A Novel 3-D Color Histogram Equalization Method With Uniform 1-D Gray Scale Histogram

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***Abstract*—The majority of color histogram equalization methods do not yield uniform histogram in gray scale. After converting a color histogram equalized image into gray scale, the contrast of the converted image is worse than that of an 1-D gray scale histogram equalized image. We propose a novel 3-D color histogram equalization method that produces uniform distribution in gray scale histogram by defining a new cumulative probability density function in 3-D color space. Test results with natural and synthetic images are presented to compare and analyze various color histogram equalization algorithms based upon 3-D color histograms. We also present theoretical analysis for nonideal performance of existing methods.**

***Index Terms*—Color image enhancement, gray scale histogram equalization, 3-D color histogram equalization.**

I. Introduction

THE USAGE of digital images has rapidly increased with growing public consumption of entertainment and communication appliances, such as digital TV's, digital cameras, scanners, mobile phone cameras, and personal media players. The expectation of a higher image quality prompts researchers to develop cutting-edge techniques for image enhancement. Histogram equalization has been one of the most widely used techniques due to its effectiveness and simplicity in contrast enhancement. Therefore, histogram equalization has become embedded in most consumer digital cameras. Histogram equalization modifies the pixel values in such a way that the intensity histogram of the resulting image becomes uniform. The output image then makes use of all the possible brightness values, thus, resulting in enhanced contrast [1].

First, we will review previous studies on color histogram equalization methods based upon 3-D histograms. The histogram equalization of a color image is more complex than 1-D equalization due to multidimensional nature of color signal. A typical color image has three color components: red (R), green (G), and blue (B). Trahanias and Vanetsanopoulos [2] proposed to use a 3-D color histogram instead of independently applying 1-D histogram equalization to each R, G, and B channel. They defined ideal output probability density function (pdf) to be uniform in the color space, and the cumulative distribution function (cdf) to be accumulation of pdfs within a box of size $\mathrm{R} \times \mathrm{G} \times \mathrm{B}$ in 3-D color space. Although uniform pdf in gray scale dramatically enhances contrast of the images, uniform pdf in 3-D color space does not result in uniform pdf in luminance domain with the box shape cdf. Most of the natural images that are equalized using this method show higher concentration of bright pixels. We analyze the theory behind this less-than-ideal performance of contrast enhancement in Section II. Menotti *et al.* [3] partially overcame this lack of contrast enhancement by defining a new cdf that is a multiplication of the marginal cdfs of each color channel. However, this heuristic method does not work properly when color correlation is low. Other approaches for multidimensional histogram equalization include weighted 1-D marginal histogram equalization [4], and iterative matching of 1-D marginal pdf [5].

This work elucidates the reason behind nonideal performance of 3-D color histogram equalization algorithms, and proposes a new definition of cdf in RGB color space that will result in uniform luminance distribution after equalization. Since gray scale histogram equalization is a powerful and effective tool for contrast enhancement, achieving uniform luminance pdf is an important feature for image enhancement.

There are many other color histogram equalization methods that are not directly related to the 3-D histogram. Mlsna and Rodriguez [6] introduced a histogram explosion method in 3-D color space. This method expands the color space of an image by equalizing 1-D histogram along a line from a central point in color space to the R, G, and B boundary points. The same author also applied this method in CIELUV color space [7]. Pitas proposed a multichannel histogram equalization method [8] using conditional probability density functions in HSI color space, and Lucchese suggested an equalization in x-y color space [9].

Several new approaches are based upon optimization. Kim and Yang interpolated the discrete pdf with Gaussian functions and applied nonlinear optimization [10]. Morovic and Sun found 3-D color histogram transformation using linear programming [11]. Arici *et al.* defined a cost function composed of image change, histogram deviation from the target, and histogram smoothness [12]. Chen *et al.* proposed gray-level grouping (GLG) that groups adjacent low values of histogram bins and then redistributes these groups iteratively [13]. Most of the histogram equalization algorithms use a histogram of the whole image. However, the use of an adaptive or local histogram enhances each region with different mapping depending

Manuscript received August 21, 2009; revised January 18, 2010 and June 02, 2010; accepted August 03, 2010. Date of publication August 26, 2010; date of current version January 14, 2011. This work was supported in part by the Ministry of Knowledge Economy (MKE), Korea Industrial Technology Foundation (KOTEF) through the Human Resource Training Project for Strategic Technology, the Acceleration Research Program of the Ministry of Education, Science and Technology of Korea and the Korea Science and Engineering Foundation, and Ewha W. University under Grant 2008-1806-1. The associate editor coordinating the review of this manuscript and approving it for publication was Prof. Jesus Malo.

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Digital Object Identifier 10.1109/TIP.2010.2068555

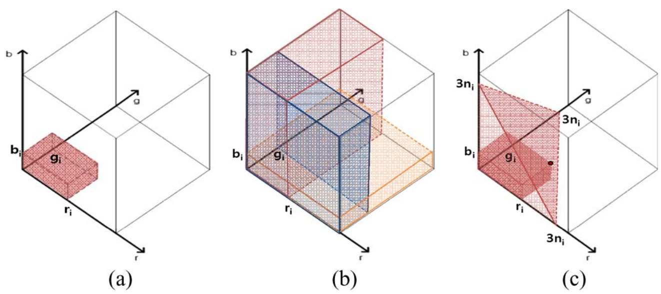

Fig. 1. Support region of input cdf (C_{in}) of each method. (a) Trahanias method $C_{\text{in}}(r_i, g_i, b_i) = prob\{(0 \le r \le r_i), (0 \le g \le g_i), (0 \le b \le b_i)\} = \sum_{r=0}^{r_i} \sum_{g=0}^{g_i} \sum_{b=0}^{b_i} p(r, g, b)$. (b) Multiplication of three marginal cdfs in the Menotti method $C'_{\text{in}}(r_i, g_i, b_i) \equiv C^R_{\text{in}}(r_i) \times C^G_{\text{in}}(g_i) \times C^B_{\text{in}}(b_i)$. (c) Proposed iso-luminance-plane method. $C_{\text{in}}(r_i, g_i, b_i) = prob\{r + g + b \le 3n_i\} = \sum_{r+g+b \le 3n_i} p_{\text{in}}(r, g, b)$.

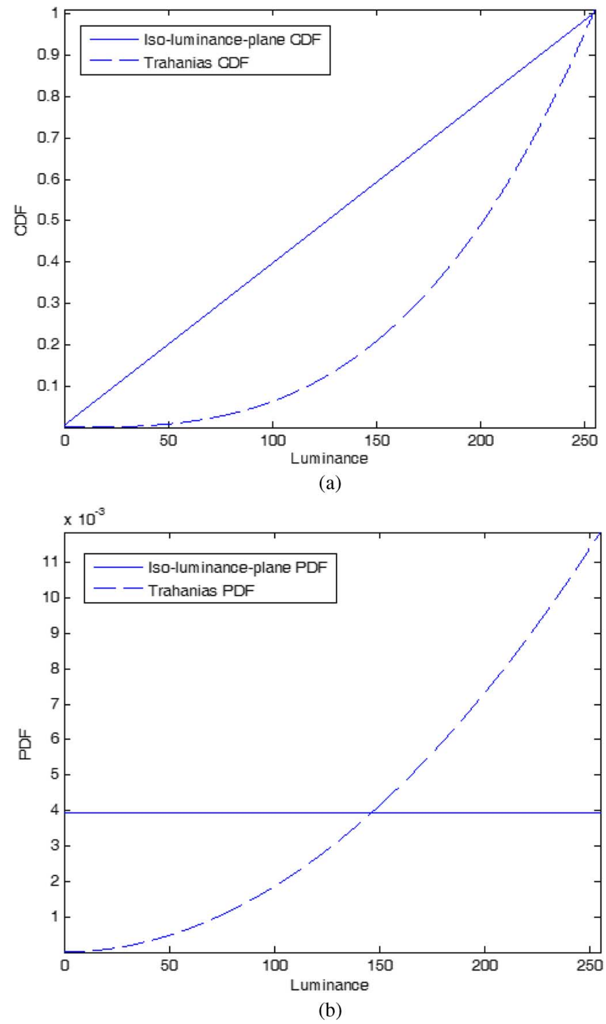

Fig. 2. Gray scale pdf and cdf of Trahanias and iso-Luminance-Plane methods. (a) Theoretical gray scale cdfs on Trahanias and iso-Luminance-Plane methods. (b) Theoretical gray scale pdfs on Trahanias and iso-Luminance-Plane methods.

upon local image histogram. Therefore, it can show details in the background with additional complexity [14], [15], .

A histogram may have a "spike" where a particular bin has large number of pixels, or a "gap" where the corresponding bin is empty. Traditional histogram equalization algorithms modify the pixel value while leaving spikes or gaps as they are. However, recent methods employing histogram smoothing redistribute spikes and fill gaps to achieve uniform pdf [12], [13], [16], [17]. Therefore, recent methods using histogram smoothing can increase entropy, while traditional algorithms cannot. Bassiou and Kotropoulos [16] applied probability smoothing in HSI color coordinates. They demonstrate increase in entropy and decrease in Kullback-Leibler divergence. Other works also employ bin redistribution that increases entropy. Since the current method does not employ bin redistribution, entropy is not increased. Numerous works have also been published based upon models of subjective human color vision [18], [19]. Recently, Lee *et al.* proposed a method based upon the exposure-color characteristics of a camera [20]. This method uses the nonlinear relationship between exposure and color of a camera to correct color after intensity modification. Therefore, this algorithm can be applied to the embedded histogram equalization algorithm of a specific camera model.

Naik and Murthy [21] proposed a new framework that enables one to apply a class of gray scale image enhancement methods to color images. This generic framework is also applied to the color histogram equalization: 1-D histogram equalization is applied to the luminance component, and a hue preserving transformation is applied to find the new color values. Therefore, the result of this algorithm is the same as our proposed method, except for a numerical rounding off error. However, our method has a different theoretical basis which is derived from the 3-D color histogram. We can achieve a uniform distribution in gray scale by defining a new cdf in color space.

This paper proposes a new cdf in 3-D color space which yields the uniform histogram for the luminance component. We compare the color histogram equalization methods based upon the 3-D histogram using natural and synthetic images and analyze the reasons for the different performance. The organization of this paper is as follows. Typical histogram equalization of gray image is summarized in Section II, and our algorithm is presented in Section III. The experimental results are demonstrated in Section IV, and finally, our conclusions are presented in Section V.

II. Review of Previous Work Based upon the 3-D Color Histogram

First, we will briefly describe the 1-D gray scale histogram equalization method, which is the basis for 3-D histogram equalization. Second, we will compare the histogram equalization algorithms based upon the 3-D histogram. Finally, we will analyze the reasons that cause the different performances.

A. Gray Scale Histogram Equalization

Each bin of a histogram in a gray scale image represents the number of pixels having the same gray value in the image. The histogram equalization method enhances the contrast of an image by mapping the pixel values in such a way that the histogram of the resulting image becomes uniform [1]. Because this algorithm mandates the use of all gray levels uniformly, it

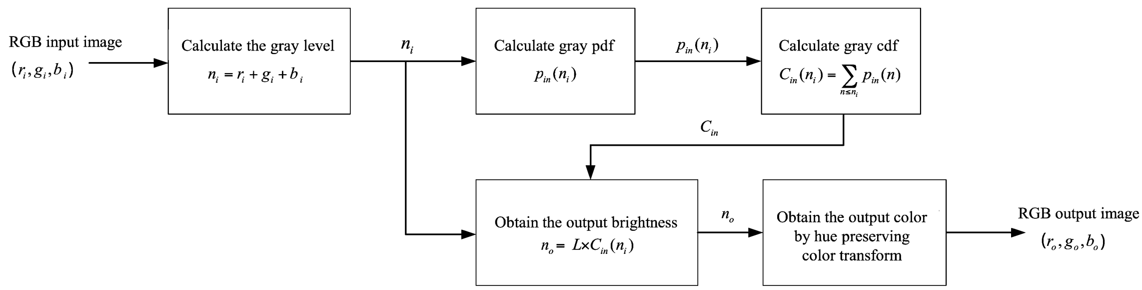

Fig. 3. Block diagram of the proposed histogram equalization method. Cdf of gray level is calculated and the output gray level is obtained from the cdf. Equalized color components are obtained by applying a hue preserving color transform to the enhanced luminance.

is quite effective in enhancing the contrast of overexposed or underexposed images. This method is widely employed in many consumer digital cameras and mobile phone cameras due to its simplicity and efficacy.

We first describe the histogram equalization of a gray scale image. We will then extend it to 3-D in the following subsections. Let the original input image be I_{in} and the histogram equalized image I_{out}. The pdfs of them are denoted as p_{in}, and p_{out} and the corresponding cdfs are C_{in}, and C_{out}, respectively. We denote the intensity of the original input image as n_i and the modified intensity of the resulting output image as n_o. Since the output pdf should be uniform, i.e., $p_{\text{out}} = 1/L$, where L is the number of intensity levels. The ideal output cdf is

$$C_{\text{out}}(n_o) = \sum_{k=0}^{n_o} p_{\text{out}}(k) = (n_o+1)/L \qquad \text{for } n_o = 0, \ldots, L-1. \tag{1}$$

Since $C_{\text{in}}(n_i) = C_{\text{out}}(n_o)$ after the histogram equalization, we can obtain the output intensity using (1). We present the 3-D histogram equalization in the following subsection.

B. Previous Methods Based upon 3-D Color Histogram Equalization

A histogram equalization method applied to a color image is more complicated than that of a gray image because the 3-D histogram requires three components of a color space such as R, G, and B. Trahanias and Venetsanopoulos [2] defined the cdf in RGB color space as

$$\begin{aligned} C_{\text{in}}(r_i, g_i, b_i) &= prob\{(0 \le r \le r_i), (0 \le g \le g_i), (0 \le b \le b_i)\} \\ &= \sum_{r=0}^{r_i} \sum_{g=0}^{g_i} \sum_{b=0}^{b_i} p_{\text{in}}(r, g, b) \end{aligned}$$

where

$$0 \le r_i, g_i, b_i \le L-1. \tag{2}$$

The summation volume is a rectangular box as shown in Fig. 1(a). The desired output cdf is given as

$$\begin{aligned} C_{\text{out}}(r_o, g_o, b_o) &= \sum_{r=0}^{r_o} \sum_{g=0}^{g_o} \sum_{b=0}^{b_o} p_{\text{out}}(r, g, b) \\ &= \sum_{r=0}^{r_o} \sum_{g=0}^{g_o} \sum_{b=0}^{b_o} \frac{1}{L^3} \\ &= \frac{(r_o+1)(g_o+1)(b_o+1)}{L^3}. \end{aligned} \tag{3}$$

Note that the output pdf is defined to be uniform in the color space, which means $p_{\text{out}}(r, g, b) = 1/L^3$ for $0 \le r, g, b \le L$. The output color (r_o, g_o, b_o) is the nearest value satisfying $C_{\text{out}}(r_o, g_o, b_o) = C_{\text{in}}(r_i, g_i, b_i)$ and the shift of each color component is the same, i.e., $r_o - r_i = g_o - g_i = b_o - b_i$. This shifting method is a way of reserving the hue [21]. Since we must limit the range of resulting color to $[0\ L-1]$, the resulting color may not match the assigned intensity n_o for some pixels whose gamut fall outside of the realizable range. If we apply this histogram equalization to a natural image which has a high correlation between color components, the distribution of bright pixels increases. To investigate the reason for this higher distribution on bright intensity levels, we analyze a simplified case where R, G, and B components are the same, i.e., $r = g = b = n$. Note that the correlation between the colors of this test image is equal to one. The resulting cdf C_{out} for this image is proportional to $(n+1)^3$, i.e., $C_{\text{out}} \propto (n+1)^3$ from (3) as shown in Fig. 2(a). To simplify the analysis, we assume that the intensity n is continuous. This is because the pdf of the output image, p_{out}, is the differentiation of the cdf w.r.t. n, which is

$$p_{\text{out}}(n) = \frac{d}{dn}\left(C_{\text{out}}^{\text{RGB}}\right) \propto (n+1)^2. \tag{4}$$

The resulting pdf after equalization, p_{out}, is proportional to $(n+1)^2$. As shown in Fig. 2(b), resulting pdf after equalization has higher distribution at bright levels. Thus, the image becomes brighter after the histogram equalization. The theoretical average brightness of this pdf is 194.0, while that of the uniform distribution is 127.5 when L = 255. This tendency of higher density for bright pixels can be observed in Figs. 4(b), 6(b), 8(b), and 10(b) in our experiments. Experimental results in [3] and [16] also confirm this same trend. To reduce over-enhancement, Menotti proposed to adopt an input cdf that multiplies each marginal cdf of three channels, i.e.,

$$C_{\text{in}}(r_i, g_i, b_i) \equiv C_{\text{in}}^{R}(r_i) \times C_{\text{in}}^{G}(g_i) \times C_{\text{in}}^{B}(b_i). \tag{5}$$

Fig. 1(b) shows the support region for the three marginal cdfs. We analyze the output pdf utilizing the same gray image used in the previous case. If the 1-D marginal cdf is $C_{\text{out}}^{1}(n)$, then the 3-D output cdf becomes $C_{\text{out}}(n) = \left(C_{\text{out}}^{1}(n)\right)^3$. Since the output pdf is uniform in 3-D color space, we have: $C_{\text{out}}(r, g, b) \equiv \left(C_{\text{out}}^{1}(n)\right)^3 \propto (n+1)^3$. Therefore, $C_{\text{out}}(r, g, b) = \left(C_{\text{out}}^{1}(n)\right)^3 \propto (n+1)^3$, or $C_{\text{out}}^{1}(n) \propto (n+1)$. Consequently, the pdf is uniform, i.e.,

TABLE I
AVERAGE BRIGHTNESS OF TEST IMAGES AFTER HISTOGRAM EQUALIZATION

	Original	Trahanias	Menotti	Naik	Iso Luminance Plane	Separate RGB Equalization
Two color chart image	112.1	176.7	127.2	128.0	127.8	128.0
Synthetic Image	63.7	190.4	153.4	128.6	128.5	170.3
Lena	127.8	166.4	130.5	128.0	127.8	128.0
Pepper	110.5	158.1	129.0	128.0	127.8	128.0

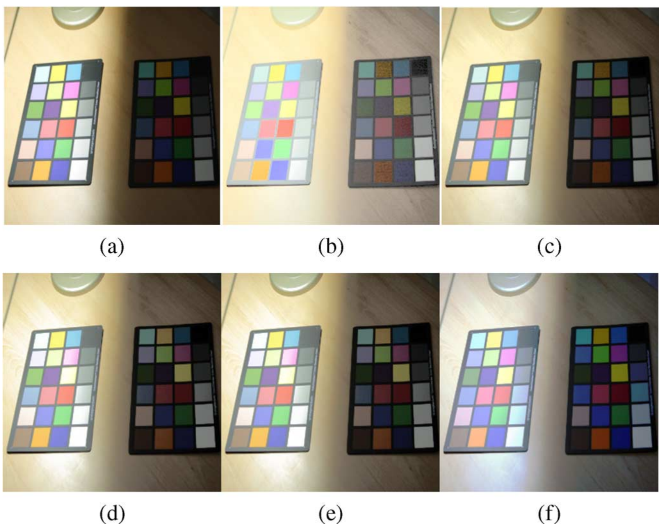

Fig. 4. Results of the histogram equalization on two Macbeth chart image. (a) Input image. (b) Result of Trahanias's method. (c) Result of Menotti's method. (d) Result of Naik's method. (e) Result of the proposed iso-luminance-plane method. (f) Equalized image of each RGB color channel. Images (c) through (e) are similar while (b) is brighter than the others.

$p_{\text{out}}(n) = (d/dn)C^1_{\text{out}}(n) = 1/L$. This method shows satisfactory results for most natural images which have high correlations between color components.

However, Menotti's method also results in an overenhanced image when the correlation between colors is not high as shown in Figs. 10(c), and 11(c). To overcome this limitation, we propose a new cdf, which results in a uniform pdf in the intensity domain regardless of the correlation of R, G, and B components in an image.

C. Generalization of Gray Scale Image Enhancement to Color Images

Naik and Murthy [21] proposed a scheme to generalize any gray scale image processing to color images. First of all, the scheme produces an intensity image. It then applies a gray scale image enhancement algorithm to obtain a new intensity image, which is an enhanced version of the original. The intensity is defined as $n_i = (r_i+g_i+b_i)/3$, and the enhanced level is denoted similarly as $n_o = (r_o+g_o+b_o)/3$. The algorithm updates color components using scaling and shifting to match the change in intensity, i.e., $(r_o, g_o, b_o) = (\alpha r_i + \beta, \alpha g_i + \beta, \alpha b_i + \beta)$.

The scaling and shifting of color is known to preserve the hue. If the intensity ratio $\alpha = n_o/n_i$ is less than one, then the output is $(\alpha R_i, \alpha G_i, \alpha B_i)$, and if $\alpha > 1$, it applies a similar rule to the complementary color components to avoid a gamut problem where the resulting color falls outside of the range of realizable RGB space. This generic framework can be applied to color histogram equalization: we apply 1-D gray scale histogram equalization in the intensity domain and obtain a new color from the modified intensity values by applying the scaling and shifting. The 1-D gray scale histogram of this method is uniform. Therefore, the result of this algorithm is equivalent to our proposed method.

III. PROPOSED METHOD: A CDF WITH AN ISO-LUMINANCE-PLANE BOUNDARY

In Section II-B, we observed that the R, G, and B box summation cdf does not generate a uniform pdf in the intensity domain. We will now propose a new 3-D histogram equalization method to obtain the uniform distribution in the intensity domain. Fig. 3 depicts the block diagram of the proposed method. We define the new 3-D cdf C_{in} as

$$C_{\text{in}}(r_i, g_i, b_i) = prob\{r+g+b \le 3n_i\} = \sum_{r+g+b\le 3n_i} p_{\text{in}}(r,g,b) \tag{6}$$

where $n_i = (r_i + g_i + b_i)/3$ is the input intensity. The summation volume is bounded by a plane whose intensity is n_i as shown in Fig. 1(c). Note that the input cdf is a function of the intensity. Since we can define the luminance as $(r+g+b)/3$, the plane can be regarded as a constant luminance plane. The term "iso-luminance plane" comes from this property. Since the ideal output pdf is uniform over all values of n, the output cdf is

$$C_{\text{out}}(n_o) = n_o/L. \tag{7}$$

This iso-luminance definition of cdf results in a histogram equalization identical to the gray scale histogram equalization. Since $C_{\text{out}}(n_o) = C_{\text{in}}(r_i, g_i, b_i)$, we obtain $n_o = L \cdot C_{\text{in}}(r_i, g_i, b_i)$.

Since we have the luminance component of the equalized image, each color component can be obtained without gamut problem by scaling or shifting as shown in the previous section. Shifting was adopted in [2], [3], while scaling and shifting were applied in [21]. Since the two methods did not show much difference, we chose to follow the method in [21].

Now we will estimate the computational complexity and memory requirement of the proposed method. The input image cdf C_{in} is a function of the intensity, i.e., $r_i + g_i + b_i$, therefore, it needs 1-D array with length $3L$. First, we obtain the intensity pdf by counting pixels that correspond to the same intensity. Calculation of pdf requires increment operation for each pixel. Second, input cdf is calculated by summing up pdfs from 0 to $L-1$, i.e., $C_{\text{in}}(n) = C_{\text{in}}(n-1) + p_{\text{in}}(n)$ for $n > 0$, with $C_{\text{in}}(0) = p_{\text{in}}(0)$. Thirdly, once we calculate the equalized luminance from (7), we can obtain the color components from the scaling and shifting as in [21]. These two operations need several multiplications and additions per pixel. We observe that

TABLE II
MEAN ABSOLUTE ERROR FROM THE LINEAR CDF

	Trahanias	Menotti	Naik	Iso LuminancePlane	Separate RGB Equalization
Two color chart image	0.20	0.016	0.0019	0.0015	0.016
Synthetic Image	0.25	0.11	0.0047	0.0038	0.17
Lena	0.18	0.050	0.0019	0.0015	0.017
Peppers	0.14	0.068	0.0017	0.0014	0.061

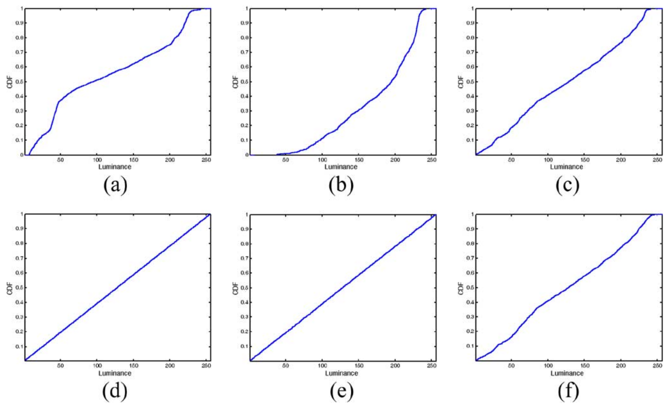

Fig. 5. Gray scale cdfs of the resultant images of Fig. 4. (a) Cdf of the original image. (b) Cdf of Trahanias's method. (c) Cdf of Menotti's method. (d) Cdf of Naik's method. (e) Cdf of the proposed iso-luminance-plane method. (f) Cdf of equalized image of each RGB color channel. The cdfs (c) through (e) are almost linear, therefore, the corresponding pdfs are uniform, while pdf (b) is not uniform since the cdf is not linear.

Fig. 6. Results of the histogram equalization on Lena. (a) Input image. (b) Result of Trahanias's method. (c) Result of Menotti's method. (d) Result of Naik's method. (e) Result of the proposed iso-luminance-plane method. (f) Equalized image of each RGB color channel.

the computational complexity is proportional to the number of pixels.

IV. Experimental Results and Analysis

We will now compare the performance of the four methods explained in Sections II and III using color chart image, Lena, Pepper, and a synthetic image. Fig. 4(a) shows a test image consisting of two Macbeth charts under different lighting conditions. Histogram equalized images using the Trahanias [Fig. 4(b)], the Menotti [Fig. 4(c)], the Naik [Fig. 4(d)], our proposed iso-luminance method [Fig. 4(e)], and 1-D histogram equalized image for each RGB color channel [Fig. 4(f)]. Fig. 4(c), (d), and (e) show similar results. However, Fig. 4(b) is brighter than the other images as predicted in Section II-B. Table I shows the average brightness of equalized images of all methods. Note that the average brightness of the Naik method and the iso-luminance plane method is around 127.5, which is the average when the pdf has uniform distribution. The average brightness of the Trahanias method is higher than the other method. However, it does not coincide with the theoretical value 194.0, since the color correlation is not one as our simplified assumption.

Fig. 5 shows the cdfs of each resultant image. Naik's algorithm and our proposed algorithm result in similar linear cdf. Linear cdf means that the corresponding pdf is uniform, because the pdf is the slope of the cdf. However, the Trahanias method produces a cdf similar to a cubic curve as predicted in (3). The mean absolute error of the cdfs from the linear cdf is shown in Table II. The Naik method and the proposed method show smaller error compared to the Trahanias or Menotti methods. In general, results of the Menotti method are different from separate RGB channel equalization. However, the gray cdfs of the two methods, Fig. 5(c) and (f), are similar. This is because marginal cdf of R, G, and B channels are similar for the two color chart images. We notice that the Menotti algorithm is equivalent to independent 1-D color channel equalization if the marginal cdf of each color component is identical by observing (5). Despite of the similarity of gray cdf, result images of the two methods, Fig. 4(c) and (f), look different due to color mismatch.

Fig. 6 and Fig. 8 show results of color histogram equalization algorithms on the Lena and Pepper images, and Fig. 7 and Fig. 9 represent the corresponding gray level cdfs. The characteristic of each equalization method is consistent regardless of test images.

We designed a synthetic image to illustrate the different characteristics of the Menotti method as shown in Fig. 10. Fig. 10(a) is a test image where $\mathrm{R} = 64$, and G and B are identical and increase linearly left to right from 0 to 127. Fig. 10(b)-(e) shows the resultant images of the four methods. The result of the Trahanias method, Fig. 10(b), is the brightest of all. Note that the result of the Menotti algorithm, Fig. 10(c) is different from ours, since this test image does not have a high correlation between R and G or B. Fig. 11 shows the cdfs of each resultant image. Note that the cdfs of the Naik method and our iso-luminance-plane method increase linearly, while those of the Trahanias and the Menotti methods are nonlinear. The theoretical cdf of the

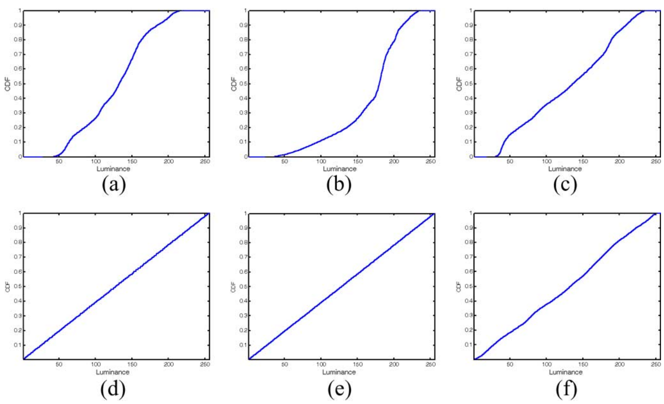

Fig. 7. Gray scale cdfs of the resultant images of Fig. 6. (a) Cdf of the original image. (b) Cdf of Trahanias's method. (c) Cdf of Menotti's method. (d) Cdf of Naik's method. (e) Cdf of the proposed iso-luminance-plane method. (f) Cdf of equalized image of each RGB color channel.

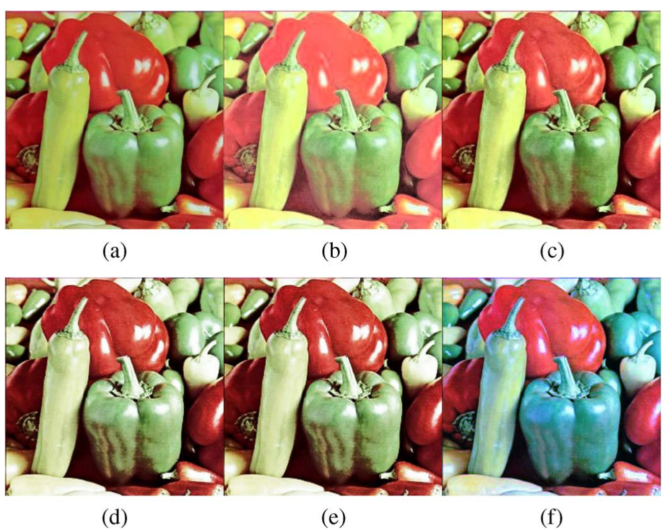

Fig. 8. Results of the histogram equalization on Pepper. (a) Input image. (b) Result of Trahanias's method. (c) Result of Menotti's method. (d) Result of Naik's method. (e) Result of the proposed iso-luminance-plane method. (f) Equalized image of each RGB color channel.

Trahanias method is n^3 while that of the Menotti method is $n^{3/2}$ for this particular test image.

V. Conclusion

We compared the performance of color histogram equalization methods based upon the 3-D histogram in RGB color space. We analyzed the theoretical basis for the brightening or over-equalization effect of the Trahanias algorithm by presenting intensity cdf and pdf. The Menotti method shows satisfactory results for most natural images. However, we found that the performance of the Menotti algorithm depends upon the correlation of color components. Evaluation results with natural and synthetic images confirm our theoretical analysis. We introduced the iso-luminance-plane cdf and demonstrated that the proposed method results in uniform pdf in gray level. Therefore, we conclude that the proposed method enhances luminance contrast effectively.

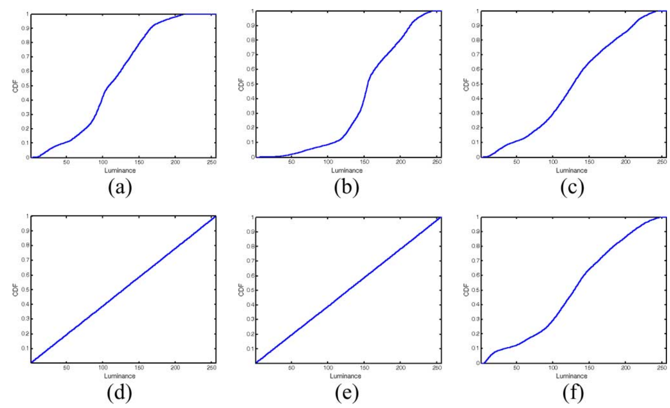

Fig. 9. Gray scale cdfs of the resultant images of Fig. 8. (a) Cdf of the original image. (b) Cdf of Trahanias's method. (c) Cdf of Menotti's method. (d) Cdf of Naik's method. (e) Cdf of the proposed iso-luminance-plane method. (f) Cdf of equalized image of each RGB color channel.

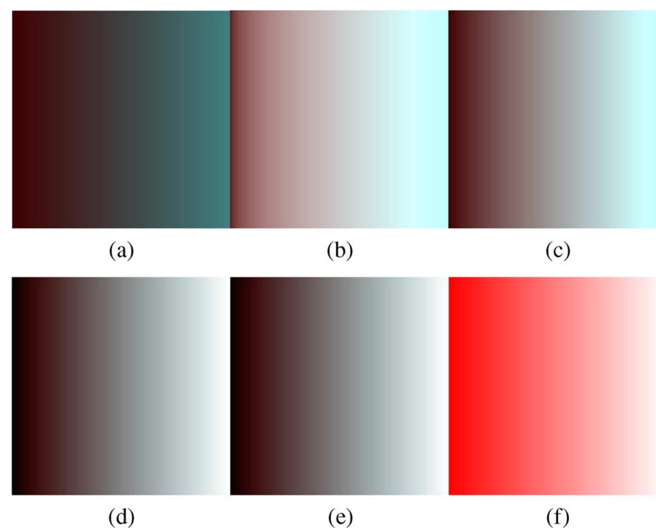

Fig. 10. Results of the histogram equalization with a synthetic test image. (a) Input image where $\mathrm{R} = 64$, G and B are identical and increase linearly left to right from 0 to 127. (b) Resultant image of the Trahanias method. (c) Result of the Menotti method. (d) Result of the Naik method. (e) Result of the iso-luminance-plane method. (f) Equalized image of each RGB color channel.

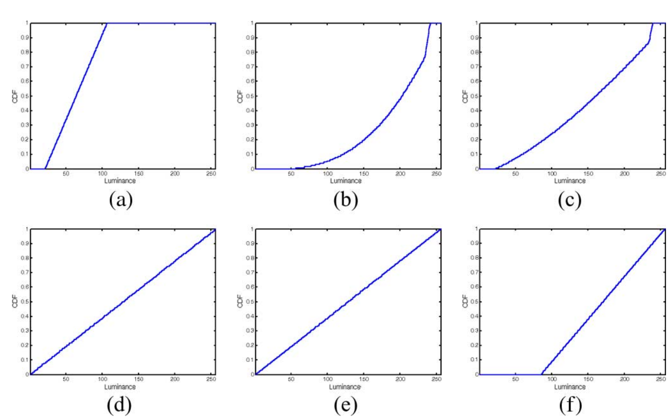

Fig. 11. Gray scale cdfs of the resultant images of Fig. 10. (a) Cdf of the original image. (b) Cdf of Trahanias's method. (c) Cdf of Menotti's method. (d) Cdf of Naik's method. (e) Cdf of the proposed iso-luminance-plane method. (f) Cdf of equalized image of each RGB color channel.

ACKNOWLEDGMENT

The authors would like to thank the anonymous reviewers for their valuable comments and suggestions which significantly improved this paper.

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