Enhancement of Low Light Images Via Illumination Map Estimation Using Variational Optimization based Retinex Models

Dissertation Submitted to the

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in

Computer Science and Engineering

By

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(ME(Computer)/2018-19/03)

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Maharashtra State, India

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

Certificate

This is to certify that the dissertation entitled **" Enhancement of Low Light Images Via Illumination Map Estimation Using Variational Optimization based Retinex Models "**, which is being submitted herewith for the award of ’Master of Engineering’ in ’Computer Science and Engineering’ of North Maharashtra University, Jalgaon. This is the result of the work carried out by **Priyanka B. Waghmode** under my supervision and guidance. The work in this dissertation has not formed earlier for the basis of the award of any degree or diploma or other similar title of this for any examining body or university.

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Declaration

I hereby declare that I have formed, completed and written the dissertation entitled " Enhancement of Low Light Images Via Illumination Map Estimation Using Variational Optimization based Retinex Models". It has not previously submitted for the basis of the award of any degree or diploma or other similar title of this for any other examining body or University.

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Dissertation Approval Sheet

Priyanka B. Waghmode has done the appropriate work related to the "Enhancement of Low Light Images Via Illumination Map Estimation Using Variational Optimization based Retinex Models" in the partial fulfilment for the award of Master of Engineering in Computer Engineering of Nort Maharashtra University, Jalgaon(M.S.) and approved for the degree of Master of Engineering

Place:
Date:

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Abstracts

Image Enhancement is one of the important requirements in Digital Image Processing which is very important in making an image useful for various applications which can be seen in the areas of Video Surveillance, Digital photography, Medicine, Geographic Information System, Industrial Inspection , Law Enforcement and many more Digital Image Applications. Image Enhancement is used to improve the quality of poor images. The focus of this dissertation is an attempt to improve the quality of digital images using various Retinex Model like Single Scale Retinex Model, Multi-Scale Retinex Model,Multi-Scale Retinex Model with color Restoration. Also this dissertation focused on Power Law Transformation, Histogram Equalization and Adaptive Histogram Equalization. In this dissertation i have applied various Retinex Model, Power Law Transformation,Histogram Equalization and Adaptive Histogram Equalization on color images with different color space.

Keyword: Retinex Algorithm, SSR,MSR,MSRCR,Hostogram,Image Enhancement.

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Chapter 1

Introduction

Retinex Theory was formulated by Edwin H. Land In 1964. His theory and an extension, the "reset Retinex" were further formalized by Land and Mc Cann [1]. It was the first attempt to simulate and explain the human visual system how it perceives colours, based on experiments using Mondrian patterns.

1.1 Introduction

Besides digital photography, retinex algorithms are used to make the information in astronomical photos visible and detect, in medicine, poorly visible structures in X-rays or scanners. In brief it helps to achieve many features such as sharpening, colour constancy processing and dynamic range compression [5]. The Retinex Image Enhancement Algorithm is an automatic image enhancement method that enhances a digital image in terms of dynamic range compression, colour independence from the spectral distribution of the scene illuminate, and colour/ lightness rendition. The digital image enhanced by the Retinex Image Enhancement Algorithm is much closer to the scene perceived by the human visual system, under all kinds and levels of lighting variations, than the digital image enhanced by any other method [6]. Image enhancement technology has permeated in many areas of science, engineering and civilian, such as biomedicine images, astrophotography, satellite pictures, computer vision, surveillance systems, civilian cameras, etc.[7]

1.2 Problem Definition

Our system will enhance the input image by applying retinex algorithms: Multi-Scale Retinex with color Restoration (MSRCR), Multi-scale Retinex with Chromaticity Preservation (MSRCP) and Automated Multi-Scale Retinex with Color Restoration (AMSRCR). Thus, the Problem definition can be proposed as follows: To implement the Algorithms: MSRCR, MSRCP and AMSRCR. Also, these algorithms require implementation of Single-Scale Retinex (SSR) algorithm and the SimplestColorBalance algorithm [35].

1.3 Objective

- To implement Single-Scale Retinex and Color Restoration Algorithms.
- To implement Multi-Scale Retinex with Color Restoration using above algorithms (MSRCR).
- To implement Multi-Scale retinex with Chromaticity preservation- MSRCP.(a modified version of above algorithm).
- To implement Automated Multi-Scale Retinex with Color Restoration algorithm. (An automated (image independent) approach to MSRCR)- AMSRCR.

1.4 Scope

The Retinex Image Enhancement Algorithm is an automatic image enhancement method that enhances a digital image in terms of dynamic range compression, colour independence from the spectral distribution of the scene illuminate, and colour/ lightness rendition. So, the scope of this project is to implement the Retinex based image Enhancement Algorithms, which involves the implementation of following three models of retinex algorithms:

- Multi-Scale Retinex algorithm with color Restoration (MSRCR)

- Multi-Scale Retinex algorithm with Chromaticity Preservation (MSRCP)
- Automated Multi-Scale Retinex algorithm with Color Restoration (AMSRCR)

1.5 Existing System

The existing image enhancement techniques like auto gain/offset, gamma correction, histogram equalization and homomorphic filtering heavily depend on input images. For auto gain/offset, it could achieve dynamic range compression but at the loss of details due to saturation and clipping. For gamma correction, it is good to improve pictures either too dark or too bright but it is a global function applied to the picture, thus there is no enhancement involved. For histogram equalization and homomorphic filtering, they all failed for bi-modal pictures, which include both dark and bright areas. But for retinex, it could achieve satisfactory results for both pictures, thus its benefits are obviously to see.[8]

1.6 Outline

This project report is organized into six chapters: Chapter 1 introduces the project; chapter 2 describes related work and reviews previous works; Chapter 3 presents the technology that will be used. Chapter 4 presents the system analysis and design in detail, chapter 5 presents the results and Chapter 6 is the Conclusion.

Chapter 2

Related Work

An image is an array, or a matrix, of square pixels (picture elements) arranged in columns and rows .An Image is a 2D function f(x, y) , where x and y are spatial coordinates and amplitude of f at any pair of coordinates (x, y) is called the intensity or gray level of the image.

2.1 Digital Image Processing

Image processing is a method to perform some operations on an image, in order to get an enhanced image or to extract some useful information from it. It is a type of signal processing in which input is an image and output may be image or characteristics/features associated with that image. Nowadays, image processing is among rapidly growing technologies. Image processing basically includes the following three steps:

- Importing the image via image acquisition tools;
- Analysing and manipulating the image;
- Output in which result can be altered image or report that is based on image analysis.

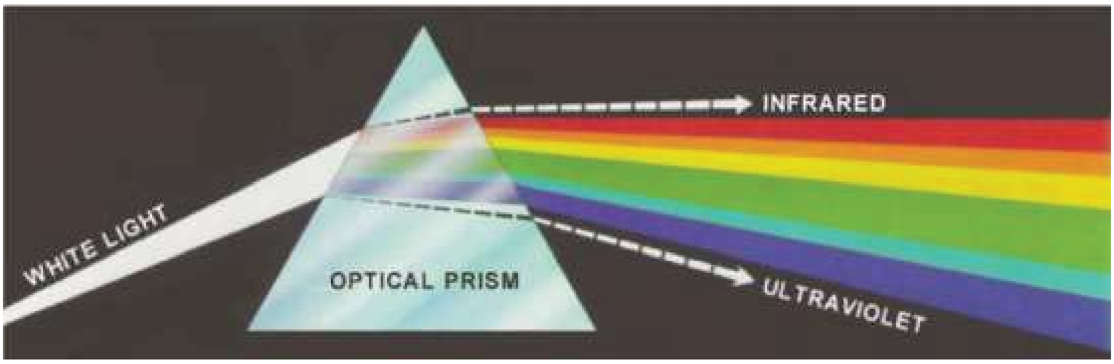


Figure 2.1: Color spectrum seen by passing White light through a prism

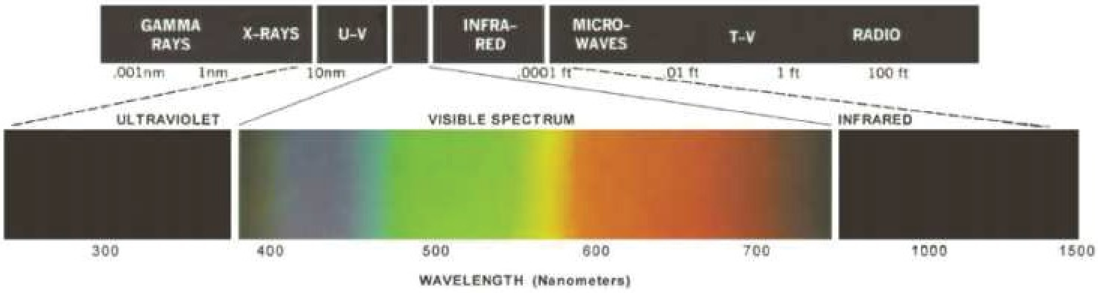


Figure 2.2: Wavelengths comprising the visible range of the electromagnetic spectrum

2.1.1 Light and visible spectrum

If a beam of white light passes through a glass prism, the human can see that the beam of light is broken and the six colors of the spectrum appear: red, orange, yellow, green, blue and violet (Figure2.1). This is known as refraction and was discovered by Sir Isaac Newton in 1666. In this way, you can understand that white light, existing everywhere, is composed of a spectrum of colors and collided with a body, it absorbs any of these components and reflects others. The reflected colors are what our eyes can perceive. [4]

Basically, the colors that human perceive depend on the nature of the light reflected from the object. So the visible range by human eyes can be seen (Figure 2.2) as a little part within the electromagnetic spectrum and include wavelengths from 380 nm to 780 nm. The human eye perceives light from each of these wavelengths as a different color. [4]

Primary color is a color that cannot be obtained by mixing any other one. This is an idealized model, based on the biological response of the receptor cells of the human eye (cones) in the presence of certain frequencies of light and noise, and is dependent on the subjective perception of the human brain. Mixing two primary colors gives rise to a secondary color. The theories of traditional and modern color disagree on which are the primary colors. The modern color theory distinguishes between light and pigment colors (Figure 2.3,Figure 2.4). [5]

- Light primary colors (RGB model): Red, green and blue.
- Primary pigment colors (CMY Model): Cyan, magenta and yellow.
- Traditional primary colors (RYB Model): Red, yellow and blue.This model is the precursor CMY model. It is considered obsolete by science and industry.

It is called secondary when a color is obtained by mixing two primary colors and which in turn is complementary color of a third primary color, which is not involved in its preparation. [5]

- Secondary colors light (RGB model) and Cyan, magenta yellow
- Secondary colors pigment (CMY Model): Orange, green and violet.

2.1.2 Digital image

The term image refers to a two dimensional function of light intensity f (x, y) where x and y denote the spatial coordinates and the value of f at any point (x, y) is proportional to the intensity of the image at that point. A digital image can be written as a matrix whose row and column indices identify a point in the image and whose value coincides with the level of light intensity at that point. Each element of the array corresponds to an element in the image and is called pixel. [4]

$$f(x,y) = \begin{bmatrix} f(0,0) & f(0,1) & \dots & f(0,N-1) \\ f(1,0) & f(1,1) & \dots & f(1,N-1) \\ \vdots & \vdots & \ddots & \vdots \\ f(M-1,0) & f(M-1,1) & \dots & f(M-1,N-1) \end{bmatrix} \tag{2.1}$$

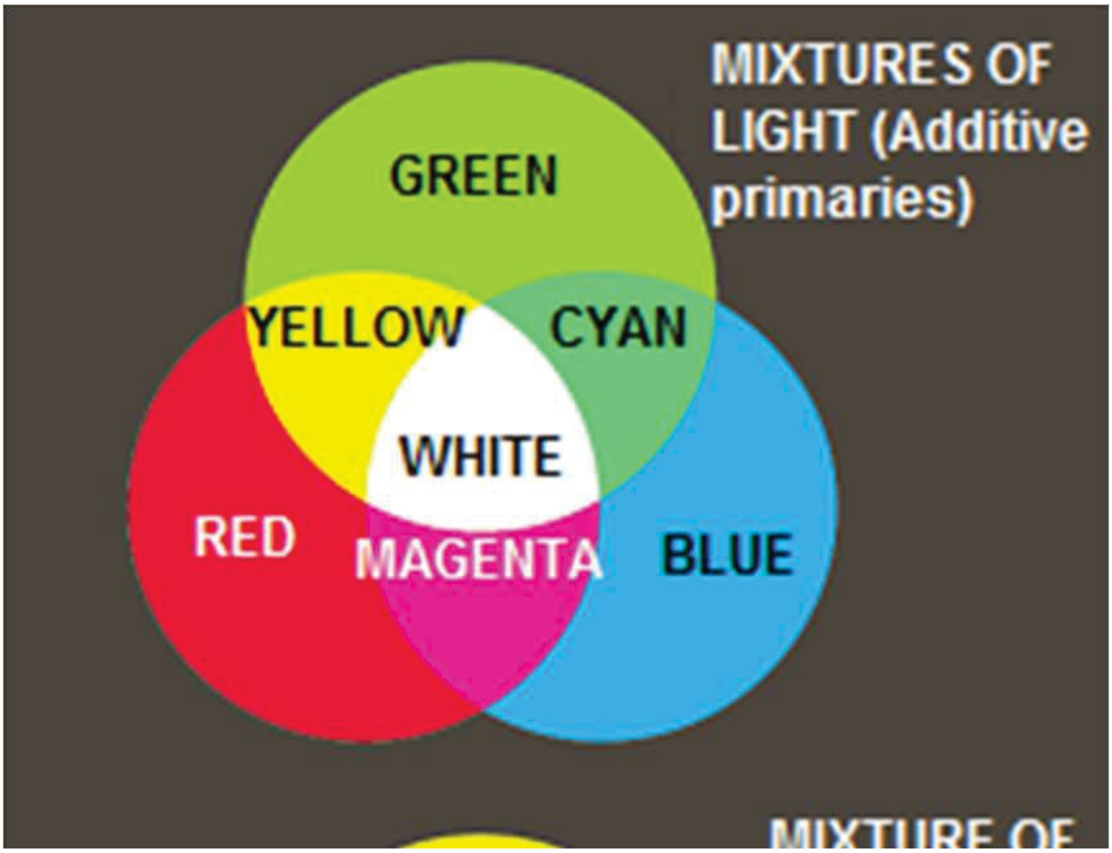


Figure 2.3: Primary and secondary colors of light

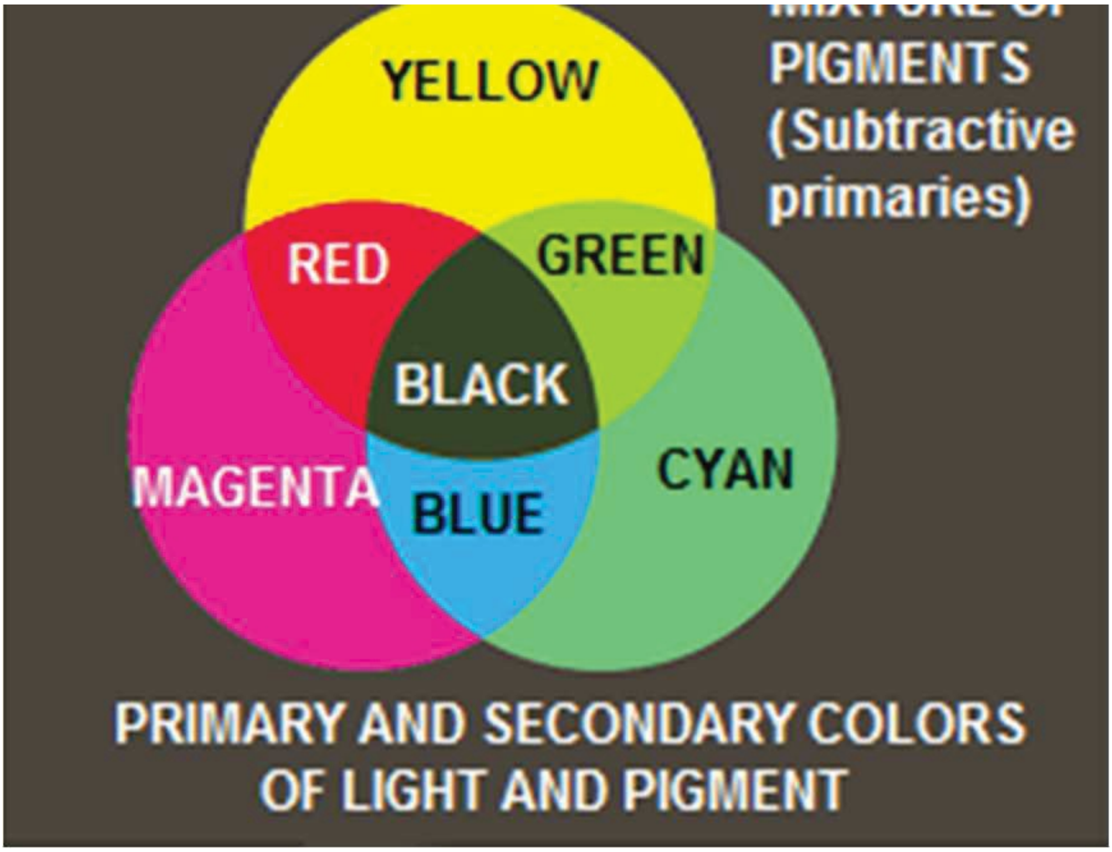


Figure 2.4: Primary and secondary colors of pigments

Figure 2.5: Digital Image of "Lenna" with different number of pixels

The notation of coordinates widely accepted by most of the books is shown in equation (1) where the image has M rows and N columns determining the origin at the point f (0,0).

Figure 2.5 shows four version of the same picture where the difference is the number of pixels in each of them. This means that the pixel is only one division unit without a particular actual size. Only when the image resolution is given, a particular size to the pixel is assigned.

2.1.3 Classification of digital image

There are many kind of classification of digital image. A Basic classification should be: bitmap and vector images. [2] Vector images are obtained based on lines, each responding to a mathematical equation. An image of this type is formed by controlled strokes coordinates. Vector graphics have the disadvantage that they do not have the level of detail of bitmaps. The advantage is that you can reduce and enlarge without losing quality since the lines are redrawn when resizing. Bitmap images were described in point 2.1.2. These kinds of images are used in this project. Figure 2.6 shows differences between

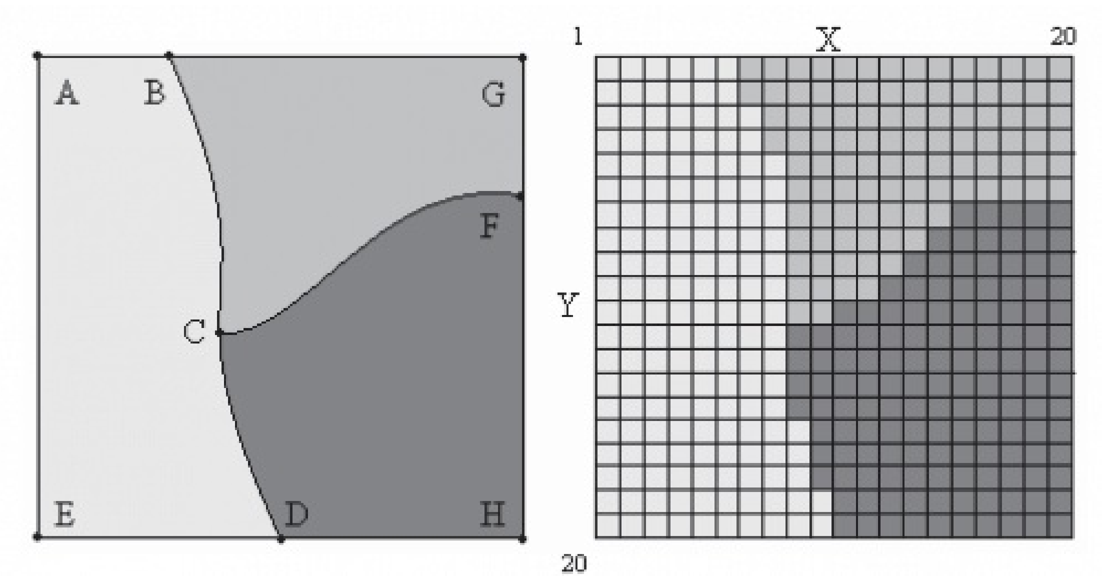


Figure 2.6: a) Vector and b) bitmap images

bitmap and vector images

2.1.4 Color spaces

Color spaces are a defined range of colors that in combination with physical device, it allows representations of color in analog and digital way [7].A color model is an abstract mathematical model describing the way colors can be represented as tuples of numbers [4]

There are many types of model color but only the first 3 are important in this project. [8]

- Grayscale
- RGB
- HSV
- Others: YCbCr, HLS, CMY, etc.

Grayscale

An intensity scale is also known as monochrome or grayscale level and to a digital image is an MxN array of values where each pixel is a single sample containing the

Figure 2.7: a) Greyscale images y b) Grey levels of greyscale images

information of the image intensity. In a grayscale image (figure 7a) each pixel has a brightness value between 0 (black) to 1 (white). Commonly, this mode uses up to 256 shades of gray (8 bits per sampled pixel). Another way of representation is as percentage (figure 7.b) The 3 characteristics that can define a color are hue (color), value (lightness or darkening) and saturation (color purity). Thus the conversion of a color image to a grayscale image is not performed in a unique way, however in its most common approach [8], it is to retain information on the brightness and discard the values of hue and saturation. Assuming the colors red, green and blue are signs of light, the approximation of an image in grayscale from a color image is given by equation (2.3) where 0 is the value of less intensity, referring to the color black and 1 is the value of greater brightness or white.

$$GRAY = (0.30 \cdot R) + (0.59 \cdot G) + (0.11 \cdot B) \tag{2.2}$$

RGB model

An RGB image is defined as an array of 3xMxN pixels where each pixel corresponds to the red, green and blue components of a color image. The main purpose of the RGB model is the sensing, representation and display of images in electronic devices such as televisions, computers, cell phones, etc. [4]

The RGB model can be viewed as a stack of 3 scale image intensities to be

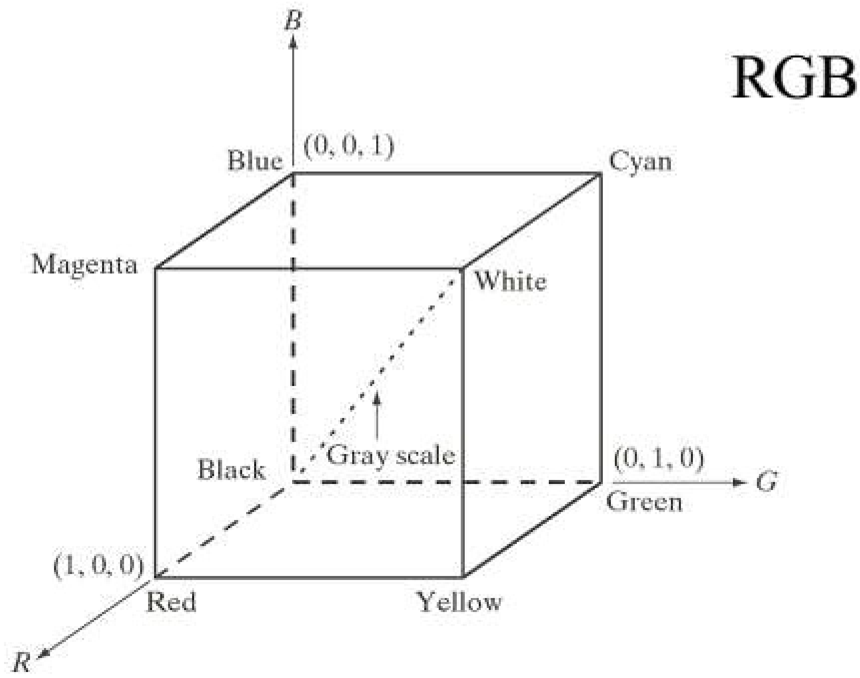


Figure 2.8: Schematic of the RGB color cube. Points along the main diagonal have gray values, from black at the origin to white at point (1,1,1)

displayed on a color monitor (which has 3 color inputs, red, green and blue). Colors red, green and blue are known as primary colors, and the combination of these different intensities in colors produces human visible spectrum. Figures 8 and 9 show a 3D representation of the RGB model.

Generally the intensity of each of the components is measured on a scale from 0 to 255 (1 byte per component)

This model is the most used to display digital images on a screen in the current formats so it is very important in the image processing.

HSV model

The HSV model is based on the human perception of color and describes, according to CIE [quote]:

- Hue: The "attribute of a visual sensation according to which an area appears to be similar to one of the perceived colors: red, yellow, green, and blue, or to a combination of two of them".

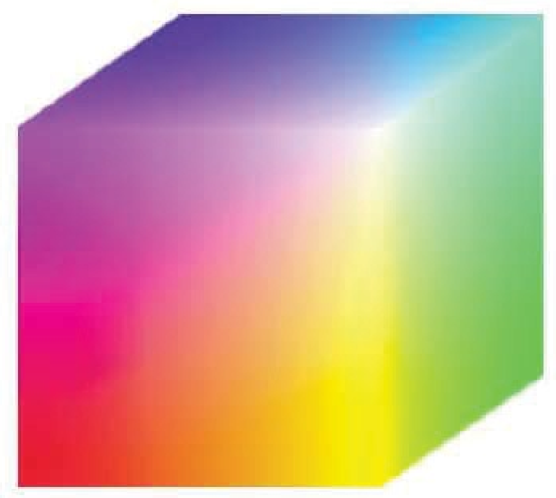


Figure 2.9: RGB 24-bits color cube

- Saturation: Colorfulness of an area judged in proportion to its brightness.

The HSV color model is based in the RGB model, but it is a cylindrical coordinate model. It uses the following three components [9]

- H (hue) is usually represented in a circumference, so the degree says the color of that pixel, but it is also used in a percentage way for some applications.
- S (saturation), the representation of this component is the distance from the cylinder axe.
- V (value, also called B, brightness), this is the component used in the transform. Usually, it is represented from 0 to 1 (also in Matlab). If the value is 0, it means that the pixel is black, regardless of the other two components (for this reason, the HSV model can also be interpreted and represented like a cone) (figure 2.10).

The transformation from RGB to HSV is given by [9]:

$$V = MAX \tag{2.3}$$

Hence, the formula indicates that for a pixel, the Value or Brightness is the maximum value of any of the RGB components. For example, if R is 0.7, G is 0.5 and B is 0.1 (normalized), the value for this pixel is 0.7.

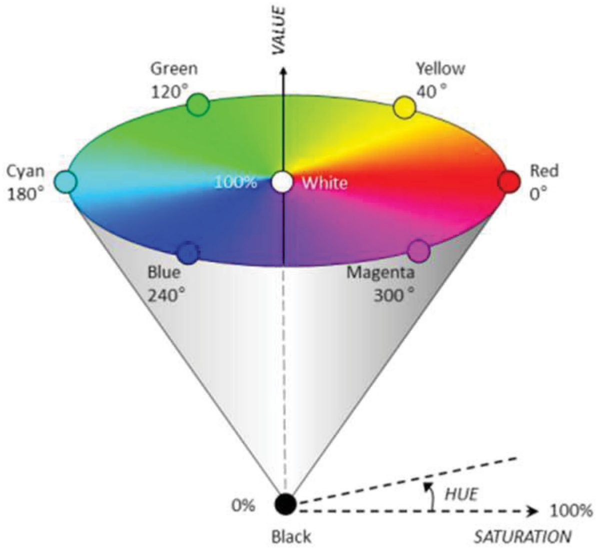


Figure 2.10: Cone of HSV model

$$H=\begin{cases} \text{Undefined} & \text{if MAX} = \text{MIN} \\ 60^{\text{º}}\ x\ \dfrac{G-B}{MAX-MIN} + 0^{\text{º}}, & \text{if MAX} = \text{R and } G \geq B \\ 60^{\text{º}}\ x\ \dfrac{G-B}{MAX-MIN} + 360^{\text{º}}, & \text{if MAX} = \text{R and } G < B \\ 60^{\text{º}}\ x\ \dfrac{B-R}{MAX-MIN} + 120^{\text{º}}, & \text{if MAX} = \text{G} \\ 60^{\text{º}}\ x\ \dfrac{R-G}{MAX-MIN} + 120^{\text{º}}, & \text{if MAX} = \text{B} \end{cases}$$

$$S=\begin{cases} 0, & \text{if MAX} = 0 \\ 1 - \dfrac{MIN}{MAX}, & \text{Otherwise} \end{cases}$$

Figure 2.11: a) Original picture. b) Component brightness of original picture

2.1.5 Digital Image processing

The digital image processing is the set of techniques applied to digital images in order to improve quality or facilitate the search for information [10].

The field that handles the processing of digital images is the digital image processing. Most processing techniques act treating the image as a two dimensions signal and then applying standard signal processing techniques of one dimension. Among the most common processing operations are:

Intensity Transformation

Exists for the spatial domain techniques that operate directly on the image pixels. The processes discussed in this report are denoted by the expression

$$g(x, y) = T[f(x, y)] \tag{2.4}$$

where the function f(x,y) is the input image, g(x,y) is the output image (processed image) and T is an operator on f, which is an operator defined in a specific neighborhood (x,y) on a point (x,y).

Knowing that the main space to define neighborhoods about some point (x,y) approach is to use a square or rectangular region centered at (x,y) as shown below in the following scheme.

The way to do this is to move starting pixel by pixel, that is, starting from the upper left corner as it moves, different neighborhoods are included. The operator T is applied to each location (x,y) thus g output can be obtained at that location. Only the pixels in the neighborhood are used to calculate the value of g(x,y).

Intensity transformation functions; the simplest form of the transformation T is when the neighborhood size is 1x1 (one pixel). In this case, the value of g(x,y) depends only on the intensity at that point f, and T becomes a transformation function intensities or gray Levels. As depend only on the intensity values, and not explicitly on (x,y), these functions are usually written in simplified form as;

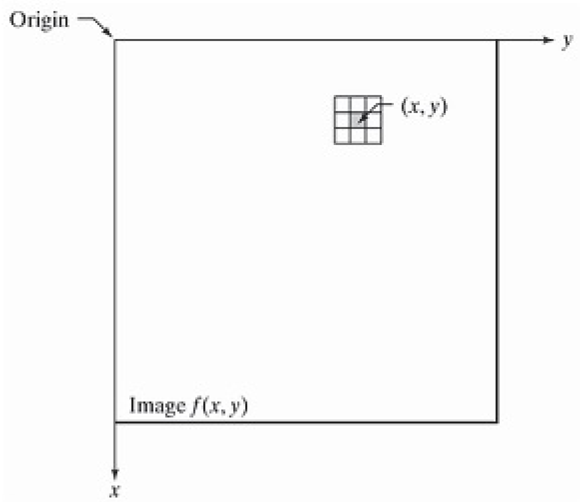


Figure 2.12: Spatial Domain

$$s = T(r)$$

Where r denotes the intensity of f and s the intensity of g, both on a corresponding point (x,y) of the image [4].

Some of these techniques are;

- Linear
  - Negative; Invert the order of the intensity values.

    $$T(r)=L-1-r$$

  - Brightness; change of the average intensity of the image

    $$T(r) = r \pm B$$

    (B is real number)
  - Contrast; change of the dynamic range of the image.

    $$T(r) = r \cdot B$$

    (B is real number)

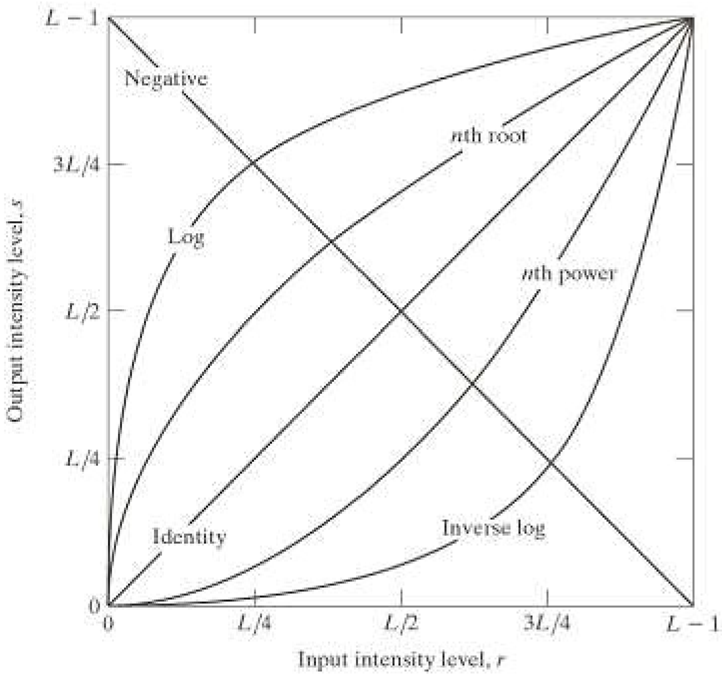


Figure 2.13: Basic transformations

- Nonlinear;
  - Log; It is used to display low levels of intensity with greater dynamic range.

$$T(r) = clog(1 + r)$$

  - Log power-law; It is similar to the log transformation. The advantage is the variety of transformations to modify the value of n

$$T(r) = c\,r^n$$

  - Histogram equalization;
- Thresholding;
  - change a gray scale image in binary image (black and white) through a threshold

$$T(r) = \begin{cases} 0, & if r < T \\ 255, & if r > T \end{cases}$$

Geometric transformation;

Geometric transformation modify the spatial relationship between pixels. In terms of digital image processing a geometric transformation consists of two basic operations [11]:

- A spatial transformation that defines the relocation of the pixels in the image plane.
- Interpolation of gray levels, which are related to mapping the intensity values of the pixels in the transformed image.

Transformations into frequency domain

- Fourier Transformation
- Filter

for this project,intensity transformation is used.

2.1.6 Image Enhancement

The main definition of enhancing is to make something greater in value, desirability or attractiveness. The term of enhancement implies a process to improve the visual quality of the image. Image Enhancement transforms images to provide better representation of the subtle details. The principal objective of enhancement is to process an image so that the result is more suitable than the original image for a specific application. Image enhancement processes consist of a collection of techniques that seek to improve the visual appearance of an image or to convert the image to a form better suited for analysis by a human or a machine. In an image enhancement system, there is no conscious effort to improve the fidelity of a reproduced image with regard to some ideal form of the image, as is done in image restoration.

Actually, there is some evidence to indicate that often a distorted image, for example, an image with amplitude overshoot and undershoot about its object edges, is more subjectively pleasing than a perfectly reproduced original. Enhancement of an image is necessary to improve appearance or to highlight some aspect of the image is converted from one into another acquired, scanned, transmitted, copied or printed many types of noise can be present in the image. Image enhancement has come to specifically mean a process of smothering irregularities or noise that has somehow corrupted the image. The term “image enhancement” has been widely used in the past to describe any operation that improves image quality by some criteria. However, in the recent years the meaning of the term has evolved to denote image-preserving noise smoothing.

This primarily serves to distinguish it from similar-sounding terms, such as image restoration and image reconstruction, which also taking specific meaning. Image enhancement has played and will continue to play an important role into different fields such as medical, industrial, military and scientific applications. In addition to these applications, image enhancement is increasingly being used in consumer electronics. Internet Web users, for instance, not only rely on built-in image processing protocols such as JPEG (Joint Photographic Expert Group) and interpolation, but they also have become image processing users equipped with powerful yet inexpensive software such as Photoshop. Users not only retrieve digital images from the Web but they are now able to acquire their own by use of digital cameras or through digitization services. Image enhancement is an indispensable tool for researchers in a wide variety of fields:

- In forensics, image enhancement is used for identification, evidence gathering and surveillance. Images obtained from fingerprint detection, security videos analysis and crime scene investigations are enhanced to help in identification of culprits and protection of victims.
- In atmospheric sciences IE is used to reduce the effects of haze, fog, mist and turbulent weather for meteorological observations. It helps in detecting shape and structure of remote objects in environment sensing. Satellite images undergo image restoration and enhancement to remove noise.
- Astrophotography faces challenges due to light and noise pollution that can be minimized by IE. For real time sharpening and contrast enhancement several cameras have in-built IE functions. Moreover, numerous softwares allow editing such images to provide better and bright results.

- In oceanography the study of images reveals interesting features of water flow, remains concentration, geomorphology and bathymetric patterns to name a few. These features are more clearly observable in images that are digitally enhanced to overcome the problem of moving targets, deficiency of light and obscure surroundings.

- IE techniques when applied to pictures and videos help the visually impaired in reading small print, using computers and television and face recognition. Several studies have been conducted that highlight the need and value of using IE for the visually impaired.

- The technique of image enhancement is often employed by virtual restoration of historic paintings and artifacts in order to reduce stains and crevices. Color contrast enhancement, sharpening and brightening are just some of the techniques used to make the images bright. IE is a powerful tool for restorers who can inform decisions by viewing the results of restoring a painting beforehand. It is evenly useful in discerning text from worn-out historic documents.

- In the field of e-learning, IE is used to clarify the contents of chalkboard as viewed on streamed video; it improves the content readability and helps students to focus on the text.Similarly, collaboration through the whiteboard is facilitated by enhancing the shared data and diminishing artifacts like shadows and blemishes.

- Medical imaging uses IE techniques for reducing noise and sharpening details to improve the visual representation of the image. Since minute details play a critical role in diagnosis and treatment of disease, it is essential to highlight important features while displaying medical images. This makes IE a necessary aiding tool for viewing anatomic areas in MRI, ultrasound and x-rays to name a few.

- Numerous other fields including law enforcement, microbiology, biomedicine, bacteriology, climatology, meteorology, etc., benefit from various IE techniques. These benefits are not limited to professional studies and businesses but extend to the common users who employ IE to cosmetically enhance and correct their images.

The following image(figure 2.14 explains the different types of image enhancement techniques.

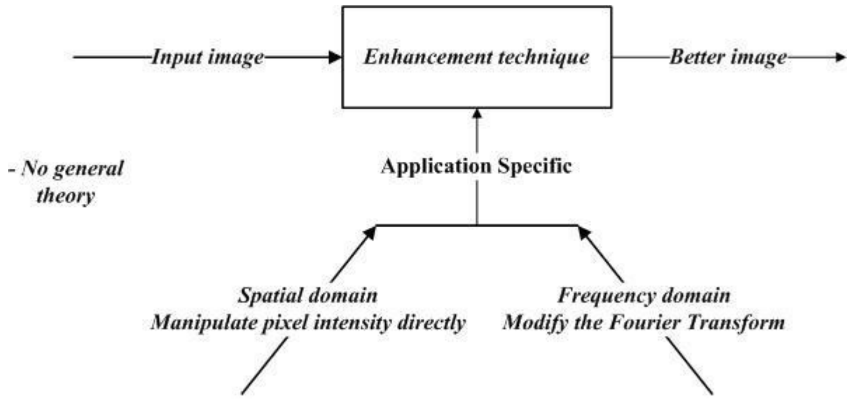


Figure 2.14: Image enhancement techniques

In this project, spatial domain is considered.

Table 2.1: Your first table.

Histogram Equalization	Adjusting the global contrast of an image. It is most effective method for gray scale images
Adaptive histogram Equalization	It is extension of HE and used within an image for local enhancement. It contains dark region and low contrast
Bi- histogram equalization	It maintains the intensity mean of the original image, which suppresses the over enhancement problem
Laplacian	It is mostly used for edge enhancement

2.1.7 Frequency Domain Technique

Frequency domain method operates on the Fourier transform of an image. Image enhancement in the frequency domain is straightforward. We simply compute the Fourier transform of the image to be enhanced, multiply the result by a filter and take the inverse transform to produce the enhanced image. In frequency domain methods, the image is first transferred in to frequency domain. It means that, the Fourier Transform of the image is computed first. All the enhancement operations are performed on the Fourier transform of the image and then the Inverse Fourier transform is performed to get the resultant image. These enhancement operations are performed in order to modify the image brightness, contrast or the distribution of the grey levels. As a consequence the pixel value of the output image will be modified according to the transformation function applied on the input values [15]. The convolution theorem is the foundation of frequency domain techniques. Consider the following spatial domain operation:

$$g(x, y) = h(x, y) * f(x, y) \tag{2.5}$$

The following frequency domain relationship given by the convolution theorem

$$G(u, v) = H(u, v)F(U, v) \tag{2.6}$$

Where g, f and h having Fourier transform G, H and F respectively. H is known as the transfer function of the process. Many image enhancement problems can be viewed in the form of the above equation. The main aim is to select a transfer function that changes the image in such a way that certain features of an image are enhanced. Examples: edge detection, noise removal.

There are mainly three types of filters

- Low pass filter
- High pass filter
- Band pass filter

In Low-pass filtering, sharp transitions and edges in the gray levels of an image contribute significantly to the high frequency content of its Fourier Transform. By attenuating a specified range of high-frequency components in the frequency domain, blurring is achieved. Through Low-pass filtering this task is performed.

By High-pass filtering, Image sharpening can be achieved in the frequency domain. Low-frequency components will attenuated by high pass filter the without disturbing high frequency information.

Band-pass filtering is a method in which the reflectance and illumination components can be filtered independently. The illumination component of an image is generally classified by slow spatial variation on the other hand the reflectance component of an image tends to vary abruptly. These characteristics lead to associating the low frequencies of the Fourier transform of the natural log of an image with illumination and high frequencies with reflectance thus it is filtered individually.

2.1.8 Comparison between Spatial Domain Technique And Frequency Domain Technique

- Spatial domain is manipulation of pixels of an image. It is the technique for changing the representation of an image and used in many field such as sharpening and smoothing images. Whereas Frequency domain is the manipulation of Fourier transforms to enhance an image and perform purely with convolution theorem and it is used in changing the position of an image.
- The advantage of spatial domain technique is that it is simple to understand and the complexity of these techniques is very low which helps in real time implementation. Whereas Frequency domain technique having advantages which include low computation complexity, easy to view, manipulation of image's frequency composition and the special transformed domain property is easily applicable.

The disadvantages of spatial domain technique is that it does not provides adequate robustness and perceivably. Whereas the disadvantage of Frequency Domain is that it cannot enhance properly every part of an image simultaneously and the automation of image enhancement is also very difficult. Table 2.2 shows the areas where Spatial Domain technique and Frequency domain technique are applied [16].

Table 2.2: Your first table.

Techniques	**Feature**
Spatial Domain technique	It is used to alter The gray level value Of individual pixels and hence the overall contrast of the entire image. It is not possible to selectively enhance edges or other required information effectively.
Frequency domain technique	It is used to Easily enhance edges And other subtle information because they are high frequency content and frequency domain operates on frequency content of an image. In this technique, all parts of an image are not enhanced in uniform manner

2.2 BASICS OF RETINEX THEORY

Retinex is the theory of human color vision proposed by Edwin Land to account for color sensations in real scenes. Color constancy experiments showed that color does not correlate with receptor responses. In real scenes, the content of the entire image controls appearances. A triplet of L, M, S cone responses can appear any color. Land coined the word "Retinex" (the contraction of retina and cortex) to identify the spatial image processing responsible for color constancy. Further, he showed that color sensations are predicted by three lightnesses observed in long-, middle-, and short-wave illumination. Retinex is also used as the name of computer algorithms that mimic vision's spatial interactions to calculate the lightnesses observed in complex scenes.

2.2.1 Overview

Edwin H. Land, the inventor of hundreds of film patents, was struck by experiments showing that color sensations in real complex images depend on scene content. Film responds to the light falling on each tiny local region. Land realized that vision's mechanisms were very different from film. His early experiments studied the colors observed in red and white projections [1]. He realized color appearance required both the cone responses to a local region and the neural spatial processing of the rest of the scene. He proposed the Retinex Theory.

Land coined the word Retinex to describe three independent spatial channels. In 1964 he wrote: "We would propose that all of the receptors with maximum sensitivity to the long-waves in the spectrum, for example, operate as a unit to form a complete record of long-wave stimuli from objects being observed. (For convenience of reference, let us call this suggested retinal-cerebral system a "retinex.")" [2, 3, 4, 5]. It is the word that describes the mechanism that performs the comparison of scene information to create the array of sensations of lightness in three channels

2.2.2 Cone Quanta Catch

Visible light falls on objects that reflect some of it to the eye. Color vision depends on the spectrum of the illumination falling on an object and the spectrum of its reflectance. The product of these spectra describes the light coming to the eye. There are three types of cones in normal observers that are called L for long-wave-, M for middle-wave-, and S for short-wave-sensitive cones. The receptors' spectral sensitivities multiplied by the light falling on the retina determines the L, M, S cone responses, namely, the "quanta catch" of the cones. The cones convert the quanta catch to nerve signals that pass through many spatial comparisons in the visual system. The cone quanta catch is the important transition from the physics of light to the physiology of vision. However, it is just the first step in the process. Figure 2.1 illustrates a laboratory experiment that generates equal L, M, S quanta catches from different reflectance papers. Light passes through filters that determine the spectrum of each illumination falling on circular pieces of paper. The light coming to the eye from the papers is modified again by the reflectance spectra of the papers. Further, in this experiment there is no light coming from the black surrounds. On the left, there is a tungsten light source at the top. There is a filter that absorbs more middle-wave than long- and short-wave visible light (magenta arrows). The green circular paper reflects more middle-wave than long- and short-wave light. The light coming to the eye is the product of these spectra. The integrals of that light using the three cone spectral sensitivities determine the L, M, S quanta catch values.

On the right, there is the same tungsten light source at the top. There is a different filter that absorbs more long-wave than middle- and short-wave light (cyan arrows). The right-red paper reflects more long-wave than middle- and short-wave light. In this experiment, the spectra of the two illuminants and the two reflectances were adjusted to generate the same triplet of LMS cone quanta catches. Under these conditions, the left-green and right-red papers are identical retinal stimuli. They appear equal to each other, but that color is neither red nor green.[17]

2.2.3 Mondrian Experiments

Land's color Mondrian experiment is similar, with the exception that he used a complex array of papers to simulate real-world scenes. The important difference is that in complex scenes, a particular quanta catch can appear in any color: red, green, blue, yellow, white, or black. Figure 2.2. shows the double color Mondrian experiment [6]. It used two identical Mondrians made of color papers, and three different, non-overlapping spectral illuminants (long-, middle-, and short-wave visible light). In this experiment observers reported the colors of papers in the Mondrians. In this illustration, we will look at the circular red and green papers. Land adjusted the illuminant mixtures of light from the two sets of three projectors. The same amounts of L, M, S light came from the green circle on the left as from the red circle on the right. First, he turned on just the long-wave lights. He adjusted the amounts of illumination on the left-green and right-red circles so the meter readings were equal. Then, he did the same for middle- and short-wave light. The left-green and right-red circles had equal quanta catches by the L, M, S cones.

Two identical sets of matte colored papers, with separate L, M, S illuminating projectors with voltage transformers for control of the amount of light. Telephotometer readings were projected above the Mondrians. The experimenter separately measured the L, M, S radiances from a green circle in the left Mondrian. Then, he adjusted the L, M, S radiances from a red circle on the right Mondrian to be the same. Observers reported different red and green colors produced by identical light stimuli.

In this complex scene, observers reported that equal quanta catches appeared green on the left and red on the right. Observers reported color constancy, namely, that the red paper looked red and the green paper looked green despite the identical cone quanta catch.

Land repeated this experiment with all the Mondrian papers. A constant L, M, S quanta catch could generate any color sensation. The presence of the complex scene introduced more information to the visual system. The red and green papers appeared equal in Fig. 2.1. The red paper looked red and the green paper looked green in Fig. 2.2. The scene's spatial content stimulated vision's spatial image processing mechanisms to generate color constancy. The post-receptor visual processing plays a dominant role in color appearance in real scenes. Land's word "Retinex" gave this spatial process a name. As well, he proposed a theoretical mechanism.[17]

2.2.4 Retinex Mechanism

Figure 2.3. illustrates the pair of Mondrians in only long-wave light with more light on the left than on the right. Their appearances are nearly constant. This is a common observation: humans are insensitive to large changes in uniform illumination.

The left Mondrian has more illumination than the right. Observers report that the left set is slightly lighter than the right. Each corresponding area is nearly the same lightness in the left and right Mondrians as shown in Figure 2.3

As illustrated in Figure 2.3, the left-green circle looked dark when it generated the same L cone quanta catch as the lighter right-red circle. Vision's spatial image processing rendered the red and green papers with different lightnesses in long-wave light. The lightnesses are stable with large changes in overall illumination.

Figure 2.4. illustrates the Mondrian viewed in only middle-wave light. The left-green circle now looks light and the right-red looks dark. In the experiment they had the same M cone quanta catch. Vision's spatial image processing rendered the red and green papers with different and opposite lightnesses in Fig. 2.4.

Now, the left Mondrian has less illumination than the right. In this wave band the pattern of lightnesses differs from that in long-wave light. That lightness pattern is indifferent to the amount of uniform illumination. Land adjusted the left side and right side illumination so that the circles had equal meter readings

In summary, if the two Mondrians are side by side in the same band of wavelengths, but different overall intensities, the observers report nearly the same set of lightnesses at corresponding locations in the left and right Mondrians. However, one side is detectably lighter than the other. With large uniform changes in illumination, observers report nearly constant lightnesses of the individual papers.

The left-green paper has more long-wave and less middle-wave illumination. The right-red paper has less long-wave and more middle-wave illumination. When adjusted, those adjustments in amount of illumination make the red and green papers have identical radiances. Those adjustments do not significantly alter the lightnesses of the areas in separate illumination. When viewing the Mondrian in combined illumination, in color, those changes in illumination do not change the color appearances of the red and green papers.

These observations led Land to propose the Retinex theory. The triplet of apparent lightnesses, not cone quanta catches, determines the color appearance. Constant LMS lightnesses generate constant colors. That hypothesis led to a study of color appearances in L, M, S bands of light. Do all red colors have the same triplet of lightness appearances? Does a red color always look [light, dark, dark] in L, M, S light? Does a green always look [dark, light, dark]? Does color appearance always correlate with the triplet of L, M, S lightnesses?

The experiment is easy. Find a red, a green, and a blue filter. Be sure that the filters exclude the other two-thirds of the spectra. With a green filter you should just see greens with different lightnesses. You should not see a mixture of greens and yellows and blues. If you do, you need a filter with a narrower band of transmission.

Identify a group of red objects. Look at them sequentially through the L, M, S filters. Look at them in different ambient illuminations. Look at them at different times of the day. Look at them in sunlight and shadows. Red colors are always (light, dark, dark) in L, M, S light. The same dependence of the triplet of L, M, S lightnesses holds for all colors (Table 2.3). Lightness is the output of spatial image processing. It is the result of post-receptor spatial processing. That is why lightness does not correlate with cone quanta catch. However, color does correlate with three lightnesses in long-, middle-, and short-wave light.

Retinex theory predicts that the triplet of L, M, S lightnesses determines color. Colors are constant with changes in illumination because the triplet of lightnesses is nearly constant.

Land's observation still stands: The triplet of lightnesses correlates with color. The observation is important because a variety of different phenomena can influence lightness, such as simultaneous contrast, the Corn sweet effect, and assimilation. Regardless of the cause of the lightness changes, when two identical physical objects look

Table 2.3: Correlation table of color appearances and the apparent lightnesses in L, M, S illumination.

Color Apperance	**Apperance in L-Light**	**Apperance in M-Light**	**Apperance in S-Light**
Red	Light	Dark	Dark
Yellow	Light	Light	Dark
Green	Dark	Light	Light
Cyan	Dark	Light	light
Black	Dark	Light	light
Mangenta	Light	Dark	light
White	Light	Light	light
Black	Dark	Dark	Dark

different, color appearances correlate with their L, M, S lightnesses. In the color assimilation display (Fig. 2.5), there are two sets of nine red squares that have the same reflectance and appear the same (top left). However, if these red squares are surrounded by yellow and blue stripes, they look different (top center): the left red squares fall on top of the yellow stripes, and the right ones on the blue stripes. The left squares appear a purple red, while the right ones appear a yellow orange. In other words, the left squares appear more blue and the right ones more yellow.

In the L separation the corresponding squares are lighter on the right of the separation; in the M separation these patches are lighter; in the S separation they are darker on the right. Land's Retinex predicts that whenever L and M separations are lighter and S separation is darker, then that patch will appear more yellow. Whenever S separation is lighter and L and M separations are darker, then that patch will appear more blue. Colors correlate with L, M, S lightnesses [17].

2.2.5 Retinex in Image Processing

The effect was described in 1971 by Edwin H. Land, who formulated "retinex theory" to explain it. The word "retinex" is a portmanteau formed from "retina" and "cortex", suggesting that both the eye and the brain are involved in the processing.

The effect can be experimentally demonstrated as follows. A display called a "Mondrian" (after Piet Mondrian whose paintings are similar) consisting of numerous colored patches is shown to a person. The display is illuminated by three white lights, one projected through a red filter, one projected through a green filter, and one projected through a blue filter. The person is asked to adjust the intensity of the lights so that a particular patch in the display appears white. The experimenter then measures the intensities of red, green, and blue light reflected from this white-appearing patch. Then the experimenter asks the person to identify the color of a neighboring patch, which, for example, appears green. Then the experimenter adjusts the lights so that the intensities of red, blue, and green light reflected from the green patch are the same as were originally measured from the white patch. The person shows color constancy in that the green patch continues to appear green, the white patch continues to appear white, and all the remaining patches continue to have their original colors.

Color constancy is a desirable feature of computer vision, and many algorithms have been developed for this purpose. These include several retinex algorithms. These algorithms receive as input the red/green/blue values of each pixel of the image and attempt to estimate the reflectances of each point. One such algorithm operates as follows: the maximal red value rmax of all pixels is determined, and also the maximal green value gmax and the maximal blue value bmax. Assuming that the scene contains objects which reflect all red light, and (other) objects which reflect all green light and still others which reflect all blue light, one can then deduce that the illuminating light source is described by (rmax, gmax, bmax). For each pixel with values (r, g, b) its reflectance is estimated as (r/rmax, g/gmax, b/bmax). The original retinex algorithm proposed by Land and McCann uses a localized version of this principle.

Although retinex models are still widely used in computer vision, actual human color perception has been shown to be more complex.

Land described that the fundamental challenge of color vision shifted to the ability to predict lightness; that is, the spatial interactions found in post-receptor neural processes. In 1967 Land and McCann proposed a computational model for calculating lightness from the array of all scene radiances [18]. The model compared each pixel with every other pixel in an image. The goal was to calculate the sensation of image segments that equaled what observers saw. In the past 50 years, there have been many implementations and variations of this process. They are called Retinex algorithms. It is curious that Land reserved the use of the term “Retinex” to describe three independent lightness channels. Today’s usage of the word includes a much wider range of computer algorithms that build calculated appearances out of arrays of radiances.

To calculate lightnesses in complex scenes, one must:

- Capture scene radiances.
- Convert scene radiances to cone and rod quanta catches.
- Calculate lightness using all pixels in the scene.
- Compare calculated lightness with observer matches.

The Land and McCann model used:

- Edge ratios.
- Gradient threshold (found to be unnecessary in later studies).
- Multiplication of edge ratios (made long-distance interactions).
- Reset to maxima (scaled the output).
- Average of many spatial comparisons

The first computer implementation of the model used an array of 20 by 24 pixels. McCann, McKee, and Taylor showed that long-, middle-, and short-wave computed lightnesses predicted observer matches of color Mondrians in color constancy experiments.

Since the late 1960s, computer imaging has shown remarkable advances. Digital images have replaced film in most of photography. Computer graphics has made image synthesis ubiquitous. Retinex image processing has grown with the advances in digital imaging. In the early 1980s Frankle and McCann introduced a multi-resolution algorithm that allowed efficient comparison of all pixels in the image. Jobson and Kotera with their colleagues have studied the NASA Retinex. Rizzi and colleagues have developed the Milan Retinex. Sobol extended that Retinex algorithm was used in the design of commercial cameras. Other algorithms have used Retinex spatial processing in color gamut-mapping applications.

The important feature of real complex scenes is that the illumination is rarely uniform. Shadows and multiple reflections increase the dynamic range of light coming to our eyes and to cameras. The application of Retinex algorithms to high dynamic range (HDR) scenes has become a major topic of research and engineering applications. The limits of HDR scene capture and reproduction are controlled by optics, namely, optical veiling glare. Camera glare limits the range of light on the sensor, just as intraocular glare limits the range of light on the retina. The scene content controls the range of light in images. Vision's post-receptor neural processes compensate for veiling glare. That explains humans' high dynamic range of appearances from low-dynamic-range retinal images. The spatial mechanisms modeled by Retinex algorithms play a major role in compensating for glare and generating our range of color and lightness sensations.

Over the years many variations of spatial processing mimicking human vision have been called Retinex algorithms.[19]

2.2.6 Retinex in Image Enhancement

The retinex theory is first proposed by Land to model the imaging process of the human visual system. This theory assumes that the scene in human's eyes is the product of reflectance and illumination. Most retinex based enhancement algorithms use different ways to estimate the illumination and remove it to obtain the reflectance as the enhanced image. The details and textures can be enhanced by illumination removal. While the enhanced results look over-enhanced and unnatural since the result does not meet with human vision system. It is well-known that human eye perception is a combined effect of reflectance and illumination. It is unreasonable to remove the illumination and only regard the reflectance as an improved result. Other retinex based algorithms firstly use logarithmic transformation to transform product into sum to reduce the computational cost, and then employ a variational model for enhancement. Note that the logarithmic transformation stretches low values and compresses high values, increasing the contrast of low intensities and decreasing the contrast of high intensities. The resulting reflectance is usually smoothed and loses some details which can be manageable. In many papers, some novel retinex based image enhancement approach using illumination adjustment is proposed in which some new variational model is established that is different from conventional models, where the model does not need the logarithmic transformation and is more appropriate for the decomposition because reflectance is constrained in image domain. So a fast alternating direction optimization method was adopted to solve the proposed old model, where the reflectance and illumination can be computed and decomposed. Then a simple and effective post-processing method of the decomposed illumination is used to make an adjustment for image enhancement. The enhanced image is obtained by combining the reflectance and the adjusted illumination. The naturalness of enhanced images can be preserved while details enhanced. Meanwhile, reflectance and illumination can be obtained as a by-product of the enhanced Image and this method has good clarity on naturalness preservation and detail enhancement due to the illumination adjustment and precise computed reflectance. Hence their common principle is to assign a new value to each pixel in an image based on spatial comparisons of light intensities. So with increase in better performance of retinex algorithm it is developed into many forms according to its application in grey images, colour images and mostly in real time image processing in field of medical images and texture feature parameters.

The Retinex image enhancement algorithm [20] [21] [22] is an image enhancement method that enhances an image with dynamic range compression. It also provides colour constancy. It gives a computational human vision model. It deals separates two parameters. At first the illumination information is estimated and then the reflectance is obtained from using division. It is based on the image formation model which is given [1] by

$$I(x, y) = L(x, y)r(x, y) \tag{2.7}$$

Where I is the input image, L is illumination and r is reflectance. The image is first converted into the logarithmic domain in which multiplications and divisions are converted to additions and subtractions that makes the calculation simple. The sensitivity of human vision reaches a logarithmic curve. Retinex is based on the centre/surround algorithm [23] .The given centre pixel value is compared with the surrounding average pixel values to get the new pixel value. The input value of the centre surround functions is obtained by its centre input value and its neighbourhood. An array of photoreceptor responses is there for each image location. This is given as input to the retinex algorithm which has the receptor class for each location in the image. The algorithm calculates a series of paths. For a single receptor class, it estimates the lightness values as a spatial array. For computing each path, a starting pixel (x1) is first selected [24].Then a neighbouring pixel (x2) is randomly selected. The difference of the logarithms of the sensor responses at the two positions is then calculated. The position of pixel x2 is obtained by adding the previous step with the accumulator register which is given by:

$$A(x2) = A(x2) + \log_{10}(x2) - \log_{10}(x1) \tag{2.8}$$

Where $A(x2)$ is the accumulator registers for pixel $(x2)$.

Counter register $N(x2)$ for position $x2$ is incremented. All registers and counters are set to zero when the calculation starts.

The accumulation of position (xi) on the path is calculated by [24]:

$$A(xi) = A(xi) + \log_{10}(x1) \tag{2.9}$$

Chapter 3

Proposed Work

Image enhancement improves the quality of images for human viewing. There are often serious discrepancies existing between images and the direct observation of the real scenes. Human perception has natures of dynamic range compression and color rendition on the scenes. It can compute the details across a large range of spectral and lightness variations, thus it is color constant. Single-scale Retinex (SSR) was defined as an implementation of center/surround Retinex. Superposition of weighted different scale SSR balances both dynamic range compression and tonal rendition, which is Multiscale Retinex (MSR). For color images, spatial averages of the three color bands are far from equal, thus the output appears grey. To address this issue, a weight factor for different channels is introduced which is Multiscale Retinex with color restoration (MSRCR). In this paper, SSR, MSR and MSRCR systems for image enhancement are implemented and their performances are compared using MATLAB as the software tool.

3.1 Introduction

The human visual system is better than machines when processing images. Observed images of a real scene are processed based on brightness variations. The images captured by machines are easily affected by environmental lighting condition, which tends to reduce its dynamic range[1]. On the contrary, the human visual system can automatically compensate the image information by psychological mechanism of color constancy[2]. Color constancy, an approximation process of human perception system, makes the perceived color of a scene or objects remain relatively constant even with varying illumination conditions. Land [3] proposed a concept of the Retinex, formed from "retina" and "cortex", suggesting that both the eye and the brain are involved, to explain the color constancy processing of human visual systems. Although single-scale retinex (SSR) algorithm could support different dynamic-range compressions, the multi-scale retinex (MSR) can better approximate human visual processing by transforming recorded images into a rendering which is much closer to the human perception[4] of the original scene. MSR is good for gray images. But it could be a problem for the color images because it does not consider the relative intensity of color bands. This can be seen from MSR output which is the relative reflectance‘s[5] in the spatial domain. Considering the images out of gray world, whose average intensity for the three color bands are far from equal, the output pixel values of MSR for three channels will be more close, which makes it look more gray.The solution to this problem is MSRCR that introduces weights for three color channels depending on the relative intensity of the three channels in the original images

3.2 Retinex in Image Processing

Land described that the fundamental challenge of color vision shifted to the ability to predict lightness; that is, the spatial interactions found in post-receptor neural processes. In 1967 Land and McCann proposed a computational model for calculating lightness from the array of all scene radiances. The model compared each pixel with every other pixel in an image. The goal was to calculate the sensation of image segments that equaled what observers saw. In the past 50 years, there have been many implementations and variations of this process. They are called Retinex algorithms. It is curious that Land reserved the use of the term “Retinex” to describe three independent lightness channels. Today’s usage of the word includes a much wider range of computer algorithms that build calculated appearances out of arrays of radiances. To calculate lightnesses in complex scenes, one must: Capture scene radiances, Convert scene radiances to cone and rod quanta catches, Calculate lightness using all pixels in the scene, Compare calculated lightness with observer matches. The Land and McCann model used: Edge ratios, Gradient threshold (found to be unnecessary in later studies), Multiplication of edge ratios (made long-distance interactions), Reset to maxima (scaled the output) (introduced dependence on scene content, e.g., simultaneous contrast) Average of many spatial comparisons. The first computer implementation of the model used an array of 20 by 24 pixels. McCann, McKee, and Taylor showed that long-, middle-, and short-wave computed lightnesses predicted observer matches of color Mondrian's in color constancy experiments.

Since the late 1960s, computer imaging has shown remarkable advances. Digital images have replaced film in most of photography. Computer graphics has made image synthesis ubiquitous. Retinex image processing has grown with the advances in digital imaging . In the early 1980s Frankle and McCann introduced a multi-resolution algorithm that allowed efficient comparison of all pixels in the image. Jobson and Kotera with their colleagues have studied the NASA Retinex. Rizzi and colleagues have developed the Milan Retinex. Sobol extended that Retinex algorithm was used in the design of commercial cameras. Other algorithms have used Retinex spatial processing in color gamut-mapping applications.

The important feature of real complex scenes is that the illumination is rarely uniform. Shadows and multiple reflections increase the dynamic range of light coming to our eyes and to cameras. The application of Retinex algorithms to high dynamic range (HDR) scenes has become a major topic of research and engineering applications. The limits of HDR scene capture and reproduction are controlled by optics, namely, optical veiling glare. Camera glare limits the range of light on the sensor, just as intraocular glare limits the range of light on the retina. The scene content controls the range of light in images. Vision's post-receptor neural processes compensate for veiling glare. That explains humans' high dynamic range of appearances from low-dynamic-range retinal images. The spatial mechanisms modeled by Retinex algorithms play a major role in compensating for glare and generating our range of color and lightness sensations.

Over the years many variations of spatial processing mimicking human vision have been called Retinex algorithms.[2]

The different types of retinex algorithms are:

- Single Scale Retinex algorithm (SSR)

- Multiscale Retinex algorithm (MSR)
- Multiscale retinex with Color Restoration algorithm (MSRCR)

3.2.1 Single Scale Retinex (SSR)

The basics of SSR include a logarithmic photoreceptor function that approximates the vision system based on a center/surround [6] function. The SSR is given by:

$$R_i(x,y) = \log_i - \log[F(x,y)I_i(x,y)] \tag{3.1}$$

where $I_i(x,y)$ is image distribution in the ith color band,$F(x,y)$ is the normalized surround function[7] such that:

$$\iint F(x,y)dxdy = 1 \tag{3.2}$$

The purpose of the logarithmic manipulation is to transform a ratio at the pixel level to a mean value for a larger region. The general form of the center/surround retinex is similar to the Difference-of-Gaussian (DOG) function widely used in natural vision science to model both the receptive fields of individual neurons and perceptual processes. The only extensions required are i) to greatly enlarge and weaken the surround Gaussian (as determined by its space and amplitude constants) and ii)to include a logarithmic function to make subtractive inhibition into a shunting inhibition (i.e., arithmetic division). The surround space function computes the average of the surrounding pixel values and assigns it to the center pixel. Land [3] proposed an inverse square spatial surround function:

$$F(x,y) = K * exp(-\frac{r^2}{c^2}) \tag{3.3}$$

Moore suggested the exponential formula with absolute parameter:

$$F(x,y) = exp(-\frac{r}{c} \tag{3.4}$$

Hurlbert [8] suggested:

$$F(x, y) = K * exp(-\frac{r^2}{c^2} \tag{3.5}$$

For a given space constant, the inverse-square surround function accounted for a greater response from the neighboring pixels than the exponential and Gaussian functions. The spatial response of the exponential surround function was larger than that of the Gaussian function at distant pixels. Therefore, the inverse-square surround function was more commonly used in global dynamic range compression and the Gaussian surround function was generally used in regional dynamic range compression[9]. The exponential and Gaussian surround functions were able to produce good dynamic range compression over neighboring pixels. The selection of space constant is related with visual angle in the direct observation. But the value cannot be theoretically modeled and determined. Basically there is a trade-off between dynamic compression, (for example, details in the shadow) and color rendition. SSR is incapable of simultaneously providing sufficient dynamic range compression and tonal rendition. It also introduces halos around the objects.

3.2.2 Multiscale Retinex (MSR)

In order to preserve both the dynamic range compression and color rendition, Multiscale retinex, which is a combination of weighted different scales of SSR [10], is a good solution:

$$R_{MSR_i} = \sum_{n=1}^{N} w_n R_{n_i} \tag{3.6}$$

where N is the number of the scales, Rni is the ith component of the nth scale, wn is the weight of the nth scale. For MSR, the number of scales needed, scale values and weight values are important. Experiments showed that three scales are enough for most of the images and the weights can be equal. Generally fixed scales of 15, 80 and 250 can be used, or scales of fixed portion of image size can be used. The weights can be adjusted to weigh more on dynamic range compression or color rendition [11]. The MSR based images have significant dynamic range compression in the boundary between the light parts and dark parts and reasonable color rendition in the whole image scale.

MSR combined various SSR weightings, selecting the number of scales used for the application and evaluating the number of scales that can be merged. Important issues to be concerned were the number of scales and scaling values in the surround function, and the weights in the MSR. The best weights had to be chosen in order to obtain suitable dynamic-range compression at the boundary between light and dark parts of the image, and to maximize the brightness rendition [12] over the entire image. MSR worked by compensating for lighting variations to approximate the human perception of a real scene. There were two methods to achieve this: (1) compare the psychophysical mechanisms between the human visual perceptions of a real scene and a captured image, and (2) compare the captured image with the measured reflectance values of the real scene.

Thus the method involved combining specific features of MSR with processes of SSR, in which the center/surround operation was a Gaussian function. The logarithm was then applied after surround function processing (i.e., two-dimensional spatial convolution). Next, appropriate gain and offset values were determined according to the retinex output and the characteristics of the histogram. These values were constant for all the images. This procedure yielded the MSR function. However, it is difficult to predict whether the color of the reproduction will be accurate; and it has issues of color sensitivity [13].

3.2.3 Multiscale retinex with Color Restoration algorithm (MSRCR)

To address the drawback of MSR with regard to color restoration, we introduced weights for three color channels depending on the relative intensity of the three channels in the original images. The relative intensity of three channels is given by:

$$I_i(x,y) = \frac{I_i(x,y)}{\sum_{j=1}^{s} I_i(x,y)} \tag{3.7}$$

I_i is the i^{th} band of the input image and S is the total number of color bands.

The color restoration [14] is given by:

$$C_i(x, y) = f[I_i(x, y)] \tag{3.8}$$

The best overall color restoration function is given by:

$$C_i(x, y) = \beta \log[\alpha I_i(x, y)] \tag{3.9}$$

where β is the gain constant and α controls the strength of non-linearity. The general form of the MSRCR can be summarized by the following equation:

$$I_i(x, y_= \frac{d_{max}}{r_{max} - r_{min}} * (I_i(x, y) - r_{min}) \tag{3.10}$$

where $i = 1, \ldots..N$, ws is the weight of the scale, I_i is the ith band of the input image, and N is the number of bands in the input image. The surround function M_s is defined by:

$$M_s(x, y) = Kexp[{\sigma^2}_s/(x^2 + y^2)] \tag{3.11}$$

where σ_s is the standard deviation of the S^{th} surround function, and

$$\iint Kexp[{\sigma^2}_s/(x^2 + y^2)]dxdy = 1 \tag{3.12}$$

$$F_i(x, y) = G_f \log big[\frac{I_i(x, y)}{\sum_{n=1}^{N} I_n(x, y)} - O_f] \tag{3.13}$$

The G_f and Of are color restoration factors defined as gain and offset respectively. The final gain and offset values are needed to scale the output of the $\log$ domain operations to the (R, G, B) color space, and G_f and Of control the degree to which the color restoration function $F(x, y)$ affects the overall color of the output image. These constants, the number of scales, S, and the widths of the surround functions γ_s, are image independent in the sense that we apply the same (canonical) set of constants to every image that we process.

Some of the images processing related issues in MSRCR are:

- Negative Offset:
  This is an attempt to increase the dynamic range (i.e. visual contrast) provided by the device but is often photometrically incorrect and results in false zeroes. The effect of the MSRCR is to produce a harsher-than-normal contrast. A simple correction, i.e. application of a positive offset to the original image can mitigate this effect.

- Automatic Gain and Offset [15]:
  A negative offset is typically applied to map the minimum value to black and then a gain is applied to map the resultant maximum value to white. Care is taken to ensure that actual white exists in the scene. The MSRCR is very resilient to such adjustments. Since the difference between the MSRCR outputs in the original and the auto/gain case is insignificant, the result is not shown here.

- Positive Offset:
  Typically brightness in an image is increased by applying a positive offset, which often manifests itself as an overall haziness in the input image. Though the application of the MSRCR reduces this haziness, there is still a sense of haziness overall. Further alleviation of this effect can be achieved by reducing the final offset value; O_r from its canonical value. In this paper, color problems were focused utilizing MSRCR as an image processing technique to solve the problems of the accuracy of the color of the reproduction. The main practical consequence of MSR is that it is not appropriate for applications which are sensitive to color. The results of MSRCR prove that it is efficient to avoid graying out effects. It maintains good color rendition and color constancy.

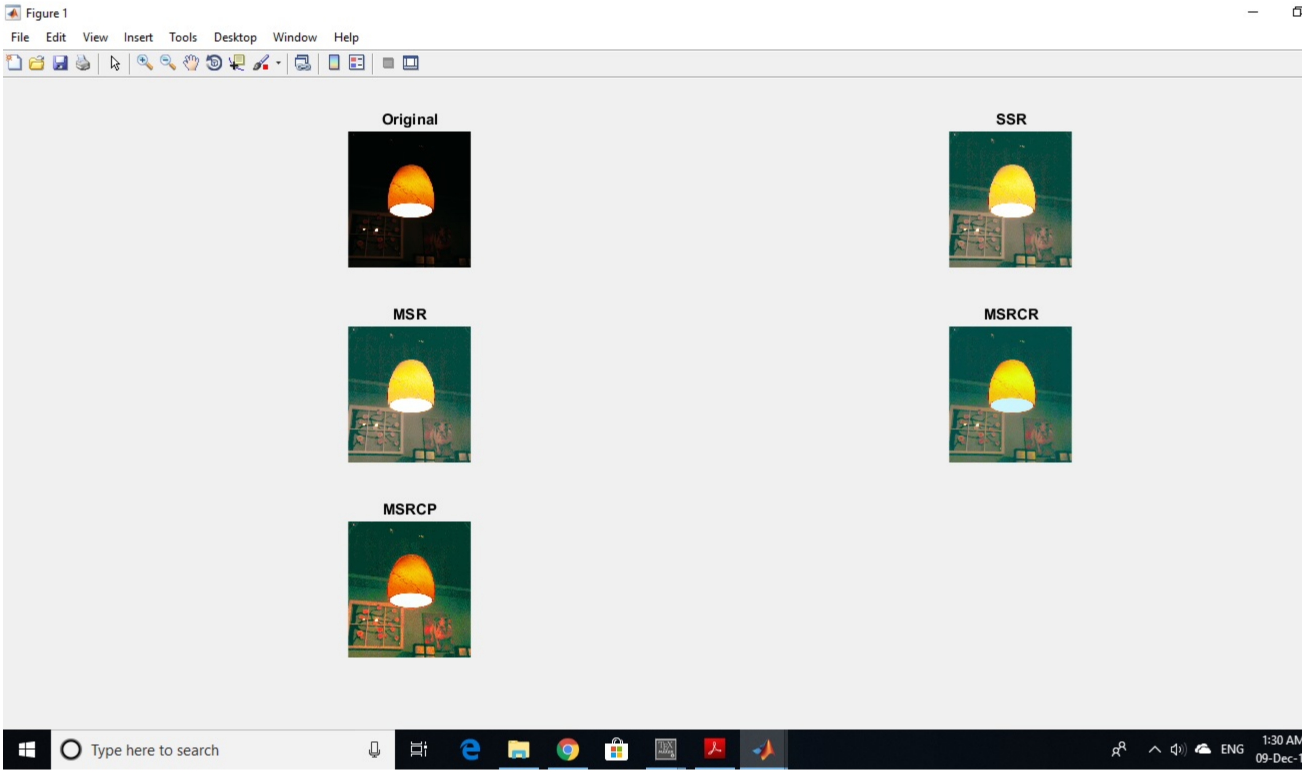


Figure 3.1: Result of Retinex Model

3.3 Power Law Transformation

Image enhancement can be carried out in the spatial or the Fourier domains and one of the important parameters to be looked at in this context is contrast enhancement. In the spatial domain, the methods used may be further classified into: gray level transformations, histogram processing, etc. As mentioned above, histogram equalization suffers from the fact that it may sometimes decrease the contrast. Histogram specification or matching can be tailor-made to suit the images but requires lot of user input. Similarly, power law transformations or piece-wise linear transformation functions also require lot of user input. In the former case one has to choose the exponent appearing in the transformation function, while in the latter case one has to choose the slopes and ranges of the straight lines which form the transformation function.

The power-law transformation is usually defined as

$$s = cr^{\gamma} \tag{3.14}$$

where s and r are the gray levels of the pixels in the output and the input images, respectively and c is a constant. These power law transformation functions are shown

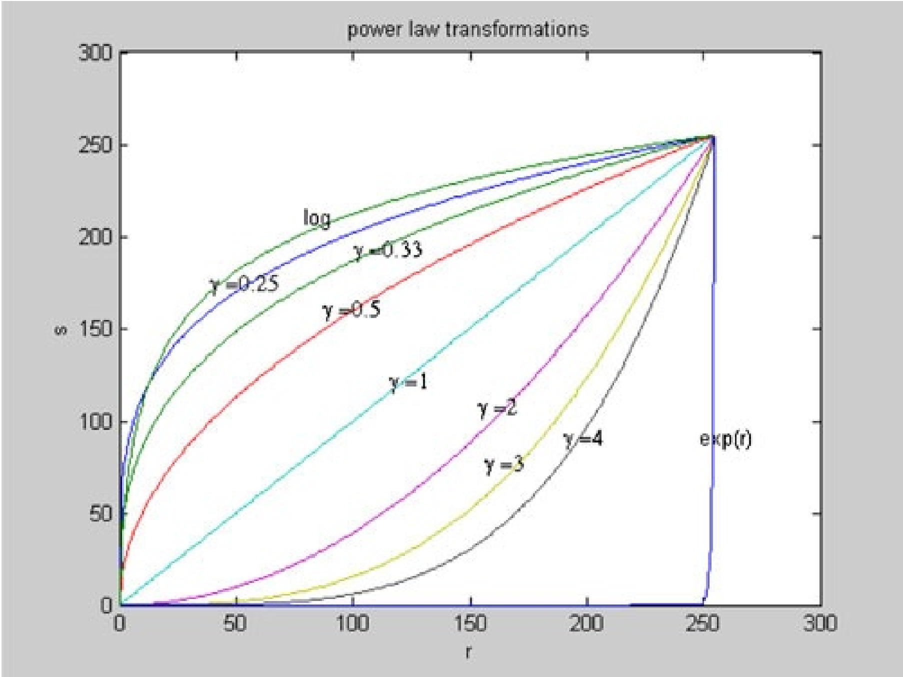


Figure 3.2: Plot of power law transformation for various γ with input gray level along X axis and output gray level along Y axis.

graphically in the diagram (figure 3.2). Figure 3.2 shows the plot of power law transformation with the input gray level r along the x axis and the output gray level s on the y axis for various values of γ . We will now consider that these transformations are applied on a low contrast image. We assume that the background and foreground peaks have almost merged together in such a low contrast image. Let r_{max} be the dominant peak in the histogram. If r_{max} has a large value (in the range 150–255), then it is seen from the above graph that contrast stretching occurs by choosing $\gamma > 1$ whereas for dark images (r_{max} lies in the range 0–100), we see that choosing $\gamma < 1$ leads to contrast stretching. We can of course, automate this procedure for choosing the appropriate exponent, by finding out the peak value in the histogram. However, we can further generalize this procedure so that the most appropriate value of the exponent is chosen.

3.4 Histogram Equalization

An image histogram is a type of histogram that acts as a graphical representation of the tonal distribution in a digital image. It plots the number of pixels for each tonal value. A histogram is a representation of a frequency distribution. The histogram of a digital image with G total possible intensity levels in the $[0, G-1]$ is defined as the discrete

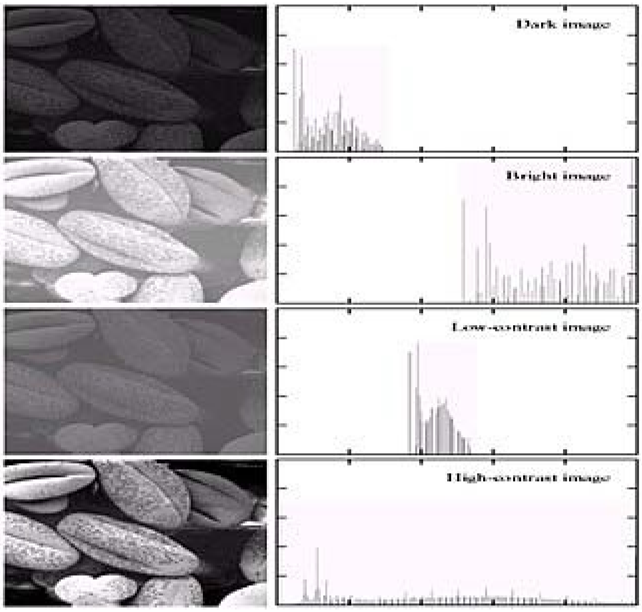


Figure 3.3: Seed Image and its histogram

function:

$$p(\gamma_k) = \frac{n_k}{n} \tag{3.15}$$

Where γ_k is the intensity level in the original raw image n_k is the number of pixels in the image whose intensity level is n is the total no of pixels.

Histogram equalization is used to enhance the contrast of the image, it spreads the intensity values over full range. Histogram equalization technique can't be used for images suffering from non-uniform illumination in their backgrounds as this process only adds extra pixels to the light regions of the image and removes extra pixels from dark regions of the image resulting in a high dynamic range in the output image.The goal of histogram equalization is to spread out the contrast of a given image evenly throughout the entire available dynamic range.

In histogram equalization technique, it is the probability density function (pdf) that is being manipulated. To make it simple, what histogram equalization technique does is that, it changes the pdf of a given image into that of a uniform probability density function that spreads out from the lowest pixel value (0 in this case) to the highest pixel value $(L-1)$. This can be achieved quite easily if the pdf is a continuous function. However, since we are dealing with a digital image, the pdf will be a discrete function. Lets suppose we have an image x , and let the dynamic range for the intensity γ_k varies from 0 (black) to $L1$ (white). This pdf can be approximated using the probability based on the histogram $p(\gamma_k)$ as follow:

$$pdf(x) = p(\gamma_k) = \frac{total\ pixels\ with\ intensity\ \gamma_k}{total\ pixels\ I\ image\ x} \tag{3.16}$$

From this pdf, we can then obtain the cumulative density function (cdf) as follows:

$$cdf(x) = \sum_{k=0}^{L-1} p(\gamma_k) \tag{3.17}$$

Where $p(\gamma_k)$ is the probability for pixel of intensity. The output of a pixel from the histogram equalization operation is then equal to the cdf of the image or mathematically :

$$p(s_k) = \sum_{k=0}^{L-1} p(\gamma_k) \tag{3.18}$$

To get the value of the pixel, $p(s_k)$ needs to be multiplied by $L1$ and then round it to the nearest integer

3.4.1 Equalization on Color Image

- **Equalize R, G, B components independently (method1)**
  This scheme is one of the mostly used methods for color image processing. Each channels of RGB space are processed using Histogram Equalization independently[2].After the Equalize the R,G,B components we concate all the three components and get the better image compare to input image.

- **Equalize tha V Component from HSV Color Space (method 2)**
  In order to process color image in RGB color space using this scheme, image first must be transformed to hue, saturation and luminance (HSV) color space.Here Brightness is a synonym of intensity. Hue represents the impression related to the

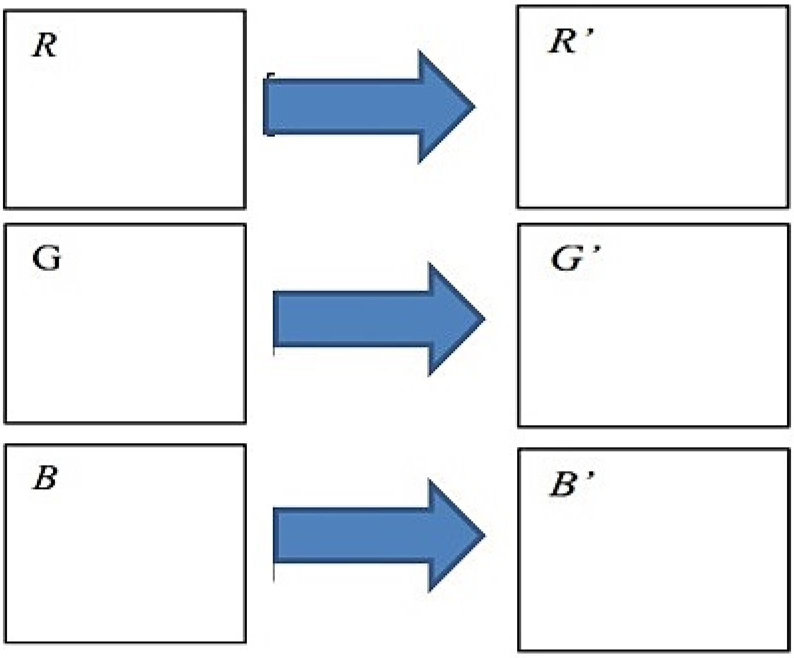


Figure 3.4: Block diagram showing the implementation of Method 1

dominant wavelength of the color stimulus Saturation shows the relative color purity (amount of white light in the color). Hue and Saturation taken together are called the chromaticity coordinates (polar system). In this method we apply the Histogram Equalization on V component on HSV color space .After the Equalize the V we combine the V with H and S .Then we get the better image compare to input image.

$HSV \rightarrow H, S, V$

$V \rightarrow V(equalize)$

$HSV(equalize) \rightarrow H, S, V(equalize)$

- **Equalize the Y Component from YIQ Color Space(method 3)**

  In order to process color image in RGB color space using this scheme, the image first must be transformed to YIQ color space[4][5].

  Here

  The Y component represents the luma information, and is the only component used by black-and-white television receivers.

  I stands for in-phase

  Q stands for quadrature

  I and Q represent the chrominance information.

In this method we apply the Histogram Equalization on Y component on YIQ color space .After the Equalize the Y we combine the Y with I and Q .Then we get the better image compare to input image.

$YIQ \rightarrow YIQ$

$Y \rightarrow Y(equalize)$

$YIQ(equalixe) \rightarrow Y, I, Q(equalize)$

3.5 Adaptive Histogram Equalization(AHE) method

This is an extension to traditional Histogram Equalization technique. It enhances the contrast of images by transforming the values in the intensity image I. Unlike HISTEQ, it operates on small data regions (tiles), rather than the entire image. Each tile's contrast is enhanced, so that the histogram of the output region approximately matches the specified histogram. The neighboring tiles are then combined using bilinear interpolation in order to eliminate artificially induced boundaries. The contrast, especially in homogeneous areas, can be limited in order to avoid amplifying the noise which might be present in the image.

- Algorithm Steps:
  1. Obtain all the inputs: Image, Number of regions in row and column directions, Number of bins for the histograms used in building image transform function (dynamic range), Clip limit for contrast limiting (normalized from 0 to 1)
  2. Pre-process the inputs: Determine real clip limit from the normalized value if necessary, pad the image before splitting it into regions
  3. Process each contextual region (tile) thus producing gray level mappings: Extract a single image region, make a histogram for this region using the specified number of bins, clip the histogram using clip limit, create a mapping (transformation function) for this region.
  4. Interpolate gray level mappings in order to assemble final CLAHE image: Extract cluster of four neighbouring mapping functions, process image re-

gion partly overlapping each of the mapping tiles, extract a single pixel, apply four mappings to that pixel, and interpolate between the results to obtain the output pixel; repeat over the entire image.

In low contrast images, the features of interest may occupy only a relatively narrow range of gray scale, with the majority of gray levels occupied by “uninteresting areas” such as background and noise. These “uninteresting areas” may also generate large counts of pixels and hence, large peaks in the histogram. In this case, the global histogram equalization amplifies the image noise and increases visual graininess or patchiness. The global histogram equalization technique does not adapt to local contrast requirements, and minor contrast differences can be entirely missed when the number of pixels falling in a particular gray range is small.

Adaptive Histogram Equalization (AHE) is a modified histogram equalization procedure that optimizes contrast enhancement based on local image data. The basic idea behind the scheme is to divide the image into a grid of rectangular contextual regions, and to apply a standard histogram equalization in each. The optimal number of contextual regions and the size of the regions depend on the type of input image, and the most commonly used region size is 8x8 (pixels). In addition, a bi-linear interpolation scheme is used to avoid discontinuity issues at the region boundaries.

Figure 3.5 illustrates the application of the interpolation scheme at the boundaries. Gray level assignment at the sample positions indicated by the white dot are derived from gray-value distributions in the surrounding contextual regions. The points A, B, C, and D are the centers of the surrounding contextual regions; region-specific gray level mappings (gA(s), gB(s), gC(s) and gD(s)) are based on the histogram equalization of the pixels contained. Thus, assuming that the original pixel intensity at the sample point is s, its new gray value s’ is calculated by bilinear interpolation of the gray-level mappings that were calculated for each of the surrounding contextual regions:

$$s' = (1-y)((1-x)g_A(s) + xg_B(s)) + y(((1-x)g_c(s) + xg_D(s)) \tag{3.19}$$

where x and y are normalized distances with respect to the point A. This gray

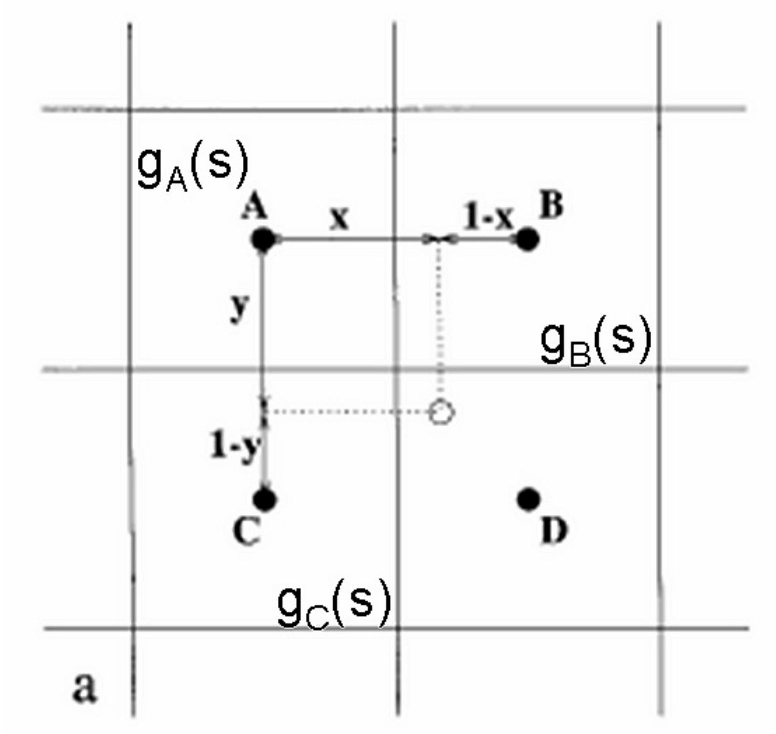


Figure 3.5: Bilinear interpolation to eliminate region boundaries[From Zuiderveld, 1994].

level interpolation is repeated over the entire image

AHE is able to overcome the limitations of the standard equalization method as discussed earlier, and achieves a better presentation of information present in the image. However, AHE is unable to distinguish between noise and features in the local contextual regions. Hence, background noise is amplified in "flat" or "featureless" regions of the image, which is a major drawback of the method.

3.5.1 Contrast Limited Adaptive Histogram Equalization (CLAHE)

The noise problem associated with AHE can be reduced by limiting contrast enhancement specifically in homogeneous areas. These areas can be characterized by a high peak in the histogram associated with the contextual regions since many pixels fall inside the same gray level range. The Contrast Limited Adaptive Histogram Equalization (CLAHE) limits the slope associated with the gray level assignment scheme to prevent saturation, as illustrated in Figure 3.6. This process is accomplished by allowing only a maximum number of pixels in each of the bins associated with the local histograms. After "clipping" the histogram, the clipped pixels are equally redistributed over the whole

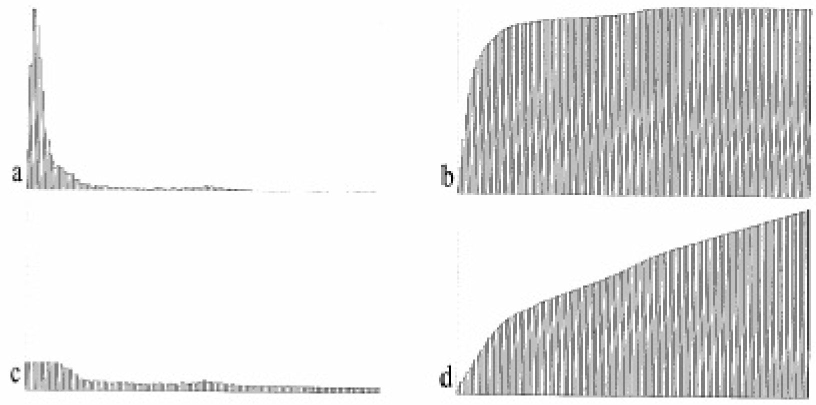


Figure 3.6: Principle of contrast limiting as used in CLAHE. (a) Histogram of a contextual region containing many background pixels. (b) Calculated cumulative histogram. (c) Clipped histogram with excess pixels redistributed throughout the histogram. (d) Cumulative clipped histogram with maximum slope set to the clip limit [From Zuiderveld, 1994].

histogram to keep the total histogram count identical

The clip limit is defined as a multiple of the average histogram contents and is actually a contrast factor. Setting a very high clip limit basically limits the clipping and the process becomes a standard AHE technique. A clip or contrast factor of one prohibits any contrast enhancement, preserving the original image. The main advantages of the CLAHE transform are its modest computational requirements, ease of use and excellent results on most images. The CLAHE image has less amplified noise and avoids the brightness saturation in the standard histogram equalization.

CLAHE does have its limitations. Since the method is aimed at optimizing contrast, there no direct 1-to-1 relationship between the gray values of the original image and the CLAHE processed result. Pixels of the same gray level in the original image may be mapped to different gray levels in the output image, because of the equalization process and bilinear interpolation. Consequently, CLAHE images are not suited for quantitative measurements that rely on physical meaning of image intensity [Zuiderveld, 1994].

Chapter 4

Implementation

The uneven illumination, particularly high dynamic lighting environment, causes many problems. For example, the images acquired by digital cameras, camcorders, or other terminals tend to be too bright or dark in certain areas, the target is difficult to be identified and some other issues.

To solve the problems for the quality of image acquisition caused by uneven illumination, a series of methods had been put forward successively, including histogram equalization, image enhancement in gradient field, homomorphic filter and the Retinex theory. Among these methods, the Retinex has become a research hotspot recently as it could achieve a good balance in dynamic range compression, edge enhancement and color constancy [1]. There are three classical algorithms based on the Retinex theory, they are SSR (Single Scale Retinex), MSR (Single Scale Retinex) and MSRCR (Multi-Scale Retinex with Color Restoration). However, SSR could only choose one dimension, it was difficult to simultaneously ensure the dynamic range compression and color fidelity [1, 2]. Although MSR can ensure the dynamic range compression and color fidelity, it could not achieve the high color fidelity, as it simply weighted the different scales linearly [3]. While MSRCR could achieve color fidelity much further, it was not conducive to real-time applications, because a lot of parameters needed to be set [4]. Furthermore, the above three algorithms may produce halo and color distortion in high contrast regions [5], since the illuminant image was obtained by Gaussian low-filter. In order to overcome such problems as halo and color distortion for the traditional Retinex, many improved algorithms have been proposed. For example, the halo was reduced through bilateral filter to obtain the illuminant image, but due to being ignorant of the correlations between each channel of the color image, it could not decrease the color distortion [6]. Based on this, some researchers combined the Weber's law converted the image into HSV space, which realized the reduction of 4th International Conference on Mechatronics, Materials, Chemistry and Computer Engineering (ICMMCCE 2015) © 2015. The authors - Published by Atlantis Press 2218 both halo and color distortion. However, it was not conducive to real-time application, as a lot of parameters needed to be set [7].

To further reduce halo and color distortion, this paper has proposed an improved Retinex image enhancement algorithm based on bilateral filter. And the results demonstrated that it could suppress both the halo and color distortion effectively.

4.1 Retinex theory and its typical algorithms

Retinex (abbreviation of Retina and Cortex) theory is a model been used to explain how the human visual system perceive color and brightness of objects. It is also the interpretation of color constancy indicating the color of the same objects is constant, though they are under different lighting. Briefly, the basic principle of Retinex theory is that the original image can be divided into illuminant and reflected image, and the enhancement can be achieved through reducing the effects of illuminant image on the reflected. As shown as in formula (4.1)

$$S(x, y) = R(x, y) * L(x, y) \tag{4.1}$$

Where $L(x, y)$ represents incident light or illuminant image deciding the dynamic range achieved by image pixels $R(x, y)$ represents reflective properties or reflected light deciding the interior properties of image $S(x, y)$ represents the original image. And the visual effects can be improved, mainly by obtaining the reflective properties or reflected image.

4.1.1 Single Scale Retinex(SSR)

The SSR algorithm based on center/surround Retinex approved by Edwin Land is firstly improved and realized by Jobson and his colleagues [10]. And the illuminant image is also obtained by Gaussian low filter as in formula (5.1)

$$R_{SSR}(x, y) = \log S(x, y) - \log(S(x, y) \otimes F(x, y)) \tag{4.2}$$

Where the symbol $\otimes$ represents convolution operation. $F(x, y)$ is Gaussian surrounding function in the following formula

$$F(x, y) = \gamma\ exp(-\frac{(x^2 + y^2)}{\sigma^2} \tag{4.3}$$

$$\iint F(x, y)dxdy = 1 \tag{4.4}$$

Where γ is a normalization constant, σ is the scale of surrounding function, and the smaller σ is, the more contrast is enhanced, but the more distinct the halo phenomenon becomes. Conversely, the larger σ is, although the less contrast is enhanced, the more effectively the halo is suppressed. Large numbers of experiments indicate that, if σ is between 80 and 100, the balance can be maintained.

Chapter 5

Result and Discussion

In this project, many low light images tested but only three images result kept in this report along with original images and enhanced images using different Retinex model, Power Law Transformation, Histogram Equalization and Adaptive Histogram Equalization. Also compared all these results with respect to Absolute Mean Difference(AMD),Root Mean Square and Entropy

5.1 Retinex Model

The main focus of this work is to enhance the low light images and this project is implemented in MATLAB tool. Figure 5.1 shows the original low light image of lamp and enhanced image using Single-Scale Retinex(SSR) model. It is clear enhancement in Figure 5.1(b). The background objects of in figure 5.1(b) are more clear than original image. The Absolute Mean Difference(AMD),Root Mean Square and Entropy for Single Scale Retinex(SSR) Model of enhanced image of lamp is $69.8401, 15.7384$ and 4.9043 respectively

Figure 5.2 shows the original low light image of lamp and enhanced image using Multi-Scale Retinex(MSR) model. It is clear enhancement in Figure 5.2(b). The background objects of in figure 5.2(b) are more clear than original image. The Absolute Mean Difference(AMD),Root Mean Square and Entropy for Multi-Scale Retinex(MSR) model of enhanced image of lamp is $69.9617, 15.7384$ and 5.0033 respectively

(a) (b)

Figure 5.1: a) Input Image b)Enhanced Image using SSR

(a) (b)

Figure 5.2: a) Input Image b)Enhanced Image using MSR

(a) (b)

Figure 5.3: a) Input Image b)Enhanced Image using MSRCR

Figure 5.3 shows the original low light image of lamp and enhanced image using Multi-Scale Retinex with Color Restoration(MSRCR) . It is clear enhancement in Figure 5.3(b). The background objects of in figure 5.3(b) are more clear than original image. The Absolute Mean Difference(AMD),Root Mean Square and Entropy for Multi-Scale Retinex with Color Restoration((MSRCR) model of enhanced image of lamp is $67.0909, 15.7330$ and 6.3657 respectively

Now consider second input image of palace. This image is also taken in low light and will test it for different Retinex Models. Figure 5.4 shows the original low light image of palace and enhanced image using Single-Scale Retinex(SSR) model. In the original image (figure 5.4 (a)) the palace,the valley, edges of rock,small bushy plants and lamps are not clear but these are very clear in the enhanced image(Figur 5.4 (b)). The Absolute Mean Difference(AMD),Root Mean Square and Entropy for Single Scale Retinex(SSR) Model of enhanced image of palace is $103.9633, 15.9031$ and 6.8944 respectively

Figure 5.5 shows the original low light image of palace and enhanced image using Multi-Scale Retinex(MSR) model. In the original image (figure 5.5 (a)) the palace,the valley, edges of rock,small bushy plants and lamps are not clear but these are very clear in the enhanced image(Figure 5.5 (b)). The Absolute Mean Difference(AMD),Root Mean Square and Entropy for Multi Scale Retinex(MSR) Model

(a) (b)

Figure 5.4: a) Input Image b)Enhanced Image using SSR

(a) (b)

Figure 5.5: a) Input Image b)Enhanced Image using MSR

of enhanced image of palace is $104.7167, 15.9115$ and 7.1499 respectively

Figure 5.6 shows the original low light image of palace and enhanced image using Multi-Scale Retinex with COlor Restoration(MSRCR) model. In the original image (figure 5.6 (a)) the palace,the valley, edges of rock,small bushy plants and lamps are not clear but these are very clear in the enhanced image(Figure 5.6 (b)). The Absolute Mean Difference(AMD),Root Mean Square and Entropy for Multi Scale Retinex with COlor Restoration(MSRCR) Model of enhanced image of palace is $92.2710, 15.9138$ and 7.7566 respectively

Now consider third input image of robot. This image is also taken in low light and will test it for different Retinex Models. Figure 5.7 shows the original low light image of robot and enhanced image using Single-Scale Retinex(SSR) model. In the original image of robot (figure 5.7 (a)) the robot,laptop, laptop keypad and background strips are not clear but these are very clear in the enhanced image(Figur 5.7

(a) (b)

Figure 5.6: a) Input Image of Palace b)Enhanced Image of Palace using MSRCR

(a) (b)

Figure 5.7: a) Input Image of Robot b)Enhanced Image of Robot using SSR

(b)). The Absolute Mean Difference(AMD),Root Mean Square and Entropy for Single Scale Retinex(SSR) Model of enhanced image of robot are $76.3404, 15.9245$ and 6.8248 respectively

Figure 5.8 shows the original low light image of robot and enhanced image using Multi-Scale Retinex(MSR) model. In the original image of robot (figure 5.8 (a)) the robot,laptop, laptop keypad and background strips are not clear but these are very clear in the enhanced image(Figur 5.8 (b)). The Absolute Mean Difference(AMD),Root Mean Square and Entropy for Multi Scale Retinex(MSR) Model of enhanced image of robot are $76.3157, 15.9242$ and 6.9686 respectively

Figure 5.9 shows the original low light image of robot and enhanced image using Multi-Scale Retinex with Color Restoration(MSRCR) model. In the original im-

(a) (b)

Figure 5.8: a) Input Image of Robot b)Enhanced Image of Robot using MSR

(a) (b)

Figure 5.9: a) Input Image of Robot b)Enhanced Image of Robot using MSRCR

age of robot (figure 5.9 (a)) the robot,laptop, laptop keypad and background strips are not clear but these are very clear in the enhanced image(Figur 5.9 (b)). The Absolute Mean Difference(AMD),Root Mean Square and Entropy for Multi Scale Retinex with Color Restoration(MSRCR) Model of enhanced image of robot are $74.7684, 15.9179$ and 7.0533 respectively


(a)


(b)

Figure 5.10: a) Input Image b)Enhanced Image using Power Law Transformation

5.2 Power Law Transformation

Now test above three images like bulb, palace and robot for Power Law Transformation. Figure 5.10 shows the original low light image of lamp and enhanced image using Power Law Transformation . It is clear enhancement in Figure 5.10(b). The background objects of in figure 5.10(b) are more clear than original image. The Absolute Mean Difference(AMD),Root Mean Square and Entropy for Power Law Transformation of enhanced image of lamp is $0.1068, 0.1233$ and 5.2476 respectively

Figure 5.11 shows the original low light image of palace and enhanced image using Power Law Transformation. In the original image of palace (figure 5.11 (a)) the palace,the valley, edges of rock,small bushy plants and lamps are not clear but these are very clear in the enhanced image(Figure 5.11 (b)). The Absolute Mean Difference(AMD),Root Mean Square and Entropy for Power Law Transformation of enhanced image of palace is $0.1857, 0.1957$ and 7.2592 respectively

Now consider third input image of robot. This image is also taken in low light and will test it for Power Law Transformation Figure 5.12 shows the original low light image of robot and enhanced image using Power Law Transformation. In the original image of robot (figure 5.12 (a)) the robot,laptop, laptop keypad and background strips are not clear but these are very clear in the enhanced image(Figur 5.12 (b)). The Abso-

(a) (b)

Figure 5.11: a) Input Image of Palace b)Enhanced Image of palace using Power Law Transformation

(a) (b)

Figure 5.12: a) Input Image of Robot b)Enhanced Image of Robot using Power Law Transformation

lute Mean Difference(AMD),Root Mean Square and Entropy for Power Law Transformation of enhanced image of robot are 0.1953, 0.2010 and 6.2899 respectively

5.3 Histogram Equalization

Now test above same three images like bulb, palace and robot for Power Law Transformation. Figure 5.13 shows the original low light image of lamp and enhanced image using Histogram Equalization. It is clear enhancement in Figure 5.13(b). The background objects of in figure 5.13(b) are more clear than original image. The Absolute Mean Difference(AMD),Root Mean Square and Entropy for Histogram Equalization of

(a) (b)

Figure 5.13: a) Input Image b)Enhanced Image using Histogram Equalization

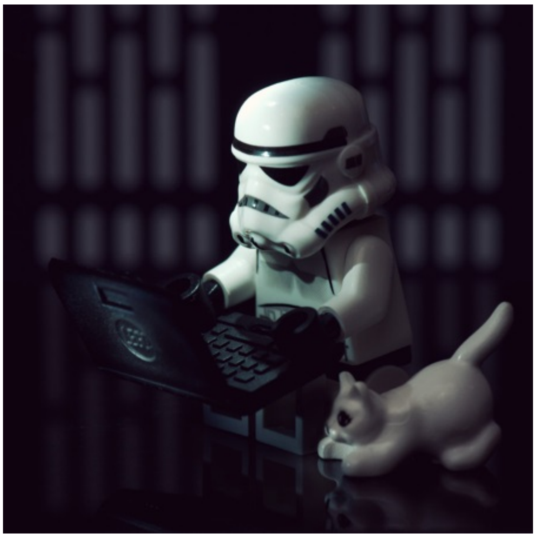
(a) (b)

Figure 5.14: a) Input Image of Palace b)Enhanced Image of palace using Histogram Equalization

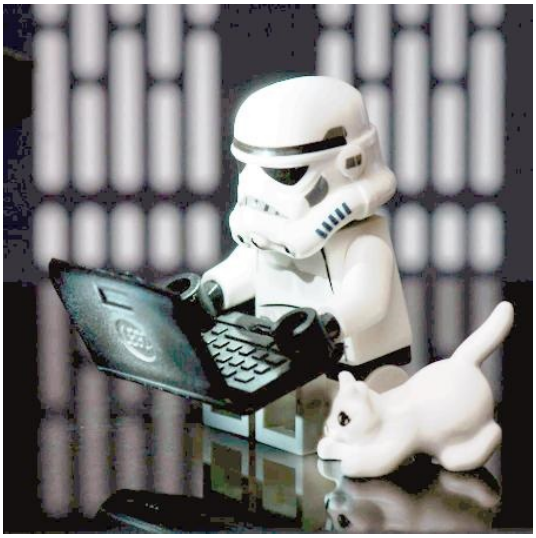
enhanced image of lamp is $104.7539, 15.7363$ and 4.6140 respectively

Figure 5.14 shows the original low light image of palace and enhanced image using Histogram Equalization. In the original image of palace (figure 5.14 (a)) the palace,the valley, edges of rock,small bushy plants and lamps are not clear but these are very clear in the enhanced image(Figure 5.14 (b)). The Absolute Mean Difference(AMD),Root Mean Square and Entropy for Histogram Equalization of enhanced image of palace are $89.3506, 15.6912$ and 5.9325 respectively

Now consider third input image of robot. This image is also taken in low light and will test it for Histogram Equalization Figure 5.15 shows the original low light



(a)



(b)

Figure 5.15: a) Input Image of Robot b)Enhanced Image of Robot using Histogram Equalization

image of robot and enhanced image using Histogram Equalization. In the original image of robot (figure 5.15 (a)) the robot,laptop, laptop keypad and background strips are not clear but these are very clear in the enhanced image(Figur 5.15 (b)). The Absolute Mean Difference(AMD),Root Mean Square and Entropy for Histogram Equalization of enhanced image of robot are 93.1594, 15.1385 and 5.5086 respectively

5.4 Adaptive Histogram Equalization

Now test same above three images like bulb, palace and robot for Power Law Transformation. Figure 5.16 shows the original low light image of lamp and enhanced image using Adaptive Histogram Equalization. It is clear enhancement in Figure 5.16(b). The background objects of in figure 5.16(b) are more clear than original image. The Absolute Mean Difference(AMD),Root Mean Square and Entropy for Adaptive Histogram Equalization of enhanced image of lamp is 12.9948, 10.1784 and 5.6053 respectively

Figure 5.17 shows the original low light image of palace and enhanced image using Adaptive Histogram Equalization. In the original image of palace (figure 5.17 (a)) the palace,the valley, edges of rock,small bushy plants and lamps are not clear but these are very clear in the enhanced image(Figure 5.17 (b)). The Absolute Mean Difference(AMD),Root Mean Square and Entropy for Adaptive Histogram Equalization of

(a) (b)

Figure 5.16: a) Input Image b)Enhanced Image using Adaptive Histogram Equalization

(a) (b)

Figure 5.17: a) Input Image of Palace b)Enhanced Image of palace using Adaptive Histogram Equalization

enhanced image of palace are 40.3042, 14.5370 and 7.4680 respectively

Now consider third input image of robot. This image is also taken in low light and will test it for Adaptive Histogram Equalization Figure 5.18 shows the original low light image of robot and enhanced image using Adaptive Histogram Equalization. In the original image of robot (figure **??** (a)) the robot,laptop, laptop keypad and background strips are not clear but these are very clear in the enhanced image(Figure **??** (b)). The Absolute Mean Difference(AMD),Root Mean Square and Entropy for Adaptive Histogram Equalization of enhanced image of robot are 30.0744, 12.6623 and 7.2511 respectively

(a) (b)

Figure 5.18: a) Input Image of Robot b)Enhanced Image of Robot using Adaptive Histogram Equalization

Table 5.1: Comparison for Lamp Image.

Technique	Lamp		
	AMD	RMSE	Entropy
SSR	69.840	15.7384	4.9043
MSR	69.9617	15.7384	5.0033
MSRCR	67.0909	15.7330	6.3657
PLT	0.1068	0.1233	5.2476
HE	104.7539	15.7363	4.6140
AHE	12.9948	10.1784	5.6053

Now compare these three images using different Retinex Models, Power Law Transformation, Histogram Equalization and Adaptive Histogram Equalization shown in table 5.1,5.2 and 5.3 .

Table 5.2: Comparison for Palace Image.

Technique	Lamp		
	AMD	RMSE	Entropy
SSR	69.840	15.7384	4.9043
MSR	69.9617	15.7384	5.0033
MSRCR	67.0909	15.7330	6.3657
PLT	0.1068	0.1233	5.2476
HE	104.7539	15.7363	4.6140
AHE	12.9948	10.1784	5.6053

Table 5.3: Comparison for Lamp Image.

Technique	Lamp		
	AMD	RMSE	Entropy
SSR	69.840	15.7384	4.9043
MSR	69.9617	15.7384	5.0033
MSRCR	67.0909	15.7330	6.3657
PLT	0.1068	0.1233	5.2476
HE	104.7539	15.7363	4.6140
AHE	12.9948	10.1784	5.6053

Chapter 6

Conclusion

In this thesis, methods that we applied balances the requirements of both appearance enhancement and being faithful to the original appearance of an image has been proposed and applied to the enhancement of full color images. Results have shown the effectiveness of our algorithm in improving the contrast and colorfulness of the original images. In this thesis, It is shown that we can get better image from different Retinex Algorithms,Power Law Transformation, Histogram Equalization and Adaptive Histogram Equalization specification on color images gives us better results.

The Retinex Image Enhancement Algorithm is an automatic image enhancement method that enhances a digital image in terms of dynamic range compression, colour independence from the spectral distribution of the scene illuminate, and colour/ lightness rendition. The digital image enhanced by the Retinex Image Enhancement Algorithm is much closer to the scene perceived by the human visual system, under all kinds and levels of lighting variations, than the digital image enhanced by any other method.