

# Quadrants Dynamic Histogram Equalization for Contrast Enhancement

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**Abstract** — *In this paper, we introduce 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<sup>1</sup>.*

**Index Terms** — Histogram equalization, dynamic histogram equalization, contrast enhancement, partitioned histogram.

## I. 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.

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].

In order to overcome the limitations of HE, several brightness preserving methods have been proposed [5]-[10]. Generally, these enhancement methods can be classified into two categories – partitioned histogram equalization (PHE) or dynamic partitioned histogram equalization (DPHE). The PHE and DPHE utilize histogram statistical information to separate the original histogram into several sub-histograms. The difference between the DPHE and PHE is each sub-histogram in the DPHE is assigned to a new enhanced dynamic range instead of using the original dynamic range.

One of the popular PHE-based methods is the mean brightness 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.

A bi-histogram equalization method has been also proposed by Wan et al. in [6], called the dualistic sub-image histogram equalization (DSIHE). The DSIHE algorithm separates the histogram into two sub-histograms with equal number of pixels, where the median of the input image is used as the separating point instead of mean brightness of the input image. Wan et al. claimed that, the enhanced image preserves the mean brightness and entropy of the input image.

In order to optimize the mean brightness preservation of the input image, an improved version of the BBHE, called minimum mean brightness error bi-histogram equalization (MMBEBHE), has been introduced by Chen and Ramli [7]. Similar to the BBHE, this method has two sub-histograms, but the separating point is set by finding the minimum mean brightness error between the input and the enhanced images.

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 recursively until the desired numbers of sub-histograms are met. Then, the HE approach is applied independently on each of the sub-

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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.

Recently, the bi-histogram equalization plateau limit (BHEPL) is proposed in [10] to control the enhancement rate of 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 enhancement rate 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 plateau limit; 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 the mean brightness of the original image without suffering from intensity saturation and over-enhancement.

The methods [5]-[10] discussed above are based on dividing the original histogram into several sub-histograms by using either the median or mean brightness. Although the mean brightness is well preserved by the aforementioned methods, these methods cannot further expand the region of sub-histogram located near to the minimum or maximum value of the dynamic range. This problem is demonstrated in Fig. 1, where  $X_m$  is the mean of input image and  $L$  is the number of gray levels ( $L=256$  for an 8-bit image). In low contrast image, most of the PHE-based methods can preserve the mean brightness of the image but fail to emphasize on the image details due to the non-expandable side sub-histogram.

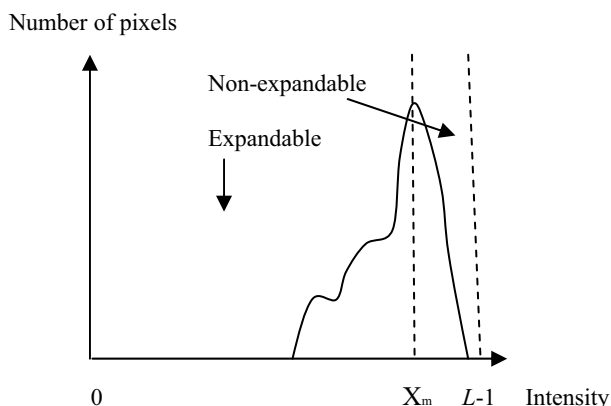


Fig. 1. An example of expandable and non-expandable sub-histograms.

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  $1 \times 3$  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  $1 \times 3$  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 the complexity of the algorithm.

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 mean brightness 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).

It should be mentioned that the scope of this paper focuses on enhancement of images obtained low illumination environment. In addition, we want to propose a method to overcome the narrow non-expandable side sub-histogram of an ill-illuminated image histogram as presented in Fig. 1. Therefore, we propose 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.

The rest of this paper is organized as follows. In Section II, the methodology of the proposed QDHE will be discussed in detail. Then, Section III presents some experimental results and discussions. Finally, Section IV serves as the conclusion of this framework.

## II. QUADRANTS DYNAMIC HISTOGRAM EQUALIZATION (QDHE)

In this section, we discuss the algorithmic construction of the proposed QDHE method in great details. The QDHE consists of four processes, namely the histogram partitioning, clipping, gray level range allocation and histogram equalization.

### A. 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 separating points.

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:

$$m_1 = 0.25 \times \{I_{width} \times I_{height}\} \quad (1)$$

$$m_2 = 0.50 \times \{I_{width} \times I_{height}\} \quad (2)$$

$$m_3 = 0.75 \times \{I_{width} \times I_{height}\} \quad (3)$$

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.

### B. 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 of the 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. 2(b) and 2(c). A clipping threshold value is set to the histogram in Fig. 2(b). Then, bins with higher value than the threshold value are replaced by the threshold value itself as shown in Fig. 2(c).

### C. New Gray Level Range Allocation

As discussed in the previous section, 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.

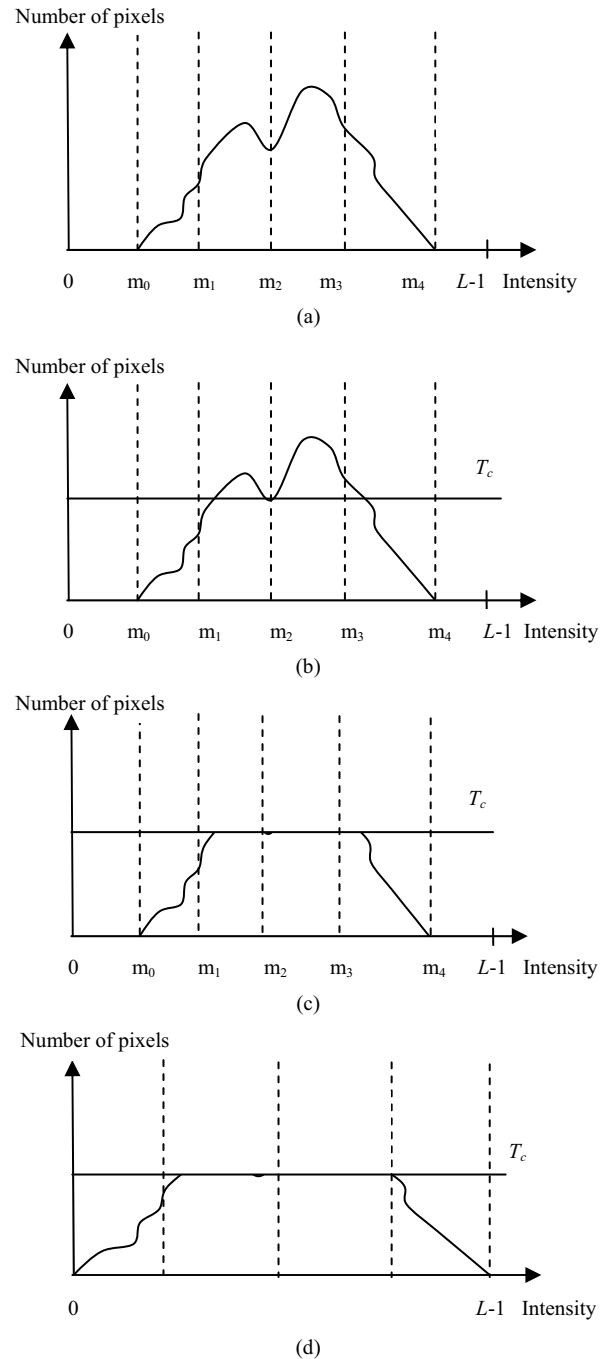


Fig. 2. An example process of the QDHE method (a) Histogram partitioning, (b) Before clipping, (c) After clipping, (d) After new gray level allocated.



Fig 3. Simulation results of the “Genting” image (640×840). (a) Original image, (b) HE-ed image, (c) BBHE-ed image, (d) RMSHE-ed image, (e) RSIHE-ed image, (f) DHE-ed image, (g) BPDHE-ed image, (h) BHEPL-ed image, (i) QDHE-ed image.

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 described as follows:

$$span_i = m_{i+1} - m_i \tag{4}$$

$$factor_i = span_i \times (\log_{10} M_i)^\gamma \tag{5}$$

$$range_i = (L - 1) \times factor_i / \sum_{k=1}^4 factor_k \tag{6}$$

where  $span_i$  is the dynamic gray level used by  $i$ -th sub-histogram in the input image.  $m_i$  is the  $i$ -th separating point,  $M_i$  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  $\gamma$  is the amount of emphasis given to  $M_i$ . Thus,  $\gamma$  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  $\gamma$ , (6) can be re-written as:

$$range_i = (L - 1) \times span_i / \sum_{k=1}^4 span_k \tag{7}$$

In the  $i$ -th sub-histogram the new dynamic range is allocated from  $[i_{start} \ i_{end}]$  defined by (8) and (9) respectively.

$$i_{start} = (i - 1)_{end} + 1 \tag{8}$$

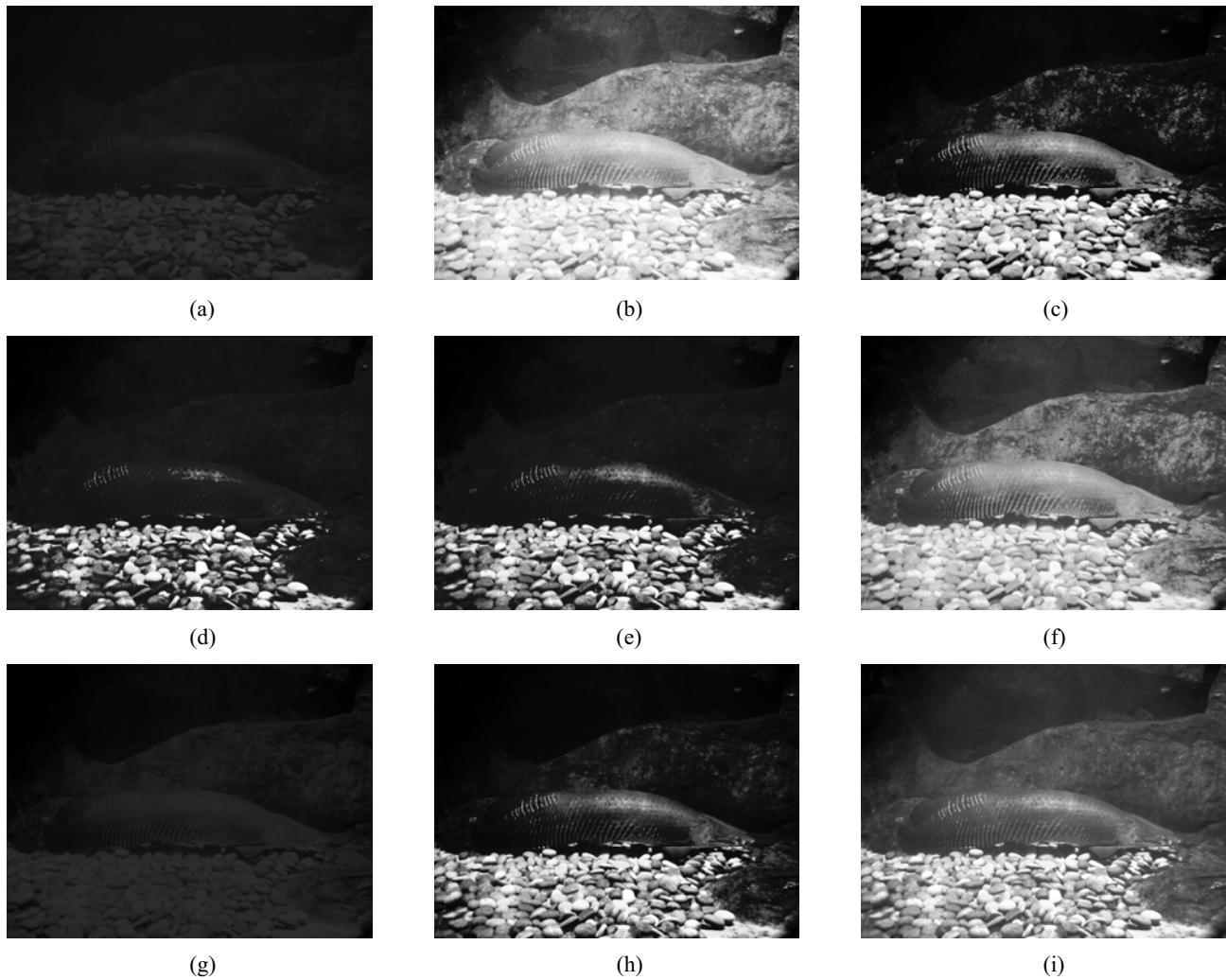


Fig. 4. Simulation results of the “Fish 1” image (2048×1536). (a) Original image, (b) HE-ed image, (c) BBHE-ed image, (d) RMSHE-ed image, (e) RSIHE-ed image, (f) DHE-ed image, (g) BPDHE-ed image, (h) BHEPL-ed image, (i) QDHE-ed image.

$$i_{end} = i_{start} + range_i \quad (9)$$

$i_{end}$  are used instead of the minimum and maximum intensities in the output dynamic range.

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. 2(d).

#### D. 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 in (10)

$$y(x) = (i_{start} - i_{end}) \times cdf(X_k) + i_{start} \quad (10)$$

where  $cdf(X_k)$  is the cumulative density function in that sub-histogram. In (10) a general HE equation is used but  $i_{start}$  and

### III. RESULTS AND DISCUSSIONS

In this section, we demonstrate the performance of the proposed QDHE method by comparing with other seven existing HE-based methods: the conventional HE, BBHE, RMSHE, RSIHE, DHE, BPDHE and BHEPL. The RMSHE and the RSIHE are divided into four sub-histograms by using  $r=2$ . The experiment results are collected using low light environment images and in namely ‘Genting’, ‘Fish 1’ and ‘Fish 2’ as shown in figs 3 to 5 respectively.

In order to visualize the detail preserving capability, we show the histogram of simulated results for the ‘Fish 2’ image in Fig. 6. The histograms of resultant ‘Fish 2’ images after applying with those methods are illustrated in Fig. 6.

Based on Figs. 3(b), 4(b) and 5(b), 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

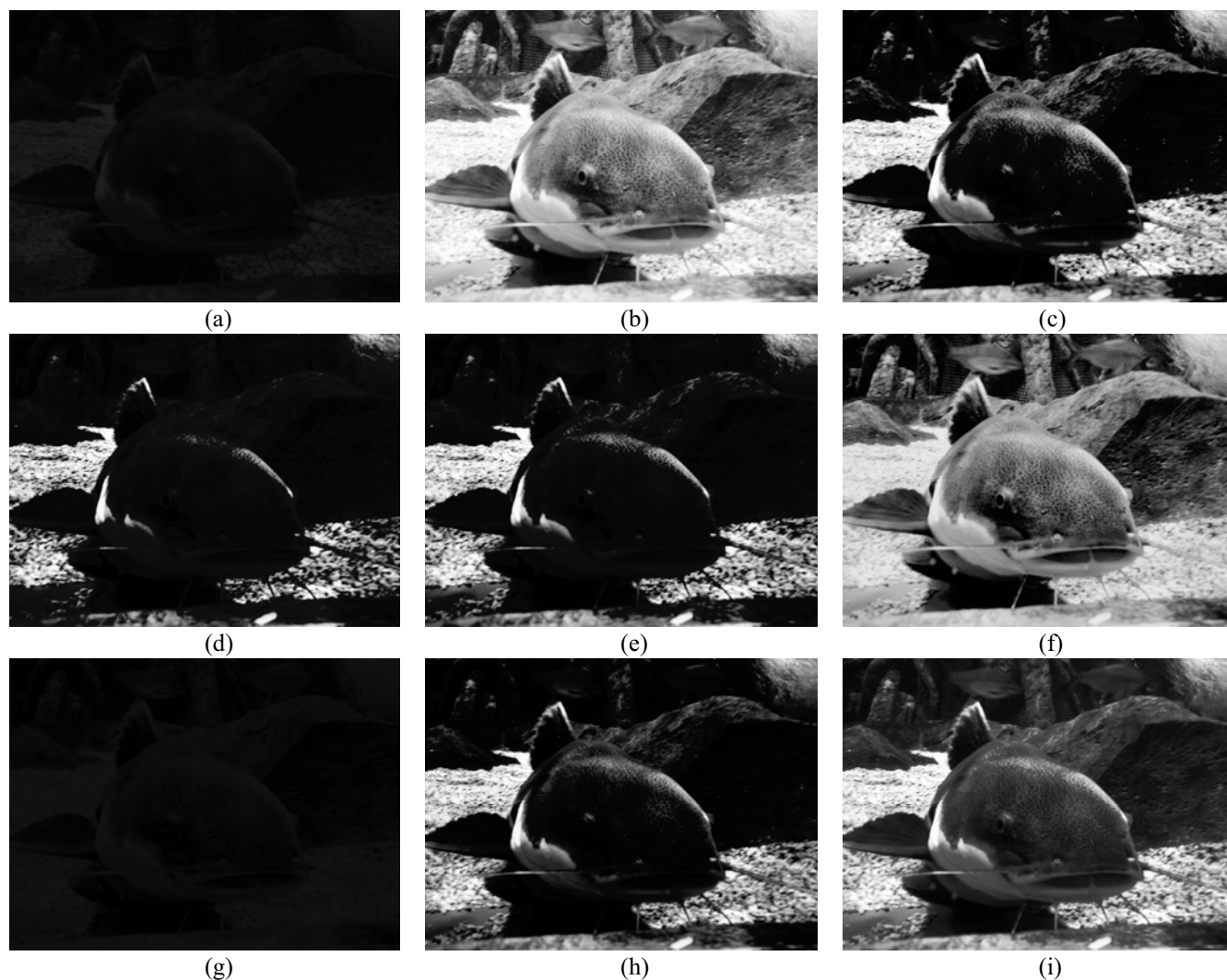


Fig. 5. Simulation results of the “Fish 2” image (2548×2049). (a) Original image, (b) HE-ed image, (c) BBHE-ed image, (d) RMSHE-ed image, (e) RSIHE-ed image, (f) DHE-ed image, (g) BPDHE-ed image, (h) BHEPL-ed image, (i) QDHE-ed image.

intensity saturation is very high. It can be seen at the small stones with bright intensity in Figs. 4(b) and 5(b). This is proven in Fig. 6(b) as the HE-ed histogram is concentrated on the right side of the histogram.

For the BBHE, RMSHE, RSIHE and BHEPL 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. 3(c), 3(d), 3(e) and 3(h); the background of the ‘Fish 1’ image in Figs. 4(c), 4(d), 4(e) and 4(h); and the fish body of the ‘Fish 2’ image in Figs. 5(c), 5(d), 5(e) and 5(h). 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. In addition, the ‘Fish 2’ image histograms of the BBHE, RMSHE, RSIHE and BHEPL methods in Figs. 6(c), 6(d), 6(e) and 6(h), respectively, obviously show that the sub-histogram at the left side in each histogram is not successfully expanded.

Among the implemented state-of-the-art methods, in term 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. 3(f)) and intensity saturation (i.e., as shown on small bright stone regions of the Fig. 5(f)). Moreover, the evidence of the intensity saturation problem is clearly shown in Fig. 6(f) 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.

From Figs. 3 to 5, 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. 6(g), the histogram of the ‘Fish 2’ image is equalized and concentrated only on the left side of the histogram.

On the other hand, 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

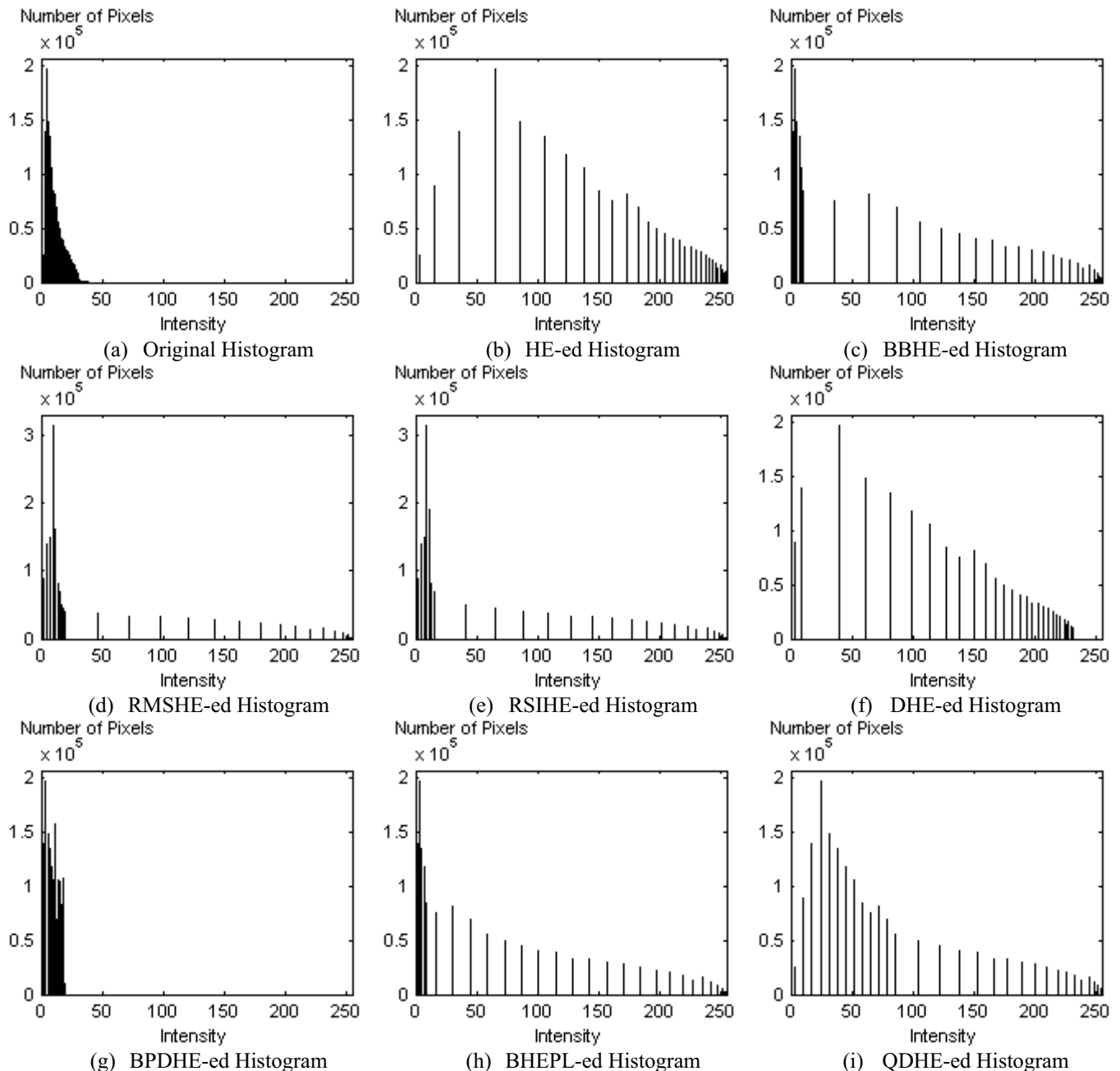


Fig. 6. Histogram of the simulation results on Fig.5. (a) Original histogram, (b) HE-ed histogram, (c) BBHE-ed histogram, (d) RMSHE-ed histogram, (e) RSIHE-ed histogram, (f) DHE-ed histogram, (g) BPDHE-ed histogram, (h) BHEPL-ed histogram, (i) QDHE-ed histogram.

successfully preserved image details. The concrete proof could be seen, for examples, at the faces of the people in Fig. 3(i), the background, and the fish body of the Fig. 4(i) and white stone regions of the Fig. 5(i). The problems of intensity saturation, noise amplification, and over-enhancement are avoided.

Furthermore, the QDHE-ed histogram in Fig. 6(i) 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.

To further demonstrate the capability of proposed method in extracting the details from the images, the discrete entropy is performed as the quantitative evaluation [15]. The discrete entropy  $E(x)$  is defined as:

$$E(x) = -\sum_{k=0}^{255} p(X_k) \times \log_2 p(X_k) \quad (11)$$

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 computed for the methods implemented are tabulated in Table 1.

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. This study further analyzes the capability of the tested techniques

based on execution time. Table II shows the average execution time of sample images. Overall, the QDHE is ranked third after the HE and the BBHE methods in terms of execution time speed. The QDHE method obtains almost similar processing time with the RMSHE, the RSIHE and the BHEPL methods, which demonstrate almost similar computation complexity among them. In addition, the proposed QDHE method needs shorter execution time computation compared to the DHE and the BPDHE. This shows that the proposed QDHE has less complexity than the DHE and the BPDHE methods. Furthermore, previous subjective analysis has also favored the QDHE by producing better processed images.

**TABLE I**  
**DISCRETE ENTROPY OF THE EXPERIMENTAL RESULTS (BITS)**

Method	Genting	Fish 1	Fish 2
HE	5.05	4.46	4.99
BBHE	5.01	4.45	4.97
RMSHE	4.86	4.20	4.76
RSIHE	4.93	4.19	4.72
DHE	5.00	4.95	4.99
BPDHE	4.67	4.34	4.73
BHEPL	5.02	4.41	4.97
QDHE	<b>5.08</b>	<b>4.98</b>	<b>5.01</b>

**TABLE II**  
**AVERAGE EXECUTION TIME OBTAINED FROM SAMPLE IMAGES**

Method	Average execution time (ms)
HE	<b>223.1</b>
BBHE	256.7
RMSHE	283.3
RSIHE	283.9
DHE	383.6
BPDHE	553.2
BHEPL	289.5
QDHE	279.3

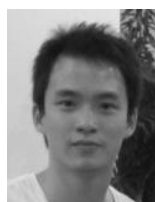
#### IV. CONCLUSION

In this paper a novel DPHE-based method, called the QDHE, is presented. The HE is a simple and effective method. However, it leads to over-enhancement and intensity saturation problems. For the ill-illumination images, HE-based brightness preserving methods fail to extract the detail information of the images. Although the DHE is a powerful method for enhancing the low contrast images, it leads to noise amplifying and intensity saturation problems in some cases. From the experiment results, the proposed QDHE is the most robust method to extract the details of the low contrast images. Observing from the simulation results obtained, the QDHE has produced the best performance for both qualitative and quantitative evaluations.

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#### BIOGRAPHIES



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