

Adaptive Contrast Enhancement Methods with Brightness Preserving

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Abstract — *Brightness preserving methods are very high demand to the consumer electronic products. Numerous histogram equalization (HE)-based brightness preserving methods tend to produce unwanted artifacts. Thus, we propose two methods to overcome the drawbacks. The first proposed method divides the histogram based on the median, and iteratively divides into the lower and upper sub-histograms, to produce a totally four sub-histograms. The separating points in the lower and upper sub-histograms are assigned to a new dynamic range and clipping process is implemented to each sub-histogram. Finally, the conventional HE is implemented. The second method is the extension of the bi-histogram equalization plateau limit (BHEPL). This method segments the histogram of input image based on its mean value. Then, clipping process is implemented to each sub-histogram based on their median value. The proposed methods are compared with several conventional methods. The experiment results show that, both of the proposed methods outperform those conventional methods by producing clearer enhanced image with brightness and details preserving ability¹.*

Index Terms — **Histogram equalization, brightness preserving, contrast enhancement.**

I. INTRODUCTION

Histogram Equalization (HE) [1] is an effective contrast enhancement technique with the fundamental idea to obtain a uniform enhanced histogram. First, the HE constructs a cumulative histogram from the original histogram. Second, this cumulative histogram is normalized to intensity value of the output image. Then, the normalized cumulative histogram is acted as a transfer mapping function to the original image. However, the HE tends to produce intensity saturation problem due to the shifting of the original mean brightness. Moreover, the HE also leads to over-enhancement, which produces unnatural phenomena and noise amplifying to the enhanced images [2].

To overcome the abovementioned drawbacks, a brightness preserving method has been proposed by Kim [3] so called as brightness preserving bi-histogram equalization (BBHE). To achieve the brightness preserving, the BBHE segments the original histogram into two portions by the mean of the input histogram. Then, these two portions are equalized independently using the conventional HE. As the result, the BBHE enhances the contrast of the images while preserving

the mean brightness. Yet, in some cases, the BBHE still suffers from intensity saturation.

In 1999, dualistic sub-image histogram equalization (DSIHE) [4] was introduced by Wan et al. Similar to the BBHE, the DSIHE also decomposes the input histogram into two portions. Nevertheless, the DSIHE equally divides the total number of the pixels into two sub-histograms. As the consequent, the DSIHE maintains the mean brightness and increases the entropy of the image as well.

Yet, optimally maintain the original mean brightness, minimum mean brightness error bi-histogram equalization (MMBEBHE) [5] has been introduced by Chen and Ramli in 2003. This algorithm calculates the minimum mean brightness error between the input and the enhanced image. Then, the MMBEBHE employs the optimal point as the separating point instead of the mean or the median of the input histogram.

A multiple sub-histogram method has been introduced by Chen and Ramli [6] in 2003, named recursive mean-separate histogram equalization (RMSHE). The algorithm divides the original histogram into 2^r sub-histograms, where r is the integer value. First, the RMSHE segments the input histogram into two sub-histograms by the original mean. Then, the RMSHE recursively segments each sub-histogram until the desired 2^r sub-histograms are obtained. Finally, conventional HE is implemented to each sub-histogram.

A similar approach is proposed by Sim et. al. [7] in 2007, named recursive sub-image histogram equalization (RSIHE). However, the RSIHE is segmented by median of the each sub-histogram instead of the mean in the RMSHE. A similar problem encountered for the both RMSHE and RSIHE while these two techniques will lead to insignificant enhancement as the value of r is increased.

Recursively separated and weighted histogram equalization (RSWHE) [8] is proposed by Kim and Chung. Generally, the RSWHE uses the similar technique by the RMSHE and the RSIHE. Unlike previous methods, weightening function is applied to the input histogram. There are two versions for the RSWHE; segmented by mean (RSWHE-M) and segmented by median (RSWHE-D). From the experimental results, the RSWHE-M method is found to be better than the RSWHE-D in term of brightness preserving.

Dynamic histogram equalization (DHE) [9] is proposed with the objective to stretch the contrast and preserve the details of the original image. The DHE partitions the histogram of input image based on local minimal and assigns a new dynamic range for each sub-histogram. To ensure many dominating portions, the DHE further segments the large sub-histogram through a repartitioning test. Nonetheless, the DHE neglects the mean brightness preserving and tends to intensity saturation artifact.

To overcome the drawback of the DHE, brightness preserving dynamic histogram equalization method (BPDHE) [10] has been introduced as the extension of the DHE. First,

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the BPDHE segments the histogram of input image using local maximal. By doing this, the algorithm is claimed to be better in term of maintaining the mean brightness than local minimal. Similar to the DHE, the HE is then implemented after assigning a new dynamic range for each sub-histogram. In order to maintain the mean brightness, brightness normalization is applied to ensure the enhanced image has the similar mean brightness of the input image.

Recently, bi-histogram equalization plateau limit (BHEPL) [11] is proposed as the hybrid of the BBHE and clipped histogram equalization. Similar to the BBHE, the BHEPL divides the histogram of input image by using the mean brightness of the image. Then, both of the sub-histograms are clipped by each mean of the occupied intensity respectively. Finally, conventional HE is executed in each sub-histogram independently.

To overcome the unwanted over-enhancement and noise amplifying, clipped histogram equalization (CHE) [2] is proposed to manipulate the enhancement rate. First, a clipping level is determined and the histogram is clipped based on this clipped level. The clipped portion is then re-distributed to the entire dynamic range. Although the CHE can control the over-enhancement and noise amplifying artifacts, it requires user to determine the clipping level. Furthermore, the re-distributed process may require more time processing which could increase the complexity in the real time system.

Brightness preserving is highly demand for the consumer electronic products, such as television and monitor. Therefore, numerous brightness preserving methods (as discussed previously) are introduced to enhance the contrast while maintaining the original mean brightness. However, in some cases, many of them introduce unwanted artifacts such as intensity saturation, over-enhancement and noise amplifying.

In this work, two extensions of the BHEPL are proposed. First, a novel method is proposed as the extension of the RSIHE, called dynamic quadrants histogram equalization plateau limit (DQHEPL). The proposed DQHEPL divides the histogram of input image into four sub-histograms, assigns a new dynamic range for each sub-histograms while maintaining the second separated point as the mean brightness. Then, clipping process is implemented. The second method is bi-histogram equalization median plateau limit (BHEPL-D). Unlike the BHEPL, the proposed algorithm clips the histogram using the median of the occupied intensity.

The rest of this paper is organized as follows. Section II discusses the methodology of DQHEPL method. The details of the BHEPL-D method are explained in section III. In section IV, we present the results and discussions. Finally, we bring a conclusion in the last section.

II. DYNAMIC QUADRANTS HISTOGRAM EQUALIZATION PLATEAU LIMIT (DQHEPL)

The proposed DQHEPL method uses the fundamental idea of the RSIHE. Although the rise of iteration level r will produce better brightness preservation, it actually declines the effectiveness of the HE and yields an output image without a

good enhancement [12]. Thus, in this work, we divide the input histogram into four sub-histograms, which is shown in Fig. 1(b). m_0 and m_4 are the minimum and maximum intensity values of the input image respectively, where L is the number of gray levels (i.e. for 8 bits image, $L=256$). Then, three separating points are defined as follows:

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

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

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

where m_1 , m_2 and m_3 are intensity values with the total number of pixels at 0.25, 0.50 and 0.75 of entire number of pixels in the histogram respectively. I_{width} and I_{height} represent the width and height of the images respectively.

To avoid the intensity saturation and over-enhancement problems, the proposed DQHEPL method adopts the basic idea of the CHE to control the enhancement rate of the algorithm [2]. This can be done by defining a plateau limits to each sub-histogram, as shown in Fig. 1(c). To determine the plateau limits automatically, the DQHEPL calculates the average occupied intensity in each sub-histogram as the plateau limit. Each plateau limit is identified as follows:

$$P_i = \frac{1}{m_i - m_{i-1}} \times \sum_{k=m_{i-1}}^{m_i} h(X_k) \quad (4)$$

where $h(X_k)$ is the histogram at the intensity level k .

After determination of the plateau limits, clipping process is applied. The clipped i th histogram, h_{ci} can be determined as follows:

$$h_{ci}(X_k) = \begin{cases} h(X_k) & h(X_k) \leq P_i \\ P_i & h(X_k) > P_i \end{cases} \quad (5)$$

where $h_{ci}(X_k)$ is the clipped histogram at intensity level k .

To overcome the main limitation of the RSIHE which is non-expendable sub-histograms and maintaining the original mean brightness, the proposed DQHEPL method maintains the separating point m_2 as the brightness preserving. The separating points of m_1 , m_2 and m_3 are then assigned to a new grey level (i.e. denoted as n_1 , n_2 and n_3 respectively) as follows:

$$n_1 \cong m_2 \times \frac{m_1 - m_0}{m_2 - m_0} \quad (6)$$

$$n_2 \cong m_2 \quad (7)$$

$$n_3 \cong (L - 1 - m_2) \times \frac{m_3 - m_2}{m_4 - m_2} + m_2 \quad (8)$$

where n_0 and n_4 is assigned to the minimum and maximum output intensity value (i.e. $n_0=0$ and $n_4=L-1$).

Finally, the transform function in (9) is implemented to map the intensity level of each sub-histogram independently from Fig. 1(c) to Fig. 1(d).

$$Y(X) = n_{i-1} + (n_i - n_{i-1}) \times \frac{\sum_{k=m_{i-1}}^{m_i} h_{ci}(X_k)}{M_i} \quad (9)$$

where M_i is the total of the clipped histogram at i -th sub-histogram, as follows:

$$M_i = \sum_{k=m_{i-1}}^{m_i} h_{ci}(X_k) \quad (10)$$

III. BI-HISTOGRAM EQUALIZATION MEDIAN PLATEAU LIMIT (BHEPL-D)

In this section, we give a detail description of the proposed BHEPL-D method. In the beginning of the process, the BHEPL-D segments the histogram of input image using the input mean brightness, m as shown in (11). The segmented histogram is illustrated in Fig. 2(a).

$$m = \sum_{k=0}^{L-1} p_{in}(X_k) \times k \quad (11)$$

where $p_{in}(X_k)$ is the input probability density function at the intensity level k .

After segmenting the input histogram into lower histogram, h_L and upper histogram, h_U , the BHEPL-D creates a plateau limit for each sub-histogram. The plateau limit in the lower and upper sub-histograms is denoted as P_L and P_U respectively. Unlike the BHEPL, the BHEPL-D sets the plateau limit as the median of the occupied intensity. The plateau limit is set as shown in Fig. 2(b). Mathematically, P_L and P_U can be determined using (12) and (13) respectively.

$$P_L = \text{median}[h_L(X_k)] \quad (12)$$

where $k = 0, 1, 2, \dots, m$

$$P_U = \text{median}[h_U(X_k)] \quad (13)$$

where $k = m+1, m+2, m+3, \dots, L-1$

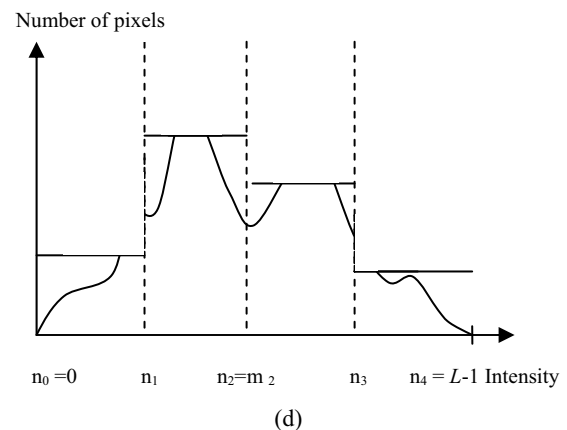
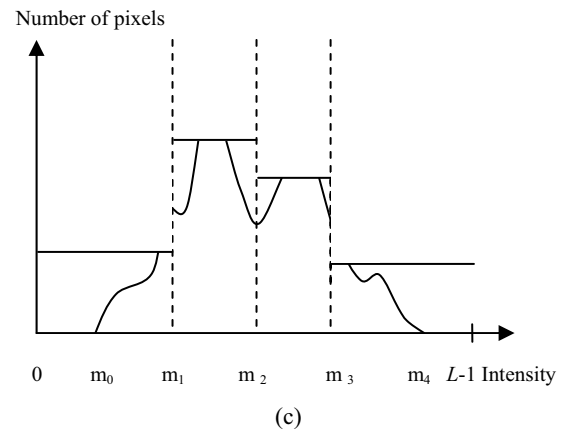
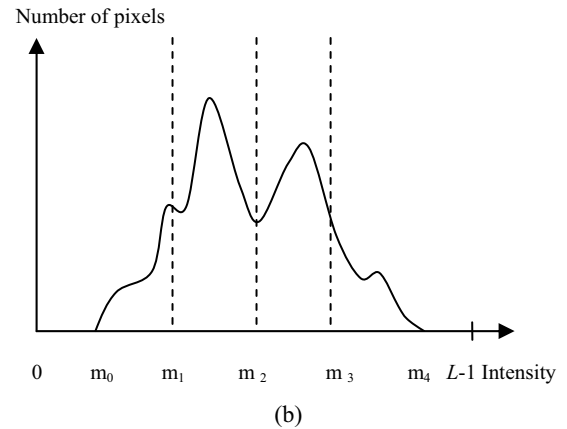
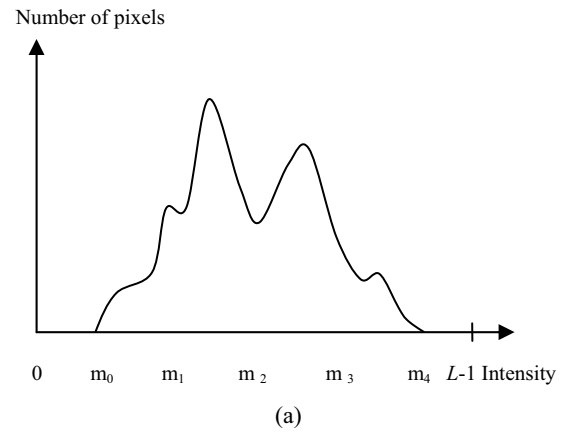


Fig. 1. A procedure of DQHEPL. (a) Histogram of input image, (b) Segmented histogram (c) Clipped histogram based on mean, (d) New gray level allocating.

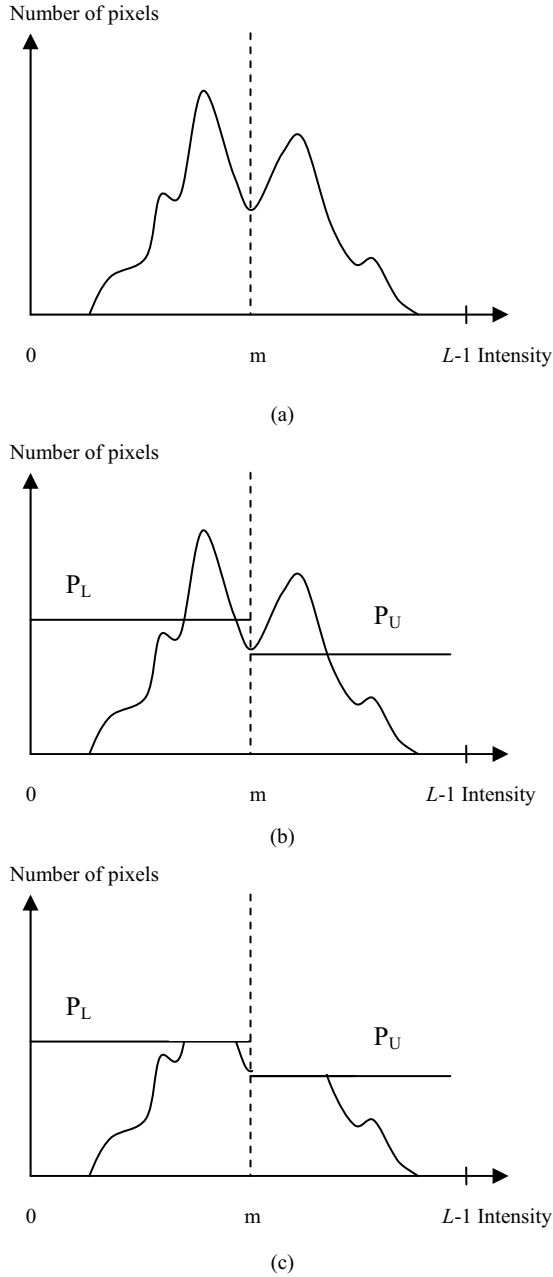


Fig. 2. A procedure of BHEPL-D. (a) Segmented histogram, (b) Two plateau limits based on median, (c) Clipped histogram.

In order to avoid over-enhancement, the BHEPL-D clips each sub-histogram respectively by using these two plateau limits. This can be seen in Fig. 2(c). The clipping process is used to control the enhancement rate of the original histogram. Thus, the enhanced image will not tend to over-enhancement and intensity saturation problems. Hence, more information and entropy are obtained by the enhanced image. The clipped lower histogram, h_{CL} and clipped upper histogram, h_{CU} are denoted as (14) and (15) respectively.

$$h_{CL}(X_k) = \begin{cases} h_L(X_k) & h_L(X_k) \leq P_L \\ P_L & h_L(X_k) > P_L \end{cases} \quad (14)$$

$$h_{CU}(X_k) = \begin{cases} h_U(X_k) & h_U(X_k) \leq P_U \\ P_U & h_U(X_k) > P_U \end{cases} \quad (15)$$

After the clipped histogram is obtained, the conventional HE is implemented to each sub-histogram, which can be represented as follows:

$$Y_L = X_0 + (X_m - X_0) \times \sum_{k=0}^m \frac{h_{CL}(X_k)}{M_{CL}} \quad (16)$$

and

$$Y_U = X_{m+1} + (X_{L-1} - X_{m+1}) \times \sum_{k=m+1}^{L-1} \frac{h_{CU}(X_k)}{M_{CU}} \quad (17)$$

where M_{CL} and M_{CU} are the total number of pixels in the clipped lower and upper histograms respectively.

In order to reduce the extensive computation as in the CHE, the proposed BHEPL-D does not redistribute the clipped portion back into the clipped histogram. Thus, the BHEPL-D is simple to be implemented.

IV. RESULTS AND DISCUSSIONS

The performance of the proposed DQHEPL and BHEPL-D methods are tested on numerous images. In this paper, three out of these images namely 'Girl', 'Dinner' and 'Car' are selected to demonstrate the capability of the proposed methods. The qualitative analysis involves performance comparison with nine existing brightness preserving methods, namely HE, BBHE, DSIHE, MMBEBHE, RMSHE, RSIHE, BPDHE, RSWHE-M and BHEPL. For a fair comparison, the RMSHE, the RSIHE and the RSWHE-M methods are divided into four sub-histograms as similar to the proposed DQHEPL method.

From the qualitative results of the image 'Girl', there are over-enhancement and intensity saturation phenomena (i.e. on the hair and the attire of the girl) produced by the HE, the BBHE, the DSIHE, the MMBEBHE and the BPDHE methods are shown in Figs. 3(b), (c), (d), (e) and (h) respectively. Moreover, these methods tend to noise amplifying on the background of the images.

Similar problems are observed in Fig. 3(g) for the RSIHE method. In Figs. 3(f), (i) and (j), enhanced images are acceptable. However, in Figs. 3(f) and (i), the RMSHE and RWSHE methods produce unnatural and insignificant enhancement on the face and hair of the girl image. It is because, the non-expandable sub-histograms employed by both methods reduce the effectiveness of the HE.

Yet, in Fig. 3(j) the enhanced image produced by BHEPL method also amplifies the noise level on the image background. The best performance is produced by two proposed DQHEPL and BHEPL-D methods as shown in Figs.

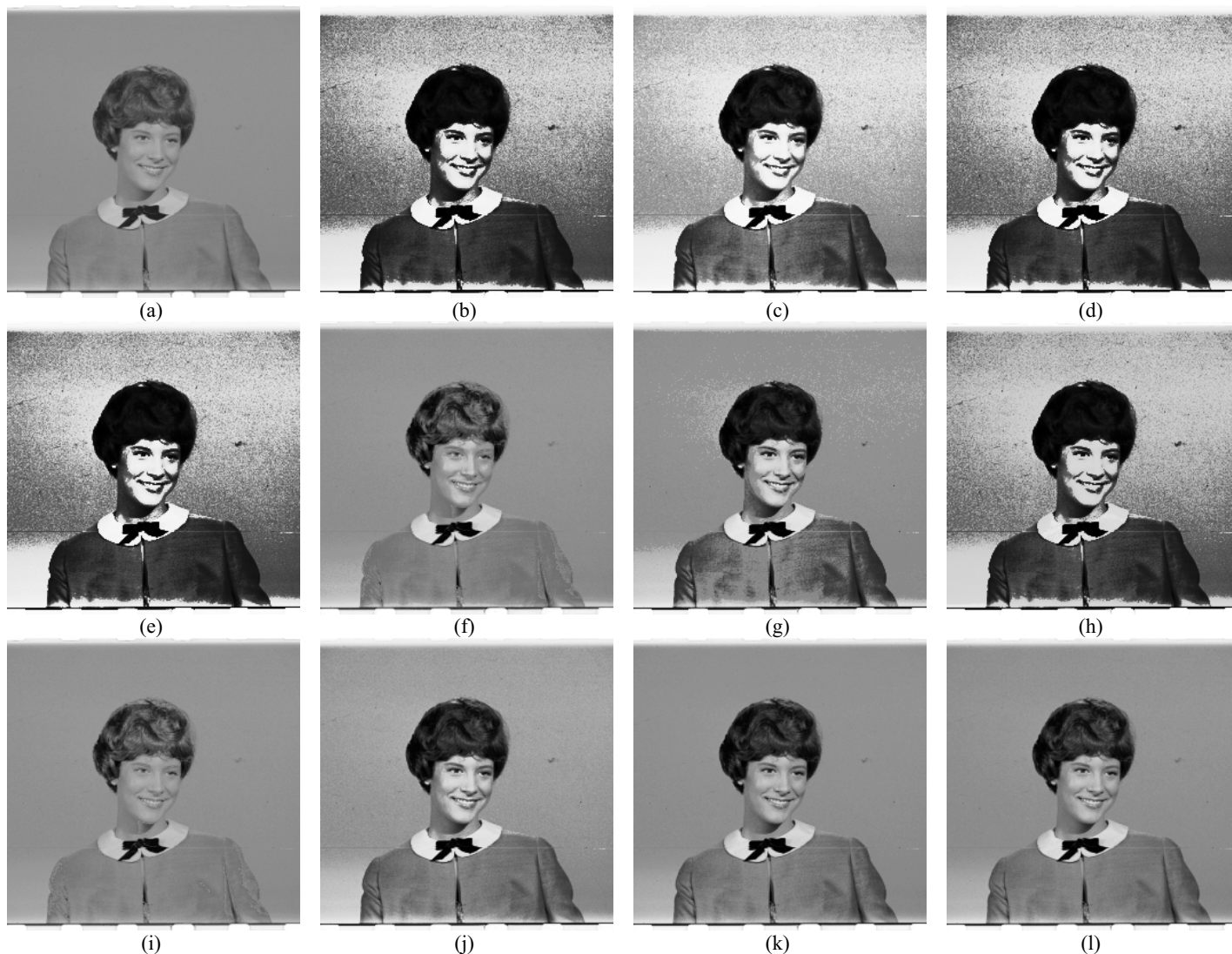


Fig. 3. Image of 'Girl'. (a) Original image, (b) HE-ed image, (c) BBHE-ed image, (d) DSIHE-ed image, (e) MMBEBHE-ed image, (f) RMSHE-ed image, (g)RSIHE-de image, (h) BPDHE-ed image, (i) RWSHE-M-ed image, (j) BHEPL-ed image, (k)DQHEPL-ed image, (l) BHEPL-D-ed image.

3(k) and (l) respectively. Both proposed methods are free from the abovementioned drawbacks.

Two low contrast images have been tested and the results are shown in Fig. 4 and Fig. 5. The histograms of all resultants image in Figs. 5 are illustrated in Fig. 6. These histograms are given to provide a clearer effect on those tested techniques on suppression or stretching process of an intensity levels range. Obviously, the HE failed to maintain the original brightness of the images. Furthermore, the HE also introduced the intensity saturation problem to the images. For example, the table tends to be white patches in the 'Dinner' image and similar to that of the signboard of the 'Car' image. Similarly, this phenomenon can also be observed in Figs. 4(c) to (e) and Figs. 5(c) to (e) for the BBHE, the DSIHE and the MMBEBHE methods. This can be proven from the result shown in the histogram of these three methods shown in Figs. 6(c) to (e) which are squeezed to the right and left tails of the histogram.

Unnatural images are introduced by the RMSHE, the RSIHE and the RWSHE methods as shown by images (f), (g) and (i) respectively in Figs. 4 and 5. This phenomenon can be clearly seen at the floor and the people in the 'Dinner' image

as well as the teddy bear and the car in the 'Car' image. Further evidence is presented in Figs. 6(f), (g) and (i), where the middle of the histogram are equalized without expanded.

The insignificant enhancement is obtained for the BPDHE method, due to the small ratio brightness of the method. This can be clearly observed in Fig. 4(h) and Fig 5(h). As a proof, from Fig. 6(h), the BPDHE-ed histogram of 'Car' image is not equalized to its full dynamic range.

The acceptable and natural enhanced images are produced by the BHEPL method in Fig. 4(j) and Fig. 5(j). However, the BHEPL method produces intensity saturation problem (i.e. the table in Fig. 4(j) and the signboard in Fig. 5(j)). For the 'Car' image, this phenomenon is evidenced from Fig. 6(j), where some intensity levels are squeezed to the right tail of the histogram.

The proposed DQHEPL method can slightly improve the intensity saturation problem of the images as compared to the BHEPL method (i.e. capability to reduce the suppression effect on the histogram of Fig. 6(k) as compare to Fig. 6(j)). Yet, it does not handle the intensity saturation problem well as shown in Fig 4(k) and Fig 5(k). Fortunately, the proposed



Fig. 4. Image of 'Dinner'. (a) Original image, (b) HE-ed image, (c) BBHE-ed image, (d) DSIHE-ed image, (e) MMBEBHE-ed image, (f) RMSHE-ed image, (g) RSIHE-de image, (h) BPDHE-ed image, (i) RWSHE-M-ed image, (j) BHEPL-ed image, (k) DQHEPL-ed image, (l) BHEPL-D-ed image.

BHEPL-D can significantly improve the performance. For example, no saturation problem is observed especially on the table and the lighting regions in the 'Dinner' image and the signboard regions in the 'Car' image. For the 'Car' image as shown in Fig 6(l), the histogram of BHEPL-D-ed 'Car' image is successfully distributed evenly to its full dynamic range as compared to other conventional methods.

To prove the robustness of the proposed methods, four quantitative tests have been executed in this work. In this work, 120 images are used in the quantitative measurements. The first test is average absolute mean brightness error (AAMBE), based on:

$$AAMBE = \frac{1}{N} |E(X) - E(Y)| \quad (18)$$

where N is the total number of sample images (i.e. 120), $E(X)$ and $E(Y)$ are the input and output mean brightness respectively. A lower value of AAMBE requests a better maintaining original mean brightness.

Another two quantitative tests are used to measure the richness of details and appropriateness for the enhanced images in consumer electronic product [13]. They are average peak signal noise ratio (APSNR) and average entropy (AE) of the enhanced images. The higher value of the APSNR indicates less significant noise level is amplified while the higher value of AE bring more informational of the images. Mathematically, both of the quantitative measurements are given as follows:

$$APSNR = \frac{1}{N} 20 \log_{10}(L - 1/\sqrt{MSE}) \quad (19)$$

where MSE is the mean square error, as defined in (20).

$$MSE = \sum_{i=0}^{I_{width}-1} \sum_{j=0}^{I_{height}-1} \frac{[f(i, j) - g(i, j)]^2}{I_{width} \times I_{height}} \quad (20)$$



Fig. 5. Image of ‘Car’. (a) Original image, (b) HE-ed image, (c) BBHE-ed image, (d) DSIHE-ed image, (e) MMBEBHE-ed image, (f) RMSHE-ed image, (g)RSIHE-ed image, (h) BPDHE-ed image, (i) RWSHE-M-ed image, (j) BHEPL-ed image, (k)DQHEPL-ed image, (l) BHEPL-D-ed image.

where $f(i,j)$ and $g(i,j)$ are the input and output intensity value at the location (i,j) respectively.

$$AE = -\frac{1}{N} \sum_{k=0}^{255} p_{out}(X_k) \times \log_2 p_{out}(X_k) \quad (21)$$

where $p_{out}(X_k)$ is the probability density function of the output images at intensity level k . To measure the complexity of the proposed methods, the average execution time (τ) is also recorded.

The results for the quantitative analysis are tabulated in Table 1. For the AAMBE quantitative test, obviously the HE, BBHE and DSIHE methods fail to preserve the original mean brightness. As discussed previously, these three methods tend to produce intensity saturation and information loss. The evident can be clearly seen in Table 1, where these three methods are ranked the first three lowest values for the APSNR value.

From the Table 1, the MMBEBHE and the BPDHE produce lower AAMBE values than the proposed two methods. However, the MMBEBHE produces unnatural enhanced

TABLE I
QUANTITATIVE MEASUREMENTS

Method	AAMBE	APSNR (dB)	AE (bits)	τ (ms)
Original	-	-	6.50	
HE	36.51	14.69	6.33	193.13
BBHE	14.00	18.47	6.34	194.96
DSIHE	16.13	17.39	6.34	196.92
MMBEBHE	2.02	21.75	6.32	218.62
RMSHE	9.82	21.50	6.23	217.02
RSIHE	9.74	20.58	6.22	224.34
BPDHE	2.09	22.77	6.31	240.51
RSWHE-M	7.15	25.03	6.30	225.96
BHEPL	8.65	21.59	6.43	196.70
DQHEPL	5.74	25.35	6.45	227.68
BHEPL-D	6.35	27.33	6.49	196.46

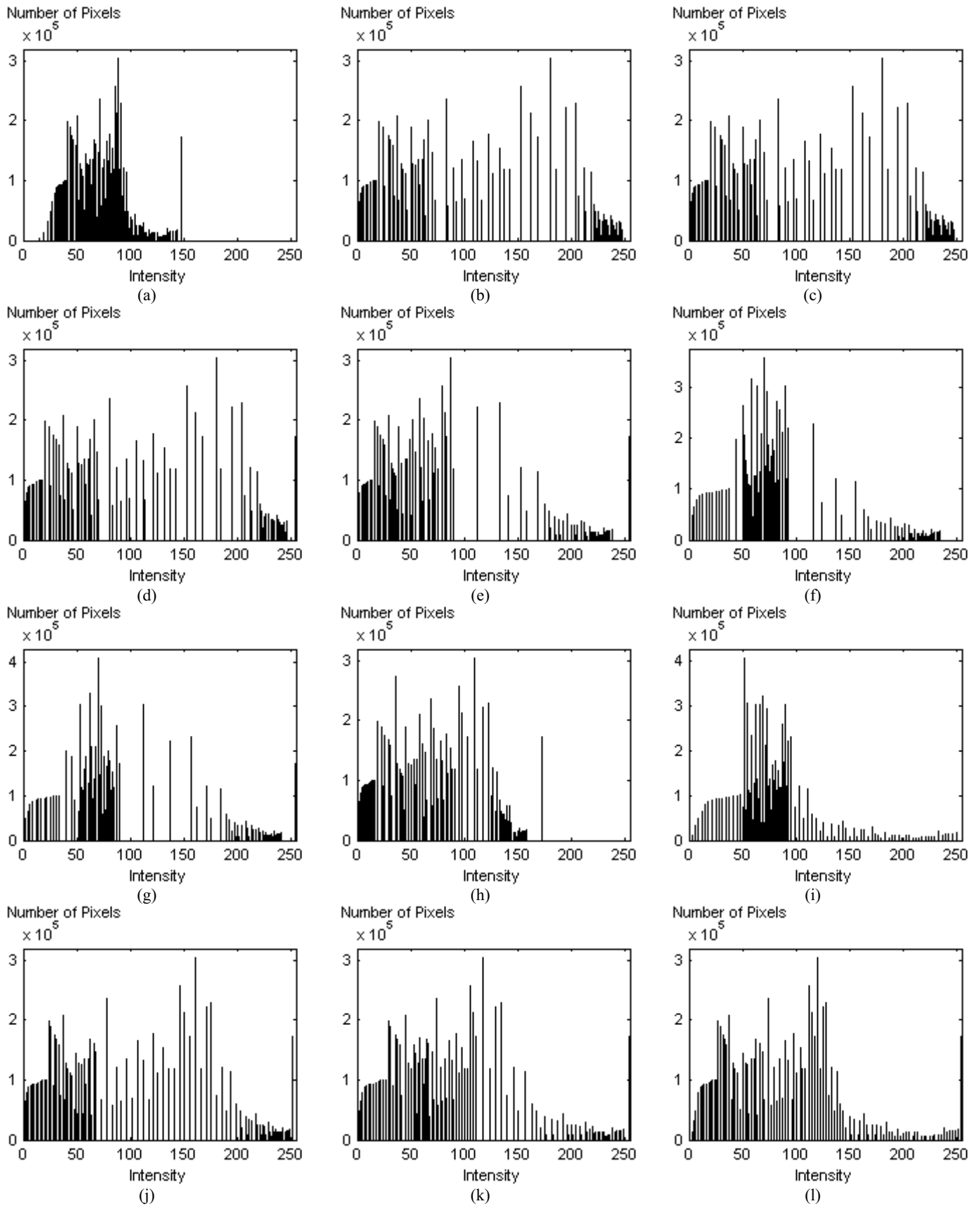


Fig. 6. Histogram of simulated 'Car' image. (a) Original histogram, (b) HE-ed histogram, (c) BBHE-ed histogram, (d) DSIHE-ed histogram, (e) MMBEBHE-ed histogram, (f) RMSHE-ed histogram, (g) RSIHE-de histogram, (h) BPDHE-ed histogram, (i) RWSHE-M-ed histogram, (j) BHEPL-ed histogram, (k) DQHEPL-ed histogram, (l) BHEPL-D-ed histogram.

images, while the BPDHE method produces insignificant enhancement to the resultant images. Thus, these two methods may lead to details loss. As evidence as tabulated in the Table 1, as the AE values for the MMBEBHE and the BPDHE methods are less than the proposed DQHEPL and BHEPL-D methods.

Although the proposed BHEPL-D and DQHEPL methods are ranked the fourth and third lowest in term of AAMBE test as tabulated in Table 1, these two proposed methods are ranked the first and second highest values respectively for APSNR and AE quantitative tests. The proposed BHEPL-D method is the best in term of less noise amplifying and details preserving (i.e. APSNR=27.33, AE=6.49) and followed by the proposed DQHEPL method (i.e. APSNR=25.35, AE=6.45). Thus, the qualitative and the quantitative tests suggest the proposed BHEPL-D as the best among all the methods.

The average execution time is processed with using 120 images with size of 2048×1036. The Table 1 suggests that, the processing time of the proposed DQPLHE method is more complex although it can reduce the intensity saturation effect. However, except for the HE and the BBHE methods, the proposed BHEPL-D method needs less processing time than the other conventional methods, providing less computation complexity.

V. CONCLUSION

In this paper, two novel contrast enhancement and brightness preserving methods have been proposed. The first method is referred to dynamic quadrants histogram equalization plateau limit (DQHEPL), an extension version of the RSIHE. The DQHEPL segments the histogram of input image based on its median value. In the upper and lower sub-histograms, the DQHEPL iteratively divides both sub-histograms based on its median value. Unlike the RSIHE, the lower and upper sub-histograms are expandable. The second method is the extension of the BHEPL and referred to the Bi-histogram Equalization Median Plateau Limit (BHEPL-D). Similar to the BHEPL, the BHEPL-D method divides the histogram of input image based on its mean value of the histogram. Then the BHEPL-D method engages the median value of histogram as the plateau limit instead of the mean in the BHEPL method. The experiment results show that, both of the proposed methods are able to maintain the mean brightness while preserving the details of the image. Moreover, the proposed methods do not produce any unwanted artifacts that occurred in conventional methods. However, in terms of the details preserving, the BHEPL-D outperforms the DQHEPL and other conventional methods. Moreover, the BHEPL-D method requires faster processing time.

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