DEVELOPMENT OF CONTRAST ENHANCEMENT ALGORITHM FOR IMAGES CAPTURED UNDER INSUFFICIENT ILLUMINATION

By

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LIST OF ABBREVIATIONS

DFT	Discrete Fourier Transform
DWT	Discrete Wavelet Transform
FFT	Fast Fourier Transform
HE	Global histogram equalization
IDWT	Inverse Discrete Wavelet Transform
IFFT	Inverse Discrete Fourier Transform
LHE	Local histogram equalization
MSR	Multiple scale retinex
SSR	Single scale retinex

LIST OF SYMBOLS

SYMBOL	MEANING
Υ_H	High frequency gain
Υ_L	Low frequency gain
D_0	Cut-off frequency
ψ	Wavelet basis function
φ	Wavelet scale function
σ^2	Variance

PEMBANGUNAN ALGORITMA PENINGKATAN BEZA JELAS BAGI IMEJ YANG DITANGKAP DI BAWAH PENCAHAYAAN TIDAK MENCUKUPI

ABSTRAK

Banyak kaedah telah dicadangkan untuk meningkatkan beza jelas imej berdigit. Dalam peningkatan imej, matlamat utama adalah untuk memperbaiki kontras dalam imej. Imej yang berkualiti tinggi mengandungi pelbagai maklumat. Kualiti imej sangat mudah terjejas oleh pencahayaan, iklim atau peralatan yang telah digunakan untuk menangkap imej. Beberapa keadaan seperti pencahayaan yang tidak mencukupi menyebabkan imej yang lebih gelap di mana imej itu mungkin mengalami kehilangan maklumat. Oleh itu, tesis ini meletakkan kaedah penambahbaikan yang optimum untuk mengekalkan maklumat dalam imej. Kaedah yang dicadangkan ini dilakukan pada imej cahaya yang tidak mencukupi. Algoritma yang dicadangkan diuraikan oleh wavelet Haar untuk mendapatkan pekali penguraian dalam semua arah imej, menyesuaikan nilai ambang koefisien wavelet, kemudian rekonstruksikan imej. Akhirnya, buat postprocessing yang sesuai untuk imej yang dibina semula. Hasil percubaan menunjukkan bahawa kaedah yang dicadangkan berjaya meningkatkan kualiti imej dan kontras dan ini terbukti dengan beberapa eksperimen. Kaedah yang dicadangkan menunjukkan hasil yang baik untuk peningkatan imej. Sama ada peningkatan kontras imej, atau tahap pencemaran bunyi. Kaedah yang dicadangkan telah meningkatkan nilai kontras lebih daripada lima puluh ribu pada masa yang sama, varians dikawal kurang dari sepuluh ribu.

DEVELOPMENT OF CONTRAST ENHANCEMENT ALGORITHM FOR IMAGES CAPTURED UNDER INSUFFICIENT ILLUMINATION

ABSTRACT

Many methods have been proposed to improve the contrast, quality and to optimize the insufficient illumination images. In the image enhancement, the main goal is to improve the contrast in the images. Images with high quality contain a great variety of information. The images quality is very easily affected by lighting, climate or equipment’s that have been used to capture the image. Some of these conditions such as insufficient illumination lead to darker images where the image may suffer information loss. Therefore, this thesis puts forward an optimized enhancement method in order to retain the information in the image. This proposed method performs on the insufficient light images. The proposed algorithm is decomposed by Haar wavelet to obtain the decomposition coefficient in all directions of the image, adjusts the threshold values of wavelet coefficient, then reconstruct the image. Finally, do the suitable postprocessing for the reconstructed image. The experimental results demonstrate that the proposed method successfully improves the image quality and contrast and these proven by a series of experiments. The proposed method shows good results for image enhancement. Whether it is in the image contrast enhancement, or extent of noise pollution. The proposed method was enhanced the contrast value more than fifty thousand at the same time, the variance was controlled less than ten thousand.

CHAPTER 1

INTRODUCTION

In this chapter, a study on the significance of the project, which is to enhance the contrast of the images captured under insufficient light, will be presented. This will be presented by the overview given in Section 1.1. Then, in Section 1.2, problems with the current contrast enhancement techniques will be highlighted. Next, Section 1.3 presents the objectives of this project. After that, Section 1.4 will summarize the contribution of this work. Then, Section 1.5 will present the scope of this project. Section 1.6 will present the organization of this dissertation.

1.1 Overview

Image processing is widely used in many scientific and engineering applications, including imaging, biometric and security systems. Such as Zou studied the photogrammetry image processing precision error compensation method [1], Image contrast enhancement is the best example of an extensive subject of study in several image processing fields such as contrast enhancement. For example, Li and Zhang had studied specific area that infrared image contrast enhancement Based on De - fog Mode [2]. For the insufficient illumination image processing, Liu and Jia had proposed a method of underground illumination uneven image processing based on homomorphic Filtering Principle [3]. The use of wavelet to analyze the data has been the most recent mainstream research method. Chi and Zhang had studied the image enhancement method based on anti - symmetric biorthogonal Wavelet reconstruction [4].

Digital image processing is currently one of the popular research fields. Digital image processing is the process of converting signals from a scene into digital signal, and then process it with a computer through some software. The software can be written by using programming language. Examples of the programming language that can be used are C++ and Matlab [5]. There are also some libraries to support digital image processing. One of the popular programming libraries in this research is OpenCV.

Digital image processing can be used for many applications. It can be used to filter out noise from image that has been corrupted. It can also enhance the contrast of the image, so that the image becomes better in quality. Image processing is also can be used to recover, cut, or segment images. This research field also includes image compression and many more.

In general, there are three main purposes of image processing [6]. The first purpose is to improve the visual quality of the image. The researches involved in this area are the brightness correction, colour transformation, and contrast enhancement. Sometimes, this is also related with image geometric transformation to improve the image quality. The second purpose is to extract some features or special information contained in the image. These extracted features or information often facilitate the analysis of images by computers. The process of extracting a feature or information is a pattern recognition or computer vision pre-processing. The extracted features can include many aspects, such as frequency domain features, grayscale or colour features, boundary features, regional features, texture features, shape features, topological features, and relational structures. The third purpose is for image data conversion, coding and compression, in order to facilitate the image storage and transmission.

Currently, there is a rapid development in digital image processing research field. Several factors contribute to this condition. The first one is the development of computer. With the introduction of powerful, yet cheap computer, it is possible to easily manipulate image data digitally. Then, the development of mathematics, especially the creation and perfection of discrete mathematic, helps researchers to develop robust image processing techniques. The development of this research is also due to the demands of applications from various fields.

An image can be modelled by the following equation:

$$f = r \times i \tag{1.1}$$

Where f is the captured image, r is the reflectance of the object, and i is the illumination that illuminates the scene. Image that is captured under insufficient light, for example, image captured at night, has low value of i. Therefore, as component i lower down the value observed r, objects in this kind of image will appear to have similar intensity levels. Therefore, image under insufficient light normally has low contrast. With this low contrast, it is difficult to see the image details, and some useful information may be hidden in the scene.

Therefore, in this dissertation, the task is to enhance the image contrast. The purpose of image enhancement is to improve the quality of image. Image enhancement is not only change the intensity of the pixel, it also can highlight the interest parts in the image. By strengthening the high-frequency components of the image, the process can make the outlines of the objects on the image to become clearer and make small details of the image to appear. On the other hand, by enhancing the image's low-frequency components, it can reduce the noise in the image, and makes the image become smoother.

1.2 Problem Statements

In the real life, inadequate illumination during image acquisition can cause dark image. As many information cannot be seen in such images, this causes inconveniences to the life of people. Therefore, this project will study image enhancement algorithms that are applicable for images under condition of insufficient illumination. This type of research has always getting attentions of researchers in the field of image processing, which has the important theoretical and practical values.

The lack of light to a certain extent, changed the original appearance of the image [7]. Consequently, this increases the difficulty to further processing this dark image. In image processing, one of the most basic and direct methods to segment objects in dark images is by using the information from different regions of the image to identify different objects in the scene. For grayscale images, if there is a big difference between the brightness information between different objects, methods such as binarization based on the histogram can be used to enhance the details. However, because this technique involves quantization, the image will lost most of its frequency information.

For night images, there are many algorithms have been developed by researchers [8]. However, one single algorithm cannot be perfect to deal with any situation. Therefore, in this research, previous image enhancement methods will be reviewed in order to see their strength and weaknesses.

One of the popular image enhancement method is Histogram Equalization method (HE) [9]. Despite of its popularity, the main disadvantage of HE is that this process is a global process, where data selection is not included in the process. Thus, HE may increase the contrast of the background noise and reduce the contrast of useful signal. In some cases, HE makes the histogram bins merged, and thus reduce the intensity variation inside the image. Due to this merging, some image details may disappear. HE may also introduce artefacts that can make some processed images look unnatural.

An image can also be enhanced by frequency domain methods [10]. However, frequency domain methods also have disadvantages. Many of the filters have natural defects in their design. An example is the Butterworth filter. This filter has a smooth frequency characteristic at both inside and outside of the pass band, but with a longer transition zone. This design is likely to cause distortion in the transition zone.

1.3 Research Objectives

There are two main objectives of this research. These objectives are listed as follows:

1) To develop a new image enhancement algorithm that is suitable for images that have been captured under insufficient light.

2) To evaluate the performance of the proposed method by comparing it with other enhancement methods.

1.4 Scope of the Dissertation

In this dissertation, the project aims to improve the quality of images taken under insufficient light. This type of images gives more challenges to do the enhancement. This is because not only these images have low contrast, their information also lost due to the suppression of the reflectance image component. Images captured under sufficient light are not the priority of this research.

The research is also limited to 8-bit-depth grayscale image. This is to reduce the complexity of the process. In this project, if the original input images are color images, they will be converted first to grayscale images using commercial software. However, the outputs of the methods are always the grayscale images.

Both image enhancement methods based on spatial domain and frequency domain are considered. This is because it is expected that a better understanding on image enhancement process will be obtained from this wide research areas.

1.5 Organisation of Dissertation

This dissertation is organized as follows. Chapter One gives the introduction of the project. Chapter Two will show the basic methods in the image processing for image enhancement purpose. Image enhancement methods are mainly divided into two kinds of enhancement methods. They can be operated in the spatial domain or in frequency domain. These methods will be presented in Chapter Two. Next, Chapter Three will present the methodology of the proposed method. The proposed algorithm used is based on the wavelet transform, which is a popular image transform in recent years. Then, Chapter Four will present the simulation results and discussions. In this chapter, the performance of the proposed method is compared with the previous algorithm. The last chapter, which is Chapter Five, will conclude this research work. In addition of that, suggestions for future work are also provided in this chapter.

CHAPTER 2

LITERATURE REVIEW

This chapter reviews some of the basic image processing methods that are useful to enhance digital images. Advantages and disadvantages of the image enhancement methods by previous researches are studied in this chapter. This chapter will be organized as follow. Section 2.1 will review common image enhancement methods in spatial domain. Section 2.2 will review retinex method. Section 2.3 will review frequency domain contrast enhancement techniques. Section 2.4 will summarize this chapter.

2.1 Image Enhancement Methods in Spatial Domain

Spatial domain method is referring to a method that directly change the pixel values of the image. For spatial domain processing, the process refers to spatial coordinates (x,y). The spatial domain processing can be defined by the following equation:

$$g(x, y) = T[f(x, y)] \tag{2.1}$$

Where $f(x,y)$ is the input image, $g(x,y)$ is the processed image, and T is an operation for $f(x,y)$ [11]. Function T is also known as the mapping function. It can be based on one to one mapping of pixel intensity, or based on a group of intensity around coordinates (x,y) to map a single output pixel.

There are many purposes of the method. Images captured under insufficient light usually are dark images. The contrast of the image is poor. Therefore, the image can be enhanced in terms of its contrast. Contrast enhancement methods are presented in Section 2.1.1. Under insufficient light, during the acquisition, the aperture of the camera is left open for a longer time as compared with the acquisition under normal light. This is to allow more light information to reach image's sensor. However, this condition may lead to noisy image. Therefore, in this chapter, image enhancement by noise reduction algorithm is reviewed. The noise is reduced using smoothing methods. The methods are presented in Section 2.1.2. On the other hand, the edges of the objects in dark images are normally weak. Thus, one possible way to enhance the appearance of the dark image is by detecting the edges. Thus, a few edge detection algorithms are reviewed in Section 2.1.3.

2.1.1 Contrast Enhancement Methods

In this section, only two spatial domain methods that are normally used to improve the image contrast are presented. The first method is the global histogram equalization (HE). This method is simple, and popular in practical applications. This method will be reviewed in Subsection 2.1.1.(a). The second method is the local histogram equalization method (LHE). This method will be reviewed in Subsection 2.1.1.(b).

2.1.1 (a) Global Histogram Equalization Method (HE)

Global histogram equalization method (HE) is a popular contrast enhancement method. The method tries to maximize the entropy value of an image by flattening the histogram of the image. This method has been used by many researchers to enhance digital images, including images which have been captured under insufficient illumination. Examples of these works are the works from [12], which used HE to enhance the contrast of images with insufficient light.

HE works by using the following theory. If the pixel values of an image occupy a wide range of grey level and are evenly distributed, then such image tends to have rich grey tones and have high contrast. However, pixels with dark grey tones are normally dominate insufficient light images, make their histogram plots skewed toward the low intensity values. As a consequence, the intensity values of the dark images are not evenly distributed. Therefore, it is expected that the image does not have a good contrast.

In order to change the distribution of the pixels inside the image, histogram of the input image can be manipulated. Histogram of the image can be illustrated by a bar chart of number of occurrences of the intensity, versus the intensity value, with normally low intensity value located on the left side. Another alternative of histogram is the plot of probability of the occurrences of the intensity value, versus the intensity value.

The histogram's shape can be modified by the global histogram equalization technique. This technique is also simply known as histogram equalization (HE). HE generates a transform function T as in Equation (2.1), that automatically generated by simply supplying the image's histogram to this technique. As the input histogram is depending to the intensity distribution of the original image, transformation function T may differ from one image to another.

The basic principle of HE is to broaden the range of the intensity values for majority of pixels, and compress the grayscale values that have less occurrences on the image. As a result, this process extends the dynamic range of the image, and therefore improves the contrast of the image. Then, the image will become clearer.

In order to understand the concept under HE, consider the continuous grey value function and use the variable f to represent the input intensity. In general, it is assumed that the range of f is [0, L-1], where L is the number of intensity levels of an image. Normally, intensity f=0 presents black color, and intensity f=L-1 present the white color. In the case where r satisfies these conditions:

$$g = T(f), \qquad 0 \le f \le L-1 \tag{2.2}$$

Where g in this equation is the continuous output value. Several assumptions are used:

a) $T(f)$ is a monotonically increasing function on interval $0 \leq f \leq L$-1.

b) Given $0 \leq f \leq L$-1, the range of output g is $0 \leq T(f) \leq L$-1.

Then, when the inverse function is used:

$$f = T^{-1}(g), \qquad 0 \leq f \leq L - 1 \tag{2.3}$$

Under this situation, condition (a) changes to condition (c) below:

c) $T(f)$ is a strictly monotonically increasing function on interval $0 \leq f \leq L$-1 [2].

Condition (a) requires that $T(f)$ to be a monotonically increasing function in order to ensure that output grey level is not less than the corresponding input value. This assumption is also used to prevent grayscale transformation of artificial defects. Condition (b) ensures that the output grey scale is in the same range as the input grayscale. Finally, condition (c) guarantees that the reflections from g to f are one-by-one, preventing any overlap.

The abovementioned discussions are for continuous function. Since the data of the image is in discrete nature, some modifications are needed. For the discrete values, HE processes the discrete probability instead of the probability density function. Summation is used instead of the integration. For a digital image of size $M \times N$ pixels, the probability of occurrence of grey scale value P_f is given as [13]:

$$P_f(f_k) = \frac{n_k}{MN}, \qquad k = 0,1,2,\ldots,L - 1 \tag{2.4}$$

Where MN is the total number of pixels in the image, n_k is the number of pixels of grey scale f_k, and L is the number of possible grey levels in the image. The equation for discrete transform function is as follows

$$g_k = T(f_k) = (L-1)\sum_{j=0}^{k} P_f(f_j) = \frac{(L-1)}{MN}\sum_{j=0}^{k} n_j, \qquad k = 0,1,2,\ldots,L-1 \tag{2.5}$$

The implementation of HE is simple. It has been used in many applications, where contrast enhancement is needed. However, histogram bins merging makes small details on the image disappears. HE also introduces intensity saturation artifact to some of the input images, make the resultant images appears unnatural.

2.1.1 (b) Local Histogram Equalization Method (LHE)

The method of HE explained in Section 2.2.1.(a) is a global processing method. The pixels are modified based on a single transformation function created from the grey scale distribution of the input image. HE applies the enhancement globally on all pixels of the image. However, in the certain application, it is necessary to enhance the details of the small areas in the image. In these areas, the effects of some pixels may be ignored in the calculation of global transformations, because the global transformation does not need to ensure the desired local enhancement. The solution is to design the transform function based on the grey distribution in the field of each pixel in the image.

The local histogram equalization (LHE) works by defining a neighborhood and move the center of the region from one pixel to another. At each position, LHE calculates the histogram of the points in the neighborhood, and get the histogram equalization done in the current contextual region. This function is used to map the grey scale of the neighborhood center pixel. Then, the center of the neighborhood is moved to an adjacent pixel position and the process is repeated.

Xu (2017) have used LHE to enhance dark images, which are images captured under insufficient light [14]. Xu (2009) used LHE to enhance the contrast for the dark medical images [15]. Liu (2012) used the same method to enhance the dark license plate number [16].

LHE is effective on enhancing local details. However, the output image from this method is normally appears unnatural. This is because the transformation function used at a pixel most probably is not the same with the transformation function of other pixels. Because LHE needs to process each pixel independently, its processing time is higher than HE. However, to speed up the processing, manipulations on the local histogram can be done. When the neighborhood is doing the translation for each pixel, since only one row or one column in the neighborhood is changed, the histogram obtained from the previous position can be updated with new data in each step of movement. Therefore, if the size of the contextual region is $m \times n$ pixels, instead of updating mn elements of the local histogram, this method only updates $2m$ or $2n$ elements [17].

2.1.2 Image Smoothing Methods

Image smoothing is used to reduce the noise from digital image. In this section, two simple image smoothing methods are reviewed. The first one is the mean filter. The mean filter will be presented in Subsection 2.1.2(a). The second method is the geometric mean filter. This method will be discussed in Subsection 2.1.2(b).

2.1.2 (a) Mean Filter

Mean filter is a typical pre-filtering algorithm, which is used to reduce the noise, or to make the image blur or smooth. The mean filter is ideal for removing the particle noise in the image obtained by scanning and also for the image correction after excessive sharpening. Wei (2012) used the mean filter to remove the image noise [18]. Hao (2013) used the improved mean filter to enhance the contrast of dark images [19]. The process involves a filter, which known as the template or window. By considering the target pixel, a template which includes surrounding pixels is used. The target pixel is normally located on the center of the eight surrounding pixels. The filter calculates the arithmetic mean of the sample inside the template, and replace the original center pixel value with the average of all pixels in this template. Mathematical expression of mean method:

$$g(x,y) = \frac{1}{M}\sum f(x,y) \tag{2.6}$$

Where (x,y) is the spatial coordinates, $f(x,y)$ represents the input pixels, $g(x,y)$ represents the output pixels, and M is the total number of pixel samples within the template.

The mean filter can effectively reduce the noise pollution caused by excessive sharpening. This is because the noise is generally high frequency components, so taking the average value of the template can greatly reduce the noise value. The mean filter also has its own congenital defects. Usually this method will make the image seriously degraded and losing information [20].

2.1.2 (b) Geometric Mean Filter

Hong (2008) used geometric mean filter to remove the noise as a pre-processing method [21]. Geometric mean filter is similar to the mean filter explained previously in Subsection 2.1.2.(a). The main purpose of this filter is to eliminate excessive sharpening that is caused by noise pollution. Geometric mean filter can be expressed by using the following equation.

$$g(x,y) = \left[f(x_1,y_1)\times f(x_2,y_2)\times f(x_3,y_3)\times \ldots \times f(x_n,y_n)\right]^{\frac{1}{n}} \tag{2.7}$$

Where $f(x,y)$ represents the input intensity at coordinates (x,y), $g(x,y)$ represents the output intensity and n represents the filtering template size.

The image distortion obtained by this method is smaller than the mean filter, because the internal mathematical reason. The disadvantage of the geometric mean filter is that it cannot solve all the excessive sharpening problems. Also it is not the effective way to remove specific noise [22].

2.1.3 Edge Detection Methods

Detecting edges from dark images is challenging. Therefore, this section will review some well-known edge detection methods. Edges can be detected by using differential operators. First order differential operators are presented in Subsection 2.2.3.(a). Second order differentiator is presented in Subsection 2.2.3.(b).

2.1.3 (a) First Order Differentiators

When trying to determine an unknown function from the information expressed in the form of an equation describing at least one derivative of an unknown function, such an equation is called a differential equation. The differential equation is divided into two themes according to whether the unknown function is univariate or multivariate. This will result ordinary differential equation and partial differential equation. A differential equation is to satisfy the following relation:

$$f'(x) = f(x) \tag{2.8}$$

The order of the differential equation is defined as the highest order of the derivative in the function. For example, Equation (2.8) is a first order differential function. Examples of first order differentiators are the Roberts operator, Prewitt operator, and Sobel operator.

Robert Operator

Robert edge detection operator, also known as gradient crossover operator. It is an operator that utilizes the local differential operator to find the edges by using the differences between the two adjacent pixels in the diagonal direction. By using this operator, the outcome of detecting vertical edges is better than that of oblique edges, where it shows high positioning accuracy and being sensitive to noise.

$$\begin{bmatrix} (x,y) & (x+1,y) \\ (x,y+1) & (x+1,y+1) \end{bmatrix}$$

Figure 2.1: Coordinates in 2×2 matrix.

Consider the following neighboring coordinates, shown by a matrix in Figure 2.1. At current coordinates (x,y), the Robert operations can be expressed by the following equation:

$$g(x,y) = \left|f(x,y) - f(x+1,y+1)\right| + \left|f(x+1,y) - f(x,y+1)\right| \tag{2.9}$$

The operations can be considered as a result from a linear convolution of the input image f with two 2×2 Robert template components. Assume that these components are R_x and R_y, the operations can be written as:

$$g = |f \otimes R_x| + |f \otimes R_y| \tag{2.10}$$

Where $\otimes$ stands for linear convolution. The templates are defined as [23]:

$$R_x = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \tag{2.11}$$

$$R_y = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \tag{2.12}$$

Prewitt Operator

In order to detect the edge while at the same time reducing the effect of noise, Prewitt increased the size of the template from 2×2 pixels to become 3×3 pixels.

Figure 2.2 shows a notation used for 3×3 neighboring pixels to illustrate the process related to Prewitt operator.

$$\begin{bmatrix} a_0 & a_1 & a_2 \\ a_7 & (x,y) & a_3 \\ a_6 & a_5 & a_4 \end{bmatrix}$$

Figure 2.2: Coordinates in 3×3 matrix.

In Figure 2.1, the center pixel is at coordinates (x,y). Thus, the image f processed by Prewitt operator is given as:

$$g(x,y) = | a_2 + a_3 + a_4 - a_0 - a_7 - a_6 | + | a_0 + a_1 + a_2 - a_6 - a_5 - a_4 | \tag{2.13}$$

Similar to Roberts operation, the operation of Prewitt can also be presented by Equation (2.10). However, R_x and R_y for Prewitt operations are given as:

$$R_x = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \tag{2.14}$$

$$R_y = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix} \tag{2.15}$$

R_x is a horizontal template, whereas the R_y is a vertical template. Each point in image f is convoluted with these two templates as in Equation (2.10) and produces an edge image [24].

Sobel Operator

On the basis of Prewitt, the weighted method is used to calculate the difference. The Sobel operator can further suppress the noise effect, and therefore it can provide more accurate edge information. Yet, it will also detect many false edges. When the accuracy requirements are not very high, commonly Sobel operator will be used as edge detection method [25]. By referring to Figure 2.2, Sobel operations can be expressed as:

$$g(x,y) = | a_2 + ca_3 + a_4 - a_0 - ca_7 - a_6 | + | a_0 + ca_1 + a_2 - a_6 - ca_5 - a_4 | \quad (2.16)$$

Where c is a constant that is used as weight to the filter. In Sobel, the value of c is equal to 2. Sobel operations can also be expressed as in Equation (2.10). However, the horizontal template R_x and the vertical template R_y are given as:

$$R_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \quad (2.17)$$

$$R_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \quad (2.18)$$

2.1.3 (b) Second Order Differentiator

In this section, the second order differentiator that is reviewed is the Laplacian operator. The principle is that a unimodal function forms the edges. The Laplacian operations applied to the image f is defined as:

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} \quad (2.19)$$

with

$$\frac{\partial^2 f}{\partial x^2} = f(x+1,y) + f(x-1,y) - 2f(x,y) \quad (2.20)$$

and

$$\frac{\partial^2 f}{\partial y^2} = f(x, y+1) + f(x, y-1) - 2f(x, y) \tag{2.21}$$

According to the above three formulas, a discrete Laplacian operator can be expressed as:

$$\nabla^2 f(x, y) = f(x, y+1) + f(x, y-1) + f(x+1, y) + f(x-1, y) - 4f(x, y) \tag{2.22}$$

The Laplacian operations can be executed by using convolution. Equation (2.22) can be implemented as a convolution mask that is shown in Figure 2.3 [26].

$$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

Figure 2.3: The Laplacian filter

2.2 Image Enhancement Methods using Retinex

The retinex theory is a model that expresses the perception of human visual systems, originally proposed by Land and McCann (1963). This theory states that human visual systems are more likely to perceive relative brightness, or local brightness, than absolute brightness. The relative brightness of the pixel can be determined by the ratio of the brightness of the pixel and the average brightness of the area around it. According to the study of Land and McCann, the calculation of relative brightness can be seen as a high-pass filtering process. With the Gaussian function *G* for example, the operation process to input image *f* can be expressed as

$$L(x) = \frac{f(x)}{(f \otimes G)(x)} \tag{2.23}$$

By taking logarithm of Equation (2.23), the following equation is obtained:

$$\log L(x) = \log f(x) - \log(f \otimes G)(x) \tag{2.24}$$

Where log*L(x)* represent output function, log*f(x)* represent input function, *G(x)* represent Gaussian function. In this section, two types of retinex filter are reviewed. The first one is the single scale retinex, which will be presented in Subsection 2.2.1. The second retinex type is the multiscale retinex, which will be presented in Subsection 2.2.2.

2.2.1 Single Scale Retinex

From Equation (2.24), the single scale retinex in mathematical form is given by the following equation [27]:

$$R(x, y) = \log f(x, y) - \log(f(x, y) \otimes G(x, y)) \tag{2.24}$$

Next, by rewriting back Equation (1.1),

$$f(x, y) = i(x, y)r(x, y) \tag{2.25}$$

Where i represents the illuminance, r represents the reflectance, and f is the observed image. Equations (2.24) and (2.25) can be rewritten as Equation (2.26)

$$R(x, y) = \log \frac{i(x, y)r(x, y)}{\tilde{i}\,\tilde{r}} \tag{2.26}$$

Where $\tilde{i}$ and $\tilde{r}$ are the average value of illuminance and reflectance, respectively. As the illumination i changes very slowly, it can be assumed that $i(x, y) \approx \tilde{i}$. Thus, Equation (2.26) can be simplified to:

$$R(x, y) \approx \log \frac{r(x, y)}{\tilde{r}} \tag{2.27}$$

Equation (2.27) shows that this method can reduce the shadows in the image, as it emphasizes the reflectance component r. The surround function G is a Gaussian function:

$$G(x,y) = C\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \tag{2.28}$$

Where α is the standard deviation of the filter. It controls the scale of the spatial detail, C is a regularization factor. The kernel of the Gaussian function should fulfil the following requirement:

$$\int F(x,y)dxdy = 1 \tag{2.29}$$

2.2.2 Multi Scale Retinex

Multi scale retinex is a combination of a weighted sum from the outputs of different single scale retinex operations. The multi-scale retinex is presented in Equation (2.30)

$$R_{MSR} = \sum_{n=1}^{N} W_n R = \sum_{n=1}^{N} W_n\left[f(x,y) - \log(f(x,y)\otimes G_n(x,y)\right] \tag{2.30}$$

Where N is the number of scale used, and W_n is weight associated with the n-th scale. Multi scale retinex is proven to enhance image resolution in certain region. Yet, it still sharing the same problem with single scale retinex, where their outputs may in faded appearance.

2.3 Image Enhancement Methods in Frequency Domain

In addition to spatial domain image processing, digital image can also be processed in frequency domain. To do such processing, some transformations are needed. Popular methods for transforming an image from spatial domain to frequency domain are by using Fourier transform, or wavelet transform. It is found that some of the image processing problems that are not easy to be dealt with in the spatial domain, are easier to be solved by frequency domain processing. Some properties or the image are also easier to be understood in frequency domain as compared to spatial domain.

French mathematician, Fourier, has pointed out that any periodic function can be expressed as the sum of the sinusoidal and cosine waveforms of different frequencies. Each of these sinusoidal or cosine waveform is multiplied by a different coefficient, so that their sum will construct that periodic function. The Fourier series or transformations can be reconstructed back, by using the inverse Fourier transform, without losing any information. This is one of the most important features of this representation because it allows researchers to work in the frequency domain. The signal does not lose any details when it returns to the original domain of the function. In short, Fourier series and transformation are the tools to solve practical problems, it is widely used as a basic tool to learn and use.

The Fourier transform of a continuous variable function is defined by the following equation

$$\Im\{f(t)\}=\int_{-\infty}^{\infty} f(t)e^{-j2\pi\mu t}\,dt \tag{2.31}$$

Where μ is a continuous variable. Because t is accumulated, *f(t)* is a function of μ. In order to express this fact clearly, it can be rewritten as:

$$\Im\{f(t)\}=F(\mu) \tag{2.32}$$

On the contrary, given $F(\mu)$, f(t) can be obtained by using the inverse transform.

$$f(t)=\Im^{-1}\{F(\mu)\} \tag{2.33}$$

$$f(t)=\int_{-\infty}^{\infty} F(\mu)e^{j2\pi\mu t}\,d\mu \tag{2.34}$$

Equations (2.33) and (2.34) are collectively referred to as Fourier transform pairs.

Image processing in frequency domain, which using Fourier transform, is normally using the flow as shown in the block diagram shown in Figure 2.4. As shown by this figure, an image $F(x,y)$ in the spatial domain is first transformed into frequency domain by using the Fourier transform, to obtain $F(u,v)$. Before this transformation, some preprocessing may be required. The Fourier coefficients $F(u,v)$ are then multiplied with the transfer function $H(u,v)$. This multiplication presents the filtering process. After that, the result from this multiplication, $G(u,v)$, is transformed back to spatial domain by using inverse Fourier transform. Some post processing may be required before the output image $G(x,y)$ is obtained. The following subsection will show the operation of various filters on the frequency domain.

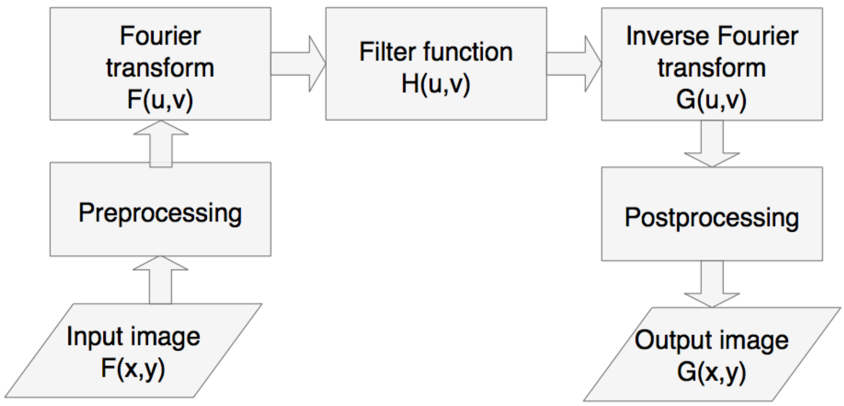

Figure 2.4: Frequency domain enhancement processing

2.3.1 Ideal High Pass Filter

A two-dimensional ideal high-pass filter is defined as

$$H(u,v)=\begin{cases} 0, & D(u,v)\leq D_0 \\ 1, & D(u,v)>D_0 \end{cases} \tag{2.35}$$

Where *Do* is the cutoff frequency, *D(u,v)* is the distance between the midpoint of the frequency domain *(u,v)* and the centre of the frequency rectangle, which is

$$D(u,v)=\left[(u-P/2)^2+(v-Q/2)^2\right]^{1/2} \tag{2.36}$$

Where the *P* and *Q* are new image size after filling. The principle is to eliminate all the frequencies inside the circle with a radius of cut-off frequency, and maintain all the frequencies outside the circle [28]. The shape of this filter is shown in Figure 2.5.

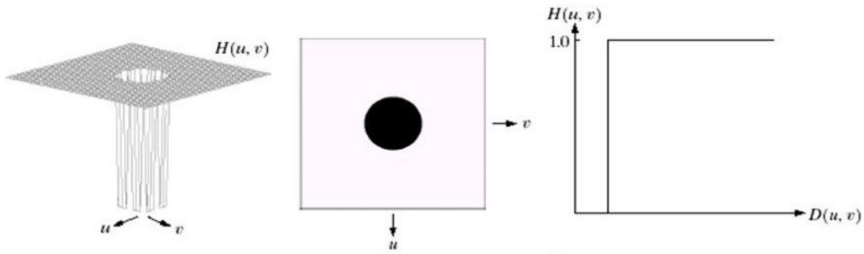

Figure 2.5: Ideal high pass filter's model: cutaway view; function curve

2.3.2 Butterworth High Pass Filter

Given the cutoff frequency *Do* and the filter order *n*, Butterworth high-pass filter is defined as:

$$H(u,v)=\frac{1}{1+[D_0/D(u,v)]^{2n}} \tag{2.37}$$

The shape of this filter is shown in Figure 2.6. From this figure, it can be seen that the low frequency component in *F(u,v)* will be attenuated when it multiplying a value of *H(u,v)*, because at low frequency, the value of *H(u,v)* is much smaller than 1. At high frequency component, the value of *H(u,v)* is close to 1, which will retain the value of *F(u,v)*. This is follow the definition of the high-pass filter [29].

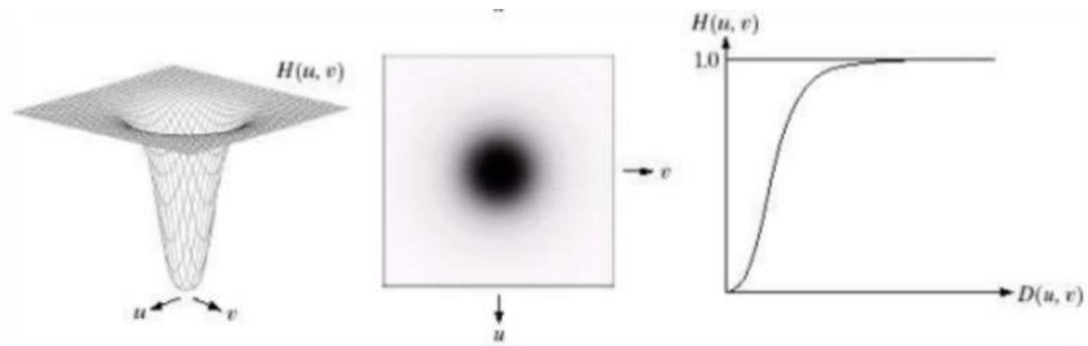

Figure 2.6: Butterworth high pass filter’s model; cutaway view; function curve

2.3.3 Gaussian High Pass Filter

Transfer function of Gaussian high pass filter is given as follow [30]:

$$H(u,v)=1-e^{-D^2(u,v)/2D_0^2} \tag{2.33}$$

The shape of the filter is shown in Figure 2.7. This filter has high amplitude at high frequency, and low amplitude at low frequency.

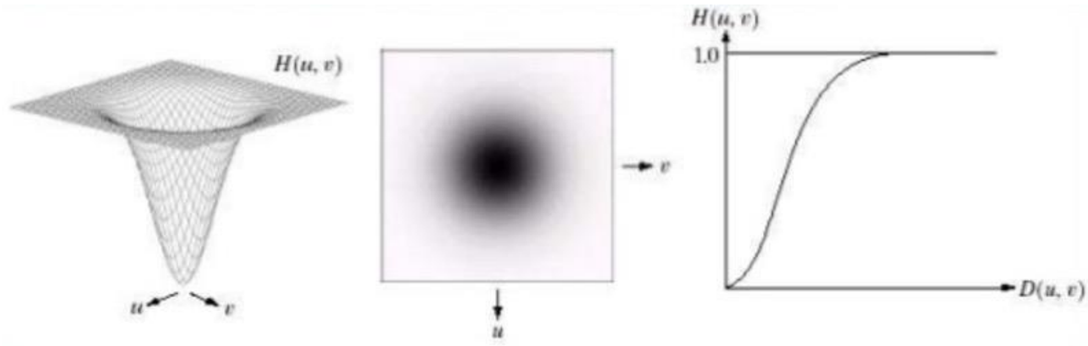

Figure 2.7: Gaussian high pass filter’s model; cutaway view; function curve

2.3.4 Homomorphic Filtering

Image that has been captured under insufficient light normally will be dominated by dark areas. Yet, some of the areas that receive light, appear bright. Although the objects in the image have low contrast, the contrast between bright and dark regions in the image is very large. When this situation occurred, the image’s dynamic range is very large (i.e., the black part is very dark, whereas the white part is very bright).