CONTRAST OPTIMIZATION BY REGION ADAPTATION (COBRA) FOR GREY SCALE IMAGES

MUHAMMAD MAHMOOD AHMED

MASTER OF COMPUTER SCIENCE

UNIVERSITI MALAYSIA PAHANG

UNIVERSITY MALAYSIA PAHANG

DECLARATION OF THE THESIS AND COPYRIGHT

Author's full name : Muhammad Mahmood Ahmed

Date of birth : 15th July, 1957

Title : Contrast Optimization By Region Adaptation (COBRA) for grey scale Images

Academic Session : 2011 - 2013

I declare that this thesis is classified as:

☐ **CONFIDENTIAL** (Contains confidential information under the Official Secret Act 1972)

☐ **RESTRICTED** (Contains restricted information as specified by the organization where research is done)

☑ **OPEN ACCESS** I agree that my thesis to be published as online open access (Full text)

I acknowledge that Universiti Malaysia Pahang reserves the right as follows:

1. The thesis is the property of Universiti Malaysia Pahang.
2. The library of Universiti Malaysia Pahang has the right to make copies for the purpose of the research only.
3. The library has the right to make copies of the thesis for academic exchange.

Certified by:

(Student's Signature)	(Signature of Supervisor)
Passport Number: ZC1155521	Professor Dr. Jasni Mohamad zain
Date:	Date:

CONTRAST OPTIMIZATION BY REGION ADAPTATION (COBRA) FOR GREY SCALE IMAGES

MUHAMMAD MAHMOOD AHMED

Thesis submitted in fulfillment of the requirements
for the award of degree of
Master of Science in Computer Science

Faculty of Computer System and Software Engineering
UNIVERSITI MALAYSIA PAHANG

APRIL 2013

SUPERVISOR'S DECLARATION

I hereby declare that I have checked this thesis and in our opinion, this thesis is adequate in terms of scope and quality for the award of the degree of Master of Science in Computer Science

Signature

Name of Supervisor : PROFESSOR DR. JASNI MOHAMAD ZAIN

Position : DEAN AND PROFESSOR

Date :

Signature

Name of Co-supervisor : DR. M. MASROOR AHMED

Position : SENIOR LECTURER

Date :

UMP

STUDENT'S DECLARATION

I hereby declare that the work in this thesis is my own except for quotations and summaries which have been duly acknowledged. The thesis has not been accepted for any degree and is not concurrently submitted for award of other degree.

Signature

Name : MUHAMMAD MAHMOOD AHMED

ID Number : MCC12001

Date :

DEDICATION

This thesis is dedicated to my parents who as family elders inculcated the thought in the family that education is a journey from cradle to eternity. This philosophy and encouragement of my parents is the source of inspiration for me to return back to education after a long gap and produce this research work.

This thesis is also dedicated to my elder brother who throughout his life desired for my uplift through continuous education. In his memories, his desires remained a motivation for me to complete this research project.

This thesis is also dedicated to all those who believe in quest for knowledge and richness of education at any age.

ACKNOWLEDGEMENTS

The completion of this thesis is possible only due to the guidance, help and inspiration of several individuals who in one way or another contributed and extended their valuable assistance in the preparation and completion of this study.

First and foremost my utmost gratitude Dr. Jasni Mohammad Zain, whose encouragement helped me overcome all hurdles for the timely completion of this thesis. Her invaluable guidance, continuous encouragement and constant support made this research possible. She has always impressed me with her outstanding professional conduct and elegant attitude. Her consistent support throughout my work made the research possible. I am truly grateful for her responsiveness and futuristic attitude in conducting this research.

I also would like to express very special thanks to my co-supervisor Dr. Mohammad Masroor Ahmed for his suggestions and co-operation throughout the study. I specially express gratitude for his patient and persistent efforts to keep me focused on ultimate research goals despite my candid views about various aspects of research. My special thanks to Dr. Farzana Masroor for the time spent in proofreading and correcting my many mistakes. I would like to acknowledge her comments and suggestions, which were crucial for attaining accuracy in the writing of this thesis.

My sincere thanks go to all my lab mates and members of the staff of the Computer Science Department, UMP, who helped me in many ways and made my stay at UMP pleasant and unforgettable.

I acknowledge my sincere indebtedness and gratitude to my parents for their love, dream and sacrifice throughout my life. I acknowledge their sincerity and sacrifice for consistently encouraging me to carry on my higher studies in Malaysia despite the fact that they critically needed my company and care due to their very old age. I cannot find appropriate words that could properly describe my appreciation for their devotion, support and desire for me to progress in life by attaining higher educational qualification despite fragile stage of their life. I am also very grateful to all my siblings who always urged and supported me to make progress in life through higher education. I am also thankful to my immediate family, daughter and sons for their sacrifice, patience, and understanding that were inevitable to make this work possible.

Above all thanks to Allah almighty for giving me strength to overcome most of the hurdles and giving me the serenity to go around the rest of the hurdles to complete the research despite many devilish up-thoughts to give it up half way. Thanks Allah

ABSTRACT

Medical images form a part of real world images which come with a wide variety of contrast and brightness. The acquired images almost invariably require contrast enhancement. Some of the underlying contrast enhancement methods do not produce predictable results. Contemporary contrast enhancement frequently relies on histogram equalization (HE). In practice, HE produces unexpected results. Such, inconsistent results make reliability of HE questionable. As a result HE is unacceptable in sensitive areas like medical field. The situation leads to a detailed analysis of HE, which brings out that foundation of HE is based on density not contrast. As this foundation is unrelated to contrast, resulting contrast changes are unpredictable. As a solution, a novel method based on factors directly related to contrast is proposed. This method separates the image into dark and bright regions. Based on this concept the proposed method named Contrast Optimization by Region Adaptation (COBRA) is developed by optimizing the contrast ratio of separated regions. To achieve this optimization, the whole image is shrunk to a lower scale which provides necessary space for readjustment of contrast ratio. Then the constituents grey levels are raised exponentially to revert back to original scale. This exponential reversion, adjusts the contrast ratio of separated regions to optimum. This contrast optimization fulfills deficiency in real world images. Due to contrast based foundation of the proposed method, the resultant enhancement in similar type of images is consistent. These predictable results, yield high reliability which makes the proposed method trustworthy for critical areas like medical field. Additionally the results reveal that the histogram of the enhanced image represents similarity with the original image. This similarity is measured using DICE and Jaccard methods. Based on the similarity figures, comparative analysis was carried out between the proposed method and HE. The analysis verified that the proposed method achieves excellent results on brain MRIs, additionally it performs well on general medical and common bench mark images.

ABSTRAK

Imej perubatan membentuk sebahagian daripada imej dunia sebenar yang datang dengan pelbagai pilihan kontras dan kecerahan. Imej-imej yang diperolehi selalunya memerlukan peningkatan kontras. Sebahagian daripada kaedah berdasarkan peningkatan kontras menghasilkan keputusan yang tidak boleh dijangka. Peningkatan kontras kontemporari kerap bergantung kepada penyamaan histogram (histogram equalization (HE)). Dalam amalan, HE menghasilkan keputusan yang sukar dijangka. Keputusan yang tidak konsisten membuatkan kebolehpercayaan HE dipersoalkan yang menjadikan HE tidak boleh diterima di bidang-bidang sensitif seperti bidang perubatan. Keadaan ini membawa kepada analisis terperinci HE, yang terbukti bahawa asas HE berdasarkan kepadatan dan bukannya kontras. Oleh kerana asas ini adalah tidak berkaitan dengan kontras, ini membuatkan perubahan kontras yang terhasil adalah tidak menentu. Sebagai penyelesaiannya, kaedah baru berdasarkan kepada faktor yang berkaitan dengan kontras secara langsung dicadangkan. Kaedah ini memisahkan imej dengan kombinasi kawasan terang dan gelap. Berdasarkan konsep ini, kaedah ini dinamakan sebagai "Contrast Optimization by Region Adaptation" (CORBA) telah dibangunkan dengan mengoptimumkan nisbah kontras kawasan pisahan kontras tersebut. Untuk mencapai pengoptimuman ini, seluruh imej akan dikecilkan ke skala rendah yang memberikan ruang yang sepatutnya untuk penjajaran nisbah kontras. Selepas itu, unsur yang berwarna kelabu akan diangkat untuk kembali ke skala asal. Kaedah pengembalikkan eksponen ini mengubah nisbah kontras kawasan pisahan ke tahap optimum. Kaedah pengoptimuman kontras ini memenuhi kekurangan di dalam dunia sebenar pengimejan. Oleh kerana kaedah yang dicadangkan berlandaskan kontras asas, maka ini menyebabkan penambahbaikan imej. Keputusan yang dijangka ini berada di tahap kepercayaan yang tinggi dan ini membuatkan kaedah yang dicadangkan boleh dipercayai untuk digunapakai di dalam bidang kritikal seperti bidang perubatan. Selain itu juga keputusan membuktikan histogram imej yang dipertingkatkan mempunyai persamaan dan mewakili imej asal. Persamaan ini diukur dengan menggunakan kaedah DICE dan Jaccard. Berasaskan persamaan angka, analisis perbandingan dijalankan antara kaedah yang dicadangkan dan HE. Hasil ujian ini mengesahkan bahawa kaedah yang dicadangkan memberikan keputusan yang baik pada MRI otak, imej-imej perubatan dan imej piawai.

TABLE OF CONTENTS

UMP

UMP

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

All images are acquired to present, the snapped reality, to the user. These images, needs to be enhanced to split and present all the contained details, about this reality, to the viewer. Such splitting of details, attempts to bring out any obscured objects, enhance contrast, preserve suitable brightness and suppress noise. Consequently this clear and sharp- well defined - image will have improved accuracy in interpretation, which is likely to remain consistent among multiple interpreters. To attain this consistency, features of the initial image have to be analyzed critically to select the most suitable method for contrast enhancement.

An image could present multiple brightness levels and may have diverse features with varying degree of contrast. Various techniques are developed to analyze the images, process the contained data to transform the image into brighter and sharper (higher contrast) output. Contrast improvement can be done in two domains; spatial and frequency. In frequency domain methods, the image is first transferred into frequency and then enhancement operations are performed in order to modify the image brightness, contrast or the distribution of the grey levels. After which the image is transformed back into spatial domain as an enhanced output image. For changing image into frequency Fourier Transform is applied to the input image and after completion of image processing reverse Fourier Transform is applied to produce resultant image. Resultant image has modified pixel values according to the processing function applied to the input image. This domain is specially reputed for filters to eliminate noise and employing convolution and de-convolution. It is also a powerful tool to apply masks to sharpen image contrast. However, frequency domain is mathematically intense, and is relatively less straight forward especially when it comes to applying complex fast Fourier Transform. Moreover frequency domain does not take local neighborhood into consideration. The method is limited to global application on the whole image.

The study selected spatial domain as the area of research for its straightforwardness, simplicity and the ability to consider local neighborhood for contrast enhancement. Spatial domain deals with grey levels, their concentration and spread. For contrast improvement, middle, mean and variance of existing grey levels is acquired and their values are corrected to the desired value. The shift in brightness is measured and is suitably adjusted to match the original brightness. Corrected data is used to regenerate the output image with improved contrast and brightness.

At present vast variety, of contrast enhancing methods is available for example ANN based method (Csapodi and Roska, 1996), Fuzzy logic based methods (Hanmandlu and Jha., 2006), HEbased methods (Najafi and Zargari, 2011; Murahiraand Taguchi, 2011; Chen et al., 2011), etc. Out of all these choices HE because of its simplicity, straight forwardness and computational efficiency earned wide spread popularity (Wang et al., 2008). Besides, unlike ANN based and fuzzy logic based methods HE along with its variants completely eliminated the involvement of expert radiologist for manually analyzing and marking the problematic images under observation (Yang and Wu, 2010; Maragatham et al., 2011). Additionally, for getting reliable results we need to have large amount of data (for doing extensive training) which occasionally may become difficult to obtain. Over and under fitting problem of ANN.The case of fuzzy logic based methods is not much different from that of ANN. Even fuzzy logic needs human expert to define fuzzy rules. Now to define ideal rules that neatly (exactly/precisely) define the problematic area there is no standard rule according to which all radiologist reach to exactly the same marking for same data set. In the absence of such standardization the situation becomes challenging. Consequently, the results obtained may need to be processed further for fine tuning (required / desired precision). This uncertain situation creates a strong need to have a fully automatic image contrast enhancing method that un-conditionally controls the inter-observer and intra-observer variability thereby producing generally acceptable results.

HE is one such method which is fully automatic, computationally fast and does not require an expert radiologist in pre-processing and post processing stages (images are not subjected under further process to improve results) (Thomas et al., 2011; Shanmugavadivu and Balasubramanian, 2011). However, just for confirmation purposes, it needs to have an expert radiologist. Complete mathematical details of HE are presented in Chapter 2. Regarding the processing of HE, two fundamentally important things are associated with HE. They are “global processing” (Arici et al., 2009) and “local processing” (Wu et al., 2010).

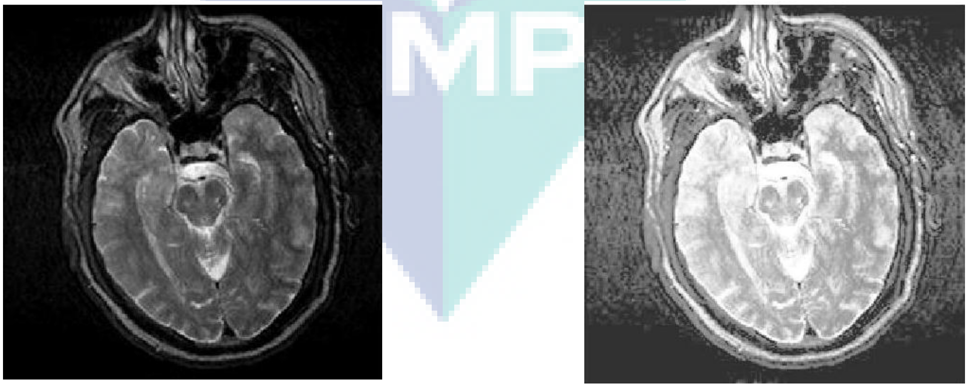
Global processing considers the whole image as one piece / single unit. Conceptually, HE in its original form is supposed to be applied globally (Chang and Chang, 2010). As a result of global application HE does raise the contrast of a low contrast image but at the same time it brings down the brightness of image (Cheng and Ruan, 2010). Certainly, for analyzing high sensitive and critical brain MRIs, the cost that HE demands for raising the contrast is unaffordable both for medical experts and for the patients under treatment (Fan and Zhou, 2011; Sundaram et al., 2011). An apparent cause for these unwanted results lies in HE’s fundamentally incomplete conceptual construction of model.

Conceptually HE models the data by studying the available grey levels. In order to know the contribution of each and every grey level, the model obtains the histogram of these grey levels. This histogram is then stretched to cover the entire range of grey levels which is from 0 to 256. However, it may be noted that HE in its present form never mentions “contrast” it only targets the density of the pixels (Ziaei et al., 2008; Lakshmanan et al., 2008). In image processing “Contrast” and ‘Density” are two different things. Contrast is the difference between maximum and minimum grey value whereas, density is the number of times one specific grey value is appearing. HE only manipulates the density for restoring the required level of contrast, which seems to be unrealistic. Though HE aims to bring back the required contrast but surprisingly it compromises over the core element of “Contrast” in its construction. The unavailability of this core element undoubtedly makes it un-reliable method for meeting the objectives. This situation creates pressing demand for researchers either to include the core element of “Contrast” in the original model or provide an alternate equally efficient and highly reliable model for restoring the lost contrast of medical images.

However, the researchers tried to control the deficiencies of HE by limiting the application area of HE in an image. This is known as local application. For local application the image is divided into parts and each part is processed locally (Kim and Chung, 2008; Wang and Ward, 2007). Normally, an image has varying brightness in different areas. To bring out similar results in the output, image is divided into sub-images and HE applied to all parts separately (Park et al., 2008). Such local processing preserves brightness, but, if the sub-images become too many then the output image is same as input image without any change. This approach is implemented by many techniques namely bi histogram equalization (BBHE), According to (Wang and Ye, 2005;Sim and Tan, 2007; Menotti et al., 2007; Chen, et al., 2003b), BBHE splits input image into two parts by their input mean before applying HE separately. Later, dualistic sub image histogram equalization (DSIHE) was proposed which decomposes the image by the measure of entropy and applies HE. Both BBHE and DSIHE could not resolve all the cases generating artifacts in images needing higher brightness. As in (Chen, et al., 2003b), splitting of the image was proposed repeatedly by implementing recursive mean separate histogram equalization (RMSHE), which improves brightness but as iterations increase, output image converges to input image. Article (Menotti, et al., 2007) (Wang and Ye 2005) brought forward Minimum Mean Brightness Error Bi – Histogram (MMBEBHE) which can maximize brightness. All these methods HE, BBHE, DSIHE, RMSHE, MMBEBHE offer improvements but none balances contrast and brightness to the desired level. As in (Menotti, et al. 2007) all the Local HE methods are generally computational intensive as local HE is to be processed for every pixel.

In fact, diverse details, normally, present in an image need appropriate processing for improving contrast and adjusting brightness. Improving contrast and brightness, however, are competing requirements (Reza, 2004). Improving one generally deteriorates the other. A single technique does not resolve all the issues. In real life, enhancing one aspect may deteriorate the other. Therefore, the user must look for the relevant technique to interpret image for one's own purpose while minimizing the effect of some of the unavoidable drawbacks. As an ensuing effort, there is a constant struggle to improve [eliminate] the existing drawbacks in the presently existing techniques. The effort is aimed at improving accuracy of reading image details by enhancing contrast and realistically adjusting brightness of the given image. This improved accuracy is likely to make image interpretation more persistent which would also increase consistency among multiple interpreters.

Despite, concerted efforts to reduce the drawbacks of HE and make it effective for contrast enhancement, its issues are not resolved in totality and practically it affects all image fields as the technique is widely used for contrast enhancement. Although these ill effects are not desired in any field, but in medical field these are critical factors (Zhang et al., 2008). These issues cause inaccuracies and unpredictability in results. Hence this contrast enhancement method is not trustworthy (Sengee et al., 2009). This situation necessitates confirmatory tests which, in turn, increase response time for follow up medical procedures. One such medical area is brain MRIs. HE was used in this area and the results on some of the images indicate that it cannot be relied upon. One such result is shown in figure 1.1.



(a) (b)

Figure 1.1: Visual comparison of original (a) and HE enhanced (b) image

As the impact of HE shortfalls on medical images is more critical, the issue needs to be elaborate further. Let us take a second brain MR image and try to enhance it using HE method. A raw image from brain atlas is presented in figure 1.2 before enhancement.

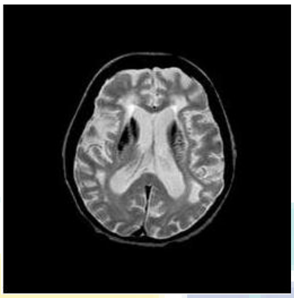


Figure 1.2: A raw image from brain atlas

Source: Brain Atlas n.d.

Histogram of this image is presented in figure1.3

.

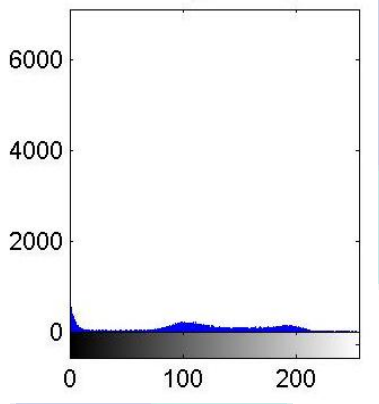


Figure 1.3: Histogram of original image - covers almost all grey levels

In the next figure 1.4 the same image is enhanced by HE method. Instead of contrast enhancement the image becomes monotonic and loses sharpness.

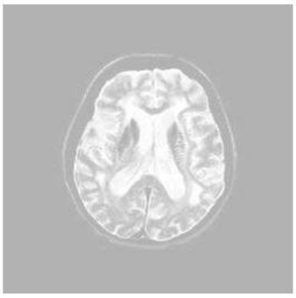


Figure 1.4: Image becomes monotonic by using HE

This monotonic image is due to missing dark grey levels in the image which is also evident in histogram of the enhanced image given in figure 1.5 confirming the absence of initial about 150 grey levels.

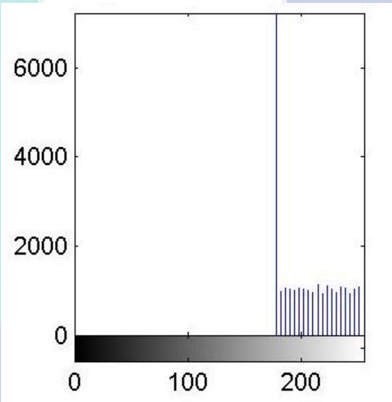


Figure 1.5: HE applied image- CPD ends up washing out grey levels from 0-160

Initial grey levels get trimmed off due to CPD when it is calculated based on uniform distribution of intensity and wide coverage of grey level range of the original image. Primarily HE is not based on factors which are contrast specific; instead it is based on density related factors (Yeganesh et al., 2008). To fix this issue, it is paramount to establish what factors affect contrast and most importantly how to manipulate those factors to improve contrast.

The study researches factors related to contrast and proposed a method based on these factors. Input image is pre-processed to transform it to initial parameters for contrast enhancements. Then it is, split image into dark and bright regions. Now contrast is enhanced for both the regions. Both regions form the output image.

This proposed method is contrast specific, retain brightness of the original image and it is simple & straight forward for implementation. It neither lose image data, during processing, nor is it computationally intensive. This method considers local neighborhood for enhancement purpose.

Proposed method is optimized for contrast enhancement of brain MRIs, with an aim to have exceedingly reliable performance with high accuracy. Additionally this reliability should be validated in a wider group of images, which must include generic medical images and day to day common images.

1.2 PROBLEM BACKGROUND

Real world images with various contrast levels are not reliably enhanced by current day methods HE is the core enhancement techniques used in most of the methods in the industry(Thomas, 2008; Kim and Paik, 2008; Sengee and Choi, 2008). Primarily HE is a density based method which makes its formulation divergent from contrast. This divergence of HE from contrast is the source of all issue in the application of this technique. HE is applied to the overall image. HE does offer some contrast improvement but HE mostly fails to preserve the brightness of the input image. In HE middle grey level of output image becomes the mean value of histogram completely disregarding the mean value of input image. For input images with histogram centered at high (nearing 255) or low (nearing 0), the mean brightness has a large shift. This may change image outlook drastically (Menotti et al., 2007). The method is effective in differentiating the boundaries of different objects but smooth and small details within these objects may be lost. Another outcome is excessive contrast where small objects have large clear back ground (when few grey levels cover large section of the image) (Yun et al., 2011). HE may also introduce nonexistent artifacts in the output image. These factors affect all images including medical images. Medical area being sensitive needs special attention of such low reliability for contrast enhancement.

1.3 PROBLEM STATEMENT

In view of varying contrast in the images, processing for contrast enhancement has become a mandatory step for real life images. Out of various methods currently being used for image processing, HE is a widely relied upon method. HE has global application on image and therefore does not address the segment specific solution. To resolve neighborhood specific issues in the image, the approach for applying HE was changed and image was divided into many segments for HE application. However, the actual issue with HE is different – it is not based on contrast specific factors; instead its foundation is on probability density (PD) and cumulative density function (CDF). Therefore it really does not improve contrast but re adjusts density and as a bi product contrast alters somewhat but unpredictably. The drawbacks of HE are carried forward to other methods which employ HE in different ways.

Although these issues affect images of all categories but its impact is critical on medical images specially, in brain area. In this sensitive area, interpretation accuracy gets affected which being vital to precision in diagnosis decreases reliability of HE. Hence, further confirmatory tests are needed to discover true facts. This increases response time and initiation of corrective medical procedures is delayed. This delay cause's loss of precious time under emergent conditions which may make fatal difference is critical cases.

1.4 SCOPE OF STUDY

The study is to improve low contrast brain MR images by analyzing the limitations of current image processing methods and proposing a new algorithm to enhance image contrast. This research focuses on enhancing contrast of only grey scale images. The study tests the developed algorithm on a broad spectrum of medical images. Although not a part of the basic objective, but once the method is available, the study will extend method testing for general category of medical images and common bench mark images to check its usefulness in these areas as well. The method will be analysed for stability and robustness by using noisy and noise free images. For the implementation of the algorithm Matlab is used with its proprietary language. The images for study are taken from brain web (Brain Web 2012), and brain atlas (Brain Atlas n.d.). The study is carried out on natural and synthetic images. For the purpose of the comparisons similarity measuring methods Jaccard & Dice has been used.

1.5 OBJECTIVES

(i) To propose a simple and straightforward method for processing grey scale, low contrast brain MRIs which is directly based on contrast factors and is free of expert involvement.

(ii) To evaluate the performance of the proposed method for general medical grey scale images.

(iii) To validate the proposed method under noisy and noise free conditions.

.

1.6 THESIS ORGANIZATION

After this introduction the thesis is organized as follows:

CHAPTER 2 covers the review of existing methods for image processing and also highlights their short comings and drawbacks.

CHAPTER 3, in pursuance of known issue presented in chapter2, presents critical deficiencies in HE.

CHAPTER 4, in view of drawbacks of HE covered in chapter 3, presents proposed method as a solution.

CHAPTER 5 covers results of proposed method on brain MRIs, general medical images and common images. Further chapter 5 presents discussion and analyses.

CHAPTER 6 concludes the thesis by highlighting the extent of success of the proposed method, contribution of the study and future direction for further research in this area.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

The real world imaging has all sorts of data with no certainty in contrast and brightness, frequently resulting into inaccurate and inconsistent interpretation. In sensitive fields such as medicine, image clarity and object identification is crucial for accurate clinical diagnosis (Zhiming and Jianhua, 2006). This has led to an increased demand for carrying out image enhancement (Yang and Sun, 2010; Sun et al. 2005). Sharp and bright images facilitate interpretability of image details with accuracy by human viewers. A visual comparison of low and high contrast image is shown in figure 2.1.

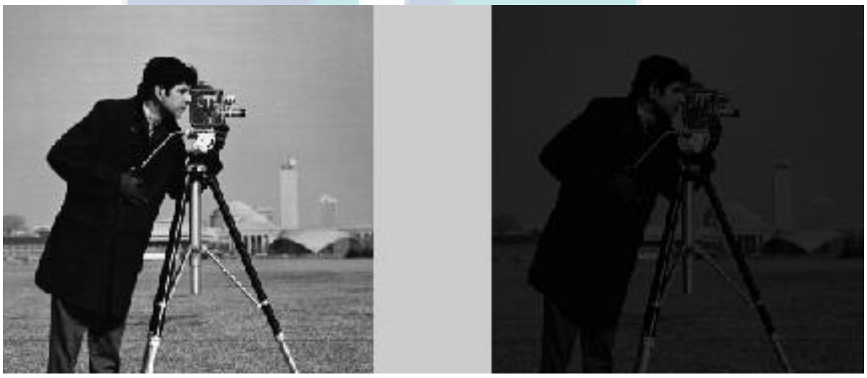


Figure 2.1: Visual comparison of a Normal and Low contrast image

Researchers have evolved techniques to enhance the image contrast by processing the image. This processing is categorized in two domains.

2.2 DOMAINS OF THE IMAGE FOR PROCESSING

Image processing methods can be categorized into two domains: Frequency domain and Spatial Domain. These domains are explained in detail in subsequent text.

2.2.1 Frequency Domain

Frequency is known as the number of times a periodic function repeats itself during a unit change in independent variable. In case of images frequency is the number of time repetition occurs while grey level is the same. In frequency domain methods, first Fourier transform is applied to the image to convert it to frequency domain. Next, enhancement operations are applied on this Fourier transform and then image is reverted back to spatial domain through inverse Fourier transform. These enhancement operations re-distribute the grey levels of the image which enhances the pixel value (intensities) of the output image. Therefore mathematically transfer function may be represented as follows. $F(u,v) = H(u,v)f(x,y)$. Whereas u, v are the frequency domain variables and x, y are the spatial domain variables. According to Fourier series any function which is periodic can be written as the sum of sine and cosine, each multiplied by a different coefficient. However for non-periodic functions with finite area under the curve - an integral of sine and cosines multiplied by a weighting function is used which is termed as Fourier transform. An image is completely represented in frequency domain by Fourier transform in two dimensions. However for understanding we will initially proceed with only one dimension of the image. Further, a frequency may be continuous or discrete. We would take discrete case to understand the concept. For such a case, Discrete Fourier Transform (DFT) is used which, for a single dimension, is given by the following equation.

$$F(u) = \frac{1}{M}\sum_{x=0}^{M-1} f(x)e^{-j2\pi ux/M} \quad \text{for } u = 0,1,2,\ldots,M-1 \tag{2.1}$$

Whereas F(u) represents frequency domain and f(x) represents spatial domain. Inverse Discrete Fourier transform (IDFT) is given by

$$f(x) = \sum_{u=0}^{M-1} F(u)e^{j2\pi ux/M} \quad \text{for } x = 0,1,2,\ldots,M-1 \tag{2.2}$$

The 1/M multiplier is sometimes used with inverse function instead of the transform. If f(x) is of finite duration discrete Fourier transform and its inverse always exist. In actuality frequency domain to represent the image must have two dimensions, which then is given by the following equation.

$$F(u,v) = \frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)e^{-j2\pi(ux/M+vy/N)}$$
$$\text{for } u = 0,1,2,\ldots,M-1, v = 0,1,2,\ldots,N-1 \tag{2.3}$$

Whereas u, v represent frequency variable and x, y represent spatial domain variables. For inverse DFT for the two dimensions the equation is given by the following.

$$f(x,y) = \sum_{u=0}^{M-1}\sum_{v=0}^{N-1} F(u,v)e^{j2\pi(ux/M+vy/N)}$$
$$\text{for } x = 0,1,2,\ldots,M-1, y = 0,1,2,\ldots,N-1 \tag{2.4}$$

Fourier Transform is applied to access and modify the geometric characteristics of a spatial domain image. After the image is translated into its sinusoidal components, it is easy to examine or process certain frequencies of the image, thus modifying the pixel values in spatial domain. For processing the image many filters are used to reduce noise, edge detection and adjustment of pixel intensity. Some of the filters that are used in frequency domain are low frequency, high frequency, smooth low pass and smooth high pass filters. Once in frequency domain the image is multiplied with frequency filter function and then it is transformed back into spatial domain. The filter function is shaped so as to attenuate some frequencies and enhance others. For example, a simple low function is *1* for frequencies smaller than the *cut-off frequency* and *0* for all others The limitations of the frequency domain are that it is mathematically very intense, can only be applied globally which disregards local neighborhood factors. Therefore it does not enhance image to meet local contrast deficiency. To have a broader view to enhance image contrast effectively let us explore spatial Domain as well.

2.2.2 Spatial Domain

Spatial domain deals with each pixel which makes the image. It deals with every pixel at its physical location. If a pixel is processed this way with only pixel data, it is called point operation. If the pixel is moved from its location like rotation or scaling it is called geometric operations. This study, for image enhancement, deals with point operations. In point operation pixels values are mapped to a new value through transformations to achieve desired enhancement. This transformation is achieved by applying various methods in spatial domain. To achieve image enhancement these methods exclusively deal with the pixels of the given image. Hence image processing simply transforms a given image I to an output image O by applying a transform function F. The value of each pixel in the given image and output image is given by i and o and the expression is given by $o = F(i)$. Over the years, researchers have proposed many methods which implement these transformation functions. Subsequent text provides a brief overview of the concepts and methods which are used in spatial domain.

Thresholding: It is a useful way of separating the image areas which are of interest from those areas which form background. For a pre-determined threshold value T this transform function is given by the expression $o = \begin{cases} 1 & \text{if} \quad i > T \\ 0 & \text{if } i =< T \end{cases}$ In the simplest implementation black pixels are separated from white pixels; black ones represent back ground and white one represent foreground. It is possible to set multiple thresholds to establish band of segment which interest us. The method has limitations that it would segment the image into different areas but within the segmented area contrast would remain constant. As such the method is only useful in segmentation. It has limited utility for contrast enhancement.

Adaptive thresholding: As the name suggests it take into account the neighborhood of the image and adapts the threshold value according to neighborhood. Therefore it does not remain a pure point processing method. The method improves upon basic thresholding for the purpose of segmentation but is still not useful for contrast enhancement.

Logarithmic Transformation: The transform function while using log increases the grey level range of the pixels at lower grey level range. Therefore it further darkens the dark areas in the image. It is given by the formula $\mathrm{o} = \mathrm{c} * \log(1 + \mathrm{i})$. It application may be done very selectively as it is hard to exactly establish image deficiency which needs this kind of transformation. Therefore the use of this kind of method may be expert dependent for each time this method is applied.

Contrast Stretching This transformation is achieved by adjusting the image pixels range; so that it covers the whole range of values that is from 0 -255 for a grey scale 8 bit images. This transformation is given by the formula $\mathrm{o} = \mathrm{i} - \mathrm{c}\left(\frac{\mathrm{b}-\mathrm{a}}{\mathrm{d}-\mathrm{c}}\right) + \mathrm{a}$. Whereas b-a is the new range and d-c is the old range of image. Previous starting point of the image is c and the new starting point is a. The limitation of this transformation is that a single outlying pixel with either a very high or very low frequency can severely disturb the calculations in this transformation. Secondly if the image is already spread to the whole scale the output image remains same as input image. Therefore the method may only be used effectively by expert involvement that too only on selective images.

Histogram Equalization This is a sophisticated method which is simple, straight forward and computes the function based on the intensity of histogram. This transform function is given by $\mathrm{o} = 255 * \sum_{0}^{\mathrm{i}} \frac{\mathrm{n_i}}{\mathrm{n}}, \quad \mathrm{k} = 0,1,2, \ldots \ldots \mathrm{L} - 1$. This transform function represents that o, output grey level is derived by cumulative density of input image at I grey level. This method has been improved further by successive attempts of researchers over more than two decades. Currently this method is widely in use. Improvements in the method were generally aimed at integrating local neighborhood into this method. This was then termed as local histogram equalization. Although the method has benefits of simplicity, straightforwardness and lack of dependence on human experts, it has a major drawback that its calculations are dependent on image density instead of contrast. This may be misleading and lead to unpredictability in results.

2.2.3 Method Chosen for Detailed Research and Justification

The study has picked up spatial domain over frequency domain and within the spatial domain Histogram Equalization is selected as the method to be reviewed in detail and a new method proposed in the light of this review. This approach is justified in subsequent text. This research considered frequency domain in detail but as discussed earlier frequency domain is intensive in mathematical calculations. Moreover frequency domain is constrained to be applied to the images at global scale. This would ignore local factors and hence it becomes disadvantage and local details in output image are compromised. Therefore even if mathematical computational challenges are resolved, suitability of frequency domain is limited to masks and filters. Therefore for contrast enhancement, it is neither straightforward nor simple to apply those methods which belong to frequency domain. On the other hand spatial domain in general consists of methods which enhance the image by point processing. Some of the methods take local neighborhood into consideration and modify point processing technique. All these methods are simple and straightforward and they are significantly less intense in mathematics. Therefore for the purpose of this research spatial domain is chosen over frequency domain. In spatial domain many methods exist as discussed in earlier text. Among these methods, as discussed in the earlier text, contrast stretching, logarithmic transform and thresholding has usage for select few images and it also needs pre hand knowledge of those images. Histogram equalization (HE) which also falls in spatial domain is simple, straightforward, automatic and free of expert involvement. HE computes its transform function from the input image. However, it has a significant drawback that its calculations are based on intensity not contrast. Despite this drawback, it has wide usage for its qualities mentioned earlier. Therefore our research with in the spatial domain will focus on HE. While focusing on HE, due to its advantages, the cardinal drawback that it is founded on intensity not contrast will have to be resolved in our proposed solution. Therefore this study due to all the factors discussed earlier will review HE is details and analyze the building blocks of its foundation to reach at true facts to propose an accurate solution. As the drawback is pointed out in the foundation of HE, there is a likelihood that while fixing this issue it leads to evolvement of a new method. Still for commonality of positive aspect it will be

HE with which will remain most relevant for comparative analyses of the proposed method.

2.3 REVIEW OF HISTOGRAM EQUALIZATION

Histogram equalization (HE) is a well-known method to enhance image contrast. It is simple, straightforward and effective method in which the image is converted to histogram and then it is equalized (Zhiming et al., 2006). Grey levels of input image are mapped to output image on the basis of probability distribution. Consequently, the histogram is flattened as shown in Fig 2.2, and the dynamic range of grey levels is stretched. Flattening of the histogram increases contrast and stretching of the grey level range refines the objects thus increasing the readability of image. It effectively enhances the overall contrast of the whole image (Chen and Ramli, 2003a). Like all evolved methods, HE has some undesired side effects.

HE mostly fails to preserve the brightness of the input image. When probability distribution is applied to the input image grey level, the range is stretched and histogram is uniformly flattened. The existing middle grey level becomes the mean value of histogram – completely disregarding the mean value of input image. This shift in histogram is presented in figure 2.2.

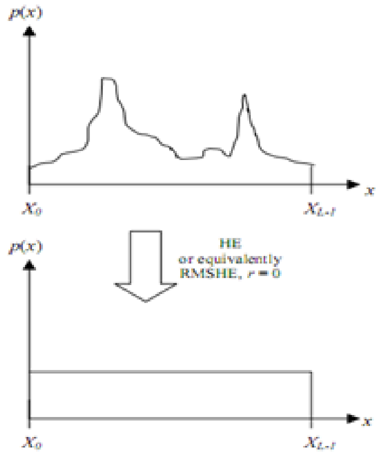


Figure 2.2: HE flattens histogram and adjusts brightness to mean

Source: Chen and Ramli, 2003a

Therefore, the output image has its mean brightness at the middle irrespective of the mean brightness of the input image. For input images with histogram cantered at high (nearing 255) or low (nearing 0), the mean brightness of the output image shifts significantly by HE. Accordingly, while the contrast of the image is enhanced effectively, yet as a side outcome, image brightness is not retained - this may change image outlook drastically (Menotti et al., 2007). HE improves contrast based on the overall details of the whole image. The method is effective in differentiating the boundaries of different objects but smooth and small details within these objects may be lost. Another outcome is excessive contrast where small objects have large clear back ground (when few grey levels cover large section of the image) (Yun et al., 2011) and saturating artifacts in the output image (Wang et al., 2005).

Therefore the drawbacks of HE can be summed up as; shifting brightness, loss of details and equal contrast enhancement in response to varying contrast deficiencies in image components. This introduces artifacts deteriorating the image quality making it difficult to read the actual data and discard clutter.

A direct solution which the researchers evolved was dealing with the image at the issue level i.e. local level. Instead of taking the whole image as one piece, literature survey reveals that, research got focused on enhancing the image by taking care of all the specific deficiencies at local level.

Local level processing necessitates splitting of histogram and/or image. Criterion is developed based on which the image could be split. As a pursuing step, HE is applied on all the parts independently. Known drawbacks of HE are due to its global scope of application. The scope is now curtailed to individual parts of the image. Therefore, the desired outcome is now more probable. After having applied HE, the parts are integrated to generate the output image. During integration, algorithms are used to avoid overlapping boundaries preventing blocking of details in adjacent parts. Number of image parts is an important aspect influencing the outcome of the process.

Number of sections tends to dictate the trend of results; if the number of partitions is kept low, the image virtually behaves as one unit and consequently the approach edges towards the drawbacks of global processing (Chen and Ramli, 2003a). If the number of sections is too high, each part becomes so small that it virtually has no reference environment as neighborhood. Therefore, no enhancement occurs – overall output image is nearly the same as input image. Hence technically, the approach swings between "global processing drawbacks" and "no image enhancement". While devising method to implement this approach, an intelligent balance is to be sort with an objective of desired image outcome.

Based on the above thought, the survey exhibits that, researchers devised methods on different logics and criteria to fulfill requirements of imaging in advancing technologies. Some of these, local level, methods are Bi-histogram equalization (BBHE) (Yeong-Taekgi, 1997), dualistic sub-image histogram (DSIHE), minimum mean brightness error bi-histogram equalization (MMBEBHE) (Kim, 1997; Wang, et al., 2005)etcetera. As all these methods fall within the local processing zone. The results produced by such methods have some common improvements and drawbacks, which reflect on the basic approach of local processing (Sim, et al., 2007).

Local processing, to a relatively larger degree, preserves brightness (Kim, 1997; Wang et al., 2005; Menotti, et al., 2007). Local Processing (LP), tones down the contrast to, provide more natural look with respect to immediate neighborhood. LP tends to avoid image distortion and produces a natural outlook of the output image. However, as no approach is free from shortcomings, some of the imperfections in the procedures are: it brings improvement but does not resolve the image brightness and contrast issues in entirety. As mentioned earlier, the approach swings between "global processing drawbacks" and "no image enhancement". The additional steps in local processing require higher computational effort, increasing the time and hardware requirement.

Although local processing approach has demonstrated improvement over global processing, the existing shortcomings offer wide range of research space for introducing new algorithms and methods. This is aimed at enhancing the image further while avoiding image deterioration. Since HE is one of the major methods used in both global and local approaches, it is important to deal with it in detail. LP use the same HE but scope is curtailed to individual image pieces instead of whole image, which is the case for global processing. Hence in essence, the concept of local processing stems from global processing. Therefore it is paramount that we first understand global processing in detail.

The remaining portion of this chapter is organized as follows: section two briefly explains Global processing leading to detailed elaboration of HE along with its mathematical formulation. Section three covers local processing - explaining optimization of image divisions in separate headings of bi or multi divisions. - In which, following techniques are elaborated: BBHE, DSIHE, MMBEBHE, MCBHE, RMSHE, MBPHE, DHE and BPDHE. Section four presents discussion and analyses. Section five concludes by summarizing the histogram techniques discussed in the paper.

2.4 GLOBAL PROCESSING

As mentioned earlier, global processing takes the contents of the whole image and processes it by Histogram Equalization (HE) technique. The methodology of HE is to uniformly distribute the available grey levels of an image over the entire range of the grey levels. The whole method is implemented in three steps. First, the grey levels with their number of occurrence are counted. The probability density function (PDF) is calculated in order to know the proportion of various constituent grey levels. PDF for a given image ***I*** is given by the formula:

$$d(I_k) = \frac{n^k}{n} \tag{2.5}$$

Where k= 0, 1, 2 ……., L-1. , and I_k is a specific grey level, n^k is the number of times I_k appears in the input image ***I*** and n is total number of pixels. Plot of number of pixels for each grey level n^k against I_k is called histogram. Second, the cumulative density function (CDF) of grey level is computed by

$$c(\bar{\boldsymbol{I}}) = \sum_{j=0}^{k} d(I_j) \tag{2.6}$$

Where$I_k = \boldsymbol{I}$ for k=0, 1, 2 ...L-1 Third, on the basis of this CDF a grey level transform function is derived (Zhiming, et al., 2006)[1] .

$$f(I) = I_0 + (I_{L-1} - I_0)c\,(I) \tag{2.7}$$

This transfer function maps the input grey level with the output grey level by stretching the input image and mapping it to complete dynamic range of (I_0, I_{L-1}). Output image is generated using this processed histogram. Let the output image be $\boldsymbol{O}$ = { O(I, j) }. Then it can be represented by

$$\bar{\boldsymbol{O}} = f(I) \tag{2.8}$$

$$= \{f(I(i,j)) \mid \forall I(i,j) \in I\} \tag{2.9}$$

Significant contrast enhancement is achieved by HE due to dynamic range expansion. Resultant image now comprises of all the grey levels in the domain i.e. from 0 to L. HE also flattens the output histogram uniformly. HE is effective in differentiating the boundaries of different objects.

However, at times, during the stretching, smooth and small details within the objects may be lost. Excessive contrast may be witnessed when few grey levels cover large section of the image (Yun, et al., 2011). At places image may be distorted due to local deterioration of visual quality of the image in those parts (Menotti, et al., 2007). Theoretically it can be calculated that mean of a flat uniformly distributed histogram is the middle grey level. Therefore output image mean shifts to middle grey level introducing visual deterioration in the image, making the HE an unsuitable option for consumer electronics.

When shortcomings in global processing became evident, research shifted to enhancing the image by parts with respect to immediate surroundings. This is a solution orientated approach aimed at dealing with the image in much greater details. The approach is termed as Local Processing.

2.5 LOCAL PROCESSING

A review of the HE suggests that though the approach has revolutionized the low contrast image enhancement domain, but it has its shortcomings. The reason; it was applied to the whole image. Whole image did not have exactly uniform contrast deficiency. Corrective measure calculated by global approach was uniform for the whole image. This created lop sided results: on some parts of the image contrast correction was good, on some parts it made no difference and on some it produced over contrast. So a perfectly fine solution only succeeded partially due to faulty application strategy. This gave rise to local processing (LP), which fixed the strategy to apply the method. LP applied the same method of HE, but prepared proper grounds for it first (Jiang and Zhang, 2006; Eramine and Mould, 2005). LP attempted to split the image into sufficient parts to reach a level where contrast deficiency, for each part, tended to become uniform. Image enhancement solutions based on factors in one section did not affect any other section. Local processing was comparatively better at retaining the input image brightness by trying to retain mean grey level (Kim et al., 1998). Preserving the brightness of the input image avoided non-existent artifacts. As mentioned earlier in local approach, primary difference is to prepare the grounds for applying HE locally which involves splitting of the image. Splitting of image requires criteria based on which image can be split.

Criterion for partitioning the image could be based on multiple factors. Some of the possible factors making up the criteria could be histogram mean, median, brightness error, threshold, clustering, recursion, variance, shape of the histogram and the area of the image. The criterion for partitioning is always relevant to the processing technique and number of pieces the image is partitioned into. Image can be divided around mean intensity or a predetermined grey level value called threshold. Histogram can be divided to ensure that no dominating grey levels exist in any part. Division may consider all peaks and valleys. Image can be divided in two equal area sub-images i.e. a bright and dark sub-image with aim to have Shannon’s entropy for the output image at maximum. Based on the division criteria the number of parts must be optimized for the technique which is being implemented.

2.5.1 Optimizing Image Divisions

As image processing progressed from global to local, various local techniques were developed. All the techniques required the image to be dealt by parts. It became crucial to establish the right number of divisions for the intended technique. According to present day techniques, image partitioning can be broadly categorized in two groups: bi-sections and multi-sections partitioning.

Bi-sectioning intends to partition around mean grey level aiming at preserving input image brightness. The input image brightness was retained only if the histogram was ideally shaped around the partitioning boundary. Accordingly, the brightness intensity though improved, but still fell short of ideal value. Contrast of the image improved only to the extent that it was not affected by any section other than the local section.

When bi-sectioning offered some improvement, researchers, to accrue more benefits, divided the image further and thereby leading the process to *multi-sectioning*. Increasing number of partitions improved enhancement but, for large numbers, (very small size of) partition virtually remained unchanged during the processing. Consequently the output image was almost same as input image. With growing number of partitions the whole processes was computationally intensive and also mean intensity was no longer preserved. For few divisions, the process tends to become global. Hence, a balance must be established to will ensure that image enhancement is optimized, to achieve suitable brightness and natural look which is free from non-existent artifacts. With all these considerations in the focus, researches developed local processing techniques. These are in two major categories; Multi-Sectioning and Bi-Sectioning.

2.5.2 Bi-Sectioning Methods

Brightness Preserving Bi-Histogram Equalization (BBHE)

The method divides the image around the mean intensity value. The image is formally defined as

$$f(\bar{\boldsymbol{X}}) = \{f(X(i,j))|\ \forall X(i,j) \in X\} \tag{2.10}$$

Partitioning is based on mean or median which is the average intensity of all the constituent pixels of the input image. Mathematically both the parts can be defined as follows:

$$X_U = \{X(i,j)|\ X(i,j) > X_m,\ \ \forall X(i,j) \in \bar{\boldsymbol{X}}\} \tag{2.11}$$

$$X_L = \{X(i,j)|\ X(i,j) \leq X_m,\ \ \forall X(i,j) \in \bar{\boldsymbol{X}}\} \tag{2.12}$$

After bi-sectioning the histogram, the two parts are equalized independently. Finally the results obtained through this operation are joined together to produce an image with enhanced contrast. The aggregate image is

$$\bar{\boldsymbol{X}} = X_U \cup X_L \tag{2.13}$$

And the output image is defined as

$$\bar{Y}(i,j) = \begin{cases} X_0 + (X_m - X_0)\ C_L(x), & if \quad x \leq x_m \quad (2.14) \\ X_{m+1} + (X_{L-1} - X_{m+1})\ C_U(x), & if \quad x > x_m \quad (2.15) \end{cases}$$

Compared to HE the brightness of the resultant image will improve. The mean brightness of the output image will be between input mean and the middle grey level. The method attempts to preserve mean brightness but succeeds fully only in cases where the histogram is quasi-symmetrical around the partitioning point. Brightness shift of output image from mean intensity is reduced. Artifacts and non-uniform contrast reflects improvement but is not resolved completely (Kim, 1997).

Dualistic Sub-Image Histogram Equalization (DSIHE)

The method is an extension of BBHE, but in the partitioning combines "Equal area sub- image" & "Input mean or median intensity value" criteria to bisect the histogram into two parts which can be represented by the following equations. Whereas the symbol X_m is the mean of image, X_L is the lower and X_U is the upper sub-image. The method then separately equalizes the histogram of both the sub-images. The method prevents significant shift in the mean intensity, of output image, with respect to medium intensity of input image. This is specially so for images with extensive concentration of grey levels in small histogram area. This represents small objects with large contrasting region (Wang, et al., 1999).

Minimum Mean Brightness Error Bi-HE Method (MMBEBHE)

The underlying principle for the method is same as BBHE and DSIHE. Both BBHE and DSIHE decompose image based on consideration about input image alone but MMBEBHE partitions image on a "threshold level" l_{th} where input and output image have the minimum difference in brightness. For a given image $\bar{\boldsymbol{I}}$ two sub-images $I = [0, l_{th}]$ and $I = [l_{th} + 1, L-1]$. After having divided the image into two sub-images based on threshold value, classical HE is applied to both sub-histograms. Finally by combining the two sub- images output image is generated (Chen, et al., 2003b).

Multilevel Component Based Histogram Equalization (MCBHE)

This method resembles BBHE. In this method the image is divided into sub-images on the criteria of "Input mean or median intensity value". The two sub-images are termed as foreground and background. For a given image $\bar{\boldsymbol{I}}$, the two sub-images may be represented by I_b background image and I_f foreground image, where I_m is the mean intensity of the image.

$$\bar{\boldsymbol{I}} = I_b \cup I_f \tag{2.16}$$

The sub-images are represented by the following equations.

$$I_b = \{I(i,j) | I(i,j) < I_m \forall I(i,j) \in \bar{\boldsymbol{I}}\} \tag{2.17}$$

$$I_f = \{I(i,j) | I(i,j) \geq I_m,\ \forall I(i,j) \in \bar{\boldsymbol{I}}\} \tag{2.18}$$

At this stage grey levels of each sub-image are analyzed at multiple thresholds set at predetermined points. Let the threshold be T_{x_i} and s_x be the incremental step for next threshold value. Then $\boldsymbol{s_x}$ increment is represented by

$$s_x = \left\lfloor \frac{\max(I_x) - \min(I_x)}{N_x + 1} \right\rfloor \tag{2.19}$$

Where the symbol x represents the foreground or background image. The sub-images are processed iteratively using each successive threshold which is given by

$$T_{x_i} = \min(\, I_x) + \, iS_x i = 1,2,\, ..., \tag{2.20}$$

Grey levels above or below the threshold are clumped together to identify connected components which is represented by

$$C_{x_i} = C_{xL_i} \cup C_{xG_i} \tag{2.21}$$

Where as C_{xL_i} are the grey level values below threshold T_{x_i} and C_{xG_i} are the value of grey level above threshold. These values of grey levels are connected components; the existing range of these connected components is stretched to the relevant range of grey level resulting in enhanced component contrast. The entire enhanced component aggregate to constitute output image (Jafar, et al., 2007).

2.5.3 Multi-Sectioning Methods

Recursive Mean Separate HE Method (RMSHE)

Researchers motivated by the improvement in image enhancement due to bipartitions, intended dividing the image into more parts for further enhancement. RMSHE divide the input image histogram recursively into still smaller sections up to a limit ‘m’ producing 2m images. Fig 3 depicts the idea of recursive division of input histogram. HE is applied to each one of these parts independently. The brightness of the input image is better preserved as number of recursions increase. As the method deals with a lot of sub-images, the method is computationally intensive. If the recursion level is kept at 0 the method translates to HE method as shown in figure 2.1, if recursion level is 1 the method represents bi-sectioning methods which is shown in figure 2.3 below..

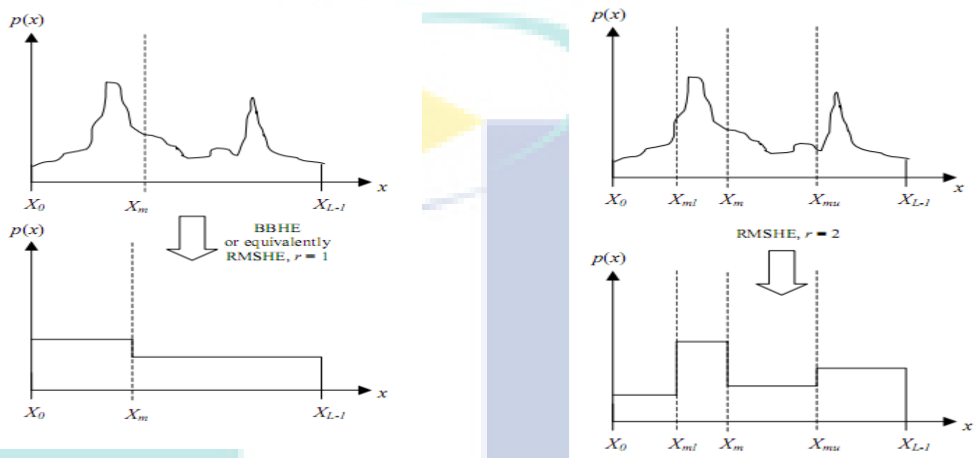


Figure 2.3: RMSHE with different recursion levels

Source: Chen, S -D; Ramli, A R, 2003a

Basically, RMSHE is a generalization of HE and BBHE. In standard HE method, the output mean is computed with the help of following equation.

Output's mean of classical HE.

$$E(Y_{HE}) = \frac{X_0 + X_{L-1}}{2} \tag{2.22}$$

Output's mean of classical BBHE.

$$E(Y_{BBHE}) = \frac{X_m + X_G}{2} \tag{2.23}$$

Output's mean of the two newly observed histograms is given by:-

$$X_{ml} = 2 \int_{X_0}^{X_m} xp(x)dx \tag{2.24}$$

$$X_{mu} = 2 \int_{X_m}^{X_{L-1}} xp(x)dx \qquad (2.25)$$

Adding together the newly found histograms:-

$$\frac{X_{mu} + X_{ml}}{2} = \frac{2\int_0^{X_m} x.px(dx) + 2\int_{X_m}^{X_{L-1}} x.px(dx)}{2} \qquad (2.26)$$

$$= \int_0^{X_m} x.px(dx) + \int_{X_m}^{X_{L-1}} x.px(dx) \qquad (2.27)$$

$$= \int_{X_0}^{X_{L-1}} x.px(dx) \qquad (2.28)$$

$$= X_m \qquad (2.29)$$

Output mean E(Y) for RMSHE with recursion level (r = n) i.e. for larger n , E(Y), converge to the input mean X_m(Chen, S -D; Ramli, A R, 2003a) .

$$E(Y) = X_m + \left[\frac{(X_G - X_m)}{2^n}\right] \qquad (2.30)$$

Mean Brightness Preserving Histogram Equalization (MBPHE)

This method has the flexibility of implementing any one of the Bi-sectional and multi-sectional partitions. It uses “Input mean or median intensity value” to divide the input image into sub-images, which are then equalized independently. As the input histogram has to be perfectly balanced around separating point which is very rare therefore in reality, the method although successful to some extent, fails to preserve mean intensity.

When the method implemented in multi-partitioning, the slicing of histogram is done recursively on the basis of “Input mean or median intensity value” or the “Shape-based Partitioning”. The detection of partitioning boundaries requires complicated algorithm which in turn increases computational time. The method puts a lot of conditions on preserving the mean intensity. Consequently, no worthwhile enhancement is achieved from the method (Chen, S -D; Ramli, A R, 2003a).

Dynamic Histogram Equalization (DHE)

The aim of the method is to avoid loss of any details in any part of the image. The method has three parts, partitioning the image, allocating related grey level dynamic ranges to each sub-histogram and thirdly applying HE on each of the sub-histograms. To achieve the aim the method divides histogram into a number of sub-histograms. Division is based on the criteria of "Shape-based Partitioning". The division continues until no dominating portion exists in any of the resulting sub-histograms. Managing histogram with no dominating parts is the glaring strength of the method which gives it the characteristics of preserving features of even small object. Now, for each sub-histogram, the cumulative distribution of histogram values (CDF) and the related dynamic range in the input image is considered. Based on these two facts dynamic grey level range is sliced and allotted to each sub-histogram. This allotment of proportionate stretched range ensures that no details are lost and small features are not dominated. This brings out a moderate and a natural contrast spread to each part of the whole image. Further, separate transform function for each sub-histogram is calculated. HE generates the output image by mapping the grey level of input image through individual histograms (Abdullah-Al-Wadud, et al., 2007).

Brightness Preserving Dynamic Histogram Equalization (BPDHE)

The method is an extension and a step further in achieving the refinement over DHE. The method divides the histogram into sub-parts on the basis of shape. The division continues till no highs or dominating parts are left in any of the newly created sub-histograms. The method now maps each sub-histogram to a new dynamic range. At this step, the adjustment in the dynamic range will shift the mean brightness, so in this method a new step of normalization is introduced. Normalization aims at making the average intensity of the output image same as the input image. This will result into mean intensity of output image almost matching the mean intensity of input image. It nearly preserves brightness and hence produces better enhancement (Ibrahim and Kong 2007).

2.6 OUTCOME OF GLOBAL AND LOCAL PROCESSING

2.6.1 Outcome of Global Processing

Image processing is considered necessary, as images have uncertain contrast and brightness in real world (Tsai and Yeh 2008). The image was initially processed by histogram equalization method. It is simple, robust and easy to implement. HE has good contrast improvement. However, as the technique is applied uniformly to the whole image it makes no difference to some parts of the image and in some other parts it results into over contrast. Moreover, HE does not preserve the brightness of input image. This generates artifacts in the output image and HE is not suitable for use in consumer electronics. In general the technique is very robust and performs well. All its drawbacks stem from the fact that it is applied globally. Subsequent techniques, called local processing, take advantage of high performance of HE but cut down on its drawback by shifting the application scope from Global to Local.

2.6.2 Outcome of Local Processing

Local techniques processed the image in parts. The image was initially processed in two parts. Some of the main techniques using image bisections are BBHE, DSIHE, MMBEBHE and MCBHE. BBHE uses input image mean to divide the histogram in two parts for processing. Compared to HE the brightness of the resultant image will improve. The mean brightness of the output image will be between input mean and the middle grey level. The method attempts to preserve mean brightness but succeeds fully only in cases where the histogram is quasi-symmetrical around the partitioning point. Mean intensity is mostly not preserved, loss of brightness, artifacts and non-uniform contrast is not completely resolved. DSIHE is an extension of BBHE and is used where small objects exist against large backgrounds. During partitioning it also considers equal area property along with mean brightness of input image. It has similar results as of BBHE. MMBEBHE is a variant of bi-sectioning the image technique; it displays improvement to preserve the brightness of input image. Contrast and brightness comparison is shown in figure 2.4.

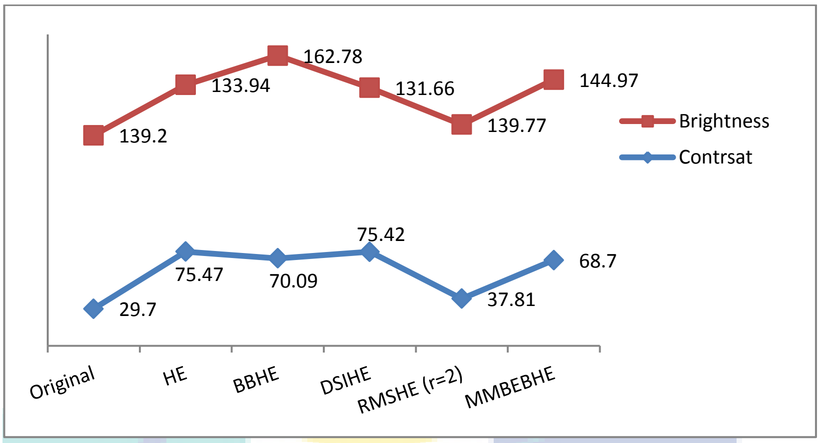


Figure 2.4: Brightness & Contrast for given techniques and original image

Source: Menotti, et al., 2007

The comparison of the absolute mean brightness error (AMBE) is shown in the following figure 2.5

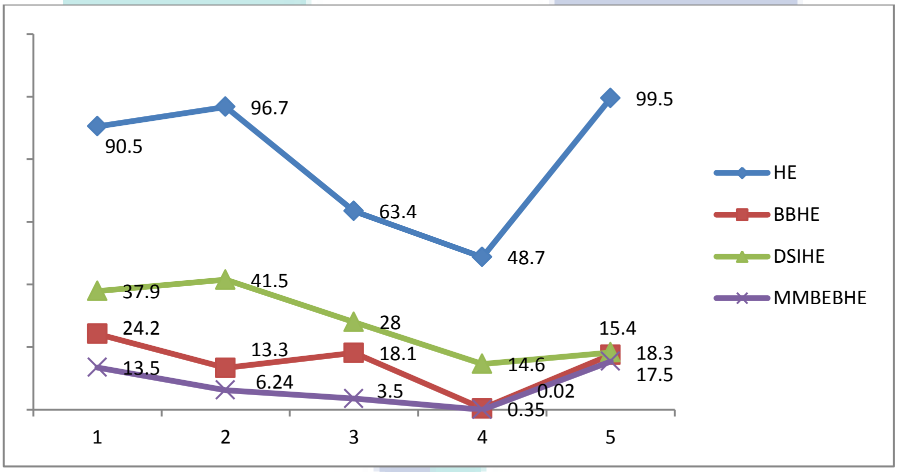


Figure 2.5: AMBE for HE and some of local processing methods

Source: Chen, et al., 2003b

MCBHE uses bisection but also combines multiple thresholds with it. It is successful in preserving details and contrast. The technique basically for segmentation is also useful in image enhancement to a large extent.

As shown in figure2.6, amongst the discussed techniques MMBEBHE holds the best signal to noise ratio (PSNR) which is an indicator of qualitative edge over other discussed techniques.

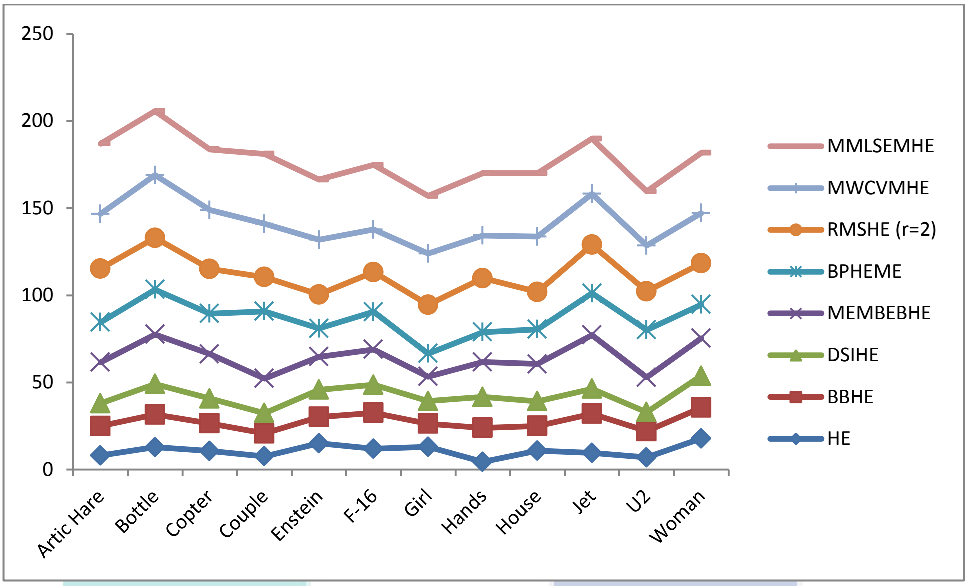


Figure 2.6: PSNR using HE and local processing methods

Source: Menotti, et al., 2007

The improvement achieved in image enhancement, due to bisection, lead researchers to divide the image into multiple parts. This was to take care of left over contrast deficiency. Multiple image techniques are RMSHE, MBPHE, DHE and BPDHE. RMSHE uses the input mean to partition the image. It then recursively continues to bisect the sub-images till the desired size of the image pieces is reached. If the recursion level is kept to 0, the process converts to HE. If recursion level is 1, it is BBHE and as the recursion grows the image results continue to improve further. However, if the recursions are increased to too many, the image pieces are too small to be enhanced. Hence output image tends to remain as input image. The technique is as good as BBHE. MBPHE tends to preserve brightness but suffers from the issues common to the techniques of bi or multi sectioning. The method puts a lot of conditions on preserving the mean intensity. Consequently, no worthwhile enhancement is achieved from the method. DHE during partitioning the histogram leaves no dominating parts in any of sub-histograms. DHE while stretching of histogram maintains a proportion between existing grey levels and full range of grey level. This brings out a moderate and a natural contrast spread to each part of the whole image. Proportionate processing also retains small details even in dominating neighborhoods. Due to proportionate stretch of dynamic range, mean intensity of input image is lost. BPDHE improved over DHE further by normalizing the output histogram. Normalization tends to maintain the average intensity of the output image same as the input image. The method almost preserves the brightness intensity of the input image and hence produces better results.

Overall, all the local techniques were computationally intensive. These techniques required partitioning of images. If partitions were kept few, the process tended to near HE with its loss of input image brightness issue. If the partitions were too many, the image pieces hardly change tending to generate the output image almost same as input image.

2.7 SUMMARY

The purpose of images is to interpret the ground reality through imagery means. To interpret ground reality accurately the image needs to present all the details with accuracy. Image should have natural contrast and adequate brightness for easy interpretation. This will also help interpretation to be persistent among multiple image readings. Consequently the interpretation will also remain consistent among different viewers. Practically images have various levels of contrast and brightness effecting interpretations. For improving image interpretation contrast needs to be enhanced and brightness needs to be adjusted. The available details in an image almost invariably require processing to achieve appropriate contrast and brightness for accurate interpretation. Improving contrast and brightness are competing requirements. Improving one generally deteriorates the other. A single technique does not resolve all the issues. Although significant progress is made in the field of contrast enhancement, it has not reached a robust and proven state where it can satisfactorily produce consistent results for a broad spectrum of images. In real life, enhancing one aspect may deteriorate the other. As an ensuing effort, there is a constant struggle to improve known drawbacks in currently existing techniques. Gap analyses between the required and practically achieved enhancement uncovers a huge research space motivating researchers to continue their efforts for improving robustness of existing techniques and evolving new ones. Work in this research area will improve the accuracy of available details, unmask fresh details, further enhance contrast and adjust brightness to provide more natural image outlook. The whole effort is focused at making interpretations persistently accurate and consistent among multiple viewers.

CHAPTER 3

DETAILED ANALYSIS OF HISTOGRAM EQUALIZATION

3.1 INTRODUCTION

This chapter, in view of the backdrop of existing contrast enhancement methods, explains the outcome of using HE for processing medical images. First the chapter mentions various enhancement methods and the placement of HE within these methods. Next, the chapter explains unsatisfactory performance of HE which, though, effects all images but is of greater concern for medical field. This extra caution in medical field is due to critical need for reliable image accuracy to support decisions for human life. Then the chapter attempts to establish the cause of this deteriorated HE performance by a detailed study of HE building blocks. Then the chapter using this analysis uncovers inherent deficiencies in HE. Next the chapter presents the response of researchers to HE drawbacks – elaborating local processing techniques and their effectiveness. Finally the chapter ascertains that HE is unsuitable for medical images due to its drawbacks; moreover, response to HE drawbacks in the form of local processing techniques has not resolved HE issues. Therefore the chapter concludes that HE including it's variants is not a reliable technique to be trusted for medical field.

3.2 PLACEMENT OF HE IN EXISTING METHODS

Amongst the contemporary methods HE stands out for its simplicity, straightforwardness, automation, computational speed and near independence from expert input. Unlike ANN and fuzzy logic based technique HE does not a need an expert input for marking images and specifying areas of interest in the images.

Moreover ANN type algorithms require huge volume of data of similar kind for training the algorithm to adapt to the desired pattern. Therefore, HE for its simplistic features is a widely used technique in image processing which includes its application in medical field as well.

3.3 OUTCOME OF USING HE ON MEDICAL IMAGES

As discussed in chapter 1, medical images provide necessary support for facilitating diagnostic process. For this purpose, good contrast helps whereas poor contrast might cause ambiguities. During enhancement, if a non-existing feature creeps into the image (false positive) or an existing feature is dropped (false negative) – the image could, crucially, mislead the diagnosis. Therefore the accuracy level of enhancement techniques used for medical images must be well ascertained and predictable which will establish the reliability and trustworthiness of .the employed technique. As discussed in chapter one, amongst many techniques HE is a widely relied upon technique in contrast enhancement. However, using HE in critical area of medical field yields unpredictable results. A raw brain MRI is taken from brain atlas and HE is applied to the image. Original image and processed image is presented in figure 3.1.

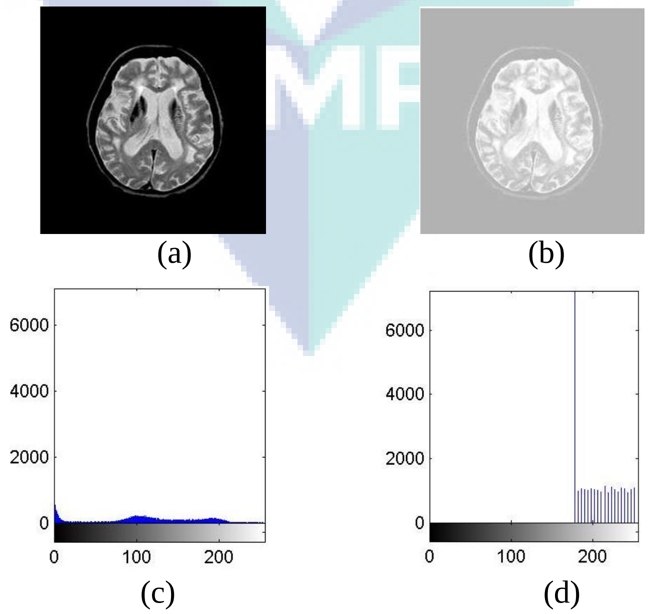


Figure 3.1: Comparison of MRI and histogram original (a, c) and HE (b, d)

Source: Brain atlas

Figure 3.1(a) shows original image and figure 3.1(b) shows HE enhanced image which lost sharpness, became hazy and monotonic. Histograms of processed image in figure 3.1(d) shows significant change of image data compared to histogram of original image in figure 3.1(c). Data change is very obvious in the shape of washout from 0-160 grey level in the processed image. This deterioration in visual quality of image and its confirmation by washout in the histogram instigates us to find out its cause. To, find this cause, foundation and mathematical models of HE has to be analyzed critically which will bring out any inherent deficiencies of HE.

3.4 FUNDAMENTALS OF HISTOGRAM EQUALIZATION

The purpose of applying HE to an image is to enhance contrast. Contrast of an image is the difference in luminosity of adjacent grey levels. Objects stand out from neighborhood due to contrast. So, difference in grey levels of objects and its neighborhood is the primary factor to consider while establishing or enhancing contrast. Unfortunately, HE does not include, these factors, in its formulation; instead it uses density as its basis.

3.4.1 Mathematical Formulation

HE used frequency of occurrence for each grey level to calculate probability density. Take a raw image R probability density function is given by$d(R_k) = \frac{n^k}{n}$. Where *K = 0,1,...L-1* and n^k is the occurrence for grey level *k* and n is the total number of pixels in image *R*. Next cumulative density is calculated which is given by $c(\overline{\boldsymbol{R}})$

$$c(\overline{\boldsymbol{R}}) = \sum_{j=0}^{k} d(R_j) \tag{3.1}$$

Where$R_k = r$ for *k=0, 1, 2 ...L-1*. Further, CDF is used to calculate new grey levels for the processed image. A single grey level $f(r)$ is given by (Zhiming and Jianhua 2006).

$$f(r) = R_0 + (R_{L-1} - R_0)c\,(r) \tag{3.2}$$

The processed image **P** = {P(i, j)} which is expressed by

$$\overline{\boldsymbol{P}} = f(R) \tag{3.3}$$

$$= \{f(R(i,j)) |\ \forall\ R\ (i,j) \in \boldsymbol{R}\} \tag{3.4}$$

The description show, during formulation of its process, HE does not take into account object grey levels or their difference at any place in its formulation. It is evident from equation 3.1 – 3.4 that HE only uses pixel density which forms basis for further computations.

3.4.2 Basic Calculations in HE Application

Consider application of HE on an image represented by matrix $\mathrm{X} = \begin{bmatrix} 5 & 8 & 6 \\ 9 & 5 & 7 \\ 5 & 6 & 8 \end{bmatrix}$. Pixel value 5 occurs 3 times, pixel value 6 occurs 2 times and so on till the last pixel value 9 which occurs only once. Total Number of pixels in the image is 9 and total number of existing bins is five. Next HE calculates probability density (PD) by dividing number of occurrences with total number of pixels i.e. for grey level 5 PD is 3/9 and for the last bin 9 - PD is 1/9. Then HE calculates cumulative probability density (CPD) starting with the first bin i.e. CPD for first bin for pixel value 5 is 3/9 and for second bin pixel value 6 is 5/9 and so on till the last bin for pixel value 9 where CPD is 9/9. Finally CPD is multiplied with complete range of grey levels i.e. 256 to get the new pixel value. For image X data for all the above steps is summarized in Table 3.1.

Table 3.1: Complete data, used in HE application for image X

S. No	Pixel Value	Frequency	PD	CPD	CDF	New Pixel Value
1	5	3	3/9	3/9	3/9*256	85
2	6	2	2/9	5/9	5/9*256	142
3	7	1	1/9	6/9	6/9*256	170
4	8	2	2/9	8/9	8/9*256	227
5	9	1	1/9	9/9	9/9*256	256
		Total = 9				

Complete HE formulation is based on probability density and cumulative density function. To confirm this finding let us take another image Y = $\begin{bmatrix} 27 & 192 & 39 \\ 228 & 27 & 106 \\ 27 & 39 & 192 \end{bmatrix}$ and apply HE on this image. HE steps are calculated same way as for the first image, the result, of which, is shown in table 3.2

Table 3.2: Complete data used in HE application for image Y

S. No	Pixel Value	Frequency	PD	CPD	CDF	New Pixel Value
1	27	3	3/9	3/9	3/9*256	85
2	39	2	2/9	5/9	5/9*256	142
3	106	1	1/9	6/9	6/9*256	170
4	192	2	2/9	8/9	8/9*256	227
5	228	1	1/9	9/9	9/9*256	256
		Total = 9				

Comparing the results in table 3.1 and 3.2 it is clear that pixel value for image X and Y written in column two are, way far, different, but, importantly, occurrences are same for successive grey levels which are shown in column three of both the tables. Therefore the entire HE calculated data shown in column 3 to 6 is identical in both the tables. In fact, mathematically it is well concluded that HE data remains identical for all the images with same size and with identical occurrences for successive grey level.

It is obvious that, for constant data in column 3 – occurrences - HE completely ignores the figures in column 2 – the actual grey levels. From successive grey levels in column 2, differential can be calculated which we defined earlier as contrast. Therefore it is strikingly evident that HE ignores both contrast itself and data leading to contrast.

It is for this reason that processing of HE claimed as contrast enhancement needs reassessment. Contrast deficiency with respect to immediate neighborhood is neither calculated nor fixed. Truly, change in contrast is not targeted; in fact, HE processing, which is purely calculated on density, only substitutes the constituent grey levels. New grey levels are elaborated in last column in table 3.1 and 3.2. Understandably, when HE alters image constituents grey levels, it affects contrast in a roundabout way. It is purely a matter of chance, for this change, to be an improvement in contrast. Practically, the image has unpredictable characteristics of contrast changes. Additionally, during image processing another important aspect is image brightness.

For understanding image brightness, consider column 5 of table 3.1 and 3.2 it presents CPD – which starts from first grey level with density and then adds the density figure to the next level and then total is taken to the third level, and so on, till the last level. In this way the density is carried forward. Average density will be the middle grey level, which means the brightness of the image will be governed by this middle grey level. Hence, the image may lose brightness which may introduce nonexistent artifacts. Therefore, HE becomes an unacceptable option in applications for electronics equipment where retention of this brightness in important.

Therefore HE is not an image enhancement technique; instead, it is a density based technique to substitute constituent grey levels which may change contrast in a roundabout way. HE neither takes into account contrast nor does it consider factors affecting contrast. As a side effect HE may lose brightness introducing nonexistent artifact.

As a solution to these issues, researchers divided the image into various sections and then applied HE separately in each section. This was called local processing. If this technique successfully overcomes shortcomings of HE, medical images could be benefitted. ..Next the study discusses the effectiveness of local processing in recovering the performance of HE.

3.5 RESULT OF USING LOCAL PROCESSING

After discovering HE drawbacks, researchers changed approach and introduced local processing techniques. In these techniques image is partitioned first and then same HE is applied as core enhancement method. The purpose is to curtail the drawbacks of HE to individual sections. Hence it reduces the effect of indiscriminate change in image by HE. But the actual drawback is still carried forward in local processing because it is not the scale of application but basic formulation of HE which is misconceived on density instead of contrast. Furthermore, this partitioning of images as a measure to cater for HE flaws leads to additional computational requirements, moreover, complicated algorithms are required to split the image and join sections after processing.

Local processing only restricts the scale of application by partitioning the image hence, curtailing the shortcomings of HE. Actual drawbacks of HE are not addressed and therefore those still persist the same way. The study therefore does not consider local processing as a solution to HE shortcomings. Hence, even with this technique, HE remain an unreliable method for enhancing contrast and it remains a matter of greater concern for medical images

3.6 CRITICAL DEFICIENCIES IN HE

The foundation of HE processing is based on PD and CDF with complete disregard to grey level values of input image and hence contrasts. This CDF governs histogram stretch which distorts the linear stretch. Whereas, contrast is raised by linear stretch, its distortion makes the stretch uncertain. Hence, yielded contrast is unpredictable. Clearly, HE falls short of any theoretical or mathematical justification rationalizing use of PD and CDF for contrast enhancement. This is also evident from the results of HE application; contrast enhancement is just a side effect which at times is positive, many times it is over or under contrast. As another side effect output image always loses brightness. HE also introduces annoying and nonexistent artifact.

Even by applying local processing technique HE shortcomings are not resolved in totality, because these techniques only limit the canvass of application by partitioning the image. This approach, does not attempt any fix for the basic issues of HE. Additionally, local processing is computationally intensive and involve complex algorithm for partitioning and rejoining the image parts.

Therefore HE is a roundabout method which alters image and resultantly affects contrast unpredictably not relating to actual contrast deficiency. Hence HE does not attempt any contrast specific solution despite its claim as a contrast enhancement technique.

3.7 SUMMARY

After detailed analyses of Histogram Equalization method it was well established that HE does not deal with contrast instead it deals with density. HE, in fact, alters the grey levels of the image based on cumulative probability density which is calculated from probability density. As the image constituent grey levels undergo change, it does produce changes in contrast however, this change adheres to density changes not contrast requirements. Analyzing image histogram before and after HE processing makes it evident that for brain MRIs and similar images, initial grey levels in output image would be missed out by density based transform function. Due to which, image would lose sharpness and tend to become monotonic. In addition to basic HE this drawback trickles down in all the local processing techniques where HE is the ultimate core method used after pre-processing. Although these drawbacks in local processing techniques are curtailed to individual sections which restricks loss of some image features, like brightness but basic HE drawbacks remain unresolved. Hence, a comprehensive solution valid for both basic HE and it's variants employed in local processing needs to be evolved.

CHAPTER 4

METHODOLOGY

4.1 INTRODUCTION

The study in this chapter illustrates methodology. From this point onwards, first the chapter explains data set used for developing and testing methodology. This set contains three types of data; brain MRI, general medical and common images. The chapter further discusses the evolvement of proposed method explaining its attributes: idea, concept, mathematical formulation, pseudo code, flow diagram and algorithm. Finally, chapter concludes by summarizing the explained idea.

4.2 DATA SET

Dataset used in the study has three categories of images: brain MRIs, general medical images and common bench mark images. First category is brain MRI, second category is general medical images which is a mix of synthetic and natural images. Second category includes images with noise and non-uniformity. While processing the image, these details are mentioned along with the images. Both first and second category is taken from (Brain Web 2012) and (Brain Atlas n.d.). Third category contains common bench mark images, like Lena, Cameraman and others. However, as the scope of the study is restricted to grey scale image, these common images will not be used as color images, instead they will be converted to grey scale and then used in this study.

4.2.1 Data Description

The specifications of images contained in each category are explained in subsequent text.

Category One

For the proposed method, Ideal candidate image in this category should have intensity distribution of grey levels which is uniformly distributed around the mid-point. This will have a twin quasi-symmetrical histogram, each one located equidistant on either side of the separation point. Even if the proportion of pixels on each side of the separation point is disturbed, the effectiveness of the proposed method is suitably retained as long as separation point is logically arrived at.

Category Two

This category will include image with same description as in category one – additionally it may have non-uniformity in the image. Further, the image may be natural or synthetic. An image with intensity distribution making quasi symmetrical shape around the mid-point is best suited for our proposed method. A deviation from this description, in this category, will proportionally off set the performance output of the proposed image.

Category three

The description of the image for this category is the same as category one and two but with noise added.

4.2.2 Quantification of Test Data

The images from the above dataset were taken for processing and then tests were compared for HE and the proposed method. Most of the images were of 256 x 256 sizes. The tests used for the analysis were DICE, Jaccard, false-negative and false-positive. Grounds for the selection of the tests are covered in detail in Chapter 5. A total of 134 specimens were processed: 35 from first category, 28 from second category, 21 from third category and then 60 images were tested in which all categories were mixed. Single or multiple tests were carried out on the processed images; Out of these 70 tests were on images from first category, 72 tests were on images from second category and 44 tests were on images from third category. Because, at places, multiple tests were involved on a single output image, therefore the count at places exceeds the total number of processed images. After testing each category separately, another batch of 60 mixed images were enhanced and tested. The results and trend analyses of these specimens are discussed in Chapter 5.

4.3 REQUIREMENTS FOR A NEW TECHNIQUE

The study has brought out clearly that good contrast is the key to accurate presentation of low level details contained in the image, whereas, poor contrast makes these details ambiguous. The extent of availability of image details, determines readability of the image. To, accurately, reach at the ground reality snapped in the image improvement in image contrast should be based on the difference between the image and ground truth. This gap, if any, should be reduced by processing. In all medical equipment where HE is employed as enhancement technique - contrast related drawbacks suffered by the output images stem from HE shortcomings. Chapter three provided critical analysis highlighting inherent deficiencies of HE. This analysis brought forward the requirements that any new contrast enhancement method must meet to be reliably useful for medical images. Following are those requirements:

(i) The foundation of the method should be based on contrast.
(ii) The method should be simple, straightforward and automatic.
(iii) The method should be free from the input of human experts.
(iv) The method should maintain image details and retain image brightness.
(v) The method should consider immediate neighbourhood for enhancing contrast realistically.

(vi) The method should meet contrast deficiency, instead of indiscriminate processing.

(vii) The method should have high reliability by providing predictable contrast enhancement persistently

(viii) Brain being our focus and sensitive area, proposed method should be optimised for MRIs. Additionally, the new method should have satisfactory performance for general medical and common bench mark images.

(ix) The method should perform consistently with stability for a wide variety of image types. To validate this requirement, proposed method should be tested for sufficiently large volume of images belonging to data set.

(x) The method should be robust enough to work with stable performance even under noisy conditions.

4.4 PROPOSED IDEA

To meet the requirements listed before, the solution must be based on factors which affect contrast directly. As already mentioned processing for contrast enhancement should reduce the gap between image and ground reality. For enhancing the image contrast the study came up with a new idea. Most of the existing image processing techniques increase the grey levels to enhance contrast (Kaur et al, 2011), (Chen et al, 2011). This study, however, divided the image into two regions: darker and brighter region -- darker region, is dimmed while elevating the brighter region. This solution reduced contrast deficiency in the image more realistically while retaining natural outlook of the image.

The authors of (Iwanaimi et al, 2012) and (Tan et al, 2012) presented the idea of dividing the image in regions but enhanced contrast using HE. Our proposed method however, makes a more innovative use of the regions which is explained in the later text.

4.5 CONCEPTUALIZING THE IDEA

Images have varying details, during acquisition, with no certainty in contrast or brightness. Hence, for a reliable contrast enhancement, the image must first be brought to a predictable initial platform with certainty in image details. Then from this predictable platform an enhancement method should be perfected to raise the contrast of the image.

Just as an athlete needs running space before he makes a long jump – this intermediate platform must provide expansion space for processing algorithm to enhance the image to a final output. Therefore input image is scaled down to reach this intermediate platform which is also initial parameter for final processing. This concept is shown in figure 4.1.

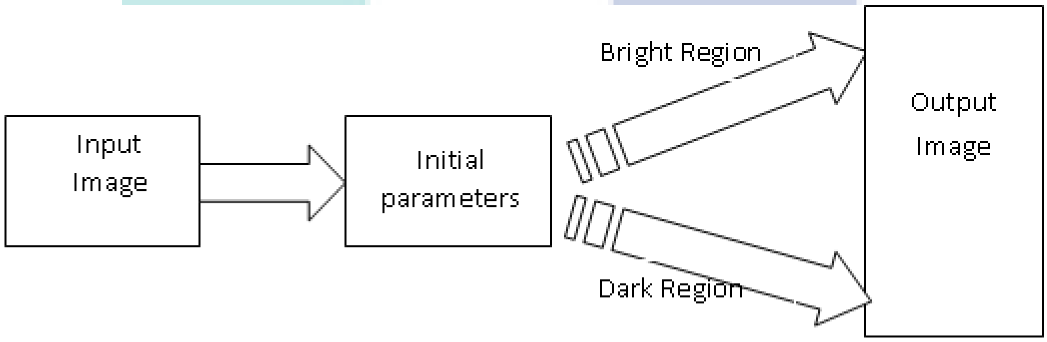


Figure 4.1: Schematic view of proposed idea

The concept of scaling down the scale of the image to a lower scale and remapping the image has been picked up from image stretching (Xu et al, 2010).However, instead of stretching the image is shrunk which is done by treating image as one piece globally – hence it is called global adaptation. Shrinking is chosen to gain some expansion room for subsequent processing in which image is expanded. Additionally, actual grey level range of given image is extracted from histogram. This range is mapped to the new reduced scale. Because this mapping is at a reduced scale, it is termed as tentative equalization. This globally adapted tentative equalization (GATE) while shrinking the image retains contours of original histogram which maintains desired similarity between features of GATE processed and original image. From this stage this reduced image –pre-processed to serve as initial parameter - is fed to final stage for processing.

In the processing phase, this shrunk image which is received from intermediate stage as initial parameter is separated in darker and brighter region. These regions are then enhanced by shifting their grey levels in opposite direction. This is achieved mathematically by exponential increment of grey levels. Exponential rise has a unique attribute of moving the range outwards – shifting low values further lower and high values further higher – keeping center point at the original value which, in turn, serves as the separation point for regions.

This proposed method for a perfect input from intermediate stage will provide perfect enhancement in the final stage. However, it is a challenge to achieve a uniformly distributed quasi symmetrical histogram as initial parameters when the input could be from a wide variety of real world images. So practically, results in the final enhancement will be proportionate to the accuracy measure of initial parameters. Hence GATE needs to cover maximum variations to bring image data to a uniform intermediate stage.

The idea of using exponential power is picked up from gamma correction for hardware devices specially CRTs (Juric and Klepac, 2011). The idea also has a mention of it mathematical effects on image processing. Moreover, authors of (Doustan and Hassanpour, 2010) published a method to balance gamma factor across image to improve image quality. Our proposed concept, however, develops the idea by using exponents (similar to gamma) into a synchronized, well integrated - pre-processing, intermediate and final enhancement stage to present a fully functional end to end contrast enhancement method.

4.6 PROPOSED METHOD

The proposed method is called Contrast Optimization By Regions Adaptation **(COBRA)**. The method optimizes adaptation of brighter and darker regions to maximum contrast. As explained in preceding paragraphs this method achieves this contrast enhancement in two steps: First initial parameters of the image are obtained by Global Adaptation to Tentative Equalization **(GATE)**. The method is shown diagrammatically in figure 4.2.

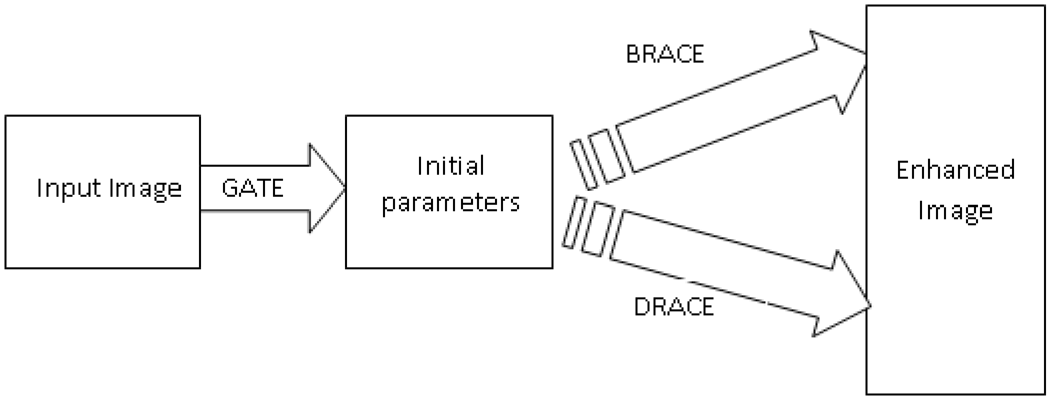


Figure 4.2: Schematic view of proposed concept COBRA

Second this GATE applied image is enhanced by Brighter Region Adaptation for Contrast Enhancement **(BRACE)** & Darker Region Adaptation for Contrast Enhancement **(DRACE)**.

4.7 CONTRAST OPTIMIZATION BY REGIONS ADAPTATION (COBRA)

The proposed method COBRA encapsulates three sub processes, which are GATE, BRACE and DRACE. These are explained in subsequent text.

4.7.1 Global Adaption for Tentative Equalization (GATE)

Images have all sorts of composition. These diverse images will have divergent results if processed through the same algorithm. Hence to enhance wide variety of images while keeping resultant divergence to minimum, input images must be brought to a common standing before contrast enhancement can be applied. To bring all diverse images to a common platform GATE, implements multiple steps.

As a first step GATE reduces the scale which, as mentioned earlier, provides for expansion room for processing the image in next stage. Implementation of this phase was termed as Global Adaptation for Tentative Equalization (GATE). This step is illustrated in figure 4.3

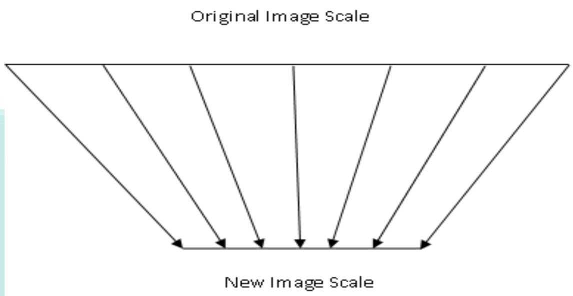


Figure 4.3: Reducing the scale – a step in GATE

In our study various scales were experimented. As scaling down is aimed at providing expansion space for subsequent contrast enhancement in which the grey levels are raised back to full range from 0-255. For our purpose a scale of 1:4, when, used gave very encouraging results on a wide variety of images. Therefore, for all calculations in this study, the image is scaled down to 25% of grey scale. Next histogram spread is established by calculating the min and max value of the existing grey levels. Existing histogram spread is compared with the GATE scale. With this ratio each grey level is mapped to new range. Now the image histogram is adjusted to overlap start and end point of image histogram to the GATE scale as shown in the figure 4.4.

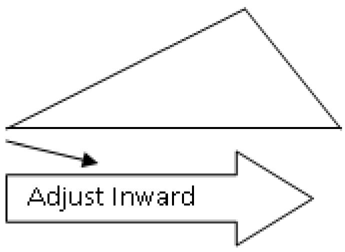


Figure 4.4: Adjusting least grey level for new Minima

Next the image histogram is shifted inwards to form new maxima for the GATEd histogram as shown in figure 4.5.

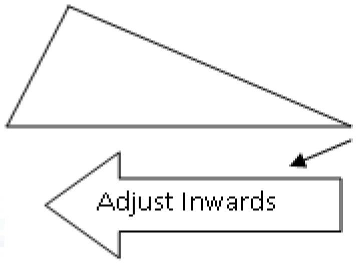


Figure 4.5: Adjusting the max grey level for new Maxima

COBRA funnels input image through GATE to be transformed as initial parameter for the next phase. The characteristics of these initial parameters are as follows:

(i) Image has reduced scale

(ii) Histogram is almost quasi symmetrical around mid-point.

(iii) Min and max grey level of original histogram form min and max of new grey level range.

(iv) Contours of original histogram are retained – preserving image brightness and details.

4.7.2 Image Division into Regions

The study now establishes the division point between bright and dark regions of the image. These separated regions are enhanced by decreasing the grey level ranges of darker regions and increasing the grey levels of brighter regions. Division point is established by visual examination. Two images are generated programmatically, which comprise of gradually increasing grey levels; one vertically and one horizontally. For finding out brighter and darker regions these images are shown in Figure 4.6.

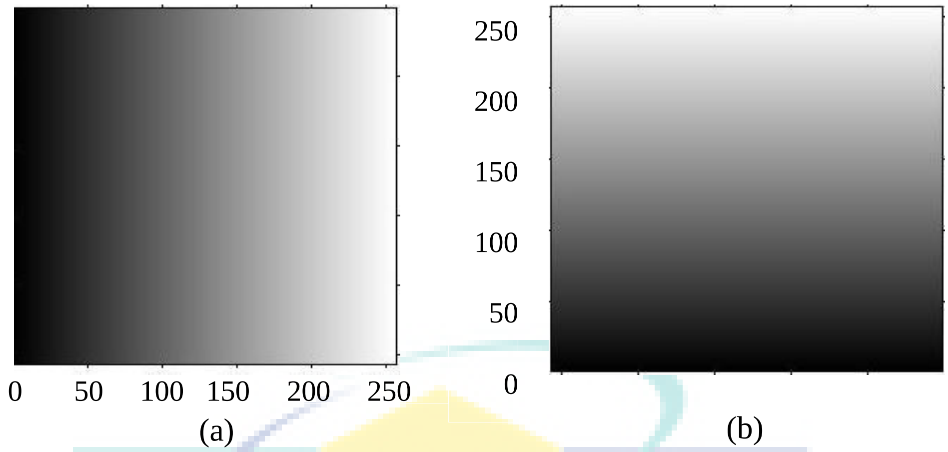


Figure 4.6: Presentation of horizontal (a) and vertical (b) grey level

These images, show that 0-70 is almost complete dark range which is commonly used for dark region, whereas, 70-120 is the transformation range, 120-200 forms usual bright area and from 200-250 grey level is excessive brightness which may eat up details. Therefore, to cater for contrast deficiencies a method needs to be developed which decreases the grey levels of dark region (0 -120) and enhances the grey levels above 120 for bright region. Enhancement should gradually taper off starting from grey level 200-250. Hence the study for the purpose of proposed method will keep cross over point from dark to bright region at grey level 120. In the light of above divisions, symbolically, a typical image histogram is presented in figure 4.7.

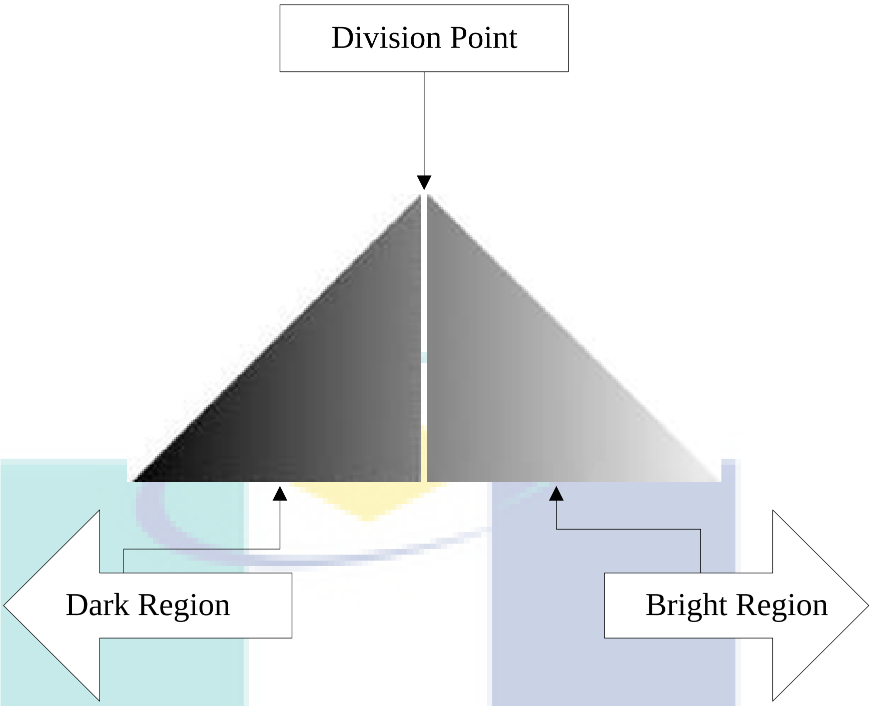


Figure 4.7: Darker and brighter regions separated at the division point

As an output from this step the image is divided into two parts. Importantly, this step may also be applied to a part of the image to achieve more localized effect. For this application, relevant histogram range is specified – this range is considered the input image and the whole process is carried forward.

4.7.3 Brighter Regions Adaption for Contrast Enhancement (BRACE)

Brighter region is suitably adapted by increasing the grey levels to meet maximum required values. This is done by brighter region adaptation for contrast enhancement (BRACE). This method is presented diagrammatically in figure 4.8.

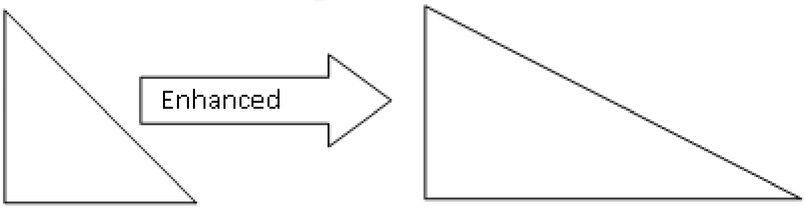


Figure 4.8: BRACE enhances contrast of bright region by increase in grey levels

In this step BRACE is handed over the bright region (from partitioning point to 255) for enhancement. BRACE used input from GATE which provides it the image bright region at a reduced scale. Image is then exponentially raised to enhance contrast. This exponential rise by BRACE enhances grey levels for bright region (of shrunk image supplied by GATE) and also expands the grey levels back to normal image scale. This process, if unchecked, will increase beyond 255 at some input value. Therefore the process starts tapering off a few grey levels short of 255 to avoid exceeding the ceiling.

4.7.4 Darker Regions Adaption for Contrast Enhancement (DRACE)

Usually all histogram methods increase grey levels for contrast enhancement, throughout the complete range of grey levels In contrast to that trend, in our proposed method darker region is further darkened to adapt to the required contrast This is achieved by decreasing the grey levels for this region. The process is called Dark Region Adaptation for Contrast Enhancement (DRACE). It is presented diagrammatically in figure 4.9.

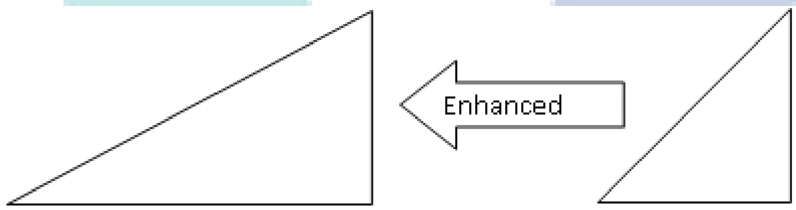


Figure 4.9: DRACE decreased the grey level range to enhance contrast

Our study uses exponential power to reduce the grey levels for the darker range. The study tunes exponential power for reducing grey levels by DRACE in a way that GATEd - scaled down - image returns back to normal range of grey levels by this step.

4.8 PSEUDO CODE FOR THE PROPOSED ALGORITHM

Pseudo code for the proposed method is as follows:

1. If the input image is noisy
   Apply noise filter
   else move to next step.
2. Set minPoint is equal to minimum value of image histogram
   Set maxPoint is equal to maximum value of image histogram
   Set the reduced scale to be used for shrunk (GATE) image.
   Calculate histogram spread of the image by subtracting minPoint from maxPoint.
   Calculate ratio of reduction by dividing GATE scale with histogram spread

   Compute new grey level for reduced scale by multiplying each grey level with ratio calculated above.
3. Now process enhancement of the image.

   If the original image grey level is below the ceiling limit
   enhance grey levels by raising them exponentially.
   else Tapper off the grey levels smoothly to the ceiling limit of the image.
4. Store the output image in repository.

4.9 PROPOSED WORKFLOW

All the conceived parts integrate together to form the proposed method. An end to end functioning of this integration is given in the flow diagram shown in figure 4.10.

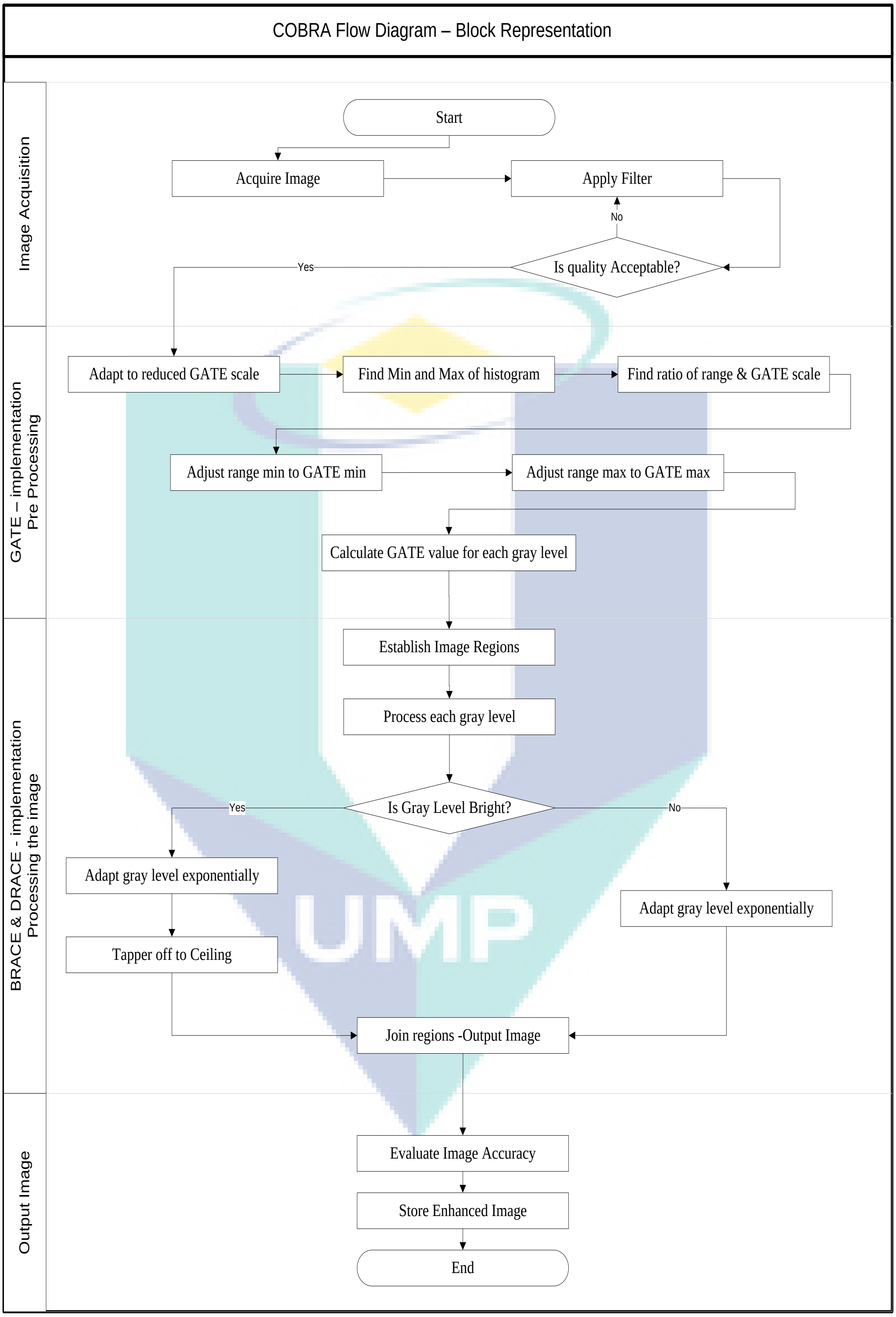


Figure 4.10: Flow diagram connecting different stages of proposed method

4.10 MATHEMATICAL FORMULATION OF THE IDEA

Conceived ideas are always formulated mathematically to be implemented. Mathematical formulation for different parts of the proposed method is given in subsequent text.

4.10.1 Pre-Processing GATE

This step is implemented by establishing ratio between reduced scale N used for GATE and original image histogram spread S then mathematical expression for the ratio R is given by:

$$R = N / S \tag{4.1}$$

This ratio is used to find out new grey level G for each original grey level O

$$G = R * O \tag{4.2}$$

Next, it was observed that in reality histogram of the image rarely started from 0. Therefore zero adjustment is made by taking first existing grey level as the starting point. Hence, for minimum scale reading M mathematical expression was modified as:

$$G = R * (O - M) \tag{4.3}$$

Next the new GATE has the flexibility of starting from a chosen point instead of 0. Hence for a Minimum point in GATE scale K mathematical expression is modified as follows:

$$G = R * (O - M) + K \tag{4.4}$$

This adaptation accounted of details, spread and gaps in the histogram of the original image. Hence the process retained image data and histogram contours which, in turn, preserved image features and brightness.

It is important to note that all medical images have large black background. Once HE was applied to such images, it resulted in significant washouts as is explained in chapter 2 in literature review. This made the percentage of background very relevant to our study. In contrast, our proposed method is completely free from the relevance of the percentage of the black background. The proposed method divides the image in brighter and darker regions. This is done on grey level value, subsequent processing is on the pixel values. Number of pixels in black area i.e. percentage of black background plays no role. Hence the problem of washouts in HE which was caused by large black background is not an issue any more.

4.10.2 Processing DRACE and BRACE

In an attempt to develop mathematical expression for encapsulating the conceived idea all mathematical functions were studied which include addition, multiplication and exponential increment. These functions are presented graphically in figure 4.11.

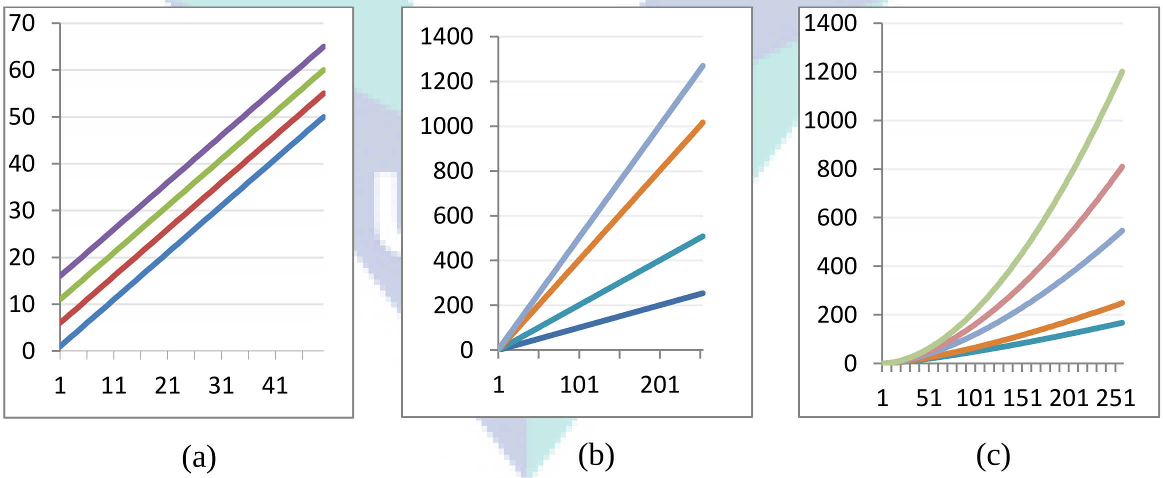


Figure 4.11: Trend in various mathematical functions

Figure 4.11(a) shows addition – in which 5 is added to successive graph lines. The whole graph line shifts up by the amount of addition. Next figure 4.11(b) presents multiplication; with each increasing multiple the maximum point of the line shifts up while the minimum point keeps hinged at zero rotating the line in an arc. Third figure 4.11(c) presents exponential increase which shows that output values initially dip followed by an increase. With using higher power settings the dip for the output values shifts right and the magnitude of subsequent rise increases further.

Analyzing these figures it reveals that figure 4.11(b) suits GATE to reduce scale but it has to be applied in reverse order – hence it will be applied in the form of division. Exponential rise in figure 4.11(c) matches the pattern of processing stage (DRACE & BRACE). Applying exponential increment will decrease initial output values and increase output values. This applied to our grey level range will move dark ranges to darker areas and bright range to brighter areas. In essence, it will move the grey levels outwards. Therefore in figure 4.11(c) the dip will correspond to separation point of regions, graph left of dip will present dark area and right of dip will be bright area. To synchronize this graph with enhancement pattern of actual image, appropriate exponent has to be selected – one for DRACE and one for BRACE. However, study revealed that a well calculated, fine-tuned, single power setting could be used for both.

To practically develop a mathematical expression first, regions are to be established in actual image. As discussed in Para 4.7.2 a separation range, in general, exist at 120 to 130 grey levels. Next we overlapped many curves of 4.11(a) and 4.11(c). This overlapping was on the pattern as shown in figure 4.12. It was found that curve in 4.11(c) using power exponent 1.4 suits our pattern – initially reducing values and reversing at the separation point and increasing the values. However the scale of the curve line was much larger than required which necessitated scaling down the original values. These original values were scaled down by the following formula: $(p / r)^{1.4} = o$, in the formula p represents input pixel value, r represents reduction factor and o represents output value. As the crossover point is 120 to 130, let us take average of 125 where this expression provides an output value that equals the supplied pixel value. Therefore at this point the equation should be equal from where we can find out the reduction scale r. Mathematical expression is given by $(p / r)^{1.4} = o$. Now to calculate the values at the crossover point let us replace p and o by 125. The expression becomes $(125/r)^{1.4} = 125$. Now the expression is simplified $(r)^{1.4} = (125)^{1.4}/125$, after this simplification the value of r is established $r = 3.9 \approx 4$. This comes out to be about

4. Therefore a power exponent of 1.4 has to be employed in conjunction with initially reducing the image by a scale of 4.

Next consideration is the ceiling of the grey levels. During calculation the output value should not overshoot the ceiling of 256 (the maximum grey level). With a reduction scale of 4 various powers were tried. Use of 1.4 power and reduction scale of 4 provides most suitable combination. This has been deduced from calculated data which is attached as appendices from A1 through A7. From these 7 appendices data for partitioning point and ceiling for various power exponents is extracted. For ease of consultation partitioning point figure is turned green and ceiling point is turned red. Extracted data is presented in table 4.1 for easy understanding.

Table 4.1: Partitioning point and ceiling

S.NO	**Power Exponent**	**Partitioning Point**	**Ceiling**
1	1.3	Does not cross over	
2	1.35	210	243
3	1.4	126	210
4	1.5	64	161
5	1.6	39	128
6	1.7	29	104
7	1.8	22	87

Analyzing the data we find out that for power 1.3 at serial number 1, output values remain below the input value, so this is not a usable case. For power exponent of 1.35, we notice that ceiling is 243 which is close to 256 (desirable) but the partitioning point is at 210. This is a very high figure as the image is split around grey level range of 120-130. Therefore this is not a usable combination. For serial number 4 -7, power exponent from 1.5 – 1.8 partitioning point is very low. This would even surrender some black area to bright area for processing. Therefore this is also not usable. For serial number 3 using power exponents 1.4 partitioning is ideally places at 126 and the ceiling is placed at 210. This means when input value is 210, output value will reach 256. This could however be delayed by suitable tapering. Then, this combination at serial number 3 will mathematically satisfy the requirement of the proposed algorithm.

Employing this mathematical derivation, implementation of initial and final stage of COBRA is represented graphically in figure 4.12.

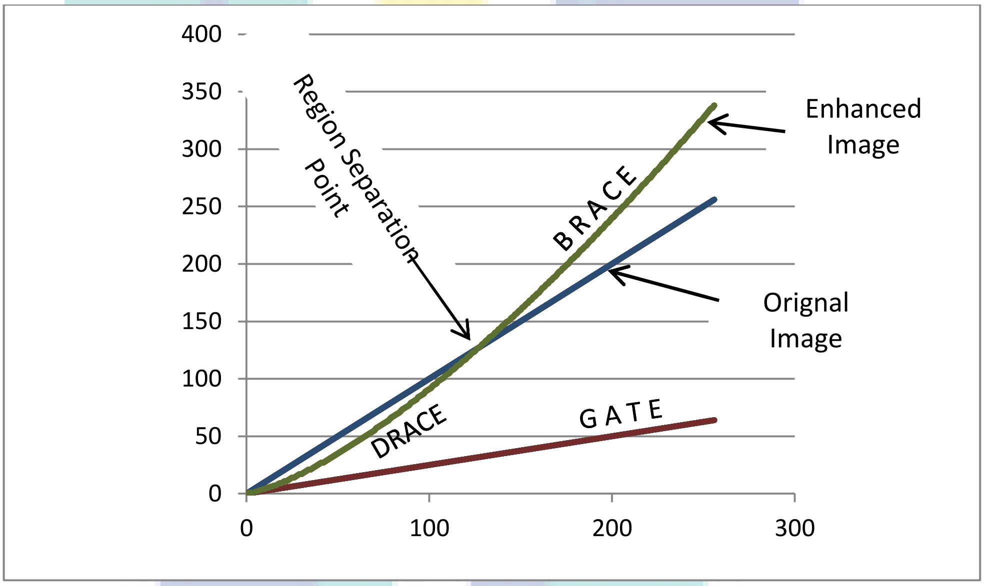


Figure 4.12: Graphical presentation of COBRA stages

This figure shows that the original image graph which is marked as 'original image' forms a straight line. During (pre-processing) first stage of the proposed method GATE employs division to drop the image to 25% of original size. This image graph is marked as GATE in figure 4.12. Final processing uses an exponent which is tuned from1.4. This single power meets the requirements for both DRACE and BRACE. Application of this power is presented by green line in figure 4.12. This green line is marked DRACE in the initial portion which shows a dip for decreasing grey level of dark region. The same line reverses to show an increase of grey levels when BRACE takes its affect. Reversal point is represents the separation point of regions and is marked in the figure. Therefore the figure shows how mathematical implementation of the proposed method dims the grey levels of dark area 0-130, and increase the Grey levels from 130-200, significantly, in turn, producing high level of contrast while preserving details. In the last part of grey level range 200-255 the proposed method controls over contrast by gradually shaving off the increment in grey levels. Hence it avoids losing image details due to over enhancement.

To select the most suitable reduced scale (for GATE) and subsequent power setting (for DRACE and BRACE), a lot of experimentation was carried out. Resulting curves of many power exponents were analyzed and critically assessed. A power curve whose shape matched our needs was chosen. With the original image as input, this output curve, though of desired shape, was placed much above the original image curve. To get it overlapping the original image curve initial input values were reduced. These reduced values then became the GATE scale. A lot of values were experimented to ensure that DRACE crosses over the original image line at grey level 130. This brought out suitable exponent value for DRACE. Next to find out BRACE exponent, different exponent values were experimented. For various values the ending figures of grey levels over shot the maximum of 256. Therefore - for BRACE - ceiling was additional consideration. Power exponent had to be only sufficient to curtail the ending figures with in the maximum value of 256 as far as possible. To achieve this retention, it needed final tapering but minimum tapering was desirable. In a nutshell, considering the required curvatures of graph to meet contrast deficiency, it scaling down to overlap it with the original image line (GATE scale), cross over for separation point at 130 (DRACE) and enhancing bright area, while keeping grey levels within the ceiling limits of 256 (BRACE) - a figure of 25 percent (1:4 scale) for reduction and a power exponent of 1.4 for both dark and bright regions met all the needs for the categories of images described in the data set.

4.11 ASSUMPTIONS FOR BASING ALGORITHM

The study, next, will present algorithm for the proposed method. Before presenting the algorithm it is important to know the assumptions which form the bases of this algorithm. These assumptions are a listing of relevant knowledge which is gained till this point. This listing helps readers to be on the same grid to understand the algorithm. These assumptions are listed below.

(i) Data set used in developing and testing the algorithm is covered earlier in paragraph 4.2. Primarily the algorithm focuses on Brain MRIs but is also aims to have valid and acceptable results for other medical and common bench mark images.

(ii) For our algorithm, the whole image is taken as one piece and the method is applied globally.

(iii) During GATE image is shrunk down to 25% of normal grey level scale, when it is being pre-processed as initial parameter.

(iv) Separation point of dark and bright region is established as 120-130 grey level for the images in data set.

(v) Exponent used for enhancement of both DRACE and BRACE is 1.4.

(vi) Re-joining the image after enhancement is automatic as only one exponent is used for both DRACE and BRACE.

4.12 ALGORITHM OF THE PROPOSED METHOD

Following are the steps to implement algorithm of the proposed method:

(i) *Step I*: A suitable brain MRI is taken from an available repository.

(ii) *Step II:* Eliminate noise by an effective and suitable filter like winner

(iii) *Step III:* Apply **GATE**

- Set new image scale (for our study 1:4)
- Select new grey level range for the new scale (0 -64).
- Find input image minimum and maximum and establish histogram spread.
- Establish ratio of histogram spread with new range.

- Remap each existing grey level to the new range.
- Adjust histogram min/max to new range min/max.

(iv) *Step IV*: Use appropriate power exponent (in our case 1.4) on the GATEd image to ensure it separated into two regions.

(v) *Step V:* From GATEd initial parameter, enhance image darker **(DRACE)** and brighter region **(BRACE)**: Dimming the darker area and elevating the brighter region.

Case I: DRACE: Use power exponent on each grey level of GATEd dark region (0-30) to decrease the grey level for enhancement and also bring back the output value within normal range of grey levels (0-120)

Case II:

- BRACE: Use power exponent on each grey level in GATEd bright region (30-64) to enhance its contrast by increasing grey levels. Additionally, the output value of grey levels will be back in normal range (120-256) for bright regions.

- Taper off at the last part of the range to limit the values of grey levels, so they do not exceed maximum ceiling of 256.

(vi) *Step VI:* Power exponent will produce a combined output image constituting both brighter and darker regions.

(vii) *Step VII:* Evaluate accuracy of output image by employing DICE and Jaccard similarity measuring method to establish the similarity measure between output and input image.

(viii) *Step VIII:* Store enhanced image to be used later for interpretation or use, both, by viewers and by automated systems.

4.13 SUMMARY

In view of the, deteriorations surfacing in medical images due to drawbacks in HE when HE is used as underlying contrast enhancement method - the study proposed a novel method –contrast optimization by region adaptation (COBRA) – as a solution. This new method is based on factors directly related to contrast. In this method, image histogram is analyzed in detail - grey level ranges are divided into dark and bright regions - and contrast deficiency is rectified by processing both the dark and bright regions to bring them to ideal contrast. Hence a practically reliable method is presented which can be trusted for critical area of medical field.

Implementation of the proposed method is achieved in two steps. First Input image is preprocessed to be transformed into initial parameters. This process is termed as Global Adaptation for Tentative Equalization (GATE). The process maps the image histogram uniformly on a pre-determined reduced scale used by GATE. This tentatively equalizes histogram on reduced scale. The process converts the image to parameters which are used as input by the final, processing, stage. Better accuracy in achieving initial parameters, guarantees proportionately better output image.

Next stage is final enhancement which takes initial parameters from first stage and shifts grey levels ranges for contrasting regions outwards. This implementation dims the dark regions –DRACE- and elevates grey levels of bright regions - BRACE. This stage uses exponential power to raise the grey levels from GATE scale to normal range. This rise, automatically, adjusts enhancement of the image because this process increase grey levels at higher range and dims grey levels at the darker end. Hence, selection of proper exponent is critical to achieve that matches requirements of COBRA.

Furthermore, these contrasting ranges crossover at partitioning point which in important to note because during processing, grey level shift traverses from one direction to the other at this point. Hence a small region on both sides of this boundary might have compromised contrast.

It is of great significance that the histogram contours of the original image are almost retained during the pre-processing stage and subsequently during enhancement. This is a great edge in the design of this method due to which it preserves the details of the image and also output image has natural tone as it maintains resemblance with the original image despite enhancement in contrast.

CHAPTER 5

RESULTS AND DISCUSSION

5.1 INTRODUCTION

This chapter covers the results in details which are accrued using data sets as discussed in the previous chapter which are specialty image like brain MRI, general medical images and common images. First, using all three types of data sets, processing of images is covered in noisy and noise free environment by applying both HE and proposed method. Secondly, comparison is drawn between all three images; original, HE and proposed images. Further is the same part, image histograms are analyzed in detail. Third, these processed images are tested for similarity with the original image using DICE and Jaccard similarity measuring method. Next, based on comparative analyses, the chapter draws the conclusion that the proposed method performs excellent on MRIs, has convincingly good results on general and medical & common images. Finally the chapter covers those areas where the method is not so effective; the method does not enhance a small image region which lies around the boundary of dark and bright region. Additionally, the image contrast is also not enhanced well close to minimum and maximum as there is no room for shifting grey levels to achieve more contrast.

5.2 SELECTION OF METHODS FOR COMPARISON

Our proposed method focuses at enhancing contrast of the image. However, in the problem background, in the employment of HE, the change in image data was presented with striking evidence. This shift of data appeared as washouts in the histogram of output image. As discussed the chapter three in the foundation of histogram – large black background - as is the case in medical images – will have more pronounced washouts. Therefore in our research an important, connected aspect, is preservation of image data. To establish success of this preservation a suitable testing method is needed. Although, contrast measurement is a conventional comparison technique in processed images, it may be out of context to use contrast measurement in our case. It is because our study aims at resolution of histogram washouts and contrast is merely a measure of difference in luminosity of contrasting areas which is given by the following three formulas. First formula is given by $\frac{I - I_{\rm b}}{I_{\rm b}}$, which is proposed by Weber, I is the brightness of the feature and $I_{\rm b}$ is brightness of background. Michelson proposed the contrast to be expressed by $\frac{I_{\rm max} - I_{\rm min}}{I_{\rm max} + I_{\rm min}}$, in this formula $I_{\rm max}$ is maximum brightness and $I_{\rm min}$ is minimum brightness. A third formula Root Mean Square Contrast is given by $\sqrt{\frac{1}{MN}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}(I_{ij} - \bar{I})^2},$ which calculates standard deviation of the pixels. In the formula I_{ij} are element of the two dimensional image of size M by N and $\bar{I}$ is average intensity of the image. These contrast formulas would mathematically calculate intensities of the processed image but the result has little relevance to loss or shift is grey scale data. Another method used for image comparison is structured similarity index matrix method (SSIM). This method is an improvement over PSNR and MSE method. SSIM considers pixels as inter dependent when they are spatially close. For calculations the method used variance and average for pixels in same neighborhood. The method is complex and it does not serve our purpose of measuring simple similarity in a straightforward way. Further another method used conventionally for image quality measurement is discrete entropy (DE). This method is also not directly related to our study. After considering all the above methods the study chooses DICE and Jaccard method for measuring image similarity for its straightforward approach. It is because these methods are relevant to our focus of research.

In section 2 it was established that HE shifts image data from the original place (washouts) and places it at a different place where it did not exist before(false echoes).

As our proposed method has claims of improving these two aspects, a comparative analysis needs to be done between our proposed method and HE. Therefore measurement of these two aspects is necessary. For measuring similarity DICE and Jaccard for its simple mathematics is most suited for our study. Additionally for measuring false echoes and missing details, false positive and false negative test are suitable. Therefore the study will use DICE, Jaccard, false-negative and false-positive for ratifying performance of the proposed method.

5.3 RESULTS USING PROPOSED METHOD

An image given in figure 5.1 presenting normal brain is downloaded from Brain Atlas. This image like all MRIs has dark background and represents object and areas of interest with different grey levels.

Figure 5.1: A sample image from brain atlas

The image histogram is represented by Figure 5.2.

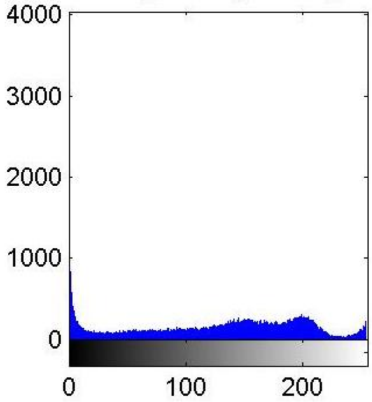
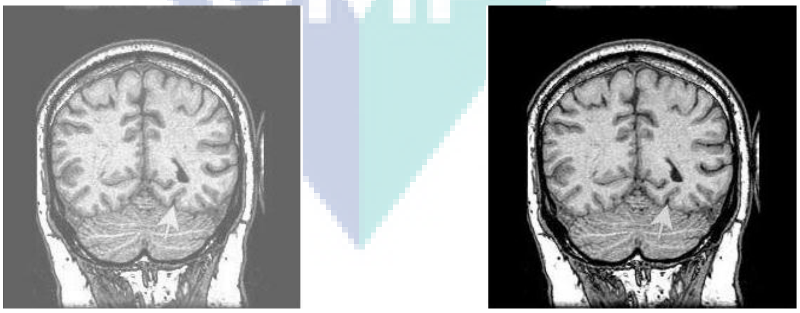


Figure 5.2: Histogram of the sample image

This histogram shows a uniform distribution of grey levels in the image which means that image has almost all 256 grey levels. This histogram also represents high frequency close to zero relating to significant black region of the image, further histogram shows a frequency of about 4 to 500 all along with gradual increasing trend which shows a uniform spread till about grey level of 220, from then on a decrease is evident and then an increase at about 235 to 255 grey levels indicating some very bright areas in the image. To improve the accuracy interpretation of the image the image contrast is desired to be enhanced. HE is the main stay method for image enhancement as is mentioned earlier in this study. HE is applied and results are compared to the original image. These results are shown in figure 5.3.



(a) (b)

Figure 5.3: HE (a) makes image hazy compared to original image (b)

These results are shown on the left and the original image is placed on the right for visual comparison. HE processed image shows loss of sharpness in the image. Dark region has become lighter and the brightness in the area of interest has reduced which constitutes an overall deterioration in image contrast. These changes in the image are a result of the way HE is designed. As HE does not directly deal with contrast, it rather deals with image density. Probability density is calculated as the first step which divides density of each grey level by total number of pixels. Next cumulative density is calculated which adds density of each grey level with all previous grey levels and then divides it with total number of pixels in the image. This necessarily establishes a ratio ranging from 0 at the first grey level and increasing to 1 at the last grey level. Values nearing zero are rounded off to zero. For an image of the kind under study where grey levels are uniformly distributed while multiplying cumulative density probability (CDP). With the grey level range, the lower part of the range is washed out. That is the fact represented in histogram when HE is applied to image in Figure 5.4.

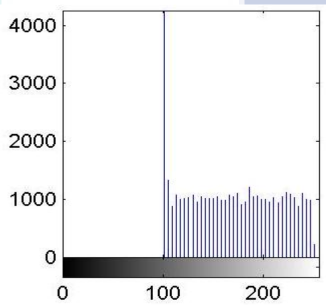
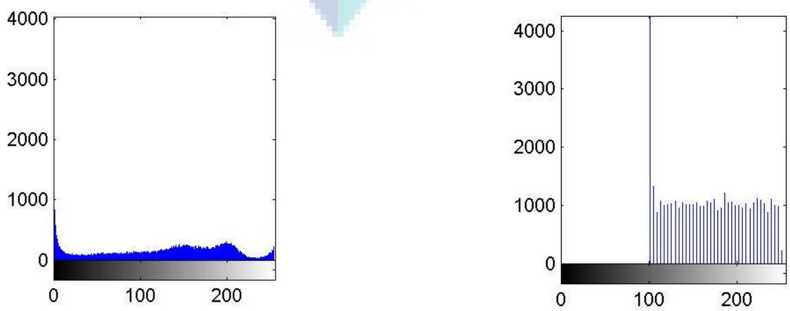


Figure 5.4: HE method loses initial image data

That is why the image contrast is deteriorated and brightness is lost resulting in image becoming mild. The histogram given above is a clear representation of the logical explanation of the limits of HE method. This will become more evident once both the histograms are compared with each other which is done in figure 5.5.

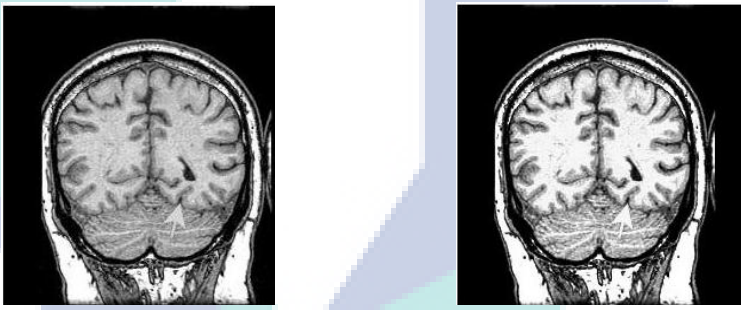


(a) (b)

Figure 5.5: HE (b) and original histogram (a) has no resemblance

Looking at the histogram it becomes clear that HE does not follow the pattern of the original image histogram; it by no means is even close to the pattern of the original image histogram. Moreover, the initial grey levels ranging from 0 to 100 are missing due to which the darkness of the image is lost. This obscure image details and makes image smoggy.

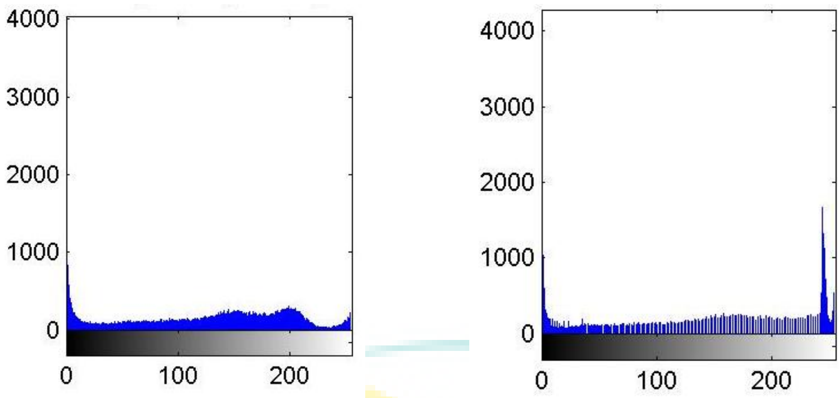
Next proposed method -which directly deals with contrast -is applied to the image. The image in first stage was brought to initial parameters from which contrast could be raised predictably. Then this method is applied to enhance the contrast of the image. Enhanced image using proposed method along with original image is shown in figure 5.6 below



(a) (b)

Figure 5.6: Proposed method (b) offers marked enhancement over original image (a)

Comparing enhanced image with the original image it is evident that contrast has improved and the features have become sharper, while the image maintained brightness. Considering the histogram of the processed image by the proposed method the comparison with the histogram of the original image reveals that the proposed method has the same pattern of histogram which indicated that it preserves all image details. The proposed histogram is spread on the whole range of grey levels reflecting a uniformly bright image as is shown in figure 5.7.



(a) (b)

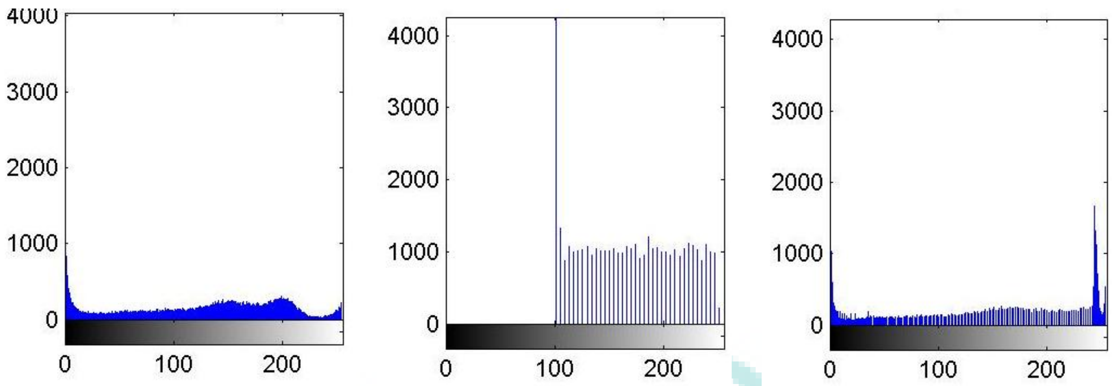
Figure 5.7: Matching contours of proposed method (b) with original image (a) indicate retention of image features

Due to the two factors discussed above, contrast of the image is well enhanced over the original image. To have a good idea of how well the proposed method stand in comparison to HE. Let us place all the images together for comparison as in figure 5.8.

(a) (b) (c)

Figure 5.8: Proposed method (c) displays a marked edge over HE (a) and original image (b)

On the left is HE and on the right is proposed method with Original Image in the middle. It is clearly evident that the proposed method is significant improvement over original image and proposed method compared to HE has remarkable edge both in contrast and brightness. Comparing the histogram of all three together is given in the figure 5.9.



(a) (b) (c)

Figure 5.9: Proposed histogram(c) has resemblance with original (a) but HE(b) changes image data which may be crucial

It is clear that the histogram of HE does not have any relevance to original image histogram. Grey level range of HE is also not connected to original image range. Whereas, histogram of proposed method maintains a resembling pattern of peaks and valleys, moreover, grey levels range of proposed and original image is similar.

As an outcome of the analyses, the suitability of proposed method compared to HE techniques may be established. For this purpose HE enhanced image and proposed method enhanced image is placed below in figure 5.10.

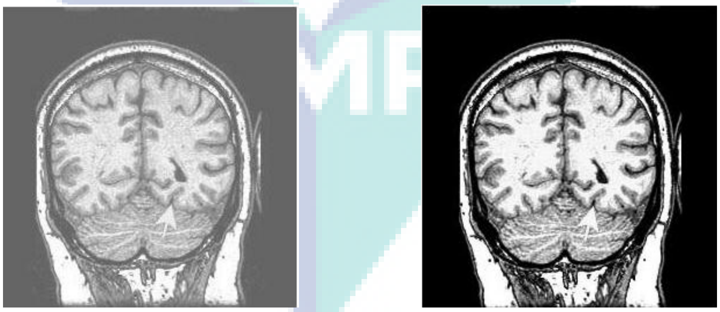
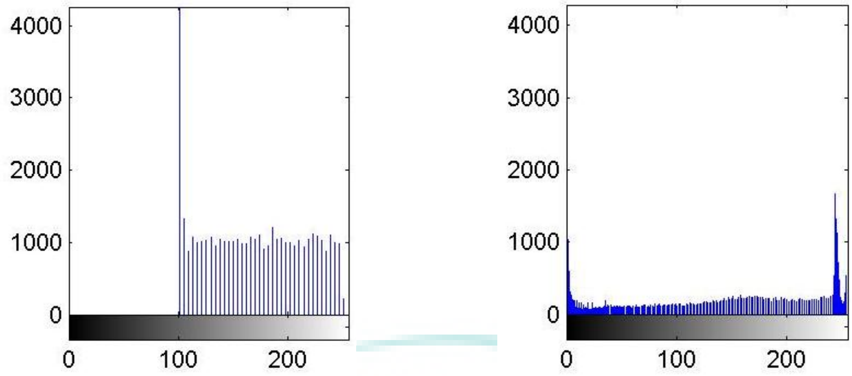


Figure 5.10: Proposed method (b) outperforms HE (a)

These characteristics need to be confirmed by histogram analyses as well. Histogram of both these images is give in Figure 5.11



(a) (b)

Figure 5.11: Proposed method (b) has good stretch of grey levels - HE(a) loses initial grey levels

These histogram show that proposed method has an adaptive nature of histogram, which adapts to the pattern of original image histogram and the range of the histogram is from 0 to 255 grey levels. Whereas first 100 grey levels of HE are completely missing and in the later part of the range the bins have gaps and HE histogram pattern is unrelated to original image. These facts make proposed method much more feasible for image enhancement.

After visual inspection let us have a look at the statistics of some tests which we run to compare both the methods with the original image. Dice and Jacquard test is for proposed and HE method comparing the processed image with the original one is given in Figure 5.12

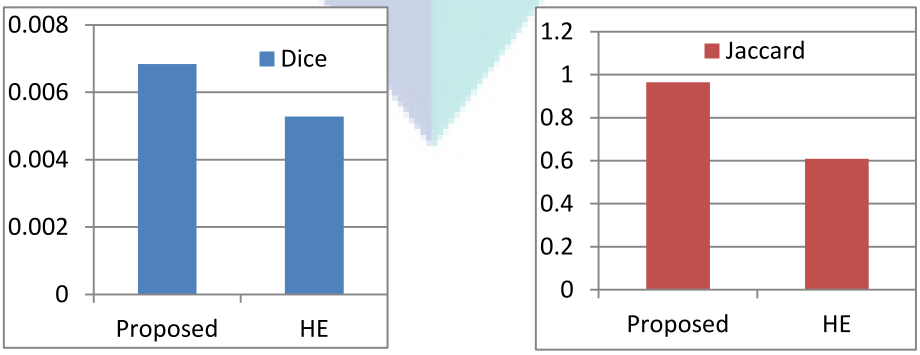


Figure 5.12: Jaccard and DICE depict better performance of proposed method

Both the test confirms much better similarity of image processed by proposed method compared to the HE one. Same fact was indicated, initially, by visual analyses and histogram pattern. The overall analyses of the proposed results in comparison with HE is summarized in the table 5.1

Table 5.1: Comparison of proposed method and HE results

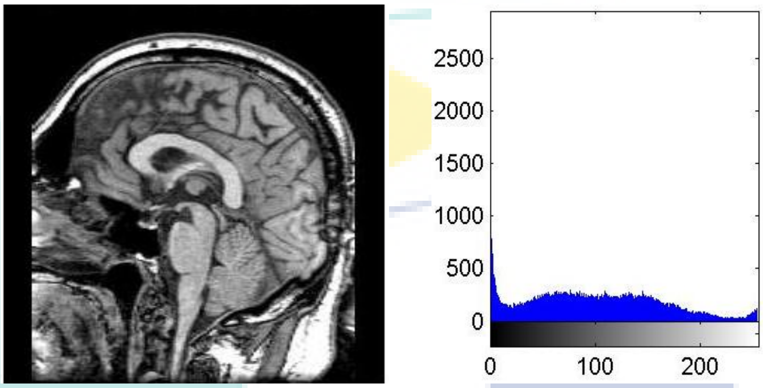
	Proposed	**HE**
Brightness	Brightness improvement over original Image is better than HE	Loses brightness of the original image.
Contrast	Contrast improvement over original Image is better than HE	Contrast over original image is deteriorated.
Histogram Pattern	Similar to original image	Not relevant to original image.
Histogram Stretching	Maintains complete range till grey level 255.	Shrinks to last grey levels from about 100 – 255.
Jacquard Test	Better than HE	HE is inferior
Dice Test	Better than HE	HE is inferior

.

Now that the results of the proposed method are established for one image, it is important to run a number of images to validate the reliability of results. The volume of images will be taken from dataset explained in the previous chapter, which is in three categories. Image volume of all three categories will be processed for validating the proposed method.

5.4 RESULTS OF BRAIN MRI

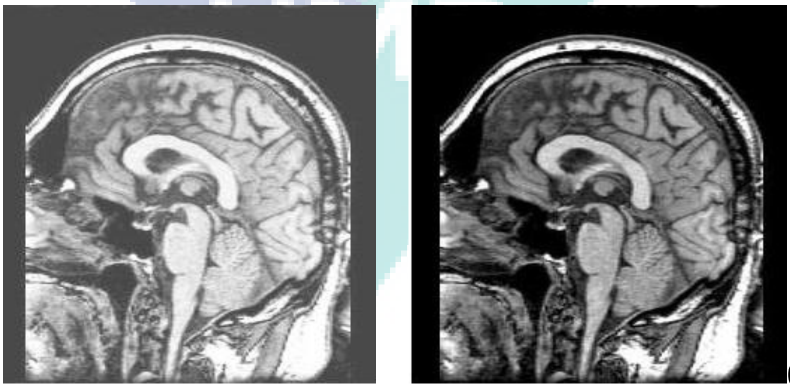
A new image 069.JPG is downloaded from brain atlas and processed with HE and proposed method and the results are compared for analyses. Original image and the histogram of the histogram in given in figure 5.13



(a) (b)

Figure 5.13: An original image (a) from brain atlas and its histogram (b)

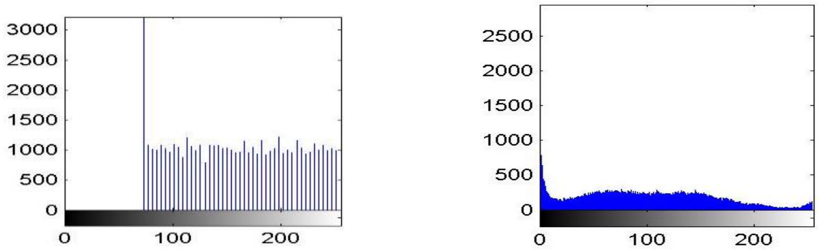
Histogram equalization is applied to original image and the resultant image is compared with original image in figure 5.14.



(a) (b)

Figure 5.14: HE (a) loses Image sharpness compared to original image (b)

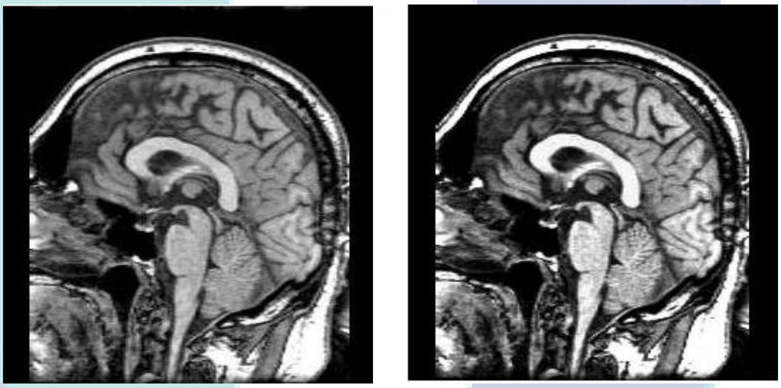
Histogram of the original image is compared with the histogram of the HE applied image in figure 5.15.



(a) (b)

Figure 5.15: HE (a) drops initial grey levels compared to original histogram (b)

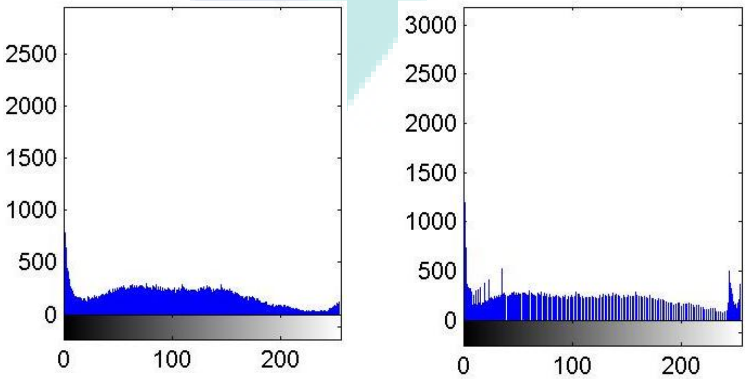
Now the proposed method is applied to enhance image contrast. Resultant image is compared with the original image in figure 5.16



(a) (b)

Figure 5.16: Natural enhancement by proposed method (b) over original image (a)

This reflects clearly that contrast is enhanced significantly. Further histogram of the proposed image is compared to the original image in figure 5.17



(a) (b)

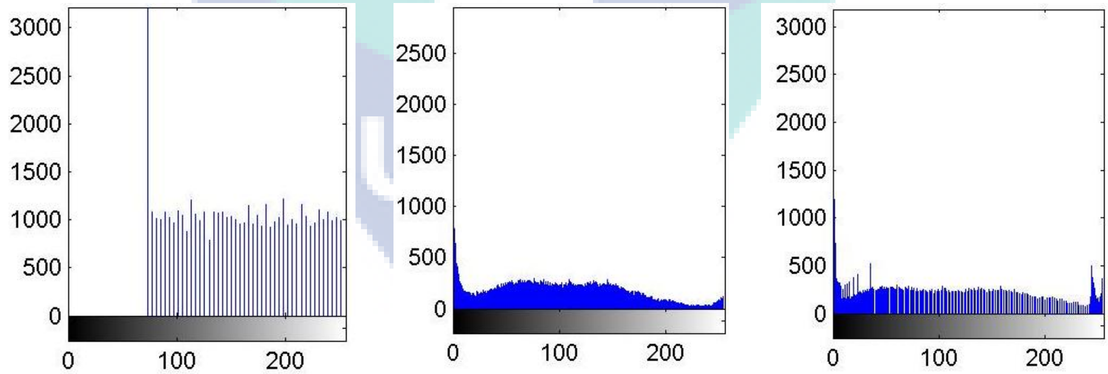
Figure 5.17: Contour resemblance in original (a) and proposed (b) histograms

A comparison of all three images; original, HE and proposed method is given in figure 5.18.

(a) (b) (c)

Figure 5.18: Sharp contrast is achieved by proposed method (c) compared to HE (a)

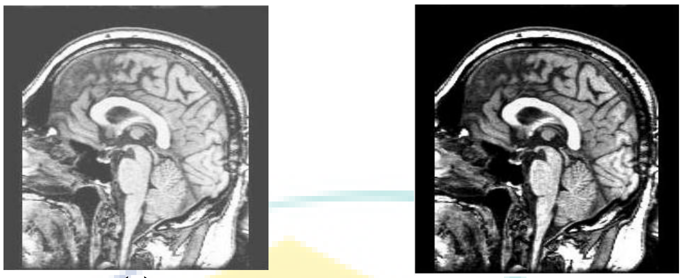
This comparison of all three clearly brings out an edge of the proposed method over the HE method while enhancing contrast and retaining details and brightness of the image. In addition to image quality, histogram needs to be examined for details which are given in figure 5.19.



(a) (b) (c)

Figure 5.19: HE (a) has washouts whereas the proposed method (c) retains even the histogram contours compared to original image (b)

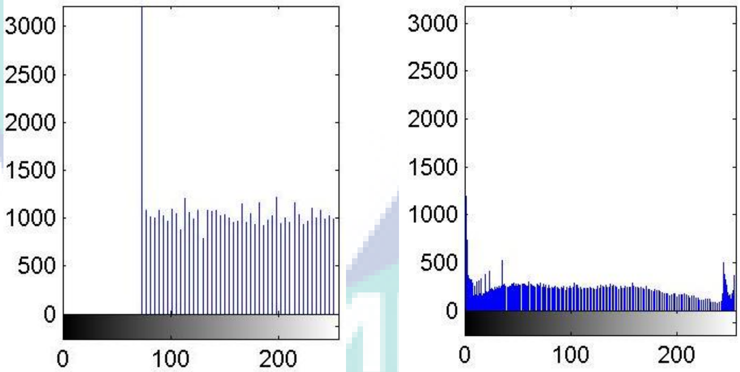
Contrast, brightness and the details preservation is clearly visible in histograms of all three in figure 5.19. This brings us to comparison of HE and the proposed method which reveals a clear margin in contrast and brightness over HE method as is depicted in figure 5.20.



(a) (b)

Figure 5.20: Proposed method (b) presents better contrast compared to HE(a)

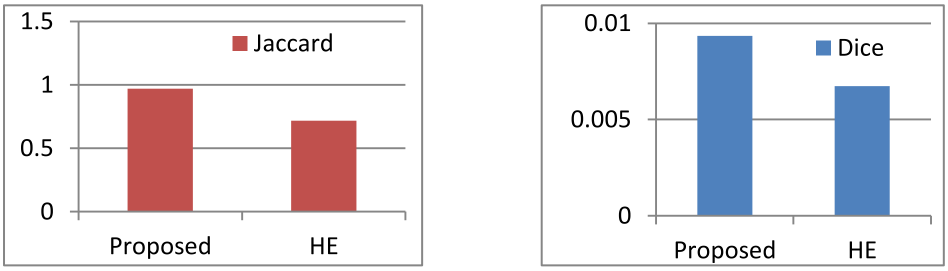
Histogram of both these images is clear in presenting the proposed method's preservation of details and brightness while enhancing contrast as shown in figure 5.21.



(a) (b)

Figure 5.21: Missing data in HE (a) and good stretch in proposed (b) present good performance of proposed method

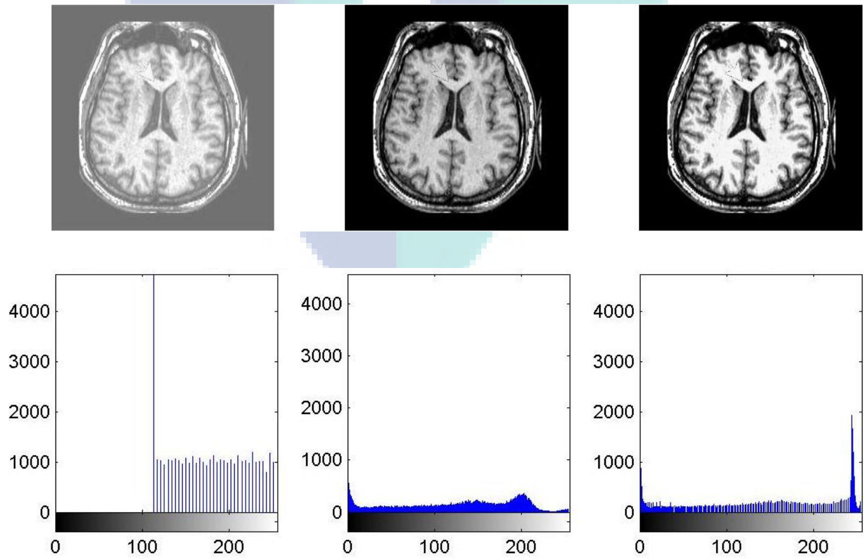
Jaccard and DICE test which measure similarity of both HE and proposed method with original image is given in figure 5.22 below.



(a) (b)

Figure 5.22: Proposed method has better rating in both DICE (b) and Jaccard (a)

After having established the results of proposed method, these results need to be validated by running a volume of images. The study applied proposed method on significant volume of data from the data set which has been discussed earlier. Some of the images are presented here as test cases to consolidate the validation of the proposed method. For this validation both HE and proposed method were used – processed images and their histogram were compared and results complied. To establish similarity, Jaccard and DICE similarity measuring methods were used. This effort established the trend of the results. Ten such cases of processed images along with their histogram are given in subsequent test. First Image - 082.JPG from normal brain image is given in figure 5.23.



(a) (b) (c)

Figure 5.23: Comparison of HE (a) original image (b) and proposed method (c)-first image

These resultant images confirm same trend in results as explained in earlier. Second image (cerebrovascular disease) is processed and results are given in figure 5.24.

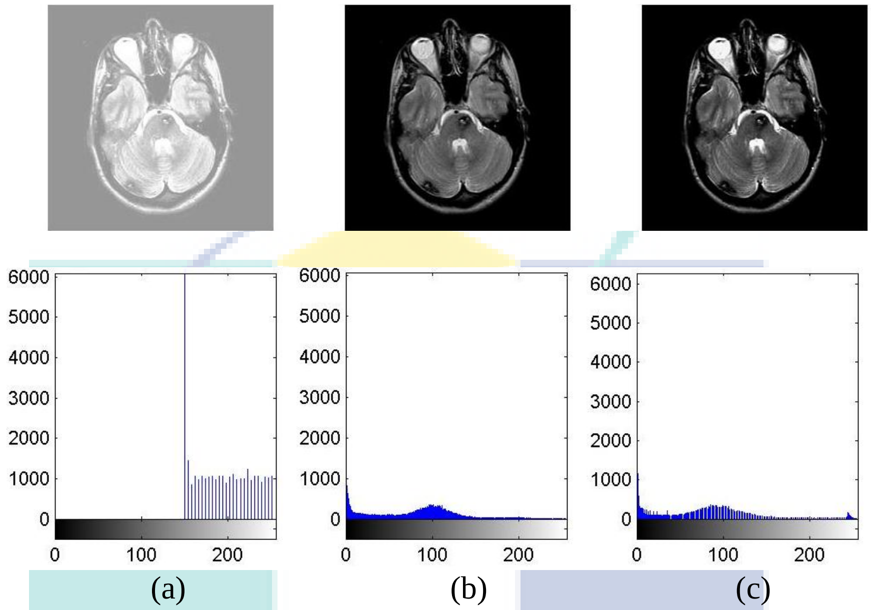
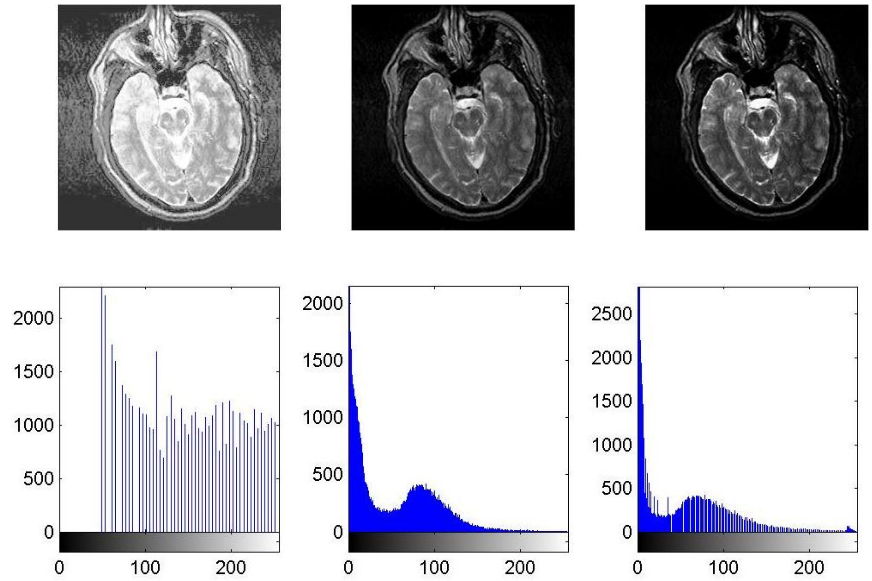


Figure 5.24: Comparison of HE(a) original image (b)and proposed method (c) -second image

The images show identical results in histogram and image visual outlook. Details and histogram patron is retained by proposed method. Brightness and contrast is improved. Next image with cerebrovascular disease (009.jpg) is shown in figure 5.25.

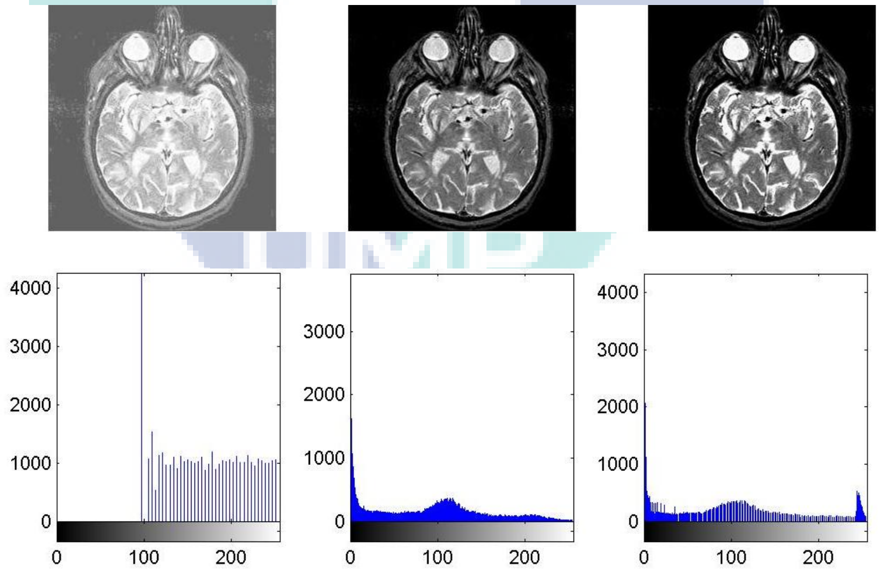
UMP



(a) (b) (c)

Figure 5.25: Comparison of HE(a) original image (b)and proposed method (c) - third image

Results of fourth image after processing are shown in figure 5.26.



(a) (b) (c)

Figure 5.26: Comparison of HE (a) original image (b) and proposed method (c) -fourth image

In the same sequence, fifth image displaying degenerative disease (010.jpg) is used for comparison after enhancement employing HE and proposed method and the results are shown in figure 5.27.

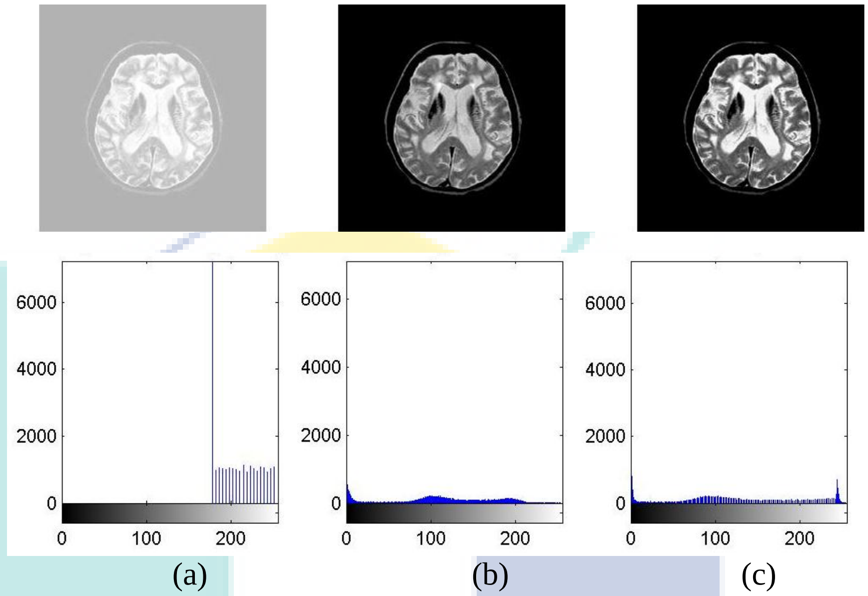


Figure 5.27: Comparison of HE (a) original image (b) and proposed method (c) -fifth image

Next in the line of testing is the sixth image describing degenerative disease (020A.jpg) which is displayed in figure 5.28.

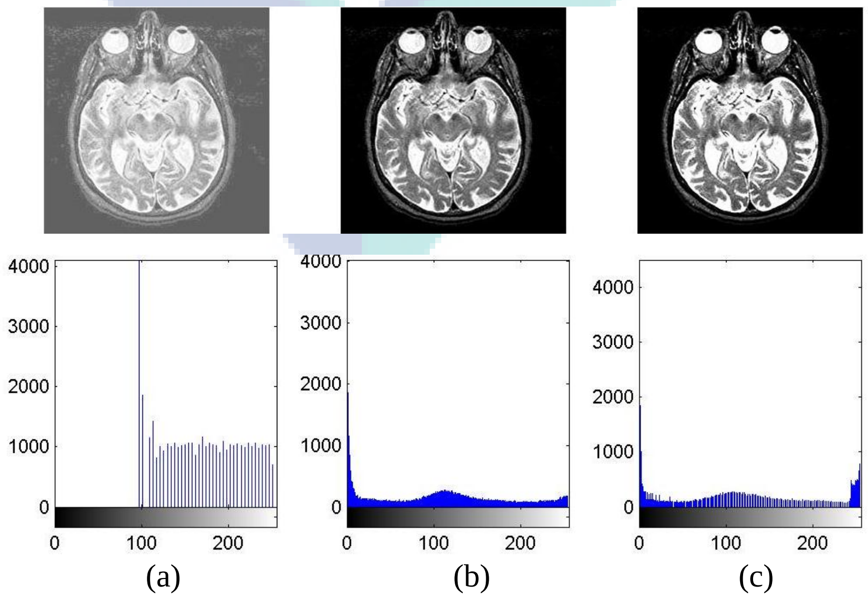
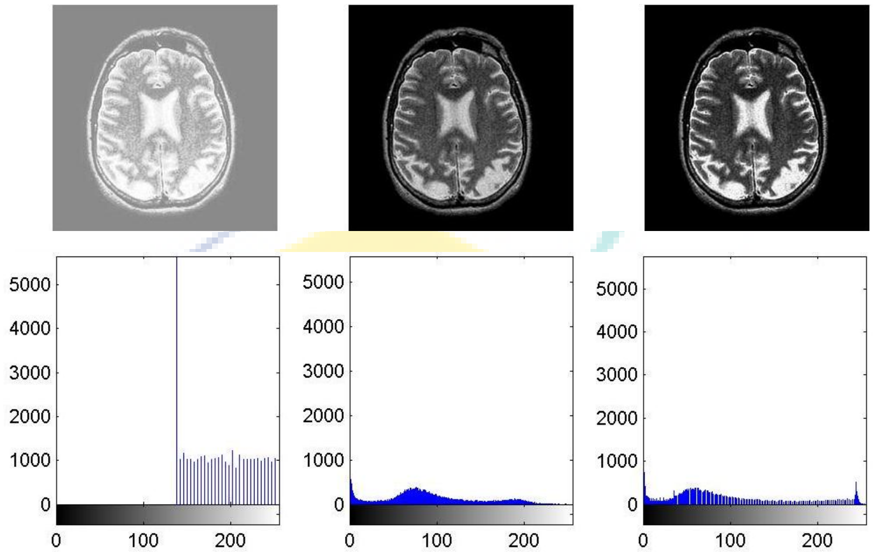


Figure 5.28: Comparison of HE (a) original image (b) and proposed method (c) -sixth image

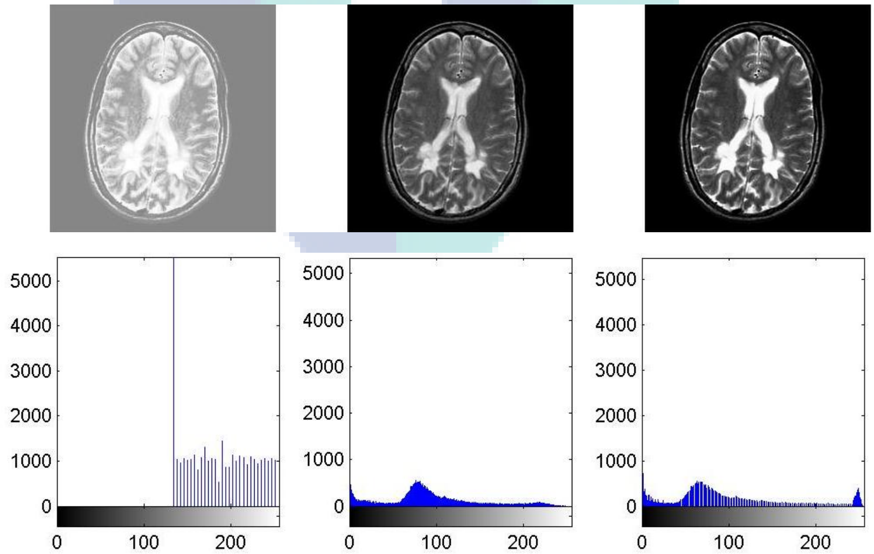
Next for testing is an image from brain MRI, degenerative disease (010.jpg). This is enhanced using both HE and proposed method and then compared mutually and with the original image. The results are shown in figure 5.29.



(a) (b) (c)

Figure 5.29: Comparison of HE (a) original image (b) and proposed method (c) -seventh image

Introducing a new ailment inflammatory disease, eight image (013.jpg) is enhanced using the same methods and the outcome is presented in figure 5.30.



(a) (b) (c)

Figure 5.30: Comparison of HE (a) original image (b) and proposed method (c) - eighth image

Ninth image (013.jpg) showing inflammatory disease is processed using the same techniques: HE and proposed method. Results are presented in figure 5.31.

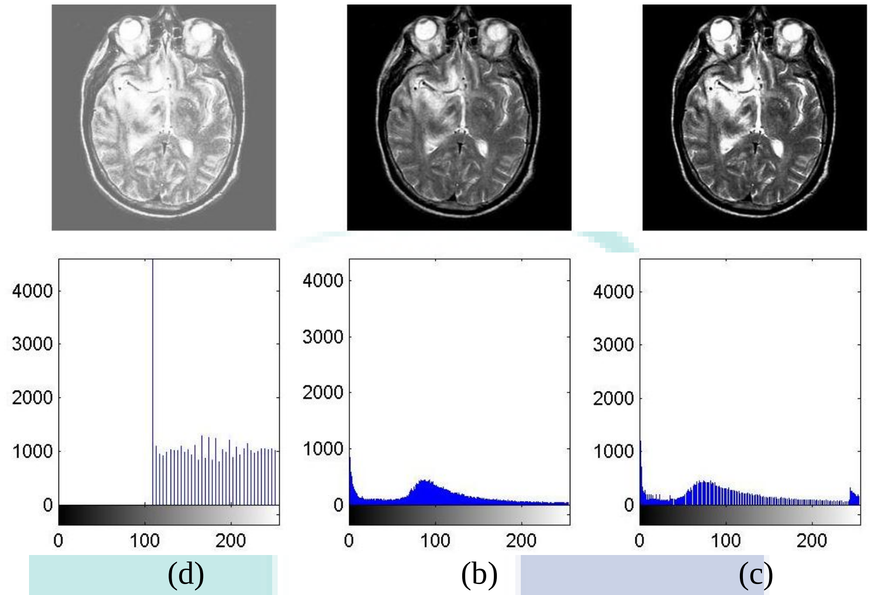


Figure 5.31: Comparison of HE (a) original image (b) and proposed method (c) -ninth image

Finally the tenth image (016.jpg) in this category represents neo-plastic disease. Results of this image after applying enhancement methods are shown in figure 5.32.

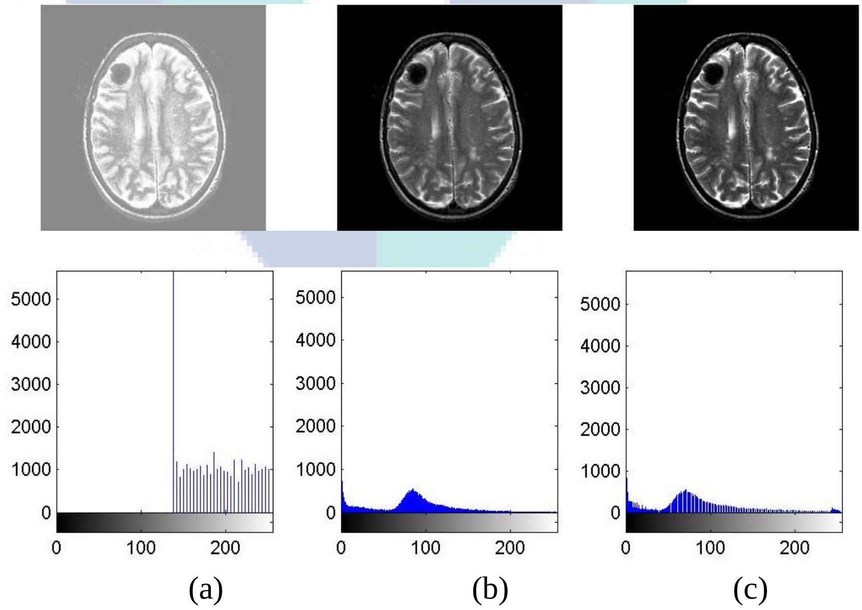


Figure 5.32: Comparison of HE (a) original image (b) and proposed method (c) -tenth image

5.4.1 Comparison of the above Images and Histograms

In the previous paragraph ten images are processed by HE and proposed method, Visual comparison is tabulated in table 5.2.

Table 5.2: Comparison results of brain MRIs

	Proposed	**HE**
Brightness	Brightness improvement over original Image is better than HE	Loses brightness of the original image.
Contrast	Contrast improvement over original Image is better than HE	Contrast over original image is deteriorated.
Histogram Pattern	Similar to original image	Not relevant to original image.
Histogram Stretching	Maintains complete range till grey level 255.	Shrinks to last grey levels from about 100 – 255.
Jacquard Test	Outperforms HE	HE is behind
Dice Test	Outperforms HE	HE is behind

Comparison of the histogram of above ten images shows that the histogram in case of HE does not maintain any relation to the contours of original image. Gaps in histogram of output image and the missing grey levels are an outcome of purely dealing with CPD and PD with no reference to input image contrast. Therefore, contour pattern of output image and input image is unrelated. Whereas, the proposed method shows only a minor departure from the original histogram contours, gaps between the grey levels are much less and that too the gaps have much less width. Hence the details of the original image are maintained during the enhancement processing. This is why a similarity trend exists between histogram of original and proposed method histogram whereas, histogram of HE unrelated.

5.4.2 Comparative Trend of HE and Proposed Method

In the preceding paragraph ten images, all brain MRIs were processed by HE and proposed method and a comparison was drawn between them. Let us now, establish a similarity trend, based on mutual comparison of these results, between enhanced images and the original image. For establishing these trends Jaccard and DICE similarity measuring methods were used. First DICE method is applied on both HE and proposed method. For the purpose of these tests 15 images were used from brain MRIs including 10 processed in the study earlier. The graphs presenting trends is shown in figure 5.33

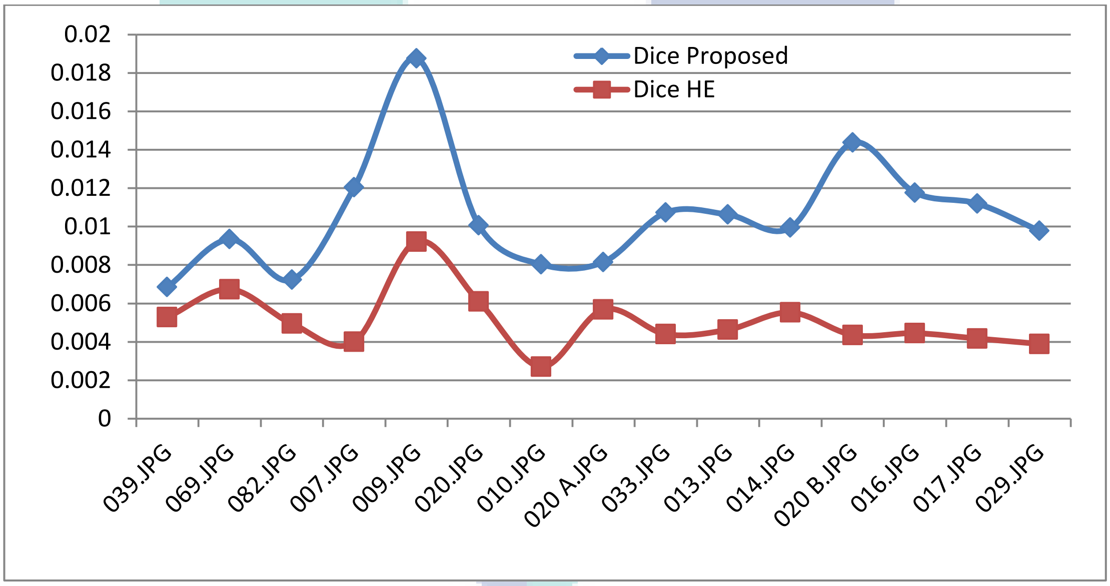


Figure 5.33: DICE test for medical images from first category

DICE test shows that all the images tested maintain a higher trend of similarity for proposed method compared to HE. Next Jaccard test is carried out on same set of images and output trend is represented graphically in figure 5.34.

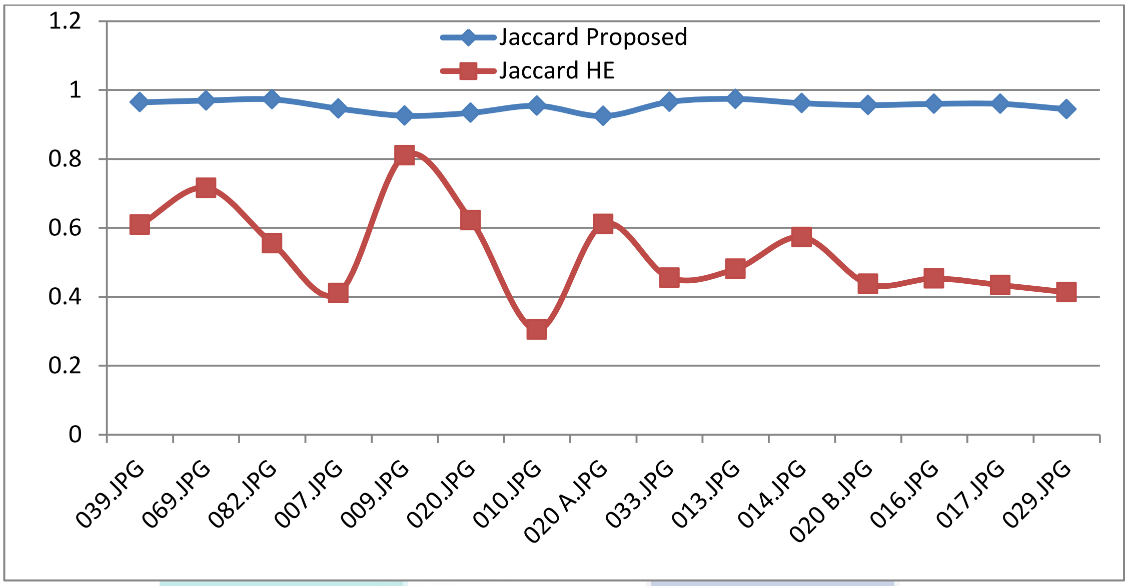


Figure 5.34: Jaccard test for medical images of first category

In both DICE and Jaccard tests proposed method outperforms HE which is based on the fact that proposed method maintians the histogram contours of the orignal image thereby preserving image details. Moreover, gaps in grey levels introduced in the output image are much less in number and much shorter in width indicating good preservance of orignal image details. These two factors preserve image details during enhancement and outperform HE. Missing grey levels and resembling contours give rise to false negitive and positive which for the first category of images is figure 5.35.

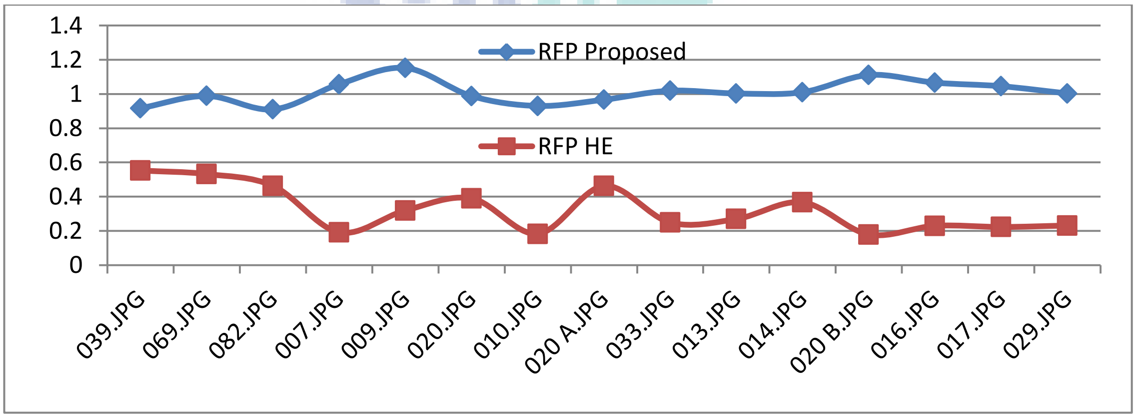


Figure 5.35: False positive test displays higher trend of proposed method for medical images of first category

Now first category medical images are tested for false negative and the results are presented by the graphs in figure 5.36

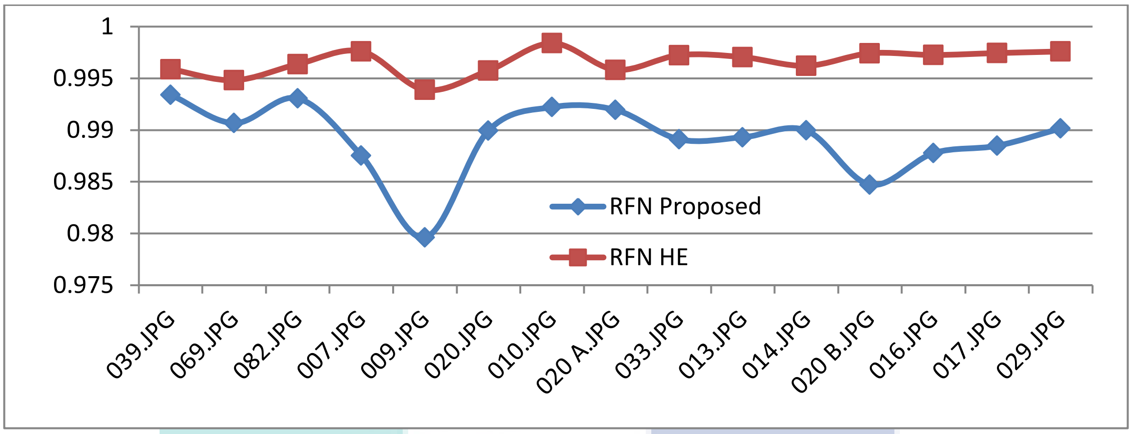


Figure 5.36: False negative test reveals better trend of proposed method for medical images of first category

This trend of high false positive by proposed method in figure 5.35 and high flase negitive by HE in figure 5.36 is an indication reflected by various hitograms (figure 5.23 – figure 5.32) of original, HE and proposed method images. These histograms show, proposed method tends to covers the complete grey level range, definitely, including all grey levels of the orignal image but additionaly extending it to ranges not covered originally which leads to false positve. Moreover, these histograms show washouts by HE – so existing grey levels are missed out – making this nagitive but a false one. Hence a higher false positive for proposed method and a higher false negitive for HE stands to understandable logic.

5.5 RESULTS FOR GENERAL MEDICAL IMAGES.

This is the second category of images as explained in data set in the first chapter. For this category, in addition to natural images, synthetic images are chosen to test the proposed method. Moreover, some of the images are taken with noise to test the success of the method with noisy images. The study validates the proposed method by processing 10 images, of this category. Results of these images are given in subsequent text. Resultant images could be visual examined and histograms are presented for comparative analysis. First image is shown in figure 5.37.

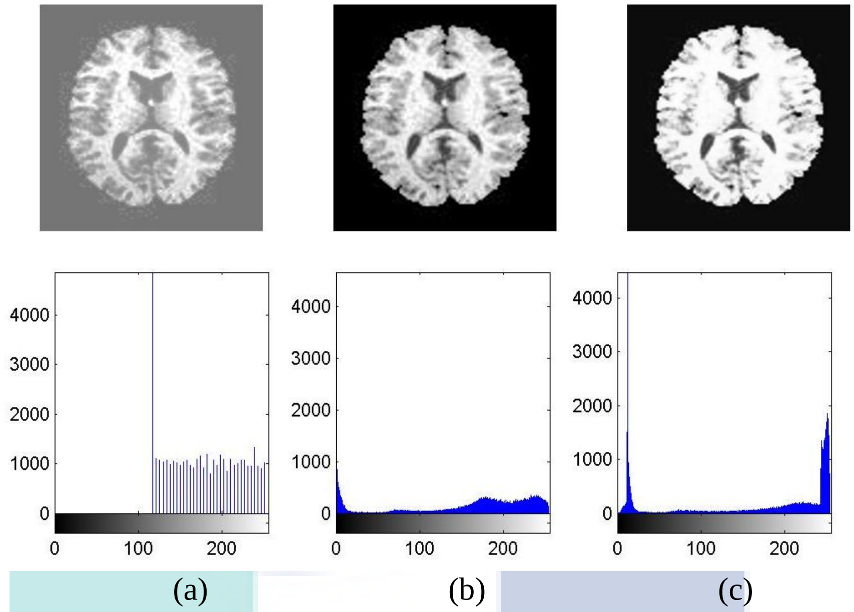


Figure 5.37: Comparison of HE (a) original image (b) and proposed method (c) -synthetic noise introduced category– image 1

In the same category – general medical images next image is processed and presented in figure 5.38.

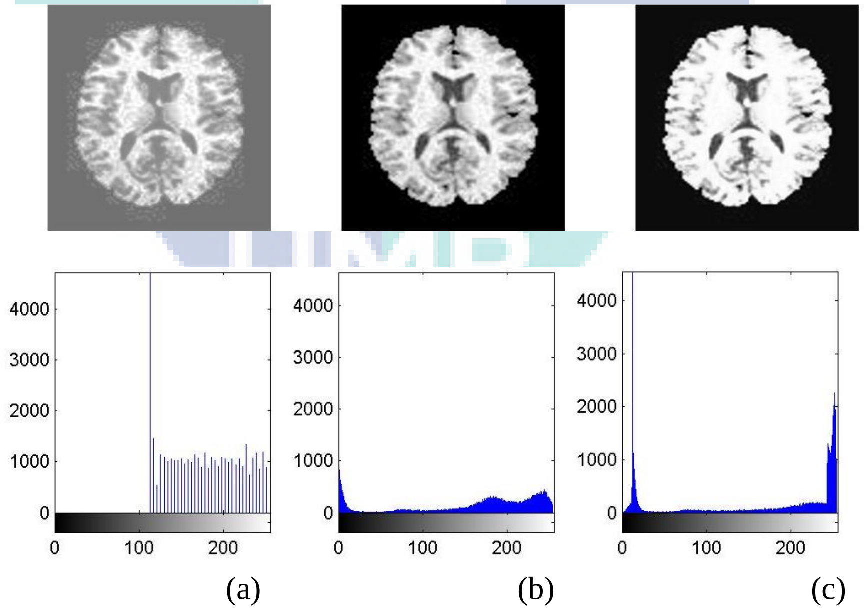
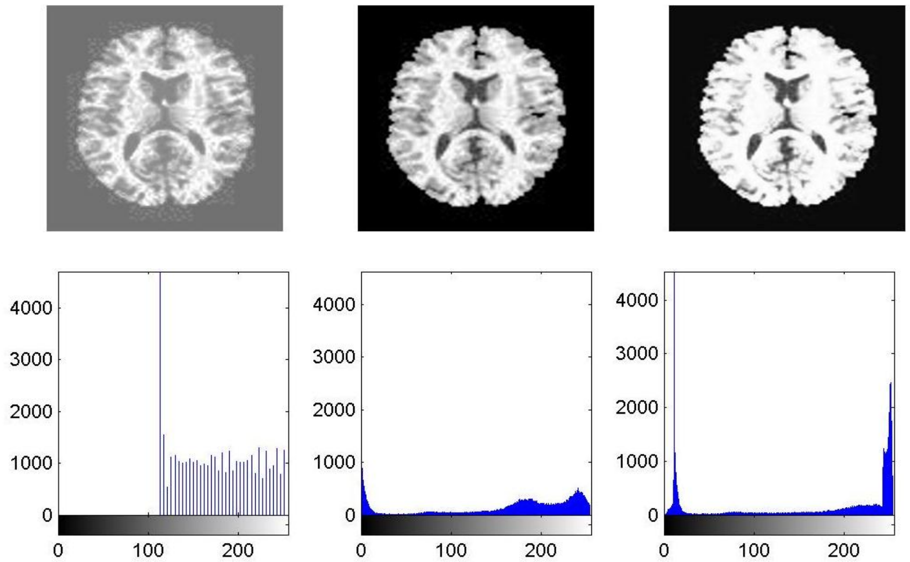


Figure 5.38: Comparison of HE (a) original image (b) and proposed method (c) -synthetic noise introduced category– image 2

In the sequence, processing of the third image is consistent with existing trend of the results which is clear in figure 5.39.



(a) (b) (c)

Figure 5.39: Comparison of HE (a) original image (b) and proposed method (c) -synthetic noise introduced category– image 3

The above three test show that visual quality of the images is improved and histogram shows that HE has washouts in the initial grey levels whereas proposed enhances the contrast while retaining histogram contours similar to the original histogram. After the above three test , 15 more images of similar kind were tested. The results of all the 18 images are then run through DICE similarity measuring method and the graph of the results is presented, for analysis, in figure 5.40.

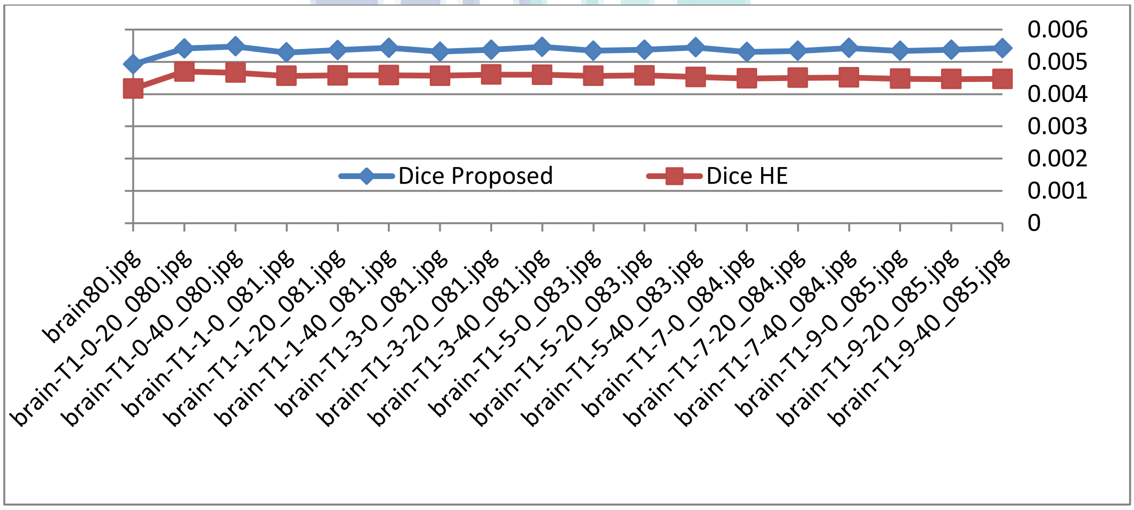


Figure 5.40: Dice Comparison HE & Proposed Method for synthetic images with noise and non-uniformity

In these 18 images non uniformity ranges from 0 - 40 percent whereas noise ranges from 0 – 9 percent. Despite the noise and non-uniformity, proposed method works as designed to enhance contrast. Therefore proposed method, though not a noise eliminating but performs equally well without getting distracted by noise. Additionally, the proposed perform equally well on natural and synthetic images.

Although the method is developed for brain MRI and other medical images, it was tested to find out its effectiveness for common bench mark images. Like the previous analyses – for comparative analyses between HE and proposed method - these images after processing were tested through DICE, Jaccard, false negative and false positive methods. DICE test is given in figure 5.52 below.

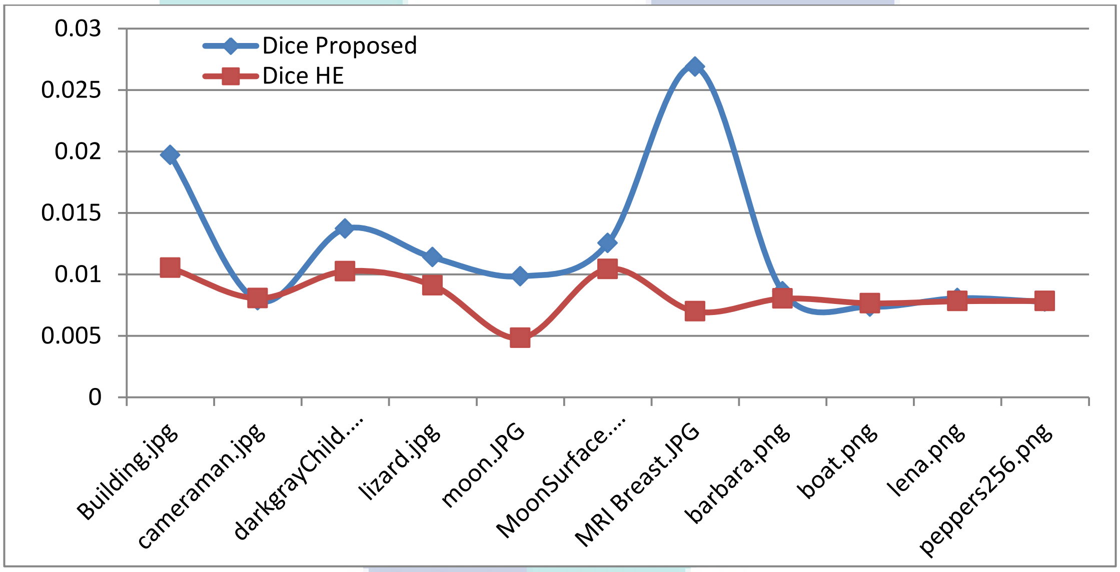


Figure 5.41: DICE test for common images shows better trend of proposed method**.**

Results of Jaccard test are given below in figure 5.53.

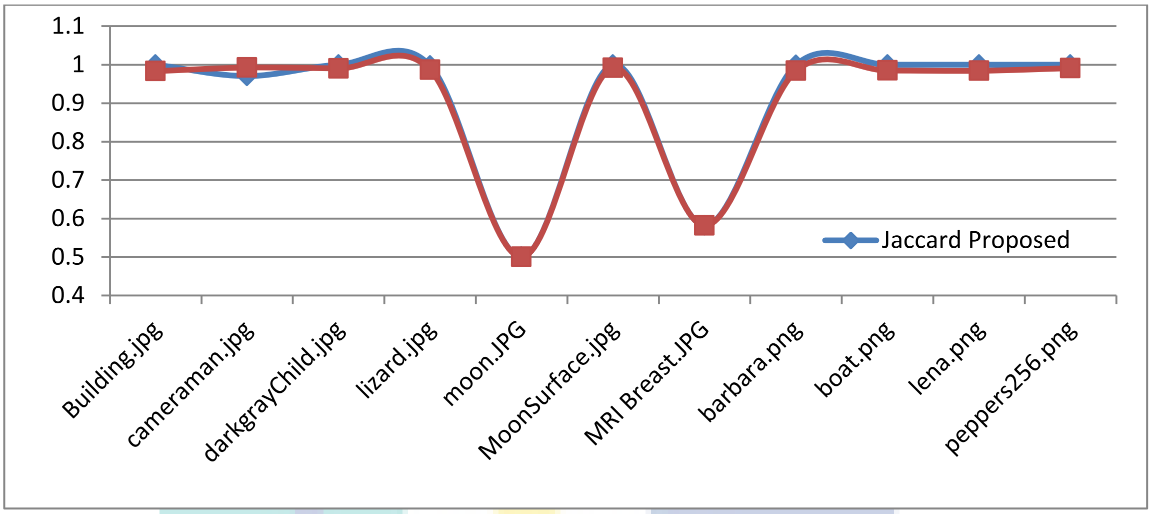


Figure 5.42: Jaccard test shows identical results of HE and proposed method

For the proposed method similarity measure is way better in DICE and is marginally better in Jaccard graph. This is clearly indicated in histogram which shown similarity of contours between proposed method and original image and does not show any relevance between HE and original image. On the same lines, the study now tests for false echoes - results of false echoes are presented in next two figures. False positive is presented in figure 5.54.

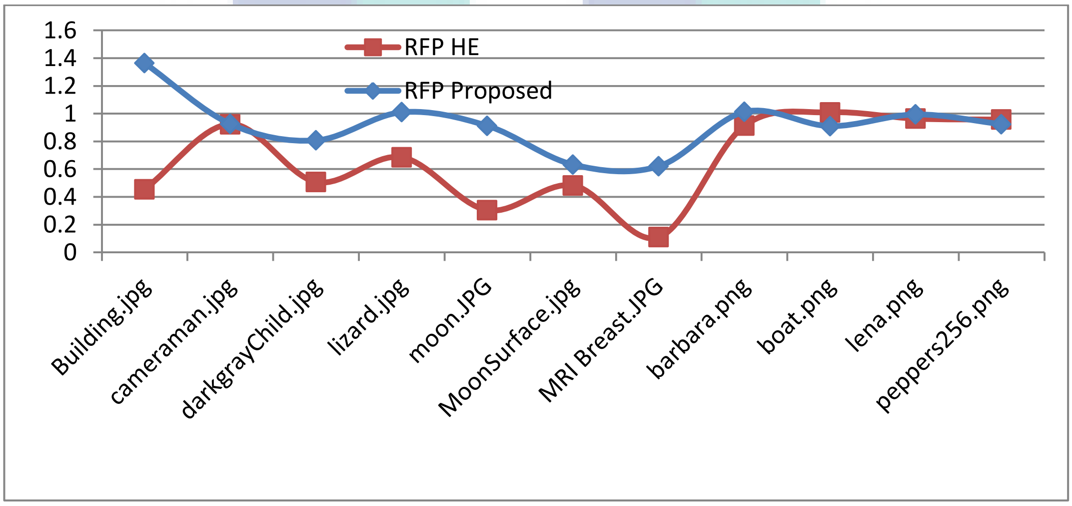


Figure 5.43: Proposed method has higher false positives

Next, results of false negative are given below in figure 5.55.

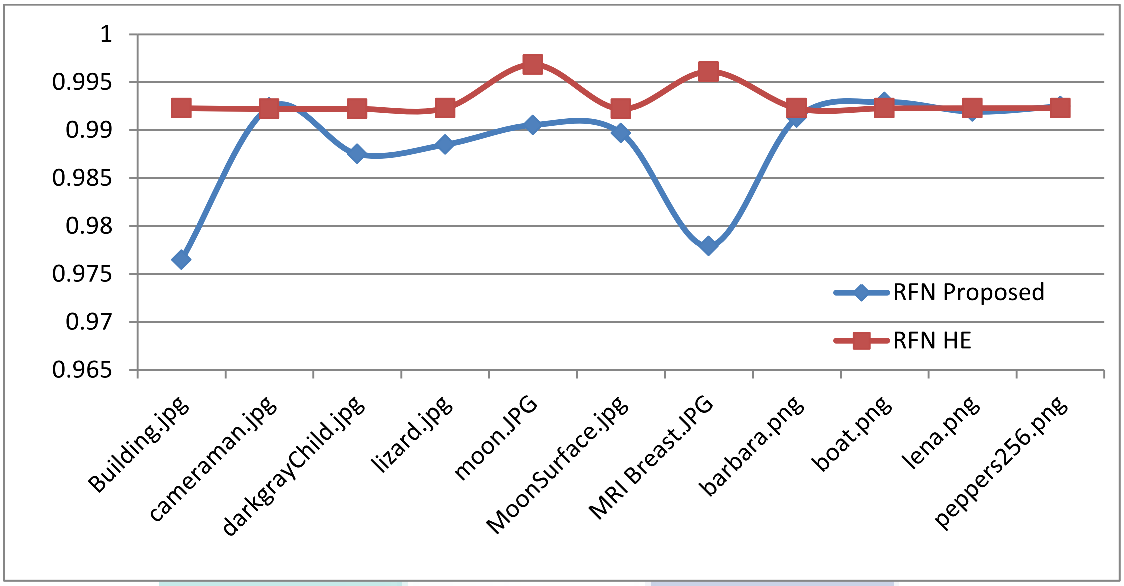


Figure 5.44: Proposed method has better false negative trend

Compared to each other, proposed method has more false positives and HE has more false negatives. By analyzing histogram for each, it is evident that HE has washouts which turn out to be negative but they are false as pixels do exist in these grey levels in the original image. Similarly, proposed method stretches the grey level range and covers those grey levels which were blank in original image. Hence pixels values for these grey levels are mathematically placed which did not exist in the original image. This is positive as values exist in processed image but it is false as same values did not exist in the original image.

In addition to these test already carried out, the study carried out more test to ascertain the effectiveness of proposed method on a broader scale. Total of five groups of images were processed by HE and proposed method. These groups had images ranging from 7 to 12 in each group. Processed images were tested for similarity using DICE similarity method. Graphs for similarity are shown from figure 5.56 to 5.60. First graph is shown in figure 5.56 below.

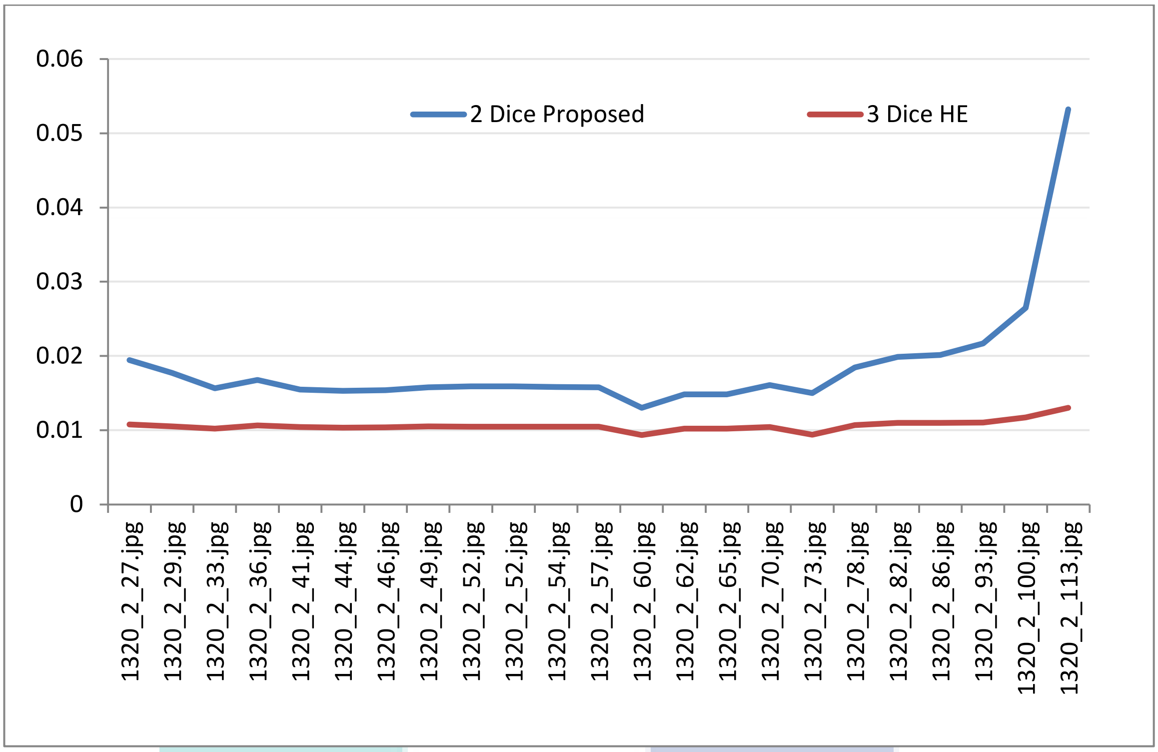


Figure 5.45: DICE Comparison HE & Proposed Method

Results of DICE carried out on next group of images are given in figure 5.57.

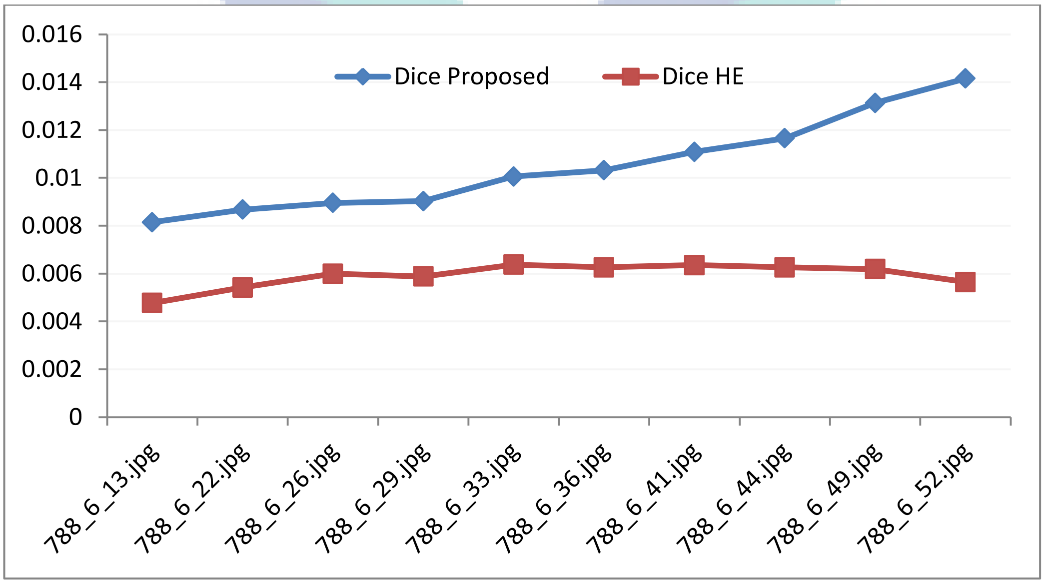


Figure 5.46: DICE Similarity Comparison HE & Proposed Method

Further the results of DICE for next 7 images are given below in figure 5.58.

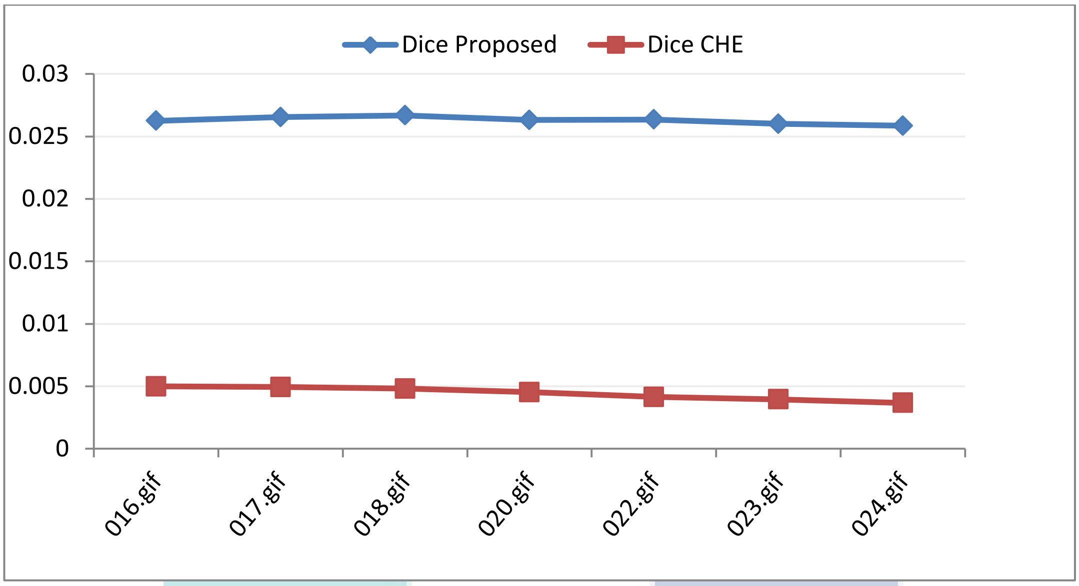


Figure 5.47: DICE Similarity Comparison HE & Proposed Method

Ten more images are tested by DICE and comparative output in given in figure 5.59.

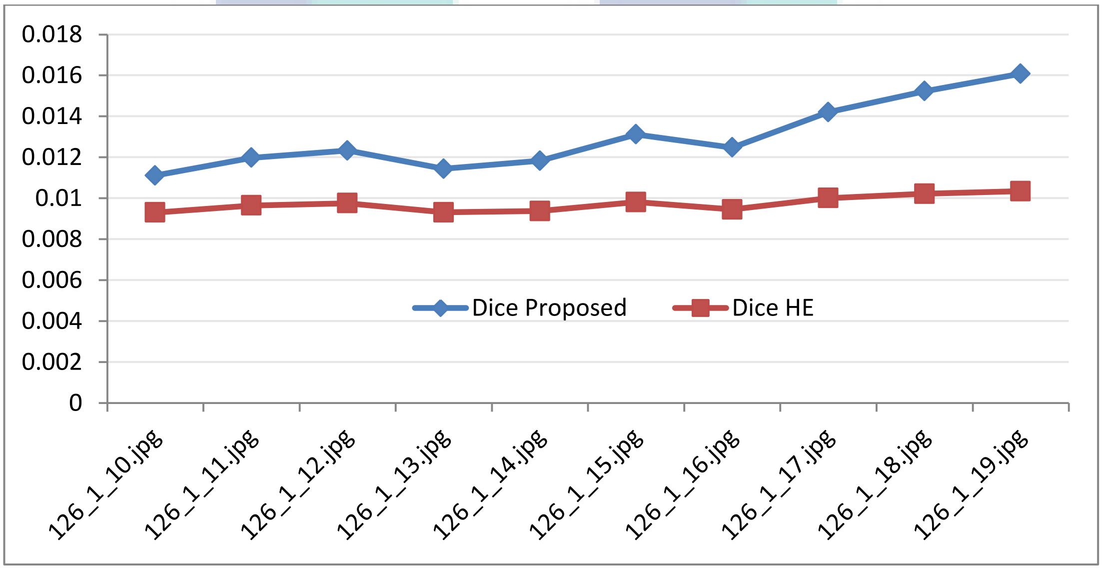


Figure 5.48: DICE Comparison HE & Proposed Method

Furthermore in the last group 10 images are tested by DICE similarity test and graphs representing the results are given in figure 5.60.

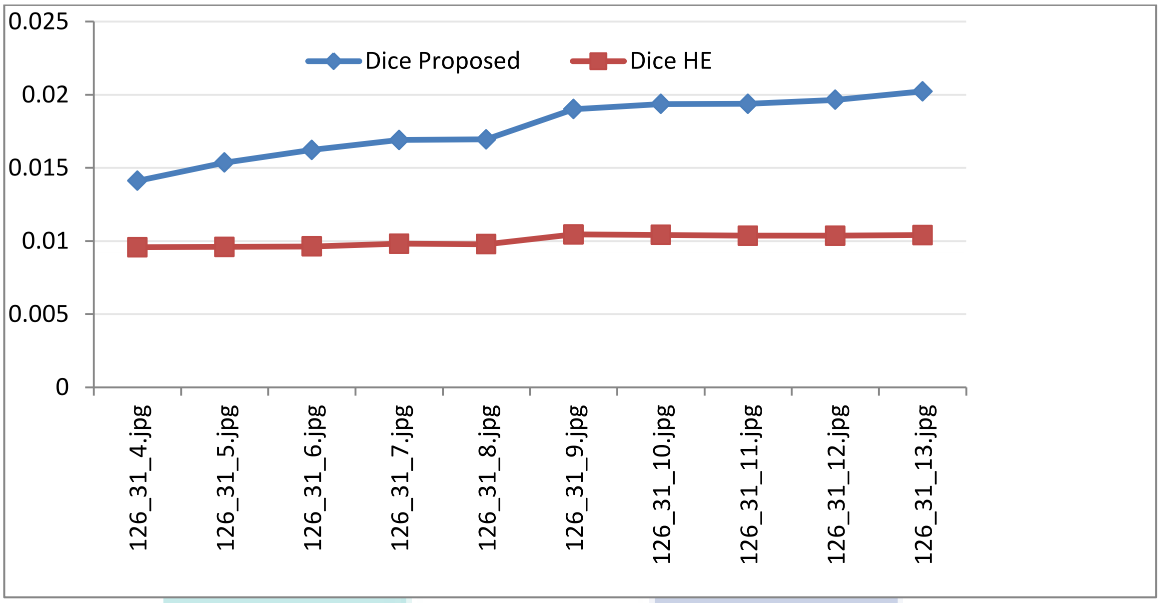


Figure 5.49: DICE Comparison HE & Proposed Method

The images used were multiple images with different characteristics. For these images, comparative similarity for HE and proposed method with the original images was established. All five groups of images maintain the same trend in similarity, which, shows that proposed method outperforms HE in similarity. As discussed earlier, this is clearly evident in histogram for proposed method which maintains almost same contours as of original image.

5.6 DISCUSSION AND ANALYSIS

Proposed method was applied on a considerable volume of images, consisting of all data categories defined in dataset in chapter 1. The results were similar on all categories; results displayed only slight variation is the trend: the method yielded excellent results on brain MRIs, performed convincingly well on general medical and common images; it maintained its performance on noisy and noise free images. In addition to this, the method performed equally well on both real and synthetic images.

This remarkable performance might be understood well if the histogram of enhanced image is analyzed in details.

For this analysis histograms of all the images were examined in detail to understand image data changes and its effects on image attributes. The contours of histogram were near identical to the histogram of the original image but were proportionally stretched to full range. There were either no gaps or very little gaps with small width. This pattern indicates that proposed method raises contrast well while it maintains brightness of the image. Moreover it will ensure greater similarity with the original image. This fact is evident in trend analyses for similarity by applying DICE and Jaccard similarity measuring method in figures 5.33, 5.34, 5.52, 5.53, 5.56 – 5.60. Loss of image data is none or insignificantly small. As there are no washouts in grey levels, large changes in image attribute are not expected. The trend shows that the processed image histograms were stretched well covering the complete range of grey levels. Due to this stretch, it places pixel values at blank places – this will raise the value of false positive for the method. This trend for high false positive is confirmed by trend analyses in figure 5.35 &5.54. However, more importantly this stretch will raise the contrast of the image improving visual quality of the image. This is evident in all processed images. Histogram of the processed image depicts a quasi-symmetrical tendency. In turn, this will provide an output image with natural contrast. The histogram also shows spreading of the grey levels to extremes at both ends (low and high) which are a design feature of the proposed method. This may end up masking objects or images features if these are at ranges very close to these extremes. As both ends are processing grey levels in opposite direction, there has to a point in between both these extremes where this function reverses from one direction to the other. This, in fact, is the partitioning point which splits darker and brighter region. Around this point for a small range there is no change in contrast. Hence, contrast for this range is either mildly raised or not raised at all. Conversely, a relation of satisfactory enhancement is represented at all other points of performance curves.

Examining the histograms of all processed images from enhancement angle, a relation exists between enhancement and the selected mathematical expression of GATE, DRACE and BRACE. For all histogram of original images which are complaint with the division point (130) - given in the formula - the enhancement is good. For the same formula exponents(1.4) and reduced scale of 25%, as the division point of input image is moved towards zero some bright areas in output image will surrender to black region and if the division point of input image is shifted towards max value, output image lose some dark area to bright areas. In both cases contrast will suffer. The solution lies in readjusting the division point in formula to a new value. As the value increase from 1.4 onwards it will be optimized for division point shifting towards zero and then the related reduction scale has to be reduced below the current 25% scale. If the exponent is reduced below 1.4 the optimization division point shifts towards max values and the related scaling down for GATE has to be changed from 25% to a higher values.

Considering the details of histogram a brief summary of image attributes achieved by comparative performance of HE and the proposed method is given in table 5.3.

Table 5.3: Comparative analysis of HE and proposed method

Brightness	**Proposed Method**	**HE Method**
Contrast	Brightness improvement over original Image is better than HE	Loses brightness of the original image.
Histogram Pattern	Contrast improvement over original Image is better than HE	Contrast over original image is deteriorated.
Histogram Stretching	Similar to original image	Not relevant to original image.
Jaccard Test	Maintains complete range till grey level 255.	Shrinks to last grey levels from about 100 – 255.
DICE Test	Better than HE	HE less similar.
	Better than HE	HE less similar.

CHAPTER 6

CONCLUSION

6.1 INTRODUCTION

This chapter concludes the study by summarizing the results achieved by the proposed method. Additionally it presents a gist of analysis of mutual comparison of image enhanced by proposed method with original and HE processed image. The chapter, then, describes the extent of success in meeting the objectives which were defined by the study in chapter one. Further, the chapter presents contribution of the proposed method in modifying the current contrast enhancement techniques used for dataset (brain MRIs, medical and common images). Moreover, the chapter illustrates the impact of this contribution on quality and extent of contrast enhancement for images of the dataset. Finally, the chapter covers future directions by pointing out those areas of the study which could be researched further.

6.2 SUMMARY OF RESEARCH FINDINGS

The research has attempted to answer the questions posed in first chapter. Real world images need contrast enhancement to improve the perception of facts recorded by the image. This processing, gains more importance in sensitive areas like medical field where correct diagnosis depends upon accurate image readings. Therefore reliable and accurate image enhancement techniques are important for all images but these methods are vital in medical fields. Amongst contemporary techniques HE is widely relied upon for medical images. Though the shortcomings of these techniques, discussed in chapter 2, affect images in general but these become critical limitations for medical images.

Hence an alternate method is required for image processing which should reliably enhance the accuracy of contrast. Let us see how the study moved forward to respond to this question.

Images present ground reality which will be interpreted accurately if the images present all the details with natural contrast and brightness. Practically, during acquisition, images could contain a wide variety of contrast and brightness which may make the image noisy, obscure objects and make the image monotonic. Therefore, acquired images almost invariably require processing, aimed at, achieving appropriate contrast and brightness.

HE though widely used has some fundamental misconceptions. Instead of contrast HE is based on grey level density. Consequently, in all HE applications, as image density gets altered a change occurs in contrast; out of which, to expect enhancement is just a matter of chance. Moreover, for most of the cases, output image loses brightness which introduces annoying, nonexistent, artifacts. These HE drawbacks affect all image fields but its impact on medical field is critical as image accuracy is a vital input for correct diagnosis.

After detailed analyses an alternate method purely dependent on contrast was proposed. The method is called contrast optimization by regions adjustment (COBRA). The method pre- processes the image to initial parameters which is done through global adjustment by tentative equalization (GATE). In this process image histogram is analyzed which is then tentatively adjusted to a smaller scale, generally one fourth, to make it suitable for subsequent processing. Additionally, histogram is shifted in the center to acquire a quasi-symmetrical shape. Moreover, it is ensured that all the original histogram contours are maintained to ensure retention of details and brightness of given image. Next it enhances the bright and dark regions. The proposed method realistically adjusts the dark region by employing DRACE – dark region adaptation for contrast enhancement – while, for bright region improvement the method uses BRACE - bright region adjustment for contrast enhancement. Both DRACE and BRACE use exponential power to raise the current image contrast. Exponents have the property of raising the higher frequencies at the cost of lower frequencies. The study after a lot of research adjusted the power parameter to a suitable value to acquire the desired image enhancement. During this process image histogram contours are almost maintained. Due to this contour preservation, output image has natural contrast and retains near original brightness. Proposed method is applied on brain MRI, general medical and common images. Results are very encouraging. These results have to be evaluated in the light of objectives defined by the study. It is important to establish the extent, to which, these objectives have been met. Total of three objectives were set by the study. These objectives have been met with impressive success in all three areas: brain MRIs, general medical images and noisy images. Let us analyze the three objectives one by one.

First objective: To propose an algorithm for enhancing low contrast brain MR images.

Study has shown that the proposed method COBRA has, impressively, improved visual quality of contrast in brain MRI images; contrast enhances while image brightness is retained. Output image is free from any artifacts. Output histogram almost maintains same histogram contours as of input image, thereby, retaining all image details. Similarity measuring methods; DICE and Jaccard show that, on MRI images, proposed method outperforms HE with a significant margin. Additionally, proposed method is simple and convenient to implement. Therefore first objective is achieved by the proposed method with excellent success.

Second objective: To validate the proposed algorithm for general medical field images.

Although a contrast enhancement method must perform well in its primary focus, but to attain wider acceptability, it must also perform satisfactorily for a larger spectrum of images. Hence, proposed method is tested on images other than brain MRIs. This includes general medical area, in which, proposed method compared to HE has much better results on all three aspects: contrast enhancement, brightness and image details. Additionally, artifacts are significantly reduced. These, improvements are consistent with the results of DICE and Jaccard which are similarity measuring methods. Comparing contrast, brightness and image details, for common images, proposed method convincingly performs better than HE but, in some cases, its performance is similar as HE (as explained in detail in chapter 4). Image histogram for output image is similar to input image. This trend, in common images is also evident in DICE and Jaccard similarity measuring method. Hence for second objective, first sub category (general medical field), proposed method achieved excellent success, whereas, for second sub category (common images), proposed method still maintained the same excellence success in most of the cases. Hence overall, second objective is largely achieved by proposed method with outstanding success rate.

Third objective: To validate the proposed method for noisy and noise free images.

Proposed method COBRA performs equally well with impressive results on noisy and noise free images. Contrast, image brightness and image details are not affected adversely by image noise. Although, proposed method does not eliminate noise because it is not a de-noising procedure but it works perfectly well in conjunction with noise filters Therefore third objective is achieved with obvious success as impressive results achieved by the proposed method are unaffected by image noise.

Overall all the objectives, defined by the study, are achieved with excellent success rate by the proposed method. Hence the study resolved the problem posed in first chapter.

6.3 CONTRIBUTIONS

Chapter two reviewed the existing HE based methods of image processing and the drawback in the application of HE in global and local processing. This study is an attempt to fill this gap highlighted by literature review in specific areas to meet the stated objectives in chapter one. In addition to basic purpose, the study has an impact on overall technology for image processing techniques. The method contributes to over all techniques in spatial domain. This contribution by the proposed method is significant which needs to be seen in the backdrop of HE drawbacks.

In-depth analyses of histogram equalization brought out glaringly that HE does not base its processing on contrast instead it makes all calculations based on image density. As a result of these calculations HE alters the grey levels for the output image. Due to change in constituent grey levels contrast gets changed but indiscriminately. Moreover density based processing of grey levels shifts the mean to the middle grey level loosing image brightness. As mentioned earlier, to restrict HE drawbacks, image was divided and HE was applied to individual parts. The processed parts were then joined together to regenerate the output image. This, to some extent, improved image enhancement but basic HE issues were not resolved. For medical field, local processing marginally reduced the drawbacks of HE with insignificant impact on diagnoses and response time. Many Local processing techniques were developed some of which are BBHE, DSIHE, MMBEBHE, MCBHE, RMSHE, MBPBHE, DHE and BPDHE. These local processing techniques differed on two aspects: criteria of dividing the image and number of divisions. These techniques did make some difference but overall none of them resolved the primary issues of HE. Despite restraining HE drawbacks to individual sections, HE drawbacks trickled down to local processing, because ultimately it was HE which was the core technique even in local processing. Moreover, local processing came at a cost; all local methods were computationally intensive and required complex algorithm to split and rejoin the images.

So in a nutshell, employing HE in, both, global and local sense, contrast and brightness have come out to have inverse characteristics. Improving one generally deteriorates the other. Although some progress is made by successive techniques, none of the local processing variants of HE application resolved known issue to an acceptable level. Image processing by HE has not reached a state where it can produce consistent results in contrast and brightness for different category of images.

With this background, proposed method was presented which intends eliminating the drawbacks of HE by a formulation of factors which are directly based on contrast. The method directly replaces global processing method in which HE was applied earlier. Brightness and contrast of images improved remarkably. Furthermore, artifacts were eliminated as brightness was retained. Proposed method also retained all image details which were demonstrated by a histogram similar to histogram of the original image.

Next its employment in local processing is in two ways. First; local processing could still partition images but instead of HE, now, proposed method could be used as core enhancement technique. This would get rid of HE issues in local processing. However as mentioned earlier local processing is computationally intensive and uses complex algorithm for partitioning and subsequently aggregating the images. This additional cost would still exist. Therefore this approach does not utilize all the benefits possible by the proposed method.

A more effective application of proposed method is, however, to forgo local processing altogether and just use the proposed method COBRA. This is better option as the results of proposed method are free from the drawbacks associated with HE and the implementation is easy and straightforward. Additionally by adopting this approach additional cost due to local processing like higher computation requirements and algorithm complexities, are avoided. In essence, this approach converges to the already discussed global application of the proposed method. This approach therefore maximizes benefits from the enhancements achieved by the proposed method.

Furthermore, it is of great significance that the histogram contours of the original image are almost maintained during the pre-processing stage and subsequently during enhancement. This is a great edge in the design of this method due to which it preserves the details of the image. Hence, despite enhanced contrast, output image has natural tone and high resemblance with the original image. The proposed method, therefore, outperforms the existing HE based techniques in presenting low level image details; it improves unmasking obscured objects, enhancing contrast and avoiding washouts.

Making all details, existing in the image, readable - with clarity and completeness, without ambiguity and loss of data - is worthwhile, only, if it can be translated correctly to actual facts snapped by the image. This translation is called interpretation. Impact of study on interpretation capacity of image establishes the usefulness of proposed method. As proposed method presents the image with hair splitting details, improved image features are sharp, with natural contrast, appropriate brightness and minute details. Such an enhanced image will have accurate interpretations persistently which is likely to remain consistent among multiple viewers. Such improvement in interpretation is significant contribution especially in medical field where accurate findings are vital to clinical analyses.

Therefore in a nutshell following are the contributions of proposed method COBRA:

(i) Implementation is easy and straight forward.

(ii) COBRA, by employing contrast specific factors, eliminates drawbacks of HE and avoids additional processing needed for local HE application.

(iii) The proposed method, COBRA, contributes significantly by one global approach to cater for both (local and global) processing of the image.

(iv) Employing COBRA unmasks, hair splitting, low level details which removes ambiguities and improves clarity and sharpness of image features.

(v) Output image histogram has nearly the same contours as of input histogram which indicates that image data is not lost during processing. Hence, output image has natural contrast, brightness is appropriate and similarity with the original image is suitably retained.

(vi) The proposed method, COBRA, improves accuracy of image reading significantly, thereby, impressively improving precision and consistency in image interpretations.

(vii) Although COBRA benefits a wide range of imagery areas it, however, especially impacts medical field, in which, it improves the ability of quick, easy and accurate diagnosis resulting into reduced response time and higher success rate of ensuing medical procedures.

6.4 LIMITATIONS OF THE PROPOSED METHOD

Advantages and drawbacks of any research come to the forefront only when the proposed novelty is implemented and put to full range of test. Although proposed method offers significant improvement in contrast enhancement it has its shortcomings. Some of the limitations which came to light during testing mostly effect common images. These, drawbacks are based on some ranges of grey level, in which, enhancement of image is not pronounced.

At the partitioning point, the effect of enhancement is very mild or nonexistent. This is because; at partitioning point opposing regions (dark and bright) adjoin each other. Due to which, the dimming effect (by dark region) and elevating effect (by bright region) cancels out, at this point, and contrast enhancement is partially or completely nullified. Additionally, there is a tapering effect that leads into this point and leads out of it till contrast values are completely free of this effect. This makes a small range of grey levels around this partitioning point void of intended enhancement. Also image at the start point i.e. zero grey level and the last range i.e. close to grey level 256 does not have any room for shifting of the grey level on either side. Therefore if an object lies close to these points, the enhancement in contrast might only be mild. These effects are visible on 'cameraman' amongst common images in chapter four.

6.5 FUTURE DIRECTION

Research is carried out only on relevant aspects of the subject that too within the scope of the study. At times, connected aspects of proposed novelty come to surface during development. All such aspects which are connected but do not fall within scope are left for future research.

One such aspect in proposed method is to determine the splitting point accurately for contrasting regions. It is because the whole method revolves around the splitting of the image. Therefore, a reliable technique is need of the hour. From a variety of methods artificial neural network (ANN) is one such method. Hence an ANN based method needs to be developed to establish grey level standard for each category. These categories should include images of common grey level ranges for dark and bright areas. Once a candidate image has to be enhanced, it must associate itself to a category based on its constituent grey level ranges. This association algorithm may be developed using a probabilistic determination, for which Hidden Markov Model (HMM) is a suitable choice. The category, once associated, my serve as a template to establish contrast deficiency of candidate image. The contrast can, then, be enhanced by our proposed method. To develop such standards ANN may be trained on sufficient volume of images in each category. This will build a library of templates for different categories of images. The library can be linked through HMM to candidate image for a systematic enhancement. This integrated approach will bring the final refinement to our proposed method.

Any future research may be directed to attempt the objective to develop an ANN based library for different image categories and a HMM model for establishing association of the candidate image with most pertinent category. Finally this template may be integrated with our proposed method to optimize image enhancement.

REFERENCES

Abdullah-Al-Wadud, M. ,Kabir, M. H., Dewan, M. A. A. and Chae, O. 2007. A Dynamic Histogram Equalization for Image Contrast Enhancement. *IEEE Trans. On Consumer Electronics*, **53**(2): 593–600.

Arici, T., Dikbas, S. and Altunbasak, 2009. Y.A Histogram Modification Framework and Its Application for Image Contrast Enhancement. *IEEE Transactions on Image Processing*, **18**(9): 1921-1935.

Chang, Y. C., Chang, C. M. 2010. A simple histogram modification scheme for contrast enhancement. *IEEE Trans Consum Electron*,**56**(2): 737-742.

Chen, L. H., Yang, Y. H. and Chen. C. S. 2011. A monotonic constrained regression framework for histogram equalization and specification. *Proceedings of 18th IEEE International Conference on Image Processing,* pp. 1549-1552.

Chen, S. D. and Ramli, A. R. 2003a. Contrast enhancement using recursive mean-separate histogram equalization for scalable brightness preservation, *IEEE Trans. Consumer Electronics*, **49**(4): 1301-1309.

Chen, S.D. and Ramli, A.R. 2003b. Minimum mean brightness error bi-histogram equalization in contrast enhancement', *IEEE Trans. Consum. Electron.*,**49**(4): 1310–1319

Cheng, F., Ruan, S. 2010. Image Quality Analysis of a Novel Histogram Equalization Method for Image Contrast Enhancement. *IEICE Transactions INF. & SYST*. **E93-D**(7): 773–1779.

Csapodi, M. and Roska, T. 1996. Adaptive histogram equalization with cellular neural network. *Proceedings of IEEE International Workshop on Cellular Neural Networks and their Applications*,**8**:1-6.

Doustar, M. F. and Hassanpour, H. 2010. A locally-adaptive approach for image gamma correction.*Proceedings of 10th International Conference on Information Science, Signal Processing and their Applications (ISSPA 2010)*, pp.72-76

Eramian, M. and Mould, D. 2005. Histogram equalization using neighbourhood metrics. *Proceedings of IEEE 2nd Canadian Conference on Computer and Robot Vision*, pp. 397-404.

Fan, B. and Zhou, F. 2011. Feature map guided medical image enhancement using (HE) lut mapping with anchor point group. *Proceedings of IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC)*, pp. 1-6.

Hanmandlu, M. and Jha., D. 2006. An Optimal Fuzzy System for Color Image Enhancement, *IEEE Trans. Image Process.* **15**(10): 2956–2966.

Ibrahim, H. and Kong, N. S. P. 2007 Brightness preserving dynamic histogram equalization for image contrast enhancement, *IEEE Trans. Consum Electron*., **53**(4): 1752-1758.

Iwanami, T., Goto, T., Hirano, S. and M. Sakurai. 2012. An Adaptive Contrast Enhancement Using Regional Dynamic Histogram Equalization. . *Proceedings of IEEE International Conference on Consumer Electronics,*pp.719-722.

Jafar, I., and Ying, H. 2007. Multilevel component-based histogram equalization for enhancing the quality of grey scale image. *IEEE International Conference on Electro/Information Technology*, pp.563-568.

Jiang, J. L., and Zhang, Y. S. 2006. Local histogram equalization with brightness preservation, *Electronic Journal,***34**(5): 861-866.

Juric, S.and Klepac, V. 2009. Gamma and gamma correction in television production. *Proceedings of 51st International Symposium ELMAR Zagreb, Croatia.* pp 83-86.

Kaur, M., Kaur, J. andKaur. J. 2011. Survey of Contrast Enhancement Techniques based on Histogram Equalization. *International Journal of Advanced Computer Science and Applications(IJACSA) ,***2**(7):137-141

Kim, Marry and Chung, Min Gyo. 2008. Recursively Separated and Weighted Histogram Equalization for Brightness Preservation and Contrast Enhancement, *IEEE Trans. Consumer Electronics*, **54**(3): 1389–1397.

Kim, T. and Paik, J. 2008. Adaptive contrast enhancement using gain controllable clipped histogram equalization. *IEEE Transactions on Consumer Electronics,* **54**(4): 1803-1810.

Kim, T. K., Paik, J. K. and Kang, B. S. 1998. Contrast Enhancement System Using Spatially Adaptive Histogram Equalization With Temporal Filtering, *IEEE Transactions on Consumer Electronics,***44**(1): 82-87.

Lakshmanan, R., Nair, M., Wilscy, M. and Tatavarti. R. 2008. Automatic Contrast Enhancement for Low Contrast Images: A Comparison of Recent Histogram Based Techniques. *Proceedings of IEEE International Conference on Computer Science and Information Technology (ICCSIT),* pp. 269-276.

Maragatham, G., Roomi, S.M.M., Prabu, T.M. 2011. Contrast enhancement by object based Histogram Equalization. *Proceedings of IEEE World Congress on Information and Communication Technologies (WICT),* pp.1118-1122.

Meotti, D., Najman, L., Facon, J., and de Araujo, A.A. 2007. Multi-Histogram equalization method for contrast enhancement and brightness preserving. *IEEE Trans. Consum. Electron.* **53**(3): 1186-1194.

Murahira, K., Taguchi, A. 2011. A novel contrast enhancement method using differential grey levels histogram. *Proceedings of IEEE International Symposium on Intelligent Signal Processing and Communications Systems (ISPACS),* pp. 1-5.

Najafi, T. and Zargari, F. 2011. A hybrid method for contrast enhancement. *Proceedings of IEEE International Conference on Consumer Electronics.* pp. 352-355.

Park, G., Cho, H. and Choi, M. 2008. A Contrast Method using Dynamic Range Separate Histogram Equalization. *IEEE Transactions on Consumer Electronics*, **54**(4):1981–1987.

Reza, A. M. 2004. Realization of the Contrast Limited Adaptive Histogram Equalization (CLAHE) for Real-Time Image Enhancement. *Journal of VLSI Signal Processing,***38**: 35- 44.

Sengee, N. and Choi, H. K. 2008. Brightness preserving weight clustering histogram equalization. *IEEE Transactions on Consumer Electronics,* **54**(3): 1329-1337.

Sengee, N., Bazarragchaa, B., Tae Yun Kim, Heung Kook Choi. 2009. Weight Clustering Histogram Equalization for Medical Image Enhancement. *Proceedings of IEEE International Conference on Communications Workshops, pp.1-5.*

Shanmugavadivu, P. and Balasubramanian, K. 2011. Image edge and contrast enhancement using un-sharp masking and constrained histogram equalization. *Proceedings of International Conference on Logic, Information, Control & Computation*, **140:** 129-136.

Sim, K. S., Tso, C. P. and C. P. Tan, C. P. 2007. Recursive sub-image histogram equalization applied to grey scale images, *Pattern Recognition Letters*,**28**(10):1209-1221.

Sun, C., Ruan S., Shie, M., and Pai, T. 2005. Dynamic contrast enhancement based on histogram specification, *IEEE Trans. Consum. Electron.*,**51**(4):1300–1305.

Sun, X., Rosin, P.L., Martin, R. R. and Langbein, F. C. 2009. Bas-Relief Generation Using Adaptive Histogram Equalization. *IEEE Transactions on Visualization and Computer Graphics*, **15**(4): 642–653.

Sundaram, M., Ramar, K., Arumugam, N., Prabin, G. 2011. Histogram based contrast enhancement for mammogram images. *Proceedings of International Conference on Signal Processing, Communication, Computing and Networking Technologies (ICSCCN)*, pp. 842-846.

Tan, T.L., Sim, K.S. andTso, C.P. 2012. Image enhancement using background brightness preserving histogram equalization. *Electronic Letters*. **48**(3)

Thomas, G. 2008. Image segmentation using histogram specification. *Proc. Of IEEE Int. Conf. On Image Process.* pp. 589–592.

Thomas, G., Flores Tapia, D., Pistorius, S. 2011. Histogram Specification: A Fast and Flexible Method to Process Digital Images. *IEEE Transactions on Instrumentation and Measurement*, **60**(5):1565-1578.

Tsai, C. M. and Yeh, Z. M. 2008. Contrast enhancement by automatic and parameter-free piecewise linear transformation for color images. *Proceedings ofIEEE Trans. Consum. Electron*, **54**(2): 213–219.

Wang, C., and Ye., Z. 2005. Brightness preserving histogram equalization with maximum entropy: A variational perspective. *IEEE Trans. Consum. Electron.*,**51**(4): 1326–1334.

Wang, Q. and Ward, R. K. 2007. Fast image/video contrast enhancement based on weighted thresholdhistogram equalization. *IEEE Transactions on Consumer Electronics*,**53**(2): 757–764.

Wang, Qian., Chen, Liya and Shen, Dinggang. 2008. Fast histogram equalization for medical image enhancement. *Proceedings of IEEE 30th Annual International Conference of the Engineering in Medicine and Biology Society*, pp. 2217-2220.

Wang, Y., Chen, Q. and Zhang, B. 1999. Image enhancement based on equal area dualistic sub-image histogram equalization method. *IEEE Trans. Consum. Electron.*,**45**(1): 68–75

Wu, P. C., Cheng, F. C. Chen, Y. K. 2010. A novel histogram equalization for image contrast enhancement with mean brightness preservation. *Proceedings of IET International Conference on Frontier Computing. Theory, Technologies and Applications*, pp. 175-180.

Xu, Bailei.,Zhuang, Yiqi., Tang, Hualian and Zhang, Li. 2010. Object-Based Multilevel Contrast Stretching Method for Image Enhancement. *IEEE Transactions on Consumer Electronics*,**56**(3): 1746-1754.

Yang, F. and Wu, J. 2010. An improved image contrast enhancement in multiple peak images based on histogram equalization. *Proceeding of IEEE International Conference on Computer Design and Applications (ICCDA)*, **1**: 346-349.

Yang, S.-C., Wang, C.-M., Hsu, H.-H., Chung, P.-C., Hsu, G.-C., Juan, C.-J. and Lo, C.-S. 2009. Contrast Enhancement and Tissues Classification of Breast MRI Using Kalman Filter-Based Linear Mixing Method. *Computerized Medical Imaging and Graphics*, **33**(3): 187–196.

Yang, Y., Su, Z., and Sun, L. 2010. Medical image enhancement algorithm based on wavelet transform. *Electronic Letters.* **46**(2): 120-121

Yeganeh, H., Ziaei, A., and Rezaie, A. 2008. A novel approach for contrast enhancement based on Histogram Equalization. *Proceedings of International Conference on Computer and Communication Engineering (ICCCE)*, pp. 256-260.

Yeong-Taekgi, M. 1997. Contrast Enhancement Using Brightness Preserving Bi-Histogram Equalization, *IEEE transaction on Consumer Electronics***43**(1):

Yun, S., J., Kim, S. 2011. Contrast Enhancement using weighted histogram equalization. *Proceedings of IEEE International Conference on Consumer Electronis, pp. 203-204*

Zhang, X., Yu, G., Lan and Wang, T. Fu. 2008. Entropy Based Local Histogram Equalization for Medical Ultrasound Image Enhancement. *Proc. of 2nd Int. Conf. on Bio informatics and Biomedical Engineering (ICBBE)*, pp. 2427-2429.

Zhiming, W. and Jianhua, T. 2006. A fast implementation of adaptive histogram equalization. *Proc. IEEE International Conference on Signal Processing.*

Ziaei, A., Yeganeh, H., Faez, K., andSargolzaei, S. 2008. A novel approach for contrast enhancement in biomedical images based on histogram equalization. *Proceedings of the 1st Int. Conf. on Bio-Medical Engineering and Informatics (BMEI) on New Development and the Future,* I: 855-858.

UMP

APPENDIX A1

EMPIRICAL DATA FOR 25% SCALE AND MULTIPLE EXPONENTS

Input G levels	Reduced to 25%	Power 1.3	Power 1.35	Power 1.4	Power 1.5	Power 1.6	Power 1.7	Power 1.8
0	0	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	0.25	0.165	0.154	0.144	0.125	0.109	0.095	0.082
2	0.5	0.406	0.392	0.379	0.354	0.330	0.308	0.287
3	0.75	0.688	0.678	0.668	0.650	0.631	0.613	0.596
4	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000
5	1.25	1.337	1.352	1.367	1.398	1.429	1.461	1.494
6	1.5	1.694	1.729	1.764	1.837	1.913	1.992	2.075
7	1.75	2.070	2.129	2.189	2.315	2.448	2.589	2.738
8	2	2.462	2.549	2.639	2.828	3.031	3.249	3.482
9	2.25	2.870	2.988	3.112	3.375	3.660	3.969	4.305
10	2.5	3.291	3.445	3.607	3.953	4.332	4.748	5.203
11	2.75	3.725	3.918	4.122	4.560	5.046	5.583	6.177
12	3	4.171	4.407	4.656	5.196	5.800	6.473	7.225
13	3.25	4.629	4.910	5.208	5.859	6.592	7.417	8.344
14	3.5	5.097	5.426	5.777	6.548	7.422	8.412	9.535
15	3.75	5.575	5.956	6.363	7.262	8.288	9.459	10.796
16	4	6.063	6.498	6.964	8.000	9.190	10.556	12.126
17	4.25	6.560	7.052	7.581	8.762	10.126	11.702	13.524
18	4.5	7.066	7.618	8.213	9.546	11.095	12.896	14.989
19	4.75	7.581	8.195	8.859	10.352	12.098	14.138	16.521
20	5	8.103	8.782	9.518	11.180	13.133	15.426	18.119
21	5.25	8.634	9.380	10.191	12.029	14.199	16.760	19.783
22	5.5	9.172	9.988	10.877	12.899	15.296	18.139	21.511
23	5.75	9.718	10.606	11.575	13.788	16.424	19.563	23.302
24	6	10.271	11.233	12.286	14.697	17.581	21.031	25.158
25	6.25	10.830	11.870	13.009	15.625	18.768	22.542	27.076
26	6.5	11.397	12.515	13.743	16.572	19.983	24.096	29.057
27	6.75	11.970	13.169	14.489	17.537	21.227	25.693	31.099
28	7	12.550	13.832	15.245	18.520	22.499	27.332	33.203
29	7.25	13.135	14.503	16.013	19.521	23.798	29.012	35.368
30	7.5	13.727	15.182	16.791	20.540	25.125	30.733	37.593
31	7.75	14.325	15.869	17.580	21.575	26.478	32.495	39.879
32	8	14.929	16.564	18.379	22.627	27.858	34.297	42.224
33	8.25	15.538	17.267	19.188	23.696	29.264	36.139	44.629
34	8.5	16.153	17.977	20.007	24.782	30.695	38.020	47.093
35	8.75	16.773	18.694	20.836	25.883	32.152	39.941	49.615
36	9	17.399	19.419	21.674	27.000	33.635	41.900	52.196

APPENDIX A2

EMPIRICAL DATA FOR 25% SCALE AND MULTIPLE EXPONENTS

continued

Input G levels	Reduced to 25%	Power 1.3	Power 1.35	Power 1.4	Power 1.5	Power 1.6	Power 1.7	Power 1.8
37	9.25	18.030	20.151	22.522	28.133	35.142	43.898	54.835
38	9.5	18.666	20.889	23.378	29.281	36.674	45.934	57.531
39	9.75	19.307	21.635	24.244	30.444	38.230	48.007	60.285
40	10	19.953	22.387	25.119	31.623	39.811	50.119	63.096
41	10.25	20.604	23.146	26.002	32.816	41.415	52.267	65.963
42	10.5	21.259	23.911	26.895	34.024	43.043	54.453	68.888
43	10.75	21.920	24.683	27.795	35.246	44.694	56.675	71.868
44	11	22.585	25.461	28.704	36.483	46.369	58.934	74.904
45	11.25	23.254	26.246	29.622	37.734	48.067	61.229	77.996
46	11.5	23.928	27.036	30.548	38.998	49.787	63.560	81.144
47	11.75	24.606	27.832	31.481	40.277	51.530	65.927	84.347
48	12	25.289	28.635	32.423	41.569	53.295	68.329	87.604
49	12.25	25.976	29.443	33.373	42.875	55.083	70.767	90.917
50	12.5	26.668	30.257	34.330	44.194	56.893	73.240	94.284
51	12.75	27.363	31.077	35.295	45.527	58.724	75.747	97.705
52	13	28.062	31.902	36.268	46.872	60.577	78.290	101.181
53	13.25	28.766	32.733	37.248	48.231	62.452	80.866	104.710
54	13.5	29.474	33.570	38.236	49.602	64.348	83.477	108.293
55	13.75	30.185	34.412	39.230	50.986	66.265	86.122	111.930
56	14	30.901	35.259	40.233	52.383	68.203	88.801	115.619
57	14.25	31.620	36.112	41.242	53.793	70.162	91.514	119.362
58	14.5	32.343	36.970	42.259	55.214	72.142	94.260	123.158
59	14.75	33.070	37.833	43.282	56.648	74.143	97.039	127.006
60	15	33.800	38.701	44.313	58.095	76.163	99.852	130.907
61	15.25	34.534	39.574	45.350	59.553	78.205	102.697	134.861
62	15.5	35.272	40.453	46.394	61.024	80.266	105.576	138.866
63	15.75	36.013	41.336	47.445	62.506	82.347	108.487	142.924
64	16	36.758	42.224	48.503	64.000	84.449	111.430	147.033
65	16.25	37.507	43.117	49.567	65.506	86.570	114.407	151.195
66	16.5	38.259	44.015	50.638	67.023	88.710	117.415	155.407
67	16.75	39.014	44.918	51.716	68.552	90.871	120.455	159.671
68	17	39.773	45.825	52.799	70.093	93.050	123.527	163.986
69	17.25	40.535	46.737	53.890	71.645	95.249	126.631	168.353
70	17.5	41.300	47.654	54.986	73.208	97.468	129.767	172.770
71	17.75	42.069	48.576	56.089	74.782	99.705	132.934	177.238
72	18	42.840	49.501	57.198	76.368	101.961	136.133	181.757
73	18.25	43.616	50.432	58.313	77.964	104.237	139.363	186.326

APPENDIX A3

EMPIRICAL DATA FOR 25% SCALE AND MULTIPLE EXPONENTS

continued

Input G levels	Reduced to 25%	Power 1.3	Power 1.35	Power 1.4	Power 1.5	Power 1.6	Power 1.7	Power 1.8
74	18.5	44.394	51.367	59.435	79.572	106.531	142.624	190.945
75	18.75	45.175	52.306	60.562	81.190	108.843	145.916	195.615
76	19	45.960	53.250	61.696	82.819	111.175	149.239	200.335
77	19.25	46.748	54.198	62.835	84.459	113.524	152.592	205.105
78	19.5	47.538	55.150	63.981	86.110	115.893	155.976	209.924
79	19.75	48.332	56.107	65.132	87.771	118.279	159.391	214.793
80	20	49.129	57.068	66.289	89.443	120.684	162.836	219.712
81	20.25	49.929	58.033	67.452	91.125	123.106	166.312	224.680
82	20.5	50.732	59.002	68.621	92.818	125.547	169.817	229.698
83	20.75	51.538	59.976	69.795	94.521	128.006	173.353	234.765
84	21	52.346	60.953	70.975	96.234	130.482	176.918	239.880
85	21.25	53.158	61.935	72.161	97.958	132.976	180.514	245.045
86	21.5	53.972	62.920	73.352	99.691	135.488	184.139	250.259
87	21.75	54.789	63.910	74.549	101.435	138.018	187.794	255.521
88	22	55.610	64.904	75.752	103.189	140.565	191.478	260.832
89	22.25	56.432	65.902	76.959	104.953	143.129	195.192	266.191
90	22.5	57.258	66.903	78.173	106.727	145.711	198.935	271.599
91	22.75	58.087	67.909	79.391	108.511	148.310	202.707	277.055
92	23	58.918	68.918	80.616	110.304	150.926	206.508	282.560
93	23.25	59.752	69.931	81.845	112.107	153.560	210.339	288.112
94	23.5	60.588	70.948	83.080	113.920	156.210	214.198	293.712
95	23.75	61.427	71.969	84.320	115.743	158.877	218.086	299.361
96	24	62.269	72.994	85.565	117.576	161.562	222.003	305.056
97	24.25	63.114	74.022	86.815	119.417	164.263	225.949	310.800
98	24.5	63.961	75.054	88.071	121.269	166.980	229.923	316.591
99	24.75	64.811	76.090	89.332	123.130	169.715	233.926	322.430
100	25	65.663	77.129	90.597	125.000	172.466	237.957	328.316
101	25.25	66.518	78.172	91.868	126.880	175.234	242.016	334.249
102	25.5	67.376	79.219	93.144	128.769	178.018	246.104	340.230
103	25.75	68.236	80.269	94.425	130.667	180.819	250.220	346.257
104	26	69.098	81.323	95.711	132.575	183.636	254.363	352.332
105	26.25	69.963	82.381	97.002	134.491	186.469	258.535	358.453
106	26.5	70.830	83.441	98.298	136.417	189.319	262.735	364.622
107	26.75	71.700	84.506	99.599	138.352	192.184	266.963	370.837
108	27	72.573	85.574	100.904	140.296	195.066	271.218	377.098
109	27.25	73.447	86.645	102.215	142.249	197.964	275.501	383.407
110	27.5	74.325	87.720	103.530	144.211	200.878	279.812	389.761

APPENDIX A4

EMPIRICAL DATA FOR 25% SCALE AND MULTIPLE EXPONENTS
continued

Input G levels	Reduced to 25%	Power 1.3	Power 1.35	Power 1.4	Power 1.5	Power 1.6	Power 1.7	Power 1.8
111	27.75	75.204	88.798	104.850	146.182	203.808	284.150	396.163
112	28	76.086	89.880	106.175	148.162	206.753	288.515	402.610
113	28.25	76.970	90.965	107.504	150.151	209.715	292.908	409.104
114	28.5	77.857	92.054	108.839	152.148	212.692	297.328	415.643
115	28.75	78.746	93.145	110.178	154.155	215.685	301.776	422.229
116	29	79.637	94.240	111.521	156.170	218.694	306.250	428.861
117	29.25	80.531	95.339	112.869	158.194	221.718	310.752	435.539
118	29.5	81.427	96.441	114.222	160.226	224.758	315.281	442.262
119	29.75	82.325	97.546	115.580	162.267	227.813	319.836	449.031
120	30	83.226	98.654	116.942	164.317	230.884	324.419	455.846
121	30.25	84.128	99.765	118.308	166.375	233.970	329.028	462.707
122	30.5	85.033	100.880	119.680	168.442	237.072	333.664	469.613
123	30.75	85.941	101.998	121.055	170.517	240.188	338.327	476.564
124	31	86.850	103.119	122.435	172.601	243.321	343.016	483.561
125	31.25	87.762	104.243	123.820	174.693	246.468	347.732	490.603
126	31.5	88.676	105.371	125.209	176.793	249.630	352.475	497.690
127	31.75	89.592	106.501	126.602	178.902	252.808	357.244	504.823
128	32	90.510	107.635	128.000	181.019	256.000	362.039	512.000
129	32.25	91.430	108.772	129.402	183.145	259.207	366.860	519.222
130	32.5	92.352	109.911	130.809	185.279	262.430	371.708	526.490
131	32.75	93.277	111.054	132.220	187.420	265.667	376.582	533.802
132	33	94.204	112.200	133.635	189.571	268.920	381.482	541.159
133	33.25	95.133	113.349	135.054	191.729	272.187	386.408	548.561
134	33.5	96.063	114.501	136.478	193.895	275.468	391.360	556.008
135	33.75	96.996	115.656	137.906	196.070	278.765	396.338	563.499
136	34	97.932	116.814	139.338	198.252	282.076	401.342	571.034
137	34.25	98.869	117.975	140.775	200.443	285.402	406.371	578.614
138	34.5	99.808	119.140	142.215	202.642	288.742	411.427	586.239
139	34.75	100.749	120.306	143.660	204.848	292.097	416.508	593.907
140	35	101.692	121.476	145.109	207.063	295.467	421.615	601.620
141	35.25	102.638	122.649	146.562	209.285	298.851	426.747	609.378
142	35.5	103.585	123.825	148.020	211.516	302.249	431.905	617.179
143	35.75	104.534	125.004	149.481	213.754	305.662	437.088	625.024
144	36	105.486	126.185	150.947	216.000	309.089	442.297	632.914
145	36.25	106.439	127.370	152.416	218.254	312.531	447.532	640.847
146	36.5	107.394	128.557	153.890	220.516	315.987	452.791	648.824
147	36.75	108.351	129.747	155.368	222.785	319.457	458.076	656.845

APPENDIX A5

EMPIRICAL DATA FOR 25% SCALE AND MULTIPLE EXPONENTS

continued

Input G levels	Reduced to 25%	Power 1.3	Power 1.35	Power 1.4	Power 1.5	Power 1.6	Power 1.7	Power 1.8
148	37	109.311	130.940	156.849	225.062	322.941	463.386	664.910
149	37.25	110.272	132.136	158.335	227.347	326.439	468.721	673.019
150	37.5	111.235	133.334	159.825	229.640	329.951	474.082	681.171
151	37.75	112.200	134.536	161.318	231.940	333.478	479.467	689.367
152	38	113.167	135.740	162.816	234.248	337.019	484.878	697.606
153	38.25	114.136	136.947	164.318	236.563	340.573	490.313	705.889
154	38.5	115.106	138.157	165.823	238.886	344.142	495.773	714.216
155	38.75	116.079	139.369	167.333	241.217	347.724	501.259	722.585
156	39	117.053	140.584	168.846	243.555	351.320	506.769	730.998
157	39.25	118.030	141.802	170.363	245.901	354.931	512.304	739.454
158	39.5	119.008	143.023	171.884	248.254	358.555	517.863	747.954
159	39.75	119.988	144.246	173.409	250.614	362.192	523.447	756.496
160	40	120.970	145.473	174.938	252.982	365.844	529.056	765.082
161	40.25	121.954	146.701	176.471	255.358	369.509	534.690	773.711
162	40.5	122.940	147.933	178.007	257.740	373.188	540.348	782.382
163	40.75	123.927	149.167	179.547	260.131	376.881	546.031	791.097
164	41	124.916	150.404	181.091	262.528	380.587	551.738	799.854
165	41.25	125.907	151.643	182.639	264.933	384.307	557.469	808.655
166	41.5	126.900	152.885	184.191	267.345	388.040	563.225	817.498
167	41.75	127.895	154.130	185.746	269.764	391.787	569.005	826.384
168	42	128.891	155.377	187.305	272.191	395.548	574.809	835.312
169	42.25	129.890	156.627	188.868	274.625	399.322	580.638	844.283
170	42.5	130.890	157.879	190.434	277.066	403.109	586.491	853.297
171	42.75	131.892	159.134	192.004	279.514	406.909	592.368	862.353
172	43	132.895	160.392	193.578	281.970	410.723	598.269	871.451
173	43.25	133.900	161.652	195.155	284.432	414.551	604.194	880.593
174	43.5	134.907	162.915	196.737	286.902	418.391	610.143	889.776
175	43.75	135.916	164.180	198.321	289.379	422.245	616.116	899.002
176	44	136.927	165.448	199.910	291.863	426.113	622.113	908.270
177	44.25	137.939	166.718	201.502	294.354	429.993	628.134	917.580
178	44.5	138.953	167.991	203.097	296.852	433.886	634.179	926.932
179	44.75	139.969	169.266	204.696	299.357	437.793	640.248	936.327
180	45	140.986	170.544	206.299	301.869	441.713	646.340	945.763
181	45.25	142.005	171.824	207.906	304.388	445.646	652.457	955.242
182	45.5	143.026	173.107	209.515	306.914	449.592	658.596	964.763
183	45.75	144.048	174.393	211.129	309.447	453.551	664.760	974.325

APPENDIX A6

EMPIRICAL DATA FOR 25% SCALE AND MULTIPLE EXPONENTS
continued

Input G levels	Reduced to 25%	Power 1.3	Power 1.35	Power 1.4	Power 1.5	Power 1.6	Power 1.7	Power 1.8
184	46	145.073	175.680	212.746	311.987	457.523	670.947	983.930
185	46.25	146.098	176.970	214.366	314.534	461.508	677.158	993.576
186	46.5	147.126	178.263	215.990	317.088	465.505	683.392	1003.264
187	46.75	148.155	179.558	217.618	319.648	469.516	689.650	1012.994
188	47	149.186	180.856	219.249	322.216	473.540	695.931	1022.766
189	47.25	150.218	182.156	220.883	324.790	477.576	702.236	1032.579
190	47.5	151.252	183.458	222.521	327.371	481.626	708.564	1042.434
191	47.75	152.288	184.763	224.162	329.959	485.688	714.916	1052.330
192	48	153.325	186.070	225.807	332.554	489.763	721.290	1062.268
193	48.25	154.364	187.379	227.455	335.155	493.851	727.688	1072.248
194	48.5	155.405	188.691	229.107	337.763	497.951	734.110	1082.269
195	48.75	156.447	190.005	230.762	340.378	502.064	740.554	1092.331
196	49	157.491	191.322	232.421	343.000	506.190	747.022	1102.435
197	49.25	158.536	192.641	234.082	345.628	510.329	753.513	1112.580
198	49.5	159.583	193.962	235.748	348.263	514.480	760.027	1122.766
199	49.75	160.632	195.286	237.416	350.905	518.643	766.564	1132.994
200	50	161.682	196.612	239.088	353.553	522.820	773.124	1143.263
201	50.25	162.733	197.940	240.763	356.208	527.009	779.707	1153.573
202	50.5	163.787	199.271	242.442	358.870	531.210	786.313	1163.924
203	50.75	164.842	200.604	244.124	361.538	535.424	792.942	1174.316
204	51	165.898	201.939	245.809	364.213	539.650	799.594	1184.749
205	51.25	166.956	203.276	247.498	366.894	543.889	806.268	1195.223
206	51.5	168.016	204.616	249.190	369.582	548.140	812.966	1205.738
207	51.75	169.077	205.958	250.885	372.276	552.404	819.686	1216.294
208	52	170.139	207.302	252.583	374.977	556.680	826.429	1226.891
209	52.25	171.203	208.649	254.285	377.685	560.968	833.195	1237.529
210	52.5	172.269	209.998	255.990	380.399	565.269	839.984	1248.207
211	52.75	173.336	211.349	257.698	383.119	569.582	846.795	1258.927
212	53	174.405	212.702	259.410	385.846	573.907	853.629	1269.687
213	53.25	175.475	214.058	261.124	388.579	578.244	860.485	1280.487
214	53.5	176.547	215.416	262.842	391.319	582.594	867.364	1291.329
215	53.75	177.620	216.776	264.563	394.065	586.956	874.266	1302.211
216	54	178.695	218.138	266.288	396.817	591.330	881.190	1313.133
217	54.25	179.771	219.503	268.015	399.576	595.716	888.136	1324.096
218	54.5	180.849	220.869	269.746	402.341	600.115	895.105	1335.100
219	54.75	181.928	222.238	271.480	405.113	604.525	902.097	1346.144
220	55	183.009	223.609	273.217	407.891	608.948	909.110	1357.228

APPENDIX A7

EMPIRICAL DATA FOR 25% SCALE AND MULTIPLE EXPONENTS

continued

Input G levels	Reduced to 25%	Power 1.3	Power 1.35	Power 1.4	Power 1.5	Power 1.6	Power 1.7	Power 1.8
221	55.25	184.091	224.982	274.957	410.675	613.383	916.146	1368.353
222	55.5	185.174	226.358	276.701	413.466	617.830	923.205	1379.518
223	55.75	186.259	227.735	278.447	416.263	622.289	930.286	1390.723
224	56	187.346	229.115	280.197	419.066	626.759	937.389	1401.969
225	56.25	188.434	230.497	281.950	421.875	631.242	944.514	1413.255
226	56.5	189.523	231.881	283.706	424.691	635.737	951.661	1424.581
227	56.75	190.614	233.267	285.465	427.512	640.244	958.831	1435.947
228	57	191.707	234.656	287.227	430.341	644.762	966.023	1447.354
229	57.25	192.800	236.046	288.992	433.175	649.293	973.236	1458.800
230	57.5	193.896	237.439	290.760	436.015	653.836	980.472	1470.287
231	57.75	194.992	238.833	292.532	438.862	658.390	987.730	1481.814
232	58	196.090	240.230	294.306	441.715	662.956	995.010	1493.380
233	58.25	197.190	241.629	296.084	444.574	667.534	1002.312	1504.987
234	58.5	198.291	243.030	297.864	447.439	672.124	1009.636	1516.633
235	58.75	199.393	244.433	299.648	450.310	676.726	1016.982	1528.320
236	59	200.497	245.839	301.434	453.188	681.339	1024.350	1540.046
237	59.25	201.602	247.246	303.224	456.071	685.964	1031.740	1551.812
238	59.5	202.709	248.655	305.017	458.961	690.601	1039.151	1563.618
239	59.75	203.816	250.067	306.813	461.856	695.249	1046.585	1575.463
240	60	204.926	251.480	308.611	464.758	699.910	1054.040	1587.348
241	60.25	206.037	252.896	310.413	467.666	704.582	1061.517	1599.273
242	60.5	207.149	254.314	312.218	470.580	709.265	1069.016	1611.238
243	60.75	208.262	255.733	314.025	473.499	713.960	1076.536	1623.242
244	61	209.377	257.155	315.836	476.425	718.667	1084.078	1635.286
245	61.25	210.493	258.579	317.650	479.357	723.385	1091.642	1647.369
246	61.5	211.611	260.005	319.466	482.295	728.115	1099.228	1659.492
247	61.75	212.730	261.433	321.286	485.239	732.857	1106.835	1671.655
248	62	213.850	262.863	323.108	488.188	737.610	1114.464	1683.856
249	62.25	214.972	264.295	324.934	491.144	742.374	1122.114	1696.098
250	62.5	216.095	265.728	326.762	494.106	747.150	1129.786	1708.378
251	62.75	217.219	267.164	328.594	497.073	751.938	1137.479	1720.698
252	63	218.345	268.602	330.428	500.047	756.737	1145.194	1733.058
253	63.25	219.472	270.042	332.265	503.026	761.547	1152.930	1745.456
254	63.5	220.600	271.484	334.105	506.012	766.369	1160.688	1757.894
255	63.75	221.730	272.928	335.948	509.003	771.202	1168.467	1770.371
256	64	222.861	274.374	337.794	512.000	776.047	1176.267	1782.888

APPENDIX B1

LIST OF PUBLICATION

Ahmed, M. Mahmood, Zain, Jasni. Mohammd, Ahmed, M. Masroor. Dec 03-05, 2012“Image partitioning methods in spatial and frequency domain.” *International conference on computational science and information management (ICoCSIM 2012)* **1:**152-157

Ahmed, M. Mahmood, Zain, Jasni. Mohammd, Ahmed, M. Masroor. Nov 26-28, 2012“A study on the validation of HE as a contrast enhancement technique.” *International Conference on Advanced Computer Science Applications and Technologies (ACSAT 2012)* article 130