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**COLOR IMAGE DENOISING AND ENHANCEMENT USING
WAVELET TRANSFORM**

By

ANANDA SELVA KARTHIK.T

Reg. No. 0920107001

of

KUMARAGURU COLLEGE OF TECHNOLOGY

(An Autonomous Institution affiliated to Anna University of Technology, Coimbatore)

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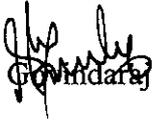
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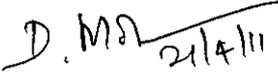
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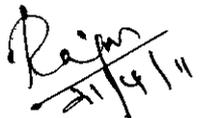
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(Prof. Govindaraju. S)
Project Guide


(Dr. Rajeswari Mariappan)
Head of the Department

The candidate with university Register no. 0920107001 is examined by us in the project viva-voce examination held on ...21/4/11.....


Internal Examiner


External Examiner

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ABSTRACT

Color images are corrupted by noise. The application of image enhancement methods in the three-channel of images (**R, G, B**), on the one hand increases noise, on the other hand tends to have a color deviation, because of the high correlation of R, G, B. In this proposed method, color images are denoised and enhanced in a color space (**HSV and HSI**) at the same time by using **Wavelet transform**. It is used due to its self-adaptive selection of **low** or **high** frequency component. This results in good range of compression, improved visual effects and the true effects of the color. The comparison of results in HSV and HSI color have been obtained and presented.

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LIST OF ABBREVIATIONS

RGB	Red Green Blue
HSV	Hue Satruation Value
HSI	Hue Saturation Intensity
CIE	Commission Internationale de l'Eclairage
HSL	Hue Saturation Intensity
HCI	Hue Chroma Intensity
STFT	Short Time Fourier Transform
CWT	Continuous Wavelet Transform
DWT	Discrete Wavelet Transform

CHAPTER 1

INTRODUCTION

Over the last two decades, there have been explosive growth in both the diversity of techniques and the range of applications of image processing. However, the area of color image processing is still not covered extensively.

Consumers use the convenience of color imaging over traditional grayscale imaging. With advances in image sensors, digital TV, image databases, and video and multimedia systems, and with the proliferation of color printers, color image displays, DVD devices, and especially digital cameras and image-enabled consumer electronics.

Color image processing appears to have become the main focus of the image-processing research community. Processing color images or, more generally, processing multichannel images, such as satellite images, color filter array images, microarray images, and color video sequences, is a nontrivial extension of the classical grayscale processing.

Recently, there have been many color image processing and analysis solutions, and many interesting results have been reported. Concern on filtering, enhancement, restoration, edge detection, analysis, compression, preservation, manipulation, and evaluation of color images.

The surge of emerging applications, such as single-sensor imaging, color-based multimedia, digital rights management, art, and biomedical applications, indicates that the demand for color imaging solutions will grow considerably in the next decade.

Color is the perceptual sensation of light in the visible range incident upon the retina. Color is the most visually striking feature of any image and it has a significant bearing on the scenic beauty of an image. To understand color, it is necessary to understand the nature of light. Different wavelengths of light are perceived as different colors. The Color image processing appears to have become the main focus of the image-processing research community. Processing color images or, more generally, processing multichannel images, such as satellite images, color filter array images, microarray images, and color video sequences, is a nontrivial extension of the classical gray scale processing.

The noise in the color images will be enhanced as well as color images are enhanced. Most papers related to the image denoising either talk about gray-scale image or not take denoising and enhancement into account in company.

If we directly apply the gray-scale image enhancement to the three channel of color image for enhancing them, color may decline. The reason is that high correlation of the red, green, blue channels, it will results in deviation.

In recent years the application of wavelet theory is a very wide range of technologies. Because of its self-adaptive selection of low or high frequency, it has a good time frequency characteristic, we use wavelet transform to enhance and denoise at the same time.

The work presented in this paper is transforming RGB color space to HSV and HSI color space, The dynamic range of color images, the different impact on color saturation and luminance by noise are all considered.

CHAPTER 2

COLOR IMAGE PROCESSING

2.1 INTRODUCTION

Color is the perceptual sensation of light in the visible range incident upon the retina. Color is the most visually striking feature of any image and it has a significant bearing on the scenic beauty of an image. To understand color, it is necessary to understand the nature of light. Different wavelengths of light are perceived as different colors. Color is the brain's reaction to a specific visual stimulus. Although we can precisely describe color by measuring its spectral power distribution (the intensity of the visible electro-magnetic radiation at many discrete wavelengths) this leads to a large degree of redundancy. The reason for this redundancy is that the eye's retina samples color using only three broad bands, roughly corresponding to red, green and blue light. The signals from these color sensitive cells (cones), together with those from the rods (sensitive to intensity only), are combined in the brain to give several different "sensations" of the color.

2.1.1 What is a color image ?

Color image is a digital image that includes color information for each pixel. A color image has three values per pixel and they intensity and chrominance of light. Each pixel is a vector of color components. Color images can be modeled as three band monochrome image data, where each band of data corresponds to a different color. The actual color information stored in the digital image data is the brightness information in each spectral band.

Color images usually consists of three separate image representation called color planes, with pixel values in each plane corresponding to the intensity of a certain color at a specific point in the image. Each color space consists of an array of pixel values similar to that of the gray scale representation. The most popular system in RGB, where three color planes are used to represents the intensity of red, green and blue in the scene.

Color image processing is motivated by two main factors:

- ✓ Color is a powerful descriptor simplifying object recognition.
- ✓ One can distinguish between thousands of color shades and intensities.

There are two major areas of color image processing:

- ✓ Full-color processing – images are acquired with a full-color sensor (TV camera, color scanner);
- ✓ Pseudocolor processing colors are assigned to a particular monochrome intensity or intensity range.

2.2 FUNDAMENTALS OF COLOR

If the light is achromatic (no colors), its only attribute is its intensity. Examples of achromatic light: images produced by a b&w TV set, monochrome pictures.

Chromatic light spans the EM spectrum from approximately 400 to 700 nm. The basic quantities used to describe a chromatic light source are

Radiance: the total amount of energy from the source.

Luminance: energy an observer perceives from the source,(for example, an observer might barely perceive any light from a source radiating in an infrared region), and

Brightness: the human sensation by which an area exhibits more or less lights.

Lightness: the sensation of an area's brightness relative to a reference white in the scene.

Chroma: the colorfulness of an area relative to the brightness of a reference white.

Due to the absorption characteristics of the human eye, we see colors as variable combinations of so-called *primary colors of light*: red(R), green (G), blue (B). The following wavelengths are designated to them in 1931: 700 nm, 546.1 nm, and 435.8 nm.

The amounts of red, green, and blue needed to form any particular color are called the *tristimulus* values and are denoted as X, Y, Z .

therefore, a color is specified by its *trichromatic coefficients*:

$$x = \frac{X}{X+Y+Z}, \quad y = \frac{Y}{X+Y+Z}, \quad z = \frac{Z}{X+Y+Z}$$

We notice that $x + y + z = 1$

2.3 LIGHT AND COLOR

The frequency of light determines the color. The amount of light determines the intensity. The famous Einstien relation is given by

$$E = hv = \frac{hc}{\lambda}$$

As stated earlier, the visible spectrum is approximately between 400nm to 700nm. The human visual system receives electromagnetic energy having wavelength in the range 400-700 nm as visible light. Lightness of brightness refers to the amount of light a certain color reflects or transmits. Light that has a dominant frequency is called chromatic. A chromatic light has no color and it contributes only to intensity. The intensity is determined by the energy, whereas brightness is determined by the perception of the color; hence it is psychological. Color depends primarily on the reflectance properties of an object.

2.4 COLOR INFORMATION

The colors a human being perceives in day-to-day life arise from a very diverse physiochemical process. Some objects are light sources, while others merely reflect the incident light. Basically there are three color formation processes

1. Additive process

In additive color information, the spectral distributions corresponding to two or more light rays get added. The additive color formation is employed in TV monitors.

2. Subtractive process

Subtractive color formation occurs when the light is passed or transmitted through a light filter. A filter partly absorbs part of light that reaches it transmits the rest. It occurs when color slides are projected onto screen.

3. Pigmentation

A pigment consists of colored particles in suspensions in a liquid. These particles can absorb or reflect the light that reaches them. When a light ray reaches a surface covered with a pigment, it is scattered by the particles, with successive and simultaneous events of reflection, transmission and absorption. These events determine the nature of the light reflected by surface. Color information through pigmentation allows one to see colors in a painting.

2.5 RESOLUTION

Resolution gives the degree of distinguishable details. Resolution can be broadly classified into

1. Spatial resolution

Spatial resolution is the smallest discernible detail in the image. Spatial resolution depends on the number of pixels. The principal factor determining spatial resolution is sampling.

2. Gray-level resolution

Gray-level resolution refers to the smallest discernible change in the gray level. It depends on the number of gray levels.

CHAPTER 3

COLOR SPACE

3.1 INTRODUCTION

Color spaces indicate color coordinate systems in which the image values of a color image are represented. The difference between two image values in a color space is called color distance. The numbers that describe the different color distances in the respective color model are as a rule not identical to the color differences perceived by humans. As humans, we may define a color by its attributes of brightness, hue and colorfulness. A computer may describe a color using the amounts of red, green and blue phosphor emission required to match a color. A printing press may produce a specific colour in terms of the reflectance and absorbance of cyan, magenta, yellow and black inks on the printing paper. In the following, the standard color system XYZ, established by the International Lighting Commission CIE (Commission Internationale de l'Éclairage), will be described. This system represents the international reference system of color measurement.

The color spaces are on the basis of

- ✓ Physics and Technics-Based Color Spaces(RGB,YUV,YIQ)
- ✓ Uniform Color Spaces(CIELAB & CIELUV color space)
- ✓ Perception-Based Color Spaces(HSI,HSV)

3.2 CMY(K) (Cyan Magenta Yellow (Black))

This is a subtractive based color space and is mainly used in printing and hard copy output. The fourth, black, component is included to improve both the density range and the available color gamut. CMY(K) is fairly easy to implement but proper transfer from RGB to CMY(K) is very difficult (simple transforms are, to put it bluntly, simple). CMY(K) is device dependent, non-linear with visual perception and reasonably unintuitive.

3.3 YIQ, YUV, YCbCr, YCC (Luminance - Chrominance)

These are the television transmission color spaces, sometimes known as transmission primaries. YIQ and YUV are analogue spaces for NTSC and PAL systems respectively while YCbCr is a digital standard. These color spaces separate RGB into luminance and chrominance information and are useful in compression applications (both digital and analogue). These spaces are device dependent but are intended for use under strictly defined conditions within closed systems. They are also quite unintuitive, unless of course you are a TV engineer.

3.4 CIE

There are two CIE based color spaces, CIELuv and CIELab. They are nearly linear with visual perception, or at least as close as any color space is expected to sensibly get. Since they are based on the CIE system of color measurement, which is itself based on human vision, CIELab and CIELuv are device independent but suffer from being quite unintuitive despite the L parameter having a good correlation with perceived lightness. To make them more user friendly, the CIE defined two analogous spaces - CIELhs or CIELhc where h stands for hue, s for saturation and c for chroma. In addition CIELuv has an associated two-dimensional chromaticity chart which is useful for showing additive color mixtures, making CIELuv useful in applications using CRT displays. CIELab has no associated two dimensional chromaticity diagram and no correlate of saturation. CIELhs can therefore not be defined.

3.4.1 Why is there more than one color space?

Different color spaces are better for different applications, for example some equipment has limiting factors that dictate the size and type of color space that can be used. Some color spaces are perceptually linear, i.e. a 10 unit change in stimulus will produce the same change in perception wherever it is applied. Many color spaces, particularly in computer graphics, are not linear in this way. Some color spaces are intuitive to use, i.e. it is easy for the user to navigate within them and creating desired colors is relatively easy. Other spaces are confusing for the user with parameters with abstract relationships to the perceived color. Finally, some color spaces are tied to a specific piece of equipment (i.e. are device dependent) while others are equally valid on whatever device they are used.

3.5 COLOR GAMUT

A color gamut is the area enclosed by a color space in three dimensions. It is usual to represent the gamut of a color reproduction system graphically as the range of colors available in some device independent color space.

3.6 CIE System

The CIE has defined a system that classifies color according to the HVS (human visual system). Using this system we can specify any color in terms of its CIE co-ordinates and hence be confident that a CIE defined color will match another with the same CIE definition. A brief a superficial description follows below. The CIE has measured the sensitivities of the three broad bands in the eye by matching spectral colors to specific mixtures of three colored lights. The spectral power distribution of a color is cascaded with these sensitivity functions to produce three tri-stimulus values. These tri-stimulus values uniquely represent a color, however since the illuminant and lighting and viewing geometry will affect the measurements these are all carefully defined. The three CIE tri-stimulus values are the building blocks from which many color specifications are made.

3.7 RGB COLOR MODEL

The RGB color model is based on a Cartesian coordinate system. The color sub space is a cube, in which RGB primary values are at the three corners, the secondary colors(cyan, magenta and yellow) are at other three corners. Black is at the origin and white is at the farthest from the origin corner. The gray scale (points of equal RGB values) extends from black to white along the straight line. Images represented in the RGB model consist of three component images (one for each primary color) that are combined into a composite color image. The number of bits used to represent a pixel is called the **pixel depth**. Assuming that each component image uses 8 bits, each RGB color pixel is said to have a depth of 24 bits. Such RGB color images are frequently called **full-color images**.

The total number of colors in a 24-bit color image is $(2^8)^3 = 16\,777\,216$.

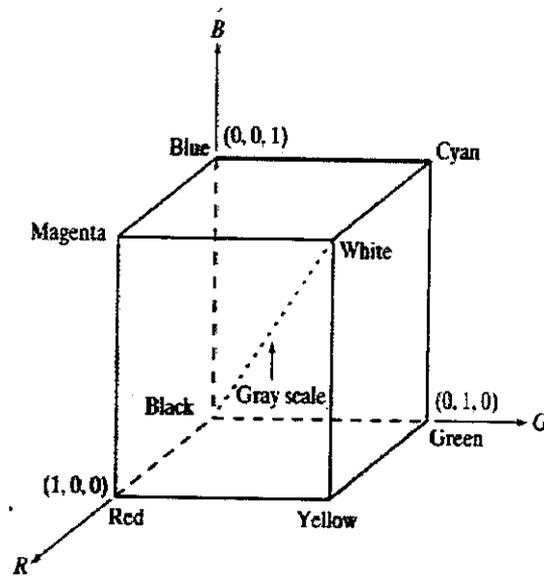


Figure 3.1-RGB color model

The rational numbers are the color value components that are normalized with respect to intensity in the range $[0, 1]$. It is mostly used in cameras and monitors.

Mathematically we can represent color image by means of using three dimensions matrixes. One dimension for red color and the other for blue color and the thrid one is for green color. It can be stored as a m -by- n -by-3 data array that defines the red ,green and blue components for each individual pixel. The color of each pixel is determined by the combination of red,green and blue intensities stored in each color plane at each pixel location.

CHAPTER 4

COLOR SPACE TRANSFORMATION

4.1 INTRODUCTION

4.1.1 What is the need for color space transformation?



RGB is most common being used in virtually every computer system, television and video. It is easy to implement. However, high correlation between channels, significant perceptual non-linearity with visual perception, device dependency and mixing of chrominance and luminance data make RGB not a very favorable choice for color image processing. It is also computationally intensive. Thus we seek for another color spaces which are more suitable for processing.

Transformations like,

- ✓ RGB-HSV/HSI
- ✓ RGB-YUV
- ✓ RGB-YCbCr

From the above color transformations, the HSV/HSI method is the best choice for multi – resolution based image contrast enhancement application. It has the perfect separation of chrominance and luminance values. The color space is quite similar to the way in which humans perceive color.

4.2 HSL (hue saturation lightness)

HSL type color spaces are deformations of an RGB color cube. If you imagine the RGB cube tipped cube onto the black corner then the line through the cube from black to white defines the lightness axis. The color is then defined as a position on a circular plane around the lightness axis. Hue is the angle from a nominal point around the circle to the color while saturation is the radius from the central lightness axis to the color.

Alternative examples to HSL include HSV (Hue Saturation Value), HSI (Hue Saturation Intensity) and HCI (Hue Chroma Intensity).

They are device independent and correlate well with visual perception. This is not the case, they are simply linear transforms from RGB and as such share all the shortcomings of RGB. The one and only advantage of these color spaces is that they allow a user to intuitively specify colors making them a good choice in user interfaces

4.2.1 HSV COLOR SPACE

The HSV (Hue, Saturation, Value) model, also known as HSB (Hue, Saturation, Brightness), defines a color space in terms of three constituent components. It is a non-linear transform of the RGB color space. Perfect separation of the luminance component from the chrominance. Information makes it advantageous in image processing. It is also extremely intuitive. However, it is non-linear and device dependent. It is widely used in the field of color vision.

HUE:

In HSV, hue represents the dominant wavelength of light (color).

SATURATION:

Saturation indicates the range of gray in the color space. It ranges from 0 to 100%. Sometimes the value is calculated from 0 to 1. When the value is '0,' the color is grey and when the value is '1,' the color is a primary color. A faded color is due to a lower saturation level, which means the color contains more gray.

VALUE:

Value is the brightness of the color and varies with color saturation. It ranges from 0 to 100%. When the value is '0' the color space will be totally black. With the increase in the value, the color space brightness up and shows various colors

Formula :

RGB to HSV

$$\max = \max(R,G,B)$$

$$\min = \min (R,G,B)$$

$$H = (G-B) / (\max - \min) , \max = R$$

$$H = 2 + (B-R) / (\max - \min) , \max = G$$

$$H = 4 + (R-G) / (\max - \min) , \max = B$$

$$H = H * 60 , H \geq 0$$

$$H = H + 360 , H < 0$$

$$S = (\max - \min) / \max$$

$$V = \max(R,G,B)$$

HSV to RGB

$$\text{Hex} = H / 60$$

$$\text{Secondary color} = \text{Hex} - \text{Primary color}$$

$$a = (1-S)V$$

$$b = (1 - (S * \text{Secondary color}))V$$

$$c = (1 - (S * (1 - \text{Secondary color})))V$$

$$\text{if primary color} = 0 \quad \text{then } R=V, G=c, B=a$$

$$\text{if primary color} = 1 \quad \text{then } R=b, G=V, B=a$$

$$\text{if primary color} = 2 \quad \text{then } R=a, G=V, B=c$$

if primary color= 3 then $R=a$, $G=b$, $B=V$

if primary color= 4 then $R=c$, $G=a$, $B=V$

if primary color= 5 then $R=V$, $G=a$, $B=b$

where S and V value are in the interval [0 1], H value between 0 to 360°

4.2.2 HSI COLOR SPACE

The HSI model owes its usefulness to two principal facts. First the intensity component I is decoupled from the color information in the image. Second the hue and saturation components are intimately related to the way in which human being perceive color. These features make the HSI model an ideal tool

HUE:

In HSV, hue represents color. In this model, hue is an angle from 0 degrees to 360 degrees.

Angle	Color
0-60	Red
60-120	Yellow
120-180	Green
180-240	Cyan
240-300	Blue
300-360	Magenta

SATURATION:

Saturation indicates the range of gray in the color space. It ranges from 0 to 100%. Sometimes the value is calculated from 0 to 1. When the value is '0,' the color is grey and when the value is '1,' the color is a primary color. A faded color is due to a lower saturation level, which means the color contains more gray.

INTENSITY:

It is the average of the of the three components in the HSI model. It is measured with respect to a line perpendicular to the triangle and passing through its center. Intensities along the line lying below the triangle tend to form dark down to black. Conversely intensities above the triangle tend to form light upto white.

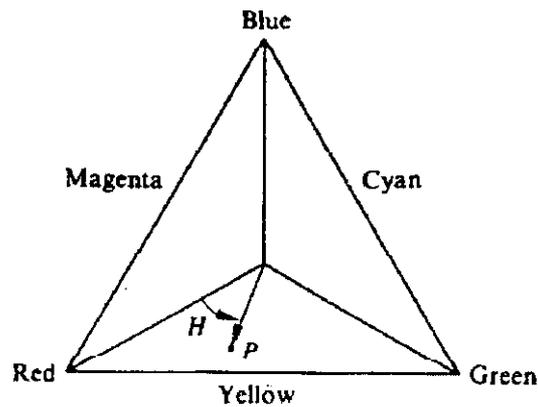


Fig 3.1 HSI color triangle

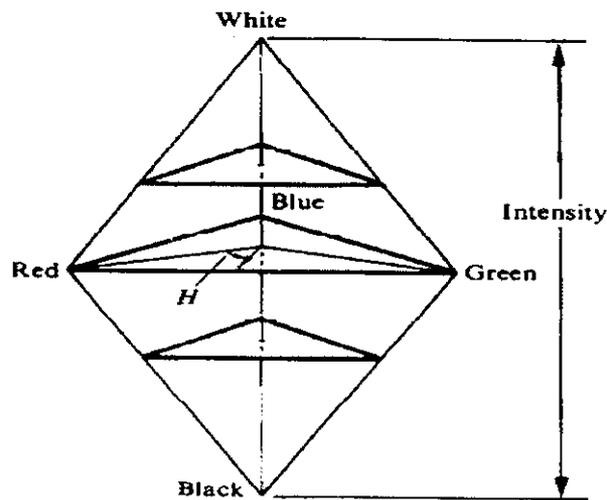


Fig 3.2 HSI color solid

Combining hue, saturation and intensity in a 3D color space yields the three-sided pyramid like structure as shown in figure 3.2. Any point on the surface of the structure represented the

purely saturated color. The hue of that color is determined by its angle w.r.to the red axis and its intensity by its perpendicular distance from the dark point .

Colors in the HSI model are defined with respect to normalized red, green and blue values given in terms of RGB primaries

$$r = R/(R+G+B)$$

$$g = G/(R+G+B)$$

$$b = B/(R+G+B)$$

Where, as before, the assumption is that R,G,B have been normalized and they are in the range [0 1]. So that r, g, b values are also in the interval [0 1].

$$r + g + b = 1$$

This is the equation of the plane that contains the HSI triangle.

Formula :

RGB to HSI

$$I = 1/3(R + G + B)$$

$$S = 1 - \frac{3}{R + G + B} \times [\min(R, G, B)]$$

$$H = \theta \quad \text{if } B \leq G$$

$$360 - \theta \quad \text{if } B > G$$

Where

$$\theta = \cos^{-1} \left[\frac{1}{2[(R-G)+(R-B)]} / [(R-G)^2 + (R-B)(G-B)]^{1/2} \right]$$

HSI to RGB**RG sector ($0^{\circ} \leq H < 120^{\circ}$)**

$$B = I(1 - S)$$

$$R = I[1 + [S \times \cos H / \cos(60^{\circ} - H)]]$$

$$G = 1 - (R + B)$$

GB sector ($120 \leq H < 240$)

$$H = H - 120^{\circ}$$

$$R = I(1 - S)$$

$$G = I[1 + [S \times \cos H / \cos(60^{\circ} - H)]]$$

BR sector ($240^{\circ} \leq H < 360^{\circ}$)

$$H = H - 240$$

$$B = I[1 + [S \times \cos H / \cos(60^{\circ} - H)]]$$

$$G = I(1 - S)$$

$$R = 1 - (G + B)$$

$$b = (1 - (S \times \text{Secondary color}))V$$

$$c = (1 - (S \times (1 - \text{Secondary color})))V$$

4.3 NOISE SOURCES

Noise, arising from a variety of sources, is inherent to all electronic image sensors. There are many types of noise sources that decrease the quality of color images are

- ✓ **Cross color noise** that is caused by the mixing of the signals of adjacent color image samples.
- ✓ **False color noise** that is an inherent weakness of single-plate sensor cameras and produces colors not actually present in the image scene.
- ✓ **Color phase noise** that produces color blotches in dark gray areas or generates color shifts.

- ✓ **Quantization noise** that is inherent in the amplitude quantization process and occurs in the analog-to-digital converter.
- ✓ **Banding noise** that is introduced by the camera, when it reads data from the digital sensor.
- ✓ **Fixed pattern noise** that includes the so-called “hot” and “dead” pixels.
- ✓ **Random noise**, like *photon noise*, *dark current noise*, and *read out noise*, among many others.
- ✓ Additionally, transmission errors, periodic or random motion of the camera system during exposure, electronic instability of the image signal, electromagnetic interferences, sensor malfunctions, optic imperfections, or aging of the storage material all degrade the image quality.

4.4 COLOR BALANCING ALGORITHM

The integration-to-gray algorithm and its photofinishing applications :

It works by setting the averaged color of an image to a predefined gray. It is probably the oldest color balance algorithm that is successfully used in consumer photography. The color correction is achieved by “adjusting the intensity of the printing light so that when integrally passed through said transparency, it has the same printing characteristics as light which prints substantially as gray”

The Retinex algorithm :

The retinex theory proposes that the visual system computes three “lightness” images, one from each of the three color channels independently. The red, green, and blue lightness values at each spatial location determine the color we see at that location.

The chromaticity convergence algorithm :

It is a very common perceptual observation that the specular highlight from surface reflection often appears white or desaturated color.

If there are other colored surfaces in the image, the chromaticity diagram has many line segments pointing to a common intersection point which is the illuminant chromaticity point. This method of estimating the light source chromaticity is called the chromaticity convergence algorithm.

The gamut mapping algorithms :

Let R, G, B be the color responses of an image capture device, such as a digital camera. Without loss of generality, let us assume that each color channel is represented with only eight-bit precision, i.e., $R, G, B = 0, 1, \dots, 255$. For any color image captured by the device, it turns out that many of the (R, G, B) values will not occur. The total volume of the (R, G, B) values that occur in an image is called the color gamut of that image

Bayesian estimation and the color by correlation algorithm :

If one examines the color histograms of many images, it becomes quite apparent that not all colors are created equal – some are present more frequently than others. It estimate the likelihood that an input image was taken under any illuminant and choose the most likely illuminant as an estimate of the scene illuminant . This is called the Bayesian estimation approach.

The first thing to notice is that for color balance applications, it seems sufficient to partition natural light sources into about 10–20 different illuminants, depending on the precision required for the estimate. For each of these illuminants, many color images can be taken to compile the probability distribution that a color will occur under an illuminant. A correlation matrix is then put together, in which each column represents one illuminant and each row represents a color. A given element in the correlation matrix thus contains the probability of occurrence of the color represented by that row and under the illuminant represented by that column. An input image is represented as a column vector, with the i th element representing the same color as represented by the i th row in the correlation matrix. If a color is present in the image, the element is set to 1, otherwise, it is set to 0. The input column vector is then correlated

with each column of the correlation matrix (element-by-element multiplication and summation) to derive the likelihood of the illuminant corresponding to the column. The operation basically adds up all the probabilities of the colors present in the image.

The most likely illuminant is chosen as the illuminant estimate color-by-correlation algorithm is very fast and is claimed to be quite accurate. It is very important to note that each color present in an image is only counted once and therefore, this method is not sensitive to large areas of dominant color. A threshold is imposed so that an accidental color pixel will not cause the probability of that color to be added.

CHAPTER 5

IMAGE ENHANCEMENT AND TRANSFORMS

5.1 IMAGE ENHANCEMENT

The objective of image enhancement is to improve the interpretability of the information present in images for human viewer. An enhancement algorithm is one that yields a better quality image.

Image enhancement techniques emphasis specific image features to improve the visual perception of an image. They are classified into two broad categories as

1. Spatial domain method
2. Transform domain method

The spatial domain method operates directly on pixels, whereas the transform domain method operates on the Fourier transform of an image and then transform it back to the spatial domain.

5.2 IMAGE ENHANCEMENT IN SPATIAL DOMAIN

The spatial domain technique deals with the manipulation of pixel values. The spatial domain technique can be broadly classified into

1. Point operation
2. Mask operation
3. Global operation

5.2.1 POINT OPERATION

In point operation, each pixel is modified by an equation that is dependent on the other pixel values.

The point operation is represented by

$$g(m,n) = T[f(m,n)]$$

Types of point operation includes

1. Brightness modification
2. Contrast manipulation
3. Histogram manipulation

5.2.2 MASK OPERATION

In mask operation, each pixel is modified according to the values in a small neighbourhood of pixels.

5.2.3 GLOBAL OPERATION

In global operation, all the pixel value in the range are taken into consideration. Usually, frequency domain operation are global operation.

5.3 NEIGHBOURHOOD OPERATION

In neighbourhood operation, the pixel in an image are modified based on some function of the pixel in their neighbourhood. Linear spatial filtering is often referred to as convolving a mask with an image. The filter masks are sometimes called convolution masks or convolution kernels.

5.3.1 LIMITATION OF AVERAGING FILTER

The limitation of averaging filter are given below

1. Averaging operation leads to the blurring of an image. Blurring affects feature localization.
2. If the averaging operation is applied to an image corrupted by impulse noise then the impulse noise is attenuated but not removed.
3. A single pixel, with a very unrepresentative value can effect the mean value of all pixel in its neighbourhood significantly.

5.3.2 MEDIAN FILTER

Median filter are statistical non-linear filter that are often described in the spatial domain. A median filter smoothness the image by utilising the median of the neighbourhood. The concept of median filter was introduced by turkey in 1997. Its extension to two-dimensional image was discussed by partin1978. Median filters performs the following tasks to find each pixel value in the processed image.

1. All the pixel in the nieghbourhood o the pixel in the original image which are identified by the mask are sorted in the ascending (or) descending order.
2. The median of the sorted value is computed and is choosen as the pixel value for the processed image.

When median filter is applied to an image , the pixel value which are very different form their neighbourhood pixels will be eliminated. By eliminating the effect of such odd pixels, the values are assigned to the pixels that are representative of the values of the typical neighbourhood pixels in the original image.

5.4 IMAGE TRANSFORMS

Image transforms are extensively used in image processing and image analysis. Transform is a mathematical tool, which allows us to move from one domain to another domain. The transform do not change the information content present in the signal. Most of the image transforms like Fourier transform, Discrete cosine transform, wavelet transform, etc., give information about the frequency contents in an image. It is to be noted that all the transform will not give frequency domain information. Transforms plays a significant role in various image processing application such as image analysis, image enhancement, image filtering, and image compression.

5.4.1 NEED FOR TRANSFORM

Transform is basically a mathematical tool to represent a signal. The need for transform is given as follows

- i) **Mathematical convenience** : every action in time domain will have an impact in frequency domain.
The complex convolution operation in the time domain is equal to simple multiplication operation in the frequency domain.
- ii) **To extract more information** : transform allow us to extract more relevant information information.

Image transform is basically a representation of image. There are two reason for transforming an image from one representation to another. First, the transformation may isolate critical components of the image data in more compact form so that they can be stored and transmitted effectively. The different types of transform discussed in the section are

1. Fourier transform
2. Walsh transform
3. Hadamard transform
4. Slant transform
5. Discrete transform
6. KL transform
7. Radon transform
8. Wavelet transform

CHAPTER 6

WAVELET TRANSFORM

6.1 INTRODUCTION

Wavelet analysis is developed in the largely mathematical literature in the 1980's and began to be used commonly in geophysics in the 1990's. Wavelets can be used in signal analysis, image processing and data compression. They are useful for sorting out scale information, while still maintaining some degree of time or space locality. Wavelets are used to compress and store fingerprint information by the FBI. Because the structure functions are obtained by scaling and translating one or two "mother functions", time-scale wavelets are particularly appropriate for analyzing fields that are fractal. Wavelets can be appropriate for analyzing non-stationary time series, whereas Fourier analysis generally is not. They can be applied to time series as a sort of fusion between filtering and Fourier analysis. Wavelets can be used to compress the information in two dimensional images from satellites or ground based remote sensing techniques such as radars.

Wavelets are useful because as you remove the highest frequencies, local information is retained and the image looks like a low resolution version of the full pictures. With Fourier analysis, or other global functional fits, the image may lose all resemblance to the picture, after a few harmonics are removed. This is because wavelets are a hierarchy of local fits, and retain some time localization information, and Fourier or polynomial fits are global fits, usually. In general, you can think of wavelets as a compromise between looking at digital data at the sampled times, in which case you maximize the information about how things are located in time, and looking at data through a Fourier analysis in frequency space, in which you maximize your information about how things are localized in frequency and give up all information about how things are located in time. In wavelet analysis we retain some frequency localization and some time localization, so it is a trade-off.

6.2 why wavelet ?

The transform of a signal is just another form of representing the signal. It does not change the information content present in the signal. The Wavelet Transform provides a time-frequency representation of the signal. It was developed to overcome the short coming of the Short Time Fourier Transform (STFT), which can also be used to analyze non-stationary signals. While STFT gives a constant resolution at all frequencies, the Wavelet Transform uses multi-resolution technique by which different frequencies are analyzed with different resolutions.

A wave is an oscillating function of time or space and is periodic. In contrast, wavelets are localized waves. They have their energy concentrated in time or space and are suited to analysis of transient signals. While Fourier Transform and STFT use waves to analyze signals, the Wavelet Transform uses wavelets of finite energy.

The wavelet analysis is done similar to the STFT analysis. The signal to be analyzed is multiplied with a wavelet function just as it is multiplied with a window function in STFT, and then the transform is computed for each segment generated. However, unlike STFT, in Wavelet Transform, the width of the wavelet function changes with each spectral component. The Wavelet Transform, at high frequencies, gives good time resolution and poor frequency resolution, while at low frequencies, the Wavelet Transform gives good frequency resolution and poor time resolution.

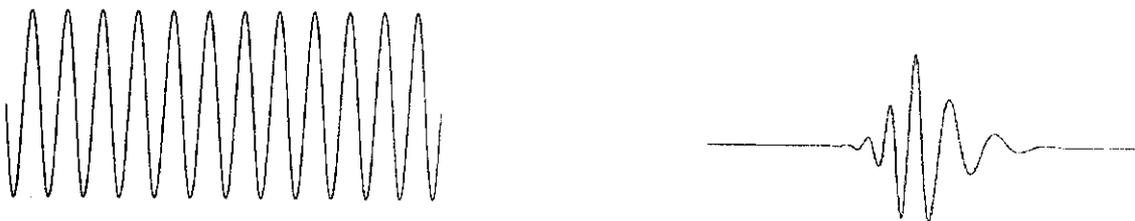


Figure 6.1(a) wave -(b) wavelet

6.3 PROPERTIES OF WAVELET

The function integrates to zero, i.e., it has a wavy appearance

$$\int_{-\infty}^{\infty} \psi(t) dt = 0$$

It is square integrable, i.e., it has finite energy

$$\int_{-\infty}^{\infty} |\psi(t)|^2 dt < \infty$$

6.4 CONTINUOUS WAVELET TRANSFORM

The continuous wavelet transform (CWT) of a one dimensional signal is given by

$$W_f(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \psi^* \left(\frac{t-b}{a} \right) dt$$

The continuous wavelet transform is a function of two variables a and b . here, a is the scaling parameter and b is the shifting parameter $\psi(t)$ is the mother wavelet function. The shifting parameter gives the time information in the wavelet transform. It indicates the location of the window as it is shifted through the signal. The scale parameter gives the frequency information in the wavelet transform. A low scale corresponds to a wavelet of smaller width, which gives the detailed information in the signal. A higher scale corresponds to the wavelet of larger width, which gives the detailed information in the signal.

Time-scale wavelets are defined in reference to a "mother function" $\psi(t)$ of some real variable t . The mother function is required to have several characteristics: it must oscillate, and it must be localized in the sense that it decreases rapidly to zero as $|t|$ tends to infinity. It is also very helpful to require that the mother function have a certain number of zero moments, according to:

$$0 = \int_{-\infty}^{\infty} \psi(t) dt = \dots \int_{-\infty}^{\infty} t^{m-1} \psi(t) dt$$

The mother function can be used to generate a whole family of wavelets by translating and Scaling the mother wavelet.

$$\psi_{(a,b)}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right), a > 0$$

Here b is the translation parameter and a is the scaling parameter.

6.5 DISCRETE WAVELET TRANSFORM

The discrete wavelet transform(DWT) is obtained by filtering the signal through a series of digital filter at different scales. The scaling operation is done by changing the resolution of the signal by the process of subsampling. The DWT can be computed using either convolution or lifting based procedure. In both methods the input sequence is decomposed into low-pass and high-pass sub-bands, each consisting of half the number of samples in the original sequence.

SUB-BANDCODING:

Sub-band coding is a procedure in which the input signal is divided into several frequency bands. Sub-band coding can be implemented by using filter banks. The filter bank is a collection of filters having a common input or common output. When the filters have the common input they form an analysis bank, and when they share a common output, they form an synthesis bank. The basic idea of the filter bank is to partition a signal dyadically at the frequency domain.

6.5.1 2D SUBBAND CODING

Filters are one of the most widely used signal processing functions. Wavelets can be realized by iteration of filters with rescaling. The resolution of the signal, which is a measure of the amount of detail information in the signal, is determined by the filtering operations, and the scale is determined by up sampling and down sampling (sub sampling) operations.

The DWT is computed by successive lowpass and highpass filtering of the discrete time-domain signal as shown in figure 6.2. This is called the Mallat algorithm or Mallat-tree decomposition. Its significance is in the manner it connects the continuous-time multiresolution to discrete-time filters. The low pass filter is denoted by G while the high pass filter is denoted by

H. At each level, the high pass filter produces detail information, D_{k+1} , while the low pass filter associated with scaling function produces coarse approximations, A_{k+1} .

At each decomposition level, the half band filters produce signals spanning only half the frequency band. This doubles the frequency resolution as the uncertainty in frequency is reduced by half. In accordance with Nyquist's rule if the original signal has a highest frequency of ω , which requires a sampling frequency of 2ω radians, then it now has a highest frequency of $\omega/2$ radians. It can now be sampled at a frequency of ω radians thus discarding half the samples with no loss of information. This decimation by 2 halves the time resolution as the entire signal is now represented by only half the number of samples. Thus, while the half band low pass filtering removes half of the frequencies and thus halves the resolution, the decimation by 2 doubles the scale.

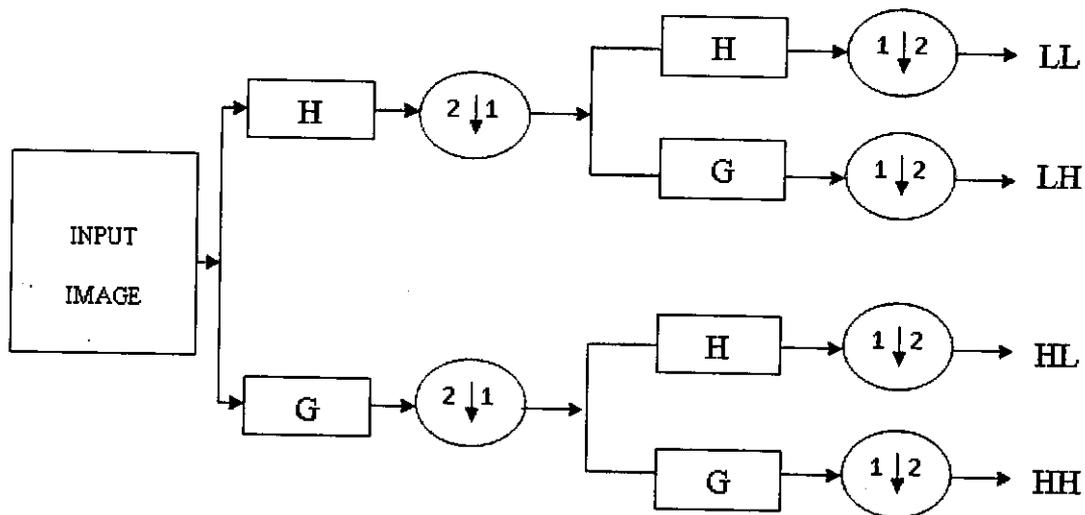


Figure 6.2 Image Decomposition

With this approach, the time resolution becomes arbitrarily good at high frequencies, while the frequency resolution becomes arbitrarily good at low frequencies. The filtering and decimation process is continued until the desired level is reached. The maximum number of levels depends on the length of the signal. The DWT of the original signal is then obtained by concatenating all the coefficients, A_{k+1} and D_{k+1} , starting from the last level of decomposition.

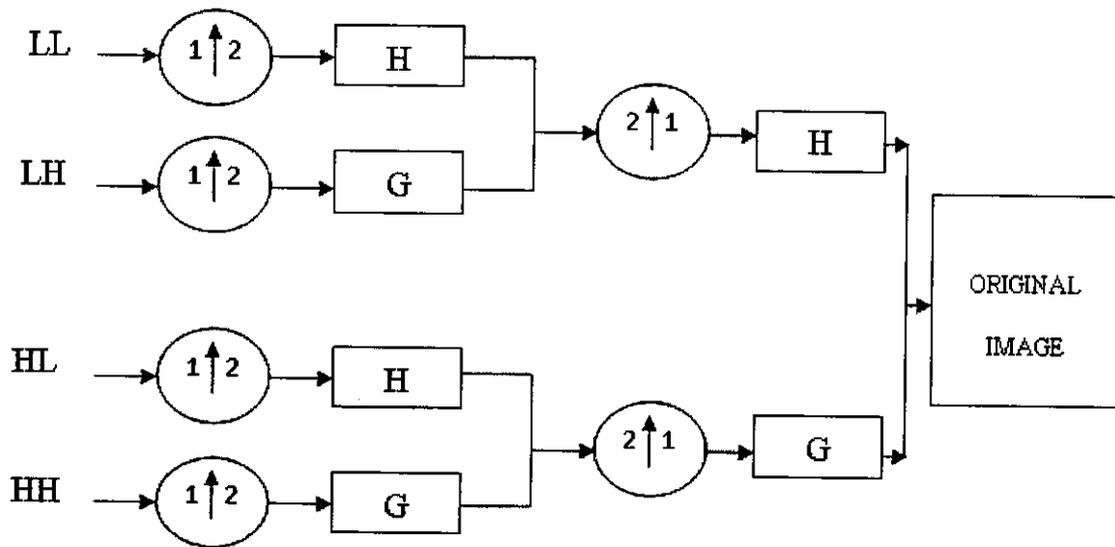


Figure 6.3 Image Reconstruction

Figure 6.3 shows the reconstruction of the original signal from the wavelet coefficients. Basically, the reconstruction is the reverse process of decomposition. The approximation and detail coefficients at every level are upsampled by two, passed through the low pass and high pass synthesis filters and then added.

This process is continued through the same number of levels as in the decomposition process to obtain the original signal. The Mallat algorithm works equally well if the analysis filters, G and H , are exchanged with the synthesis filters, G .

6.6 MULTIREOLUTION ANALYSIS

The foundations of Retinex are the color invariance and the illumination-reflectance model. As the illumination reflectance model reveals the physical theory of imaging, an image $f(x, y)$ can be described as $f(x, y) = i(x, y) \times r(x, y)$, the illumination $i(x, y)$ is characterized by slow change, and reflection $r(x, y)$ is caused by mutations, in particular edges of some objects [2]. If we do Fourier transform of the image, select the appropriate filter function, it will compress the high dynamic range of color image, but the noise in the high frequency information are also increased and the image enhanced by Retinex will have 'halos' and the detail may also blurred.

The 2D multiresolution analysis is given by

$$v_i = v_{i+1} \oplus w_{i+1}$$

V_i which is the low frequency part of the image decomposed by wavelet transform, W_{i+1} is composed of $cD_{j+1}^{(h)}$, $cD_{j+1}^{(v)}$, $cD_{j+1}^{(d)}$ which are the high frequency part. i is the scale of wavelet transform, \oplus is synthesis of operation symbol.

We can assume

$$W = W_i \oplus W_{i-1} \dots \oplus W_2 \oplus W_1$$

$$v_0 = v_i \oplus W$$

As V_j is the constant imaginary part and the illumination imaginary part $i(x, y)$ can also be taken as constant imaginary part, V_j can also be known as $i(x, y)$. Because W is composed of all detail parts of image and the reflectance imaginary part $r(x, y)$ which mainly composed of the details of image, W can also know as $r(x, y)$. The illumination reflectance model can be approximately described by wavelet transform as

$$f(x, y) = V_i(x, y)W(x, y)$$

6.7 WAVELET TYPES

According to Meyer(1993), two fundamental types of wavelets can be considered the Grossmann Morlet time-scale wavelets and the Gabor-Malvar time-frequency wavelets. The more commonly used type in geophysics is probably the time-scale wavelet. These wavelets form bases in which a signal can be decomposed into a wide range of scales, is called a "multiresolution analysis". From this comes the obvious application in image compression, as one can call up additional detail as required until the exact image at the original resolution is reconstructed. The intervening coarse resolution images will look like the full resolution one, just fuzzier. This is not true in general of Fourier analysis, where throwing out the last few harmonics can cause the picture to change dramatically.

6.7.1 LIST OF WAVELETS

Discrete wavelets

BNC wavelets

Coiflet (6,12,18,24,30)

Daubechies biorthogonal wavelets

Daubechies wavelet(2,4,6,8,10,12,14,16,18,20)

Binomial QMF

Haar wavelet

Mathieu wavelet

Legendre wavelet

Symlet

Continuous wavelet

Real valued

Beta wavelet

Hermitian wavelet

Hermitian hat wavelet

Mexican hat wavelet

Shannon wavelet

Complex valued

Complex Mexican hat wavelet

Morlet wavelet

6.7.2 MORLET WAVELET

The morlet wavelet is obtained by multiplying the Fourier basis with a Gaussian window. The expression of a morlet wavelet is given as

$$\psi(t) = \exp(j\omega_0 t) \exp\left(\frac{-t^2}{2}\right)$$

On taking the Fourier transform, we get the spectrum of the morlet wavelet which is given by From the above expression it is clear that spectrum of the morlet wavelet consists of two Gaussian functions shifted to ω_0 and $-\omega_0$

6.7.3 MEXICAN HAT WAVELET

Mexican hat wavelet is the second order derivative of the gaussian function. The expression of Mexican hat wavelet is given as

$$\psi(t) = (1-t^2) \exp\left(\frac{-t^2}{2}\right)$$

On taking the fourier transform of the equation, we will get the spectrum of the Mexican wavelet which is given by

$$\psi(\omega) = -\omega^2 \exp\left(\frac{-\omega^2}{2}\right)$$

the two-dimensional wavelet is popularly known as the laplacian operator. The Laplacian operator is widely used in edge detection.

6.7.4 SHANNON WAVELET

The expression of the Shannon wavelet is given as below

$$\psi(t) = \frac{\sin(2\pi t) - \sin(\pi t)}{\pi t}$$

The Shannon wavelet has poor time resolution ,but it has frequency localization is excellent.

6.8 DAUBECHIES WAVELET

The filter coefficients $h(n)$ defines the dilation equation is given by

$$\phi(x) = \sqrt{2} \sum_{n=0}^{2N-1} h(n) \phi(2x - n)$$

The solution of which is called scaling function. We take the following normalization of Φ , and of the coefficients $h(n)$

$$\int_{-\infty}^{\infty} \phi(x) dx = 1, \sum_{n=0}^{2N-1} h(n) = \sqrt{2}$$

With the filter coefficients and the scaling function Φ the corresponding Daubechies wavelet is given by

$$\psi(x) = \sqrt{2} \sum_{n=2-2N}^1 (-1)^n h(1-n) \phi(2x - n)$$

Where it is also denoted by D_{2N} .

The property which gives the certain degree of approximation quality of the wavelet and leads to the vanishing moments to the filter coefficients is given by

$$\sum_{n=0}^{2N-1} (-1)^n n^k h(n) = 0, k = 0, 1, \dots, N-1$$

Relationship Between Wavelet And Filter:

If the spaces V_0 and W_0 are subspaces of V_1 then the scaling function $\Phi(x)$ and the wavelet function $\psi(x)$ can be expressed as in terms of the basis function V_1 as

$$\phi(x) = 2 \sum_k h_k \phi(2x - k)$$

$$\psi(x) = 2 \sum_k g_k \phi(2x - k)$$

these equations are known as a two-scale relationship. Where h_k and g_k are the filter coefficients that uniquely define the scaling function $\Phi(x)$ and the wavelet function $\psi(x)$.

6.9 WAVELET BASED DENOISING

Images are often corrupted by noise during its acquisition or transmission. Image denoising is used to remove the additive noise while retaining as much as possible the important feature. Wavelet denoising attempts to remove the noise present in the signal while preserving the signal characteristic, regardless of its frequency component. The wavelet based methods mainly rely on the thresholding the DWT coefficients. Thresholding is a simple non-linear technique which operates one at a time. In its most basic form, each coefficient is thresholded by comparing against the threshold. If the coefficients is smaller than threshold, it is set to zero, otherwise the coefficients is kept or modified. Wavelet-based denoising is widely popular due to properties such as sparsity and multi-resolution structure.

Image denoising using DWT consists of three steps namely,

- i) Image decomposition
- ii) Thresholding of wavelet coefficients
- iii) Image reconstruction

6.9.1 WAVELET SHRINKAGE DENOISING

Denoising by thresholding in wavelet domain was developed by Donoho. In wavelet domain, the large coefficients corresponds to the signal, and small ones represent mostly noise.

SHRINKAGE STRATEGIES

The standard thresholding of the wavelet coefficients is governed mainly by either 'hard' or 'soft' thresholding function.

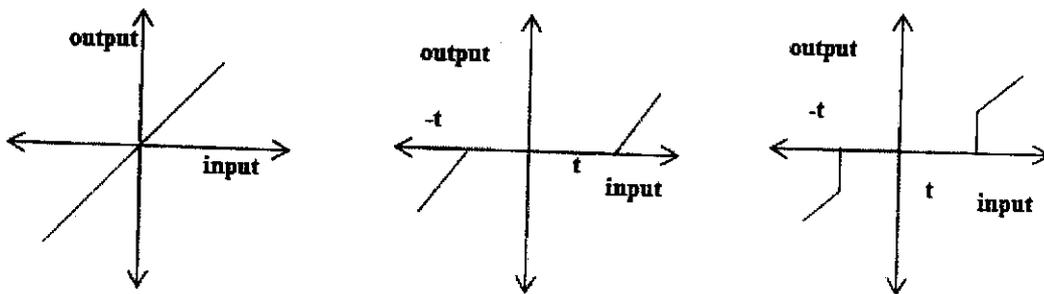


Figure 5.5 Thresholding function a) linear b)soft c) hard

Where $\lambda = t$.

The linear function is not useful for denoising as it does not alter the coefficients. In hard thresholding, the wavelet coefficients below the threshold λ are made zero and coefficients above threshold are not changed. If x, y denote the input and the output then the hard threshold $T_h(y, \lambda)$ is given by

$$T_h(y, \lambda) = y, \text{ if } |y| \geq \lambda$$

0, otherwise

In soft thresholding, the wavelet transform coefficients are shrink towards zero by an offset λ . Generally soft thresholding gives fewer artifacts and preserves the smoothness. The soft thresholding operator $T_s(y, \lambda)$ is given by

$$T_s(y, \lambda) = \begin{cases} y - \lambda, & \text{if } y \geq \lambda \\ y + \lambda, & \text{if } y \leq -\lambda \\ 0, & \text{otherwise} \end{cases}$$

The choice of the threshold plays the crucial role in image processing.

6.9.2 THRESHOLD SELECTION

A small threshold may yield a result close to the input, but the result may be still noisy. A large threshold produces a signal with large number of zero coefficients. This leads to an overly smooth signal. The smoothness will suppress the detail and edges of the original image, thus causing blurring and ringing artifacts.

Universal threshold: Originally Donoho and Johnstone proposed universal threshold. The universal threshold is given by

$$\lambda_{univ} = \sqrt{2 \ln(M)} \times \sigma_w$$

M is the signal size and σ_w^2 is the noise variance.

CHAPTER 7

PROPOSED WORK

7.1 PROPOSED FLOW

HSV and HSI color space

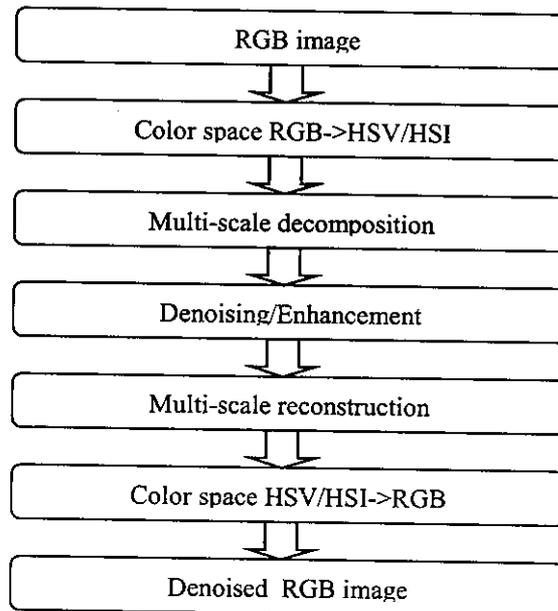


Figure 7.1 Flow chart of the proposed flow

STEP 1: Enhancement of HUE part

STEP 2: Denoising of Saturation part

STEP 3: Denoising and enhancement of Value/ Intensity

7.2 PROPOSED METHOD

1. The true color image is converted into color spaces like HSV and HIS

HSV:

From the above color transformations, the HSV method is the best choice for multi – resolution based image contrast enhancement application. It has the perfect separation of chrominance and luminance values. The HSV color space is quite similar to the way in which humans perceive color.

HSI:

In HSI, Hue, Saturation and Intensity are better used to detect the color. Say if we want to deal in the brightness it is in "I". Moreover, 85% of the noise tends to be in "I" component. So it is better to process "I" for noise-removal rather than the three R = G= B components. Hue tells us purity of color while Saturation tells us brightness + admixture of color with other ones. That's why color detection operates on H +S components and the amount of "tolerance" one wants to have in color detection.

2. The 2D discrete wavelet transform is applied to the converted color spaces and it is separated as low frequency and high frequency, which is shown in the figure 6.2 below

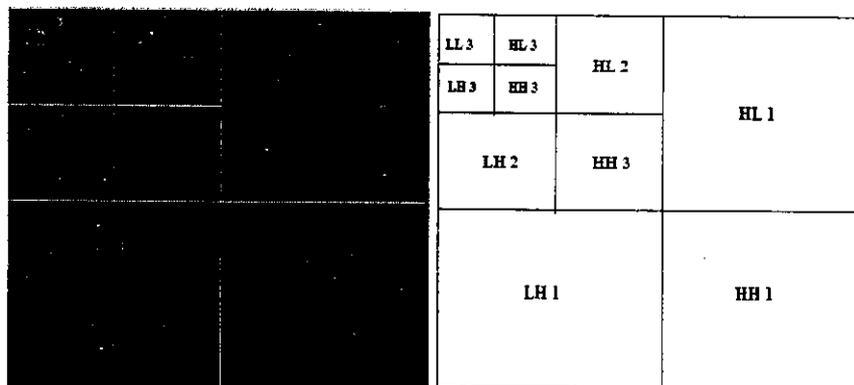


Figure 7.2 3-Level Decomposition

Here

- ✓ LH1, HL1 and HH1 represents the detail images.
- ✓ LL1 corresponds to approximation image.

To obtain the next level of wavelet coefficients, the sub-band LL3 alone is further decomposed.

3. The enhancement of the noised part is done by means of median filter

Median filter

The median filter is also a sliding-window spatial filter, but it replaces the center value in the window with the median of all the pixel values in the window. As for the mean filter, the kernel is usually square but can be any shape. An example of median filtering of a single 3x3 window of values is shown below as unfiltered values.

unfiltered values		
6	2	0
3	97	4
19	3	10

in order:

0, 2, 3, 3, 4, 6, 10, 15, 97

median filtered		
*	*	*
*	4	*
*	*	*

Center value (previously 97) is replaced by the median of all nine values (4).

Note that for the first (top) example, the median filter would also return a value of 5, since the ordered values are 1, 2, 3, 4, 5, 6, 7, 8, 9. For the second (bottom) example, though, the mean filter returns the value 16 since the sum of the nine values in the window is 144 and $144 / 9 = 16$. This illustrates one of the celebrated features of the median filter: its ability to remove 'impulse'

noise (outlying values, either high or low). The median filter is also widely claimed to be 'edge-preserving' since it theoretically preserves step edges without blurring. However, in the presence of noise it does blur edges in images slightly.

4. The denoising of the noised part is done by wavelet based thresholding

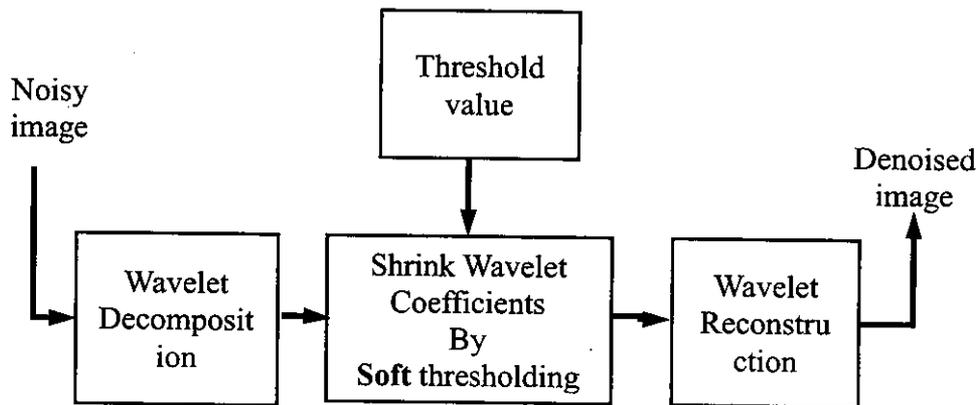


Figure 7.3 Denoising by Thresholding

Thus the noisy image undergoes wavelet decomposition by Daubechies wavelet as shown in the figure. By the calculated threshold value, noised wavelet coefficients are shrunk by means of soft thresholding. Then it is reconstructed, which gives the denoised image.

Realizing the process is given by

- i) Decompose the noised image by wavelet transformation, the decomposing level is J .
- ii) Make statistic to the energy distribution of every sub-band.
- iii) Initial threshold can be selected according to $\lambda_{univ} = \sqrt{2 \ln(M)} \times \sigma_w$
- iv) Fix threshold for every sub-bands.
- v) Calculate wavelet coefficients according to the formula.
- vi) Perform inverse wavelet transform for low and high frequency as mentioned above.

5. After the reconstruction process the corresponding color space i.e either HSV or HSI is converted into the true color space that is RGB color space.

Then the resulted image undergoes performance measures.

7.3 PARAMETRIC MEASURE

Here PSNR is used for analysis of the resulted image

PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. It is most easily defined via the mean squared error (MSE) which for two $m \times n$ monochrome images I and K where one of the images is considered a noisy approximation of the other is defined as:

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

The PSNR is defined as

$$PSNR = 10 \cdot \log_{10} \left(\frac{MAX_I^2}{MSE} \right)$$

(Or)

$$PSNR = 20 \cdot \log_{10} \left(\frac{MAX_I}{\sqrt{MSE}} \right)$$

Here, MAX_I is the maximum possible pixel value of the image. When the pixels are represented using 8 bits per sample, this is 255. More generally, when samples are represented using linear PCM with B bits per sample, MAX_I is $2^B - 1$. For color image with three RGB values per pixel, the definition of PSNR is the same except the MSE is the sum over all squared value differences divided by image size and by three.

CHAPTER 8

RESULTS AND DISCUSSION

The experimental results are obtained by the algorithm and the original and the denoised test images of the color image denoising on HSV and HSI color space are

8.1 HSV COLOR SPACE:

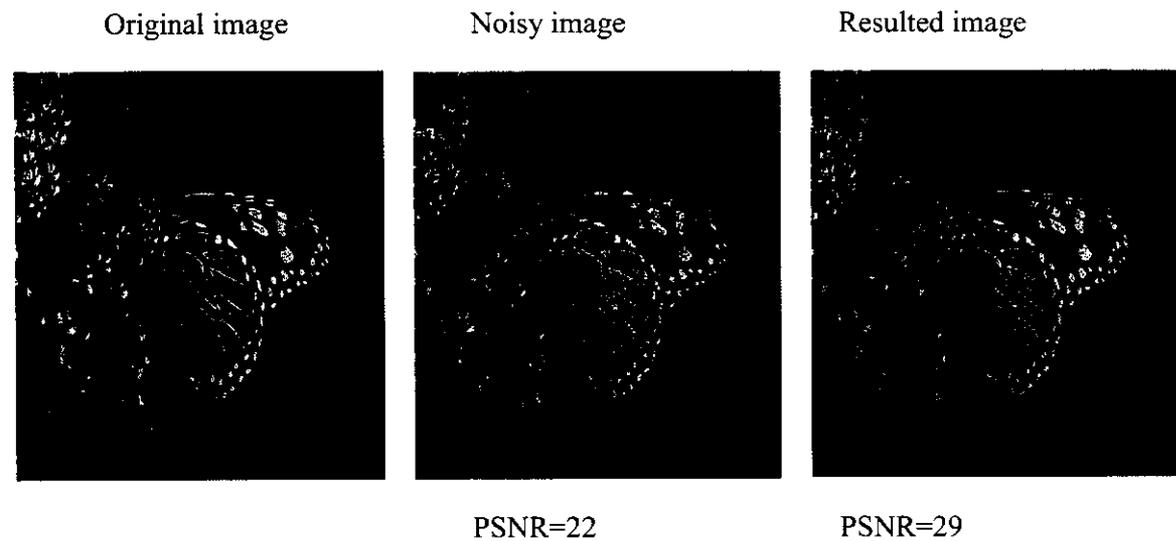


Fig 8.1 Monarch on HSV color space

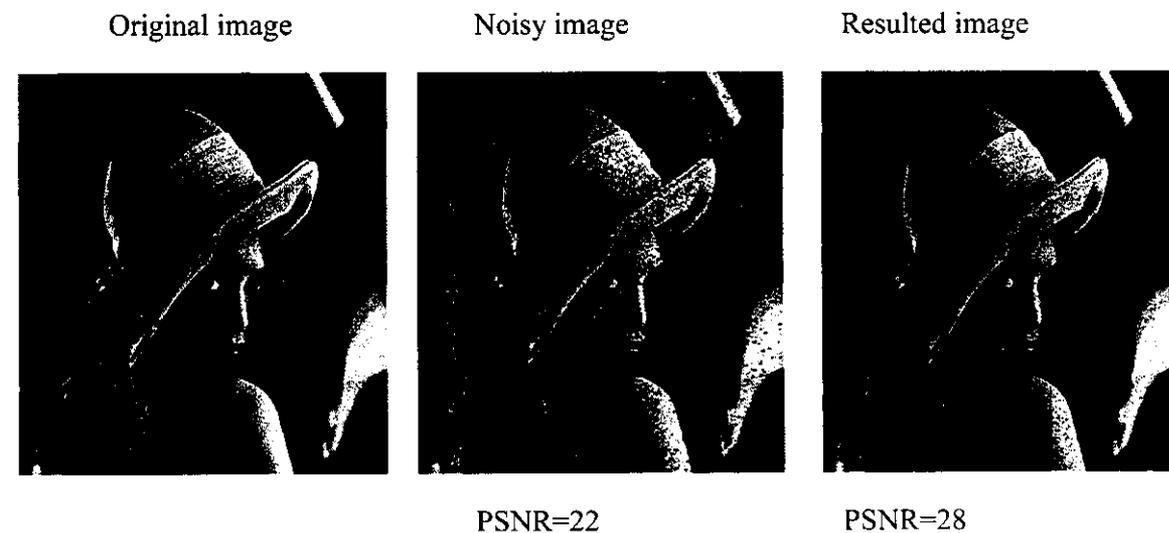


Fig 8.2 Lena on HSV color space

From the figure 8.1 by our proposed method based on HSV color space the resulted image has the PSNR= 29, and it is clear that the edges of the monarch is preserved. The contrast of the image is maintained as that of the original image.

Also in the figure 8.2 Lena the resulted image has the PSNR =28, where edges are preserved and the noised region are effectively smoothened.

Similarly other test images are processed by this method on HSV color space and their performance is measured on the basis of PSNR as tabulated as follows.

Table 8.1 Performance measure of the resulted image based on HSV color space

FIGURE	PARAMETER	NOISY IMAGE	DENOISED IMAGE
MONARCH	PSNR	22	29
LENA	PSNR	22	28
ICE CREAM	PSNR	22	28
APPLE	PSNR	22	25
FLOWER	PSNR	22	28

8.2 HSI COLOR SPACE

The experimental results are stated on HSI color space

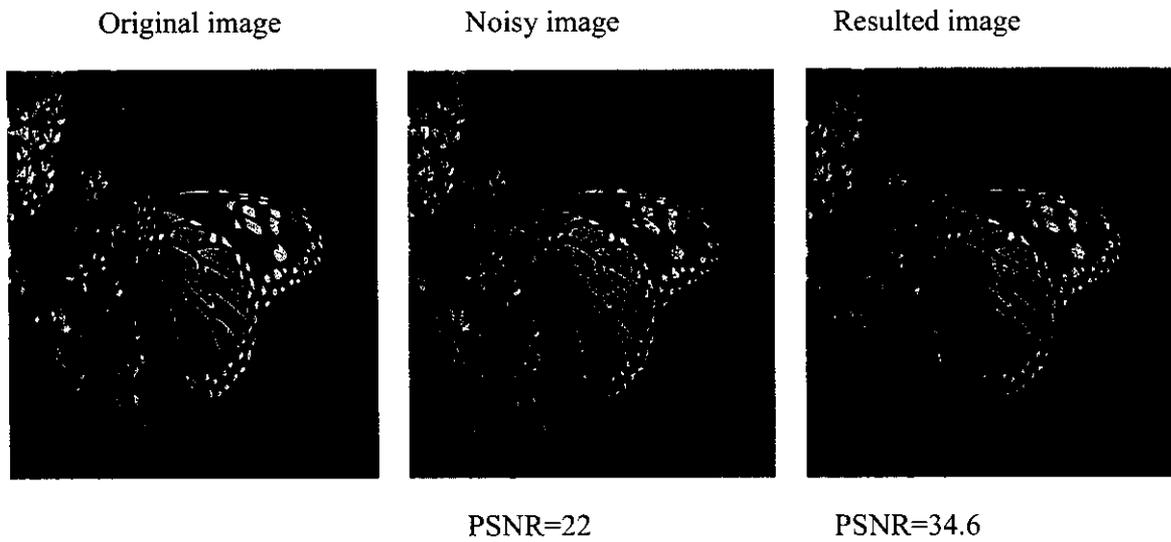


Fig 8.3 Monarch on HSI color space

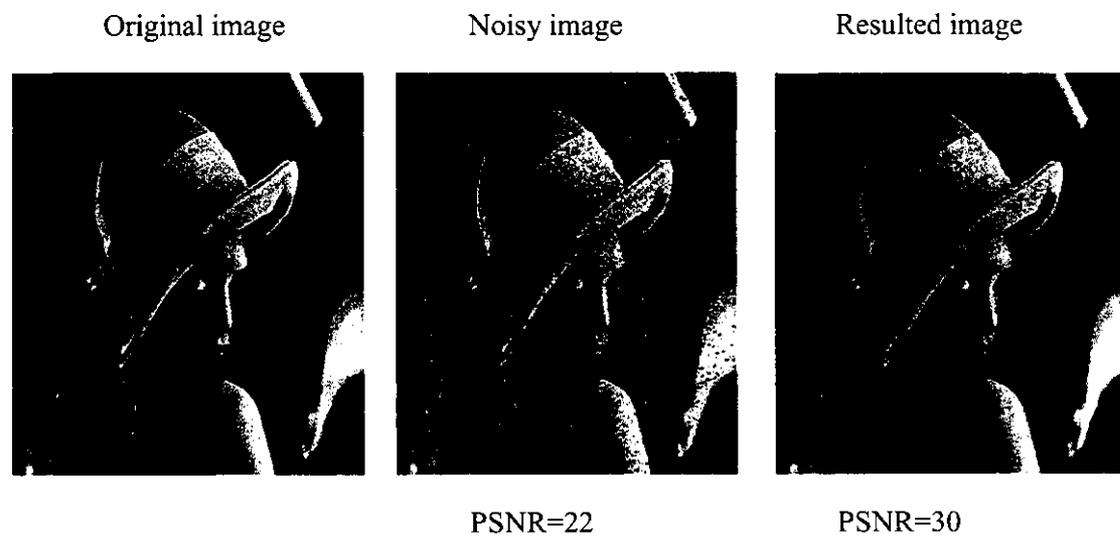


Fig 8.4 Lena on HSI color space

From the figure 8.3 by our proposed method based on HSI color space the resulted image has the PSNR= 29, and it result with better enhancement. The noised region is effectively reduced.

Also in the figure 8.4 Lena, the resulted image has the PSNR=30, Here the noise level is reduced with better improved visual effects

Similarly other test images are processed by this method on HSI color space and their performance is measured on the basis of PSNR as tabulated as follows

Table 7.2 Performance measure of the resulted image based on HSI color space

FIGURE	PARAMETER	NOISY IMAGE	DENOISED IMAGE
MONARCH	PSNR	22	35
LENA	PSNR	22	30
ICE CREAM	PSNR	22	31
APPLE	PSNR	21.7	26
FLOWER	PSNR	22	28

8.3 DISCUSSION

The approach presented in this paper is an evolution of work on true color images based on color spaces. The criteria in this evaluation are perceived noisiness, perceived blurriness, and overall visual quality. Whereas the random occurrence of black and white pixels in an image is generally termed as 'salt & pepper' noise is reduced by our approach.

A close inspection reveals that the resulted images have both fewer ringing artifacts and better reservation of details as shown in the above figures 7.1,7.2,7.3, & 7.4.

The human eyes are less sensitive to the brightness of the background details of an image. For comparison of denoising and enhancement results, we use Peak Signal to Noise ratio (PSNR). From the tabulated value based on the color spaces as shown in the table, the PSNR value of the denoised image is better than the noised image. The effect of enhancement is visible in the denoised image. More over the visual results are better for the human eyes

CHAPTER 9

CONCLUSION AND FUTURE WORK

9.1 CONCLUSION

The project work has attempted color image processing method of synchronous denoising and enhancement algorithm, on perception based color spaces like HSV and HSI. Which retain good impartiality and has good enhancement result.

9.2 FUTURE WORK

In future, it is proposed to explore more effective color space from Human Visual System and do further work for different noise.

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