IMAGE ZOOMING USING WAVELET COEFFICIENTS

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

Master of Technology

in

Computer Science and Applications

Submitted By

Himanshu Jindal
(Roll No. 651103003)

Supervised By

Dr. Singara Singh
Assistant Professor

SCHOOL OF MATHEMATICS AND COMPUTER APPLICATION
THAPAR UNIVERSITY
PATIALA – 147004

July 2014

CERTIFICATE

I hereby certify that the work being presented in the dissertation entitled, **"Image Zooming Using Wavelet Coefficients"**, in partial fulfillment of the requirements for the award of degree of Master of Technology in **Computer Science and Applications** submitted to the School of Mathematics and Computer Applications of Thapar University, Patiala, is a authentic record of my own work carried out under the supervision of **Dr. Singara Singh** and refers other researcher's work which are duly listed in the reference section.

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

(Himanshu Jindal)

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

(Dr. Singara Singh)

Assistant Professor,

School of Mathematics and Computer Applications,

Thapar University, Patiala

Countersigned By -

Dr. Rajesh Kumar

Head,

School of Mathematics and Computer Applications,

Thapar University, Patiala

Dr. S.K. Mohapatra

Dean

(AcademicAffairs)

Thapar University, Patiala

ACKNOWLEDGMENT

I would like to acknowledge everyone who supported me during my experience at Thapar University and my work on this dissertation. First and foremost I would like to thank God for providing me with faith, self-confidence and ability to complete the dissertation.

It would be a great pleasure for me to acknowledge the guidance, assistance and help received from **Dr. Singara Singh**, Assistant professor, SMCA, Thapar Univeristy, Patiala. I am very grateful for his continual support, encouragement and invaluable suggestions. His enthusiasm and optimism made this experience both rewarding and encourageable.

I extend my deep gratitude towards **Dr. Rajesh Kumar**, Head, SMCA, Thapar University, Patiala for providing the timely facilities and infrastructure that helped in completion of the dissertation.

I would like to take this opportunity to express my sincere appreciation and thanks to my friends and family for their strong moral support and constant encouragement throughout this research. I am also thankful to all staff members of SMCA for their kind cooperation and sincere help.

Himanshu Jindal

Himanshu Jindal

Roll No: 651103003

M.Tech (CSA)

ABSTRACT

The work in this dissertation involves an algorithmic approach to zoom a given image in wavelet domain and to get a sharper image using with various interpolation techniques. The exploration is an attempt to develop quantitative measures that can automatically predict perceived image quality.

An objective image quality metric can play a variety of roles in image processing applications. First, it can be used to dynamically monitor and adjust image quality; second, it can be used to optimize algorithms and parameter settings of image processing systems. Second, it can be used to benchmark image processing systems and algorithms as zoomed images are sharper as compared to other methods. Hence keeping all this in mind on this source of information, Discrete Wavelet Transform (DWT) with various interpolation techniques had been applied upon variances to obtain their values. Performance is measured by calculating Peak Signal to Noise Ratio (PSNR), and the proposed method gives much better *PSNR* compared to other methods. This algorithm can help in medical science to get the minutest details for detection of cancer.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

In this Chapter, the basics related to images and their properties are discussed. Special emphasis has been given on image zooming, which is the topic of this dissertation. Apart from different image zooming techniques often referred to as Interpolation techniques and pixel replication have been discussed. *DWT* has also been discussed along with different Image quality parameters which are estimated by finding the *PSNR* values between the original and its zoomed version.

1.2 IMAGE

An image is an optical counterpart or appearance of an object, which is produced by reflection from a mirror, refraction by a lens, or the passage of luminous rays through a small aperture and their reception on a surface. This synonym has been consistent for over the years that directly or indirectly describes the importance of an existence of image. In this modern world of computers we understand the importance of image, however it is also necessary to understand the fundamentals aspects of an image, and clearly how far we can use image as an object to understand further divisional aspects so as it can shed light on further queries on understanding them conceptually clear. Here, an image is an array, or a matrix, of square pixels (picture elements) arranged in columns and rows.

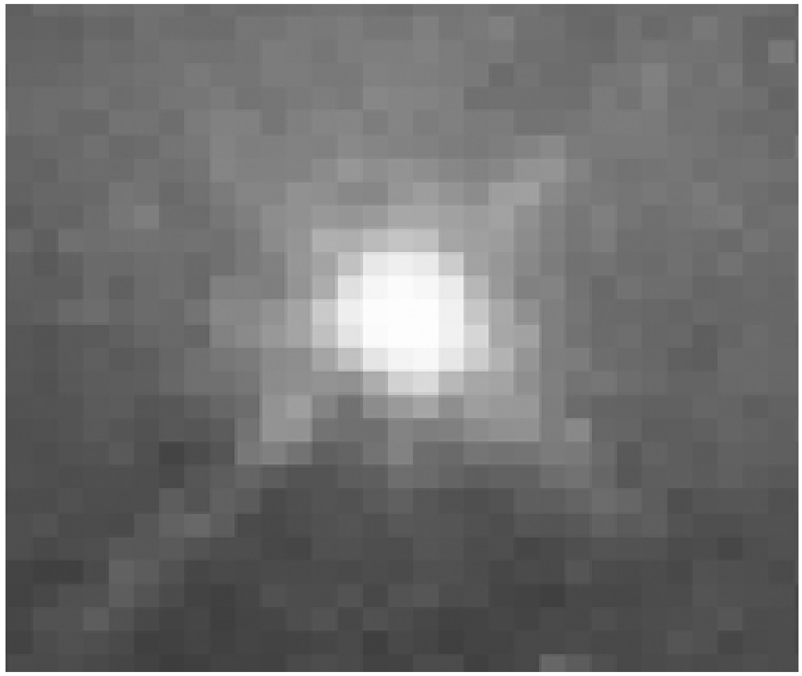
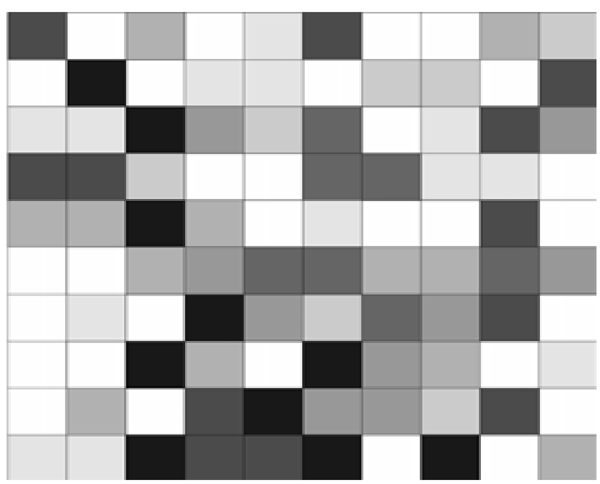


Figure 1.1 An image arranged in array of columns and rows

An image is a visual representation of something. The pixel of an image of 8 bits per pixel has an intensity which ranges from 0 to 255 on a gray scale image. Gray scale image is considered to be a black and white image.



(a)

Figure 1.2(a) Pixel having various colors based on gray scale

(b)

Figure 1.2(b) Each pixel has value from 0 to 255 on gray scale

1.3 IMAGE ZOOMING

Performing zooming of an image is an important task used in many applications, including the World Wide Web, Digital Video, Digital Video Discs(DVDs), and scientific imaging. When zooming operation is performed on an image then the pixels are inserted into the image in order to expand the size of the image.

The major task is the interpolation of the new pixels forms the surrounding original pixels. Weighted medians have been applied to similar problems requiring interpolation, such as interlace to progressive video conversion for television systems. Zooming commonly requires a change in the image dimensions by a non-inter factor, such as a 50 % zoom where the dimensions must be 1.5 times the original. Image Zoom allows the user to change image sizes. There are several ways the user can zoom images through the interface as well as the ability to zoom single images or an entire page of images. Image Zoom allows the user to change image sizes within a web page. There are several ways the user can zoom images through the interface as well as the ability to zoom single images or an entire page of images. Both individual images and whole pages of images can be zoomed.

1.3.1 Need of Zooming

It allows the user to zoom in on an image for exploration of the image's details. Depending on the zoom factor, showing the entire high resolution image from the beginning will not provide the user with an overview of the entire image thus removing the context of the details viewed.

By providing zooming functionality, a user can zoom into just one selective area of the image that is needed to be understood by the user. The user is in this way not bothered with the details of uninteresting parts of an image.

Image zooming is done more accurately by various interpolation techniques & various algorithms.

Figure 1.3 Image of a Rose

Figure 1.4 Zoomed image of rose

1.4 TYPES OF ZOOMING

1.4.1 PIXEL REPLICATION

The first way in image zooming process to zoom an image so that it would be easily displayed on screen considering the initial pixel values available for an image. Pixel Replication is a type of up-sampling of a digital image, whose resultant is affected onto the image after increasing the number of pixels in an image, but without adding any source data or detail on selected image. The new colored pixels are often interpolated using the original pixels. Image quality is not often very high when images are enlarged in this manner.

$$\begin{bmatrix} 1 & 3 \\ 4 & 5 \end{bmatrix} \longrightarrow \begin{bmatrix} 1 & 1 & 3 & 3 \\ 1 & 1 & 3 & 3 \\ 4 & 4 & 5 & 5 \\ 4 & 4 & 5 & 5 \end{bmatrix}$$

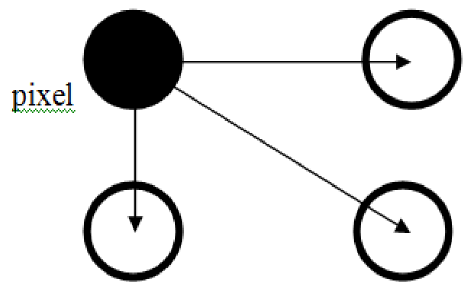


Figure 1.5 Pixel Replication

The following images are the images of example of pixel replication.

Figure 1.6 Original image of a Boy

Figure 1.7 Zoomed image of Boy

1.4.2 INTERPOLATION

Interpolation is the process of using known data values to calculate the unknown data values. The process of Interpolation is applied in the same manner method of constructing new data points within the range of a discrete set of known data points. In Engineering and Science, one often has a number of data points, obtained by sampling/experimentation, which represent the values of a function for a limited number of values of the independent variable. It is often required to interpolate (i.e. calculate) the value of that function for an intermediate value of an independent variable.

There are various interpolation techniques that are used for image zooming. These are –

- Linear Interpolation
- Bilinear Interpolation
- Bi-cubic Interpolation

- Nearest neighbour Interpolation

Out of all the above mentioned, Linear Interpolation is very much easy & is a simple technique when compared to others and is used to calculate the unknown values that lie within the upper and lower range of pixel values.

These interpolation techniques are described as under –

1.4.2.1 Linear Interpolation

It is a simple technique used to estimate unknown values that lie between known values. Linear interpolation is a first degree method that passes a straight line through every two consecutive points of the input signal.

Linear Interpolation takes two data points, say (x_a,y_a) and (x_b,y_b), and the interpolated is given by:

$$y = y_a + (y_b - y_a) \times (x - x_a)/(x_b - x_a) \qquad \ldots(1.1)$$

Example-

Linear interpolation for a 2 × 2 matrix

$$v_1(m, 2n) = u(m, n) \text{ for } 0 \le m \le M - 1; 0 \le n \le N - 1 \qquad \ldots(1.2)$$

$$v_1(m, 2n + 1) = \frac{1}{2}[u(m, n) + u(m, n - 1)] \text{ for } 0 \le m \le M - 1; 0 \le n \le N - 1 \qquad \ldots(1.3)$$

Linear interpolation along columns gives

$$v(2m, n) = v_1(m, n) \rightarrow correct\ expression \qquad \ldots(1.4)$$

$$v(2m, n) = v_1(2m, n) \qquad \ldots(1.5)$$

$$v(2m + 1, n) = \frac{1}{2}(v_1(m, n) + v_1(m + 1, n)) \qquad \ldots(1.6)$$

for $0 \le m \le M - 1, 0 \le n \le 2N - 1$(corrected version)

$$v(2m + 1, n) = \frac{1}{2}[v_1(2m, n) + v_1(2m + 2, n)] \qquad \ldots(1.7)$$

for $0 \le m \le M-1, 0 \le n \le 2N-1$

(assume input image is zero outside $[(0, M-1) \times (0, N-1)]$)

Example –

$$\begin{bmatrix} 1 & 7 \\ 3 & 1 \end{bmatrix}$$

$\downarrow$ Zero Interlace

$$\begin{bmatrix} 1 & 0 & 7 & 0 \\ 0 & 0 & 0 & 0 \\ 3 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$\downarrow$ Interpolate rows

$$\begin{bmatrix} 1 & 4 & 7 & 3.5 \\ 0 & 0 & 0 & 0 \\ 3 & 2 & 1 & 0.5 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$\downarrow$ Interpolate columns

$$\begin{bmatrix} 1 & 4 & 7 & 3.5 \\ 2 & 3 & 4 & 2 \\ 3 & 2 & 1 & 0.5 \\ 1.5 & 1 & 0.5 & 0.25 \end{bmatrix}$$

<u>Example for linear interpolation</u>

1.4.2.2 Bilinear Interpolation

It is used for interpolating functions of two variables. Bilinear interpolation is one of the basic resampling techniques. It can be used to produce a reasonably realistic image. An algorithm is used to map a screen pixel location to a corresponding point on the texture map. A weighted average of the attributes (color, alpha, *etc*.) of the four surrounding texels is computed and applied to the screen pixel. This process is repeated for each pixel forming the object being textured.

When an image needs to be scaled up, each pixel of the original image needs to be moved in a certain direction based on the scale constant. However, when scaling up an image by a non-integral scale factor, there are pixels that are not assigned appropriate pixel values. In this case, those holes should be assigned appropriate RGB or grayscale values so that the output image does not have non-valued pixels.

For solving bilinear interpolation, we first do linear interpolation in the *x*-direction.

This yield

$$f(R_1) \approx \frac{x_2-x}{x_2-x_1} f(Q_{11}) + \frac{x-x_1}{x_2-x_1} f(Q_{21}) \text{ where } R_1 = (x, y_1) \qquad \ldots(1.8)$$

$$f(R_2) \approx \frac{x_2-x}{x_2-x_1} f(Q_{12}) + \frac{x-x_1}{x_2-x_1} f(Q_{22}) \text{ where } R_2 = (x, y_2) \qquad \ldots(1.9)$$

We proceed by interpolating in the *y*-direction.

$$f(P) \approx \frac{y_2-y}{y_2-y_1} f(R_1) + \frac{y-y_1}{y_2-y_1} f(R_2) \qquad \ldots(1.10)$$

This gives us the desired estimate of $f(x, y)$.

$$f(R_1) \approx \frac{f(Q_{11})}{(x_2-x_1)(y_2-y_1)} (x_2-x)(y_2-y) + \frac{f(Q_{21})}{(x_2-x_1)(y_2-y_1)} (x-x_1)(y_2-y) + \frac{f(Q_{12})}{(x_2-x_1)(y_2-y_1)} (x_2-x)(y-y_1) + \frac{f(Q_{22})}{(x_2-x_1)(y_2-y_1)} (x-x_1)(y-y_1) \qquad \ldots(1.11)$$

Thus the output image of bilinear interpolation is –

Figure 1.8 Output Image of bilinear interpolation

1.4.2.3 Bi-cubic Interpolation

It is used for interpolating data points on a two dimensional regular grid. In image processing, bi-cubic interpolation is often chosen over bilinear interpolation or nearest neighbor in image resampling, when speed is not an issue. In contrast to bilinear interpolation, which only takes 4 pixels (2×2) into account, bi-cubic interpolation also considers the 16 pixels around it (for a total of 4×4 pixels) while computing an average. Images resampled with bi-cubic interpolation are smoother and have fewer interpolation artifacts.

Suppose the function values f and the derivatives f_x, f_y and f_{xy} are known at the four corners (0,0), (1,0), (0,1), and (1,1) of the unit square. The interpolated surface can then be written as-

$$p(x, y) = \sum_{i=0}^{3} \sum_{j=0}^{3} a_{ij} x^i y^j \qquad \ldots(1.12)$$

Thus the output image of bicubic interpolation is –

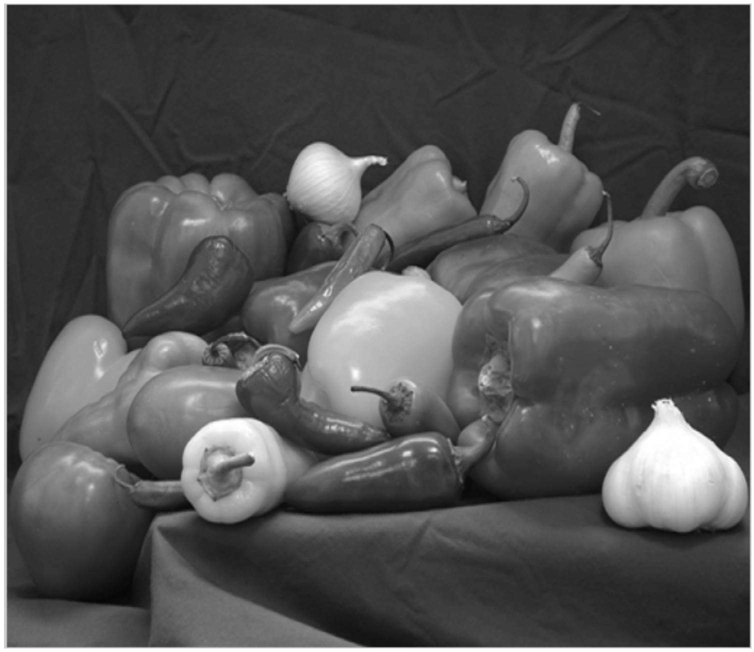


Figure 1.9 Output Image of bicubic interpolation

1.4.2.4 Nearest-Neighbour Interpolation

It is a simple method of multivariate interpolation in one or more dimensions. Nearest neighbour is the most basic and requires the least processing time of all the interpolation algorithms because it only considers one pixel, the closest one to the interpolated point. This has the effect of simply making each pixel bigger.

Thus the output image of nearest neighbour interpolation is –

Figure 1.10 Output Image of nearest neighbor interpolation

1.5 DISCRETE WAVELET TRANSFORM

The *DWT* is an implementation of the wavelet transform using a discrete set of the wavelet scales on an image and translations obeying some defined rules prescribed as per the given format, and it can be executed as per the available values of the image, and then can further be divided into 4 subbands and each of the part can further be evaluated individually, and independent values can be obtained applying different set of rules on all the four different images. In other words, this transform decomposes the signal into mutually orthogonal set of wavelets, which is the main difference from the Continuous Wavelet Transform (CWT), and its implementation for the discrete time series sometimes called Discrete-Time Continuous Wavelet Transform (DT-CWT).

After applying *DWT,* the image is divided into subbands on the basis of low and high filters, say LL, HL, LH and HH where *'l'* is for low filter and *'h'* is for high filter. The LH, HL and HH subbands are quite uninformative. The low-pass filter is a kind of a predictor *i.e.* it tells about the average value of a group of pixels. The high-pass filter stores the errors that got created by low-pass predictors. LH and HL stores the errors that is used to get to average values of column-errors across rows, or vice versa, whereas HH stores LH's and HL's errors.

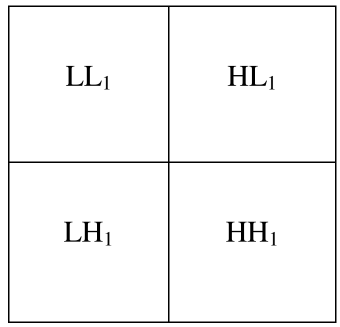


Figure 1.11(a) First level decomposition showing subbands of *DWT*

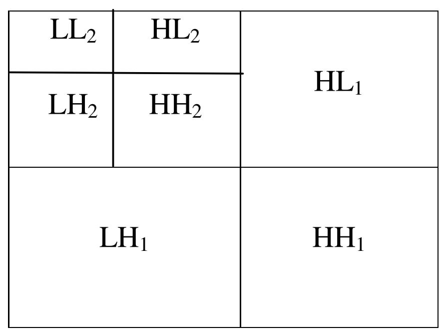


Figure 1.11(b) Second level decomposition showing subbands of *DWT*

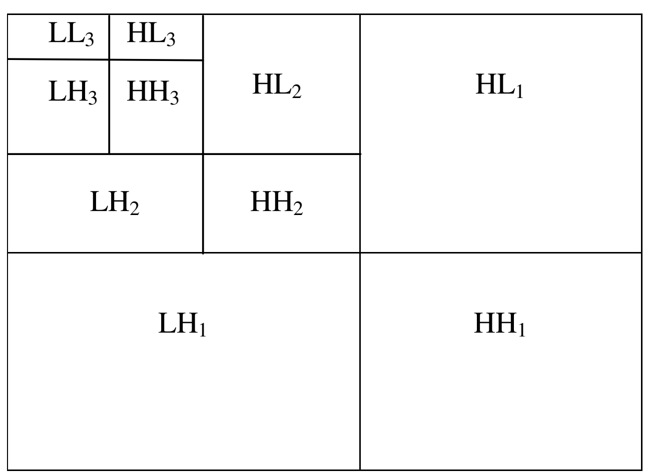


Figure 1.11(c) Third level decomposition showing subbands of *DWT*

The operation of *DWT* consists of generating the string by queuing image lines and then executing decomposition. After this operation, we can obtain strings by queuing the columns from the found sub-images and another decomposition for each string is applied. The resulting decomposition, in the simplified version extended up to the next level of operation.

Since *DWT* helps in understanding the properties of an image in a broader aspect, the advantage is that the cosine transform previously carries out a division into squared blocks, while the *2D-DWT* works in its totality. Moreover the decomposition into sub bands gives a higher flexibility in terms of scalability in resolution and distortion.
The *DWT* of a signal is calculated by passing it through a series of filters. First the samples are passed through a low pass filter with impulse response resulting in a convolution of the two:

$$\tilde{y}[n] = (x \times g)[n] = \sum_{k=-\infty}^{\infty} x[k]g[n-k] \qquad \ldots(1.13)$$

The signal is also decomposed simultaneously using a high-pass filter. The outputs giving the detail coefficients (from the high-pass filter) and approximation coefficients (from the low-pass). It is important that the two filters are related to each other and they are known as a quadrature mirror filter. However, since half the frequencies of the signal have now been removed, half the samples can be discarded according to Nyquist's rule. The filter outputs are then sub sampled by 2.

$$y_{low}[n] = \sum_{k=-\infty}^{\infty} x[k]h[2n-k] \qquad \ldots(1.14)$$

$$y_{high}[n] = \sum_{k=-\infty}^{\infty} x[k]g[2n-k] \qquad \ldots(1.15)$$

This decomposition has halved the time resolution since only half of each filter output characterizes the signal. However, each output has half the frequency band of the input so the frequency resolution has been doubled.

The wavelet can be constructed from a scaling function which describes its scaling property of resizing the image. The restriction that the scaling functions must be orthogonal to its discrete translations implies some mathematical conditions on them which are mentioned everywhere. One referral example for the same can be taken as the dilation equation -

$$\phi(x)=\sum_{k=-\infty}^{\infty} a_k \phi(Sx - k)\, S_x \qquad \ldots(1.16)$$

Here S is a scaling factor (usually chosen as 2). Moreover, the zone between the function must be normalized and scaling function must be orthogonal to its integer translates from the prior value.

$$\int_{-\infty}^{\infty} \emptyset(x)\emptyset(x+l)dx = \delta_{0,l} \qquad \ldots(1.17)$$

After introducing some more conditions we can obtain results of all this equations we describe a finite set of coefficients which define the scaling function and the wavelet. The wavelet is obtained from the scaling function as -

$$\varphi(x) = \sum_{k=-\infty}^{\infty}(-1)^k a_{N-1-k}\, \varphi(2x-k) \qquad \ldots(1.18)$$

Here N is an even integer. The set of wavelets than forms an orthonormal basis which we use to decompose signal. Only few of the coefficients a_k are nonzero which simplifies the calculations and makes it easy to understand and adapt.

Thus the output image after applying *DWT* is –

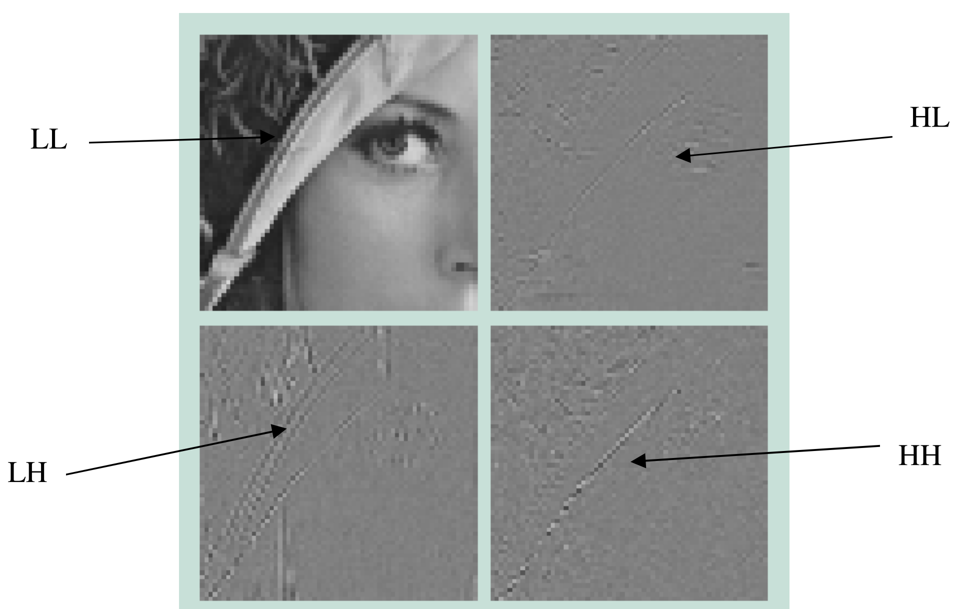


Figure 1.12 Output image of *DWT*

1.5.1 Inverse Discrete Wavelet Transform

The inverse *DWT* can reconstruct the original signal from the wavelet spectrum. It may be taken in consideration that that the wavelet that is used as a base for decomposition will not be altered if we want to reconstruct the original signal again after experimentation, *e. g.* by using Haar wavelet we obtain a wavelet spectrum; it can be used for signal reconstruction using the same wavelet.

1.6 Types of Wavelets

1.6.1 Haar wavelets

The first *DWT* was invented by the Hungarian mathematician Alfréd Haar. For an image data to be evaluated is represented by a list of 2^n numbers, where *n* is the size of image, the Haar Wavelet transform may be considered to simply unique pair up input values, storing the difference and passing the sum. This process is repeated recursively, pairing up the resultants to provide the next scale which further provides 2^n - 1 differences and one final sum.

1.6.2 Daubechies wavelets

The most commonly used set of discrete wavelet transformation was derived by the Belgian mathematician Ingrid Daubechies in 1988. This formulation is based on the use of recurrence relations to generate progressively finer discrete samplings of an implicit and of existing Mother Wavelet Function; each resolution is twice that of the previous scale. Further innovating during the course of improving the existing study, Daubechies derives a family of wavelets, the first of which is the Haar Wavelet. Interest in this field had exploded since then, and many variations of Daubechies' original wavelets were developed which are used in today's date as well.

1.6.3 The Dual-Tree Complex Wavelet Transform

The Dual-Tree Complex Wavelet Transform (CWT) is relatively recent enhancements to the *DWT*, with important additional properties are emphasized. It is nearly shift invariant and directionally selective in two and higher dimensions. It achieves this with a redundancy factor of only 2^d substantially lower than the un-decimated *DWT*.

The multidimensional (M-D) dual-tree *CWT* is non separable but is based on a computationally efficient, separable Filter Bank (FB).

1.7 PROPERTIES OF DISCRETE WAVELET TRANSFORM

The 'Haar' Discrete Wavelet Transform has object fully defined the desirable properties of wavelets in as the motive to highlight the ability to adapt prospective. Firstly, it can be utilized in O(n) operations; secondly, it not only captures a notion of the frequency content of the input, by examining it at different scales, but also temporal content related to the original information, i.e. the times at which these frequencies occur. A new operation is oriented of combining, these two properties make the Fast wavelet transform (FWT) an alternative to the conventional Fast Fourier Transform (FFT).

1.8 TIME COMPLEXITY OF DISCRETE WAVELET TRANSFORM

If coefficients are of a constant length (i.e. their length is independent of N), then $x \times h$ and $x \times g$ each take O(N) time. The wavelet filter bank does each of these two O(N) convolutions, then splits the signal into two branches of size N/2. But it only one after another splits the upper branch convolved with first coefficient (as contrasted with the Fast Fourier Transform, which recursively splits both ends of the image). This leads to the following recurrence relation.

$$T(N) = 2N + T\left(\frac{N}{2}\right) \qquad \ldots(1.19)$$

This leads to an O(N) time for the entire operation, as can be shown by a geometric series expansion of the above relations.

1.9 APPLICATIONS OF DISCRETE WAVELET TRANSFORM

The discrete wavelet transform has a huge number of applications in various fields like science, engineering, mathematics and computer science. It is used mostly for signal coding, to represent a discrete signal in more redundant form which often used anonymously for data compression. The wavelet can be used for practical applications in signal processing of accelerations for gait analysis or in digital communications.

1.10 IMAGE QUALITY

An image formation is formed on the image plane of the camera and then measured electronically or chemically as per the availability to produce the photograph. The image formation process may be described by the ideal pinhole camera model, where only light rays from the depicted scene that pass through the camera aperture can fall on the formation plane. In a real world scenario, this ideal model is only an approximation of the image formation process, and image quality may be described in terms of how well the camera approximates the pinhole model.

Quality in an image is a characteristic of its property that measures the perceived its degradation (typically, compared to an ideal or perfect image). Imaging systems may introduce some amounts of hindrance or artifacts in the signal, so the quality assessment towards an image is an important problem.

In some cases, the image for which quality should be determined is primarily not the result of a photographic process in a camera, but the result of storing or transmitting the image. A typical example can be clearly understood when the image is shrunk and later stored or transmitted, and then broken for again for further understanding. By considering a bulk property of an image and determining a quality measure for each of them, statistical methods can be used to determine an overall quality and relative measure of the compression adopted for the image.

By defining image quality in terms of a deviation from the stand alone situation, quality measures become technical in the sense that they can be objectively determined in terms of deviations from the ideal models. Image quality can, however, also be related to the subjective perception of an image.

Subjective measures of quality also refer to the fact that, although the camera's deviation from the ideal models of image formation and measurement in general is undesirable and corresponds to diminished objective image quality, these deviations can also be used for artistic effects in image production, corresponding to high subjective quality in case the property to image formation is satisfied.

1.11 IMAGE QUALITY FACTORS

There are many factors that can refer to the quality of an image.

1. Sharpness :- Sharpness of an image determines the amount of detail an image can convey. System sharpness is affected by the lens and sensor. In real terms, sharpness is affected by camera shake, focus accuracy, and atmospheric disturbances. Lost sharpness can be restored by sharpening, but sharpening has limits. Over sharpening, can degrade image quality by causing "halos" to appear near contrast boundaries. Images from many compact digital cameras are sometimes over sharpened to compensate for lower image quality.

2. Noise:- is a random variation of image density, visible as grain in film and pixel level variations in digital images. It arises from the effects of basic physics, the photon nature of light and the thermal energy of heat inside image sensors. Typical noise reduction (NR) software reduces the visibility of noise by smoothing the image, excluding areas near contrast boundaries. This technique works well, but it can obscure fine, low contrast detail.

3. Dynamic range:- It is the higher node or the range of light levels a camera can capture, usually measured in f-stops, exposure value, or zones of all factors of two in exposure. It is closely related to noise: high noise implies low dynamic range.

4. Tone reproduction:- It is the relationship between scene brightening and the reproduced image brightness.

5. Contrast:- It may only be known as gamma, is the slope of the tone reproduction curve in a log-log space. High contrast usually involves loss of dynamic range loss of detail, or clipping, in highlights or shadows.

6. Color:- Accuracy is an important but ambiguous image quality factor. Many viewers prefer enhanced color saturation; the most accurate color isn't necessarily the most pleasing. Nevertheless it is important to measure a camera's color response: its color shifts, saturation, and the effectiveness of its white balance algorithms.

7. Distortion:- Distortion is considered to be an aberration that causes straight lines to curve. It can be troublesome for architectural photography and metrology. Distortion tends to be noticeable in low cost cameras, including cell phones, and low cost DSLR lenses. It is usually very easy to see in wide angle photos.

8. Vignetting:- It may also be referred to as light falloff, darkens images near the four corners. It can be relevant when observed with wide angle lenses.

9. Exposure:- The accuracy can be an issue with fully automatic cameras and with video cameras where there is little or no opportunity for post-exposure tonal adjustment. Some even have exposure memory: exposure may change after very bright or dark objects appear in a scene.

10. Lateral chromatic aberration(LCA):- It is a lens aberration that causes colors to focus at different distances from the image centre when captured for an infinite exposure. It is most visible near corners of images. *LCA* is worst with asymmetrical lenses, which includes ultrawides, true telephotos and zooms. It is strongly affected by demosaicing.

11. Lens flare:-, It is referred to as a stray light in lenses and optical systems caused by reflections between lens elements and the inside barrel of the lens. It can cause image fogging (as the image with loss of shadow detail and color) as well as "ghost" images that can occur in the presence of bright light sources in or near the field of view.

12. Artifacts :- The image softwares like Raw Conversion can cause significant visual artifacts, including data compression and transmission losses over sharpening and loss of fine, low-contrast detail.

Similarly we can also differentiate different properties when we Scan an image instead of capturing the image. The Scanning factors that affect the image quality can be quantified.

1.12 SCANNING FACTORS

1. Resolution :- The increasing resolution of an image enables for a finite value detail for an image. At some point, however, added resolution will not result in an appreciable gain in image quality, only larger file size. The key is to determine the resolution necessary to capture all significant detail present in the source document.

2. Bit Depth: - The increasing bit depth, or number of bits that are used to represent each pixel, enables the capture of more gray shades or color tones. Dynamic range is the terminology referred while using the keys express the full range of tonal variations from lightest light to darkest dark. A scanner's capability to capture dynamic range is governed by the bit depth used and output as well as system performance. Increasing the bit depth will affect resolution requirements, file size, and the compression method used.

3. Enhancement :- Enhancement processes improve scanning quality but their use raises concerns about fidelity and authenticity. The basic and the foremost typical enhancement features in scanner software or image editing tools include descreening, despeckling, deskewing, sharpening, use of custom filters, and bit-depth adjustment which may vary from tool application available in different softwares.

4. Color :- Capturing and conveying color appearance is arguably the most difficult aspect of digital imaging. Good color reproduction depends on a number of variables, such as the level of illumination at the time of capture, the bit depth captured and output, the capabilities of the scanning system, and mathematical representation of color information as the image moves across the digitization chain and from one color space to another.

5. System Performance :- The periphery of equipments used and its performance over time affects the overall image quality. Different systems with the same stated capabilities (e.g., dpi, bit depth, and dynamic range) may produce dramatically different results. System performances are measured via tests that check for resolution, tone reproduction, color rendering, noise, and artifacts for a particular image.

6. File Format:- The file format for master images should support the resolution, bit-depth, color information, and meta data for self properties. An example for the same can be assumed that there is little sense in creating a full color image, only to save it in a format that cannot support more than 8 bits in GIF images. The format should also handle being stored uncompressed or compressed using either lossless or lossy techniques. It should be open and well-documented, vividly supported, and cross-platform compatible. Although there is interest in other formats, such as PNG, SPIFF, and Flashpix, most cultural institutions rely on TIFF to store their master images. For access, derivative images in other formats may be created.

7. Compression:- Lossy compression can have a negative impact on image quality, especially if the level of compression is high. In general, the higher capability of a file, the more efficient and sustainable the compression. A referral example for the same can be taken as a scan of a page at 600 dpi is 4 times larger than a 300 dpi version, but often only twice as large in its compressed state. The more complex the image, the poorer the level of compression that can be obtained in a lossless or visually lossless state. With photographs, lossless compression schemes often provide around a 2:1 file size ratio; with lossy compression above 10 or 20:1, the effect may be obvious towards the total distortion of image and its overall quality.

1.13 IMAGE QUALITY PARAMETERS

PSNR is a core 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. Since many signals have a very wide dynamic range, *PSNR* is usually expressed in terms of the logarithmic decibel scale. In easy terms it may also be referred to as the higher the *PSNR* value of an image, higher the quality of zooming is analyzed. *PSNR* is referred to as easily defined via the Mean Squared Error(MSE).

The mathematical implementation for the image may be considered to be the a mandatory implementation while dealing with standard *2D* array of data or matrix.

The mathematical representation of the *PSNR* is as follows:

$$PSNR = 20\ \log_{10}\left(\frac{MAX_f}{\sqrt{MSE}}\right) \qquad \ldots(1.20)$$

where the MSE (*Mean Squared Error*) is:

$$MSE = \frac{1}{mn}\sum_0^{m-1}\sum_0^{n-1}\|f(i,j) - g(i,j)\|^2 \qquad \ldots(1.21)$$

This can also be represented in a text based format as:

$$MSE = \left(\frac{l}{m\times n}\right) \times sum\big(sum((f-g)^2)\big) \qquad \ldots(1.22)$$

$$PSNR = 20 \times \log \frac{(\max(\max(f)))}{((MSE)^{0.5})} \qquad \ldots(1.23)$$

where

f **-** represents the matrix data of our original image.

g **-** represents the matrix data of our degraded image in question.

m - represents the numbers of rows of pixels of the images and i represents the index of that row.

n - represents the number of columns of pixels of the image and j represents the index of that column.

MAX_f **-** is the maximum signal value that exists in our original "known to be good" image.

PSNR is most commonly used to measure the quality of reconstruction of lossy compression codes. The signal in this case is the original data, and the noise is the error introduced by compression. When comparing compression codes, *PSNR* is an approximation to human perception of reconstruction quality. Although a higher *PSNR* generally indicates that the reconstruction is of higher quality, in some cases it may not. 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 and same content.

For colored images with three RGB values per pixel, which defines the *PSNR* of the image is the same except the *MSE* is the sum over all squared value differences divided by image size and by three. Alternately, for color images the image is converted to a different color space and *PSNR* value is reported against each channel of that color space.

Typical values for the *PSNR* in lossy image and video compression are between 30 and 50 dB, provided the bit depth is 8 Bit, where higher is better. For 16 bit data typical values for the *PSNR* are between 60 and 80 dB. Acceptable values for wireless transmission quality loss are considered to be about 20 dB to 25 dB.

Using the same set of tests images, different image enhancement algorithms can be compared systematically to identify whether a particular algorithm produces better results. The metric under investigation is the *PSNR*. If we can show that an algorithm or set of algorithms can enhance a degraded known image to more closely resemble the original, then we can more accurately conclude that it is a better algorithm.

The *MSE* for our practical purposes gives room to compare the true pixel value of an available image to a lower image. The *MSE* refers to the average of the squares of the errors between the experimental image and a noisy image. The error is the amount by which the values of the actual image differ from the degraded image.

The proposal is that the higher the *PSNR*, the better degraded image has been reconstructed to match the original image and the better the reconstructive algorithm. This would occur because we wish to minimize the *MSE* between images with respect to the maximum signal value of the image.

When an evaluation on an image for evaluating the *MSE* between two identical images, the value will be zero and hence the *PSNR* will be undefined. The main limitation of the acquired metric is that it relies strictly on numeric comparison and does not actually take into account any level of biological factors of the human vision system such as the Structural Similarity Index (SSIM).

For color images, the *MSE* is taken over all pixels values of each individual channel and is averaged with the number of color channels. Another option may be to simply perform the *PSNR* over a converted luminance or grayscale channel as the eye is generally four times more susceptible to luminance changes as opposed to changes in chrominance. This approximation is left up to the experimenter who may give different variables.

1.14 CONCLUSION

We finally come to a conclusion that where an image is reconstructed with double the size of the image, which have more accurate image quality and then various operations can be performed on the image. An image is zoomed so that in an order to clearly look at all the aspects of the zoomed area and to see the minutest of the pixel change that exist on the image.

CHAPTER 2

LITERATURE SURVEY

2.1 INTRODUCTION

In this Chapter, we have reviewed various research papers that have explored the various studies that have been done to understand the properties of an image through various operations. Meaningful research has been added to the developed study to extend the existing study to a new parameter. In the chapter various research papers have been added by virtue of extracts of all the papers that have been considered for reference.

2.2 LITERATURE SURVEY

Methodology for changing digitally interpolating images to higher resolution is also available in today's date. Thus Allebach *et al.* (1996) suggested two phases: Rendering and Correction. The first phase i.e. Rendering phase is edge-directed. From the low resolution image data, high resolution edge map is generated by first filtering with a rectangular center-on-surround-off filter and then performing piecewise linear interpolation between the zero crossings in the filter output. The Rendering phase is based on Bilinear Interpolation Modified to prevent interpolation across edges, as determined from the estimated high resolution edge map. During the second phase i.e. Correction phase, the mesh values were modified on which the rendering is done to account for the disparity between the true low resolution data, and that predicted by a sensor model operating on the high resolution output of the rendering phase. The entire process is repeated iteratively. It analyzes the values and gives experimental results which demonstrate the efficacy of our interpolation method.

An edge-directed interpolation algorithm for natural images has been suggested by Li *et al.* (2001). The basic idea is to first estimate local covariance coefficients from a low-resolution image and then use these covariance estimates to adapt the interpolation at a higher resolution based on the geometric duality between the low-resolution covariance and the high-resolution covariance. The edge-directed property of covariance-based adaptation attributes to its capability of tuning the interpolation coefficients to match an arbitrarily oriented step edge. A hybrid approach of switching between bilinear interpolation and covariance-based adaptive interpolation is proposed to reduce the overall computational complexity. Two important applications of the new interpolation algorithm are studied: resolution enhancement of grayscale images and reconstruction of color images. Simulation results demonstrate that our new interpolation algorithm substantially improves the outcome quality of the interpolated images over conventional linear interpolation.

Gupta *et al.* (2007) suggested a new interpolation technique using exponential B-spline, which is super-set of the B-spline. An interpolation kernel of exponential B-spline was proposed. Having it as a different approach, an exponential B-spline interpolation kernel using simple mathematics based on Fourier approximation is presented. A high signal to noise ratio can be achieved because exponential B-spline parameters can be set depending on the signal characteristics. The analysis of these interpolated kernels shows they have better performance in high and low frequency components as compared to other conventional nearest neighbour, linear, spline based methods.

Mueller *et al.* (2007), discussed that it has become feasible to use more robust and computationally complex algorithms that increase the resolution of images without distorting edges and contours with the ever increasing computational power of modern day processors. A novel image interpolation algorithm was presented that uses the new contour let transform to improve the regularity of object boundaries in the generated images. By using a simple wavelet-based linear interpolation scheme as an initial estimate, then used an iterative projection process based on two constraints to drive our solution towards an improved high-resolution image. Experimental results show that new algorithm significantly outperforms linear interpolation in subjective quality, and in most cases, in terms of *PSNR* as well.

Majority of digital cameras use a color filter array to capture the colors of the scene and need color interpolation to generate full resolution color details. To provide a full-color image, an interpolation process, commonly referred to as CFA demosaicking is optimized. A large number of demosaicking methods using a directional or adaptive color correlation have been suggested by Jeong *et al.* (2008). In such conventional methods, however, there is the problem of artifacts occurring on the edges of color boundaries. In order to suppress such undesirable artifacts around line edges, the proposed method first determines line edge patterns and interpolates missing pixels along detected directions. Experimental results demonstrate that the proposed method produces visually pleasing images and outperforms existing demosaicking methods in terms of *PSNR* which provides vibrant results.

Lukin (2008) has presented a new algorithm of spatial interpolation that can be used as a part of more complex motion-adaptive or motion-compensated values. It is based on edge-directional interpolation, but adds several features to improve quality and robustness, spatial averaging of directional derivatives, "soft" mixing of interpolation directions, and use of several interpolation iterations. Reasonably high quality of the proposed algorithm is demonstrated by visual comparison and *PSNR* measurements instead of original values of the image as presented. Analyzing an image by the process of Deinterlacing by virtue of which an image is converted for interlaced-scan video sequences into progressive scan format. Furthermore it involves interpolation of missing lines of video data.

There are many interpolation methods in image processing. Among them, Bilinear and Bi-Cubic are more popular. There were methods that suffer from low quality edge blurring and aliasing effect. On 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, Hajizadeh *et al.* (2009) recommended a new method that uses least directional differences of neighbour pixels, based on preceding bilinear and Bi-cubic interpolation methods for images. The qualitative and quantitative results of proposed technique show that this method improves Bilinear and Bi-Cubic interpolations. The proposed algorithm can also be applied both to RGB and gray level images, where the ratios of quantitative and qualitative resultants are accessed according to the RGB colors and grayscale of an individual image.

Today in the modern era of image processing there is a need of fast and effective image processing interpolation using median filter. Zhang *et al.* (2009) proposed a same fundamental. The interpolation algorithm consists of two basic steps. First, a non-linear iterative procedure is utilized to interpolate the pixel whose direction can be easily determined by local information. Second, according to the introduced assumption that image interpolation can be regarded as a local image filtering process, the remaining pixels are interpolated by the proposed fast median filter method. Experimental results show that the proposed algorithm provides better performance than traditional techniques (e.g. bilinear interpolation, bicubic interpolation) both in subjective quality and objective quality with similar complexity. In particular, the proposed method is comparable to the well-known *NEDI* algorithm in visual quality, however, with much lower computational complexity. Therefore, the proposed algorithm can be exploited for real-time applications due to the merits of low computational complexity and good image quality which is substantially acceptable with favourable results.

Lukin *et al.* (2009) considered 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 which is being customized, dependence of the result on initial approximation, convergence speed, and heuristics to facilitate convergence and improve the visual quality of the resulting image which finally results in variant *PSNR* values. Enhancing an image to a higher resolution or we may refer it as "super-resolution" is typically used for a high-resolution image produced from several low-resolution noisy observations.

There are different varieties and sizes of consumer devices have different resolution sizes of display panels, digital images are frequently required to be resized for each display adaptation. Choi *et al.* (2009) has defined *DCT*-based distortion measures to quantitatively evaluate both scaling and shape distortion generated by downsizing. By utilizing the distortion measures, a novel content-aware image retargeting algorithm is proposed. The proposed algorithm can not only satisfy demands of users without the loss of semantic information in images but also is computationally efficient since the digital images are typically stored in *DCT*-based compression format. Final resultant values show that the proposed method can achieve higher subjective quality with significantly reduced computational loads as compared with existing methods.

In image processing, there is various partial tool analysis and Partial Differential Equations is an important tool in image processing and analysis. A Partial Differential Equations mode for image zooming is introduced by Gao *et al.* (2009). This model expedites on higher order nonlinear partial differential equation. The resulted nonlinear equation is solved by an explicit finite difference schemes. Numerical results on actual digital images are given to show effectiveness and reliability of the proposed using above said methodology.

There is always a possibility of modification on an image. Modification of the new edge-directed interpolation method is presented by Tam *et al.* (2009). The modification eliminates the prediction error accumulation problem with adopting a modified training window structure, and further extends the covariance matching into multiple directions for suppressing the covariance mismatch problem applying that there may never be repetitive *PSNR* in an image. Test results shows that the proposed method achieves remarkable subjective performance in preserving the edge smoothness and sharpness among other methods available in literature survey. It has also been depicted that the values demonstrates consistent objective performance among a variety of images available for inspection.

Extending the properties of an image from its original property is the process for Image Interpolation. Dengwen (2010) suggested that an edge-directed Bicubic Convolution Interpolation which can well adapt to the varying edge structures of images. The test results show that Bicubic Convolution Interpolation reduces common artefacts such as blurring, blocking and ringing *etc*. And thus significantly outperforms some existing interpolation methods in terms of both subjective and objective measures to enhance from original proportions/properties of a regular image.

An important aspect in image is to identify the color difference on a same surface of viewing plane, which is normally not visible through a general vision. Hence to further understand the basic of color identification, Wang *et al.* (2010) have proposed a color filter algorithm which is simple and effective. It is based on a linear interpolating kernel which results in a nontrivial boost on the *PSNR* of red and blue channels. The algorithm can be implemented efficiently for efficient results with differentials.

Adaptive Directional Window selection for the edge-directed interpolation has been discussed by Wong *et al.* (2010). The new window coordinate selection can solve the problem of covariance mismatch in high frequency and texture regions. It makes use of a practical directional elliptic window which works according to the edge direction sliding along an edge and then subsequently chooses the best window evaluated by choosing the elliptic window which has the lowest *MSE*. Initial evaluation results prescribe that by the implemented technique can generate a high quality interpolated image which is better than other edge directed interpolation approaches. Same tests have been conducted on different images to justify the value of this approach successfully.

Zooming is the process of selecting/highlighting a specific area on the image. Jiechao *et al.* (2010) presented two algorithms for zooming images. One combines the methods of pixel replication and bilinear interpolation, by making a choice between them through the difference of adjacent pixels. The other one, based on LAZ (locally adaptive zooming method), improves the cubic spline interpolation method. Both methods have been described in a precise manner. A variation in results have demonstrated that *LAZ* is more suitable in the situation where time-saving is the prime medium and latter emphasizes the quality of magnified image, especially color ones.

The main objective from an image is to first understand the conceptual properties of an image and further objective is to recover high-resolution image from low-resolution image. Feng *et al.* (2010) proposed an edge-adaptive interpolation algorithm for Super-resolution reconstruction. The first step is to obtain a high-resolution image, from a low-resolution image is formed by bilinear interpolation and its edges are detected. Secondly, the edge of the original high-resolution image is refined by two approaches: the first is based on the geometric duality between the low-resolution covariance and the high-resolution covariance while the second is based on its local structure feature. Experimental results demonstrated that the proposed algorithm outperforms three requirement based traditional linear interpolation methods to improve the interpolation effect for super-resolution reconstruction.

Image interpolation problems by means of combining structure tensor with kernel regression methods. Liu *et al.* (2010) proposed an anisotropic structure tensor to adapt the diffusivity along or across the geometric structure of image, for instance image edges. Resultant values show that our new algorithm significantly outperforms the steering kernel regression in persevering edge and improving the visual quality.

A novel image zooming algorithm, called the curvature interpolation method (CIM), which is partial- differential-equation (PDE) based and easy to implement. In order to minimize artifacts arising in image interpolation such as image blur and the checkerboard effect, the *CIM* first evaluates the curvature of the low-resolution image. After interpolating the curvature to the high-resolution image domain, the *CIM* constructs the high-resolution image by solving a linearized curvature equation, incorporating the interpolated curvature as an explicit driving force. It has been numerically verified by Kim *et al.* (2011), that the new zooming method can produce clear images of sharp edges which are already denoised and superior to those obtained from linear methods and *PDE*-based methods of no curvature information. The algorithm provides variable results that are given to prove effectiveness and reliability of the new terminology.

An adaptive edge-directed interpolation algorithm using multidirectional neighbour pixels have been suggested by Yun *et al.* (2011). In order to restore multidirectional edges, a missing pixel is estimated as a weighted sum of 12 neighbour pixels. Based on the geometric duality between a low resolution image and a high resolution image, interpolation coefficients are predicted using Wiener filter theory. In order to reduce the computational complexity, interpolation region selection method is used. An edge map for a low resolution image is obtained by canny edge detector. By analyzing edge continuities, only long edge regions are interpolated using 12 neighbour pixels which expand from the origin in multi-directions. Short edge regions are interpolated by new edge-directed interpolation, and even regions are interpolated by a linear interpolation which gives rise to average values. Simulation results show that a proposed method restores major edges with several directions better than other methods in involving subjective tests while showing relative performance in objective tests.

There may be some hidden prognoses in an image, hence image resizing is widely applied in many fields such as medical image processing, consumer electronics and space application. Li *et al.* (2011) presented a two-phase adaptive image zooming method for gray-scale image magnifying. For each local area under processing, the first work is trying to find a best-matched remote window within the image based on the structural similarity. The second step is then applying the relationship of pixels in the remote window for evolving interpolation functions, which is then used to calculate the expected values of pixels for filling the enlarged grid. The interpolation function varies as the sample window moving across the whole image. Experiment results show that the proposed method is superior to pixel replication and bilinear techniques in terms of visual quality and also emerges the hidden aspects of an image.

Scaling/resizing operation plays an important role in resizing digital images. Scaling is used to perform shrinking (subsampling) and zooming (oversampling) on digital images. Zooming implies enlargement or magnification of an image for better view. Theoretically, Chadda *et al.* (2012) presents broad categorization and comparison of image zooming techniques. Various techniques range from traditional pixel replication, interpolation and advanced techniques based on fuzzy logic. A combination of fuzzy and interpolation gives best results. From implementation point of view *PSNR* and *SSIM* are used to compare the performance of these techniques and provide a differential of individual variables.

Olivier *et al.* (2012), presented the nearest neighbor value (NNV) algorithm for high resolution image interpolation which is being obtained on basis of differential values on a proposed algorithm and conventional nearest neighbor algorithm is that the concept applied, to estimate the missing pixel value from an image. In other words, the proposed concept selects one pixel, among four directly surrounding the empty location, whose value is almost equal to the value generated by the conventional bilinear interpolation algorithm. The method demonstrated higher performances in terms of high resolution when compared to the conventional interpolation algorithms mentioned.

Utilization of various reconstruction modes for image enhancement are utilized in normal studies of image processing, in view of that we refer to cubic-spline interpolation (CSI) scheme which is on same parameters and has same operational structure. Within the parametric *CSI* scheme, it is difficult to determine the optimal parameter for various target images. Lin *et al.* (2012) proposed a novel method involving the concept of opportunity costs to identify the most suitable parameter for the function needed in the *CSI* scheme.

A new image interpolation technique using the bilateral filter to estimate the unknown high-resolution pixels have been presented by Hung *et al.* (2012). Compared with the least-squares estimation, a small-kernel bilateral filter has the advantages of fast computation and stability. The range distance of the bilateral filter is estimated using a novel maximum a posterior estimation, in order to consider both the diagonal and vertical–horizontal correlations. For the consideration of global consistency, the pixel-based soft-decision estimation (SAI) is proposed to constrain the consistency of edge statistic within a local window. Experimental results show that the interpolated images using the proposed algorithm give an average of 0.462, 0.413, 0.532 and 0.036 dB *PSNR* improvement compared with that using the bicubic interpolation, linear minimum mean squares error estimation, new edge-directed interpolation (NEDI) and *SAI* respectively. The result quality agrees with the PSNR as well. More importantly, the proposed algorithm is surprisingly fast and it requires around 1/60 computational cost of the *SAI*.

An automatic digital method for image inpainting has been suggested in which many a times one confronts an image that has an issue related to its presentation. This sort of a problem is referred to as Image inpainting. It is the art of predicting damaged regions of an image. The manual way of image inpainting is a time consuming and difficult to identify minute pixels within an image. Therefore, a novel statistical image inpainting algorithm based on Kriging interpolation technique was proposed by Jassim (2013). Kriging technique automatically fills the damaged region in an image using the information available from its surrounding regions in such manner that it uses the spatial correlation structure of points inside the k×k block.

Exploring an image to achieve a higher *PSNR* is necessary to understand an image biologically, named as, "Image enhancement" - which 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 ample of techniques for image enhancement. Image interpolation is used to do enhancement of any image. Patel *et al.* (2013) has given overview about different interpolation techniques like nearest neighbor, bilinear, bicubic, new edge-directed interpolation (NEDI), data dependent triangulation (DDT), and iterative curvature-based interpolation (ICBI), hence enhancing the study for obtaining a better image resolution.

Jean (2013) discussed about The Bayer Pattern after analysing digitalization which has become a mode of enhancing the image quality of a an object when captured. For digitalization of images, Digital cameras are being used, these objects are more powerful but even if they are smaller, the CCD sensors still associate only one color to each pixel. This mosaic of color, called The Bayer Pattern, must be processed in order to obtain a high resolution color image. Each pixel of this interpolated image has a full spectrum of color based on the colors of the neighbouring pixels. This process is referred as demosaicing or demosaicking.

Lakshman *et al.* (2013) proposed an image interpolation algorithm exploiting sparse representation for natural images. It involves three main steps: (i) to obtain an initial estimate for high resolution image using linear methods like FIR filtering, (ii) to promote sparsity for selected dictionary through iterative thresholding, and (iii) extracting high frequency information from the approximation to refine the initial estimate. For the sparse modeling, a shearlet dictionary is chosen for yielding a multiscale directional representation. The proposed algorithm is compared to several state-of-the-art methods. It provides an average *PSNR* gain of around 0.8 dB as compared to cubic spline interpolation method.

In current scenario, it is not necessary that an image is clicked in high resolution, but there may be a possibility that an image is clicked in low resolution (e.g. mobile phones with low resolution camera and computed tomography (CT) scan medical images) is very challenging problems. It is because of the errors due to quantization and sampling. Over the last several years; significant improvements have been made in this area; however, it is still very challenging. In particularly, zooming of such images is very complicated. For zooming, the process of re-sampling is normally employed. Therefore, Roy *et al.* (2013) focused on investigating the effect of interpolation functions on zooming low resolution images. For this purpose, ideally, an ideal low-pass filter is preferred, however, it is difficult to realize in practice. Therefore, four interpolation functions (nearest neighbor, linear, cubic B-spline and high-resolution cubic spline with edge enhancement) are investigated for the low resolution medical *CT* scan images. From the results, it is found that cubic B-spline and high-resolution cubic spline have a better frequency response than nearest neighbour and linear interpolation functions. When these functions are applied for the purpose of zooming digital images, the best response was obtained with the high-resolution cubic spline functions.

Lakshman *et al.* (2013) suggested a method which involves three steps for proposing an image interpolation algorithm exploiting sparse representation for natural images which are (i) to obtain estimation of the high resolution image by using FIR filtering, (ii) promoting sparsity for a selected dictionary using thresholding and (iii) extracting frequency information which is high from the approximation and adding it to the initial estimate. The proposed algorithm is compared to several state-of-the-art methods and formulated that an average *PSNR* gain of around 0.7 dB is made for the sparse modelling in which a shearlet dictionary is yielded for a multiscale directional representation.

The process of Super Resolution (SR) aims at extracting a high resolution image from low resolution image. Sharma *et al.* (2013), proposed a technique that uses Redundant Wavelet Transform to enhance the resolution of an image using a single low resolution image. The proposed method decomposes the input image into different subbands and then all subbands are interpolated. Combining all the interpolated subbands using Inverse Redundant Wavelet Transform provides the proposed super resolution image. The algorithm is tested with various wavelet types and their performance is compared. The technique is applied on various images which gave higher quantitative *PSNR* and visual results in comparison to other conventional and state-of-art image super resolution techniques.

A new scaling algorithm is proposed for image scaling consisting of a *DWT* based interpolation and bicubic interpolation by Remimol *et al.* (2014) as during the times there may exist an image, that requires scaling, whose fundamental is to use a technique scale down or scale up the pictures or video frames to fit to the application and it is very important in image processing applications. Thus, a simple 'Haar' wavelet based *DWT* interpolation is performed to the image to achieve higher *PSNR* and then bicubic interpolation is carried out to get higher visual quality. The sub band coding based *DWT* divides the image into four quadrants according to frequency. To reduce the artifacts, bicubic interpolation is performed to all the four frequency quadrants. This method achieves less *MSE* and high average *PSNR*. Thus via this *DWT* we can achieve an image quality by a factor more than 8 dB than the existing interpolation methods. The proposed method greatly reduces the image artifacts like blurring, thus this approach is better than existing methods in visual quality.

As reviewed by Sinha *et al.* (2014), several interpolation techniques available to obtain a high quality image and thus various available interpolation techniques to achieve similar purpose was presented. The difference between the proposed algorithm and conventional algorithms (in estimation of missing pixel value) is that if standard deviation of image is used to calculate pixel value rather than the value of near most neighbor, the image gives the better result being obtained analyzing the missing pixel. The proposed method had demonstrated higher performances in terms of *PSNR* and *SSIM* when compared to the conventional interpolation algorithms and has also eliminated the missing pixel.

2.3 CONCLUSION

In conclusion from this Chapter, it has been analyzed from various researches that how the image property transforms when various operations are performed on an image by combining with other techniques and results came out for sharper image as output which has more quality with respect to color, sharpness and less distortion, blurring or noise. But to the far, still there is somewhat distortion or loss of image came out for all the researches. All researchers have given a solution for getting a better image but cannot be used in long run for getting a sharper image in medical science.

CHAPTER 3

IMAGE ZOOMING ALGORITHM USING WAVELET COEEFICIENTS

3.1 INTRODUCTION

The chapter emphasizes one developing the concept to find unique values of an image which has been calculated on the basis of *PSNR*. Here the application of *DWT* is applied by using a discrete set of the wavelet scales on an image and translations obeying some defined rules prescribed as per the given format. The resultant values after the application of algorithm is far better as compared to normal images. They rely on the objective of being with the fact that more the *PSNR* value, the quality resolution and property of the image increases.

3.2 PROPOSED ALGORITHM

Step 1. Transform the image and apply process *DWT* on image.

Step 2. Image is transformed into 4 subbands, say *CA, CH, CV, CD*.

Step 3. Apply zooming methods on each of the four images.

Step 4. Combine into single part applying inverse of *DWT*.

Step 5. The property of the image is double the original size.

Step 6. Compare the current size of the image to original size.

Step 6.1 If the size of the image is not same as of original, make it as of original size.

Step 7. Find *PSNR*.

3.3 IMPLEMENTATION

1. Select X, where X = image.
2. Transform X to A i.e. Apply *DWT* to image.
3. Image is divided into four equal parts. A' = 4.

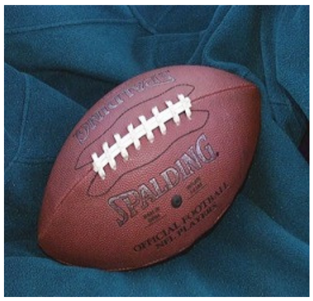
4. On A' apply various methods like Replication (**R**) or interpolation like linear(**i**) , bilinear (**b**), cubic (**c**), bi-cubic (**b_c**), nearest (**N**) & spline (**S**).

5. $X = A'$.

6. A' is 2×(X).

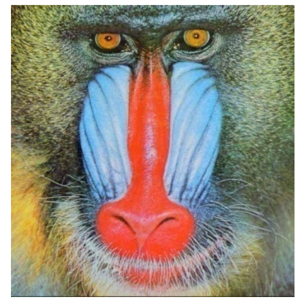
7. Convert A' to size of X. Thus X'' has the equal size of X

8. Evaluate PSNR between X and X''.



(a)

(b)



(c)

(d)

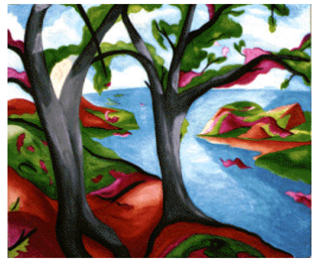
(e)

(f)

(g)

(h)

(i)

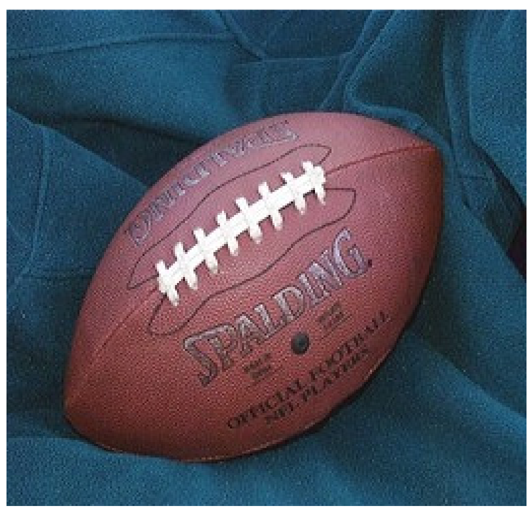


(j) **(k)** **(l)**

Figure 3.1 Image of (a) Football (b)Airplane (c) Baboon (d) Tape (e) Office (f) Lena (g) Onion (h)Pears (i) Peppers (j)Sailboat (k)Trees (l)Canoe

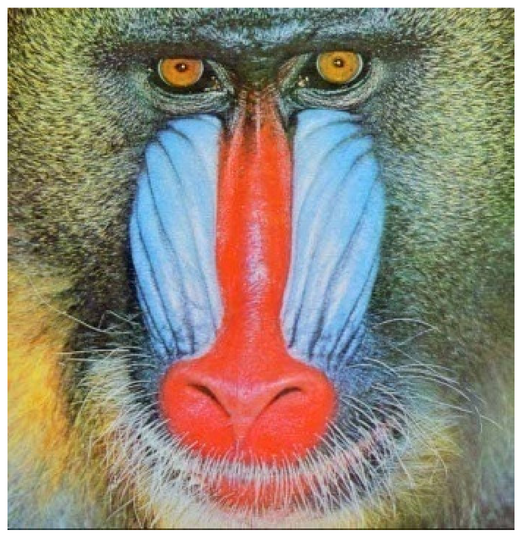
3.4 RESULTS

The images shown in Figure 3.1 are zoomed by 2 using DWT with various interpolation techniques and these images are shown in Figure 3.2. The *PSNR*(dB) calculated between original images and zoomed images are shown in Table 3.1.



(a)

(b)



(c)

(d)

(e)

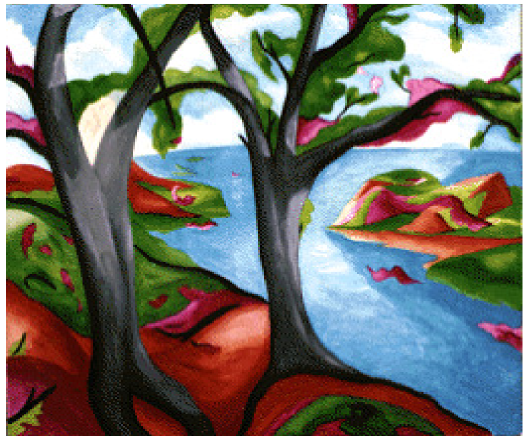
(f)

(g)

(h)

(i)

(j)



(k)

(l)

Figure 3.2 Zoomed images by 2 of (a) Football (b)Airplane (c) Baboon (d) Tape (e) Office (f) Lena (g) Onion (h)Pears (i) Peppers (j)Sailboat (k)Trees (l)Canoe Images

Table 3.1 Calculated *PSNR*(dB) using *DWT* with various Interpolation Techniques

Methods → / Images ↓	**DWT with Pixel Replication**	**DWT with Linear Interpolation**	**DWT with Bilinear Interpolation**	**DWT with Bi-cubic Interpolation**	**DWT with Spline Interpolation**	**DWT with Nearest Neighbor Interpolation**
Football	62.1444	65.1423	66.1123	69.1223	72.3544	74.6268
Airplane	63.2432	65.5544	61.1754	68.2324	74.1646	71.4145
Baboon	60.0028	57.2344	59.3321	66.0032	67.7835	65.2972
Tape	59.7733	56.9092	65.2232	61.2232	73.6646	63.0744
Office	58.6288	56.6789	60.5454	59.4344	68.1805	68.2909
Lena	62.3321	53.4565	67.5443	65.3023	74.5855	68.4338
Onion	61.7639	54.3454	66.4456	60.0120	77.5574	69.5248
Pears	63.2180	58.2322	68.7765	63.7885	76.1646	67.1476
Peppers	60.7421	56.9879	65.6654	66.5560	77.3646	66.1501
Sailboat	60.1035	55.1022	61.1123	64.7877	72.8123	68.6920
Trees	56.5938	53.4544	57.5543	55.5023	67.7169	65.2211
Canoe	62.9805	57.6676	64.1009	66.9023	74.7294	66.3292

The various interpolation techniques with *DWT* are applied on various images and calculated *PSNR* values as shown above in table 3.1. In *DWT* with Pixel Replication, the minimum value obtained is 56.5938 dB and maximum value is 63.2432 dB; the minimum value obtained is 53.4544 dB and maximum value is 65.5544 dB in *DWT* with Linear Interpolation; the minimum value obtained is 57.5543 dB and maximum value is 68.7765 dB in *DWT* with Bilinear Interpolation; the minimum value obtained is 55.5023 dB and maximum value is 69.1223 dB in *DWT* with Bi-Cubic Interpolation; the minimum value obtained is 67.7169 dB and maximum value is 77.5574 dB in *DWT* with Spline Interpolation and the minimum value obtained is 63.0744 dB and maximum value is 74.6268 dB in *DWT* with Nearest Neighbour Interpolation . The difference from remaining interpolation techniques were 11.1231 for minimum value and 14.3142 for maximum value. Thus we have observed that the *DWT* with Spline Interpolation is far better than other interpolation techniques.

3.5 COMPARISON WITH EXISTING ALGORITHM

It is very much necessary to conclude a study and then to compare it with the existing system and to find the relative degree of improvement on the initial phase and current phase. Having a view of the current operational mode we have had a pragmatic approach towards the current values of an image specified by its individual value attributes which had been calculated for attaining *PSNR* of an individual image by applying *DWT* and hence resulting in finding a differential values provided by a single image using different techniques.

A model graph had been prepared in an order to depict the difference of values of the image when taken in consideration.

Table 3.2 Graphical Depiction of Compared Values of *PSNR*(dB)

Image ⟶ / Technique ↓	Lena	Peppers	Airplane	Baboon
Li *et al.* (2001)	28.9711	25.9223	33.4687	23.5409
Mueller *et al.* (2007)	30.2921	29.3912	24.0612	25.8587
Gupta *et al.* (2007)	31.5587	30.9822	28.4022	24.6343
Zhang *et al.* (2009)	33.6223	31.7465	30.4934	32.4623
Jiechao *et al.* (2010)	33.9879	34.3757	32.2515	30.3891
Lin *et al.* (2012)	35.3798	32.6584	32.2454	30.5001
Olivier *et al.* (2012)	33.1655	34.5060	32.9235	35.4771
Lakshman *et al.* (2013)	34.8154	28.4012	31.4134	30.8412
Sharma *et al.* (2013)	33.0844	32.8033	32.4376	29.3343
Jassim *et al* (2013)	41.3416	43.9334	40.3283	33.3432
Remimol *et al.* (2014)	44.1245	41.9420	39.4889	42.2254
Sinha *et al.* (2014)	27.4432	26.3324	27.3432	28.5564
Proposed Algorithm	74.5855	77.3646	74.1646	67.7835

The above tabular notation depicts the obtained values of images on which the various operations had been applied by different researches, where observational value is recorded parallel to Proposed Algorithm, stating the application of DWT applied before obtaining the resultant values. The marginal difference is more than 22% when calculated as an average for all the values when compared.

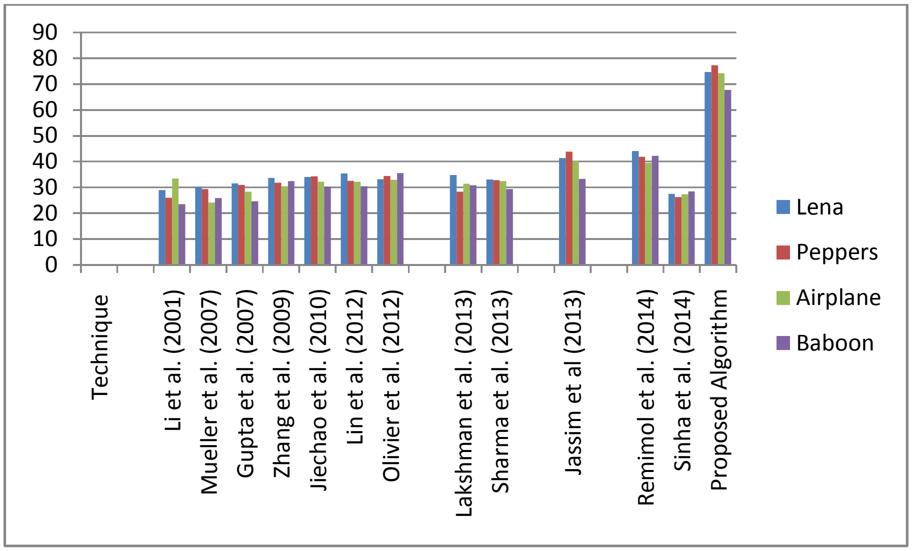


Figure 3.3 Graphical notation of abstracted value based tabulation

Hence when we observe the graphical notation of the comparison chart, we identify that the existing study and operations performed on images to obtain PSNR values, which are relatively low as compared to the embedded study that has been carried out in thesis work, by implementing the images with DWT which enhances the overall presentation of image. The above operation of implementing the various operational values have been the same for all the literature surveys on a single image, and the same image is calculated with higher values depicting the variation of change.

3.6 CONCLUSION

We have successfully implemented operation on an image through proposed algorithm, and found results, which contribute towards the fundamental building of a new research methodology for image processing. These values may vary when we take a different image in consideration. The sum up of the entire process is that the algorithm defines the analogy for implementing various operations on an image for achieving the objective.

CHAPTER 4

CONCLUSION AND FUTURE SCOPE

4.1 CONCLUSION

Throughout the research work, our motive had been to enhance the property aspect of the image, by performing various operations on the image and during the course of these operations, we had finally applied *DWT*. In the research paper, we have described all the aspects various images without and with application of interpolation techniques and *DWT* Algorithm application. The applicability of *DWT* processing, is a function by virtue of which is an implementation of the digital wavelet transform using a discrete set of the wavelet scales on an image and translations obeying some defined rules prescribed as per the given format, and it can be executed as per the available values of the image, and then can further be divided into 4 different parts and each of the part can further be evaluated individually, and independent values can be obtained applying different set of rules on all the four different images. In other words, this transform decomposes the signal into mutually orthogonal set of wavelets.

In conclusion, in *DWT*-based operations are appropriate that transforms with the image have a positive impact on performance of enhancing the property aspects.

4.2 FUTURE SCOPE

Since, much of research work on image processing is done, the future scope of the research work can be accessed or implied on the following directions:

- The first extension of the existing study can be implemented on Mammography based imaging. By using the functional capability of *DWT* same can be applied on the medical science imaging technique to improve upon existing image processing system in Mammography.

- The second extension can be made on customization of improved property of images by a two step formulation, first to apply *DWT* and then to watermark the obtained image with maintained image quality.

REFERENCES

[1] Allebach J., Wong P.W., "Edge-directed interpolation", International Conference on Image Processing, Volume 3, pp 707-710, 1996.

[2] Chadda S., Kaur N., Thakur R., "Zooming Techniques for Digital Images: A Survey", International Journal of Computer Science And Technology, Vol. 3, Issue 1, pp 519-523, 2012

[3] Choi K.-S., Ko S.-J., "Fast Content-Aware Image Resizing Scheme in the Compressed Domain", Transactions on Consumer Electronics, Vol. 55, No. 3, pp 1514-1521, 2009.

[4] Dengwen Z., "An Edge-Directed Bicubic Interpolation Algorithm", 3rd International Congress on Image and Signal Processing, Volume 3, pp 1186-1189, 2010.

[5] Feng W. X., Fei L. H., "An Edge-Adaptive Interpolation Algorithm for Super-Resolution Reconstruction", International Conference on Multimedia Information Networking and Security,Volume 2, pp 81-84, 2010.

[6] Gao R., Song J. P., Tai X. C., "Image Zooming Algorithm Based On Partial Differential Equations Technique", International Journal of Numerical Analysis and Modeling, Volume 6, Number 2, pp 284–292, 2009.

[7] Gupta R. B., Lee B. G., Lee J. J., "A New Image Interpolation Technique Using Exponential B-Spline", International Journal of Emerging Trends & Technology in Computer Science, Dongseo University, Busan, S.Korea, pp 169-176, 2007.

[8] Hajizadeh M., Helfroush M. S., Tashk A., "Improvement of Image Zooming Using Least Directional Differences based on Linear and Cubic Interpolation", 2nd International Conference on Computer, Control and Communication, pp 1-6, 2009.

[9] Hung K.-W. Siu W.-C., "Fast Image Interpolation Using The Bilateral Filter", The Institution of Engineering and Technology Image Processing, Vol. 6, Iss.

7, pp. 877–890, 2012.

[10] Jassim F. A., "Image Inpainting by Kriging Interpolation Technique", World of Computer Science and Information Technology Journal, Vol. 3, No. 5, pp 91-96, 2013.

[11] Jean R., "Demosaicing with The Bayer Pattern", International Conference of Acoustic, Speech and Signal Processing, University of North Carolina, pp 11-15, 2013.

[12] Jeong B. G., Kim H. S., Kim S. C., Eom I.K., "Edge-Adaptive Demosaicking For Reducing Artifact Along Line Edge", Congress on Image and Signal Processing, pp 316-319, 2008.

[13] Jiechao W., Zhiwei L., Min Z., "Two New Proposed Image Zooming Methods", 6th International Conference on Wireless Communications Networking and Mobile Computing, pp 1-4, 2010.

[14] Kim H., Cha Y., Kim S., "Curvature Interpolation Method for Image Zooming", IEEE Transactions on Image Processing, Vol. 20, No. 7, pp 1895-1903, July 2011.

[15] Lakshman H., Lim W.-Q, Schwarz H., Marpe D., Kutyniok G., Wiegand T., "Image Interpolation Using Shearlet Based Iterative Refinement", International Conference on Image Processing , IEEE, Aug 2013.

[16] Lakshman H., Lim W.-Q, Schwarz H., Marpe D., Kutyniok G., Wiegand T., "Image Interpolation Using Shearlet Based Sparsity Priors", The International Conference on Image Processing, IEEE, pp 655-659, 2013.

[17] Li J., Xin M., Jin J., "An Evolutionary approach for Gray-level Image Zooming", NASA/ESA Conference on Adaptive Hardware and Systems, pp 383-389, 2011.

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

[19] Lin T. C., Truong T. K., Hong S. H., Wang L., "Novel Approaches to the Parametric Cubic-Spline Interpolation", Image Processing and Computer Vision, Volume 4, pp 448-454, 2012.

[20] Liu H., Wei Z., "An Edge-adaptive Structure Tensor Kernel Regression for Image Interpolation", 2nd International Conference on Future Computer and

Communication, Vol 2, pp 681-685, 2010.

[21] Lukin A., “High-Quality Spatial Interpolation of Interlaced Video”, Laboratory of Mathematical Methods of Image Processing, Computer Vision and Graphics, pp 301-307, 2008.

[22] Lukin A., Krylov A. S., Nasonov A., “Image Interpolation by Super-Resolution”, Innovations and Advanced Techniques in Computer and Information Sciences and Engineering, pp 483-489, 2009.

[23] Mueller N., Lu Y., Do M. N., “Image Interpolation Using Multiscale Geometric Representations”, International Society for Optics and Photonics, Electronic Imaging, pp 11-16, 2007.

[24] Olivier R., Hanqiang C., “Nearest Neighbor Value Interpolation”, International Journal of Advanced Computer Science and Applications, Vol. 3, No. 4, pp 318-321, 2012.

[25] Patel V., Mistree K. , “ A Review on Different Image Interpolation Techniques for Image Enhancement”, International Journal of Emerging Technology and Advanced Engineering, Volume 3, Issue 12, pp 129-133, 2013.

[26] Remimol A.M., Sekar K., “A Method of DWT with Bicubic Interpolation for Image Scaling”, International Journal of Computer Science Engineering, Vol. 3 No.02, pp 131-135, 2014.

[27] Roy R., Pal M., Gulati T., “Zooming Digital Images using Interpolation Techniques”, International Journal of Application or Innovation in Engineering & Management, pp 34-45. Volume 2, Issue 4, 2013.

[28] Sharma A., Swami P. D., “ Redundant Wavelet Transform Based Image Super Resolution”, International Journal of Engineering Research and Applications, Vol. 3, Issue 4, pp.2055-2062, 2013.

[29] Sinha A., Kumar M., Jaiswal A.K., Saxena R., “Performance Analysis Of High Resolution Images Using Interpolation Techniques In Multimedia Communication System”, Signal & Image Processing : An International Journal, Vol.5, No.2, pp 39-49, 2014.

[30] Tam W.-S., Kok C.-W., Siu W.-C., “A Modified Edge Directed Interpolation For Images”, 17^{th} European Signal Processing Conference, Glasgow, Scotland, pp 283-287, 2009.

[31] Wang M., Blu T., "Generalized Yuv Interpolation of CFA Images", 17th International Conference on Audio Language and Image Processing, Hong Kong, pp 1062-1065, 2010.

[32] Wong C. S., Siu W. C., "Adaptive Directional Window Selection for Edge-Directed Interpolation", 19th International Conference on Computer Communications and Networks, pp 1-6, 2010.

[33] Yun Y., Bae J., Kim J., "Adaptive Multidirectional Edge Directed Interpolationfor Selected Edge Regions", TENCON 2011- Conference , pp 385-388 , 2011.

[34] Zhang J., Ma S., Zhang, Zhao D., "Fast and Effective Interpolation Using Median Filter", Pacific-Rim Conference on Multimedia, pp. 1176–1186, 2009.