

**ADAPTIVE LOCAL FUZZY BASED REGION
DETERMINATION IMAGE ENHANCEMENT
TECHNIQUES FOR NON-UNIFORM ILLUMINATION
AND LOW CONTRAST IMAGES**

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FOR NON-UNIFORM ILLUMINATION AND LOW CONTRAST
IMAGES**

by

ABDULLAH AMER MOHAMMED SALIH

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requirements for the degree of
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DEDICATION

بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

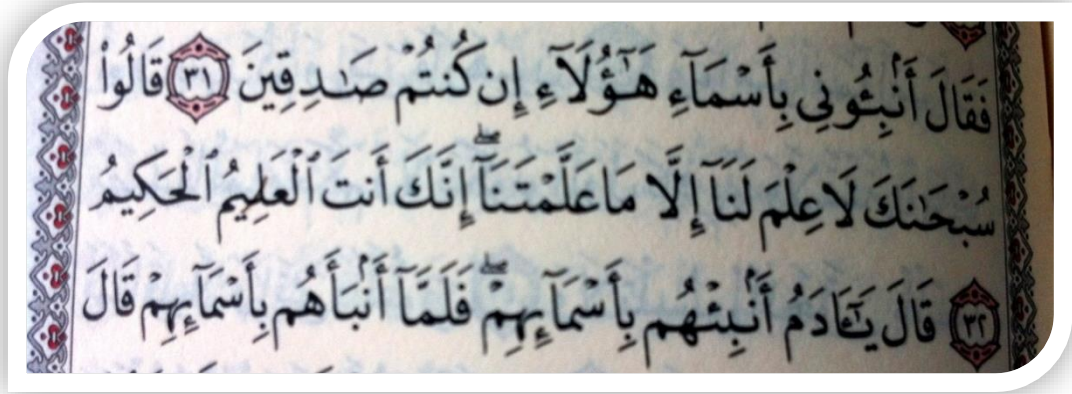
Many difficulties and challenges I had faced during my Ph.D. degree journey, and in every difficulty, my mind says that “I will not make it, I will not continue”. But, in every time I stuck, I just pray to Almighty ALLAH SWT, asking HIM to rescue me from my plight, HE put me in these challenges just to hear my prayers, and in this, I dedicate this thesis for the sake of Almighty ALLAH SWT.

I ask ALLAH to give the benefit from this work to the whole mankind.

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LIST OF ABBREVIATIONS

AFELCE	-	Adaptive Fuzzy Exposure Local Contrast Enhancement
AHEA	-	Adaptive Histogram Equalization Algorithm
ALEBRD	-	Adaptive Local Exposure Based Region Determination
ARID		automatic region on interest determination method
C	-	Contrast Improvement Analysis
dB	-	Decibel
DT-CWT	-	Dual-tree Complex Wavelet Transform
E	-	Entropy
e.g.	-	(exempligratia) For example
EME	-	Measure of Enhancement
EMEE	-	Measure of Enhancement by Entropy
et al.	-	(et alia): and others
etc.	-	(et cetera): and so forth
FACE	-	Fuzzy Adaptive Contrast Enhancement
FFT	-	Fast Fourier Transform
FHE	-	Fuzzy Logic and Histogram Equalization
FIM		Fuzzy Intensity Measure
FRB	-	Fuzzy Rule-Based
HE	-	Histogram Equalization
HSI	-	Hue-Saturation-Intensity
HSV	-	Hue-Saturation-Value
HVS	-	Human Visual System
i.e.	-	That is

MRI	-	Magnetic Resonance Imaging
MSE	-	Mean Squared Error
MSR	-	Multi-Scale Retinex
MSRCR	-	Multi-Scale Retinex Color Restoration
No	-	Number
POSHE	-	Partial Overlapped Sub-block Histogram Equalization
POSLT	-	Partially Overlapped Sub-block Logarithmic Transformation
PSNR	-	Peak signal-to-noise ratio
RGB	-	Red-Green-Blue
SSR	-	Single Scale Retinex
UIQI	-	Universal Image Quality Index

**TEKNIK PENINGKATAN KAWASAN DAN PENINGKATAN IMEJ
BERASASKAN FUZI TEMPATAN ADAPTIF UNTUK IMEJ
BERILUMINASI TIDAK SERAGAM DAN BERKONTRAS RENDAH**

ABSTRAK

Peningkatan kontras setempat adalah satu kaedah bagi memperbaiki keterlihatan perincian setempat sesuatu imej dengan meningkatkan kontras di rantau tersebut. Kini, para penyelidik telah menunjukkan minat dalam menyelesaikan masalah pencahayaan yang tidak seragam. Walau bagaimanapun, kebanyakan teknik ini membahagikan imej kepada dua bahagian sahaja iaitu kawasan yang terdedah-lebih dan terdedah-kurang, dan cuba meningkatkan kontras rendah pada kedua-dua rantau menggunakan pendekatan yang sama. Tetapi, semua kaedah ini tidak mantap dan telah direka khusus untuk menyelesaikan masalah tertentu pada sesuatu masa. Kekangan ini telah memotivasikan kajian ini dengan mencadangkan teknik baharu bagi menyelesaikan masalah yang dinyatakan. Pada mulanya, Kaedah Penentuan Kawasan Berasaskan Pendedahan Tempatan Adaptif (ALEBRD) dicadang untuk menentukan dan membahagikan imej kepada tiga rantau iaitu kawasan yang terdedah-lebih, terdedah-kurang dan terdedah-baik. Keputusan menunjukkan kaedah ALEBRD yang dicadang menghasilkan prestasi penentuan rantau yang lebih baik berbanding kaedah konvensional. Berdasarkan analisis kualitatif, ia dapat menentukan ketiga-tiga rantau dengan ketepatan yang tinggi. Kemudian, kontras setiap rantau akan dipertingkatkan menggunakan teknik peningkatan kontras setempat baharu yang dinamakan Peningkatan Kontras Setempat Pendedahan Kabur Adaptif (AFELCE). Kaedah AFELCE yang dicadang dengan direka bentuk khusus untuk meningkatkan kontras setiap rantau menggunakan kaedah berbeza. Teknik AFELCE yang dicadangkan

berjaya meningkatkan kontras 300 imej berkontras rendah dan berilluminasi tidak seragam yang diambil dari tiga pangkalan data imej iaitu imej-imej piawai, bawah air dan sperma manusia mikroskopik. Kaedah AFELCE yang dicadangkan mengatasi kaedah terkini secara kualitatif dan kuantitatif. Secara kualitatif, kaedah AFELCE yang dicadangkan berjaya meningkatkan kontras imej tersebut dengan menghasilkan imej pencahayaan yang lebih seragam dengan kontras yang tinggi. Secara kuantitatif, kaedah AFELCE yang dicadangkan memberi purata tertinggi untuk parameter Entropi (E), Pengukur Peningkatan (EME) dan Indeks Universal Kualiti Imej (UIQI) bagi pangkalan data imej piawai dengan nilai masing-masing 7.582, 42.75 dan 0.94. Keputusan yang sama diperoleh untuk imej bawah laut dengan ia menghasilkan purata nilai tertinggi E , EME dan UIQI dengan nilai masing-masing 7.124, 41.13 dan 0.89. Sementara itu, bagi pangkalan data imej mikroskopik sperma manusia, ia memberikan nilai-nilai tertinggi dalam E dan EME iaitu masing-masing 7.602 dan 42.51.

ADAPTIVE LOCAL FUZZY BASED REGION DETERMINATION IMAGE ENHANCEMENT TECHNIQUES FOR NON-UNIFORM ILLUMINATION AND LOW CONTRAST IMAGES

ABSTRACT

Local contrast enhancement is an approach to improve the local visibility detail of an image by increasing the contrast in local regions. Recently, researchers have shown an interest in solving the issue of non-uniform illumination. However, most of these techniques divide the image into two parts only namely over-exposed and under-exposed regions and try to enhance the poor contrast in both regions using same approach. However, these methods are not robust and they are specifically designed to solve a specific problem at one time. This limitation has motivated this study to propose a new technique to solve the abovementioned problems. In the beginning, Adaptive Local Exposure Based Region Determination (ALEBRD) method is proposed to determine and divide the image into three regions namely under-exposed, over-exposed, and well-exposed regions. The results show that the proposed ALEBRD method produced better region determination performance than the other state-of-the-art methods. Based on the qualitative analysis, it could determine those three regions with high accuracy. After that, contrast of each region will be enhanced using a new local contrast enhancement technique called Adaptive Fuzzy Exposure Local Contrast Enhancement (AFELCE). The proposed AFELCE method is specifically designed to enhance the contrast of each region using different approaches. The proposed AFELCE technique successfully improves the contrast of 300 low-contrast and non-uniform illumination images, taken from three different databases namely standard, underwater, and microscopic human sperm images. The proposed AFELCE method

qualitatively and quantitatively outperforms the state-of-the-art methods,. Qualitatively, the proposed AFELCE method has successfully enhanced the contrast of those images by producing more uniform illumination images with high contrast. Quantitatively, the proposed AFELCE method produces the highest average of Entropy (E), Measure of Enhancement (EME) and Universal Image Quality Index (UIQI) for the standard image database with values of 7.582, 42.75 and 0.94 respectively. The similar results obtained for the underwater database images, where it produces the highest average of E , EME and UIQI values with 7.124, 41.13 and 0.89 respectively. While for the microscopic human sperm image database, it produces the highest values for E and EME with values of 7.602 and 42.51 respectively, and . This study is suitable to be applied to a real time applications. Based on the good results obtained for standard, underwater, and microscopic human sperm images, the developed system has high potential and suitable to be applied to a real time applications.

CHAPTER ONE

INTRODUCTION

1.1 Background

An image is a tool to deliver messages or information to the recipient that is better than a text (Cheddad et al., 2010). After the development of cameras, photography has turned out to be a tool for communication. With the decrease in the price of digital cameras and digital computers, digital image processing has become humans' part of daily lives. At present, image processing is far and wide applied in areas of medical purpose, satellites, military, forensics, entertainment, corporate presentation and industrial application.

The main objective of image processing in these regions is to obtain images which are appropriate for further studies (Umbaugh and Umbaugh, 2010). For instance, x-ray and MRI microscopic enable doctors to be aware of the disease indications effortlessly. Another example is the electronic developed manufacturing, where computer vision is functional of examination for the printed circuit board to make sure that the products are of quality (Wang et al., 2016).

In uncontrolled circumstances, most of the recorded images are low in contrast with non-uniform illumination effects. These circumstances take place owing to the short supply of lighting sources and the inappropriate focus in the image acquisition process (Hsu et al., 2017). Low contrast images with the weak edges (i.e. low-intensity differences) are regarded a daunting challenge in the field of computer vision and pattern recognition. Moreover, non-uniform illumination complicates the way the

information in the images is delivered. This may result into affecting the accuracy of the consequences analyses such as character recognition (Ahmad et al., 2015), bridge painting rust defects recognition (Liao and Lee, 2016) and 2D barcode recognition (Kong and Isa, 2017a).

Generally, enhancement of non-uniform illumination images can be grouped into three categories: histogram modification based (HMB) (Rubin et al., 2006; Wharton et al., 2007), fuzzy logic based (FLB) (Hasikin and Isa, 2014; Magudeeswaran and Ravichandran, 2013) and other algorithms (Jiao and Baoguo, 2009; Wang et al., 2013a). The conventional based HMB algorithms for non-uniform illumination image enhancement are Histogram-Adaptive Image Segmentation (Rubin et al., 2006) and Human Visual System based Multi-Histogram Equalization (HVSME) (Wharton et al., 2007). Histogram Adaptive Image Segmentation is used to widen the dynamic range of segmented low contrast regions which affects the improved contrast and brightness of the resultant image. However, HVSME splits up the image into different regions of illumination to solve such non-uniform illumination issue.

Examples of fuzzy logic based (FLB) algorithms which place an emphasis on solving non-uniform illumination issues are Fuzzy Logic based Histogram Equalization (FHE) (Magudeeswaran and Ravichandran, 2013) and Adaptive Fuzzy Contrast Factor Enhancement (Hasikin and Isa, 2014). FHE primarily calculates the fuzzy histogram by the fuzzy set theory before dividing the fuzzy histogram that is equalized separately each part of the division of fuzzy histogram in order to consume Histogram Equalization (HE) method. AFCFE fuzzifies an image and splits it into two regions by using the single threshold value derived from the contrast factor. The

separated regions are then modified via a sigmoid function and defuzzified to achieve the enhanced image.

Furthermore, several other methods have been applied to enhance the contrast of the non-uniform illumination and low contrast images. These methods fall under the third category of non-uniform illumination image enhancement. These methods are Partially Overlapped Sub-block Logarithmic Transformation (POSLT) (Jiao et al., 2009) and Naturalness Preserved Enhancement Algorithm (NPEA) (Wang et al., 2013a). They were proposed to increase the contrast of non-uniform illumination images. POSLT splits the input image into several partially overlapped sub-images and then puts on a logarithmic transformation to each sub-image. The results are then summed up and divided by the frequency of transformation. NPEA, on the other hand, proposes a bright pass filter that decomposes the illumination and reflectance from the input image.

1.2 Problem statement

Insufficient lightening and inappropriate camera settings leads to non-uniform illumination images, specifically over-exposed, under-exposed and well-exposed regions. It is very important to classify those regions. Classification is a major pre-processing step to be used later in contrast enhancement, image segmentation, and other image processing techniques. Recently, researchers have shown an increased interest in determining the regions in non-uniform illumination images, such as, the Exposure, Fuzzy Intensity Measure (FIM) and Adaptive Backlit techniques. All these techniques are concerned with dividing the image into two principal regions: over-exposed and under-exposed regions. However, they neglect the other part of the image.

Moreover, they are not robust methods because they are specifically designed to solve one single issue, which is highly problematic.

Non-uniform illumination images have several factors that possibly affect on the image quality, one of which is the illumination condition. In other words, poor illumination circumstance during the image acquisition process will produce a non-uniform illumination image. The difference of the intensity level will cause difficulties to sub-sequent analytical processes such as segmentation processes based on either the discontinuity principle or the similarity principle. The discontinuity principle extracts the regions that differ in properties such as intensity, color, texture, or other image statistics, while the similarity principle groups the pixels based on common properties to extract coherent regions. However, intensity of a given object would vary due to non-uniform illumination which would make the segmentation process difficult. Therefore, enhancement of non-uniform illumination image is necessary to simplify the segmentation process by reducing the discontinuity problem.

Image contrast enhancement is one of the main themes in the field of digital image processing. The process of image enhancement could be applied as a make-up of an assortment for methods intended to improve the visual appearance of an image or to transfer the image to another form, thus making it suitable for inspection by a human or appliance (Ahmed et al., 2015). The theory of image quality ought to be well-defined earlier in terms of image contrast enhancement progression. Even if there are numerous elements that will affect the quality of the image, contrast, illumination, spatial resolution, and noise have been acknowledged as the main issues. Contrast denotes to the average pixel intensity of an image, while illumination is referred to the lighting that excites humans' visual sensation. Spatial resolution is generally well-defined as the number of pixels per inch of an image. In the meantime, noise is an

unwelcome disturbance that causes variability in the pixel value. The standardization of image brightness is, also another critical issue that disturbs the quality of the image. It is determined by the illumination situation during the process of image acquisition. Imperfect lighting sources lead to a difference in image brightness, which creates an image with non-uniform illumination (Hyunchan et al., 2013).

In general, image contrast enhancement could be divided into five categories which are contrast enhancement, noise reduction, edge crisping, color image enhancement and multispectral image enhancement. In uncontrolled circumstances, most of the captured images are low in contrast with non-uniform illumination effects. These circumstances take place due to the inadequate lighting sources and indecorous focus during the image acquisition procedure (Hasikin and Isa, 2014). Low contrast images with feeble edges (*i.e.* low-intensity differences) represent a challenge in the field of computer vision and pattern recognition. In addition, non-uniform illumination is possible to cause technical hitches to obtain the information in the image. As a consequence, this may possibly affect the accurateness of the preserved details such as: character recognition (Mohiuddin and Mao, 2014), bridge painting rust defects recognition (Lee and Chang, 2005), and 2D barcode recognition (Hu et al., 2009).

Low contrast and non-uniform illumination issues have been studied by many researchers using Fuzzy based contrast enhancement techniques. Those techniques handle the imperfection and the uncertainty of an image by representing the image as a fuzzy set. The application of fuzzy sets by Russo and Ramponi, (1994) offers a solution to such problem that is implemented for the meticulousness of traditional mathematics besides the characteristic imprecision of the reality. Fuzzy histogram equalization is proposed to grip the vagueness of gray values. After partitioning the histogram based on the local maxima, the function is applied to the pixels in each

partition of the histogram to perform equalization. However, implementation of the fuzzy histogram is a challenging task, especially in the non-uniform illumination images, having over-exposed and under-exposed regions.

The new graphical method of image enhancement is the “IF...THEN...ELSE” fuzzy rule system (Russo and Ramponi, 1994; Isa et al., 2009). A region of pixels measures the initiator amount of the rule in the technique. The pixel selected to be enhanced is transformed by the resulting part of the rule. This method integrates human perception to create soft judgments on each situation. For example, Feng et al. (2009) proposed a fuzzy enhancement method, which was applied to dark and night-time images. However, this method has limited real-time applications in the real-world. Another example is the HSV image enhancement uses different membership functions proposed by Verma et al., (2010), HSV image enhancement uses different membership functions has been proposed. The image information is successfully maximized, but this technique still suffers from the over- or under-saturation of the enhanced image. As a result, the original shape of the histogram is not preserved.

Several methods have also been proposed to apply fuzzy logic image enhancement for the fuzzification of the intensity of color images, thereby overcoming the uncertainty produced by the low contrast. The images were first categorized as over-exposed or under-exposed by applying the respective exposure parameter. Hanmandlu and Jha, (2006) considered the exposure parameter and two different membership functions by fuzzifying the under-exposed regions and the over-exposed regions through the Gaussian membership function (GMF), S-membership function and the Trapezoidal membership function (TMF), respectively. The single membership function which demonstrated better speed performance was later employed by other researchers (Hasikin and Isa, 2012; Verma et al., 2010).

All the above-mentioned studies have used the objective measure which is was constructed by concerning the entropy, contrast, and visual factors of the image. Decreasing this objective measurement was found to magnificently improve the image. On the other hand, the image enhancement procedure is an optimized quantitative method that are necessarily used for optimization method. It could constantly conduct to improve the image features. Based on this, the process requires additional complicated optimization techniques.

An optimization procedure should be conducted exhaustively to enhance the features of image. Yet, such optimization is computationally complex in practice. Therefore, a near-optimal design is required to provide an enhanced image at reduced computational time.

1.3 Objectives

The current thesis aims to achieve the following three main objectives:

- 1- To propose a new region determination method that distinguishes between over-exposed, well-exposed and under-exposed regions.
- 2- To propose a new fuzzy based contrast enhancement by applying different approaches to the determined regions from Objective (1).

1.4 Scope of the Research

The scope of the current study is the improvement of image enhancement algorithm for non-uniform illumination and low contrast images. The method performed on colored images for the purpose of evaluating the performance of the

proposed algorithms. This is due to the focus of the proposed algorithm which is contrast improvement and linearization of the non-uniform illumination of images. The colour spaces used in this system are RGB and HSV color spaces which are commonly used in the state-of-the-art research.

Developing and testing the proposed image region determination and contrast enhancement algorithm was achieved in this study by employing MATrix LABoratory (MATLAB) R2016a and worked in a computer with an Intel® Core™ i5-M520 CPU @ 2.40 GHz processor, running on Microsoft Windows 10 Home 64-bit operating system. The test images which are used for evaluating the proposed methods were collected from public images library namely California Institute of Technology database and converted to HSV images. Three image databases used in this research are standard, underwater and microscopic human sperm non-uniform illumination images. These datasets were tested using the proposed algorithms and were evaluated through qualitative and quantitative analyses.

1.5 Thesis Outline

The thesis consists of five chapters. This chapter briefly presents preliminary backgrounds about non-uniform illumination images, problem statements, research objectives, and research scope. The remaining chapters of the thesis are structures and organized as follows.

The first part of the thesis is the introduction of this research, which shows and explains all the parts of the thesis briefly, describes all the difficulties and the problem statement that this work is facing. It will include the objectives of the work and the scopes of the project.

The literature review of previous studies in this area is presented in Chapter 2 with a focus on non-uniform illumination and low contrast images. The literature review also provides a historical and systematic background of the research, which serves as the guideline for the practical or empirical part of the work reported in the thesis.

Chapter 3 presents the overall approach used in this study to perform local contrast enhancement to the non-uniform illumination and low contrast images. The chapter also highlights the main contributions of the work reported in the thesis, including development of a new image region determination technique that is capable of dividing the image into three regions: over-exposed, well-exposed and under-exposed. In addition, this chapter proposes a new local contrast enhancement technique to enhance the non-uniform illumination and low contrast images. It also describes the methodology of both methods and systematically explains the procedure of implementing both methods step by step.

Chapter 4 reports the main results obtained through the two proposed methods. It starts by reporting the results for region determination, and then continues presenting the results for contrast enhancement. The conclusion of the whole thesis is presented in Chapter 5. In addition, this chapter provides suggestions and directions for future work.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

Recently, the quantity and quality of digital images have been increasing by leaps and bounds. A digital image is more favorable than an analog image in terms of cost since it is easily manipulated for processing or enhancing purposes. With such great advantage and advancement of computer hardware and network technology, digital images are increasingly used in many kinds of applications, including the medical field (Denzil B. et al., 2017; Han et al., 2017; Summers, 2017), fingerprint analysis (Baldini et al., 2017; Gaikwad and Musande, 2017; Mustonen et al., 2017), crime evidence (Murray et al., 2017; Volgaard, 2017; Watalingam et al., 2017), industrial area (Amza and Cicic, 2015; Mataei et al., 2018; Zolfaghari et al., 2018) and astronomy (Cárcamo et al., 2018; Gabbard et al., 2017; Morris et al., 2017). Generally, the human eye is like an image decoder, which is capable of converting a certain wavelength in the light spectrum into colors. However, the human eyes is limited to sensing and processing a limited range of wavelengths from electromagnetic radiation (Gonzalez et al., 2009). This range of electromagnetic wavelengths that can be sensed by the human eye is called a visible light. To date, there have been many different types of advanced digital imaging acquisition devices that are able to capture the image, which is constructed by electromagnetic radiation wavelength beyond the human eye visible light region. X-ray machines (Endrizzi, 2018), tomography machines (Ding et al., 2018), MRI scanners (Perlo et al., 2016), ultrasound machines (Alison Noble, 2016), and microscopes (Tan and Isa, 2017) represent a few examples of sophisticated medical

imaging devices which are used to capture internal structures and characteristics of the human body in order to aid in medical diagnosis and treatment (Hao et al., 2018). This makes strengthens the role of digital images and enables them to act as a core data type in medical informatics applications.

Digital image processing is categorized into six main categories, namely, image restoration, color image processing, image compression, image segmentation, object recognition and image enhancement. Image restoration is concerned with recovering a degraded image using a model of degradation of the original image formation. Color image enhancement it is a process of improving the image quality but take the color space into consideration by enhancing the image base on RGB, HSV, HSB, HSI or YCbCr etc. color spaces. Image compression, as the name implies, is applied to reduce the size of the image in order to shrink the storage required for saving the image. Its practical use has been increasing through the Internet, which is characterized by a significant pictorial content. Meanwhile, image segmentation is used to partition the image into constituent parts or into several objects. However, segmentation is considered as one of the most difficult tasks in image processing (Kong and Isa, 2017b). A perfect segmentation leads to a successful solution of image problems requiring or demanding identification of individual objects. Otherwise, weak or erratic segmentation algorithms will lead to failures. In general, the more accurate the segmentation, the more likely the recognition is to succeed. Object recognition is the process of labeling a certain type of object that is assigned based on its descriptors. Image enhancement is the process of adjusting digital images in order to have a better quality image for display or analysis purposes. On the other hand, image enhancement is one of the most popular fields in digital image processing and one of the widest

areas. This process is applied in order to remove noise and sharpen or brighten an image.

Image enhancement can be categorized into three major categories: frequency, spatial, and fuzzy domains. The frequency domain modifies the Fourier Transform of an image, while the spatial domain is a direct manipulation of pixels (Gonzalez et al. 2009; Jaya and Gopikakumari 2015). The fuzzy domain converts the image from gray-scale of 0-255 range to 0-1 range in order to fuzzify it (Bloch, 2015).

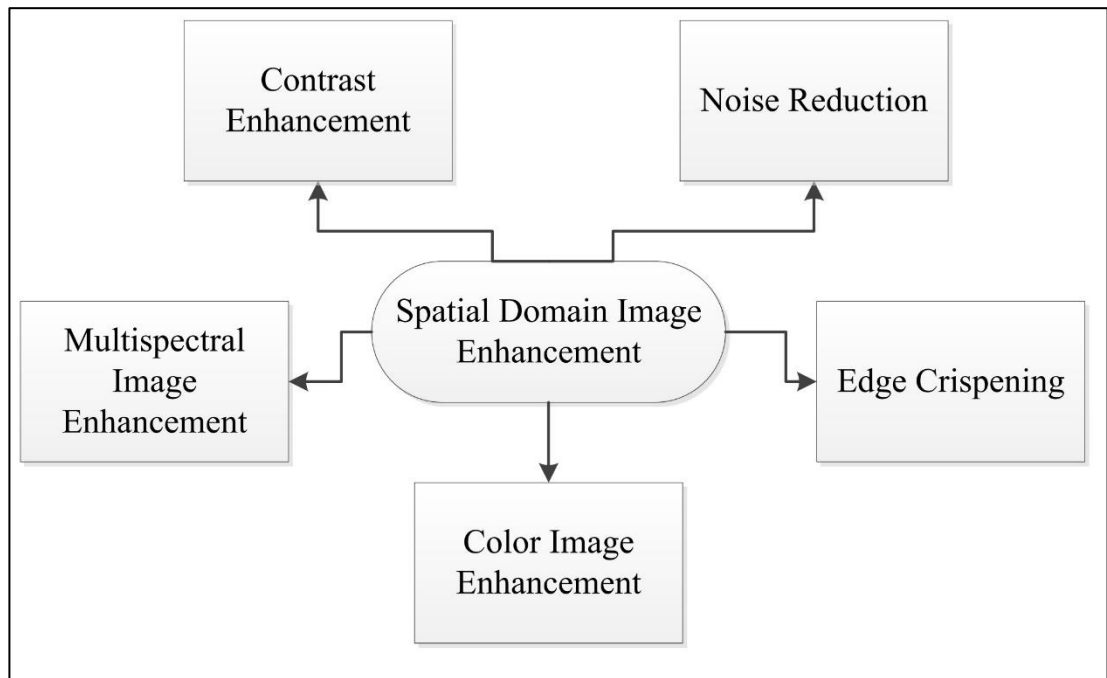


Figure 2.1: Spatial Domain Image Enhancement Categories.

For the process of the spatial domain image enhancement, it can be roughly categorized into five categories which are contrast enhancement, noise reduction, edge crispening, color image enhancement and multispectral image enhancement as shown in Figure 2.1. In non-controlled situations, most of the recorded images are low in contrast with non-uniform illumination effects. These conditions occur due to the

insufficient sources of lighting and improper focus during the image acquisition process (Hasikin and Isa, 2014).

Non-uniform illumination images and low contrast images are two common cases which have attracted the attentions of researchers in the past few decades (Baig et al., 2012; Cho et al., 2007; Hasikin and Isa, 2013; Kondo and Yan, 1999; Wharton et al., 2007). In general, image enhancement of non-uniform illumination images can be categorized into three main categories: Histogram Modification Based (HMB), Fuzzy Logic Based (FLB), and other algorithms as shown in Figure 2.2. A detailed explanation of image enhancement methods is presented in Section 2.4.

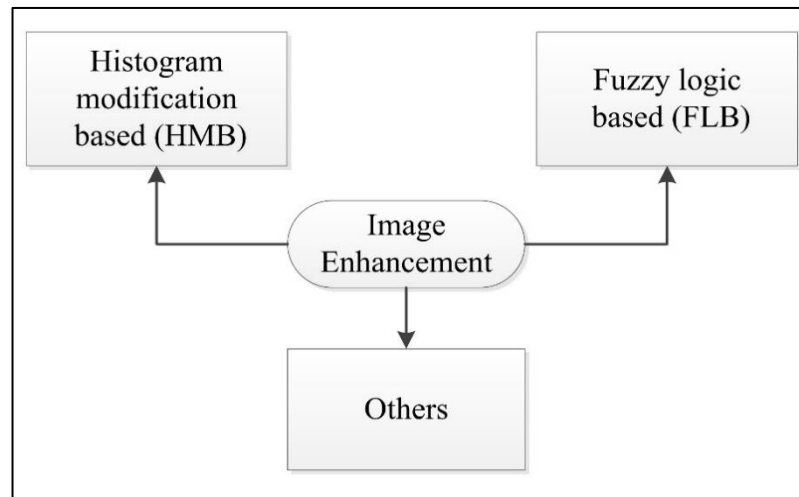


Figure 2.2: Image Enhancement for Non-uniform Illumination Categories.

This chapter provides a discussion of the basic ideas of the non-uniform illuminated images, low contrast images and the state-of-the-art techniques to solve these problems. In Section 2.2, the basic concept and image formation of a digital image are discussed. The characteristic of the non-uniform illuminated image and low contrast image are also included in this section. It is followed by a review of the literature on the conventional approaches of region determination in Section 2.3, while

a review of previous research on the image enhancement approaches is presented in Section 2.4. Finally, Section 2.5 summarizes the literature review of previous research.

2.2 Digital Image Processing

Digital image processing is a study of two-dimensional signal processing. An image is taken as an input which is processed by employing, computational methods such as mathematical operations and algorithms. An output can be either an enhanced image or a set of extracted attributes from the input image (Gonzalez, 2009). For instance, the input image can be a picture, photography or a video frame. In general, the aims of digital image processing, are to (i) observe the hidden objects in the image through visualization, (ii) create a better and sharper image through image sharpening and restoration, (iii) seek the object of interest using an image retrieval; (iv) measure various features in a given image and/or (v) distinguish the objects contained in the image using image recognition (Santhi and Tripathy, 2015). Image processing techniques can be classified into two types: analog and digital image processing. (Digital image processing refers to the conversion of the input images, into digital images and a series of mathematical operations are performed on the digital images to process them. For example, analog image processing is used for hard copies, such as photographs and printouts while digital image processing is implemented for manipulating digital images using computers (Ammon, 2017)).

In the image acquisition stage, an image is acquired from image acquisition devices, such as camera, webcam, and others. Image enhancement is a process of manipulating an image, so that the unseen or, partially seen and hidden details of the image can be brought out and the noise is removed. Hence, the output image is more

suitable for a particular task than the original image. After having a clearer image, image segmentation is applied to partition image into multiple regions and entail the separation of the image into regions based on the same characteristics. In the representation and decryption stage, raw pixel data from the output segmented image are represented as a boundary or a complete region depending on whether the application is concentrated on external shape characteristics or internal properties of that image. Then, the feature of interest is extracted and highlighted by describing the processed data. Finally, based on the descriptors, a label is assigned to an object in the recognition step, and therefore the object could be identified as the final output.

2.2.1 Image Formation

Digital image processing deals with 2-D images at most of the image processing applications, and those 2-D images can be formed that the image $I(x, y)$ is defined as a two-dimensional representation of objects on the imaging plane. Figure 2.3, x and y represent the horizontal and vertical axis of continuous spatial coordinate, on the typical Cartesian coordinate system, respectively. The magnitude of the image I at any particular pair of coordinates (x, y) is known as the intensity of the image.

For a monochrome image, the intensity can also be called as grey level. A monochrome image is a dull, washed-out grey look image. On the other hand, a color image is called chromatic image. The intensity value of the image is a continuous tonal value (Hakonen et al., 2014; Jarvis et al., 1976; Wu and Memon, 1997). Today, many sensors are being developed to replace the five human senses and receptors to detect and measure the changes of the environment. For electronic imaging applications, the imaging sensor is developed to replace the important role played by the human eye in

observing the change of the surroundings. The typical imaging sensor employed in electronic imaging devices called Charge-Couple Device (CCD) is arranged in an array. Each CCD represents one pixel of the image. During image acquisition, an electronic imaging device is employed. Incoming illumination from the source is incident on the scene element, which is the object, being observed. This amount of reflected energy is called reflectance components. Once the electronic imaging device is activated to compute the scene element, each CCD sensor senses and transforms the incoming energy into a voltage by combining the input electrical power and the sensor material that is sensitive to light.

The output of conventional sensors is a continuous voltage signal that is indicative of the measured intensity and spatial behaviour from the physical phenomenon. In order to process and display the image using a computer, this image is required to be first converted from an analog format into a digital format, which is a readable form by the computer. This process of conversion involves sampling and quantization for digitizing the spatial coordinate values and the intensity values of the analog image, respectively. However, the sensed data by most sensors today is generated as a digital waveform that is reliable and processed by a computer and displayed as a digital image (Mather and Koch, 2011).

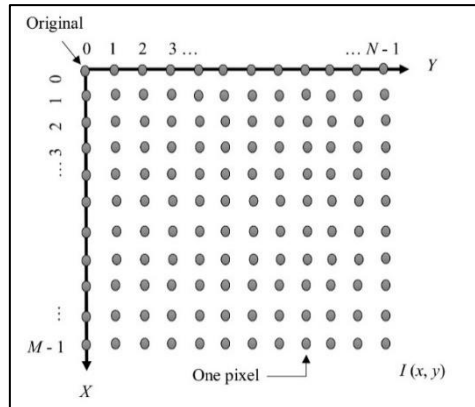


Figure 2.3: Formation of digital image (Gonzalez and Woods, 2010).

An image normally consists of two components which are illumination and reflectance (Gonzalez, 2009). Illumination is referred as lighting that excites human's visual sensation (Hanumantharaju et al., 2011). Reflectance is the effectiveness of an object in reflecting the incident light (Gonzalez, 2009). It can be categorized into three categories, which are Lambertian, Specular and Hybrid (Nayar et al., 1988). The Lambertian surface reflects the incident light in all directions. The Specular surface reflects the light according to laws of reflection, where the angle of incident and angle of reflection is equal. A hybrid model which consists of both Lambertian and Specular properties is the surface that mostly exists in the real world (Yang and Dimitris, 2008). In reality, an object observed would be bright if illumination is high. Otherwise, it would be dark. Under a constant illumination condition, a high reflectance object would be brighter than a low reflectance object. Usually, the bright area of an image has a higher intensity value compared to the dark area. These three phenomena (i.e. Lambertian, Specular and Hybrid) show that an image observed would be the product of illumination and reflectance of the scene (Gonzalez, 2009; Land and McCann, 1971).

2.2.2 Non-uniform Illumination Image

There are numerous factors that could affect image quality; one of them is the illumination condition. A poor illumination condition during the image acquisition process will produce a non-uniform illumination image (Leung et al., 2005). This situation occurs commonly at a night time (Lin and Shi, 2014), in the microscopic

image (Hasikin and Isa, 2012) and in complex industrial environment (Wei, 2013). In a non-uniform illumination image, a monochrome object might contain different level of intensity due to the light transition. The differences in the intensity level will cause difficulties to the subsequent processes of analysis such as the segmentation process (Lee et al., 2012; Wang et al., 2013). The segmentation process is based on either discontinuity principle or similarity principle. The discontinuity principle extracts the regions that differ in properties such as intensity, color, texture or other image statistics; while the a similarity principle groups the pixels based on common properties to extract coherent regions (Gonzalez and Woods, 2010). However, the intensity of a given object would vary due to the non-uniform illumination which would make the segmentation process a difficult task. Therefore, the enhancement of non-uniform illumination image is necessary to simplify the segmentation process.

Six examples of non-uniform illumination images will be used to explain problems that are encountered in certain application. Figure 2.4 shows the multiple types of non-uniform illumination images in diverse applications. These applications can be underwater, closed-circuit television (CCTV) security cameras, satellite, microscopic, x-ray and MRI images as shown in Figures 2.4(a) to (f) respectively. Figures 2.4(a) show the underwater image that has an unbalanced contrast as pointed by the arrows while leaving some details of the image unobservable. Figure 2.4(b) displays a CCTV image that is affected by over bright street lights that hide important data such as the colors of cars, the number of people in the street, etc. In Figure 2.4(c), a satellite image suffers from an unbalanced contrast by having dark regions as under-exposed regions which are evidenced by the arrows in the image.

Figure 2.4(d) shows a microscopic image with improper camera settings, which lead to insufficient lightning on the resultant image. Figure 2.4(e) presents an X-ray

image having high-intensity lightning that makes the wrist area too bright (i.e. over-exposed). This results in losing important information from that area because of the too bright lighting, while the edges of the fingers are invisible due to the under-exposed region. Hence, such image becomes unable to deliver proper information to the person in charge. In Figure 2.4(f), it is an MRI image that suffers from the unbalanced distribution of the non-uniform contrast at its corners as indicated by the arrow, which makes it unclear to be read properly by a human viewer.

All these images are random examples of the most significant applications of image processing and computer vision affected by non-uniform illumination, which is considered as a major issue in such applications. Such challenging issue can deliver wrong information to the receiver by hiding important information as it becomes either being too dark or too bright. Sometimes, there can be even too dark and too bright regions at the same image. The information in the underwater, CCTV, satellite, microscopic, X-ray and MRI images are very sensitive to the field they belong to. Therefore, it is very important to provide a solution to this issue and deliver high quality, balanced contrast and uniform images in all the above-mentioned applications. As previously mentioned, non-uniform illumination of an image is commonly caused by insufficient lightening, improper camera settings, and the position of the light source. These may cause certain regions of the images appear darker and/or brighter than other regions. Non-uniform illumination leads to three major regions, over-exposed, under-exposed and well-exposed regions. The over-exposed region pixels are skewed towards the high intensity and most of the pixels are saturated at the highest intensity (Nnolim, 2015). On the other hand, the under-exposed region pixels are

skewed towards the low intensity and most of the pixels are saturated at the lowest intensity.

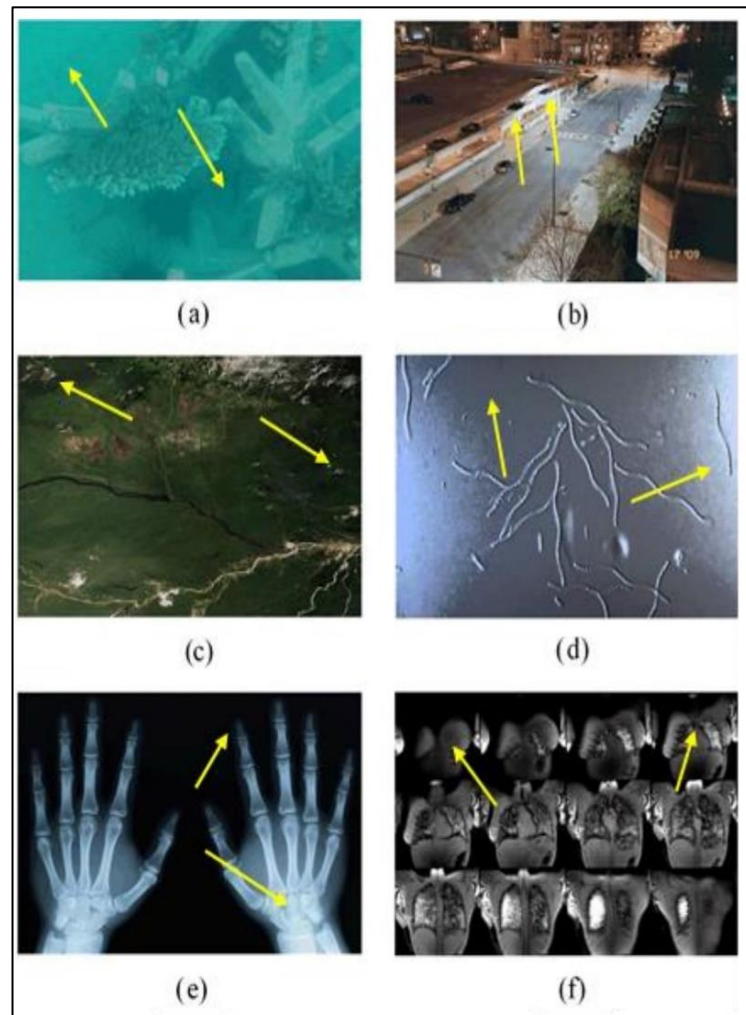


Figure 2.4: Examples of non-uniform illumination images, (a) underwater image, (b) CCTV image, (c) satellite image, (d) microscope image, (e) x-ray image, (f) MRI image.

When all pixels have the exact same intensity it will make it harder to get information from that image. For the well-exposed region, it falls between the over-exposed region and under-exposed region. Figure 2.5 shows these three non-uniform illumination images, each one presenting one region with the histogram of each image. The purpose of the showing histogram of each image is to see the contrast distribution

in a given image. Non-uniform illumination affects these regions of digital images by making it either too bright or too dark, thus resulting into a loss of visual information.

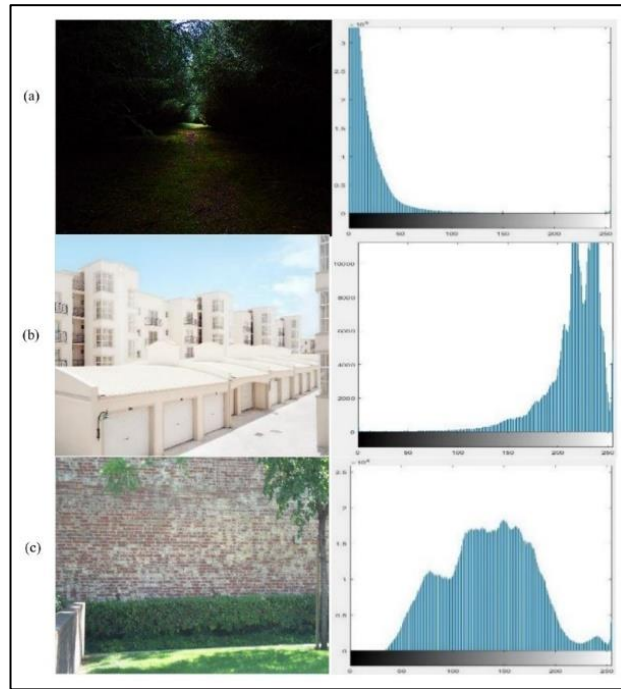


Figure 2.5: Image types, (a) Under-exposed image, (b) Over-exposed image, and (c) well-exposed image.

Non-uniform illumination is one of the challenging problems in face recognition applications, because of the difference in the illumination condition that would cause dramatic changes in face appearance (Beghdadi et al., 2013). Microscopic images are also facing the same non-uniform illumination problem, which it affects the captured image by removing important information from the image when the gray levels of objects are the same as the gray level of the background. Since the non-uniform illumination images cause problems in these applications of digital imaging, there is still a need to improve the illumination condition of these images.

2.2.3 Low Contrast Image

Contrast refers to the magnitude of intensity in the differences of an object's surface which is recorded in an image (Sridhar, 2011). In low contrast images, there are a large number of pixels spread within a small portion of an available intensity range (Acharya and Ray, 2005). These images are generated due to fact that the variation of scene brightness is much smaller than the dynamic range of the camera (Russ, 2011). There are several reasons behind such low contrast image including the inferior quality imaging device, the inadequate imaging method and even the adverse external conditions such as haze, rain, and fog (Arici et al., 2009). In brief, most of the non-uniform illuminated images encounter the problem of low contrast.

For example, Figure 2.6 provides examples of low contrast images. Although the man's face is the dark region with bright background and that occupies completely the dynamic range of the intensity level as shown in the histogram, most of the pixels are distributed in the dark area. This is because only a small amount in the histogram shown as bright pixels exists in the background area of that image. These bright pixels are unable to be noticed in the intensity dynamic range, which renders the image a low contrast image. In Figure 2.6(b), there is a non-uniform illumination image, where the man's face is bright with an over-exposed background at the widow area. In this image, the unbalance lightening leads to non-uniform illumination and it pushes the pixels intensity to be in the most right area in the histogram. Thus, in the enhancement of the non-uniform illuminated image, both illumination correction and contrast enhancement are important. Figure 2.6(a) and Figure 2.6(b) show an example of non-uniform image and a low contrast image respectively. For Figure 2.6(a), the histogram is distributed at the low intensity area, thus the image become darker. While for Figure 2.6(b) the intensity distributed at the highest range thus the image become brighter.

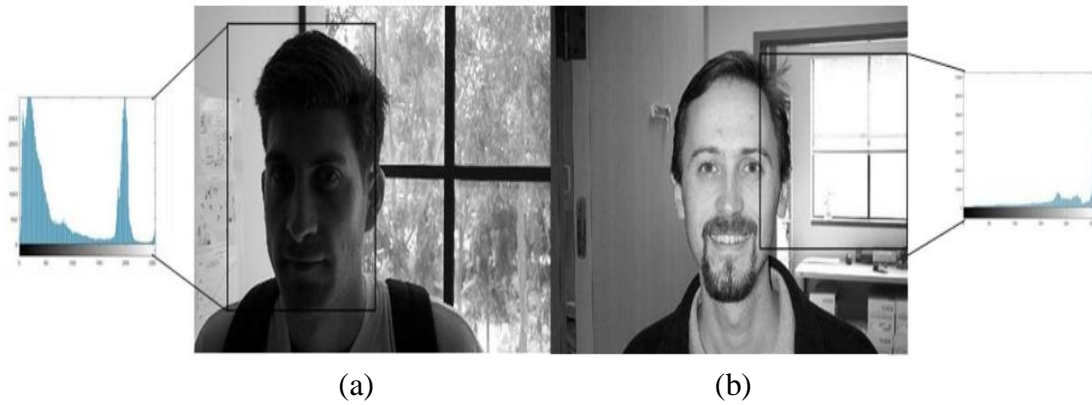


Figure 2.6: (a) Non-uniform illuminated image and the histogram, (b) Low-contrast image and the histogram.

Figure 2.7 provides examples of non-uniform illumination and low contrast images with its histogram.

2.3 Region Determination Techniques

Image region determination is one of the most important pre-processing stages in the digital image processing field, because it is able to divide the image into several different regions. Each region will have its own gray levels/intensities range. This small range of intensity value could make image processing flexible, when specific image processing could be applied to a specific region. (Those more apocopate and resultant images could be produced). The state-of-the-art region determination techniques commonly determines the image regions based on its surroundings by using feature attributes such as intensity, color, and edges (Achanta et al., 2009)

Image region determination algorithms are classified into two schemes known as local and global schemes (Cheng et al., 2015). The local region determination-based methods are implemented in order to investigate the limitation of image regions with respect to (small) local neighbourhoods. In local region determination, researchers

have devoted significant efforts to divide the image into regions, each of which belongs to one group of contrast. For example, Hanmandlu et al. (2009), Hasikin and Isa (2014) and Lee et al. (2015) have proposed local image region determination methods, namely; the Exposure, Fuzzy Intensity Measure and Adaptive Backlit Region Detection respectively.

In the Exposure method (Hanmandlu et al., 2009), the authors proved that the proposed method has successfully distinguished between the two main regions (i.e. over-exposed and under-exposed) of the image. It uses a single threshold value applied on the V channel from the HSV image color space to divide the input image into those regions. The V channel pixel's range is between [0 - 1]. If the intensity of a pixel is above the threshold, the pixel will be considered as over-exposed. However, if the intensity of a pixel is below the threshold value, then the pixel will be considered as under-exposed. The commonly used threshold value is 0.5. In general, this method considers only two types of regions (i.e. under- and over-exposed). In reality, some pixels do not belong to either one of these two regions. By having proper and enough amount of lighting, the pixel is already well-exposed. However, the technique failed to assign pixels into either under- or over-exposed regions.

The Fuzzy Intensity Measure (FIM) determination method (Hasikin and Isa, 2014) overcome the limitation of the Exposure method by dividing the image into two regions through a new threshold T which is more adaptive as compared to the Exposure method. Yet, the FIM method divides the image only into two regions (i.e. under- and over-exposed) which is still unable to identify the well-exposed region. Due to this limitation, the Adaptive Backlit Region Detection method (Lee et al., 2015) emerged as a method that assigns two thresholds: $c1$ and $c2$ rather than one threshold. If the intensity value is less than $c1$, the corresponding pixel is determined as a dark region.