IMAGE CONTRAST ENHANCEMENT BASED ON THE INTENSITY OF REGIONS' PIXELS

MAHMOOD SALAH HAITHAMI

FACULTY OF COMPUTER SCIENCE AND INFORMATION TECHNOLOGY
UNIVERSITY OF MALAYA
KUALA LUMPUR

2018

IMAGE CONTRAST ENHANCEMENT BASED ON THE INTENSITY OF REGIONS' PIXELS

MAHMOOD SALAH HAITHAMI

DISSERTATION SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF COMPUTER SCIENCE

FACULTY OF COMPUTER SCIENCE AND INFORMATION TECHNOLOGY
UNIVERSITY OF MALAYA
KUALA LUMPUR

2018

UNIVERSITY OF MALAYA

ORIGINAL LITERARY WORK DECLARATION

Name of Candidate: MAHMOOD SALAH HAITHAMI

Matric No: WGA150036

Name of Degree: MASTER OF COMPUTER SCIENCE

Title of Project Paper/Research Report/Dissertation/Thesis ("this Work"): IMAGE CONTRAST ENHANCEMENT BASED ON THE INTENSITY OF REGIONS' PIXELS

Field of Study: Image Processing

I do solemnly and sincerely declare that:

(1) I am the sole author/writer of this Work;
(2) This Work is original;
(3) Any use of any work in which copyright exists was done by way of fair dealing and for permitted purposes and any excerpt or extract from, or reference to or reproduction of any copyright work has been disclosed expressly and sufficiently and the title of the Work and its authorship have been acknowledged in this Work;
(4) I do not have any actual knowledge nor do I ought reasonably to know that the making of this work constitutes an infringement of any copyright work;
(5) I hereby assign all and every rights in the copyright to this Work to the University of Malaya ("UM"), who henceforth shall be owner of the copyright in this Work and that any reproduction or use in any form or by any means whatsoever is prohibited without the written consent of UM having been first had and obtained;
(6) I am fully aware that if in the course of making this Work I have infringed any copyright whether intentionally or otherwise, I may be subject to legal action or any other action as may be determined by UM.

Candidate's Signature Date:

Subscribed and solemnly declared before,

Witness's Signature Date:

Name:

Designation:

IMAGE CONTRAST ENHANCEMENT BASED ON THE INTENSITY OF REGIONS' PIXELS

ABSTRACT

With digital cameras becoming more available and inexpensive instruments nowadays, capturing high definition photographs is made easier. Picture quality produced by digital cameras is affected by atmospheric changes, light conditions, quality of capturing devices, and operator expertise. Thus, image quality is heavily affected by the degree of variation in these factors, that its quality might degrade up to a point where image contrast enhancement is needed. Furthermore, improving the image's contrast makes it easier to perceive features that were otherwise unviewable. Various methods were proposed to enhance the contrast. Most of the methods use either local or global statistical information of an image to produce a transformation function or multiple transformation functions, respectively. The prominent drawbacks of these methods are over/under enhancement or artifacts formation. These drawbacks are produced because images may have different regions and each region may require different degree of enhancement. To overcome the aforementioned drawbacks, an image contrast enhancement method based on the intensity of regions' pixels is proposed. The proposed method consists of two steps: segmentation, and pixel value correction. The image is first segmented into regions based on the luminance and contrast level, then, for each region, contrast stretching with adaptive gamma correction are used to enhance the contrast. Qualitative and with quantitative results both demonstrate that the performance of the proposed method is better than other techniques in the field of image contrast enhancement.

Keywords: contrast enhancement, regions, gamma correction, histogram stretching.

PENINGKATAN KONTRAS IMEJ BERDASARKAN KEAMATAN PIKSEL PADA KAWASAN

ABSTRAK

Dengan kamera digital menjadi alat yang lebih mudah dan murah pada masa kini, menangkap gambar definisi tinggi menjadi lebih mudah. Kualiti gambar yang dihasilkan oleh kamera digital dipengaruhi oleh perubahan atmosfera, keadaan cahaya, kualiti menangkap peranti, dan kepakaran pengendali. Oleh itu, kualiti imej amat dipengaruhi oleh tahap variasi dalam faktor-faktor ini, bahawa kualitinya mungkin merosot hingga ke tahap di mana peningkatan kontras imej diperlukan. Selain itu, meningkatkan kontras imej menjadikannya lebih mudah untuk melihat ciri-ciri yang tidak dapat dilihat. Pelbagai kaedah dicadangkan untuk meningkatkan kontras. Kebanyakan kaedah menggunakan maklumat statistik tempatan atau global bagi imej untuk menghasilkan fungsi pembetulan nilai pixel. Kelemahan yang ketara dalam kaedah ini adalah penambahan atau pembentukan artifak. Kelemahan ini dihasilkan kerana imej mungkin mempunyai wilayah yang berlainan dan setiap wilayah memerlukan tahap peningkatan yang berbeza. Untuk mengatasi kelemahan yang disebutkan di atas, kaedah peningkatan kontras imej berdasarkan intensiti piksel kawasan dicadangkan. Kaedah yang dicadangkan terdiri daripada dua langkah: segmentasi, dan pembetulan nilai pixel. Imej pertama kali dibahagikan kepada rantau berdasarkan tahap pencahayaan dan kontras, maka bagi setiap rantau, pembetulan gamma penyesuaian digunakan untuk meningkatkan kontras. Kualitatif dan dengan hasil kuantitatif kedua-duanya menunjukkan bahawa prestasi kaedah yang dicadangkan adalah lebih baik daripada teknik lain dalam bidang peningkatan kontras imej.

Katakunci: peningkatan kontras, rantau, pembetulan gamma, peregangan histogram.

ACKNOWLEDGEMENTS

In the name of God, Most Gracious, Most Merciful. I would like to I would like to thank Almighty Allah for granting me perseverance and strength I needed to complete this thesis.

I would like to express a great thankfulness to my supervisor, Dr. Hamid A. Jalab for his support, guidance, suggestions and encouragement over the past years of this research. My supervisor gave me the opportunity to carry out my research with little obstacles. The comments from him had a significant impact on this study. I would like to thank the Faculty of Computer Science and Information Technology, University of Malaya for providing me a great academic environment.

I would like to express the deepest appreciation to my parents for their faith, continuous support and encouragement. Also, to my wife and my daughter who was born while I am doing my research. Thank you all.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS AND ABBREVIATIONS

AGC	:	Adaptive Gamma Correction
AGCWD	:	Adaptive Gamma Correction with Weighting Distribution
BERF	:	Blocking Effect Reduction Filter
CDF	:	Cumulative Density Function
CEBR	:	Contrast Enhancement Based on the Intensity of Regions' Pixels
CLAHE	:	Contrast-Limited Adaptive Histogram Equalization
CLAHS	:	Clap-Limited Histogram Specification
CVC	:	Contextual and Variational Contrast Enhancement
DE	:	Discrete Entropy
HE	:	Histogram Equalization
HM	:	Histogram Matching
HSV	:	Hue, Saturation, Value color model
PDF	:	Probability Density Function
ROI	:	Region of Interest
RGB	:	Red, Green and Blue color model

CHAPTER 1: INTRODUCTION

Since the digital cameras are publicly available and cheap, capturing images are now quite easy. Some images may be taken in a bad weather or low light condition and they demand enhancement. So, editing software and enhancement methods have been developed over the past years. There are different aspects of image enhancement and one of the aspects -yet important one- is contrast enhancement. By using contrast enhancement methods, images would be more pleasant to ordinary people. More importantly, wide variety of applications need contrast enhancement to extract hidden details of images, such as, medical images processing (Al-Najdawi, Biltawi, & Tedmori, 2015), astrophotography, texture analysis, video processing (Rahman, Rahman, Hussain, Khaled, & Shoyaib, 2014) and satellite image processing (Lisani, Michel, Morel, Petro, & Sbert, 2016).

Contrast enhancement is not a new topic to be investigated, however, the conventional methods either fail to enhance wide range of images, doesn't provide satisfactory results, introduce artifacts or needs human intervention. Thus, new methods are proposed to tackle issues that previous methods didn't solve probably.

In this chapter, six sections are constructed to provide preliminary background information about the problem. The first and second topics contain a necessary background about contrast enhancement and a clear description of the problem to be addressed, respectively. Research questions are formulated in the third topic to guide the research path. In the fourth topic, an aim is set, and four objectives are constructed to achieve the aim of this study. The last two topics are the main contributions of the research, and the outline of the whole dissertation, respectively.

1.1 Background

In this section, essential background about digital images and image contrast are presented. First, the content of gray and color images is discussed, then the definition of image contrast will be explored. Finally, enhancing the contrast in general will be discussed.

1.1.1 Gray and Color Images

A digital image is a numeric representation of two-dimensional matrix. Each element in the matrix represent an intensity of a pixel. A pixel is a small physical point in a display screen. Figure 1.1 depicts an example of a digital gray image along with a sample of its numeric representation.

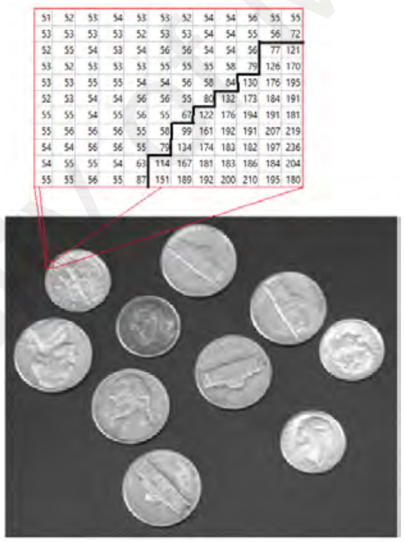


Figure 1.1: Example of gray image pixels' intensity

In a gray image, intensity values are in the range of [0-255]. Where 0 and 255 represent the darkest and brightest value that a pixel can have, respectively. As depicted in Figure 1.2.

Figure 1.2: Numeric gray values representation

However, colorful images are represented using a three-dimensional matrix. The three dimensions represent the intensity value of the three-color channels (i.e. red, green and blue). So, each pixel has three intensity values. Figure 1.3 illustrates a color image with its' three-color channels.

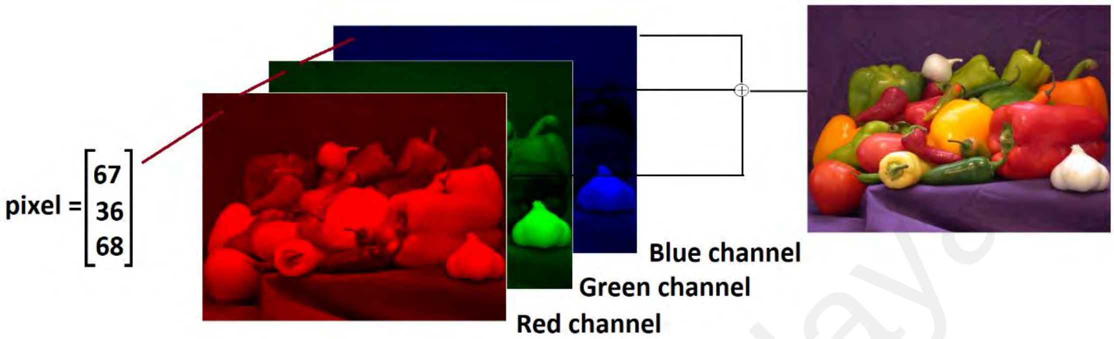


Figure 1.3: An example of a color image with its' RGB channels

This color representation of an image is called RGB color model. It is very common to represent images with RGB color model, however, using this model for intensity correction would affect the color of the original image (Rahman et. al., 2016).

Different color models are available in image processing domain, such as Lab, HSV, and YUV (Ibraheem, Hasan, Khan, & Mishra, 2012). In this research, HSV (hue, saturation, value) color model is adapted because, it has a good capability of representing the colors of human perception (Rahman et al., 2016). HSV model separates the brightness information (V) from the color information (H and S) (Tsai & Yeh, 2008), as it is clearly seen in Figure 1.4. Notice that, the Hue (H) determines the color, the Saturation (S) determines the amount of gray and the Value (V) determines the brightness level. Unlike the RGB model, HSV uses normalized values [0-1] to represent the intensity of each channel.

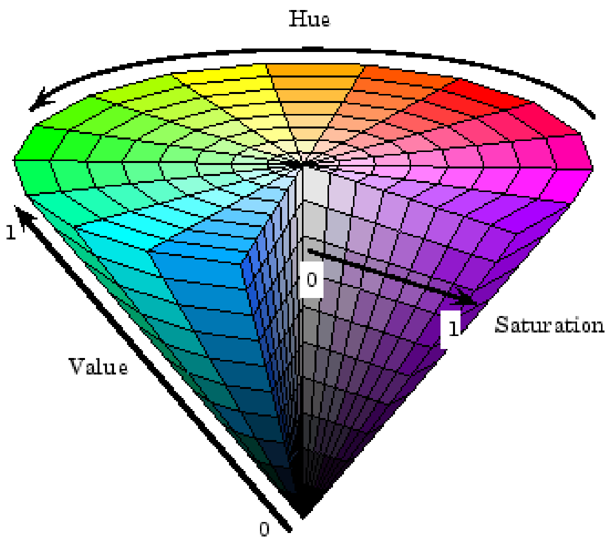
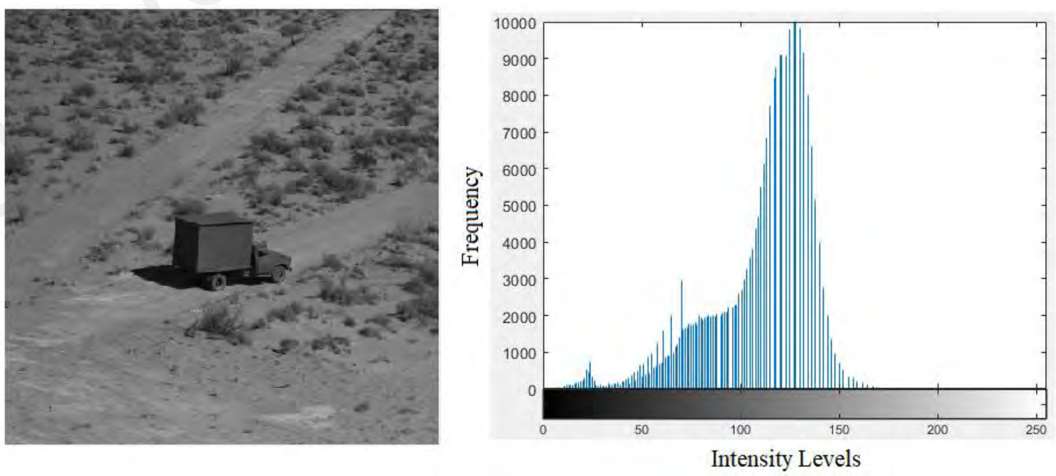


Figure 1.4: HSV color model single hexagon cone

(Ibraheem et al., 2012)

1.1.2 Image Histogram and Probability Density Function

As it is known, before applying any processing or constructing transformation functions, images should be analyzed first. Histogram is a fundamental tool to analyze the images. Histogram is graphical representation of the distribution of the pixels' intensity. It plots the number of pixels for each intensity value. By looking at the histogram for a specific image, a viewer will be able to judge the entire intensity distribution at a glance. An example is shown in Figure 1.5.



(a) **(b)**

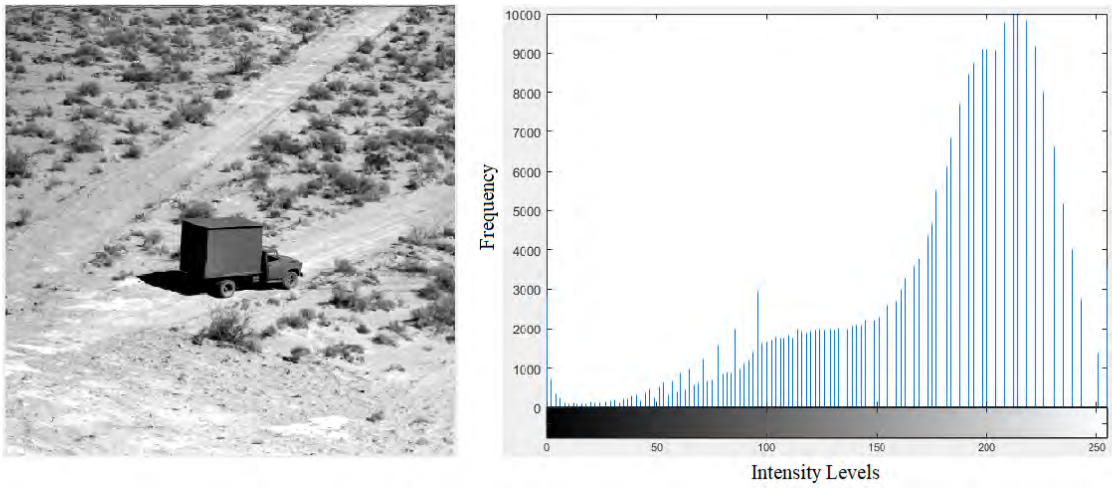
Figure 1.5: (a) is a gray image and (b) is the Histogram of (a). The total number of pixels in (a) is 262,144 pixels.

By using the histogram of an image, a probability density function (PDF) can be constructed. PDF of an image is a function that estimate the probability of occurrences of each particular intensity value. For instance, the histogram in Figure 1.5 (b) shows that the number of occurrences of a pixel that have an intensity value of “128” (mid-gray) is equal to 10149 pixels. Now the PDF of the intensity value “128” is equal to the number of occurrences divided by the total pixels in the image, so, PDF(128) = 10149/262144 ≈ 0.03871. In other words, the probability that a pixel would have intensity value of 128 is 3.871%.

1.1.3 The Full Dynamic Range and Image Contrast

The term “full dynamic range” is used in different ways in different fields. However, in image processing, the full dynamic range of an imaging system is defined as the ratio of the minimum detectable intensity to the maximum measurable intensity level in the system. In other words, the full dynamic range determine the lowest and highest intensity levels that a system can represent and, accordingly, that an image can have. Referring to Figure 1.5 (b), the full dynamic range is 256 intensity levels, starting from 0 and up to 255, yet, the dynamic range of the captured image is smaller than the full dynamic range. So, different images may have different dynamic ranges.

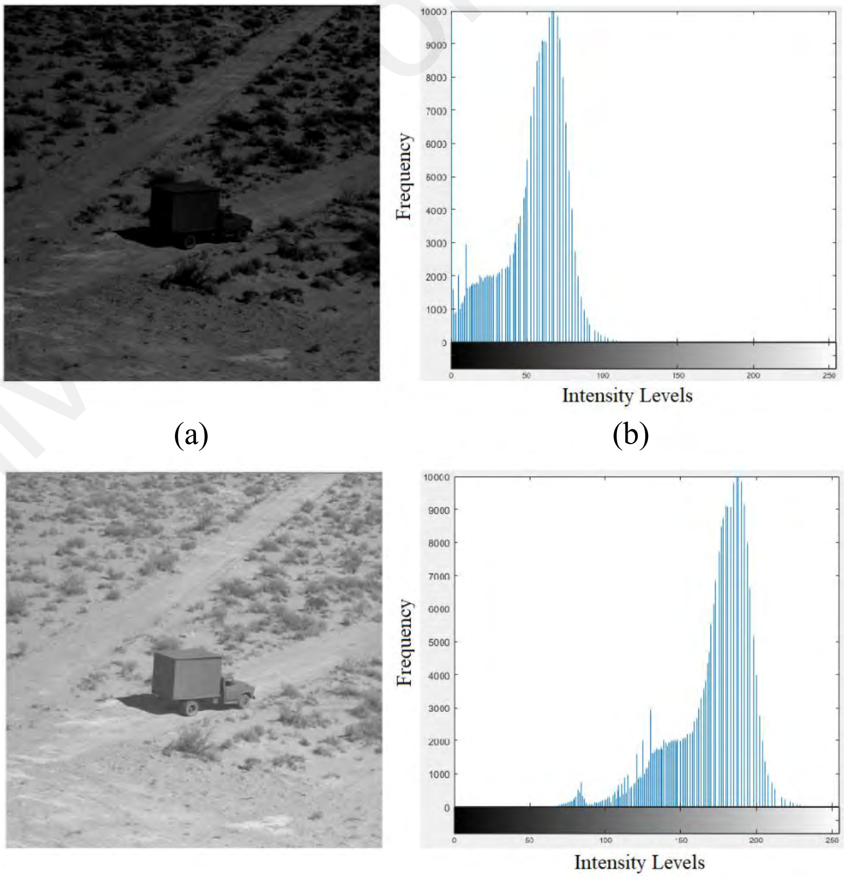
This concept is tightly related to image contrast, which is defined as the difference in intensity between the highest and lowest intensity level in an image. When a vast number of pixels in an image are clustered within a low dynamic range, the image would have a dull appearance. On the contrary, an image with high dynamic range commonly has a clear and high contrast image, as Figure 1.6 shows. Notice that the image in Figure 1.6 is higher contrast than the one in Figure 1.5.



(a) (b)

Figure 1.6: (a) and (b) is an enhanced image and its histogram, respectively. The original image is in Figure 1.5. Notice the difference between this Figure and Figure 1.5

A very common observation is that increasing or decreasing the brightness will not enhance the contrast, as shown in Figure 1.7. Notice the difference contrast between Figure 1.6 and Figure 1.7.



(a) (b)

(c) (d)

Figure 1.7: An example of the effect of brightness manipulation. Image (a) and (b) are the result of decreasing and increasing the brightness by 60 intensity levels, respectively.

To utilize the full dynamic range as in Figure 1.6, a function should be formulated first. This function transforms the pixel intensity from its' current value to another value based on some criteria. This function is called a *transformation function.* Transformation functions will be discussed in more detail in chapter 2.

1.2 Problem Statement

The existing enhancement techniques can be categorized into two groups, global enhancement and local enhancement (C. Lee, Lee, & Kim, 2013). Although they perfectly enhance some types of images, however, each one of them are suffering from some drawbacks. For instance, a method that uses a global technique, may enhance images with overall low contrast very well. But with images that has heterogenous regions, global technique may fail severely. Global enhancement methods transform each pixel of an image using a single transformation function and different parts of image might demand different types of enhancement. Thus, global techniques may create over-enhancement and/or under-enhancement problems at some parts of an image (Rahman et al., 2016).

Local enhancement techniques are proposed to over-come the limitation of global methods. Local enhancement methods construct a transformation function based on the neighborhood pixels (Iwanami, Goto, Hirano, & Sakurai, 2012). However, the lack of global brightness may create artifacts (Celik & Tjahjadi, 2011). Added to that, it is hard to control the amount of enhancement (C. Lee et al., 2013).

To further illustrate the problem of both global and local enhancement methods, tests on a synthetic image was performed, as it is shown in Figure 1.8. The synthetic image consists mainly of two regions. The first region is considered dark and contains the number "1", while, the second region is brighter than the first one and contains the number "2". The synthetic image is tested with a global and a local enhancement method, namely, Adaptive Gamma Correction (AGC) (Rahman et al., 2016) and Contrast-Limited Adaptive Histogram Equalization (CLAHE) (Zuiderveld, 1994), respectively.

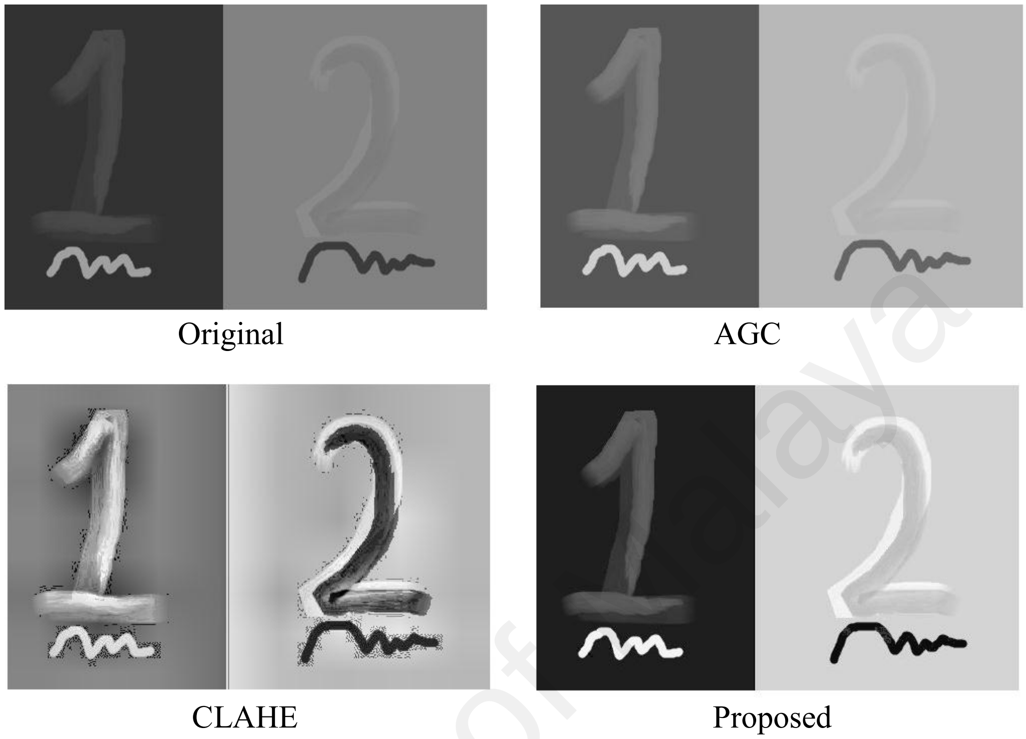


Figure 1.8: Comparative tests of global, local and proposed method on a synthetic input image. AGC and CLAHE are global and local enhancement methods, respectively. CLAHE is applied with a clip-limit = 0.4

The image's average intensity value is 95. AGC categories this image as dark because its' average is less than 127, thus, it brightened the whole image. The dark region is enhanced to some extent while the bright region is de-enhanced. In other hand, CLAHE adapt the local information and enhance each pixel with respect to its rank among the surrounding neighbors pixels (Zuiderveld, 1994). CLAHE enhanced the image strongly and introduced artifacts, as it is clearly shown in Figure 1.8. Added to that, the enhanced image looks unnatural, as it can be seen in the number "2" in both the original and enhanced image.

To over-come the mentioned limitations, a new method should be proposed with respect to image regions, enhancement rate, minimized artifacts and automation of selecting the proper adjustment values.

Enhancing an image that has heterogenous properties (e.g. an image that has bright/dark area and/or has high/low contrast level) may demand different types of enhancement. Thus, segmenting the image before applying any enhancement method is a must. The result from this process will create regions that have coherent properties. Adjusting the enhancement rate properly is important and failing to do so may produce undesired enhancement. To that end, each region should have an appropriate enhancement based on its statistical information.

Local enhancement methods may introduce some artifacts to images, such as halo artifacts and blocking artifacts. Also, they may over-enhance images and\or amplify noises. Therefore, the proposed solution should not create artifacts. However, if any artifacts are founded, it should mitigate those artifacts properly.

Some methods need human intervention to enhance the image probably as in (Girdhar, Gupta, & Bhullar, 2015). However, in many applications, human intervention is not suitable and not effective. Therefore, the proposed method should automatically/adaptively enhance the contrast of images.

To that end, an image contrast enhancement method based on the intensity of regions' pixels was proposed to overcome the previous limitations of image enhancement methods.

1.3 Research Questions

To guide the research path and to achieve the research goal, several questions were formulated.

1. How to segment an image into coherent regions?

2. What is the proper contrast enhancement method to be used for enhancing the regions without introducing artifacts?

3. How to adjust the enhancement parameters without demanding human intervention nor using predefined fixed values?

4. How to evaluate the proposed contrast enhancement method?

1.4 Aim and Objectives of the Research

The aim of this study is to develop an effective contrast enhancement method that divides the images into regions and then enhance each region individually without introducing artifacts. The proposed method should first analyze the images and extract global information. Based on the extracted information, the proposed method should then segment the image into coherent regions. Since each region demands different degree of enhancement, the proposed method should adjust the enhancement parameters, accordingly.

Consequently, four objectives had been set to answer the research questions. They provide a description of the actions that had been taken to achieve the research aim. It proceeds as follow:

- To study and critically analyze the recent techniques of contrast enhancement.
- To develop a method to enhance the contrast of different regions in an image.
- To test and evaluate the proposed method on a variety of images.

- To compare the results found in the proposed method with standard contrast enhancement methods.

1.5 Research Contributions

A very common observation for most of the available methods is that any single method may not achieve good results on different types of images. And the reason is that different types of image may hold different characteristics. To enhance variety of images, complexity of images should be appreciated. Therefore, the proposed method considers this phenomenon by dividing the image into regions and enhance each region based on its' current contrast level. For instance, regions with moderate contrast should be enhanced less than regions with low contrast level. Thus, the proposed method is suitable to be used with a variety types of images, such as, medical images and natural scenes.

The current enhancement techniques either enhance the whole image or divide the image into blocks. Such a simple segmentation technique may not work well. Therefore, in this study, hybrid technique is proposed which segments the image into regions rather than blocks.

Most of the local enhancement methods don't consider the naturalness of the original image. It is true that the contrast enhancement is the main goal, however, enhancing the image dramatically affects the naturalness of the image and makes the image visually unpleasant. Consider for example a natural scene image where preserving the naturalness of the image is an important aspect. The proposed method put this issue into consideration as illustrated in chapter 4 (experimental results).

Finally, one of the goals of this study is to propose parameter-free contrast enhancement method. All the parameters are collected from the image itself and there is no need for human intervention.

1.6 Dissertation Outline

This section describes the main elements of this dissertation. The entire thesis contains five chapters and each chapter convey a distinct idea, yet, they are relevant to each other.

Chapter 1 explains essential background about digital images and contrast enhancement. After that, a problem statement is conveyed with an example. Next, statement of intent is described along with the required steps (an aim and objectives) that had been taken to achieve the desired solution. Finally, contributions and a general outline of this study are pointed out.

In chapter 2, a critical analysis of the literature is reported. Pitfalls of the conventional methods as well as the new methods are exposed. Since contrast enhancement methods can be categorized into two types (global and local) (C. Lee et al., 2013), the chapter is mainly divided into two sections. Global methods are first discussed followed by local methods.

Chapter 3 illustrate the proposed methodology to solve the contrast enhancement problem. The proposed method contains several stages and each stage is explained in detail.

In chapter 4, experimental results are presented. Then, interpretation of the result is explained. Added to that, comparisons between the proposed method and other methods are justified. Consequently, qualitative result as well as quantitative results are reported.

Finally, chapter 5 concludes this study briefly and demonstrates the limitations and further research suggestions.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

The current methods in the literature can be categorized into mainly two groups, namely, global enhancement and local enhancement methods (C. Lee et al., 2013). As it shown in Figure 2.1. Global enhancement methods are more popular in practical applications than local ones due to its' stability and low computational cost (C. Lee et al., 2013; Rahman et al., 2016). However, local enhancement methods are more effective than global enhancement methods because they can improve the regional contrast (Iwanami et al., 2012).

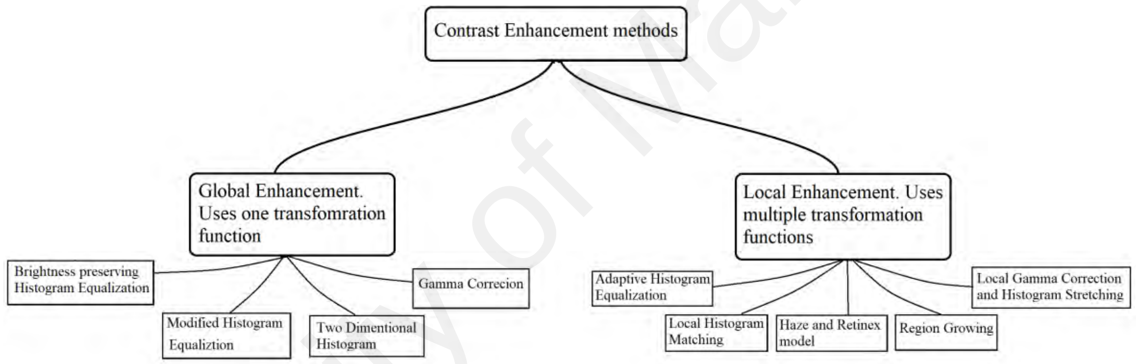


Figure 2.1: Contrast enhancement method types

The difference between the two methods is that, global enhancement methods apply one transformation function for the whole image. On the other hand, local enhancement methods construct a transformation function for each block or -sometimes- for each pixel based on the surrounding neighbors.

2.1.1 Transformation function

The transformation function is, simply stated, a mathematical equation that corrects the pixels intensity. Based on the type of enhancement, a mathematical equation is defined. For instance, to increase a brightness of an image, a simple linear equation is used such as:

$$f(x) = x + c \tag{2.1}$$

The variables $f(x)$ is a transformation function while x and c are an input pixel intensity and a constant variable, respectively. The constant variable c can be set to any value, however, for illustration purpose is fixed to 80. The effect of the previous brightness adjustment equation is show in Figure 2.2.

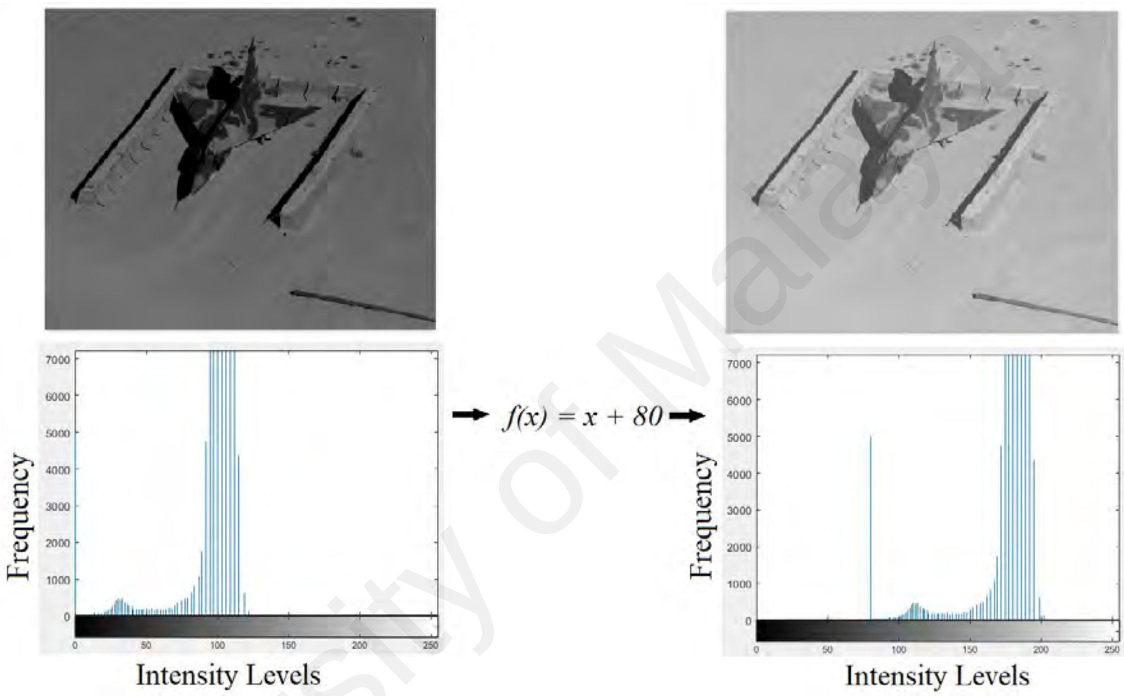


Figure 2.2: An example of a simple transformation function. This function increases the brightness of an image

However, to enhance the contrast of an image, another transformation function is used. For instance, consider this transformation function

$$f(x) = x + (x - 160) \tag{2.2}$$

This function darkens all pixels' intensity below 160 while brightens all pixels' intensity above 160. Better contrast is achieved because pixels' intensities are redistributed over the entire dynamic range. The effect of this transformation function is depicted in Figure 2.3.

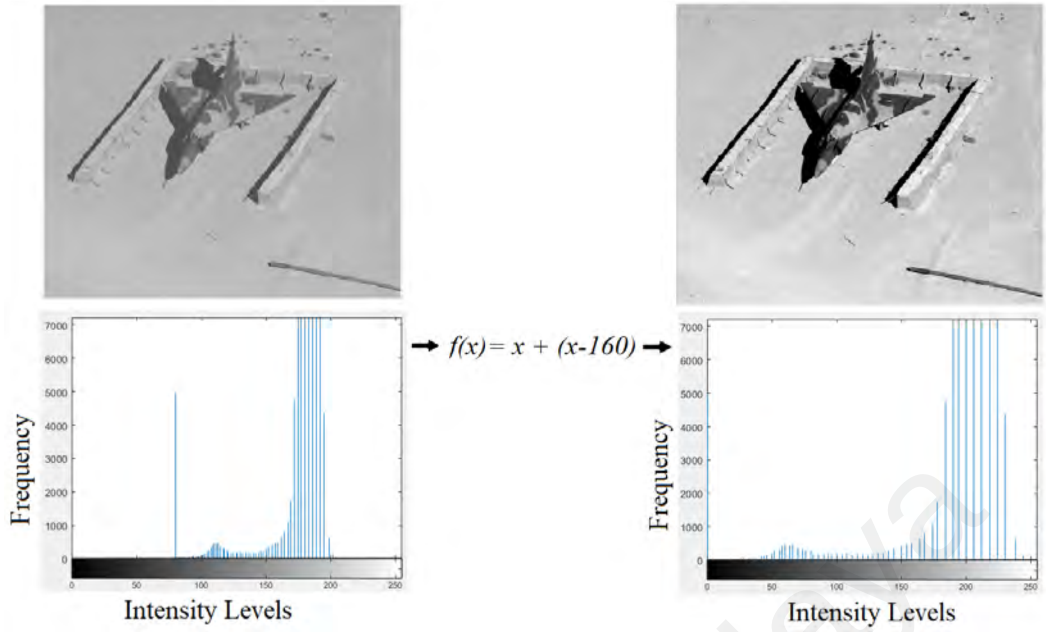


Figure 2.3: Simple transformation function for contrast enhancement.

In this chapter both enhancement methods' types are discussed. Thus, this chapter is divided into two sections. The first section discusses the global methods, while, the second section reviews the local methods.

2.2 Global Contrast Enhancement methods

Global contrast enhancement methods are used frequently in a variety of applications due to its simplicity and its low computational complexity (C. Lee et al., 2013; Rahman et al., 2016). Global enhancement methods analyze the image first, then they produce one transformation function. After that, the transformation function is applied to the entire image pixels.

One of the most remarkable contrast enhancement method is Histogram Equalization (HE) (Gonzalez & Woods, 2006). This method is very old, yet, it is used by so many other enhancement methods in the literature such as in (K. Singh & Kapoor, 2014), (Santhi & Wahida Banu, 2015) and (Tang & Mat Isa, 2017). Therefore, it is convenient to start this section by explaining HE with examples to expose its strength and its weakness.

2.2.1 Histogram Equalization

The most renowned contrast enhancement method is Histogram Equalization (HE) (Gonzalez & Woods, 2006). It applies a monotonic transformation function to the pixels' intensity of an image. The monotonic transformation function is constructed based on the cumulative density function (CDF) of the image's histogram. To further illustrate this method mathematically, let X = {*X(i, j)*} represent a given image consists of *L* discrete intensity levels denoted as $\{x_0, x_1, \ldots, x_{L-1}\}$, where *X(i, j)* denotes an intensity in the image at the pixel location (i, j) and $X(i, j) \in \{x_0, x_1, \ldots, x_{L-1}\}$.

For gray image, x_0=0 and x_{L-1} = 255. Now, for the image X, the probability density function (PDF) is defined as:

$$\mathrm{PDF}(x_k) = \frac{\mathrm{n}^k}{n}, \qquad \text{for } \mathrm{k} = 0, 1, \ldots, \mathrm{L} - 1 \tag{2.3}$$

The variable n^k represents the number of occurrences of intensity level x_k in the image X and n is the total number of pixels in the image. Based on the PDF, the cumulative density function is defined as:

$$\mathrm{CDF}(x_k) = \sum_{0}^{k} \mathrm{PDF}(x_k) \tag{2.4}$$

, or

$$\mathrm{CDF}(x_k) = \mathrm{PDF}(\mathrm{X} \leq x_k) \tag{2.5}$$

Note that $\mathrm{CDF}(x_{255-1})$ = 1, by definition.

Having said that, the transformation function that HE used, is defined as:

$$f(x) = (L - 1) \times CDF(x_k) \tag{2.6}$$

In a case of a gray image L-1= 255. Equation (2.6) becomes:

$$f(x) = 255 \times CDF(x_k) \tag{2.7}$$

The effect of this transformation function can be seen in Figure 2.4, for instance. In Figure 2.4, (a) and (b) are a gray image and its histogram, respectively. The graph (c) in Figure 2.4 is a plot of the constructed transformation function. The enhancement is achieved by mapping the input intensities to the output intensities based on the transformation function. As shown in Figure 2.4 (c), this transformation function compresses intensities that have a low probability while distributes intensities that have a high probability. Thus, in this example, intensities between 0 and 37 have low probability, therefore, they mapped to 0. On the contrary, intensities between 150 and 190 have high probability, thus, they distributed to a range between 150 and 255.

HE uniforms the image's histogram and distributes it over the entire intensity range, which in result, enhance the contrast of the image (Gonzalez & Woods, 2006). However, in some cases HE makes some images either washed out or darker than the original image due to the mean shift that HE produces (Gu et al., 2015).

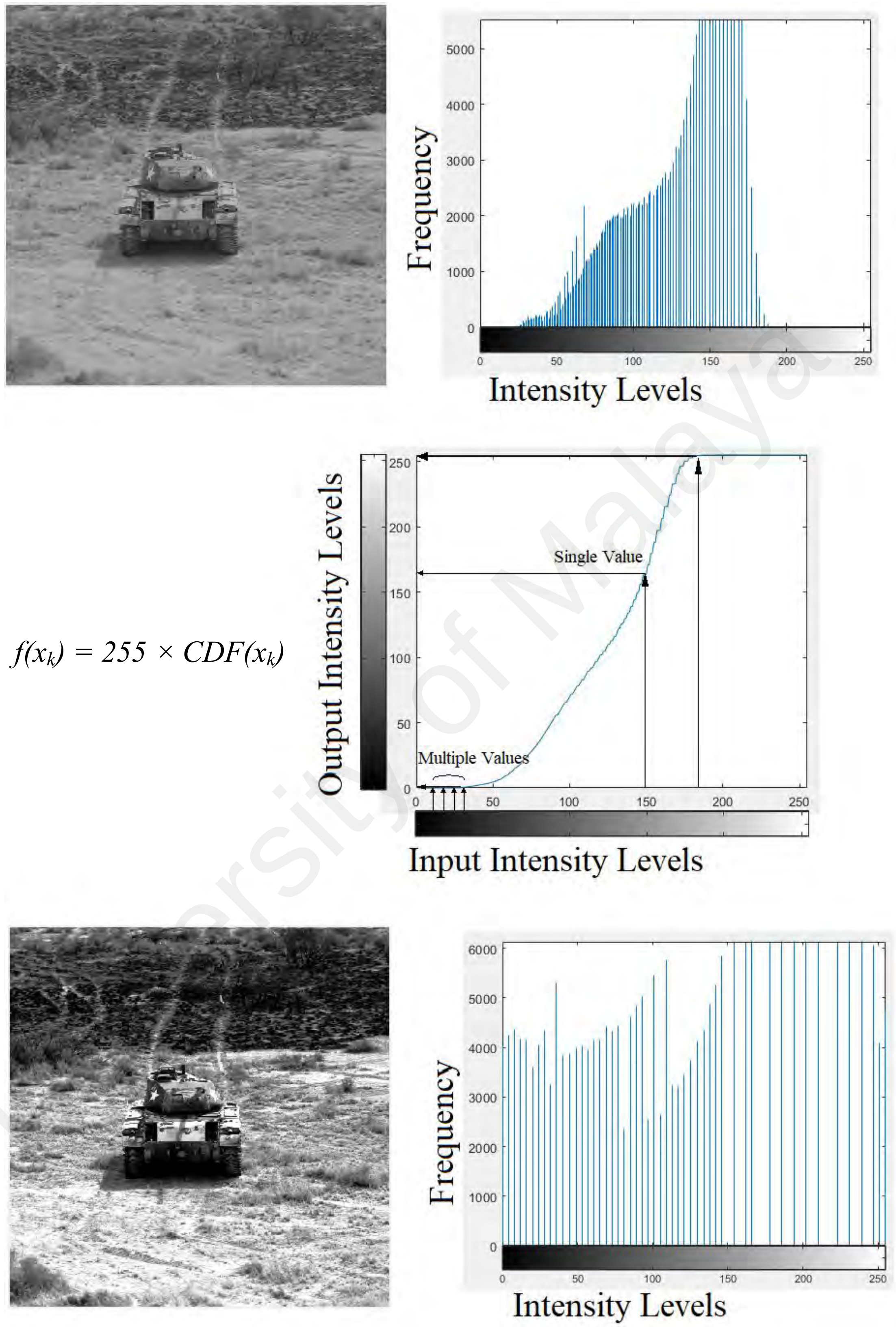


Figure 2.4: An example of the Histogram Equalization (HE) effect. The first row contains an image with its histogram. The second row represents the graph of the transformation function *f(x$_k$)* while the last rows represents the enhanced image with its histogram.

The problem of the mean-shift that HE produces can be clearly seen in Figure 2.5. Therefore, some methods were proposed to preserve the brightness of an image (Jiang et al., 2015).

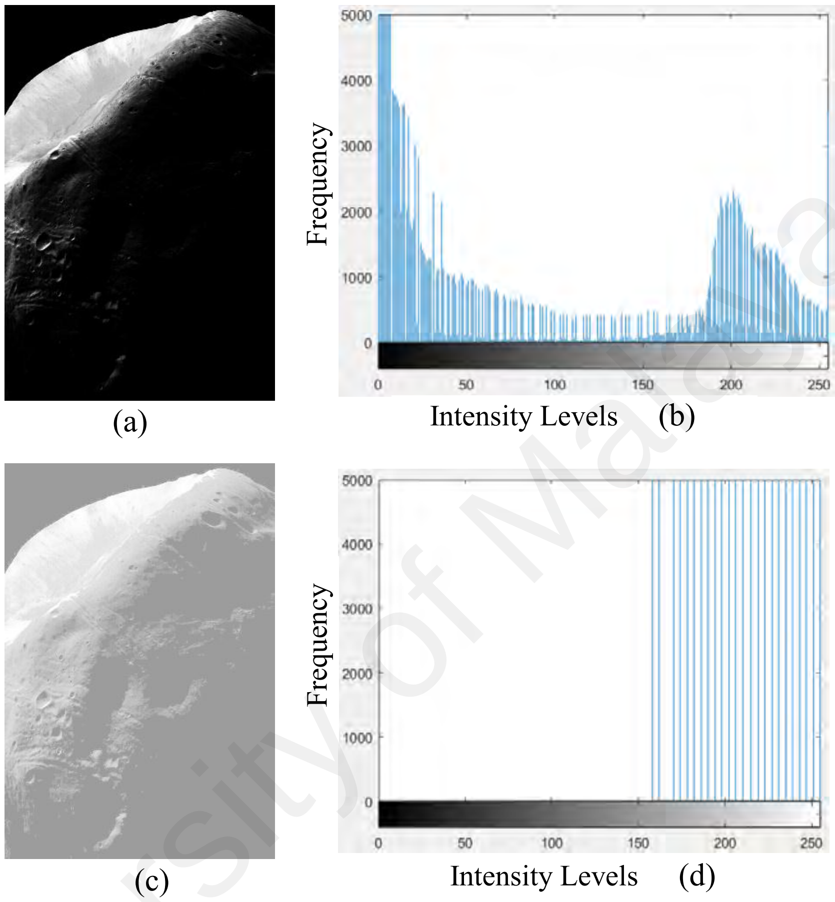


Figure 2.5: An example of the mean-shift that HE produces. (a) and (b) are the original image and its histogram, respectively. (c) and (d) are the enhanced image and its histogram

2.2.2 Modified-Histogram Equalization methods

HE is an effective technique because it spreads the narrow histogram and it is adaptive to the histogram information. However, it may change the brightness dramatically and introduce artifacts (Qadar et. al., 2015), as shown in Figure 2.5. Therefore, HE variations were proposed.

In order to enhance an image and suppress annoying artifacts, image's histogram should be modified before applying HE (Q. Wang & Ward, 2007). They proposed a method called "Weighted Thresholded HE" (WTHE). Their goal was to propose a fast contrast enhancement method for images/videos without creating artifacts. The idea is to clamp the amount of enhancement in HE by modifying the images' probability density function (PDF). To modify the images' PDF, they proposed a power law piecewise function. This function fastens the original PDF at a predefined upper/lower threshold, then transforms all values between the upper and lower thresholds using a normalized power law function with an exponent r > 0. The most important parameter that controls the degree of enhancement is the exponent "r" (Q. Wang & Ward, 2007), yet, this parameter is fixed and it needs to be readjusted manually for different types of applications.

According to (K. Singh & Kapoor, 2014), an image can be classified into under exposed and over exposed based on the histogram bins concentration trends. The method's target is to enhance the contrast of gray scale images that have low exposure. It divides an image's histogram into two sub-histograms (i.e. under exposed and over exposed) based on the following formulas:

$$X_a = L(1 - exposure) \tag{2.8}$$

$$exposure = \frac{1}{L} \times \frac{\sum_{l=1}^{L} h(l)l}{\sum_{l=1}^{L} h(l)} \tag{2.9}$$

Where *L*, *l* and *exposure* are number of intensity levels, an intensity level and measure of intensity exposure of the image, respectively. And *h(l)* is a histogram bin for the intensity level *l*. The process of histogram sub division and clipping is depicted in Figure 2.6.

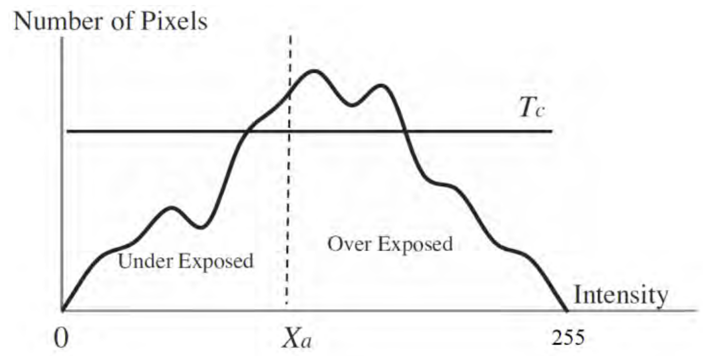


Figure 2.6: The process of histogram sub division and clipping

(K. Singh & Kapoor, 2014)

To manage the enhancement rate, the sub-histograms are clipped using an average number of gray level occurrences T_c, as shown in Figure 2.6. Finally, Histogram Equalization “HE” is applied for each clipped sub-histogram and they are combined to form the enhanced image. Although this method is easily implemented, and it doesn’t demand any parameters, the image brightness may get over-enhanced and may produce unsatisfactory results (Z. Huang et. al., 2016).

The previous approach is also adapted by (Santhi & Wahida Banu, 2015). The goal is to enhance the images while at the same time maintain the mean brightness. First, the input image’s histogram is divided into four sub-histograms based on its median, recursively. To clamp the enhancement rate, the sub-histograms are clipped based on the image mean. Finally, HE is applied to each sub-histogram individually. This method successfully preserves the original brightness, however, preserving the brightness is not always a demanding feature such as in dimmed images where enhancing the brightness is essential.

A similar approach based on dividing the image histogram was proposed by (Tang & Mat Isa, 2017). The aim is to address HE problems, specially, its’ adverse feature of over-emphasizing of histogram bins with enormous frequency. To preserve the brightness, the proposed method divides the image's histogram into two sub-histograms by using the median. Then, the probability density function "PDF" of each sub-histogram are modified to prevent the low bins from being compressed by the dominant bins. The first and second sub-histogram's PDF are modified using Equation (2.10) and Equation (2.11), respectively.

$$new\_PDF_{first}(l) = log\left[PDF_{first}(l) + 1\right] \tag{2.10}$$

$$new\_PDF_{second}(l) = log[PDF_{second}(l) + 1] \tag{2.11}$$

Where $PDF_{first}(l)$ and $PDF_{second}(l)$ is the PDF of the intensity level l of the first and second sub-histogram, respectively. Finally, both sub-histograms are enhanced by using HE method, individually. An example is depicted in Figure 2.7 to show the effect of this method (Tang & Mat Isa, 2017).

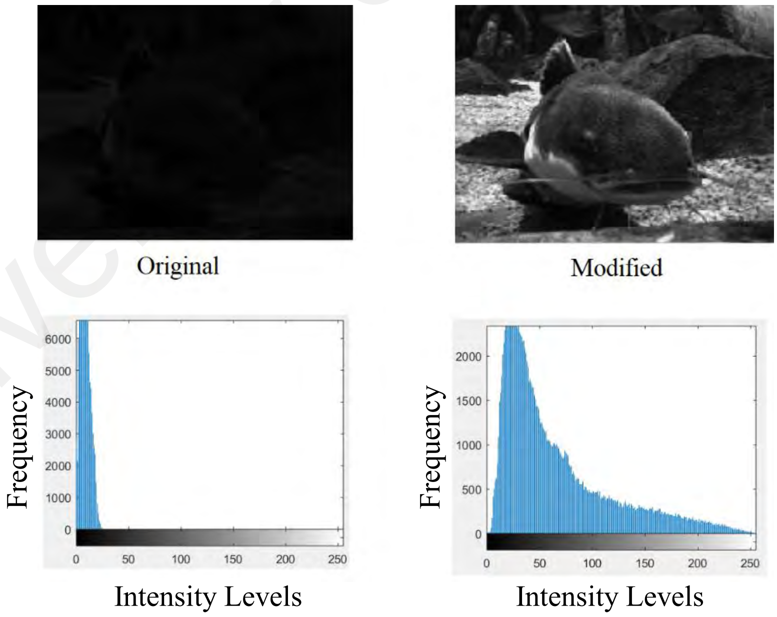


Figure 2.7: An example of enhancing an image by modifying its histogram. (Tang & Mat Isa, 2017)

2.2.3 Two-Dimensional Histogram Enhancement

Histogram Equalization based enhancement methods enhance the images to some extent. However, the enhanced images may suffer from severe distortions. Therefore, non-HE global enhancement methods were proposed. All previous methods don't consider the spatial information; thus, they fail to enhance the image effectively or they introduce unpleasant artifacts.

(Celik & Tjahjadi, 2011) acknowledged the importance of the local spatial information and proposed a method called "Contextual and Variational Contrast Enhancement" (CVC). CVC construct a transformation function based on a two-dimensional histogram. The 2-D histogram is constructed by dividing the image into blocks and recording the numbers of intensity pairs within each block. This 2-D histogram is modified with a priori probability that emphasis the probability of the high intensity differences. Furthermore, a smooth 2-D target histogram is constructed by minimizing the Frobenius norm of the modified input 2-D histogram and the uniformly distributed 2-D histogram. Finally, the enhancement is achieved by mapping the diagonal elements of the input 2-D histogram to the diagonal elements of the target histogram. CVC achieved good results compared with previous methods, however, it suffers from high computational complexity. Added to that, CVC doesn't treat large histogram values properly, thus, it may create over-enhancement artifacts (C. Lee et al., 2013).

Using the 2-D histogram, Lee proposed different enhancement technique called "Layered Difference Representation of 2-D Histogram" (LDR) (C. Lee et al., 2013). LDR construct a logarithmic 2-D histogram for each intensity-level pair and calculate the distance for each pair. The distances are ordered in a tree-like shape structure (C. Lee et al., 2013). The goal is to construct a transformation function that assign a high distance value to pairs that occur frequently in an input image. LDR assumes that all pixels have the same importance though background regions are less important than foreground objects (J.-T. Lee et. al., 2014).

2.2.4 Gamma Correction

(S.-C. Huang, Cheng, & Chiu, 2013) proposed “Adaptive Gamma Correction with Weighting Distribution” (AGCWD). AGCWD applies normalized power-law function to the histogram of an image -as in (Q. Wang & Ward, 2007)- then it uses an adaptive gamma correction instead of HE. The gamma parameter in AGCWD is defined as a complement of the cumulative density function (CDF) of the weighted histogram. AGCWD may not give satisfactory results because the amount of enhancement is bounded by the minimum and maximum pixel’s intensity which means that this method doesn’t utilize the full dynamic range in some cases.

Different types of images may demand different types of enhancement techniques. Consequently, (Rahman et al., 2016) proposed a method called “ Adaptive Gamma Correction for image enhancement” (AGC). AGC categorizes an input image based on its statistical information. If the image has a standard deviation $\sigma \leq 21.25$, then it considered as a low contrast image, otherwise, the image is considered as a moderate or high contrast. This threshold was set empirically. Moreover, AGC further divide the both categories into bright image and dark image. Based on their method, the image is considered bright if its mean $\mu \geq 127.5$ and dark otherwise. The enhancement is achieved by applying the gamma function and it is formulated as $c \times I^{\gamma}$ where c, I and γ are a constant that control the brightness, input image and gamma value, respectively (Rahman et al., 2016). Note that, the gamma function here (denoted as “γ”) is different from the gamma function in Mathematics (denoted as “Γ”). The low and moderate-high categories have different gamma value. Figure 2.8 illustrate the transformation function for each type.

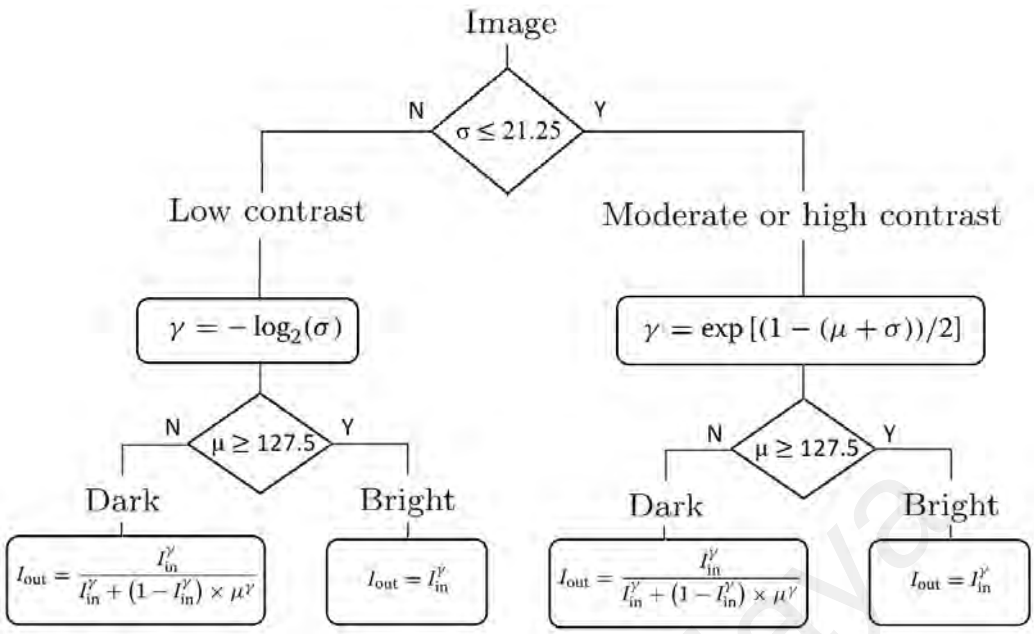


Figure 2.8: Transformation functions of AGC for each image category.

AGC achieved satisfactory results in some cases but it fails to enhance images that have mixture of different illuminations and\or contrast levels. In such cases, AGC will fail to categorize the images, thus, it may enhance part of the image while at the same time de-enhance the other parts.

All the discussed global enhancement techniques are summarized along with their advantages/disadvantages in Table 2.1.

Table 2.1: Summary of global enhancement methods with their advantage/disadvantage

Author	Method	Advantages	Disadvantages
(Gonzalez & Woods, 2006)	It applies a monotonic transformation function to the pixels' intensity of an image. The monotonic transformation function is constructed based on the cumulative density function (CDF) of the image's histogram.	- It uniforms the image's histogram and distributes it over the entire intensity range. - It is easy to be implemented and has low computational complexity.	- Suffers from mean shift problem which in-return de-enhance the images. - The amount of enhancement needs to be controlled.
(Q. Wang & Ward, 2007)	It Clamps the amount of enhancement in HE by modifying the images' probability density function (PDF) by using a power law piecewise function.	- It doesn't create artifacts. - It has low computational complexity	- Not suitable for all types of images. - The most important parameter (exponent) in this method -that controls the degree of enhancement- is set manually.
(Celik & Tjahjadi, 2011)	A 2-D histogram is constructed. Then, it is modified with a priori probability that emphasis the probability of the high intensity differences. A smooth 2-D target histogram is constructed by using the modified 2-D histogram. the enhancement is achieved by mapping the diagonal elements of the input 2-D histogram to the diagonal elements of the target histogram.	- The method acknowledges the importance of the local spatial information.	- It doesn't treat large histogram values properly, thus, it may create over-enhancement artifacts.

Table 2.1, Continue

Author	Method	Advantage	Disadvantage
(C. Lee et al., 2013)	This method constructs a logarithmic 2-D histogram for each intensity-level pair and calculate the distance for each pair. The goal is to construct a transformation function that assign a high distance value to pairs that occur frequently in an input image.	- Doesn't produce artifacts	- It assumes that all pixels have the same importance though background regions are less important than foreground objects.
(S.-C. Huang et al., 2013)	It a applies normalized power-law function to the histogram of an image. Then it uses an adaptive gamma correction instead of HE. The complement of the cumulative density function of the weighted histogram is the gamma parameter in this method.	- Produce good result if the images have a dim appearance. - Doesn't produce artifacts.	-It may not give satisfactory results because the amount of enhancement is bounded by the minimum and maximum pixel's intensity.
(K. Singh & Kapoor, 2014)	It Divides an image's histogram into under exposed and over exposed. Furthermore, each sub-histogram is clipped to manage the enhancement rate. Finally, Histogram Equalization is applied to each sub-histogram.	- It successfully enhances the contrast of gray scale images that have low exposure. - This method is parameter-free.	- The images' brightness may get over-enhanced and may produce unsatisfactory results

Table 2.1, Continue

Author	Method	Advantage	Disadvantage
(Santhi & Wahida Banu, 2015)	The input image's histogram is divided into four sub-histograms based on its median, recursively. To clamp the enhancement rate, the sub-histograms are clipped based on the image mean. Finally, HE is applied to each sub-histogram individually.	- It maintains the mean brightness of an input image.	- Preserving the brightness is not always a demanding feature such as in dimmed images where enhancing the brightness is essential.
(Rahman et al., 2016)	An input image is categorized into four groups based on its statistical information. The enhancement is achieved by applying a gamma function with different parameters for each category.	- It enhances a variety types of images. - Doesn't produce artifacts	- It fails to enhance images that have mixture of different illuminations and\or contrast levels.
(Tang & Mat Isa, 2017)	The images' histogram is divided into two sub-histograms based on the median. Then, PDF of each sub-histogram are modified by using logarithmic function to prevent the low bins from being compressed by the dominant bins. The enhancement is achieved by applying HE to both sub-histograms.	- it prevents HE's adverse feature of over-emphasizing of histogram bins with enormous frequency.	- it doesn't produce satisfactory results.

All previous methods use an image information for constructing one transformation function to enhance the contrast of the entire image. They tend to fail to enhance all types of images because they apply one transformation function only, though, different parts of the images may demand different transformation function. To achieve a maximum enhancement, multiple transformation functions must be employed. Those methods are called local enhancement methods and they will be discussed in the next section.

2.3 Local Contrast Enhancement methods

Local contrast enhancement methods construct a transformation function to enhance each pixel or each block in an image. In other words, the image will have multiple transformation functions. Although this approach is more effective than the global methods, local enhancement methods have several problems such as over-enhancement and computational complexity (Celik & Tjahjadi, 2011; Rahman et al., 2016). This section will go through various local contrast enhancement methods and will critically analyze them.

2.3.1 Adaptive Histogram Equalization (AHE)

Technical Report was made by Pizer et al. describing adaptive histogram equalization and its variations (Pizer et al., 1986). The word "adaptive" means that a method is adapting the change within specific area, such as a block, and the enhancement is applied accordingly. Each intensity pixel is transformed based on the histogram of the surrounded pixels (Contextual Region) (Pizer et al., 1986). Although the enhancement is effective, it suffers from a high computational complexity. Added to that adaptive enhancement introduces over-enhancement and noise amplification.

2.3.2 Variations of Adaptive Histogram Equalization

To solve the high complexity calculations, JY Kim introduced partially block-overlapped histogram equalization (Joung-Youn Kim, Lee-Sup Kim, & Seung-Ho Hwang, 2001). Instead of applying HE to each pixel surrounded by a block of pixels, JY Kim applied the HE to the whole block then he shifted the block by a predefined step-size. The enhancement is achieved by applying histogram equalization for each sub-block. Therefore, some areas will be equalized more than one time. To eliminate the blocking artifacts, JY Kim proposed blocking effect reduction filter (BERF) (Joung-Youn Kim et al., 2001). BERF is a low-pass filtering effect of 15 by 15 convolution mask. According to (Joung-Youn Kim et al., 2001), this filter eradicates the blocking artifacts and adjust the brightness of neighboring sub-blocks to be equal. However, at some sub-block boundaries, intensity-level discontinuities may be generated and appears as blocking effects. To distinguish between the original image's edges and the artifact boundaries, the edge information of the original image can be used for each block.

2.3.3 Local Histogram Matching

To solve the over-enhancement artifacts of the adaptive HE, Iyad proposed a method that employ the Histogram Matching method (Jafar & Ying, 2007). Histogram Matching (HM) is a contrast enhancement method that maps the intensity levels of an image's histogram based on a desired histogram distribution. The mapping is achieved, such that, the difference between the corresponding values of the input and output cumulative distribution functions is minimized. Particularly, for each input intensity level *i* the output intensity level o is selected such that:

$$o = \arg min_{o \in [0,255]} |CDF_{input}(i) - CDF_{desired}(o)| \quad (2.8)$$

After that, a block is drawn around each pixel then the centered pixel is enhanced by applying Histogram Matching technique (Gonzalez & Woods, 2006). For each pixel surrounded by neighborhood, the target histogram is automatically calculated to satisfy two conditions, **(i)** the target histogram should be close to the uniform distribution as in the HE method and **(ii)** the target histogram's mean brightness should be the same as the original histogram's mean brightness. To that end, (Jafar & Ying, 2007) proposed 4 linear transformation functions based on the original histogram's mean brightness. The computational complexity of this method is severely high.

2.3.4 Haze and Retinex model

All the previous local methods are using Histogram Equalization (HE) in one way or another to enhance the images. However, HE-based methods have several disadvantages. Therefore, none-HE based methods were proposed.

To enhance the contrast of hazy images, (Kaiming He, Jian Sun, & Xiaoou Tang, 2011) proposed a method that uses a dark channel prior and a conventional haze model. The formula of the conventional haze model is defined as follows (Fattal, 2008):

$$I(x) = J(x)t(x) + \big(1 - t(x)\big)A \tag{2.9}$$

where *I(x)* is the observed intensity, A represents the global atmospheric light, J is the scene radiance and t is the medium transmission represents the light that reach the camera and not scattered. With a homogenous atmosphere, $t(x) = e^{-\beta d(x)}$, where β and $d(x)$ are scattering coefficient of the atmosphere and the pixel's scene depth. Notice that when the scene depth increase, the amount of a scattering is also increased which increase the haziness, as shown in Figure 2.9.

(a) (b)

Figure 2.9: an example of a hazy image. (a) and (b) are the original and enhanced image, respectively

Thus, to enhance hazy-outdoor images, it is crucial to estimate t. Now, to recover the scene radiance, the previous Equation (2.9) became

$$J(x) = \frac{I(x) - A}{t(x)} + A \tag{2.10}$$

To estimate A and t, they proposed a dark channel prior. The dark channel prior is a matrix that holds statistics values of the haze-free outdoor images. Their assumption is that at least one of the three-color channels (RGB) has very low intensity at some pixels within a block. To define the dark channel prior mathematically, let I is an input image, x is an intensity pixel and Ω is a block centered at x. Then the dark prior channel is defined as:

$$dark(x) = \min_{c \in \{R,G,B\}}(\min_{y \in \Omega(x)}(I^c(y))) \tag{2.11}$$

The atmospheric light A can be estimated by taking the brightest intensity in the dark prior channel and the transmission map is formulated as follows:

$$t = 1 - \frac{c \times dark(x)}{A} \tag{2.12}$$

Where c is a constant. Note that t is calculated for each pixel centered in a block.

This method enhances the contrast of hazy to some extent. However, this method is a local enhancement method, hence, it inherits the problem of the local techniques such as over-stretching and high computational complexity (Kim et. al., 2013).

Inspired by the hazy model, Dong proposed a method to enhance low light images and videos (Dong et al., 2011). He noticed that by inverting the intensities of dark images, they would become similar to hazy images. Figure 2.10 is an example taken from (Dong et al., 2011).

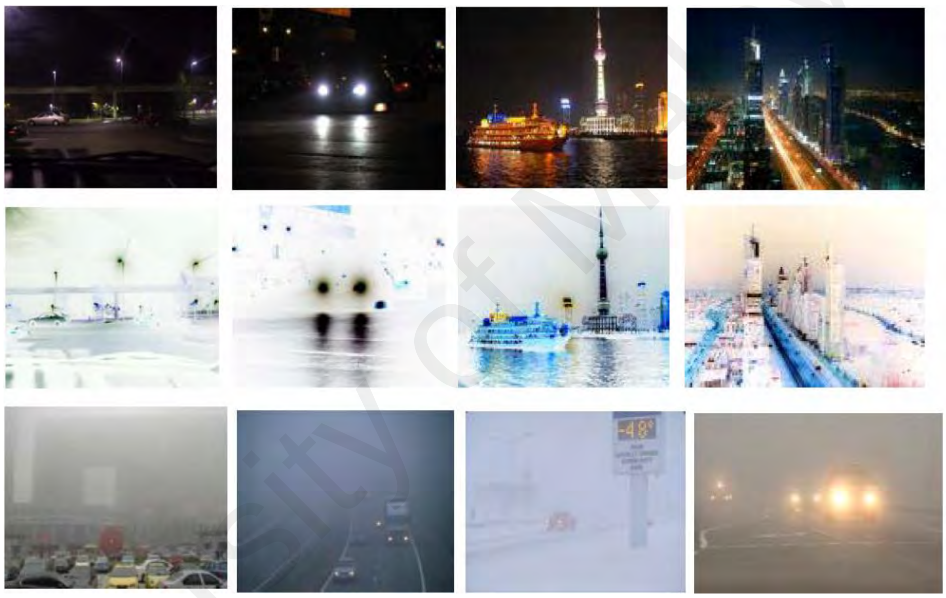


Figure 2.10: First row: dark images. Second row: inverted images of the first row. Third row: haze examples (Dong et al., 2011)

After inverting the images, the enhancement is achieved by applying the previously explained method (Kaiming He et al., 2011). Then the images are inverted back again. This method estimates the atmospheric light by selecting a pixel with the highest sum of RGB channels. The transmission map $t(x)$ is equal to the one in (Kaiming He et al., 2011) if $0.5<t(x)<1$, or $t(x)=2t(x)^2$, otherwise. Empirically, it found that the estimated $t(x)$ emphasis the enhancement of low-lighting areas. This method enhance the dark images to some extent, however, the basic model that they depend on is lacking in physical explanation (Guo, Li, & Ling, 2017).

Another technique is proposed to improve the visuality of dark images (D. Wang, Niu, & Dou, 2014). This technique is based on a piecewise stretch function on the Luminance component extracted with Retinex theory in HSV color model. Retinex theory was originally proposed by (Land, 1977) and it decomposed the observed pixel's intensity to luminance component "L" and reflection component "*R*". The formalization of this model as:

$$I(x, y) = L(x, y) \times R(x, y) \tag{2.13}$$

Where I represent the observed intensity level at location (*x, y*). The luminance component of the pixel at location (*x, y)* can be estimated within a block by using the Gaussian transformation as a convolution function, as follows:

$$L(x, y) = G(x, y) * I(x, y) \tag{2.14}$$

The "*" represents a convolution operator. In other words, the luminance component is estimated by calculating the Gaussian average around the pixel at location (x, y). Now, the proposed method in (D. Wang et al., 2014) convert the RGB color model to HSV to get the value channel (i.e. HSV color model). Then, the luminance component *L(x, y)* is extracted from the value channel using the Retinex model. After that, it inverts it. Next, it applies non-linear piece-wise mapping function to enhance the inverted luminance component. Finally, the method inverts back the luminance component and merged into the value channel again. The entire process is depicted in Figure 2.11 (D. Wang et al., 2014).

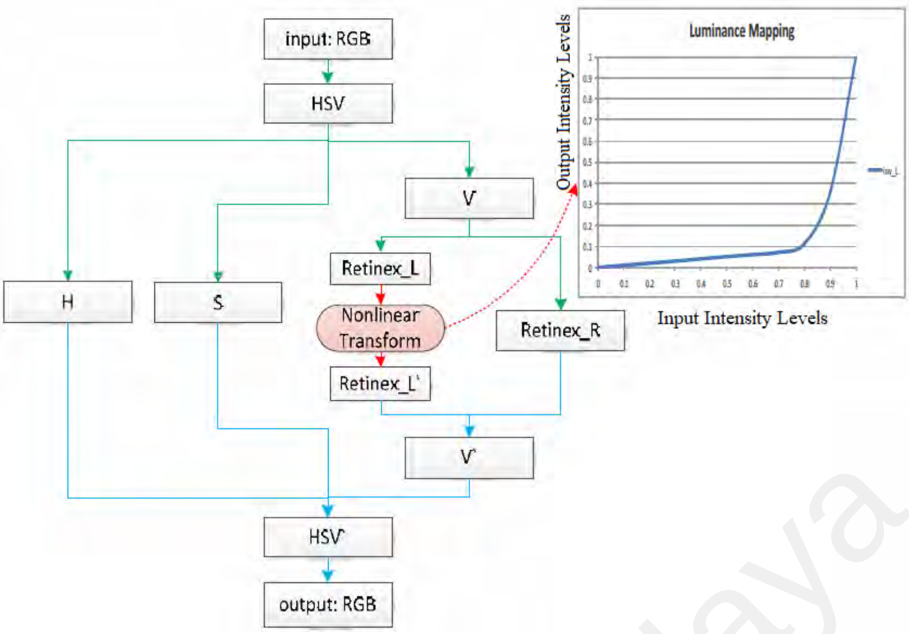


Figure 2.11: The framework of the proposed method (D. Wang et al., 2014)

According to (Jianhua Pang, Zhang, & Wencang Bai, 2017), this enhancement method suffers from halo artifacts and it doesn't work well with very dark images.

2.3.5 Region growing methods

Contrast enhancement is an important aspect of medical image processing domain. In fact, the old conventional contrast enhancement methods were proposed to enhance medical images (Pizer et al., 1986). Some methods divide a medical image into foreground and background in order to enhance only the foreground. To do so, those methods selects a seed point and add the neighbors' pixels based on a threshold, hence, this process called "Region Growing". Single seed may be selected as in (Verma, Hanmandlu, Susan, Kulkarni, & Jain, 2011), or multiple seeded as in (Senthilkumar, Umamaheswari, & Karthik, 2010). It is concluded from the literature that region-growing based algorithms needs to be further strengthen (Girdhar et al., 2015).

Ultrasound images have two constrains: **(i)** They suffer from low contrast and **(ii)** they have speckle noise (Girdhar et al., 2015). Therefore, Girdhar et al. proposed a region-growing based contrast enhancement (Girdhar et al., 2015). This method consists of several stages. The first and second stages are drawing a polygon around the Region of Interest (ROI) manually and selecting the center pixel, respectively. The third stage is dividing the ROI into foreground and background using a region growing technique. Extracting the foreground is based on the following equation:

$$\frac{I(x,y) - mean}{mean} \leq \frac{\min\left(\frac{|I-mean|}{mean}\right)+\max\left(\frac{|I-mean|}{mean}\right)}{2} \tag{2.15}$$

Where I is the input ROI and mean is the average intensity. If the mean intensity is assumed to be 127.5 and the lowest and highest intensity are 0 and 255, respectively. Then based on the previous equation, the proposed method will include all pixels that has an intensity $I(x, y) \leq 191.25$. In other words, a pixel is considered as a background if it has a very bright intensity. Finally, the foreground is enhanced using a simple linear stretching formula. This method successfully preserves the homogeneity between pixels within the ROI, due to the use of the linear stretching function for enhancement. However, this method doesn't work well with images that are complex and contain multiple heterogenous regions. Added to that, selection of the ROI demands human intervention, which is not suitable for many applications. Consequently, (Kaur, Girdhar, & Kanwal, 2016) designed an algorithm to mitigate the noises and to extract ROI automatically. To remove the blurriness and alleviates salt-and-pepper noises from CT images, Gaussian filter and Median filter are used. However, to remove multiplication noises, a curvelet transformation technique is used as in (M, 2012). To extract the ROI, level set function is used (C. Li, Xu, Gui, & Fox, 2005). After extracting ROI, un-sharp masking is used, and the result image is overlapped with the original image.

2.3.6 Local Gamma Correction and Local Histogram Stretching

Some images that are captured in non-uniform illumination conditions suffer from low visibility, thus, it is hard to perceive the details. To enhance such images, (Y. Li, Liu, & Liu, 2015) proposed a method called “Adaptive local gamma correction based on mean value adjustment”. The aim of this method is to enhance both local and global contrast. Accordingly, this method applies one global gamma transformation function for the entire image to enhance the global contrast. Then, for each pixel surrounded by neighborhood pixels, a local gamma function is calculated and used to enhance the local details. The global gamma function is defined as:

$$f(x) = 255 \times \left(\frac{x}{255}\right)^{\frac{1}{1 + a\cos\left(\frac{\pi x}{2 \times 128}\right)}} \tag{2.16}$$

Where *a* is a constant and its default value is 0.4 (Y. Li et al., 2015). The transformation graph of this formula is depicted in Figure 2.12 (the red curve represents the transformation function). As it shown from the graph in Figure 2.12, this transformation function increases the brightness of the dark pixels and vice versa for the bright pixels. However, this transformation function is not enough to extract the hidden details. Therefore, they proposed local gamma function to enhance the contrast locally in addition to the previous function.

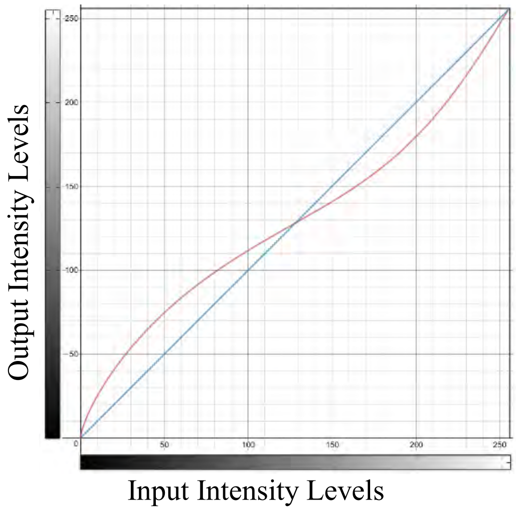


Figure 2.12: Graph of the proposed global Gamma function in (Y. Li et al., 2015)

The local contrast is enhanced by increasing the difference between a pixel and its neighborhood (Y. Li et al., 2015), thus, more difference means stronger contrast. To control the amount of enhancement locally, the proposed method modifies the local histogram within a block before applying a local gamma correction. The local gamma enhancement function in this method is defined as

$$g(x) = 255\left(\frac{x}{255}\right)^{1-k\times cdf_{\Omega}^{\sim}(x)} \quad (2.17)$$

Where $cdf_{\Omega}^{\sim}$ is modified cumulative density function of a square window whose center is the current pixel x. And k is a constant calculated based on the local mean value. This method requires high computational time. Added to that, the used global transformation function is not adaptive to the image's histogram, therefore, some image may de-enhanced, instead.

(Abdul Ghani & Mat Isa, 2015) proposed "dual-image Rayleigh-stretched contrast-limited adaptive histogram specification". The aim is to enhance the visibility and contrast of underwater images. They enhance the image globally and locally to correct the images' color and to improve their contrast as well. To enhance the image globally, the proposed method stretches the histograms of the three-color channels (i.e. RGB), individually. The stretching is achieved by dividing the histograms into two parts from the middle, then, the first part is stretched to 95% of the entire dynamic range. Similar procedure is applied to the second part also, as depicted in Figure 2.13. All first parts of the corresponding color channels are composed to form over-enhanced image and same procedure is applied to the second part to form under-enhanced image. An average between the two generated image is taken to form the globally enhanced image. Now, to enhance the color, the globally enhance image are decomposed into HSV. S and V are enhanced using clap-limited histogram specification CLAHS; which divides an image into tiles and each tile is enhanced using Histogram Specification as in (Gonzalez & Woods, 2006). The Rayleigh distribution is used in CLAHS as a mapping guide.

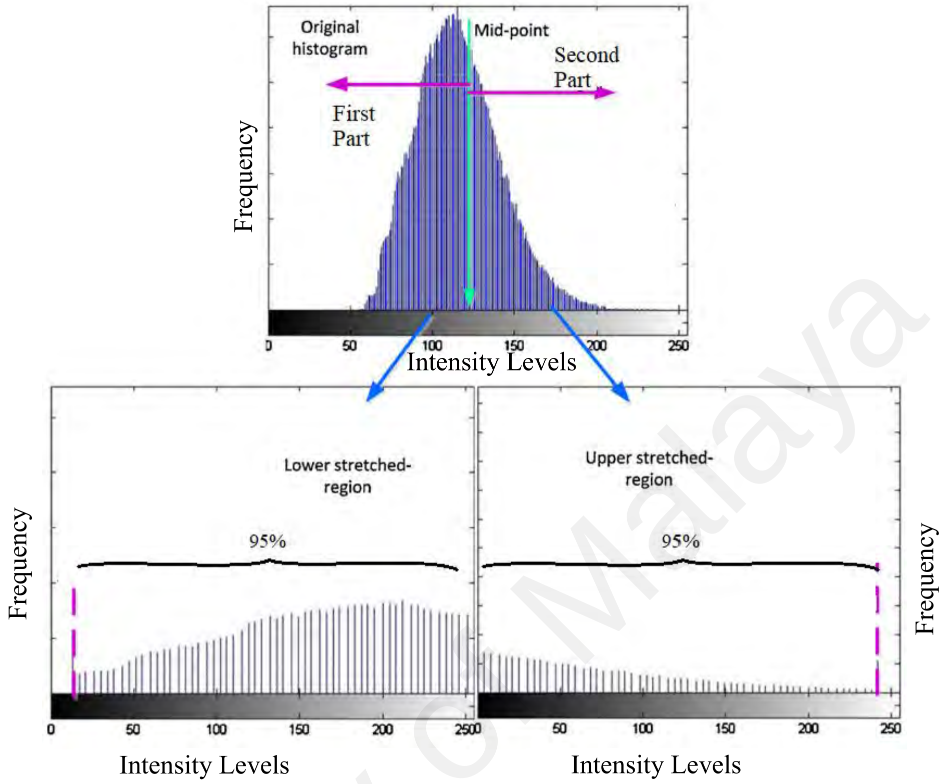


Figure 2.13: Sub-histogram stretching applied to RGB channels individually (Abdul Ghani & Mat Isa, 2015)

A simple local enhancement method was proposed by (A. Singh, Yadav, & Singh, 2016). Their goal was to use the global brightness information to enhance the local contrast while preserving the brightness of the original image. Within a sub-block of 3-by-3 pixels, the following transformation function is used:

$$O(x,y) = I(x,y) + [local_{mean} - global_{mean}] \tag{2.18}$$

Where $O(x,y)$, $I(x,y)$, $local_{mean}$ and $global_{mean}$ are the output pixel, input pixel, mean of the current block and mean of the image, respectively. The motivation behind this formula is to utilize the full dynamic range and stretch the histogram by darken and brighten the intensities below and above the image's mean, respectively. This method is simple and fast; however, it may de-enhance the images that have different illumination regions. The limitations of this method are discussed in the next chapter.

According to (Liu & Zhao, 2014; Zhang, Xie, Ma, & Qin, 2014), retaining the brightness and enhancing the contrast are both important criteria in image enhancement methods. Therefore, Huang proposed an adaptive method to enhance low-contrast near-infrared images while at the same time retaining the brightness (Z. Huang et al., 2016). The near-infrared images are captured with 8-bit imaging system, which means that they are gray images. They constructed the following formula to enhance each pixel in an image with respect to its' neighbor pixels:

$$I_{out}(x) = I_{in}(x)\left(\frac{I_{in}(x)}{\frac{1}{|W_x|}\sum_{y\in W_x} I(x,y)}\right)^{\gamma} \tag{2.19}$$

Where I, I_{out}, y, W_x and $|W_x|$ represent the input image, the output image, the neighbor of the pixel point x, the neighborhood set of the pixel point x, and the total number of the set, respectively. To simplify this equation, it can be rewritten as follows:

$$I_{out}(x) = I_{in}(x)\left(\frac{I_{in}(x)}{\mu(W_x)}\right)^{\gamma} \tag{2.20}$$

Within a block of pixels, this formula always darkens the targeted pixel if it is below the block's mean $\mu(W_x)$ and vice versa if it is above the block's mean $\mu(W_x)$, as shown in Figure 2.14. Generally, the Gamma value "γ" in this equation doesn't dramatically change the behavior as in Traditional Gamma Correction "TGC" (Gonzalez & Woods, 2006). In TGC, darkening or brightening the pixels depends on whether "γ" is bigger than 1 or not, respectively (Song, Wang, & Bai, 2016).

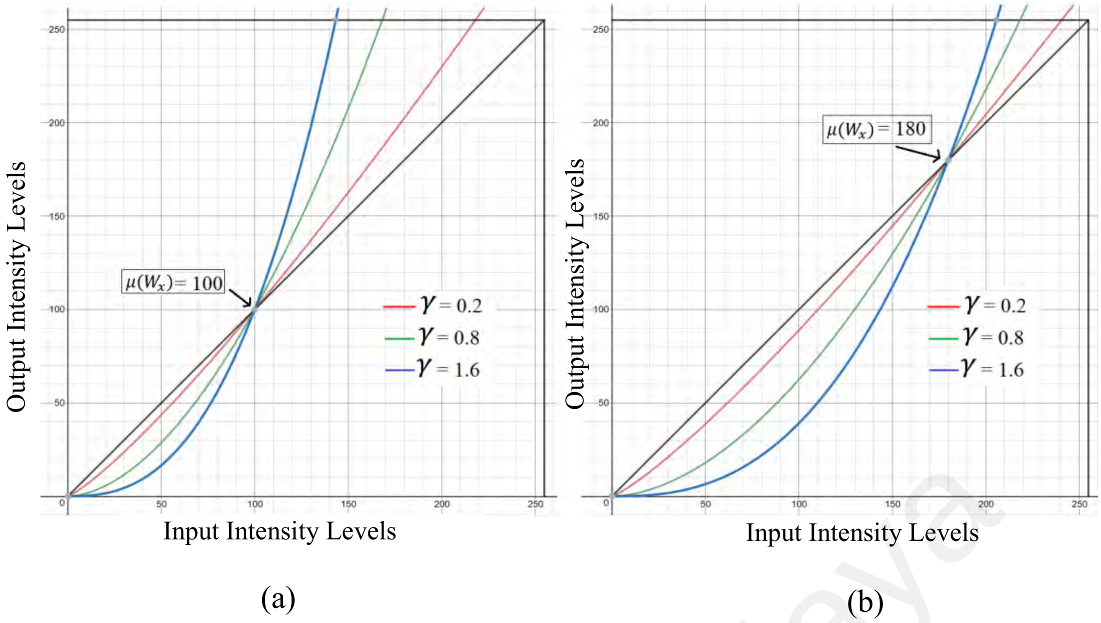


Figure 2.14: Transformation curves created by Equation (2.20) with different values of γ. (a) and (b) are the transformation function with a block's mean intensity of 100 and 180, respectively.

Note that, the transformation curve after the mean value $\mu(W_x)$ has a sharp incline. For instance, look at the green curve in Figure 2.13 (a); all targeted pixels that has a value x > 166 are mapped to one value 255. This indicates that the intensity range [167-255] is compressed to 255. The Gamma value γ is defined as:

$$\gamma = 1 - CDF(x) \tag{2.21}$$

Where CDF(x) is the cumulative density function of the intensity x. According to (Z. Huang et al., 2018; Tan, Li, & Guan, 2017), this Gamma method may yield saturation artifacts and loss of details in luminous regions.

All the discussed global enhancement techniques are summarized along with their advantages/disadvantages in Table 2.2.

Table 2.2: Summary of local enhancement methods with their advantage/disadvantage

Author	Method	Advantage	Disadvantage
(Joung-Youn Kim et al., 2001)	HE is applied to a whole block of pixels instead of applying HE to only one pixel at a time. Then the block is shifted by a predefined step-size.	- It has low computational complexity compared with the Adaptive HE	- It produces over-enhancement artifacts.
(Jafar & Ying, 2007)	Histogram matching is applied to each pixel surrounded by a block of pixels. The matched histogram is constructed based on the means of the input image.	- It handles the over-enhancement artifacts probably.	- It suffers from severe computational complexity.
(Kaiming He et al., 2011)	Hazy model is used and to estimate the depth of a pixel, dark channel prior is proposed.	- It is effective with hazy images.	- It produces over-stretching artifacts - It suffers from high computational complexity.
(Dong et al., 2011)	It enhances low light images/videos by using hazy model. The low light image is inverted to mimic the properties of a hazy image, then, hazy model is applied. Finally, the image is inverted back to the original form.	- It enhances dark images to some extent.	- The basic model used in this method is lacking in physical explanation.

Table 2.2, Continue

Author	Method	Advantage	Disadvantage
(D. Wang et al., 2014)	This technique is based on a piecewise stretch function on the Luminance component extracted with Retinex theory in HSV color model.	- It produces satisfactory results with moderate low-light images.	- It doesn't work well with very dark images. - It suffers from halo artifacts.
(Y. Li et al., 2015)	This method uses gamma function to distribute the dark intensities as well as bright intensities locally and globally. The used gamma parameter is a cosine function with a predefined amplitude.	- It produces good results with images that have different illumination conditions	- It suffers from high computational complexity - It de-enhances some images because the used global transformation function is not adaptive to the image's histogram
(Abdul Ghani & Mat Isa, 2015)	It is proposed to enhance the visibility of underwater image by stretching the three-color channels (RGB). Each channel's histogram is divided into two parts and each part is stretched by a predefined amount. To enhance the color of an image, the image is converted into HSV. Only the V-channel is enhanced by using clap-limited histogram specification (CLAHS). Rayleigh distribution is used in CLAHS as a mapping guide	- It produces good result not only under-water images, but also dimmed dark images.	

Table 2.2, Continue

Author	Method	Advantage	Disadvantage
(Girdhar et al., 2015)	Manually, region of interest ROI is selected. Then, ROI is segmented into foreground and background based on a linear formula. Finally, foreground is enhanced by using linear stretching formula.	- It is easy to implement. - It preserves the homogeneity between pixels within the ROI, due to the use of the linear stretching formula.	- It demands human intervention. - It doesn’t work well with images that are complex and contain multiple heterogenous regions.
(Kaur et al., 2016)	Multiple filters are used to remove noises. After that, ROI is extracted using level set function. Finally, un-sharp masking is applied.	- It doesn’t produce artifacts. - It doesn’t need human intervention to extract ROI	
(A. Singh et al., 2016)	The image is first divided into small blocks. Then, each block is enhanced by using a simple linear equation that employ the block’s mean and the image’s mean.	- It is easy to implement it. - Has low computational complexity compared with other local methods	- Produce limited result. - De-enhance the images if they have different lighting conditions.
(Z. Huang et al., 2016)	For each pixel in an image, gamma correction is used with a block’s mean as denominator and the pixel intensity as numerator. This formula always darkens the targeted pixel if it is below the block’s mean and vice versa if it is above the block’s mean	- It enhances infrared image effectively.	- It may produce saturation artifacts and loos of details in luminous regions.

From the previous discussions in this chapter, a conclusion can be drawn that global enhancement methods may fail to enhance images that captured in an environment with different illumination conditions. Such images would have heterogenous regions. The regions may demand different amount of enhancement, therefore, enhancing those images globally would enhance some region and de-enhance the others. On the other hand, local enhancement (adaptive enhancement) method ignores the global information of the images and, as a result, these methods create artifacts and/or over-enhancement. To tackle this issue, both local and global information should be considered. Therefore, hybrid technique called contrast enhancement based on the intensity of regions' pixels (CEBR) were proposed.

2.4 Summary

Various global and local enhancement methods were discussed in this chapter. First, the performance of global methods is analyzed, followed by local methods. To accomplish comprehensive survey, conventional as well as contemporary enhancement methods were reviewed.

From the discussion in this chapter, it is evident that the available contrast enhancement algorithms are not suitable for a wide variety of images. An algorithm produces a good result for some images may break down on some other ones. To enhance a wide variety of images, a hybrid technique that utilizes a regions-segmentation mechanism along with an adaptive transformation function, is proposed.

CHAPTER 3: METHODOLOGY

The proposed method consists of two major steps. The first step is regions creation, while, the second step is regions enhancement. Block diagram of the proposed method is depicted in Figure 3.1.

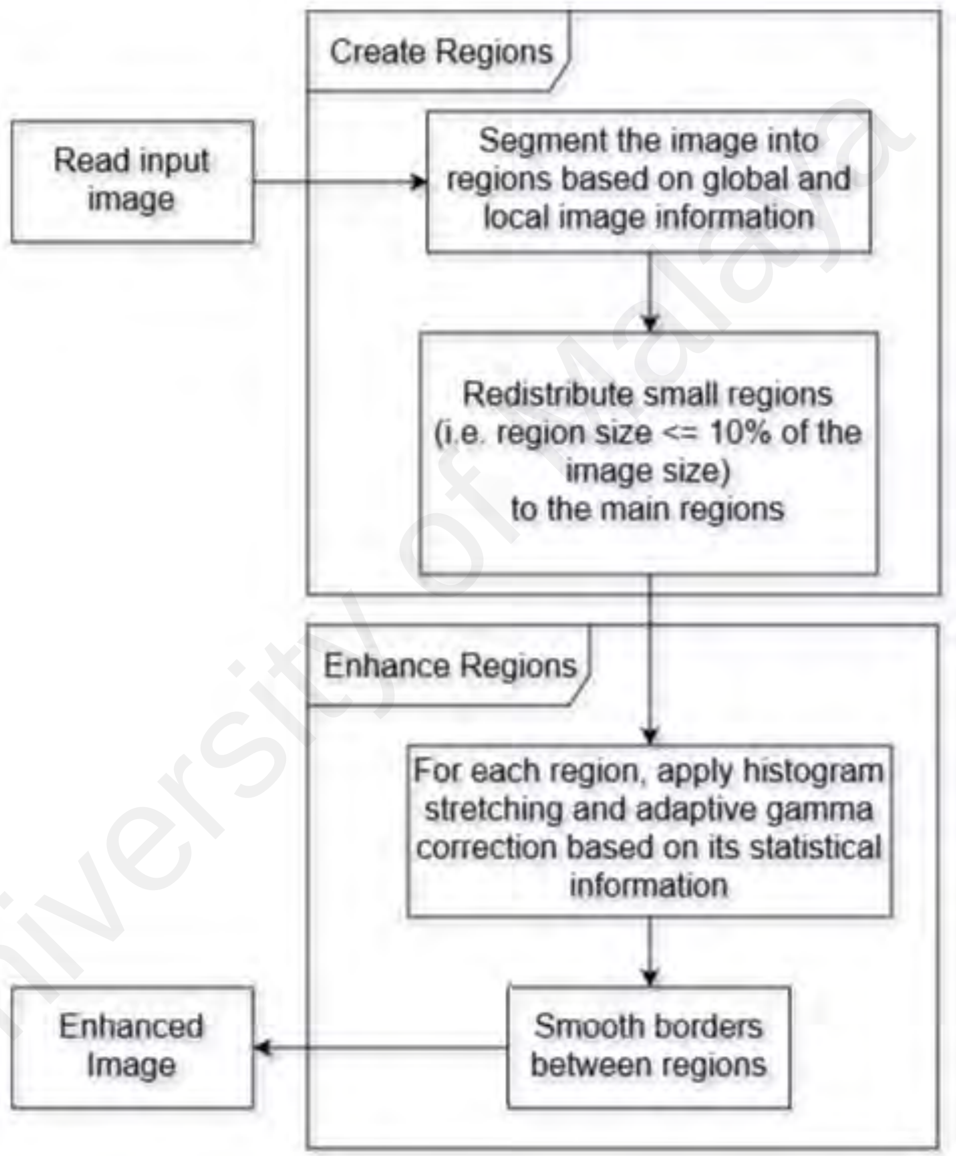


Figure 3.1: Block diagram of the proposed method

To create regions, global and local image information is used. However, the result of this process may produce excessive number of regions. Therefore, small regions should be redistributed to the big one. Empirically, regions that have $size \leq 10\%$ of the image size are considered small. And to enhance regions' contrast, histogram stretching, and adaptive gamma correction are adopted. So, each region would have different enhancement parameters. After that, all the regions are combined. A sharp intensity transition may appear between the adjacent regions which cause unnatural appearance at the regions' borders. Consequently, simple smoothing algorithm is proposed.

The rest of this chapter is organized as the following. Section 3.1 describes the color model that will be used in the proposed contrast enhancement method. Section 3.2 and section 3.3 define the proposed Region growing algorithm and how to redistribute the small regions, respectively. Section 3.4 and section 3.5 illustrates the proposed enhancement technique and describes a simple smoothing algorithm to make the image visually pleasant, respectively. The last section concludes the whole chapter.

3.1 Color Images

Several color models are available in image processing domain, such as, RGB, LAB, HSV and YUV (Gonzalez & Woods, 2006). It is very common to find images with RGB color space, however, using this model for intensity transformation would lead to change the color of the original image. On the other hand, HSV model is appropriate for intensity transformation because it separates the brightness information (V) from the color information (H and S) (Rahman et al., 2016). Thus, to enhance the contrast of a colorful image -without manipulating the original colors of the image-, only the V-channel should be enhanced.

For the proposed method (CEBR), HSV model is adopted. And contrast enhancement is achieved by first converting the RGB model to the HSV as in (Ibraheem et al., 2012), then applying the proposed CEBR to the Value channel. Finally, converting back the HSV model to the RGB model. This process is illustrated in Figure 3.2.

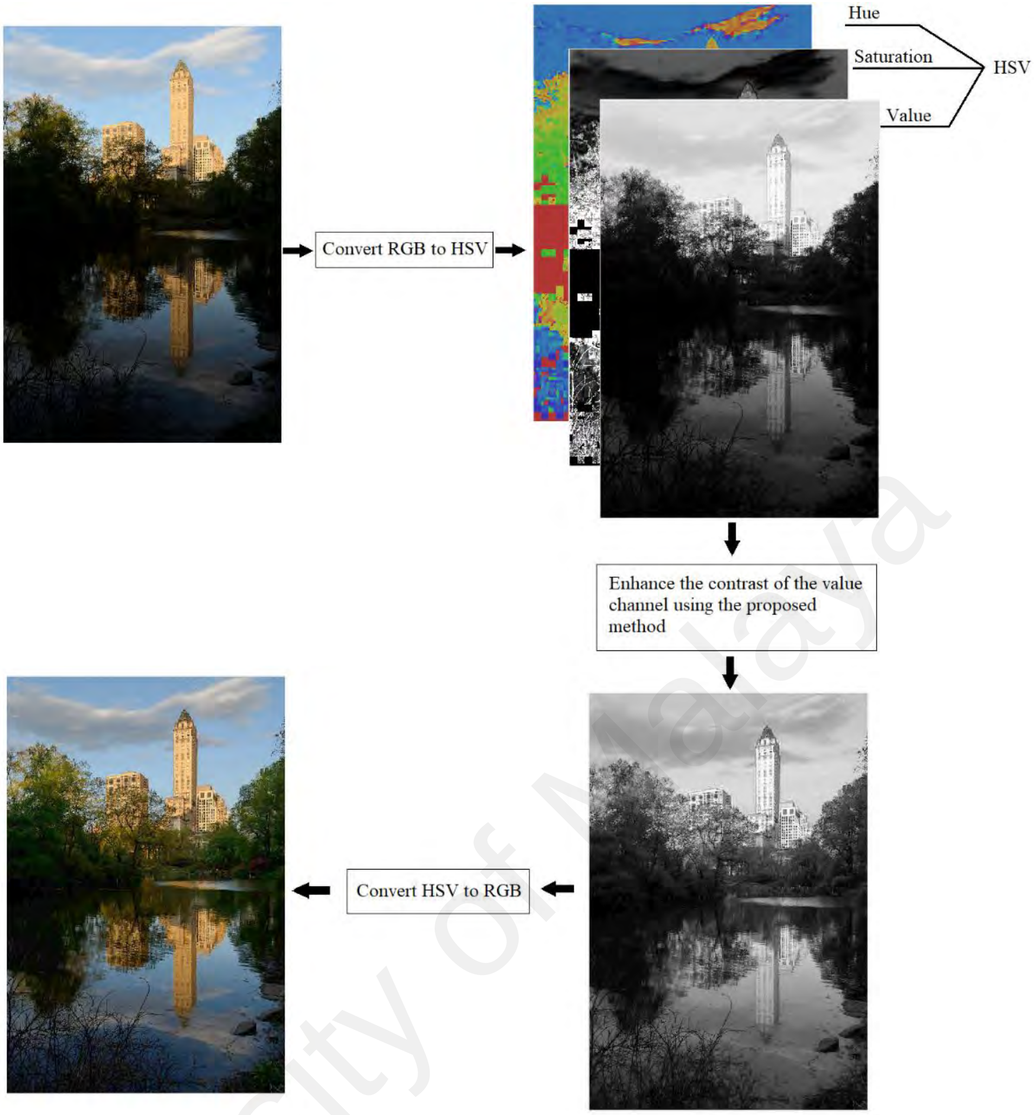


Figure 3.2: An example of enhancing the value channel in HSV color model. The enhancement is applied only to the Value channel

3.2 Region Growing and Image Segmentation

An image may consist of different regions. And Each region may have different characteristics in terms of brightness and contrast. Therefore, each region in the image may demand different degree of enhancement.

To segment the image into regions, the proposed method divides the image into blocks then a *Seed* block is selected randomly. After that, distance between the *Seed* block and the adjacent blocks are calculated in term of brightness and contrast level. The adjacent blocks will be added to the *Seed* block if the distance between them are less than a threshold. Next, the neighbor blocks of the recently added blocks are also investigated (i.e. neighbors of neighbors of the *Seed* block). They will be added if they satisfy the previous condition. The previous procedures are repeated until there are no other blocks that can be added further. At the end, one region is created. All the previous steps are then applied to create other regions. The algorithm stops when each block in the image belongs to its' corresponding region.

As previously stated, the threshold determines the maximum distance allowed between the *Seed* block and its' neighbors in order to add them to the Seed block. Here, two distance terms were considered, namely, the brightness and the contrast level. Therefore, two distance thresholds were defined; a threshold for brightness "τ" and another one for contrast level "δ". Note that those thresholds are important because they determine the number of regions to be extracted from an image. So, defining fixed thresholds would be ineffective since each image may have different characteristics.

Having said that, those thresholds should be calculated -adaptively- based on the image information. For instance, if the images have low contrast, the distance thresholds should be low as well, otherwise, all blocks in the image would be added to the Seed block. In such a case, the algorithm will fail to segment the image into regions. On the other hand, in images where the contrast is high, the distance threshold should be high as well. Failing to do so would leads to reject all neighbor blocks, and each block would be a region by itself.

The proposed region growing algorithm is depicted in Figure 3.3 and it is formulated in 7 steps as follows:

1. Divide the image into blocks of size 8*8 pixels.
2. Select a *Seed* block and calculate its' brightness and contrast level.
   a. To get the brightness of the *Seed* block, mean intensity value is calculated using equation (1).

$$\mu(block) = \frac{1}{M \times N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} block_{ij} \tag{3.1}$$

   where μ is the mean intensity which represent the brightness of a block. M, N is the width and height of the block, respectively. i, j is the pixel location at the x-axis and y-axis, respectively. And $block_{ij}$ represent a pixel's intensity at location i, j.

   b. To calculate the contrast level, equation (2) is used (Peli, 1990).

$$\sigma(block) = \sqrt{\frac{1}{M \times N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \left(\mu(block) - block_{ij}\right)^2} \tag{3.2}$$

3. Investigate the 8-connected neighbors' block and calculate their brightness and contrast level using (1) and (2) respectively.
4. For each neighbor block, calculate the Manhattan distance in term of brightness. The brightness is calculated using equation (3.1).

$$D_b(Seed, block) = |\mu(Seed) - \mu(block)| \tag{3.3}$$

5. For each neighbor block, calculate the Manhattan distance in term of contrast level using equation 3.2.

$$D_c(Seed, block) = |\sigma\ (Seed) - \ \sigma\ (block)| \quad (3.4)$$

6. To add a neighbor's block to the Seed block (region growing), two conditions should be satisfied.

   a. Condition 1: The brightness distance $D_b \leq \tau$, where τ is brightness threshold and it is calculated as follows:

$$\tau = \sigma(Image) \quad (3.5)$$

where Image is the impute image and σ is the standard deviation and it is calculated using equation (3.2).

   b. Condition 2: The contrast distance $D_c \leq \delta$, where δ is the contrast level threshold and it is calculated as follows:

$$\delta = \left(1 - \frac{D_b(Seed, block)}{\tau}\right) \times \tau \quad (3.6)$$

7) After the investigation of the 8-connected blocks has finished, investigate the neighbors of the recently added blocks and apply step 3 to 5. The algorithm should stop when it can't add any new blocks. At this stage, one region is created.

8) Repeat the previous steps 1 to 6 several times until all blocks in the image belong to a region.

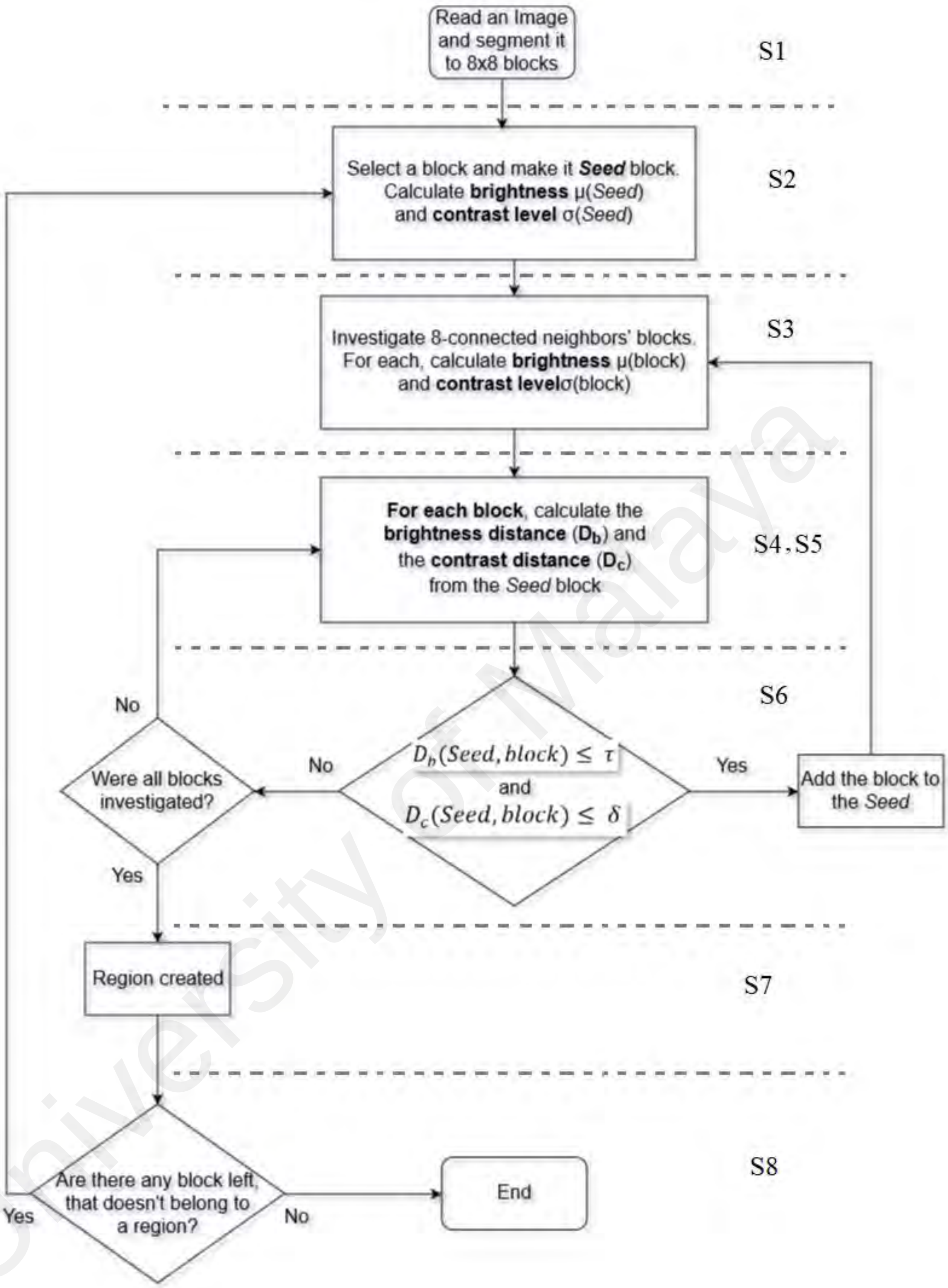


Figure 3.3: Flowchart of the proposed region growing algorithm

Figure 3.4 illustrates the results of the proposed region growing algorithm on an image. There are so many regions created (as shown in Figure 3.4) because some seed blocks have either higher or lower contrast level than the surrounding blocks.

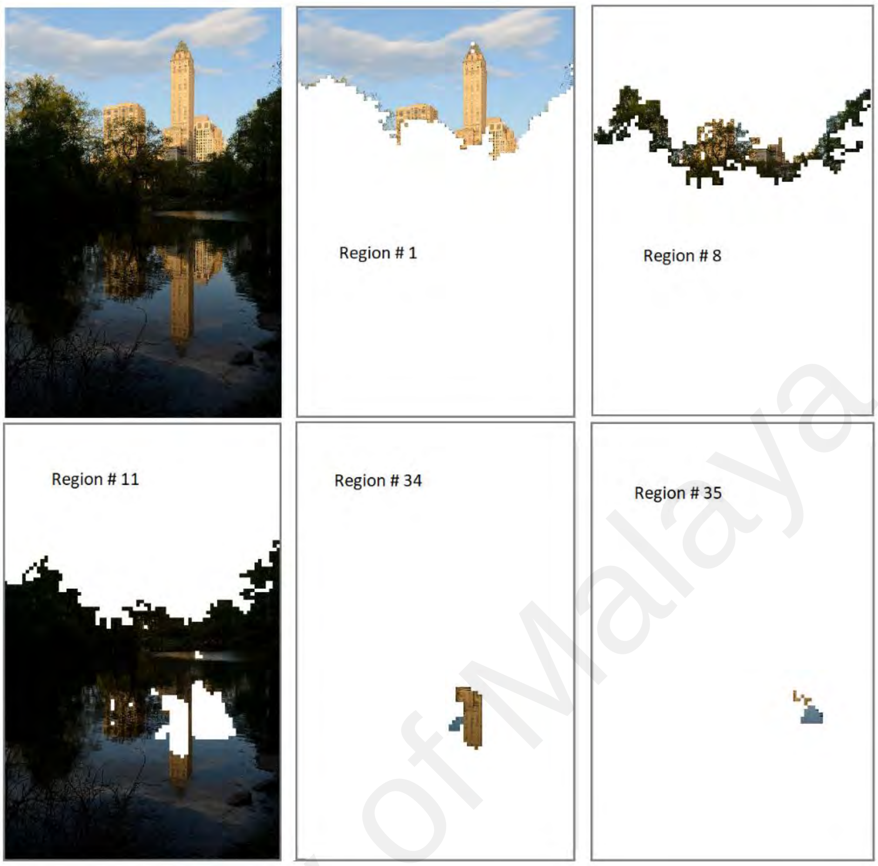


Figure 3.4: Some results of the proposed region growing algorithm applied on an image. For illustration purposes, only 5 regions are selected out of 39 regions.

(a) (b)

Figure 3.5: The effect of enhancing the image without diffusing small regions. (a) is the original image and (b) is the enhanced version.

Each region will get different enhancement amount; therefore, those small regions may create artifacts. Figure 3.5 in the previous page, depicts the artifacts created after enhancing all regions. To solve this issue, diffusing algorithm where proposed. before the enhancement is applied, this algorithm redistributes those small regions into the big ones based on their intensity and spatial information.

3.3 Redistributing Small Regions' Pixels

A region is considered small if it is less than or equal to 10% of the image size. This ratio was set empirically. After identifying the small regions, each pixel in those small regions should be distributed to the nearest big region in terms of the spatial and brightness distances.

- The distance in term of brightness between the big region and a pixel is calculated as follows:

$$Di_n = |\mu(BigRegion_n) - Small(i,j)| \tag{3.7}$$

Where Di_n is the Manhattan distance. μ is the mean intensity which represent the brightness of a region. $MainRegion_n$ represents a big region that has a number 'n'. $Small(i,j)$ represents a pixel intensity in a small region at location 'i' and 'j' (i and j represent the x-axis and y-axis respectively).

- And the spatial distance at the eight directions (i.e. up, up-right, right, right-down …etc) between a pixel in small region and a main region is calculated using the following equation.

$$SD_n\big(BigRegion_n, Small(i,j)\big) = \sum_{d=1}^{8} ECdistance_d(\,BigRegion_n, Small(i,j)\,) \tag{3.8}$$

Where SD_n is the total spatial distance of the eight directions between a Big region and pixel in a small region. And $ECdistance_d$ represents the Euclidian distance at a specific direction 'd'. Figure 3.6 is an example.

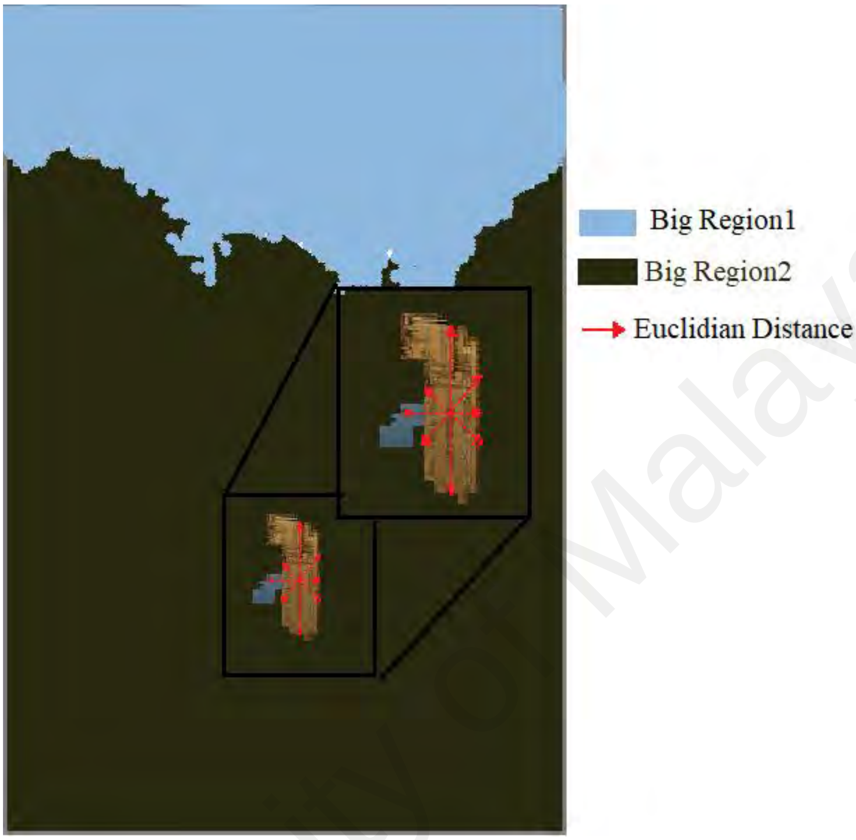


Figure 3.6: An example that shows the calculation of the spatial distances at the 8 directions.

The two distances (i.e. brightness distance "Di_n" and spatial distance "SD_n") should be both used to determine the target region. A pixel in a small region is assigned to a region that has the lowest distance. To use both distances (i.e. Di_n and SD_n) the following equation is formulated.

$$TD_n\left(BigRegion_n, Small(i,j)\right) = \left(\frac{Di_n}{MaximumDi} \times 0.5\right) + \left(\frac{SD_n}{MaximumSD} \times 0.5\right) \quad (3.9)$$

$$MaximumSD = width + height + \sqrt{width^2 - height^2} \quad (3.10)$$

TD is the total distance between a region and a pixel in a small region. "Di_n" and "SD_n" are the brightness and spatial distance, respectively. "*MaximumDi*" is the maximum distance in term of intensity value (i.e. for gray images *MaximumDi* = 255). And "*MaximumSD*" is the maximum spatial distance that a pixel can have.

The result of distributing the small regions is shown in Figure 3.7. Enhancement at this stage will not produce blocking artifacts as in Figure 3.5.

Figure 3.7: The result after distributing the small regions using the proposed algorithm.

3.4 Region Enhancement

Since the image is divided into different coherent regions, they can be enhanced by any enhancement method. Global enhancement method is chosen over local ones because local methods may create local artifacts (Celik & Tjahjadi, 2011). Also, at this stage, global method will not create over-enhancement and/or under-enhancement problems to the image because the global method is not applied to the whole image; instead, it is applied to regions.

To fully achieve maximum enhancement results while preserving the naturalness of an image, two enhancement methods are chosen. The first one is histogram stretching (often called normalization or contrast stretching (Gonzalez & Woods, 2006)). And the second enhancement method is gamma correction.

3.4.1 Histogram Stretching

Histogram stretching becomes very useful when the acquired image doesn't utilize the full dynamic range. This method doesn't create intensity artifacts because it preserves the intensity order (Gonzalez & Woods, 2006). In most cases, the extracted regions may not utilize the full dynamic range properly. For instance, Figure 3.7 depicts two different regions extracted from an image. Those regions don't utilize the full dynamic range, as shown in Figure 3.8.

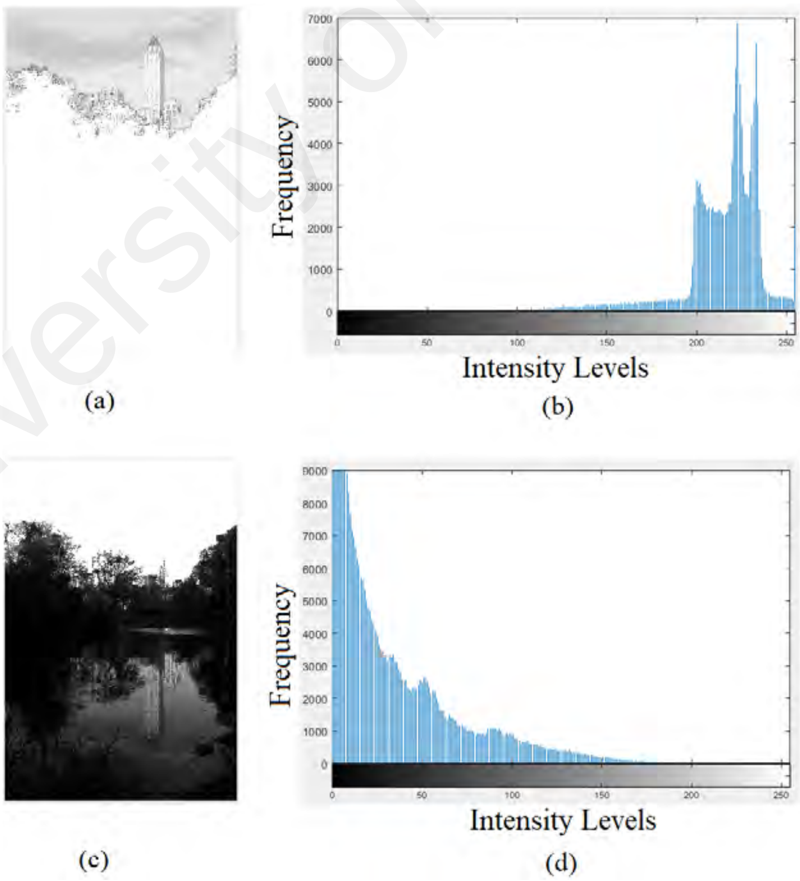


Figure 3.8: Extracted regions with their histogram. (a) and (b) are region1 and region2, respectively. (c) and (d) their corresponding histograms.

As can be noticed from Figure 3.8, the histogram of region1 is clustered around 225, hence, the dark intensities are not utilized. In other hand, region2 doesn't utilize the bright intensities.

To stretch those histograms the following formula is given:

$$P_{out} = (b - a) \times \left(\frac{P_{in} - min}{max - min}\right) + a \tag{3.11}$$

where P_{out} is the output pixel and P_{in} is the input pixel. The maximum and minimum intensity of the target range are b and a, respectively. And the maximum and minimum intensity of the current range are max and min, respectively. Since the goal is to stretch the histogram to its maximum range (i.e. when a=0 and b=255), the previous formula can be rewritten as follows:

$$P_{out} = 255 \times \left(\frac{P_{in} - min}{max - min}\right) \tag{3.12}$$

Although histogram stretching enhances the regions to some extent, yet, it may not produce satisfactory results. Especially, when the intensity range of the regions are large. Therefore, additional enhancement method is needed to further enhance the regions.

3.4.2 Adaptive Gamma Correction

To further enhance the regions, adaptive gamma correction is used. Gamma correction is a nonlinear function that used to encode and decode luminance in display systems (Poynton, 2003). Gamma correction -in its simplest form- is defined by a power-law equation (Gonzalez & Woods, 2006):

$$Image_{out} = L * \left(\frac{Image_{in}}{L}\right)^{\gamma} \tag{3.13}$$

Where L is a positive constant that represent the maximum intensity level (i.e. in gray images, L=255), $Image_{out}$ is the output image, $Image_{in}$ is the original image, and γ is the gamma value. Notice that Gamma here is not the same as the Gamma function in mathematics noted as " Γ ".

There are two advantages of using gamma as a transformation function. The first advantage is that Gamma has a smoothing curve, thus, it will not produce over-enhancement artifacts unlike the conventional contrast enhancement techniques (Histogram Equalization and its variations). While the second advantage is that, Gamma value can be adjusted to enhance bright regions as well as dark regions. For instance, to enhance bright regions, Gamma value "γ" can be set to be bigger than 1 to redistribute bright intensities over the entire dynamic range and "1/γ" is used to redistribute dark intensities. Figure 3.9 depicts the plots of Gamma function over various values of γ (Gonzalez & Woods, 2006).

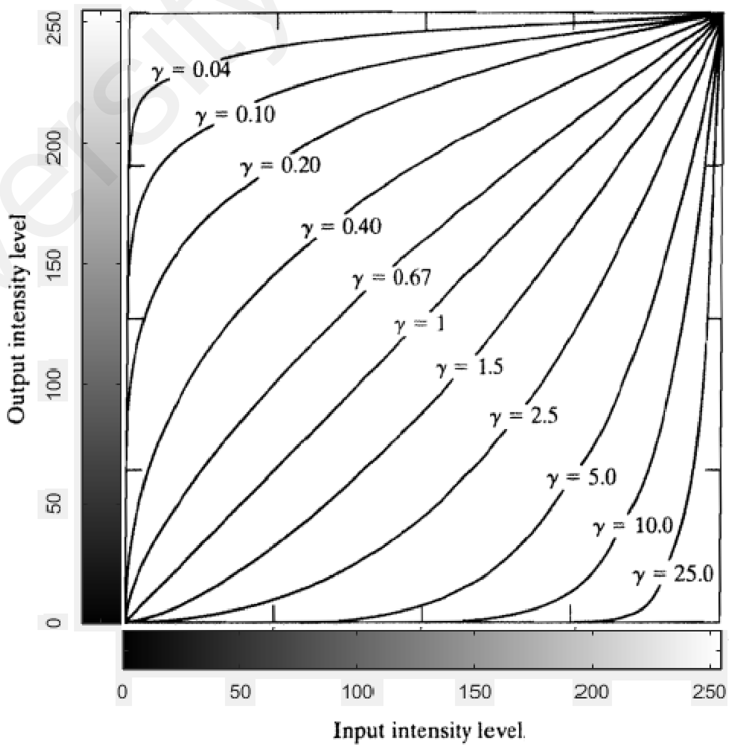


Figure 3.9: Plots of gamma equation for various values of γ

(Gonzalez & Woods, 2006)

Histogram stretching as well as Gamma correction can be both combined to formulate one equation. Both equations (3.12) and (3.13) are used to define the proposed enhancement function:

$$Region_{out} = 255 \times \left(\frac{255 \times \left(\frac{Region_{in} - min}{max - min} \right)}{255} \right)^{\gamma} \quad (3.14)$$

$$Region_{out} = L * \left(\frac{Region_{in} - min}{max - min} \right)^{\gamma} \quad (3.15)$$

Where $Region_{in}$ and $Region_{out}$ are the input and output region's pixel intensity, respectively. The maximum and minimum pixel intensity in the region are *max* and *min*, respectively. And γ represents the gamma value.

A predefined value of Gamma will not guarantee to enhance all types of regions. Therefore, Gamma value should be defined based on the regions' information. Consequently, different values of Gamma should be applied for each region.

Adaptive Gamma function is defined as follows:

$$\gamma = \varepsilon + \left(1 - \frac{\sigma(Region_n)}{Max(\sigma)} \right) \quad (3.16)$$

Where ε is constant that determine the minimum enhancement amount. Since gamma value of 1 doesn't change intensity distribution (As in Figure 3.9), ε is set to be 1. $\sigma(Region_n)$ is a function that calculate the contrast level of a region number *n* and $Max(\sigma)$ is the maximum contrast level that a region can have, and it calculated using the following simple equation:

$$Max(\sigma) = \frac{L}{2} \quad (3.17)$$

Where L represents the full dynamic range (e.g. for gray images, the full dynamic range =255)

However, using both Histogram Stretching, and Gamma Correction may produce over enhancement artifacts, thus, correlation between both enhancement methods should be constructed. Therefore, based on the amount of histogram stretching, Gamma value should be defined. If the amount of histogram stretching is high, gamma value should be low and vice versa. The final equation for the proposed Gamma Correction is reformulated as follows:

$$\gamma = \varepsilon + \left(1 - \frac{\sigma(Region_x)}{Max(\sigma)}\right) \times (1 - str) \tag{3.18}$$

Where str is the stretching amount and it calculated by:

$$str = 1 - \left(\frac{max - min}{L}\right) \tag{3.19}$$

Where max and min are the maximum and minimum pixel intensity of the target region, respectively. The effect of equation (3.18) on the two regions' histogram is depicted in Figure 3.10.

As it is clearly shown in Figure 3.10, region1 demands a Gamma value $\gamma \geq 1$. Therefore, $\gamma = 1.7370$ using the proposed equation (3.18). And for region2, dark intensities should be redistributed using a Gamma value $\gamma \leq 1$. Therefore, for the dark region $\gamma = 0.6009$. Those Gamma values are employed in equation (3.15) to form the transformation function for each region.

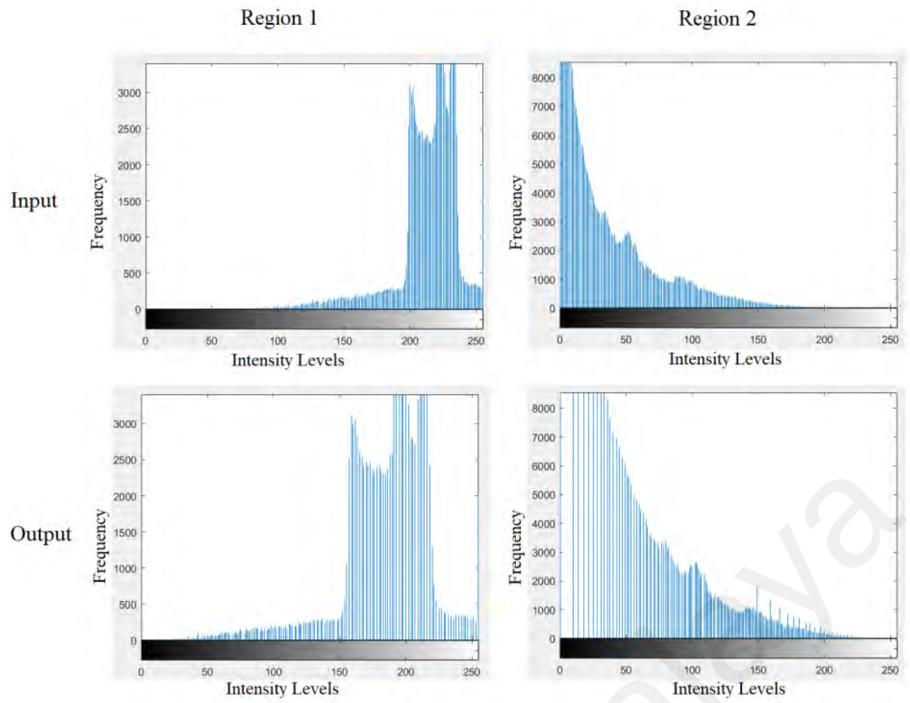


Figure 3.10: The effect of the proposed transformation function on the regions' histogram.

After enhancement is applied, all enhanced regions are combined to form one image. The enhancement result is depicted in Figure 3.11.

(a) (b)

Figure 3.11: (a) and (b) are the original and the enhanced image using the proposed method.

3.5 Smoothing Regions' Borders

Accordingly, a sharp intensity transition at the regions' border may occur (As in Figure 3.12). Therefore, simple smoothing algorithm is proposed.

(a) (b)

Figure 3.12: An example of the sharp transition between regions. (a) and (b) are the enhanced image with and without the proposed smoothing algorithm, respectively

The algorithm consists of two steps. The first step is to define small block (e.g. 5 by 5 block) and slides through the entire enhanced image until the block reaches a region's border. The intensities within the block at that location are replaced by the average between the current enhanced intensities and the original intensities.

3.6 Summary

In this chapter, hybrid technique called contrast enhancement based on the intensity of regions' pixels (CEBR) were discussed. This hybrid enhancement technique is effective and, at the same time, suitable for a large variety of images. The method first divides the image into regions by using the proposed Region growing algorithm. Small regions were diffused into the big ones based on its spatial and intensity distances. Histogram stretching, and Gamma correction were combined to achieve maximum enhancement results without introducing artifacts. The proposed Gamma correction function change its value based on the regions' information. To mitigate the sharp transition created at the borders after combining the regions, simple smoothing filter were briefly explained.

CHAPTER 4: EXPERIMENTAL RESULTS AND EVALUATIONS

4.1 Introduction

In this proposed method has two goals: (i) enhancing the images properly while at the same time (ii) preserving the naturalness of the images. To demonstrate the contribution of the proposed CEBR, different types of enhancement methods were tested for a variety of both grey and color images. To further highlight the contribution of the proposed CEBR, conventional as well as new methods were tested. Those methods are Histogram Equalization (HE) (Gonzalez & Woods, 2006), Multiscale Retinex with Color Restoration (MSRCR) (Jobson, 2004), Weighted Approximated Histogram Equalization (WAHE) (Arici, Dikbas, & Altunbasak, 2009), Contextual and Variational Contrast Enhancement (CVC) (Celik & Tjahjadi, 2011), Layered Difference Representation of 2D histograms (LDR) (C. Lee et al., 2013), Adaptive Gamma Correction with Weighting Distribution (AGCWD) (S.-C. Huang et al., 2013), Adaptive Gamma Correction (AGC) (Rahman et al., 2016) and Global Local Image Enhancement (GLE) (A. Singh et al., 2016). Both qualitative and quantitative results imply that the performance of the proposed method (CEBR) is better than or equal to the other methods.

4.2 Qualitative Results

Different low contrast standard images have been chosen for the qualitative assessment.

Figure 4.1 shows the “Beans” image and enhancement results with their histograms produced by nine methods including the proposed method. The original Beans image doesn’t utilize the full dynamic range and thus the contrast is low. HE and MSRCR almost succeeded enhancing the image, however, it increased the brightness level of the original image. CVC created artifacts and the quality of the image is degraded. WAHE, AGC, AGCWD and GLE didn’t utilize the full dynamic range and thus they didn’t produce satisfactory results. LDR enhanced the image properly and utilized the full dynamic range as well as the proposed CEBR.

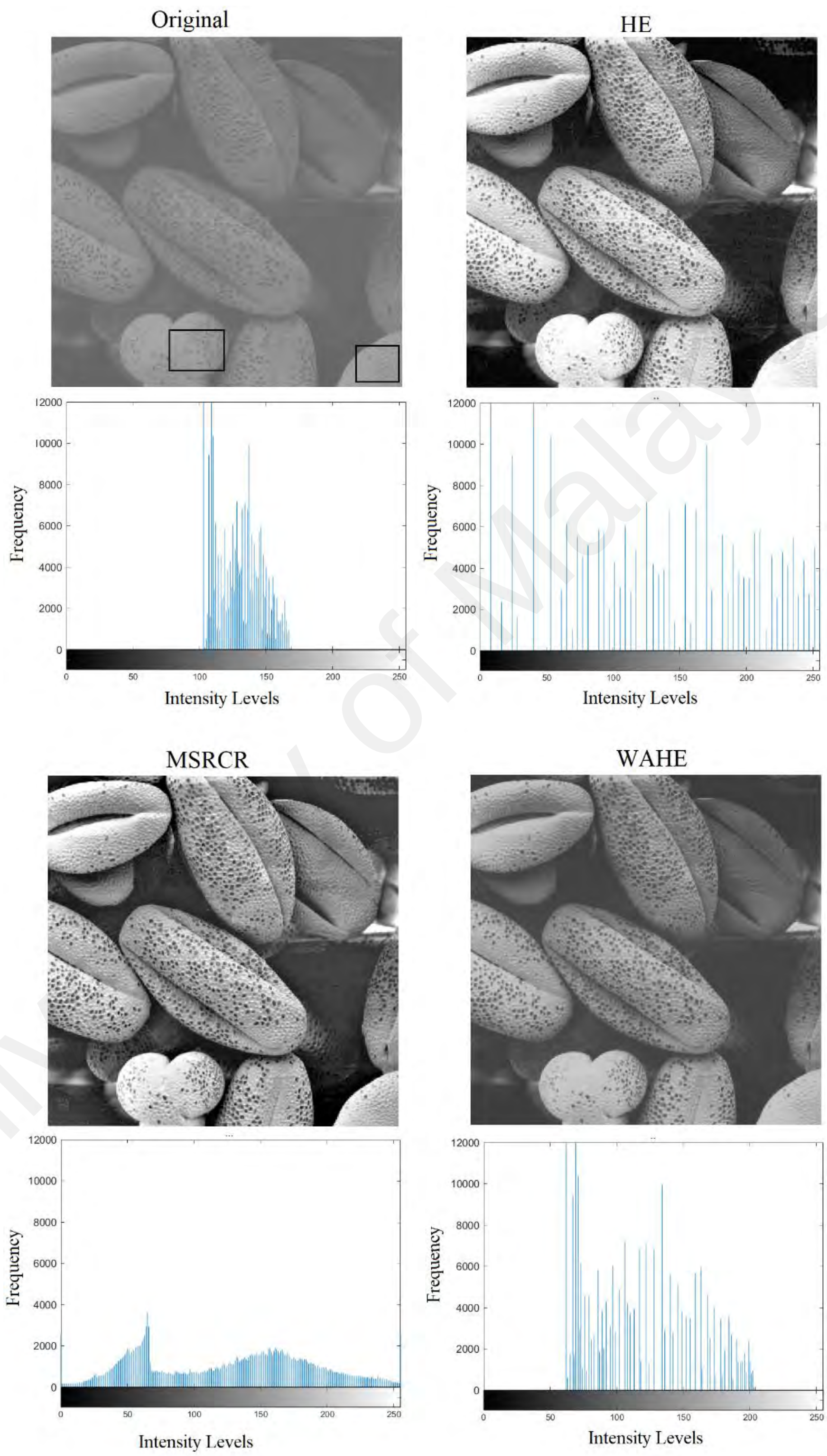


Figure 4.1: Beans image. Original image with the enhancement results generated by various methods. Each image is attached with its statistical histogram.

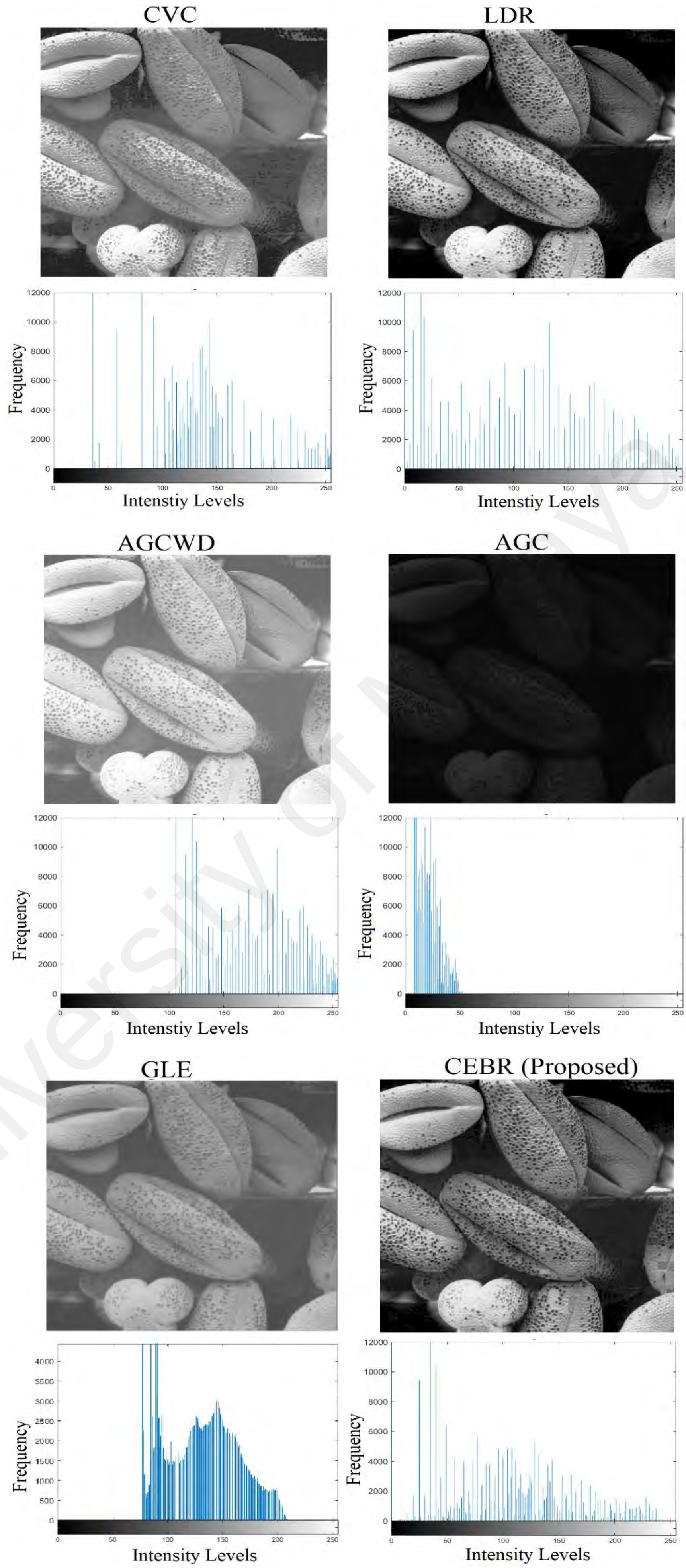


Figure 4.1, Continue

Figure 4.2 shows the “Buildings” image and enhancement results with their histograms produced by the nine methods including the proposed method. “Buildings” image has two main different illumination regions. The building along with the sky is the bright region while the trees is the dark region. HE and MSRCR over-enhanced the image, hence, they produced a distorted image. AGCWD and AGC didn’t enhance the dark region well and they increased the brightness of the buildings, therefore, the buildings are de-enhanced (washed out). CVC and LDR got the almost the same results, they increased the brightness a little, but they fail to achieve satisfactory results. GLE increased the contrast of the buildings but it severely darkened the trees area. WAHE and the proposed CEBR achieved better result than the other methods, however, the trees at WAHE is darker than CEBR and hence some details are not easily perceived. The proposed achieved satisfactory results because the proposed method divides the image into two regions; buildings with the sky is one region and the trees are the other region. Each region received proper enhancement parameters.

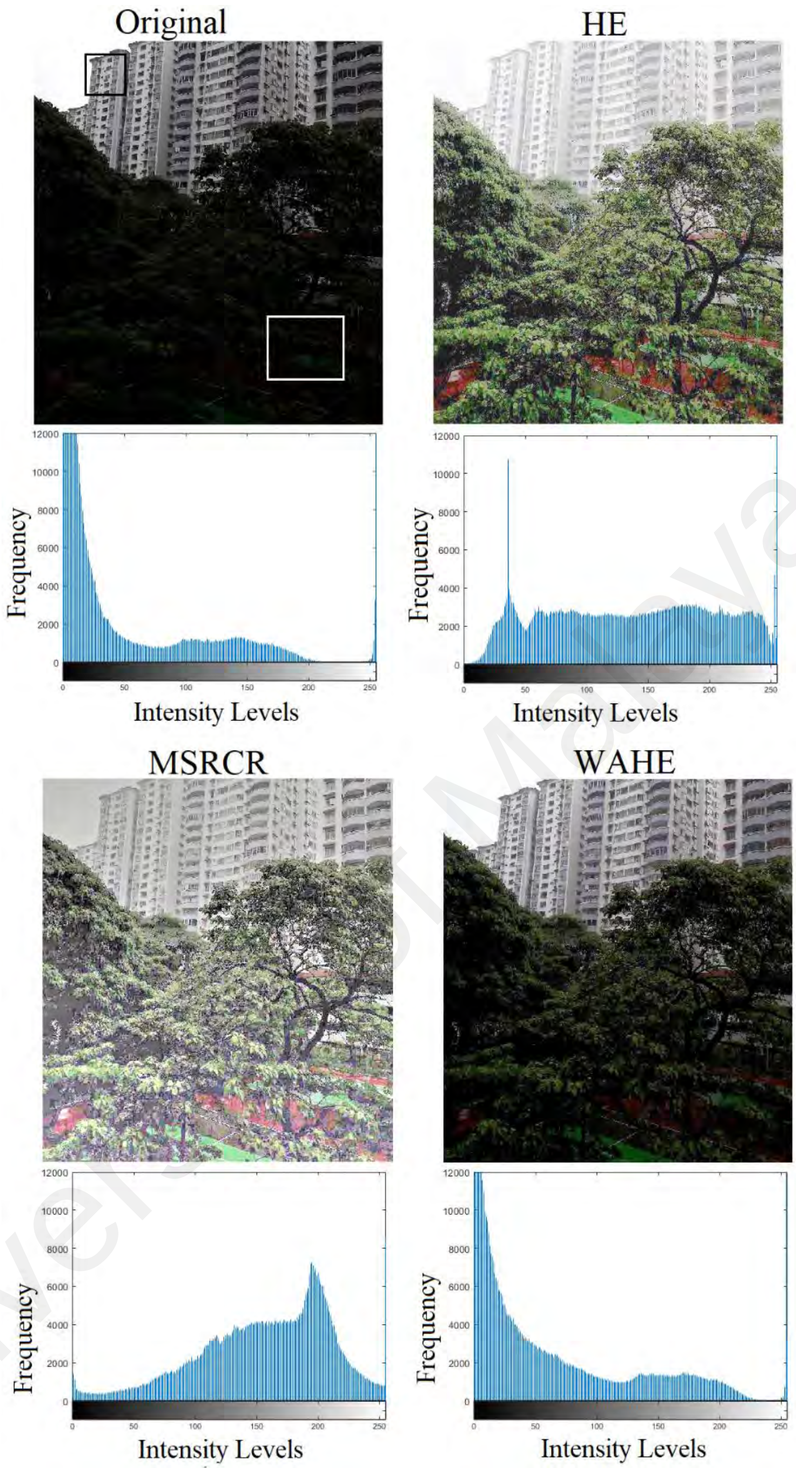


Figure 4.2: Buildings image. Original image with the enhancement results generated by various methods. Each image attached with its statistical histogram.

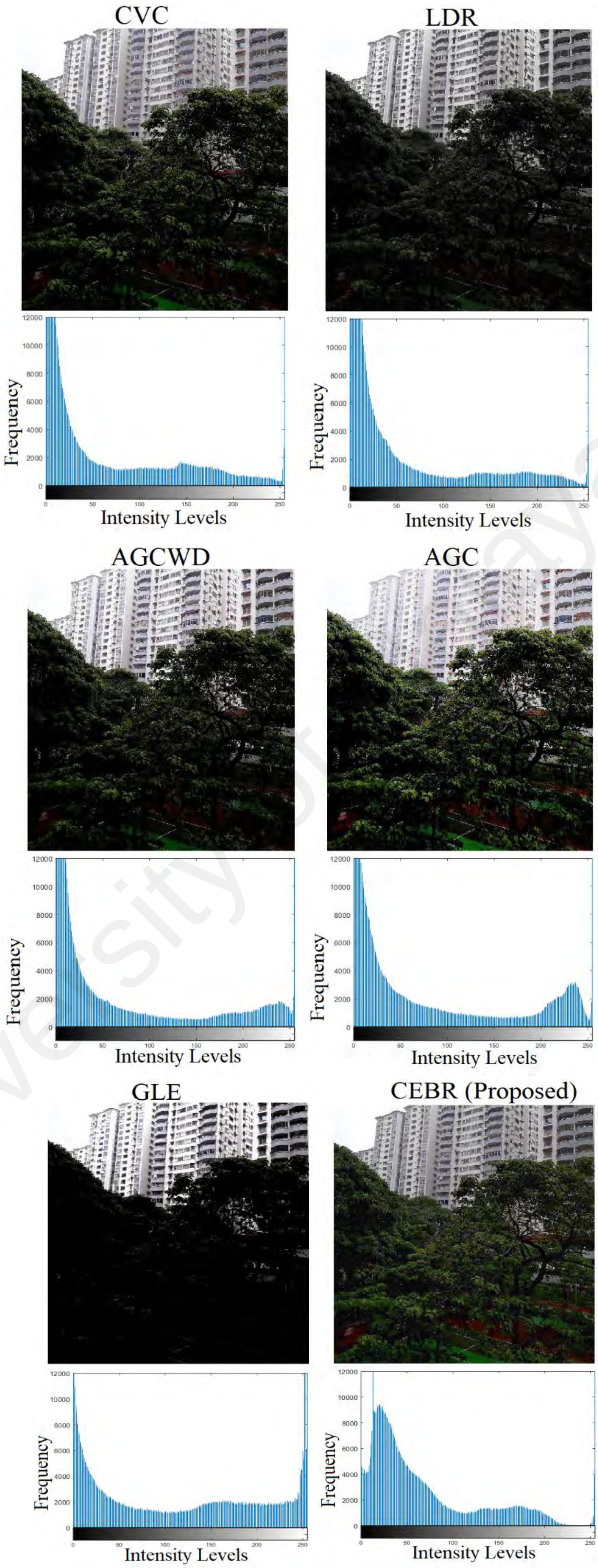


Figure 4.2, Continue

Figure 4.3 shows “Mars” image and the enhancement results along with their histograms. HE and MSRCR created sever distortions as clearly shown in Figure 4.3. While WAHE and LDR enhance the image to some extent, CVC compressed the dynamic range which leads to lower global contrast level. AGCW, AGC and GLE didn’t enhance the dark areas and washed out the bright area in the image. The proposed CEBR divided the image into bright region and dark region and each region enhanced with different gamma value, thus, it achieved satisfactory results.

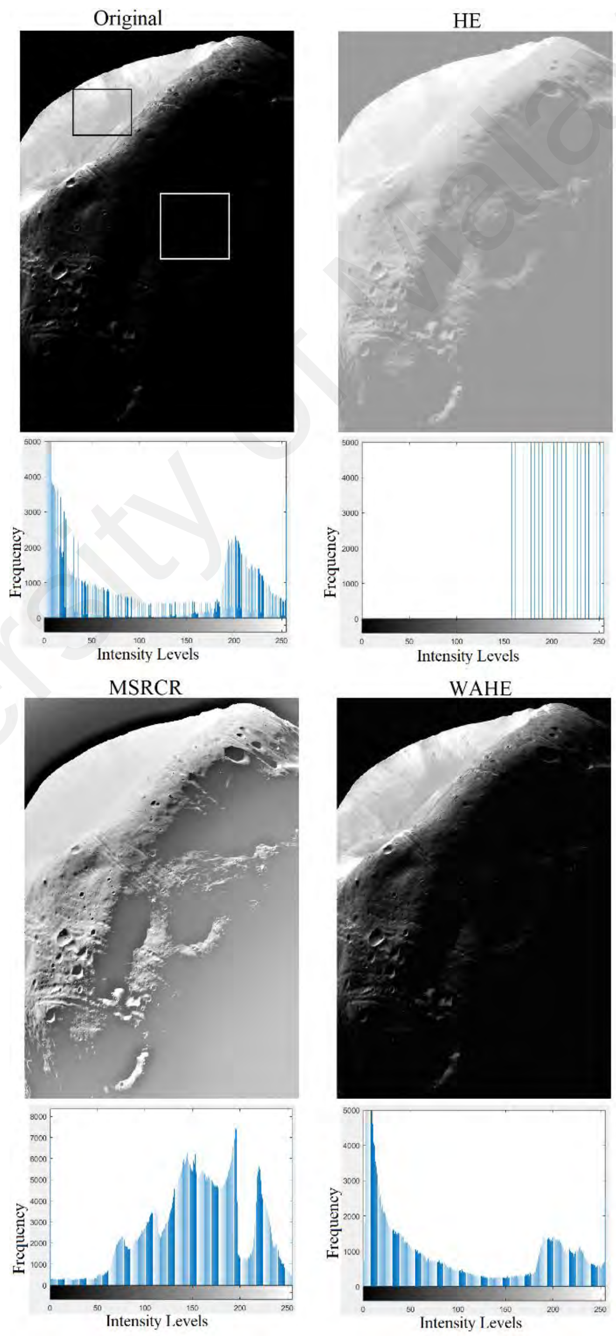


Figure 4.3: Mars image. Original image with the enhancement results generated by various methods. Each image attached with its statistical histogram.

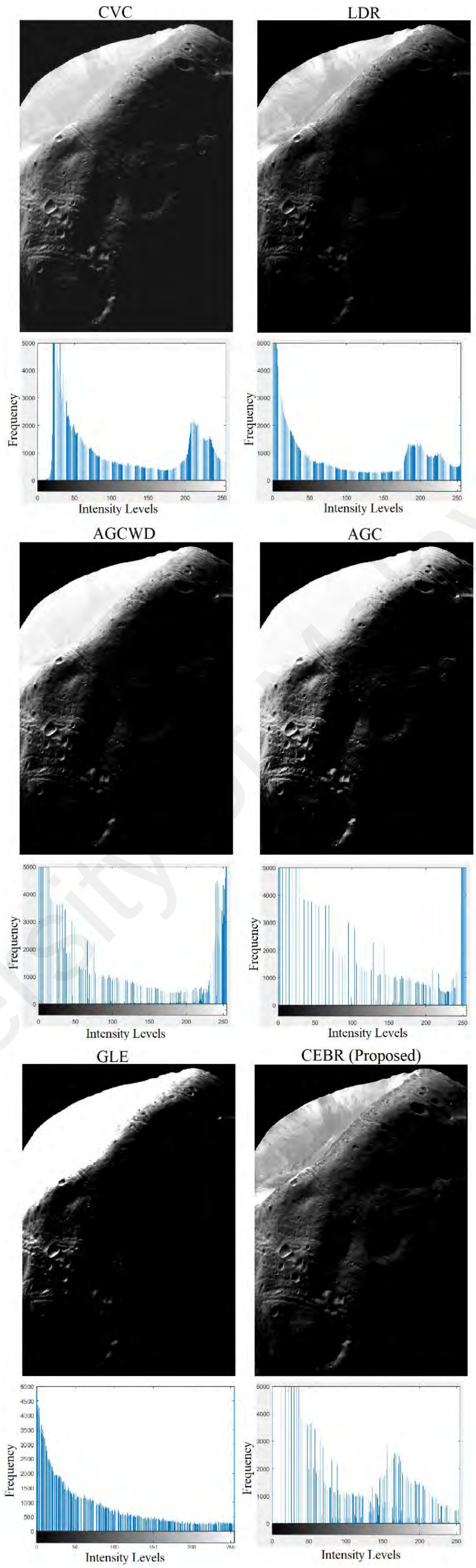


Figure 4.3, continued

In Figure 4.4, HE and MSRCR images suffers from annoying artifacts and both methods deteriorated the image quality. WAHE increased the image brightness a little, though, it should darken the sky and the building, instead. Therefore, WAHE didn't enhance the image probably. CVC and LDR produced almost identical results, as it can be verified by their histograms. However, both methods didn't achieve satisfactory results, added to that, contrast of the bright regions (sky, cloud and building) are de-enhanced. AGCWD and AGC compressed the bright intensities in order to enhance the dark area, thus, they produce dull image. GLE darken all the pixels that has intensities less than the median and vice versa for the bright intensities, therefore, it washed out the building along with the sky and at the same time it dimmed the dark regions. Although it achieved high global contrast level, it de-enhanced the local contrast. The proposed CEBR considered the image's regions and it divided it accordingly. Different enhancement parameters were applied for each region; therefore, the proposed method enhanced the image and preserved the naturalness of the image.

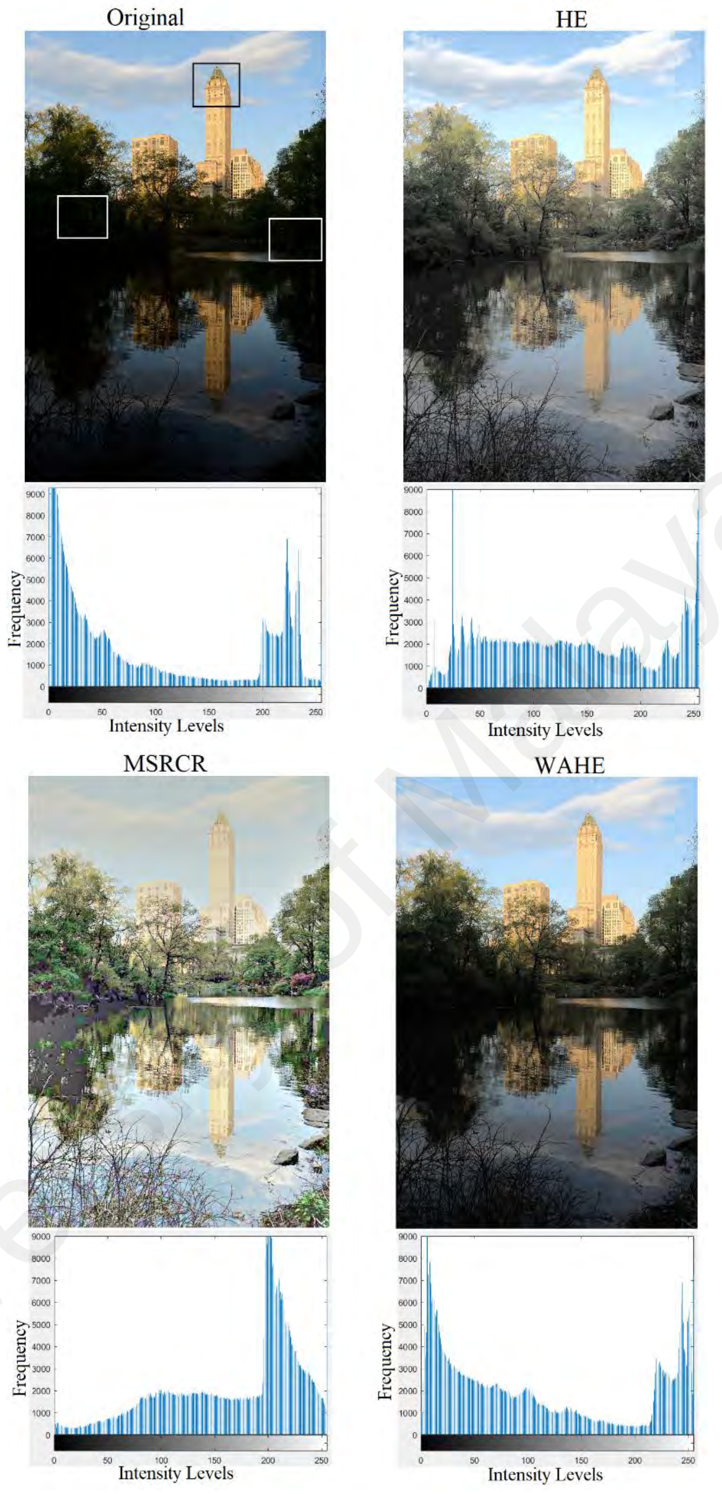


Figure 4.4: Lake image. Original image with the enhancement results generated by various methods. Each image attached with its statistical histogram.

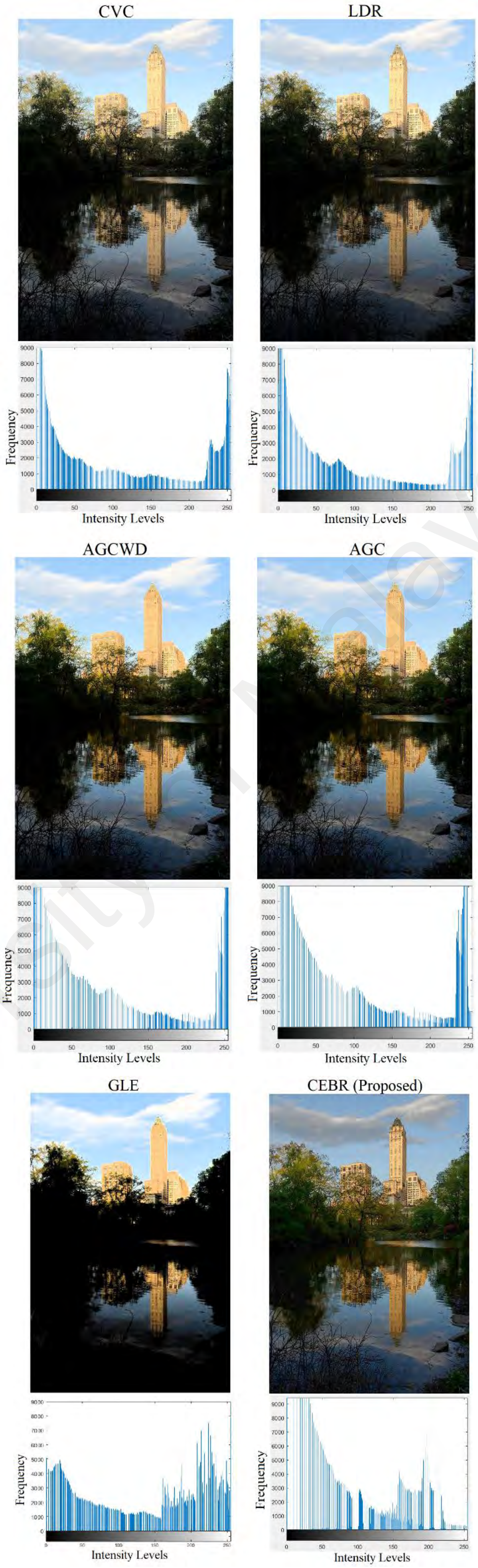


Figure 4.4, Continue

Figure 4.5 depicts horses on a grassy land. The original image is considered a bright image, since, most of its pixel is clustered between 127 and 255. HE uniforms the histogram; therefore, it distorted the original histogram and caused an over-enhancement. MSRCR retained the original histogram and enhanced the image to some extent. However, the dark intensity range was not utilized properly. WAHE stretched the bright intensity levels but it didn’t utilize the entire dynamic range. Meanwhile, CVC and LDR successfully utilized the entire dynamic range, hence, they produced better results than the other methods. AGCWD and AGC compressed and shifted the histogram towards the bright range, therefore, they produced unpleasant results. GLE blackened the horses’ skin and brightened the grassy lands, therefore, the details of the grasses is washed out. The proposed CEBR utilized the entire dynamic range and, hence, it increased the contrast. The white blaze on the horse head as well as the grass details can be noticed effortlessly.

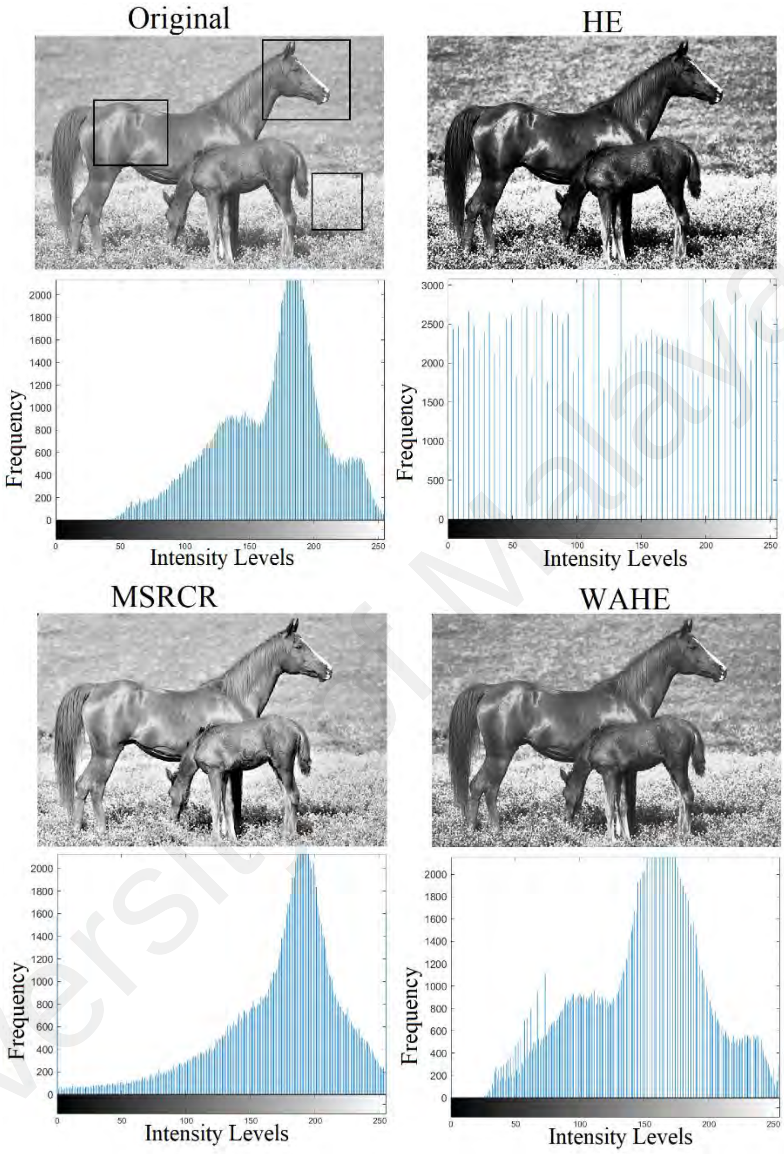


Figure 4.5: Horses image. Original image with the enhancement results generated by various methods. Each image attached with its statistical histogram.

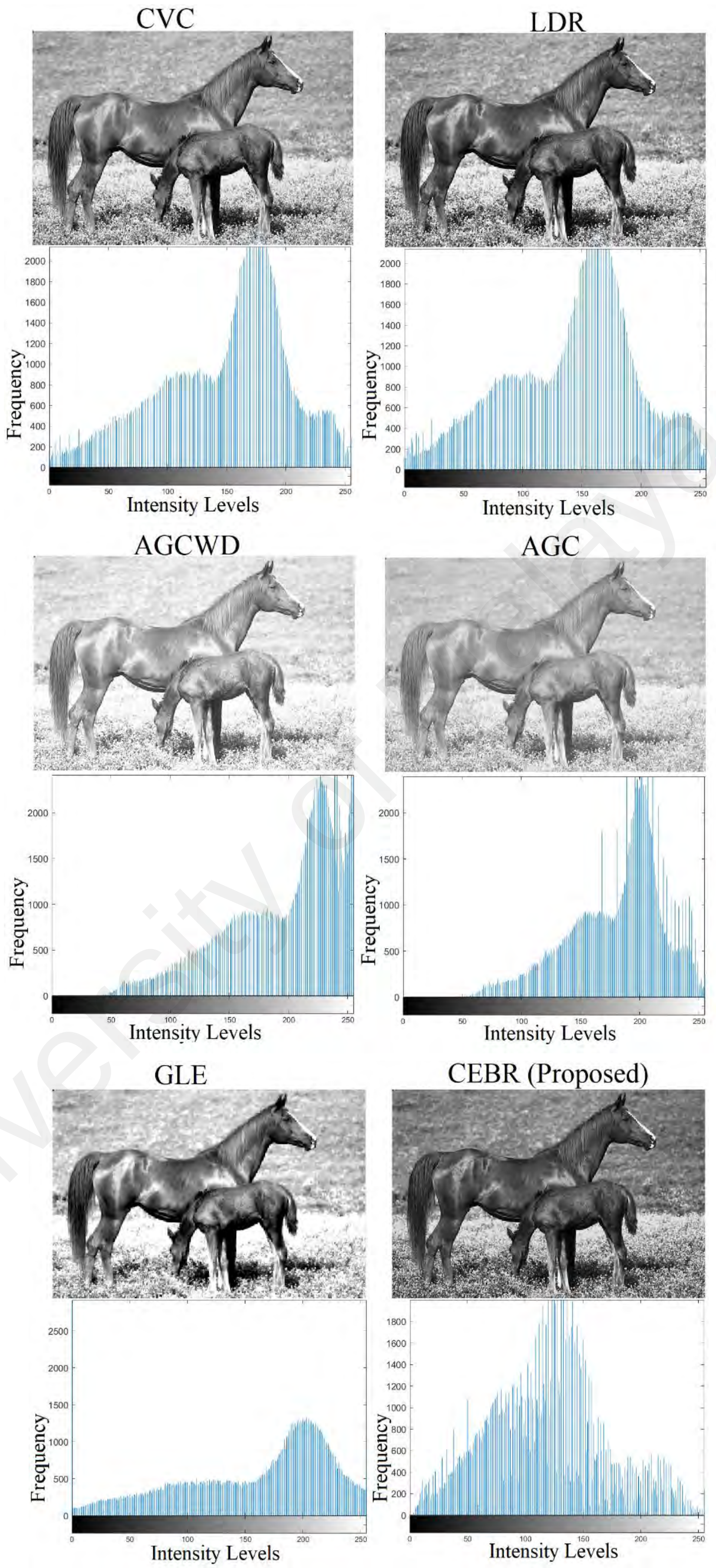


Figure 4.5: Continue

Figure 4.6 is captured during the sun set and it depicts a car parking surrounded by some trees. As it can be clearly seen from Figure 4.6, the parking area and the trees are dark and has low contrast, while, the sky is bright. Therefore, the camera couldn't capture both regions (i.e. sky area and parking area) with a considerable amount of contrast du to the camera's limitations. HE equalized the image's histogram and enhanced the dark area successfully, though, it didn't enhance the sky nor preserved the details of small clouds. In the other hand, MSRCR enhanced the image locally and ignored the global brightness. Hence, the sky is completely washed out and the parking area is over-enhanced to a point where it lost the naturalness of the original image. WAHE enhanced the image to some extent but it didn't utilize the entire dynamic range as it is clearly seen from the histogram of the enhanced image. CVC and LDR are considered a global enhancement technique and both use 2-D histogram to formulate one transformation function. Although CVC achieved better result than LDR, both methods didn't utilize the middle gray range. AGCWD and AGC stretched the dark range and compressed the bright range (referring to their histograms in Figure 4.6). As a result, the sky area is washed out and the details of the clouds are lost. GLE de-enhanced the original image and produced an unpleasant image because it compressed both the dark and bright range. The proposed CEBR divided the image into two regions and each one enhanced individually. Therefore, the sky details are enhanced as well as the parking area. The details of the clouds as well as the parking area can be easily perceived.

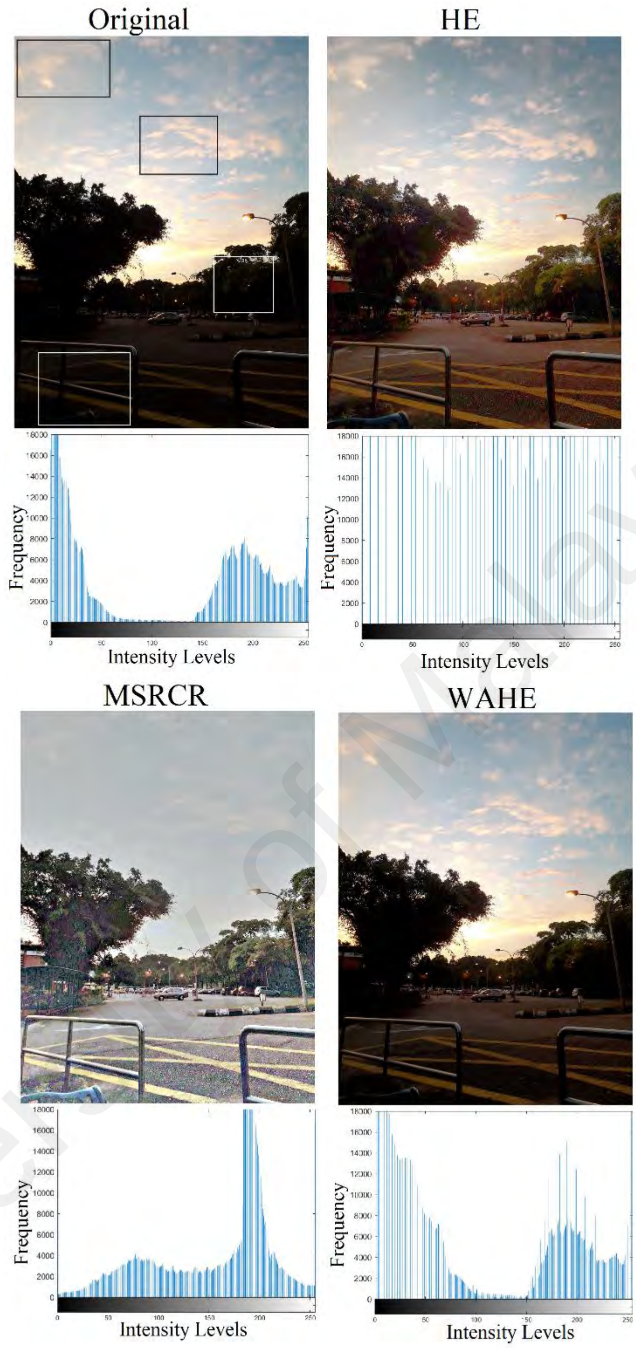


Figure 4.6: Parking image. Original image with the enhancement results generated by various methods. Each image attached with its statistical histogram.

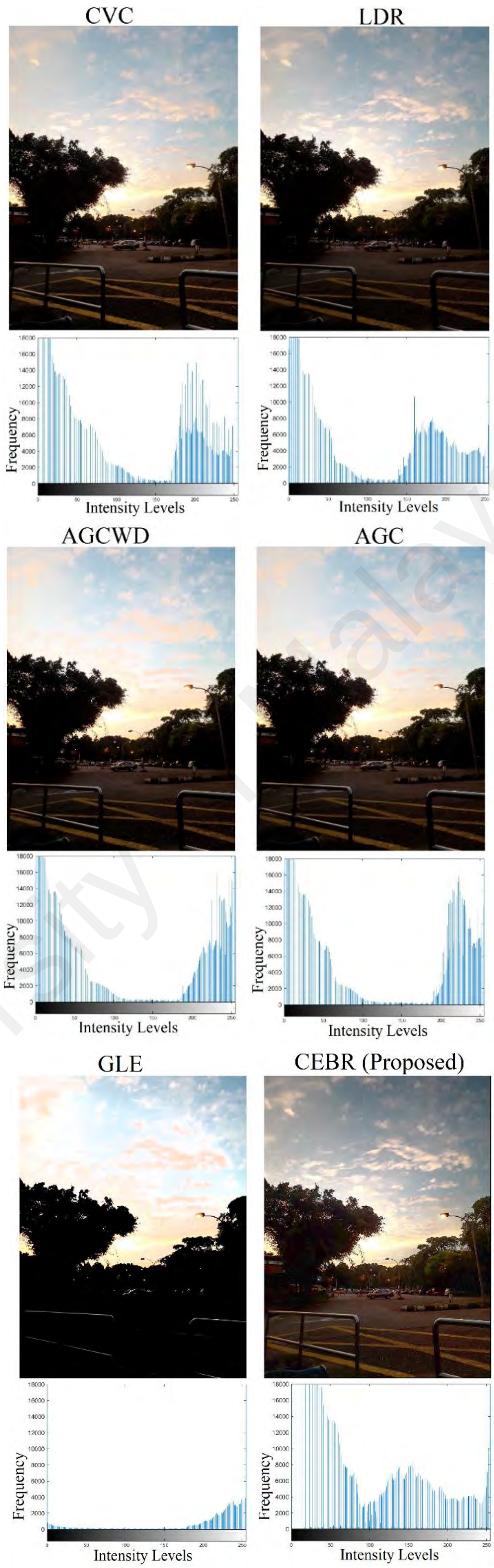


Figure 4.6: Continue

4.3 Quantitative Results

Since the perception of the visual quality may differs from one person to another, numerical justification is a must. Nevertheless, there is no universally accepted criterion for quantitative evaluation (S.-C. Huang et al., 2013; Rahman et al., 2016). In this paper discrete entropy (DE) is selected to assess the contrast level as in (Celik & Tjahjadi, 2011; Rahman et al., 2016).

4.3.1 Discrete Entropy

In information theory, discrete entropy is a statistical measure of uncertainty or randomness of a random variable. In images, high entropy value indicates more details which implies that the image has higher contrast. On the other hand, low entropy means that the image has low contrast (Rahman et al., 2016).

To define the discrete entropy, consider an input image X of size H×W pixels and its histogram denoted as H, i.e., H $= \{h(i)|0 \leq i \leq L\}$, that have L intensity levels, where $h(i) \in [0, \mathbb{Z}^{+}]$. $h(i)$ represents the number of occurrences of intensity level i in the image. Then the probability of the intensity level $p(i)$ is equal to:

$$p(i) = \frac{h(i)}{H \times W} \tag{4.1}$$

And the discrete entropy is defined as follows:

$$DE(X) = \sum_{i=0}^{L} p(i) \times \log\left(\frac{1}{p(i)}\right) \tag{4.2}$$

Table 4.1: Discrete Entropy values of various methods compared with the proposed method

Image\Method	Original	HE	MSRCR	WAHE	CVC	LDR	AGCWD	AGC	GLE	CEBR (proposed)
Beans	5.592	5.3921	7.7562	5.5904	5.5187	5.5919	5.5895	4.8466	6.7161	6.2644
Buildings	6.2046	7.8613	7.6307	7.0291	6.9436	6.8222	6.8178	7.1839	4.0822	7.3
Mars	3.6209	3.7847	7.5517	3.9568	4.0956	3.7541	3.3506	3.1754	1.9907	3.4507
Lake	7.0956	7.6301	7.5065	7.5672	7.3223	7.2271	7.2132	7.3455	4.807	7.7111
Average	5.6283	6.167	**7.6113**	6.0358	5.97	5.8488	5.7428	5.6378	4.399	**6.1816**

Table 4.1, illustrates the entropy value for various methods (conventional methods as well as new methods) – namely HE (Gonzalez & Woods, 2006), MSRCR (Jobson, 2004), WAHE (Arici et al., 2009), CVC (Celik & Tjahjadi, 2011), LDR (C. Lee et al., 2013), AGCWD (S.-C. Huang et al., 2013), AGC (Rahman et al., 2016) and GLE (A. Singh et al., 2016). As can be seen from Table 4.1, the proposed method attained on average a high contrast enhancement rate. Although MSRCR on average has the highest entropy, it suffers from severe distortions, which in results, leads to achieve high contrast images that are visually unpleasant. The amount of annoying artifact produced by MSRCR are shown in the qualitative section, especially, in Figure 4.4 and Figure 4.3. HE also achieved a high entropy value because it compresses the intensity levels that has low probability. HE equalizes histograms bins of images, therefore, it called "Histogram Equalization". This phenomenon is shown in the HE's histograms in Figure 4.4, Figure 4.3 and Figure 4.2. This feature makes HE produces a high contrast level and achieves a high entropy level, as well. Yet, the proposed method has on average an entropy value higher than HE. That is because, the proposed method divides the image into regions and redistributes the intensities for each region. The difference in entropy between HE and the proposed method is not high, however, the proposed method didn't introduce annoying artifacts. Added to that, the proposed method retained the naturalness of the image. This can be clearly seen in the qualitative section.

Graph chart is depicted in Figure 4.7 based on Table 4.1 to further illustrates the average entropy achieved by various methods.

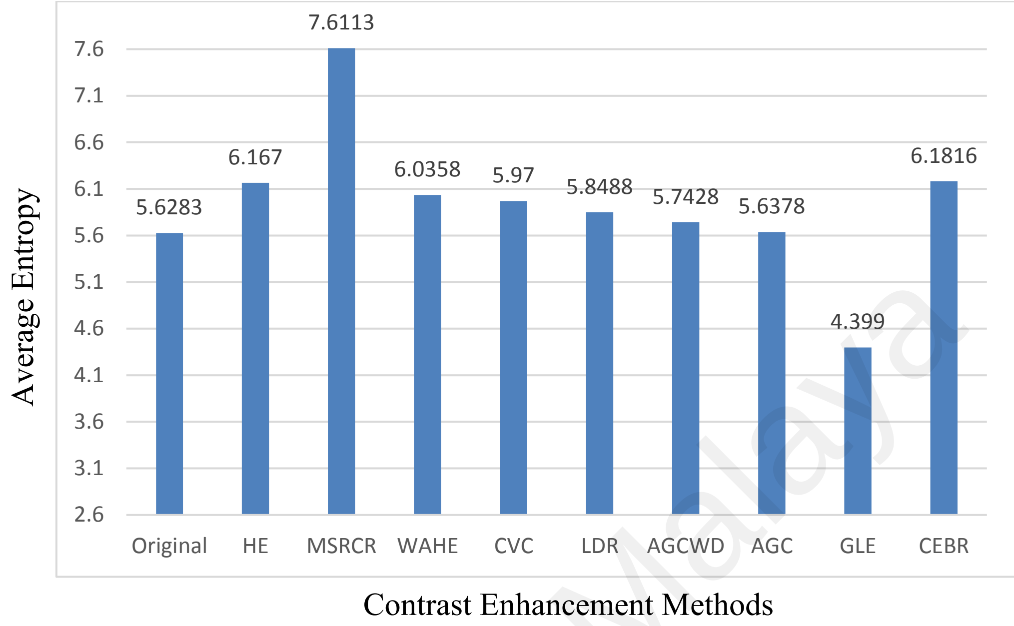


Figure 4.7: A chart that depicts the average DE values in Table 4.1

Since WAHE depends on modified histogram equalization, it also achieved a high entropy values as in HE method.

As it can be seen from Table 4.1, the proposed CEBR has the highest entropy value among the recent proposed methods (i.e. methods were proposed in 2013 and above), which indicates that the proposed method achieved higher contrast level than the other methods. Among the recently proposed methods, the second highest entropy on average was achieved by LDR. From the previous section, it is clearly seen that LDR enhances the original images to some extent, therefore, it achieved relatively high contrast level.

It is clear from the chart in Figure 4.7 that GLE de-enhanced the images because it achieved on average an entropy less than the original image's etnropy. This also can be easily seen in the qualitative sections. On average AGC didn't increase the contrast. Because, AGC depends on the standard deviation of the images' histogram to decide the amount of contrast that the images demand. However, it is known that the standard deviation is sensitive to the outliers, thus, it may provide misleading information about the original contrast of the images. Consider for example Figure 4.4 in the previous section, the original image's histogram has an outlier. The outlier represents the bright region that the image acquired (i.e. building and sky). Although AGCWD achieved an entropy value higher than AGC, AGCWD didn't enhance the images very well.

4.4 Summary

In this chapter, experiment results were presented for both qualitative and quantitative measurements. For the qualitative part, different methods were compared against the proposed method. The proposed method achieved relatively higher contrast level than the other method. It improved the details of the images. Added to that, the proposed method retained the naturalness features of the original images. For the quantitative part, discrete entropy was selected to assess the contrast level. Higher entropy means the image has richer details. The proposed method attained high entropy level compared to the other methods. This is evident that the performance of the proposed method is better than other conventional methods.

CHAPTER 5: CONCLUSION

5.1 Research Discovery

At the present time, digital cameras are embedded in almost every cellphone, thus, capturing an image became easier than ever before. However, capturing a good image depends on many factors, such as lack of operator expertise and illumination conditions. Therefore, some images are degraded and have low contrast, and hence, they demand enhancement methods to solve such problems. Image enhancement techniques has been widely used in medical image processing, texture synthesis, atmospheric sciences, astrophotography, satellite image analysis, remote sensing, digital photography, surveillance, and video processing applications.

Various contrast enhancement methods were studied and analyzed in this dissertation. The motivation behind those enhancement techniques is to extract the hidden details/characteristics of the images. Although they enhance the images to some extent, they tend to fail to enhance wide range of images. According to the discussion in the second chapter, enhancement methods can be categorized into global and local methods.

Global methods analyze the captured image and produce one transformation function to enhance the entire image. The implementation of such methods is fast and easy, but in some cases, they over/under-enhance some areas in the image. Local methods considered the limitations of the global methods; therefore, they focus on enhancing the image locally by constructing a transformation function for each pixel/block based on the neighboring pixels/blocks.

It is evident from the literature that contrast enhancement is still an open area for further investigations. Having said that, this study had the aim of developing another enhancement technique that increases the local visibility of images while at the same time preserve the naturalness of the original images. To achieve that, contrast enhancement method based on the intensity of regions' pixels CEBR has been proposed.

5.2 Contributions

An effective contrast enhancement method was developed to enhance a variety of images that have different degradation effects. Although there are plenty of methods in the literature, they fail to enhance a variety of images due to the nature of images that may have different regions with different illumination conditions. The proposed method acknowledges this phenomenon and proposed a new approach to enhance the images by dividing them into regions. As it can be seen in the Qualitative section, the proposed method succeeded to enhance a variety of images because it treats the images as regions rather than a whole. This feature gives an advantage to the proposed method. Consequently, the proposed method successfully redistributes the intensities over the entire dynamic range -as it can be seen in Figure 4.4- and it enhances each region independently from other regions. Enhances each region independently allows the proposed method to achieve relatively high entropy as it can be noticed in Table 4.1 in the Qualitative section.

As opposed to other methods which needs human intervention in order to set predefined parameters, the proposed method doesn't need any human intervention. Both processes' parameters (i.e. dividing the images into regions and enhance each region) don't need to be optimized nor human intervention is required.

As it can be seen from the Qualitative Figures (i.e. Figure 4.1 to Figure 4.6), the proposed method didn't introduce any artifacts as opposed to other contrast enhancement methods. Added to that, it didn't de-enhance the original image and the naturalness of the original images was persevered successfully. This feature is due to the adaptivity of the enhancement's technique that the proposed method employs.

The contributions of this study are summarized as follows:

- A new contrast enhancement method that increases the local contrast while at the same time preserves the naturalness of the images.
- The proposed CEBR doesn't enhance the pixels or blocks of an image -as local techniques in the literature-, but rather enhances coherent regions of an image.
- To enhance the individual regions, Histogram Stretching and Gamma Correction are fused together to formulate the proposed enhancement function.
- The gamma value in the enhancement function is set adaptively based on the regions' statistical information, therefore, no need for human intervention.
- Contemporary methods as well as conventional methods were tested against the proposed CEBR.
- Experimental results show that the adaptive gamma parameter is set well to produce expected improvement of the images.
- Entropy is a useful tool to measure the richness of the details in the output image. The proposed CEBR achieved on average high entropy value.

5.3 Limitations and Future Work

Although the proposed method showed a promising future, it has limitations. The proposed method is not as fast as the global enhancement methods because it has several stages before applying the enhancement function. The time is mostly consumed by region creation stage. Also, in some cases, the proposed method divides the image into small regions and reunions them again to constitute only one region. This implies that some images don't need to be divided in the first place. In the future work, Analysis of Variance (ANOVA) can be employed to test the amount of contrast level within the blocks and between the blocks. Based on that, it can be decided whether to divide the image into regions or not.

The success of the proposed method depends mainly on the segmentation criteria. Therefore, the proposed method may get strengthen by using various segmentation techniques. One direction of future work could be segmentation based on texture rather than contrast level.

REFERENCES

Abdul Ghani, A. S., & Mat Isa, N. A. (2015). Enhancement of low quality underwater image through integrated global and local contrast correction. *Applied Soft Computing*, *37*, 332–344. https://doi.org/10.1016/j.asoc.2015.08.033

Al-Najdawi, N., Biltawi, M., & Tedmori, S. (2015). Mammogram image visual enhancement, mass segmentation and classification. *Applied Soft Computing*, *35*, 175–185. https://doi.org/10.1016/j.asoc.2015.06.029

Arici, T., Dikbas, S., & Altunbasak, Y. (2009). A Histogram Modification Framework and Its Application for Image Contrast Enhancement. *Image Processing, IEEE Transactions On*, *18*(9), 1921–1935. https://doi.org/10.1109/TIP.2009.2021548

Celik, T., & Tjahjadi, T. (2011). Contextual and variational contrast enhancement. *IEEE Transactions on Image Processing*, *20*(12), 3431–3441. https://doi.org/10.1109/TIP.2011.2157513

Dong, X., Wang, G., Pang, Y., Li, W., Wen, J., Meng, W., & Lu, Y. (2011). Fast efficient algorithm for enhancement of low lighting video. *Proceedings - IEEE International Conference on Multimedia and Expo*, *3*, 3–8. https://doi.org/10.1109/ICME.2011.6012107

Fattal, R. (2008). Single image dehazing. In *ACM SIGGRAPH 2008 papers on - SIGGRAPH '08* (Vol. 2, p. 1). New York, New York, USA: ACM Press. https://doi.org/10.1145/1399504.1360671

Girdhar, A., Gupta, S., & Bhullar, J. (2015). Region Based Adaptive Contrast Enhancement of Medical Ultrasound Images. In *2015 IEEE International Conference on Computational Intelligence & Communication Technology* (pp. 750–753). IEEE. https://doi.org/10.1109/CICT.2015.120

Gonzalez, R. C., & Woods, R. E. (2006). *Digital Image Processing (3rd Edition)*. Prentice-Hall, Inc.

Gu, K., Zhai, G., Wang, S., Liu, M., Zhoi, J., & Lin, W. (2015). A general histogram modification framework for efficient contrast enhancement. In *2015 IEEE International Symposium on Circuits and Systems (ISCAS)* (pp. 2816–2819). IEEE. https://doi.org/10.1109/ISCAS.2015.7169272

Guo, X., Li, Y., & Ling, H. (2017). LIME: Low-Light Image Enhancement via Illumination Map Estimation. *IEEE Transactions on Image Processing*, *26*(2), 982–993. https://doi.org/10.1109/TIP.2016.2639450

Huang, S.-C., Cheng, F.-C., & Chiu, Y.-S. (2013). Efficient Contrast Enhancement Using Adaptive Gamma Correction With Weighting Distribution. *IEEE Transactions on Image Processing*, *22*(3), 1032–1041. https://doi.org/10.1109/TIP.2012.2226047

Huang, Z., Zhang, T., Li, Q., & Fang, H. (2016). Adaptive gamma correction based on cumulative histogram for enhancing near-infrared images. *Infrared Physics & Technology*, *79*, 205–215. https://doi.org/10.1016/j.infrared.2016.11.001

Huang, Z., Zhang, Y., Li, Q., Zhang, T., Sang, N., & Hong, H. (2018). Progressive Dual-Domain Filter for Enhancing and Denoising Optical Remote-Sensing Images. *IEEE Geoscience and Remote Sensing Letters*, *15*(5), 759–763. https://doi.org/10.1109/LGRS.2018.2796604

Ibraheem, N. a, Hasan, M. M., Khan, R. Z., & Mishra, P. K. (2012). Understanding Color Models : A Review. *ARPN Journal of Science and Technology*, *2*(3), 265–275. https://doi.org/10.1.1.679.8051

Iwanami, T., Goto, T., Hirano, S., & Sakurai, M. (2012). An adaptive contrast enhancement using regional dynamic histogram equalization. In *2012 IEEE International Conference on Consumer Electronics (ICCE)* (pp. 719–722). IEEE. https://doi.org/10.1109/ICCE.2012.6162054

Jafar, I., & Ying, H. (2007). A new method for image contrast enhancement based on automatic specification of local histograms. *International Journal of Computer Science and …*, *7*(7), 1–10. https://doi.org/10.1.1.533.8846

Jiang, G., Wong, C. Y., Lin, S. C. F., Rahman, M. A., Ren, T. R., Kwok, N., … Wu, T. (2015). Image contrast enhancement with brightness preservation using an optimal gamma correction and weighted sum approach. *Journal of Modern Optics*, *62*(7), 536–547. https://doi.org/10.1080/09500340.2014.991358

Jianhua Pang, Zhang, S., & Wencang Bai. (2017). A novel framework for enhancement of the low lighting video. In *2017 IEEE Symposium on Computers and Communications (ISCC)* (pp. 1366–1371). IEEE. https://doi.org/10.1109/ISCC.2017.8024714

Jobson, D. J. (2004). Retinex processing for automatic image enhancement. *Journal of Electronic Imaging*, *13*(1), 100. https://doi.org/10.1117/1.1636183

Joung-Youn Kim, Lee-Sup Kim, & Seung-Ho Hwang. (2001). An advanced contrast enhancement using partially overlapped sub-block histogram equalization. *IEEE Transactions on Circuits and Systems for Video Technology*, *11*(4), 475–484. https://doi.org/10.1109/76.915354

Kaiming He, Jian Sun, & Xiaoou Tang. (2011). Single Image Haze Removal Using Dark Channel Prior. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *33*(12), 2341–2353. https://doi.org/10.1109/TPAMI.2010.168

Kaur, A., Girdhar, A., & Kanwal, N. (2016). Region of Interest Based Contrast Enhancement Techniques for CT Images. In *2016 Second International Conference on Computational Intelligence & Communication Technology (CICT)* (pp. 60–63). IEEE. https://doi.org/10.1109/CICT.2016.21

Kim, J.-H., Jang, W.-D., Sim, J.-Y., & Kim, C.-S. (2013). Optimized contrast enhancement for real-time image and video dehazing. *Journal of Visual Communication and Image Representation*, *24*(3), 410–425. https://doi.org/10.1016/j.jvcir.2013.02.004

Land, E. H. (1977). The retinex theory of color vision. *Scientific American*, *237*(6), 108–128. https://doi.org/10.1038/scientificamerican1277-108

Lee, C., Lee, C., & Kim, C.-S. (2013). Contrast Enhancement Based on Layered Difference Representation of 2D Histograms. *IEEE Transactions on Image Processing*, *22*(12), 5372–5384. https://doi.org/10.1109/TIP.2013.2284059

Lee, J.-T., Lee, C., Sim, J.-Y., & Kim, C.-S. (2014). Depth-guided adaptive contrast enhancement using 2D histograms. In *2014 IEEE International Conference on Image Processing (ICIP)* (pp. 4527–4531). IEEE. https://doi.org/10.1109/ICIP.2014.7025918

Li, C., Xu, C., Gui, C., & Fox, M. D. (2005). Level set evolution without re-initialization: A new variational formulation. In *Proceedings - 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, CVPR 2005* (Vol. I, pp. 430–436). https://doi.org/10.1109/CVPR.2005.213

Li, Y., Liu, X., & Liu, Y. (2015). Adaptive Local Gamma Correction Based on Mean Value Adjustment. In *2015 Fifth International Conference on Instrumentation and Measurement, Computer, Communication and Control (IMCCC)* (pp. 1858–1863). IEEE. https://doi.org/10.1109/IMCCC.2015.395

Lisani, J.-L., Michel, J., Morel, J.-M., Petro, A. B., & Sbert, C. (2016). An Inquiry on Contrast Enhancement Methods for Satellite Images. *IEEE Transactions on Geoscience and Remote Sensing*, *54*(12), 7044–7054. https://doi.org/10.1109/TGRS.2016.2594339

Liu, N., & Zhao, D. (2014). Detail enhancement for high-dynamic-range infrared images based on guided image filter. *Infrared Physics & Technology*, *67*, 138–147. https://doi.org/10.1016/j.infrared.2014.07.013

M, D. (2012). Wavelet and Curvelet based Thresholding Techniques for Image Denoising. *International Journal of Advanced Research in Computer Science and Electronics Engineering (IJARCSEE)*, *1*(10), 77–81. Retrieved from http://www.ijarcsee.org/index.php/IJARCSEE/article/view/286

Peli, E. (1990). Contrast in complex images. *Journal of the Optical Society of America A*, *7*(10), 2032. https://doi.org/10.1364/JOSAA.7.002032

Pizer, S. M., Amburn, E. P., Austin, J. D., Cromartie, R., Geselowitz, A., Greer, T., … Zuiderveld, K. (1986). Adaptive histogram equalization and its variations. *Computer Vision, Graphics, and Image Processing*, *39*(3), 355–368. https://doi.org/10.1016/S0734-189X(87)80186-X

Poynton, C. (2003). The CIE system of colorimetry. In *Digital Video and HDTV* (pp. 211–231). Elsevier. https://doi.org/10.1016/B978-155860792-7/50087-2

Qadar, M. A., Zhaowen, Y., Rehman, A., & Alvi, M. A. (2015). Recursive weighted multi-plateau histogram equalization for image enhancement. *Optik - International Journal for Light and Electron Optics*, *126*(24), 5890–5898. https://doi.org/10.1016/j.ijleo.2015.08.278

Rahman, S., Rahman, M. M., Abdullah-Al-Wadud, M., Al-Quaderi, G. D., & Shoyaib, M. (2016). An adaptive gamma correction for image enhancement. *EURASIP Journal on Image and Video Processing*, *2016*(1), 35.

https://doi.org/10.1186/s13640-016-0138-1

Rahman, S., Rahman, M. M., Hussain, K., Khaled, S. M., & Shoyaib, M. (2014). Image enhancement in spatial domain: A comprehensive study. In *2014 17th International Conference on Computer and Information Technology (ICCIT)* (pp. 368–373). Cham: IEEE. https://doi.org/10.1109/ICCITechn.2014.7073123

Santhi, K., & Wahida Banu, R. S. D. (2015). Adaptive contrast enhancement using modified histogram equalization. *Optik - International Journal for Light and Electron Optics*, *126*(19), 1809–1814. https://doi.org/10.1016/j.ijleo.2015.05.023

Senthilkumar, B., Umamaheswari, G., & Karthik, J. (2010). A novel region growing segmentation algorithm for the detection of breast cancer. In *2010 IEEE International Conference on Computational Intelligence and Computing Research* (pp. 1–4). IEEE. https://doi.org/10.1109/ICCIC.2010.5705725

Singh, A., Yadav, S., & Singh, N. (2016). Contrast enhancement and brightness preservation using global-local image enhancement techniques. In *2016 Fourth International Conference on Parallel, Distributed and Grid Computing (PDGC)* (Vol. 4th, pp. 291–294). IEEE. https://doi.org/10.1109/PDGC.2016.7913162

Singh, K., & Kapoor, R. (2014). Image enhancement using Exposure based Sub Image Histogram Equalization. *Pattern Recognition Letters*, *36*(1), 10–14. https://doi.org/10.1016/j.patrec.2013.08.024

Song, Q., Wang, Y., & Bai, K. (2016). High dynamic range infrared images detail enhancement based on local edge preserving filter. *Infrared Physics & Technology*, *77*, 464–473. https://doi.org/10.1016/j.infrared.2016.06.023

Tan, F., Li, Y., & Guan, M. (2017). Automatic Windowing for Highly Dynamic Industrial X-ray Image Based on Short-Term Energy of Gray Histogram. *Journal of Nondestructive Evaluation*, *36*(3), 54. https://doi.org/10.1007/s10921-017-0432-6

Tang, J. R., & Mat Isa, N. A. (2017). Bi-histogram equalization using modified histogram bins. *Applied Soft Computing*, *55*, 31–43. https://doi.org/10.1016/j.asoc.2017.01.053

Tsai, C. M., & Yeh, Z. M. (2008). Contrast enhancement by automatic and parameter-free piecewise linear transformation for color images. *IEEE Transactions on Consumer Electronics*, *54*(2), 213–219. https://doi.org/10.1109/TCE.2008.4560077

Verma, O. P., Hanmandlu, M., Susan, S., Kulkarni, M., & Jain, P. K. (2011). A Simple Single Seeded Region Growing Algorithm for Color Image Segmentation using Adaptive Thresholding. In *2011 International Conference on Communication Systems and Network Technologies* (pp. 500–503). IEEE. https://doi.org/10.1109/CSNT.2011.107

Wang, D., Niu, X., & Dou, Y. (2014). A piecewise-based contrast enhancement framework for low lighting video. In *Proceedings 2014 IEEE International Conference on Security, Pattern Analysis, and Cybernetics (SPAC)* (pp. 235–240). IEEE. https://doi.org/10.1109/SPAC.2014.6982691

Wang, Q., & Ward, R. (2007). Fast Image/Video Contrast Enhancement Based on

Weighted Thresholded Histogram Equalization. *IEEE Transactions on Consumer Electronics*, *53*(2), 757–764. https://doi.org/10.1109/TCE.2007.381756

Zhang, F., Xie, W., Ma, G., & Qin, Q. (2014). High dynamic range compression and detail enhancement of infrared images in the gradient domain. *Infrared Physics & Technology*, *67*, 441–454. https://doi.org/10.1016/j.infrared.2014.09.003

Zuiderveld, K. (1994). Contrast Limited Adaptive Histogram Equalization. In *Graphics Gems* (pp. 474–485). Elsevier. https://doi.org/10.1016/B978-0-12-336156-1.50061-6