quality of processed image. The mean square error (MSE), signal to noise ratio (SNR), peak signal to noise ratio (PSNR), structural correlation (SC), and average difference (AD) are the objective measures used and few results are listed in table 5.3.

For testing of algorithm, the original image is treated as a super resolved image. This image is decomposed using wavelet and the vertical subimage is used as reference. Now the original high resolution is down sampled by two using neatest neighbor method to generate low resolution input image. It is decomposed using wavelet transform, its vertical subimage is processed using novel algorithm developed and the high resolution vertical image is reconstructed. Resultant reconstructed image and reference are used for computing objective measures.

Table 5.3 Objective measures for reconstructed vertical subimage

SR NO	Image	Type	Resolution	RMSE	SNR (dB)	PSNR (dB)	SC	AD
1	Horizontal	Bmp	189 x 181	89.99	- 4.51	65.82	0.032	1.03
2	Vertical	Bmp	261 x 265	342.02	0.5492	52.47	0.436	4.98
3	Flowers	Jpg	1482 x 984	8.07	- 4.28	89.93	0.12	0.85
4	Mandate	Jpg	298 x 298	18.20	- 4.54	81.80	0.074	0.98
5	Mandrill	Bmp	512 x 512	38.70	- 3.74	74.26	0.092	1.78
6	Woman	Bmp	499 x 512	4.38	- 0.64	98.05	0.41	0.56
7	Kids	Jpg	512 x 644	1.17	- 4.6	109.0	0.062	0.22
8	Lena	Bmp	800 x 600	0.83	- 4.99	117.09	0.032	0.12
9	Peppers	Png	800 x 600	0.49	- 4.30	117.88	0.02	0.12
10	Matlogo	Bmp	920 x 880	7.21	- 5.31	91.06	0.059	0.39
11	Text	Bmp	500 x 432	0.1589	- 5.05	129.21	0.017	0.02
12	Budha	Jpg	768 x 1024	1.35	- 4.39	107.78	0.016	0.20
13	Tulip	Jpg	1472 x 978	5.47	- 3.64	93.81	0.13	0.77
14	Jellyfish	Bmp	1588 x 1098	1.48	- 5.49	106.89	0.0075	0.10

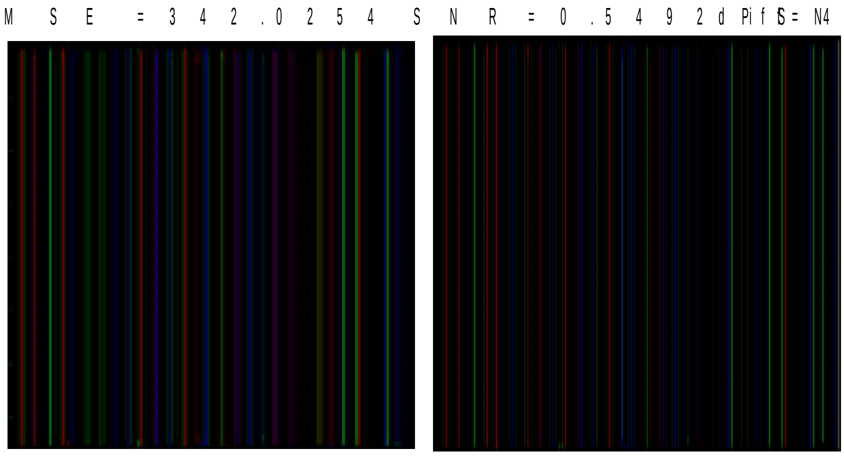


Figure 5.30 Vertical Original and super resolved subimages

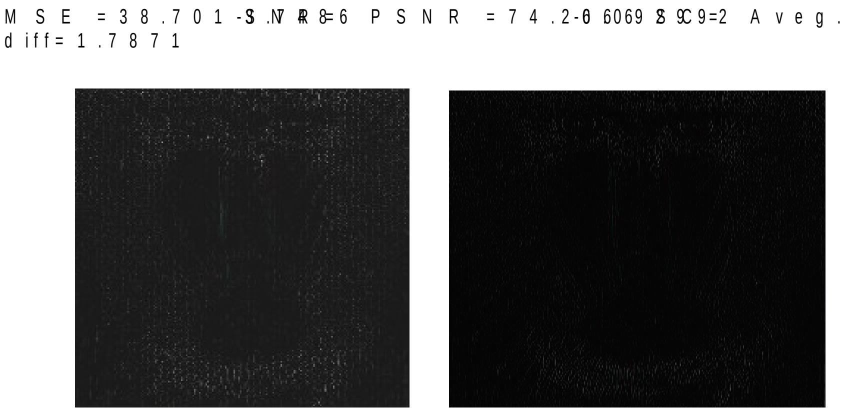


Figure 5.31 Vertical super resolved subimages of mandrill image

5.5.4 Super Resolving Diagonal Subimage

Diagonal component has high frequency vertical as well as high frequency horizontal signals. Visual quality of image is mainly defined by low frequency components and high frequency components typically contribute in defining originality of image. As such the detail component has importance from information point of view. The diagonal component of image mostly includes the diagonal lines of original image. While interpolating this component by conventional method, unwanted components get added and these diagonal edges contribute more error in interpolated image. It is necessity to design appropriate algorithm especially for diagonal component that minimizes the error.

Though natural images are smooth, it includes fine details in the form of lines and curves. Curves are mainly constituted by diagonal lines. Even though natural images include less diagonally correlated pixels, effect of these pixels is noticeable. Structural images have large number of curves and lines. In cervical structure, the pixel has correlation with its first, second or other neighboring diagonal. It is possible to find diagonal with which the correlation of pixel exists but it is difficult to process and calculate the value of new pixels. For the simplicity, the research work has made the assumption about the correlation. The assumption is that the diagonal pixel has correlation with its nearest pixel on the same diagonal only. And the assumption is observed to be true for natural images.

For processing, there is need to check the correlation of pixel with its nearest left or nearest right diagonal pixel and process accordingly. There are two ways to find the correlating pixels and further process them.

1. The diagonal edges are separated according to their directions into two sets: left diagonals and right diagonals and then process each one independently.
2. Instead of separating diagonals into two sets, check the diagonal correlation of existing pixels and then compute value of each newly added pixel accordingly.

In this research work, the first approach is implemented using following algorithm:

Algorithm:

1. Check the correlation of pixels and separate the diagonal subimage into two diagonal sets: the left diagonals (LD) and right diagonals (RD)
2. Process them independently as in step 3 and 4
3. Left Diagonals:
    a. Upsample RD by two with zero interlacing
    b. Compute value of newly added pixel as average of its right upper diagonal and lower left diagonal neighbors
4. Right Diagonals:
    a. Upsample LD by two with zero interlacing
    b. Compute value of newly added pixel as average of its Left upper diagonal and lower right diagonal neighbors

Figures 5.32 and 5.33 demonstrate the low resolution diagonal subimage and its respective super resolved diagonal images.

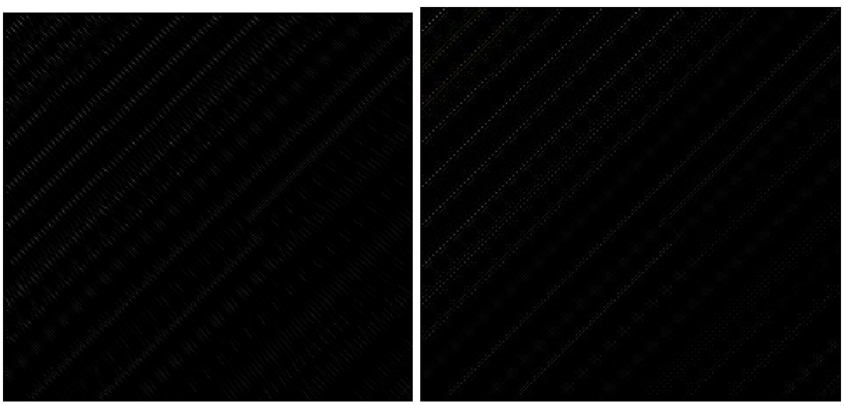


Figure 5.32 Diagonal original & super resolved subimages

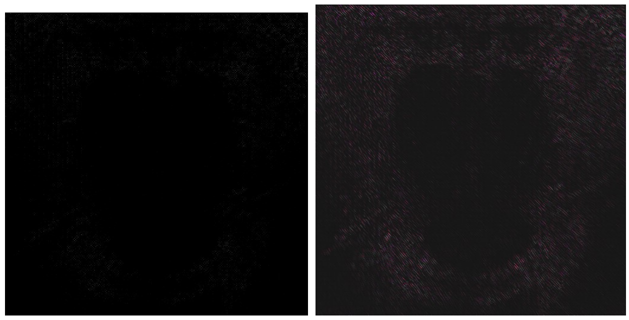


Figure 5.33 Diagonal super resolved subimages of mandrill image

Table 5.4 Objective measures for reconstructed diagonal subimage

SR NO	Image	Type	Resolution	RMSE	SNR (dB)	PSNR (dB)	SC	AD
1	Horizontal	Bmp	189 x 181	4.041	- 6.791	96.86	0.165	0.084
2	Vertical	Bmp	261 x 265	4.210	- 9.058	96.44	0.200	0.200
3	Flowers	Jpg	1482 x 984	74.47	- 9.640	67.72	0.160	3.120
4	Mandate	Jpg	298 x 298	4.600	-13. 80	95.56	0.360	1.220
5	Mandrill	Bmp	512 x 512	33.58	- 11.02	75.68	0.330	3.050
6	Woman	Bmp	499 x 512	1.810	- 20.18	104.8	0.110	0.920
7	Kids	Jpg	512 x 644	0.425	- 14.63	119.3	0.340	0.311
8	Lena	Bmp	800 x 600	0.098	- 16.66	134.0	0.320	0.131
9	Peppers	Png	800 x 600	0.205	- 15.71	126.6	0.330	0.200
10	Matlogo	Bmp	920 x 880	0.139	-15.87	130.5	0.330	0.145
11	Text	Bmp	500 x 432	0.120	-5.67	120.4	0.056	0.102
12	Budha	Jpg	768 x 1024	0.506	- 14.21	117.6	0.410	0.310
13	Tulip	Jpg	1472 x 978	3.736	- 14.97	97.64	0.350	1.270
14	Jellyfish	Bmp	1588 x 1098	2.445	-15.67	99.89	0.225	1.456

Since high resolution image is not available, the original image is treated as a super resolution image. This image is decomposed using wavelet and the diagonal subimage is used as reference. Now the original high resolution is down sampled by two using neatest neighbor method to generate low resolution input image. It is decomposed using wavelet transform, its diagonal subimage is processed using novel algorithm developed and the high resolution diagonal image is reconstructed. Resultant reconstructed image and reference are used for computing objective measures.

5.5.5 Observations

Objective measures are used to measure the visual quality of an image. Root mean squared error defines the root of average of square of error present in reconstructed image as compared to reference image.

The range of RMSE for approximate subimage is (5.14 to 32.90), for horizontal subimage is (0.21 to12.89), for vertical subimage is (0.49 to 342.02) and for diagonal subimage is (0.098 to 74.47). This measure is not suitable to define the visual quality of image. If the same error occurs in different power images then visual effect of error might not be the same.

Signal to noise ratio (SNR) is ratio of mean of square of signal power to mean square of noise power. Ideally SNR should be infinite but practically higher the SNR better is the quality. The range of SNR for approximate subimage is (28.54 to 63.04), for horizontal subimage is (- 5.83 to 5.67), for vertical subimage is (- 5.49 to 0.549) and for diagonal subimage is (- 20.18 to – 9.058). SNR is measured in dB.

From results (Table 5.1-5.4) it is observed that for few of the images, the noise power is more than signal power and SNR results into negative value. Thus PSNR is proposed to measure the quality of image.

Peak signal to noise ratio (PSNR) should be ideally infinite but practically higher PSNR is observed for better quality image. The range of PSNR in dB for approximate subimage is (40.94 to 78.06), for horizontal subimage is (59.69 to 141.87), for vertical subimage is (52.47 to 129.21) and for diagonal subimage is (67.72 to 134.00).

Structural Content (SC) is one of the objective measures. It simply shows ratio of average of square of original image to average of square of reconstructed image. Ideally it should be one. It is observed that the range of SC for approximate subimage is (0.94 to 0.99), for horizontal subimage is (0.0049 to 0.66), for vertical subimage is (0.017 to 0.436) and for diagonal subimage is (0.110 to 0.410).

The average difference (AD) measures the average of difference of original image and reconstructed image. Ideally it should be zero. It is observed that the range of AD for approximate subimage is (0.022 to 3.22), for horizontal subimage is (0.019 to 5.07), for vertical subimage is (0.02 to 4.98) and for diagonal subimage is (0.131 to 3.120).

Computations for these measures need two images: the reference high resolution image and the reconstructed image. In super resolution imaging the original high resolution image reference does not exist. Since original reference is unavailable, the available high resolution image is considered as reference image. This image is down sampled using nearest neighbor method and each subimage of this downsampled image reconstructed using the novel technique developed. This process of down sampling and then reconstructing back is not reversible. Thus the results are not truly defining the true quality of reconstructed image from super resolution point of view. Hence subjective measures seem to be better suited.

The resultant reconstructed approximate subimages are shown in fig. 5.25, 5.26 and 5.27. It is observed that the images are smooth images in which values of newly added pixels are appropriately estimated, checker board effect is not observed, and edges are not prominent in image.

The horizontal subimages of few images are super resolved. The resultant reconstructed horizontal subimages are shown in fig. 5.28 and fig. 5.29. It is observed that the horizontal lines are appropriately super resolved and do not affect the neighboring pixels.

The vertical subimages of few images are super resolved. The resultant reconstructed vertical subimages are shown in It can be observed in fig. 5.30 and fig. 5.31 that the vertical lines are appropriately super resolved and do not affect the neighboring pixels.

The diagonal subimages of few images are super resolved. The resultant reconstructed diagonal subimages are shown in fig. 5.32 and fig. 5.33. It is observed that the diagonal lines are appropriately super resolved and do not affect the neighboring pixels significantly.

5.6 Performance Measure for Super Resolution Imaging

For most of the image processing algorithms, objective measures are used as the most suitable performance measuring matrix, in which reference image/ original image exists. From the literature survey [1-54] it is found that there is no suitable quality measure for measuring visual quality of super resolution image. Objective of super resolution technique is to construct the super resolution image beyond camera limit. Thus the original super resolution image is not available for the computations of objective quality measures. The list of objective measures and their mathematical equations are discussed in chapter four. Few quality measures are used in previous section and observations are drawn. Generally, most of the researchers propose use of PSNR as quality measure for super resolution imaging. But still it is not appropriate as the true reference is not used. In this research, the new frame work for measuring quality of super resolution image using PSNR is presented.

The significant observation is that selection of an appropriate evaluation methodology or criteria is largely dependent on the objective of algorithm. Key objective of super resolution imaging is to reconstruct an appropriate super resolution image. And thus the performance of super resolution technique should test the accuracy (better performance with reference) and adaptability of the algorithm.

The accuracy of super resolution technique can be measured using existing measure such as PSNR if the true reference exists. Accuracy checks the similarity between reconstructed and the reference image. Hence to accurately measure the super resolution algorithms accuracy, the researchers should use a camera that can capture images of the same scene with varying resolutions. The higher resolution image among these is to be considered as reference image and lower resolution image than that is used as input image to reconstruct the super resolution image. Subsequently the PSNR is calculated using the reconstructed and the reference image.

For the signal processing algorithm, few standard images are used to test the results; the images are Lena, Barbara, mandrill and cameraman. These images are easily available but are not available with varying resolutions. Thus algorithm can not be tested with these images. One should prepare their own set of test images by capturing multiple images of the same scene with varying resolutions.

It is observed that due to time difference between two consecutive captures of images, the accuracy of the image may change because of environmental change or reduction of input power in case of battery operated camera. In few images this effect might be insignificant but one should not neglect it especially in medical image analysis. Hence there is need to capture these images in controlled environment.

- Capture images with camera position steady,
- Keep uniform light, and
- Use stabilized power supply.

For multiframe super resolution imaging techniques, we suggest to capture shifted images by user holding digital camera in hands while manually or automatically capturing the series of shots of the scene within a short span of time. The small vibrations of the user's hands during image capture are sufficient to capture set of input images.

It is suggested to capture these images without built in software support of camera. Most of the recent digital cameras have built in software support such as interpolation methods for resolution enhancement. Hence usually the image captured is an image having resolution higher than the camera capacity.

Moreover, images should be captured and stored in bit map format (bmp) and bit resolution of stored file format should be equal to or higher than camera. The other file format may use compression for effective storage and transmission and may affect the contents.

Often YCrCb color model is preferred by researchers for processing and it has been used in this research work too. After processing results are visualized in RGB color model. Therefore, the PSNR is measured for individual color (R, G and B) and the average is considered.

Literature survey reveals that the accuracy of results is observed to be good for some of the images while poor for some set of images. For example, the results of interpolation using nearest neighbor are good for smooth images while are bad for structured images. Therefore it is necessary to check adaptability of super resolution algorithm.

Adaptability of technique is said to be good if accuracy of results is steady for varying set of images. To test adaptability of algorithm, algorithm should be tested over wide set of images with varying frequency and varying resolution images that camera can capture. In the research work, set of images with varying frequency contents are used for testing. It is difficult to classify images as per the frequency contents. It is not possible to classify by just human visual perception. The classification of the images based on their frequency contents using wavelet is suggested.

Wavelets are good at isolating the discontinuities at edge points and can capture directional information – an important and unique feature of multidimensional signal. It can decompose a digital image into frequency sub-images, each represented with proportional frequency resolution clearly classifying the neighborhood structure. Use of wavelet transform helps separating and the processing of frequency band signals independently. The decomposition of image yields four subimages- approximate, vertical details, horizontal details and diagonal details. Classification can be done based on entropy of vertical, horizontal and diagonal sub images.

Following steps help classifying set of images. The images are classified according to horizontal frequency and vertical frequency contents.

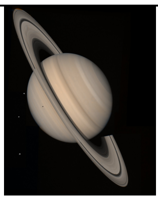
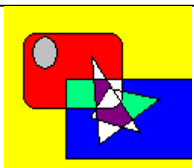
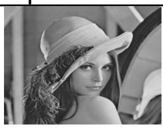
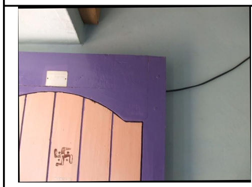
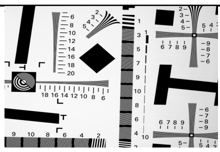
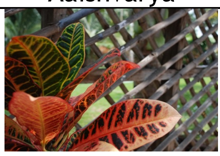
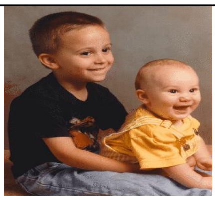
- Decompose image using wavelet.
- Compute entropy of approximate and detail sub images.
- Categorize image as Very Smooth, Smooth, High Frequency, Very High Frequency image based on entropy.
- Test set should have at least three images of each category and super resolution technique should be tested against the same.

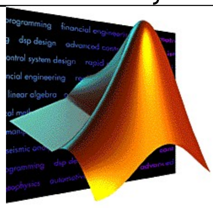
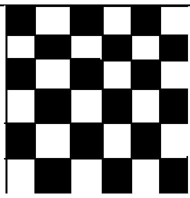
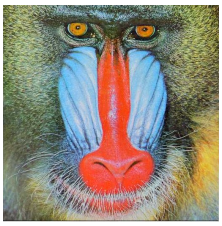
Table 5.5 lists few images along with their percentage entropies with respect to original image for classifying them into one of the categories. The range we have used for threshold is as following:

- The image with percentage of entropy of approximate subimage within range of (85-100) is classified as Very Smooth Image
- The image with percentage of entropy of approximate subimage within range of (71-84) is classified as Smooth Image
- The image with percentage of entropy of approximate subimage within range of (55-70) is classified as High Frequency Image
- The image with percentage of entropy of approximate subimage ranging below 55 is classified as High Frequency Image

Table 5.5- Percentage of entropy of detail and approx subimage

Image	Percentage of Entropy					Remark
	Approx.	Detail				
		Horizontal	Vertical	Diagonal		
Plain Yellow	100	0	0	0		Very Smooth
 X-ray	97.2855	1.2783	1.284	.15224		Very Smooth

 Saturn	85.58	5.66	6.59	2.17		Very Smooth
 Simple structure	81.67	9.8	8.4	.13		Smooth
 Lena	79.24	9.49	9.52	1.7322		Smooth
 Door	73.55	9.23	11.60	5.60		Smooth
 Switchboard	71.15	10.71	12.08	6.0495		Smooth
 Chart	70.0422	13.1232	12.9142	3.9024		High Frequency
 Aaishvarya	59.14	12.9	17.47	10.46		High Frequency
 Plant	69.37	12.90	12.81	4.90		High Frequency
 Kids	61.69	14.60	14.22	9.476		High Frequency

 Cameraman	59.1232	15.56	15.04	10.27		High Frequency
 Fabric	59.56	19.29	15.47	10.66		High Frequency
 Butterfly	53.5928	17.9556	16.5433	11.9082		Very High Frequency
 Matlogo	44.99	18.61	18.46	17.92		Very High Frequency
 Woman	47.46	15.86	19.72	16.95		Very High Frequency
 Chessboard	51.99	17.78	22.48	7.74		Very High Frequency
 Castle	50.86	17.04	16.79	15.29		Very High Frequency
 Mandrill	50.80	19.26	16.85	13.077		Very High Frequency

5.7 Reconstructing super Resolution Image from Low Resolution Color Natural Image

In today's multimedia era, color images have significant impact on human lives. The full color image with high resolution provide more information present in an image that is useful for pleasing view as well as for better analysis. Most of the applications demand for high resolution color images.

Objective of this research work is to improve the spatial resolution of color natural image using wavelet. Most of the color image capturing devices use RGB color model, these are primary colors of light. The RGB is referred as true color or full color image.

RGB color model is ideal for image color generation but when it is used for color description its scope is much limited. It is important to note that human perception is very sensitive to small change in one of the colors when other colors are fixed. Therefore individual components of RGB color image can not be processed independently.

As human eye is less sensitive to chrominance channel resolution, if RGB model is directly used for the processing the high visual distortion is introduced. Most of the researchers have suggested conversion of RGB model to YCrCb components representation. Here Y is luminance and Cr Cb is chrominance. It is proved that YCrCb color space do not have correlation among the spaces. As a result, YCrCb components can be processed independently.

In this research work, RGB is converted into YCrCb Color space as:

$Y = 0.299 \times Red + 0.587 \times Green + 0.114 \times Blue$

$Cr = R - Y = 0.701 \times Red - 0.587 \times Green - 0.114 \times Blue$

$Cb = B - Y = -0.299 \times Red - 0.587 \times Green + 0.886 \times Blue$

However, most of the natural images have correlation among neighboring pixels but in specific direction. In other words, the natural images are often comprised of directional structure [55], [56]. Natural images are highly redundant on pixel by pixel scale due to local dependencies among the pixels such as lines and textures [29]. Taking the advantage of these local features that are inherent in natural images, the super resolution algorithm is developed to reconstruct super resolution image from low resolution image. However, it is difficult task to extract these regularities. But use of wavelet makes it feasible to extract these regularities and use them for further processing.

Wavelets are good at isolating the discontinuities at edge points and can capture directional information. It can decompose a digital image into frequency subimage, each represented with proportional frequency resolution clearly classifying the neighborhood structure. Use of wavelet transform helps separating and processing of frequency band signals independently. It helps to avoid the elimination of high frequency subimages. Hence use of wavelet does not suffer from smoothing effect. It leads to produce images with sharper edges and less blocking artifacts.

Considering the time complexity, effect of blur, edge preservation and symmetry at border, Biorthogonal wavelet bior2.2 is used in this research work for preprocessing of the image. Each of the Y, Cr and Cb is decomposed using bior2.2 wavelet into four components so as to process each one independently as per its nature.

Decomposition of each color space yields four frequency subbands viz, approximate, Horizontal, Vertical and Diagonal. Each of these is processed independently. Initially each of these components is upsampled using zero interlacing and then values of newly added pixels are estimated. The estimation is based on structural relationship among pixels of subimage. The details about processing of individual subimage is explained in previous section 5.5. Before processing the approximate, horizontal, vertical and diagonal are reconstructed from wavelet transform coefficients.

After super resolving individual subimages of YCrCb the resultant subimages are converted back to RGB format using equations,

$R = Y + Cr$, $G = Y - 0.509 \times Cr - 0.194 \times Cb$ and

$B = Y + Cb$

The algorithm for reconstruction of super resolution image form low resolution natural color images is:

1. Let I_L and I_H be the low resolution and high resolution camera captured images respectively in RGB format
2. Convert the RGB image I_L into luminance Y and chrominance Cr and Cb (YCrCb format)
3. Apply wavelet transform to decompose each of Y, Cr and Cb into four components of each: approximate, horizontal, vertical and diagonal
4. The approximate, horizontal, vertical and diagonal subimages are reconstructed from wavelet coefficients for each Y, Cr and Cb
5. Individual low resolution subimage of Y- Y_A, Y_H, Y_V and Y_D are super resolved independently to yield super resolved Y_{SA}, Y_{SH}, Y_{SV} and Y_{SD}
6. Super resolved SY is reconstructed from its super resolved subimages Y_{SA}, Y_{SH}, Y_{SV} and $Y_{SD.}$
7. Individual low resolution subimage of Cr- Cr_A, Cr_H, Cr_V and Cr_D are super resolved independently to yield super resolved Cr_{SA}, Cr_{SH}, Cr_{SV} and Cr_{SD}
8. Super resolved SCr is reconstructed from its super resolved subimages Cr_{SA}, Cr_{SH}, Cr_{SV} and Cr_{SD}
9. Individual low resolution subimage of Cb- Cb_A, Cb_H, Cb_V and Cb_D are super resolved independently to yield super resolved Cb_{SA}, Cb_{SH}, Cb_{SV} and Cb_{SD}
10. Super resolved SCb is reconstructed from its super resolved subimages Cb_{SA}, Cb_{SH}, Cb_{SV} and Cb_{SD}
11. Construct the super resolved image I_S in RGB format from super resolved chrominance SCr, SCb and luminance SY
12. The PSNR is calculated based on I_H as reference image and I_S as reconstructed image and results are displayed.

The above algorithm is implemented using matlab 7.1 and tested using varying resolution and varying frequency natural captured standard and synthetic color images. The results along with results of existing interpolation methods are given in chapter six.

Chapter 6

Results

The wavelet based super resolution image reconstruction algorithm is developed and implemented in MatLab 7.1. Sample results are given in this chapter. The peak signal to noise ratio is used as objective quality performance measure. The proposed algorithm is tested over the range of natural standard images, natural camera captured images and synthetic images.

6.1 Results of Wavelet Based Super Resolution Technique

The technique presented in the thesis has been tested with both real and synthetic data. PSNR is used as quality measure. However, it is known that PSNR is not suitable when real reference do not exists. Also the techniques can be better tested if set of varying frequency and varying resolution images are used for testing. For super resolution imaging the real reference high resolution image do not exists. We have suggested a suitable framework for super resolution imaging using PSNR as quality measure so as to overcome the difficulty of real reference.

We have captured images of varying resolutions of different scenes. We capture minimum two images of same scene by keeping camera position fixed but with different resolutions such as 512 x 512 and 1024 x 1024. These captured images are classified into four groups having few images in each using suggested techniques (Chapter five): very smooth images, smooth images, high frequency images and very high frequency images. The algorithm is tested over set of these images. The low resolution captured image (say 512 x 512) is given as input LR image and the real captured high resolution image (say 1024 x 1024) is used as real reference image for computation of PSNR. For standard images such as Lena, Kids, mandrill, we decimate image by two. The decimated image is used as input LR image and the original undecimated image is used as HR reference image.

Set of images used include: Gajanan Maharaj, Balcony, Parrot, Donkey, Elephant, Cheetah, Rose, Pink rose, Castle, Butterfly, Tiger, Barbara, Peacock, Boat, Ash, Birds, Budhha, Zebra, Church, China Temple, Flower_Butterfly, River, Twintower, Mandrill, lena, Text image, Kids, UranUtang show, Alkazar show, Cheetah, Tiger family, Giraffe among many others.

The numerical results for test images are given in table 6.1, table 6.2. The PSNR for reconstructed image for wavelet based super resolution reconstruction technique developed is given in the table. The comparison is made with existing resolution enhancement techniques- Nearest neighbor, Bicubic and Bilinear Interpolation. Resolution of input low resolution image and the high resolution image are provided in the table.

Input low resolution image, original high resolution image, reconstructed high resolution images using Nearest neighbor, Bicubic and Bilinear Interpolation techniques, and the reconstructed super resolution image using the technique developed are shown in figures 6.13 to 6.35.

Table 6.1 PSNR for Developed technique and Interpolation methods for standard Images

Sr No	Image	Resolutions		Image Class	PSNR in dB for Reconstructed HR Image			
		LR Image	HR Image		Nearest Neighbor	Bicubic	Bilinear	Wavelet Based SR Method
1.	Saturn	600 x 750	1200 x 1500	Very smooth	113.80	121.93	120.93	124.00
2.	Kids	636 x 800	1272 x 1600	smooth	104.20	106.71	107.79	110.99
3.	Lena	640 x 480	1280 x 960	Smooth	102.47	106.42	107.12	109.51
4.	Parrot	640 x 480	1280 x 960	Smooth	94.73	100.25	100.08	100.71
5.	Barbara	231 x 308	462 x 616	High Frequency	90.82	91.21	91.16	91.63
6.	Rose	640 x 480	1280 x 960	High frequency	78.71	79.28	80.34	80.70
7.	Butterfly	452 x 290	904 x 580	Very High frequency	90.05	94.93	93.51	96.41
8.	Cheetah	640 x 480	1280 x 960	Very High frequency	90.28	96.28	94.05	94.23
9.	Matlogo	460 x 440	920 x 880	Very High frequency	87.26	87.11	88.54	89.99
10.	Peacock	405 x 600	810 x 1200	Very High frequency	83.63	89.28	90.92	85.11
11.	Tiger	200 x 263	400 x 526	Very High frequency	78.33	80.28	80.00	82.87
12.	Elephant	768 x 512	1536 x 1024	Very High frequency	80.02	81.28	81.53	81.72
13.	Mandrill	512 x 512	1024 x 1024	Very High frequency	73.07	76.25	78.08	79.53
14.	Donkey	600 x 400	1200 x 800	Very High frequency	70.98	76.28	77.67	77.97

Table 6.1 displays the results for standard set of images. Table includes resolutions of input and reconstructed images. The class of image such as smooth, very smooth, high frequency or very high frequency and the measured for developed technique and interpolation methods is displayed

in the table. Graphs in figure 6.1 and 6.2 shows plot of PSNRs for few images.

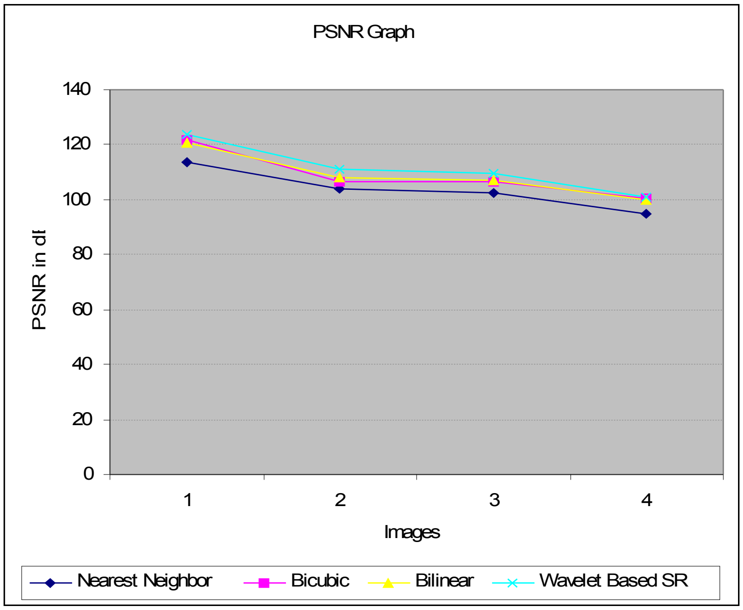


Fig. 6.1 PSNR Plot for very smooth and smooth images (images 1-4 of table 6.1)

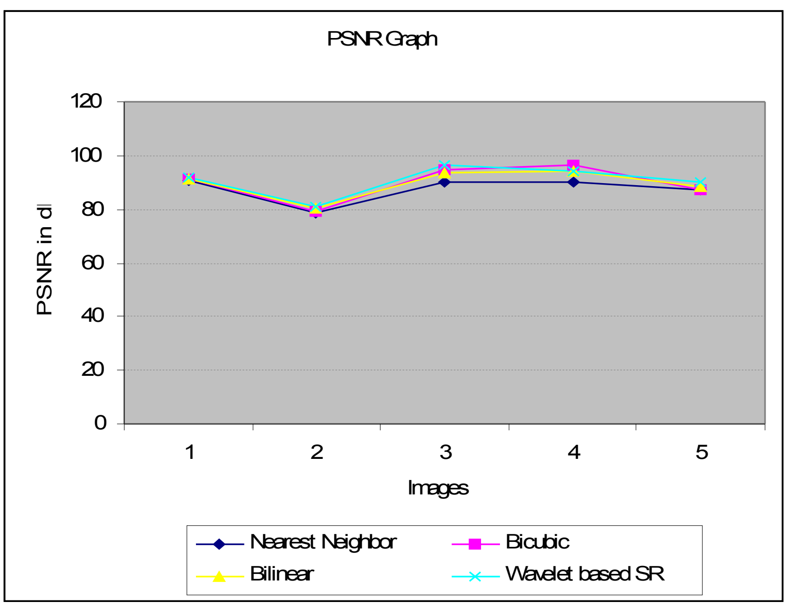


Fig. 6.2 PSNR Plot for high frequency and very high frequency mages (images 6-10 of table 6.1)

Table 6.2 PSNR for Developed technique and Interpolation methods for Real Captured Images

Sr No	Image	Original HR Size	LR Image Size	PSNR in dB for Reconstructed HR Image			
				Nearest Neighbor	Bicubic	Bilinear	Proposed SR Method
1.	Pink Rose	960 x 1280	480 x 640	92.98	97.40	97.50	97.58
2.	Aishwarya	960 x 1280	480 x 640	96.20	99.11	99.90	99.82
3.	Castle	1024x1024	512 x 512	96.73	100.96	100.37	101.85
4.	Jelly Fish	1098x1588	549 x 794	95.61	103.40	102.96	106.06
5.	Gajanan Maharaj	1280 x 960	640 x 480	102.94	108.76	109.91	119.45
6.	Zebra Image	864 x 1152	432 x 576	66.96	71.13	71.09	74.56
7.	Boat Image	960 x 1280	480 x 640	81.34	81.05	81.59	81.87
8.	Balcony	960 x 1280	480 x 640	75.60	82.25	82.36	84.86
9.	Budhha Image	864 x 1152	432 x 576	79.92	83.43	83.54	88.75
10.	Text Image	864 x 1000	432 x 500	105.67	111.25	111.22	125.46
11.	Birds Image	768 x 1024	384 x 512	81.74	84.52	84.00	86.35
12.	Church Image	960 x 1280	480 x 640	84.61	90.98	91.20	93.37
13.	Flower_ Butterfly	864 x 1152	432 x 576	90.25	94.25	94.34	95.51
14.	White Lotus	1152 x 864	576 x 432	91.72	95.99	96.01	96.78
15.	River_church	960 x 1280	480 x 640	90.15	96.28	96.52	97.51
16.	China Temple	864 x 1152	432 x 576	76.18	80.65	80.51	80.96
17.	River Image	960 x 1280	480 x 640	76.56	82.82	82.92	85.16
18.	Twin tower	864 x 1152	432 x 576	72.14	76.30	76.33	76.83
19.	Tiger family	864 x 1152	432 x 576	68.79	73.30	73.20	73.89
20.	UranUtang Show	864 x 1152	432 x 576	73.26	77.19	77.14	77.72
21.	Tulips Flowers	978 x 1472	489 x 566	81.68	84.85	85.16	85.39
22.	Alkazar Show	864 x 1152	432 x 576	78.40	82.42	82.25	83.00
23.	Blue Flowers	978 x 1482	489 x 741	77.42	81.15	81.60	81.47
24.	Color Parrot	864 x 1152	432 x 576	72.48	76.84	76.81	77.61
25.	Golden Budhha	864 x 1152	432 x 576	75.40	78.88	78.92	79.53
26.	Lonar	576 x 432	1152 x 864	93.67	97.13	97.51	95.81
27.	Penguin	576 x 432	1152 x 864	90.95	94.35	94.65	94.73
28.	Sweety	576 x 432	1152 x 864	82.22	86.22	86.40	87.43
29.	Show Piece	864 x 1152	432 x 576	74.19	78.47	78.34	78.67
30.	Genting	576 x 432	1152 x 864	64.44	67.15	67.16	68.75
31.	Giraffe	576 x 432	1152 x 864	77.98	82.39	82.44	82.58

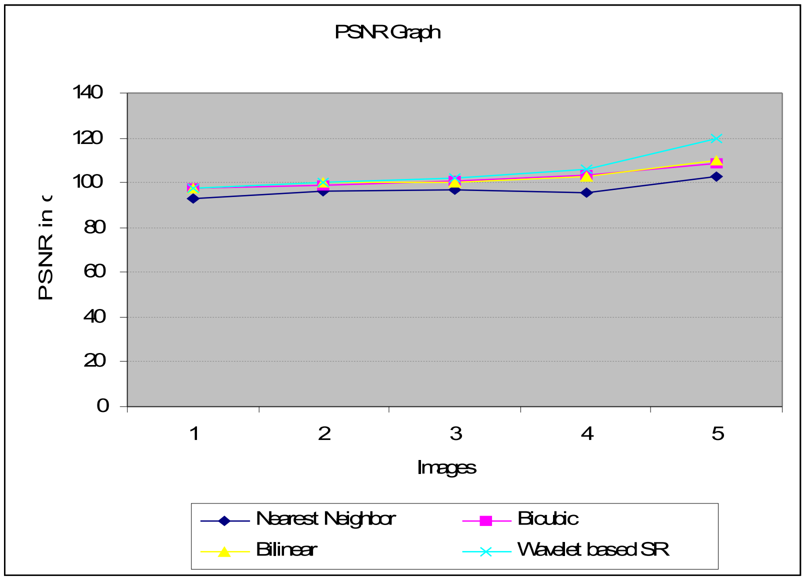


Fig. 6.3 PSNR Plot for Camera captured images
(Images 1-5 of table 6.2)

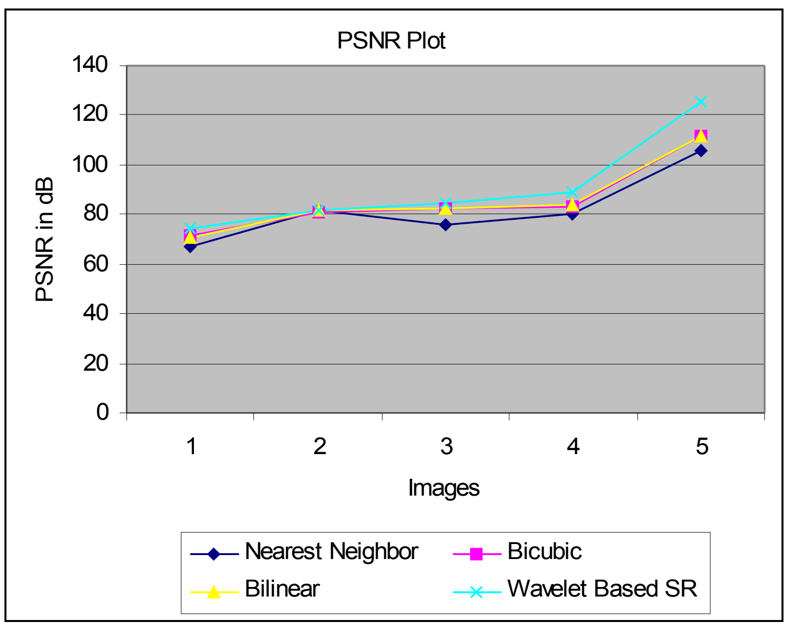


Fig. 6.4 PSNR Plot for Camera captured images
(Images 6-10 of table 6.2)

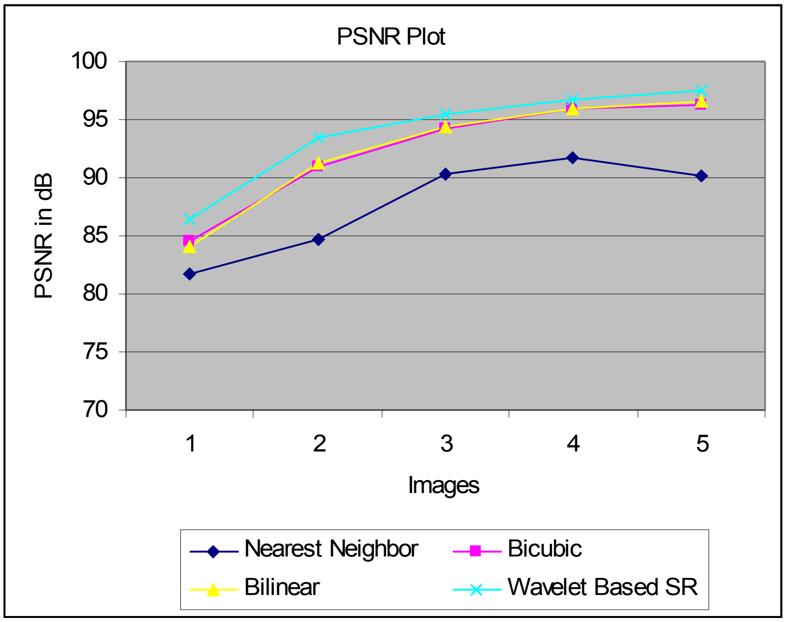


Fig. 6.5 PSNR Plot for Camera captured images
(Images 11-15 of table 6.2)

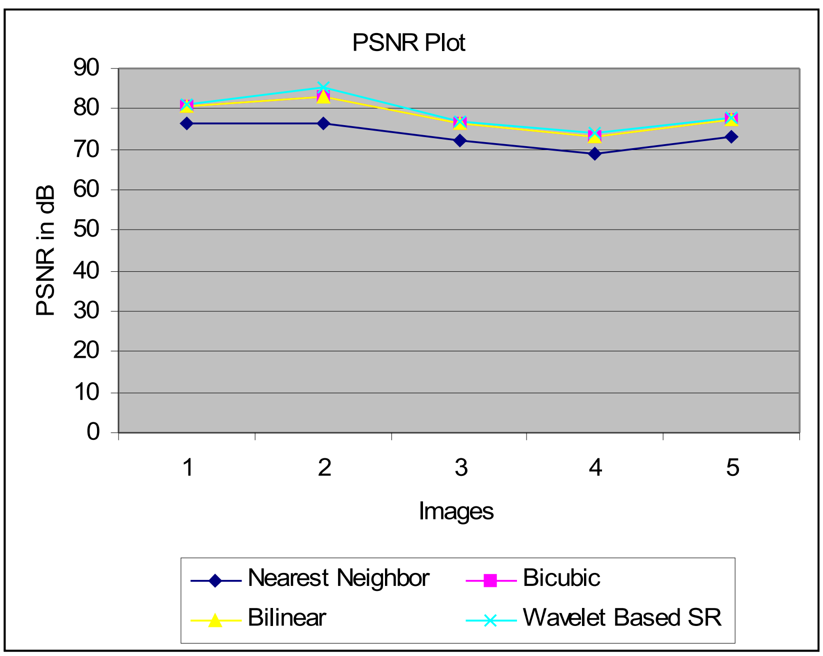


Fig. 6.6 PSNR Plot for Camera captured images
(Images 16-20 of table 6.2)

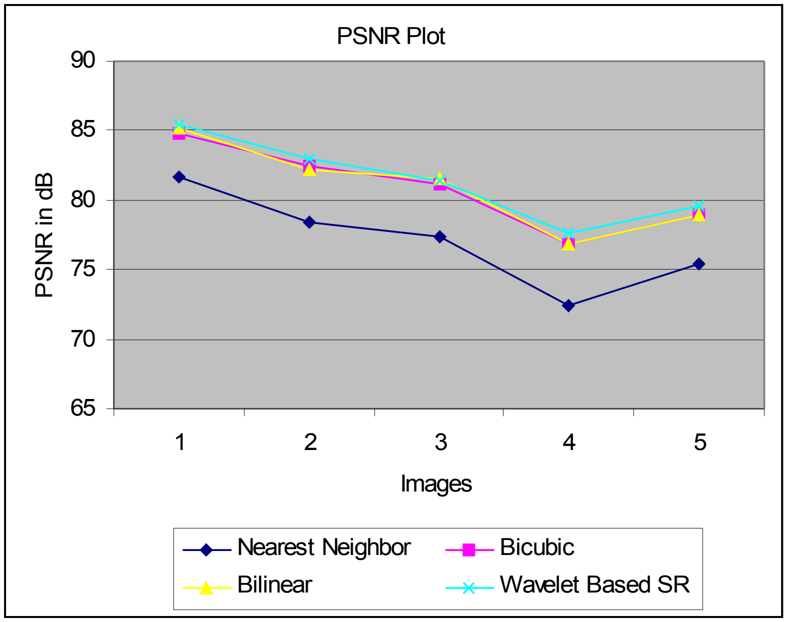


Fig. 6.7 PSNR Plot for Camera captured images (Images 21-25 of table 6.2)

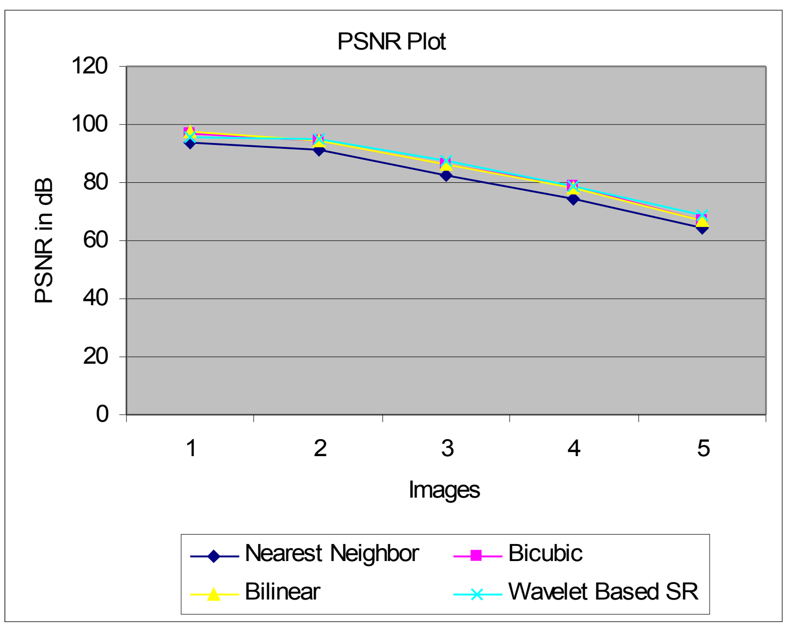


Fig. 6.8 PSNR Plot for Camera captured images (Images 26-30 of table 6.2)

Table 6.3 Varying Resolutions and Results for white lotus Image

White Lotus Image					
LR Resolution	HR Resolution	PSNR (dB)			
		Nearest Neighbor	Bicubic	Bilinear	Wavelet SR
54 x 72	108 x 144	78.74	84.00	81.75	77.68
108 x 144	216 x 288	79.16	81.84	80.94	79.66
216 x 288	576 x 432	82.36	85.81	86.22	87.49
432 x 576	864 x 1152	91.72	95.99	96.01	96.78

Table 6.4 Varying Resolutions and Results for Paris River Image

Paris River Image					
LR Resolution	HR Resolution	PSNR (dB)			
		Nearest Neighbor	Bicubic	Bilinear	Wavelet SR
80 x 60	160 x 120	76.62	77.70	77.26	76.01
160 x 120	320 x 240	77.29	79.25	79.96	80.60
320 x 240	640 x 480	78.81	82.22	82.53	82.60
640 x 480	1280 x 960	90.15	96.28	96.52	97.51

Table 6.5 Varying Resolutions and Results for Gajanan Maharaj Image

Gajanan Maharaj Image					
LR Resolution	HR Resolution	PSNR (dB)			
		Nearest Neighbor	Bicubic	Bilinear	Wavelet SR
80 x 60	160 x 120	69.74	72.01	72.62	74.00
160 x 120	320 x 240	78.16	81.07	81.38	81.81
320 x 240	640 x 480	89.99	96.11	96.17	99.62
640 x 480	1280 x 960	102.94	108.76	109.91	119.45

Table 6.6 Varying Resolutions and Results for Tigers Image

Tigers Image					
LR Resolution	HR Resolution	PSNR (dB)			
		Nearest Neighbor	Bicubic	Bilinear	Wavelet SR
72 x 54	144 x 108	51.37	53.42	54.43	54.75
144 x 108	288 x 216	53.68	55.71	56.73	57.07
288 x 216	576 x 432	59.07	61.86	62.55	63.48
576 x 432	1152 x 468	68.79	73.30	73.20	73.89

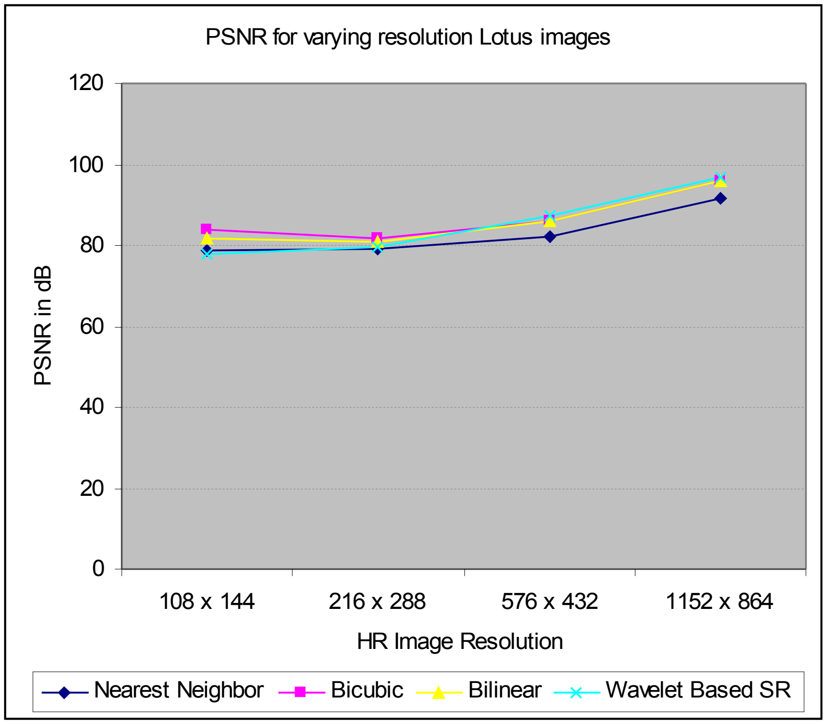


Fig. 6.9 PSNR Plot for Lotus image with varying resolutions (Table 6.3)

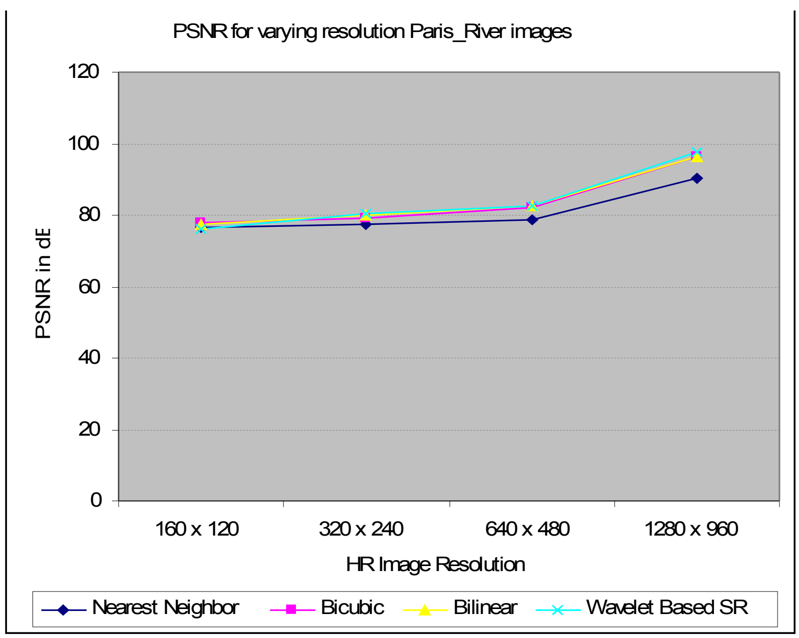


Fig. 6.10 PSNR Plot for Paris River with varying resolutions (Table 6.4)

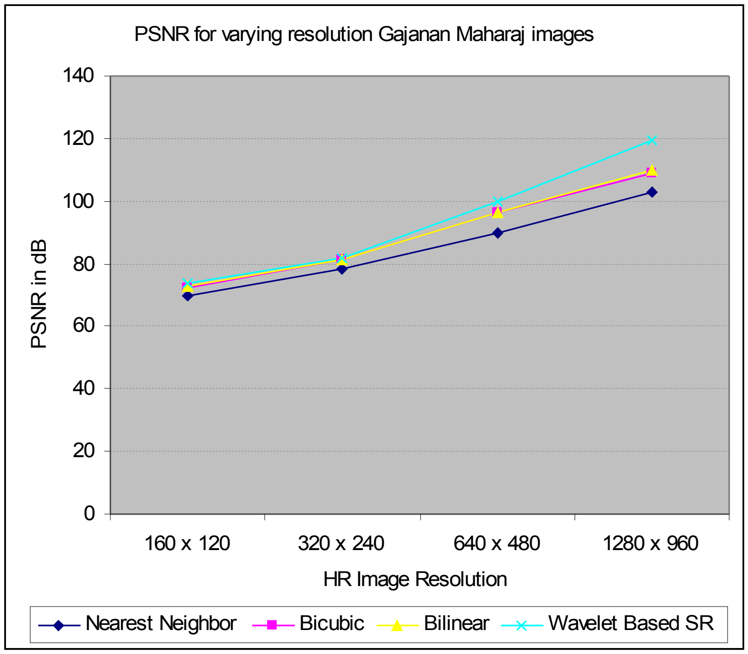


Fig. 6.11 PSNR Plot for Gajanan Maharaj with varying resolutions (Table 6.5)

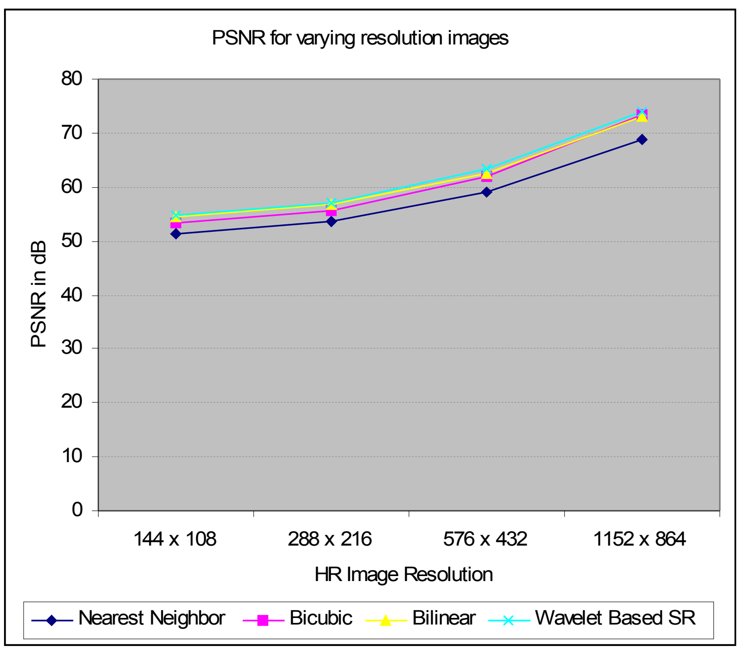


Fig. 6.12 PSNR Plot for tigers image with varying resolutions (Table 6.6)

LR Image

Resolution =480 x 640

HR Image

Resolution = 960 x 1280

Nearest Neighbor

PSNR= 102.9479

Bicubic

PSNR= 108.7658

Bilinear

PSNR= 109.9122

Wavelet Based SR

PSNR= 119.4539

Fig. 6.13 The Gajanan Maharaj Image Results

LR Image

Resolution =480 x 640

Original HR Image

Resolution = 960 x 1280

Nearest Neighbor

PSNR=75.6926

Bicubic

PSNR=82.2524

Bilinear

PSNR=82.3627

Wavelet Based SR

PSNR=84.8611

Fig. 6.14 The Balcony Image Results

LR Image

Resolution = 480 x 640

HR Image

Resolution = 960 x 1280

Nearest Neighbor

PSNR=94.733

Bicubic

PSNR=100.256

Bilinear

PSNR=100.082

Wavelet Based SR

PSNR=100.7112

Fig. 6.15 The Parrot Image Results

LR Image

Resolution = 432 x 576

HR Image

Resolution = 864 x 1152

Nearest Neighbor

PSNR=90.9516

Bicubic

PSNR=94.3546

Bilinear

PSNR=94.6532

Wavelet Based SR

PSNR=94.7313

Fig. 6.16 The Penguin Image Results

LR Image | **HR Image**


Resolution = 612 x 768


Resolution = 1224 x 1536

Nearest Neighbor


PSNR=82.0107

Bicubic


PSNR=81.2881

Bilinear


PSNR=81.5364

Wavelet Based SR


PSNR=81.7206

Fig. 6.17 The Elephant Image Results

LR Image | **HR Image**

Resolution = 480 x 640

Resolution = 960 x 1280

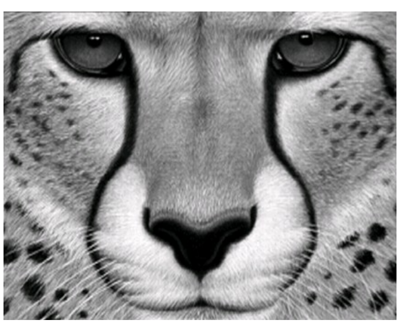
Nearest Neighbor

PSNR=90.2857

Bicubic

PSNR=96.2881

Bilinear



PSNR=94.0578

Wavelet Based SR

PSNR=94.2361

Fig. 6.18 The Cheetah Image Results

LR Image

Resolution = 480 x 640

HR Image

Resolution = 960 x 1280

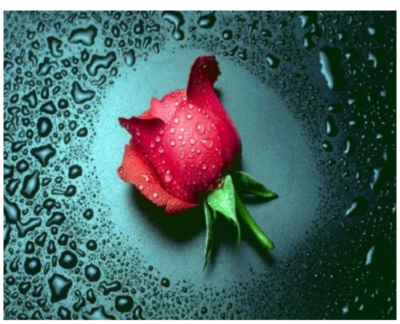
Nearest Neighbor

PSNR=78.7179

Bicubic

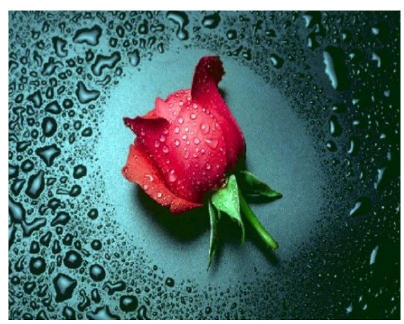
PSNR=79.2881

Bilinear



Bilinear PSNR=80.3429

Wavelet Based SR



PSNR=80.7095

Fig. 6.19 The Rose Image Results

LR Image

Resolution = 480 x 640

HR Image

Resolution = 960 x 1280

Nearest Neighbor

PSNR=92.9895

Bicubic

PSNR=97.4081

Bilinear

PSNR=97.5045

Wavelet Based SR

PSNR=97.5891

Fig. 6.20 The Pink Rose Image Results

LR Image

Resolution = 512 x 512

HR Image

Resolution = 1024 x 1024

Nearest Neighbor

PSNR=96.7356

Bicubic

PSNR=100.9678

Bilinear

PSNR=100.3732

Wavelet Based SR

PSNR=101.8522

Fig. 6.21 The Castle Image Results

LR Image

Resolution = 576 x 432

HR Image

Resolution = 1152 x 864

Nearest Neighbor

PSNR=77.9813

Bicubic

PSNR=82.3988

Bilinear

PSNR=82.4401

Wavelet Based SR

PSNR=82.5856

Fig. 6.22 The Giraffe Image Results

LR Image

Resolution = 263 x 200

HR Image

Resolution = 526 x 400

Nearest Neighbor

PSNR=78.3399

Bicubic

PSNR=80.2881

Bilinear

PSNR=80.0058

Wavelet Based SR

PSNR=82.8755

Fig. 6.23 The Tiger Image Results

LR Image

Resolution = 616 x 462

HR Image

Resolution = 1232 x 924

Nearest Neighbor

PSNR=90.8269

Bicubic

PSNR=91.2127

Bilinear

PSNR=91.1613

Wavelet Based SR

PSNR=91.6323

Fig. 6.24 The Barbara Image Results

LR Image

Resolution = 600 x 405

HR Image

Resolution = 1200 x 810

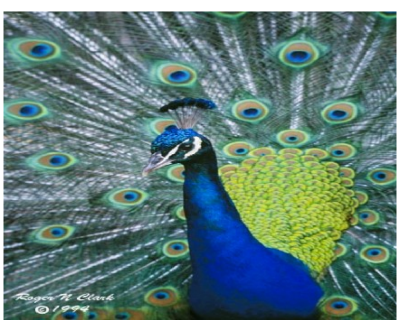
Nearest Neighbor

PSNR=83.6375

Bicubic

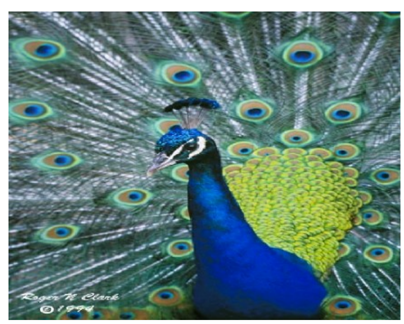
PSNR=89.2881

Bilinear



PSNR=90.9228

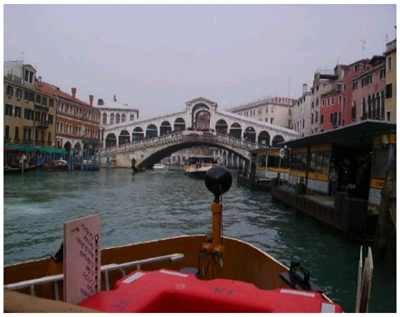
Wavelet Based SR



PSNR=85.1154

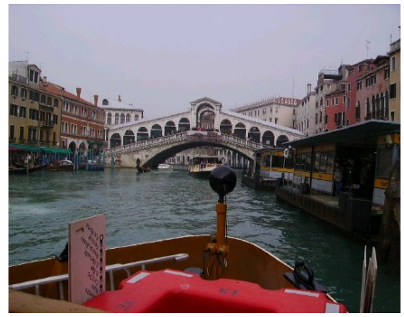
Fig. 6.25 The Peacock Image Results

LR Image



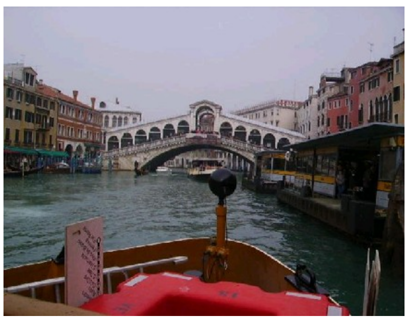
Resolution = 480 x 640

HR Image



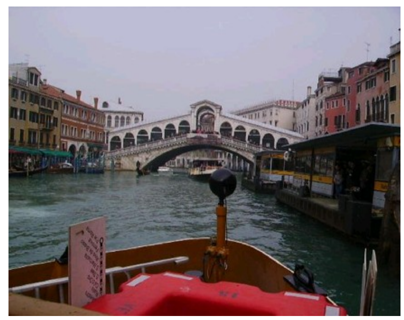
Resolution = 960 x 1280

Nearest Neighbor



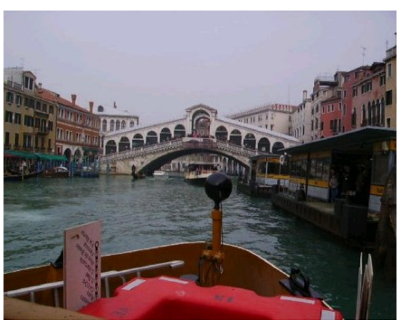
PSNR=81.34

Bicubic



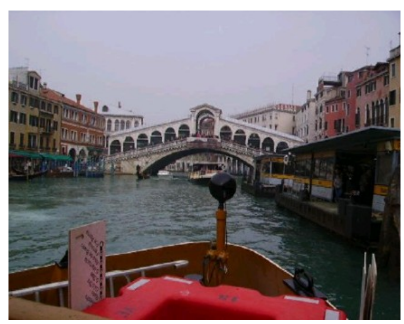
PSNR=81.0528

Bilinear



PSNR=81.5932

Wavelet Based SR



PSNR=81.8751

Fig. 6.26 The Boat Image Results

LR Image

Resolution = 480 x 640

HR Image

Resolution = 960 x 1280

Nearest Neighbor

PSNR = 96.2002

Bicubic

PSNR = 99.1178

Bilinear

PSNR=99.9004

Wavelet Based SR

PSNR=99.8257

Fig. 6.27 The Aishwarya Image Results

LR Image

Resolution = 384 x 512

HR Image

Resolution = 768 x 1024

Nearest Neighbor

PSNR=81.7413

Bicubic

PSNR=84.5283

Bilinear

PSNR=84.0093

Wavelet Based SR

PSNR=86.3537

Fig. 6.28 The Birds Image Results

LR Image

Resolution = 432 x 576

HR Image

Resolution = 864 x 1152

Nearest Neighbor

PSNR=79.9206

Bicubic

PSNR=83.436

Bilinear

PSNR=83.5418

Wavelet Based SR

PSNR=88.7508

Fig. 6.29 The Budhha Image Results

Fig. 6.30 The Zebra Image Results

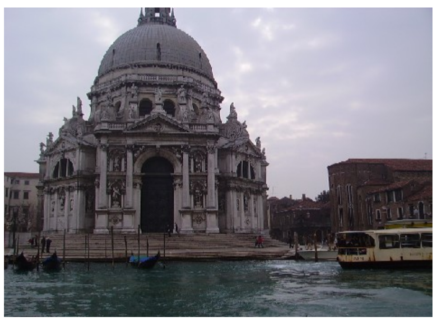
LR Image

Resolution = 480 x 640

HR Image

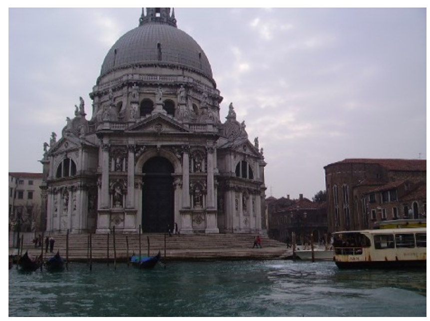
Resolution = 960 x 1280

Nearest Neighbor



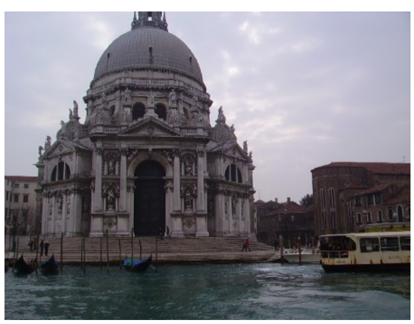
PSNR=84.617

Bicubic



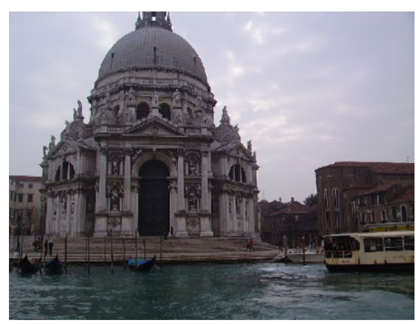
PSNR=90.9882

Bilinear



PSNR=91.2059

Wavelet Based SR



PSNR=93.3728

Fig. 6.31 The Church Image Results

LR Image

Resolution = 432 x 576

HR Image

Resolution = 864 x 1152

Nearest Neighbor

PSNR=76.1851

Bicubic

PSNR=80.6585

Bilinear

PSNR=80.5184

Wavelet Based SR

PSNR=80.9646

Fig. 6.32 The China Temple Image Results

LR Image

Resolution = 432 x 576

HR Image

Resolution = 864 x 1152

Nearest Neighbor

PSNR=90.2576

Bicubic

PSNR=94.1592

Bilinear

PSNR=94.347

Wavelet Based SR

PSNR=95.5181

Fig. 6.33 The Flowers_Butterfly Image Results

LR Image

Resolution = 480 x 640

HR Image

Resolution = 960 x 1280

Nearest Neighbor

PSNR=76.569

Bicubic

PSNR=82.8228

Bilinear

PSNR=82.9293

Wavelet Based SR

PSNR=85.1649

Fig. 6.34 The River_Bridge Image Results

LR Image

Resolution = 576 x 432

HR Image

Resolution = 864 x 1152

Nearest Neighbor

PSNR=72.143

Bicubic

PSNR=76.3026

Bilinear

PSNR=76.3319

Wavelet Based SR

PSNR=76.8328

Fig. 35 The Twin Tower Image Results

6.3 Observations

The algorithm is tested for set of images and results along with PSNR are displayed in earlier section. The observations are listed ahead.

Parrot is widely used natural image, which has very bright colors. It is 24-bit RGB colored bitmap image. The High resolution image size is 960 x 1280 and input image size is 480 x 640. The peak signal to noise ratio is 100.71 dB for developed Wavelet based SR technique, 94.73 dB for nearest neighbor, 100.25 dB for Bicubic, 100.08 dB for Bilinear interpolation. The result shows that the developed technique gives the better performance than conventional interpolation methods.

Aishwarya is widely used natural image, which does not contain large amount of high frequency or oscillating patterns. It is 24-bit RGB colored bitmap image. The High resolution image size is 960 x 1280 and input image size is 480 x 640. The peak signal to noise ratio is 97.51 dB for developed Wavelet based SR technique, 90.15 dB for nearest neighbor, 96.28 dB for Bicubic, 96.52 dB for Bilinear interpolation. The result shows that the developed technique gives the better performance than conventional interpolation methods.

Cheetah is widely used natural image, which has maximum low frequency components and few high frequency components. It is 24-bit RGB bitmap image. The high resolution reference image size is 960 x 1280 and size of the low resolution input image is 480 ×640. The peak signal to noise ratio is 94.23 dB for developed Wavelet based SR technique, 90.28 dB for nearest neighbor, 96.28 dB for Bicubic, 94.05 dB for Bilinear interpolation. The result shows that the developed technique gives the better performance than nearest and bilinear interpolation methods.

Peacock is widely used natural image, which contains large amount of high frequency or oscillating patterns. It is 24-bit RGB colored bitmap image. The High resolution image size is 1200 x 810 and input image size is 600 x 405. The peak signal to noise ratio is 85.11 dB for developed Wavelet based SR technique, 83.63 dB for nearest neighbor, 89.28 dB for Bicubic, 90.92 dB for Bilinear interpolation.

Barbara is popular choice from the class of natural test images that exhibits large amount of high frequency and oscillating patterns. It is 24-bit RGB bitmap image. The high resolution reference image size is 1232 x 924 and size of the low resolution input image is 616 x 462. The peak signal to noise ratio is 91.63 dB for developed Wavelet based SR technique, 90.82 dB for nearest neighbor, 91.21 dB for Bicubic, 91.16 dB for Bilinear interpolation. The result shows that the developed technique gives the better performance than interpolation methods.

Rose is another natural image, which has maximum red and green basic colors, and surrounded by water drops textures. It is 24-bit RGB colored bitmap image. The high resolution reference image size is 960 x 1280 and size of the low resolution input image is 480 ×640. The peak signal to noise ratio is 80.70 dB for developed Wavelet based SR technique, 78.71 dB for nearest neighbor, 79.28 dB for Bicubic, 80.34 dB for Bilinear interpolation. The result shows that the developed technique gives the better performance than interpolation methods.

Donkey is another natural image, which is mainly a smooth image with slight oscillating pattern observed at the fur on the neck. It is 24-bit RGB colored bitmap image. The high resolution reference image size is 880 x 1200 and size of the low resolution input image is 440 × 600. The peak signal to noise ratio is 77.97 dB for developed Wavelet based SR technique, 70.98 dB for nearest neighbor, 76.28 dB for Bicubic, 77.67 dB for Bilinear interpolation. The result shows that the developed technique gives the better performance than interpolation methods.

Butterfly with flower is camera captured real color image, which has prominent color patches distributed all over the image. It is 24-bit RGB colored JPG image. The high resolution reference image size is 864 x 1152 and size of the low resolution input image is 432 x 576. The peak signal to noise ratio is 95.51 dB for developed Wavelet based SR technique, 90.25 dB for nearest neighbor, 94.15 dB for Bicubic, 94.35 dB for Bilinear interpolation. The result shows that the developed technique gives the better performance than interpolation methods.

Zebra is camera captured real color image, which has prominent color lines distributed all over the body. It is 24-bit RGB JPG image. The high resolution reference image size is 864 x 1152 and size of the low resolution input image is 432 x 576. The peak signal to noise ratio is 74.56 dB for developed Wavelet based SR technique, 66.96 dB for nearest neighbor, 71.13 dB for Bicubic, 71.09 dB for Bilinear interpolation. The result shows that the developed technique gives the better performance than interpolation methods.

Budha is camera captured real color image, which is smooth image. It is 24-bit RGB JPG image. The high resolution reference image size is 864 x 1152 and size of the low resolution input image is 432 x 576. The peak signal to noise ratio is 88.75 dB for developed Wavelet based SR technique, 79.92 dB for nearest neighbor, 83.43 dB for Bicubic, 83.54 dB for Bilinear interpolation. The result shows that the developed technique gives the better performance than interpolation methods.

The results show that the PSNR is good for camera captured real images with varying resolutions. These results are compared with interpolation, and it is found that the results obtained by using the developed algorithm are better. For images having maximum curvatures it is observed that PSNR is bit poorer.

Chapter 7

Conclusions

This chapter presents summary of research work. The core aim of chapter is to presents conclusions drawn. Chapter ends with future scope that identifies some future research directions.

7.1 Preface

A technique for reconstruction of super resolution image reconstruction using low resolution natural color image has been developed. The core aim of this research is to improve the spatial resolution of still image without losing high frequency components and avoiding smoothing of an image so as to preserve originality of an image.

Generally, interpolation methods such as nearest neighbor, bilinear and bicubic are used to improve resolution of an image. Interpolation technique is based on the assumptions that there exists interpixel redundancy and interpixel correlation in all directions. These assumptions are not fully true and hence results of interpolation show loss in high frequency information and introduces blurring effect. However, most of the natural images have correlation among neighboring pixels but in specific direction. Super resolution technique has been developed by exploiting well these local features inherent in natural images. Difficulty in identifying these regularities has been resolved by wavelet transform.

It is possible to avoid the smoothing of an image and removal of high frequency components using the wavelet transform. The wavelet transform helps to find the directional correlation among pixels within image. Since natural image has directional correlation it is possible to add the detail information by using the prediction technique and to reconstruct high resolution image from single low resolution image. For the correct prediction, the wavelet transform is used to decompose the image and the new value of the pixel is predicted according to the nature of the image.

Major class of super resolution methods utilizes frequency domain formulation of super resolution problem. The spatial domain image is transformed to frequency domain using Wavelet transform. The major wavelets are Daubechies Wavelet, Coiflets Wavelet and Biorthogonal Wavelet.

A major disadvantage of Daubechies and Coiflet wavelets is their asymmetry, which can cause artifacts at borders of the wavelet sub-band. Bi-orthogonal wavelets are compactly supported and symmetric. Considering the time complexity, effect of blur, edge preservation and symmetry at border, Biorthogonal wavelet bior2.2 is used in this research work for preprocessing of an image. Wavelet transform bior2.2 is used to decompose the image. Decomposition yields four subbands. Each of these subbands is processed independently. Initially each of these subimages is upsampled using zero interlacing and then values of newly added pixels are estimated. The estimation is based on structural relationship among pixels within subimage.

It is observed that values of pixels in approximate subimage have correlation with all directional neighboring pixels. Hence the kernel is defined so as to estimate values of newly added pixels by averaging of neighboring pixels.

It is observed that values of pixels in horizontal subimage have correlation with neighboring pixels in horizontal direction. Hence the kernel is defined so as to estimate value of newly added pixels by considering horizontal neighbors only.

It is observed that values of pixels in vertical subimage have correlation with neighboring pixels in vertical direction. Hence the kernel is defined so as to estimate value of newly added pixels by considering vertical neighbors only.

The diagonal subimage mostly includes the diagonal lines of original image. While interpolating this component by conventional method, unwanted components get added and these diagonal edges contribute more error in interpolated image. In this research work, according to nature of diagonal edges newly added pixel values is estimated.

Peak Signal to noise ratio, objective measure is proposed by most of the researchers to measure quality of super resolution image. A computation for this measure needs two images: the reference high resolution image and the reconstructed image. In super resolution imaging the original high resolution image reference does not exist. Hence new framework for quality performance measure for super resolution imaging is developed.

The final algorithm of reconstructing super resolution image using low resolution natural color image is implemented. Implementation includes conversion from RGB to YCrCb color subspaces, decomposition of each color subspace using bior2.2, processing each subimage independently to yield super resolved subimages based on its nature, reconstructing super resolved Y, Cr and Cb using them and conversion of YCrCb to RGB color subspaces. Algorithm is tested over the set of natural and synthetic images and concluding remarks based on results are presented ahead.

7.2 Concluding Remarks

The researchers have presented the different techniques to reconstruct the super resolution image such as reconstruction based, learning based and wavelet based. Each of these techniques has few limitations. And hence yet none of the technique has been fully developed so as to suit super resolution imaging. Generally, interpolation methods such as nearest neighbor, bilinear and bicubic are used to improve resolution of an image. These traditional interpolation techniques mix up the values of neighboring pixels and thus mix up different information across whole image. Thus loosing important part of possible final resolution enhancement provided by whole resolution enhancement method. These resolution enhancement techniques are not suitable for super resolution image reconstruction as proper care of high frequency components is not taken.

Considering these facts, the novel technique 'Reconstruction of super resolution image using low resolution natural color image' has been developed. Since single image is used for reconstruction of high resolution image, it solves the problems of the application where multiple images are not easily available. The presented technique identifies local features of low resolution image and then enhances its resolution appropriately. Hence the problem of blurring that exists in interpolation techniques has been overcome. The technique has been tested against both set of synthetic images and natural color images of varying resolutions and varying frequency contents. The results show that the technique have overcome the problems of blur and checker board effect; the edges are well preserved and the originality of images is preserved well. PSNR is used as quality measure. It is noticed that the higher PSNR is observed for the developed technique than the existing methods.

7.3 Future Scope

The wavelet based super resolution algorithm using low resolution natural color image has been presented in this thesis. The results are compared with existing resolution enhancement techniques. It is observed that it performs better for natural as well synthetic images, low as well as high frequency images. Nonetheless, there is always a room for improvement. There are several areas in which future research may be performed. Few are listed below:

- In this thesis, the standard basis functions of wavelet are used for transformation but it may be possible to use the segment of the image as a basis function for transformation.
- The technique presented in this thesis uses wavelet for single level decomposition of image; the technique can be further extended that uses the multilevel decomposition of image.
- The work presented in this thesis is limited to still images; future research can apply this method to video sequences. It would be a natural extension to attempt wavelet based SR technique to video.

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