NEW CONTRAST ENHANCEMENT TECHNIQUE FOR NON-UNIFORM ILLUMINATION DIGITAL COLOUR MEDICAL IMAGES

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NEW CONTRAST ENHANCEMENT TECHNIQUE FOR NON-UNIFORM ILLUMINATION DIGITAL COLOUR MEDICAL IMAGES

by

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LIST OF ABBREVIATIONS

ANAs	ANtinuclear Antibodies
B	blue
CAD	Computer Aided Diagnosis
CAT	Computerized Axial Tomography
CCD	Charge-Coupled Device
CLAHE	Contrast Limited Adaptive Histogram Equalizer
CMYK	Cyan, Magenta, Yellow and blacK
CIE L*a*b*	Lightness-colour-opponent dimensions
CIN	Cervical Intraepithelial Neoplasia
CS	Contrast Stretching
CT	Computerized Tomography
dB	decibel
DCT	Discrete Cosine Transform
DNA	DeoxyriboNucleic Acid
DWT	Discrete Wavelet Transform
EIA	Enzyme Immunosorbent Assay
ELISA	Enzyme-Linked ImmunoSorbent Assay
EME	Enhancement Measurement Error
FITC	Fluorescein IsoThioCyanate
FT	Fourier Transform
G	green
GC	Gamma Correction
H	hue

HDTV	High Definition Television
HE	Histogram Equalization
HEp-2	Human Epithelial type 2
HPV	Human PapillomaVirus
HSIL	High-grade Squamous Intraepithelial Lesion
HSL	Hue-Saturation-Lightness
HSV	Hue-Saturation-Value
HUSM	Hospital Universiti Sains Malaysia
ICPR	International Conference on Pattern Recognition
IIF	Indirect ImmunoFluorescence
JIA	Juvenile Idiopathic Arthritis
LSIL	Low-grade Squamous Intraepithelial Lesion
MATLAB	MATrix LABoratory
MCTD	Mixed Connective Tissue Disease
MIA	Multiplex ImmunoAssay
MRI	Magnetic Resonance Imaging
MSE	Mean-Squared Error
NA	Not Available
NILM	Negative for Intraepithelial Lesion or Malignancy
Pap	Papanicolau
PET	Positron Emission Tomography
R	red
RGB	Red-Green-Blue
S	saturation
SLE	Systemic Lupus Erythematosus

SPECT	Single Photon Emission Computed Tomography
SNR	Signal-to-Noise Ratio
SS	Sjögren Syndrome
SSc	Scleroderma and Systemic Sclerosis
UCTD	Undifferentiated Connective Tissue Disease
UIQI	Universal Image Quality Index
V	value
YCbCr	luminance and chrominance

LIST OF SYMBOLS

b	constant parameter for contrast adjustment of bright intensities
c_t	contrast
C	number of columns contained in the image
CT	image contrast
C_1	first constant parameter for $SSIM$
C_2	second constant parameter for $SSIM$
C_3	third constant parameter for $SSIM$
E	exposure
ET	exposure threshold
f	original image
f_{bright_1C}	intensity value of the pixel in the bright region
f_{dark_1C}	intensity value of the pixel in the dark region
$f_{enh\_bright\_1C}$	new intensity value of the pixel for the bright region
$f_{enh\_dark\_1C}$	new intensity value of the pixel for the dark region
f_{enh_1C}	a new grey level or R, G or B intensity value
f_{enh_3C}	enhanced colour image
f_{even_1C}	more even illumination image with one dimensional
$f_{even_{1C_{min}}}$	minimum intensity value of the pixel in f_{even_1C}
$f_{even\_1C_{max}}$	maximum intensity value of the pixel in f_{even_1C}
f_{gray}	greyscale image
f_h^2	fuzzifier

$f_{\max\_1C}$	maximum grey level or RGB intensity value of an image
$f_{\min\_1C}$	minimum grey level or RGB intensity value of an image
f_{ori_1C}	an original grey level or RGB intensity value of a pixel (x, y)
f_{ori_3C}	original image with three dimensional
F_{xy}	input image at corresponding (x, y) coordinate
g	enhanced image
g_i	output pixel after mapping
G_{xy}	enhanced image at corresponding (x, y) coordinate
H	hue intensity value in degrees on the colour circle
H'	hue intensity value in radians on the hexagon
i	intensity level of f_{ori_1C}
$\bar{\imath}$	average intensity of the f_{ori_1C}
I	intensity of the image
i_b	normalized intensity value of blue colour space
i_B	intensity value of blue colour space
i_g	normalized intensity value of green colour space
i_G	intensity value of green colour space
i_{min}	minimum intensity of the f_{ori_1C}
i_{max}	maximum intensity of the f_{ori_1C}
i_r	normalized intensity value of red colour space
i_R	intensity value of red colour space
$i_{x,y}$	intensity value at spatial position (x, y)

$I(x, y)$	an image
k	intensity of the image
$\bar{k}$	average intensity of the image
l	luminance
L	total number of intensity levels
M	number of rows of the digital image
MSE	mean squared error between input image and enhanced image
N	number of columns of the digital image
n_i	number of pixels at intensity level i
n_t	total number of pixels in an image
$p(i)$	normalized histogram of f_{ori_1C}
$p(k)$	histogram component of the image at intensity k
$PSNR$	Peak Signal-to-Noise Ratio
r	pixel values of the image f
R	number of rows contained in the image
RT	region threshold
s	pixel values of the image g
S	saturation intensity value
$SSIM$	Structural Similarity Index
s_t	structure
t	processing time
T	transformation function
V	luminance intensity value
x	horizontal axis of continuous spatial coordinate

(x, y)	coordinate on the spatial domain
y	vertical axis of continuous spatial coordinate
α	exposure operator
α_l	exponent for luminance l
β	fuzzified factor
β_{c_t}	exponent for contrast c_t
γ	typical constant value in the range within 0.95 to 1.05 for greyscale image and in the range within 1.01 to 1.05 for colour image
γ_{s_t}	exponent for structure s_t
σ_F	standard deviations of input image
σ_G	standard deviations of enhanced image
σ_{GF}	cross-covariance of enhanced and input images
σ_i	standard deviation intensities of f_{ori_1C}
$\mu(i_{x,y})$	degree of membership of intensity value $i_{x,y}$ in the fuzzy set
μ_F	local averages of input image
μ_G	local averages of enhanced image
$\mu_o(i_{x,y})$	modified Gaussian membership functions for overexposed region
$\mu_u(i_{x,y})$	modified Gaussian membership functions for underexposed region
/	associate the membership value with its intensity value $i_{x,y}$

TEKNIK PENINGKATAN KONTRAS BAHARU UNTUK IMEJ PERUBATAN WARNA DIGITAL BERILUMINASI TIDAK SERAGAM

ABSTRAK

Disertasi ini mempermukakan satu algoritma peningkatan bukan linear yang baru untuk digital imej perubatan yang mempunyai iluminasi tidak seragam dan kontras yang rendah. Imej perubatan mikroskopik untuk sel servik dan sel epitelium manusia jenis kedua telah digunakan sebagai kajian kes dalam kaji selidik ini. Biasanya, imej sel yang ditangkapi daripada kamera video atau kamera digital mengalami masalah beriluminasi tidak seragam dan kontras yang buruk disebabkan oleh pencahayaan yang terlalu banyak atau tidak mencukupi, kualiti peranti pemerolehan imej dan/atau keadaan persekitaran. Masalah iluminasi yang tidak seragam tidak disertai dalam kebanyakan kaedah-kaedah penambahan kontras yang telah dibangunkan ketika operasi peningkatan kualiti imej sel. Walaupun kajian-kajian yang terdahulu mengusulkan dua jenis kaedah penambahan kontras gelap dan terang yang tidak linear, setiap kaedah digunakan untuk menambahbaikkan seluruh imej sel. Dengan itu, setiap imej yang dihasilkan mempunyai hanya suatu kawasan yang berkontras terlalu tinggi disertai dengan suatu kawasan lain yang berkontras terlalu rendah. Algoritma yang diusulkan menyelesaikan masalah iluminasi tidak seragam dengan dua fungsi keahlian kabur Gaussian yang telah diubahsuai untuk kawasan-kawasan yang telah ditentukan terlebih dahulu dengan pendedahan yang rendah dan tinggi. Selepas memperolehi imej sel yang beriluminasi lebih seragam, algoritma yang diusulkan seterusnya menyelesaikan masalah kontras yang rendah dengan menggunakan teknik peningkatan kontras baharu yang tidak linear untuk

meningkatkan kostras di kawasan imej gelap dan di kawasan imej terang masing-masing. Akhirnya, penggabungan piksel-piksel setiap kawasan imej yang telah ditambahbaikkan akan dilaksanakan untuk menghasilkan satu imej yang telah ditambahbaikkan. Menurut analisis kualitatif dan analisis kuantitatif, hasil ujikaji dalam format imej kelabu dan imej warna telah menunjukkan bahawa algoritma yang diusulkan dapat menghasilkan imej yang lebih nyata dan berinfomasi, ampliflikasi hingar yang paling kurang, pembezaan antara sel dan latar belakang yang lebih baik, kontras dan iluminasi yang lebih baik, disertai dengan kebolehan mengekalkan imej semula jadi diperbandingkan dengan kaedah-kaedah yang lain.

NEW CONTRAST ENHANCEMENT TECHNIQUE FOR NON-UNIFORM ILLUMINATION DIGITAL COLOUR MEDICAL IMAGES

ABSTRACT

This dissertation presents a new non-linear contrast enhancement algorithm for non-uniform illumination and low contrast digital colour medical images. In this research study, medical microscopic cervical cell and human epithelial type 2 (HEp-2) cell images were employed as case studies. Commonly, the captured cell images from the video camera or digital camera have uneven illumination and poor contrast due to inadequate lighting, the quality of the image acquisition devices and/or environmental conditions. The problem of non-homogenous illumination is not considered by most of the developed contrast enhancement approaches when performing operations to improve the cell image quality. From the previous studies, although two non-linear dark and bright contrast enhancement methods were proposed, but each method was utilized to enhance the entire cell image. As a result, each resultant image contained only one enhanced region while degraded the contrast of another region extremely. Firstly, this proposed algorithm tackles the non-uniform illumination issue by implementing two modified Gaussian fuzzy membership functions to predetermined underexposed and overexposed regions. After obtaining more even illumination cell images, this proposed algorithm addresses the low contrast problem by proposing new non-linear dark region bright region contrast enhancement techniques to enhance dark and bright regions individually. Lastly, the enhanced pixels of each region are combined to form an enhanced image. According to the qualitative and quantitative analysis, the experimental results in greyscale and

colour format showed that the proposed algorithm tends to provide clearer and informational enhanced images, least noise amplification, better differentiation between the cell and the background, better contrast and illumination, and capable to preserve the image naturalness as compared with other methods.

CHAPTER 1

INTRODUCTION

1.1 Introduction

Human is characterized as a visual being in perceiving the surrounding information based on visual inspection. This is mainly because images are better than any other information form for us to perceive. However, the image of an object can appear in various ways for perception by humans, such as presented in greyscale or colour format, appeared clearly or degraded by some degrading mechanisms. Hence, image enhancement is one of the image processing applications played a vital role in modern technologies in further improving the interpretability or perception of information in images for human viewers, and providing better input for other automated image processing approaches [1-13]. Certain features of interest or obscured details in the input image can be extracted by image enhancement technique. It is conducted by producing a modified version of the input image by remapping the image data values in the intensity range of 0 to 255.

Image enhancement technique can be utilized to improve the image quality either subjectively or objectively. One classic example of objective improvement of an image is reducing the noise amplification in an image or increasing peak signal-to-noise ratio ($PSNR$) of an image. Meanwhile, subjective image improvement can be revealed with certain features for easier viewing by modifying the colours or intensities, and this is most likely depending on the perception of each individual.

Besides real life photography, image enhancement plays a pivotal part in medical image analysis, forensics, satellite and aerial imaging, remote sensing, art studies, atmospheric sciences, fingerprint matching and etc [2, 5, 8, 12-15]. In this research study, image enhancement in medical image analysis is focused.

As known, medical imaging is a process of generating visual representations of the interior of a body, such as organs and tissues, and exposing the internal structures hidden by the bones, muscles and skins, for diagnostics, medical and surgical intervention, and clinical analysis. The medical image acquisition is carried out by using medical equipment that depends on various sources of illumination. For example, X-ray radiography, Magnetic Resonance Imaging (MRI), Computerized Tomography (CT), ultrasound, microscopic imaging, endoscopy, and nuclear medicine imaging techniques, including Positron Emission Tomography (PET) and Single Photon Emission Computed Tomography (SPECT) [16-18] are some well-known medical imaging techniques employed in the medical field nowadays. By establishing a database of normal anatomy and physiology, medical imaging can be used to identify abnormalities [19-21]. Some diagnostics for medical reasons require the doctors to take out the cells and tissues from the body. Hence, the medical imaging is utilized to produce the visual representations of the characteristics consisted in the cells and tissues for diagnostic purpose.

Similar to any other digital image application, the quality of the medical images can be easily degraded, either caused by mishandling or quality of the image acquisition devices, illumination condition, noise and external environmental conditions. These issues may cause the acquired medical images having low contrast, poor or uneven illumination and noise distortion. Furthermore, if the medical images with poor quality are employed in Computer Aided Diagnosis (CAD) system, it

might affect the accuracy for segmentation and detection, which in turn causing false diagnosis.

As the advancement in medical imaging equipment and the rise of interest to understand various medical diseases, there is a growing demand of image processing on medical image to extract valuable and meaningful information which is difficult to be viewed by the human naked eyes easily and improve the image quality before getting an accurate segmentation and detection from medical images. With clearer medical images, the diseases can be earlier and correctly detected using CAD, and then the treatment can be carried out more effectively in order to cure the diseases from the patients. With the aid of very clear and informative medical images, the doctors can directly observe these images for fast checking up to identify the diseases suffering from the patients instead of diagnosing the patients according to the symptoms.

1.2 Research Motivation

CAD has become one of the research focus areas in medical imaging. This trend is motivated by the helpfulness and effectiveness of CAD in aiding radiologists and clinicians in the detection and interpretation of diseases. CAD system provides an assessment of a disease using image-based information alone or combined with other relevant diagnostic data. Moreover, it can also be used to provide complementary and supportive decision in interpreting the medical images, which in turn aiding clinicians' diagnosis [22, 23].

Prior to the existence of an effective CAD system, diagnosis is solely depends on the experienced and skillful radiologists and/or physicians. The visual examination carried out by them is a slow, tedious, subjective and expensive process [22, 24]. Therefore, this scenario provided great motivation for the researchers to encounter this issue using computer assisted or automated cell image analysis systems for disease detection and diagnosis.

Leaps and bounds made in the computer and imaging technologies, together with lower prices and general availability of medical imaging tools have contributed to the revolution and improvement of CAD system. Currently, there are at least four types of efforts in CAD research area. Firstly, visual detection assist is a qualitative analysis and interactive quantitative analysis of the objects of interest in the medical images by either enhancing the salient features of the objects or suppressing the background noises. Feature extraction assist is the second type of effort targeting to extract the feature of the objects of interest for further quantitative analyses by using techniques, such as boundary delineation, tree-structure reconstruction, fiber tracking, texture analysis, and etc. Another type of effort is automated detection and classification of the objects of interest, by integrating data mining, medical image analysis, and signal processing technologies. Lastly, estimation of the anatomical and functional tissue properties not explicitly revealed in the medical images is developed based on mathematical modeling [25].

Significant development efforts have been constantly done by the researchers to supplement or replace the human visual inspection by using computer analysis. However, the performance of CAD system still requires further improvement in the computational method and algorithm in order to meet with real application needs and effective diagnosis. The most significant problem that usually cause false

segmentation, detection and diagnosis by CAD is due to the less effective to obtain enhanced medical images with good contrast and containment of significant detail information [22]. This is the first type of effort in CAD research area and is motivated in this research work.

In the past, many different image enhancement techniques for medical images had been developed by modifying from the conventional and relative simply image enhancement approaches in order to provide a robust pre-processing approach [16, 19-21]. The function of these image enhancement techniques is just to improve the image contrast and reduce the noises. Commonly, these image enhancement processes are done globally and locally. These image enhancement techniques have successfully implemented for processing and analysis in CAD. However, the resultant image after enhancement process are still cannot provide a good segmentation and detection and caused false diagnosis due to some of the significant image contents are not extracted. Thus, a great potential for enhancing and interpreting useful diagnostic information from these images more accurately has interested the researchers by developing more advances medical image enhancement algorithms [26]. Moreover, the development of medical image enhancement method with greater informational throughput has received much attention by the researchers. This is done by conducting two different image enhancement methods based on dark and bright regions of interest [27-31]. Recently, the researchers found that the image quality can be further improved by considering the problem suffered by most of the medical images, which is non-uniform illumination effect [32]. This may cause certain regions of the medical images appearing darker and/or brighter than other regions. As such, different techniques of medical image enhancement are developed currently in order to correct the problem of uneven illumination contained in the

input image and then the contrast of the resulting medical image is enhanced based on dark and bright regions of interest.

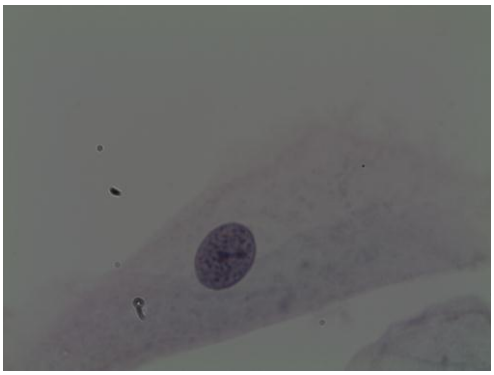
1.3 PROBLEM STATEMENT

Although there is available CAD for cervical cell images, but the available tools for image analysis and quantification are still not accurate enough to transmit significant information about the content of cervical cell images [33]. Up to now, CAD still provide secondary opinion in interpreting the cervical cell images by rescreening the samples that have been screened by the cytotechnologists [22]. Cytotechnologists who are critically trained and have well experience are mainly responsible to do Papanicolau (Pap) smear screening task. However, as large numbers of Pap smear samples are taken by the women, cytotechnologists are likely to make an erroneous determination due to tiredness, eye strain, visual habituation after prolonged periods of evaluating the samples [33, 34]. For HEp-2 cell images, some automatic HEp-2 cell classification systems were proposed in the recent years [35]. As this type of cell images is still conducted in the research stage, thus the assessment of HEp-2 cell images is carried out subjectively by the cytotechnologists.

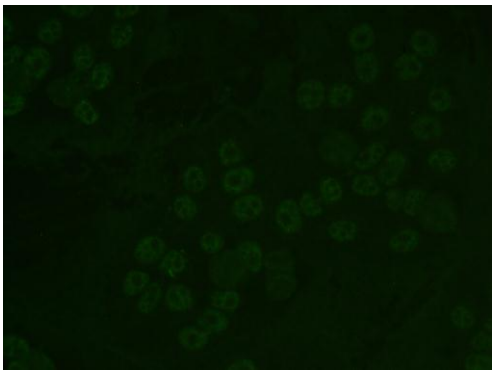
Typically, the captured cell images have poor contrast and suffer from non-uniform illumination problem. The reason of the captured cell images having low contrast is that the most commercial image acquisition devices, such as cameras and video camera, employed commonly have limited dynamic range as compared to the human visual system. On the other hand, cell images captured under improper lighting condition may cause the entire images look too bright or too dark or some image regions appear too bright or too dark than other regions. As a result, the cell

boundaries may obscure or hazy and the textures of the cells cannot be clearly visualized. Sequentially, the size and shape of the nucleus and cytoplasm, and the staining pattern of the HEp-2 cells may be incorrectly determined and recognized. These issues may bring difficulty to the human experts when visualizing the morphological features on these cell images or may cause segmentation and detection processes wrongly, which in turn leads to false diagnosis.

To illustrate the non-homogenous illuminated and low contrast cell image, the histogram of that image in greyscale format can be visualized as shown in Figure 1.1. The input images that are employed have 24-bit colour depth. Thus, each channel of colour plane or each greyscale layer has 8-bit, consisting dynamic range from 0 to 255. It can be observed that all the intensity values are concentrated on the left side of the possible range of intensity levels and the histogram of that image has narrow dynamic range.

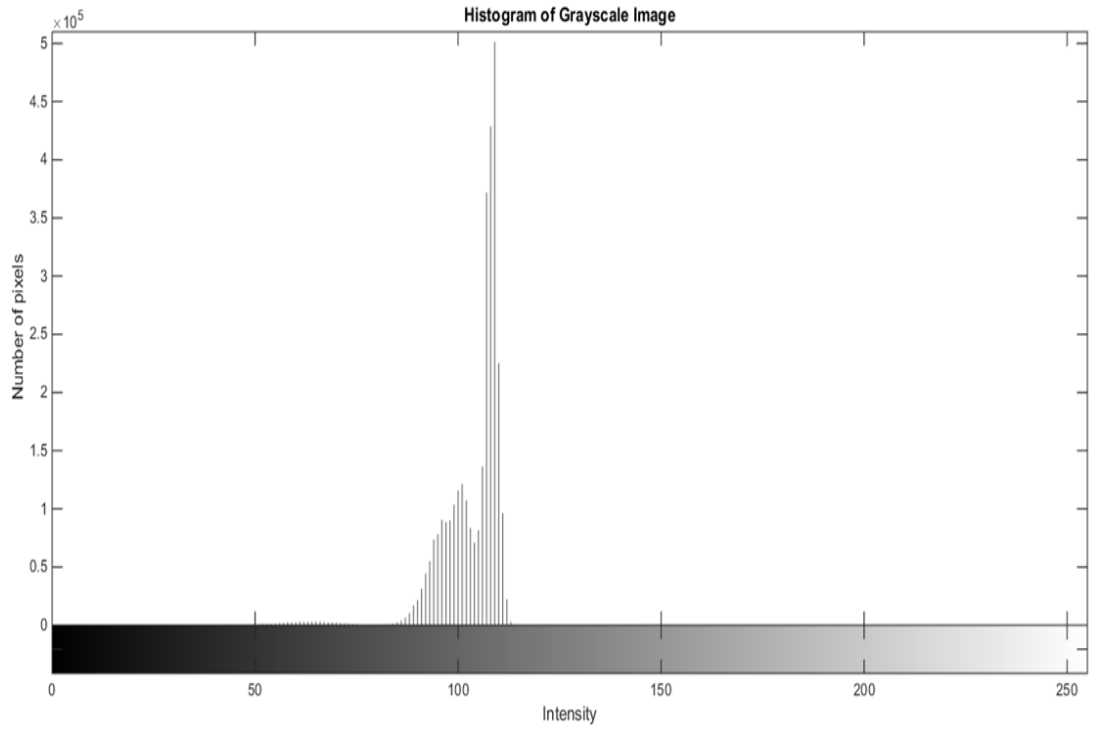


(a) Original cervical cell image

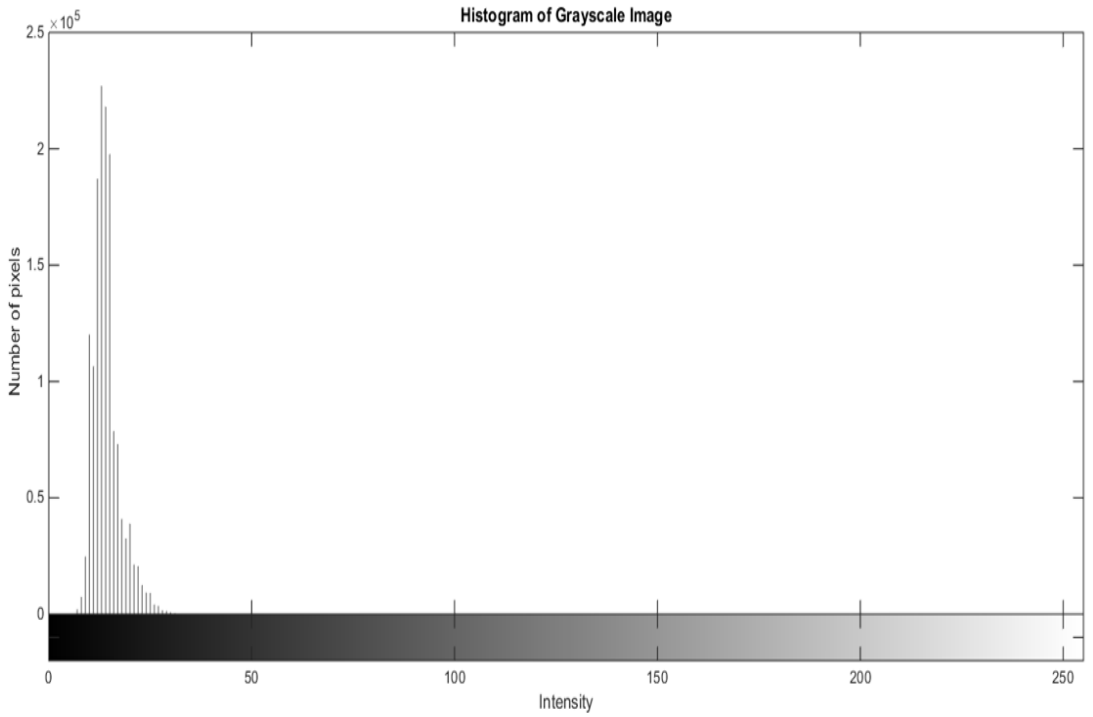


(b) Original HEp-2 cell image

Figure 1.1: Samples and their histograms of cervical cell and HEp-2 cell images.



(c) Histogram of image (a) in greyscale format



(d) Histogram of image (b) in greyscale format

Figure 1.1: Continued.

From the past research, most of the researches enhanced the contrast of HEp-2 cell images using linear contrast enhancement method. This method stretches the intensity values to the possible dynamic range available linearly and improves the overall image contrast globally. Therefore, it lacks of providing the flexibility on selecting the region of interest for the enhancement to carry out. On the other hand, for the cervical cell images, non-linear bright and non-linear dark contrast enhancement techniques had been proposed. These techniques are capable to enhance the contrast of the specific regions of interest locally, such as the nucleus and cytoplasm. The limitation of the previous approaches is a resultant image after processing was produced with only one particular enhanced region of interest. In order to have both clearer nucleus and cytoplasm for observation, they cannot provide both enhanced regions of interest in a single cell image. Generation of two or three output cell images are needed for visualizing the nucleus and the cytoplasm separately using two or three non-linear contrast enhancement methods. This leads to large time consuming for processing. Moreover, the tuning ranges on the parameters of the previously proposed non-linear bright and dark contrast enhancement techniques are small to obtain optimum contrast enhancement.

One of the challenges is to increase the overall contrast of the cell images or enhance the contrast of dark or bright area of the cell images by proposing different contrast enhancement techniques. But, the existing methods are less concentrated on non-uniform illumination cell images. Probably, some regions of most of the cell images are too dark or too bright. This is because some regions of the cell images might expose too much or too little light during image acquisition using a low light microscope or fluorescence microscope. In many past publications on the contrast enhancement topics of cervical cell and HEp-2 cell images, the resultant images are

interpreted subjectively using qualitative measurement instead of analysed objectively using the quantitative evaluation measure.

In order to overcome aforementioned encountered drawbacks in the current contrast enhancement algorithm of medical microscopic images, a suitable non-linear contrast enhancement algorithm must be developed as research motivation. The requirements of this algorithm are capable to produce more homogenous illumination cell images, improve the contrast of the cell images and produce the clearer specific regions of interest in a single image.

1.4 RESEARCH OBJECTIVES

To overcome the aforementioned limitations, this research project comes out two objectives as follows:

- To propose a new non-linear contrast enhancement algorithm for non-uniform illumination and poor contrast medical microscopic cell images, such as cervical cell and HEp-2 cell images, based on dark and bright regions and produce the enhanced result that contained two enhanced regions in a single image.
- To evaluate the performance of the proposed technique with other state-of-the-art techniques using qualitative analysis and quantitative analysis.

1.5 SCOPE OF RESEARCH

The scope of the research project is focused on the development of a new non-linear contrast enhancement algorithm for non-uniform illumination and poor contrast medical images. Contrast enhancement is one of the image enhancement

techniques which can improve the contrast of the images. The type of medical images implemented in this study is microscopic images. Cervical cell and HEp-2 cell images are the two microscopic medical images employed in this project.

In this research project, the cell images are processed in both greyscale and colour spaces. There are wide varieties of colour spaces can be used in the contrast enhancement on the colour images, which are Red-Green-Blue (RGB), Hue-Saturation-Value (HSV), Hue-Saturation-Lightness (HSL), Lightness-colour-opponent dimensions (CIE L*a*b*) and luminance and chrominance (YCbCr) colour spaces. For experimental purposes, RGB and HSV colour spaces are selected because these colour spaces are commonly used in the research on the colour images. In addition, the image samples employed in this research and typical images are stored in the format of RGB colour space by the image acquisition devices. Therefore, the input images can be processed directly using a proposed contrast enhancement algorithm without needing to convert to other colour spaces. The reason for choosing an HSV colour space for processing is that intensity values of only one colour plane are required to carry out for modification, which is the value colour plane. This is because most of the detail information of the input image is stored in this plane, meanwhile hue and saturation colour planes stored the wavelength and bandwidth information of the input image. Furthermore, the input images are also converted to a greyscale image for grey level modification as this might bring out the detail in the input image without caring on the colour components. RGB image is converted to a greyscale image by removing hue and saturation information while maintaining only luminance information.

Another scope of this research project is the input image with 24-bit colour depth is concentrated. Each Red, Green and Blue component in the 24-bit colour depth image has 8-bit and is able to keep the intensity within 0 and 255. This format is the standard format, typically utilized in most of image acquisition devices for storing the information of the captured image. Contrast enhancement operations conducted in this format return a modified version of the original image by remapping the data values to fill the possible available range of intensity levels within 0 and 255.

The development and testing of proposed contrast enhancement algorithm is achieved using MATrix LABoratory (MATLAB) R2015a and worked in a computer workstation with an Intel® Core™ i5-2410M CPU @ 2.30GHz processor, running Microsoft Windows 7 Home Premium 64-bit operating system.

1.6 Dissertation Outline

This thesis is comprised of five main chapters which organize the entire study of this research project and are listed as follows:

Chapter 1 (Introduction) describes briefly the topic of research with the reasons for requiring these enhanced microscopic medical images. Moreover, this chapter also contains problem statement, research objectives, scope of research and thesis arrangement of this research project.

Chapter 2 (Literature Review) gives several basic literature reviews on the research area related to this dissertation. This includes an overview of the image processing, fundamental concepts of digital image and image enhancement. Moreover, it also reviews the research background, namely, medical image

enhancement, which had been done to address similar studies and analyse its limitations. General overviews of cervical cancer and autoimmune diseases in this study are also discussed in this chapter. The morphological features about the normal cells and the abnormal cells for cervical cancer and autoimmune diseases are explained in detail so that the readers can know the features that are visualized by the pathologists during diagnosis and are also the meaningful information needed to be observed in this project. Comparisons between several image enhancement techniques on microscopic medical images, such as cervical cell and HEp-2 cell images, in previous studies are carried out in order to improve the contrast and quality of those images for diagnosis of cervical cancer and autoimmune diseases. The limitations of these state-of-the-art methods are stated as well.

Chapter 3 (Methodology) introduces the software that is implemented in this project and explains in detail the process steps of each major development phases, which need to be carried out in order to enhance the quality and contrast of cervical cell and HEp-2 cell images. The information about data samples employed in this study is provided as well.

In Chapter 4 (Results and Discussion), the simulated experimental results of proposed contrast enhancement algorithm and other state-of-the-art methods are produced for comparison and discussion. Meanwhile, the performance and effectiveness of this proposed technique and previous approaches are evaluated and validated using qualitative analysis and quantitative analysis.

Chapter 5 (Conclusion) summaries the findings of the overall research works in this thesis and highlights the significances and contributions of this completed research work. In addition, future improvements are suggested for this developed system in order to improve the overall performance of this proposed technique.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

In the recent decades, the quantity and quality of digital images are increasing in leaps and bounds. Digital image is more favourable than analogue image at the cost and the digital image is easily manipulated for processing or enhancing purposes. With this great advantage and advancement of computer hardware and network technology, digital images are used in many kinds of applications, such as in medical field, in analysing fingerprints and evidence, in industrial area, in astronomy and other purposes. Generally, the human eye is like an image decoder, which is capable of converting a certain wavelength in the light spectrum into colours as we seen. However, human eye is limited by only able to sense and process a limited range of wavelengths from electromagnetic radiation, which is from about $0.43\mu m$ to $0.79\ \mu m$ [1]. This range of electromagnetic wavelengths that can be sensed by the human eye is called visible light. Presently, there are many different types of advanced digital imaging acquisition devices that are able to capture the image that constructed by electromagnetic radiation wavelength beyond the human eye visible light region, i.e. cannot be seen using human eye. X-ray machines, tomography machines, MRI scanners, ultrasound machines and microscopes are few examples of sophisticated medical imaging devices used to capture internal structures and characteristics of the human body for aiding in medical diagnosis and treatment. This made the digital images play a vital role as a core data type in medical informatics applications.

However, most of the digital images acquired may not have a perfect image quality that is meaningful for human to visualize. Image enhancement, which is one of the steps of image processing, serves as a useful tool to solve this issue. The digital images used in the medical field plays a significant role in the diagnosis and treatment as they deal with lives. In the medical field, the image enhancement process is implemented to extract any hidden information in the image acquired and reduce any unwanted feature from the image. In this study, the medical images such as images of cervical cells and HEp-2 cells are studied. A broad variety of fatal diseases can be diagnosed easily with a better quality in these medical images.

In the next section of this chapter, a review of the image processing is studied. This includes fundamental concepts of digital image, image enhancement and medical image enhancement. In Section 2.3, discussion on cervical cells and HEp-2 cells are concentrated to understand their cell formations and also differences of their morphological features between normal and abnormal cells. Moreover, the contrast enhancement techniques for cervical and HEp-2 cell images that had been proposed by the previous researches are reviewed in Section 2.4. Finally, this chapter is concluded in Section 2.5.

2.2 Image Processing

Image processing is a study of two-dimensional signal processing. An image is taken as an input, computational methods, such as mathematical operations and algorithms, are employed for processing the input image and an output obtained can be either an enhanced image or a set of extracted attributes from the input image [1, 4, 36]. For instance, the input image can be a picture, photography or a video frame.

The aims of image processing are to observe the hidden objects in the image through visualization, create better and sharper image through image sharpening and restoration, seek image of interest using image retrieval, measure various features in the image and/or distinguishing the objects contained in the image using image recognition [11]. Image processing techniques can be categorized into two types, which are analogue image processing and digital image processing. Digital image processing refers to the conversion of the input images into digital images and a series of mathematical operations performed on the digital images using a digital computer. In comparison, analogue or optical image processing conducts a series of mathematical operations on the analogue images directly [1]. For examples, analogue image processing is used for hardcopies, such as photographs and printouts while digital image processing is implemented for manipulating digital images using computers [11]. Digital image processing includes image acquisition, image enhancement, image segmentation, image restoration and detection, and etc.

The fundamental steps that commonly used in digital image processing are shown in Figure 2.1.

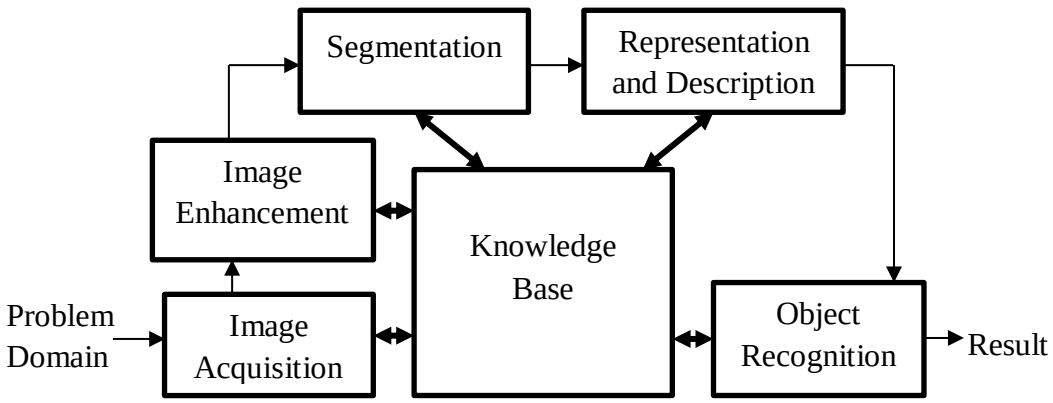


Figure 2.1: Fundamental steps in digital image processing

In image acquisition stage, an image is acquired from image acquisition devices, such as camera, webcam and others, and the image is in digital form. Image enhancement is a process of manipulating an image, so that unseen, partially seen and hidden details from the image can be brought out and noise is removed. Hence, the output image is more suitable than the original image for a particular task. After having a clearer image, image segmentation is applied to partition a digital image into multiple regions and then entails the separation of image into regions of the same characteristic. In representation and description stage, raw pixel data from the output segmented image are represented as a boundary or a complete region depending on the application, whether it is concentrated on external shape characteristics or internal properties of that image, respectively. Then, the feature of interest is extracted and highlighted by describing the processed data. Lastly, based on its descriptors, a label is assigned to an object in the recognition step, therefore the object is identified as output or conclusion on this image processing operation [1].

2.2.1 Basic Concept of Digital Image

An image $I(x, y)$ is defined as a two-dimensional representation of objects on the imaging plane. x and y represents horizontal axis and vertical axis of continuous spatial coordinate, respectively, on the typical Cartesian coordinate system. The magnitude of image I at any particular pair of coordinates (x, y) is known as the intensity of the image. For a monochrome image, the intensity can also be called as grey level. A monochrome image is a dull, washed-out grey look image. On the other hand, a colour image is called chromatic image. The intensity value of the image is continuous tonal value [1, 37, 38].

Nowadays, many sensors are developed to replace five senses and receptors of the human to detect and measure the change from the environment. For electronic imaging applications, imaging sensor is developed to replace the important role of the human eye to observe the change from surrounding. The typical imaging sensor employed in electronic imaging devices is Charge-Coupled Device (CCD) arranged in an array. Each CCD represents one pixel of the image. Figure 2.2 shows the process of digital image acquisition. During image acquisition, an electronic imaging device is employed. Incoming illumination from the source is incident on the scene element, which is the objects, being observed. This incoming source illumination is reflected by the objects and then captured by the electronic imaging device. This amount of reflected energy is called reflectance components. The product of illumination and reflectance components forms an image, which contains the details of the scene element being reflected. Once the electronic imaging device is activated to capture the scene element, each CCD sensor senses and transforms the incoming energy into a voltage by combining the input electrical power and the sensor material that is sensitive to light. The output of conventional sensors is a continuous voltage signal that is indicative of measured intensity and spatial behaviour from the physical phenomenon. In order to process and display the image using a computer, this image is required to be first converted from an analogue format into a digital format that is in a readable form by the computer. This conversion process involves sampling and quantization for digitizing the spatial coordinate values and the intensity values of the analogue image, respectively. However, the sensed data by most sensors today is generated as digital waveforms that are readable and processed by a computer, and displayed as digital image [1].

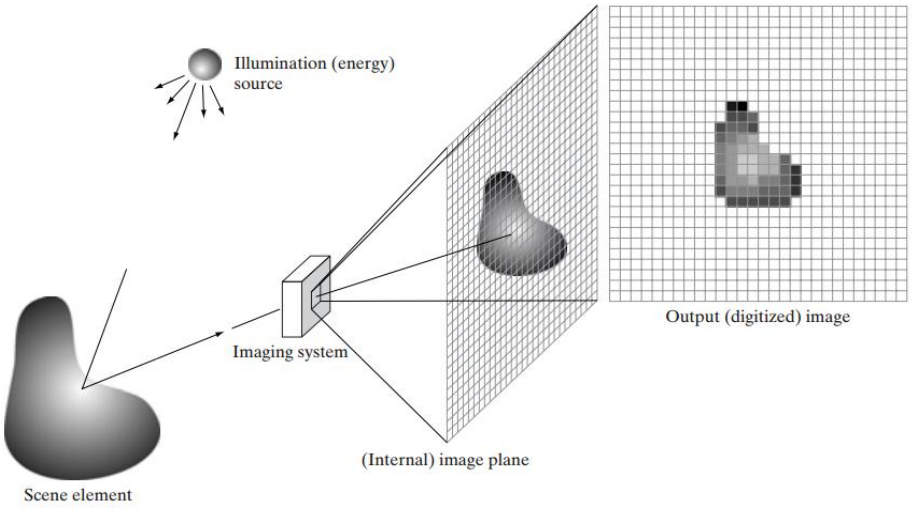
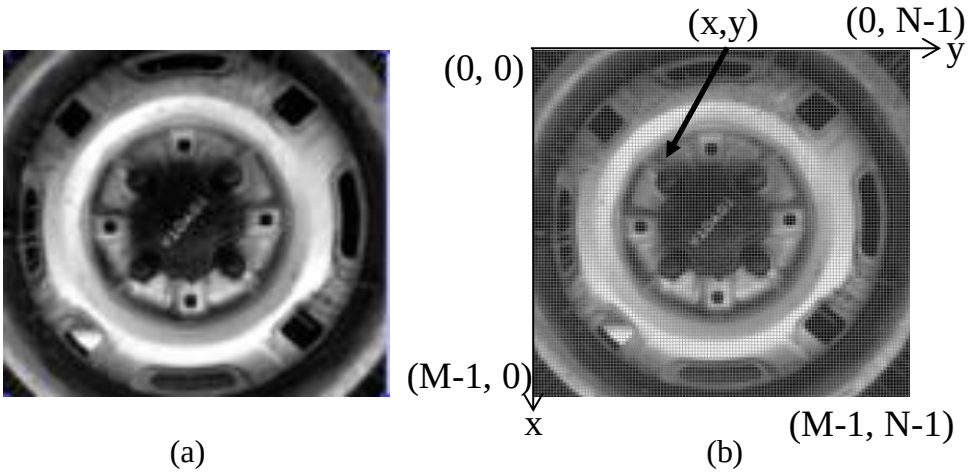


Figure 2.2: Digital image acquisition process [1]

An image is referred as a digital image when the values of two spatial coordinates and intensity are all finite and discrete quantities. A digital image I(x,y) as shown in Figure 2.3 (b) can be defined as a two-dimensional grid of finite, individual picture elements. These picture elements can also be known as image elements, pixels, pels and dots and are arranged on two-dimensional, discrete spatial coordinates (x,y). In the two-dimensional spatial coordinates of the digital image, x represents the horizontal axis of discrete spatial coordinate ranging from 0,2,3,……,M-1 and y represents the vertical axis of spatial coordinate in discrete form ranging from 0,2,3,……,N-1. The indices M and N denote number of rows and number of columns of the digital image, respectively. Normally, an origin of this two-dimensional spatial coordinates of the digital image is located at the top-left corner of the image. The origin of the image may be varied for other imaging system.



(a) (b)

(c)

246	232	215	206	205	203	201	200	185	164	131	108	95	99	107
254	246	227	212	202	198	201	203	196	182	154	121	122	118	92
254	250	237	222	202	194	198	200	195	192	174	138	128	117	105
253	253	248	238	213	198	195	197	196	197	190	163	138	124	115
239	248	254	253	239	213	194	195	196	194	192	187	166	141	124
199	205	217	248	254	235	210	194	193	198	198	194	186	170	154
156	147	148	183	236	250	240	219	203	204	202	197	193	187	175
141	147	137	134	173	223	249	246	225	208	202	196	197	194	181
111	102	101	134	142	168	221	248	247	223	206	200	197	194	185
112	93	99	103	125	138	166	218	246	247	225	210	201	196	190
113	97	95	95	92	115	134	154	211	250	246	231	216	202	197
85	92	90	85	85	81	106	132	156	218	245	246	237	219	208
105	112	113	113	112	108	110	129	129	157	221	240	243	239	231
165	173	175	182	182	178	179	172	165	138	176	222	234	243	248

(d)

Figure 2.3: (a) Original image $I(x, y)$ (b) Digitized image (c) Selected region in small, blue square of the original image (d) Pixel values of the selected region

Each pixel represents a point or square area on the digital image possessing an intensity value I and a location address (M, N). This can be visualized from Figures 2.3 (c) and (d). The intensity of a pixel is a function of two spatial coordinates. For the digital images, the intensity value of a pixel is digitized tonal value [1, 37, 38].

Currently, a variety of electronic imaging devices are developed according to the types of electromagnetic radiation. Electromagnetic radiation is used as a source of illumination during digital image acquisition for detection, medical diagnosis, analysis, classification and other purposes. The most common imaging medium is the one that utilizes visible light as its source to create digital photograph, namely, digital camera and digital video camera. Digital radiography, CT and Computerized Axial Tomography (CAT) are digital X-ray images which are generated by using X-ray as source. The most energetic and shortest electromagnetic wave, which is gamma ray, are also used to produce digital gamma ray imaging such as PET, SPECT and digital scintigraphy for nuclear medicine. Contrary to gamma ray, the least energetic and longest electromagnetic waves, radio waves are used in MRI in medicine. Besides electromagnetic radiation, the other important available sources of energy include electron microscopy, ultrasonic and acoustic. For example, electron microscopy is used for acquiring digital cell images. The presence of the digital images has allowed the images be able to analysis, manipulate, process and display using software on the computers [1].

Moreover, an image can also be represented into one or more colour channels that define the intensity or colour at a particular location to give a visual data representation. All the greyscale images do not possess colour information. These images are comprised of black, white and shades of grey colour of pixels. For 8-bit greyscale image, their intensity values of the corresponding black, white and shades

of grey colour of pixels are 0, 255 and 1 to 254, respectively. A greyscale image which has assigned only two tonal or bi-tonal value, which is 0 or 1, to the intensity of each pixel is normally referred to black and white image. For colour images, they contain three or more channels and can be introduced based on variety of colour spaces such as RGB, HSV, Cyan, Magenta, Yellow and blacK (CMYK), CIE L*a*b* and other colour spaces [1, 38].

After digital images have been captured, the image quality of each image is evaluated based on their general characteristics like spatial resolution, contrast, dynamic range, brightness, luminance, noise, saturation and etc. Spatial resolution is a measure of how well the smallest discernible detail in an image can be distinguished from the neighbour detail [1]. In order to obtain more details in an image, the spatial resolution of the image must be higher as more pixels per image area. This can be achieved by increasing the sampling frequency when sampling the spatial coordinate values. Contrast describes the difference between the largest and the smallest intensity levels or colours within the image [1]. Dynamic range is defined as the ratio of maximum to minimum measurable, detectable intensity levels within the image [1, 39]. Noise normally masks the smallest detectable intensity level while saturation determines the greater detectable intensity level. The larger the dynamic range, the more tonal information are obtained as more potential shades can be represented [1]. If the dynamic range of the image increases, meaning that the separation or spanning between the bright and the dark regions of the image is also increased, which in turn produces the image with high contrast. Brightness of a digital image reflects the achromatic concept of intensity while luminance is a measure of the amount of energy perceived by an observer from a light source [1].

2.2.2 Image Enhancement

Image enhancement is one of the significant and difficult steps in the digital image processing that contributes in the visually appealing fields, but does not raise the inbuilt information contents of an image [9, 40, 41]. It is a process of manipulating an image by modifying its attributes in order to produce a more suitable and meaningful result than the original image for a specific task and a human viewer [1]. The goal of carrying out image enhancement is to improve the interpretability or perception of information in images for human viewers, and to provide better input for other automated image processing approaches, such as analysis, segmentation, detection and recognition [1-13]. The images after executing image enhancement are transformed to better representation of the subtle details and without undesirable deterioration. They have also improvement on the visual appearance and the image clarity, less ambiguity between different regions of the image, and the original image becomes more conducive for computer to process as well [14, 42].

Usually, the causes of having poor quality of the image are due to the poor quality of image acquisition devices, transmitting through a noisy channel, faulty memory locations in hardware [8, 43], insufficient lighting during image capturing [12] or the adverse external conditions [14] during image acquisition like atmospheric disturbances [6-8, 43]. Because of these causes, image may suffer from poor contrast, introduce noises [2, 5, 12], loss of information [6, 7], and has poor illumination [4, 44] or non-uniform illumination in the image [12], blurring and incorrect colour balance [36]. Having the image with low contrast and noise, it is hard to clearly extract considerably key features from the original image and may produce wrong information in the system operation [43]. Therefore, it is necessary to enhance the contrast, and remove the noise and blurring of the original image in

order to increase the quality of the image. For colour images, the image enhancement is required to process luminance and colour information in order to obtain sharp details, provide rich in colour and better visual effects without any shifting or distorting of colour [36].

As mentioned in Chapter 1, image enhancement plays a vital role in several areas such as real life photographs, medical image analysis, satellite imaging, aerial imaging, remote sensing, High Definition Television (HDTV), art studies, forensics, atmospheric sciences, fingerprint matching and etc [2, 5, 8, 12-15]. The proper choice of image enhancement is greatly influenced by imaging modality, the task at hand and visual perspective [2, 3, 8, 10, 13, 15]. Due to the image enhancement is application-specific and problem oriented [1, 3, 8, 15], various choices of image enhancement techniques were proposed by the researchers in order to select and modify particular image attributes for a certain application. In other words, image enhancement technique that is effective for one field or problem might not be adequate for the other. Hence, there is none of the particular techniques are robust and effective for any image data set or any kind of images in all fields. For instance, medical imaging employs techniques that provide high contrast, sharpness and noise removal, while videos utilize the techniques that can resolve the issue of low resolution and motion blur. Therefore, an approach that is quite powerful for enhancing medical images might not be the best method for enhancing video frames. Successively, this makes image enhancement field is getting interesting and expanding in the research field.

No general unifying theory of image enhancement is available and presented by any researchers. The ultimate judge on how well a particular image enhancement technique operates is subjective and determined by the human viewers, which are the