Image Super Resolution by Fast Edge Adaptive Interpolation

Dissertation submitted in partial fulfillment of the requirements for the award of degree of

Master of Technology
in
Computer Science and Applications

Submitted By
Richa Grover
(Roll No. 601203021)

Under the supervision of
Dr. Singara Singh Kasana
Assistant Professor

SCHOOL OF MATHEMATICS AND COMPUTER APPLICATIONS
THAPAR UNIVERSITY
PATIALA – 147004

June 2014

Certificate

I hereby certify that the work which is being presented in the dissertation entitled," Image Super Resolution by Fast Edge Adaptive Interpolation", in partial fulfillment of the requirements for the award of degree of Master of Technology in Computer Science and Applications submitted in School of Mathematics and Computer Applications(*SMCA*), Thapar University,Patiala, is an authentic record of my own work carried out under the supervision of **Dr. Singara Singh Kasana** and refers other researcher's work which are duly listed in the reference section.

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

Richa

(Richa Grover)

Roll No. 601203021

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

25/6/14

(Dr. Singara Singh Kasana)

Assistant Professor

SMCA

Countersigned by:

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

(Dr. S. K. Mohapatra)
Dean (Academics Affairs)
Thapar University
Patiala

Acknowledgement

I wish to express my deep gratitude to **Dr. Singara Singh Kasana** for providing his able guidance and support throughout the dissertation. I thank my supervisor for his time, patience, consideration and valuable inputs. Their enthusiasm and optimism made this experience both rewarding and enjoyable.

I would like to extend my special thanks to **Dr. Rajesh Kumar**, Associate Professor and Head, *SMCA*, for his enthusiasm and encouragement that triggered me for the dissertation work.

I would also like to express my gratitude to **Dr. S. K. Mohapatra,** Senior Professor and Dean of Academic Affairs, Thapar University, for making provisions of infrastructure such as library facilities, labs equipped with net facilities which is immensely required for the learners to equip themselves with the latest in the field.

I am also thankful to the entire faculty and staff members of *SMCA* for their direct-indirect help and cooperation which made my stay at Thapar University memorable.

I would like to thank my husband and my brother for their constant support, without their timely reviewing of my document, none of this would have been possible. I would also like to thank my mother, since she consistently empowered me to keep trying and do my work timely and efficiently.

Most importantly, I would like to give God the credit for all his blessings to give shape to the efforts I have put into this report.

Finally, my special thanks go to authors whose works I have consulted and quoted in this work.

Abstract

Super-resolution is a term given to a set of techniques which process and enhance the resolution of images. Thus it is the process of generating an image with a higher resolution than the original input image, by estimating the pixel intensities on an up-sampled grid by various means.

In this dissertation, Introduction gives a clear idea about the image processing operations known to be applied in various applications dealing with images, along with the brief introduction about image super-resolution by interpolation techniques.

Literature survey provides an insight on the previous related work that has been done in the field of image zooming interpolation techniques.

Lot of side effects appear when an image's resolution is increased, in order to reduce those artifacts and produce crisp images a new algorithm is proposed which is based on the combination of three different techniques.

The complete set of steps involved in the method results in super resolved images with a comparable appearance like that of original, with much clear, detailed view and least artifacts which transpire with previous methods. The colors in the various patterns are not mixed into the adjoining areas with contrasting colors, thus reducing edge blurring and providing a smooth and presentable natural-image.

The improvement provided by the proposed algorithm over the existing algorithms is evidently visible in the *HR* images and also through a quantitative measure known as Peak Signal to Noise Ratio. The proposed algorithm provides maximum *PSNR* improvement of 6.53 db over *MEDI*, 7.80 dB over *NEDI*, 6.26 dB over *SAI* and 5.41 dB over *iNEDI*. This implementation is well suited for applications that need low turn-around time.

Table of Contents

List of Figures

List of Tables

Abbreviations

HR	High Resolution
SAI	Soft-decision-adaptive interpolation
iNEDI	Improved New Edge Directed Interpolation
LR	Low Resolution
MSE	Mean Square Error
MEDI	Modified Edge Directed Interpolation
NEDI	New Edge Directed Interpolation
PSNR	Peak Signal to Noise Ratio
DT-CWT	Dual-Tree Complex Wavelet Transforms
PWLS	Perceptually Weighted Least Square
LMMSE	Linear Minimum Mean Square Error
CHF	Circular Harmonic Functions
2D	2 Dimensional

Chapter 1 Introduction

1.1 Introduction

This chapter gives an overview of the general terms such as Image Zooming**,** Image Super Resolution, Interpolation and the basic types of interpolation algorithms and Characteristics of Image Super Resolution Techniques. This also includes the outline of the work presented in this dissertation.

1.2 Image Zooming

An image is the optical representation of an object illuminated by a radiation source. Digital images are the most widespread and suitable means of presenting or distributing information. They portray spatial information about the objects in the scene that human eyes can recognize using the natural visual and mental abilities. Most of the information that a human receives is in pictographic form. Thus our discussion will be focusing on analysis and processing of images

Each digital image consists of a finite number of elements, each of which is arranged in a grid and has a particular location and value. These elements are often referred to as picture elements or in short pixels. Pixels can also be considered as numbers representing the brightness value of the image at a particular location. An image is basically a grid or a matrix of pixels arranged in columns and rows.

Image zooming is the method of magnification and enlargement of images to get a detailed view of digital images. Over-sampling is another name given to image zooming. While zooming, an up-sampled grid is taken containing the new locations which have no color intensities assigned to them as shown in figure 1.1. Various transformations are applied to those unknown pixel positions with the help of the inherent information available from the input image thus getting an output image which is a much detailed, up-scaled image. However it is hard to balance the speed and quality of output while performing such transformations. Image zooming is one of the most fundamental image processing operations.

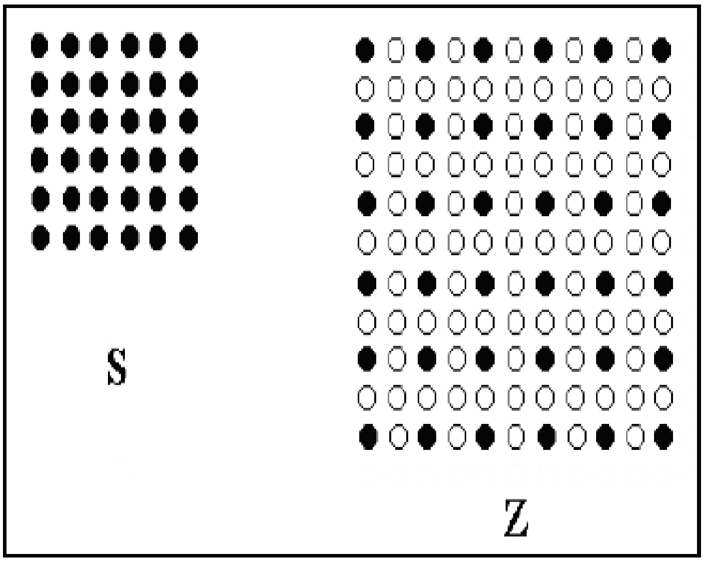


Figure 1.1 Up-sampled grid containing unknown pixels.

The image *S* is zoomed by 2 times in horizontal and vertical direction to get image *Z* as shown in figure 1.1. The empty circles are the unknown pixel values and these are calculated using zooming technique while the black discs are the pixels from the original *LR* image to be zoomed. Image *S* is zoomed into image *Z* by taking double the size of original data matrix and keeping an empty pixel space in left, in the diagonal next position and below every known pixel from the original *LR* image, thus image *Z* has got new pixels, each being surrounded by known pixels from the original *LR* image, which need to be calculated using appropriate zooming technique or procedure.

Traditional image zooming techniques used linear techniques for up-sampling the images. As the linear techniques are incapable of introducing new information into the image, the lack of new high frequency content leads to a variety of undesirable image artifacts such as blocking, staircase edges and blurring.

1.3 Image Super Resolution by Interpolation

HR cameras digitize scenes at a much finer scale and so contain more information than *LR* cameras. All pictures and images cannot be stored in *HR* form due to equipment, memory, transmission on internet, bandwidth limitations. Thus such *LR* images need to be enlarged for various applications and use using image super-resolution.

Image super-resolution is a term given to a set of techniques which process and enhance the resolution of images. Thus it is the process of generating an image with a higher resolution than the original input image, by estimating the pixel intensities on an up-sampled grid. The input image set may consist of one or more images or frames which are also known as the training images. These algorithms try to extract details from the training images in order to reconstruct frames to be utilized so as to create a high resolution image as output. This paper focuses on single frame super-resolution (Su *et al.*, 2005) which takes only one image as the training image. Single frame super-resolution works on the principle of fusing and synthesizing artificial details by interpolating the inherent content available as input.

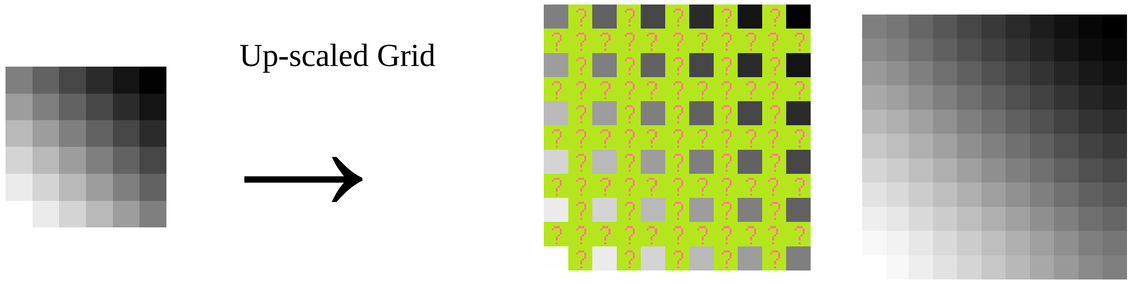
1.3.1 Interpolation: A Method for Image Zooming

Image interpolation is the technique used to find the intensity for the pixel with no information about the color intensity at a point, with the help of its neighbor pixels with known intensity values. When an image zooming algorithm is applied to an image, an enlarged image is obtained as an output which gives a detailed view of the objects found in the selected image as input, thus giving a better view for analysis.

There is a vast range of image zooming algorithms. Traditional nearest neighbor interpolation, bi-cubic, spline algorithm, *NEDI* and algorithms on image interpolation based on fuzzy logic and wavelet transforms are the most common algorithms being discussed and sort after in research. Every interpolation algorithm has its own characteristics. Few are attributed to be fast while others generate a high quality enlarged image at expanse of being slow. Image processing is one of the fastest growing research fields. A lot of work has been done in this field and it continues for further improvements and new innovations.

The image quality highly depends on the used interpolation technique. Image interpolation works in two directions, and tries to achieve a best approximation of a pixel's color and intensity based on the values at surrounding pixels. The following example illustrates how the first basic step of interpolation is performed.

Image interpolation is involved in almost all applications where digital images are involved, such as image magnification, image transformation, lossy image compression and reconstruction, medical image generation and so on.



(a) (b) (c)

Figure 1.2 2*D* Interpolation (a) Original image (b) Before interpolation (c) After interpolation

The interpolation algorithm as well as the prior noise level in quality of the original image decides the kind of distortion and the level of degradation observed in the interpolated image. Most common types of degradation that affect the results are the unavoidable ghosting effects, zigzag appearance of edges and the blurring effects near the edges as shown in the figure 1.3. Jagging is the blocks-look which is formed by simple replication of pixels, blurring is the un-clarity of the image and ghosting is the distortion of the image.

Processing of images to change size, resolution or orientation is common in electronic devices like mobile phones, television sets, and digital cameras. Performing such processes is not always best in terms of visual quality, computational ease and turn-around time. Performance is observed superior in smooth areas, but not in areas containing edges.

(a) (b) (c) (d)

Figure 1.3 Common Artifacts in Interpolated Images (a) Original Image (b) Jagzag around edges and Jagging in image (c) Blurring of edges and overall image (d) Ghosting in Image

The four broad categories of image interpolation techniques are given as follows:

Linear Techniques: Linear techniques (Parker *et al.,* 1983; Han, 2013) use linear space-invariant filters to interpolate the high-resolution samples. Most common interpolation filters are nearest neighbor, bilinear, bi-cubic, quadratic and various varieties of spline functions. Maximum of the effort put in this approach is focused on finding new filters which can reduce artifacts introduced by the traditional filters. The relative simplicity and efficiency of linear interpolation techniques brings them among the most common functions that are provided by commercial software packages such as Matlab and Adobe Photo-Shop.

Non - Linear Techniques: (Li *et al.,* 2001; Zhang *et al.,* 2006) use non-linear optimization processes constrained by certain image features. In (Li *et al.*, 2001), the problem is viewed from a geometric perspective. An image is first linearly interpolated and then the regions of constant intensity are wrapped in such way that the boundaries get sharpened between regions. (Zhang *et al.,* 2006), a nonlinear interpolation technique uses directional filtering and data fusion. Observation sets defined in two orthogonal directions produce an estimate of values which are fused by the *LMMSE* technique into a much better estimate. Thus edges are preserved by adding constraints on their orientation.

Statistical Techniques: Statistical techniques (Zhang *et al.*, 2008; Xie *et al.*, 2010; Mishiba *et al.,* 2010) attempt to estimate the high-resolution image based on the properties of the given low-resolution image. (Zhang *et al.,* 2008) follows *SAI* technique that works by learning and adapting to varying scene structures using a *2-D* piecewise autoregressive model, thus being able to properly handle edges in the formation of *HR* images. The approach in (Xie *et al.,* 2010) classifies the high-frequency patches of low-resolution image with corresponding labels and then computing the distances between matching patches of low-resolution image and middle-frequency patches of training set. The patch with the minimum distance within training set is taken as the candidate patch for replacement. In (Mishiba *et al.,* 2010) a new smoothness filter is introduced which is based on the edges properties and structures found in the low resolution images, thus follows an edge-adaptive approach.

T**ransform Techniques:** Transform techniques (Liyakathunisa *et al.,* 2009; Jagadeesh *et al.,* 2011; Zhang *et al.,* 2013) work on the principle of multi-level decomposition, followed by interpolation at each level and extrapolation of higher resolution levels. These approaches aim at synthesizing the high frequency components of the higher level decomposition on the basis of the frequency content contained at lower levels of decomposition. In (Liyakathunisa *et al.,* 2009) the data being processed is divided into an even half and an odd half and each part is processed based on another requiring lesser memory than the ordinary wavelet transform for implementation, using in-place computation, It is followed by Convolution that leads to the high resolution image. In (Jagadeesh *et al.,* 2011) dual-tree complex wavelet transforms is employed to recover the high frequency components which provides an image with good visual clarity. In another approach, (Zhang *et al.,* 2013) the high-frequency sub-images are interpolated according to the bi-cubic interpolation algorithm and by inverse wavelet transformation the image is reconstructed which is fused with a high-resolution image obtained from the original low-resolution image by bi-cubic interpolation.

Out of these four categories, the first one that is the linear techniques is not an adaptive technique. Statistical techniques and non-linear techniques are used in specialized applications such as medical imaging and super-resolution, where a sequence of *LR* image frames is combined to form a single high-resolution image.

1.3.2 Subdivision of Algorithms

There are two basic categories in which interpolation algorithms can be grouped: adaptive and non-adaptive. Non-adaptive methods treat all pixels equally and do not adapt to the situation of the neighborhood of a pixel whereas adaptive methods process or interpolate the new pixels intelligently depending on the surroundings of the pixels they are processing on, So the image zooming depends on the type of algorithm being used for enlargement.

Non-Adaptive Algorithms: These algorithms adopt a fixed pattern for all the new pixels to be interpolated. The fixed pattern followed in the approach brings the advantage of ease to performance and low calculation cost. Depending on the complexity, these algorithms use varying number of neighboring pixels for interpolation. Increasing the size of the window containing the neighboring pixels leads to better accuracy, but this result in much longer processing time required in getting the final *HR* image as output. These algorithms can be used to both resize and distort an image. Nearest Neighbor, Bilinear, Bicubic are the examples of Non adaptive interpolation algorithms.

Adaptive Algorithms: Adaptive interpolation estimates the new pixel values using features of surrounding pixels (Zhang *et al.,* 2008) and involves much of calculations. A different pattern is applied on a pixel-by-pixel basis when they detect the presence of an edge around, minimizing the interpolation artifacts which generally are most anticipated to happen near edges. Some of these algorithms are not suitable to be used for distortion or rotation of an image. Genuine Fractals, Photo Zoom, Smart Edge are few of the effective adaptive interpolation algorithms.

1.4 Characteristics of Image Super Resolution Techniques

Image super resolution is used to enhance the resolution of an image to get a detailed view of a part or whole of an image by computing the new pixel positions in the up-scaled grid. There are following reasons that make image super resolution an area for research:

Quality: Clarity and appearance of the image is an important aspect that must be retained. When an image is enhanced some areas get blurred or the image quality decreases, a good algorithm takes care of such artifacts.

Speed: The algorithm should not take much time to process and enlarge an image, slow operations infuriate the users.

Memory Requirement: Zooming operation requires a lot of memory for its processing and storage of intermediate results. Better algorithms works with minimum of memory allocated to do the processing.

Smoothness: Neighboring pixels except for the edge pixels should have continuity in color. A mismatch in color combination leads to deterioration of the quality of the image.

1.4.1 Comparative Study of Image Zooming Techniques

The image zooming techniques can be compared for the generated interpolated image on the basis of visual properties and computational complexity.

i. Visual Properties:

- **Geometric Invariance**: The geometric features, subjective matter and size of objects in an image should be preserved by the method.
- **Contrast Invariance**: The luminance properties of the objects present in the image should be preserved and in addition to maintaining high contrast of the image.
- **Edge Preservation**: The boundaries, sharpness and edges should be retained after applying the method.
- **Noise**: The resulted image should be free of noise. The method should work for noisy images as well as that for noise free images.
- **Over-Smoothing**: There should be no rise to blocky regions in an interpolated

image.

- **Application Awareness**: There are different requirements and behaviors expected by different applications like efficiency, clarity, quality, sharp edges. The method should serve the purpose.

ii. Computational Property:

- **Sensitivity to Parameters**: The method should be generalized and its performance should not vary as the internal parameters of images change. These methods range from replication, Nearest-neighborhood interpolation (Parker *et al.,* 1983), Bilinear (Parker *et al.,* 1983), Bicubic, Cubic-spline (Han, 2013), b-spline (Han, 2013), Wavelet-based (Liyakathunisa *et al.,* 2009 ; Jagadeesh *et al.*, 2011).

1.5 Contribution of Dissertation

This dissertation consists of four Chapters. Current chapter discusses the fundamentals related to the image super resolution problem. Chapter 2 provides an insight on the related research work that has already been done in the field of Interpolation and Super Resolution. Chapter 3 discusses the detailed design with implementation details of the proposed algorithm, followed by results and discussion, provided with the *PSNR* values and *CPU* time comparison obtained for various images. Thus proving the efficiency of the proposed method compared to the bi-cubic, *NEDI (*Li *et al.*, 2001), *MEDI*, *SAI*. In the last chapter conclusions and future work is provided.

Chapter 2 Literature Survey

2.1 Introduction

In this chapter, literature survey related to image super resolution is carried out. Section 2.2 contains the survey about the Basic Interpolation Methods. Section 2.3 concentrates on the various Edge Detection and Adaptation based Interpolation Methods. Section 2.4 gives an idea about Interpolation Methods which are Learning based, extract features in the images and enforce the learnt information on the pixels to be interpolated. Section 2.5 provides an insight on Image Zooming methods which use Training image Dataset, extract best suitable patches from corresponding low and high resolution Patches to place into the final output image. Section 2.6 includes the Image Super Resolution Methods which are based on image decomposition using Wavelet Transforms. The last section 2.7 concludes the methods studied in Literature Survey.

Some of the previous image interpolation techniques that have been researched upon are given below.

2.2 Basic Interpolation Methods

Chen *et al.* (1994) used sampling theory and properties of human vision, to design a new interpolation filter named as perceptually weighted least square and used it for interpolation. It keeps the ripple response at minimum around edges.

Allebach *et al.* (1996) presented a new method for digitally interpolating images to higher resolution, consisting of two phases: rendering and correction. In the rendering phase a high resolution edge map is generated by filtering with a rectangular center-on-surround-off filter followed by piecewise linear interpolation between the zero crossings in the filter output. In the correction phase, the mesh values are modified on which the rendering is based to account for the disparity between the true low resolution data, and that predicted by a sensor model operating on the high resolution output of the rendering phase. The process is repeated iteratively for efficacy of our interpolation method.

A new algorithm is proposed by El-Khamy *et al.* (2004) that preserve image edges using the PBP approach which is based on optimizing the standard cubic image interpolation formula by iteratively estimating the optimum values of the separated or combined parameters at each pixel.

Zhang *et al.* (2006) proposed a nonlinear interpolation technique using directional filtering and data fusion which preserves edge sharpness and reduces ringing artifacts. Observation sets defined in two orthogonal directions produce an estimate of values which are fused by the linear minimum mean square-error estimation technique into a much better estimate. A simplified version of the *LMMSE*-based interpolation algorithm is also introduced in this paper which reduces computational cost without much affect on interpolation performance.

Sunder *et al.* (2008) proposed an algorithm in which the magnitude part of the color image is super-resolved first and then the orientation part of the super-resolved point is replaced by orientation of bilinear interpolated orientation found in the low resolution image considering and processing all the three color bands as vector instead of processing each band separately which also reduces the color artifacts.

A perception-motivated interpolation algorithm is proposed by Zi *et al.* (2012) wherein the image is first divided into regions and then different interpolation modes are applied on each to join and produce the *HR* image in least time.

Chao *et al.* (2013) proposed an interpolation algorithm based on weighted least squares by fusing the multiple interpolation results calculated in different directions by Newton interpolation formula, wherein the weight matrix in the least squares method is determined according to the correlation among the pixels in the original image.

2.3 Edge Detection and Adaptation based Interpolation Methods

Li *et al.* (2001) proposed an edge-directed interpolation algorithm which approximates the unknown pixels by using a hybrid approach of choosing either bilinear interpolation or covariance-based adaptive interpolation. The covariance of the image pixels in a training window are calculated and used for the computation of the prediction coefficients. It considers only the four nearest neighboring pixels along the diagonal edges which further depend on their diagonal neighbors for covariance calculation, thus forming a large interpolation kernel or say training window size. Such large kernel size reduces the visual quality and the peak signal-to-noise ratio of the interpolated image. Moreover the computational cost and the time taken for processing of the image are very high.

Asuni *et al.* (2008) proposed a new algorithm by suggesting a modification in the training window used in *NEDI* technique *(*Li *et al.,* 2001) in order to reduce numerical instability and making the window used to estimate the low resolution covariance adaptive. Remarkable improvements in the interpolation quality are possible to be obtained, preserving the edge features and natural appearance as that of *LR* image. The implementation of the algorithm is however still computationally complex.

An edge-adaptive image interpolation method was introduced by Mishiba *et al.* (2010), introducing a new smoothness filter which is edge-directed. Images produced are visually better with higher *PSNR*s and lesser computational complexity than the usually known methods.

Tam *et al.* (2010) presented a modification of the new edge-directed interpolation method which adopts a modified training window structure, and extends the covariance matching concept into multiple directions to suppress the covariance mismatch problem and ultimately eliminates the prediction error accumulation problem that happens with *NEDI*, thus achieving a great deal of subjective performance in preserving the edge smoothness, sharpness and demonstrating consistent objective performance.

Wang *et al.* (2010) proposed an algorithm to construct high-resolution image from low-resolution image by using bilinear interpolation and then the edges are detected and refined. The refining of edges is done by either using geometric duality between the low-resolution covariance and the high-resolution covariance as a basis or by using the local structure features as a second approach.

Thong *et al.* (2011) proposed a new method for image expansion. In this method the fidelity and the sharpness of the expanded image was taken into consideration, confronting the problem of over-smoothening or blur out of image details around the edges by using an Lagrange time delay model which works on edge information and is robust and comparable in accuracy.

Zhou *et al.* (2011) proposed an algorithm which extends the classical bicubic convolution interpolation. It includes the correlation between color channels and detection of edges to guide the scheme that estimates the missing pixels.

2.4 Features and Learning Based Interpolation Methods

Zhang *et al.* (2008) proposed *SAI* technique that estimates missing pixels in groups rather than one at a time, learning and adapting to varying scene structures using a *2-D* piecewise autoregressive model. The pixel structure dictated by the learnt model parameters, estimated in a moving window in the input low-resolution image, is enforced by the process onto a block of pixels. This approach preserves the Edges, textures and spatial coherence of interpolated images. Common interpolation artifacts are greatly reduced.

Colonnese *et al.* (2010) proposed an algorithm consisting of the first order filter belonging to the class of the CHF to find the local image directionality features in the low-resolution image. The interpolation algorithm shows low computational complexity.

Kang *et al.* (2012) proposed a method an image is first interpolated using *SAI* and then the artifacts produced in small-scale edge areas are detected and removed by fusing the intermediate image with the bicubic interpolated image. Thus also avoiding zigzag and blurring around strong edges that appear with bicubic interpolation.

2.5 Training Images Based Image Zooming Methods

Xie *et al.* (2010) proposed an example-based algorithm which tends to reduce the super-resolving time for real time application and maintains the quality of image by first classifying the high-frequency patches of low-resolution image with corresponding labels and then computing the distances between matching patches of low-resolution image and middle-frequency patches of training set. The patch with the minimum distance within training set is taken as the candidate patch for replacement. Very few candidates are selected among the patches labeled with non-edge and for flat patches the matching step is canceled by directly replacing high-resolution patches by enlarged interpolation of low-resolution patches which helps in reducing the computational complexity effectively.

Chen *et al.* (2011) proposed a method based on self-similarity using image database also referred to as image codebook, containing corresponding low-frequency and high-frequency components. Nine low-frequency nearest neighbors are found and the corresponding high-frequency components are then weighted to add to the low-frequency to obtain the super-resolution image. The enlarged image consistent with the source image is formed by this method.

2.6 Wavelet Based Image Zooming Methods

Liyakathunisa *et al.* (2009) proposed lifting scheme to interpolate and get the high resolution image. The forward lifting wavelet transforms divides the data being processed into an even half and an odd half and processes each part based on another thus require lesser memory than the ordinary wavelet transform for its implementation, using in-place computation. Convolution thereafter leads to double the input size so as to give the high resolution image.

Jagadeesh *et al.* (2011) proposed an edge directional interpolation method which employs *DT-CWT* to recover the high frequency components which provides an image with good visual clarity. Thus sharp-magnified image are obtained without blurring and loss in clarity.

Zhang *et al.* (2013) proposed a new method to combine the super-resolution algorithm based on *PLS* regression with the Wavelet Bi-cubic ratio interpolation algorithm. In the first step the original low-resolution image is decomposed into high-frequency and low-frequency sub-images by using wavelet transform, then the high-frequency sub-images are interpolated according to the bi-cubic interpolation algorithm and by inverse wavelet transformation the image is reconstructed. In the second step, a high-resolution image is obtained from the original low-resolution image by bi-cubic interpolation and it is fused with the reconstructed image formed in step one by inverse wavelet transformation. Then, the fused image is taken as training samples to restore original image by partial least squares method. The experimental data shows that the algorithm gets better effect than the traditional algorithms.

2.7 Conclusion

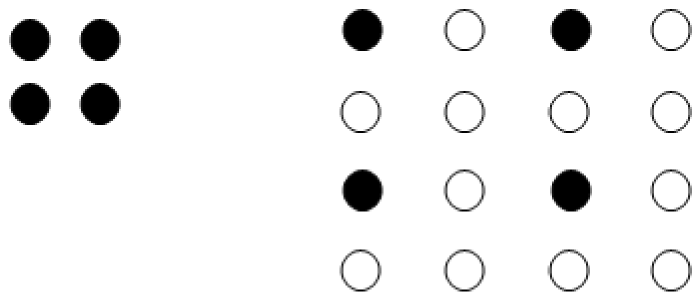
Methods studied in this chapter belong to various categories. While some methods follow the Learning and Training Dataset, Wavelet Transforms based approaches. Others are edge directed and adaptive interpolation methods focusing on the local features. These methods vary in performance, interpolated image quality, speed and computational complexity. There is a tradeoff between speed and visual quality of the interpolated images.

It is observed that performance is found effective in smooth areas, but not in areas containing edges. Thus, better quality high resolution images are obtained when the pixel color values are interpolated taking utmost care of the edges in the original images.

Chapter 3 Super Resolution using Fast Edge Adaptive Interpolation

3.1 Problem Statement

In the super resolution process by interpolation, new pixels are inserted into the super resolution version of the image. In this process, a lot of artifacts might be introduced, depending on the underlying technique and method for the processing, thus deteriorating the quality of the super resolved image. These artifacts occur because new pixels are estimated and put into the image when an image is zoomed. After going through the literature survey, it has been observed that these artifacts are more prominent in the edge area of the images as compared to the smooth areas. So there is the need to consider edges present in the input image in image super resolution algorithms.



A B

(a) (b)

Figure 3.1 Interpolation of Image (a) Original *LR* Image (b) New pixels introduced for processing of *HR* Image from *LR* Image information

The image *A* is zoomed by 2 times to get image *B* in horizontal and vertical direction as shown in Figure 3.1. The empty circles are the unknown pixel values and these are calculated using zooming technique while the black discs are the pixels from the original *LR* image to be zoomed. In Figure 3.1 image *A* is zoomed into image *B* by taking double the size of original data matrix and keeping an empty pixel space in left, in the diagonal next position and below every known pixel from the original *LR* image, thus image *B* has got 12 new pixels, each being surrounded by known pixels from the original *LR* image, which need to be calculated using appropriate zooming technique or procedure. How these new unknown pixels are estimated or computed is what actually determines the visual quality of the enlarged interpolated image which again comprises of the edges and scarcity of detrimental artifacts such as blurring and blocking effects.

There are various algorithms which are known to be used to find the unknown pixels but most of them are somewhat limited in terms of their robustness, accuracy and speed. The procedures on which we focus are edge-directed and edge-adaptive interpolation algorithms. Such algorithms are driven by the aim to preserve the edges contours in the enlarged image, avoiding blurring and blocks formation, thus maintaining the visual quality of the interpolated images.

This area of research remains active due to the constant need and thirst to find out a way to zoom images in least amount of time, with least of computational complexity required for the processing with appealing and presentable output image. Some algorithms work on groups of pixels together to reduce the time required for the processing while others update single pixel information at a time but in another efficient approach, thus new approaches give way for further advancements and improvements to make the process still better and robust. These algorithms try to recover missing pixel information keeping an assumption or belief that there is some relationship between a low resolution image and the high resolution image.

3.2 Proposed Algorithm

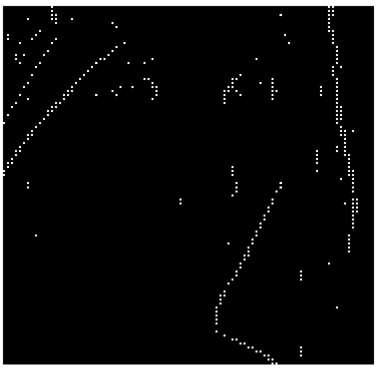
A new approach to image super resolution by a simple and fast image interpolation method based on the combination of three different procedures is given next.

In the first phase of three phase algorithm, edges in the original *LR* image are determined and marked. Figure 3.2 shows the edges determined in this step. This information is updated into the *HR* image matrix following the relationship between a low resolution image and the high resolution image.

The original *HR* color images are down sampled by a factor of two, that is, from $2M \times 2N$ to $M \times N$, to get the *LR* images, from which the expanded *HR* images of original size are reconstructed by different methods. The *PSNR* of the interpolated-reconstructed images is measured using the original High-Resolution test images. When an image is directly down sampled, it loses pixel information and the source image which is then available for interpolation, consists of artifacts, such as zigzags in edges due to loss of smoothing pixels present in the original images which can be seen in figure 3.2. These artifacts and properties are inherited in the interpolated output image due to inheritance of information from the source *LR* image.

Figure 3.2 Edge-pixels marked as found in the input image.

Determination and marking of edges leads the algorithm to be able to process the areas near edges in efficient way in the subsequent phases. The edges marked in the *HR* image appear to be dotted as the *LR* image edge information is spread onto the *HR* image matrix, *LR* image information being one-fourth of the *HR* image information. The dotted appearance of edges in the intermediate result is shown in figure 3.3. The dotted edges are then made regular by using interpolation on the dotted horizontal, vertical and diagonal edge pixels, marking the pixel point in-between every 2 edge pixels, thus converting the dotted line into solid form as shown in the figure 3.4.



(a)

(b)

Figure 3.3 Marked dotted-edges (a) Marked dotted-edges in intermediate result (b) marked edges zoomed for visual clarity and understanding of the intermediate result containing the dotted-edges.

Figure 3.4 Solid marked edges.

In second phase, the interpolated values are modified using a refining procedure that reduces the zigzag and staircase appearance in the curved edges. In the third phase, moving average interpolation is applied to the positions of empty pixels so as to estimate the non-edge pixels with color information from surrounding neighbor pixels. The complete set of steps involved in the method results in super resolved images with a comparable appearance like that of original *LR* image, with much detail and least artifacts which transpire with previous methods. The colors in the various patterns are not spilled out or mixed into areas of contrasting colors, thus reducing edge blurring and providing a smooth and presentable natural-image. The details of each step involved in the proposed algorithm are given in the next section.

3.2.1 Steps of the Algorithm

Input: Image of size $M \times N$.

Step 1: Find out edges in the image to be up-scaled. Gray values between edges and smooth areas are discontinuous and have sharp changes. Edge detection can be performed to determine the exact locations of the pixels constituting the edges.

a. Find out the difference of each pixel with its neighboring pixels and compare the difference with a threshold. If the difference is greater than threshold, there is a color difference i.e. a sharp change in gray values, so it can be considered as an edge pixel.

b. Mark that pixel as an edge pixel.

Step 2: Take another up-scaled grid Y with i and j as column row and column index respectively. Fill and mark the $y_{2i+1,2j+1}$ pixels to be edge, non-edge pixels, with information that is processed in the last step. $y_{2i+1,2j+1}$ pixels are filled by directly copying the original input image grid.

$Y_{2i,2j}$, $Y_{2i+1,2j}$, $Y_{2i,2j+1}$ are still left over pixel positions that are yet to be interpolated and are not marked to be edge /non-edge pixels. Positions marked as edge pixels seem to be scattered and the edges or say lines and curves are discontinuous in nature thus giving dotted appearance in the marking matrix.

Step 3: Form the regular lines, curves by using interpolation as given by (3.1), (3.2), (3.3), (3.4).

Join the dotted horizontal, vertical, diagonal edge pixels by interpolating and marking the pixel point in-between every 2 edge pixels, thus converting the dotted line into solid form.

$$Y_{2i,2j} = \frac{1}{n}\left(\hat{Y}_{2i-1,2j-1} + \hat{Y}_{2i+1,2j+1} \right) \qquad (3.1)$$

$$Y_{2i,2j} = \frac{1}{n}(Y^{\wedge}_{2i+1,2j-1} + Y^{\wedge}_{2i-1,2j+1}) \tag{3.2}$$

$$Y_{2i+1,2j} = \frac{1}{n}(Y^{\wedge}_{2i+1,2j+1} + Y^{\wedge}_{2i+1,2j-1}) \tag{3.3}$$

$$Y_{2i,2j+1} = \frac{1}{n}(Y^{\wedge}_{2i-1,2j+1} + Y^{\wedge}_{2i+1,2j+1}) \tag{3.4}$$

Where *n* is 2 for both the pixels being edge marked and ^ symbolizes the edge pixel. If either of the terms in the *RHS* is non-edge no value is assigned to the *LHS* and the pixel remains non-edge.

Step 4: The edges formed in step 3 are now regular and solid with no gaps, but still the curves are zigzag and show staircase appearance. So, in this step those curved edges are processed to give a smooth appearance by considering the edge pixel sets in the forms shown in figure 3.5, hence reducing the staircase effects in the edges.

Step 5: This is the fifth major phase of the algorithm, wherein the non-edge pixels are interpolated with relevant color intensities. A non-edge pixel can be surrounded by edge pixels or it can be in a non-edge area which is smooth and has no edge nearby.

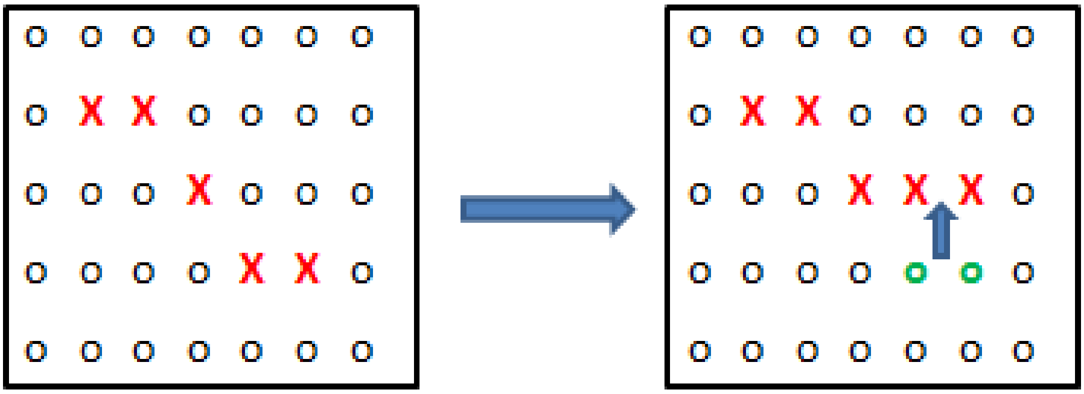
Take simple average of the neighboring pixels which are not marked as edge and assign to the current pixel. Leaving the edge pixels in the average makes the algorithm edge adaptive. The interpolation applied to $Y_{2i+1,2j}, Y_{2i,2j}, Y_{2i,2j+1}$ in (3.5), (3.6), (3.7) have to be done in sequence as $Y_{2i+1,2j}$ makes use of $Y_{2i,2j}$ in its calculation which is further used in calculation for $Y_{2i,2j+1}$.

$$Y_{2i,2j} = \frac{1}{n}(Y^{\wedge}_{2i-1,2j-1} + Y^{\wedge}_{2i-1,2j+1} + Y^{\wedge}_{2i+1,2j-1} + Y^{\wedge}_{2i+1,2j+1}) \tag{3.5}$$

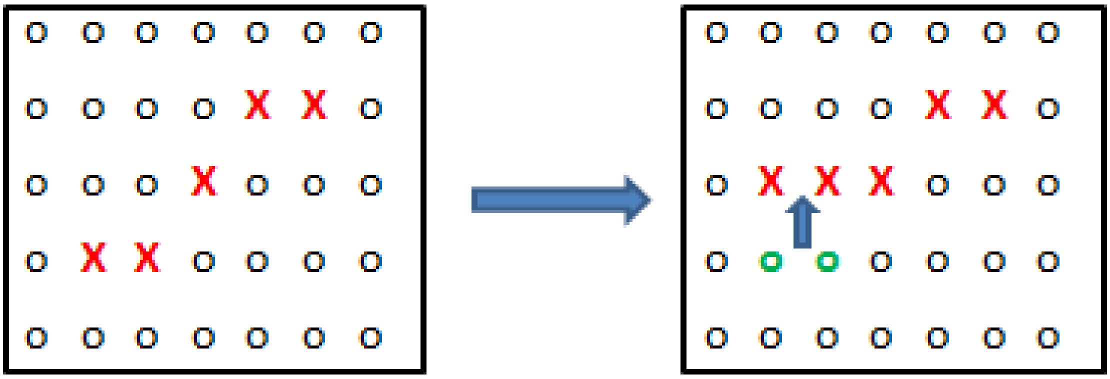
$$Y_{2i+1,2j} = \frac{1}{n}(Y^{\wedge}_{2i,2j} + Y^{\wedge}_{2i+1,2j+1} + Y^{\wedge}_{2i+2,2j} + Y^{\wedge}_{2i+1,2j-1}) \tag{3.6}$$

$$Y_{2i,2j+1} = \frac{1}{n}(Y^{\wedge}_{2i-1,2j} + Y^{\wedge}_{2i-1,2j+2} + Y^{\wedge}_{2i+1,2j} + Y^{\wedge}_{2i+1,2j+2}) \tag{3.7}$$

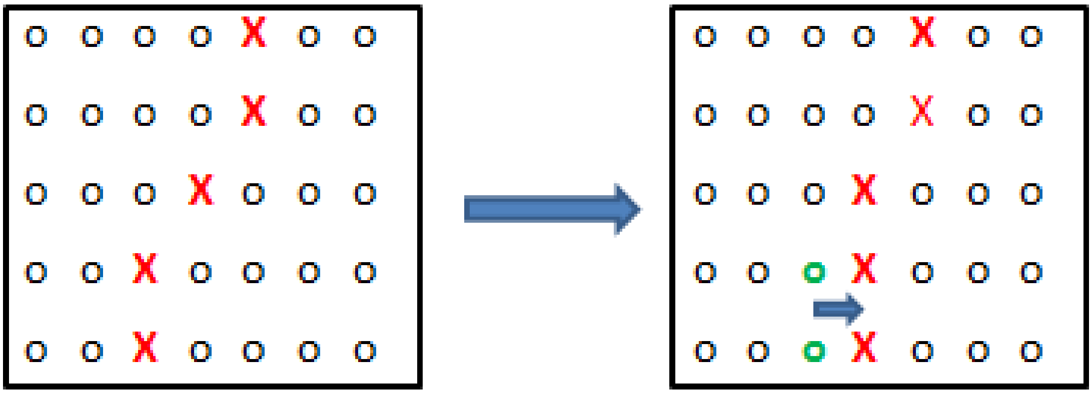
Where *n* is the number of non-edge neighbor pixels and ^ indicates the non-edge pixel in the equations. If a pixel is surrounded by all 4 edge-pixels than n comes out to be 0 and in such case again a simple average of the 4 edge pixels is taken for interpolation, taking *n* as 4. Thus the colors are not spilled out or mixed into areas of unlike colors and gives a smooth and presentable natural image as edges are used as boundaries.



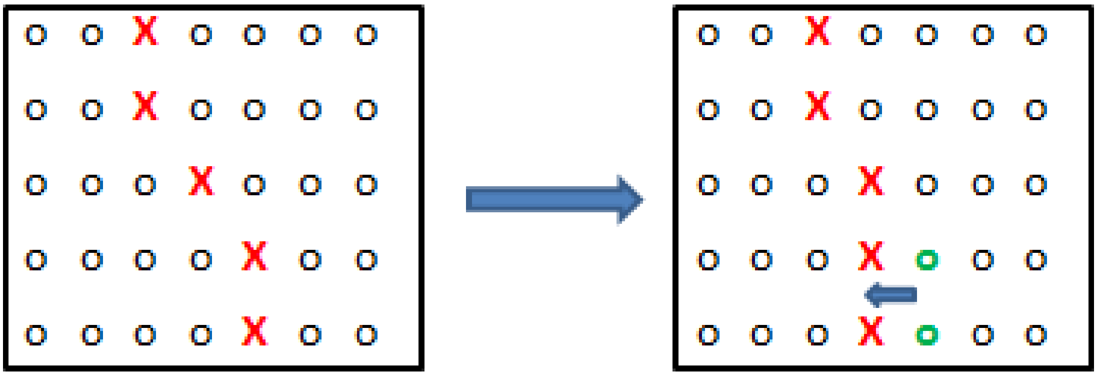
(a)



(b)



(c)



(d)

Figure 3.5 Staircase Reduction in curves (a) Staircase reduction in curves one set of edge pixels (b) Staircase reduction in curves second set of edge pixels (c) Staircase reduction in curves third set of edge pixels (d) Staircase reduction in curves fourth set of edge pixels.

3.3 Results

Proposed algorithm is implemented in *MATLAB* version 7.5.0.342 (R2007b) and is applied on different images with a zooming factor 4. Several test images including baboon, boat, cycle, airplane, barbara, lena, bikes and light house are used. The interpolated output images are shown in figures 3.7, 3.8, 3.9 and 3.10.

The justification of a zooming algorithm requires the assessment of the visual quality of the zoomed pictures. Figure 3.10 shows two examples of enlarged pictures obtained using the proposed algorithm. To assess the quality of the interpolated images obtained by using the proposed technique we refer to peak signal to noise ratio in this paper. *PSNR* is given by (3.8).

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right) \qquad 3.8$$

$$MSE = \frac{1}{H\times W}\sum_{i=0}^{H}\sum_{j=0}^{W}\left|L_{i,j} - Y_{i,j}\right|^2 \qquad 3.9$$

where $L_{i,j}$ and $Y_{i,j}$ are the pixels in the original image and the interpolated image at location (*i*,*j*) respectively. *MSE* used in (3.8) is computed using (3.9) and *H* and *W* are the Hight and width of the *HR* image matrix.

For colored images in RGB representation, each channel is treated as an independent grayscale image. The interpolated image of the three channels are at last recombined which gives the final image for comparison. Thus, the PSNR is computed as

$$\overline{PSNR} = (PSNR_{red} + PSNR_{green} + PSNR_{blue})/3 \qquad 3.10$$

Where $PSNR_{red}, PSNR_{green},\ PSNR_{blue}$ are the PSNR values for the red, green, and blue channels of the color images respectively computed using (3.8). The notation PSNR is used to imply both PSNR and PSNR with respect to the grayscale and color images in concern. High PSNR value of the interpolated images implies less distortion and is thus more favorable.

In our experiments, to show the true power of the interpolation algorithms, the original *HR* color images are down sampled by a factor of two, that is, from 2*M* ×2*N* to *M* ×*N*, to get the *LR* images, from which the expanded *HR* images of original size are reconstructed by different methods. The *PSNR* of the interpolated-reconstructed images is measured using the original High-Resolution test images. When an image is directly down sampled, it loses pixel information and the source image which is then available for interpolation, consists of artifacts, such as zigzags in edges due to loss of smoothing pixels present in the original images such bare minimum amount of artifacts are bound to be inherited by the interpolated images.

The proposed method is compared with bi-cubic interpolation, *NEDI (*Li *et al.,* 2001), *MEDI*, *iNEDI* and *SAI* depending on the data available from existing methods (Zhang *et al.,* 2008; Tam *et al.,* 2010; Kang *et al.,* 2012; Zhou *et al.,* 2011). Table 3.1 and 3.2 tabulates the *PSNR* (*dB*) results of the different methods for grayscale and colored images respectively. PSNR values of the compared algorithms is taken from the comparison tables given in the existing methods (Zhang *et al.,* 2008; Tam *et al.,* 2010; Kang *et al.,* 2012; Zhou *et al.,* 2011). The highest *PSNR* value is shown in bold in each row. The proposed method significantly outperforms the other methods for most of the testing images, and exceeds the average *PSNR* value by a minimum of 3*dB* in average. This algorithm provides maximum 6.53 *dB* higher than *MEDI*, maximum 7.80 *dB* higher than *NEDI (*Li *et al.,* 2001), maximum 6.26 dB higher than *SAI and* maximum 5.41 *dB* higher than *iNEDI*.

Table 3.1 PSNR Comparison for grayscale images

Image	Resolution	MEDI	NEDI (Li *et al.*, 2001)	SAI	iNEDI	Proposed
Baboon	256×256 => 512×512	22.46	23.21	23.28	23.64	**26.96**
Boat	256×256 => 512×512	29.20	29.69	--	29.15	**31.33**
Bicycle	256×256 => 512×512	18.90	20.33	--	20.02	**25.43**
Grayscale F16	256×256 => 512×512	32.44	31.46	31.13	30.71	**32.67**
Barbara	256×256 => 512×512	24.65	22.05	23.58	--	**29.85**
	Average	25.53	25.35	23.43	25.88	**29.25**

Table 3.2 PSNR Comparison for colored images

Image	Resolution	BiCubic	NEDI (Li *et al.*, 2001)	SAI	Proposed
Lena	256×256 => 512×512	32.30	33.76	34.74	**35.27**
Bikes	256×384 => 512×768	25.53	25.35	26.53	**29.96**
Light house	455×325 => 910×650	27.04	26.43	26.78	**31.06**
	Average	28.29	28.513	29.35	**32.09**

*PSNR values of the compared algorithms is taken from the comparison tables given in the existing methods (Zhang *et al.*, 2008; Tam *et al.*, 2010; Kang *et al.*, 2012; Zhou *et al.*, 2011).

Table 3.3 PSNR Comparison for images using different edge detectors in proposed algorithm.

Images	Log	Prewitt	Roberts	Sobel	Canny	Threshhold
Baboon	25.81	24.09	**28.14**	27.09	25.96	26.96
Boat	31.14	**31.65**	29.49	29.35	29.38	31.32
Bicycle	24.89	21.32	25.34	25.27	24.43	**25.43**

Grayscale F16	32.03	32.49	32.19	32.40	30.98	**32.67**
Lena	33.56	34.53	34.65	34.48	32.49	**35.27**
Bikes	28.28	29.65	**30.17**	29.25	29.73	29.96
Light house	31.03	31.72	30.88	**31.91**	28.01	31.06
Average	29.53	29.35	30.12	29.96	28.71	**30.38**

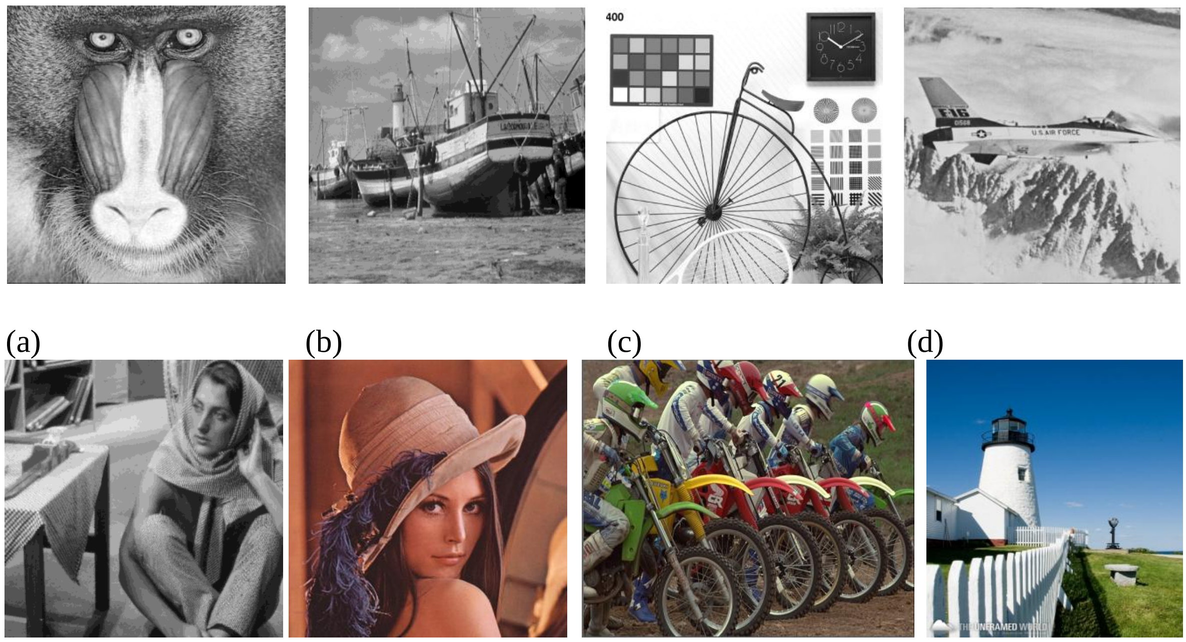
PSNR values compared in table 3.3 shows that the proposed algorithm works better for threshold method described in the dissertation to detect edges and process the image further. Other previously known edge detecting methods Prewitt, Roberts and Sobel also give better results for other few images depending on different underlying structures and kind of edges found in different images, still the results given by the threshold method are comparable and quite near to the maximum *PSNR* level that is found for those edge detectors.

Table 3.4 CPU Time Comparison for images by *NEDI* and the Proposed Algorithm

Image	*NEDI (*Li *et al.,* 2001)	Proposed (in seconds)
Baboon	51.4959	**1.9500**
Boat	139.9173	**2.8236**
Bicycle	46.9251	**2.0124**
Grayscale F16	39.2343	**1.5912**
Barbara	139.7145	**3.0420**
Lena	135.0033	**3.2916**
Bikes	180.2592	**4.0248**
Light house	281.5194	**4.0716**
Average	126.7586	2.8509

Table 3.4 provides the analysis of the *CPU* Time taken by *NEDI (*Li *et al.,* 2001) and the Proposed Algorithm which shows that even in terms of computation complexity, turn-

around time this algorithm performs quite better as the average of *CPU* Time taken by proposed algorithm is 2.8509 whereas as the average of *CPU* Time taken by *NEDI* is 126.7586. The values given in the table 3.4 are approximation values as these values vary each time the algorithms are run on same machine for same image. *CPUTIME* returns the *CPU* time in seconds that has been used by the *MATLAB* process since *MATLAB* started. Thus subtracting the *CPUTIME* when the program started from when the program ended gives the total time taken by the program to execute and give output for the algorithm in implementation.



(a) (b) (c) (d)

(e) (f) (g) (h)

Figure 3.6 Set of testing images (a) Baboon (b) Boat (c) Cycle (d) Airplane (e) Barbara (f) Lena (g) Bikes (h) Light house

(a)

(b)

(c)

(d)

Figure 3.7 Boat Image Comparison (a) Original Boat Image (b) Boat Image Zoomed by NEDI (c) Boat Image Zoomed by iNEDI (d) Boat Image Zoomed by Proposed Algorithm

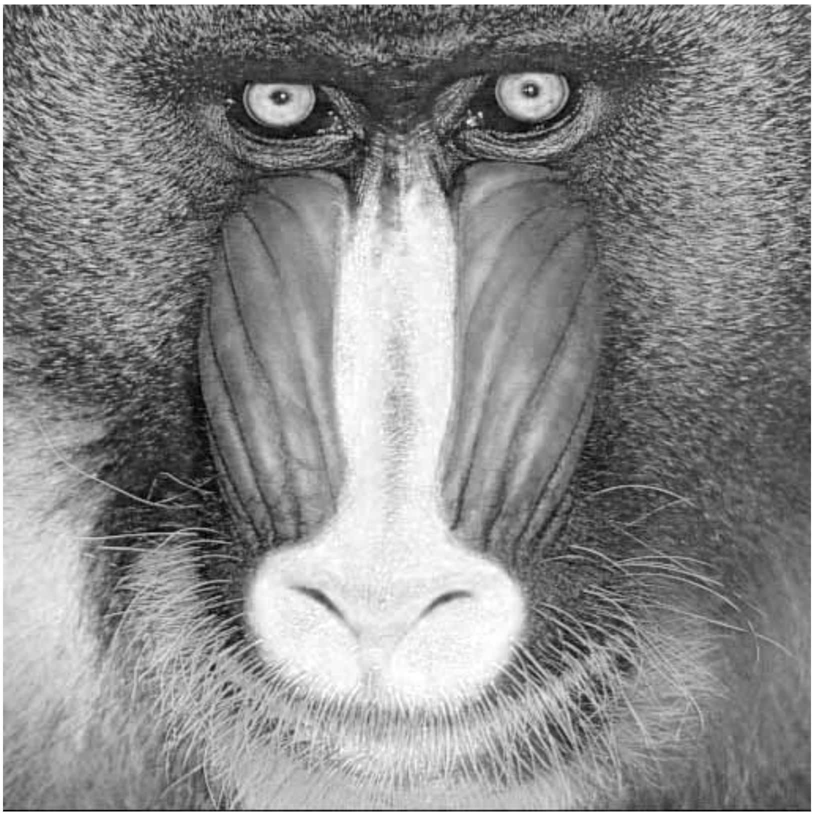
(a)

(b)

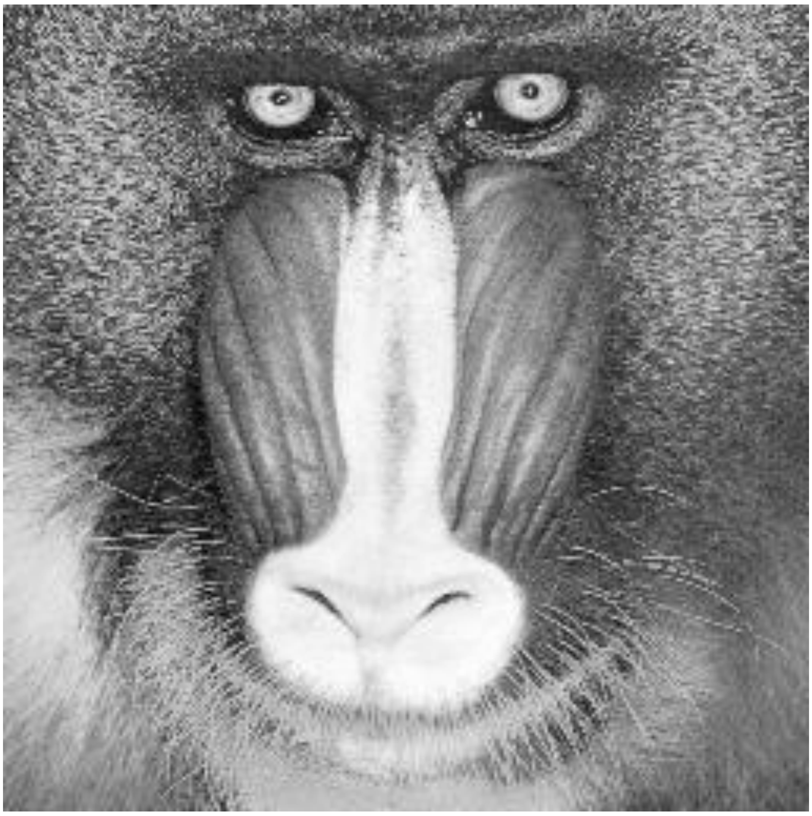
(c)

(d)

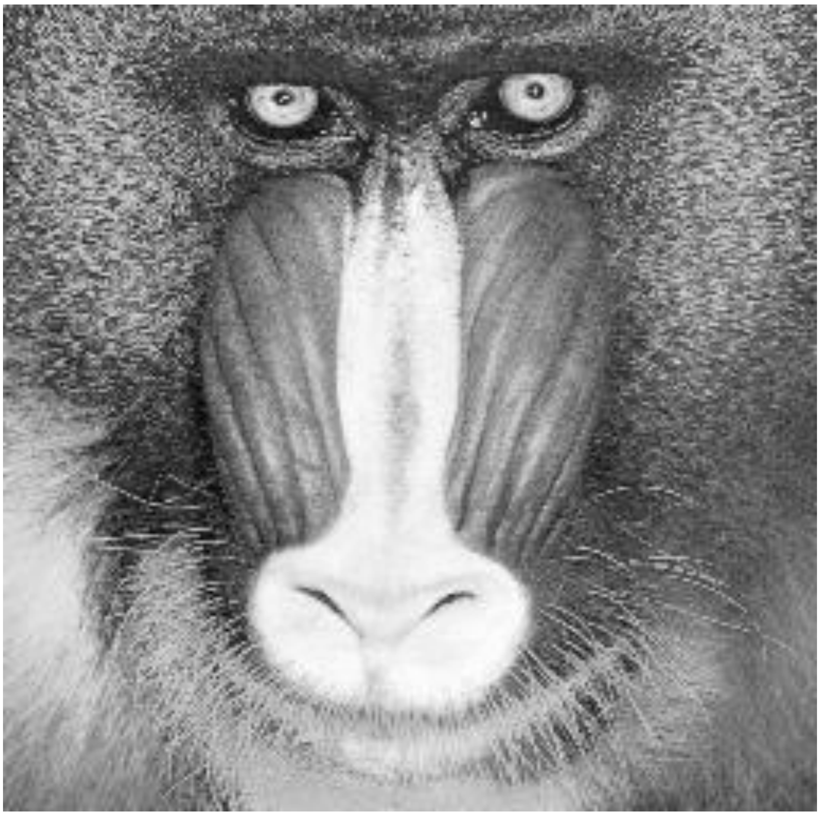
Figure 3.8 Airplane Image after Interpolation (a) Original Airplane Image (b) Airplane Image after being interpolated by NEDI (c) Airplane Image after being interpolated by iNEDI (d) Airplane Image after being interpolated by Proposed Algorithm.



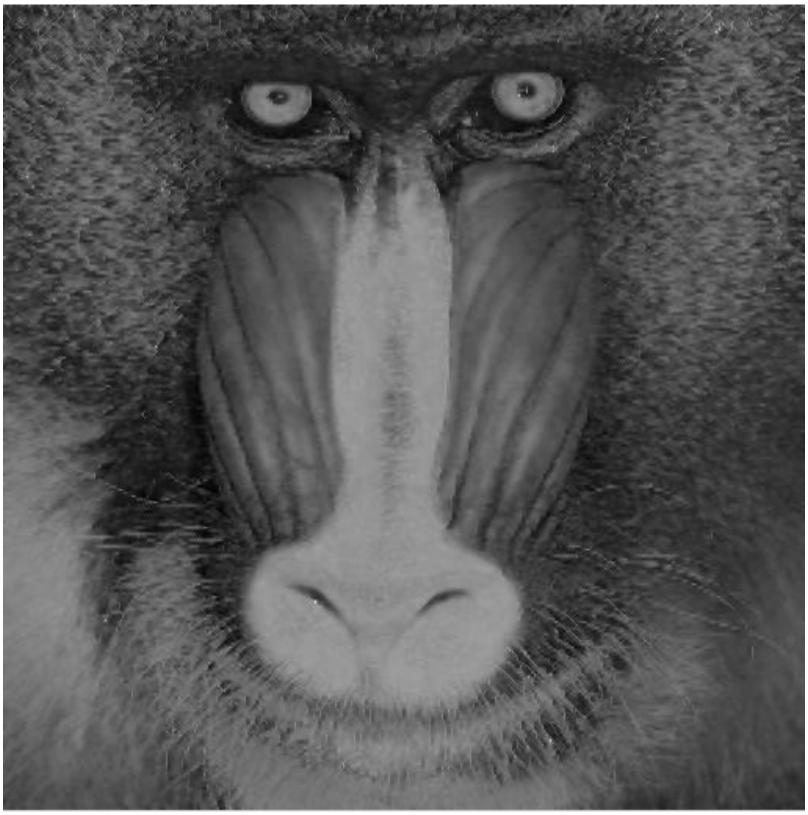
(a)



(b)



(c)



(d)

Figure 3.9 Baboon Image after Interpolation (a) Original Baboon Image (b) Baboon Image 4 times Zoomed by NEDI (c) Baboon Image 4 times Zoomed by iNEDI (d) Baboon Image 4 times Zoomed by Proposed Algorithm

(a)

(b)

(c)

(d)

(e)

(f)

Figure 3.10 Visual quality for LR images with no loss of information (a) Part of original image Lena without loss of data (b) Output Lena image of the proposed algorithm without safe guard against over-fitting (c) Part of original image Baboon without loss of data. (d) Output Baboon image of the proposed algorithm without safe guard against over-fitting. (e) Part of original image Colored Beans without loss of data (f) Output Colored Beans image of the proposed algorithm without safe guard against over-fitting.

3.4 Conclusion

In this chapter, edge adaptive interpolation based algorithm for super resolution of digital images is proposed. In this algorithm, edges present in an image are estimated using threshold technique. These edges are refined using interpolation technique. Non-edge pixels are interpolated to get the final super resolution image. Proposed algorithm is also compared with existing algorithms to show its effectiveness. The proposed algorithm provides maximum *PSNR* improvement of 6.53 db over *MEDI*, 7.80 dB over *NEDI*, 6.26 dB over *SAI* and 5.41 dB over *iNEDI.*

Chapter 4 Conclusion and Future Work

4.1 Conclusion

In this dissertation, an edge adaptive image zooming algorithm has been proposed based on the combination of three different procedures. The complete set of steps involved in the method results in super resolved images with a comparable appearance like that of original *LR* image, with much detail and least artifacts which transpire with previous methods. The colors in the various patterns are not spilled out or mixed into areas of contrasting colors, thus reducing edge blurring and providing a smooth and presentable natural-image. As the results shown in Table 3.1 and 3.2 are analyzed, the *PSNR* of proposed algorithm is higher than the interpolation methods, which conclude that the quality of resultant image of proposed algorithm is better than the other interpolation methods. In addition to *PSNR* values, table 3.4 gives a clear idea that even in terms of computation complexity, turn-around time this algorithm performs quite better as the average of *CPU* Time taken by proposed algorithm is as small as 2.8509 whereas as the average of *CPU* Time taken by *NEDI* is 126.7586. This leads to the conclusion that proposed algorithm provides better results both visually and quantitatively.

4.2 Future Work

The future work would involve the improvement of the proposed algorithm for the illumination and brightness of the images. The procedure used in the proposed algorithm can be combined with other existing algorithms and the results can be improved visually as well as quantitatively.

[1] Allebach J. and Wong P. W., “Edge Directed Interpolation”, International Conference on Image Processing, Lausanne, Vol. 3, pp. 707-710, 16-19 Sep, 1996.

[2] Asuni N. and Giachetti A., “Accuracy Improvements and Artifacts Removal in Edge based Image Interpolation”, International Conference of Computer Vision Theory and Applications, pp. 58-65, 2008.

[3] Carson C., Belongie S., Greenspan H. and Malik J., “Image Segmentation using Expectation-Maximization and its Application to Image Querying”, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 24, No. 8, pp.1026-1038, Aug 2002.

[4] Chao S., Xiu C. and Lu S., “Improved Super-Resolution Algorithm of Single-Frame Image based on Least Square Method”, 25th Chinese Control and Decision Conference, Guiyang, pp. 2648-2651, 25-27 May, 2013.

[5] Chen H. and Ford G. E., “An FIR Image Interpolation Filter Design Method based on Properties of Human Vision”, IEEE International Conference on Image Processing, Austin, Vol. 3, pp. 581-585, 13-16 Nov, 1994.

[6] Chen S., Gong H. and Li C., “Super Resolution from a Single Image based on Self Similarity”, International Conference on Computational and Information Sciences, Chengdu, pp. 91-94, 21-23 Oct, 2011.

[7] Colonnese S., Randi R., Rinauro S. and Scarano G., “Fast Image Interpolation using Circular Harmonic Functions”, 2nd European Workshop on Visual Information Processing, Paris, pp. 114-118, 5-6 July, 2010.

[8] Hadhoud M. M., Khamy S. E., Dessouky M. I., Salam B. M. and Samie F. E. A., “A New Edge Preserving Pixel-by-Pixel Cubic Image Interpolation Approach”, Proceedings of the Twenty-First National Radio Science Conference, pp. 1-9, 16-18 Mar, 2004.

[9] Han D., “Comparison of Commonly Used Image Interpolation Methods”, 2nd International Conference on Computer Science and Electronics Engineering, pp. 71-74, Jan 2013.

[10] Jagadeesh P. and Pragatheeswaran J., “Image Resolution Enhancement based on Edge Directed Interpolation using Dual Tree-Complex Wavelet Transform”, International Conference on Recent Trends in Information Technology, Chennai, pp. 759-763, 3-5

June, 2011.

[11] Kang X., Li S. and Hu J., "Fusing Soft-Decision-Adaptive and Bicubic Methods for Image Interpolation", 21st International Conference on Pattern Recognition, Tsukuba, pp. 1043-1046, 11-15 Nov, 2012.

[12] Li X. and Orchard M. T., "New Edge Directed Interpolation", IEEE Transactions on Image Processing, Vol. 10, No. 10, pp. 1521-1527, Oct 2001.

[13] Liyakathunisa L., Kumar C. N. R. and Ananthashayana V.K., "Super Resolution Reconstruction of Compressed Low Resolution Images Using Wavelet Lifting Schemes", Second International Conference on Computer and Electrical Engineering, Dubai, Vol. 2, pp. 629-633, 28-30 Dec, 2009.

[14] Mishiba K., Suzuki T. and Ikehara M., "Edge-adaptive Image Interpolation Using Constrained Least Squares", 17th IEEE International Conference on Image Processing, Hong Kong, pp. 2837-2840, 26-29 Sep, 2010.

[15] Parker J. A., Kenyon R. V. and Troxel D. E., "Comparison of Interpolating Methods for Image Resampling", IEEE Transactions on Medical Imaging, Vol. 2, No. 1, pp. 31-39, Mar 1983.

[16] Su K., Tian Q., Xue Q., Sebe N. and Ma J., "Neighborhood Issue in Single-Frame Image Super-Resolution", IEEE International Conference on Multimedia and Expo, 6-8 July, 2005.

[17] Sundar M. D. V. and Narayana E. V., "Vector-Magnitude based Super Resolution for Color Images", IEEE Conference on TENCON, Hyderabad, pp. 1-6, 19-21 Nov, 2008.

[18] Tam W. S., Kok C. W. and Siu W. C, "Modified Edge-Directed Interpolation for Images", Journal of Electronic Emerging, 013011, Vol. 19, No. 1, pp. 1-20, Jan–Mar, 2010.

[19] Thong L. W., Sim K. S. and Tso C. P., "Grayscale Image Magnification using Edge-directed Lagrange Time Delay Interpolation Model", IEEE International Conference on Signal and Image Processing Applications, Kuala Lumpur, pp. 439-443, 16-18 Nov, 2011.

[20] Wang X. and Ling H., "An Edge-Adaptive Interpolation Algorithm for Super-Resolution Reconstruction", International Conference on Multimedia Information Networking and Security, Nanjing, pp. 81-84, 4-6 Nov, 2010.

[21] Venkata N. D., Kite T. D., Geisler W. S., Evans B. L. and Bovik A. C., "Image

Quality Assessment Based on a Degradation Model", IEEE Transactions on Image Processing, Vol. 9, No. 4, pp. 636-650, Apr 2000.

[22] Xie Q., Hong C. and Cao H., "Improved Example-based Single-Image Super-Resolution", 3rd International Congress on Image and Signal Processing, Yantai, Vol. 3, pp. 1204-1207, 16-18 Oct, 2010.

[23] Zhang L. and Wu X., "An Edge-Guided Image Interpolation Algorithm via Directional Filtering and Data Fusion", IEEE Transactions on Image Processing, Vol. 15, No. 8, pp. 2226-2238, Aug 2006.

[24] Zhang L., Sun Y., Xie X., Tian Z., Xing Y. and Chen F., "Image Restoration based on Partial Least Squares Regression and Wavelet Bi-cubic Ratio Interpolation",6th International Congress on Image and Signal Processing, Hangzhou, Vol. 1, pp. 379-383, 16-18 Dec, 2013.

[25] Zhang X. and Wu X., "Image Interpolation by Adaptive 2-D Autoregressive Modeling and Soft-Decision Estimation", IEEE Transactions on Image Processing, Vol. 17, No. 6, pp. 887-896, June, 2008.

[26] Zi L., Du J., Meiyu L. and Lee J., "A Perception-Motivated Image Interpolation Algorithm", 10th World Congress on Intelligent Control and Automation, Beijing, pp. 4754-4759, 6-8 July, 2012.

[27] Zhou D. and Shen X., "An effective color image interpolation algorithm", 4th International Congress on Image and Signal Processing, Shanghai, Vol. 2, pp. 984-988, 15-17 Oct, 2011.