CHAPTER 1

INTRODUCTION

Due to portability and easy implementation, digital camera has become an additional multipurpose function embedded in cell phone by many manufacturers. However, the quality of the images captured using cell phone camera is usually poor as a result of low contrast [1]. In low-light environment(e.g.,in a dark room or during night time), the lacking in natural light-source leads to poor and lowly contrasted images. To overcome this drawback, recently light emitting diodes (LEDs) are used to assist in the dark environment [2]. However, in long distance image captures, the lighting from LEDs is insufficient to brighten the course between the image capturing device and the object. Moreover, the lighting from LEDs is reflected during capturing in some cases; especially the subject of the image involves transparent glasses, such as an aquarium. In either case, the image captured produces annoying artifacts as a result of low contrast.

Here, a histogram equalization (HE)-based technique, called **Quadrant dynamic histogram equalization (QDHE)**, for digital images captured from consumer electronic devices.

Initially, the proposed QDHE algorithm separates the histogram into four (quadrant) sub-histograms based on the median of the input image. Then, the resultant sub-histograms are clipped according to the mean of intensity occurrence of input image before new dynamic range is assigned to each sub-histogram. Finally, each sub-histogram is equalized. Based on extensive simulation results, the QDHE method outperforms some methods existing in literature, which can be considered as state-of-the-arts, by producing clearer enhanced images without any intensity saturation, noise amplification, and over-enhancement.

1.1 Applications

Medical diagnosis:

The QDHE algorithm has been used to enhance images of medical scans, such as X-rays and CT scans. This can help doctors to identify abnormalities that may not be visible in the original images.

Image processing:

The QDHE algorithm has been used to enhance images for a variety of purposes, such as image compression, image restoration, and image segmentation.

Computer vision:

The QDHE algorithm has been used to improve the performance of computer vision algorithms, such as object detection and recognition. The QDHE algorithm is a versatile and effective technique for image enhancement. It can be used to improve the quality of images for a variety of applications.

1.2 Literature Survey

Quadrants dynamic histogram equalization (QDHE) is a technique that is used to improve the contrast of images by dividing the image into four quadrants and then applying histogram equalization to each quadrant separately. This can help to reduce the problem of over-enhancement that can sometimes occur with global histogram equalization.

The QDHE technique was first introduced in the paper "Quadrants dynamic histogram equalization for contrast enhancement" by Ooi and Isa (2010). The authors showed that QDHE can reduce the problem of over-enhancement and improve the contrast of images with a wide range of brightness values. Since then, there have been a number of other papers that have investigated the QDHE technique and proposed improvements to the algorithm. For example, Chen and

Ramli (2012) proposed a method for adaptively selecting the dynamic range for each quadrant. Li and Li (2014) proposed a method for improving the contrast of images with low contrast. Hassan and El-Sakka (2015) proposed a hybrid contrast enhancement technique that combines QDHE with other techniques.

Overall, the QDHE technique is a powerful technique that can be used to improve the contrast of images. It is effective in reducing the problem of over-enhancement and can be used to improve the contrast of images with a wide range of brightness values. However, it is important to use QDHE carefully to avoid introducing artifacts into the image.

1.3 Histogram Equalization

For contrast enhancement, histogram equalization (HE) [3] is a simple and widely utilized method in literature. The fundamental idea of HE is to remap the intensity values of the input image into new intensity levels through a transform function created from cumulative density function (cdf). Although this method is capable to increase the contrast of an image, the enhanced image tends to have unnatural enhancement and intensity saturation artifacts, due to the error in brightness mean-shifting [4].

1.4 Drawbacks of Histogram Equalization

Although this method is capable to increase the contrast of an image, the enhanced image tends to have unnatural enhancement and intensity saturation artifacts, due to the error in brightness mean-shifting [4]. In order to overcome the limitations of HE, several brightness preserving methods have been proposed [5]-[10].

1.5 Objectives of the Present Study

Some potential objectives of **Quadrants Dynamic Histogram Equalization (QDHE)** in image processing are as follows:

1.Enhanced Contrast

2.Preservation of Local Details

3.Adaptability to Image Content

4.Reduction of Artifacts

5.Improved Visual Quality

1.6 Scope of the Present Study

To achieve above mentioned objectives, the thesis is divided into five chapters. The First chapter deals with the introduction, literature survey, objectives and scope of the present study. The Second chapter Briefs about the existing algorithms that is variants of Histogram Equalization with their methodologies and results. The Third chapter Briefs about the proposed algorithm along with their methodology and results. The Fourth chapter describes the experimental setup and results between the existing algorithms and local derivative pattern is compared. Finally, the conclusion is well described in the chapter 5.

CHAPTER 2

VARIANTS OF HISTOGRAM EQUALIZATION

2.1 Histogram Equalization

2.1.1 Introduction

Histogram Equalization is like tuning the contrast of an image by redistributing pixel intensities, enhancing its overall visibility and detail. It balances the histogram to spread out pixel values, maximizing the dynamic range for improved visual clarity.

2.1.2 Methodology

Histogram equalization is a popular technique in image processing used to enhance the contrast and overall visual quality of an image. It works by redistributing the pixel intensities in a way that maximizes the utilization of the available intensity range. The process involves calculating the histogram of the image, which represents the frequency of occurrence of each pixel intensity level. Then, a cumulative distribution function is computed, and the pixel intensities are transformed based on this function. By stretching the histogram across the entire intensity range, histogram equalization can effectively amplify details and bring out hidden features. This technique finds applications in various domains, including computer vision, medical imaging, and digital photography, enabling images to appear more vibrant and visually appealing.

For contrast enhancement, histogram equalization (HE) [3] is a simple and widely utilized method in literature. The fundamental idea of HE is to remap the intensity values of the input image into new intensity levels through a transform function created from cumulative density function (cdf). Although this method is capable to increase the contrast of an image, the enhanced image tends to have unnatural enhancement and intensity saturation artifacts, errorin brightness mean-shifting

2.1.3 Results

Based on Figs. 2.1(a), 2.1(b) and 2.1(c), the conventional HE is able to successfully enhance the contrast of those images. However, it also amplifies the noise level of the images. Moreover, the tendency for the conventional HE to produce intensity saturation is very high. It can be seen at the small stones with bright intensity in Figs. 2.1(b) and 2.1(c).

Fig:2.1(a)

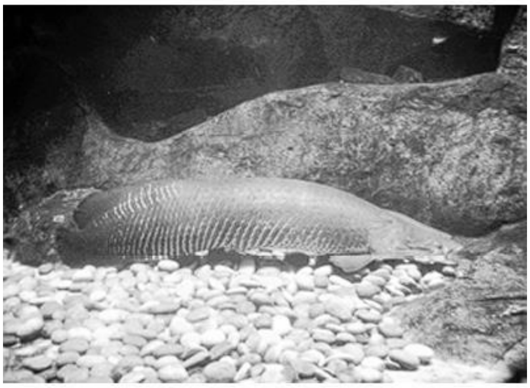


Fig:2.1(b)

Fig:2.1(c)

This is proven in Fig. 2.1(d) below as the HE-ed histogram is concentrated on the right side of the histogram

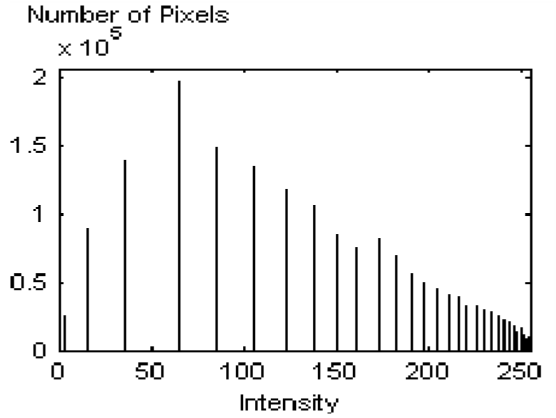


Fig:2.1(d)

2.2 Mean Brightness Preserving Bi-Histogram Equalization

2.2.1 Introduction

Mean Brightness Preserving Bi-Histogram Equalization retains the average brightness of an image while enhancing its contrast through dual histogram manipulation, ensuring balanced enhancement without altering the overall luminance. It partitions the histogram into two segments, preserving the mean brightness during the intensity redistribution process for nuanced image enhancement

2.2.2 Methodology

One of the popular PHE-based methods is the meanbrightness preserving bi-histogram equalization (BBHE) introduced by Kim [5]. At the beginning, the BBHE divides the original histogram into two sub-histograms based on the mean brightness of the input image. Then, HE is implemented independently in each sub-histogram. Consequently, the mean brightness can be preserved because the original mean brightness is retained.

2.2.3 Results

For the BBHE method, the contrast of the image is improved, but the problem of intensity saturation occurs in some regions of the image as well. This problem can be clearly demonstrated on the human objects in Figs. 2.2(a); the background of the ‘Fish ’ image in Figs. 2.2(b); and the fish body of the

Fig:2.2(a)

Fig:2.2(b)

Fig:2.2(c)

Fish’ image in Figs. 2.2(c). From the experimental results, the drawback of these four methods is obviously seen by only preserving the mean brightness of the images without emphasizing on the image details significantly.

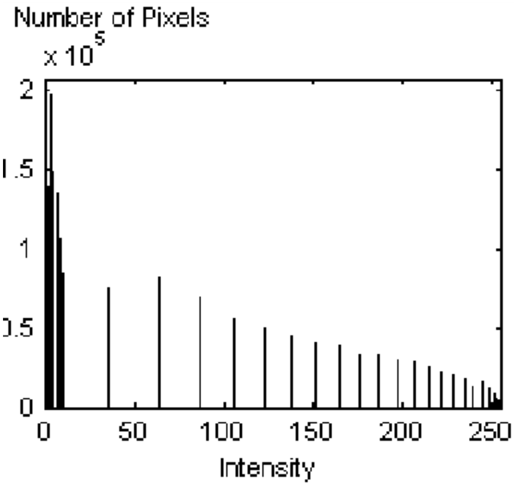


Fig:2.2(d)

In addition, the 'Fish 2.2(b)' image histogram of the BBHE method in Figs. 2.2(d) respectively, obviously show that the sub-histogram at the left side in each histogram is not successfully expanded

2.3 Recursive Mean - Separate Histogram Equalization

2.3.1 Introduction

Recursive Mean-Separate Histogram Equalization iteratively enhances image contrast by recursively partitioning the histogram and equalizing each segment independently, preserving local brightness and improving overall visual quality with reduced artifacts. It refines contrast enhancement by iteratively applying histogram equalization to smaller regions, ensuring fine-grained adjustments while maintaining image fidelity.

2.3.2 Methodology

In addition, another version of the BBHE, called recursive mean-separate histogram equalization (RMSHE) is also proposed by Chen and Ramli [8]. This method recursively separates the histogram into multi sub-histograms instead of two sub-histograms as in the BBHE. Initially, two sub- histograms are created based on the mean brightness of the original histogram. Subsequently, the means brightness from the two sub-histograms obtained earlier are used as the second and third separating points in creating more sub-histograms. In a similar fashion, the algorithm is executed recursivelyuntil the desired numbers of sub-histograms are met. Then, the HE approach is applied independently on each of the sub- histogram. A similar recursive technique based on median of the input histogram segmentation, called the recursive sub- image histogram equalization (RSIHE), is proposed by Sim *et al*. in [9]. However, no significant enhancement is performed by the RMSHE and RSIHE when the number of divided sub- histograms is large.

2.3.3 Results

For the RMSHE, RSIHE methods, the contrast of the images are improved, but the problem of intensity saturation occurs in some regions of the image as well. This problem can be clearly demonstrated on the human objects in Figs. 2.3(a), 2.3(b)

Fig 2.3(a)

Fig 2.3(b)

The background of the 'Fish ' image in Figs. 2.3(c), 2.3(d) ; and the fish body of the 'Fish' image in Figs. 2.3(e) and 2.3(f) . From the experimental results, the drawback of these four methods is obviously seen by only preserving the mean brightness of the images without emphasizing on the image details significantly.

Fig 2.3(c)

Fig 2.3(d)

Fig 2.3(e)

Fig 2.3(f)

In addition, the ‘Fish 2’ image histograms of the RMSHE, RSIHE methods in Figs. 2.3(g) and 2.3(h) respectively, obviously show that the sub-histogram at the left side in each histogram is not successfully expanded.

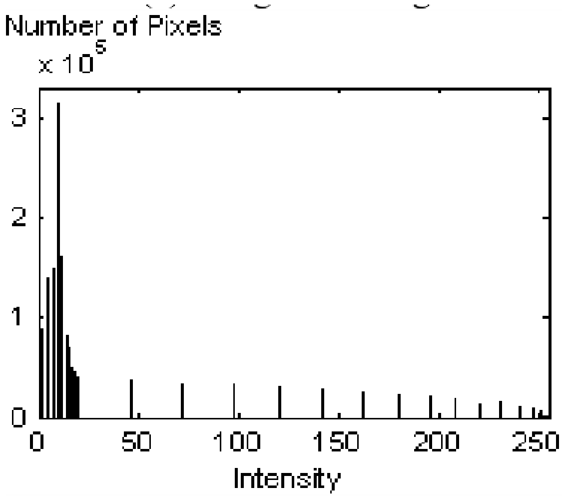


Fig 2.3(g)

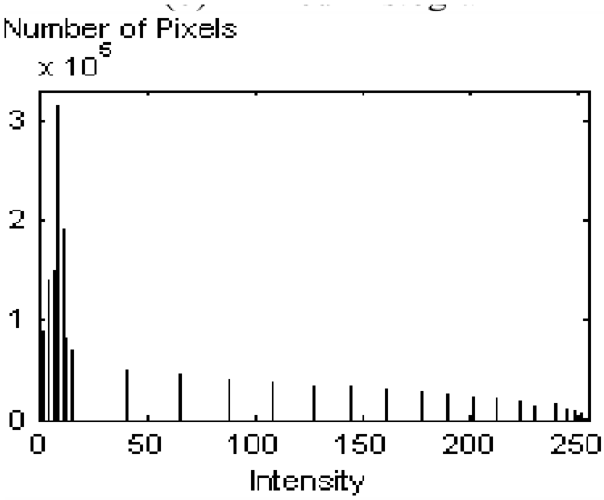


Fig 2.3(h)

2.4 Bi Histogram Equalization Plateau Limit

2.4.1 Introduction

Bi-Histogram Equalization Plateau Limit prevents over-enhancement by limiting contrast adjustment in regions where the histogram is already sufficiently spread, maintaining natural image appearance and preventing artifacts. It establishes a threshold to prevent excessive contrast enhancement in areas with already broad histograms, preserving image integrity and preventing unrealistic visual effects.

2.4.2 Methodology

Recently, the bi-histogram equalization plateau limit (BHEPL) is proposed in [10] to control the enhancement rateof the BBHE. In general, the BBHE applies more stretching process to the contrast of high histogram regions and compresses the contrast of low histogram regions. This may cause intensity saturation as the intensities are squeezed in the low histogram regions. In order to deal with the intensity saturation problem, a clipping process is applied to each sub- histogram of the BBHE in order to control the enhancementrate by setting the plateau limit as the average number of intensity occurrence. If the bins for any intensity exceed the plateau limit, those bins will be replaced by the level of plateaulimit; otherwise remain the same as original bins of the input histogram. Finally, the HE is implemented to the clipped sub- histograms. By doing this, the resultant image will maintain themean brightness of the original image without suffering from intensity saturation and over-enhancement.

2.4.3 Results

For the BHEPL method, the contrast of the image is improved, but the problem of intensity saturation occurs in some regions of the image as well. This problem can be clearly demonstrated on the human objects in Figs: 3(h); the background of the ‘Fish 1’ image in Fig:4(h); and the fish body of the ‘Fish 2’ image in Fig:5(h).

Fig 2.4(a)

Fig 2.4(b)

Fig 2.4(c)

From the experimental results, the drawback of these four methods is obviously seen by only preserving the mean brightness of the images without emphasizing on the image details significantly.

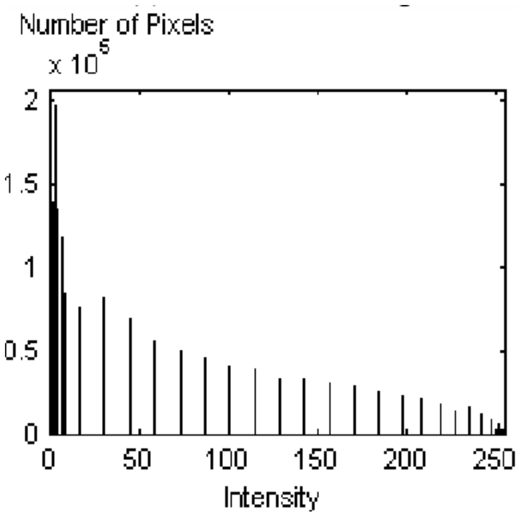


Fig 2.4(d)

In addition, the ‘Fish 2’ image histograms of the BHEPL methods in Figs. 2.4(d), respectively, obviously show that the sub-histogram at the left side in each histogram is not successfully expanded.

2.5 Dynamic Histogram Equalization

2.5.1 Introduction

Dynamic Histogram Equalization dynamically adjusts contrast based on local image characteristics, effectively enhancing details in both bright and dark regions for improved visual clarity and depth. By adaptively redistributing pixel intensities, it ensures optimal contrast enhancement across varying regions of the image, enhancing overall perceptual quality.

2.5.2 Methodology

For DPHE, there are only two methods existing in literature. The first method is the dynamic histogram equalization (DHE), proposed by Wadud *et al.* in [11]. Without using the mean and median for partitioning, the DHE partitions the original histogram based on local minima. In order to eliminate the spikes and voids in the histogram, a 1×3 smoothing filter is applied across the image. Then, a new dynamic range is assigned to each sub-histogram based on the original dynamic range and the number of pixels in that sub-histogram. Generally, the DHE does not consider the mean brightness preservation. Moreover, the 1×3 smoothing filter is constructed for brightness preserving. Thus, the DHE may cause saturation and it is insufficient to smooth a noisy histogram. As a result, the local minima will be wrongly misclassified and increase thecomplexity of the algorithm.

2.5.3 Results

Among the implemented state-of-the-art methods, in terms of enhancing the contrast as well as preserving the image details, the DHE outperforms other conventional methods. However, the DHE tends to produce noise artifacts on the images (i.e., as shown on the sky region of the “Genting” image and the background of Fig. 2.5(a)) and intensity saturation (i.e., as shown on small bright stone regions of the Fig. 2.5(b).

Fig 2.5(a)

Fig 2.5(b)

Moreover, the evidence of the intensity saturation problem is clearly shown in Fig. 2.5(c) where the DHE method only stretches the intensity range of the ‘Fish 2’ image with high pixels distribution, while intensity range with low pixels distribution is suppressed.

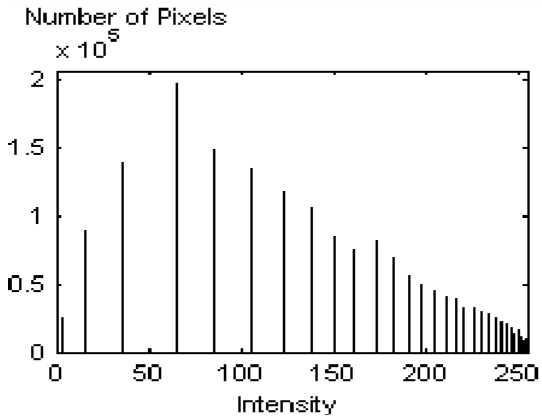


Fig 2.1(d)

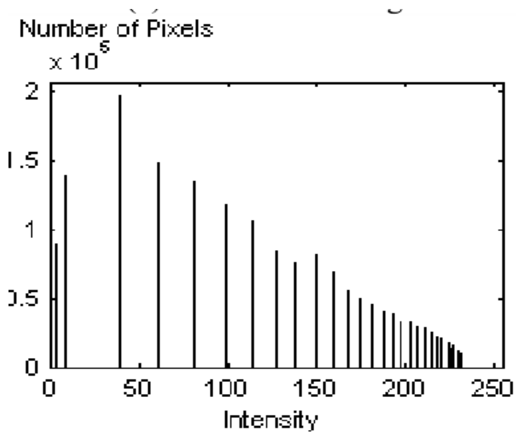


Fig 2.5(c)

2.6 Brightness Preserving Dynamic Histogram Equalization

2.6.1 Introduction

Brightness Preserving Dynamic Histogram Equalization maintains the average brightness of an image while dynamically enhancing contrast, ensuring natural-looking results with improved visual detail. By adaptively redistributing pixel intensities based on local image characteristics, it optimizes contrast enhancement without altering the overall luminance, preserving the image's natural appearance.

2.6.2 Methodology

The second DPHE-based method is the brightness preserving dynamic histogram equalization (BPDHE) proposed by Ibrahim and Kang [12]. Generally, the BPDHE is the improvement of the DHE. Similarly, a smoothing filter is applied to histogram before the histogram partitioning process is carried out. Conversely, the BPDHE uses the local maxima as the separating point rather than the local minima. For this reason, Ibrahim and Kang claim that the local maxima are better for mean brightness preservation. After the HE is implemented to each sub-histogram, brightness normalization is used to ensure the enhanced meanbrightness as a close approximation to the original mean brightness. Although the BPDHE performs well in mean brightness preserving, the ratio for brightness normalization plays an important role. A small ratio value leads to insignificant contrast enhancement. For large ratio (i.e., ratio value more than 1), the final intensity value may exceed the maximum intensity value of the output dynamic range. The exceed pixels will be quantized to the maximum intensity value of gray levels and produce intensity saturation problem (in MATLAB environment).

2.6.3 Results

The BPDHE method produces the worst performance. It fails to perform well when applied on low contrast images. The small value from the ratio of brightness normalization (i.e. less than 0.1) causes loss of image details and insignificant contrast enhancement .As shown in the Fig. 2.6(a), the histogram of the ‘Fish 2’ image is equalized and concentrated only on the left side of the histogram.

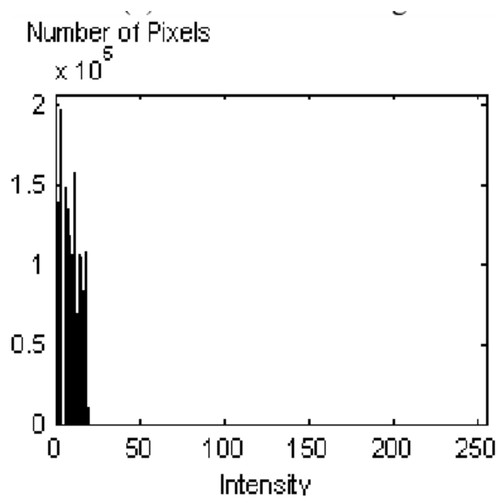


Fig 2.6(a)

2.7 Summary

It is mentioned that the scope of this work focuses on enhancement of images obtained low illumination environment. Therefore, proposed a **novel DPHE- based method, named quadrants dynamic histogram equalization (QDHE),** by dividing the original histogram into four sub-histograms (i.e., quadrants) based on the median brightness of the input image as the separating points. However, before the original histogram is partitioned, a clipping process is used to manipulate the enhancement rate based on the average number of intensity occurrence. Then, each sub-histogram is assigned with a new dynamic range. Finally, the HE approach is applied independently on each sub-histogram.

CHAPTER 3

QUADRANTS DYNAMIC HISTOGRAM EQUALIZATION

3.1 Introduction

Quadrants Dynamic Histogram Equalization (QDHE) is an advanced image processing technique designed to enhance image contrast while preserving critical details and minimizing artefacts. Unlike traditional histogram equalization methods that apply uniform transformations to entire images, QDHE operates on distinct quadrants or regions within an image. By segmenting the image into smaller parts and applying adaptive histogram equalization techniques to each quadrant independently, QDHE ensures that local details are effectively preserved and enhanced, leading to superior visual quality and improved perceptual balance.

This approach makes QDHE particularly well-suited for applications such as medical imaging, remote sensing, surveillance, digital photography, and industrial inspection, where the accurate representation of image features is crucial. By dynamically adjusting the histogram equalization process based on the characteristics of each quadrant, QDHE offers enhanced flexibility, adaptability, and performance compared to traditional methods, making it a valuable tool for a wide range of image enhancement tasks in various domains.

Quadrants Dynamic Histogram Equalization (QDHE) is renowned for its ability to adaptively process images, tailoring enhancement techniques to specific regions within an image. This fine-grained approach ensures that contrast enhancement is applied where needed, preserving nuances and avoiding over-amplification in homogeneous areas. QDHE's effectiveness lies in its capacity to mitigate artifacts commonly associated with global histogram equalization.

3.2 Methodology

The QDHE consists of four processes, namely the histogram partitioning, clipping, gray level range allocation and histogramequalization.

3.2.1 Histogram Partitioning:

As mentioned previously, the separating point based on local minima and maxima in the DHE and BPDHE, respectively, may be falsely detected due to the noisy input histogram, even a smoothing filter is first applied prior to partitioning the histogram. Therefore, the QDHE utilizes the median intensity value of the input image histogram in partitioning the histogram. Initially, the histogram of the original image is divided into two sub-histograms. Similarly, the medians from the two partitioned sub-histograms are used as separating points to further divide the two sub-histograms into two smaller sub-histograms each. Thus, there are a total of four sub-histograms obtained. Then, the minimum and maximum intensity values of the input histogram are set as the separatingpoints.

The partitioning approach used in the QDHE algorithm is similar to the RSIHE (*r*=2, where *r* is the recursion level). The median-based partition approach tends to segment the number of pixels equally in each sub-histogram. Hence, each separating point can be calculated using the following equations:

M1 = 0.25 * { I width * I height }-------------------------------- (1)

M2 = 0.50 * { I width * I height }-------------------------------- (2)

M3 = 0.275 * { I width * I height } --------------------------------(3)

where m_1, m_2 and m_3 are intensities set to 0.25, 0.50 and 0.75, respectively, for the total number of pixels in the histogram of the input image. I_{width} and I_{height} represent the width and height of the input image, respectively.

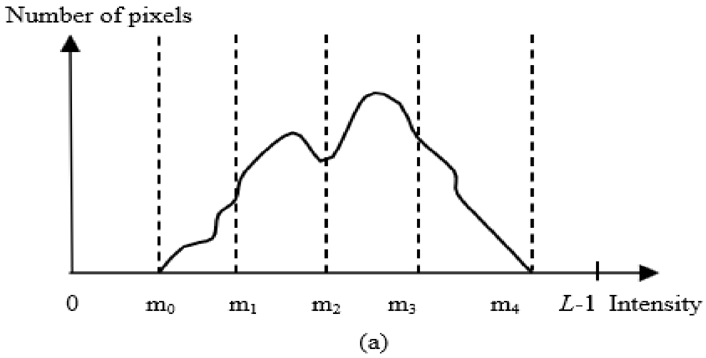


Fig 3(a) Histogram Partitioning

3.2.2 Clipping Process:

The reason behind the clipping process is to control the enhancement rate of HE in order to overcome unnatural and over-enhancement of the processed image to occur. An automatic clipping process, the self-adaptive plateau histogram equalization (SAPHE) [13] initially introduced by Wang et. al. for the infrared image contrast enhancement. However, the algorithm may fail to implement in the natural image due to unsuccessful local peak detection. Thus, a modified-SAPHE [14] is introduced to locate median value ofthe non-empty bins as the clipping threshold, T_c. However, in order to reduce the computational complexity, T_c is replaced by the average of the number of intensity in the proposed QDHE. The clipping process is illustrated in Figs. 3(b) and 3(c). A clipping threshold value is set to the histogram in Fig. 3(b). Then, bins with higher value than the threshold value are replaced by the threshold value itself as shown in Fig. 3(c).

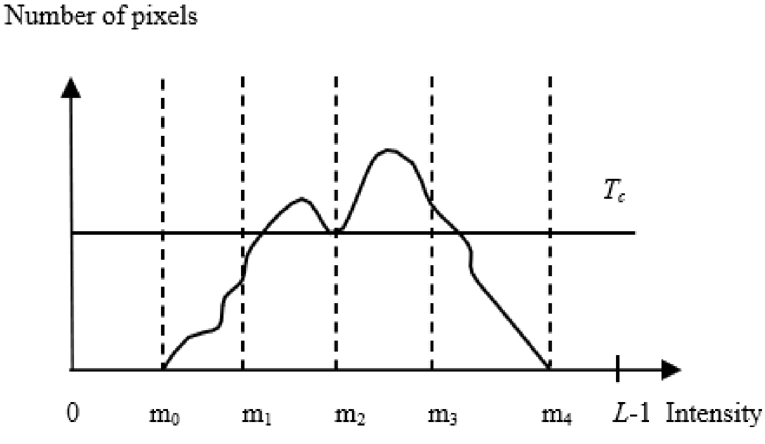


Fig 3(b) Before Clipping

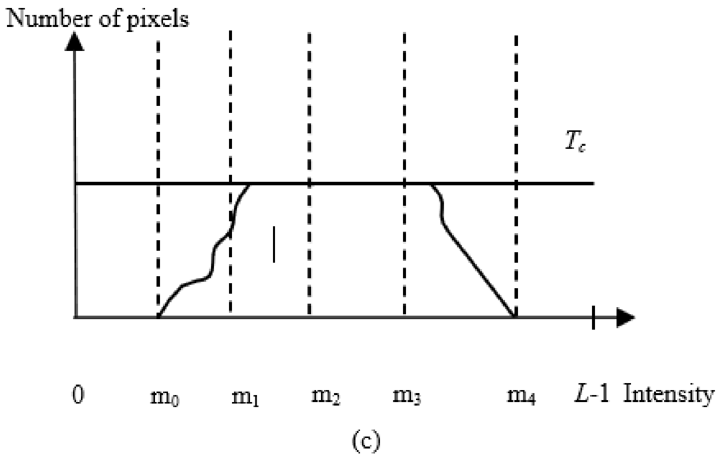
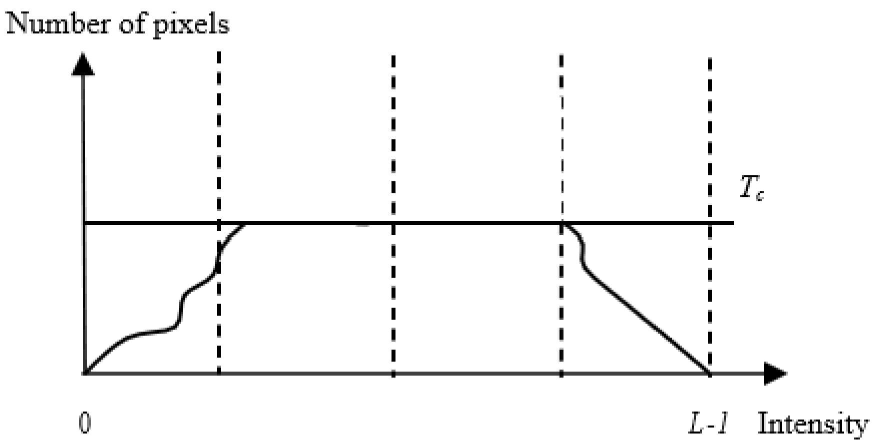


Fig 3(c) After Clipping

3.2.3 New Gray Level Allocation:

PHE-based methods only perform the enhancement process in each sub-histogram between two separating points. Thus, the sub-histograms may not ensure the balance space in each sub-histogram for sufficient contrast enhancement. This is because contrast enhancement obtained in a narrow stretching space is less significant and wide stretching space introduces redundant contrast enhancement. This phenomenon particularly occurs when the side of the sub-histogram is narrow. Consequently, the processed image tends to suffer from loss of image details and intensity saturation artifact.



(d)

Fig 3(d) After new Gray Level Allocation

In order to balance the enhancement space for each sub- histogram, the proposed QDHE allocates a new gray level dynamic range based on the ratio of gray level spans and total number of pixels for each sub-histogram. This concept is also adopted by the DHE. Mathematically, this process is describedas follows:

$$span_i = m_{i+1} - m_i$$

$$factor_i = span_i \times (\log_{10} M_i)^{\gamma}$$

$$range_i = (L-1) \times factor_i / \sum_{k=1}^{4} factor_k$$

where span i is the dynamic gray level used by i-th sub- histogram in the input image. mi is the i-th separating point, Mi is the total number of pixels in i-th sub-histogram. Range I is given as the dynamic level range for i-th sub-histogram in the output image and Û is the amount of emphasis given to Mi. Thus, Û can be adjusted by user to determine the span of each sub-histogram in the output histogram. Since the proposed QDHE method consists of almost equal total number of pixels in each sub-histogram, thus, (5) does not significantly affect the new dynamic range. In order to reduce the complexity of the QDHE and remove the parameter Û, (6) can be re-written as:

$$range = (L - 1) \times span / \sum 4\ span$$

In the I - th sub-histogram the new dynamic range is allocated from [I start I end] defined by below equations respectively.

$$I\ start = (i - 1)\ end + 1$$

$$I\ \ end = I\ start + range\ i$$

The first I start value is initialized to the minimum intensity value of the new dynamic range. An example of locating new dynamic is presented in Fig.3(d).

3.2.4 Histogram Equalization:

After the new dynamic ranges have been determined for all the quadrant sub-histograms, the final step in the QDHE is to equalize each sub-histogram independently. If the I - th histogram is allocated at gray level from [I start I end], then the output of histogram equalization, y(x) of this partition can be determined by using the transfer mapping function below

$$y(x) = (I\ start - I\ end\ ) \times cdf\ \ (X\ k\ ) + I\ start$$

where cdf (Xk) is the cumulative density function in that sub histogram. In equation above general HE equation is used but I *start* and I *end* are used instead of the minimum and maximum intensities in the output dynamic range.

3.3 Results and Discussions

In this section, we demonstrate the performance of the proposed QDHE method by comparing with the conventional HE-based method .

HE (Histogram Equalization) –

Histogram equalization (HE) is an image processing technique that enhances contrast by redistributing intensity values across the histogram. By spreading out intensity levels, it improves visual quality and detail, especially in images with low contrast or uneven lighting. However, it may amplify existing noise or artifacts.

QDHE(Quadrants Dynamic Histogram Equalization) –

A histogram equalization (HE)-based technique, called quadrant dynamic histogram equalization (QDHE), for digital images captured from consumer electronic devices. Initially, the proposed QDHE algorithm separates the histogram into four (quadrant) sub-histograms based on the median of the input image. Then, the resultant sub-histograms are clipped according to the mean of intensity occurrence of input image before new dynamic range is assigned to each sub-histogram. Finally, each sub-histogram is equalized. Based on extensive simulation results, the QDHE method outperforms some methods existing in literature, which can be considered as state-of-the-arts, by producing clearer enhanced images without any intensity saturation, noise amplification, and over-enhancement. Furthermore, image details of the processed image are well preserved and highlighted. For this reason, the proposed QDHE algorithm is suitable for images captured in low-light environments – an unavoidable situation by many consumer electronics products such as camera devices in cell phone

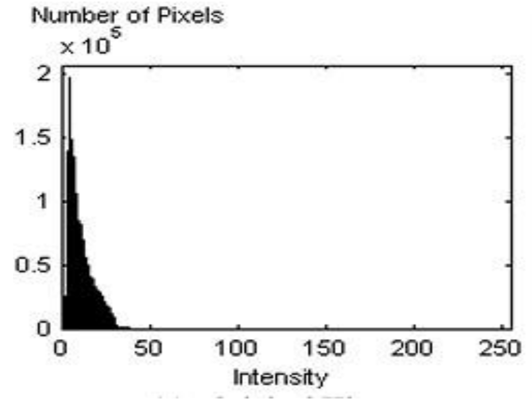


Fig 3.3(a)Original image

Fig 3.3(b)Original Histogram

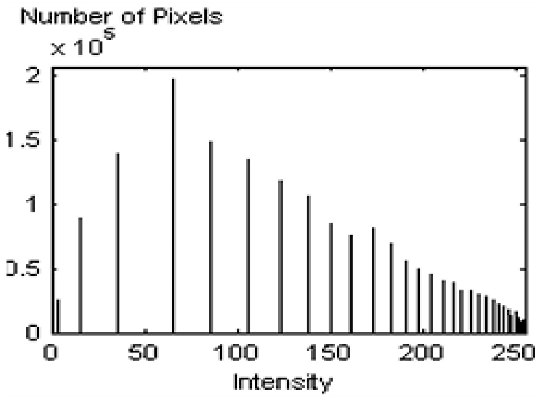


Fig 3.3(c) HE-d image

Fig 3.3(d) HE Histogram

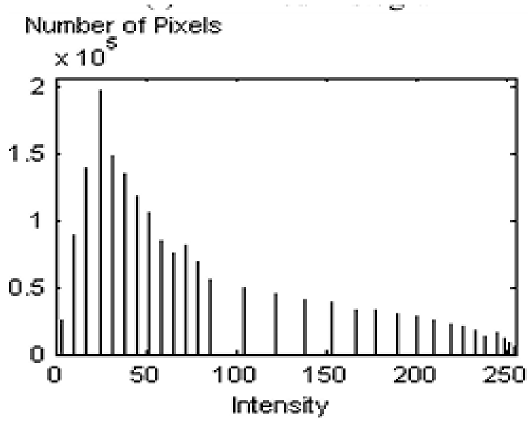


Fig 3.3(e) QDHE -d image

Fig 3.3(f) QDHE Histogram

3.3.1 Proposed QDHE Performance

The proposed QDHE method yields the best performance as compared to others. The contrast for all tested images is successfully enhanced; thus, producing better and clearer images. Furthermore, the QDHE method has successfully preserved image details .The concrete proof could be seen, for examples, at the faces of the people in fig.3i, the background, and the fish body of the fig.(5i). The problems of intensity saturation ,noise amplification, and over enhancement are avoided.Furthermore, the QDHE-ed histogram in Fig. 6i shows that the histogram is distributed more evenly than other conventional methods. All ranges of intensity level are evenly stretched and, thus, the details in all intensity level are successfully preserved and clearly highlighted.

3.3.2 Final Output

Fig 3.3.2 (a) Original image

Fig 3.3.2(b) HE-d Image

Fig 3.3.2(c) QDHE- d image

3.4 Summary

Based on extensive simulation results, the QDHE method outperforms some methods existing in literature, which can be considered as state-of-the-arts, by producing clearer enhanced images without any intensity saturation, noise amplification, and over-enhancement. Furthermore, image details of the processed image are well preserved and highlighted. For this reason, the proposed QDHE algorithm is suitable for images captured in low-light environments – an unavoidable situation by many consumer electronics products such as camera devices in cell phone

CHAPTER 4

QUALITATIVE & QUANTITATIVE ANALYSIS

4.1 Experimental Results

To further demonstrate the capability of proposed method in extracting the details from the images, the discrete entropy is performed as the quantitative evaluation The discrete entropy $E(x)$ is defined as:

$$E(x) = -\sum_{k=0}^{255} p(X_k) \times \log_2 p(X_k)$$

where $p(X_k)$ is the normalized probability of the k-th gray level. Higher value of the entropy indicates that more information is brought out from the images. The discrete entropy computedfor the methods implemented are tabulated in Table 1.

Table 1

Images	DISCRETE ENTROPY	SSIM-Structural Similarity Index	PSNR-Peak Signal-to-Noise Ratio
Original_image	5.0142155	—	—
HE	5.3386846	7.951348686125634	0.4405146156329332
QDHE	5.4497023	9.358995615242337	0.4940024729331975

According to Table I, the QDHE produces the highest entropy, thus becomes the best method to bring out the details of the images .Overall, both qualitative and quantitative analyses favor the proposed QDHE algorithm as the best contrast enhancement technique for low contrast images.

High Entropy:

- Indicates greater randomness or uncertainty in the image.
- Implies better preservation of information.
- May result in more detailed and nuanced representations.

High PSNR (Peak Signal-to-Noise Ratio):

- Signifies better image quality.
- Indicates closer resemblance to the original image with minimal distortion.
- Reflects reduced noise and improved signal fidelity.

High SSIM (Structural Similarity Index):

- Reflects a higher degree of similarity between the processed and original images.
- Considers structure, luminance, and contrast.
- Indicates better preservation of image structure and texture.

Balancing Factors:

- When comparing image processing techniques, a balance between these factors is crucial.
- Optimal results aim for information preservation, high image quality, and similarity to the original image.

CHAPTER 5

CONCLUSION

This work explains a novel DPHE-based method, called the QDHE, for enhancing low contrast images. The QDHE is able to extract the details of the low contrast images without over-enhancement and intensity saturation problems. The QDHE is more robust than the HE and DHE methods. The simulation results show that the QDHE has produced the best performance for both qualitative and quantitative evaluations.

The QDHE method is based on the DPHE method, which is a brightness preserving enhancement method. The DPHE method is able to preserve the brightness of the image while enhancing the contrast. However, the DPHE method can sometimes lead to over-enhancement and intensity saturation problems. The QDHE method addresses these problems by using a novel weighting function. The weighting function is designed to preserve the brightness of the image while enhancing the contrast without over-enhancement or intensity saturation.

The QDHE method was evaluated on a set of low contrast images. The results showed that the QDHE method was able to extract the details of the low contrast images without over-enhancement or intensity saturation. The QDHE method was also more robust than the HE and DHE methods.

REFERENCES

[1] H. Siddiqui and C.A. Bouman, "Hierarchical Color Correction for Camera Cell Phone Images,"IEEE Trans. Image Processing, vol.17, no.11, pp.2138-2155, Nov. 2008

[2] M. Gamadia, N. Kehtarnavaz, and K. R. Hoffman, "Low-Light Auto-Focus Enhancement for Digital and Cell-Phone Camera Image Pipelines," IEEE Trans. Consumer Electronics, vol.53, no.2, pp.249-257, May 2007

[3] R. C. Gonzalez and R. E. Woods, Digital Image Processing, 2nd ed., Prentice Hall, 2002.

[4] T. Kim, and J. Paik, “Adaptive contrast enhancement using gain-controllable clipped histogram equalization”, IEEE Trans. Consumer Electronics, vol. 54, no. 4, pp. 1803-1810, Nov. 2008.

[5] Y. T. Kim, “Contrast enhancement using brightness preserving bi-histogram equalization”, IEEE Trans. Consumer Electronics, vol. 43, no. 1, pp. 1-8, Feb. 1997.

[6] Y. Wan, Q. Chen and B. M. Zhang, “Image enhancement based on equal area dualistic sub-image histogram equalization method”, IEEE Trans. Consumer Electronics, vol. 45, no. 1, pp.68-75, Feb. 1999.

[7] S. D. Chen and A. R. Ramli, “Minimum mean brightness error bi-histogram equalization in contrast enhancement”, IEEE Trans. Consumer Electronics, vol. 49, no. 4, pp. 1310-1319, Nov. 2003.

[8] S. D. Chen and A. R. Ramli, “Contrast enhancement using recursive mean separate histogram equalization for scalable brightness preservation”, IEEE Trans. Consumer Electronics, vol. 49, no. 4, pp. 1301-1309, Nov. 2003.

[9] K. S. Sim, C. P. Tso, and Y. Y. Tan, “Recursive sub-image histogram equalization applied to gray-scale images”, Pattern Recognition Letters, vol. 28, pp. 1209-1221, July 2007.

[10] C. H. Ooi, N. S. P. Kong, and H. Ibrahim, “Bi-histogram with a plateau limit

for digital image enhancement”, IEEE Trans. Consumer Electronics, vol. 55, no. 4, pp. 2072-2080, Nov. 2009.

[11] M. A. A. Wadud, M. H. Kabir, M. A. A. Dewan, and O. Chae, “A dynamic histogram equalization for image contrast enhancement”, IEEE Trans. Consumer Electronics, vol. 53, no. 2, pp. 593-600, May. 2007.

[12] H. Ibrahim and N. S. P. Kong, “Brightness preserving dynamic histogram equalization for image contrast enhancement”, IEEE Trans. Consumer Electronics, vol. 53, no. 4, pp. 1752-1758, Nov. 2007.

[13] B. J. Wang, S. Q. Liu, Q. Li, and H. X. Zhou, “A real-time contrast enhancement algorithm for infrared images based on plateau histogram”, Infrared Physics & Technology, vol. 48, no. 1, pp. 77-82, April 2006.

[14] N. S. P. Kong, H. Ibrahim, C. H. Ooi, and D. C. J. C., “Enhancement of microscopic images using modified self-adaptive plateau histogram equalization”, ICCTD '09. International Conference on Computer Technology and Development, 2009 , vol.2, pp.308-310, 13-15 Nov. 2009