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Automatic Contrast-Limited Adaptive Histogram Equalization With Dual Gamma Correction

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ABSTRACT We propose automatic contrast-limited adaptive histogram equalization (CLAHE) for image contrast enhancement. We automatically set the clip point for CLAHE based on textureness of a block. Also, we introduce dual gamma correction into CLAHE to achieve contrast enhancement while preserving naturalness. First, we redistribute the histogram of the block in CLAHE based on the dynamic range of each block. Second, we perform dual gamma correction to enhance the luminance, especially in dark regions while reducing over-enhancement artifacts. Since automatic CLAHE adaptively enhances contrast in each block while boosting luminance, it is very effective in enhancing dark images and daylight ones with strong dark shadows. Moreover, automatic CLAHE is computationally efficient, i.e., more than 35 frames/s at 1024 × 682 resolution, due to the independent block processing for contrast enhancement. Experimental results demonstrate that automatic CLAHE with dual gamma correction achieves good performance in contrast enhancement and outperforms state-of-the-art methods in terms of visual quality and quantitative measures.

INDEX TERMS CLAHE, luminance enhancement, contrast enhancement, gamma correction, dark image, over-enhancement.

I. INTRODUCTION

Image contrast enhancement is the key technology to improve visual quality of digital images. It has been widely used in computer vision, pattern recognition, medical imaging, remote sensing imaging and computational photography. Poor image quality is caused by many factors: Poor image sensors, non-uniform exposure, short shutter cycle, and weak ambient light (weather conditions such as heavy clouds, fog, and lack of sunlight or night scenes). Images captured under these circumstances contain contrast distortions, color fading, and low intensity. Above all, captured images under low light condition often have the characteristic of poor dynamic range, low contrast, and strong noise. In practice, the low light condition would result in confusions of textures and objects, poor performance of detection, segmentation and annoying visual experience. For better image quality, it is required to enhance the contrast of dark images.

In general, image enhancement methods are classified into three categories [1]: Non-linear transfer function-based schemes, histogram-based techniques, and frequency domain methods. Non-linear transfer functions, such as gamma correction and logarithm mapping, directly modify the pixel values based on regulation [2]. Due to their easy adjustment and efficient implementation, non-linear transfer functions are commonly used for contrast enhancement. Among the non-linear transfer functions, gamma correction, which effectively represents the properties of the human visual system (HVS), has been widely used in the past several decades. Gamma correction modifies the digital values of dark images to be comfortable for human eyes. Histogram modification transforms a uniform distribution of the gray levels for image contrast enhancement [3], [4], which achieves good performance with low computational complexity. The histogram of an image indicates the relationship between gray levels and their corresponding frequency. The histogram of a gray image $P(j)$ is expressed as follows:

$$P(j) = \frac{n_j}{Num}, \quad j = 0, 1, \ldots, L-1 \tag{1}$$

where j denotes the gray level of an image, n_j is the number of pixels in the gray level j, and Num is the total number of the image pixels. It is obvious that the histogram is the probability distribution function of j. Based on $P(j)$, histogram equalization (HE) is performed as follows:

$$s_k = T(k) = (L-1)\sum_{j=0}^{k} P(j) \tag{2}$$

where s_k stands for the mapping function $T(k)$ and maps each pixel value k of the input image into s_k; L is the dynamic range of the output image. The inherent shortcoming of HE is over-enhancement in images with large smooth area, which results in unnaturalness and wash-out appearance. Dark images captured under low light condition contain large smooth area with a narrow dynamic range, and thus HE causes over-enhancement after contrast enhancement. During a couple of decades, several refinement approaches have been proposed, e.g. brightness preserving bi-histogram equalization (BBHE) [5], equal area dualistic sub-image histogram equalization (DSIHE) [6], and minimum mean brightness error bi-histogram equalization (MMBEBHE) [7]. To overcome the problems of conventional HE, Celik and Tjahjadi [8] used a Gaussian mixture model (GMM) to model the intensity distribution.

GMM plays a role in obtaining different intervals corresponding to different regions of the input image. Cheng and Huang [9] proposed a method based on histogram modification and bilateral Bezier curve (BBC). This method utilized Bezier curve to modify the CDF for smoother results. However, if the slope of the CDF at dark regions was excessively small, under-enhancement in dark regions was inevitable due to the property of the Bezier curve. Instead of using the first-order statistics, some researchers investigated exploiting the spatial information in images. Contextual and variational contrast enhancement (CVC) [10] applied a 2-D histogram to adjust different images, and thus images with high contrast were enhanced not as much as those with low contrast. Shu and Wu [11] employed a joint probability with spatial information to overcome the limitation of the histogram in contrast enhancement. These two methods [10], [11] achieved better performance in contrast enhancement, but caused under-enhancement in dark regions. Thus, they are not suitable for image enhancement of non-uniform illumination.

A pivotal issue is to preserve both naturalness and features in image enhancement without under(over)-enhancement. Multiple segmentation approaches divide the histogram of the input image into several non-overlapping sub-histograms using mean or median values as threshold [12]–[15]. Exposure-based sub-image histogram equalization (ESIHE) [12] and median-mean based sub-image clipped histogram equalization (MMSICHE) [13] redistributed the histogram by setting clip points, while segment-selective dynamic histogram equalization (SSDHE) [14] and segment dependent dynamic multi-histogram equalization (SDDMHE) [15] adjusted the dynamic range by an expansion strategy. In practice, they successfully performed contrast enhancement, but noise was also enhanced.

Contrast limited adaptive histogram equalization (CLAHE) overcomes the over-enhancement problem of HE by minimizing noise-like artifacts in homogeneous regions. In CLAHE, the image is partitioned into equally-sized rectangular blocks, and HE is performed in each block. Based on CLAHE, many studies have been done for image contrast enhancement [16]–[18]. Artur et al. [1] proposed low light image enhancement based on the statistics of the wavelet coefficients. In their method, they performed CLAHE for contrast enhancement in the low-pass sub-band. They achieved good visual quality with enhancement of low light images. However, the entire luminance of the enhanced image still looks very dim especially in dark regions. For the low light image enhancement, the key factor is to enhance the whole luminance while preserving details. Thus, it is a promising solution to combine non-linear transfer function and histogram modification for boosting the intensity while increasing the local contrast. Huang et al. [19] proposed the adaptive gamma correction with weighting distribution (AGCWD). They calculated the gamma parameter using the probability density function (PDF) which denotes the histogram of the image. AGCWD achieves better results than simple HE-based methods or gamma correction schemes. However, the tone of dark regions was not preserved well. Building off the adaptive gamma correction (AGC), Huang and Chen [20] designed hardware architecture with low complexity. Chhaya and Neeraj [21] combined AGC with range limited bi-histogram equalization (RLBBHE). They firstly performed RLBBHE to enhance the contrast as well as preserve the luminance. Then, for luminance enhancement, they conducted adaptive gamma correction based on the adjusted histogram. However, the same problem exists in AGC-based methods because they are not robust when the input image contains various objects with different gray levels. Thus, it is required that we perform gamma correction to adjust the overall luminance and use local HE to enhance the local contrast.

In this paper, we propose automatic CLAHE for image contrast enhancement with dual gamma correction. We adaptively set the clip points based on block textureness in an image. Also, we introduce dual gamma correction into CLAHE to compensate for contrast distortions. The combination of CLAHE and dual gamma correction successfully achieves good perceptual quality. First, we redistribute the block histogram in CLAHE using the clip limit points. Second, we enlarge the luminance of image blocks by applying the first gamma correction γ_1. Third, when the image block contains a large dynamic range, we select the second gamma correction γ_2 to compensate for dark regions while avoiding over-enhancement at bright regions. Since automatic CLAHE adaptively enhances the contrast and details of each block in images, it is very effective in enhancing dark images and daylight ones with strong dark shadows. Compared with existing methods, our main contributions are as follows:

1) We introduce dual gamma correction in CLAHE for luminance and contrast enhancement;
2) We adaptively set the clip points in CLAHE based on the dynamic range of each block in images;

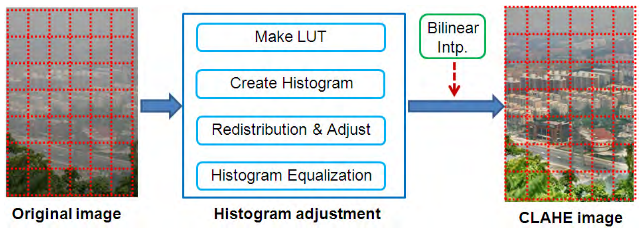

FIGURE 1. Whole framework of CLAHE.

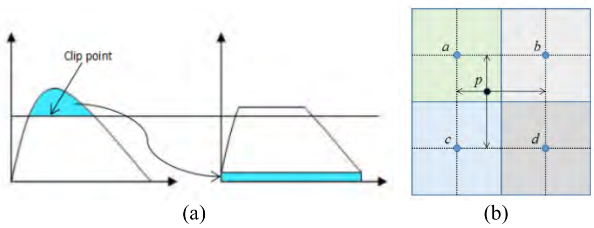

FIGURE 2. Histogram redistribution and bilinear interpolation within blocks. (a) Clip point and redistribution. (b) Bilinear interpolation.

3) We achieve low computational complexity using the independent block processing for contrast enhancement, i.e. more than 35 frames/sec at 1024 × 682 images. The rest of this paper is organized as follows. Section II briefly reviews CLAHE. In Section III, we describe the proposed method in detail. We provide our experimental results and compare them with those of some state-of-art methods in Section IV. Finally, we make conclusions of this paper in Section V.

II. CLAHE

As shown in Fig. 1, the CLAHE pipeline contains 5 main procedures. First, the image is decomposed into equally-sized rectangular blocks, and histogram adjustment is performed in each block. Histogram adjustment includes histogram creation, clipping, and redistribution. Then, the mapping function is obtained by the cumulative distribution function (CDF) of the clipped histogram. Finally, bilinear interpolation is performed between the blocks to remove possible block artifacts. CLAHE is different from the traditional HE in limiting the contrast by a clip point to cut off the peak value in the histogram of each block. The clipped pixels are redistributed to each gray level. The higher the clip point is, the more the contrast is enhanced as shown in Fig. 2(a). The clip point is calculated as follows:

$$\beta = \frac{M}{N}\left(1 + \frac{\alpha}{100} S_{\max}\right) \tag{3}$$

where M is the number of pixels in each block, N is the dynamic range in this block, S_{max} is the maximum slope, and α is the clip factor. When α is closed to 0, the clip point would be M/N so that the pixel in this block would be a constant. As α is approaching to 100, the contrast is enhanced in a large degree. Thus, the clip point is the key factor to adjust the contrast enhancement. Based on CDF, we get a mapping function to remap gray levels of image blocks as follows:

$$cdf(l) = \sum\nolimits_{k=0}^{l} pdf(l) \tag{4}$$
$$T(l) = cdf(l) \times l_{\max} \tag{5}$$

where $T(l)$ is the remapping function; l is the pixel gray level, and $l_{\max}$ is the maximum pixel value in the block. Based on CDF of the redistributed histogram in each block, we get different remapping functions. To prevent blocking artifacts, each pixel value is interpolated from the mapping functions in the surrounding blocks as shown in Fig. 2(b). Points a, b, c, and d are the center pixels of the four blocks, where p is an arbitrary pixel surrounded by the four blocks. We get the remapped pixel p by bilinear interpolation as follows:

$$T(p(i)) = m \cdot (n \cdot T_a \cdot p(i) + (1-n) \cdot T_b \cdot p(i)) + (1-m) \cdot (n \cdot T_c \cdot p(i) + (1-n) \cdot T_d \cdot p(i)) \tag{6}$$

$$\begin{cases} n = (x_b - x_p)/(x_b - x_a) \\ m = (y_c - y_p)/(y_c - y_a) \end{cases} \tag{7}$$

where $T(\cdot)$ denotes the remapping function; $p(i)$ is the value of an arbitrary pixel i with coordinate (x, y). The interpolation step removes blocking artifacts. Due to the independent processing of blocks, CLAHE achieves low computational complexity for contrast enhancement.

FIGURE 3. CLAHE results according to different clip points where $\alpha = 100$, $S_{max} = 1, 2, 3, 4, 5, 6$ (left to right, top to bottom).

III. PROPOSED METHOD

Although CLAHE has a good performance in contrast enhancement, it is limited by strong cast shadows when we are processing dark images. Fig. 3 shows the results by CLAHE with different clip points. As the clip point increases, the luminance is enhanced more. However, this luminance enhancement causes over-enhancement in contrast. Thus, the global clip point is not suitable for the enhancement of dark regions. On the other hand, blocks with uniform gray level distribution, i.e. homogeneous regions such as sky and ground, are likely to be processed with a low clip point by (19). Thus, once they are enhanced, halo artifacts appear around image details. On the contrary, the non-uniform block needs the higher clip point so that the texture and details would be effectively enhanced. In image enhancement, it is required to keep its tone. Obviously, CLAHE is not robust enough in boosting the pixel values. Hence, adaptively setting the clip point is of importance in image enhancement. In (21), $l_{\max}$ is set to a fixed value, i.e. 255 (8 bits). In this case, the very dark regions cannot be effectively enhanced in this way. Thus, it is required that $l_{\max}$ be set a larger value in certain dark blocks. To adjust the dynamic range of each block, we adopt gamma correction for $l_{\max}$. In this work, we propose automatic CLAHE for image contrast enhancement that performs gamma correction on each block while adaptively setting the clip point according to the content.

A. CONTENT ADAPTIVE CLIP POINT

In (3), the clip factor α and the maximum slope $S_{\max}$ are used to determine the clip points. We adaptively set different blocks to appropriate clip points, in the manner of assigning homogeneous regions to low clip points and texture blocks to high ones.

The average gray value and standard deviation represent textureness of a block. Based on them, the block with a larger dynamic range is assigned to a higher clip point value. Thus, we set the clip point adaptively as follows:

$$\beta = \frac{M}{N}\left(1 + P\frac{l_{\max}}{R} + \frac{\alpha}{100}\left(\frac{\sigma}{Avg + c}\right)\right) \tag{8}$$

where σ is the standard deviation of the block; Avg is mean value; and c is a small value to avoid division by 0. The more textural the block is, the bigger σ/Avg is, which is related to a large clip point; $l_{\max}$ is the maximum value in the block and R represents the entire dynamic range of the image, e.g. 8 bit images, $R = 2^8 - 1 = 255$; P and α are parameters to control the weights of the dynamic range and entropy terms, respectively. Fig. 4 shows different pixel patches and their corresponding clip points in the histogram. Notice that the textural region is assigned to a large clip value, and thus is enhanced in a large degree, and the vice versa.

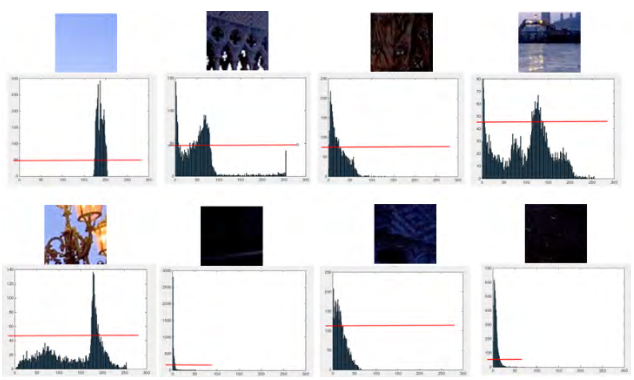

FIGURE 4. Content adaptive histogram adjustment.

B. DUAL GAMMA CORRECTION

Just-noticeable difference (JND) is the minimum difference to be perceived by HVS. We cannot perceive details in dark regions due to the high JND threshold at low intensity [22]. Gamma correction, which is constrained by the parameter $\gamma (0 < \gamma < 1)$ stretches the difference between gray levels in dark regions. In this case, details in dark regions are enhanced. Gamma correction is formulated as follows:

$$T(l) = l_{\max}\left(\frac{l}{l_{\max}}\right)^{\gamma} \tag{9}$$

In (9), $T(l)$ enhances the low intensity pixels, and the smaller γ is, the more the pixel values are improved. However, when the pixel values are transformed by gamma correction, pixels in different regions exhibit the same change by the fixed parameter. Although local gamma correction is used, it causes contrast distortions. In this work, we propose dual gamma correction, and introduce it into the CLAHE framework to compensate for contrast distortions. We first define an enhancement weight for the global gray levels of blocks by gamma correction, i.e. γ_1, as follows:

$$W_{en} = \left(\frac{L_{\max}}{L_{\alpha}}\right)^{1-\gamma_1} \tag{10}$$

where L_{max} is the maximum gray value of the image; and L_{α} is the reference gray value. Similar to the median value in [13], we empirically set L_{α} to the gray level where the cumulative density function is 0.75. Next, we obtain the enhanced maximum local $l'_{\max}$ by the weighting function W_{en}. We replace $l_{\max}$ in (21) with $l'_{\max}$ to adjust the dynamic range of the block. Thus, we get the output mapping function $T_1(l)$ as follows:

$$l'_{max} = l_{max} \times W_{en} \tag{11}$$

$$T_1(l) = l'_{max} \times cdf(l) \tag{12}$$

We combine the first gamma correction into the CLAHE framework to prevent tone distortions and over-enhancement. After conducting the first gamma correction in CDF of CLAHE, the image luminance is boosted while the original image features are preserved. It is very effective in enhancing dark regions with textures. However, when the image contains large portion of very dark regions and bright regions together, the under-enhancement problem happens in dark regions. The reason is that γ_1 mapping curve-based CLAHE increases the contrast without considering content information. To overcome this shortcoming, we perform the second gamma correction for contrast enhancement.

The second gamma correction, i.e. γ_2, acts as the minimum threshold for contrast enhancement as shown in Fig. 5. We define the second gamma correction function and the final mapping function as follows:

$$\begin{aligned} Gamma(l) &= L_{\max} \times \left(\frac{l}{L_{\max}}\right)^{2} \\ \text{If } r > D_{threshold}, T &= \max\left(T_1(l), Gamma(l)\right) \\ \text{else}, T &= Gamma(l) \end{aligned} \tag{13}$$

where $T_1(l)$ is CLAHE with γ_1 mapping function, $T_{output}(l)$ is the final mapping function; r denotes the dynamic range of the image block, e.g. when the dynamic range of a block is $[70 \sim 150]$; and $D_{threshold}$ is the predefined threshold.

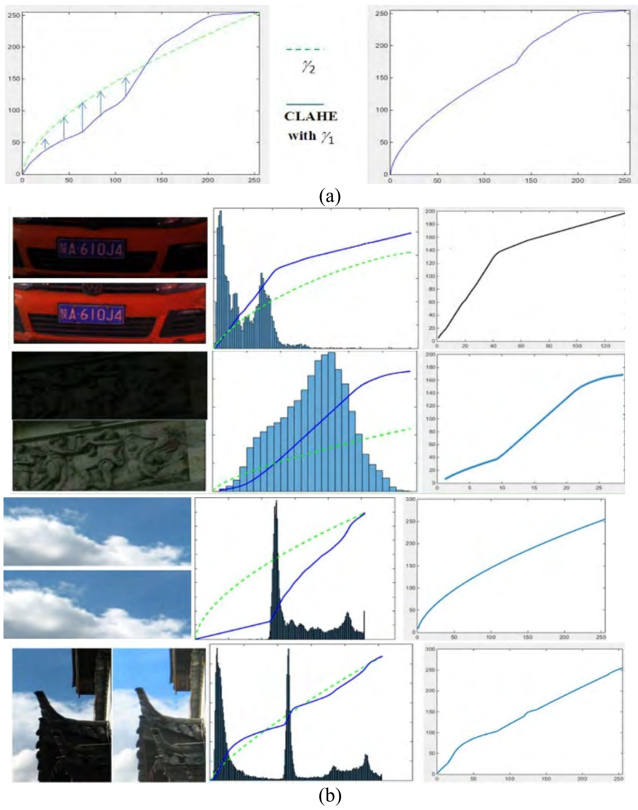

FIGURE 5. **Dual gamma correction. (a) Adjusted transform function by dual gamma correction. (b) Mapping curve adjustment and correction results in different regions by (a).**

When the dynamic range of the image block is larger than $D_{threshold}$, we perform CLAHE with dual gamma correction. In this step, when the automatic CLAHE curve with γ_1 mapping is lower than γ_2 mapping curve, we select γ_2 mapping curve for contrast enhancement. We increase the contrast in dark regions by luminance enhancement while constraining the contrast enhancement in bright regions. In [19], AGCWD provides an idea to automatically adjust gamma, which defines a weighting distribution (WD) function to adjust the histogram as follows:

$$pdf_{\omega}(l) = pdf_{\max} \times \frac{pdf(l) - pdf_{\min}}{pdf_{\max} - pdf_{\min}} \tag{14}$$

where $pdf_{\max}$ and $pdf_{\min}$ are the maximum and minimum values of the histogram, respectively. Thus, the CDF with weighting distribution is obtained as follows:

$$cdf_{\omega}(l) = \sum\nolimits_{j=0}^{l} pdf_{\omega}(j) / \sum pdf_{\omega}(l) \tag{15}$$

where $\sum pdf_{\omega}(l)$ is the sum of pdf_{ω}. Finally, AGCWD is formulated as follows:

$$T_{AGCWD}(l) = l_{\max}(l/l_{\max})^{1-cdf_{\omega}(l)} \tag{16}$$

In (16), $cdf_{\omega}(l)$ is non-decreasing, and thus 1-$cdf_{\omega}(l)$ is monotonically decreasing. That is, the dark regions may have larger gamma than the bright regions. In the step of tone mapping, the smaller the gamma is, the more the intensity is improved. Obviously, in dark regions, the uncontrollability of gamma may cause under-enhancement. It would be better if gamma is an increasing function, and thus we reassign γ_1 and γ_2 as follows:

$$\gamma_1 = \frac{\ln(e + cdf(l))}{8} \tag{17}$$

$$\gamma_2 = \frac{1 + cdf_{\omega}(l)}{2} \tag{18}$$

where e is a constant. In this function, γ_1 and γ_2 are increased by l, and thus are limited in a appropriate scope to avoid the under-enhancement in dark regions. In bright regions, γ_2 is slowly close to 1, which makes the result avoid over-enhancement in bright regions. Thus, this setting for γ_1 and γ_2 is more suitable for images with non-uniform illumination. Fig. 5 shows the adjusted transform function by the dual gamma correction and their results in different regions by adjusting the transform function. As shown in the figure, γ_1 boosts the CLAHE mapping curve (the blue line), while γ_2 acts as a threshold. The mapping part below γ_2 mapping function is replaced by γ_2 curve. In the very low levels, γ_2 mapping function is very effective in dealing with the under-enhancement problem, while in the relatively high value regions, γ_2 mapping function can smooth the transform curve. Thus, the image blocks with dark intensities are successfully enhanced while preserving tones in bright regions. As shown in Fig. 5(b), in the patch of the car plate number (first row), the histogram is uniformly distributed, and CLAHE with γ_1 is selected to enhance the contrast. In the patch of the sculpture region (second row) whose histogram is concentrated to the low intensities, γ_2 mapping function is selected to boost the pixel values. In the relatively high intensity, i.e. bright region, the CLAHE mapping curve is selected, and we get the good contrast. In the sky with cloud region (third row), γ_2 mapping function is selected to prevent over-enhancement, i.e. if the CLAHE curve is used, it would cause over-enhancement. In the patch of dark tiled roofs with bright sky (fourth row), the histogram is divided into the extremely low and high intensities. In the low intensity, i.e. dark regions, the CLAHE curve is selected to enhance the contrast, while the luminance remain unchanged by γ_2 mapping function in the high intensity, i.e. bright regions. The main purpose of the dual gamma correction is to enhance the contrast without introducing any artifacts. The γ_2 mapping curve is an efficient supplemental function to adjust contrast while removing over-enhancement artifacts.

IV. EXPERIMENTAL RESULTS

We perform experiments on a PC with Core Duo 2.33 GHz CPU and 4G RAM using Visual Studio 2010 and Windows 7 operation system. For the tests, we use 5 dark images with a very dark tone (*Carnival, Car, Basketball, Campus, Memorial Church*), and two daylight images with strong shadows (*DSCN* and *Alley*). All test images are normalized to 8 bits, i.e. 0 $\sim$ 255. The test images have the size from

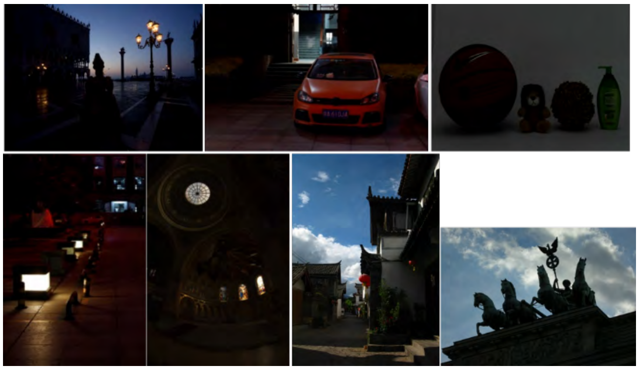

FIGURE 6. **Test images for experiments: *Carnival, Car, Basketball, Campus, Memorial Church, Alley, and DSCN.***

720 × 480 to 1368 × 1824 as shown in Fig. 6. We compare the proposed method with five other methods: CLAHE, AGCWD [19], ESIHE [12], MMSICHE [13], and channel division (ChDiv) [23]. We select CLAHE and AGCWD for comparison because the proposed method improves CLAHE by introducing adaptive gamma correction. Similar to the proposed method, ESIHE and MMSICHE also redistribute the histogram by setting clip points. ESIHE and MMSICHE set the clip point based on mean or median value. Thus, we select them for performance comparison. Moreover, we select ChDiv because it also utilizes a "divide mechanism" which decomposes the dynamic range into three channels of dark, middle and bright. In the proposed method, the block size in CLAHE is 32 × 32. We empirically set $P = 1.5$ and $\alpha = 100$ in (8); and $D_{\text{threshold}} = 50$ in (13).

A. VISUAL COMPARISONS

Fig. 7 shows visual comparisons between contrast enhancement results by the six methods. CLAHE enhances both pixel values and contrast of images, but causes halo artifacts. Halo artifacts are from over-stretching of the histogram, which are very obvious along the strong edges (see Figs. 7(a), 8(a), 9(a), 10(a), and 13(a)). They are caused by under (over)-enhancement on low (high) values when image blocks contain strong edges. Fortunately, in the proposed method, dark regions in images are successfully enhanced, and halo artifacts are effectively removed by γ_2 correction. Moreover, CLAHE produces over-enhancement results in smooth regions (see the ground in Figs. 8(a), 11(a) and 12(a)) due to the improper clip points in blocks. However, the proposed method adaptively set the clip points based on textureness of each block, thus avoiding the over-enhancement problem. Moreover, our method produces a natural-looking color tone in contrast enhancement. AGCWD yields relatively good results, which is very robust because of using weighting distribution on the gamma correction. ESIHE and ChDiv have almost the same performance in visual quality although they have different mechanisms. If there is difference, ESIHE focuses more on the contrast enhancement compared with ChDiv (see Figs. 8(c) and 8(e)). MMSICHE enhances contrast of images, but is not applicable to dark images. Dark regions are under-enhanced, i.e. the details of building in Fig. 7(d) are invisible and the plant in Fig. 8(d) is almost completely degraded. MMSICHE makes the result look unnatural due to the excessively sharp contrast (see Fig. 8(d)). Also, in Fig. 9(d), background regions become unnatural due to the over-enhancement while the basketball and teddy bear (foreground) are not perceivable. However, the proposed method produces a natural-looking color tone in the results. CLAHE produces unnatural results degraded by halo artifacts, but the other four methods outperform CLAHE in keeping details in dark regions. Note that much tone distortion is not acceptable in image enhancement.

FIGURE 7. **Experimental results in *Carnival.* (a) CLAHE. (b) AGCWD. (c) ESIHE. (d) MMSICHE. (e) ChDiv. (f) The proposed method.**

FIGURE 8. Experimental results in *Car.* (a) CLAHE. (b) AGCWD. (c) ESIHE. (d) MMSICHE. (e) ChDiv. (f) The proposed method.

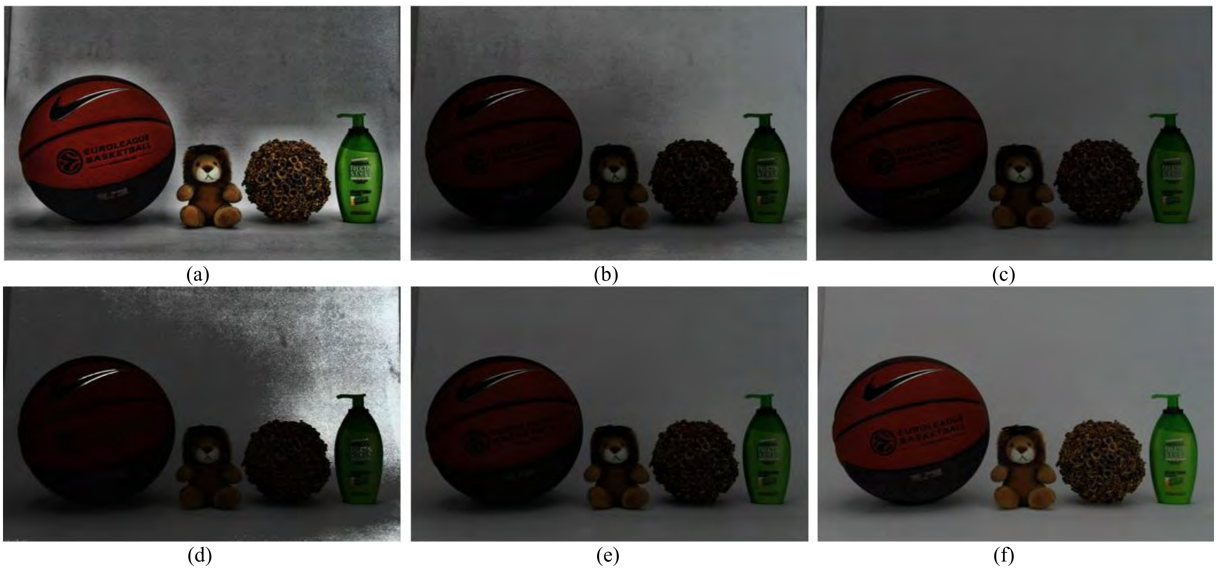

FIGURE 9. Experimental results in *Basketball.* (a) CLAHE. (b) AGCWD. (c) ESIHE. (d) MMSICHE. (e) ChDiv. (f) The proposed method.

The four methods achieve a good balance between contrast enhancement and naturalness. However, in terms of the robustness on both daylight scenes with dark shadows and dark images, the proposed method outperforms the others. As shown in Figs. 7(b), 8(b), 8(c), and 8(d), AGCWD, MMSICHE, and ChDiv are not effective because the entire intensity of the original image is low, i.e. dark images. In general, the proposed method produces visually-pleasing color appearance after contrast enhancement by achieving artifact-free contrast enhancement. Compared with the five other methods, the proposed method performs good contrast enhancement especially when the test images contain complex objects and light conditions.

B. QUANTITATIVE MEASUREMENTS

For more quantitative measurements, we choose four image quality metrics (IQM): Total variation (TV) [24], absolute mean brightness error (AMBE) [25], EME [26], and CQE [27].

(1) TV measures the statistics of noise in an image. Once the contrast of images is enhanced, noise is also amplified, especially in dark images. Thus, it is required to evaluate noise exposures. In our evaluation procedure, we obtain l_1-based TV as follows:

$$TV = \frac{1}{(m-1)(n-1)}(|I_{(x,y)} - I_{(x+1,y)}| + |I_{(x,y)} - I_{(x,y+1)}|) \quad (19)$$

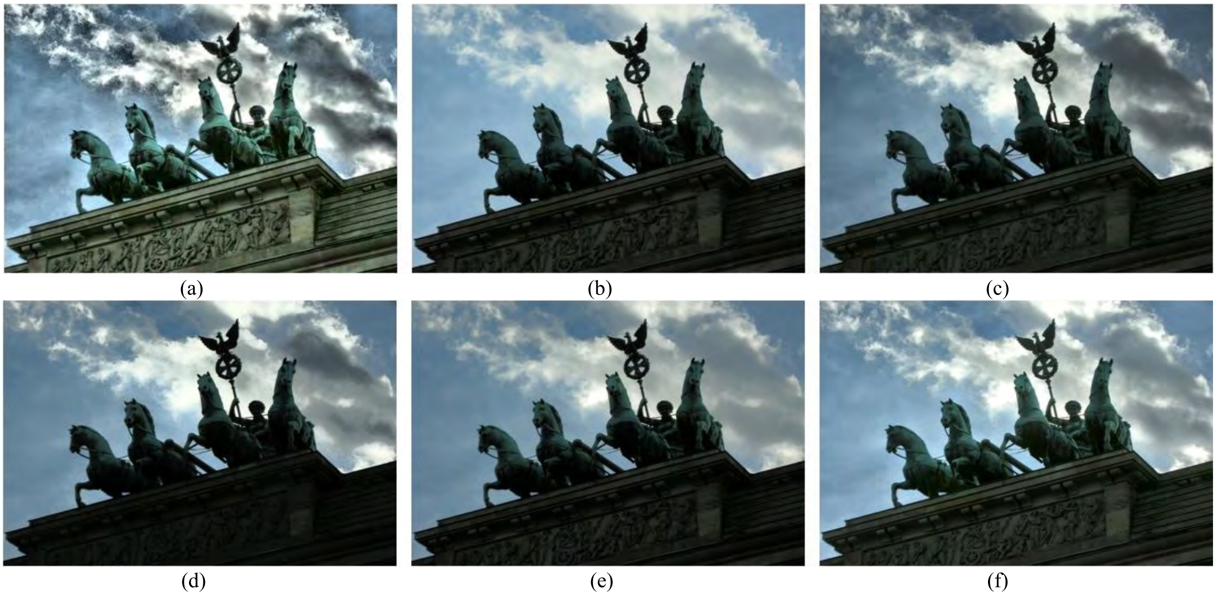

FIGURE 10. Experimental results in *DSCN.* (a) CLAHE. (b) AGCWD. (c) ESIHE. (d) MMSICHE. (e) ChDiv. (f) The proposed method.

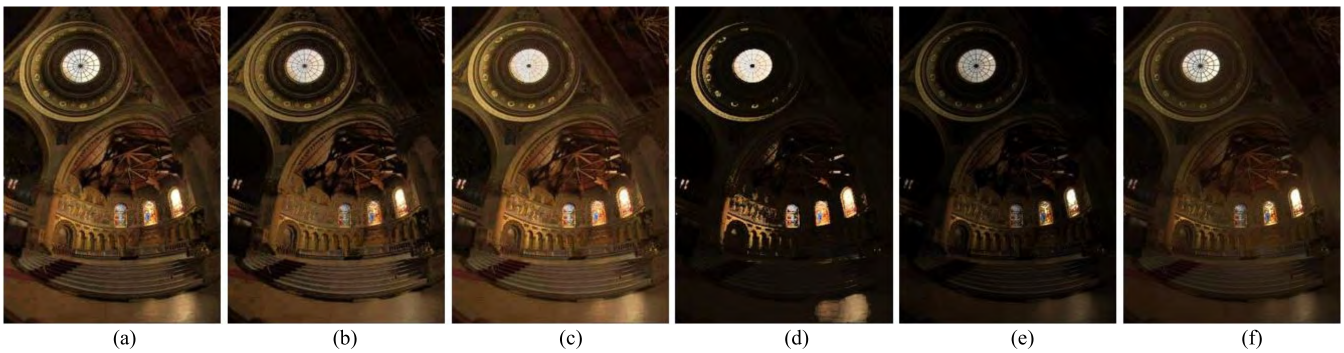

FIGURE 11. Experimental results in *Memorial Church.* (a) CLAHE. (b) AGCWD. (c) ESIHE. (d) MMSICHE. (e) ChDiv. (f) The proposed method.

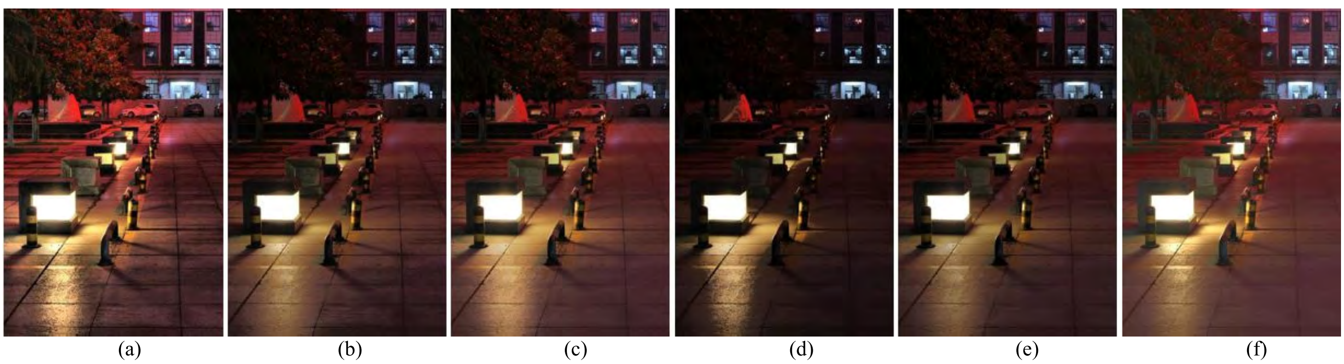

FIGURE 12. Experimental results in *Campus.* (a) CLAHE. (b) AGCWD. (c) ESIHE. (d) MMSICHE. (e) ChDiv. (f) The proposed method.

where m, n are the height and width of image I; (x, y) is the pixel coordinate. An image with strong noise has a high score in terms of TV, i.e. lower TV indicates lower noise.

(2) AMBE reflects the change of gray levels between the input image and the enhancement result. We obtain AMBE as follows:

$$AMBE = |X_\mu - Y_\mu| \tag{20}$$

where X_μ and Y_μ are the means of the original image and its enhanced result, respectively. AMBE is a measure of

(a) (b) (c) (d) (e) (f)

FIGURE 13. Experimental results in *Alley*. (a) CLAHE. (b) AGCWD. (c) ESIHE. (d) MMSICHE. (e) ChDiv. (f) The proposed method.

TABLE 1. Objective evaluation results in terms of TV, AMBE, EME, and CQE.

Metric	Method	*DSCN*	*Carnival*	*Memorial*	*Basketball*	*Alley*	*Car*	*Campus*	*Average*
TV	CLAHE	14.313	22.341	15.448	14.837	17.988	20.535	20.520	17.997
	AGCWD	6.0968	7.1335	14.003	6.9553	6.2491	7.6656	9.6068	8.2443
	ESIHE	7.0168	7.6291	14.295	4.5197	4.7008	9.8477	10.128	8.3053
	MMSICHE	5.5440	9.3446	9.6197	18.255	5.5560	8.2958	7.8007	9.2023
	ChDiv	6.1371	15.646	8.9211	4.3705	7.2540	9.0843	9.8663	8.7542
	Proposed	5.4776	12.026	7.5148	2.5197	6.5294	7.7955	7.6679	7.6679
AMBE	CLAHE	0.1351	0.1999	0.1982	0.1681	0.1546	0.2417	0.2358	0.1905
	AGCWD	0.0988	0.0512	0.1451	0.0916	0.0785	0.0920	0.1117	0.0956
	ESIHE	0.0196	0.0553	0.2249	0.0645	0.0068	0.1428	0.1661	0.0971
	MMSICHE	0.0221	0.0552	0.0368	0.0871	0.0370	0.0486	0.0325	0.0456
	ChDiv	0.0206	0.0732	0.0075	0.0645	0.0438	0.0853	0.0831	0.0540
	Proposed	0.1073	0.1217	0.0995	0.0851	0.1089	0.1297	0.1325	0.1121
EME	CLAHE	4.413	6.785	5.399	5.516	5.444	7.059	5.962	5.796
	AGCWD	4.586	10.12	6.000	7.079	5.022	6.625	5.399	6.405
	ESIHE	3.893	10.28	4.414	5.721	4.401	5.612	4.842	5.595
	MMSICHE	6.115	12.33	7.525	6.105	5.601	10.42	7.755	7.978
	ChDiv	3.221	9.351	3.589	6.012	3.948	4.341	3.584	4.864
	Proposed	5.357	13.97	13.76	5.721	9.547	13.41	8.607	10.05
CQE	CLAHE	0.4661	0.6604	0.5378	0.3421	0.7500	0.7417	0.7566	0.6078
	AGCWD	0.4050	0.4461	0.6648	0.2882	0.4671	0.5932	0.6270	0.4988
	ESIHE	0.4388	0.4472	0.8224	0.2670	0.3796	0.7550	0.7094	0.5456
	MMSICHE	0.4595	0.4715	0.7195	1.3800	0.3814	0.7188	0.6764	0.6867
	ChDiv	0.3595	0.4944	0.4961	0.2670	0.5138	0.5863	0.5529	0.4671
	Proposed	0.6553	0.9120	0.7838	0.5240	1.0444	1.0369	1.0771	0.8619

luminance change and directly related to average luminance. In some cases, lower AMBE indicates better performance because high values might be caused by an excessive change of gray levels. Such excessive change causes unnatural looking results. However, for dark images, it is required to boost the entire gray levels, which means that we need proper AMBE that reflects a balance between enhancement and perception. In our experiments, AMBE is normalized by the maximum value of 255.

(3) EME is a measure of image enhancement which finds the average ratio of the maximum to the minimum intensities in decibels. We replaced LTG with EME because many parameters need to be manually set in LTG, which is not very objective. When EME takes the average ratio in each block over the entire image, it considers the fact that the relationship between stimulus and perception is logarithmic, which is suitable for human visual perception.

$$EME = \frac{1}{k_1 k_2} \sum_{l=1}^{k_2} \sum_{k=1}^{k_1} 20 \log \frac{I^W_{\max;k,l}}{I^W_{\min;k,l} + c} \tag{21}$$

where the image is divided into $k_1 \times k_2$ blocks; c is a small constant to avoid dividing by 0; $I^W_{\max;k,l}$ and $I^W_{\min;k,l}$ are the maximum and minimum values in (k,l) block, respectively.

TABLE 2. Runtime of the proposed method.

Image size	720×480	778×584	1024×682	1920×1080	1368×1824
Runtime (ms/image)	16	17	28	83	99

Experiments are performed on a PC with Core Duo2.33 GHz CPU and 4G RAM using Visual Studio 2010 and Windows 7 operation system

In our experiments, we set $k_1 = k_2 = 32$ and $c = 0.0001$. Higher EME indicates higher image quality.

(4) CQE [27] is a no reference color image quality measure metric consists of colorfulness, sharpness, and contrast as follows:

$$CQE = m_1 \times col + m_2 \times shar + m_3 \times con \tag{22}$$

$$col = 0.02 \times \log\left(\frac{\sigma_\alpha^2}{|\mu_\alpha|^{0.2}}\right) \times \log\left(\frac{\sigma_\alpha^2}{|\mu_\beta|^{0.2}}\right) \tag{23}$$

$$con = \frac{1}{k_1 k_2} \sum_{l=1}^{k_1} \sum_{k=1}^{k_2} \left(\log\left(\frac{I_{\max,k,l}+I_{\min,k,l}}{I_{\max,k,l}-I_{\min,k,l}}\right)\right)^{-0.5} \tag{24}$$

$$shar = \sum_{c=1}^{3} \lambda_c \frac{1}{k_1 k_2} \sum_{l=1}^{k_1} \sum_{k=1}^{k_2} log\left(\frac{I_{\max,k,l}}{I_{\min,k,l}}\right) \tag{25}$$

where m_1, m_2, and m_3 are parameters in the model; α and β are opponent red-green and yellow-blue spaces, respectively; μ and σ stand for the mean and variance of α and β, respectively; λ_c is the constant in the color channel; k_1 and k_2 are the number of blocks in each direction [27].

Among the four measures, EME and CQE are consistent with the properties of the human visual system (HVS). EME considers the logarithmic relationship between the gray level and its perception, and thus is able to measure human visual perception. CQE uses colorfulness, sharpness, and contrast for image quality assessment that HVS captures visual attention. Table 1 shows objective evaluations results in terms of TV, AMBE, EME, and CQE. Although the proposed method does not provide the best performance in *Carnival*, *Alley*, and *Car* in terms of TV, it achieves the best average performance among six methods, i.e. 7.6679. In general, lower AMBE indicates better performance. However, if we want to see whether dark regions are perceived well in HVS or not, higher AMBE is needed to evaluate dark images. On the other hand, excessively high AMBE is not allowed in image enhancement. Thus, an optimal trade-off between enhancement and perception is needed. The average AMBE value of the proposed method (0.1121) is much lower than that of CLAHE (0.1905) and higher than the other methods, which indicates that CLAHE causes strong distortion in luminance while the other methods are not effective in enhancing dark regions. Thus, the AMBE evaluation results show that the proposed method successfully enhances dark regions in an image without excessive luminance change. Moreover, higher EME reflects better visual quality. Although the proposed method does not get the highest score in *DSCN* and *Basketball*, it achieves the highest average score. In terms of CQE, ESIHE and MMSICHE performs better than the proposed method in *Memorial* and *Basketball*, but the proposed method outperforms the others in the other images. The proposed method achieves good performance in color reproduction. Table 2 shows the average runtime of the proposed method. On 1024 × 682 image, the proposed method achieves the speed of 28 msec/image, i.e. more than 35 frames/sec. This is because the proposed method performs independent block processing and minimizes the redundancy for contrast enhancement.

V. CONCLUSIONS

In this paper, we have proposed automatic CLAHE for image contrast enhancement with dual gamma correction. We have introduced dual gamma correction into CLAHE to enhance contrast in an image without tone distortion and over-enhancement. First, we have redistributed the block histogram based on the dynamic range of each block in the CLAHE framework. Second, we have performed the first gamma correction γ_1 to boost the entire luminance in the image block. Then, we conduct the second gamma correction γ_2 to adjust the contrast in very dark regions. The proposed method adaptively enhances both contrast and luminance in local regions, and thus is very effective in enhancing dark images and daylight ones with strong dark shadows. Also, its computational complexity is very low due to the independent block processing for contrast enhancement, i.e. more than 35 frames/sec at 1024 × 682 images. Experimental results demonstrate that the proposed method outperforms state-of-the-arts in terms of visual quality and quantitative measurements.

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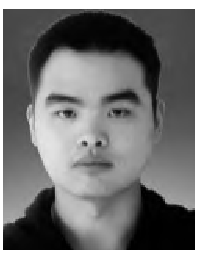

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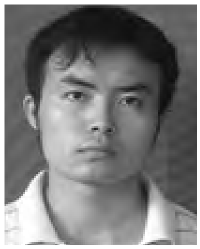

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