AN APPROACH TO ENLARGE IMAGE USING DIFFRENT INTERPOLATION TECHNIQUE AND QUANTIFICATION OF THE IMAGE

A THESIS

Submitted in partial fulfilment of the requirements for the award of the degree of

MASTERS OF TECHNOLOGY

In

PRINTING ENGINEERING AND GRAPHICS COMMUNICATION

By

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Under the guidance

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CERTIFICATE OF RECOMMENDATION

This is to certify that **Md Mahfuz Mollah (Exam Roll No- M4PRI1603, Registration No-129439 of 2014 – 15 of 14-15)** has completed her dissertation entitled, "An Approach to Enlarge Image Using Interpolation Technique and Quantification of The Image", under the supervision and guidance of **Dr.Kanai Chandra Pal, Associate Professor, Printing Engineering Department, Jadavpur University, Kolkata**. I have satisfied with his work, which is being presented for the partial fulfilment of the degree of **M.Tech In Printing Engineering and Graphics Communication,** Jadavpur University, Kolkata- 700098.

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The thesis at instance is hereby approved as a creditable study of an engineering subject carried out and presented in a manner satisfactory to warrant its acceptance as a prerequisite to the degree for which it has been submitted. It is understood that by this approval the undersigned does not necessarily endorse or approve any statement made, opinion expressed or conclusion drawn therein, but approve this thesis for the purpose for which it is submitted.

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DECLARATION OF ORIGINALITY AND COMPLANCE OF ACADEMIC ETHICS

I hereby declare that this thesis contains literature survey and original research work by undersigned candidate, as part of his Master in Printing Engineering and Graphics Communication course of study.

All information in this document have been obtained and presented in accordance with academic rules and ethical conduct.

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Thanks and Regards

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Dedicated To

My Loving Parents

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ABSTRACT

In this research work, a fast algorithm for image interpolation has been introduced. By using this method, real-time enlargement of images is accessible. The basic idea of the algorithm is to partition digital images and interpolate the pixels to get uniform into images. In addition, in order to have better performance on interpolating images, specified algorithms are assigned to interpolate each classified areas, respectively. Experimental results show that the subjective quality of the interpolated images is substantially improved by using the nearest neighbour, bilinear and cubic convolution interpolation algorithm. Nearest Neighbour Interpolation is the most efficient in terms of computation time. Cubic Convolution Interpolation requires more the computation time than that of Nearest Neighbour Interpolation. Bilinear Interpolation generates an image of smoother appearance than nearest neighbour interpolation, but the grey levels are altered in the process, resulting in blurring or loss of image resolution. In this work, the enlargement of full colour image and gray scale image has been successfully implemented. The present research work has been implemented using MatLab R2012b version.

Chapter 1

INTRODUCTION

Interpolation is a technique that pervades many an application. Interpolation is almost never the goal in itself, yet it affects both the desired results and the ways to obtain them. Notwithstanding its nearly universal relevance, some authors give it less importance than it deserves, perhaps because considerations on interpolation are felt as being paltry when compared to the description of a more inspiring grand scheme of things of some algorithm or method. Due to this indifference, it appears as if the basic principles that underlie interpolation might be sometimes cast aside, or even misunderstood. The goal of this chapter is to refresh the notions encountered in classical interpolation.

In the last decade [1], with the advent of new technologies in both civil and military domain, more computer vision applications are being developed with a demand for high-quality high-resolution images. In fact, the demand for higher-resolution images is exponentially increasing and the camera manufacturing technology is unable to cope up due to cost efficiency and other practical reasons. Therefore, for an imaging system, super-resolution overcomes the limitation in terms of image quality by enhancing the spatial resolution to generate high-resolution images of the original scene, without the need of any hardware enhancements. This is why most of the research into image resolution enhancement (or super-resolution) has been majorly directed towards developing techniques that deliver the highest possible fidelity of the reconstruction process. The computational efficiency issues and the feasibility of developing realistic applications based on resolution algorithms have attracted much less attention.

1.1 Objective of image interpolation

1. To study the existing technique of image interpolation and the image quality.
2. There will be through discussion of proposed algorithm technique to improve image interpolation approach.
3. Other proposed algorithm will be implemented for better quality image.
4. Lower resolution image converted with higher resolution image will be the primary goal.

1.2 Problem analysis and proposed approach

Image interpolation addresses the problem of generating a high-resolution image from its low-resolution version. The model employed to describe the relationship between high-resolution pixel and low resolution pixel plays the critical role in the performance of an interpolation algorithm. Conventional linear interpolation schemes that are bi-linear, bi-cubic based on space-invariant models fail to capture the fast evolving statistics around edges and annoying artefacts. Linear interpolation is generally preferred not for performance but for computational simplicity.

Many algorithms have been proposed to improve the subjective quality of the interpolated images by imposing more accurate models. Adaptive interpolation techniques spatially adapt the interpolation coefficient to better match the local structure. Iterative methods such as partial differential equation base schemes and projection onto convex schemes, constrain the edge continuity and iterations. Other approaches borrow the technique from vector quantization and morphological filtering to facilitate the induction of higher resolution image.

1.3 Purpose of image Interpolation

1.3(a) To enlarge still digital images as well as video image as per demand.

1.3(b)To get good quality images and, if required, to repair the images that may be damaged or distort during transmission.

1.3(c)To get smoother images. Manipulation of images digitally can render fancy artistic effect as often seen in the movies which can be rectified by interpolation.

1.4 Application of image interpolation

Among biomedical applications where interpolation is quite relevant, the most obvious are those where the goal is to modify the sampling rate of pixels (picture elements) or vexes (volume elements). This operation, named rescaling, is desirable when an acquisition device—say, a scanner—has a non-homogeneous resolution, typically a fine within-slice resolution and a coarse across-slice resolution. In this case, the purpose is to change the aspect ratio of vexes in such a way that they correspond to geometric cubes in the physical space [2]. Often, the across-slice resolution is modified to match the within-slice resolution, which is left unchanged. This results in a volumetric representation that is easy to handle (e.g., to visualize or to rotate) because it enjoys homogenous resolution. A related operation is reclining [3].

Suppose again that some volume has a higher within-slice than across-slice resolution. In this case, it seems natural to display the volume as a set of images oriented parallel to the slices, which offers its most detailed presentation. Physicians may however be sometimes interested in other views of the same data; for simplicity, they often request that the volume be also displayed as set of images oriented perpendicular to the slices. With respect to the physical space, these special orientations are named axial, coronal, and require at most rescaling for their proper display. Meanwhile, interpolation is required to display any other orientation—in this context, this is named realising.

The data model associated to interpolation also affects algorithmic considerations. For example, the strategy that goes by the name of multi resolution proposes to solve a problem first at the coarse scale of an image pyramid, and then to iteratively propagate the solution at the next finer scale, until the problem has been solved at the finest scale. In this context, it is desirable to have a framework where the interpolation model is consistent with the model upon which the image pyramid is based. The assurance that only a minimal amount of work is needed at each new scale for refining the solution is only present when the interpolation model is coherent with the multi resolution model.

In general, almost every geometric transformation requires that interpolation be performed on an image or a volume. In biomedical imaging, this is particularly true in the context of registration, where an image needs to be translated, rotated, scaled, warped, or otherwise deformed, before it can match a reference image or an atlas [4]. Obviously, the quality of the interpolation process has a large influence on the quality of the registration.

Interpolation is so intimately associated with its corresponding data model that, even when no re-sampling operation seems to be involved it nevertheless contributes under the guise of its data model. For example, interpolation has been defined as the link between the discrete world and the continuous one. It follows that the process of data differentiation (calculating the data derivatives), which is defined in the continuous world, can only be interpreted in the discrete world if one takes the interpolation model into consideration. Since derivatives or gradients are at the heart of many an algorithm (e.g., optimizer, edge detection contrast enhancement) the design of gradient operators that are consistent with the interpolation model should be an essential consideration in this context.

1.5 Interpolation Technique

There are so many interpolation methods mainly focussed on this three interpolation method.

1.5(a) Nearest Neighbour Interpolation

1.5(b) Bi-linear Interpolation

1.5(c) Cubic convolution Interpolation

1.6 What is image resolution?

As per [5] optical resolution is a measure of the ability of a camera system, or a component of a camera system, to depict picture detail. On the other hand, image resolution is defined as the fineness of detail that can be clearly distinguished in an image. Both the definitions apply to digital and analogue camera systems and images. However, in this research, the term resolution will only relate to digital camera systems and digital images. There are two most common classifications of digital image resolution, namely – spatial and bit-depth.

- Spatial resolution refers to the level of detail discernable in an image.

- Bit-depth refers to the number of bits or 0's and 1's that can be used to specify the colour at each pixel of an image.

Spatial resolution essentially describes the total number of pixels in an image, horizontally and vertically. For example, a digital image 300 pixel (wide) x 300 pixel (high) consists of a total of 90,000 pixels or is a 0.1 megapixel (MP) image. If this image is tripled, the dimensions will be 900 pixels (wide) x 900 pixels (high) with a total of 810,000 pixels or 0.8 MP. Clearly, the detail carrying capacity of an image is directly proportional to the number of pixels in an image. Higher the number of pixels, higher is the detail representation of the image. On the other hand, bit-depth describes the number of possible colours at each pixel. Bit-depth is also known as colour-depth. More the bits per pixel, greater are the colours at each pixel thereby increasing the colour details in the digital image. For example, a gray scale image carries 8-bits per pixel, which in turn means that a gray scale image can have 2^8 or 256 shades of gray. For colour images, if 8-bits per pixel per channel are used, then the colour digital image can have 2^{8*3} or 16,777,216 different colours. This is also known as 24-bits per pixel.

1.7 Image Degradation Factor

The acquired image usually represents the scene in an unsatisfactory manner. Since real imaging systems as well as imaging conditions are imperfect, an observed image represents only a degraded version of the original scene. These degradations in the images are caused due to various factors such as blur, noise and aliasing. Figure 1.1 shows an example of a corrupted image (left-panel) and the original scene (right-panel). Such distortions may get introduced into an imaging system due to the following reasons:

- Motion between the camera sensor and the scene or subject.
- Camera optics and lenses.
- Atmosphere.

Blur can be introduced into the image during the imaging process by factors such as motion of the scene, wrong focus, atmospheric turbulence and optical point spread function. To remove the effect of blurring on an image is known as de-blurring which is a well known image enhancement technique. If the imaging conditions at the time of acquiring an image are known, it is much easier to de-blur the image accurately. Figure 1.2 shows an example of a blurred image (left-panel) and the original scene (right-panel).

Noise is a random background event and is certainly not a part of the ideal scene/signal and may be caused by a wide range of sources such as variations in the detector sensitivity, optical imperfections and environmental changes. Although many noise models exist in literature, in this work only the additive Gaussian white noise has been considered, since it provides a good model for noise in most of the imaging systems. The noise is also assumed to be spatially uncorrelated with respect to the image, that is, there is no correlation between the image pixel values and the noise components. Figure 1.3 shows an example of a noise-corrupted image (left-panel) and the original scene (right-panel).

Another factor affecting image resolution is due to the insufficient spatial sampling of the images. As per the Shannon-Nyquist Sampling theorem [6], the sampling frequency should be greater than twice the highest frequency of the input signal. If the sampling frequency is less than twice the highest frequency, then all frequency components higher than half the sampling frequency are reflected as lower frequencies in the reconstructed signal. This is referred to as under-sampling of images which occurs in many imaging sensors. Due to under-sampling, the high-frequency components overlap with the low-frequency components and get introduced into the reconstructed image/signal causing degradation of the image.

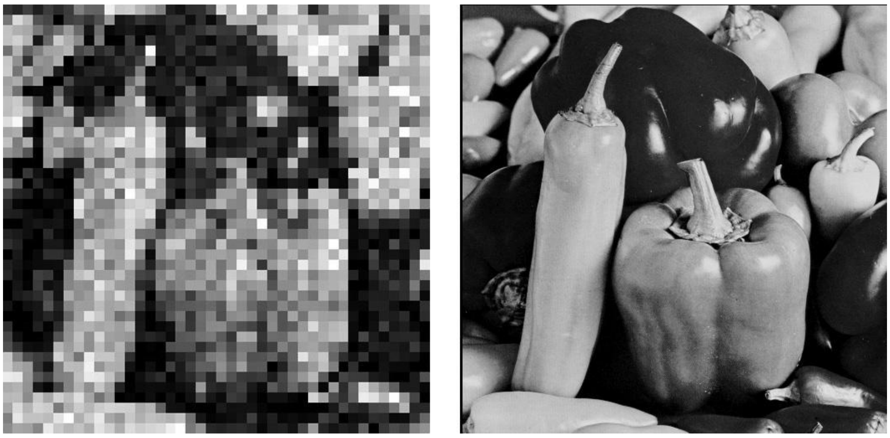


Fig. 1.1 An example of noisy, blurred and under-sampled image (left-panel) of the original scene (right-panel)

Fig. 1.2 An example of the blurred image (left-panel) of an original scene (right-panel)

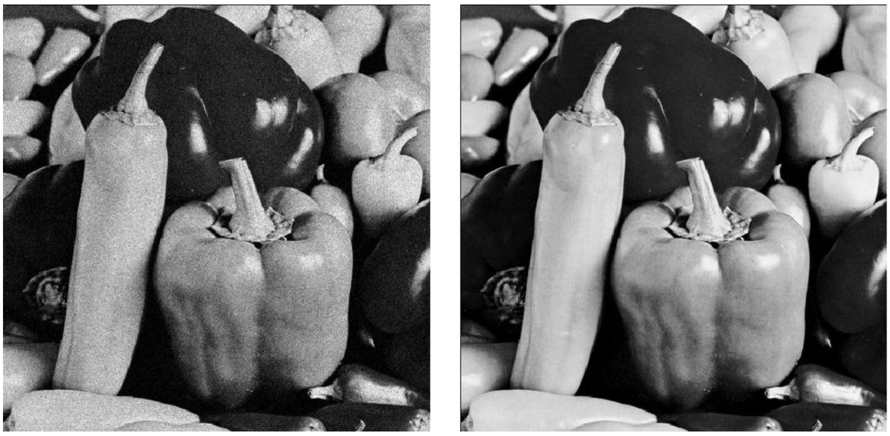


Fig. 1.3 An example of the noise-corrupted image (left-panel) of an original scene (right-panel)

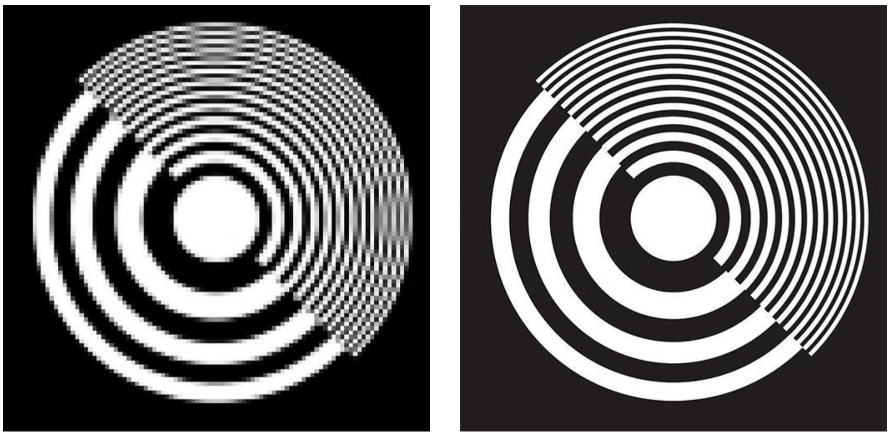


Fig. 1.4 An example of an aliased, under-sampled image (left-panel) of an original scene (right-panel)

1.8 Ringing

Ringing arises because most good synthesis functions are oscillating. In fact, ringing is less of an artefact—in the sense that it would correspond to a deterioration of the data—than the consequence of the choice of a model: it may sometimes happen (but this is not the rule) that data are represented (e.g., magnified or zoomed) in such a way that the representation, although appearing to be plagued with ringing "artefacts", is nonetheless exact, and allows the perfect recovery of the initial samples. Ringing can also be highlighted by translating by a non-integer amount a signal where there is a localized domain of constant samples bordered by sharp edges.

After interpolation, translation and re-sampling, the new samples do no more exhibit a constant value over the translated domain, but they tend to oscillate. This is known as the Gibbs effect; its perceptual counterpart is the Mach bands phenomena. Figure 1.4 shows an occurrence of ringing in the outlined area due to the horizontal translation of a high-contrast image by half a pixel.

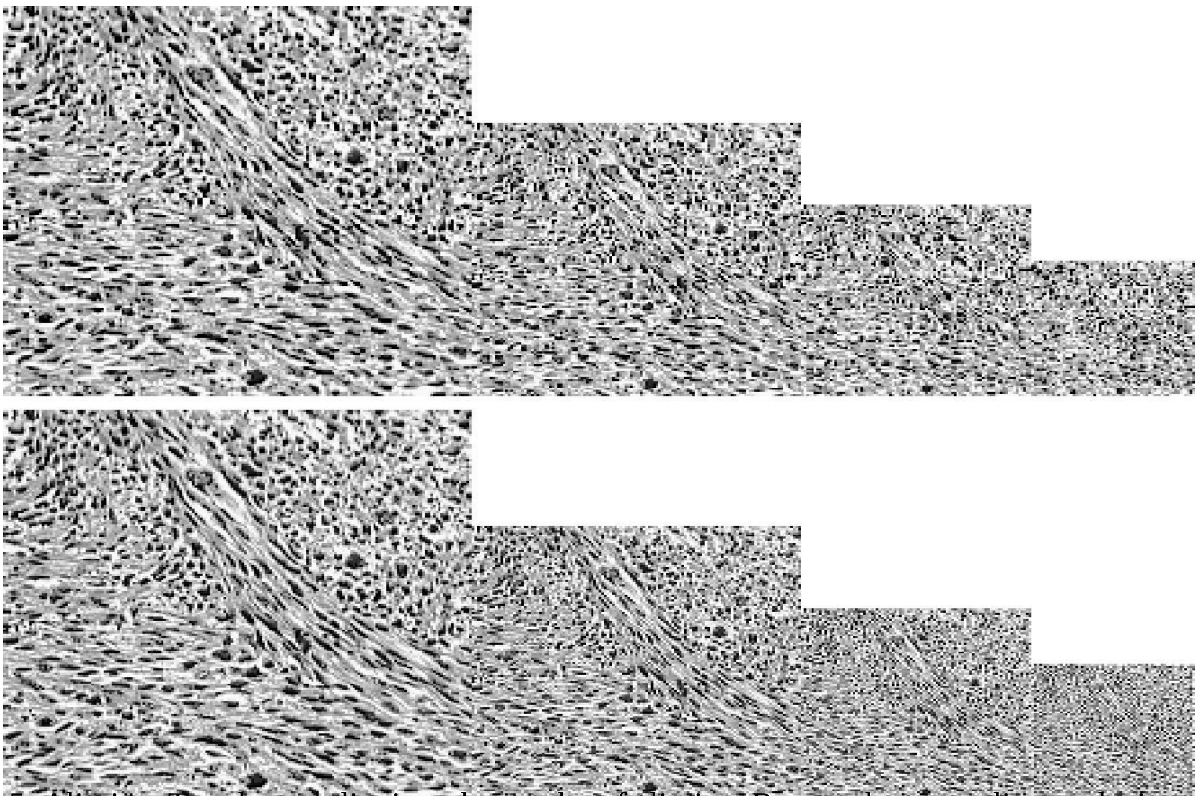


Figure1.5: Aliasing. Top: low quality introduces a lot of aliasing. Bottom: better quality results in less aliasing. Both: at too coarse scale, the structural appearance of the bundles of cells is lost.

1.9 Aliasing

Unlike ringing, aliasing is a true artefact because it is never possible to perform exact recovery of the initial data from their aliased version. Aliasing is related to the discrete nature of the samples. When it is desired to represent a coarser version of the data using less samples, the optimal procedure is first to create a precise representation of the coarse data that uses every available sample, and then only to down sample this coarse representation. In some sense, aliasing appears when this procedure is not followed, or when there is a mismatch between the coarseness of the intermediate representation and the degree of down sampling (not coarse enough or too much down sampling). Typical visual signatures of aliasing are moiré effects and the loss of texture. Figure 1.5 illustrates aliasing.

1.10 Blocking

Blocking arises when the support of the interpolate is finite. In this case, the influence of any given pixel is limited to its surroundings, and it is sometimes possible to discern the boundary of this influence zone. Synthesis functions with sharp transitions, such as those in use with the method named nearest-neighbour interpolation, exacerbate this effect. Figure1.6 presents a typical case of blocking

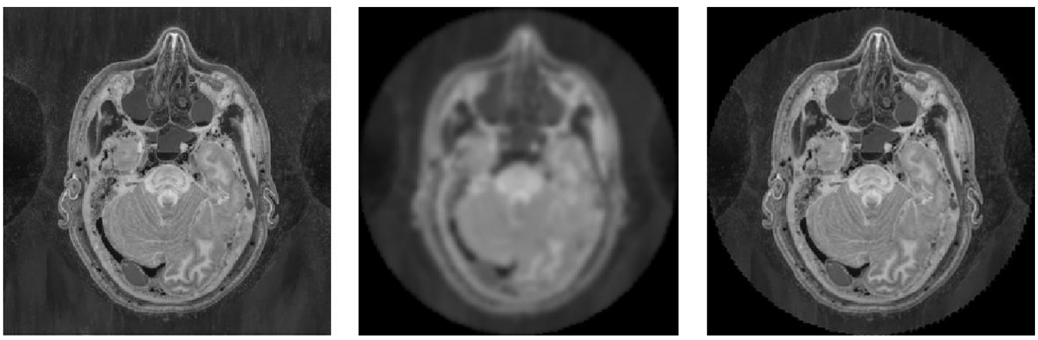


Figure 1.6 : Blurring. Iterated rotation may lose many small scale structures

when the quality of interpolation is insufficient (centre).in less loss (right).

Chapter 2

Literature Survey

In past few years, some paper has been presented on image interpolation. Different research used different approaches to get the desirable result. Some of the papers have been discussed below.

Robert G. Keys has work on the paper [7] of cubic convolution image interpolation. Cubic convolution interpolation is a new technique for *re*-sampling discrete data. It has a number of desirable features which make it useful for image processing. The technique can be performed efficiently on a digital computer. The cubic convolution interpolation function converges uniformly to the function being interpolated as the sampling increment approaches zero, With the appropriate boundary conditions and constraints on the interpolation kernel, it can be shown that the order of accuracy of the cubic convolution method is between that of linear interpolation and that of cubic spines.

EINAR MAELAND has work on the different interpolation method [8]. Study of different cubic interpolation kernels in the frequency domain reveals some new aspects of both cubic spleen and cubic convolution interpolation. The kernel used in cubic convolution is of finite support, and depends upon a parameter to he chosen at will. At the Ny-quist frequency, the spectrum attains a value which is independent of this parameter. Exactly the same value is found at the Ny-quist frequency in the cubic spine interpolation. If a strictly positive interpolation kernel is of importance in applications, the cubic convolution with the parameter value zero is recommended.

C. Caruso has work on the paper [9] of Interpolation methods comparison. In many fields, spatial interpolation is used to evaluate physical data in a continuous domain. The many different techniques offer different performances, according to the characteristics of initial data points. The aim of this paper is to provide help in choosing and evaluating the technique that best suits the data set: a few indices measure the quality of interpolation by different viewpoints. An extensive test-case is reported, involving four different interpolation methods. Data sets are generally connected with environmental topics or taken from literature.

Slavy G Mihov and v Georgi Zapryano has work on the paper [10] of Interpolation algorithms for image scaling. Nowadays, the tendency for image visualization is devises, which have determined resolution, to be used more and more. Image re sampling is essential for the purpose of correct image visualization. In this paper, parallel between different re sampling algorithms is made, and as basis for this comparison are used three methods: Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR) and Subjective Evaluation (SE). In the present paper are given qualitative and quantitative results from the execution of the above algorithms upon special, designed for the purpose, vector graphics and selected photographs. The method offered is a useful tool for doing simple tests.

Mehdi Hajizadeh, Mohammad Sadegh Helfroush, Ashkan Tashk has work on the paper[11] of improvement of image zooming using least directional differences based on linear and cubic interpolation. There are many interpolation methods, among them, bilinear (BL) and bi cubic (BC) are more popular. However, these methods suffer from low quality edge blurring and aliasing effect. In the other hand, if high resolution images are not available, it is impossible to produce high quality display images and prints. To overcome this drawback, in this paper, we proposed a new method that uses least directional differences of neighbour pixels, based on preceding bilinear and bicubic interpolation methods for images.

The qualitative and quantitative results of proposed technique show that this method improves bilinear and bicubic interpolations. The proposed algorithm can also be applied both to RGB and gray level images.

Karl S. Ni has work on the paper [12] of an adaptable -nearest neighbours algorithm for MMSE image interpolation. We propose an image interpolation algorithm that is nonparametric and learning-based, primarily using an adaptive k-nearest neighbour algorithm with global considerations through Markov random fields. The empirical nature of the proposed algorithm ensures image results that are data-driven and, hence, reflect "real-world" images well, given enough training data. The proposed algorithm operates on a local window using a dynamic k-nearest neighbour algorithm, where k differs from pixel to pixel: small for test points with highly relevant neighbours and large otherwise. Based on the neighbours that the adaptable k provides and their corresponding relevance measures, a weighted minimum mean squared error solution determines implicitly defined filters specific to low-resolution image content without yielding to the limitations of insufficient training. Additionally, global optimization via single pass Markov approximations, similar to cited nearest neighbour algorithms, provides additional weighting for filter generation. The approach is justified in using a sufficient quantity of training per test point and takes advantage of image properties. For in-depth analysis, we compare to existing methods and draw parallels between intuitive concepts including classification and ideas introduced by other nearest neighbour algorithms by explaining manifolds in low and high dimensions.

LeRoy A. Gorham and Linda J. Moore has work on the paper [13] of SAR image formation toolbox for MATLAB. While many synthetic aperture radar (SAR) image formation techniques exist, two of the most intuitive methods for implementation by SAR novices are the matched filter and back projection algorithms. The matched filter and (non-optimized) back projection algorithms are undeniably computationally complex. However, the back projection algorithm may be successfully employed for many SAR research endeavours not involving considerably large data sets and not requiring time-critical image formation. Execution of both image reconstruction algorithms in MATLAB is explicitly addressed. In particular, a manipulation of the back projection imaging equations is supplied to show how common MATLAB functions, if ft and interpolation, may be used for straight-forward SAR image formation. In addition, limits for scene size and pixel spacing are derived to aid in the selection of an appropriate imaging grid to avoid aliasing. Example SAR images generated though use of the back projection algorithm are provided given four publicly available SAR datasets. Finally, MATLAB code for SAR image reconstruction using the matched filter and back projection algorithms is provided. D. Zhou X and Shen W. Dong has work on the paper[14] Image zooming using directional cubic convolution interpolation. : Image-zooming is a technique of producing a high-resolution image from its low-resolution counterpart. It is also called image interpolation because it is usually implemented by interpolation. Keys' cubic convolution (CC) interpolation method has become a standard in the image interpolation field, but CC interpolates indiscriminately the missing pixels in the horizontal or vertical direction and typically incurs blurring, blocking, ringing or other artefacts. In this study, the authors propose a novel edge-directed CC interpolation scheme which can adapt to the varying edge structures of images. The authors also give an estimation method of the strong edge for a missing pixel location, which guides the interpolation for the missing pixel. The authors' method can preserve the sharp edges and details of images with notable suppression of the artefacts that usually occur with CC interpolation. The experiment results demonstrate that the authors' method outperforms significantly CC interpolation in terms of both subjective and objective measures.

Dianyuan Han has work on the paper [15] of Comparison of Commonly Used Image Interpolation Methods. Image magnification algorithms directly affect the quality of image magnification. In this paper, based on the image interpolation algorithm principle, features of the nearest neighbour interpolation, bilinear interpolation, bi cubic interpolation and cubic B sp line interpolation were analyzed. At the same time, their advantages and disadvantages were compared. In the experiment, image magnification performance of different interpolation algorithms was compared from subjective and objective aspects. The experimental results give the guidance for the user to choose a suitable algorithm to achieve optimum results according to different application.

Vaishali Patel, Prof. Kinjal Mistree has work on the paper [16] of A Review on Different Image Interpolation Techniques for Image Enhancement. Image enhancement is an important processing task in image processing field. By applying image enhancement, blur or any type of noise in the image can be removed so that the resultant image quality is better. Image enhancement is used in various fields like medical diagnosis, remote sensing, agriculture, geology, oceanography. There are numbers of techniques for image enhancement. Image interpolation is used to do enhancement of any image. This paper gives overview about different interpolation techniques like nearest neighbour, bilinear, bi cubic, new edge-directed interpolation (NEDI), data dependent triangulation (DDT), and iterative curvature-based interpolation (ICBI).

Alexey Lukin, Andrey S. Krylov, Andrey Nasonov has work on the paper [17] of **Image Interpolation by Super-Resolution.** Term “super-resolution” is typically used for a high resolution image produced from several low-resolution noisy observations. In this paper, we consider the problem of high-quality interpolation of a single noise- free image. Several aspects of the corresponding super-resolution algorithm are investigated: choice of regularization term, dependence of the result on initial approximation, convergence speed, and heuristics to facilitate convergence and improve the visual quality of the resulting image.

Angelos Amanatiadis and Ioannis Andreadis has work on the paper [18] of A survey on evaluation methods for image interpolation. Image interpolation is applied to Euclidean, affine and projective transformations in numerous imaging applications. However, due to the unique characteristics and wide applications of image interpolation, a separate study of their evaluation methods is crucial. The paper studies different existing methods for the evaluation of image interpolation techniques. Furthermore, an evaluation method utilizing ground truth images for the comparisons is proposed. Two main classes of analysis are proposed as the basis for the assessments: performance evaluation and cost evaluation. The presented methods are briefly described, followed by comparative discussions. This survey provides information for the appropriate use of the existing evaluation methods and their improvement, assisting also in the designing of new evaluation methods and techniques.

Chapter3

Overview of Different Interpolation Technique

It is well known from image restoration theory that image interpolation is an ill posed problem. Aside from typical spline methods, several approaches interpolate in other domains, including the Discrete Cosine Transform (DCT) domain, Discrete Wavelet Transform (DWT) domain and Fourier Domain. These methods perform some type of zero-padding in higher frequency slots, which by taking the inverse transform, results in a spatially larger image. However, instead of interpolation the result contains more characteristics of re-*scaling*, where higher resolution information is not added and edges and texture are not elucidated.

Algorithms that concentrate on particular image attributes often preserve some type of regularity including a measure that is tailored specifically to edges. In particular, uses properties in the decay of wavelet coefficients to predict unknown coefficients at higher resolution sub bands. Meanwhile, uses a low resolution correlation matrix as an approximation to obtain a high-resolution image filter based on an assumption of geometric duality. Although simple to implement, the covariance matrix is still low-resolution, and the value added is usually inadequate for complicated textures, often causing an effect similar to aliasing. In fact, in terms of generating resolution, all of these algorithms are inferior to learning-based methods where the quantity of additional information may be exceedingly large so that the method is able to enhance all types of image content.

3.1. Polynomial-based interpolation

Image interpolation aims to produce a high-resolution image by up sampling the low-resolution image. As explained in the introduction section, interpolation algorithms often assume that the observed LR image is a direct down sampled version of the HR image. Hence, the de aliasing ability during the up sampling process is important, i.e. the recovery of the high-frequency signal from the aliased low-frequency signal.

For real-time applications, conventional polynomial-based interpolation methods such as bilinear and bi cubic interpolation are often used due to their computational simplicity [19]. For example, the bi cubic convolution interpolator requires only several arithmetic operations per pixel, such that real-time processing can easily be achieved. The basic idea is to model the image signal by a low- order polynomial function (using some observed signals). However, polynomial functions are not good at modelling the signal's discontinuities (e.g. edges). Hence, the conventional polynomial-based interpolation methods often produce annoying artefacts such as aliasing, blur, halo, etc. around the edges. To resolve this problem, some adaptive polynomial- based and step function-based interpolation methods were proposed.

3.2. Edge-directed interpolation

Since edges are visually attractive to the human perceptual system, some edge-directed interpolation methods have been developed to address the edge reconstructions. In fact, the adaptive polynomial-based methods can be regarded as edge-directed methods as well. The basic idea of edge- directed methods is to preserve the edge sharpness during the up sampling process. The intuitive way is to explicitly estimate the edge orientation and then interpolate along the edge orientation. For achieving low computation, some methods further quantize the edge orientations.

However, the interpolation quality of this intuitive way is constrained by the estimation accuracy of the edge orientation. Since, the edges of natural images are often blurred, blocky, aliased and noisy, the estimation accuracy of edge orientations is usually unstable. The interpolation quality of these methods can be improved by weighting the edge orientations, as described in the next section.

3.3. Frequency Domain – Based Approach to SR

Tsai and Huang [20] proposed the frequency domain approach for solving the problem of super-resolution image reconstruction in 1984. The frequency domain approach is based on an assumption that the original high-resolution image is band-limited and exploits the translational property of the Fourier Transform. It makes use of the aliasing relationship between the Continuous Fourier Transform (CFT) of the original real scene and the Discrete Fourier Transform (DFT) of the observed low-resolution images. In their paper, the sequence of low-resolution frames is assumed to be free from distortions such as blur or noise.

Let ***f(x, y)*** be a continuous high-resolution image and ***f*** ***k(x, y)***, where k = 1, 2,…, p, be a set of p translational shifted versions of ***f(x, y)***. Thus, considering arbitrary shifts δ_{xk} and δ_{yk} of ***f(x, y)*** along the x and y coordinates respectively [13],

$$f_k(x, y) = f(x + \delta_{xk}, y + \delta_{yk}) \quad \text{for } k = 1,2\ldots p. \quad \ldots\ldots\ldots\ldots\ldots\ldots 3.1$$

The shifted image ***fk(x, y)*** was uniformly sampled using sampling periods T_1 and T_2 to generate the observed low resolution images,

$$f_k(i, j) = f(iT_1 + \delta_{xk}, jT_2 + \delta_{yk}) \quad \ldots\ldots\ldots\ldots\ldots\ldots 3.2$$

Using the shifting property of CFT, the CFT for ***fk(x, y)***, is given as:

$$F_k(u, v) = e^{j2\pi(\delta_{xk}u + \delta_{yk}v)} F(u, v \ldots\ldots\ldots\ldots\ldots .3.3$$

Using the aliasing relationship and band-limited constraint,

$$| F(u,v) |= 0, \; for \; | u |\geq L_x w_x, | v |\geq L_y w_y, \quad \ldots\ldots\ldots\ldots\ldots\ldots 3.4$$

the relationship between the CFT of the high-resolution image and the DFT of the k^{th} observed low-resolution image can be expressed as,

$$F_k(m,n) = \frac{1}{T_1 T_2} \sum_{i=-L_x}^{L_x-1} \sum_{l=-L_y}^{L_y-1} F_k\left(\frac{2\pi m}{MT_1} + iw_x, \frac{2\pi n}{NT_2} + lw_y\right) \text{ for } k = 1,2\ldots p,$$

where $w_x = 2\pi / T_1$ and $w_y = 2\pi / T_2$. By using lexicographic ordering of (
we get,

$$b = AX \,, \qquad \text{..........3.5)}$$

where, ***b*** is a column vector with the k^{th} element of the DFT coefficients of ***F***$\boldsymbol{F_k(m,n)}$, ***X*** is a column vector with the samples of the unknown CFT of ***f(x, y)*** and ***A*** is a matrix which relates the DFT of observed low-resolution images to the samples of the continuous high-resolution image. Thus, the reconstruction of the high-resolution image ***X*** requires calculating the DFT's of the observed low-resolution images, estimate the matrix ***A*** and solve eq. (3.6) which is an inverse problem.

An extension of was proposed by Kim *et al.* [21] in which they introduced a weighted recursive least square algorithm based on the aliasing relationship between the low-resolution images and high-resolution image, for reconstructing Super-Resolution image from available noisy under-sampled images. The algorithm combines filtering and reconstruction. The algorithm considered only noise and not blur. The idea was further developed by Kim and Su where they considered blur and noise together as distortions in the observed low-resolution images. Also, to stabilize the ill-conditioned nature of the inverse problem of super-resolution, the recursive algorithm of was refined to include iterative update of the regularization term.

Frequency – based techniques for estimating high-resolution images are simple to implement and directly addresses removal of aliasing artefacts. They have very low computational complexity, thereby making them highly capable of parallel implementation. Although the technique has the applicability to real-time applications, it is confined to only global translational motion and has limited ability to apply spatial domain *a priori* knowledge in the regularization term.

3.4. Spatial Domain – Based Approach to SR

Spatial domain techniques are the most popular ones developed for super resolution. The popularity is due to the fact that the motion is not limited to translational shifts only and thus a more general, global or non-global motion can also be incorporated and dealt with.

3.5. The Model OF SUPER RESOLUTION

The classic model of super-resolution in the spatial domain assumes that a sequence of N low-resolution images represent different snapshots of the same scene[22]. The real scene to be estimated is represented by a single high-resolution reference image $\underline{X}$ of size (P by P). Each LR frame, b_1, b_2,….b_N, is a noisy, down-sampled version of the reference image that is subjected to various imaging conditions such as optical, sensor and atmospheric blur, motion effects, and geometric warping. The size of each LR frame is (M by M) and $M < P$. It is convenient to represent the observation model in matrix notation.

$$\begin{bmatrix} b_1 \\ \vdots \\ b_N \end{bmatrix} = \begin{bmatrix} D_1 \cdot B_1 \cdot W_1 \\ \vdots \\ D_N \cdot B_N \cdot W_N \end{bmatrix} \underline{X} + \begin{bmatrix} e_1 \\ \vdots \\ e_N \end{bmatrix} = \begin{bmatrix} A_1 \\ \vdots \\ A_N \end{bmatrix} \underline{X} + \begin{bmatrix} e_1 \\ \vdots \\ e_N \end{bmatrix},$$

....................3.7

where, ***D*** represents the down-sampling matrix of size (M^2 by P^2), ***B*** is the blur matrix of size (P^2 by P^2) and ***W*** is the matrix representing geometric warping of size (P^2 by P^2). By grouping and rewriting eq. (3.7), the model is given as:

$$\underline{b} = A\underline{X} + \underline{e}\,, \qquad A_k = \left[D_k \cdot B_k \cdot W_k \right]_{for\ k=1,2\ldots N}.$$

...........3.8

In eq. (3.8), linear operator ***A*** (size - M^2 by P^2), represents sub-sampling, motion compensation and all the other imaging factors, the LR frames are given by $\underline{\boldsymbol{b}}$ (size - M^2 by 1) and the additive Gaussian noise is represented by $\underline{\boldsymbol{e}}$ (size - M^2 by 1). The images are represented in eq. (3.8) as vectors, shown by an underscore, and are ordered column-wise lexicographically.

3.6. Iterative Back-Projection Techniques

Super-resolution of monochrome and colour low resolution image sequences was considered by Irani and Pele [23]. They derived an iterative back projection algorithm based on computer aided tomography. The algorithm starts with an initial guess ($\boldsymbol{X^0}$) for the output high-resolution image and the imaging process (***A***) is simulated to generate low-resolution images ($\boldsymbol{b^{sim}}$) based on the initial guess. These simulated low-resolution images are then compared with the observed ones (***b***) and the error generated between them is back-projected onto the initial guess via back-projection operator (***A*^bp^**), thereby minimizing the error iteratively.

$$X^1 = X^0 + A^{bp}(b - b^{sim}) . \qquad (3.7)$$

The algorithm considers translational and rotational motion but the authors claim that the same concept can be applied to other motions also. They considered multiple motion analysis [24] in including occlusion and transparency. The algorithm successfully solves the issue of blur and noise, however due to the ill-posed nature of super resolution, the technique is unable to generate a unique solution.

3.7. Optimization Techniques

The problem of estimating a high-resolution image from a sequence of low resolution images is an inverse problem which is highly ill-conditioned. To stabilize this ill-posed nature, *Regularization* term is included. The problem of super-resolution, shown in eq. (3.8), is then solved, in the least-squares sense, by minimization of the error τ along with the addition of the regularization term. The modified equation of (3.8) is given as:

$$\tau = \sum_{k=1}^{N} \left[\underline{b}_k - A_k \underline{X}\right]^2 + \lambda \left[Q \underline{X}\right]^2 . \qquad \text{.................................. 3.8}$$

In the above equation, ***Q*** is the regularization or stabilization matrix and **λ** > 0 is the regularization parameter. Although there is no unique procedure for constructing the regularization term, it is usually chosen to incorporate *a priori* knowledge of the real high-resolution scene, such as the degree of smoothness.

In the case of Forward Looking Infrared (FLIR), images are spatially under sampled and are degraded due to aliasing effect. Alam *et al*. used weighted-nearest-neighbour and Weiner filter for estimating high-resolution images from FLIR images. An extension of this algorithm was proposed in [25] which considered a more general motion, translational and rotational. To refine it further, they introduced a simple regularization term into their cost function that enforced the smoothness of the final solution. They used steepest descent and conjugate-gradient techniques for minimization of the error between the simulated low-resolution images and the observed ones. Alam *et al*. [26] proposed a more efficient real time applicable registration and high-resolution reconstruction technique using multiple random translational shifted frames. They used weighted-nearest-neighbour and Weiner filter for estimating the high-resolution images.

3.8. Bayesian Techniques

The Bayesian techniques [27] are based on the Bayes' Theorem and treat the problem of estimating the high-resolution image as a statistical estimation problem. These techniques provide a convenient way to include *a priori* knowledge as constraints to stabilize the ill-posed nature of super-resolution image reconstruction.

The classic model of super-resolution defined in eq. (3.8) can be rewritten as:

$$b = AX + e \,. \qquad (3.9)$$

The *Maximum A-Posteriori* (MAP) estimator for the high-resolution image maximizes the *a-posteriori* probability **P{X | b}**,

$$\hat{X}_{MAP} = \arg\max_X P\{X \mid b\}.$$ 3.10

Now, applying the Bayes' theorem to eq. (2.12),

$$\hat{X}_{MAP} = \arg\max_X \left[\frac{P\{b \mid X\} P\{X\}}{P\{b\}} \right].$$ 3.11

Taking the logarithmic function,

$$\hat{X}_{MAP} = \arg\max_X \left[\log P\{b \mid X\} + \log P\{X\} \right].$$ 3.12

In eq. (3.14), on the right-hand side of the equation, the term **log P{X | b}**, is known as the log likelihood function and the term **log P{X}** is referred to as the log of the *a priori* image model. The MAP estimation model [28] provides the ability to include *a priori* knowledge and thus, effectively regularizes the ill-conditioned nature of super-resolution reconstruction.

3.10. Projection onto Convex Set (POCS) Technique

The method of Projection onto Convex Sets, popularly known as POCS was introduced by [29] in 1982. In [30], Stark explains the general technique for applying POCS in the field of image restoration. The concept of POCS applied to the problem of super-resolution was first introduced in [31]. According to the method of POCS for super-resolution reconstruction, the space of estimated high-resolution solutions is restricted by a set of constraints (closed convex sets) which characterize desirable properties, such as fidelity to data, smoothness, sharpness etc., to be consistent in the final solution. For each set of convex constraints $\boldsymbol{C_i}$, a projection operator $\boldsymbol{T_i}$ is defined. The problem is then reduced to iteratively locate, given a point in the high-resolution image space, the closest solution which intersects with all the given convex constraints, $\boldsymbol{C_i}$. The convergence can be given as:

$$X^{n+1} = T_i X^n$$
$$\Rightarrow X^{n+1} = T_m T_{m-1} \ldots T_2 T_1 X^n \quad for\ n = 0,1,2\ldots \qquad \text{...................3.13}$$

Recently POCS has been used in improving resolution from multi-camera surveillance imaging [32]. The method of POCS is simple and allows convenient inclusion of *a priori* information but has a very high computational cost and a slow convergence rate which limits its practical applicability. Also, the final solution is not unique and highly depends upon the initial guess.

3.10. Hybrid (ML + POCS) Technique

In [33] a hybrid algorithm using ML and POCS was proposed for estimating a high resolution image from multiple blurred, noisy, under-sampled low-resolution images. The hybrid technique combined the benefits of the Bayesian and the set theoretic technique. With the help of POCS, all the *a priori* knowledge could be utilized beneficially and a single optimal solution could be reached.

3.11. Adaptive Filtering Technique

Adaptive filtering approach applied to the time axis for super-resolution reconstruction was introduced in [34]. The authors proposed a few algorithms based on least squares - recursive least squares (RLS) and pseudo-RLS. For estimating the high-resolution image both steepest descent (SD) and normalized steepest descent (NSD) were applied. According to the authors, their approach allows treating linear time and space variant blurring and general motion. In their further research, the authors used Kalman filtering approach [35] for solving the problem of super-resolution. In [36] they re-derived R-SD and R-LMS as approximations of the Kalman filter. The algorithms were built with the assumption that the information regarding the motion between the images and the blur operators is known which otherwise in reality would need to be estimated to use these algorithms. This assumption is very critical for the performance of the algorithms and significantly depends on it. The Kalman filter approach is promising but is still in an experimental state as its computational cost is extremely high.

3.12. Preconditioned Techniques in Optimization

The problem of super-resolution is an inverse problem and the matrix ***A*** (eq. 3.8) contains very small singular values which are either zero (due to round off error) or approaching zero. This characteristic of matrix ***A*** makes it singular in nature and highly ill-conditioned. Due to this, the solution is very sensitive and can vary tremendously in an arbitrary manner with very small changes in the data. Thus, to make the solution unique and stable, another term is added to eq. (3.8) known as the Regularization term as shown in eq. (3.8). Most of the inverse problems (such as super-resolution) are ill-posed and the solution is tremendously sensitive to the data. This also leads to the problem of slow convergence and high computational load.

In general, pre conditioners are approximate inverses which convert the ill conditioned matrices, such as matrix ***A***, to a well-behaved one. Introducing pre conditioners in an ill-posed problem removes the need for employing regularization techniques for stabilizing the solution. Essentially, by multiplying a pre conditioner, say ***M*** with matrix ***A***, the condition number of this product, $\boldsymbol{M}^{1}\boldsymbol{A}$ is smaller than that of matrix ***A*** alone. Such pre conditioner not only makes an ill-conditioned system of equations to a well-behaved one but also increases the rate of convergence and decreases the computational load.

In [37] preconditioning of conjugate gradient using efficient block circulate pre conditioners was proposed. As per the authors, preconditioning is a technique used to transform the original system into one with the same solution, which can be solved by the iterative solver more efficiently and quickly. The unconditioned system starting from ground zero, takes a longer time to converge (due to the high computational cost involved) as compared to a preconditioned system. FFT is employed for computing the pre conditioners which thereby reduces the overall computational time of the system. Preconditioning certainly provides a promising approach for the use of super resolution in real-time environment.

3.13. Interpolation problem

An imaging system is only able to capture a true or natural scene with only finite levels of resolution as compared to the true or natural scene which has infinite levels of resolution. There are two solutions that can be implemented to increase the resolution of an imaging system - hardware or software. The best solution is the hardware improvement of the imaging system to achieve higher resolution. However, it is not always feasible to achieve higher resolution by hardware enhancement due to practical reasons. Therefore, in such a scenario, it is feasible to employ an intelligent software solution to generate higher resolution than what is captured by the imaging system. One such software solution is super-resolution image reconstruction.

Super-resolution image reconstruction refers to image processing techniques that attempts to reconstruct high quality, high-resolution images by utilising incomplete scene information contained in a sequence of geometrically warped, aliased, and under-sampled low-resolution images. This estimation of high-resolution image is also referred to as an inverse problem.

A common feature of such inverse problems is their sensitivity to even small perturbations of the data that may introduce significant errors in the reconstruction process. This makes the process ill-conditioned and intrinsically unstable. Because of this feature, most of the research on super-resolution has been directed towards increasing the robustness and the fidelity of the reconstruction process. Much less attention has been devoted to more practical issues of computational efficiency and real-time applicability of super resolution. Yet, super-resolution re construction is a very computationally intensive process that has to deal with big data sets and inherent instabilities. As a result of this, many of the developed techniques are not suitable for practical applications that require real-time or even reasonably fast processing. It is, thus, desirable to develop algorithms that maintain a proper balance between computational performance and the fidelity of the reconstruction.

Therefore in this study, the motivation for research is to explore possible new approaches for a computationally efficient yet fairly accurate super-resolution image reconstruction process to generate a high-resolution image. Also, super resolution being an inverse and ill-conditioned problem, the optimization based technique for super-resolution is reinvestigated and the significant influence of the regularization term over the fidelity of reconstruction is studied.

Image registration is a critical pre-processing step in image super-resolution. Even though, it is not the primary aim of this research, we address the issue for estimating the relative motion parameters between rotated and translational shifted low-resolution images.

3.14. The Imaging Model

The observation model for super-resolution reconstruction simulates the physical process of image acquisition. It is assumed that a sequence of N low resolution images is captured by a camera moving over a scene of interest. The objective is to reconstruct a high-resolution representation of the original scene from degraded and incomplete data represented by the LR frames. The original scene is represented by a HR reference image ***X*** of size (P by P) that we want to reconstruct. Each LR image, b_1, b_2,….b_N, is the result of sampling (decimation) of the HR reference image and is subjected to various degrading factors such as optical, sensor and atmospheric blur, motion effects, and geometric warping. The size of each LR frame is (M by M) and $M < P$.

Chapter4

4.1. Objective Function Development

Interpolation is the process of estimating the values of a continuous function from discrete samples. Image processing applications of interpolation include image magnification or reduction, sub pixel image registration, to correct spatial distortions, and image decompression, as well as others. Of the many image interpolation techniques available, nearest neighbour, bilinear and cubic convolution are the most common, and will be talked about here. Sinc Interpolation provides a perfect reconstruction of a continuous function, provided that the data was obtained by uniform sampling at or above the Nyquist rate. Sinc Interpolation does not give good results within an image processing environment, since image data is generally acquired at a much lower sampling rate. The mapping between the unknown high-resolution image and the low-resolution image is not invertible, and thus a unique solution to the inverse problem cannot be computed. One of the essential aspects of interpolation is efficiency since the amount of data associated with digital images is large.

4.2 Peak Signal to Noise Ratio (PSNR)

The PSNR is most commonly used as a measure of quality of reconstruction of loss compression codec's (e.g., for image compression). The signal in this case is the original data, and the noise is the error introduced by compression. When comparing compression codec's it is used as an approximation to human perception of reconstruction quality, therefore in some cases one reconstruction may appear to be closer to the original than another, even though it has a lower PSNR (a higher PSNR would normally indicate that the reconstruction is of higher quality). One has to be extremely careful with the range of validity of this metric; it is only conclusively valid when it is used to compare results from the same codec (or codec type) and same content

The phrase peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale.

It is most easily defined via the mean squared error (MSE) which for two m×n monochrome images I and K where one of the images is considered a noisy approximation of the other is defined as:

$$MSE = \frac{1}{m\,n}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2$$

The PSNR define as :

$$\begin{aligned} PSNR &= 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \\ &= 20 \cdot \log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) \end{aligned}$$

Here, MAXI is the maximum possible pixel value of the image. When the pixels are represented using 8 bits per sample, this is 255. More generally, when samples are represented using linear PCM with B bits per sample, MAXI is 2 B −1. For colour images with three RGB values per pixel, the definition of PSNR is the same except the MSE [24] is the sum over all squared value differences divided by image size and by three. Alternately, for colour images the image is converted to a different color space and PSNR is reported against each channel of that colour space, e.g., YCbCr or HSL.

Typical values for the PSNR in lossy image and video compression are between 30 and 50 dB, where higher is better. Acceptable values for wireless transmission quality loss are considered to be about 20 dB to 25 dB. When the two images are identical, the MSE will be zero. For this value the PSNR is undefined (see Division by zero)

Q=90, PSNR 45.53dB Q=10, PSNR 31.45dB

Original uncompressed Q=30, PSNR 3

Fig 4.1 PSNR

4.2. Image Scaling

In computer graphics, image scaling is the process of resizing a digital image Scaling is a non-trivial process that involves a trade-off between efficiency, smoothness and sharpness. With bitmap graphics, as the size of an image is reduced or enlarged, the pixels that form the image become increasingly visible, making the image appear "soft" if pixels are averaged, or jagged if not. With vector graphics the trade-off may be in processing power for re-rendering the image, which may be noticeable as slow re-rendering with still graphics, or slower frame rate and frame skipping in computer animation

Apart from fitting a smaller display area, image size is most commonly decreased (or sub sampled or down sampled) in order to produce thumbnails. Enlarging an image (up sampling or interpolating) is generally common for making smaller imagery fit a bigger screen. In “zooming” a bitmap image, it is not possible to discover any more information in the image than already exists, and image quality inevitably suffers. However, there are several methods of increasing the number of pixels that an image contains, which evens out the appearance of the original pixels.

4.3 Algorithm

Two standard scaling algorithms are bilinear and bi cubic interpolation. Filters like these work by interpolating pixel colour values, introducing a continuous transition into the output even where the original material has discrete transitions.

Although this is desirable for continuous-tone images, some algorithms reduce contrast (sharp edges) in a way that may be undesirable for line art.

Nearest neighbour interpolation preserves these sharp edges, but it increases aliasing (or jaggies; where diagonal lines and curves appear pixelated). Several approaches have been developed that attempt to optimize for bitmap art by interpolating areas of continuous tone, preserve the sharpness of horizontal and vertical lines and smooth all other curves.

4.5. Efficiency

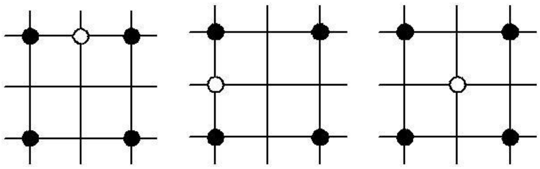
Since a typical application of this technology is improving the appearance of fourth-generation and earlier video games on arcade and console emulators, many are designed to run in real time for sufficiently small input images at 60 frames per second.

Many work only on specific scale factors: 2× is the most common, with 3×, 4×, 5x and 6x also present.

4.6. General concept of the proposed algorithm

The proposed algorithm is expected to achieve two major goals: lower computational complexity and better subjective quality. Hence, the new method can be practically applied to video sequences and videoconference.

Our proposed method interpolates images based on analysing the local structure of the images. The original images are classified into two categories: homogenous areas and edge areas. The interpolation of pixels in the different classified areas is accomplished by using individual interpolation algorithm, respectively.



(a) Horizontal (b)Vertical (c) Diagonal

Fig. 4.2. The differences of four directions (one for horizontal, one for vertical and two for diagonal).

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Our proposed method interpolates images based on analysing the local structure of the images. The original images are classified into two categories: homogenous areas and edge areas. The interpolation of pixels in the different classified areas is accomplished by using individual interpolation algorithm, respectively.

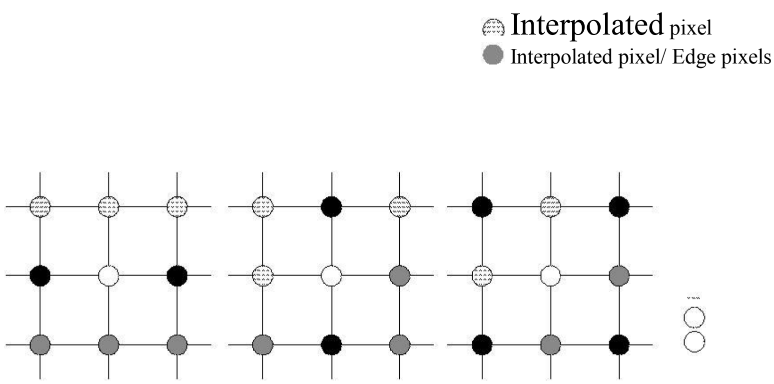
Determination of pixels to be either homogenous pixels or edge pixels is based on a preset threshold value. First, the differences of pixels values along horizontal, vertical and diagonal directions are determined in a 3*3 window, respectively. Choice of the 3*3 window can significantly reduce computational loading and structural complexity of our proposed algorithm. We determine the differences of pixel values of the four directions one by one. Fig 4.1 gives a schematic illustration to the four directions, one for horizontal, one for vertical and two for diagonal directions.

If the difference is less than the preset threshold value, a non-interpolated pixel (white dot) will be classified as a homogenous pixel. Non-interpolated points in the homogenous areas are simply filled using bilinear interpolation.

If the difference of pixel values is larger than the threshold value, the non-interpolated point is assigned as an edge pixel. After the first step, some non-interpolated pixels are remained as points in the edge areas. These pixels on edges will be left for further processing in the second step. An example of the result of the first step is demonstrated.

Fig.4.3.The result of the first step of the proposed algorithm for Lena image.

The second step of the proposed algorithm is to interpolate the edge pixels using all neighbouring pixels, which contain original pixels and interpolated pixels at the first step. Various types of neighbouring pixels are shown in Fig4.3 including black points, grey-points and spot points. For each pair of pixels, the smallest difference of pixel values implies the highest correlation between them. The edge pixel is interpolated along the direction of having minimum difference. If all of the spot points are interpolated pixels at the first step, the minimum difference is found on four directions across the white point (edge pixel). If a spot point is classified as an edge pixel, the minimum difference is obtained on the other directions excluding the edge pixel.



(a) Case 1 (b) case2 (c) case 3

Fig. 4.4 All neighbouring pixels around a non-interpolated pixel.

4.7. Image Enhancement Methods

The general form for an interpolation function is:

$G(x) = \Sigma_k c_k u(\text{distance}_k)$ Equation 1

where g(x) is the interpolation function, u(x) is the interpolation kernel, distance_k is the distance from the point under consideration, x, to a grid point, x_k, and c_k are the interpolation coefficients. The c_k s are chosen such that $g(x_k) = f(x_k)$ for all x_k. This means that the grid point values should not change in the interpolated image.

There are so many methods for image enhancement. Mainly below three methods are concerned they are namely

(a) Nearest neighbour Interpolation
(b) Bilinear Interpolation
(c) Cubic convolution Interpolation

4.8. Nearest Neighbour Interpolation

Nearest Neighbour Interpolation, the simplest method, determines the grey level value from the closest pixel to the specified input coordinates, and assigns that value to the output coordinates.

It should be noted that this method does not really interpolate values, it just copies existing values. Since it does not alter values, it is preferred if subtle variations in the grey level values need to be retained.

For one- dimension Nearest Neighbour Interpolation, the number of grid points needed to evaluate the interpolation function is two. For two-dimension Nearest Neighbour Interpolation, the number of grid points needed to evaluate the interpolation function is four.

For nearest neighbour interpolation, the interpolation kernel for each direction is:

$$u(s) = \begin{cases} 0 & |s| > 0.5 \\ 1 & |s| < 0.5 \end{cases} \qquad \text{Equation 2}$$

where s is the distance between the point to be interpolated and the grid point being considered. The interpolation coefficients $c_k = f(x_k)$.

Assume that the letters A, K, P and G represent the four neighbours and E represents the empty location value as shown in Fig.4.5

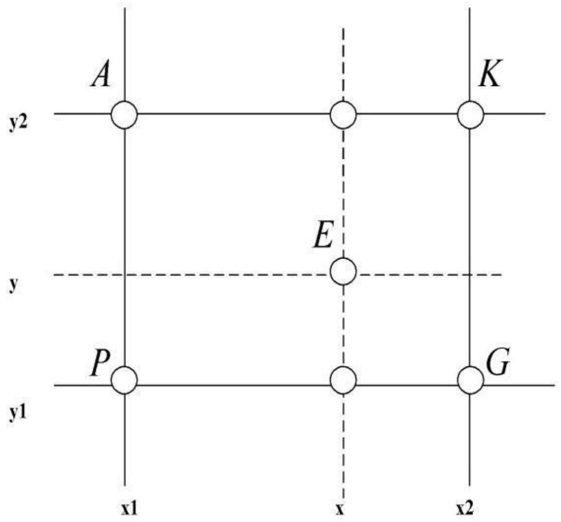


Fig. 4.5 : Four neighbours locations around an empty location E

In order to implement successfully the proposed scheme, the following steps have been respected

Let us call $L = [A, K, P, G]$ a set of four neighbours or data. In statistics, the mode is the value that occurs most frequently in a data set or a probability distribution . Here, the first step is to check whether in L there is a mode or not (i.e. if there exists a mode in L). If the mode exists then, the empty location will be assigned that mode.

If the mode does not exist in *L* (i.e., when two data in *L* appear the same number of times or when none of the *L* data repeat) then, we proceed to performing the bilinear interpolation among *L* data in order to achieve a bilinearly interpolated value or bilinear value. Once the bilinear value is obtained, we do the subtraction operations as shown by Eq.(1), Eq.(2), Eq.(3) and Eq.(4). The letter B represents the bilinear value.

A – B = V1---------------------------- (1)

K – B = V2 ---------------------------- (2)

P – B = V3 ----------------------------- (3)

G – B = V4 ----------------------------- (4)

Case1 Absolute difference mode calculation

At this stage, the mode is calculated from a given set *J* containing all the absolute differences $J = [V_1, V_2, V_3, V_4]$. If there exists a mode in *J* then, we can find out that the mode is the minimum value or not, before we can proceed further. For instance, consider the following three examples.

Example 1: $V_1 = 0.2$, $V_2 = 0.2$, $V_3 = 0.2$, $V_4 = 0.8$

In this example, the mode is 0.2 and 0.2 is the minimum value. So, in order to avoid the confusion our algorithm will only consider/select the first value from J . The selection of the first value can be achieved based on the subscripted indexing theory. Once this value is selected, we can calculate the absolute difference between this value and bilinear value and the difference obtained is assigned to the empty location.

Example 2: $V_1 = 0.2$, $V_2 = 0.8$, $V_3 = 0.8$, $V_4 = 0.8$

In this example, the mode is 0.8 and unfortunately 0.8 is not the minimum value therefore our concept, which is directed by the minimum difference value between the value yielded by the bilinear and one of the four neighbours value, cannot be respected. To solve this issue, first of all we find the value that is less or equal to the mode. In the matlab the *find* function returns indices and values of nonzero elements . The obtained elements are presented in ascending order. In this example, the value that is less or equal to the mode would be 0.8 or 0.2 but since the two values cannot be selected at the same time, we can pick the first minimum value by applying again the subscripted index method. Once the minimum value is obtained, we can find the neighbor that corresponds to that minimum value and calculate the absolute difference between that value and bilinear value, then assign it to the empty location.

Case2 When there is no absolute difference mode

This case can also be regarded as an example number three of the B part

Example 3: $V_1 = 0.2$, $V_2 = 0.2$, $V_3 = 0.8$, $V_4 = 0.8$

As shown, in this example, there is no mode when two data/elements of a set repeat the same number of times. The same when all *J* elements are different.

In both case we have to find out minimum value of J using matlab.

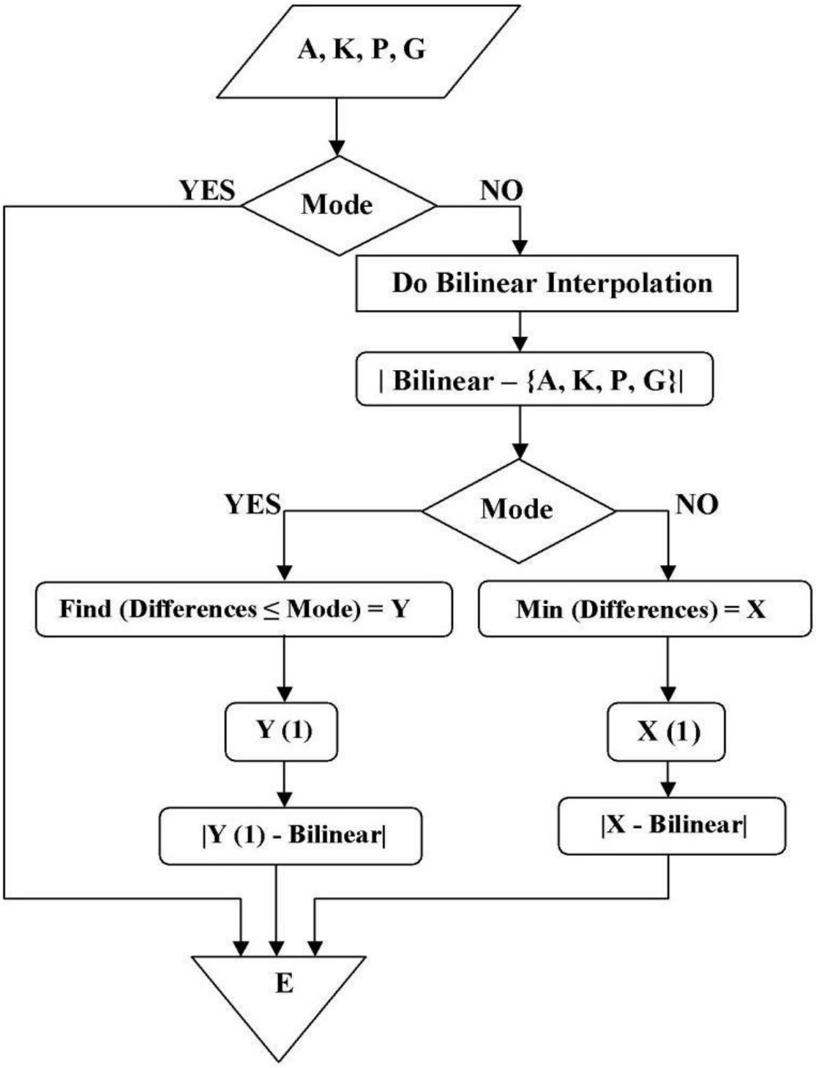


Fig.4.6 : The summary of the proposed method

4.9. Bilinear Interpolation

Bilinear Interpolation determines the grey level value from the weighted average of the four closest pixels to the specified input coordinates, and assigns that value to the output coordinates.

First, two linear interpolations are performed in one direction (horizontally in this paper) and then one more linear interpolation is performed in the perpendicular direction.

For one-dimension Linear Interpolation, the number of grid points needed to evaluate the interpolation function is two. For Bilinear Interpolation (linear interpolation in two dimensions), the number of grid points needed to evaluate the interpolation function is four.

For linear interpolation, the interpolation kernel is:

$$u(s) = \begin{cases} 0 & |s| > 1 \\ 1 - |s| & |s| < 1 \end{cases} \qquad \text{Equation 3}$$

where s is the distance between the point to be interpolated and the grid point being considered. The interpolation coefficients $c_k = f(x_k)$.

4.10 Cubic Convolution Interpolation

Cubic Convolution Interpolation determines the grey level value from the weighted average of the 16 closest pixels to the specified input coordinates, and assigns that value to the output coordinates. The image is slightly sharper than that produced by Bilinear Interpolation, and it does not have the disjointed appearance produced by Nearest Neighbour Interpolation.

First, four one-dimension cubic convolutions are performed in one direction (horizontally in this paper) and then one more one-dimension cubic convolution is performed in the perpendicular direction (vertically in this paper). This means that to implement a two-dimension cubic convolution, a one-dimension cubic convolution is all that is needed.

For one-dimension Cubic Convolution Interpolation, the number of grid points needed to evaluate the interpolation function is four, two grid points on either side of the point under consideration. For Bicubic Interpolation (cubic convolution interpolation in two dimensions), the number of grid points needed to evaluate the interpolation function is 16, two grid points on either side of the point under consideration for both horizontal and vertical directions. The grid points needed in one dimension and two-dimension cubic convolution interpolation are shown in Figure 4.5.

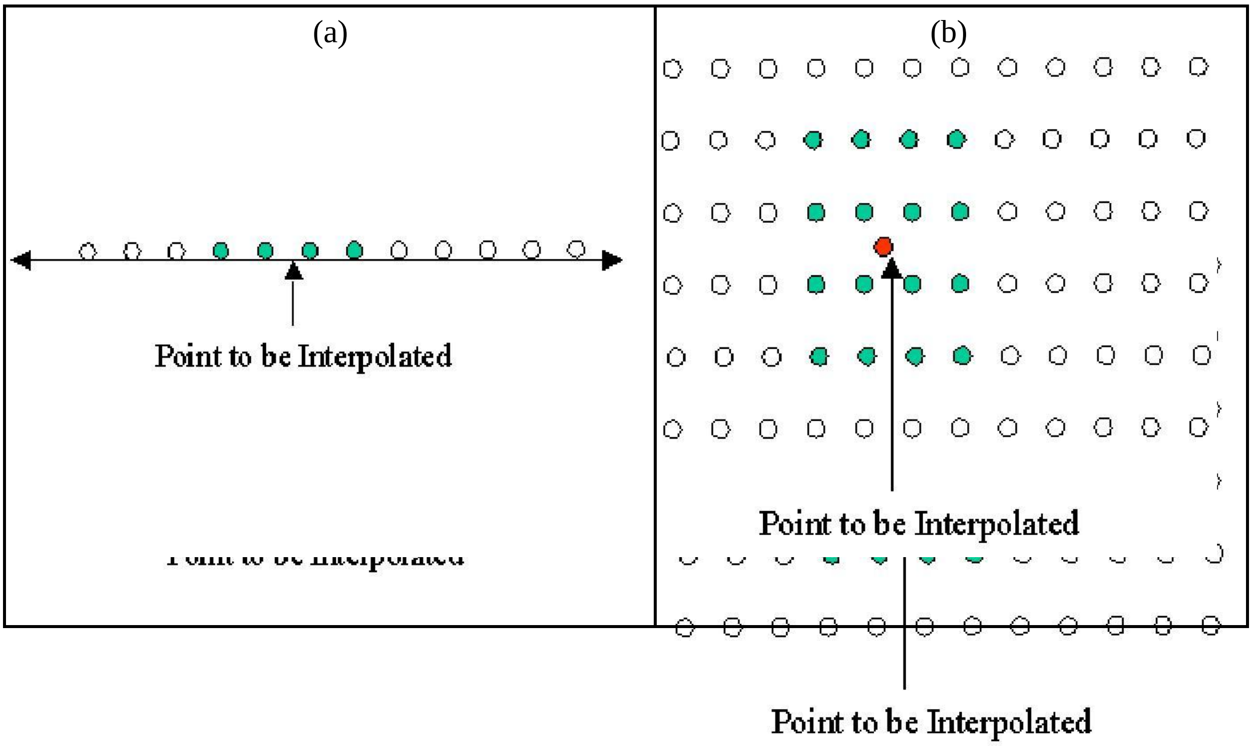


Fig.4.7 Grid points need in (a) one-dimension and (b) two-dimension cubic convolution interpolation.

The one-dimension cubic convolution interpolation kernel is:

$$u(s) = \begin{cases} 3/2|s|3 - 5/2|s|2 + 1 & 0 <= |s| < 1 \\ -1/2|s|3 + 5/2|s|2 - 4|s| + 2 & 1 <= |s| < 2 \\ 0 & 2 < |s| \end{cases} \qquad \text{Equation 4}$$

where s is the distance between the point to be interpolated and the grid point being considered.

A plot of the one-dimension cubic convolution interpolation kernel vs s is shown in Fig 4.8.

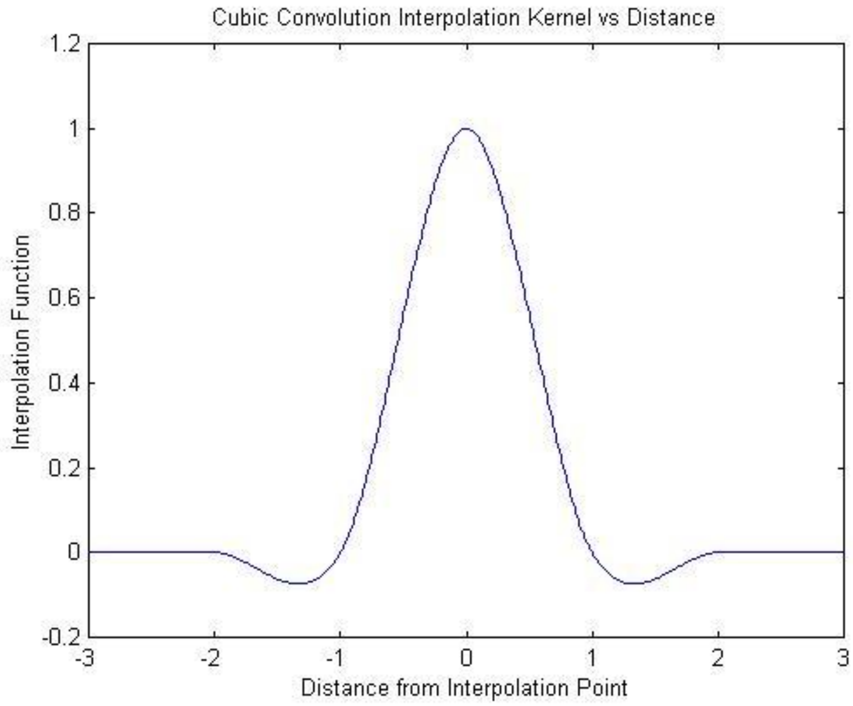


Fig.4.8 Cubic Convolution Interpolation Kernel vs s.

For two-dimensional interpolation, the one-dimensional interpolation function is applied in both directions. It is a separable extension of the one-dimensional interpolation function. Given a point (x, y) to interpolate, where $x_k < x < x_{k+1}$ and $y_k < y < y_{k+1}$, the two-dimensional cubic convolution interpolation function is:

$$g(x, y) = \sum\sum c_{j+l,k+m}\, u(distance_x)\, u(distance_y) \qquad \text{Equation 5}$$

where u(x) is the interpolation function of Equation 4, and $distance_x$ and $distance_y$ are the x and y distances from the four grid points in each direction. For non-boundary points, the interpolaticoefficients, c_{jk}'s are given by $c_{jk} = f(x_j, y_k)$.

Matlab Simulation Output

Nearest Neighbour

Original full colour image (128*128) to interpolate image (512*512)

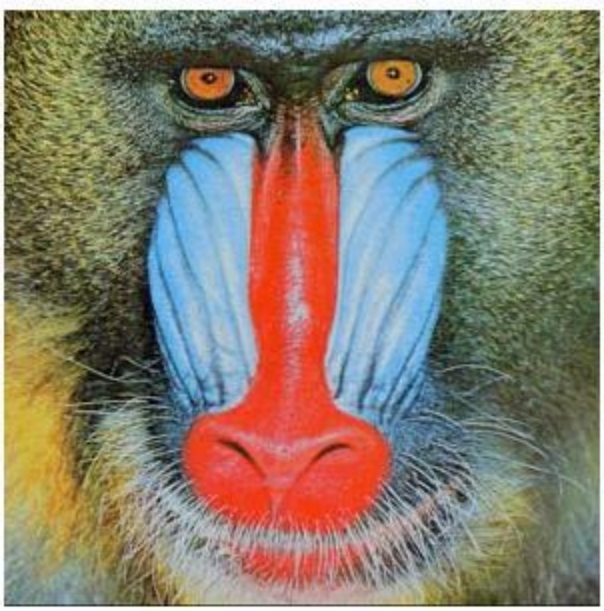


Fig. 1 Original image (128*128)

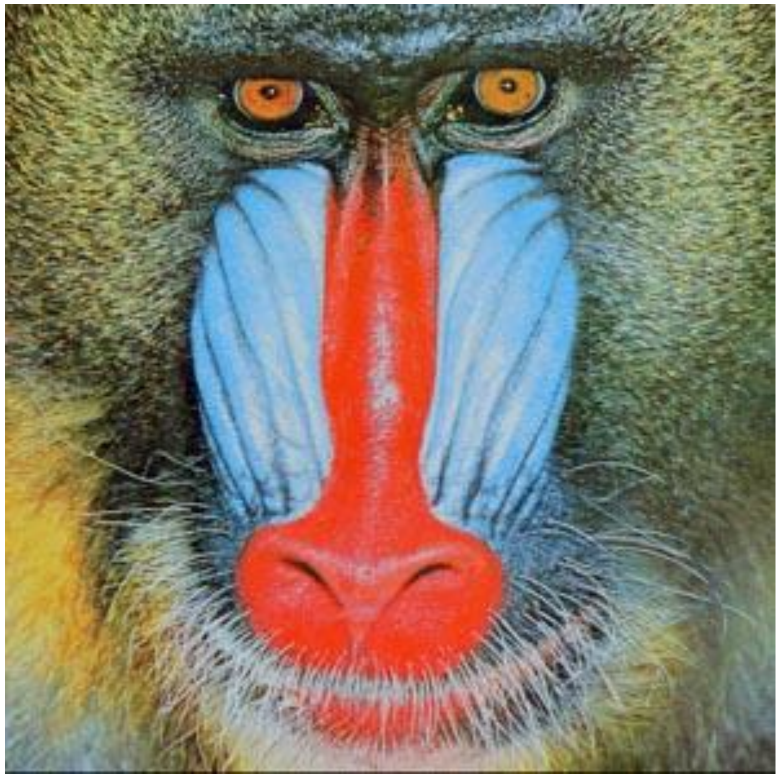


Fig 2. Interpolate image (512*512)

Fig 3 Original image (128*128)

Fig 4 Interpolate image (512*512)

Fig. 5 Original image (128*128)

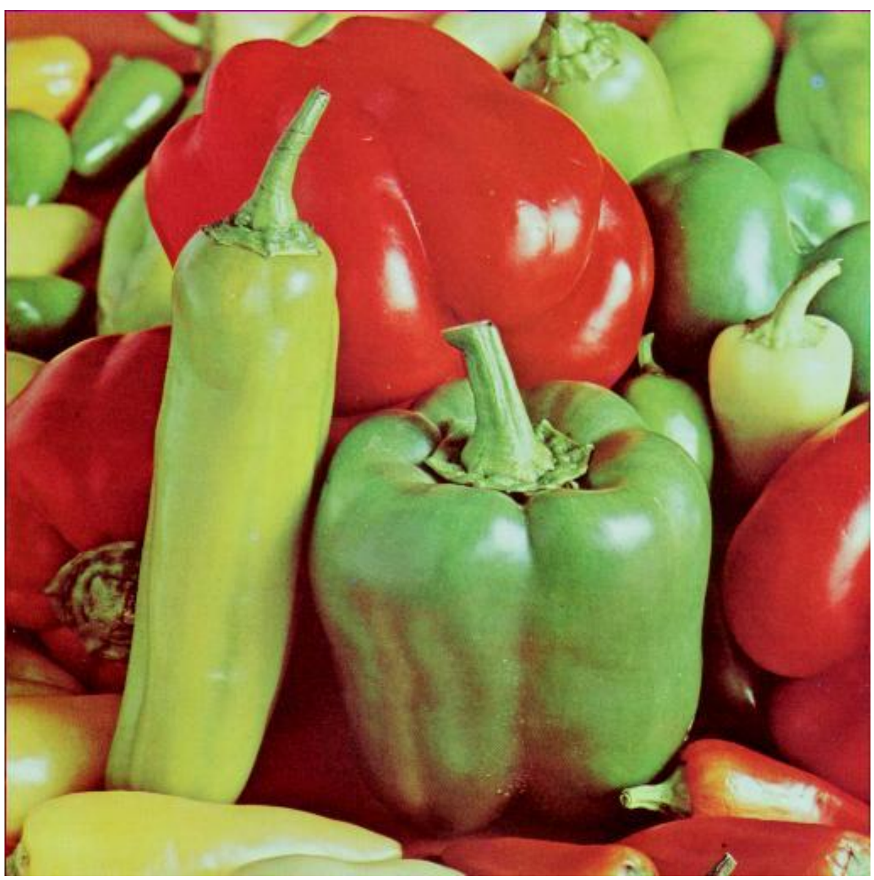


Fig 6. Interpolate image(512*512)

Fig 7 Original image (128*128)

Fig 8. Interpolate image (512*512)

Bilinear Method

Original image (128*128) to Interpolate image (512*512)

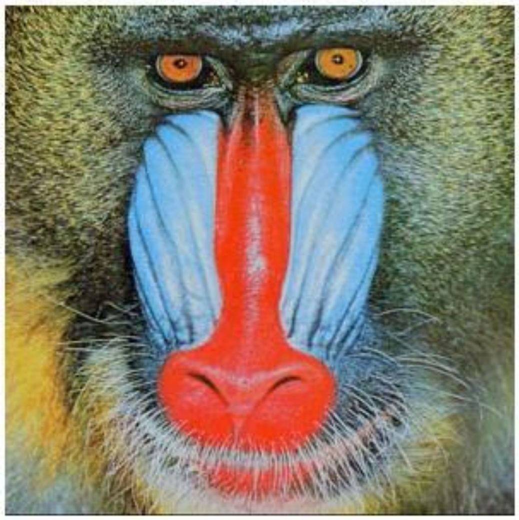


Fig 9. Original image (128*128)

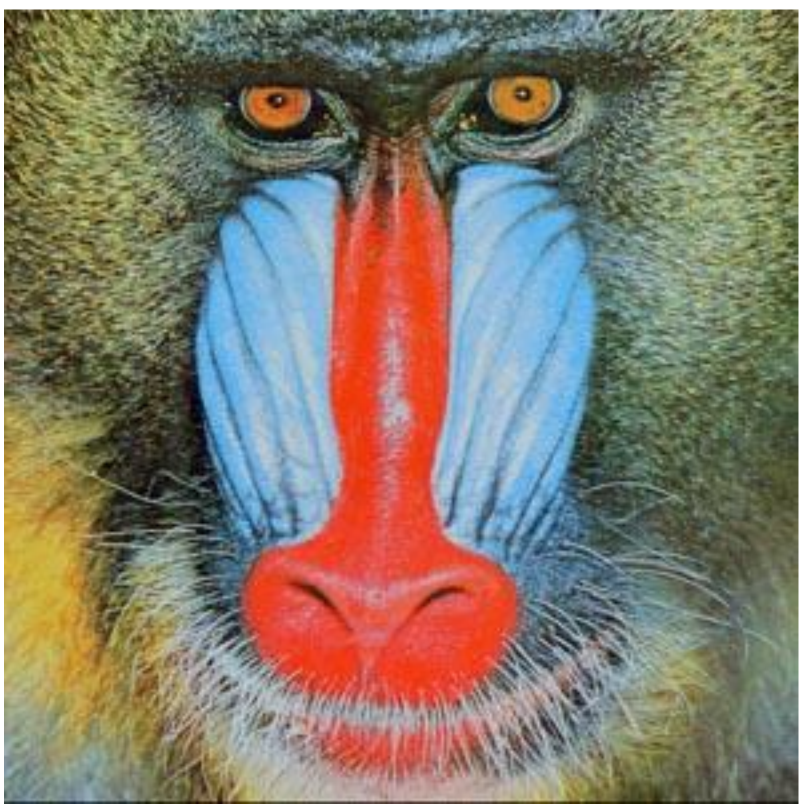


Fig. 10 Interpolate image

Fig. 11 Original Image (128*128)

Fig. 12 Interpolate image (512*512)

Fig. 13 Interpolate image (512*512)

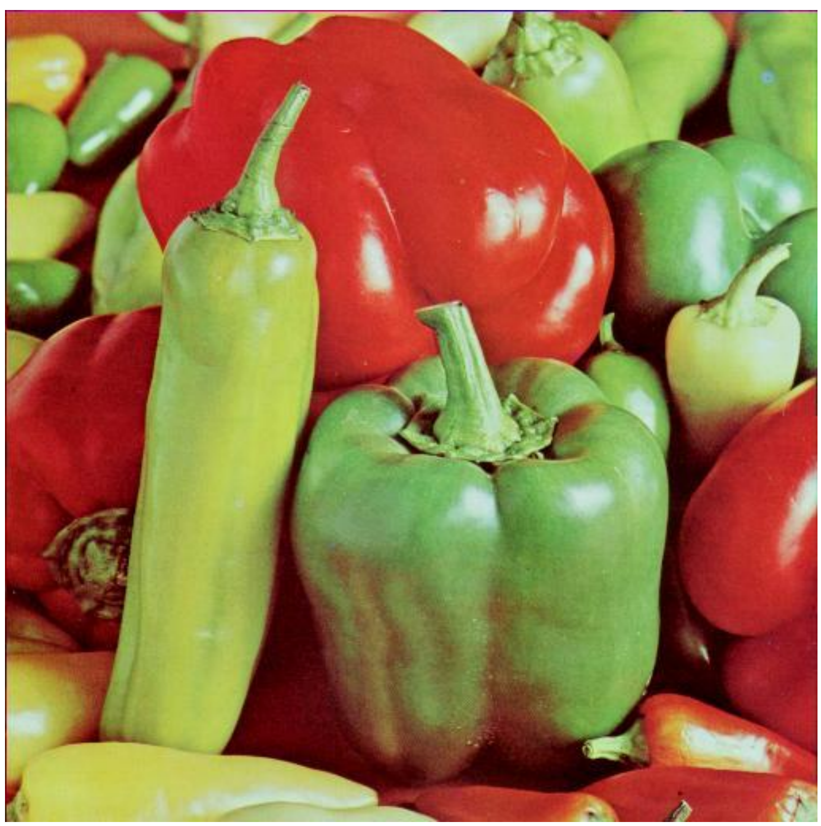


Fig 14 Interpolate Image (512*512)

Fig. 15 Original image (128*128)

Fig.16 Interpolate image (512*512)

Bi cubic Method

Original image (128*128) to Interpolate image (512*512)

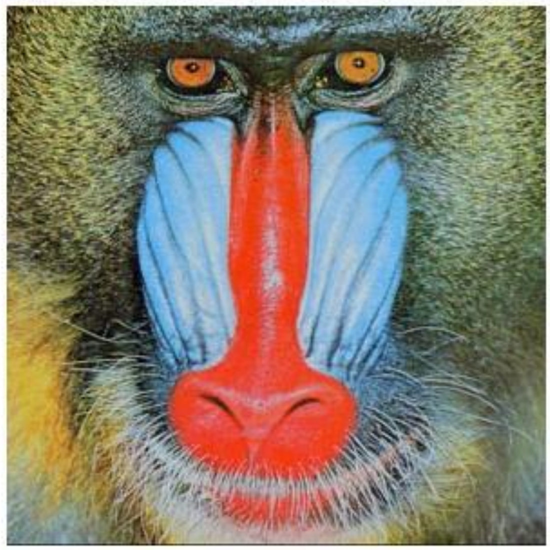


Fig. 17 Original Image (128*128)

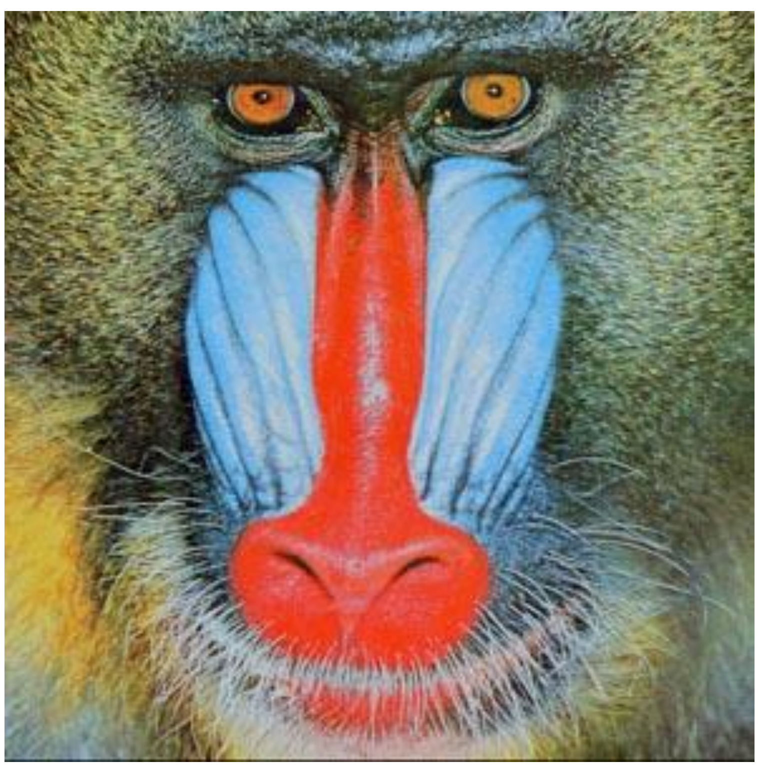


Fig. 18 Interpolate image (512*512)

Fig. 19 Original image (128*128)

Fig. 20 Interpolate image (512*512)

Fig. 21 Original mage (128*128)

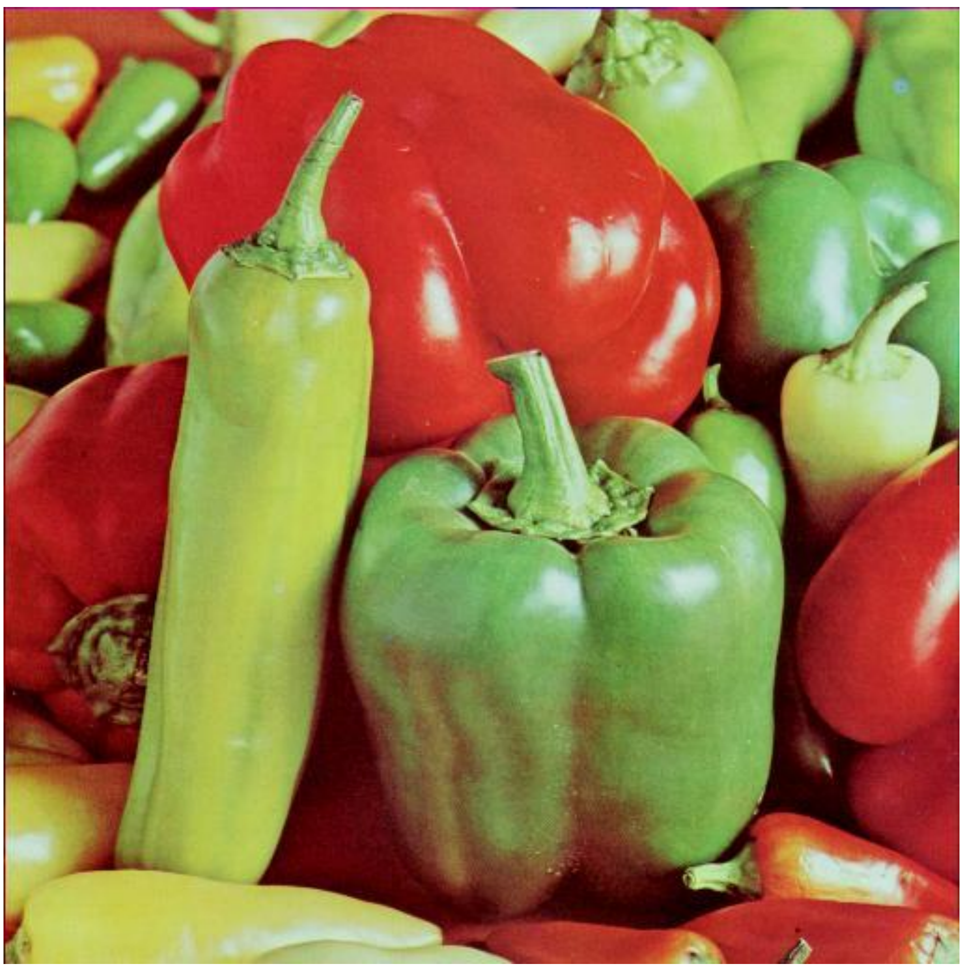


Fig. 22 Interpolate image (512*512)

Fig. 23 Original Image (128*128)

Fig. 24 Interpolate image (512*512)

Original Full Grayscle image (128*128) to Interpolate image (256*256)

Nearest Neighbour Method

(a) Girl

(b) girl1

(b) Girl2

(d)cman

Fig.25 Original gray scale image (128*128)

Nearest Neighbour Method (256*256)

(a)girl

(b)girl1

Fig.26 Nearest neighbour Interpolated gray scale image (256*256)

(c)girl2

(d)cman

Fig.27 Nearest neighbour Interpolated image (256*256)

Bilinear Method

Interpolate image (256*256)

(a)girl

(c) **girl**

Fig. 28 Bilinear Interpolated image (256*256)

(c)cman

(d)girl2

Fig.29 Bilinear interpolated image (256*256)

Bi cubic method

Interpolate image (256*256)

(a)girl

(b) girl

Fig.29 Bi cubic interpolated image (256*256)

(c)cman

(d)girl2

Fig.30 Bi cubic interpolated image (256*256)

Calculation

Full colour image (128*128) to Interpolate image (596*596)

(a) Mandril, (b) Leena, (c) Papers, (d) Flower

Table1: MET after interpolation (128*128 to 596*596)

MET (s)			
	Nearest Neighbour	Bilinear	Bi cubic
Mandril	0.045436	0.067384	0.098565
Papers	0.032658	0.054387	0.078764
Leena	0.056784	0.085432	0.091324
Flower	0.036521	0.074587	0.084537

Table2 : MET for interpolate full gray scale image 128*128 to 256*256.

MET(s)			
	Nearest Neighbour	Bilinear	Bicubic
Girl	0.026574	0.044576	0.070543
Cman	0.043245	0.053262	0.085764
Girl1	0.038976	0.046543	0.079845
Girl2	0.043216	0.068923	0.057653

6.1 Discussion on result

In this research work four full colour images has been tested namely mandril, papers, leena and flower which has resolution 128*128 with three different interpolation algorithm namely nearest neighbour interpolation, bilinear interpolation and bi cubic interpolation. Also I have tested four gray scale image namely girl, cman, girl1, and girl2 which has resolution 128*128 with three different interpolation algorithm namely nearest neighbour interpolation, bilinear interpolation, and bi cubic interpolation.

In first case which is four full colour image I try to interpolate four times that original image that is 128*bou128 to 596*596. In second case which is four full gray scale image I try to interpolate two times of original source image. The resolution of source image 128*128 and the interpolate image resolution 256*256.

The nearest neighbour and bilinear interpolation methods are very practical and easy to apply due to their simplicity. However there accuracy is limited may be their inadequate for interpolating high frequency signals. There is trade off between computational complicity and accuracy.

In this research work the image has been tested through different algorithm method for image detail that is image quality through matlab line execution times. A higher peak signal ratio would indicate higher quality of image. Comparing each other method it has been found that one could perform that better expected or not depending on interpolated.

In fact the best interpolation method for one size of enlargement may not necessarily be the best method for a different size in terms of visual resolution and MET value.

Nearest neighbour interpolation is the most efficient in terms of computational time. Bilinear interpolation requires 3 to 4 times the computational time of nearest neighbour interpolation. Cubic convolution interpolation execution time is more than that of nearest neighbour interpolation.

Nearest neighbour interpolation performs poorly. This image may be spatially of set by up to 0.5 a pixel causing a jagged or blocky appearance. Bilinear interpolation generates of an image of smoother appearance than nearest neighbour interpolation, but the gray levels are altered in the process resulting in blurring or loss of image resolution as observed.

It has been observed that the images presented, in the experimental part of this work, have lost some of their quality when they were reduced to fit in the MatLab format.

Chapter7

Conclusion and Future Scope

7.1. Introduction

Image enhancement or image scaling is one of the major operation in computer graphics. In this thesis I am trying to image enlargement from our own. Image resize algorithms are try to interpolate the suitable image intensity values for the pixels of resize image which does not directly mapped to its original image. Interpolation is the process of estimating the values of a continuous function from discrete sample. Image processing application of interpolation include image magnification or reduction, sub pixel image registration to correct spatial distortions, and image decompression as well as others. Of the many interpolation techniques available, nearest neighbour, bilinear and cubic convolution are the most common. The mapping between the unknown high resolution image and the low resolution image is not invertible, and thus a unique solution o the inverse problem cannot be computed. One of the essential aspects of interpolation is efficiency since the amount of data associated with digital image is large.

7.2. Conclusion

There are a number of techniques that can be used to enlarge an image. The three most common were presented here. All try to emulate as close as possible to an ideal Low Pass Filter. Keys implementation of Bi cubic Convolution Interpolation gave the best results in terms of image quality, but took the greatest amount of processing time. Depending on the interpolation ratio selected or set (i.e. depending on the final size desired/targeted), the interpolation algorithms, mentioned here, gave different MET as well as visual quality. Depending on the interpolation ratio selected or set (i.e. depending on the final size desired/targeted), the interpolation algorithms, mentioned here, gave different MET as well as visual quality.

7.3 Future scope

This work can be extended into many directions. Few major directions are to

1. A fundamental tool of digital image processing.
2. Bridging the continuous world and discrete world.
3. Wide application for consumer electronics to biomedical imaging.
4. Remain a hot topic after the IT bubbles break.

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Appendix

1. Program for Interpolation of Image (Nearest Neighbour)

```
function imzoom = nnbr(image,zoom);
[r c d] = size(image);      % dimensions of image data
%% zoom
rn = floor(zoom*r);
cn = floor(zoom*c);
s = zoom;
im_zoom = zeros(rn,cn,d);
%% nearest neighbour
for i = 1:rn;
    x = i/s;
    near_i = cast(round(x),'uint16');
if near_i == 0
        near_i = 1;
    end
    for j = 1:cn;
        y = j/s;
near_j = cast(round(y),'uint16');
        if near_j == 0
            near_j = 1;
        end
        im_zoom(i,j,:) = image(near_i,near_j,:);
    end
```

```
end
imzoom = im_zoom;
```


2. Program for interpolation image (Bilinear)

```
function image_zoom = blnrm2(image, zoom)
[r c d] = size(image);
rn = floor(zoom*r);
cn = floor(zoom*c);
s = zoom;
im_zoom = zeros(rn,cn,d);
for i = 1:rn;
    x1 = cast(floor(i/s),'uint32');
    x2 = cast(ceil(i/s),'uint32');
    if x1 == 0
        x1 = 1;
    end
    x = rem(i/s,1);
    for j = 1:cn;
        y1 = cast(floor(j/s),'uint32');
        y2 = cast(ceil(j/s),'uint32');
        if y1 == 0
            y1 = 1;
        end
        ctl = image(x1,y1,:);
        cbl = image(x2,y1,:);
        ctr = image(x1,y2,:);
        cbr = image(x2,y2,:);
        y = rem(j/s,1);
        tr = (ctr*y)+(ctl*(1-y));
```

```
        br = (cbr*y)+(cbl*(1-y));
        im_zoom(i,j,:) = (br*x)+(tr*(1-x));
    end
end
image_zoom = cast(im_zoom,'uint8');
```


3. Program for Interpolation of image (Bi cubic)

```
function im_zoom = bicubic_m2(image,zoom);
[r c d] = size(image);
rn = floor(zoom*r);
cn = floor(zoom*c);
s = zoom;
im_zoom = cast(zeros(rn,cn,d),'uint8');
im_pad = zeros(r+4,c+4,d);
im_pad(2:r+1,2:c+1,:) = image;
im_pad = cast(im_pad,'double');
for m = 1:rn
    x1 = ceil(m/s); x2 = x1+1; x3 = x2+1;
    p = cast(x1,'uint16');
    if(s>1)
       m1 = ceil(s*(x1-1));
       m2 = ceil(s*(x1));
       m3 = ceil(s*(x2));
       m4 = ceil(s*(x3));
    else
       m1 = (s*(x1-1));
       m2 = (s*(x1));
       m3 = (s*(x2));
       m4 = (s*(x3));
    end
```

```
    X = [ (m-m2)*(m-m3)*(m-m4)/((m1-m2)*(m1-m3)*(m1-m4))
...
          (m-m1)*(m-m3)*(m-m4)/((m2-m1)*(m2-m3)*(m2-m4))
...
          (m-m1)*(m-m2)*(m-m4)/((m3-m1)*(m3-m2)*(m3-m4))
...
          (m-m1)*(m-m2)*(m-m3)/((m4-m1)*(m4-m2)*(m4-m3))];
    for n = 1:cn
```



```
        y1 = ceil(n/s); y2 = y1+1; y3 = y2+1;
        if (s>1)
           n1 = ceil(s*(y1-1));
           n2 = ceil(s*(y1));
           n3 = ceil(s*(y2));
           n4 = ceil(s*(y3));
        else
           n1 = (s*(y1-1));
           n2 = (s*(y1));
           n3 = (s*(y2));
           n4 = (s*(y3));
        end
        Y = [ (n-n2)*(n-n3)*(n-n4)/((n1-n2)*(n1-n3)*(n1-
n4));...
              (n-n1)*(n-n3)*(n-n4)/((n2-n1)*(n2-n3)*(n2-
n4));...
              (n-n1)*(n-n2)*(n-n4)/((n3-n1)*(n3-n2)*(n3-
n4));...
              (n-n1)*(n-n2)*(n-n3)/((n4-n1)*(n4-n2)*(n4-
n3))];
        q = cast(y1,'uint16');
        sample = im_pad(p:p+3,q:q+3,:);
        im_zoom(m,n,1) = X*sample(:,:,1)*Y;
        if(d~=1)
              im_zoom(m,n,2) = X*sample(:,:,2)*Y;
              im_zoom(m,n,3) = X*sample(:,:,3)*Y;
        end
```

```
        end
    end
    im_zoom = cast(im_zoom,'uint8');
```