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Using weighted dynamic range for histogram equalization to improve the image contrast

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Abstract

In this paper, an effective method, named the brightness preserving weighted dynamic range histogram equalization (BPWDRHE), is proposed for contrast enhancement. Although histogram equalization (HE) is a universal method, it is not suitable for consumer electronic products because this method cannot preserve the overall brightness. Therefore, the output images have an unnatural looking and more visual artifacts. An extension of the approach based on the brightness preserving bi-histogram equalization method, the BPWDRHE used the weighted within-class variance as the novel algorithm in separating an original histogram. Unlike others using the average or the median of gray levels, the proposed method determined gray-scale values as break points based on the within-class variance to minimize the total squared error of each sub-histogram corresponding to the brightness shift when equalizing them independently. As a result, the contrast of both overall image and local details was enhanced adequately. The experimental results are presented and compared to other brightness preserving methods.

Keywords: Contrast enhancement; Weighted dynamic range; Brightness preserving; Within-class variance

Introduction

Enhancing contrast of images by using histogram equalization (HE) is the standard technique to improve the visual image by stretching the narrow input image histogram [1]. However, it is not the appropriate method for consumer electronics, such as TV, because it changes the brightness of the original image strongly and degrades the image quality in visualization. Various methods have been proposed to limit the level of enhancement based on modifying the input histogram with mapping functions. The brightness preserving bi-histogram equalization (BBHE) [2], the dualistic sub-image histogram equalization (DSIHE) [3], and the minimum mean brightness error bi-histogram equalization (MMBEBHE) [4] divided the input histogram into two sub-histograms by a separating point. In order to enhance the image contrast, each sub-histogram was equalized independently. The BBHE method used the gray level as the mean value of image brightness to separate an input histogram into two parts: the first one is from the minimum gray level to the mean, and the second one is from the mean to the maximum gray level. The DSIHE method also used a similar approach to enhance the image contrast, except applying the median value instead of the mean value. In practice, the DSIHE is better than the BBHE in both preserving the image brightness and conserving the information content. The simple method to find out the separated point is to test all possible gray-scale values from 0 to $L-1$ of the histogram by calculating the difference between the mean brightness of input and the mean brightness of output. The separated point is chosen as the value that achieves the minimum difference in overall brightness. Although the above methods are better than HE in keeping the brightness of images, the visualization of enhanced images is degraded seriously, sometimes in detail and overall.

Based on the BBHE, the recursive mean separate histogram equalization (RMSHE) [5] and the recursive sub-image histogram equalization (RSIHE) [6] divided an original histogram into 2^n sub-histograms, where n is a positive integer value. The RMSHE splits the histogram into two parts by using the average of input brightness before separating one more time for each sub-histogram to have four segments in total. In practice, there are 2^n sub-histograms for n separated times. Having the same

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idea with the RMSHE in separation of more segments, the RSIHE also divided the histogram as well based on the median, rather than the mean of intensity values. Of note in these approaches, the output image looks like the copy version of the input image when n is too large, i.e., there is clearly no contrast enhancement here. In [7], the brightness preserving dynamic histogram equalization (BPDHE) divided the input histogram into an arbitrary number of sub-histograms based on break points which were determined by the local minima of the histogram. Based on the total number of pixels contained in each sub-histogram, the new partitions are obtained from the dynamic ranges by the new function for resizing. After the histogram equalization step, the output image would be normalized in brightness with the original to ensure that the mean of output intensity is close to the mean of input intensity. Moreover, the authors in [8] proposed a contrast enhancement method using the dynamic range separate histogram equalization (DRSHE) approach to preserve the naturalness of images and improve the overall contrast. The weighted average of absolute color difference (WAAD) used in the DRSHE produced an output image in which the adjusted histogram looks like the uniform distribution. The dynamic ranges in this study could be controlled by the adaptive scale factor to preserve the brightness. Detecting the start and stop positions of dynamic ranges is a difficult mission; thus, this algorithm cannot be suitable for various histogram types.

Another technique to improve the contrast, the weighted threshold histogram equalization (WTHE) [9] modified the probability density function of an image histogram. In detail, each original probability density value could be replaced by a new value based on the probability density function (pdf) with an initial threshold. Nevertheless, the disadvantage of this method is determining the threshold value through a scale parameter for the good visualization with no conditions to ensure the sum of the probability density value conserved. In order to solve this trouble, the recursively separated and weighted histogram equalization (RSWHE) [10] normalized the modified probability density function. With the other solution, each sub-histogram was smoothed by changing the corresponding original probability density function with the brightness preserving weight clustering histogram equalization (BPWCHE) [11]. This approach assigned each non-zero bin of the input histogram for the clusters and computed their weights. By using three criteria to merge pairs of neighbor clusters, the sub-histograms were then equalized independently. The Global Contrast Enhancement Histogram Modification Algorithm [12] was represented as the effective method for contrast enhancement by adjusting linear operations of the input histogram and utilizing the black and white (BW) stretching to obtain the visually pleasing, artifact-free, and natural looking images. Recently, the authors in the article [13] proposed the adaptive gamma correction with weighting distribution (AGCWD) to adjust the brightness for dimmed images via the gamma correction mechanism and the probability density function of luminance pixels. In spite of achieving a better visualization in output images, failing in preservation of the overall brightness can be seen as the shortcoming of this approach. Besides that, some methods were designed to improve the contrast for low illumination color images [14], in which color restoration was used as the post-process after adjusting the brightness in the local and global region. The artificial bee colony [15] in artificial intelligence science was also used for the contrast enhancement application. In this study, the function for mapping the input to the output intensity was established based on the searching and optimization algorithm.

In this paper, the brightness preserving weighted dynamic range histogram equalization (BPWDRHE) is proposed as an efficient contrast enhancement method. The input histogram is separated by applying the Otsu method [1] to determine divided points. The purpose of this approach is to minimize each sub-histogram error corresponding to its mean brightness for histogram equalization. In order to be suitable to various input images, the region ranges can be resized by the scale factor that has been set as the initial value. As the post-processes, the HE-based histogram will be smoothed and normalized to get the pleasing visualization with protection in the output brightness.

Brightness preserving weighted dynamic range histogram equalization

The contrast enhancement method proposed in this paper consists of three steps:

- Proposed separation algorithm: Separate the input histogram and adjust sub-histogram ranges by the scale factor.
- Contrast enhancement: Apply histogram equalization for each sub-histogram independently.
- Post-process: Smooth the histogram and normalize the overall brightness.

To be clear about these steps, Figure 1 shows the flow chart of the BPWDRHE method. The framework in Figure 1 can be also applied for color images by improving the contrast of the luminance channel in the YCbCr color model.

Proposed separation: determine break points based on the minimization of the sum of weighted within-class variance

In this step, the authors proposed the algorithm to divide the image histogram into sub-histograms based on the

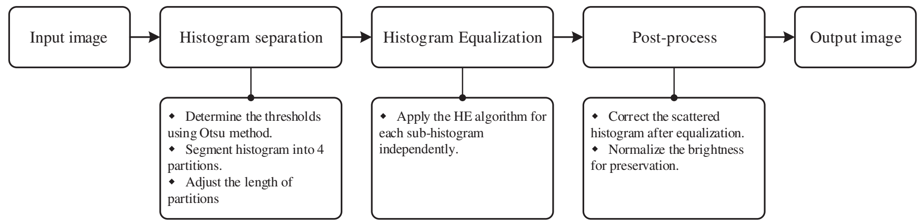

Figure 1 The flow chart of the proposed method BPWDRHE. For the color images, the method is only applied to the luminance channel of the YCbCr color space.

Otsu method [1] that is usually utilized in image segmentation applications. Unlike the separation algorithm in the study [16] when the break points were determined by using the local minimum, the proposed approach decides these points based on the minimum of variance. Therefore, this separation scheme reduced the modification of brightness from the histogram equalization of each sub-histogram. In particular, the minimization of the within-class variance is similar to the minimization of the total squared error of each sub-histogram, and it corresponds to the mean brightness. Therefore, the thresholds used in the separation process are determined as the minimum-variance gray level. In this study, these values are seen as the separated points and computed through the weighted sum of variance of the two classes σ_ω^2:

$$\sigma_\omega^2(t) = \omega_1(t)\sigma_1^2(t) + \omega_2(t)\sigma_2^2(t) \tag{1}$$

where the weights ω_1 and ω_2 are the probabilities of two classes separated by a threshold t. σ_1^2 and σ_2^2 are the variances of these classes. The individual variance class is defined as

$$\begin{aligned}\sigma_1^2(t) &= \sum_{i=0}^{t}\left((i-\mu_1(t))^2\frac{p(i)}{\omega_1(t)}\right)\\ \sigma_2^2(t) &= \sum_{i=t+1}^{255}\left((i-\mu_2(t))^2\frac{p(i)}{\omega_2(t)}\right)\end{aligned} \tag{2}$$

where $p(i)$ is the normalized histogram corresponding to the probability density function of each gray value and $\mu_i(t)$ are the class means which can be calculated as in the following equations:

$$\begin{aligned}\mu_1(t) &= \sum_{i=0}^{t}\left(\frac{i\times p(i)}{\omega_1(t)}\right)\\ \mu_2(t) &= \sum_{i=t+1}^{255}\left(\frac{i\times p(i)}{\omega_2(t)}\right)\end{aligned}. \tag{3}$$

The weights $\omega_1(t)$ and $\omega_2(t)$ in Equations 1, 2, and 3 are defined as

$$\begin{aligned}\omega_1(t) &= \sum_{i=0}^{t}p(i)\\ \omega_2(t) &= \sum_{i=t+1}^{255}p(i)\end{aligned}. \tag{4}$$

The threshold t in Equation 1 defined as the value with the minimum of the weighted sum of variance of two classes $\sigma_\omega^2(t)$ will separate the overall histogram into two distinguished regions. Therefore, it can be seen that the histogram will be separated into 2^n parts with n times in separation. In this study, four sub-histograms are generated from two times in separation. It can be explained that, actually, when n is too large, the enhancement influence on the output image is too slight, that is, it is difficult to recognize the modification in the overall brightness. Let us consider the effect of the number of sub-histograms on the brightness through the input to output gray-level function with the sample image Lena in Figure 2. In order to get some short results as in Figure 2, we applied the HE algorithm for these sub-histograms independently. In addition, some intermediate results achieved in the separation process are presented in Figure 3. With the input image shown in Figure 3a, the output images and their histograms are also shown in Figure 3b,c,d,e and Figure 3g,h,i,j, respectively. In the case of two sub-histograms ($n = 1$), the output image lost some details in the dark and light regions, so they are the main reasons of unnatural visualization in the output. The degradation in

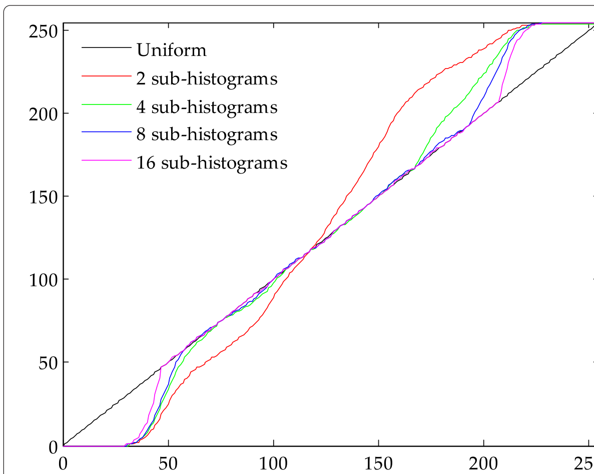

Figure 2 Mapping functions corresponding to cases of the Otsu method separation.

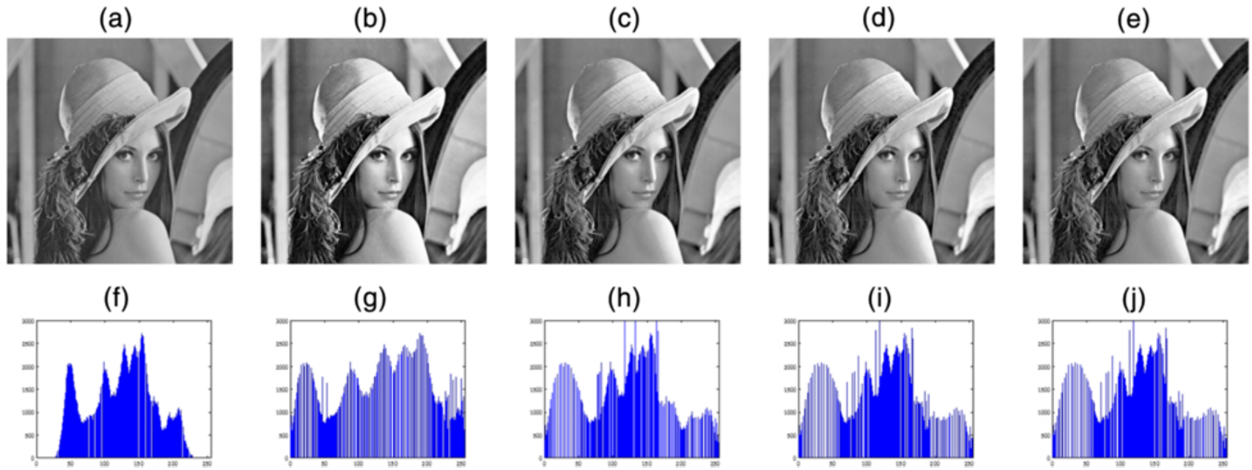

Figure 3 The intermediate results of histogram equalization using the Otsu method for Lena image. (a) The original image. **(b-e)** The output with $n = 1$, $n = 2$, $n = 3$, and $n = 4$, respectively. **(f-j)** The corresponding histograms of the images in **(a-e)**.

Figure 3b can be explained through the mapping intensity line (the red line in the Figure 2), in which the over-enhancement occurs strongly in two ranges [0,100] and [150,255]. These are the darker behavior at dark pixels and the brighter behavior at bright pixels. In practice, the larger the number of sub-histograms, the better the images. However, the mapping functions became similar to the uniform line $f(k) = k$ in Figure 2, and the mean of the output image brightness is close to the mean of the input image brightness if the number of times in the separation is too large. The comparison of the proposed separation mechanism with the others such as BBHE, DSIHE, MMBEBHE, and RSWHE is also represented in Table 1 as proof.

In this research, four sub-histograms are generated with two times in separation process for avoiding the complex computation and preserving the overall brightness. Let us denote t_1, t_2, and t_3 as the gray levels corresponding to the separating points. There are four sub-histogram ranges here as follows: $[0, t_1]$, $[t_1 + 1, t_2]$, $[t_2 + 1, t_3]$, and $[t_3 + 1, L - 1]$. Figure 4 shows the histogram sample which is separated into four segments, called DR1, DR2, DR3, and DR4 with lengths of $(t_1 + 1)$, $(t_2 - t_1)$, $(t_3 - t_2)$, and $(L - 1 - t_3)$, respectively. Although the total length of these sub-histograms is still L with $L = 2^8$ gray levels, there is a problem after separation when the authors experienced many images: the performance of enhancement when the lengths of any sub-histograms are too small.

Applying the histogram equalization algorithm for small sub-histograms does not assure an effective enhancement in the output due to a little bit of alteration. So these sub-histograms could be resized by the controllable scale factor and the fixed range to increase their lengths and conserve the total gray level. The length of the fixed range, called FR, depends on the number of sub-histograms that are generated: $\text{FR} = \frac{L}{2^n} = 64$ for $n = 2$ with a total of length $L = 256$. The lengths of resized dynamic ranges,

Table 1 Average of the means of 40 testing image brightness (denoted as AMB)

Method	AMB (50 images)
Original	120.98
BBHE [2]	133.27
DSIHE [3]	132.96
MMBEBHE [4]	123.97
RSWHE [12]	123.17
Proposed (2 sub-histograms)	135.05
Proposed (4 sub-histograms)	127.66
Proposed (8 sub-histograms)	123.77
Proposed (16 sub-histograms)	122.39

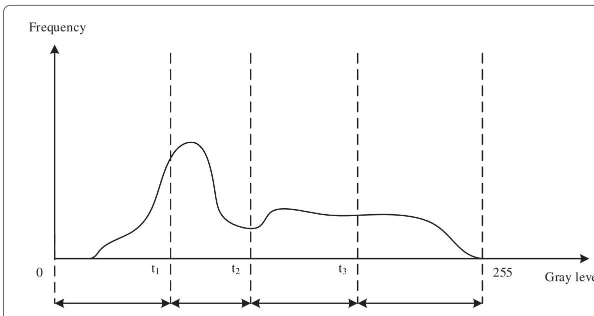

Figure 4 Example of the dynamic range separation using the Otsu method with $n = 2$.

denoted as RDR, of new sub-histograms are defined in the following equation [8]:

$$\mathrm{RDR}_i = \mathrm{FR} + \alpha\,(\mathrm{DR}_i - \mathrm{FR}) \tag{5}$$

where α is the scale factor that has a value between 0 and 1. It is noted that the proposed separation in the previous step is invalid when decreasing α to zero. The examples of an original DR and new RDR after applying a scale factor are shown in Figure 5. Let the range of the new sub-histogram be $[0, \mathrm{RDR}_i - 1]$ for the first one, and $[\min_i, \max_i]$ for ith one (with $i > 1$). Calculate the range of the ith new sub-histogram through the equations below:

$$\min_i = \sum_{k=1}^{i-1} \mathrm{RDR}_i \tag{6}$$

$$\max_i = \sum_{k=1}^{i} \mathrm{RDR}_i - 1. \tag{7}$$

In Equation 5, the scale factor needs to be chosen carefully. When $\alpha = 1$, the ranges of these sub-histograms are invariable. The smaller the scale factor, the slighter the effect of the Otsu method in separating the histogram. For $\alpha = 0$, the total histogram was segmented homogeneously, that is, the range of each partition is constant and set at 64 as the fixed range. Figure 6 presented the output images and their histograms in the cases that the scale factor was modified. Through intermediate results, it can be seen that the histogram in the case of $\alpha = 0.9$ looks similar to the one in the case of non-resizing.

Contrast enhancement: histogram equalization for each sub-histogram independently

Applying the HE approach for each sub-histogram independently is the next step in the BPWDRHE method. With the gray-level k belonging to the ith new sub-histogram ($k \in [\min_i, \max_i]$), the mapping function for the current gray level as the input is given in the following formula:

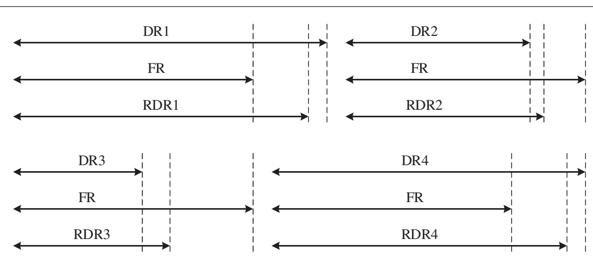

Figure 5 Resizing the dynamic range with a scale factor $\alpha = 0.85$ and number of times in separation $n = 2$.

$$f_{\mathrm{he}}(x) = \begin{cases} (\mathrm{RDR}_i - 1) \sum\limits_{k=0}^{x} \frac{n_k}{N_1}; & (i = 1) \\ (\min_i - 1) + \mathrm{RDR}_i \sum\limits_{k=\min_i}^{x} \frac{n_k}{N_i}; & (i > 1) \end{cases} \tag{8}$$

where n_k is the number of pixels of gray-level k, and N_i is the total pixels contained in the ith sub-histogram such that N_1 denotes the first sub-histogram.

Post-process: smooth the histogram and normalize the brightness

The weakness of HE-based methods is that the HE histogram distribution is very scattered, that is, the distance between two non-zero pixel bins is large. It can be explained by a few non-zero bins distributed on the huge range. Because of the over-enhancement since this behavior, the output images easily get visual artifacts. In order to deal with this problem, the modified histogram can be altered to be closer to the uniform distributed histogram, denoted as u. Using the algorithm for histogram smoothing as suggested in [12], the mapping function is defined as

$$f_s(x) = \frac{f_{\mathrm{he}} + \lambda u}{(1+\lambda)\,I + 2\gamma D^T D} \tag{9}$$

where λ is the uniform parameter and γ is the smoothing parameter, and the difference matrix D with a size of length 255×256 is bi-diagonal:

$$D = \begin{bmatrix} -1 & 1 & 0 & .. & 0 & 0 & 0 \\ : & : & : & .. & : & : & : \\ 0 & 0 & 0 & .. & 0 & -1 & 1 \end{bmatrix}. \tag{10}$$

The denominator in Equation 9, $(1+\lambda)\,I + 2\gamma D^T D$, in fact corresponding to the term operates as the averaged histogram function to make the histogram smoother. The above term can be expressed explicitly and clearly as in the matrix below:

$$\begin{bmatrix} 2\gamma + (1+\lambda) & -2\gamma & 0 & 0 & \cdots \\ -2\gamma & 4\gamma + (1+\lambda) & -2\gamma & 0 & \cdots \\ 0 & -2\gamma & 4\gamma + (1+\lambda) & -2\gamma & \cdots \\ \vdots & \vdots & \vdots & \vdots & \ddots \end{bmatrix}. \tag{11}$$

Let us examine Equation 9; when λ and γ are zero, the smoothed histogram is equal to the HE histogram, that is, there is no smoothing effect. In the case $\gamma = 0$, the smoothed histogram becomes more similar to the uniform histogram when λ increases. If the uniform parameter is set at a constant value, the overall contrast of image is reduced with the increment of γ. Figure 7a shows the mapping function for smoothing HE with various uniform parameter λ while holding the smoothing parameter

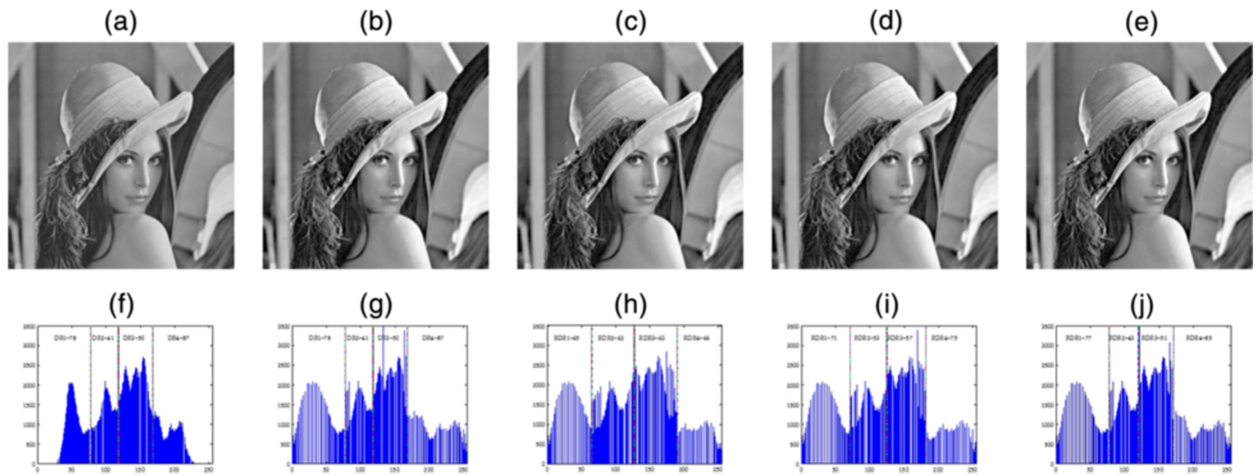

Figure 6 The intermediate results of resizing for four sub-histograms. (a) The original image. **(b-e)** The output without resizing and resizing with $\alpha = 0.1$, $\alpha = 0.5$, and $\alpha = 0.9$, respectively. **(f-j)** The corresponding histograms of images in **(a-e)**.

γ at zero. It is easy to realize that the mapping function is close to the uniform distribution under increasing λ. With $\lambda \geq 10$, the line of mapping function is similar to the that of the uniform. The histogram equalization hardly has any influences in improving contrast if the uniform parameter is too large. The effect of smoothing parameter in Equation 9 is shown in Figure 7b when the mapping functions with $\lambda \geq 1$ and modified smoothing parameter γ were considered. In this case, the larger the smoothing parameter γ, the softer the mapping function line. However, it is noted that the drawback of increasing γ is the degrading overall contrast of the output image. Because of the above reasons, choosing the unsuitable value of these parameters can be a cause of degradation of image visualization. From the summarization shown in Figure 7c, the case of $\lambda = 1$ and $\gamma = 10$ seems to be the best choice for the smoothing step.

Finally, in order to minimize the difference between the mean brightness of the output image and the original image, the modified histogram is normalized by the equation below [7]:

$$f_n(x) = \frac{B}{B_s} f_s(x) \tag{12}$$

where B and B_s are the mean brightness of the original and modified image after using the smoothing algorithm, respectively. The output image not only preserved the overall brightness but also obtained the comfortable visualization by applying the mapping function as given in Equation 12.

Results and discussions

For simulation, the authors compared the BPWDRHE with the others which are the Global HE [1], BBHE [2], DSIHE [3], MMBEBHE [4], WTHE [9], BPDHE [7], RSWHE [10], and AGCWD [13] on various images. In practice, 40 gray images [17] and 10 color images [18] of

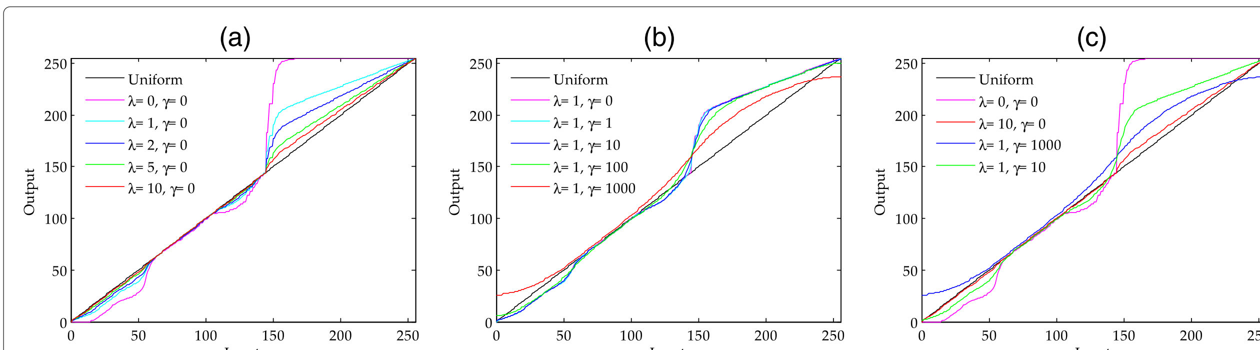

Figure 7 Mapping function of smoothed HE image with various uniform λ and smoothing γ parameters. (a) $\gamma = 0$. **(b)** $\lambda = 1$. **(c)** The summarization.

the Kodak database set are utilized for quantitative measurement. Besides that, some random images are chosen for representation and discussion. For more details, the parameters and factors have been set in the proposed separation stage as follows: $n = 2$ corresponding to four segments generated from the input histogram and $\alpha = 0.85$ for resizing the lengths of sub-histograms. Moreover, with parameters in the post-process, the authors use $\lambda = 1$ and $\gamma = 10$ to achieve efficiency in reducing negative effects from the over-enhancement and visual artifact behavior. These parameters have been chosen through the intermediate simulation, in which the experimental results are represented in Figures 2 and 3 and Table 1 (for explanation of n), Figure 6 (for description of α), and Figure 7 (for clarification of λ and γ). It is important to note that determined values for these parameters cannot be optimal for all images because the assessment for image quality depends on various aspects. In this paper, the authors try to estimate their values based on the observation of their specification. The influence of parameter n is measured by the average mean brightness (AMB) as shown in Table 1; meanwhile, the remaining parameters are proposed to overcome unexpected events from the histogram equalization scheme under visualization. However, the influence assessment of these parameters on the overall performance of the output images is necessary to be employed in the next simulation.

Assessment of the performance in contrast enhancement is never an easy mission. Although it is desirable to have an objective assessment approach to compare contrast enhancement techniques, unfortunately, there is no accepted objective criterion in the literature to provide meaningful results for every image. However, there are also some common quantitative measurements and subjective assessments for the estimation. In this research, the authors utilized the absolute mean brightness error (AMBE) [5], the discrete entropy (DE) [12], and the measure of enhancement (EME) [19] as the quantitative measurements. It is important to notice that the contrast enhancement for color images is quantified by applying these measurements on only its luminance channel. For the input image **X** and the output image **Y**, the AMBE is defined in the following function as

$$\mathrm{AMBE} = |E(X) - E(Y)| \tag{13}$$

where $E(X)$ and $E(Y)$ are the mean brightness of the images X and Y, respectively. The lower the value of the AMBE, the better the preservation in brightness. The DE of an image is described in the following function as

$$\mathrm{DE}(X) = -\sum_{i=0}^{255} p\left(x_i\right) \log p\left(x_i\right) \tag{14}$$

where $p\left(x_i\right)$ is the probability of pixel intensity x_i, which is estimated from the normalized histogram. A higher value of DE indicates that the image has richer details. In order to calculate the EME, let us divide the image into $k_1 k_2$ non-overlapping sub-blocks $X_{i,j}$ of size $w_1 \times w_2$, in this paper; its size is chosen as 8×8 for assessment. The parameter EME is computed in the following equation as

$$\mathrm{EME}(X) = \frac{1}{k_1 k_2} \sum_{i=1}^{k_1} \sum_{j=1}^{k_2} 20 \ln \frac{\max\left(X_{i,j}\right)}{\min\left(X_{i,j}\right)} \tag{15}$$

where $\max\left(X_{i,j}\right)$ and $\min\left(X_{i,j}\right)$ are the maximum and minimum gray levels, respectively, in block $X_{i,j}$. High-contrast sub-blocks give a high EME value, whereas for homogeneous sub-blocks, the EME value should be close to zero. It is worth to note that the EME is highly sensitive to noise. However, for the contrast enhancement application, this value is expected to be $\mathrm{EME}(Y) > \mathrm{EME}(X)$.

In the next step, an evaluation of the proposed method includes three simulations. Firstly, the authors assess the influence of some parameters in the separation and post-process stage on the overall performance with the quantitative and quality results. Then, the proposed method is compared to the others with subjective assessment for both gray-scale and color images. Finally, the comparison of the objective assessment based on the above quantitative measurements is presented in detail.

Parameter assessment

To evaluate the influence of parameters like n, α, λ, and γ, the authors decide to pick out a color sample from the data to investigate. The visual results as the outputs are presented in the Figures 8 and 9, while the quantitative results are shown in Table 2. The information about the values of these parameters corresponding to each image can be referred through Table 2. Compared to the original image as shown in Figure 8a, the effect of parameter n is recognized through Figure 8b,c,d. Although the changing in value of AMBE is very small, the DE and EME results show the evident influence. The trade-off between DE and EME can be realized as follows: when increasing the number of segments in separation, the local contrast factor (EME) will be decreased, while the measurement of image detail is made to be greater. This statement is verified through the observation of the cropping version in Figure 9b,c,d. The objects in Figure 9b have high contrast; however, the texture of the white object is hardly recognized. Since this sample does not belong to special cases (no small sub-histogram is generated from the Otsu separation), the effect of the resizing step by α is insignificant in the visualization (Figure 8e,f and Figure 9e,f) and also in the objective assessment (Table 2). For the uniform parameter λ, the changes in overall performance occur at all of the quantitative measurements. The increasing

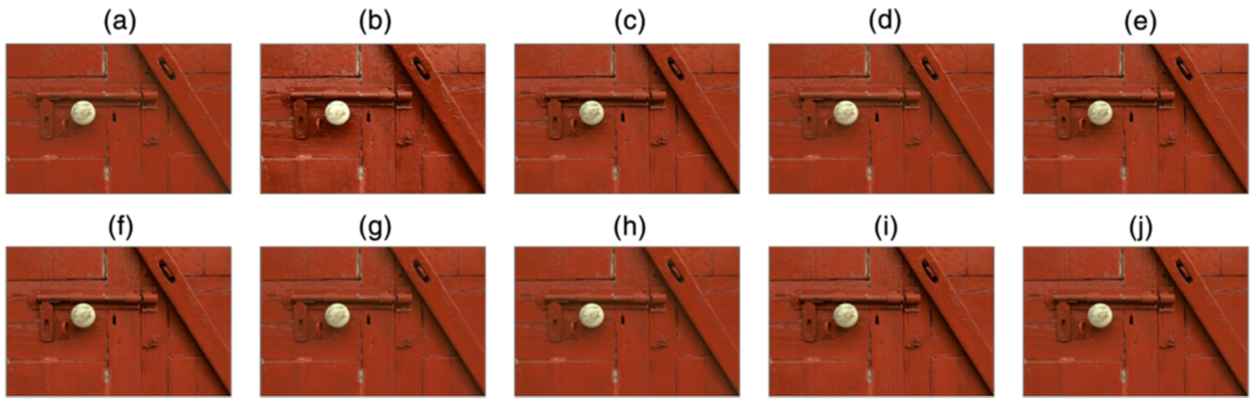

Figure 8 The influence of parameters on the visual results at the outputs. (a) The original image. **(b-j)** The outputs corresponding to cases of changing parameters (refer to Table 2 for more information).

value of λ will generate the output which looks similar to the input (the values of DE and EME reach the original value). Finally, like the case of α, the impact of the smoothing parameter γ is not enough to be detected, at least for the visualization result, while it can be only recognized through the AMBE, DE, and EME with a little bit of changing in value. With the proposed values for these parameters (as in Figures 8c and 9c), the authors want to achieve the balance of performance between the visualization and quantitative results, in which it can be seen that the values of AMBE, DE, and EME are homogeneously improved to get the stability for all images. That means the overall contrast of the input image is enhanced with the minimization of changes in brightness and loss in detail.

Subjective assessment

Gray image

Some contrast enhancement results for gray-scale images are shown in Figures 10, 11, 12, 13, 14 and 15 with three samples named the Toy, the Aircraft, and the Pentagon. For each image, the cropped version of the small area is also represented clearly for analysis in detail. In order to get the evident illustration of enhancement, Figure 16 presented the mapping functions of tested methods for gray-scale images.

For the Toy image shown in Figure 10, due to the over-contrast enhancement occurring abnormally in the Global HE, it is hard to identify the plastic balloons. Some methods including the BBHE, DSIHE, MMBEBHE, and WTHE also provide similar contrast images; however, the

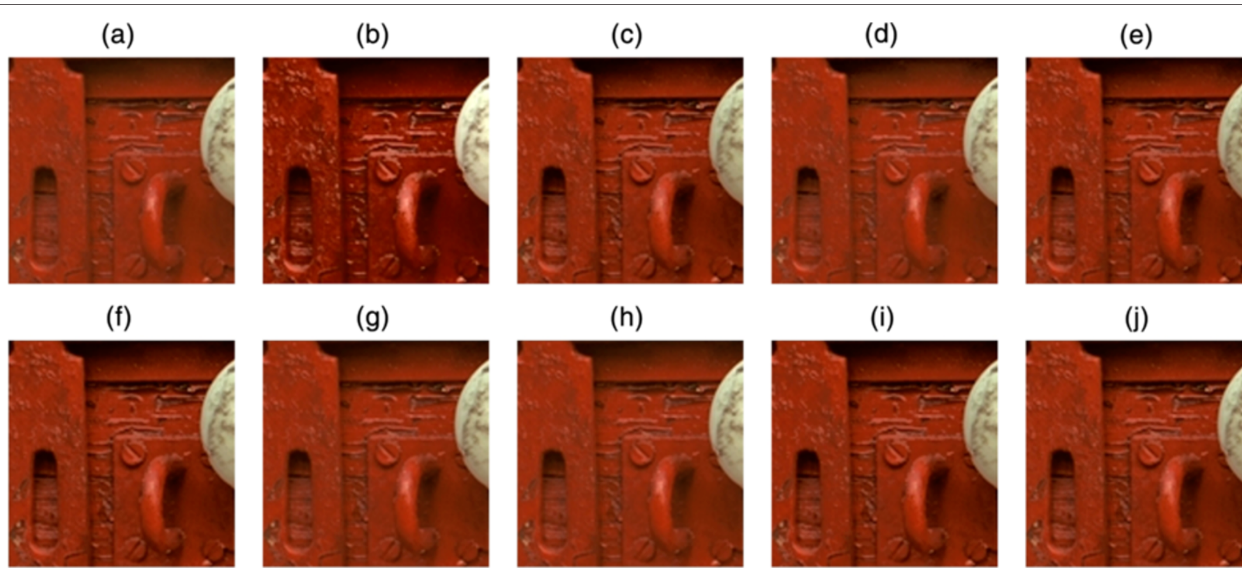

Figure 9 The small region is cropped from Figure 8 (a-j).

Table 2 Quantitative assessment of parameters on the overall performance

Figures 8 and 9	n	α	λ	γ	AMBE	DE	EME
(a)		The original image			-	3.7277	7.5317
(c)	2	0.85	1	10	0.0288	3.6578	10.8647
(b)	1	0.85	1	10	0.0334	3.6770	15.3762
(d)	3	0.85	1	10	0.0380	3.7005	9.2426
(e)	2	0.5	1	10	0.0048	3.6734	10.6417
(f)	2	1	1	10	0.0308	3.6470	10.9212
(g)	2	0.85	5	10	0.1201	3.6892	8.6789
(h)	2	0.85	10	10	0.0960	3.7042	8.1405
(i)	2	0.85	1	1	0.0167	3.6409	11.1318
(j)	2	0.85	1	100	0.0479	3.7049	10.1021

background of the output images is degraded seriously with the rough brightness. The photometric differences between some regions in the background are significant and unacceptable. Therefore, the brighter regions can be confused with the balloon shadows. The undesired behavior occurs severely in the output of the WTHE method. Therefore, many artifacts and unnatural visualization areas occur unexpectedly. Although getting a better visual quality result, the enhancement of the AGCWD method is not powerful enough to distinguish the details on the balloon to observe as shown obviously in Figure 11. The weakness of this method is not ensuring the overall brightness. For the BPDHE, RSWHE, and BPWDRHE approaches, the outputs are not distorted in the global contrast; however, the brightness of the RSWHE image is darker in general. In order to understand the effect of each approach, Figure 16a displays their mapping functions. In the gray-value range [0,40], the behaviors of some methods, such as the Global HE, BBHE, DSIHE, MMBEBHE, WTHE, and BPDHE, are similar and therefore it explained for the dark areas on the balloons. In addition, the decay of illumination on the background is clarified by the shape of mapping lines in the range [190,255].

For both the Aircraft image and its cropped area shown in Figures 12 and 13, it can be seen that some approaches, such as the Global HE, BBHE, MMBEBHE, and WTHE, enhanced the overall brightness excessively and therefore the texture on the aircraft body cannot be observed clearly. Although the DSIHE and BPDHE methods perform better than the above methods, they also enhanced some unnecessary details on the background. Observation of the contrast enhancement on the RSWHE image is quite difficult due to the slight effect. For the AGCWD method, the enhanced image looks brighter without brightness preservation and so many bright-pixel details have been removed, such as the take-off trail. Meanwhile, the proposed approach enhances the contrast at the moderate level enough to observe each component of the aircraft body and the take-off trail clearly without an alteration in the brightness. The shapes of mapping function lines of some bad visualization schemes, such as the Global HE, BBHE, and WTHE, are alike. The limitation of the value range in the WTHE technique can be understood as the main reason for a low contrast in the output. The behavior of the MMBEBHE line in the range [60,150] is the cause of losing details on the aircraft body. Since the RSWHE line is close to the uniform

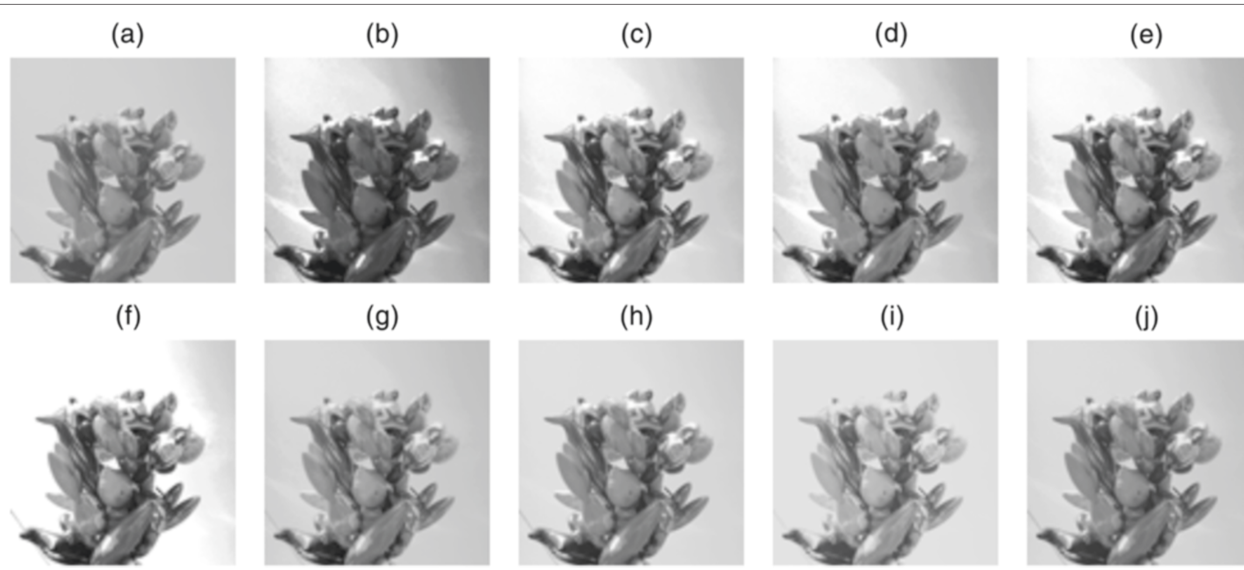

Figure 10 Comparison of enhancement methods with test image Toy. (a) Original. The enhanced image: **(b)** Global HE. **(c)** BBHE. **(d)** DSIHE. **(e)** MMBEBHE. **(f)** WTHE. **(g)** BPDHE. **(h)** RSWHE. **(i)** AGCWD. **(j)** BPWDRHE.

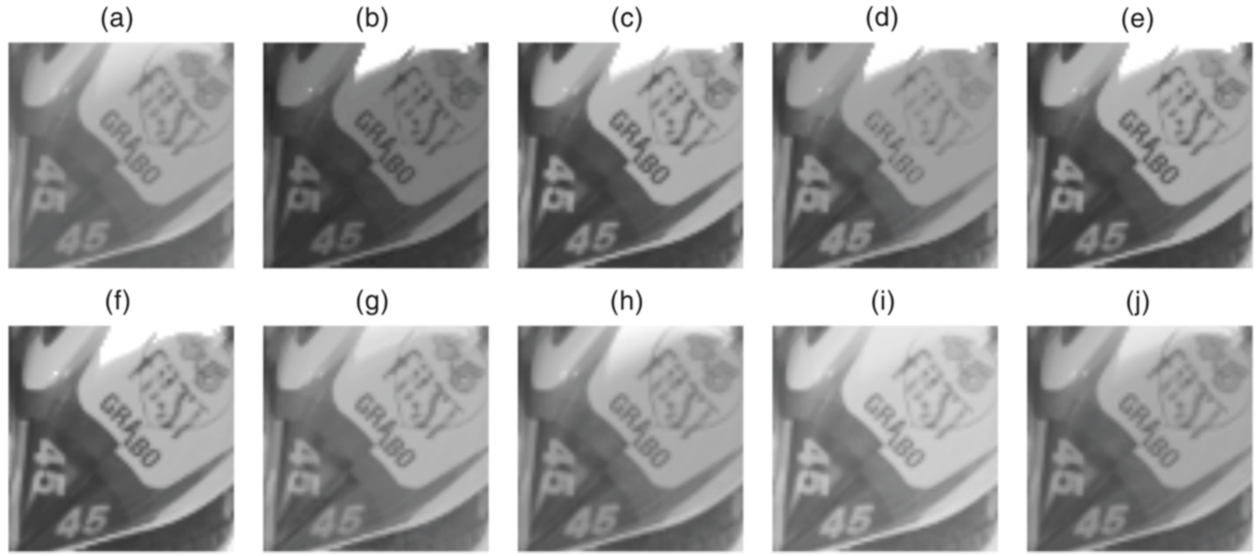

Figure 11 The small region is cropped from Toy. (a) Original. The enhanced image: **(b)** Global HE. **(c)** BBHE. **(d)** DSIHE. **(e)** MMBEBHE. **(f)** WTHE. **(g)** BPDHE. **(h)** RSWHE. **(i)** AGCWD. **(j)** BPWDRHE.

line, the output looks like the input in the contrast. For the BPWDRHE method, the gray-value ranges [0,40] and [200,250] corresponding to the bright and dark pixels are improved fairly.

Some methods including the Global HE, BBHE, MMBEBHE, and WTHE methods improved the contrast of image excessively in the two-side extension way in the Pentagon image: the bright pixels to be even brighter and the dark pixels to be even darker. As a result, some dark and bright details can be damaged seriously. The three methods such as the BPDHE, RSWHE, and BPWDRHE still maintain the general brilliance. However, some regions in the enhanced image of the BPDHE method are dimmed unexpectedly with medium brightness pixels, while an enhancement of the RSWHE method is not strong enough to recognize the modification in the contrast. In practice, these observations are displayed in detail in Figure 15. Except for the fan-shaped object

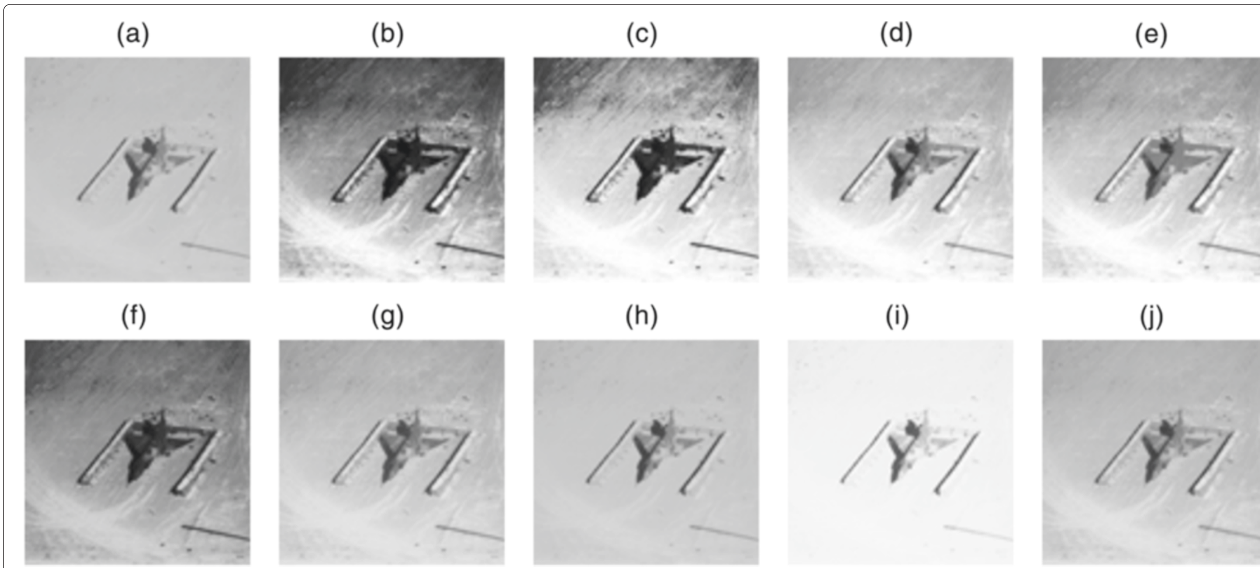

Figure 12 Comparison of enhancement methods with test image Aircraft. (a) Original. The enhanced image: **(b)** Global HE. **(c)** BBHE. **(d)** DSIHE. **(e)** MMBEBHE. **(f)** WTHE. **(g)** BPDHE. **(h)** RSWHE. **(i)** AGCWD. **(j)** BPWDRHE.

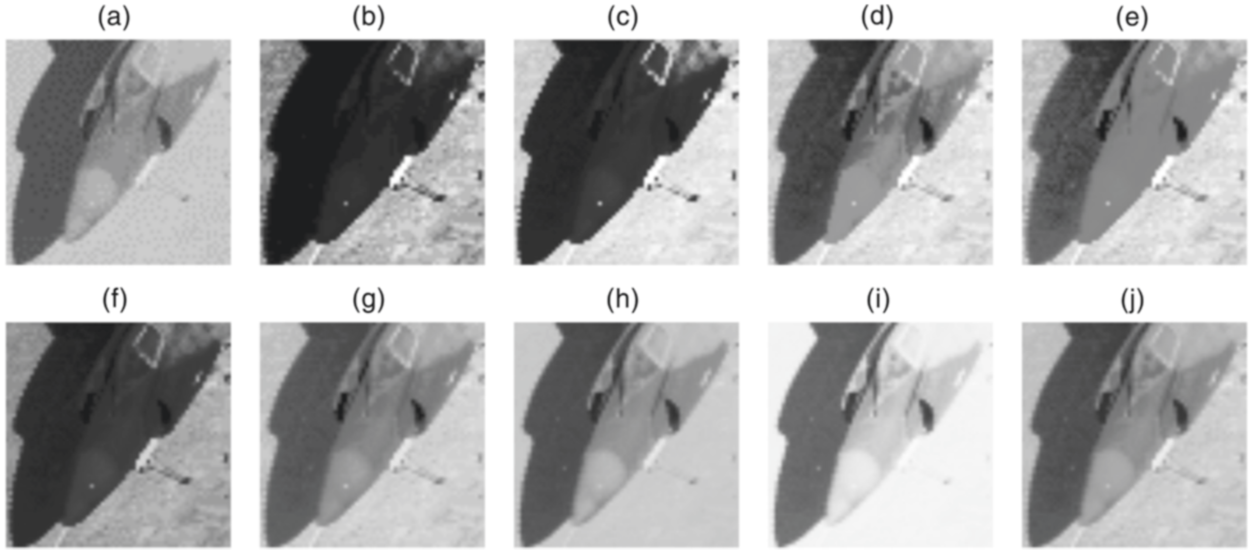

Figure 13 The small region is cropped from Aircraft. **(a)** Original. The enhanced image: **(b)** Global HE. **(c)** BBHE. **(d)** DSIHE. **(e)** MMBEBHE. **(f)** WTHE. **(g)** BPDHE. **(h)** RSWHE. **(i)** AGCWD. **(j)** BPWDRHE.

in the square detected by the very dim thin boundary in Figure 15b,c,d,e,f, the BPDHE image also gets the same behavior with medium gray levels. Only with the RSWHE and BPWDRHE methods can the object be identified easily due to its high contrast. The shape of the mapping function line in Figure 16c of the AGCWD approach in the range [125,255] explained for the brightened image. Due to getting the same result in the enhancement, the lines of the Global HE, BBHE, and MMBEBHE methods are similar to each other. The gray-level limitation in the WTHE and BPDHE produces low-contrast images in the output when the maximum gray value is 200 and 206 instead of 255 as normality. After all, the behavior of the mapping function line of the proposed method at the ranges [0,73] and [190,255] for contrast improvement and [105,170] for brightness preservation produced the pleasing visualization in the output image.

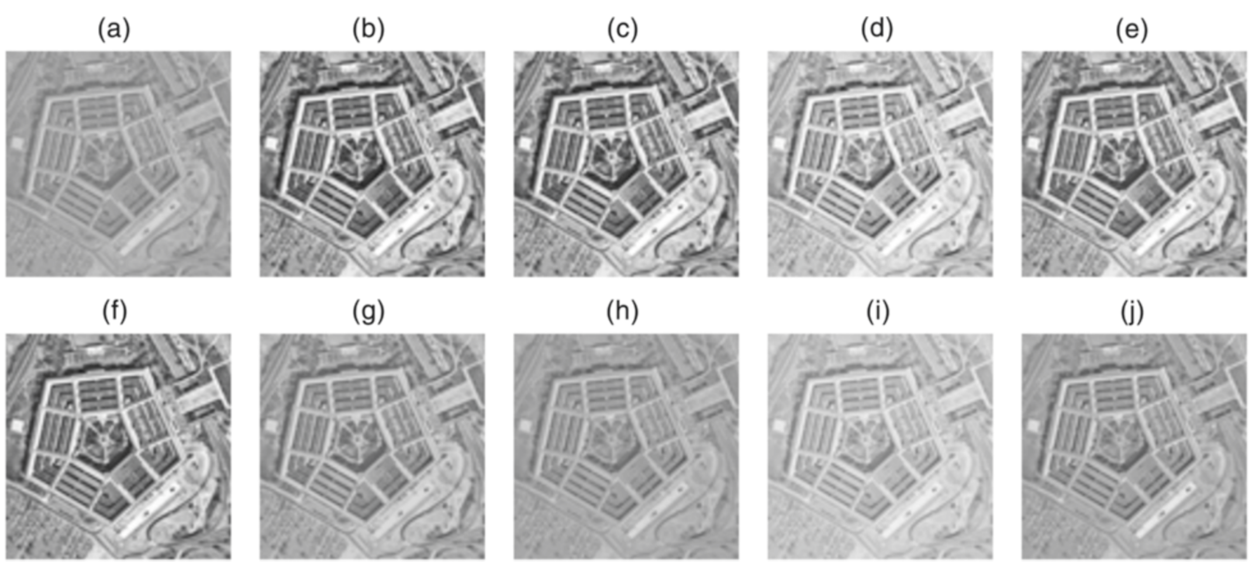

Figure 14 Comparison of enhancement methods with test image Pentagon. **(a)** Original. The enhanced image: **(b)** Global HE. **(c)** BBHE. **(d)** DSIHE. **(e)** MMBEBHE. **(f)** WTHE. **(g)** BPDHE. **(h)** RSWHE. **(i)** AGCWD. **(j)** BPWDRHE.

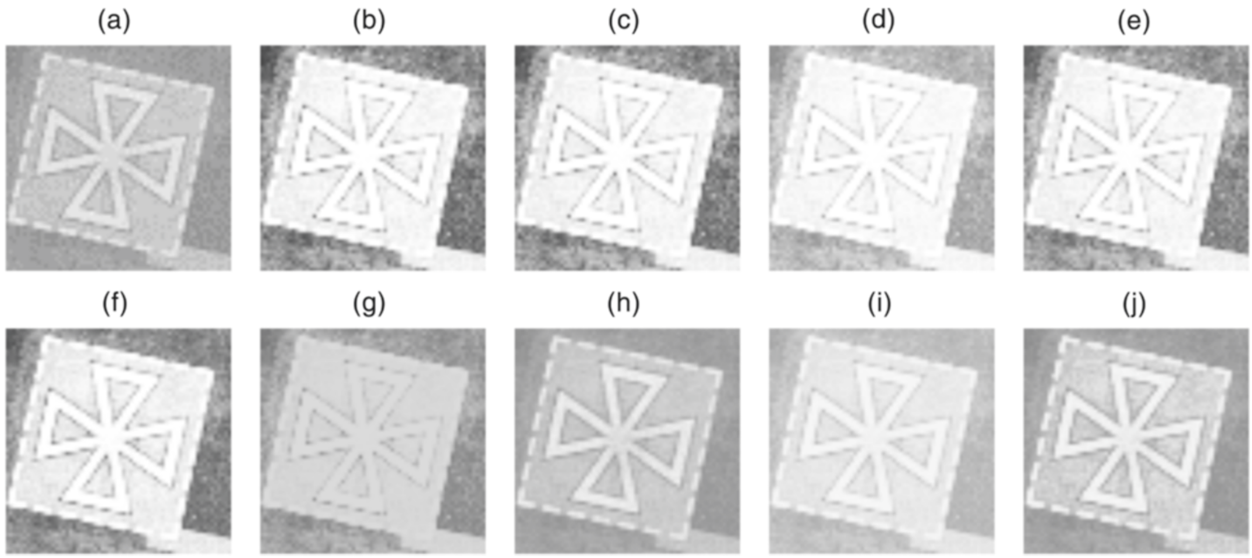

Figure 15 The small region is cropped from Pentagon. (a) Original. The enhanced image: **(b)** Global HE. **(c)** BBHE. **(d)** DSIHE. **(e)** MMBEBHE. **(f)** WTHE. **(g)** BPDHE. **(h)** RSWHE. **(i)** AGCWD. **(j)** BPWDRHE.

Color image

Contrast enhancement can be easily extended to the color images. The most obvious way to extend the color images is to apply these methods to the luminance component. However, some enhancement approaches for color images utilized the HSV (hue, saturation, value) [14] color model to improve the contrast. To consider the performance of the tested method for color images, the simulation was implemented for ten color images from the Kodak standard image library. At first, the sample color image Hats is shown in Figure 17 and the cropped version in Figure 18. In the results of the Global HE, BBHE, DSIHE, and WTHE methods, the hues of the output images are changed seriously. These studies not only darkened some areas of the wood plank and the hat shadows but also brightened some regions of the cloud and the top of the yellow hat. Therefore, many features in these regions are lost. The degradations of the MMBEBHE, WTHE, and BPDHE approaches are not as severe as the result of the above methods. To be better, the AGCWD method produced the brighter image both in overall and detail; however, recognition of the bright-pixel details on the top of the yellow hat is an impossible task due to its bad contrast. Only with the proposed method and the RSWHE are the details enhanced expectantly with no hue distortion, for instance, the texture of the wood plank looks clear. Based on the mapping function as shown in Figure 19a, it is not difficult to realize that the Global HE, BBHE, DSIHE, and WTHE methods enhanced over-contrast for the bright pixels corresponding to the pixels in the range

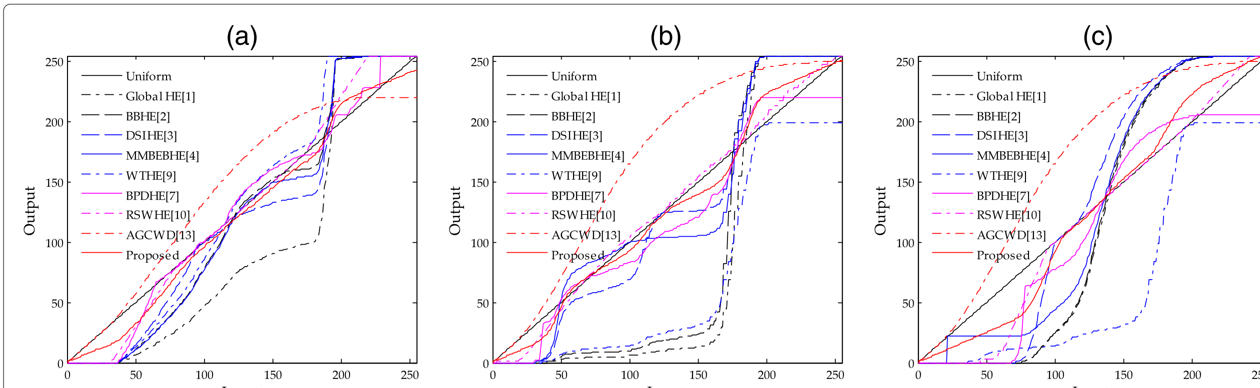

Figure 16 Mapping functions of three gray-scale images. (a) The Toy. **(b)** The Aircraft. **(c)** The Pentagon.

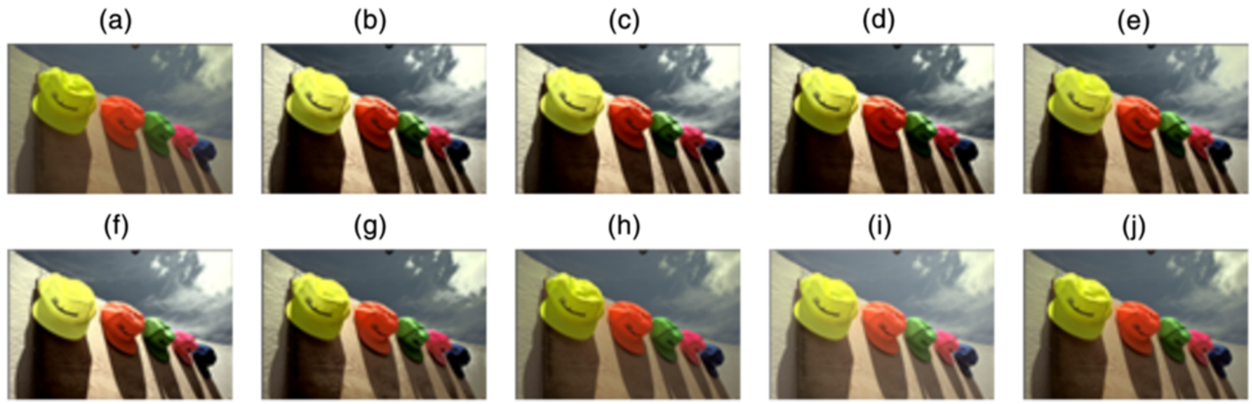

Figure 17 Comparison of enhancement methods with test image Hats. (a) Original. The enhanced image: **(b)** Global HE. **(c)** BBHE. **(d)** DSIHE. **(e)** MMBEBHE. **(f)** WTHE. **(g)** BPDHE. **(h)** RSWHE. **(i)** AGCWD. **(j)** BPWDRHE.

[150,255] and the dark pixels corresponding to the pixels in the range [0,50]. The distortion in the hue component of the cloud and the wood plank can be explained by this behavior. For this sample, only the overall contrast of the AGCWD method is limited. The output images of the RSWHE and BPWDRHE approaches look natural with the enhancement process for both dark-pixel range [0,75] and bright-pixel range [175,255]. Nevertheless, the modification on the output image after improving the contrast in the RSWHE case is not obvious.

The Wall image, the next color sample, is shown in Figures 20 and 21. The results of the Global HE, BBHE, DSIHE, MMBEBHE, and WTHE have similar contrast enhancement with cold overall hue, while BPDHE has a better visual result. The characteristic of the AGCWD is that it usually produces the output images which are brighter than the original. Therefore, some bright-pixel details having a low-contrast will be lost or realized with difficulty. In Figure 21, the object behind the glass window in the Global HE, BBHE, DSIHE, and WTHE methods is brightened so much that it is hardly observed. Except for the RSWHE and BPWDRHE, the remaining methods get the same drawback in the slight level. Considering the chroma of the door, it can be seen that the enhancement of the RDWHE mechanism is very slight. For the BPWDRHE method, the output image achieves adequate contrast in both the overall and detail. The input to output gray-level functions of the tested methods can be

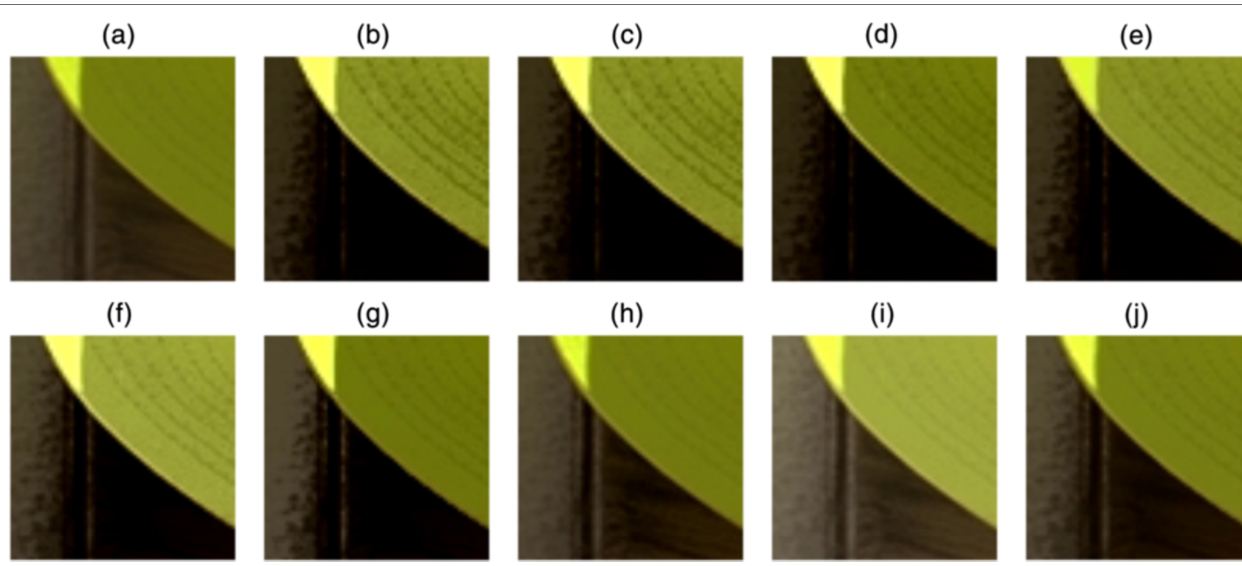

Figure 18 Comparison of enhancement methods with test image Hats (cropped from Figure 17). (a) Original. The enhanced image: **(b)** Global HE. **(c)** BBHE. **(d)** DSIHE. **(e)** MMBEBHE. **(f)** WTHE. **(g)** BPDHE. **(h)** RSWHE. **(i)** AGCWD. **(j)** BPWDRHE.

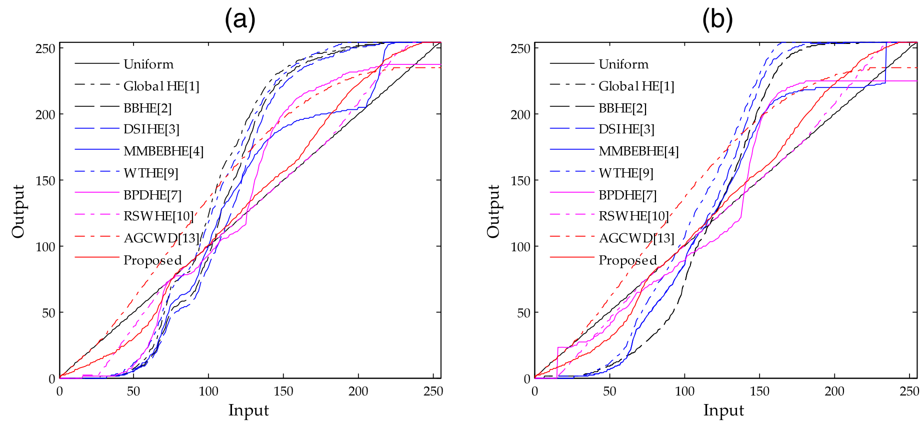

Figure 19 Mapping functions of two color images. (a). The Hats **(b)**. The Wall.

carefully considered in Figure 19b. The common shortcoming of the Global HE, BBHE, MMBEBHE, DSIHE, and WTHE is the production of the over-contrast images. The output images of these methods lose the bright and dark pixel parts. Based on the mapping function lines in Figure 19b, the pixels belonging to the range [0,50] will be darkened, while the pixels in the range [175,255] become lighter for the above methods. Therefore, details of the object behind the glass window are removed unexpectedly. Like the previous test images, the AGCWD has a tendency to produce a brighter image for the gray level larger than 50, while the overall contrast has not been preserved. The BPDHE method is similar to the AGCWD in the range [150,255]; however, it gets the same behavior of the Global HE for the over-contrast enhancement. Only two methods, the RSWHE and BPWDRHE, get the good enhancement when only improving the luminance in the sensible level. Nevertheless, the input to output function of the proposed method is smoother than that of the RSWHE.

Objective assessment

Results of the AMBE, DE, and EME measurement of 50 sample images are listed in Tables 3, 4 and 5, respectively. In Table 3, the average value of AMBEs is shown beside the results of sample images which were presented in the subjective assessment. A comparison of AMBE values shows that the proposed method and the BPDHE outperform others used in the simulation when they achieve good brightness preservation with the smallest values by the brightness normalization after equalizing the histogram. Due to focusing on brightness improvement for dimmed images without brightness preservation, the AGCWD method has the greatest value of AMBE when this method made inputs to be brighter in most of the output images. Without any solutions to limit the modification in the overall brightness, the remaining methods produce unexpected images which are different from the original in the global brightness. Based on the results of the Aircraft sample in Figure 12, it is not difficult to predict the brightness error when AMBE values of outputs of the Global

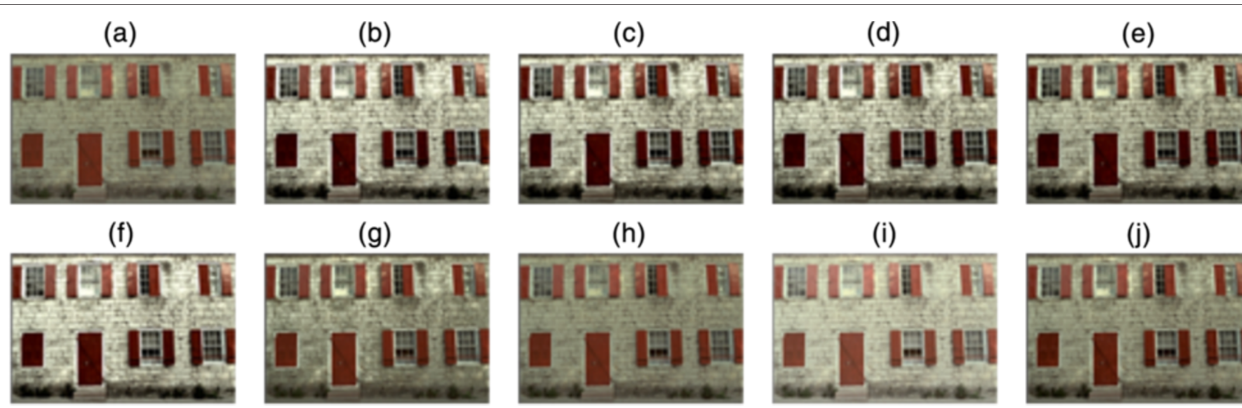

Figure 20 Comparison of enhancement methods with test image Wall. (a) Original. The enhanced image: **(b)** Global HE. **(c)** BBHE. **(d)** DSIHE. **(e)** MMBEBHE. **(f)** WTHE. **(g)** BPDHE. **(h)** RSWHE. **(i)** AGCWD. **(j)** BPWDRHE.

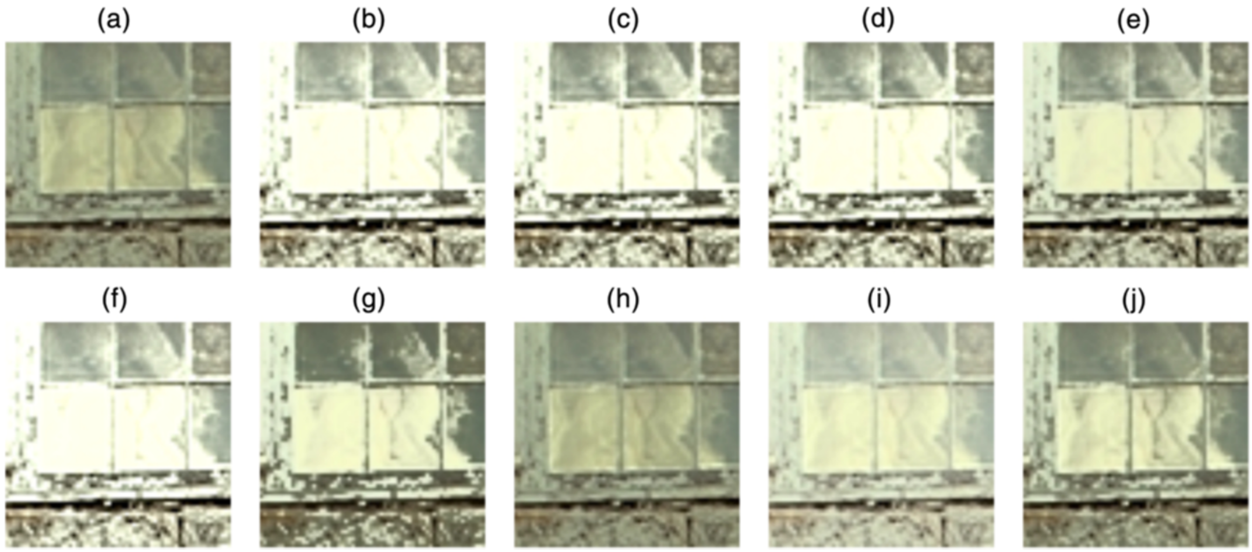

Figure 21 Comparison of enhancement methods with test image Wall (cropped from Figure 20). (a) Original. The enhanced image: **(b)** Global HE. **(c)** BBHE. **(d)** DSIHE. **(e)** MMBEBHE. **(f)** WTHE. **(g)** BPDHE. **(h)** RSWHE. **(i)** AGCWD. **(j)** BPWDRHE.

HE, DSIHE, WTHE, and AGCWD are so much higher than others. These methods generate the outputs to be either so much darker or brighter. The BBHE and DSIHE have the same idea in the histogram separation; thus, their AMBE values look similar together, except for some cases of special histograms. Meanwhile, the MMBEBHE gets the better result because its algorithm not only improves the contrast like BBHE but also minimizes the total error of brightness changes.

With the second measurement, the DE of the original image will be seen as the standard to be compared with the DE of enhanced images. The important thing to note is that the DE values of modified images are always equal or less than the original. This means that it is difficult to retain the detail of the output like the detail of the input. The behavior of losing detail occurs in most of the enhancement methods because the mapping function is nonlinear, that is, it usually has one output value for many input values. This behavior is absolutely considered through mapping function graphs as in Figures 16 and 19. The other way to explain based on histograms is that many original histogram bins grouped into one bin after enhancement can be the reason of the decrement in the DE values for over-enhanced images. It is not difficult to understand why the DE parameter of output images of these approaches is slightly reduced. Through Table 4, the performance of the proposed method and the RSWHE are quite similar in the average value of DE when both of them with high discrete entropy are better than the other methods. The Global HE gives the worst results in most of the samples with the least value of average as the loss of data of over 15%, while the remaining methods basically keep

Table 3 Absolute mean brightness error (AMBE) and average of AMBEs (AAMBE)

Method	AMBE					AAMBE
	Toy	Aircraft	Pentagon	Hats	Wall	(50 images)
Global HE [1]	29.38	47.82	11.04	7.81	10.19	30.49
BBHE [2]	5.48	1.46	6.89	23.77	17.19	12.29
DSIHE [3]	1.27	15.42	28.65	0.03	10.19	11.98
MMBEBHE [4]	3.16	6.51	1.37	1.25	1.00	2.99
WTHE [9]	27.13	55.61	12.36	22.25	23.62	29.62
BPDHE [7]	0.15	0.05	0.02	0.02	0.007	0.26
RSWHE [10]	7.70	3.48	0.80	0.76	0.45	2.19
AGCWD [13]	26.14	58.45	35.46	33.52	38.33	36.75
BPWDRHE	0.08	0.01	0.09	0.02	0.07	0.05

Table 4 Discrete entropy (DE) and average of DEs (ADE)

	DE					ADE
Method	Toy	Aircraft	Pentagon	Hats	Wall	(50 images)
Original	4.19	2.78	4.66	4.79	4.83	4.52
Global HE [1]	3.48	2.60	4.01	4.66	4.75	3.84
BBHE [2]	4.09	2.72	4.61	4.1	4.11	4.42
DSIHE [3]	4.03	2.74	4.57	4.67	4.75	4.40
MMBEBHE [4]	4.07	2.71	4.59	4.65	4.74	4.41
WTHE [9]	3.35	2.74	4.64	4.68	4.70	4.27
BPDHE [7]	4.07	2.75	4.47	4.60	4.58	4.32
RSWHE [10]	4.19	2.78	4.66	4.79	4.83	4.51
AGCWD [13]	3.61	2.78	4.62	4.74	4.79	4.30
BPWDRHE	4.15	2.77	4.64	4.77	4.81	4.48

image content at the moderate level with the largest losing grade of 6%.

The comparison of EME values in Table 5 shows that the Global HE, BBHE, DSIHE, MMBEBHE, and WTHE methods usually get higher EME values than the remaining methods. Since the EME criterion measures a form of contrast, it is no surprise that these methods give the highest values even though they hardly ever produced the most visually pleasing images. Although the enhancement grade is identified through this value with the output value greater than the value of the original image, the high results of the above methods can be the main reason for the degradation of quality. As results for the Toy sample, some methods such as the Global HE, BBHE, DSIHE, MMBEBHE, and WTHE achieve the high value of EME corresponding to the high contrast; however, their outputs are seriously damaged unexpectedly in the quality. For the AGCWD method, increasing the brightness overall can be the cause of depressing the local contrast corresponding to the EME value, especially with the Aircraft sample. Meanwhile, the EME values achieved from the proposed method are enough to realize the difference of contrast between inputs and outputs without visual artifacts.

In summary, it is important to note that the quality of an enhanced image depends on many criteria. Besides increasing the contrast in the adequate grade to avoid the occurrence of artifact unexpectedly, the efficient method needs to preserve not only the overall brightness but also the detail in the output. Based on the experimental results, the proposed method satisfied these criteria at least in this evaluation with 50 test images; however, the trade-off here is the computation fee, that is, the algorithm will need more time for enhancing the steps.

Conclusion

In this work, the authors proposed and experimented on the new contrast enhancement method for both grayscale and color image, called BPWDRHE. The BPWDRHE method enhanced the contrast with preservation of the overall brightness to generate the natural looking images. Unlike some previous techniques, the proposed method reduced the appearance of visual artifacts in the outputs.

Table 5 Measure of enhancement (EME) and average of EMEs (AEME)

	EME					AEME
Method	Toy	Aircraft	Pentagon	Hats	Wall	(50 images)
Original	4.81	3.14	8.59	5.42	14.65	14.34
Global HE [1]	13.94	25.64	40.57	15.64	39.87	28.86
BBHE [2]	10.99	18.99	36.44	15.85	42.56	26.04
DSIHE [3]	9.40	8.09	21.62	15.91	39.86	23.88
MMBEBHE [4]	11.06	8.72	23.96	14.28	38.07	24.27
WTHE [9]	10.34	15.39	32.5	12.89	34.92	22.44
BPDHE [7]	7.18	5.68	14.71	12.76	19.55	21.09
RSWHE [10]	6.60	3.37	10.16	7.03	16.65	15.12
AGCWD [13]	4.61	1.98	8.56	5.55	14.44	14.19
BPWDRHE	6.29	4.85	12.28	7.62	20.87	15.62

The novelty of proposed contrast enhancement is that the sum of weighted within-class variance was utilized to determine the break points for histogram separation based on the minimization of the total squared error of each sub-histogram corresponding to the equalization-based brightness shift. After applying the HE technique for these sub-histograms, the output image histogram will be smoothed and normalized to obtain the good visualization as the post-processes. Moreover, the BPWDRHE was estimated for gray-scale and color images and then compared to the others in various aspects with some common quantitative assessments, such as the absolute mean brightness error, the discrete entropy, and the measure of enhancement.

Competing interests
The authors declare that they have no competing interests.

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