Image Super Resolution using Fast Converging Iterative Interpolation and Back Projection

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ABSTRACT

Super resolution (SR) is one of the techniques to enhance image resolution in terms of the number of pixels and noise reduction. In SR techniques, a sequence of low resolution (LR) images captured by moderate camera is used to generate a high resolution (HR) image.

In this thesis a new Iterative Back Projection (IBP) based SR technique is proposed. In the proposed techniques, IBP technique is improved by using interpolation. This SR technique is achieved by adding an up-sampling and down sampling in each iteration. First of all, four observed LR images are generated by an observation LR model. One of these LR images is considered as a reference image, then interpolation techniques are used to increase the size of the reference image to the size of the ground truth image. This image is considered as an initial guess image. Then the size of initial image is increased and decreased respectively by using interpolation techniques. The interpolated image is decimated to four LR images. The LR images are registered to generate an HR image, then the HR image is sent back to the first step. This process is repeated iteratively until an error criterion is met. The proposed technique is called Iterative Interpolation and Back Projection (IIBP), since an interpolation (up-sampling followed by down-sampling) module is embedded in each iteration.

The embedded interpolation module speeds up the convergence of the standard IBP and generates faster results than the standard IBP. The proposed techniques are tested on various well-known benchmark images. The quantitative Peak Signal-to-Noise Ratio (PSNR) results as well as the visual results show the superiority of the proposed techniques over the standard IBP whenever limited numbers of iterations are allowed. As the number of iterations approach to infinity, generally standard IBP gives better results.

Keywords: Super Resolution, Iterative Back Projection, Image Registration.

ÖZ

Süper çözünürlük (SR) tekniği, imgelerdeki piksel çözünürlüğünü arttırabilmek ve gürültüyü azaltabilmek için kullanılan tekniklerden biridir. SR teknikleri, tekdüze bir kamera ile çekilen düşük çözünürlüklü (LR) bir dizi imgeyi kullanarak yüksek çözünürlüğe (HR) sahip iyileştirilmiş bir imge oluşturmak için kullanılır.

Bu tezde, Iteratif Geri Projeksiyon (IBP) tabanlı farklı SR teknikleri önerilmektedir. Önerilen tekniklerde, ilk önce, giriş imgesinin çözünürlüğü çiftkübik aradeğerleme ile arttırılmakta, aradeğerlenmiş imge daha sonra bulanıklık çekirdeği, farklı kaydırmalar, ve alt örnekleme ile dört LR imgeye dönüştürülmektedir. Bu dört imge tekrar aradeğerleme ile yukarı örneklenmekte ve sonrasında çakıştırılarak yüksek çözünürlüklü bir ara imge üretilmektedir. Bu imge geri projeksiyon ile ilk adıma tekrar yönlendirilerek çıkış imgesi ile ilk adımdaki giriş imgesi arasındaki hata hesaplanmaktadır. Hata önceden belirlenen bir eşik değerinden daha küçük bir seviyeye gelene kadar bu işlem iteratif bir şekilde tekrarlanmaktadır.

İkinci SR tekniği, her iteratif döngüden sonrasına bir üst örnekleme ve bir alt örnekleme ekleyerek elde edilir. Bu tekniğin ilk adımı yukarıdaki tekniğe benzemektedir. Bu teknikte çiftkübik aradeğerleme giriş imge boyutunu artırmak için kullanılır. Daha sonra, boyutu arttırılmış olan bu imgeden alt örnekleme ile dört LR imgesi elde edilir. Bu imgeler geriçatılarak HR bir ara imge elde edilir. Daha sonra bu imge alt örnekleme ile küçültülerek birinci adıma geri gönderilir. Birinci tekniğe benzer bir şekilde, hata önceden belirlenen eşik değerinden daha küçük bir seviyeye

gelene kadar, söz konusu işlem iteratif bir şekilde tekrarlanır. Bu teknik iteratif aradeğerleme geri projeksiyon (IIBP) olarak adlandırılmıştır.

Önerilen teknikler çeşitli tanınmış kriter imgeleri kullanılarak test edilmiştir. Görsel sonuçlar ile sayısal Tepe Sinyal-Gürültü Oranı (PSNR) ve Yapısal Benzerlik Endeksi ölçütleri kullanılarak yapılan performans değerlendirmesinde önerilen tekniklerin geleneksel ve alternative IBP tabanlı tekniklere sınırlı sayıda iterasyon durumunda bir üstünlük sağladığını göstermektedir. İterasyon sayısı sonsuza giderken geleneksel IBP, önerilen yöntemden daha iyidir. Hız gerektiren durumlarda ise önerilen yöntemin üstünlüğü ortaya konulmaktadır.

Anahtar Kelimeler: Süper Çözünürlük, Iteratif Geri Projeksiyon, Görüntü Kaydı, Sabit Dalgacık Dönüşümü, Ayrık Dalgacık Dönüşümü.

To my Wife and my Parents

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS/ABBREVIATIONS

C	A (constant) normalization factor
D	Decimation operator
D_k	Down-sampling operators
F_k	Encodes the motion information
g_k	k^{th} observed low resolution images
H_k	Models the blurring effects
H^{psf}	The point spread function of blur kernel
h^{BP}	Back projection kernel
n_k	An additive noise
V_k	Noise term
$x(t_1, t_2)$	A continuous high resolution scene
$X(u_1, u_2)$	Continues Fourier Transform of a scene
$X_k(u_1, u_2)$	Continues Fourier Transform of a translated scenes
ξ	Error
θ	Angel between two images
τ	Threshold
CFT	Continues Fourier Transform
CT	Computerized Tomography
CT-PET	Computed Tomography- Positron Emission Tomography
DFT	Discrete Fourier Transforms
HR	High Resolution
IBP	Iterative Back Projection

IIBP	Iterative Interpolation and BP
LAZA	Locally Adaptive Zooming Algorithm
LR	Low Resolution
MRI	Magnetic Resonance Imaging
MSE	Mean Square Error
OCR	Optical Character Recognition
PET-MRI	Positron Emission Tomography-Magnetic Resonance Imaging
PSF	Point Spread Function
PSNR	Peak Signal-to-Noise Ratio
SIAD	Smart Interpolation by Anisotropic Diffusion
SR	Super Resolution

Chapter 1

INTRODUCTION

2.1 Introduction

Super resolution (SR) is one of techniques to enhance image resolution in terms of the number of pixels and noise reduction. In SR techniques, a sequence of low Resolution (LR) images captured by moderate camera is used to generate a High resolution (HR) image. SR is an efficient and inexpensive way which is use in a lot of imaging systems. The basic idea behind the SR is to generate a HR image by using the fusion of a series of LR noisy blurred images. Each LR image contains a part of high frequency of the scene and the fusion of this high frequency pieces, make it possible to generate an image with higher resolution. Huang and Tsay[1] started researching about the SR in 1984, after that SR methods are used for many applications in different fields.

There are two principle phases of SR process. The first phase is the image registration [2] and HR image reconstruction. A closely related technique with SR is the single-image interpolation approach, which increases the size of the image with reasonable quality. Interpolation methods is described in more detail in chapter two.

The goal of this thesis is to improve resolution by using Iterative Back Projection (IBP) based SR techniques. In this context, an IBP based SR techniques is proposed. In the proposed techniques, IBP technique is improved by using interpolation. This SR technique is achieved by adding an up-sampling and down sampling in each iteration.

First of all, four observed LR images are generated by an observation LR model. One of these LR images is considered as a reference image, then interpolation techniques are used to increase the size of the reference image to the size of the ground truth image. This image is considered as an initial guess image. Then the size of initial image is increased and decreased respectively by using interpolation techniques. The interpolated image is decimated to four LR images. The LR images are registered to generate an HR image, then the HR image is sent back to the first step. This process is repeated iteratively until an error criterion is met. The proposed technique is called Iterative Interpolation and Back Projection (IIBP), since an interpolation (up-sampling followed by down-sampling) module is embedded in each iteration.

2.2 Problem Definition

Nowadays, the images obtained from mobile devices typically have quality problems, due to limited resolution capabilities of their acquisition processes. Resolution enhancement is an important image quality improvement technique, which would enhance the resolution of the images for improved post-processing, as well as, better human perception. In this context, SR methods are widely studied by the researchers and new approaches are being developed for the resolution enhancement of images/video. One of the famous SR method is IBP which is not a good technique for applications where faster processing is required. In this thesis an IBP based SR technique is presented to improve resolution.

2.3 Thesis Objectives

The aim of this thesis is speedup the convergence of the standard IBP and generates faster results than the standard IBP. This study examine image registration and interpolation to generate a HR image. Our goal is to speed up and distinguish the advantages and disadvantages of IBP methods. The IBP method will be especially studied to put the foundation to our proposed technique.

2.4 Thesis Contributions

In this thesis an IBP based SR technique is proposed to provide image resolution enhancement.

- This SR technique is achieved by adding an up-sampling and down sampling in each iteration. First of all, four observed LR images are generated by an observation LR model. One of these LR images is considered as a reference image, then interpolation techniques are used to increase the size of the reference image to the size of the ground truth image. This image is considered as an initial guess image. Then the size of initial image is increased and decreased respectively by using interpolation techniques. The interpolated image is decimated to four LR images. The LR images are registered to generate an HR image, then the HR image is sent back to the first step. This process is repeated iteratively until an error criterion is met.

2.5 Thesis Outline

The thesis is organized in five chapters. A quick introduction to SR is given in Chapter 1. In chapter 2, the SR methods are surveyed. Some interpolation techniques that will be useful in this study are examined. Also we introduce the image registration method used throughout the thesis in this chapter. In chapter 3, the IBP method is described in more details in this chapter. In chapter 4, our proposed method for image resolution enhancement is given. Finally In chapter 5 the conclusions on the experimental results and the related future work are presented.

Chapter 2

SUPER RESOLUTION

3.1 Introduction

The first limitation of the image resolution is created by the imaging acquisition devices or the imaging sensors. The spatial resolution of the image capture is determined by the sensor size or the number of sensor elements. So, for increasing the spatial resolution of an imaging system, one of the easy and straight forward ways is to increase the sensor density by reducing the sensor size. However, as the sensor size decreases, the amount of light incident on each sensor also decreases, causing the so-called shot noise [2]. Also, the hardware cost of a sensor increases by making sensor density greater or corresponding image pixel density.

Employing various signal processing tools is the other approach for enhancing the resolution. One of the famous techniques is SR. The basic idea behind SR methods is combining several LR image to reconstruct a HR image [2]. Huang and Tsay [1] started researching about the SR field in 1984, after that SR methods become common practice for many applications in different fields such as Surveillance video [3-4], remote sensing [5], Medical imaging such as Computerized Tomography (CT) scan, Magnetic Resonance Imaging (MRI), Ultrasound [6-9].

The desire for HR stems from two principal application areas:

1- Improvement of resolution for human interpretation: In these applications, human is ultimate goal for system. SR methods improve resolution and visual quality in captured image. For example, a doctor can diagnose or treat with image capture from outside and inside the patient's body.

2- Helping representation for automatic machine perception: SR methods are used to improve the resolution and image quality, for facilitating the machine processing. We can use SR methods in various problems such as Optical Character Recognition (OCR) problem and machine face recognition [10-13].

3.2 Super Resolution Approach

SR imaging is provided different approaches. One of the main steps to understand and compare these ways is to classify them logically and systematically. It seems that it would be appropriate to classify them based on the calculations in spatial and frequency domain. Accordingly, you will have two following models for SR methods [1, 14].

3.2.1 Spatial Domain Techniques

We can consider SR in spatial domain with following equations [1] .

Let X denote the HR image desired, and Y_k be the $k-th$ LR observation from the camera. Assume the camera captures K LR frames of X , where the LR observations are related with the HR scene X by

$$Y_k = D_k H_k F_k X + V_k, \qquad k = 1, 2, ..., K \tag{2.1}$$

where D_k, H_k, F_k, V_k are respectively the down-sampling operator, blurring operator, motion operator, and the noise term. These linear equations can be rearranged into a large linear system

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_K \end{bmatrix} = \begin{bmatrix} D_1 H_1 F_1 \\ D_2 H_2 F_2 \\ \vdots \\ D_K H_K F_K \end{bmatrix} X + \begin{bmatrix} V_1 \\ V_2 \\ \vdots \\ V_K \end{bmatrix} \tag{2.2}$$

Or equivalently

$$Y = MX + V \tag{2.3}$$

Furthermore, in real imaging systems, these matrices are unknown and need to be estimated from the available LR observations, leaving the problem even more ill-conditioned. Thus, proper prior regularization for the HR image is always desirable and often even crucial [1]. Some techniques at special domain are introduced in following.

- Interpolation of Nonuniformly-Spaced Samples [15-19]
- Algebraic Filtered Back-Projection Methods [20]
- Iterative Back-Projection Methods [21-24]
- Stochastic Methods [25-37]
- Set Theoretic Methods [38-40]
- Hybrid Methods [41,42]
- Optimal and Adaptive Filtering Methods [43, 44]

3.2.2 Frequency Domain Techniques

Historically, the first approach for SR was modeling in frequency domain and taking advantage of the properties of the Fourier transform [1].

Let $x(t_1,t_2)$ denote a continuous HR scene. The global translations yield K shifted images,

$$x(t_1,t_2)=x\left(t_1+\Delta_{1_k},t_2+\Delta_{2_k}\right)\qquad k=1,2,\cdots,K \tag{2.4}$$

where Δ_{1_k} and Δ_{2_k} are arbitrary shifts. Consider $X(u_1,u_2)$ and $X_k(u_1,u_2)$ are Respectively Continuous Fourier Transform (CFT) of the scene and CFT of the translated scenes. Then by the shifting properties of the CFT, the CFT of the shifted images can be written as

$$X_k(u_1,u_2)=\exp\left[j2\pi\left(\Delta_{1_k}u_1+\Delta_{2_k}u_2\right)\right]X(u_1,u_2)\,. \tag{2.5}$$

The shifted images are impulse sampled with the sampling period T_1 and T_2 to yield observed LR image $y_k(n_1,n_2)=x_k\left(n_1T_1+\Delta_{k_1},\mathrm{n}_2T_2+\Delta_{k_2}\right)$ with $n_1=0,1,2,\cdots,N_1-1$ and $n_2=0,1,2,\cdots,N_2-2$. Denote the Discrete Fourier Transforms (DFTs) of these LR images by $Y_k[r_1,\mathrm{r}_2]$. The CFTs of the shifted images are related with their DFTs by the aliasing property:

$$y_k[r_1,\mathrm{r}_2]=\frac{1}{T_1T_2}\sum_{m_1=-\infty}^{\infty}\sum_{m_2=-\infty}^{\infty}X_k\left(\frac{2\pi}{T_1}\left(\frac{r_1}{N_1}-m_1\right),\frac{2\pi}{T_2}\left(\frac{r_2}{N_2}-m_2\right)\right). \tag{2.6}$$

Assuming $X(u_1,u_2)$ is band-limited, $|X(u_1,u_2)| = 0$ for $|u_1| \geq (N_1\pi)/T_1, |u_2| \geq (N_2\pi)/T_2$ combining eqn. (2.5) and eqn. (2.56) we relate the DFT coefficients of $y_k[r_1, \mathrm{r}_2]$ with the samples of the unknown CFT of $x(t_1,t_2)$ in matrix form as

$$Y = \Phi X \qquad (2.7)$$

where Y is a $K \times 1$ column vector with the k^{th} element being the DFT coefficient $y_k[r_1, \mathrm{r}_2]$, X is a $N_1N_2 \times 1$ column vector containing the samples of the unknown CFT coefficients of $x(t_1,t_2)$, and Φ is a $K \times N_1N_2$ matrix relating Y and X. Eqn.2.7 defines a set of linear equations from which we intend to solve X and then use the inverse DFT to obtain the reconstructed image [1].

Some techniques at frequency domain are introduced in following.

- Restoration via Alias Removal [2, 45]
- Recursive Least Squares Methods [46, 47]
- Recursive Total Least Squares Methods [48]
- Multichannel Sampling Theorem Methods [49, 50]

3.2.3 General Comparison of Models

A general comparison of frequency and spatial domain SR reconstruction methods is presented in Table 2.1 [48].

Table 3.1: Frequency vs. spatial domain SR

	Frequency Domain	**Spatial Domain**
Observation model	Frequency domain	Spatial domain
Motion models	Global translation	Almost unlimited
Degradation model	Limited, LSI	LSI or LSV
Noise model	Limited, SI	Very Flexible
SR Mechanism	De-aliasing	De-aliasing A-priori info
Computation req.	Low	High
A-priori info	Limited	Almost unlimited
Regularization	Limited	Excellent
Extensibility	Poor	Excellent
Applicability	Limited	Wide
App. Performance	Good	Good

As this table shows the spatial domain are more complex and more calculating than frequency domain methods but are more flexible. Then more researches are by spatial domain [1].

3.3 Image Registration

One of the fundamental steps in most image SR processes is the registration of the images [22]. Two or more images of the same sense that taken at different times, from different viewpoints overlaying in image processing [51]. Registration is one of the basic and the principal subjects in the image processing and there are various algorithms for it [15, 52-54].

Image registration techniques used in various fields of approach such as change detection [55], estimation of wind speed and direction for weather forecasting [56], fusion of medical images [7] like Positron Emission Tomography-Magnetic Resonance Imaging (PET-MRI) [57] and Computed Tomography- Positron Emission

Tomography (CT-PET) [58], and cartography [59]. These applications divided into four principal groups according to the manner of the image acquisition [51]: different viewpoints (multiview analysis), different times (multitemporal analysis), different sensors (multimodal analysis), and scene to model registration. In general, registration methods consist of four steps: feature detection, feature matching, transform model estimation, and image resampling and transformation.

3.4 Single Image Super Resolution Algorithms

We review some of work on single image SR in this section. Primary researchers on SR deal with the property of analytic continuation of a signal. Basically, these techniques derive the missing high frequency components from a portion of the entire spectrum. This process sometimes also referred as spectral extension. Harris [60] recognized that, given a finite extent of an object and a continuous but finite portion of the spectrum of the object, the entire spectrum can be produced uniquely using the principle of analytic continuation. If the measurement be free of noise this method guides to an exact and complete reconstruction of the object spectrum. This method becomes unreliable where there are some noise. In [61] presented a new view of the problem of continuing a given segment of the spectrum of a finite object. Signal extrapolation carry out by [62]. This method depend on the notion of reducing the 'error energy'. Papoulis [63] solved a dual of same problem where in the spectrum of the band limited object is recovered from a finite segment of the object using an iterative procedure.

In [64] Freeman et al. presented an approach to low level vision tasks using belief propagation. Freeman et al. applied this approach on SR in [65]. It uses the high frequency part of the LR image as ground truth and the high frequency part of the HR image as scene to be estimated. In [66] is introduced a faster version of A faster version of the algorithm that only uses a single pass.

SR by using pixel classification is suggested by Atkins et al. [67]. In [68], Battiato et al. introduced a method namely LAZA (locally adaptive zooming algorithm). In LAZA, simple rules and conFigureurable thresholds is used to detect edges, and update the interpolation process accordingly. Then in 2003 they presented an algorithm namely SIAD (Smart Interpolation by Anisotropic Diffusion), SIAD is an algorithm which incorporates anisotropic diffusion.

Several papers are published by Muresan and Parks [70-72] on SR based on the optimal recovery principle. They model the image as belonging to a certain ellipsoidal signal class. The authors together with Kinebuchi [73] presented a wavelet-based algorithm using hidden Markov trees. In The algorithm, highest frequency coefficients was predicted by lower frequency wavelet coefficients. A one octave super resolved image is resulted by applying an inverse wavelet transform after prediction.

SR by triangulation on pixel level was presented by Su and Willis [74] in 2004. In the method, linear interpolation is used to reduce visible artifacts. In [75], Yu et al show results can be further improved by improving the algorithm that searches for the optimal triangulation of the source image.

Jensen and Anastassiou [76] presented a method in 1995. The most prominent edge with subpixel precision was detected by this method, then detected edge was used to get sharper edges in super-resolved images.

There are also a wide range of products available that rely on an algorithm more advanced than kernel-based resampling. Some worth mentioning are PhotoZoom Professional by BenVista [77], and Imagener by Kneson Software [78], Qimage by Digital Domain [79], SmartScale by Extensis [80].

Chapter 3

ITERATIVE BACK PROJECTION

4.1 Introduction

This method is similar to back projection method in tomography. In Iterative back projection (IBP) method iterative algorithm together with a method for image registration are used. Irani and Peleg [22] in this method assumed that local motion can be described by translations and rotation only, but the IBP method is applicable for other image motion models.

4.2 IBP Registration process

The authors used Keren et al. [15] method based on [83] to registration process. Horizontal shift a , vertical shift b, and rotation angle θ between images g_1 and g_2 can be written as

$$g_2(x,y) = g_1(x\cos\theta - y\sin\theta + a, y\cos\theta + x\sin\theta + b) \tag{3.1}$$

When we use Taylor's series for expanding $\sin\theta$ and $\cos\theta$ to the first two terms, the result is

$$g_2(x,y) \approx g_1(x + a - y\theta + x\theta^2/2, y + b + x\theta + y\theta^2/2) \tag{3.2}$$

Expanding g_1 to the first term of its own Taylor's series expansion gives the first-order equation

$$g_2(x,y) \approx g_1(x,y) + \left(a - y\theta - x\theta^2/2\right)\frac{\partial g_1}{\partial x} + \left(b + x\theta - y\theta^2/2\right)\frac{\partial g_1}{\partial y} \tag{3.3}$$

We can approximate error function between g_2 and g_1 after rotation by θ and translation by a and b by

$$E(a,b,\theta) = \sum\left[g_1(x,y) + \left(a - y\theta - x\theta^2/2\right)\frac{\partial g_1}{\partial x} + \left(b + x\theta - y\theta^2/2\right)\frac{\partial g_1}{\partial y} - g_2(x,y)\right]^2 \tag{3.4}$$

where the summation is over the overlapping part of g_1 and g_2.

To minimize difference between the image g_2 and the image g_1 warped by (a, b, θ), the following equation is useful

$$\begin{bmatrix} \sum g_x^2 & \sum g_x g_y & \sum A g_x \\ \sum g_x g_y & \sum g_y^2 & \sum A g_y \\ \sum A g_x & \sum A g_y & \sum A^2 \end{bmatrix} \begin{bmatrix} a \\ b \\ \theta \end{bmatrix} = \begin{bmatrix} g_x g_t \\ g_y g_t \\ A g_t \end{bmatrix} \tag{3.5}$$

where

- $g_x = \frac{\partial g_1}{\partial x}$
- $g_y = \frac{\partial g_2}{\partial y}$

- $g_t = g_2 - g_1$
- $A = xg_y - yg_x$

We can compute motion parameters a , b , and θ by solving this set of linear equations.

4.3 IBP Iteration process

In this part they iterate the following process for two given images g_1 and g_2 [15].

I. Firstly assume no motion between the frames
II. Solving eqn.(3.5) for compute approximation to motion parameters. Add the computed motion to the existing motion estimate
III. Warp frame g_2 toward g_1 using the current motion estimated and return to step two with the warped image g_2

In each iteration g_2 get closer to g_1, and as the residual corrections to (a,b,θ) computed in step two get smaller, the motion parameters become more accurate. When the corrections to (a,b,θ) approach zero, the process is finished [22].

The authors used Gaussian pyramid data structure in order to improve accuracy and speed up the process of estimating the motion parameters.

"At First, the motion parameters are computed for reduced resolution image in pyramid. The computed motion parameters are then interpolated into a larger image the motion estimate is corrected through a few iterations. This process is continued until the original full-size image is reached" [22].

4.4 IBP Super Resolution

IBP Super resolution algorithm is described in this section. There are two critical steps in IBP model, first is to construct the model for imaging process and the second step is image registration. The first step can be described as

$$g_k(y) = DH^{psf} \times f(x) + n_k \tag{3.6}$$

- g_k, k^{th} observed LR image.
- y, the pixel of LR image in influenced by the area of x of the SR image f .
- H^{psf}, the Point Spread Function (PSF) of blur kernel.
- D, decimation operator.
- n_k, an additive noise term.

In this method firstly a true SR image is assumed and several LR images are calculated based on Eqn. (3.6). The error images between the calculated LR image and observed LR images are back projected to the assumed SR image. As the process repeats, the energy of the error become smaller until finally a SR image evolves. IBP can be mathematically represented as

$$f^{(n-1)}(x) = f^{n}(x) + \sum_{y}\left(g_k(y) - g_k^{n}(y)\right) \times CH^{BP} \tag{3.7}$$

- $f^{(n)}$, estimated SR image after n iterations
- C, a (constant) normalizing factor.

- g_k^n, calculated LR image from the imaging model of $f^{(n)}$ after *n* iterations
- H^{BP} , Back projection kernel (a H^{BP} good is $H^{BP} = H^{psf}$).

The iterative process in equation (3.7) can be slow when there are impulsive errors causing the initial error to be high. Speeding up the convergence is possible when low pass filtering is applied at every iteration limiting the bandwidth by excluding the high frequency artifacts such as impulsive noise, and hence reducing the initial error in each iteration. Based on this motivation low pass filtering can be modeled by using two cascaded interpolations where the first one increases the size of the initial guess image followed by a second one decreasing the size of the same image. Chapter 4 gives the details a new method which is proposed to speed up the convergence of IBP in light of the motivation explained.

Figure 3.1 is showing the standard IBP process super resolving $n \times n$ image to $\alpha n \times \alpha n$

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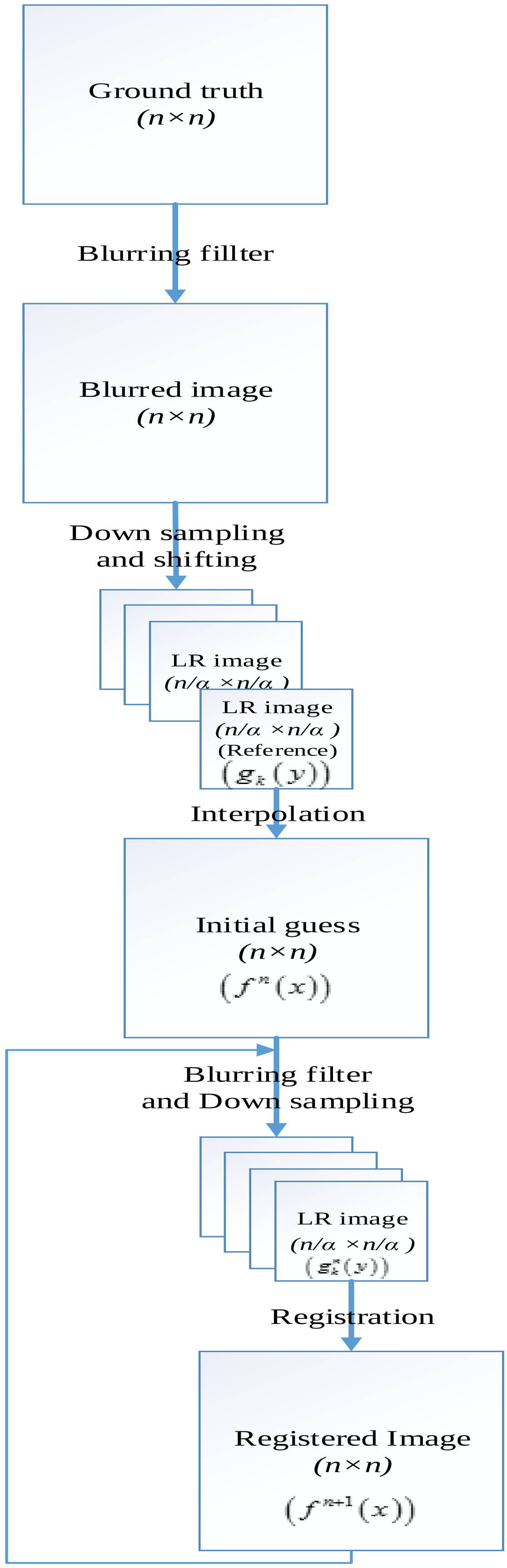


Figure 4.1: The standard IBP process super resolving $n \times n$ image to $\alpha n \times \alpha n$

Chapter 4

THE PROPOSED IBP BASED SUPER RESOLUTION TECHNIQUE

5.1 Introduction

The IBP technique is not recommended for online application or video processing. This is because; one of problems in IBP technique is its slow convergence due to artifacts that originate from shifting along the borders. In this context a new method is proposed which speeds up the convergence of the standard IBP and provide better results for applications where faster processing is required. Video processing is among the possible applications for such a method with very high speed convergence when compared with the standard IBP technique.

5.2 Experimental Methodology

The proposed method is tested on several well-known images which are obtained from three different database [85-87]. The size of the images is 512×512. Input images are 256×256 pixels and after super resolve to 512×512 pixels the output images are compared with ground truth to calculate the PSNR results. Also The proposed method is tested for super resolved images from 128×128 to 256×256, 256×256 to 512×512, and 64×64 to 128×128. Figure 4.1 shows the observation LR model which is used to reduce the size of the image. Figure 4.2 illustrates benchmark images taken from different databases

Also the proposed method is tested on four video sequences namely Akiyo, Carfone, Mother & daughter, and Miss-America. The size of Akiyo frames and Miss-America frames are 288×386 and the size of Carfone and Mother & daughter frames are 144×192. Figure 4.3 is showing a frame of the videos

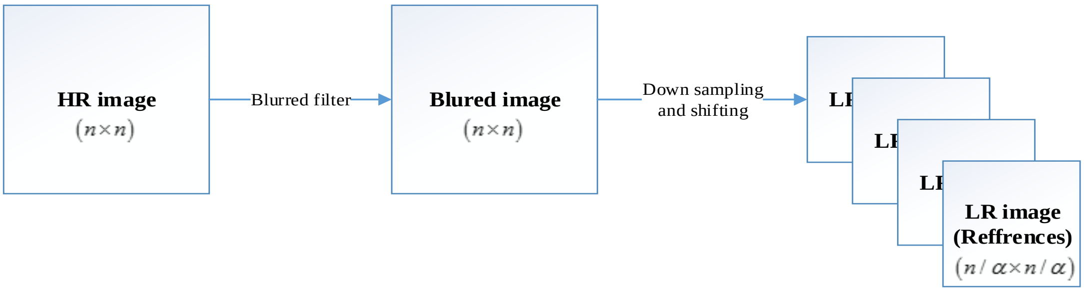


Figure 5.1: The observed LR model used to generate four LR images.

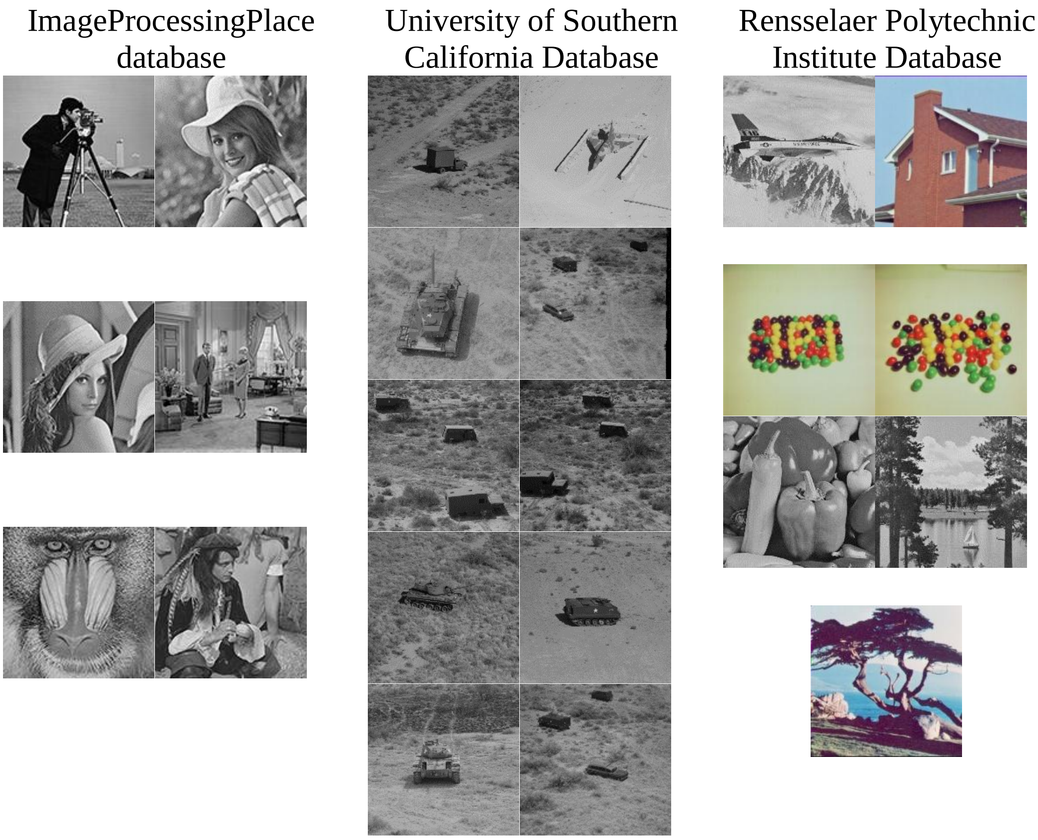


Figure 5.2: Benchmark images taken from different databases.

Figure 5.3: Benchmark video sequences used in the performance analysis.

5.3 Image SR Technique by using Interpolation and BP Iteratively

This proposed SR technique is benefiting from Iterative Interpolation and BP registration (IIBP). In the proposed techniques, IBP technique is improved by using interpolation. This SR technique is achieved by adding an up-sampling and down sampling in each iteration. First of all, four observed LR images are generated by an observation LR model. One of these LR images is considered as a reference image, then interpolation techniques are used to increase the size of the reference image to the size of the ground truth image. This image is considered as an initial guess image. Then the size of initial image is increased and decreased respectively by using interpolation techniques. The interpolated image is decimated to four LR images. The LR images are registered to generate an HR image, then the HR image is sent back to the first step. This process is repeated iteratively until some criterion is met, such as the minimization of the energy of the error or maximum number of allowed iterations is reached. The embedded interpolation module speeds up the convergence of the standard IBP and generates faster results than the standard IBP. Figure 4.4 is showing the block diagram of the SR technique by using Interpolation and BP Iteratively (IIBP).

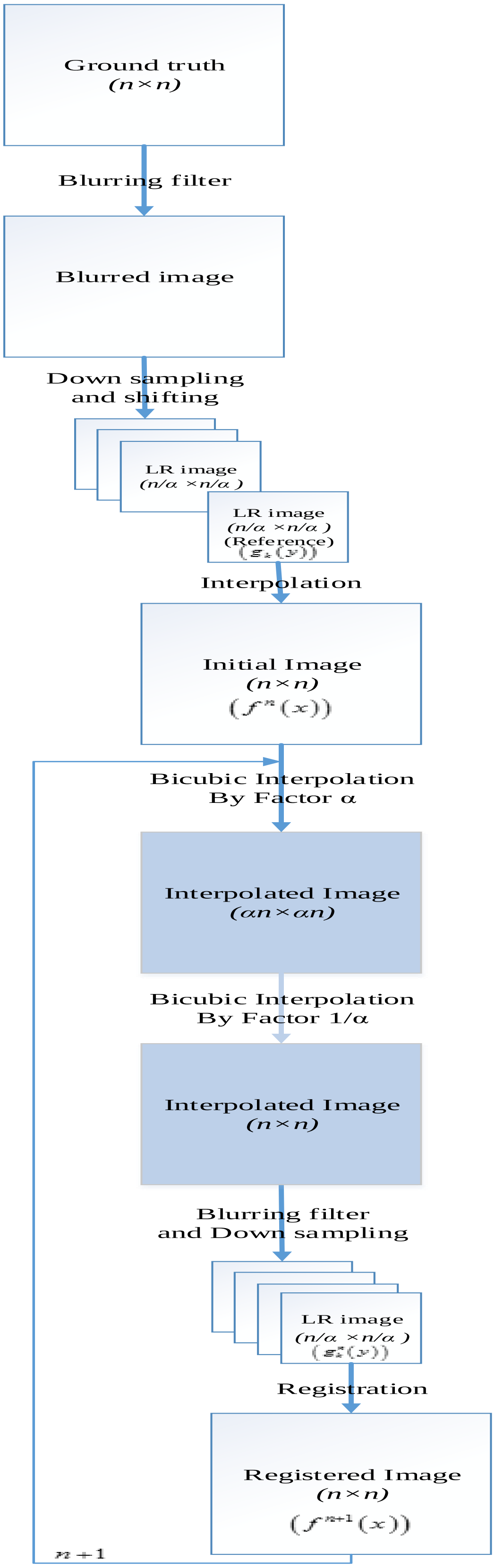


Figure 5.4: The block diagram of IIBP method

For comparison purposes, the IIBP method as well as other conventional and the alternative techniques are being tested on several well-known images. Table 4.1 shows the PSNR values in dB for Nearest Neighbor Interpolation, Bicubic Interpolation, Irani and Peleg, and the IIBP technique of the aforementioned images. The LR images are 256×256 pixels and the HR images are 512×512 pixels.

Table 5.1: The PSNR values (dB) for resolution enhancement of different images by using several SR techniques and IIBP for image size 256×256 to 512×512 .

Images	PSNR Value in dB				
	Nearest Neighbor Interpolation	Bicubic Interpolation	IBP (5 iterations)	IIBP (5 iterations)	IBP (PSNR/Iterations)
Lena	31.57	34.33	35.99	40.11	42.10/192
Mandrill	27.28	29.66	36.92	44.34	42.82/166
Cameraman	31.12	36.01	37.2	46.53	42.97/160
Living room	28.3	29.69	33.96	35.94	40.71/261
Pirate	29.54	31.18	34.51	36.84	42.10/192
Elaine	31.77	33.13	34.19	35.58	41.85/191
Truck	32.24	33.54	36.09	37.51	42.18/147
Airplane	34.35	36.16	33.45	39.96	40.49/285
Tank1	32.13	32.99	34.54	36.66	41.06/241
Car & APC1	33.39	34.8	37.7	38.8	43.18/147
Truck &APC1	29.19	30.2	33.09	33.69	40.91/245
Truck & APC2	29.37	30.41	34.05	33.99	41.54/210
Tank2	30.43	31.32	33.87	34.65	41.38/217
Car & APC2	33.58	34.34	35.02	37.069	41.40/224
Tank3	30.31	31.15	34.44	35.18	41.07/245
Car & APC3	33.56	35.1	36.05	39.22	42.14/190
Jet plane	30.19	32.67	35.33	39.29	41.80/214
House	28.88	30.82	33.07	36	40.30/301
jelly-beans1	33.72	38.2	30.59	41.04	38.67/442
jelly-beans2	31.51	36.4	30.59	40.61	38.67/441
Peppers	31.19	33.1	34.72	37.03	41.22/250
sailboat	28.98	31.08	33.61	35.13	41.69/223
tree	25.18	27.16	31.52	32.94	39.56/336
Average	**30.77**	**31.43**	**32.97**	**37.74**	**41.29/240**

In this method the PSNR result of IIBP method is approximately four dB more than normal IBP method in average and also we can see that nearest neighbor interpolation has minimum PSNR result rather than other SR technique in Table 4.1.

For more comparison IIBP technique is tested on different size of images. Tables 4.2 is showing the PSNR results of Nearest Neighbor Interpolation, Bicubic interpolation, IBP technique and IIBP technique of image size 128×128 to 256×256. Also, these methods are tested on image size 64×64 to 128×128 which is illustrated in table 4.3.

Table 5.2: The PSNR values (dB) for resolution enhancement of different images by using several SR techniques and IIBP for image size 128×128 to 256×256 .

Images	PSNR Value in dB			
	Nearest Neighbor Interpolation	Bicubic Interpolation	IBP (5 iterations)	IIBP (5 iterations)
Lena	28.89	31.33	31.93	32.7
Mandrill	25.54	26.06	30.37	32.04
Cameraman	27.17	29.18	32.32	35.73
Living room	27.3	28.49	30.07	34.72
Pirate	28.12	29.95	32.41	34.26
Elaine	30.91	32.09	34.76	36.38
Truck	31.26	32.82	32.64	34.77
Airplane	27.12	29.33	35.57	39.46
Tank1	28.49	33.73	31	38.58
Car & APC1	31.85	33.92	34.22	40.14
Truck & APC1	28.95	30.46	31.93	36.48
Truck & APC2	29.09	30.66	33.27	36.8
Tank2	30.48	31.82	32.64	34.59
Car & APC2	30.11	31.49	35.47	39.88
Tank3	30.53	31.09	31.5	33.95
Car & APC3	28.25	30.53	31.26	32.48
Jet plane	28.16	30.08	30.3	31.16
House	28.88	30.82	31.62	36
jelly-beans1	33.72	38.2	29.2	41.04
Peppers	29.69	31.35	32.47	38.16
sailboat	27.26	29.29	31.82	36.15
tree	25.18	27.16	31.52	31.87
Average	**28.95**	**31.08**	**32.22**	**35.97**

Table 5.3: The PSNR values (dB) for resolution enhancement of different images by using several SR techniques and IIBP for image size 64×64 to 128×128 .

Images	PSNR Value in dB		
	Bicubic Interpolation	IBP (5 iterations)	IIBP (5 iterations)
Lena	28.57	28.85	34.64
Mandrill	26.96	27.93	31.22
Cameraman	26.45	28.77	32.41
Living room	27.2	27.24	32.7
Pirate	27.87	29.44	33.97
Elaine	29.07	30.44	34.74
Truck	29.73	30.89	34.35
Airplane	26.33	32.48	34.31
Tank1	28.11	32.84	34.88
Car & APC1	31.26	31.78	35.63
Truck & APC1	28.93	29.09	34.64
Truck & APC2	29.06	30.55	34.9
Tank2	29.86	30.3	33.7
Car & APC2	28.57	34.27	37.94
Tank3	28.26	31.24	35.5
Car & APC3	29.25	31.75	34.98
Jet plane	26.62	27.45	30.51
House	29.26	29.35	32.63
jelly-beans1	32.73	26.17	37.28
Peppers	28.47	29.48	32.6
sailboat	26.65	28.76	32.79
tree	25.42	29.07	32.16
Average	**28.09**	**30.21**	**34.02**

It is clear that IIBP method increases the PSNR results of different image in different size rather than Bicubic interpolation and IBP technique from the above tables.

5.4 Visual result of IIBP method on single images

Figures 4.5 and 4.6 are showing the visual comparison between Bicubic interpolation, IBP technique, and the IIBP method for Lena image. The graph of PSNR results and MSE vs. iteration for IIBP technique and IBP technique are demonstrated respectively in Figure 4.7 and Figure 4.8.

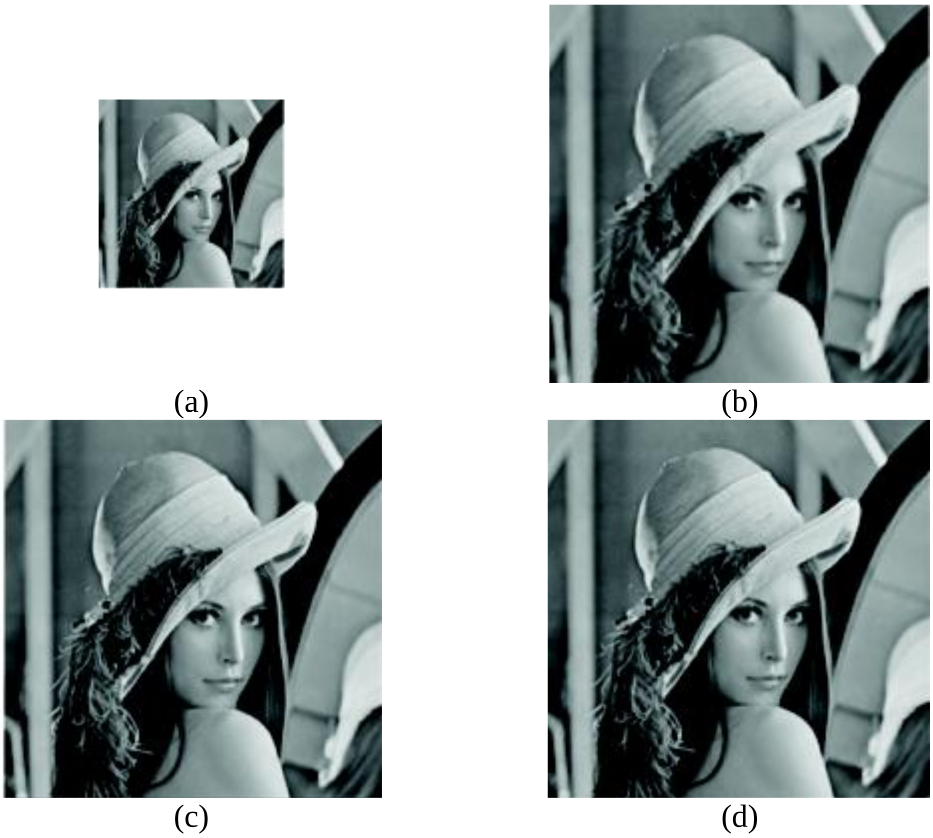


Figure 5.5: The visual comparison between: (a) original LR Lena image and the super resolved image by using (b) Bicubic interpolation, (c) Irani and Peleg SR technique, and (d) the IIBP method

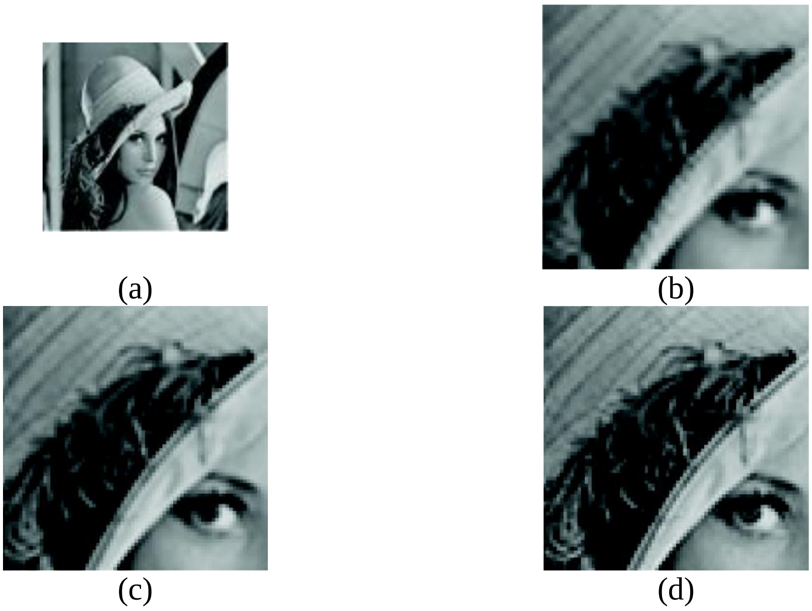


Figure 5.6: The visual comparison between: (a) original LR Lena image and the super resolved image by using (b) Bicubic Interpolation, (c) Irani and Peleg SR technique, and (d) IIBP.

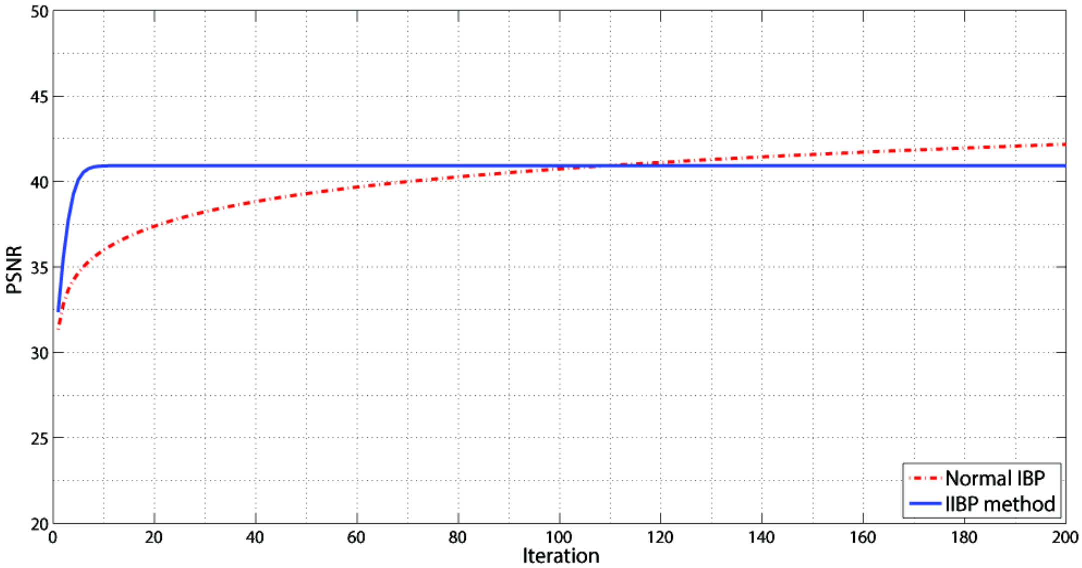


Figure 5.7: The graph of PSNR results for different number of iteration for Lena image

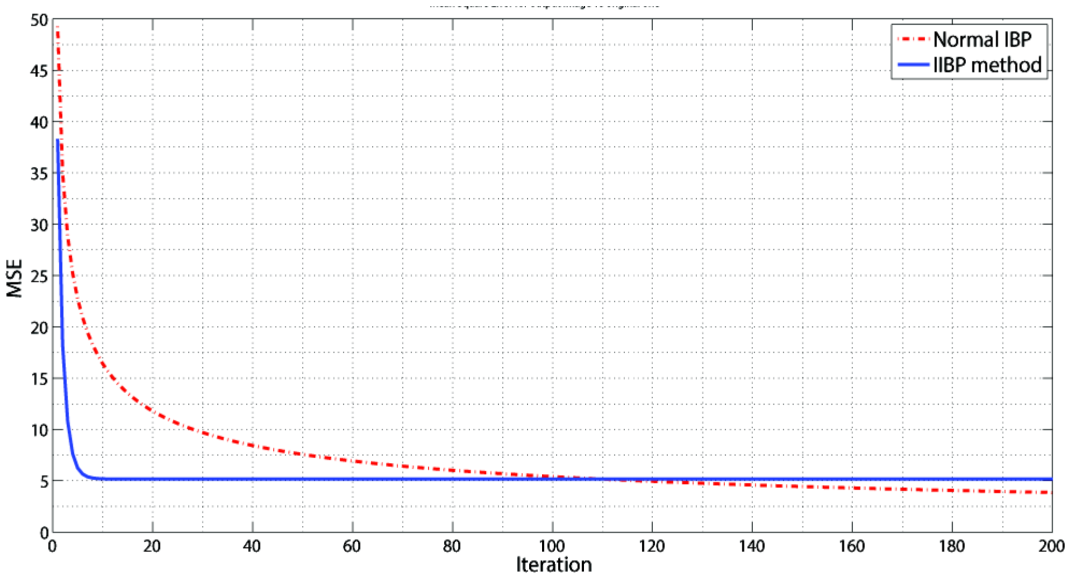
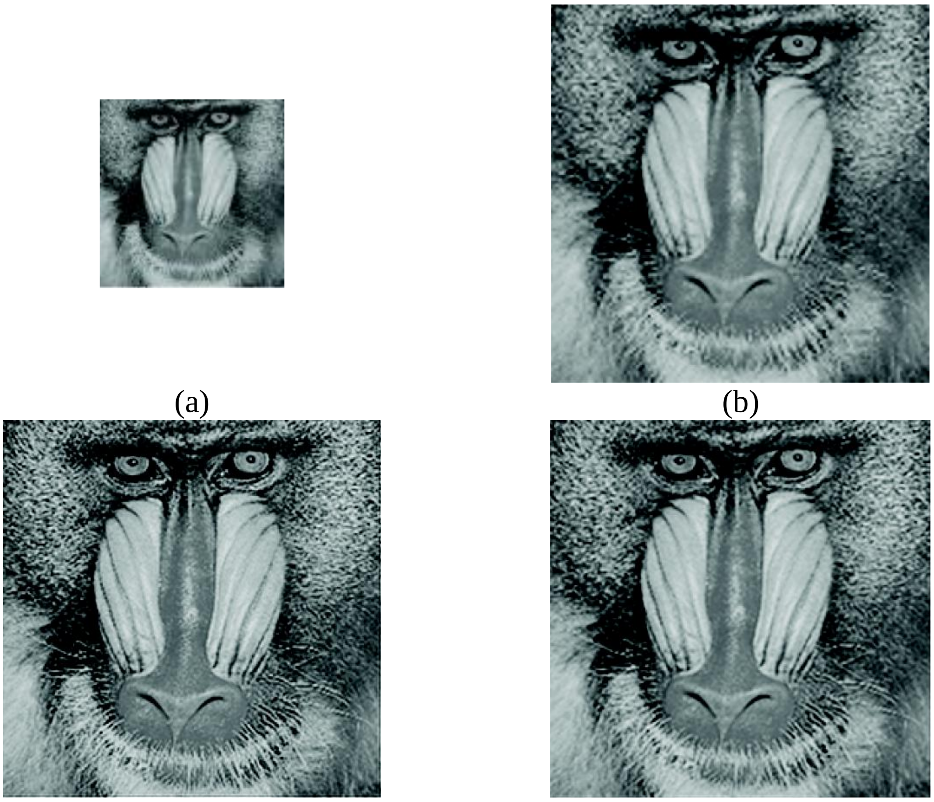


Figure 5.8: The graph of MSE for different number of iteration for Lena image

It is clear that the PSNR results and MSE of the IIBP method are converged after about five iterations. There is a fast decrease of MSE from about 37 at the first iteration to approximately 5 after about five iterations, but for IBP method this value started from 50 at the first iteration and after ten iterations this value reduces to about 17 and finally MSE of IBP method reduce to about 4 after 120 iterations, this value is a little less than MSE of IIBP at the same iteration. For PSNR results, there is a dramatic increase from about 32 dB to 41 dB after 5 iterations in IIBP method. This value is stayed on the same level until 200 iterations. On the other hand the PSNR result is started from 31.5 dB at the first iteration in IBP method and after 120 iterations this value is raised to about 42 dB.

Figure 4.9 illustrates the visual comparison of Bicubic Interpolation, IBP, and IIBP method of Mandrill image and the PSNR value and MSE of it are shown in Figure 4.10 and Figure 4.11 respectively.



(a) (b)

(c) (d)

Figure 5.9: The visual comparison between: (a) original LR Mandrill image and the super resolved image by using (b) Bicubic interpolation, (c) Irani and Peleg SR technique, and (d) IIBP.

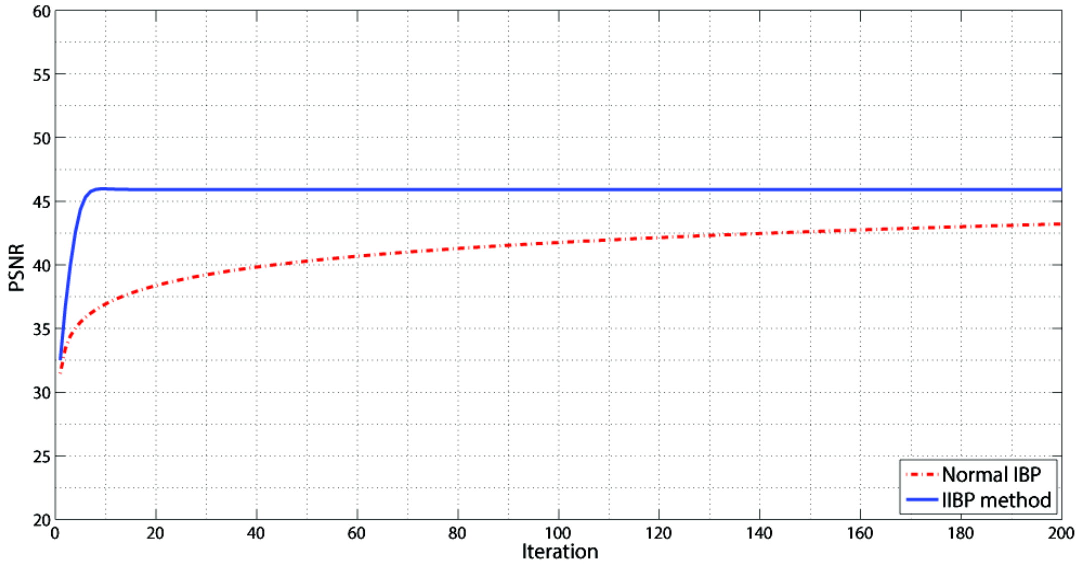


Figure 5.10: The graph of PSNR results for different number of iteration of different IBP based SR techniques for Mandrill image

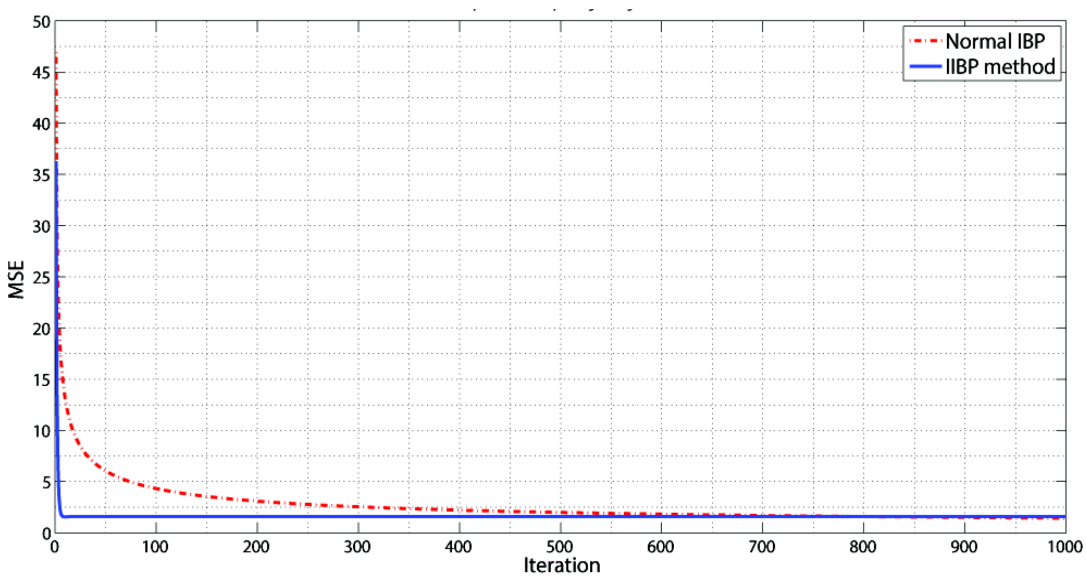


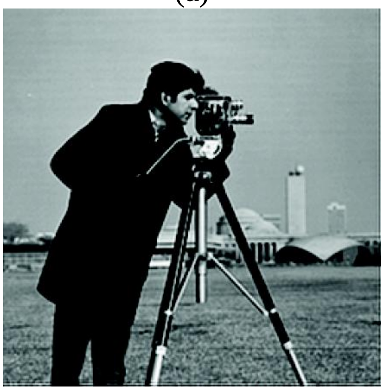
Figure 5.11: The graph of MSE results for different number of iteration of different IBP based SR techniques for Mandrill image

Similar to the Lena image, MSE of Mandrill image is converged after about five iterations in IIBP method. The MSE starts from 37 at the first iteration and this value is decreased to about 5 after five iterations and stay in this value. On the other hand

MSE is started from about 47 at the first iteration in IBP method, then this value reduced to approximately 5 after 200 iterations.

There are similar treatments on PSNR and MSE of other images. More examples are shown in following.


(a) (b)




(c) (d)

Figure 5.12: The visual comparison between: (a) original LR Cameraman image and the super resolved image by using (b) Bicubic interpolation, (c) Irani and Peleg SR technique, and (d) IIBP.

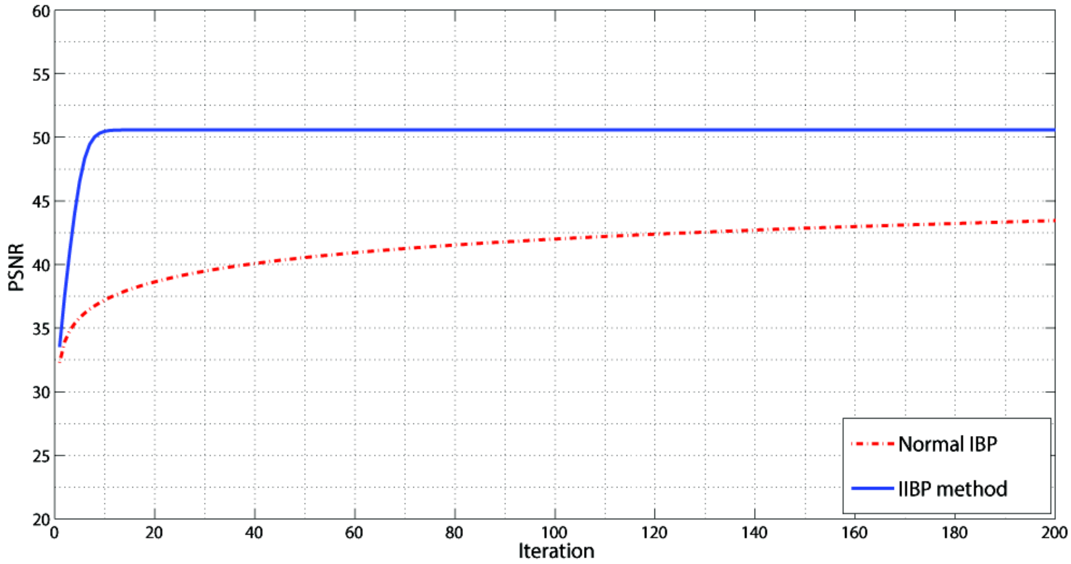


Figure 5.13: The graph of PSNR results for different number of iteration of different IBP based SR techniques for Cameraman image

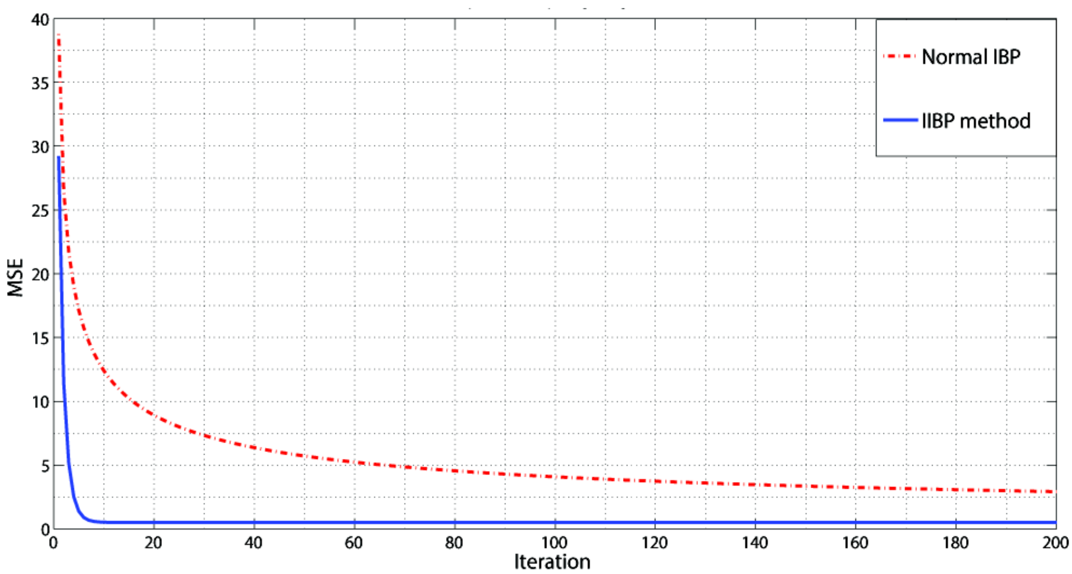


Figure 5.14: The graph of MSE results for different number of iteration of different IBP based SR techniques for Cameraman image

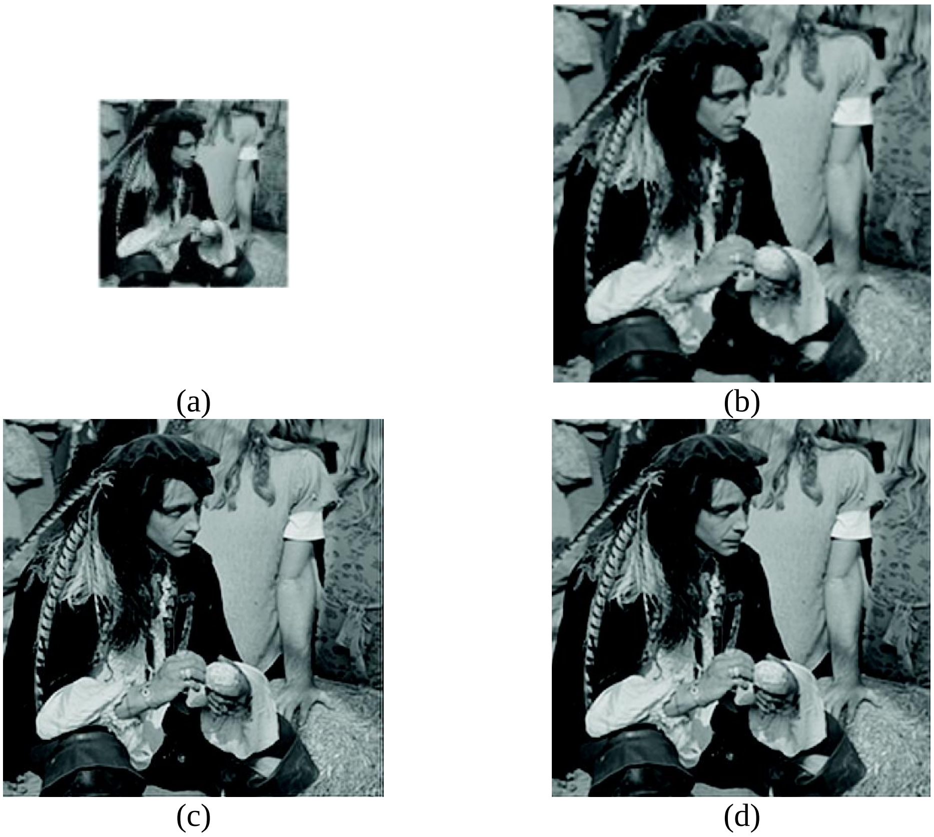


Figure 5.15: The visual comparison between: (a) original LR Pirate image and the super resolved image by using (b) Bicubic interpolation, (c) Irani and Peleg SR technique, and (d) the IIBP method

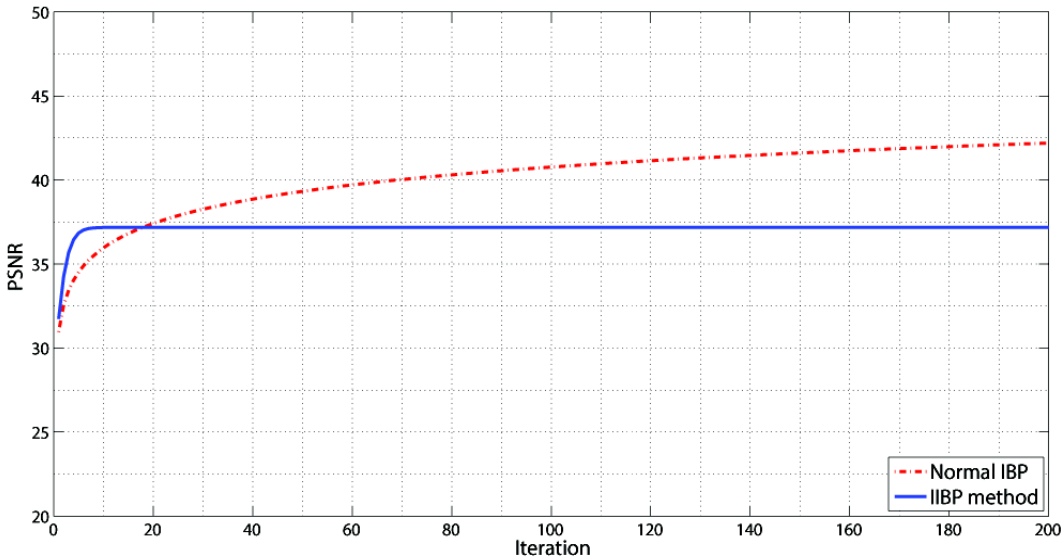


Figure 5.16: The graph of PSNR results for different number of iteration of different IBP based SR techniques for Pirate image

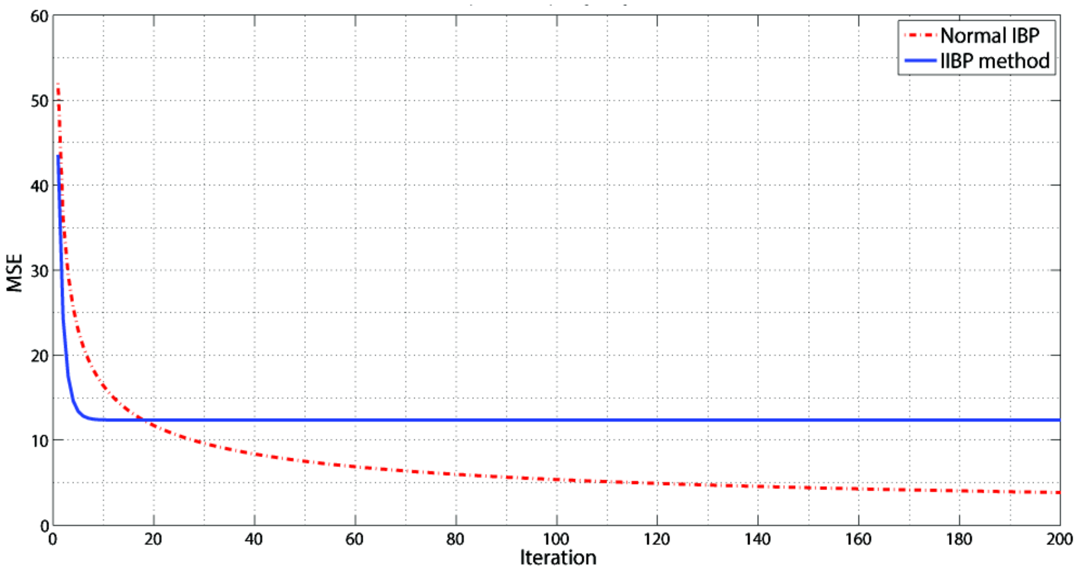
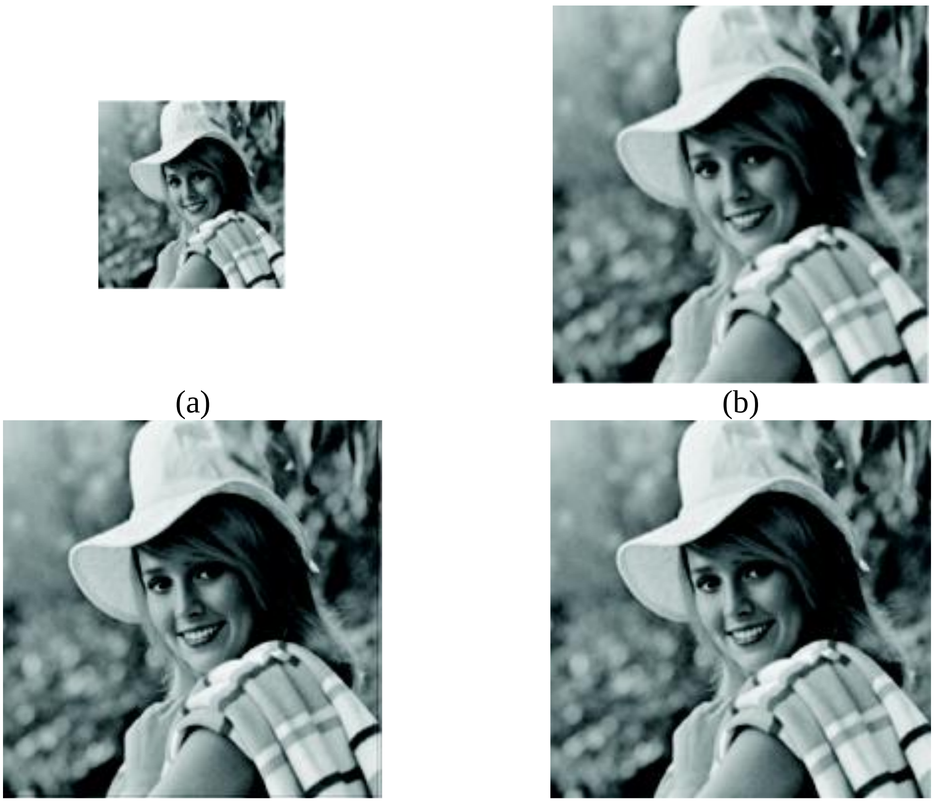


Figure 5.17: The graph of MSE for different number of iteration of different IBP based SR techniques for Pirate image


(a) (b)
(c) (d)
Figure 5.18: The visual comparison between: (a) original LR Elaine image and the super resolved image by using (b) Bicubic interpolation, (c) Irani and Peleg SR technique, and (d) the IIBP method

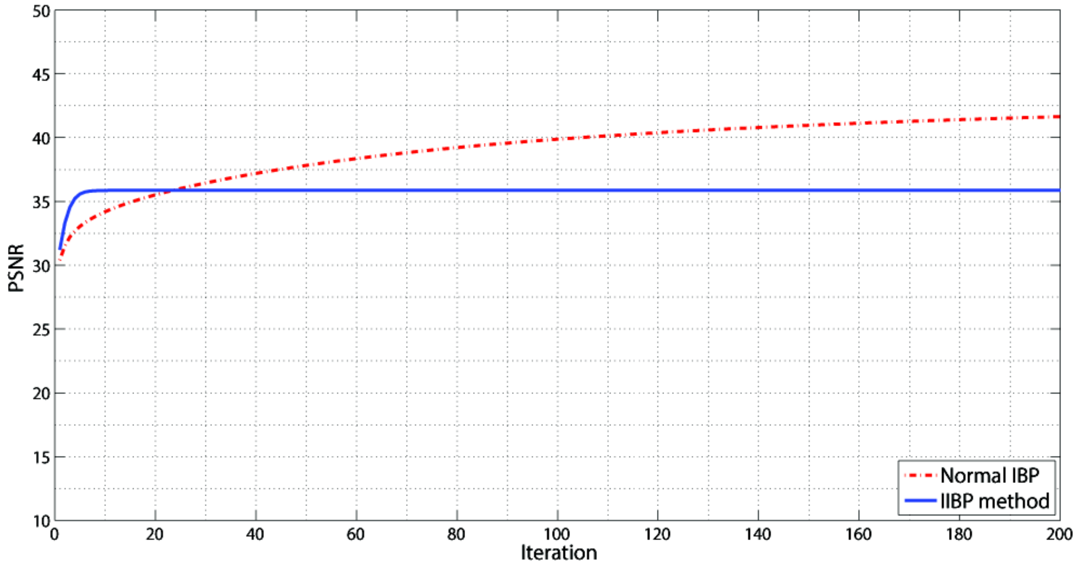


Figure 5.19: The graph of PSNR results for different number of iteration of different IBP based SR techniques for Elaine image

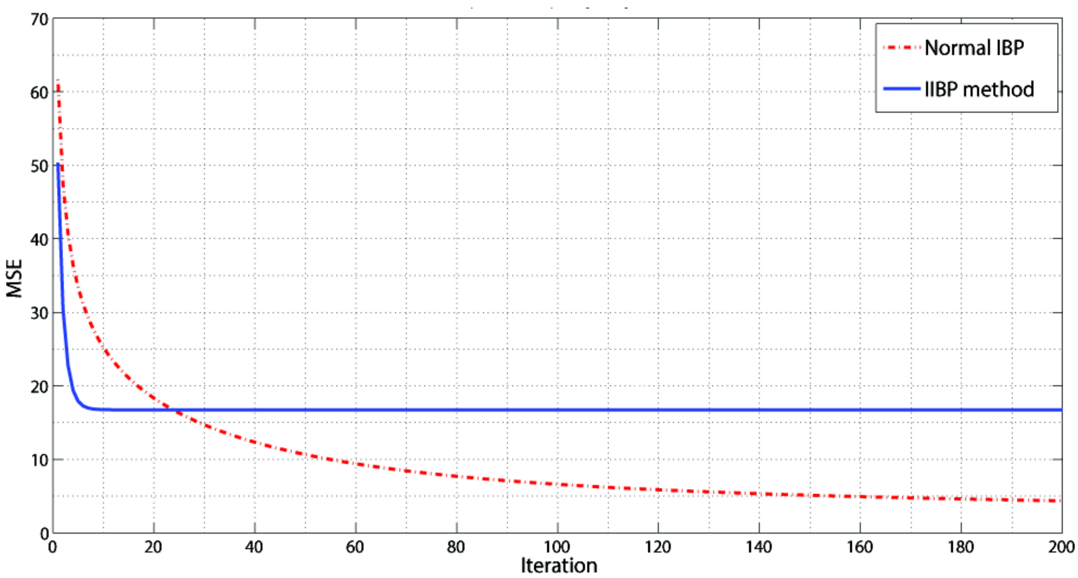


Figure 5.20: The graph of MSE for different number of iteration of different IBP based SR techniques for Elaine image

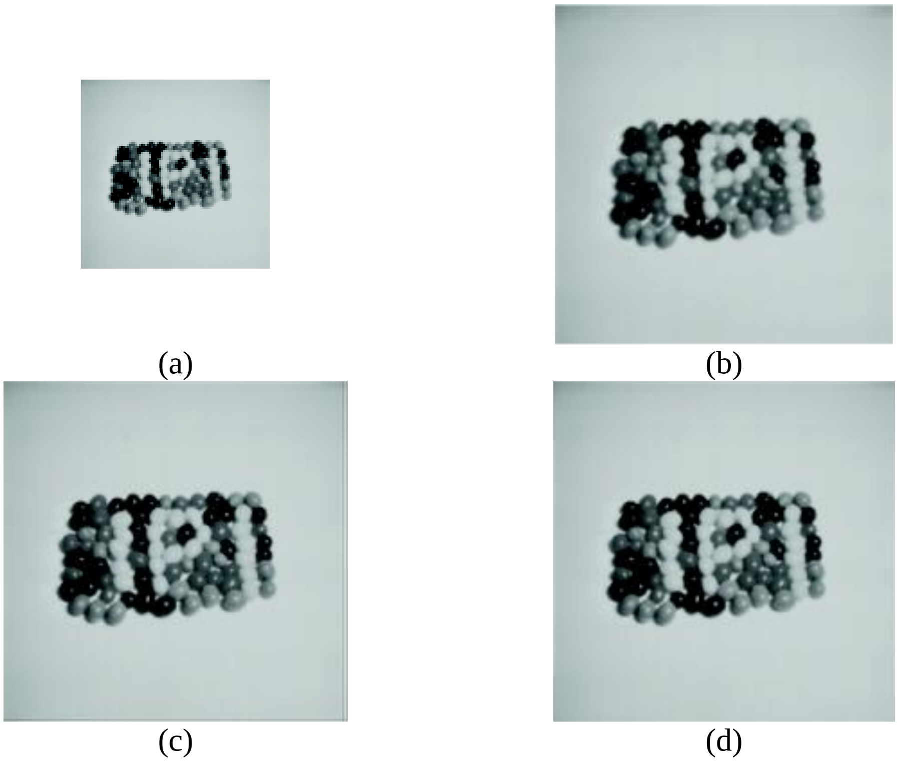


Figure 5.21: The visual comparison between: (a) original LR Jelly beans image and the super resolved image by using (b) Bicubic interpolation, (c) Irani and Peleg SR technique, and (d) the IIBP method

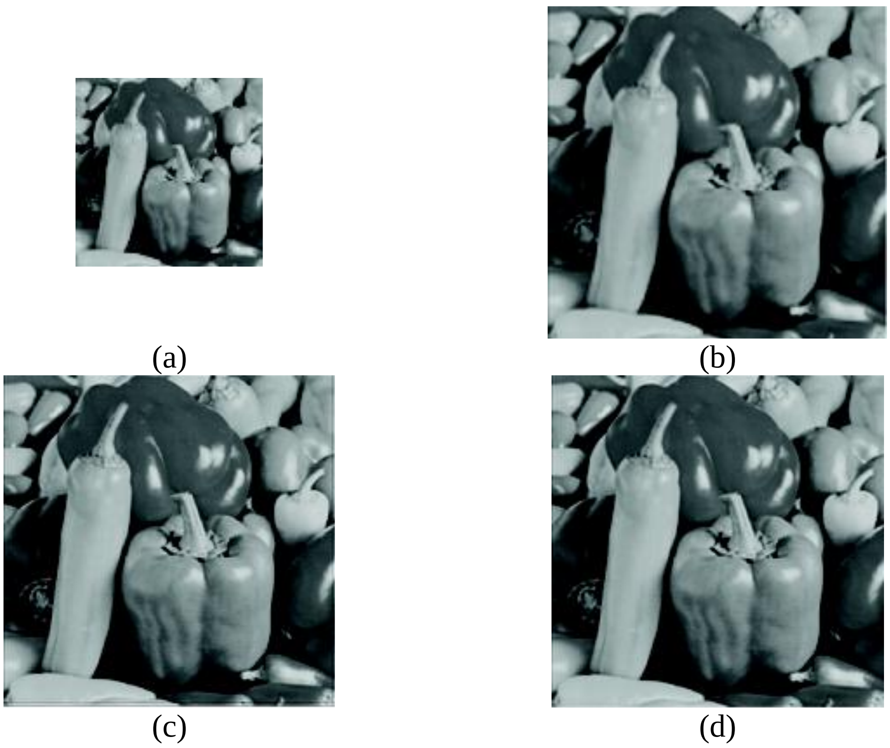
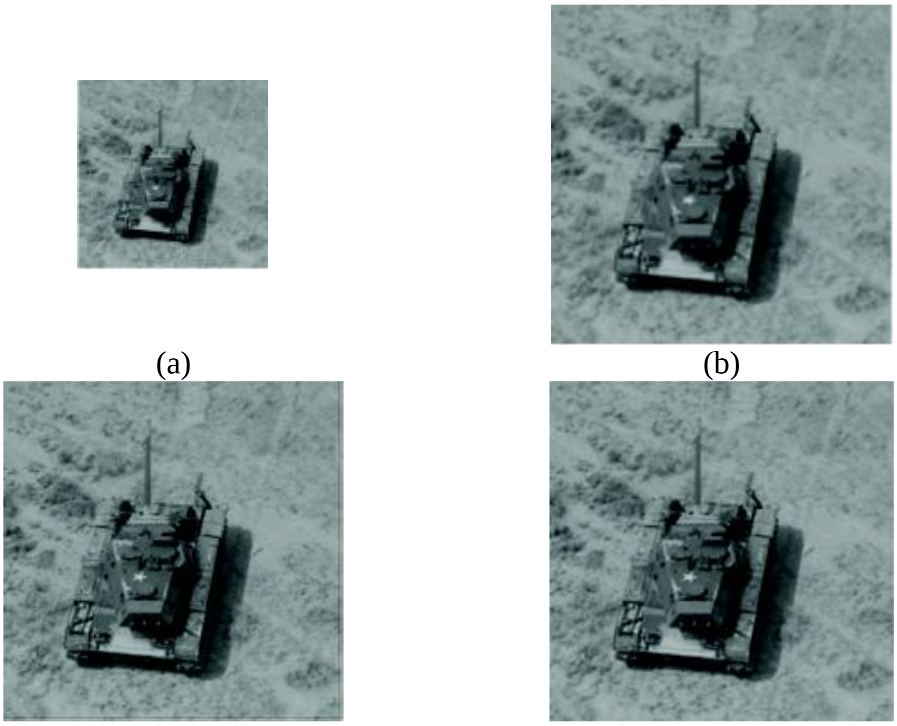


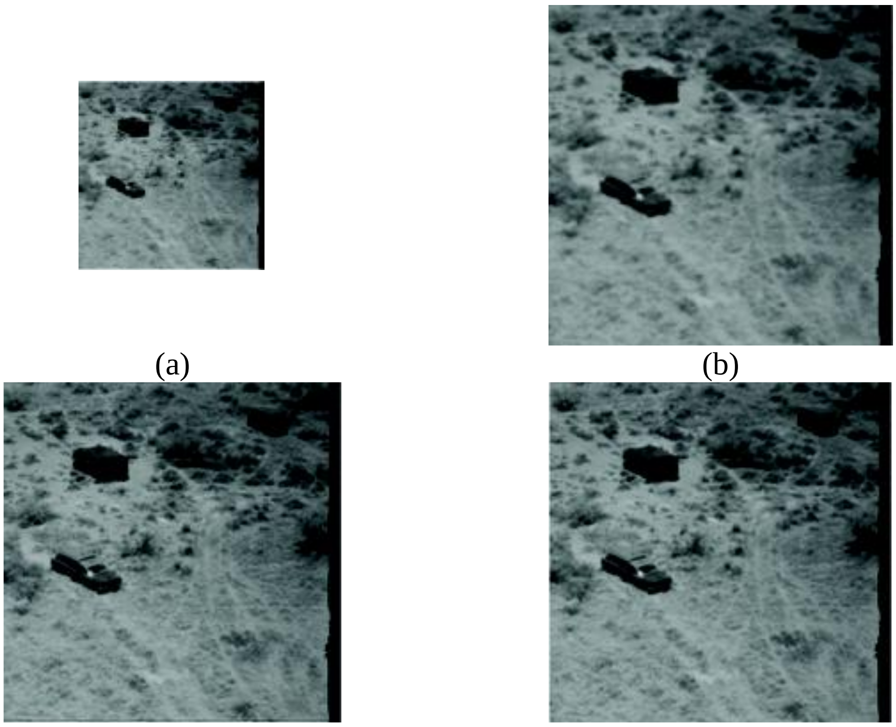
Figure 5.22: The visual comparison between: (a) original LR Peppers image and the super resolved image by using (b) Bicubic interpolation, (c) Irani and Peleg SR technique, and (d) the IIBP method



(a) (b)

(c) (d)

Figure 5.23: The visual comparison between: (a) original LR Tank image and the super resolved image by using (b) Bicubic interpolation, (c) Irani and Peleg SR technique, and (d) the IIBP method



(a) (b)

(c) (d)

Figure 5.24: The visual comparison between: (a) original LR Car and APC1 image and the super resolved image by using (b) Bicubic interpolation, (c) Irani and Peleg SR technique, and (d) the IIBP method

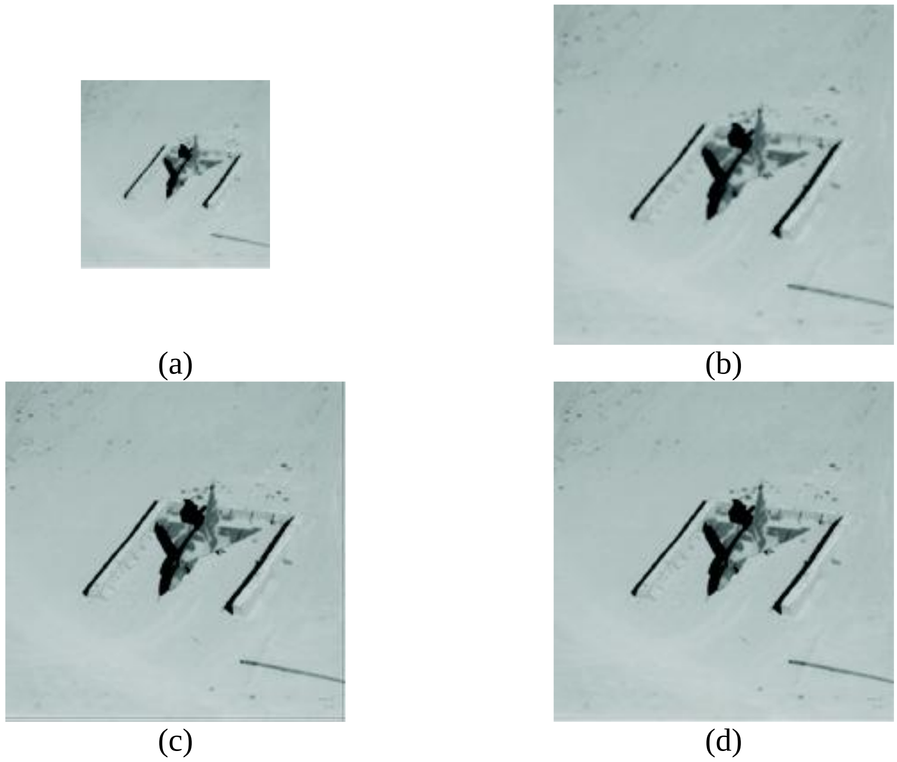


Figure 5.25: The visual comparison between: (a) original LR Airplane image and the super resolved image by using (b) Bicubic interpolation, (c) Irani and Peleg SR technique, and (d) the IIBP method

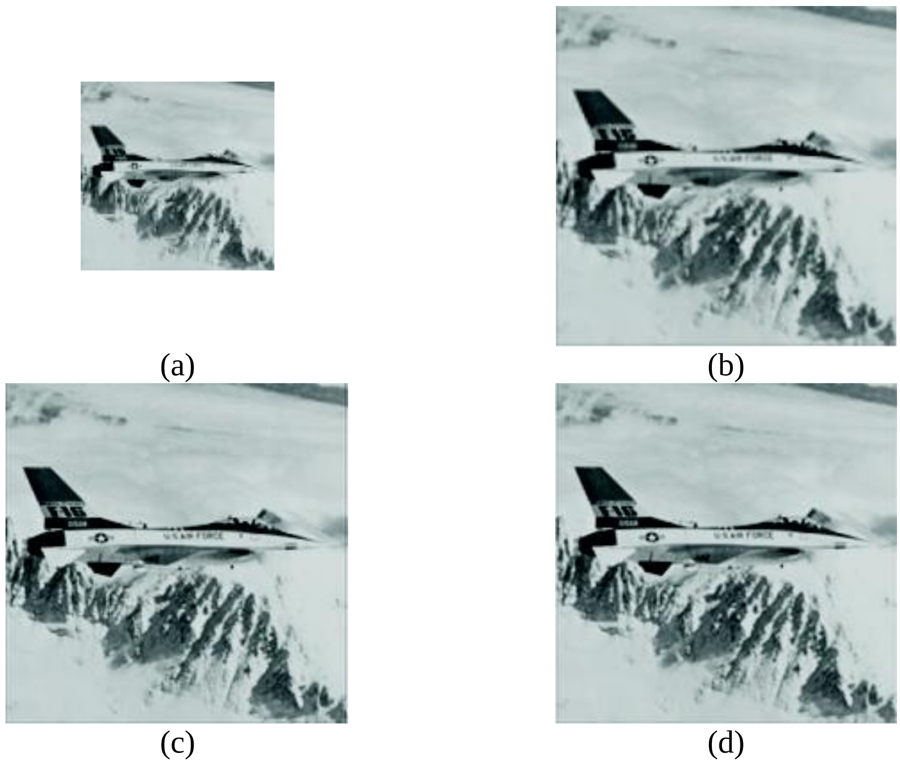


Figure 5.26: The visual comparison between: (a) original LR Airplane image and the super resolved image by using (b) Bicubic interpolation, (c) Irani and Peleg SR technique, and (d) the IIBP method

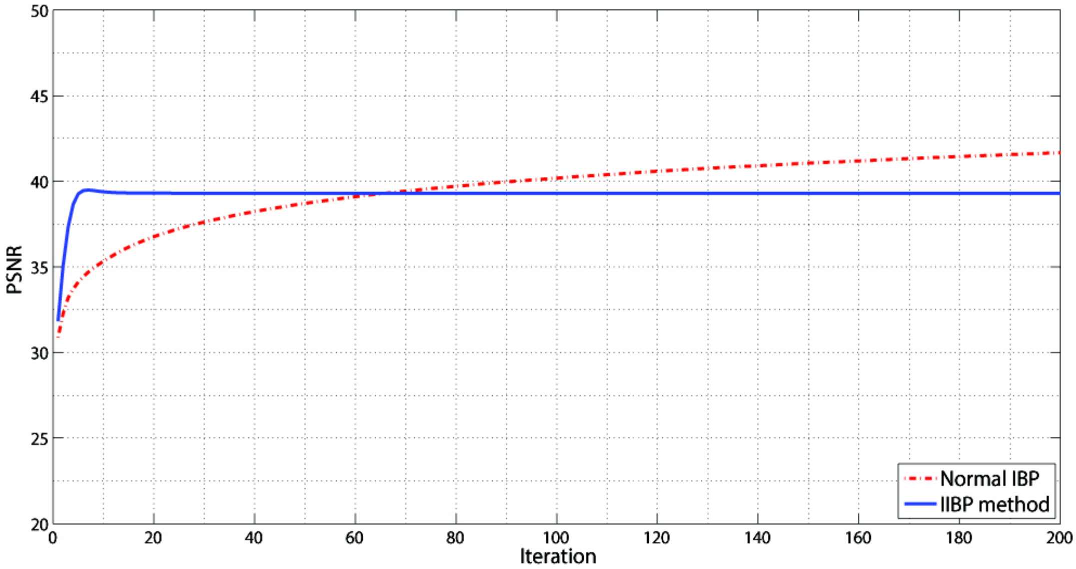


Figure 5.27: The graph of PSNR results for different number of iteration of different IBP based SR techniques for Airplane image

Figure 4.27 shows the PSNR vs. iteration for Jet plane image. We can see that after about five iterations, the PSNR of IIBP method is converged. Also, it is clear that the PSNR of IIBP method is more than another technique till about 60^{th} iterations in this graph. The PSNR of IIBP method starts from 33 dB and after about five iterations this value is increased to about 40 dB. In other hand the PSNR of IBP is started from about 30 dB, this value of PSNR is increased to about 41 dB after 200 iterations.

5.5 IIBP method on video sequences

The proposed method is tested on some video sequences such as Akiyo, Carfone, Mother & daughter, and miss_America. The four frames are considered as input to IIBP method, then reference frame is interpolated by using interpolation technique, interpolated frame consider as an initial guess. Then the size of initial guess is increased and decreased respectively by using interpolation techniques. The interpolated frame is decimated to four LR frames. The LR frames are registered to generate an HR frame, then the HR frame is sent back to the first step.Table 4.4 shows the PSNR value of different methods on aforementioned videos.

Table 5.4: The PSNR values (dB) for resolution enhancement of different video by using Bicubic interpolation, IBP, and IIBP

videos	PSNR Value in dB		
	Bicubic Interpolation	IBP (5 iterations/time(seconds))	IIBP (5 iterations/time(seconds))
Akiyo	34.37	34.75/2.42	35.16/2.48
Carfone	29.99	31.26/0.61	31.26/0.65
Mother and daughter	29.31	30.56/0.61	31.09/0.64
Mis_america	37.93	38.12/0.58	38.49/0.62
Average	**32.09**	**33.67/1.05**	**34/1.09**

Figure 5.28 illustrates the PSNR value of 100 frames of Akiyo video for IBP and IIBP methods.

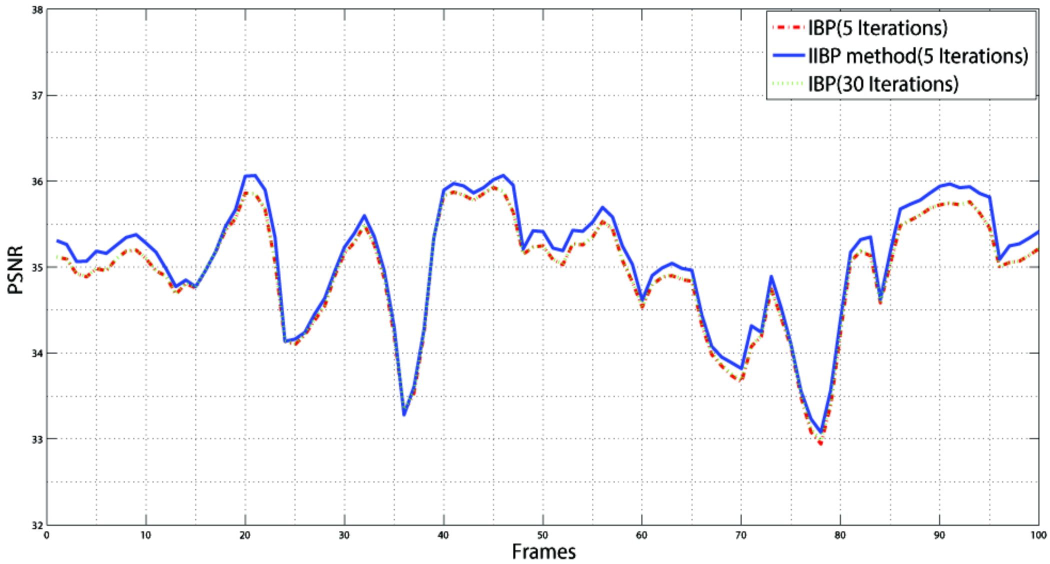


Figure 5.28: The graph of PSNR results for different number of iteration of different IBP based SR techniques for Akiyo video

Figures 4.29 and 4.30 are showing the visual comparison between IBP technique, and the IIBP method for Akiyo and mother & daughter frame.

(a)

(b) (c)

Figure 5.29: The visual comparison between: (a) original LR Akiyo frame and the super resolved image by using (b) Irani and Peleg SR technique, and (c) the IIBP method

(a)

(b) (c)

Figure 5.30: The visual comparison between: (a) original LR Mother & daughter frame and the super resolved image by using (b) Irani and Peleg SR technique, and (c) the IIBP method

5.6 Advantages and Disadvantages of Proposed Technique

It is clear that The PSNR values in proposed technique are better than the alternative methods, but it shouldn't forget that better results are always required to pay the costs. Our focus is on resolution enhancement in proposed methods and one of the costs of this improvement is time.

Although spending time in each iteration in IIBP technique is more than IBP technique, but as regard as the proposed method speeds up the convergence of the standard IBP and generates faster results than the standard IBP, an HR image is generated by at most five iterations in IIBP, it can save the time for applications where faster processing is required such as online application. Table 4.5 shows the spending time to produce an HR image by the aforementioned methods in five iterations. Also Table 4.6 illustrates the system configuration for time measurement.

Table 5.5: The spending time for resolution enhancement of different images by using several SR techniques.

Technique	Time (seconds)		
	Lena	Mandrill	Elaine
IBP [22] (5 iteration)	6.03	5.89	6.09
IIBP (5 iteration)	6.24	6.11	6.16
IBP (iteration/time)	192/220.31	166/198.18	219/253.74

Table 5.6: The system configuration used in time measurement

Model	VAIO VPC-F11-KFX
CPU	Intel Core i7, 2.8, 1333MHz
RAM	4 GB
OS	Windows 7 – home premium
Version of MATLAB	7.12.0.635 (R2011a)

Chapter 5

CONCLUSION

6.1 Conclusions

In this thesis a new Iterative Back Projection (IBP) based SR technique was proposed. In the proposed techniques, IBP technique was improved by using interpolation. This SR technique was achieved by adding an up-sampling and down sampling in each iteration. First of all, four observed LR images were generated by an observation LR model. One of these LR images was considered as a reference image, then interpolation techniques were used to increase the size of the reference image to the size of the ground truth image. This image was consider as an initial image, then the size of initial image was increased and decreases respectively by using interpolation techniques. The interpolated image was decimated to four LR images. The LR images were registered to generate an HR image, then the HR image was sent back to the first step. This process was repeated iteratively until some criterion was met.

The proposed techniques were tested on well-known images and compared by conventional and the alternative techniques by means of PSNR under limited number of iterations. Quantitative and qualitative results showed the superiority of the proposed IIBP technique over standard IBP under limited number of iterations such as 5 iterations. Note that, when the number of iterations goes to infinity, standard IBP is better than the proposed IIBP. The developed method speeds up the convergence of the standard IBP and provide better results for applications where faster processing is required. Video processing is among the possible applications for such a method with very high speed convergence when compared with the standard IBP method.

6.2 Future works

We will apply the approach to other SR techniques with iterative processing. Since the IBP technique is not a recent method we will consider the proposed techniques with recent state of the art image registrations methods.

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