“An Algorithm for Image Sharpening and Edge Detection using DWT-UM”

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CERTIFICATE

I, Amisha, hereby certify that the work which is being presented in this thesis entitled "**An Algorithm for Image Sharpening and Edge Detection using DWT-UM**" by me in partial fulfillment of the requirements for the award of degree of master of Engineering in Electronics & Communication from Thapar University (Deemed University), Patiala, is an authentic record of my own work carried out under the supervision of Mr. Ankush Kansal.

The matter presented in this thesis has not been submitted in any other University/ Institute for the award of Master of Engineering.

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Signature of the Student
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This is certified that the above statement made by the candidate is correct to the best of my knowledge.

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ABSTRACT

The field of Digital Image Processing (DIP) continues on a path of energetic growth in terms of popular and scientific interest and the number of commercial applications since 1970. The discipline of DIP covers a wide area of technical and engineering knowledge. It is built on a base of 1D and 2D signal processing theory. Broadly, image processing may be subdivided into the following categories: restoration, enhancement, coding, and understanding. The purpose of the first three categories is to improve the pictorial information either in quality (for purposes of improving visual appearance) or in transmission efficiency. In the last category, the objective is to obtain a symbolic description of the scene, leading to autonomous machine reasoning and perception. In this thesis our aim is to enhance the image for purpose of human interpretation and improving visual appearance.

To improve the visual appearance of an image, image enhancement is done through the proper increment of contrast and brightness. Brightness refers to the overall lightness or darkness of the image. Contrast is the difference in brightness between objects or regions. But to make the image more clear and informatics, sharpening of edges are done. The sharp edges which makes it more pleasant to human eye and can be used for further image processing such as edge detection, segmentation etc. The amount of edge sharpening is much better than others existing sharpening methods.

Sharpening is one of the most impressive transformations one can apply to an image since it seems to bring out image details that were not there before. A large number of algorithms have been designed for this purpose such as Unsharp Masking (UM), Gaussian and Laplacian filtering etc. In our proposed algorithm we have chose UM due to its simple calculation and less time of processing.

In this thesis we have also measured the amount of sharpness by using the percentage of rise in values parameter. Finally the results for the image enhancement by using UM and DWT-UM techniques have been compared and have shown that there is enormous enhancement in image reproduction by using the proposed algorithm.

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List of Acronyms

C:

CWT:	Continuous Wavelet Transform

D:

DCT:	Discrete Cosine Transform
DWT :	Discrete Wavelet Transform

F:

FDWT:	Forward Discrete Wavelet Transform
FIR:	Finite Impulse response
FFT:	Fast Fourier Transform

G:

GIS:	Geographical Information System

H:

HE:	Histogram Equalization

I:

IHS:	Intensity-Hue-Saturation
IDWT:	Inverse Discrete Wavelet Transform

L:

LDWT:	Lifting-based Discrete Wavelet Transform

O:

OFDM:	Orthogonal Frequency Division Multiplexing

P:

PA:	Proposed Architecture

Q:

QMF:	Quadrature Mirror Filters

S:

SRHE:	Sub Regions Histogram Equalization
SMDWT :	Symmetric Mask-based Discrete Wavelet Transform
STFT:	Short Time Fourier Transform

U:

UM:	Unsharp Masking

Chapter 1

Introduction

1.1 Images and pictures

We depend heavily on our vision to make sense of the world around us. We not only look at things to recognize them, but we can scan for differences, and obtain an overall rough feeling for a scene with a quick look. Humans have very exact visual skills: we can recognize a face in an instant; we can differentiate colors; we can process a large amount of visual information very quickly.

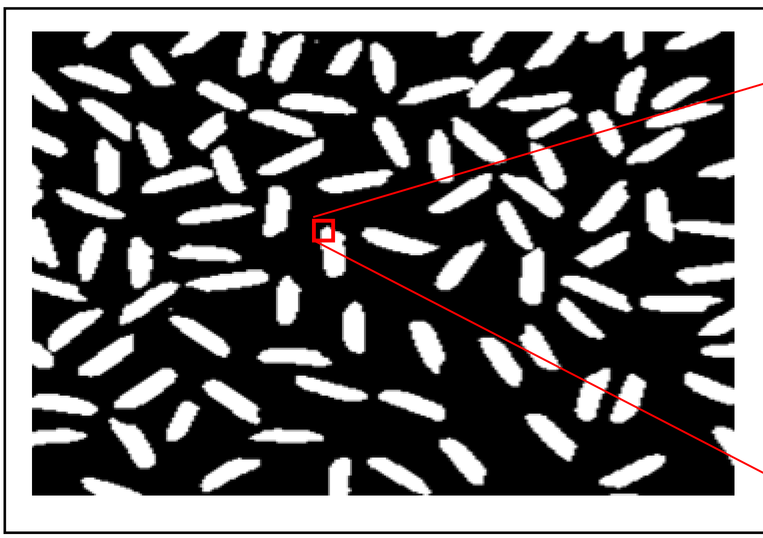
For our purposes, an image is a single picture which represents something. It may be a picture of a person, of people or nature, or of an outdoor scene, or the result of medical imaging, or a microphotograph of an electronic component, An image is represented as a Two Dimensional (2D) array of coefficients also called pixels, each coefficient representing the brightness level in that point. It is not possible to differentiate between coefficients, which are more important ones, and lesser important ones. But thinking more naturally, it is possible. Most natural images have smooth color variations, with the fine details being represented as sharp edges in between the smooth variations [1].

1.2 Types of Digital Images

Images are considered as two dimensional functions, where function values gives brightness of image at any point. We may assume that brightness values can be any real number from 0.0 to 1.0. 0 representing the black color and 1 represents the white color. This is called continuous image. But image analysis of this type of function is very difficult because they give a huge range of brightness values. Image analysis can be done easily if we make this range discrete that is also called digital image. Digital images are picture that have been converted into a computer readable binary format consisting of logical 0s and 1s [2]. Usually digital images take on integer values from 0 (Black) to 255 (White). A digital image can be considered as a large array of sampled points from the continuous image, each of which has a particular quantized brightness; these points are the pixels which constitute the digital image. The pixels surrounding a given pixel constitute its neighborhood. Here are four basic types of images:

Binary Image: -

This type of image is also called black and white image. In this type of images, each pixel is only black or white. So we only need one bit per pixel, since there are only two possible values for each pixel. Such images can therefore be very efficient in terms of storage. Examples of Binary image includes text (printed or handwriting), fingerprints, or architectural plans. An example was the image shown in fig. 1.1. In this image, we have only the two colors: white for the rice, and black for the background. Here we have observed some part of it. Every pixel has logical value either 1 or 0 value. Value 0 represents black and 1 represents white.



0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	0
0	0	0	0	0	1	1	1
0	0	0	0	1	1	1	1
0	0	0	0	1	1	1	1
0	0	0	0	1	1	1	1

Figure1.1: An example of binary image [3]

Grayscale Image: -

In this type of images, each pixel is a shade of gray, normally from black to white. The range between black and white can be divided into 256 parts. So each pixel can be represented by eight bits, or exactly one byte since $2^8 = 256$. This is a very natural range for image handling.

Other grayscale ranges are used, but generally they are a power of 2. Such images arise in medicine (X-rays), images of printed works, and indeed different gray levels are sufficient for the recognition of most natural objects. An example is the sea scene shown in fig. 1.2 with gray values ranging from 0 to 255 [4].

236	233	232	232	233	235	236
231	230	231	232	233	234	233
237	243	242	242	241	242	243
235	237	230	219	205	194	187
135	152	148	141	130	120	112
107	94	99	105	108	108	106
100	110	115	112	100	92	97

Figure 1.2: An example of grayscale image [5]

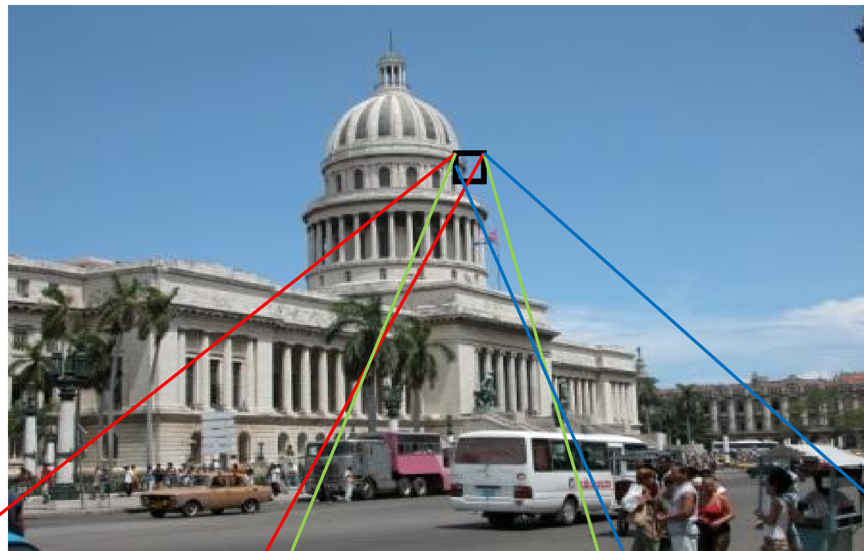
True Image or Red Green Blue (RGB) Image: -

Here each pixel has a particular color; that color is described by the amount of red, green and blue in it. If each of these colors has a range 0 to 255 this gives a total of 256^3= 16777216 different possible colors in the image. This is sufficient colors for any image. Since for every color 8 bits are required so a total of $8 \times 3 = 24$ bits required for each pixel. Such images are also called 24-bit color images.

Since each pixels have three values of red, green and blue. So image can be represented by a stack of 3 matrices; representing the red, green and blue values for each pixel [6]. An example of true color image is shown in fig.1.3, along with 3 matrices representing a small part of that image.

Indexed Image: -

This is also known as pseudo color image**.** Most color images only have a small subset of the more than sixteen million possible colors. This type of image has a linked color map or color palette, which is simply a list of all the colors used in that image.



141	122	111	109	108
158	139	120	110	104
132	124	117	115	111
126	111	110	117	115
146	114	104	110	111
132	103	90	98	110
141	117	95	96	106
107	128	106	83	113

Red

162	152	150	154	159
177	167	156	154	155
149	150	152	159	160
144	138	145	159	162
162	139	137	153	158
148	128	124	141	157
151	136	122	132	148
108	136	123	106	146

Green

181	178	183	193	204
194	191	190	193	200
165	173	184	196	203
158	159	175	197	206
175	161	168	188	200
161	150	152	176	199
161	153	149	166	188
113	147	143	137	181

Blue

Figure 1.3: An example of RGB image [7]

Each pixel has a value which does not give its color (as for an RGB image), but an index to the color in the map [8] as shown in fig 1.4. It is convenient if an image has 256 colors or less, for then the index values will only require one byte each to store. So this helps in file handling and convenience of storage.

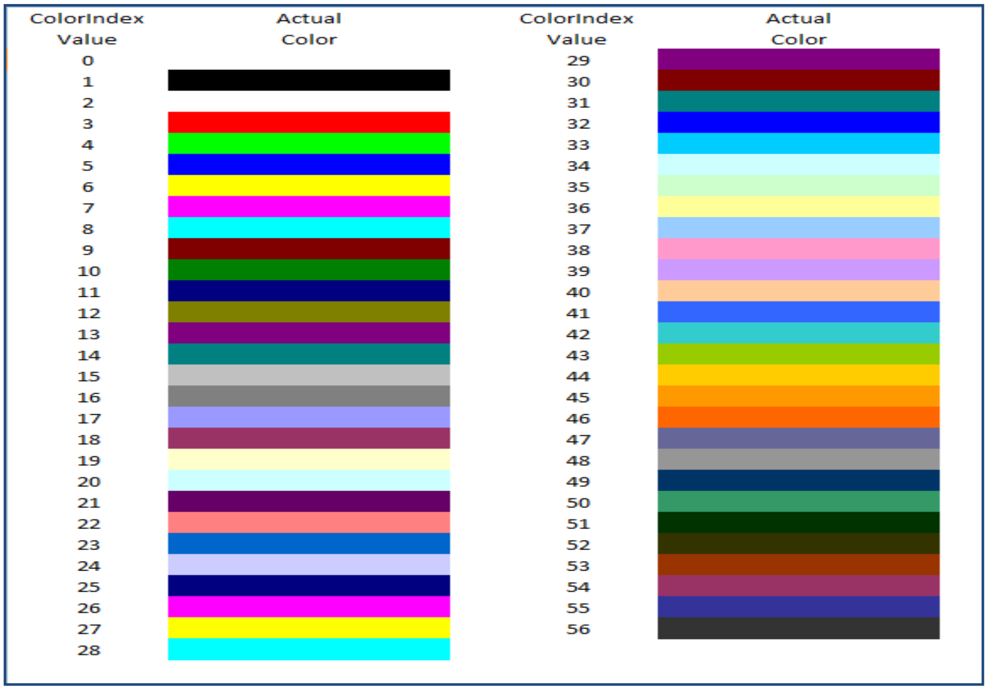


Figure 1.4 Color map or palette [9]

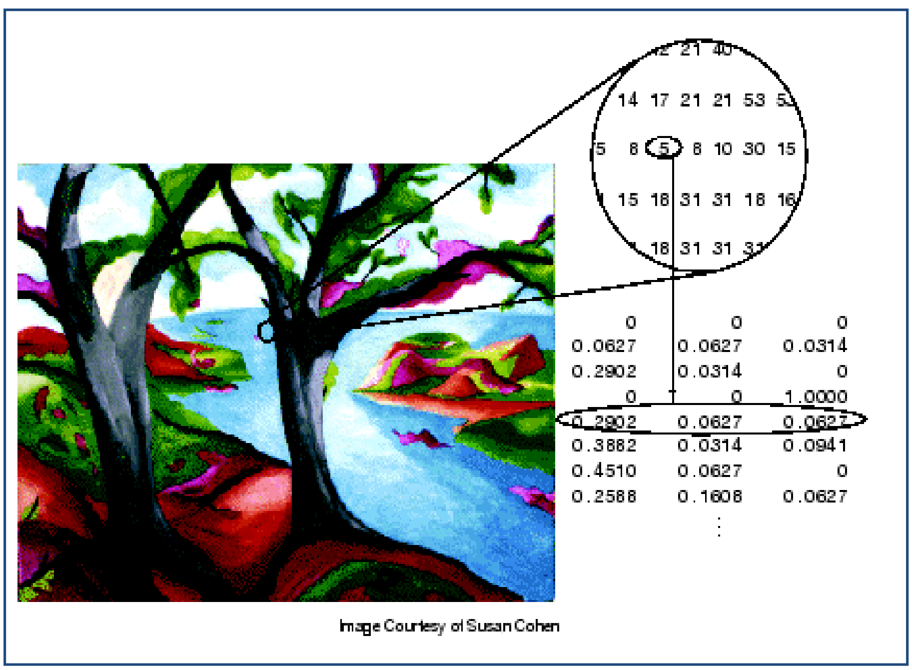


Figure 1.5: An example of indexed image [3]

Fig. 1.5 shows an example. In this image the indices, rather than being the color values of the pixels, are simply indices into the color map. Without the color map, the image would be very dark and colorless. In the fig. 1.5, for example, pixels labeled 5 correspond to 0.2902, 0.0627 and 0.0627, which is a light bluish color.

1.3 Features of Digital Image Processing

To change or modify the nature of an Image, processing is done on the pixels level. This is done to:

1. Improve its pictographic information for human interpretation,
2. Turn into it more suitable for autonomous machine perception [10].

These two features represent two separate but equally important aspects of DIP. A procedure which satisfies condition first to make an image look better may be the very worst procedure for satisfying condition second. Humans like their images to be sharp, clear and detailed; machines prefer their images to be simple and ordered.

Objectives of first may include:

- To improve the image brightness and contrast. Fig 1.6 (a) Show an original image, (b) shows the image after changing its contrast and (c) shows after increasing the brightness [11].

(a) Original image [12]

(b) Image after increasing the contrast

(c) Image after increasing the brightness

Figure 1.6: Effect of increasing contrast and brightness of an image

- To enhance the edges of an image to make it appear sharper and clear than before. Fig 1.7 shows the difference between an image and after sharpening that image [13].

(a) The original image [14]

(b) Result after sharpening

Figure 1.7: Image sharpening

- To eliminate the noise from an image. Noise is unwanted information that is added with image data during image transmission or transformation [15]. Noise may take many different forms; each type of noise requiring a different procedure of removal fig.1.8 shows a noisy image and recovered image after removing the noise

(a) The original image [16] (b) After removing noise

Figure 1.8: Removing noise from an image

- Restoration of an image. It includes removing motion blur from an image [17], removal of optical distortion and removal of periodic interference.

(a) The original image [18] (b) After removing the blur

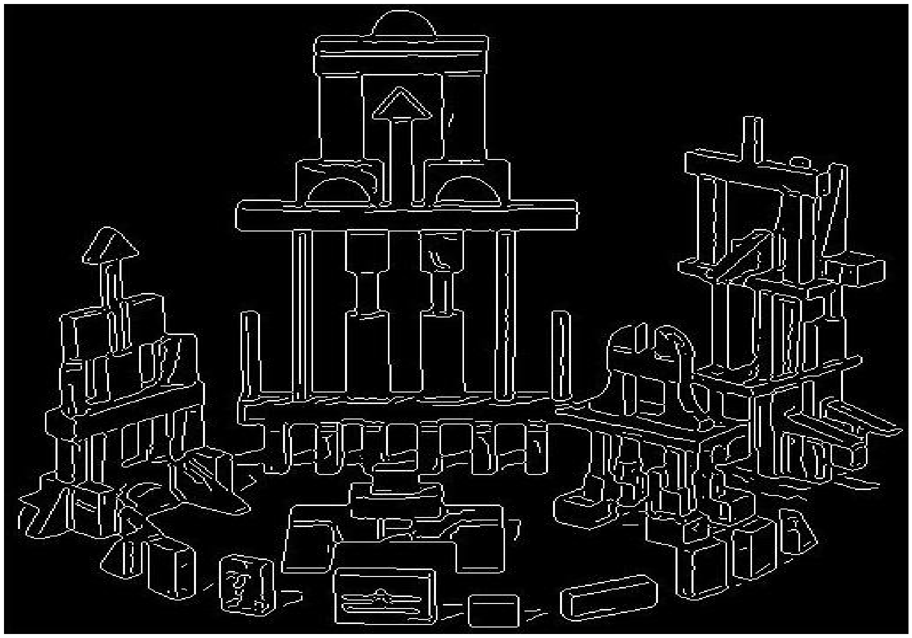
Figure 1.9: Image de-blurring

Motion blur may occur when the shutter speed of the camera is longer than the speed of the object In photographs of fast moving objects for example athletes, vehicles etc. the problem of blur may be considerable. An example is given in fig. 1.9.

Objectives of second may include:

- Removing detail from an image. For measurement or counting purposes, we may not be interested in all the detail in an image. For example, a machine inspected items on an assembly line; the only matters of interest may be shape, size or color. For such cases, we might want to simplify the image.
- Image segmentation. This involves isolating certain features of an image such as finding lines, circles or particular shape in an image.
- To measure the spread and area contained within the objects in an image. It is done by obtaining the edges of an image. So it is necessary to enhance the original image to some extent, to make the edges clearer. Edge enhancement is done as a first step in edge detection [19]. An example of edge detection is shown in fig. 1.10

(a) The original image [20]



(b) Its edge image

Figure 1.10: Finding edges in an image

1.4 Processing methods in DIP

Any image processing operation transforms the gray values of the pixels. However, image processing operations may be divided into three classes based on the information required to perform the transformation [21]. From the most complex to the simplest, they are:

1.4.1 Point operations:-

In this type of operation values of pixels are modified according to a defined rule and modification in value of a pixel does not depend on other pixel's values means they are independent of each other [22]. Although Point operations are the simplest; they contain some of the most powerful and widely used of all image processing operations. They are especially useful in image pre-processing, where an image is required to be modified before the main job is attempted. These operations act by applying a simple function given by (1.1), to each gray value in the image.

$$y = f(x), \tag{1.1}$$

Thus *f(x)* is a function which maps the range 0…255 onto itself. Simple functions include adding or subtract a constant value to each pixel or multiplying each pixel by a constant:

$$y = x \pm c \tag{1.2}$$

$$y = cx \tag{1.3}$$

In each case we may have to fiddle the output slightly In order to ensure that the results are integers in the 0…255 range. We can do this by first rounding the result (if necessary) to obtain an integer and then "clipping" the values by setting:

$$y = \begin{cases} 255 & if\ y > 255, \\ 0 & if\ y < 0. \end{cases} \tag{1.4}$$

In general adding a constant will lighten an image, and subtracting a constant will darken it. Similarly on multiplying with a constant will brighten the image and by dividing with a constant will darken the image. A sample image is shown in fig 1.11(a). After adding 75 value in each pixel we get a brighten image as shown in fig.1.11 (b) and if we subtract 75 from each pixels value of image in fig 1.11 (a) then we get a darken image as shown in fig.1.11(c)

(a) Original image [23]

(b) After adding 75 to each pixel in original image

(c) After subtract 75 to each pixel in original image

Figure 1.11: Effects of point operations on the quality of image

The complement of a grayscale image is its photographic negative [24]. If an image x of matrix m by n is of type double and so its gray values are in the range 0.0 to 1.0, we can obtain its negative with applying the point function. We have taken an image as shown in fig.1.12 (a) and do the following function and get the negative of that image as shown in fig.1.12 (b)

$$y = ones(m, n) - x(m, n) \tag{1.5}$$

(a) Original image [25]

(b) Complementary of original image

Figure 1.12: Effect of complementary or inversion

1.4.2. Neighborhood processing: -

In this type of operation modified value of a pixel not only depends on itself value but on others pixels values surrounding it also. This is called Neighborhood processing. This includes Average filtering, Laplacian filtering, high and low pass filtering etc.

The idea is to move a rectangle or other shape over the given image, this shape is also called mask [26]. We create a new image whose pixels have grey values calculated from the grey values under the mask, using a defined rule. The combination of mask and function is called a filter. If the function by which the new grey value is calculated is a linear function of all the grey values in the mask, then the filter is called a linear filter.

A linear filter can be implemented by multiplying all elements in the mask by corresponding elements in the neighborhood, and adding up all these products. This procedure is shown in fig. (1.13)

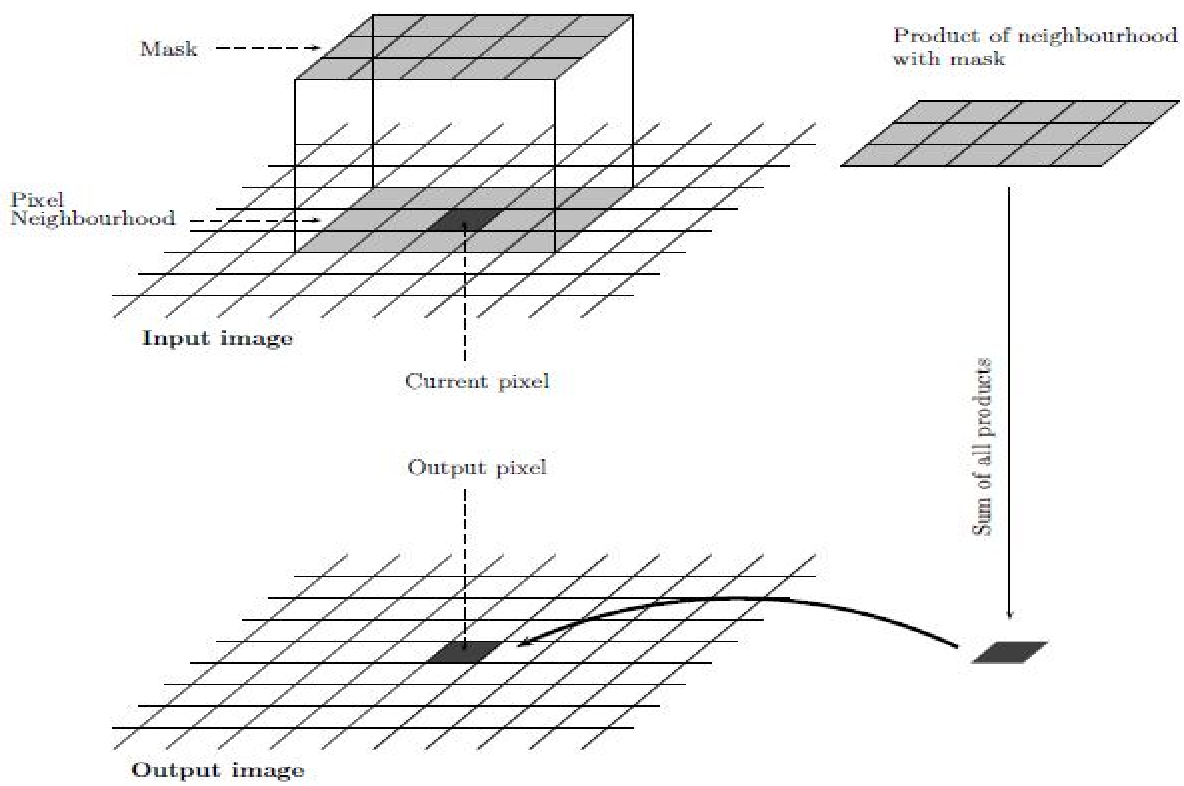


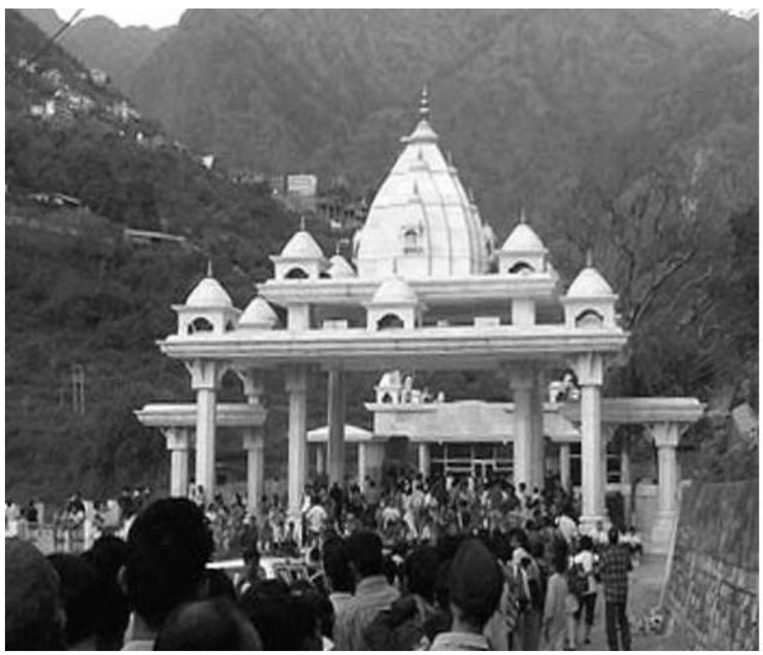
Figure 1.13: performing spatial filtering [26]

Spatial filtering thus requires three steps:

1. Position the mask over the current pixel,
2. Form all products of filter elements with the corresponding elements of the neighborhood,
3. Add up all the products.

This must be repeated for every pixel in the image.

Here we see the neighborhood processing with a sample image as shown in fig. 1.14 (a). The function used in this operation is average filtering. We have used average filter of size '7×7'. Due to average filtering high frequency components eliminates and no effect is there on the low frequency components or pixels [27]. So resultant image as shown in fig 1.14 (b) is not clear and not sharp.



(a) Original image [28]

(b) After average filtering the original image

Figure 1.14: Effect of average filtering

1.4.3. Transforms: -

In this operation entire image is processed as a single block. . A “transform” represents the pixel values in some other, but equivalent form. The Transform is of fundamental importance to image processing. Its efficiency allows us to perform tasks more quickly which would be impossible to perform any other way. For example the Fourier Transform (FT) provides a powerful alternative to linear spatial filtering; it is more efficient to use the Fourier transform than a spatial filter for a large filtering operation. FT also allows us to isolate and process particular image frequencies, and so perform low-pass and high-pass filtering with a great degree of precision. Others examples of Transform are Short Time Fourier Transform (STFT), Laplace Transform, Discrete Wavelet Transform (DWT), Discrete Cosine Transform (DCT) etc.

1.5 Unsharp Masking (UM)

The idea of Unsharp Masking (UM) is to subtract a scaled "Unsharp" version of the image from the original. We can achieve this by subtracting a scaled blurred image from the original image. The scheme for UM is shown in fig. 1.15 and is discussed by Alasdair McAndrew [29].

The input-output relation for the Unsharp masking filter can be written as follows:

$$y = x - k \times z. \tag{1.6}$$

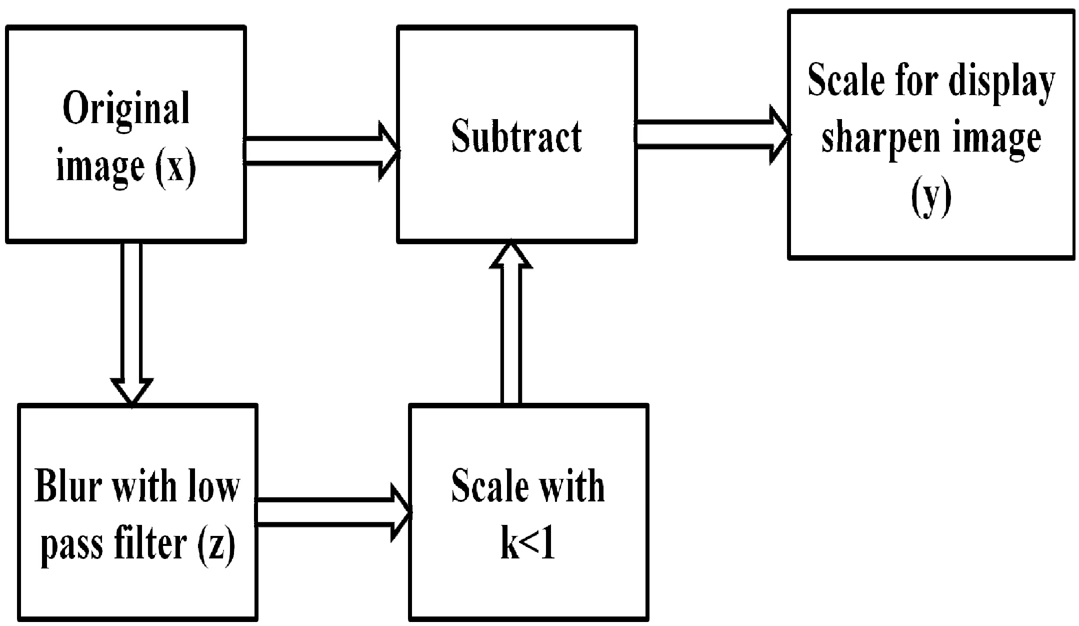


Figure 1.15: Procedure of Unsharp Masking (UM)

where *x*, *y* are the input and output images and *k* is a positive constant which controls the fraction of low pass filtered image *z* to be subtracted from the input original image. The eq. (1.6) demonstrates that an UM filter operates by subtracting appropriately weighted parts of the UM from the original image. Such a subtraction operation enhances high-frequency spatial information in the image. This occurs because high frequency spatial detail removed from the unsharp mask by low pass filter is not subtracted from the original image. In addition, here low frequency spatial details that were passed by low pass filter were almost entirely subtracted from the original image. This explains why increasing the size of low-pass filter mask usually causes to produce a sharper image.

This is a simple method, but it has two drawbacks. First it enhances the noise present in the image. Second, it enhances too much the sharp transition which leads to excessive overshoot on sharp edges [30]. For an image containing very fine detail, this method is not so effective. Here we proposed an algorithm that will derive the very fine details of an image. In this we used the concept of DWT as well as UM

1.6 Wavelets

A wavelet is a wave-like oscillation with amplitude that starts out at zero, increases, and then decreases back to zero. It can typically be visualized as a "brief oscillation" like one might see recorded by a seismograph or heart monitor. Generally, wavelets are purposefully crafted to have specific properties that make them useful for signal processing. Wavelets can be combined, using a "shift, multiply and sum" technique called convolution, with portions of an unknown signal to extract information from the unknown signal [31].

More technically, a wavelet is a mathematical function used to divide a given function or continuous-time signal into different scale components. Usually one can assign a frequency range to each scale component. Each scale component can then be studied with a resolution that matches its scale. A wavelet transform is the representation of a function by wavelets. The wavelets are scaled and translated copies (known as "daughter wavelets") of a finite-length or fast-decaying oscillating waveform (known as the "mother wavelet"). Wavelet transforms have advantages over traditional Fourier transforms for representing functions that have discontinuities and sharp peaks, and for accurately deconstructing and reconstructing finite, non-periodic and/or non-stationary signals.

1.6.1 History of wavelets

The first recorded mention of what is now called a "wavelet" seems to be in 1909, in a thesis by Alfred Haar, discussed by Daubechies [32]. Notable contributions to wavelet theory can be attributed to Zweig’s discovery of the continuous wavelet transform in 1975 (originally called the cochlear transform and discovered while studying the reaction of the ear to sound), Pierre Goupillaud, Grossmann and Morlet's formulation of what is now known as the CWT (1982), Jan-Olov Stromberg's early work on discrete wavelets (1983), Daubechies orthogonal wavelets with compact support (1988), Mallat's multi-resolution framework (1989), Nathalie Delprat's time-frequency interpretation of the CWT (1991) [33], Newland's Harmonic wavelet transform (1993) and many others since.

1.6.2 Wavelet Families

There are different types of wavelet families whose qualities vary according to several criteria. The main criteria are

- The symmetry, which is useful in avoiding de-phasing in image processing.
- The number of vanishing moments for mother wavelet (ψ) or for scaling function (ϕ) (if it exists), which is useful for compression purposes.
- The regularity, which is useful for getting nice features, like smoothness of the reconstructed signal or image, and for the estimated function in nonlinear regression analysis [3]

These are associated with two properties that allow fast algorithm and space-saving coding:

- The existence of a scaling function.
- The orthogonality or the bi-orthogonality of the resulting analysis.

They may also be associated with these less important properties:

- The existence of an explicit expression
- The ease of tabulating
- The familiarity with use

These wavelets families are:

1. Haar wavelet
2. Daubechies wavelets
3. Symlets
4. Coiflets
5. Biorthogonal wavelets
6. Reverse Bi-orthogonal wavelets

7. Meyer wavelet
8. Discrete approximation of Meyer wavelet
9. Gaussian wavelets
10. Mexican hat wavelet
11. Morlet wavelet
12. Complex Gaussian wavelets
13. Shannon wavelets
14. Frequency B-Spline wavelets
15. Complex Morlet wavelets

1.6.3 Definition of Wavelets in Terms of Parameters

There are a number of ways of defining a wavelet (or a wavelet family).

Scaling filter

An orthogonal wavelet is entirely defined by the scaling filter - a low-pass finite impulse response (FIR) filter of length $2N$ and sum 1. In bi-orthogonal wavelets, separate decomposition and reconstruction filters are defined for analysis with orthogonal wavelets. The high pass filter is calculated as the Quadrature mirror filter of the low pass filter, and reconstruction filters are the time reverse of the decomposition filters. Daubechies and Symlet wavelets can be defined by the scaling filter.

Scaling function

Wavelets are defined by the wavelet function $\psi(t)$ (i.e. the mother wavelet) and scaling function $\phi(t)$ (also called father wavelet) in the time domain.

The wavelet function is in effect a band-pass filter and scaling it for each level halves its bandwidth. This creates the problem that in order to cover the entire spectrum, an infinite number of levels would be required. The scaling function filters the lowest level of the transform and ensures the entire spectrum is covered.

For a wavelet with compact support, $\phi(t)$ can be considered finite in length and is equivalent to the scaling filtering (w). Meyer wavelets can be defined by scaling functions

Wavelet function

The wavelet only has a time domain representation as the wavelet function $\psi(t)$.For instance, Mexican hat wavelets can be defined by a wavelet function. Note that there is no discrete function of Mexican wavelet.

1.7 Discrete Wavelet Transform

The wavelet transform is a relatively new concept (about 10 years old). Image transforms are very important in digital processing they allow to accomplish less with more. There are many image transforms that are very important in digital processing. For example the Fourier Transform (FT) may be used to effectively compute convolutions of images or the Discrete Cosine Transform (DCT) may be used to significantly decrease space occupied by images without noticeable quality loss. Recall that the FT gives the frequency information of the signal, which means that it tells how much of each frequency exists in the signal, but it does not tell us when in time these frequency components exist. The time information is not required when signal is so-called stationary. The ultimate solution for this problem is the Wavelet Transform. The Discrete Wavelet Transform (DWT) is a relatively new concept. It provides time-frequency representation. There are other transforms which give this information too, such as Short Time Fourier Transform, Wigner Distributions, etc. But DWT is designed to give good time resolution and poor frequency resolution at high frequencies and good frequency resolution and poor time resolution at low frequencies [34]. This approach makes sense especially when signal at hand has high frequency components for short durations and low frequency components for long durations. Fortunately, the signals that are encountered in practical applications are often of this type. For finding DWT of any signal we specify a wavelet also called mother wavelet there are many wavelets, in the next sub-section we will study these wavelets.

1.7.1 Overview of DWT Algorithm

In wavelet analysis, a signal can be separated into approximations or averages and detail or coefficients. Averages are the high-scale, low frequency components of the signal. The details are the low scale, high frequency components. If we perform forward transform on a real digital signal, we wind up with twice as much data as we started with. That's why after filtering down sampling has to be done. The inverse process is how those components can be assembled back into the original signal without loss of information. This process is called reconstruction or synthesis. The mathematical manipulation that affects synthesis is called the inverse discrete wavelet transform. The original signal is reconstructed from the wavelet coefficients. Where wavelet analysis involves filtering and down sampling, the wavelet reconstruction process consists of up sampling and filtering. The DWT algorithm consists of Forward DWT (FDWT) and Inverse DWT (IDWT) which are done on image signals in the next sections.

The FDWT can be performed on a signal using different types of filters such as db7, db4, Symlets or Haar. The Forward transform can be done in two ways, such as matrix multiply method and linear equations. In the FDWT, each step calculates a set of wavelet averages (approximation or smooth values) and a set of details. If a data set $s_0,s_1,\ldots,s_{N-1}$ contains N elements, there will be N/2 averages and N/2 detail values. The averages are stored in the upper half and the details are stored in the lower half of the N element array.

After the FDWT stage, the resulting average and detail values can be compressed using thresholding method. In the IDWT process, to get the reconstructed image, the wavelet details and averages can be used in the matrix multiply method and linear equations.

A single wavelet transform step using a matrix algorithm involves the multiplication of the signal vector by a transform matrix, which is an N X N operation (where N is the data size for each transform step). In contrast, linear equations need only N operations. In practice matrices are not used to calculate the wavelet transform. The matrix form of the wavelet transform is both computationally inefficient and impractical in its memory consumption.

1.7.2 Scope of DWT

Generally, an approximation to DWT is used for data compression if signal is already sampled, and the Continuous Wavelet Transform (CWT) for signal analysis. Thus, DWT approximation is commonly used in engineering and computer science, and the CWT in scientific research.

Wavelet transforms are now being adopted for a vast number of applications, often replacing the conventional Fourier Transform. Many areas of physics including molecular dynamics, ab-initio calculations, astrophysics, density-matrix localization, seismology, optics, turbulence and quantum mechanics have done this change. This change has also occurred in image processing, blood-pressure, heart-rate and ECG analyses, DNA analysis, protein analysis, climatology, general signal processing, speech recognition, computer graphics and multi-fractal analysis. In computer vision and image processing, the notion of scale-space representation and Gaussian derivative operators is regarded as a canonical multi-scale representation.

One use of wavelet approximation is in data compression. Like some other transforms, wavelet transforms can be used to transform data, and then encode the transformed data, resulting in effective compression. For example, JPEG 2000 is an image compression standard that uses bi-orthogonal wavelets. This means that although the frame is over complete, it is a tight frame and the same frame functions (except for conjugation in the case of complex wavelets) are used for both analysis and synthesis, i.e., in both the forward and inverse transform.

A related use is that of smoothing/de-noising data based on wavelet coefficient thresholding, also called wavelet shrinkage. By adaptively thresholding the wavelet coefficients that correspond to undesired frequency components smoothing and/or de-noising operations can be performed.

Wavelet transforms are also starting to be used for communication applications. Wavelet Orthogonal Frequency Division Multiplexing (OFDM) is the basic modulation scheme used in a power line communications technology developed by Panasonic and in one of the optional modes included in the IEEE P1901 draft standard. The advantage of Wavelet OFDM over traditional Fast Fourier Transform (FFT) OFDM systems is that Wavelet can achieve deeper notches and that it does not require a Guard Interval (which usually represents significant overhead in FFT OFDM systems).[35]

1.7.3 Mathematical Description of DWT

DWT is an implementation of the wavelet transform using a discrete set of wavelet scales (s) and translations (τ) parameters obeying some defined rules [36]. These are discretized as

$$s = s_0^j \quad (1.6),$$

$$\tau = k \times s_0^j \times \tau_0 \quad (1.7).$$

Where j and k are the integers. Usually s_0 is taken 2 and τ_0 is 1. The discretized scaled and translated wavelet is as follows:

$$\psi_{j,k}(t) = s_0^{-j/2}\psi\left(s_0^{-j}t - k\tau_0\right) \quad (1.8).$$

Where $\psi_{j,k}(t)$ is a discrete version of continuous mother wavelet $\psi(t)$. There are different types of mother wavelets such as Haar, Daubechies, Coiflets, and Symlets etc. The DWT is defined by the following relation:

$$Y(j,k) = \sum_j \sum_k x(k)\, 2^{-j/2}\, \psi^*(2^{-j}\, t - k). \quad (1.9)$$

Where * denotes the conjugate. And Inverse DWT (IDWT) is given as:

$$x(k) = c_\psi \sum_j \sum_k Y(j,k)\psi_{j,k}(t). \quad (1.10)$$

The DWT analysis can be performed using a fast, pyramidal algorithm related to multi-rate filter banks [37]. In the pyramidal algorithm the signal is analyzed at different frequency bands with different resolution by decomposing the signal into a coarse approximation and detail coefficients. The coarse approximation is then further decomposed using the same wavelet decomposition step. This is achieved by successive high-pass and low-pass filtering of the time domain signal. These filters are called decomposition filters and to recover the signal from the approximation and detail coefficients we use the reconstruction filters. This process is called Inverse Discrete Wavelet Transform (IDWT).

For an orthogonal wavelet, in the multi resolution framework, we start with the scaling function ϕ and the wavelet function ψ. One of the fundamental relations is the twin-scale relation (1.11) in [3]:

$$\frac{1}{2}\phi\left(\frac{x}{2}\right) = \sum_{n\in Z} w_n\, \phi(x-n). \tag{1.11}$$

All the filters used in DWT and IDWT are intimately related to sequence w_n. Clearly if ϕ is compactly supported, the sequence (w_n) is finite and can be viewed as a Finite Impulse Response (FIR) filter. The scaling filter w is

- A low-pass FIR filter
- Of length 2N
- Of sum 1
- Of normalized value of $1/\sqrt{2}$

From filter w, we define four FIR filters, of length 2N and norm 1, organized in table 1.1 as follows:

The four filters are computed using the following scheme:

$$Lo\_R[k] = w[k]/norm(w), \tag{1.12}$$

$$Hi\_R[n] = (-1)^k Lo\_R[2N+1-k], \tag{1.13}$$

$$Lo\_D[k] = Lo\_R[2N+1-k], \tag{1.14}$$

$$Hi\_D[k] = Hi\_R[2N+1-k], \tag{1.15}$$

Where k=1, 2, 3… 2N.

Table 1.1 Decomposition and reconstruction filters

Filters	Low-pass	High-pass
Decomposition	Lo_D	Hi_D
Reconstruction	Lo_R	Hi_R

Lo_R and Hi_R are Quadrature Mirror Filters (QMF) and so Lo_D and Hi_D are also QMF. Now using these filters we proceed with the pyramidal algorithm.

1.7.4 Pyramidal Algorithm in 1D-DWT

In the fig. 1.16, input signal x[k] is passed from low pass filter Lo_D and high pass filter Hi_D, from that approximation coefficients (CA1) and detailed coefficients (CD1) are obtained after down-sampling by 2. This is 1st level decomposition. These are shown in the following equations:

$$CA1 = \sum_n x[n] Lo\_D[2k - n], \tag{1.17}$$

$$CD1 = \sum_N x[n] Hi\_D[2k - n]. \tag{1.18}$$

Decomposition can be done to a higher level with the approximation coefficients of previous stage.

Further we can recover the signal from detailed coefficients of all decomposition stages and approximation coefficients of the last decomposition stage as shown in fig.1.17.

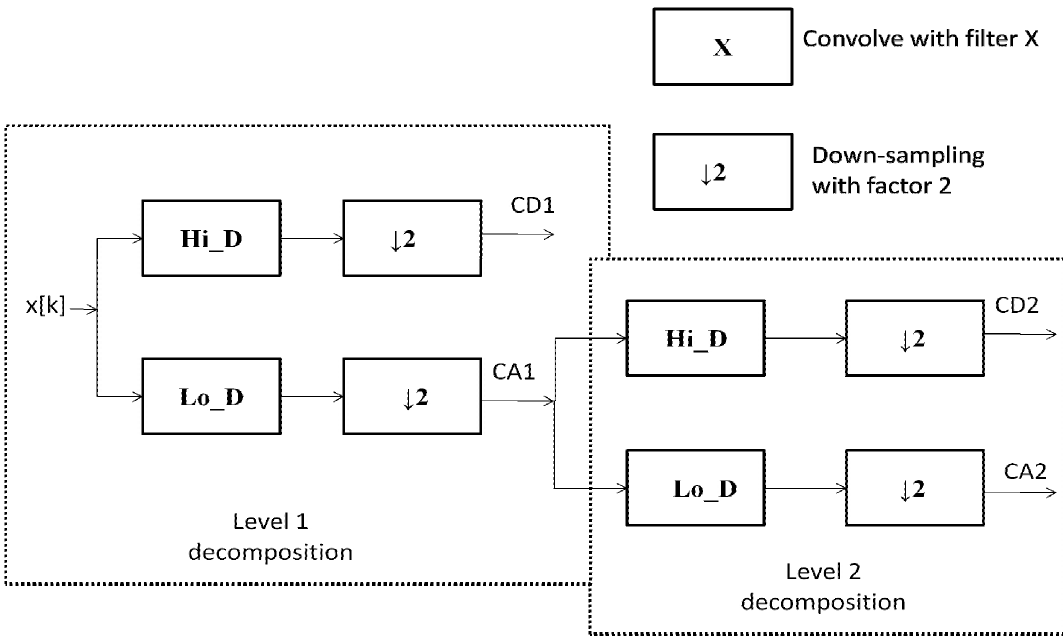


Figure 1.16: 1D DWT with pyramidal algorithm

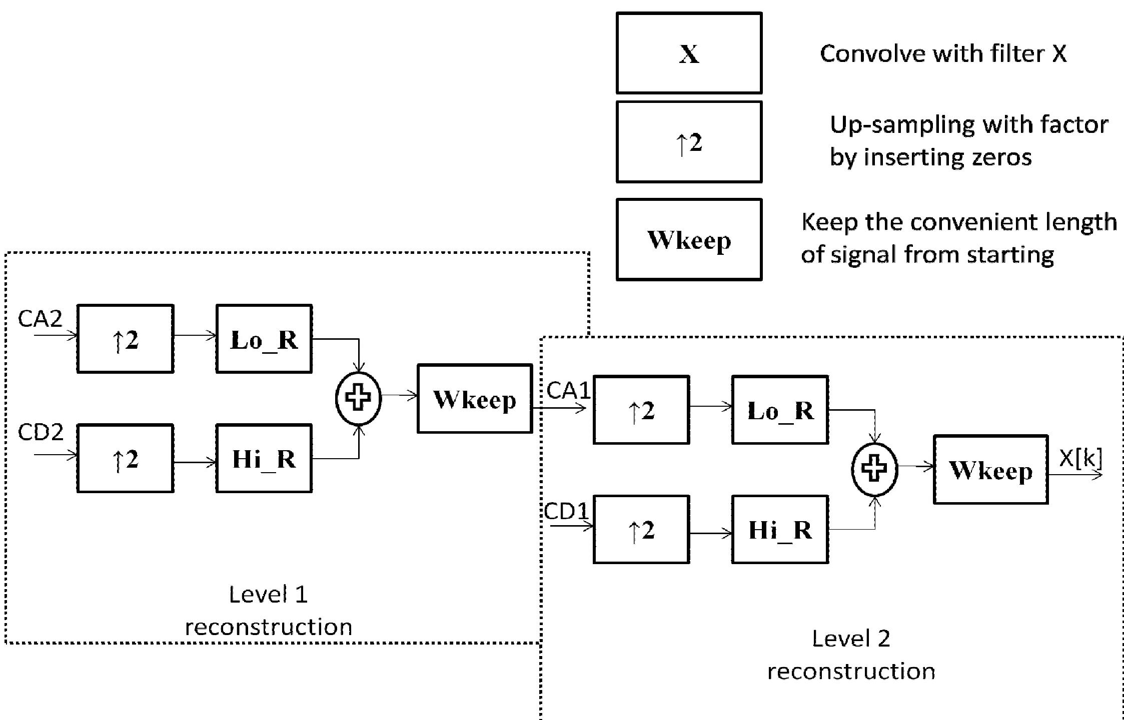


Figure 1.17: 1D IDWT with pyramidal algorithm

1.7.5 2D-DWT and Pyramidal Algorithm

In the above section we discussed about the 1-D DWT, here we will see the pyramidal algorithm of DWT for 2 dimensional signals. Since image is also a 2-D signal $x[r, c]$. Image can be considered a matrix of size $R \times C$. Where R is the number of rows and C is the number of columns. The calculation of decomposition and reconstruction filters for a given wavelet function is same as was in 1D-DWT algorithm. The only difference is that how we proceed with rows and columns. The scheme for 2-D DWT is shown in fig. 1.18.

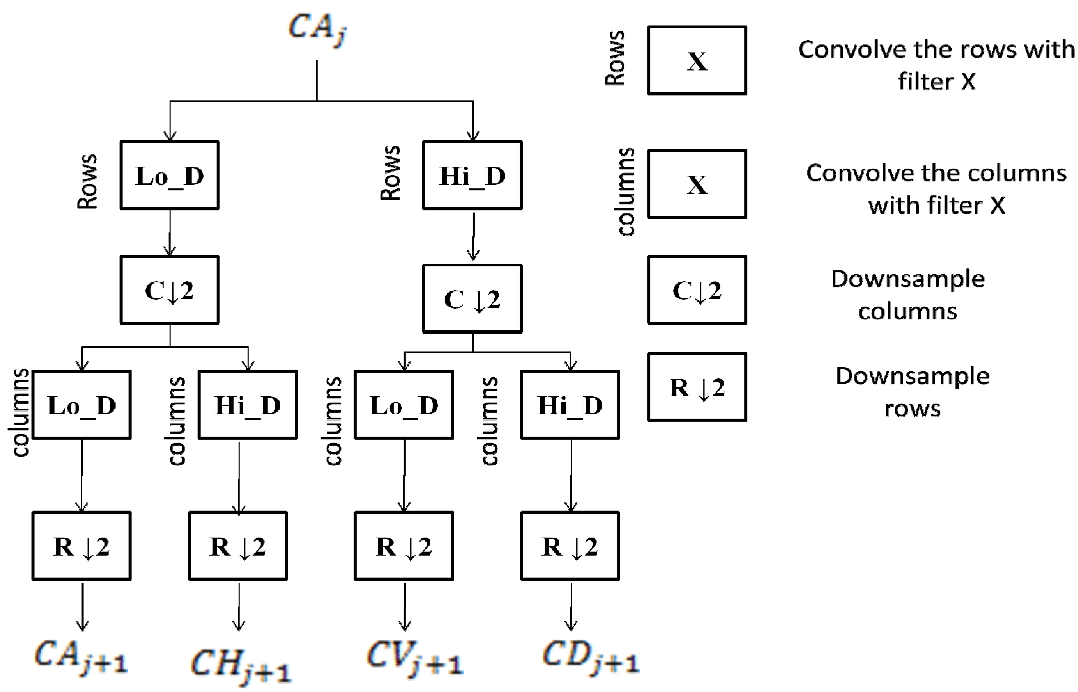


Figure 1.18: 2D DWT with pyramidal algorithm

Initialize$CA_0 = x[r, c]$. This kind of two-dimensional DWT leads to a decomposition of approximation coefficients at level j in four components: the approximation coefficients (CA_{j+1}) and the detail coefficients in three orientations horizontal (CH_{j+1}), vertical (CV_{j+1}), and diagonal (CD_{j+1}). The inverse 2 dimensional DWT can be performed like in one dimensional IDWT using same approach. The following fig.1.19 shows the procedure of getting multi-resolution of an image

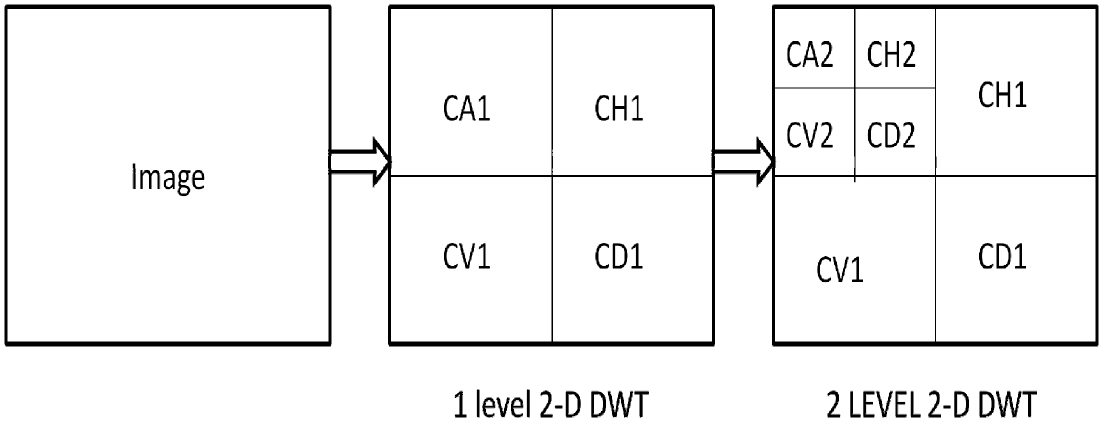


Figure1.19: 1 level and 2 level 2 DWT of an image

Here in fig. 1.20, we have taken an image of *Taj Mahal* and shown its 2D-DWT in 1 level resolution and in 2 level resolution taking symlet2 as a mother wavelet in fig.1.21 and fig. 1.22 respectively. In 1 level 2D-DWT of fig 1.20, we get one set of approximation coefficients (CA_0) and 3 sets of detail coefficients ($CH_{0,}, CV_0, CD_0$). In the 2 level 2D-DWT, we have total of 7 sets of coefficients. At first level we have 3 detail coefficients ($CH_{0,}, CV_0, CD_0$) and at the second level we have 1 set of approximation coefficient (CA_1) and 3 sets of detailed coefficients (CH_1, CV_1, CD_1))

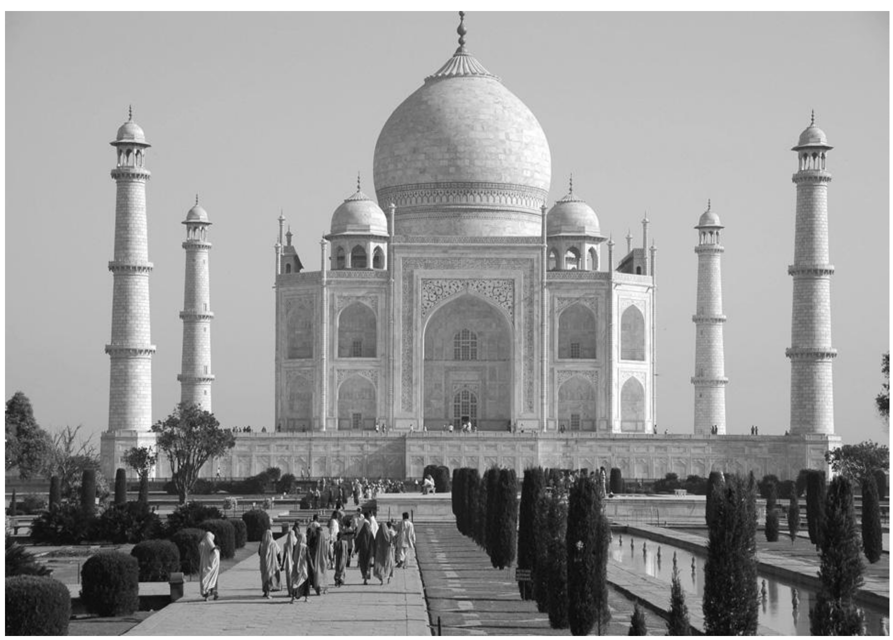


Figure 1.20: A sample picture of *Taj Mahal*

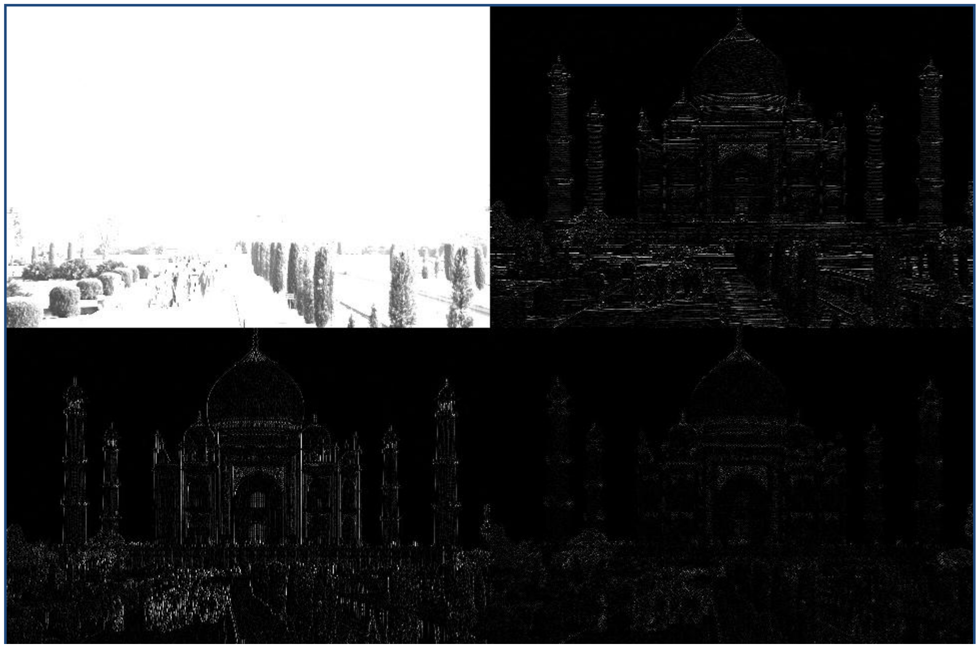


Figure 1.21: 1 level 2D DWT of *Taj Mahal*

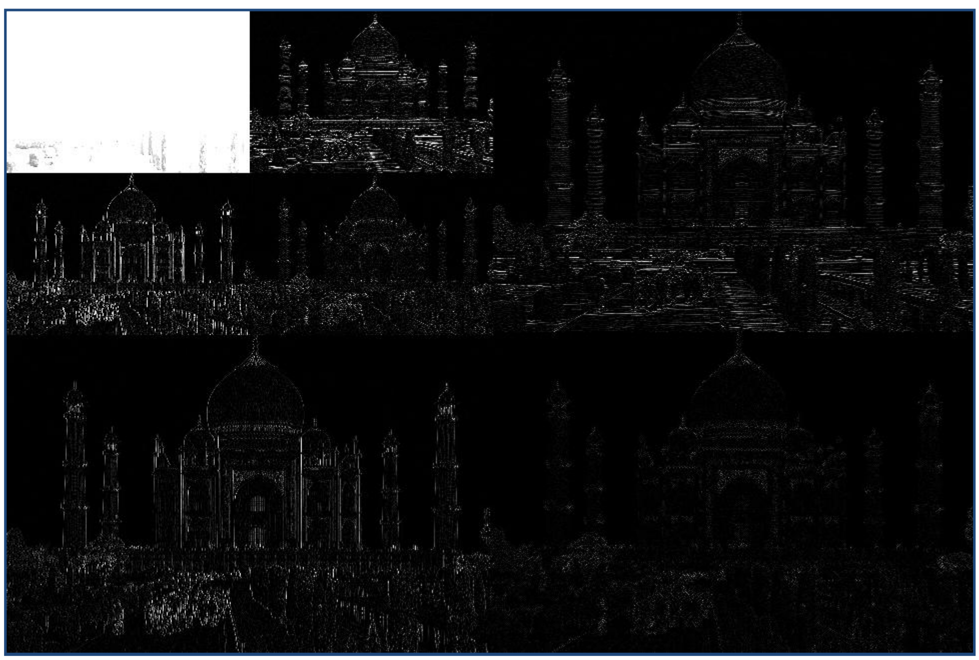


Figure 1.22: 2 level 2D DWT of *Taj Mahal*

1.8 Applications of DIP

Image processing has an enormous range of applications; almost every area of science and technology can make use of image processing methods. Here is a short list just to give some indication of the range of image processing applications [29].

1. Medicine
   - Inspection and interpretation of images obtained from X-rays, MRI or CAT scans,
   - Analysis of cell images, of chromosome types.
2. Agriculture
   - Satellite/aerial views of land, for example to determine how much land is being used for different purposes, or to investigate the suitability of different regions for different crops,
   - Inspection of fruit and vegetables distinguishing good and fresh produce from old.
3. Industry
   - Automatic inspection of items on a production line,
   - Inspection of thesis samples.
4. Law enforcement
   - Fingerprint analysis,
   - Sharpening or de-blurring of speed-camera images.

Chapter 2

Literature Review

In this chapter, the technical background of this thesis is reviewed. Many schemes have been proposed to sharp the images. In this chapter we will describe a brief knowledge of all techniques and algorithms for sharpening the images and also about the DWT. Aim of our thesis is to sharp the grayscale images but here we also reviewed the papers on the techniques which sharp the color images, for taking the different ideas about the sharpening.

A Wavelet Based Image Sharpening Algorithm is presented in [38]. The fundamental idea of image sharpening is to add to the input signal a high-pass filtered version of the signal itself. Wavelet coefficients provide multi-resolution high frequency components of an image. Making use of this property, a sharpening algorithm is proposed in this paper. First, an image containing the edge information of the original image is obtained from a selected set of wavelet coefficients. This image is then combined with the original image to generate a new image with enhanced visual quality. In addition, an effective approach to remove those coefficients related with noise rather than the real image to further enhance the image quality is designed. Experimental results demonstrate the effectiveness of the proposed algorithm for image sharpening purpose.

Amir Nooraliei et al. [39] purposed a new technique which utilizes Iraji-Jamalian Automaton (IJA) stochastic learning automaton for tuning value of alpha parameter which is used for image sharpening via gas diffusion model. The method has been applied to gray-scale images in an automatic and adaptive fashion. It is shown that the IJA automaton makes the image sharp with gas diffusion model by learning alpha parameter. The IJA automaton calculates appropriate local value for each pixel.

In the paper published by Sheida Rahmani et al. [40] introduced two new modifications to improve the spectral quality of the image. First, they proposed image adaptive coefficients for Intensity-Hue-Saturation (IHS) to obtain more accurate spectral resolution. Second, an edge-adaptive IHS method was proposed to enforce spectral fidelity away from the edges. Experimental results show that these two modifications improve spectral resolution compared to the original HIS. They proposed an adaptive IHS that incorporates these two techniques. The adaptive IHS method produces images with higher spectral resolution while maintaining the high-quality spatial resolution of the original IHS.

A fast and efficient panchromatic sharpening method that accurately estimates missing high-frequency components is presented by Jonghwa Lee et al. [41]. In this a post processing technique is used to correct color distortion. Experimental results show that the proposed method produced high-quality images and outperformed existing panchromatic sharpening methods in terms of objective quality measures such as universal image quality index, $Q4$, relative average spectral error etc.

An image sharpening algorithm which is overshooting free and particularly suitable for high magnification zooming situation is presented by Ning Xu et al. [42]. Traditional image sharpening methods usually introduce over shootings along the edges, and do not perform well for sharpening an image resulting from high magnification zooming. An algorithm discussed in this paper modifies the pixel value based on the desired changes for its gradient profile, and the sharpening parameters can be learned for the particular zooming rate. Experimental results show that the proposed algorithm outperforms the conventional image sharpening methods.

Line detection in gray-scale images is a low-level processing which has applications in, for example, determining markings and roads, etc. in Geographical Information System (GIS) map images. One traditional line detection technique utilizes template matching. In the paper a new method which is based on adaptation of the notion of wavelet-based edge detection at coarser scale levels and localization of center line pixels between the two parallel edges is presented [43]. The wavelet decomposition provides smoothed images and detail images at successive resolutions from which multi-scale edges can be obtained. A line (curve) becomes thicker at coarser scales after smoothing which provides two narrowly separated parallel strings of wavelet maxima around it; the center line (curve) between the two can be detected as the line of interest. When lines representing different markings with different gray values intersect, the method will be able to detect individual lines

Michael Wirth et al. [44] presented the effects of using different color spaces on the application of image sharpening algorithms. The processing of color images to improve sharpness is nearly always been realized in RGB color space. This paper explores the Part of the goal is to determine which color space provides a result which does not differ immeasurably from the original with respect to chromaticity. Unsharp masking and fuzzy morphological sharpening will be tested in RGB, YIQ and CIELab color spaces

Sub Regions Histogram Equalization (SRHE) is presented by Haidi Ibrahim et al. [45]. Histogram equalization (HE) based methods are commonly used in consumer electronics. Histogram equalization improves the contrast of an image by changing the intensity level of the pixels based on the intensity distribution of the input image. In SHRE First, the method partitions the image based on the smoothed intensity values, which are obtained by convolving the input image with a Gaussian filter. By doing this, the transformation function used by HE is not based on the intensity of the pixels only, but the intensity values of the neighboring pixels are also taken into the consideration. Besides, this paper also presents a more robust histogram equalization transformation function. Experimental results show that the proposed method is not only can enhance the contrast, but this method also successfully sharpens the image.

Wavelet coding performs better than discrete cosine transform in visual processing. Moreover, it is scalable, which is important for modern video standards. The transpose memory requirement and operation speed are the two major concerns in 2-D lifting-based discrete wavelet transform (LDWT) implementation. A novel algorithm called 2-D Symmetric Mask-based Discrete Wavelet Transform (SMDWT), to improve the critical issue of the 2-D Lifting-based Discrete Wavelet Transform (LDWT) as presented in [46]. It obtains the benefit of low-latency reduced complexity, and low transpose memory. The proposed method has a significantly better lifting-based latency and complexity in 2-D

DWT than normal 2-D 5/3 integer LDWT without degradation in image quality. The algorithm can be applied to real-time image/video applications.

Description of DWT and wavelet packet approach is presented by Zhengmao Ye et al. [47] to remove the noise in digital image. As a nonlinear wavelet based technique, the wavelet thresholding is effective to denoise blurring aerial images. Either the discrete wavelet transform or wavelet packets technique can be employed using wavelet decomposition. At each level of wavelet decompositions, the digital image is split into four sub bands, representing approximation (low frequency feature) and three details (high frequency features) in horizontal, vertical and diagonal directions. The proposed soft thresholding wavelet decomposition at multiple levels is a simple and efficient method for reduction of noises. For multiple level decompositions in terms of both the discrete wavelet transform and wavelet packets techniques, the approximation component will always be decomposed at each level. If the detail components are further decomposed as well similar to that of the approximation, it is the wavelet packet approach, otherwise it is the discrete wavelet transform. On a basis of the proposed thresholding technique at different levels for wavelet denoising, objective metrics can be introduced also to evaluate and compare the denoising effects of the discrete wavelet transform and wavelet packets quantitatively rather than qualitative observation, such as the metrics of the discrete entropy, energy and mutual information.

Takahiko Horiuchi et al. [48] proposed an adaptive filtering algorithm to sharp and denoise the color images. Both tasks of sharpening and denoising color images are perpetuity problems for improving image quality. This paper proposes a filtering algorithm which brings a dramatic improvement in sharpening effects and reducing flat-area noises for natural color images. First, they generated a luminance slope map, which classifies a color image into the edge areas and the flat areas with uniform color. Second, the Gaussian derivative filter is applied to sharpening each segmented edge area. In order to keep color balance, the edge-sharpening filter is applied only to the luminance component of the color image. In the flat areas, a filter based on the SUSAN algorithm is applied to reducing the background noises with preserving sharpened edges. The performance of the proposed method is verified for natural image with Gaussian noise and impulse noise.

An effective method for contrast enhancement in an image was presented by Russo [49], which was controlled by the trial-and-error tuning of one parameter. The same parameter was used for the entire image resulting in over blurring or sharpening of features in the image, H. S. Kam et al. [50] applied Russo's algorithm on impulse noise and propose an efficient method for automatically obtaining the parameter value. Each pixel is adaptively assigned a different parameter value by evaluating the local features. Results of the proposed method are compared with those of Russo's algorithm and of other methods for sharpening of image features. Experimental values indicate that the proposed method effectively tunes the operator yielding superior performance.

Sean C. Matz et al. [51] presented an approach to contrast sharpening based upon the calculation of a local measure and the use of this computed quantity as part of a nonlinear contrast enhancement method. The contrast enhancement method presented here uses the concept of a local mean edge gray value, as well as gray scale partitioning into discrete subintervals, as the basis for processing the image. This technique maps the intensity values in each of the subintervals in a continuous fashion, to intensities nearer to those of the upper and lower endpoints of each sub interval .In the case of an image corrupted by Gaussian noise, the image is first processed by a tandem of pyramidal low pass filters and then by the contrast enhancement algorithm. The result is a very smooth, sharp image.

Three edge detection operations after studying the order morphological transformation deeply are presented by [52]. The specialties of this operations and choices of the structure element are analyzed, so a new multi-scale and multi-structuring edge detection operations based on the three former operations are proposed. The operations can obtain clear and exact edge of the noisy images. By simulation and comparing with the Sobel, Canny and traditional order morphology operations, the operations are more effective on noise restraining and retaining the image details

A new technique for sharpening compressed images in the discrete-cosine-transform domain is presented by K. Konstantinides et al. [53]. For images compressed using the

JPEG standard, image sharpening is achieved by suitably scaling each element of the encoding quantization table to enhance the high-frequency characteristics of the image. The modified version of the encoding table is then transmitted in lieu of the original. Experimental results with scanned images show improved text and image quality with no additional computation cost and without affecting compressibility.

In the paper [54], the author presented a proposed architecture (PA) for the direct two-dimensional discrete wavelet transform (DWT), which performs a complete dyadic (i.e., nonstandard) decomposition of an $N_0 \times N_0$ image in approximately $N_0^2/4$ clock cycles. Therefore, it consistently speeds up the performance of other known architectures, which commonly need approximately N_0^2 clock cycles. Also, it has an AT^2 complexity, which is notably lower than that of other devices based on the "direct approach." This result has been achieved by means of carefully balanced pipelining and has two "faces." First, PA can be employed for performing processing four times faster than allowed by other architectures working at the same clock frequency (high-speed utilization), Second, it can be employed even using a four times lower clock frequency but reaching the same performance as other architectures, This second possibility allows one to reduce the supply voltage and the power dissipation respectively by four and by 16 with respect to other architectures (low-power utilization)

Chapter 3

Gaps in Studies, Objectives and Methodology

3.1 Gaps in studies

Traditional image sharpening methods usually introduce over shootings along the edges, and do not perform well for sharpening an image. As represented in literature review [38-54]. Most of these techniques make the same principle of subtracting a blurred image to its original image or adding the high filtered image to its original image. In this thesis we make the idea of sharpening by modifying the pixels values near the edges in a gray scale image.

Histogram equalization (HE) based methods are commonly used in consumer electronics. Histogram equalization improves the contrast of an image by changing the intensity level of the pixels based on the intensity distribution of the input image. But sharpening of image by HE is not so effective at the sharp edges of an image. A SHRE scheme is discussed by Haidi Ibrahim [45], in which convolution of an image is taken with a Gaussian filter. This technique used a robust function of HE also and proposed to sharp the image. But after transforming the image there is no step to modify the pixel values at the sharp edges to make it more enhanced and sharp.

A wavelet based image sharpening algorithm is discussed by Liu Ying [38]. In this algorithm, an image containing the edge information of the original image is obtained from a selected set of wavelet coefficients. This image is then combined with the original image to generate a new image with enhanced visual quality. This is the same traditional principle of adding a high filtered image to its original image to get a sharp image. There is no step to modify the wavelet coefficients of image to make it clearer. In this thesis, we proposed a new algorithm to modify the wavelet coefficients so as to make the image clearer and informatics than it was before.

3.2 Objectives:-

The primary objectives of this thesis can be summarized as follows:

- To study DWT and UM technique in detail.
- To develop an efficient algorithm based on DWT and UM.
- To show that DWT and UM can be successfully used to solve different problems in image processing and edge detection.
- To compare DWT and UM and others existing methods in amount of sharpening of a grayscale image.

3.3 Methodology

In this thesis introduction and importance of DWT in digital image processing is described. Combining DWT and UM we proposed a new technique to sharp the edges in gray scale images. Experimental results are then obtained using various images with well known characteristics in order to show the efficiency and accuracy of our proposed algorithm.

In addition natural images from different areas are also used to show the broad applicability of the proposed algorithm.

The experimental results of proposed algorithm when applied to the same test images are also reported to show the comparisons with other well-known methods. An analysis of our proposed algorithm on pixel level is also done to observe the modification in pixel values after processed with DWT-UM. And amount of sharpness is calculated by percentage of rise in values along an edge in an image.

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Chapter 4

Simulation and Experimental Results

4.1 Proposed Algorithm

Here we propose an algorithm that used the both UM and 2-D DWT transform [55]. After taking the 2-D DWT transform of image, we got the approximation (CA) and detail coefficients (CH, CV, CD). Then these coefficients are modified by processing with UM. The complete process is shown in the following fig.4.1.

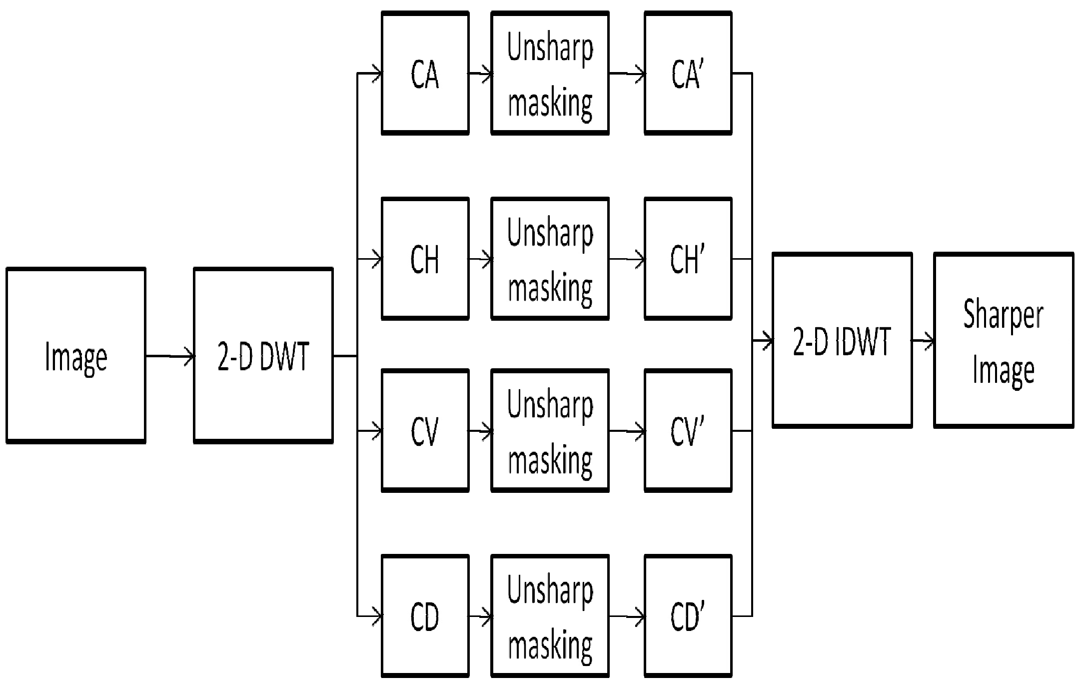
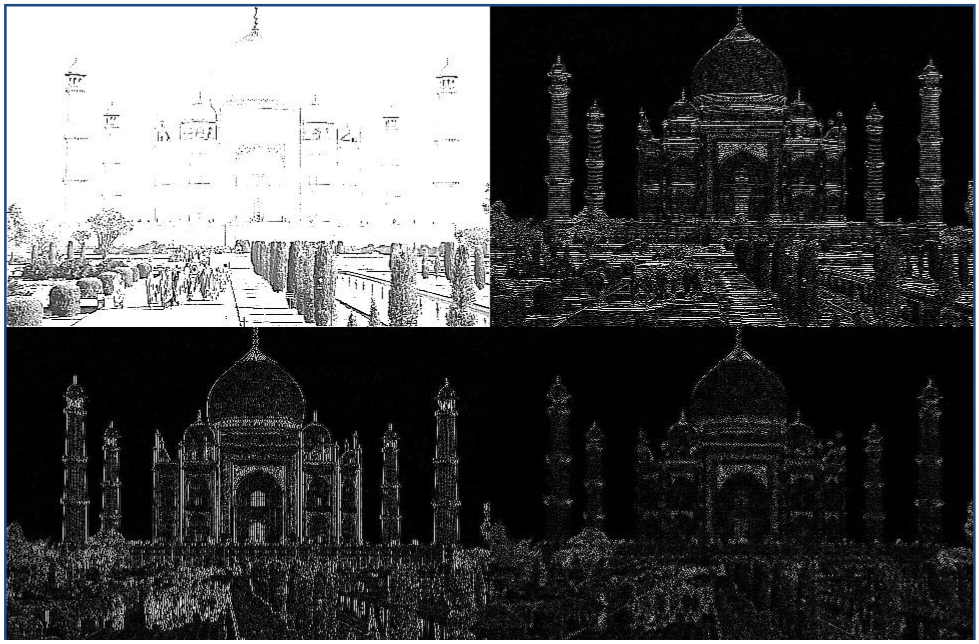
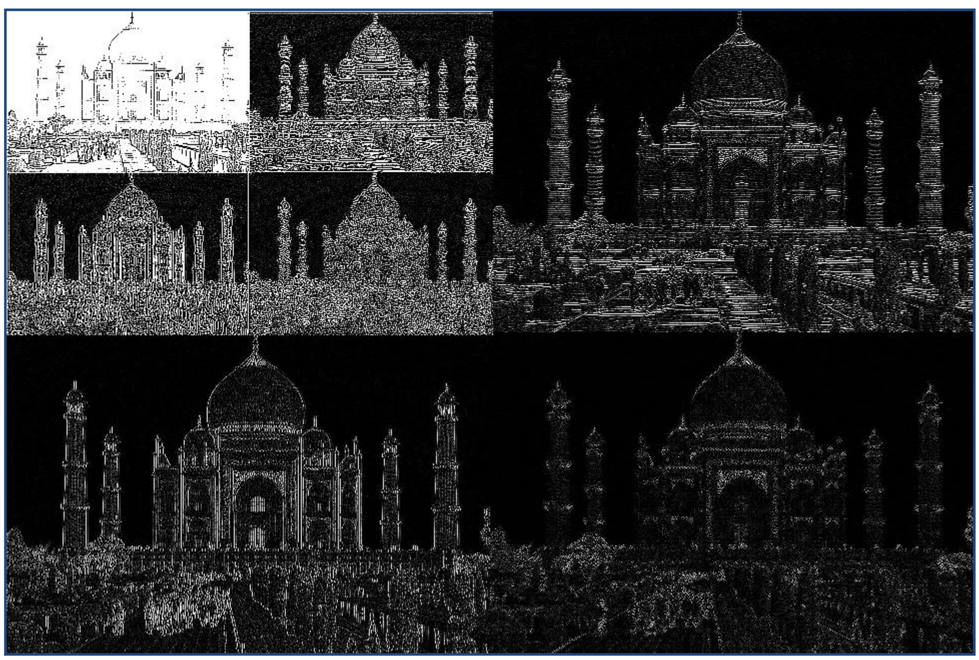


Figure 4.1: Proposed algorithm to compute the sharper image using 2D DWT and UM

In this we modified the coefficients by passing them through the UM, and got new coefficients (CA', CH', CV', CD'). One can see the difference between former 2-D DWT transform in fig. 1.21 and 1.22 and modified 2-D DWT transform of the *Taj Mahal* image fig. 4.2 (a) and (b). The main purpose of using UM on the transform is to obtain the high-frequency spatial detail.



(a) Modified 1 level 2D DWT of *Taj Mahal*

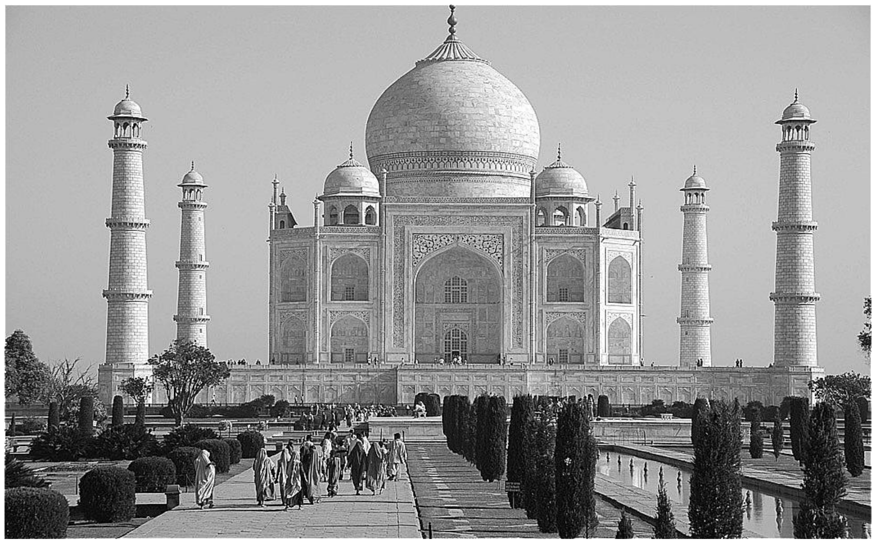


(b) Modified 2 level 2D DWT of the *Taj Mahal* [55]

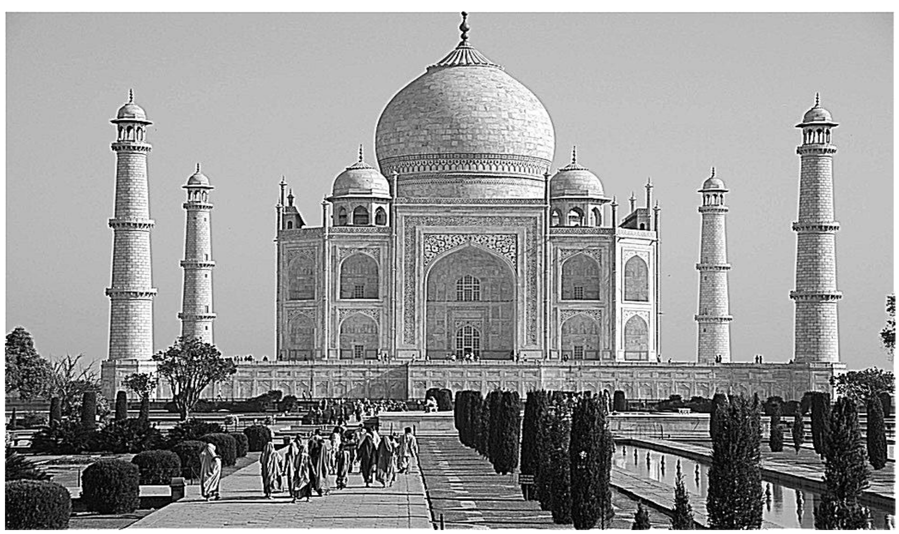
Figure 4.2: Modified 1 level and 2 level 2D-DWT of the *Taj Mahal*

4.2 Comparison between UM and Our Proposed Algorithm

UM and our proposed algorithm are applied to the test image in fig. 1.20 and fig. 4.3 compares the operation of proposed algorithm to the UM. In this process, only 1 level resolution is taken, since a higher level tends to give a very excessive overshoot on the edges.



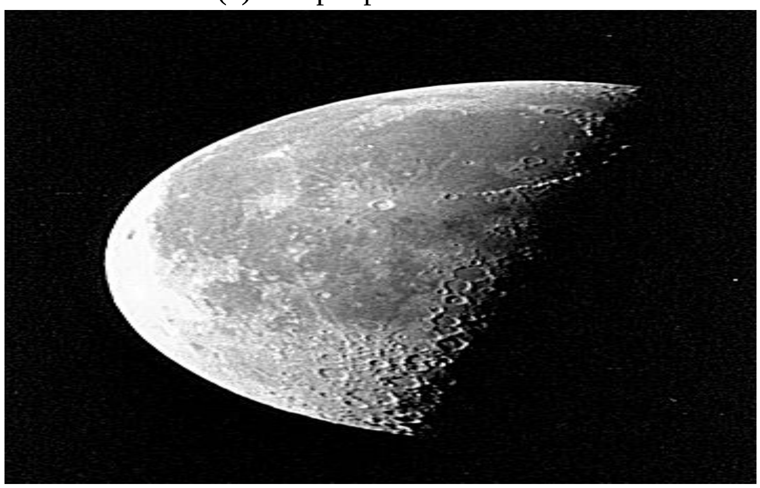
(a) Processed with Unsharp Masking



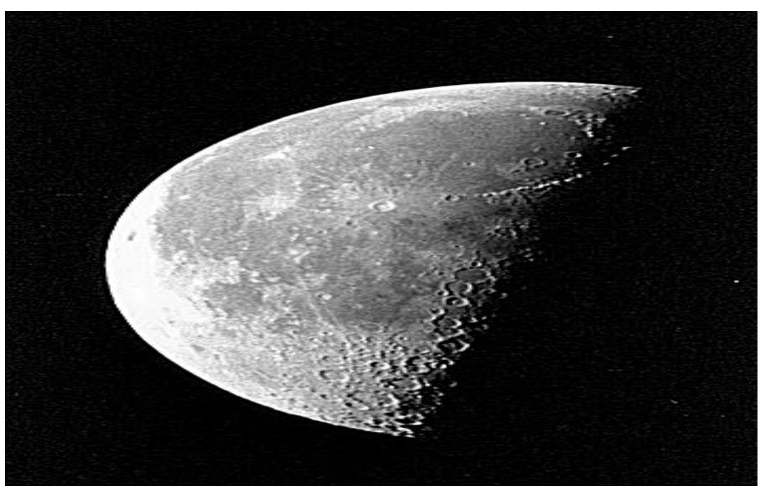
(b) Processed with our proposed scheme

Figure 4.3: Comparison between UM and DWT-UM [55]

(a) Sample picture of moon

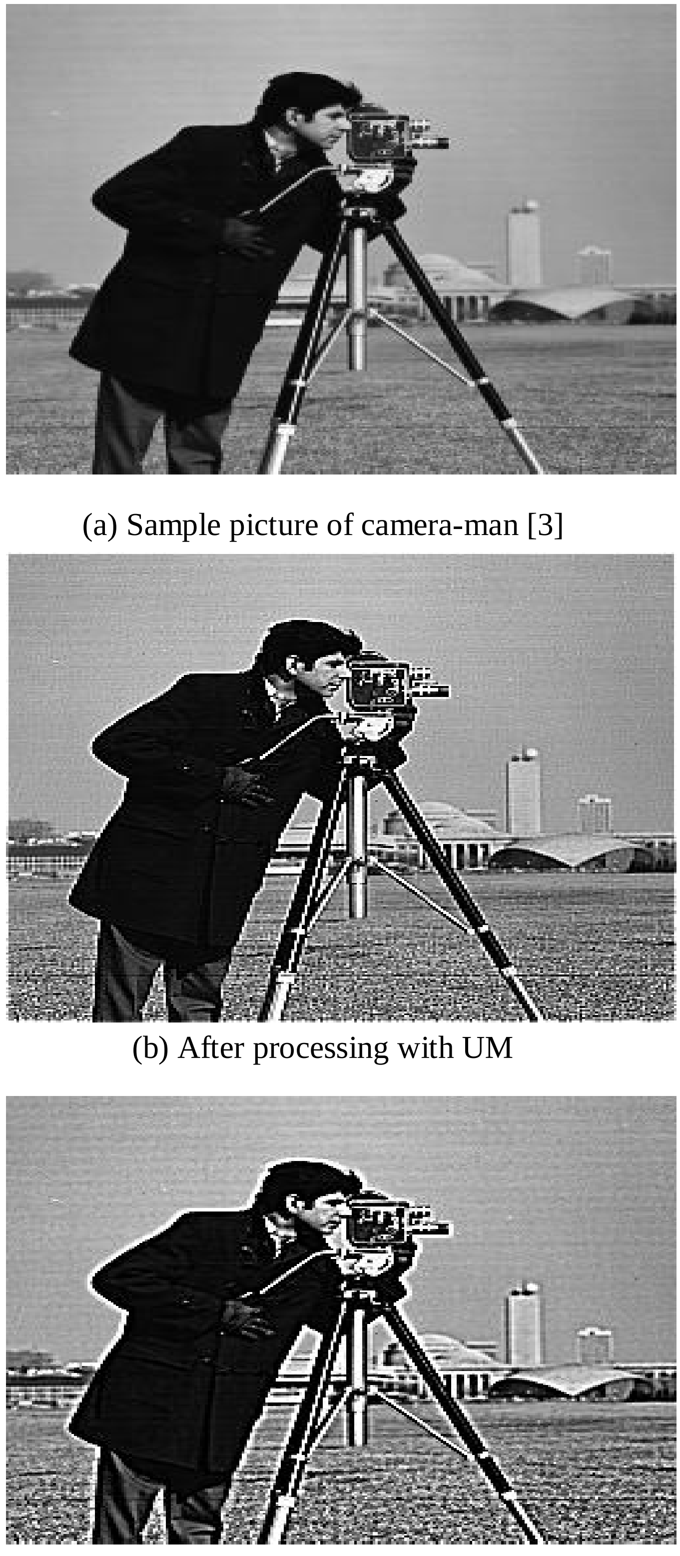


(b) After processing with UM



(c) After processing with DWT-UM

Figure 4.4: Comparison of sharpness between UM and DWT-UM [55]



(a) Sample picture of camera-man [3]

(b) After processing with UM

(c) After processing with DWT-UM

Figure 4.5: Comparison of sharpness between UM and DWT-UM [55]

(a)

(b)

(c)

Figure 4.6: Comparison of sharpness between UM and DWT-UM [55]

We can see that image obtained from our proposed algorithm is much more sharp and better than that obtained from UM. Here we have also taken some other sample images for test purpose and processed them with UM and our proposed algorithm DWT-UM (combination of DWT and UM).The comparison between them is shown in fig. 4.4, 4.5 and 4.6.

4.3 Analysis at Pixel Level

To observe the modification in coefficient values, before and after processing with DWT-UM, we have taken a part of sample picture shown in fig 4.7. Small part for observation inside the red rectangle has an edge. The values of the pixels inside this box are shown in table 1.2. Red values in the table presents low frequency elements left to the edge of building, and green values represents the edge. From the table 1.2 we observe that there is increase in values at once just after the red values. This shows the occurrence of high frequency elements or pixels or we can say the presence of edge.

Figure 4.7: Original image [56]

Here we have taken two sharpening techniques UM and DWT-UM. In each we have taken the pixel values of the same part after processing with respective technique. Now we will see observe amount of sharpness in each method.

Rise Value Parameter: One way to measure sharpness is to use the rise value of the edge, for example, at the boundary of red and green values we will take the average of red values just along with the boundary and similarly the average of green values. Then we will calculate the percentage of rise in values along the boundary. More is the percentage of rise; more is the sharpness of image.

Table 1.2: Values of pixels in a small part of original image

0.768627	0.760784	0.772549	0.764706	0.772549	**0.843137**	**0.909804**
0.768627	0.772549	0.776471	0.764706	0.768627	**0.85098**	**0.901961**
0.768627	0.768627	0.768627	0.764706	0.772549	**0.862745**	**0.905882**
0.768627	0.764706	0.764706	0.764706	0.780392	**0.870588**	**0.909804**
0.768627	0.764706	0.764706	0.768627	0.784314	**0.87451**	**0.909804**
0.768627	0.768627	0.772549	0.772549	0.784314	**0.870588**	**0.909804**
0.768627	0.768627	0.772549	0.772549	0.784314	**0.866667**	**0.905882**
0.768627	0.768627	0.772549	0.772549	0.780392	**0.866667**	**0.905882**
0.768627	0.764706	0.768627	0.768627	0.784314	**0.870588**	**0.905882**
0.772549	0.776471	0.764706	0.768627	0.780392	**0.87451**	**0.921569**

Average value of red values in 5th column (Av_{red}) =0.7792,

Average value of green values in 6th column (Av_{green}) =0.8651,

Percentage of rise in values (P_{rise}) = $\frac{(Av_{green}-Av_{red})\times 100}{Av_{red}}$

$$= \frac{(0.8651-.7792)\times 100}{.7792} = 11.02\%.$$

4.3.1 Sharpness in UM:

Fig 4.8 shows the sharpen image of original image after processing with UM method and table 1.3 shows the corresponding values of pixels.

Figure 4.8: Sharp image with Unsharp Masking (UM)

Table 1.3: Values of pixels in a small part of image processed with UM

0.781699	0.743791	0.793464	0.754248	0.718954	0.853595	0.976471
0.773856	0.781699	0.801307	0.750327	0.686275	0.87451	0.933333
0.772549	0.76732	0.771242	0.750327	0.690196	0.909804	0.939869
0.775163	0.75817	0.760784	0.747712	0.70719	0.92549	0.946405
0.773856	0.756863	0.756863	0.755556	0.713725	0.933333	0.943791
0.771242	0.768627	0.781699	0.764706	0.711111	0.918954	0.946405
0.768627	0.764706	0.776471	0.762092	0.713725	0.908497	0.935948
0.769935	0.76732	0.780392	0.764706	0.699346	0.909804	0.938562
0.766013	0.750327	0.766013	0.754248	0.715033	0.918954	0.934641
0.784314	0.797386	0.752941	0.747712	0.691503	0.926797	0.994771

Amount of Sharpness:

Average value of red values in 5th column (Av_{red}) =0.7047,

Average value of green values in 6th column (Av_{green}) =0.9080,

Percentage of rise in values (P_{rise}) = $\frac{(Av_{green}-Av_{red})\times 100}{Av_{red}}$

$$= \frac{(0.9080-.7047)\times 100}{0.7047} = 28.85\%.$$

So by using UM technique, the amount of sharpening increased from 11.02% to 28.85%. Now we will observe the performance of DWT with UM technique.

4.3.2 Sharpness in DWT-UM:

Fig 4.9 and fig 4.10 shows the 1-level 2D-DWT of original image and sharpen image after processing with DWT-UM respectively. Table 1.4 shows the values of pixels of the part taken under observation.

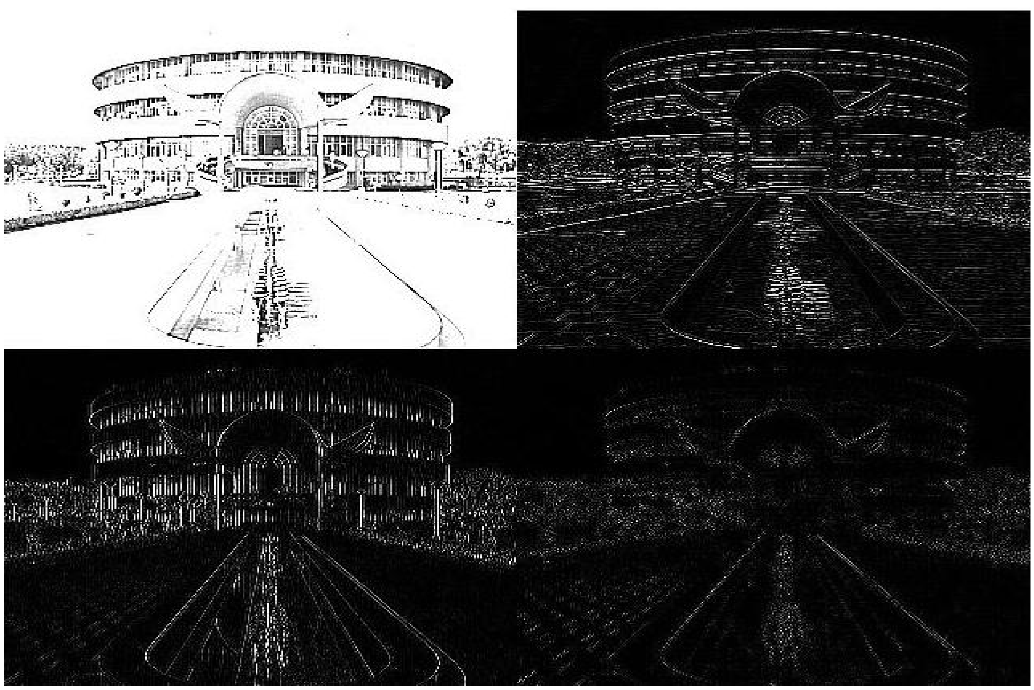


Figure 4.9: 1 level, 2D DWT of original image

Figure 4.10 Sharpen image after processed with DWT-UM.

Table1.4: Values of pixels in a small part of image processed with UM

0.773856	0.750327	0.783007	0.698039	0.640523	0.861438	1.048366
0.775163	0.798693	0.798693	0.684967	0.622222	0.879739	1.003922
0.772549	0.779085	0.760784	0.667974	0.636601	0.909804	1.024837
0.768627	0.756863	0.741176	0.658824	0.665359	0.935948	1.037908
0.771242	0.756863	0.741176	0.670588	0.681046	0.946405	1.037908
0.768627	0.769935	0.769935	0.68366	0.677124	0.930719	1.033987
0.769935	0.771242	0.768627	0.68366	0.677124	0.913725	1.016993
0.766013	0.763399	0.768627	0.677124	0.657516	0.91634	1.014379
0.763399	0.756863	0.742484	0.669281	0.670588	0.929412	1.020915
0.780392	0.792157	0.734641	0.654902	0.653595	0.950327	1.067974

Amount of Sharpness:

Average value of red values in 5th column (Av_{red}) =0.6582,

Average value of green values in 6th column (Av_{green}) =0.9194,

Percentage of rise in values (P_{rise}) = $\frac{(Av_{green}-Av_{red})\times 100}{Av_{red}}$

$$= \frac{(0.9194-.6582)\times 100}{0.6582} = 39.38\%.$$

Using rise value parameter, it is observed that there is 11.02%, 28.85% and 39.38% rise in values near the edge of original sample image, image after processed with UM method and image after processed with DWT-UM method respectively. So there is a large enhancement in sharpness by using DWT-UM.

Chapter 5

Conclusion and Future Work

In this thesis we have proposed a new algorithm that makes use of both DWT and UM techniques to update the coefficients values. The algorithm makes use of the correlation between different wavelet planes to select a set of high frequency coefficients describing the edges of the original image. The updated coefficients are used to calculate the inverse DWT, generating a new image with enhanced visual quality. Some experimental results were presented to illustrate the performance characteristics of proposed algorithm.

We examined the sharpness efficiency of our proposed algorithm at the pixel level and compared with the existing technique UM. We made a measurement on the percentage of rise in pixel values at the edges. A sample picture is observed. In original image the percentage of rise in values is found to be 11.02%. after UM processing it reached to 28.85% but after processing with DWT-UM, this percentage is increased up to 39.38% , this is much larger than UM technique.

This work focused on gray-scale images. The future scope of this work can be extended to improve the sharpening of color images.

References

[1] Joshua Gluckman, “*Higher order whitening of natural images*”, IEEE Computer Society Conference on Computer Vision and Pattern Recognition, San Diego, CA, USA, Vol. 2, pp. 354-360, 2005.

[2] Takeshi Agui, Toru Yamanouchi And Masayuki Nakajima, “*An Algebraic Description of Painted Digital Pictures*”, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.4, pp.627-634, No.6, 1982.

[3] Math Works, “*Matlab help files, Image Processing Toolbox*”, version 7.5.0.342, 2007.

[4] Houtan Haddad Larijani, Gholamali Rezai Rad, “*A New Spatial Domain Algorithm for Gray Scale Images Watermarking*”, Proceedings of the International Conference on Computer and Communication Engineering, Kuala Lumpur, Malaysia, pp.157-161, 2008.

[5] “*Sea surfing image*”
http://www.phoresia.org/wp-content/images/grain_bw.jpg

[6] Jeffrey J. Rodriguez and Christopher C. Yang, “*Effects of Luminance Quantization Error on Color Image Processing*", IEEE Transactions on Image Processing, Vol. 3, pp.850-854, No. 6, 1994

[7] “*A historical building image*”
http://www.partenia.org/images/200702/SacreCoeur5.jpg

[8] Sebastiano Battiato, Francesco Rundo and Filippo Stanco, “*Self Organizing Motor Maps for Color-Mapped Image Re-Indexing*”, IEEE Transactions On Image Processing, Vol. 16, No. 12, pp. 2905-2915, 2007.

[9] “*Color map for index image*”
http://www.ncl.ucar.edu/Applications/Images/color_9_1_lg.png

[10] Alasdair McAndrew, “*Introduction to digital image processing with Matlab*”, edition 1st, Course Technology, 2004.

[11] Pei-Shan Tsai, Chia-Kai Liang, and Homer H. Chen, "*Image quality enhancement for low backlight TFT–LCD displays*", IEEE International Conference on Image Processing, Vol. 3, pp.473-476, 2007.

[12] "*NASA Columbia* "
http://wallpapers.free-review.net/wallpapers/49/Columbia_Shuttle_-_NASA.jpg

[13] Qing Wang, Rabab Ward and Jiancheng Zou, *"Contrast Enhancement For Enlarged Images Based On Edge Sharpening", IEEE* International Conference on Image Processing, vol. 2, pp.762-765, 2005.

[14] "*Thapar University Patiala*"
http://www.apnapatiala.com/wp-content/uploads/2009/06/thapar-university-patiala.jpg

[15] Kun He, Xin-Cheng Luan, Chun-Hua Li and Ran Liu, "*Gaussian Noise Removal of Image on the Local Feature*", Second International Symposium on Intelligent Information Technology Application, Shanghai, vol.3, pp.867-871, 2009.

[16] "*Fat fish-vegetables*"
http://www.loving-long-island.com/image-files/fatfish-vegitables.jpg

[17] M. R. Banhan and A. K. Katsaggelos, "*Digital image restoration*", IEEE Signal Processing magazine, vol. 14, No. 2, pp. 24-41,1997

[18] "*Racing Car*"
http://p.webwombat.com.au/motoring/car-photos/hsv-gts-fpv-gt-p-review-5-big.jpg

[19] Xiangjian He, Wenjing Jia and Qiang Wu, "*An Approach of Canny Edge Detection with Virtual Hexagonal Image Structure*", 10th International Conference on Control, Automation, Robotics and Vision, Hanoi, Vietnam, pp. 879-882, 2008

[20] "*Wooden blocks*"
http://www.dandelionsummers.com/assets/images/master_blocks.jpeg

[21] Wilhelm Burger and Mark James Burge, "*Principles of digital image processing: fundamental techniques*", 1st edition, Springer, 2009.

[22] Zhengya Xu, Hong Ren Wu and Xinghuo Yu, "*Colour Image Enhancement by Hybrid Approach*", IEEE 10th Workshop on Multimedia Signal Processing, Cairns, Qld, pp. 252-256, 2008.

[23] "*Ganga water*" http://media-cdn.tripadvisor.com/media/photo-s/01/1f/07/fc/ganga-view-rishikesh.jpg

[24] H. Su, D. Crookes, and A. Bouridane, "*Shoeprint Image Retrieval by Topological and Pattern Spectra*", International Machine Vision and Image Processing Conference, Kildare, pp. 15-22, 2007.

[25] "*A girl on beach* " http://digital-photography-school.com/wp-content/black-and-white-beach.jpg

[26] Rafael C. Gonzalez, Richard Eugene Woods, "*Digital image processing*", 3rd edition, Prentice Hall, 2008.

[27] Radu Ciprian Bilcu and Markku Vehvilainen, "*Nonlinear Non-Local Averaging for Image De-noising*", Proceedings of the 7th Nordic Signal Processing Symposium, Rejkjavik , pp. 90-93, 2006.

[28] "*Vaishno devi temple*" http://www.mynews.in/News/dailyimage/news/vaishno%20devi%20temple--350--1.jpg

[29] Alasdair McAndrew, "*An introduction to digital image processing with Matlab, Notes for SCM2511 image processing* 1", Victoria University of Technology, Australia, 2004.

[30] Faouzi Alaya Cheikh and Moncef Gabbouj, "*Directional-Rational approach for color image enhancement*", IEEE International symposium on Circuits and System, Geneva, Switzerland, pp.563-566, 2000.

[31] O. Rioul and M. Vetterli, "*Wavelet and signal processing*", IEEE Signal Processing Magazine, vol. 8, no. 4, pp. 14–38, 1991

[32] I. Daubechies, "*Orthonormal bases of compactly supported wavelets*", Communications on Pure Applied. Mathematics, pp. 909–996, 1988.

[33] N. Delprat, B. Escudie, P. Guillemain, R.K. Martinet, Ph. Tchamitchian, and B. Torresani, "*Asymptotic wavelet and Gabor analysis: extraction of instantaneous frequencies,*" IEEE Transactions on Information Theory, vol. 38, pp. 644-664, 1992

[34] Chi Chang-yan, Zhang Ji-xian and Liu Zheng-jun, "*Study on methods of noise reduction in a stripped image*", The International archives of the photogrammetry, remote sensing and special Information Science, Beijing ,vol. 37, part B6b, 2008.

[35] Kurtis Gurley and Ahsan Kareem, "*Applications of Wavelet Transforms in Earthquake, Wind and Ocean Engineering*", Department of Civil Engineering and Geological Sciences, University of Notre Dame, Notre Dame.

[36] "*Robi Polikar, The Wavelet Tutorial*" http://users.rowan.edu/~polikar/WAVELETS/WTtutorial.html.

[37] George Tzanetakis, Georg Essl, Perry Cook, "*Audio analysis using the Discrete Wavelet Transform*", Princeton, USA.

[38] Liu Ying, Ng Tek Ming and Liew Beng Keat, "*A Wavelet Based Image Sharpening Algorithm*", International Conference on Computer Science and Software Engineering, pp.1053-1056, 2008.

[39] Amir Nooraliei and R. Iraji," *Noise reduction and image sharpening using IJA stochastic learning automaton*" International Conference on Computer Research and Development,vol.2, pp.790-794, 2010.

[40] Sheida Rahmani, Melissa Strait, Daria Merkurjev, Michael Moeller, and Todd Wittman, "*An Adaptive IHS Pan-Sharpening Method"*, IEEE Geoscience and Remote sensing letters, vol. 7, no. 4, pp.746-750, 2010.

[41] Jonghwa Lee and Chulhee Lee, "*Fast and Efficient Panchromatic Sharpening*", IEEE Geoscience and Remote sensing letters, vol. 48, no.1, pp.155-163, 2010.

[42] Ning Xu and Ye ong-Taeg Kim, "*An Image Sharpening Algorithm for High Magnification Image* Zooming", pp.27-28, 2010.

[43] Jong-Cbih Chien and C. C. Li, "*Wavelet-based line detection in gray-scale Images*", IEEE International Conference on Systems, Man, and Cybernetics, 'Computational Cybernetics and Simulation', vol 4, pp. 3670 – 3673, 1997.

[44] Michael Wirth and Denis Nikitenko, "*The effect of colour space on image sharpening algorithms*", Canadian Conference Computer and Robot Vision, pp.79-85, 2010.

[45] Haidi Ibrahim and Nicholas Sia Pik Kong, "*Image Sharpening Using Sub-Regions Histogram Equalization*", Contributed Paper Manuscript received, pp.891-895, 2009.

[46] Chih-Hsien Hsia, Jing-Ming Guo, and Jen-Shiun Chiang, "*Improved Low-Complexity Algorithm for 2-D Integer Lifting-Based Discrete Wavelet Transform Using Symmetric Mask-Based* Scheme", IEEE transactions on circuits and systems for video technology, vol. 19, no. 8, pp.1202-1208, 2009.

[47] Zhengmao Ye, Habib Mohamadian and Yongmao Ye, "*Quantitative Effects of Discrete Wavelet Transforms and Wavelet Packets on Aerial Digital Image Denoising*", 6th International Conference on Electrical Engineering, Computing Science and Automatic Control, Toluca, pp.1-5, 2009.

[48] Takahiko Horiuchi, Kunio Watanabe and Shoji Tominaga," *Adaptive Filtering for Color Image Sharpening and Denoising",* International Conference of Image Analysis and Processing, vol. 14, pp.196-201, 2007.

[49] F.Russo, "*An image enhancement technique combining sharpening and noise reduction*", IEEE Tram. Instrum. Meas, vol. 51, pp. 824-828, 2002.

[50] H. S. Kam, M. Hanmandlu and W. H. Tan, "*An Improved Image Enhancement Combining 'Smoothing and* Sharpening", vol.1, pp.36-40, 2003.

[51] Sean C. Matz and Rui J.P. de Figueiredo," *A nonlinear technique for image contrast enhancement and sharpening*", vol.4, pp.175-178, 1999.

[52] Yanlei Xu, Jiyin Zhao and Yubin Jiao, "*Gray-scale Image Edge Detection Based on Order Morphology Transformation*", Proceedings of the 7th World Congress on Intelligent Control and Automation, Chongqing, China, pp. 5970 – 5975, 2008.

[53] K. Konstantinides, V. Bhaskaran,and G. Beretta, "*Image Sharpening in the JPEG Domain"* IEEE Transactions on Image Processing, vol. 8, no. 6, pp. 874-878, 1999.

[54] Francescomaria Marino, "*Efficient High-Speed/Low-Power Pipelined Architecture for the Direct 2-D Discrete Wavelet Transform*", IEEE Transactions on Circuits and Systems-ii: Analog and Digital Signal Processing, vol. 47, no. 12, pp. 1476 – 1491, 2000.

[55] Amisha and Ankush Kansal, "*Sharpening of image with the combined roll of discrete wavelet transform and unsharp masking*", 1st International conference on emerging trends in signal processing & VLSI design, 2010.

[56] "*G.J.U.S.&T. Library*" http://www.iitmgju.org/images/gju%20building.jpg.