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An effective histogram modification scheme for image contrast enhancement

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ABSTRACT

Contrast enhancement plays a significant role in digital image processing. However, traditional histogram equalization usually results in excessive enhancement, which in return causes an unnatural look and loss of details to the target image. In this paper, we propose a novel histogram modification scheme for image contrast enhancement. First, sum of the input histogram and its standard deviation are computed. Then, gamma correction is applied on the result sum to generate a modified histogram. And finally, the traditional histogram equalization is applied on the modified histogram to produce the mapping function. In addition to preserving the mean brightness, the proposed method can enhance an image uniformly with low computation complexity. Extensive experimental results show that the proposed method not only retains features of the input image but also can enhance the contrast of all kind of images significantly.

1. Introduction

Contrast enhancement (CE) is an important image processing technique for both human perception and computer vision. It is widely used for medical image processing [1–3], video surveillance system [4], analyzing images from satellites [5,6],haze removal in intelligent transportation system [7], etc. Numerous contrast enhancement techniques have been proposed in recent years. Generally, these techniques can be broadly classified into two categories: direct enhancement methods [6,8–10] and indirect enhancement methods [5,11,12]. In direct enhancement methods, contrast is expressed by some pre-defined contrast measurements, then corresponding algorithms are devised to improve these measurements; On the other hand, indirect enhancement methods attempt to improve contrast by redistributing the probability density without defining any specific contrast terms [11]. Indirect enhancement methods attract the most researchers due to their effectiveness and intuitive implementation qualities [5,11], and they can be further divided into two groups: group (i) transform domain techniques (e.g., logarithmic transformations, power-law transformations, piece-wise linear transformation, gray-level slicing, etc.) [12–15], and group (ii) histogram processing techniques (e.g., histogram specification (HS), histogram equalization (HE), histogram modification, etc.) [16–18].

Among various contrast enhancement methods, histogram processing techniques catch the most attention. Histogram specification, (also called histogram matching) is a kind of histogram processing technique that modifies the original input histogram to follow the desired histogram through transformation function. Typical distributions for the desired output histogram are uniform, Gaussian, and exponential ones. To acquire the desired shape, one must have an accurate priori knowledge, which is almost impossible for some applications, since natural images exhibit significantly different histogram characteristics from one to another [19].

HE is the most commonly used histogram processing technique. However, this technique often fails in producing satisfactory results for certain class of images. There are basically three types of distortion: excessive brightness change/brightness saturation, noise artifacts [20], and losing of details.

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1.1. Histogram separation techniques

To overcome these shortcomings, a group of researchers presented their improved HE-based methods. Brightness preserving bi-histogram equalization (BBHE) [21] was the earliest work on maintaining the original input brightness in the output image. They first divided the original histogram into two sub-histograms based on the mean brightness. Then, traditional HE was applied on these two sub-histograms independently. Wang et al. proposed dualistic sub-image histogram equalization (DSIHE) [22], which divided the original histogram into two sub-histograms based on the median value instead of the mean value. Following the basic thoughts of BBHE, many other similar algorithms were proposed, such as minimum mean brightness error bi-HE (MMBEBHE) [23], recursive mean-separate HE (RMSHE) by Chen and Ramli [24], brightness preserving dynamic HE (BPDHE) by Ibrahim and Kong [25], and brightness preserving weight clustering HE by Sengee and Choi [26]. Although these techniques are visually more pleasing than HE, they do not provide any enhancement controllability and are not robust to noise. A recent research on preserving the input brightness was image contrast enhancement method for preserving mean brightness (ICEPMB) method [27], which was proposed by Huang and Yeh in 2013. This method composes of an automatic histogram separation module and an intensity transformation module. It can effectively preserve the mean brightness and image features. However, the contrast enhancement is not significant. The common core idea of these brightness preserving methods is to impose some constraint on the mapping interval of gray-levels using different predefined methods. These methods show certain improvement against HE, but they cannot handle the problems caused by histogram pits and histogram spikes; thereafter, they cannot achieve contrast enhancement and image features preserving simultaneously.

1.2. Histogram modification techniques

Gamma correction techniques,[1] which were developed originally to compensate for the input–output characteristic of cathode ray tube displays, make up a family of general HM techniques. In a method called weighted thresholded histogram equalization (WTHE) presented in [28], the input histogram was modified by weighting and thresholding before HE was applied. The WTHE can offer some controllability of the contrast enhancement. However, it produces artifacts on some images with slope histogram spikes [11]. Huang et al. proposed an adaptive gamma correction with weighting distribution (AGCWD) contrast enhancement method and extended their method to enhance videos [17,18].

Unlike above researchers who modified the original histogram directly by transformation functions, Arici et al. [11] changed the way histogram was counted and presented a new histogram modification framework. Only pixels that have sufficient contrast with their neighbors are counted in the histogram to avoid excessive change of smooth areas. Then, a weighted histogram approximation method (WAHE) is employed to further smooth the target histogram. Finally, Black and white stretching is performed to fully exploit the dynamic range of gray-levels. Unlike the HE method, which is an automatic process, this method offers some level of controllability and adaptability; but too many adjustable input parameters are required. Two recent improved of WAHE are automatic robust image contrast enhancement (RICE) [29] and general histogram modification framework (GHMF) [30]. RICE combines the original image, its HE result, and a visually pleasing version produced by a sigmoid transfer function to form a optimization problem, then a visual quality judging criterion based-on saliency preservation is introduced to determine the optimized parameters. The GHMF method improves image contrast using S-shaped transfer mapping.

[1] http://en.wikipedia.org/wiki/Gamma_correction.

1.3. Other unconventional techniques

There are also unconventional techniques to the histogram-based contrast enhancement problem. In a method called Gray-level grouping (GLG) [16], the input histogram bins are classified into some sub-groups according to a selected criterion; then these sub-groups are iteratively redistributed uniformly over the grayscale; and finally, these grouped bins are ungrouped. Although GLG can adjust the level of enhancement and can effectively handle histogram spikes, it is mainly designed for still images, since it has high computation complexity and cannot handle the most annoying problem in video enhancement of flickering [11]. In 2012, Celik and Tjahjadi proposed a novel image contrast enhancement method based-on Gaussian mixture modeling (GMM) [5]. They simulated the distribution of input histogram by mixed Gaussian components and split the input histogram into gray-level groups according to intersections between the Gaussian components. Then, mapping relationships were constructed in each gray-level group using corresponding major group Gaussian component and accumulative distribution function (CDF). The final mapping function was created by concatenating these mapping relationships in sequence. This method has the merit of preserving the mean brightness and naturalness of the input image, but has a main drawback of high computation complexity. On the other hand, for those images with mixture non-Gaussian distribution, such as mixture Rayleigh modal, mixture uniform modal, and mixture beta model, the GMM-based method may fail to provide satisfactory results. Another contrast enhancement method by Celik is two-dimensional histogram equalization (2DHE) algorithm [31], which utilizes co-occurrent pixel pairs in the neighborhood. In 2016, S. W. Kim, etc. improved the 2DHE method by incorporating a weighting function reflecting the properties of human visual system (HVS) [32]. They claimed that their method(referred as 2DHEHVS) could yield better perceptual similarity quality than traditional 2DHE proposed in [31]. More recently, by taking the influence of colorfulness(include the saturation and hue factors) into consideration, blind image quality measure of enhanced images (BIQME) and BIQME-optimized based image enhancement method (BOIEM) [33] was proposed, which influence contrast, sharpness, brightness, colorfulness, and naturalness of images.

1.4. Image quality assessment (IQA) metrics

In addition to visually pleasing appearance, some quantitative enhancement measurements are necessary for further comparison between the proposed method and other state-of-the-art methods. The most commonly used objective evaluation metrics are the discrete entropy (DE) [1,5,11,19,20], the absolute mean brightness error (AMBE) [1,5,6,11,17,19,20,27], quality assessment metric of contrast (QMC) [29], and the measure of enhancement (EME) [1,11,13,19,20,23]. Extensive experiments in Section 3.1 showed that EME was prone to noise and was not an accurate contrast indicator. Hence, we improved EME and proposed the modified measure of enhancement (MEME). The definitions for EME and MEME were both presented in Section 3.1.

Besides the aforementioned enhancement measurements which measure contrast in luminance, there are enhancement metrics that measure luminance and colorfulness as a whole, such as blind image quality measure of enhanced images (BIQME) [33], no-reference image quality metric for contrast distortion (NIQMC) [34], and colorfulness and patch based contrast quality index (CPCQI) [33]. For space limitation, refer to [33,34] for detailed definition about BIQME, NIQMC, and CPCQI.

(i) DE

Discrete entropy (DE) quantifies the information contained in an image, The DE of image I is defined as [11]

$$DE(I) = -\sum_{\forall k} P(k)\log(P(k)) \tag{1}$$

where $p(k)$ is the probability density function (PDF), which is defined as

$$p(k) = \frac{h_i(k)}{N} \quad \text{for} \quad k = 0, 1, \dots, K-1, \tag{2}$$

where $h_i(k)$ is the number of pixel with gray-level k, and N is the total pixel number of the image. Higher DE value indicates richer image details, and no output image processed by any transformation can have higher DE than the input image [19].

(ii) AMBE

The absolute mean brightness error (AMBE) measures the absolute difference between the input and output average intensity. The AMBE is defined as [20]

$$AMBE(I_1, I_2) = |E(I_1) - E(I_2)|, \tag{3}$$

where $E(I_1)$ and $E(I_2)$ denote the statistic mean brightness of the input and output image, respectively. Smaller value of AMBE indicates that the average intensity of the input image is better preserved.

(iii) QMC

The QMC is defined as

$$QMC(I_1, I_2) = \triangle D + \gamma \triangle E \tag{4}$$

where $\triangle E = E(I_1) - E(I_2)$, and $\triangle D = \|sign(DCT2(\hat{I}_1)), sign(DCT2(\hat{I}_2))\|_0$, $\hat{I}_1$ and $\hat{I}_2$ are downsampled images of I_1 and I_2 by a factor of 4 using the bilateral method, $sign(.)$ is used to obtain the sign, $DCT2$ stands for a discrete cosine transform for 2-D signals. The smaller the QMC value, the better the visual quality.

1.5. Brief summary

A good contrast enhancement technique should achieve obvious contrast improvement while attaining several significant qualities, some of which are listed below

(i) Self-adaptive. The adjustable parameters, if any, for enhancement technique should be obtained automatically for different types of images.

(ii) Uniform contrast. The contrast enhancement technique should adjust the entire image uniformly without over-stretching problem.

(iii) Features preservation. The technique should attain obvious contrast enhancement without excessive brightness change or obvious losing of details.

(iv) Low computation complexity. The contrast enhancement technique should be simple and has low computation complexity.

Most of the aforementioned techniques can obviously improve the contrast on some images, but may not accord with the above four criterions. Others may achieve these qualities, but the contrast enhancement is not so much discernible. To the best of our knowledge, seldom techniques can simultaneously improve the contrast significantly and achieve the above four merits.

In this paper, a novel histogram modification scheme called addition and gamma correction based histogram modification (AGCHM) is proposed. This method can effectively deal with the problem caused by histogram pits and spikes. The proposed scheme modifies the input histogram by adding a parameter on the original histogram to fill histogram pits and performing gamma correction to restrain histogram spikes. Then, traditional HE method is applied on the modified histogram to obtain the mapping function. Extensive experimental results show that the proposed method can produce very high-quality enhancement images with low computation complexity.

The following of this paper is organized as follows, Section 2 reviews conventional HE method and related HM methods. Section 3 first introduces the measure of enhancement (EME), and then presents the improved measure of enhancement (MEME) and the proposed histogram modification scheme in detail. Experimental results and discussions on gray-scale images and color images are presented in Section 4. Section 5 concludes the paper.

2. Histogram equalization and histogram modification

Many contrast enhancement techniques obtain mapping function from the original histogram or the modified version. Conventional HE technique attempts to achieve an image with a histogram that is as close to a uniform distribution as possible.

2.1. HE

Let I represent an input digital image with gray levels in $[0, K-1]$. Based on the PDF defined by (2), the CDF of image I is defined by

$$C(k) = \sum_{l=0}^{k} p(l) \quad \text{for} \quad k = 0, 1, \dots, K-1. \tag{5}$$

Based-on the CDF obtained by (5), HE maps an input gray-level k into an output gray-level $T(k)$ by the following transformation function

$$T(k) = \lfloor (K-1) \times C(k) + 0.5 \rfloor. \tag{6}$$

The increment in the output gray-level $T(k)$ can be inferred from (2), (5) and (6):

$$\triangle T(k) = T(k) - T(k-1) = (K-1) \times \frac{h_i(k)}{N}. \tag{7}$$

From (7), we can infer that the increment of gray-level of $T(k)$ is proportional to the corresponding input histogram value $h_i(k)$.

In general, the output image processed by (6) will not be exactly uniform. The gray-levels with histogram spikes (the local maximums of the histogram which are above histogram mean) may produce unusually big $\triangle T(k)$ in the output histogram and will dominate the dynamic range of the grayscale, which in return will result in washed-out appearance or excessive brightness change after equalizing histogram. On the other hand, those gray-levels with histogram pits (the local minimums of the histogram which are below histogram mean) may produce a small $\triangle T(k)$ and will be combined to their neighbors, which in return will show up patchiness effect causing the problem of losing details. One solution to these problems is to modify the input histogram to fully exploit its contrast enhancement potential.

2.2. Addition based histogram modification (AHM)

A good histogram modification scheme can deal with the problem caused by histogram spikes and histogram pits both. A suitable solution to this problem is to modify the input histogram to the extent that the output histogram is as close to a uniform histogram as possible while preserves the shape features of the origin. In other words, smooth the abrupt histogram changes caused by histogram spikes and histogram pits while preserving the ascending or descending trend of the input histogram. Then, conventional HE can be applied on the modified histogram to obtain the mapping function.

Let h_i be the input histogram and u denote the uniform histogram. The goal of the modification is to find a modified histogram $\tilde{h}$ that is as close to u as possible and makes the residual $\tilde{h} - h_i$ small. When the squared sum of the Euclidean norm is used, this can be expressed by a weighted sum of the two objectives as [11]

$$\tilde{h} = \arg\min_{h} \|h - h_i\|_2^2 + \lambda \|h - u\|_2^2, \tag{8}$$

where $\tilde{h}, h, h_i$, and $u \in R^{K\times 1}$, and $\lambda \in [0, +\infty)$ is an adjustable parameter. The solution of (8) is

$$\tilde{h} = \left(\frac{1}{1+\lambda}\right) \times (h_i + \lambda u), \tag{9}$$

Fig. 1(b)–(d) show the equalization results of 'Dawn' with three different $\lambda(0, 10, 50)$. When λ is zero, the modified histogram $\tilde{h}_i$ equals to the input histogram h_i, and conventional HE is performed on the

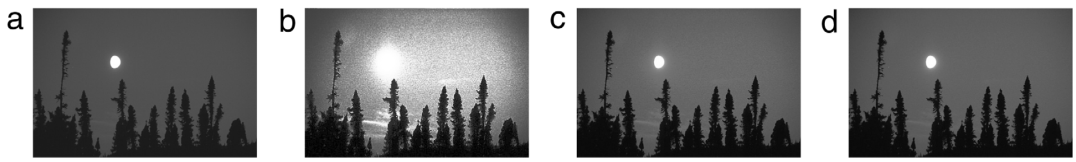

Fig. 1. Modified histogram equalization results using (6) for image 'Dawn'. From left to right, there are the Original 'Dawn', enhanced image with $\lambda = 0$, enhanced image with $\lambda = 10$, and enhanced image with $\lambda = 50$.

image. The image is over-enhanced with mass area of washed-out appearance, which makes the moon indiscernible. When λ is incremented to 10, the penalty term contributes to the result and the washed-out appearance is alleviated, though still obvious. With $\lambda = 50$, the washed-out appearance still exists, but not so much apparently. Although the level of enhancement is decreasing with increasing λ, the washed-out appearance remains occurring. This phenomena reflects the fact that, with increasing λ, Eq. (9) can effectively fill histogram pits but has less impact on histogram spikes, since (9) works as a high-pass filtering.

3. Improved enhancement measurements and the proposed method

3.1. Improved enhancement measurement

In this section, we first introduces an improved EME and then presents the proposed scheme, which incorporates gamma correction with (9) to further reduce the influence of histogram spikes.

MEME is an improved version of EME. The EME approximates the average contrast in an image by dividing the image into no-overlapping blocks, computing average logarithmic maximum to minimum intensity ratio. Let an image I be split into $k_1 \times k_2$ blocks (sub-images) and each block $B(i, j)$, with index (i, j), is of size $M_1 \times M_2$ (set as 8×8 by common practice). Then, EME is defined as [13]

$$EME = \frac{1}{k_1 \times k_2} \sum_{i=1}^{k_1} \sum_{j=1}^{k_2} \left(20 \times \ln \frac{I^w_{max;i,j}}{I^w_{min;i,j} + \varepsilon} \right), \tag{10}$$

where $I^w_{max;i,j}$ and $I^w_{min;i,j}$ are the maximum and minimum intensities in a given block $B(i, j)$, and ε is a small constant to avoid dividing by zero.

Many literatures on contrast enhancement [1,11,13,19,20,23] adopted EME as an evaluation indicator. However, just as pointed out in [13], the metric represented by (10) can be shown to be range dependent, changing itself based on the maximum and minimum range, and may not be accurate for measuring enhancement in all circumstances. This measurement has at least two shortcomings, (i) it is prone to noise as only the maximum and minimum intensities count for the contrast in any blocks but these blocks may have various statistics characteristics; (ii) it does not mix the inter-blocks contrast. Based on above analysis, a modified measure of enhancement (MEME) was proposed.

Let an image I be split into $k_1 \times k_2$ blocks, $I^w_{i,j}$ denotes the block with index (i, j), MEME was defined as

$$MEME = \alpha \times \frac{C_{I_{DC}}}{k_1 \times k_2} \times \frac{1}{k_1 \times k_2} \sum_{i=1}^{k_1} \sum_{j=1}^{k_2} C^w_{i,j}, \tag{11}$$

where I_{DC} is a thumbnail image of I. The size of I_{DC} is exact $k_1 \times k_2$, which is the same as the number of blocks. Each pixel of the thumbnail image has the value $mean(I^w_{i,j})$ (the mean of $I^w_{i,j}$). The parameter α is used to amplify the result avoiding it been too small (α was set to 100 in this paper). $C_{I_{DC}}$ and $C^w_{i,j}$ stand for inter-blocks contrast and intra-block contrast, respectively. They conform to the square root contrast as defined by Peli [35]

$$C = \sqrt{\frac{1}{L \times M} \sum_{m=1}^{L} \sum_{n=1}^{M} (I_{m,n} - mean(I_{m,n}))^2}, \tag{12}$$

where $I_{m,n}$ stands for an image with size $L \times M$. For a given image, a bigger MEME means the output image is enhanced more.

Table 1
Noise sensitivity experimental results on EME and MEME.

Growth	Noise		
	Salt & pepper	Poisson	Gaussian
Average EME Growth Rate	19.92	0.59	6.36
Average MEME Growth Rate	2.02	0.47	1.51

Noise sensitivity experiments show superiority of our proposed MEME over EME. In these experiments, the Salt & pepper, Poisson, and Gaussian noise, respectively, were added to 800 test images using the 'imnoise' function of MATLAB with default parameters. Then, the EME and MEME scores of the clean images and their noised counterparts were computed. The average growth rate on EME and MEME result were used to measure their sensitivity to noise. The growth rate is defined as

$$g = \frac{Q - q}{q}, \tag{13}$$

where Q and q are the EME or MEME value of the clean image and noised image, respectively.

As presented in Table 1, both EME and MEME showed certain noise immunity to Poisson noise, still, the MEME performed better. Although, both metrics were sensitive to the Salt & pepper noise and the Gaussian noise, the MEME provided much better results as the growth rate was much lower than that of EME, which was 2.02 to 19.92 for Salt & pepper noise, and 1.51 to 6.36 for Gaussian noise.

3.2. Gamma correction based histogram modification

To avoid histogram spikes that result in over-enhancement problem, Gamma correction can be applied on (9) to limit the influence of spikes. The gamma correction is defined as [15]

$$H = c h_i^{\gamma}, \tag{14}$$

where c and γ are positive constants and H is the corresponding output histogram. As the value of γ varying, different levels of modification can be achieved.

With $0 < \gamma < 1$, gamma correction restrains the histogram spikes and smoothes the target histogram. With the value of γ getting smaller, the output histogram becomes smoother, and the washed-appearance becomes less obvious when applying traditional HE on the modified histogram as shown by Fig. 2(a)–(d). As γ varies from zero to one, it turns from preserving the original histogram to applying the conventional HE. When γ is within the range $(0, 1]$, gamma correction can effectively smooth the histogram spikes.

3.3. Gamma correction and addition based histogram modification (GC-AHM)

Using the modified histogram of (9), Eq. (2) can be computed as

$$\widetilde{p(k)} = \frac{\left(\frac{1}{1+\lambda}\right) \times [h_i(k) + \lambda u]}{\left(\frac{1}{1+\lambda}\right) \sum_{k=0}^{K-1} [h_i(k) + \lambda u]}. \tag{15}$$

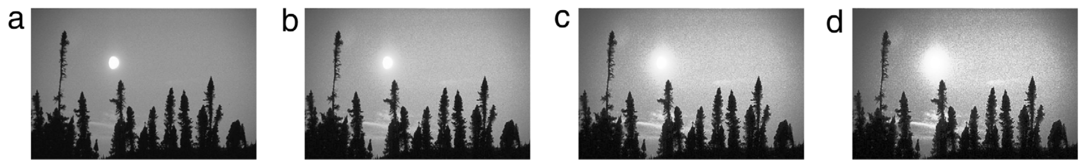

Fig. 2. Modified histogram equalization results using (14) on 'Dawn' with different values. From left to right, the value of γ is 0.2, 0.4, 0.6 and 0.8.

The fraction and denominator of (15) have common factor $(\frac{1}{1+\lambda})$, therefore, the coefficient $(\frac{1}{1+\lambda})$ in (9) is redundant for HE-based contrast enhancement method. And (9) can be further simplified as

$$\tilde{h_i} = h_i + \lambda u, \tag{16}$$

where $\tilde{h_i}$ is the newly modified histogram. Various levels of enhancement can also be achieved just by changing λ.

Modification scheme of (14) can effectively restrain histogram spikes, since it works as a low-pass filtering. On the other hand, modification scheme of (16) is capable of filling histogram pits, since it works as a high-pass filtering. Combining (14) and (16), we can obtain a new modification scheme that can smooth the target histogram more evenly. The new scheme can be formulated as

$$h_m(k) = c(h_i(k) + \lambda u)^\gamma, \tag{17}$$

where $h_i(k)$ represents the input histogram and $h_m(k)$ is the modified histogram. Parameter k represents the input gray-level on grayscale $[0, K-1]$. c is a constant, which is usually set to 1. $\gamma \in (0, 1]$, and $\lambda \in [0, +\infty)$.

For a given image, u is a constant. As λ varies in the range $[0, +\infty)$, λu changes from zero to $+\infty$. Set $\delta = \lambda u$, (17) can be further simplified as

$$h_m(k) = c((h_i(k) + \delta)^\gamma), \tag{18}$$

where δ is an addition term within range $[0, +\infty)$, and the new modification scheme is called gamma correction based addition histogram modification (GCAHM).

3.4. The choice of parameters

By changing δ or γ, or both, various levels of enhancement can be obtained using (18). As natural images vary widely, the parameters of (18) should adjust according to the fluctuant curve of the input histogram. A reasonable solution is to make the parameters δ and γ conform to some statistics features of image histogram.

(i) The choice of δ

Adding an increment on the original histogram can fill histogram pits and make the modified histogram more even. On filling the pits, the shape features of the input histogram should also be preserved, which in return retains the tone of the original image after equalization. If the original histogram itself is close to a uniform histogram, we should choose a smaller δ (compare with the average of the input histogram) to retain histogram features. Otherwise, if the original histogram is far from uniform, we should choose a bigger δ to fill histogram pits. The standard deviation (STD) of the input histogram is an effectively indicator on the closeness between the input histogram and a uniform one. In view of this, δ is determined by the standard deviation of the input histogram in this paper, which is defined as

$$\delta = \sqrt{\frac{1}{K}\sum_{k=0}^{K-1}[h_i(k) - \tilde{u}]^2}, \tag{19}$$

where h_i is the input histogram and $\tilde{u}$ is the average of h_i.

(ii) The choice of γ

The parameter γ can restrain histogram spikes. A smaller γ can restrain spikes more effectively while preserving details. On the other hand, a bigger γ can enhance image contrast more. An optimal choice of γ should be adjustable according to the contrast of the target image. However, to the best of authors' knowledge, there is no generally accepted objective criterion that measures image contrast. The mean brightness of an image can roughly reflect its contrast. For an image with mean brightness far away from the middle of the gray-levels, a bigger γ is chosen to enhance images more; otherwise, a smaller γ is employed to preserving image features. The adaptive γ can be chosen as (For convenience, take typical 8-bit image as an example)

$$\gamma = \begin{cases} (255-\mu)/255, & \mu < 128 \\ \mu/255, & \mu \geq 128, \end{cases} \tag{20}$$

where u is the mean brightness the processed image. For most natural images, their mean brightness is around 128, hence, γ is around 0.5. Therefore, another choice is to fix γ at 0.5 for simplicity.

Comparison study on qualitative performance between adaptive γ and fixed γ of 0.5 is shown in Table 2. Averagely, the differences between adaptive γ and fixed γ of 0.5 are too small and can be neglect.

In this paper, parameter γ was fixed at 0.5 for GCAHM on all experiments based on the following three discoveries from experimental results, (i) The value 0.5 of γ is suitable for restraining histogram spikes after adding a δ; (ii) It can reach a good balance between contrast enhancement and features preserving; (iii) It is computationally simplest than other values of γ, especially for hardware implementation.

4. Experimental results and discussions

Experiments are conducted on two categories, that is, gray images and color images.

4.1. Gray images

We tested the proposed method on a variety of typical 8-bit images of different resolutions including (i) 44 images from the miscellaneous series of the USC-SIPI Image Database,[2] (ii) 24 images from the Kodak Lossless True Color Image Suite,[3] (iii) 300 images from the Berkeley Image Data Set,[4] (iv) 316 images from the Ground Truth Database[5] of Department of Computer Science and Engineering University of Washington, and (v) 116 test images which we captured using different commercial cameras. All experiments were conducted on a laptop running 64-bit Windows 10 with Intel(R) Core(TM) i7-6700HQ CPU@2.6 GHz and 8.0GB RAM. All algorithms are straightforwardly implemented in MATLAB2015a without optimization. We compared the GCAHM method with the conventional HE and other contemporary methods including ICEPMB [27], AGCWD [17], and WAHE [11]. For AGCWD, the parameter α was fixed to 2 to yield the best overall performance. For WAHE, the parameter g was fixed to 1.5, as suggested in [19]. We sorted above 800 images into three groups roughly according to their mean brightness, 144 images with mean brightness less than 255/3 were classified as underexposed images; 34 images with mean brightness over $255 \times 2/3$ were grouped to overexposed images; all other 622 images were those with mean brightness within the range from 255/3 to

[2] http://sipi.usc.edu/database/.
[3] http://r0k.us/graphics/kodak/.
[4] http://www.eecs.berkeley.edu/Research/Projects/CS/vision/bsds/.
[5] http://www.cs.washington.edu/research/imagedatabase/.

Table 2
Comparative results on selecting parameter γ.

Image groups	Fixed $\gamma = 0.5$			Adaptive γ		
	144 underexposed images average	622 common images average	34 Overexposed images average	144 underexposed images average	622 common images average	34 Overexposed images average
DE	6.48	7.23	5.52	6.47	7.22	5.52
MEME	34.47	26.86	22.09	35.77	27.41	23.06
AMBE	11.49	6.66	11.20	18.58	7.12	14.32
QMC	0.048	0.038	0.069	0.080	0.042	0.079

Table 3
Objective quality assessment of CE methods. The best and the second best are boldfaced and underlined, respectively.

Image groups		144 underexposed images average	622 common images average	34 Overexposed images average	800 images Average.
Average intensity		58.36	1120.97	201.33	113.12
DE	Org	6.50	7.27	5.62	7.06
	HE	5.47	5.85	4.57	5.73
	WAHE	6.31	6.93	5.39	6.75
	ICEPMB	6.28	7.06	5.28	6.84
	AGCWD	6.35	7.03	5.28	6.83
	2DHEHVS	6.40	7.09	5.45	6.90
	GCAHM	**6.48**	**7.23**	**5.52**	**7.02**
MEME	Org	30.44	20.91	16.73	22.45
	HE	56.55	42.24	**36.72**	44.58
	WAHE	**56.65**	**44.59**	28.**47**	**46.08**
	ICEPMB	33.63	24.62	16.94	25.92
	AGCWD	31.42	25.66	28.24	26.81
	2DHEHVS	50.67	41.34	26.20	42.38
	GCAHM	34.47	26.86	22.09	28.03
AMBE	HE	69.45	16.35	57.84	27.67
	WAHE	33.21	22.23	27.14	24.42
	ICEPMB	**5.54**	**2.77**	**4.10**	**3.33**
	AGCWD	15.66	34.16	58.05	31.85
	2DHEHVS	39.20	15.49	40.07	20.81
	GCAHM	11.49	6.66	11.20	7.72
QMC	HE	0.419	0.390	0.405	0.396
	WAHE	0.176	0.161	0.107	0.161
	ICEPMB	0.129	0.098	0.108	0.104
	AGCWD	0.060	0.119	0.256	0.114
	2DHEHVS	0.160	0.114	0.143	0.123
	GCAHM	**0.048**	**0.038**	**0.069**	**0.041**

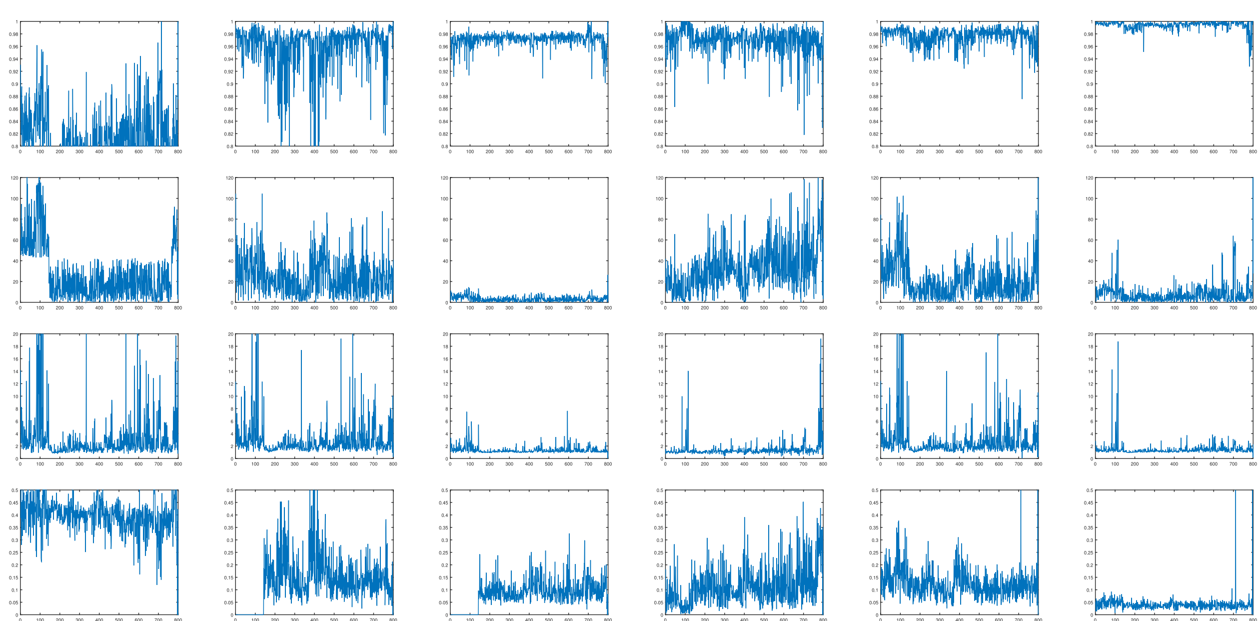

Fig. 3. Objective assessment on 800 test images. From top to bottom, the six rows plot the DE ratio, the AMBE scores the MEME ratio, and the QMC scores, respectively. The DE ratio plots the output DE result to corresponding input DE score. The MEME ratio plot the output scores to corresponding input ones,respectively. From the left row to the right, there are the HE, WAHE, ICEPMB, AGCWD, 2DHEHVS and GCAHM.

Table 4
Time complexities analysis on image with size $M \times N$ of k discrete gray-levels. For the 2DHEHVS method, w is the window size. HA, HM and MC are Histogram acquisition, Histogram modification and Getting results for short respectively.

	HE	WAHE	ICEPMB	AGCWD	2DHEHVS	GCAHM
HA	$O(MN)$	$O(MN)$	$O(MN)$	$O(MN)$	$O(MN \times w^2)$	$O(MN)$
HM		$O(k)$	$O(2k^2)$	$O(4k)$	$O(k^2)$	$O(2k)$
MC	$O(k)$	$O(k)$	$O(k)$	$O(k)$	$O(k)$	$O(k)$
Results	$O(MN)$	$O(MN)$	$O(MN)$	$O(MN)$	$O(MN)$	$O(MN)$
Total	$O(MN + k)$	$O(MN + k)$	$O(MN + k^2)$	$O(MN + k)$	$O(MN + MN \times w^2 + k^2 + k)$	$O(MN + k)$
Time (s)	**3.31**	19.36	20.84	<u>15.45</u>	497.87	18.47

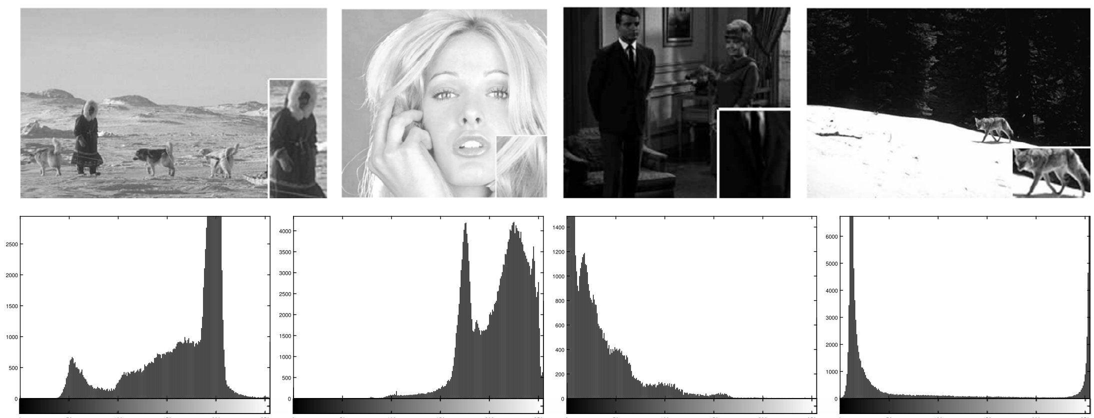

Fig. 4. Test images and their histograms.

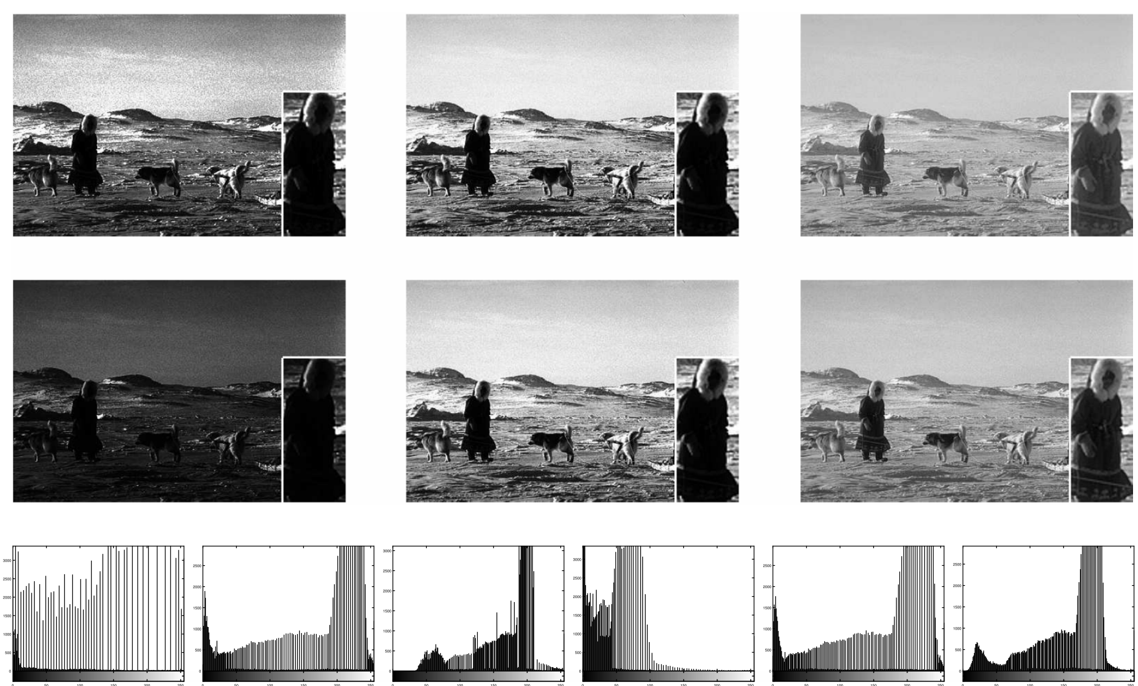

Fig. 5. Contrast enhancement comparison on 'Dogsled'. Form up to down and left to right, there are the result of HE, WAHE, ICEPMB, AGCWD, 2DHEHVS and GCAHM.

$255 \times 2/3$. Table 3 lists the average performance on the 800 test images as three groups. The best and the second best results are boldfaced and underlined, respectively. For subjective assessment, only a few typical results are listed in this paper. Finally, time complexity comparison between the proposed GCAHM method and other reference algorithms is included.

4.1.1. *Objective assessment*

(i) DE

In the case of DE, of all 800 test images, GCAHM outperformed all other four counterpart methods with only one exception, on a synthetical image, the HE, WAHE, ICEPMB, AGCWD, 2DHEHVS, and the proposed methods all provided the same DE score.

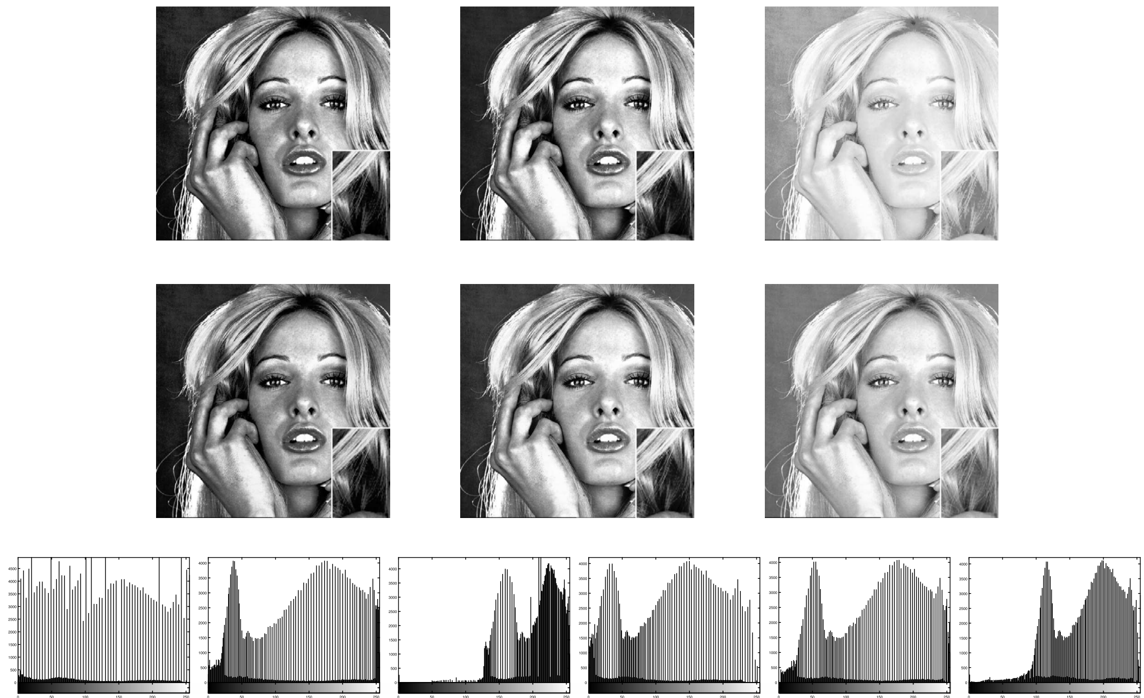

Fig. 6. Contrast enhancement comparison on 'Tiffany'. Form up to down and left to right, there are the result of HE, WAHE, ICEPMB, AGCWD, 2DHEHVS and GCAHM.

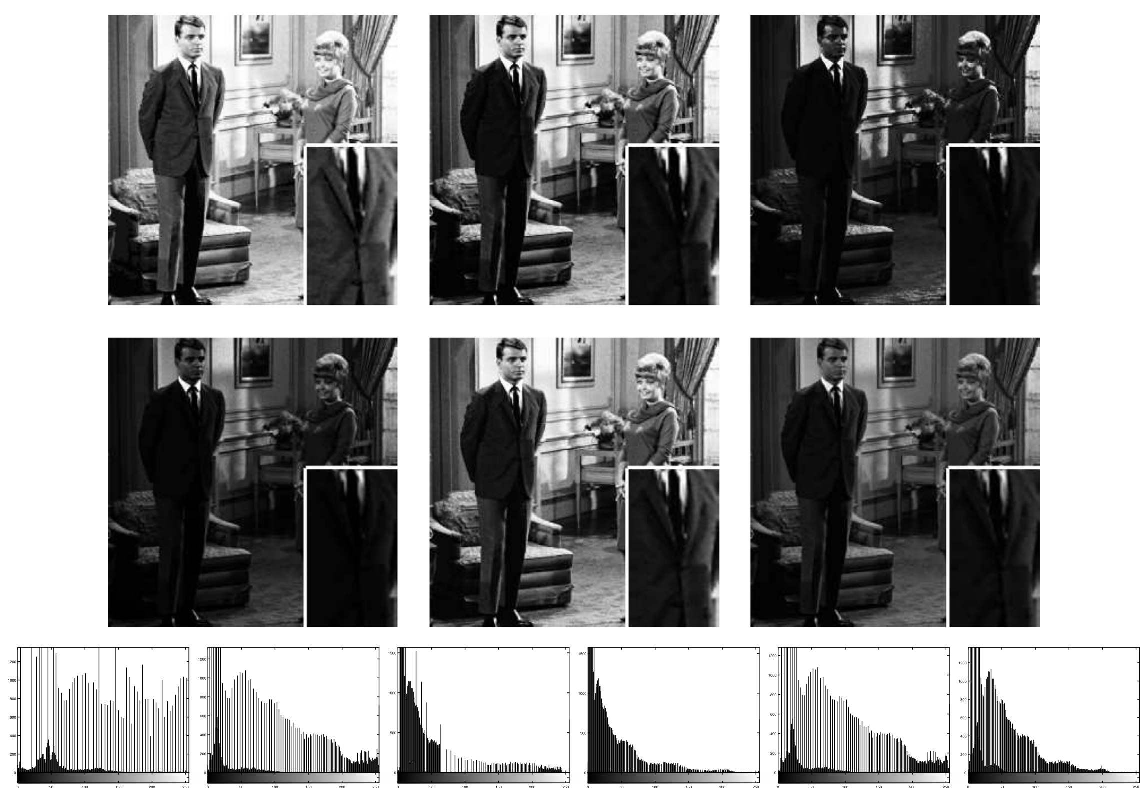

Fig. 7. Contrast enhancement comparison on 'Couple'. Form up to down and left to right, there are the result of HE, WAHE, ICEPMB, AGCWD, 2DHEHVS and GCAHM.

Fig. 3 shows the objective comparison results in graph. For all subplots in Fig. 3, the images are indexed in sequence of 144 underexposed images followed by 622 normal images, and finally the overexposed images. Most of the DE ratio for the GCAHM is far above the 0.98 baseline. In contrast, the DE ratios of WAHE, ICEPMB, and AGCWD are mostly under the 0.98 line. For the underexposed images, GCAHM

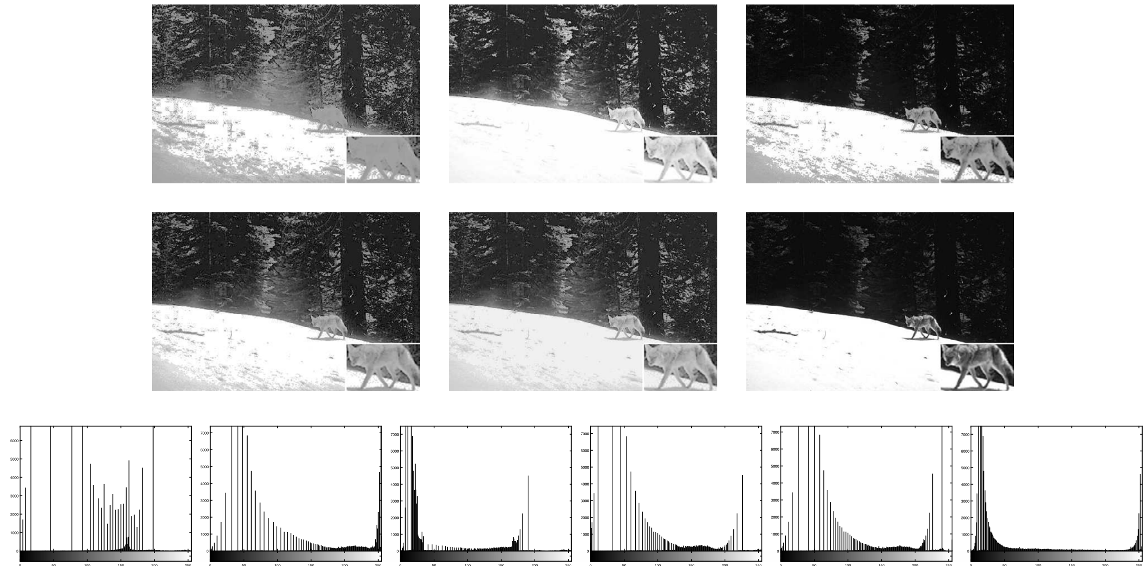

Fig. 8. Contrast enhancement comparison ‘Gray wolf’. Form up to down and left to right, there are the result of HE, WAHE, ICEPMB, AGCWD, 2DHEHVS and GCAHM.

Fig. 9. Contrast enhancement comparison on ‘Old man’. Form up to down and left to right, there are the result of HE, WAHE, ICEPMB, AGCWD, 2DHEHVS and GCAHM.

performs the best as the average DE was 99.69% close to that of the input, in contrast with 98.22% for the overexposed images. Table 3 corroborates this conclusion.

(ii) AMBE

The second row of Fig. 3 shows that, on most images, ICEPMB and GCAHM provide AMBE scores less than 20, which indicates that they are more effective on preserving the mean brightness and image tone. On the underexposed images and overexposed images, the AMBE values of GCAHM enlarge as these images need to be adjusted toward the middle of the grayscale more.

(iii) MEME

It must be pointed out that, just like in the case of EME, a bigger MEME does not necessarily mean better visual quality. In fact, HE can achieve much higher average MEME than all comparing contrast enhancement methods, even though it may not produce the visually pleasing image. The third row of Fig. 3 plots the MEME ratios defined by the output MEME scores to corresponding input MEME scores of the test images. It should be pointed out that, on some images, the MEME ratios of WAHE and HE exceed the Y coordinate and are limited to 20 for comparison convenience. ICEPMB, AGCWD, and GCAHM enhance the images moderately as their MEME ratios distribute mainly within the baselines of 1 to 3. WAHE and HE produce similar high MEME results as presented by the second row of Fig. 3. On some images, all these method fail to enhance the contrast in terms of MEME value. This occurs most frequently on AGCWD as it treads to condense the histogram toward lower gray-levels.

(iv) QMC

QMC measures the image visual quality whose value is the less the better. Except for HE and the proposed GCAHM, there are no much difference about the QMC values on average. The proposed method yields the best QMC result, which is, on average, less than half of the second best value. The fourth row of Fig. 3 plots the QMC figure, which reveal that the GCAHM method outperforms the other reference methods on almost all test images. And the QMC value of the proposed method keeps relatively small, indicating that the proposed GCAHM methods always produces visually pleasing output images.

(v) Complexity

Time complexities of HE, WAHE, ICEPMB, AGCWD, 2DHEHVS, and the proposed GCAHM methods are analyzed for image with size $M \times N$ of k discrete gray-levels using the Bachman–Landau notation. Table 4 lists the computation complexities and shows the average processing times in second over the 800 test images. The time complexity of HE is the lowest as HE does not deal with any modification of histogram before equalization. All other methods show little difference in time complexity. Because the image size $M \times N$ is considerably larger than k, the time complexity of all method can be round down to $O(MN)$. Hence, these methods can be easily applied on real-time applications.

From Table 3, we can draw the conclusion that, of the 800 test images, the proposed GCAHM method performs, averagely, the best on the DE, QMC metrics, and performs the second on the AMBE metric. Since a bigger MEME value is not equivalent to better visual quality and, compared with the MEME value of the original image, the proposed GCAHM method provides notable increase on the result MEME value. Since smaller value on QMC means better visual quality, thus, we deem that the proposed method can enhance the target image significantly and naturally.

4.1.2. Subjective assessment

On many of the images we tested, WAHE, ICEPMB, AGCWD, 2DHE-HVS,and GCAHM produce similar visually enhanced results. By and large, WAHE and HE enhance the target images more and trend to stretch the darker regions to even darker and the bright regions to

Table 5
Objective quality assessment of CE methods. The best and the second best are boldfaced and underlined, respectively.

Method	BIQME	CPCQI	NIQMC	Time (s)
BOIEM	0.617	1.050	5.271	57.526
RICE	0.616	1.050	5.270	3.124
GHMF	**0.623**	1.033	**5.338**	5.128
ROHIM	0.616	1.050	5.270	169.431
GCAHM	0.413	**1.053**	5.283	**2.875**

even brighter. On some images processed by them show unnatural washed-out appearance due to over stretching. ICEPMB performs the best on preserving the mean brightness as can be observed from Table 3. Due to applying HE on each sub-histogram, ICEPMB enhances some parts of an image but introduces artifacts on another parts. AGCWD enhances images by exploiting the dynamic ranges of darker part of gray-levels. It provides unpleasing results on most of the underexposed and overexposed images. For the underexposed images, the level of enhancement is indiscernible; on the other hand, for the overexposed images, the excessive brightness change of AGCWD provides unnatural-looking images. On most images, 2DHEHVS delivers similar results as the WAHE method, sometimes, it performs better on the scores of DE. By comparison, the proposed GCAHM seldom fails to provide a natural visually pleasing image.

Fig. 4 presents the original test images and histograms. Figs. 5–8 show their CE results. As demonstrated by Fig. 5, the HE, WAHE, AGCWD, and 2DHEHVS loss almost all details on the overcoat of the walking man due to over stretching. In contrast, the results of ICEPMB and GCAHM show different scenes, as both methods preserve most of the image features. Nevertheless, there are differences as GCAHM effectively removes the "fog" covering the test image. All methods, except for the ICEPMB, fully exploit the dynamic range of gray-level, but, only the proposed GCAHM and the ICEPMB method preserve the histogram shape as shown in the histograms of Fig. 5. In short, only the proposed GCAHM method can both fully utilize the dynamic range of gray-levels and retain the original histogram curve and image features.

Fig. 6 gives a low contrast tiffany's face enfolded by haze. All methods, except for the ICEPMB, notably enhance the target image. But, only the proposed GCAHM provides an enhanced natural look face in contrast with over-enhanced images by the other methods. We can observe that HE, WAHE, AGCWD, and 2DHEHVS change the hair around the right ear and the image background from gray to black causing abrupt tone altering. Once again, only the proposed GCAHM fully exploits the dynamic range of the gray-levels and preserves the histogram shape at the same time.

Fig. 7 presents a couple standing in a room without much light as some details on the man's business suit are indiscernible. Although, all methods clearly enhance the business suit, HE, 2DHEHVS, and WAHE enhance the image too much by blurring the details of the wall and introducing washed-out appearance to the footcloth, and HE introduces washed-out appearance to the right side of the armchair at the same time. The GCAHM method provides an image with enhanced business suit while preserving the nature tone indicating this image was photographed in a dark room.

In our experiments, there are some images on which no methods can produce any pleasing enhancement results. In this case, the GCAHM outperform the others on not providing even worse images. Fig. 8 provides such an example. The origin image of Fig. 8 describes a gray wolf walking in the snow on the fringe of a forest. All methods, except for the proposed one, introduce visible artifact regions on the bottom corners of the image. The WAHE method overstretches the image too much as it turns the 'gray wolf' into an entirely white one and blurs the border between the snow and the forest. Though, the GCAHM does not obviously enhance the target image, it does not introduce any obvious artifacts either.

4.2. Color image enhancement

We extend the proposed method and the other reference methods (HE, WAHE, AGCWD, and ICEPMB) to enhance color image by transforming the input image from RGB color space to HSV color space, and perform contrast enhancement only on the luminance channel. Representative results are presented in Fig. 9. HE results in a brightened image with washed-out appearance on the cloth and below the Adam's apple, while WAHE and 2DHEHVS alleviate the washed-out appearance but still obvious. The old man's face looks pale on the result images by WAHE and HE, since they both stretches the histogram to increase the dynamic range. The result image by ICEPMB almost has no difference with the original image, that is, ICEPMB fails to enhance the contrast. AGCWD tunes the target image dark and makes the dark regions even darker which, in return, causes the neck and collar regions almost indiscernible. GCAHM provides the best result as it enhances the image and show none of above drawbacks.

We also compare the proposed method with lately proposed color image enhancement techniques, which are GHMF, RICE, BOIEM, and RIQMC-based optimal histogram mapping (ROHIM) [36]. Experiments are conducted based on the Kodak Lossless True Color Image Suite. Performance evaluations are assessed according to the average value on BIOME, CPCQI, NIQMC, and the time consuming to process the image Suite as shown in Table 5. There are, on the whole, little difference between the enhancement methods measured by CPCQI and NIQMC. Although the proposed GCAHM was essentially devised for enhance luminance contrast, it performs pretty good on color images, ranking the first on the CPCQI score and the second on the NIQMC score, but it ranks the worst on BIQME. The reason is that the BIQME metric measures luminance contrast and color contrast as a whole, while the proposed method enhances only the luminance channel. The overall processing time for 24 images of the proposed method are 2.875 s, which are less than all the other methods. Therefore, the GCAHM method is applicable to realtime applications. On most of the 24 images, all methods produce similar enhanced images except that the GHMF treads to tune the images to darker side and the ROHIM usually tunes the images to brighter side, which, in return, may cause visually unpleasing distortion. The Kodak Lossless True Color Image Suite description for Fig. 10 is "close-up view of latch and white knob on old, outside, red, wooden door". However, the GHMF method changes the color to dark red and the ROHIM method turns it to bright yellow. The other three method produce output images with little difference. There are more detail features on the knob of the proposed GCAHM method, which can be seen on 768×512 image.

5. Conclusions

In this paper, a novel image contrast enhancement modification scheme called gamma correction and addition based histogram modification is proposed. First, the standard deviation of the original histogram is computed, and then the result is added back on the original histogram. Secondly, gamma correction is applied on the final result of the first step. Finally, the modified histogram of the second step is used to calculate the mapping function.

Extensive experiments demonstrate that, compared with the other state-of-art methods, the proposed GCAHM provides very high-quality enhancement on a variety of gray images. The result image by the proposed method is usually a natural look enhanced image with high DE value, low AMBE and QMC value. It performs the best about the DE and QMC value over all 800 test images and also shows good performance on preserving the mean brightness of the target image, which can be observed from the AMBE value of Table 3. Although essentially devised for enhance gray images, the proposed method performs equally well on enhance color images subjectively and objectively. Meanwhile, the new method is simple to implementation. According to the time complexity analysis and the very little overall processing time, one can draw a conclusion that the proposed method can be applied for real-time applications.

Fig. 10. Contrast enhancement comparison on ‘red wooden door’. Form up to down and left to right, there are the origin, result of BOIEM, RICE, GHMF, ROHIM, and GCAHM.

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