A Comparative Study of Histogram Equalization Based Image Enhancement Techniques.

Bachelors Project

Submitted by

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Declaration

I, hereby, declare that the work presented in this project is the outcome of the investigation performed by me under the supervision of Md. Tuhin Sheikh, Lecturer, Institute of Statistical Research and Training, University of Dhaka. I also declare that no part of this project has been or is being submitted elsewhere for the award of any degree.

Signed
(Md. Shahbaz Alam)
Candidate

Abstract

Contrast enhancement is an important factor in the image pre-processing step. One of the widely accepted contrast enhancement method is the histogram equalization. Histogram equalization is a well-known contrast enhancement technique due to its performance on almost all types of images. In this project we presented five widely used histogram equalization techniques- global histogram equalization(GHE), contrast limited adaptive histogram equalization(CLAHE), brightness preserving bi-histogram equalization(BBHE), dualistic sub-image histogram equalization(DSIHE) and recursive mean separated histogram equalization(RMSHE). We conducted simulation experiments using traditional metrics(*i.e.* mean squared error(MSE), peak signal to noise ratio(PSNR)) as well as more sophisticated metric such as structural similarity index(SSIM).We observed that the brightness preservation is not handled well by HE, CLAHE, BBHE and DSIHE, but it can be handled properly by RMSHE.

Acknowledgements

At first I express gratitude to the almighty Allah for the blessing and immeasurable grace for a successful completion of the report and submission.

It is a great pleasure in expressing enormous gratefulness and sincere gratitude to my respected supervisor, Md. Tuhin Sheikh, Lecturer, Institute of Statistical Research and Training (ISRT), University of Dhaka for his valuable advice and continuous help throughout the period of my project. I would like to express my thanks and gratitude to my family and friends for their enthusiastic support which gave me the strength during this work.

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Dedicated to my parents

Chapter 1

Introduction

Human beings are predominantly visual creatures. We rely heavily on our vision to make sense of the world around us. We not only look at things to identify and classify them, but we can scan for differences, and obtain an overall rough "feeling" for a scene with a quick glance. An image is a single picture which represents something. It may be a picture of a person, of people or animals, or of an outdoor scene, or a micro-photograph of an electronic component, or the result of medical imaging.

Image processing is a method to perform some operations on an image, in order to get an enhanced image or to extract some useful information from it. It is a type of signal processing in which input is an image and output may be image or characteristics/features associated with that image. Nowadays, image processing is among rapidly growing technologies. It forms core research area within engineering and computer science disciplines too (Baxes). Image processing basically includes the following three steps:

- Importing the image via image acquisition tools.
- Analyzing and manipulating the image

- Output in which result can be altered image or report that is based on image analysis.

There are two types of methods used for image processing namely, analogue and digital image processing.

Analogue image processing can be used for the hard copies like printouts and photographs.

Digital image processing is the technology that allows a number of computer algorithms to process digital images. The outcome of the process can be either images or a set of representative characteristic properties of the original image. The main purpose of digital image processing is to make an image better, extract the hidden features in an image, reduce the noise of an image, etc. Today, there is almost no area of technical endeavor that is not impacted in some way by digital image processing. Although, the application of digital image have been tremendously wide. This study mainly focuses on a particular area, image enhancement, which is one of the popular areas of image processing (3).

Image enhancement is a process consists of a collection of techniques that seek to improve the visual appearance of an image or to convert image to a form better suited for analysis by a human or machine.The principal objective of enhancement is to process an image so that the result is more suitable than the original image for a specific application (13). In general, image enhancement approaches fall into two broad categories: spatial domain methods and frequency domain methods. The term spatial domain refers to the image plane itself. In this category, approaches are based on direct manipulation of pixels. On the other hand, frequency domain processing techniques are based on modifying the Fourier transformation of an image (4). In this project we are mainly concerned with spatial domain techniques.

In spatial domain approach there are some basic gray level transformations, such as contrast enhancement, gray level slicing, histogram processing. Among these, histogram processing is a simple and effective statistical tool which is based on pictorial data representation used by statisticians. In this paper, an illustration of the application of histogram manipulation has been carried out. The basic definitions and mathematical terminology are described in the next chapter.

1.1 Background

An image histogram is a graphical representation of the pixel intensities in a digital image. It is considered as an important statistical tool in the field of image processing. It reflects many useful features of an image. For example mean intensities(brightness) and standard deviation of intensities (contrast). A tall, narrow histogram would represent large numbers of pixels with equal or nearly equal gray values. This reflects an image of low contrast in which small points of detail are difficult to differentiate. A broad histogram would represent pixels of variable gray values. This reflects an image of high contrast in which the degree of image detail is markedly enhanced (18). There are Various contrast enhancement techniques. Among them histogram equalization is a well known contrast enhancement technique. Because of its strong performance and easy algorithm in all types of images.Generally, histogram equalization can be catagorized into two segment. One is global histogram equalization(GHE) and the other is local histogram equalization(LHE) or adaptive histogram equalization(AHE) (11).

The computational simplicity makes GHE an attractive tool in many contrast enhancement applications. It applies the transformation function over the full window of the image. Although GHE enhances the contrast of an image, it shifts the mean brightness of the image. This allows for areas of lower contrast to gain a higher contrast and areas of higher contrast to gain a lower contrast (5)

In contrast, local histogram equalization(LHE) operates on small data regions , rather than the entire image. It uses sliding window method , in which local histograms are computed from the windowed neighborhood to produce a local intensities which is used to remapping each pixel (11). The intensity of the pixel at the center of the neighborhood tiles is changed according to the local intensity remapping for that pixel. it produces great contrast result but is responsible for over-amplifying noise in some homogeneous regions of an image. This is because it enhances all the local windows, disregarding the fact that some local windows might not be a candidate for enhancement. Moreover, it is also computationally expensive and time consuming.

An extension of AHE have been developed to overcome the problem of over-enhancement of noise: contrast limited adaptive histogram equalization(CLAHE) (19). CLAHE limits the amplification of noise by clipping the histogram at a predefined value before computing the CDF. The enhancement is thereby reduced in very uniform areas of the image, which prevents over enhancement of noise and reduces the edge-shadowing effect of unlimited AHE. The size of the pixels contextual region and the clip level of the histogram are the parameters of CLAHE (9).

Since GHE stretches the dynamic range of pixel intensities, it flats the density distribution of the resultant image. In spite of its high performance in enhancing contrasts of a given image, however, it is rarely employed in consumer electronics such as TV since the straight use of histogram equalization may change the original brightness of an input image, deteriorate visual quality, or, introduce some annoying artifacts. To overcome such problems, a novel extension of the histogram equalization, which will be referred to as the mean preserving bi-histogram equalization (BBHE) (6). In this method the original image is first decomposed to two sub images based on the mean, one of the sub images is the set of samples less than or equal to the mean and the other sub-image is the set of samples greater than the mean. Then the BBHE equalizes the sub images independently based on their respective histograms with the constraint that the samples in the formal set are mapped into the range from the minimum gray level to the input mean and the samples in the latter set are mapped into the range from the mean to the maximum gray level (6). Thus, the resulting equalized sub-images are bounded by each other around the input mean, which results preserving the brightness of the original images as well as enhance the contrast.

Equal Area Dualistic Sub-Image Histogram Equalization (DSIHE) also known as Dualistic Sub-Image Histogram Equalization follows the same idea as in the BBHE, which decomposes the original image histogram into two sub histogram based on the mean value. DSIHE method decomposes the the original image into two sub-images based on median. It claims that if the separating level of histogram is the median of the original image's brightness, it will yield the maximum entropy after two independent sub-equalization (16)

There are still cases that are not handled well by BBHE, as they require higher degree of preservation. Recursive mean separate histogram equalization proposes the generalization of the Brightness preserving bi-histogram equalization(BBHE) to overcome such limitation and provide not only better but also scalable brightness preservation. BBHE separates the input histogram into two based on its mean before equalizing then independently while the separation is done only once in BBHE. The RMSHE method proposes to perform the separation recursively, separate each new histogram further based on their respective means. Its recursive nature implies scalable preservation which is very useful in consumer electronic products (8; 2). there are many cases which are not handled well by HE, BBHE and DSIHE, have been properly enhanced by RMSHE.

In this paper we presented five most widely used histogram equalization techniques that are mentioned above.To demonstrate the performance of these methods, extensive simulation study has been conducted on several test images. A comparative study has been carried out among these methods traditional metrics(e.g. mean squared error(MSE), peak signal to noise ratio(PSNR)) as well as more sophisticated metric, structural similarity index(SSIM).

1.2 Aims and Objectives

- To describe and implement five popular methods of histogram equalization global histogram equalization(GHE), contrast limited adaptive histogram equalization(CLAHE), brightness preserving bi-histogram equalization(BBHE), dualistic sub-image histogram equalization(DSIHE) and recursive mean separate histogram equalization(RMSHE) on images with different level of contrast
- To compare among these five methods using traditional metrics(e.g. MSE) as well as more sophisticated metric such as SSIM

1.3 Outline of The Study

This whole project comprised to five chapters. In Chapter 2, some basics about digital image processing are discussed. Histogram based image enhancement techniques, their implementations are discussed in Chapter 3. Results and discussion are presented in Chapter 4. Finally, we end up with conclusion in Chapter 5.

Chapter 2

Fundamentals of Digital Image Processing

Chapter 3

Methodology

Histograms are the basis for numerous spatial domain processing techniques. Histogram manipulation can be used effectively for image enhancement, as shown in this chapter. In addition to providing useful image statistics, the information inherent in histograms also is quite useful in other image processing applications, such as image compression and segmentation. Histograms are simple to calculate in software and also lend themselves to economic hardware implementations, thus making them a popular tool for real-time image processing.

3.1 Histogram Processing

Histogram actually represents the probabilistic distribution of each gray level in an image. Histogram of an image normally refers to a histogram of the pixel intensity values. This histogram is a graph showing the number of pixels in an image at each different intensity value found in that image. For an 8-bit gray-scale image there are 256 different possible intensities, and so the histogram will graphically display 256 numbers showing the distribution of pixels among those gray-scale values.
Histogram processing can be broadly divided into two categories :

1. Histogram Equalization.

2. Histogram Matching(Specification).

In this study, we mainly focus on various histogram equalization techniques in gray-scale image. Histogram based techniques are very simple and effective. Histogram equalization automatically determines a transformation function seeking to produce an output image with a uniform Histogram.The basic assumption used here is that the information conveyed by an image is related to the probability of occurrence of gray levels in the form of histogram in the image.

There are numerous methods by which Histogram of an image can be equalized. Depending upon the area of Application, we can choose the different histogram equalization techniques. We will see the following five types of Histogram Equalization methods in detail:

1. Global Histogram Equalization(GHE).

2. COntrast Limited Adaptive Histogram Equalization(CLAHE).

3. Brightness Preserving Bi-Histogram Equalization(BBHE).

4. Dualistic Sub Image Histogram Equalization (DSIHE).

5. Recursive Mean Separate Histogram Equalization (RMSHE).

3.2 Global Histogram Equalization(GHE)

Global Histogram Equalization (GHE) is one of the popular methods used to enhance the contrast of image. In GHE, the histogram of whole input image is first obtained, then the Cumulative Distribution Function (CDF) is calculated and gray transfer function is derived from the CDF.

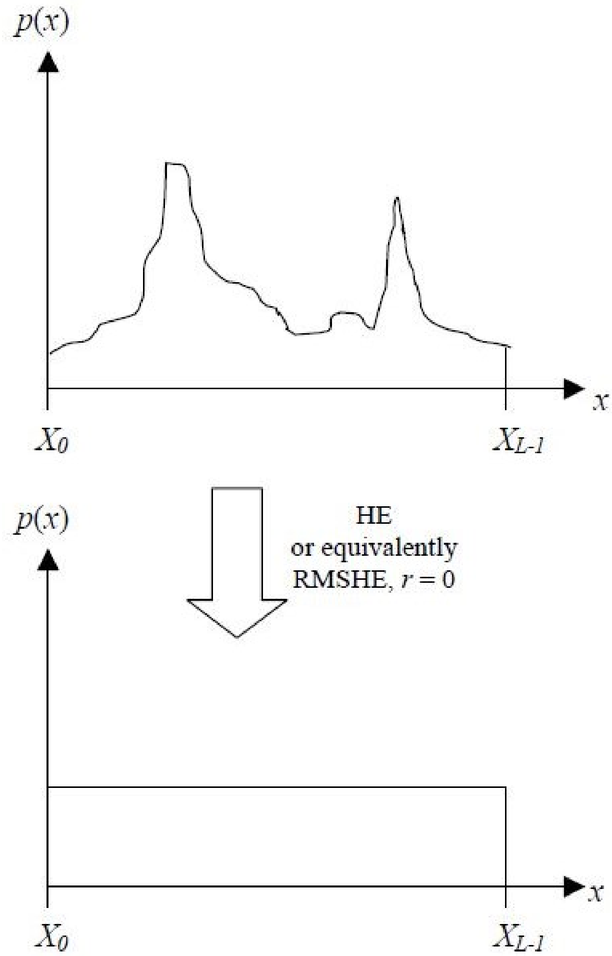

FIGURE 3.1: Histogram before and after HE or equivalently, RMSHE, r = 0

Though it is simple, it doesn't take account of local image information and often cause some contrast losses in small regions. GHE has been widely used in many areas such as medical and radar imaging. Although this global approach is suitable for overall enhancement, it fails to adapt the local brightness features of the input image and shifts the mean intensity to middle intensity level, regardless of input mean intensity. GHE is rarely used in consumer electronics such as digital cameras because it may produce undesirable distortions such as: excessive brightness change, noise-artifacts, gray-level saturation and unnatural enhancement.(12)

3.2.1 Algorithm Steps

The Histogram of digital image $X = \{X(i,j)\}$, with L discrete intensity levels denoted by $\{X_0, X_1, ..., X_{L-1}\}$, is defined as:-

$$h(X_k) = n_k, \text{ for k = 0, 1, ... , L-1} \tag{3.1}$$

Where X_k is the k^{th} intensity value and n_k is the number of pixels in the image with intensity r_k. For an MXN image, a normalized histogram known as Probability Density Function (PDF) is defined by:-

$$p(X_k) = \frac{n_k}{MN}, \text{ for k = 0, 1, ... , L-1} \tag{3.2}$$

Where $p(X_k)$ gives an estimate of the probability of occurrence of gray level X_k in an image. Based on the PDF, the Cumulative Density Function (CDF) is defined as:-

$$c(X_k) = \sum_{j=0}^{k} p(X_j), \text{ for k = 0, 1, ... , L-1} \tag{3.3}$$

GHE enhances $X = X(i,j)$, by using CDF as its transformation function. This transformation function, $f(X_k)$, is defined as:-

$$f(X_k) = X_0 + (X_{L-1} - X_0)c(X_k) \tag{3.4}$$

Then the output image produced by GHE $Y = Y(i,j$ can be expressed as :-

$$Y = f(x) \tag{3.5}$$

$$Y = f(X(i,j)|\forall X(i,j) \in X) \tag{3.6}$$

Although GHE successfully increases the contrast in the image, this method does not put any constrain in preserving the mean brightness.

3.2.2 An Example of GHE

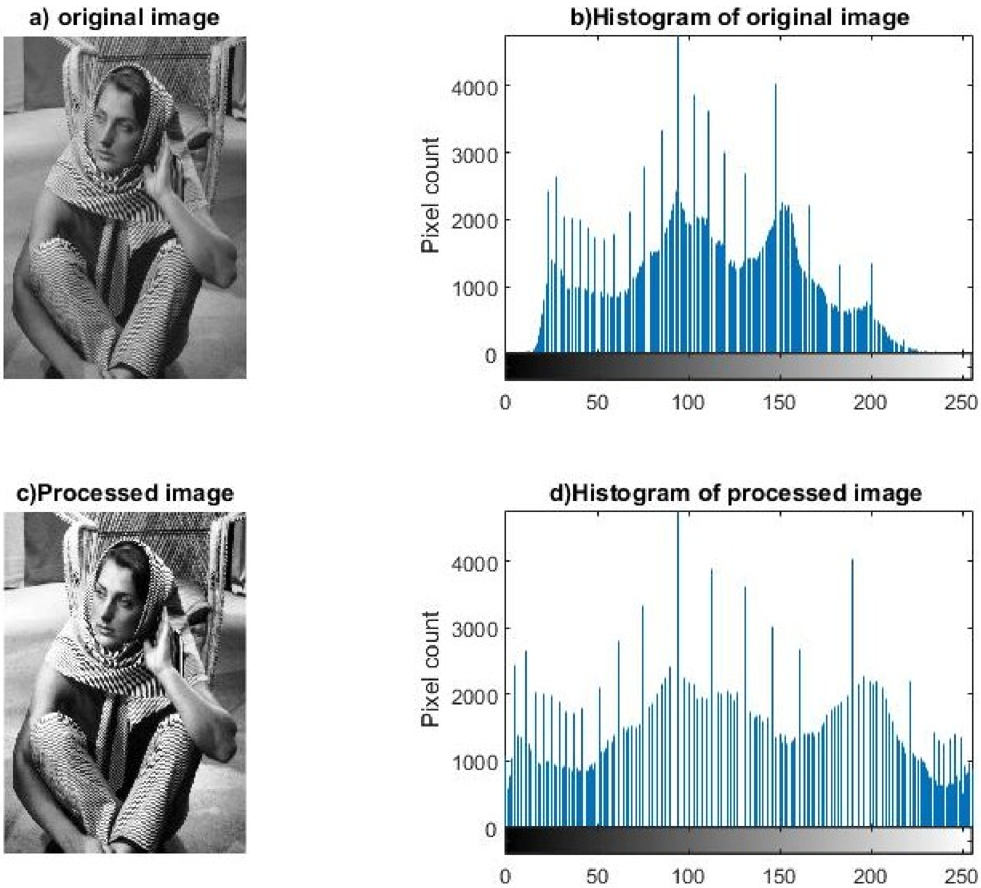

FIGURE 3.2: Contrast enhancement based on global histogram equalization. The images are a)Original image b)Histogram of original image c)GHE Processed image d)Histogram of GHE processed image.

The following figure shows a dark lower contrast image of 'barbara', it's corresponding histogram and HE processed image with the processed histogram.We can see after applying GHE, the contrast of this image is better than the original image. The contrast is enhanced in this case. The visual quality is also clear than the original one.From the processed histogram, we can say it becomes flat than the original histogram.

3.3 Contrast Limited Adaptive Histogram Equalization(CLAHE)

Adaptive histogram equalization (AHE) is an excellent contrast enhancement method for both natural images and medical and other initially nonvisual images. The basic form of the method was invented independently by Ketcham et al., Hummel and Pizer. The method involves applying to each pixel of the histogram equalization mapping based on the pixels in a region surrounding that pixel (its contextual region). That is, each pixel is mapped to an intensity proportional to its rank in the pixels surrounding it. But the basic method is slow, and under certain conditions the enhanced image has undesirable features.(10)

The Contrast Limited Adaptive Histogram Equalization (CLAHE) is an improved version of adaptive histogram equalization. Originally it was developed for medical imaging and has proven to be successful for enhancement of low contrast images such as portal films. Contrast enhancement can be defined as the slope of the function mapping input intensity to output intensity. We will assume that the range of input and output intensities are the same. Then a slope of 1 involves no enhancement, and higher slopes give increasingly higher enhancement. Thus the limitation of contrast enhancement can be taken to involve restricting the slope of the mapping function. With histogram equalization the mapping function m(i) is proportional to the cumulative histogram

$$m(i) = (DisplayRange) * (CumulativeHistogram(i))/(RegionSize). \tag{3.7}$$

Since the derivative of the cumulative histogram is the histogram, the slope of the mapping function at any input intensity, i.e., the contrast enhancement, is proportional to the height of the histogram at that intensity:

$$dm/di = (DisplayRange/RegionSize)XHistogram(i) \tag{3.8}$$

Therefore, limiting the slope of the mapping function is equivalent to clipping the height of the histogram(10).

CLAHE limits the amplification by clipping the histogram at a predefined value before computing the CDF. This limits the slope of the CDF and therefore of the transformation function. The value at which the histogram is clipped, the so-called clip limit, depends on the normalization of the histogram and thereby on the size of the neighborhood region. It is advantageous not to discard the part of the histogram that exceeds the clip limit but to redistribute it equally among all histogram bins. The redistribution will push some bins over the clip limit again (region shaded green in the figure), resulting in an effective clip limit that is larger than the prescribed limit and the exact value of which depends on the image. If this is undesirable, the redistribution procedure can be repeated recursively until the excess is negligible.

3.3.1 Algorithm Steps of CLAHE

1. First obtain all the inputs- image, length of the neighborhood regions, number of bins for histogram used in building transformation funcion, clip limit for contrast limiting(normalized from 0 to 1).

2. Determine real clip limit from the normalized value and pad the image before decomposing it into regions(tiles).

3. Extract a single image region, make a histogram for this region using the specified number of bins, clip the histogram using clip limit,create a mapping (transformation function) for this region.

4. Extract cluster of four neighboring mapping functions, process image region partly overlapping each of the mapping tiles, extract a single pixel apply four mapping to that pixel and interpolate between the results to obtain the output pixel; repeat over the entire image

3.3.2 An Example of CLAHE

The following figure shows a lower contrast image of 'tungsten' and it's associated histogram.After performing CLAHE considerable contrast enhancement is also shown.The over amplification problem of LHE is reduced by using the contrast limit.

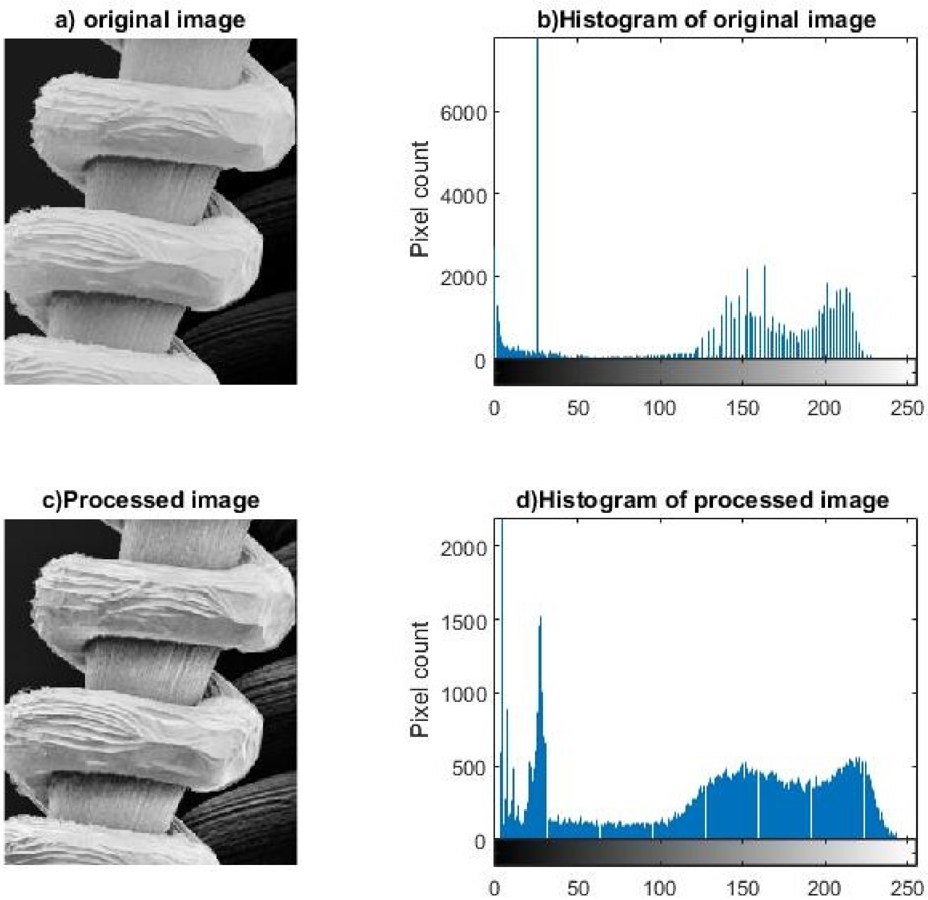

Figure 3.3: Contrast enhancement based on contrast limited adaptive histogram equalization. The images are a)Original image b)Histogram of original image c)CLAHE Processed image d)Histogram of CLAHE processed image.

3.4 Brightness Preserving Bi-Histogram Equalization (BBHE)

In order to overcome the limitations of HE, several brightness preserving methods have been proposed. One of the popular brightness preserving methods is the mean brightness preserving bi-histogram equalization (BBHE)introduced by Kim (1997). At the beginning, the BBHE divides the original histogram into two sub-histograms based on the mean brightness of the input image as shown in figure.

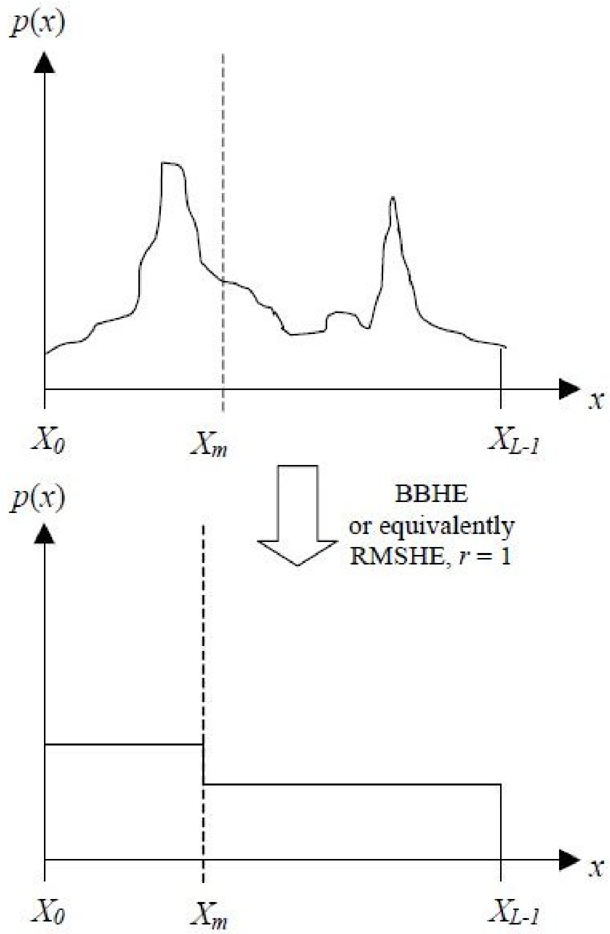

FIGURE 3.4: Histogram before and after BBHE or equivalently, RMSHE, r = 1

One of the sub image is set of samples less than or equal to the mean whereas the other one is the set of sample is greater than the mean. In this method, the separation intensity X_T is presented by the input mean brightness value, which is the average intensity of all pixels that construct the input image. After this separation process, these two histograms are independently equalized by HE. Consequently, the mean brightness can be preserved because the original mean brightness is retained.

The histogram with range from 0 to $L-1(255)$ is divided into two parts, with separating intensity X_m. This separation produces two histograms. The first histogram has the range of 0 to X_m, while the second histogram has the range of X_{m+1} to $L-1$.

3.4.1 Algorithm Steps of BBHE

Let, $X = \{X(i,j)\}$ denote a given image composed of L discrete gray levels denoted as $\{X_0, X_1, ..., X_{L-1}\}$, where $X(i,j)$ represents an intensity of the image at the spatial location (i,j) and $X(i,j) \in \{X_0, X_1, X_{L-1}\}$. For a given image $\mathbf{X}$, let X_m be the mean and assume that $X_m \in \{X_0, X_1, ..., X_{L-1}\}$. Based on the mean, the input image is decomposed into two sub-images $\mathbf{X}_L$ and $\mathbf{X}_U$ as,

$$\mathbf{X} = \mathbf{X}_L \cup \mathbf{X}_U \tag{3.9}$$

where

$$\mathbf{X}_L = \{X(i,j)|X(i,j) \leq X_m, \forall X(i,j) \in \mathbf{X}\} \tag{3.10}$$

and

$$\mathbf{X}_U = \{X(i,j)|X(i,j) > X_m, \forall X(i,j) \in \mathbf{X}\} \tag{3.11}$$

Note that the sub-image $\mathbf{X}_L$ is composed of $\{X_0, X_1, ..., X_{L-1}\}$ and the other sub-image $\mathbf{X}_U$ is composed of $\{X_{m+1}, X_{m+2}, ..., X_{L-1}\}$. Next, define the respective probability density function of the subimages $\mathbf{X}_L$ and $\mathbf{X}_U$ as,

$$p_L(X_k) = \frac{n_L^k}{n_L}, \text{ for k = 0, 1, ... , m} \tag{3.12}$$

and

$$p_U(X_k) = \frac{n_U^k}{n_U}, \text{ for k = m+1, m+2, ... , L-1} \tag{3.13}$$

in which n_L^k and n_U^k represent the respective numbers of X_k in $\{\mathbf{X}\}_L$, and $\{\mathbf{X}\}_U$,, and n_L and n_U are the total numbers of samples in $\{\mathbf{X}\}_L$ and $\{\mathbf{X}\}_U$, respectively. Note that $n_L = \sum_{k=0}^{m} n_L^k$, $n_U = \sum_{k=m+1}^{L-1} n_U^k$ and $n = n_L + n_U$. The respective cumulative density functions for $\{\mathbf{X}\}_L$ and $\{\mathbf{X}\}_U$ are then defined as

$$c_L(x) = \sum_{j=0}^{k} p_L(X_j) \tag{3.14}$$

and

$$c_U(x) = \sum_{j=m+1}^{k} p_U(X_j) \tag{3.15}$$

where $X_k = x$. Note that $C_L(X_m) = 1$ and $c_U(X_{L-l}) = 1$ by definition. Similar to the case of histogram equalization where a cumulative density function is used as a transform function, let us define the following transform functions exploiting the cumulative density functions

$$f_L(x) = X_0 + (X_m - X_0)c_L(x) \tag{3.16}$$

and

$$f_U(x) = X_{m+1} + (X_{L-1} - X_{m+1})c_U(x) \tag{3.17}$$

Based on these transform functions, the decomposed sub-images are equalized independently and the composition of the resulting equalized sub-images constitutes the output of the BBHE. That is, the output image of the BBHE, $\mathbf{Y}$, is finally expressed as

$$\mathbf{Y} = \{Y(i,j)\} = f_L(\mathbf{X}_L) \cup f_U(\mathbf{X}_U) \tag{3.18}$$

where,

$$f_L(\mathbf{X}_L) = \{f_L(X(i,j)|\forall X(i,j) \in \mathbf{X}_L)\} \tag{3.19}$$

and

$$f_U(\mathbf{X}_U) = \{f_U(X(i,j)|\forall X(i,j) \in \mathbf{X}_U)\} \tag{3.20}$$

It is to be noted that $0 \leq c_L(x), c_U(x) \leq 1$. Thus $f_L(\mathbf{X}_L)$ equalizes the sub-image $\mathbf{X}_L$ over the range (X_0, X_m) whereas $f_U(\mathbf{X}_U)$ equalizes the sub-image $\mathbf{X}_U$ over the range (X_{m+1}, X_{L-1}). As a consequence, the input image $\mathbf{X}$ is equalized over the entire dynamic range (X_0, X_{L-1}) with the constraint that the samples less than the input mean are mapped to (X_0, X_m) and the samples greater than the mean are mapped to (X_{m+1}, X_{L-1}).

3.4.2 An Example of BBHE

The following figure shows an image of aeroplane.The detailing of the image is less visible in the original image. After performing BBHE the experimented image looks better in terms of information.The original omage histogram contains high frequency in the higher gray level values.After performing BBHE the processed histogram seems to preserve the mean brightness of the original image

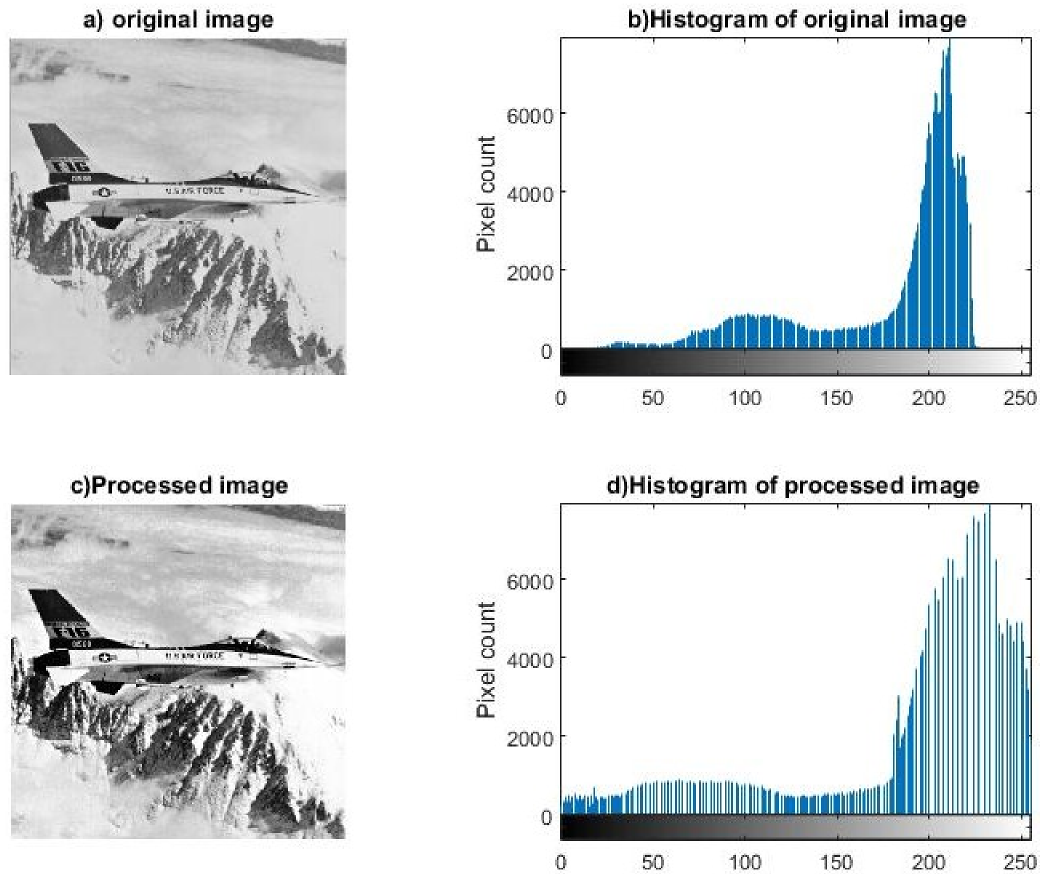

Figure 3.5: Contrast enhancement based on brightness preserving bi-histogram equalization. The images are a)Original image b)Histogram of original image c)BBHE Processed image d)Histogram of BBHE processed image.

3.5 Equal Area Dualistic Sub-Image Histogram Equalization (DSIHE)

DSIHE applies the same basic ideas used by the BBHE method of decomposing the original image into two sub-images and then equalizes the histograms of the sub-images separately. Instead of decomposing the image based on its mean gray level, dualistic sub-image histogram equalization (DSIHE) method decomposes the original image into two sub-images based on median (7). For such aim, the input image is decomposed into two sub-images, being one dark and one bright, respecting the equal area property (i.e., the sub-images has the same amount of pixels).

It can be shown that the brightness of the output image produced by the DSIHE method is the average of the equal area level of the image I and the middle gray level of the image, i.e., $l = L/2$. It is claimed that the brightness of the output image generated by the DSIHE method does not present a significant shift in relation to the brightness of the input image, especially for the large area of the image with the same gray-levels (represented by small areas in histograms with great concentration of gray-levels), e.g., images with small objects regarding to great darker or brighter backgrounds (16). It will yield the maximum entropy after two independent sub-equalization, if the seperating level of histogram is the median of the original image (12)

3.5.1 Algorithm Steps of DSIHE

Dualistic Sub-Image Histogram Equalization (DSIHE) first decomposes an input image into two sub-images based on the median of the input image (15). One of the sub image is set of samples less than or equal to the median whereas the second one is the set of samples greater than the median. Then the DSIHE equalizes the sub images independently based on their respective histograms.

Let an image $X(i,j)$ is segmented by a section with gray level of $X = X_m$ and two sub images are $\mathbf{X}_L$ and $\mathbf{X}_U$ (7), so we have:-

$$\mathbf{X} = \mathbf{X}_L \cup \mathbf{X}_U \tag{3.21}$$

Here

$$\mathbf{X}_L = \{X(i,j)|X(i,j) < X_m, \forall X(i,j) \in \mathbf{X}\}$$

and

$$\mathbf{X}_U = \{X(i,j)|X(i,j) \geq X_m, \forall X(i,j) \in \mathbf{X}\}$$

it is obvious that sub-image $\mathbf{X}_L$ is composed by gray level of $\{X_0, X_1, ..., X_{m-a}\}$, while sub image $\mathbf{X}_U$ is composed of $\{X_m, X_{m+1}, ..., X_{L-1}\}$. The aggregation of original images gray level distribution probability is decomposed into $\{p_0, p_1, ..., p_{m-1}\}$ and $\{p_m, p_{m-1}, ..., p_{L-1}\}$ correspondingly. The corresponding CDF will be

$$c_L(x) = \frac{1}{p} \sum_{j=0}^{k} p_i, \; k = 0, 1, ..., m-1 \tag{3.22}$$

$$c_U(x) = \frac{1}{p-1} \sum_{j=m}^{L-1} p_i, \; k = m, m+1, ..., L-1 \tag{3.23}$$

Based upon CDF, transform function of two sub images histogram equalized below,

$$f_L(x) = X_0 + (X_{m-1} - X_0)c_L(x), \; k = 0, 1, ..., m-1 \tag{3.24}$$

and

$$f_U(x) = X_m + (X_{L-1} - X_m)c_U(x), \; k = m, m+1, ..., L-1 \tag{3.25}$$

Finally the result of dualistic sub-image histogram is obtained after two equalized sub-images are composed into one image. Let, $Y(i,j)$ denotes the processed image then,

$$\mathbf{Y} = \{Yi, j\} = f_L(x) \cup f_U(x) \tag{3.26}$$

or, equivalently

$$Y(i,j) = \begin{cases} X_0 + (X_{m-1} - X_0)c_L(x) \\ X_m + (X_{L-1} - X_m)c_U(x) \end{cases}$$

3.5.2 An example of DSIHE

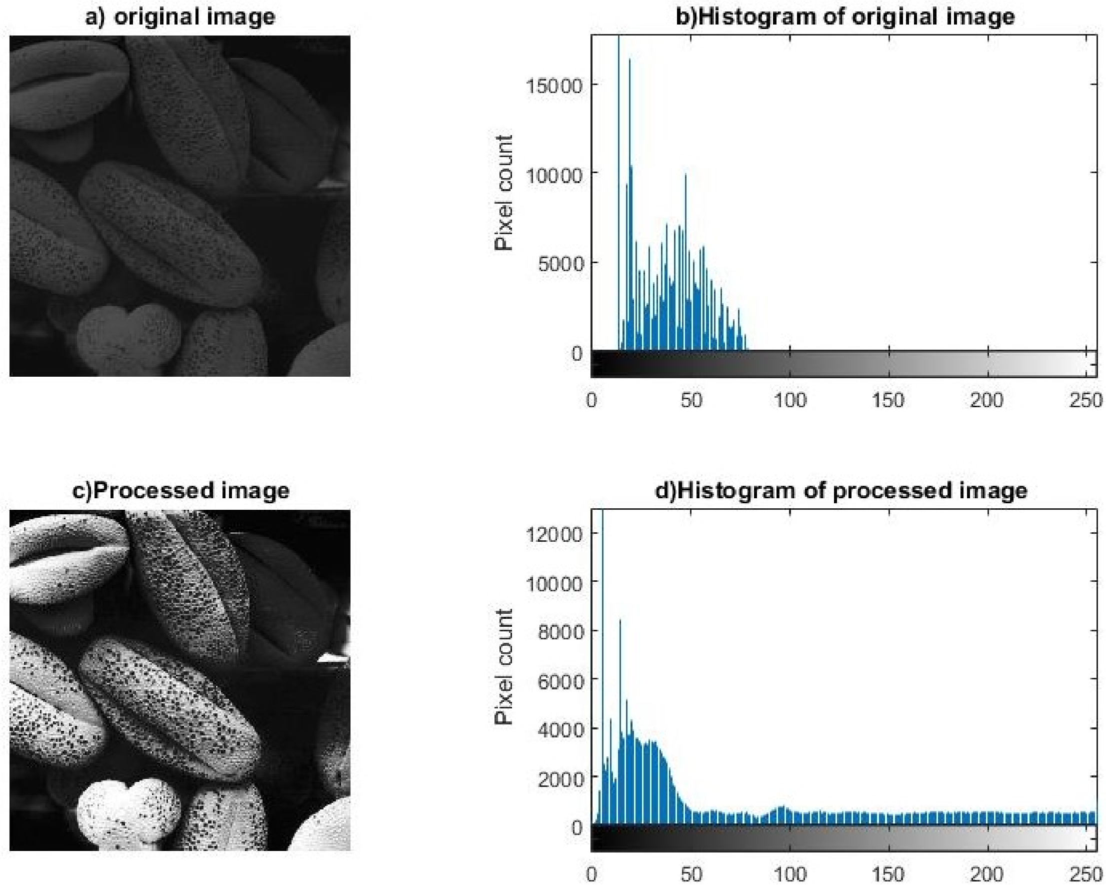

FIGURE 3.6: Contrast enhancement based on dualistic sub-image histogram equalization. The images are a)Original image b)Histogram of original image c)DISHE Processed image d)Histogram of DISHE processed image.

From the figure , we can see a dark low contrast image of pollen grain.The detailing of the image is hardly visible. After applying the DISHE, more information comes out.The mean brightness of the resulting image is increased. The contrast of the resulting image is also enhanced.

3.6 Recursive Mean-Separate Histogram Equalization

Recursive Mean-Separate Histogram Equalization (RMSHE) recursively separates the histogram into multi sub-histograms instead of two sub-histograms as in the BBHE.

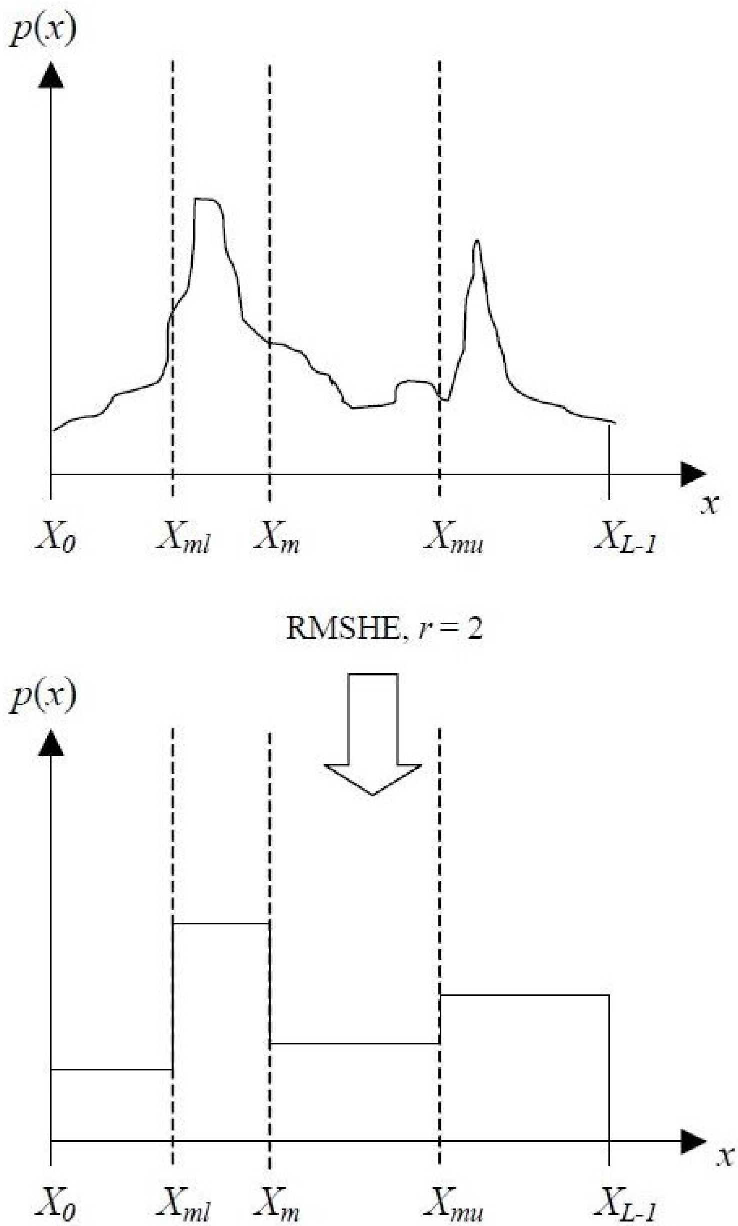

FIGURE 3.7: Recursive mean separated histogram equalization with recursion level r=2

This method proposes the generalization of the Brightness preserving bi-histogram equalization (BBHE) to overcome such limitation and provide not only better but also scalable brightness preservation In typical HE, no mean-separation is performed and thus, no brightness preservation. In BBHE, the mean-separation is done once and thus, achieve certain extends of brightness preservation. In cases where more brightness preservation is required, it is needed to perform the mean separation recursively; separate the resulting histograms again based on their respective means (8). Basically, Recursive Mean-Separate Histogram Equalization (RMSHE) is a generalization of HE and BBHE in the aspect of brightness preservation (2). One of the more mean-separation recursively results in more brightness preservation.

3.6.1 Algorithm Steps of RMSHE

Let, X_m be the mean of the image $\mathbf{X}$ and assume that $X_m \in \{X_0, X_1, ..., X_{L-1}\}$. In BBHE, the input image is decomposed into two sub-images $\mathbf{X}_L$ and $\mathbf{X}_U$ as,

$$\mathbf{X} = \mathbf{X}_L \cup \mathbf{X}_U \tag{3.27}$$

where

$$\mathbf{X}_L = \{X(i,j)|X(i,j) \leq X_m, \forall X(i,j) \in \mathbf{X}\} \tag{3.28}$$

and

$$\mathbf{X}_U = \{X(i,j)|X(i,j) > X_m, \forall X(i,j) \in \mathbf{X}\} \tag{3.29}$$

Supposed that $\mathbf{X}$ is further separated into 4 portions based on the mean of the two new histograms, X_{ml} and X_{mu}. Where,

$$X_{ml} = \frac{\displaystyle\int_{X_0}^{X_m} xp(x)dx}{\displaystyle\int_{X_0}^{X_m} p(x)dx} = 2\int_{X_0}^{X_m} xp(x)dx$$

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

where, $\int_{X_0}^{X_m} p(x)dx = \int_{X_m}^{X_{L-1}} p(x)dx = \frac{1}{2}$

Because $\mathbf{X}$ is assumed to have a symmetric distribution around X_m. The calculation procedure of corresponding CDF and transformation function are as similar as we have done in BBHE. In this method where $r = 2$, we have found four different CDF and associated four transformation function. In simple words, four individual sub images. After successfully implementing HE on each of the sub images,we append them to get the enhanced image. It can be shown that the output mean will converge to the input mean as the number of recursive mean-separation increases.

3.6.2 An example of RMSHE

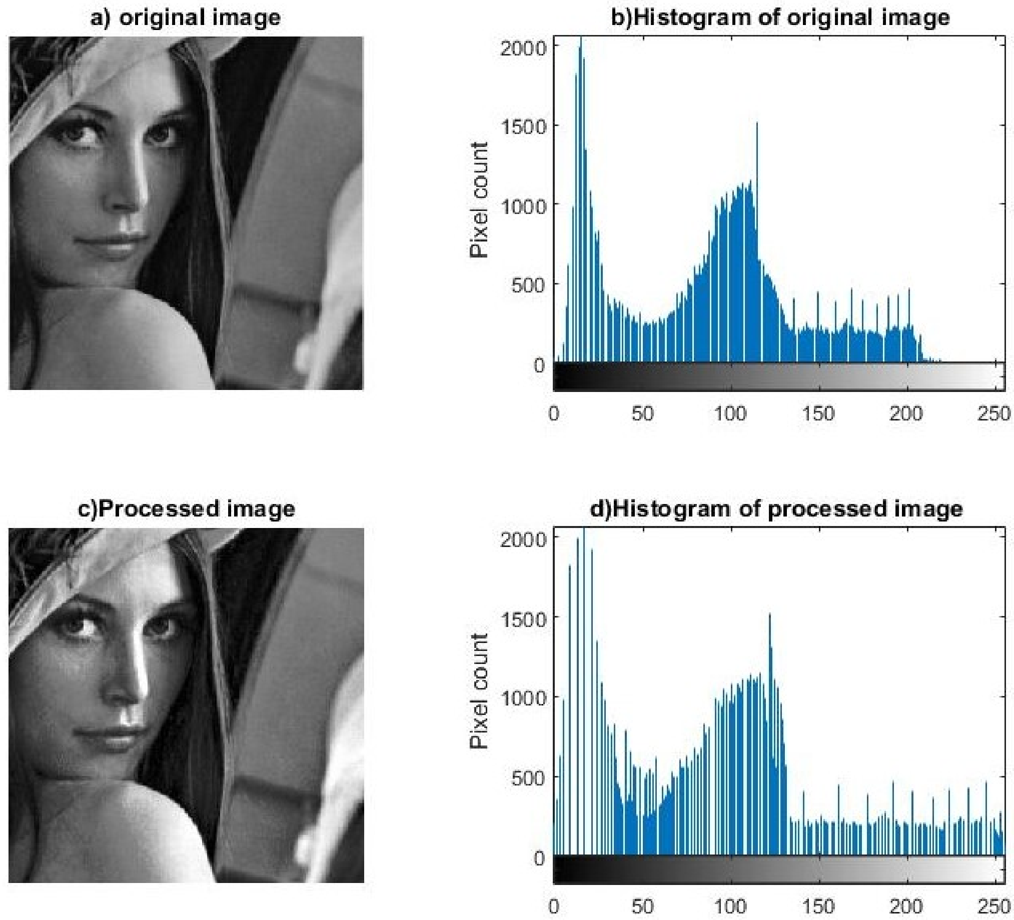

FIGURE 3.8: Contrast enhancement based on recursive mean separated histogram equalization. The images are a)Original image b)Histogram of original image c) RMSHE Processed image d)Histogram of RMSHE processed image.

The above figure contains an image of face. After applying recursive mean separated histogram equalization, the contrast of the processed image (c) is better than the original image. The contrast is enhanced in this case and the visual quality is more clear.The mean brightness of the image is also increased.

Chapter 4

Results and Discussion

Histogram equalization is a well-known contrast enhancement technique because of its strong performance on almost all types of images. In this study we discussed the description and implementation of five widely used histogram equalization techniques named global histogram equalization(GHE), contrast limited adaptive histogram equalization(CLAHE),brightness preserving bi-histogram equalization(BBHE), dualistic sub-image histogram equalization and recursive mean separated histogram equalization(RMSHE). A comparative study has been performed among these five techniques based on traditional metrics mean squared error(MSE),peak signal to noise ratio(PSNR) and structural similarity index(SSIM) which are pixel based quantitative measures.

4.1 Image Quality Assessment

Digital images are subject to a wide variety of distortions during acquisition, processing, compression, storage, transmission and reproduction, any of which may result in a degradation of visual quality. Objective image quality measures are used frequently in image processing applications. It can be classified according to the availability of an original (distortion-free) image. Most existing approaches are known as full-reference. Which means that a complete reference image is assumed to be known.(17)

The simplest and most widely used full-reference quality metrics are the mean squared error (MSE), mean absolute error(MAE), peak signal to noise ratio(PSNR).

objective image quality metric can play a variety of roles in image processing applications. First, it can be used to dynamically monitor and adjust image quality. Second, it can be used to optimize algorithms and parameter settings of image processing systems. Third, it can be used to benchmark image processing systems and algorithms.(17)

The following section described some formula that focuses on full-reference image quality assessment

4.2 Quality Assessment Based on Error Sensitivity

These measures based on the assumption that the loss of perceptual quality is directly related to the visibility of the error signal.

4.2.1 Mean Squared Error(MSE)

MSE quantifies the strength of the error signal.It is a statistical measure based on cumulative squared difference between the processed and original image. The mean squared error(MSE) between two images $\mathbf{A}(i,j)$ and $\mathbf{B}(i,j)$ can be calculated as,

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\{\mathbf{A}(i,j) - \mathbf{B}(i,j)\}^2 \tag{4.1}$$

Where, $\mathbf{A}(i,j)$ is the original image and $\mathbf{B}(i,j)$ is the processed. Both images have the same dimension MN. Note that, the size of the two images must be the same.Lower value of MSE indicates the image is of good quality.

4.2.2 Peak Signal to Noise Ratio

Peak Signal to Noise Ratio(PSNR) is a ratio between the maximum possible value of a signal and the value of a distorting noise. Normally, it is expressed in logarithmic form. The formula to calculate the PSNR between two images may be described as,

$$PSNR = -10log\frac{MSE}{S^2} \tag{4.2}$$

where S is the maximum pixel value and for 8-bit image $S = 255$. Ideally it is infinite. Practically PSNR is in the range between 25 to 40 dB (12). There is an inverse relationship between MSE and PSNR. Higher value of PSNR indicates that the image is of good quality.But the situation is not all time true. Sometimes a lower PSNR image can be visually better(14). MSE and PSNR are popular because its computational simplicity .Tough these two methods do not take into account visual sensitivity.

4.3 Quality Assessment Based on Structural Similarity

most quality measures based on error sensitivity decompose image signals using linear transformations. A new method approached in (17) to assess the quality of an image named Structural Similarity Index (SSIM).

4.3.1 Structural Similarity Index

Suppose $\mathbf{x}$ and $\mathbf{y}$ are two non-negative image signals, which have been aligned with each other (e.g., spatial patches extracted from each image). If we consider one of the signals to have perfect quality, then the similarity measure can serve as a quantitative measurement of the quality of the second signal. The system separates the task of similarity measurement into three comparisons: luminance, contrast and structure. Finally, the three components are combined to yield an overall similarity measure

$$S(\mathbf{x}, \mathbf{y}) = f(l(\mathbf{x}, \mathbf{y}), c(\mathbf{x}, \mathbf{y}), s(\mathbf{x}, \mathbf{y})) \tag{4.3}$$

An important point is that the three components are relatively independent.

For luminance function, we define

$$(l(\mathbf{x}, \mathbf{y}) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1} \tag{4.4}$$

where, μ_x and μ_y are the mean intensities of the image signals $\mathbf{x}$ and $\mathbf{y}$ respectively which is defined as,

$$\mu_x = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{4.5}$$

$$\mu_y = \frac{1}{N}\sum_{i=1}^{N} y_i \tag{4.6}$$

the constant C_1 is included to avoid instability when $\mu_x^2 + \mu_y^2$ is very close to zero. Specifically we choose

$$C_1 = (K_1 L)^2 \tag{4.7}$$

where L is the dynamic range of the pixel values (255 for 8-bit gray-scale images), and $K << 1$ is a small constant. The contrast comparison function takes a similar form

$$c(\mathbf{x}, \mathbf{y}) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2} \tag{4.8}$$

where, $C_2 = (K_2L)^2$, and $K_2 << 1$. Next, the structure comparison function can be defined as follows:

$$s(\mathbf{xy}) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3} \tag{4.9}$$

where σ_{xy} can be estimated as

$$\sigma_{xy} = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu_x)(y_i - \mu_y) \tag{4.10}$$

So combining all these three functions , we can write

$$S(\mathbf{x}, \mathbf{y}) = \frac{(2\mu_x\mu_y + C_1)(\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{4.11}$$

it is to be noted that the function $S(\mathbf{xy})$ as well as its three components satisfy the following conditions:

1. Symmetry: $S(\mathbf{x}, \mathbf{y}) = S(\mathbf{y}, \mathbf{x})$.
2. Boundness : $S(\mathbf{x}, \mathbf{y}) \leq 1$.
3. Unique maximum : $S(\mathbf{x}, \mathbf{y}) = 1$ if and only if $\mathbf{x} = \mathbf{y}$ (in discrete presentations, $x_i = y_i, \forall i = 1, 2, ..., N$)

4.4 Simulation Results

In this section we will present the results of the experiment. To demonstrate the performance of these five methods of histogram equalization namely global histogram equalization(GHE), contrast limited adaptive histogram equalization(CLAHE), brightness preserving bi-histogram equalization(BBHE), dualistic sub-image histogram equalization(DSIHE) and recursive mean separated histogram equalization(RMSHE), a simultaneous experiment on several images have been conducted. We present the results on two representative TIFF images namely $Tungsten-filament$, and $Barbara$. Both images are obtained from (3) and both are $8-bit$ gray scale images. Simulation results are presented in

We compare the results of these five methods using error sensitivity measures as well as measures that are based on human visualization system. Mean squared error(MSE), peak signal to noise ration(PSNR) and structural similarity index(SSIM) are being used as a performance metrics.

Methods	Mean	SD	SSIM	MSE	PSNR
Tungsten filament	128.11	75.31	–	–	–
GHE	127.71	73.5	0.79991	478.83	21.32
CLAHE	130.42	130.42	0.82845	347.37	22.72
BBHE	150.5	69.05	0.80593	843.65	18.86
DSIHE	140.43	72.94	0.79856	533.68	20.85
RMSHE	**133.99**	**79.97**	**0.90909**	**139.46**	**26.68**

Table 4.1: Comparison of various histogram equalization methods using objective image quality measures

Methods	Mean	SD	SSIM	MSE	PSNR
Barbara	111.5	48.15	–	–	–
GHE	127.48	73.88	0.875	969.18	18.26
CLAHE	124.24	63.91	0.824	999.86	18.13
BBHE	118.44	73.77	0.868	782.22	19.19
DSIHE	117.94	73.77	0.867	777.89	19.22
RMSHE	**115.93**	**61.01**	**0.937**	**243.36**	**24.26**

Table 4.2: Comparison of various histogram equalization methods using objective image quality measures

4.5 Visual Assessment

Visual evaluation of image quality is a highly subjective process, When an image is processed for visual interpretation, the viewer is the ultimate judge of how well a particular method works. In this section we will describe visual assessment foe figure 4.1 and figure 4.2.

Figure 4.1 shows the result of contrast enhancement on the image $Tungsten-filamnent$ using the five methods(GHE, CLAHE, BBHE, DSIHE and RMSHE) mentioned above. Among the five methods the RMSHE method yields the best improvement of contrast while preserving the mean brightness of the original image. The background detail of the image f) is better visible than the other processed image.In the original image, the background detail is quite dark and less visible in CLAHE comparative to the other processed image. BBHE and RMSHE makes the dark area into a bright area. Thus overall seems that RMSHE gives the most visually pleasing results.

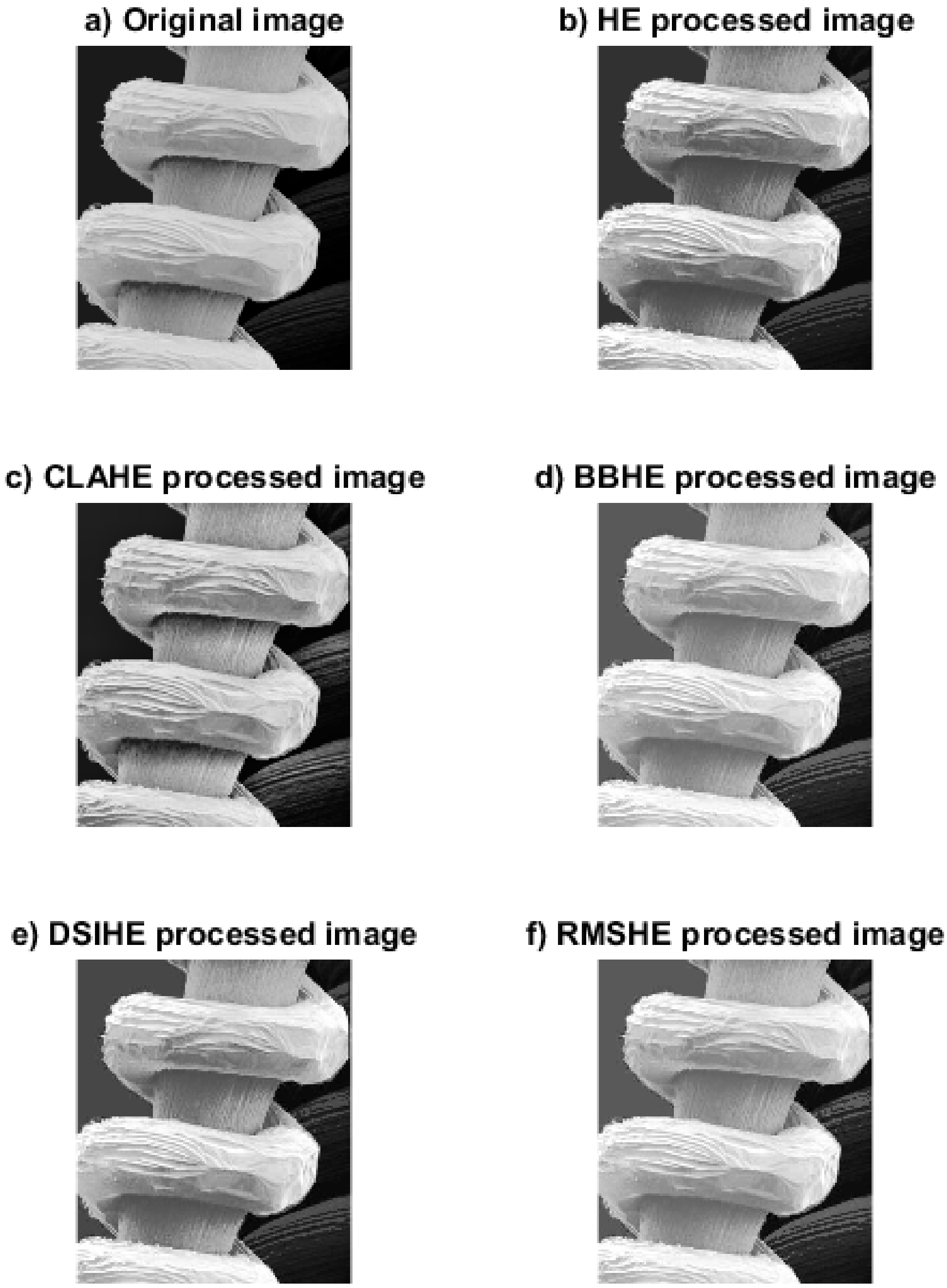

FIGURE 4.1: Contrast enhancement of $Tungsten-filament$ image. The images are a)Original image b)GHE processed image c) CLAHE Processed image d) BBHE processed image e)DSIHE processed image and f) RMSHE processed image.

Figure 4.2 shows the result of contrast enhancement on the image *Barbara* using the five competing methods. The original one is an image of women.It seems that original image is little bit blurry and the image is quite dark. GHE enhanced the image and it looks brighter.It increases both the mean brightness and contrast of the original image. CLAHE amplifies the noise especially in background and right portion of face. BBHE preserve the mean brightness but increases contrast . So, the image looks brighter especially in the right portion of the image. DSIHE enhanced the overall image in a way which is almost similar to GHE in this case .It increases both the mean brightness and contrast which gives the image a slightly better look. The Visual appearance of both GHE and DSIHE processed image is almost same here and quite impossible to differentiate them. RMSHE enhanced the image preserving the mean brightness and it looks more similar to the original image.

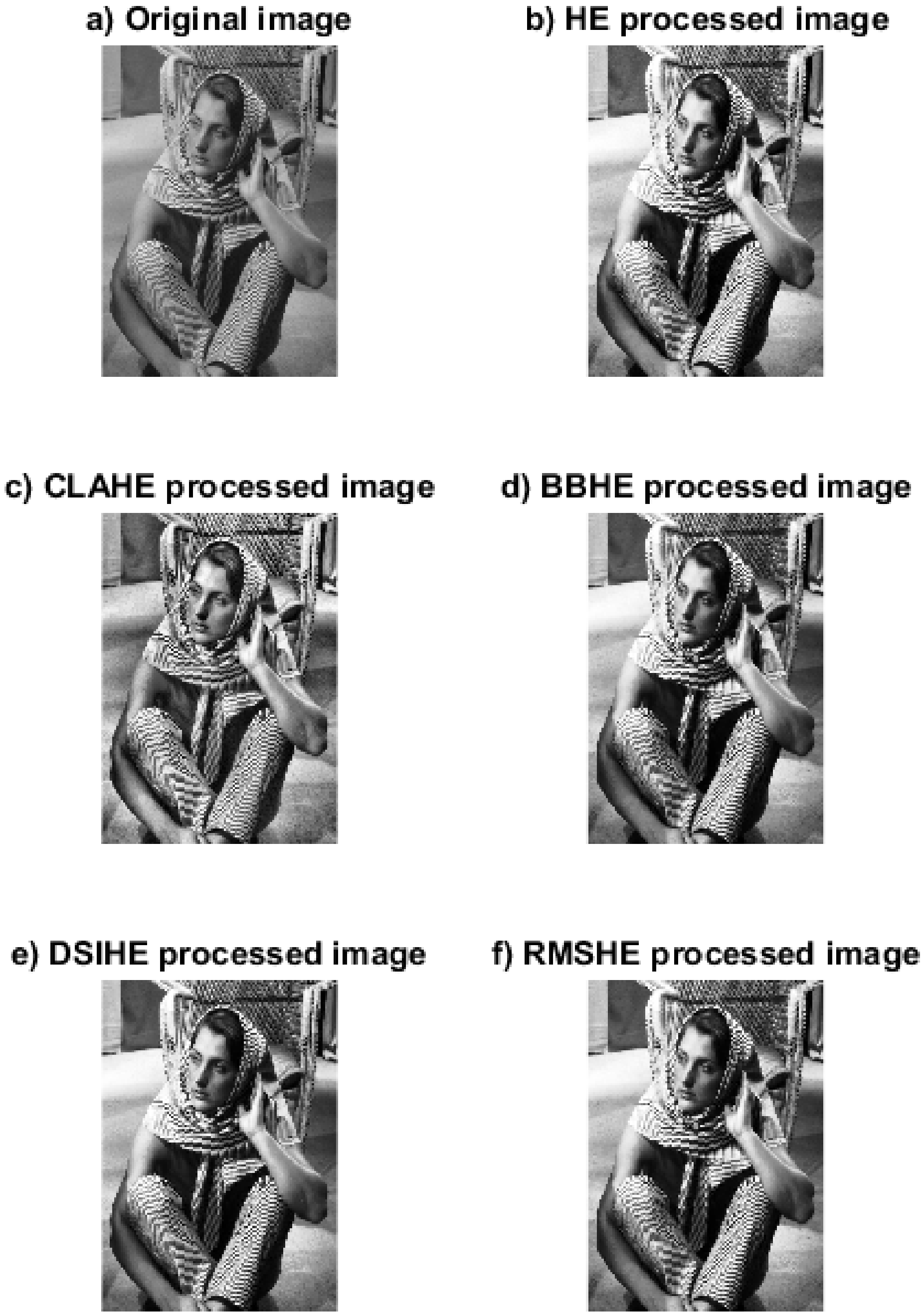

FIGURE 4.2: Contrast enhancement of *Barbara* image. The images are a)Original image b)GHE processed image c) CLAHE Processed image d) BBHE processed image e)DSIHE processed image and f) RMSHE processed image.

4.6 Result Based on Objective Assessment

In this study, we use mean squared error(MSE), peak signal to noise ratio(PSNR) and structural similarity index(SSIM) as a performance metric to assess the quality of an image.

A lower value of MSE means lower error. As we have seen before, there lies an inverse relationship between MSE and PSNR. which means a lower value of MSE translate to a high value of PSNR. Higher value of PSNR is good because it means that the ratio of signal to noise is higher. Here the signal is the original image and the noise is the error in reconstruction. So, a lower MSE value as well as a higher PSNR indicates a better image.

The SSIM value varies between 0 to 1. SSIM value 1 means the image is in best quality. So, the image with SSIM value 1 or close to 1 refers to as most structured image that possess the maximum quality.

Table 4.1 and Table 4.2 contains results for $Tungsten - filament$ and $Barbara$ image. From the table we see that for both images, recursive mean separated histogram equalization(RMSHE) has the smallest MSE, highest PSNR and highest SSIM value. Thus according to these performance metrics, RMSHE method works better than the other methods.

4.7 Scope for Further Research

In this study we compare five most frequently used histogram equalization methods. But there are other histogram equalization methods which can also be used. This study has been carried out only for the gray-scale $8 - bit$ images, it can be extended to color images. Here, we use recursion level, r = 2 to compute RMSHE. But it can be extended for higher recursion level. Research can also be conducted to find the proper mechanism that automatically selects the recursion level, r which gives the optimum output.

Chapter 5

Conclusion

Image processing is the manipulation of pictorial information to enhance and evaluate the visual qualities of the original image .Often the quality of an image is more often linked to its contrast and brightness levels which can be obtained from the gray level values. Image histogram is an important concept which provides probability of each gray level in a digital image. image enhancement based on histogram processing has been very popular because of its simplicity and effectiveness. Histogram can be processed mainly by two techniques, histogram equalization and histogram matching.

Histogram equalization is an essential technique in image enhancement. This study deals with five widely used histogram equalization technique namely global histogram equalization(GHE), contrast limited adaptive histogram equalization(CLAHE), brightness preserving bi-histogram equalization(BBHE), dualistic sub-image histogram equalization(DSIHE) and recursive mean separated histogram equalization(RMSHE).

GHE is the fundamental technique for image processing.The aim of this method is to distribute the given number of gray levels over a range uniformly, thus enhancing its contrast. But there are cases where we were to deal with local enhancement rather than overall enhancement.Contrast limited adaptive histogram equalization solves the problem of local enhancement as well as over-amplification of noise problem caused by local histogram equalization. But for both GHE and CLAHE, the transformed image mean is changed irrespective of the original image.In most cases preservation of the mean brightness of the original image is necessary. Brightness preserving bi-histogram equalization(BBHE) is a novel extension of the GHE. It divides the original image into two sub images according to the mean. Then the GHE is performed independently on both sub-images. The ultimate goal of BBHE is to preserve the mean brightness of the original image while enhancing the contrast of the original image. Dualistic sub-image histogram equalization(DSIHE) done the same except it divide the original image into two sub-images according to the median. A novel extension of BBHE is recursive mean separated histogram equalization.when more brightness preservation is required, separated histogram based on mean can further be separated based on their respective mean. This is exactly happened when we conduct rmshe. We observed that the brightness preservation is not handled well by HE,CLAHE, BBHE and DSIHE, but it can be handled properly by RMSHE. RMSHE can not only enhance image information effectively but also keep the original image luminance well enough.

Comparison among these techniques are carried out based on MSE, PSNR and SSIM. The simulation result shows that RMSHE provides the best output for the compared to other four methods.

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