Fuzzy Automatic Contrast Enhancement Based on Fuzzy C-Means Clustering in CIELAB Color Space

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Abstract*—Some traditional methods for image contrast enhancement are based on histogram equalization, which however has the drawbacks of producing visual artifacts or excessive image strengthening due to improper settings of enhancement parameters or non-smooth color adjustments in different color spaces. A novel method of Fuzzy Automatic Contrast Enhancement (FACE) is presented in this paper. FACE first performs a fuzzy clustering method to segment an image while the pixels with similar colors in the CIELAB color space are classified into smaller image clusters with similar characteristics. The pixels in each group are then spread out away from the center of the belonging cluster in the RGB color space in order to enhance the image contrast but keeping the similarity of pixel colors in the same cluster. A universal contrast enhancement variable (UCEV) was defined and optimized to maximize the image randomness (i.e. entropy of the image) in order to automatically enhance the image contrast. A more uncongested distribution of the image pixels ensures a greater image contrast. The proposed entropy-maximization process is capable of improving the image quality without any human-defined control parameters. The fully automated image enhancement process intelligently clusters the pixels with similar color characteristics and is general for the contrast enhancement of images in various color distributions. Many images with different color distributions were tested and the results showed that FACE is capable of avoiding visual artifacts and excessive strengthening. Compared with the traditional histogram equalization method, the proposed method shows higher effectiveness in contrast enhancement and performs better in retaining the colors of the original images.

Keywords—contrast enhancement; fuzzy clustering; entropy maximization

I. INTRODUCTION

In image acquisition, there are many factors (including the nature of the object material, calibration parameters for the image capture device, conditions of insufficient ambient light, etc.) that are likely to cause low-contrast images [1]. Therefore, contrast enhancement is one of the most important image processing technologies that could improve the quality of the captured low-contrast image. When the color intensity excessively concentrates in specific areas of the intensity histogram, the details and features in the concentrated area become less distinguishable leading to low contrast of the image [2]. Contrast enhancement is one way to improve the image quality and find out the details of the hidden information at the low-contrast area of the image.

Various types of intensity transformations [3, 4] have been used to improve the image contrast. Most transformation methods (such as linear, logarithm and power transformation functions) convert the original image intensity to a new intensity value leading to a new intensity distribution. However, the results of contrast enhancement depend on proper selections of shape parameters or function coefficients that are usually artificially defined by the users. There is not one optimal transformation function that is able to properly enhance the contrast of any image. Even when a transformation function is properly defined for an investigated image, it often happens that the transformation function can only enhance the contrast of some part of the image and may produce unwanted effects in other part of the image. For example, the image portion may be too bright due to over-enhancement or too dark due to under-enhancement.

Researchers have developed some automated contrast enhancement methods based on histogram equalization (HE) [5], which were mathematically derived and didn't require artificial definition of function coefficients. HE was not only widely utilized in image processing but also adopted in other data processing applications [6]. HE converts the probability density of the image intensity to a new uniformly distributed histogram of intensity. The contrast of the image is then enhanced and the image will become much clearer. However, it has been found that HE is not able to preserve the mean brightness of images [7]. Some other variations of HE [8-13] have also been developed to improve the effectiveness of the contrast enhancement. Some Bi-HE methods were developed to preserve the brightness of images but may produce some artifacts. Other multi-HE methods [14-22] may not produce artifacts but require greater computations. Some reports [23-26] showed that some other HE-based methods produced good performances of contrast enhancement of grayscale images, but the performances were not good for color images.

A new method called Fuzzy Automatic Contrast Enhancement (FACE) is presented in this paper. The proposed method will be used to transform the original image pixels to a more uncongested pixel distribution to achieve greater image contrast. The fuzziness in the enhancement procedures will preserve the smoothness of the color distribution in images and

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prevent the formations of artifacts. A contrast maximization process is proposed to automatically find the optimal amount of enhancement. In this paper, the traditional contrast enhancement methods including various types of transformation functions and the HE are first reviewed in the section 2. The proposed method is introduced and derived in the section 3. Several numerical examples are shown in the section 4. The conclusion is given in the section 5.

II. Review of Traditional Contrast Enhancement Methods

There are two major kinds of contrast enhancement methods [27]: (1) individual pixel enhancements in the spatial (color) domain, (2) global image improvement in the color frequency domain. This paper focuses on the first kind of enhancement methods. The simplest method to enhance a photo is to use transformation functions [3, 4], which directly modify the pixel intensity in the spatial domain. A more advanced method for contrast enhancement is histogram equalization (HE), which modifies the probability density of pixel intensity and delivers a more uniformly distributed pixel histogram. The image will then become much clearer.

A. Transformation Functions

A transformation function T is defined to modify the pixel points $\mathbf{x}$ in the original image using the following equation:

$$\mathbf{x}' = T(\mathbf{x}) \tag{1}$$

where $\mathbf{x}'$ is the pixel point of the enhanced image. Both the pixel points of the original image and the enhanced image are bounded in the investigated color space.

In order to maintain the intensity order of all pixel points after the enhancement process, T should be monotonically increasing. Common formats of T include linear function, logarithm function, and power function, as shown in Eqs. (2) to (4), respectively.

$$T = r\mathbf{x} + c \tag{2}$$

$$T = r\log\mathbf{x} + c \tag{3}$$

$$T = c\mathbf{x}^{r} \tag{4}$$

where r and c are the coefficients of the transformation functions. These transformation methods are simple but require proper selections of human-defined function coefficients.

B. Histogram Equalization

For an image that is mostly dark or has poor image contrast, the histogram of pixel intensity is usually skewed. The method of histogram equalization (HE) [5] can be used to move the pixel points concentrated in some part of the histogram away from each other and is expected to generate a much uniformly distributed histogram. HE considers the following transformation function for the contrast enhancement:

$$x' = T(x) \equiv \int_0^x p(u)\,du \tag{5}$$

where p is the histogram of image pixel in one investigated color space; u is a variable in the color space. In Eq. (5), an original pixel intensity x is expected to be modified to a new pixel intensity x'. To preserve the probability density, the following equation must be satisfied:

$$p(x') = p(x)\cdot\frac{dx}{dx'} \tag{6}$$

The derivative of Eq. (5) with respect to x gives:

$$\frac{dx'}{dx} = p(x) \tag{7}$$

Substituting Eq. (7) into Eq. (6), the probability density function of the modified image is now a uniform distribution (i.e. $p(x') = 1$).

HE is capable of automatically stretching out the concentrated pixel intensity in the histogram and providing a more uncongested distribution. However, the HE process in each color space is independent from the processes in the other spaces [28-31]. These indiscriminate modifications in each color space, therefore, may lead to non-smooth color changes, unwanted increment of background contrast, or artifacts.

III. Fuzzy Automatic Contrast Enhancement (FACE)

A novel method of Fuzzy Automatic Contrast Enhancement (FACE) is presented in this section. FACE utilizes a Fuzzy C-Means (FCM) clustering process to classify the pixels with similar colors together. A universal contrast enhancement variable (UCEV) is to be defined and optimized to maximize the image entropy automatically without the need of human-defined control parameters. The above two processes are expected to enhance the image contrast without the productions of artifacts and unwanted noises. More details about the proposed method is shown in the following subsections.

A. Fuzzy C-Means Clusting in the CIELAB Color Space

Suppose there are N image pixels, $\mathbf{x}_i$ for $i = 1...N$, and they are to be clustered into K groups, the center of each group is denoted as $\mathbf{c}_j$ for $j = 1...K$. The parameter u_{ij} represents the belongingness of the i^{th} pixel in the j^{th} cluster. For exact clustering methods such as K-Means [32-35], u_{ij} is either 0 or 1 (i.e. 0 stands for not belonging; 1 stands for belonging). This paper utilized Fuzzy C-Means (FCM) [36] to allow non-exact belongingness of pixels in every clusters. In other words, u_{ij} can be any real number in the interval of $[0,1]$ but the following equation must be true for all times:

$$\sum_{j=1}^{K} u_{ij} = 1 \tag{8}$$

A function of total in-group variation is defined as follows:

$$J = \sum_{j=1}^{K}\sum_{i=1}^{N}\left(u_{ij}^{m}\left\|\mathbf{x}_i - \mathbf{c}_j\right\|^2 \right) \tag{9}$$

where the power of belongingness parameter, m, ranges from 1 to 5 as suggested by the literature [37]. In this paper, $m = 3$ is considered. J is to be minimized for optimal classification of image pixels because smaller in-group variations lead to larger between-group variances [38]. A Lagrangian is then formulated as follows:

$$L = \sum_{j=1}^{K}\sum_{i=1}^{N}\left(u_{ij}^{m}\left\|\mathbf{x}_i - \mathbf{c}_j\right\|^2 + \lambda_i u_{ij} \right) - \sum_{i=1}^{N}\lambda_i \tag{10}$$

λ_i is the Lagrangian multiplier, which can be determined by solving the L-minimization problem.

The optimal fuzzy belongingness of each image pixel can be determined by satisfying the following two equalities:

$$\frac{\partial L}{\partial u_{ij}} = m u_{ij}^{m-1}\left\|\mathbf{x}_i - \mathbf{c}_j\right\|^2 + \lambda_i = 0 \tag{11}$$

$$\frac{\partial L}{\partial \mathbf{c}_j} = \sum_{i=1}^{N}\left(2u_{ij}^{m}\left(\mathbf{x}_i - \mathbf{c}_j\right)\right) = 0 \tag{12}$$

A recursive approach based on Eqs. (8), (11) and (12) is then utilized to determine the optimal parameters, as shown below:

$$\mathbf{c}_j = \frac{\sum_{i=1}^{N} u_{ij}^{m}\mathbf{x}_i}{\sum_{i=1}^{N} u_{ij}^{m}} \tag{13}$$

$$u_{ij} = \frac{1}{\sum_{l=1}^{K}\left[\frac{\left\|\mathbf{x}_i - \mathbf{c}_j\right\|}{\left\|\mathbf{x}_i - \mathbf{c}_l\right\|}\right]^{\frac{2}{m-1}}} \tag{14}$$

Eq. (13) determines the center of the j^{th} cluster based on the given belongingness of pixels. Eq. (14) then determines the belongingness parameter u_{ij} based on the given cluster center points. The recursive process continues until the value of L converges. In our implementation, the recursive approach starts with random guesses of u_{ij} and the utilized approach is able to find the same results in multiple trials. Furthermore, the FCM in the CIELAB color space performs the best classification results [39]. CIELAB color space was defined by Commission International d'Eclairage and L represents lightness; A and B are the dimensions of color components.

B. Entropy Maximization with respect to the universal contrast enhancement variable

This paper defines a universal contrast enhancement variable (UCEV), α, as the only design variable such that each new pixel point $\mathbf{x}'_i$ is given by:

$$\mathbf{x}'_i \equiv \mathbf{x}_i + \alpha\sum_{j=1}^{K} u_{ij}\left(\mathbf{x}_i - \mathbf{c}_j\right) \quad \forall i = 1 \ldots N \tag{15}$$

where α acts like the step size of a line search along a fuzzy combination of directions away from the cluster center points. A positive value of α broadens the distribution of image pixels leading to contrast enhancement (or brightening in some color spaces). A negative value of α indicates shrinking coverage of pixel distribution, which may be useful for correcting the photos that are too bright.

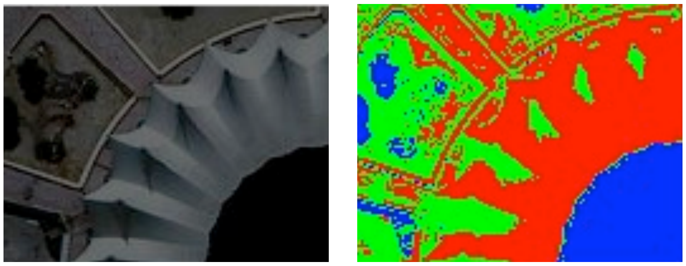
An image obtained from the Internet (with slight uniform darkening) was utilized to demonstrate the concept of fuzzy contrast enhancement. Fig. 1 (a) shows the original image for the demonstration. Fig. 1 (b) shows the results of exact clustering with $K = 3$. The colors of red, green and blue represent the belongingness of each pixel. This paper focuses on the performances of $K = 3$. Future investigations are needed for computing the optimal amount of clustering. Fig. 2 show the fuzziness in Eq. (15) is essential for smoothening the pixel colors in the process of contrast enhancement. Some artifacts can be seen in the Fig. 2 (a) where u_{ij} is either 0 or 1. It is evident that non-smooth color distributions occur at the boundaries between each cluster, as shown in Fig. 1 (b). Our implementation in Fig. 2 (b) shows that a brighter photo with enhanced contrast and smooth color distribution can be determined when u_{ij} is a real number in $[0,1]$.

The final step of the proposed FACE is to find the optimal enhancement of the image contrast. A global measurement, entropy J [40], is maximized with respect to α, as shown below:

$$\underset{\alpha}{Max} \quad J(\alpha) = -\sum_{\mathbf{x}\in\Omega}\left[p\left(\mathbf{x}'(\alpha)\right)\log_2 p\left(\mathbf{x}'(\alpha)\right)\right] \tag{16}$$

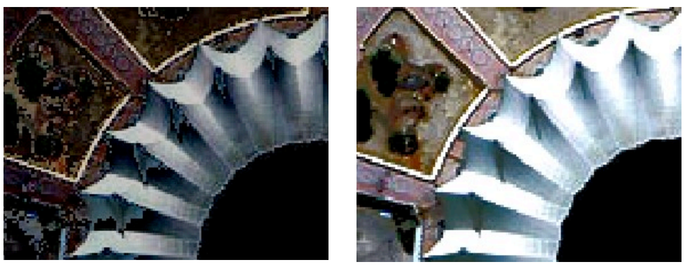
where p is the probability density of the distribution of newly determined set of image pixels $\mathbf{x}'$, obtained from Eq. (15); Ω is the gridding set for computing the image entropy, i.e. the measure of unpredictability of pixel distribution. Larger entropy represents higher "randomness" of the pixel distribution and greater variance between image pixels;

therefore, the optimization process in Eq. (16) ensures to enhance the image contrast.



(a) (b)

Fig. 1 Exact clustering of an example image: (a) the original image, (b) exact clustering results with K = 3 (color stands for cluster belongingness).



(a) (b)

Fig. 2 Contrast enhancements based on (a) exact clustering and (b) fuzzy clustering.

The expansion of the pixel distribution should be constrained within the investigated color space. In this paper, the moved pixel points that exceed the bounds of the color space stay on the bounds. Therefore, the increment of image entropy stops when some pixel points accumulate on the bounds. A greater value of α will cause greater accumulation of pixel points on the bounds and lower variance between pixel points, i.e. a lower value of entropy. This is why a maximum of entropy exists when the proposed entropy maximization strategy is used.

C. Demonstration of the proposed FACE Method

Fig. 3 shows an original rose image obtained from the Internet and uniformly darkened to demonstrate the performance of contrast enhancement. The initial entropy of the image is shown in Fig. 3 (b). Fig. 3 (c) shows how the pixel points are initially distributed in the RGB color space. In our implementation, the entropy maximization process performs the best in the RGB color space [39]. The color represents the color of each pixel in the image.

Using the fuzzy clustering and fuzzy entropy maximization processes in the proposed FACE, the maximum entropy can be found at an optimal value of UCEV, i.e. $\alpha^* = 0.6$ in this demonstration, as shown in Fig. 4 (b). It is evident that the enhanced image in Fig. 4 (a) has better quality than the original image in Fig. 3 (a). The contrast enhancement is due to the expansion of pixel distribution, shown in Fig. 4 (c).

To further exam the effect of increasing the UCEV, the experiment shown in Fig. 5 was performed. As the UCEV exceeds its optimal value, the image becomes slightly over-enhanced. As shown in Fig. 5 (a), some part of the rose petals becomes too bright and the shadows on the leaves become darker. Fig. 5 (b) shows the entropy begins to drop as the UCEV exceeds its optimal value and some pixel points start to accumulate on the boundaries of the color space, where some pixels become too bright or too dark.

In the final test, the UCEV keeps increasing until almost every pixel points are accumulated on the boundaries of the color space, as shown in Fig. 6 (c). Most pixels become too bright or too dark. The color tones of some pixels are changed, e.g. the green leave at the left lower corner becomes black and blue. The image becomes excessively over-enhanced, as shown in Fig. 6 (a), and the entropy drops to minimum, as shown in Fig. 6 (b).

This demonstration shows the proposed FACE method is capable of finding the optimal condition of contrast enhancement of images. The fuzziness in the clustering process ensures the belongingness of pixel points is not exact and makes the smooth enhancement possible. The definition of UCEV allows the contrast enhancement process to be efficiently executed with only one control parameter and provides an effect of global contrast enhancement. The entropy maximization process ensures the pixel distributions are widely broadened and not accumulated on the boundaries of the color space. At the end, an optimally enhanced image can be determined automatically by the proposed FACE method without the needs of human-defined control parameters.

IV. Numerical Examples

In this paper, 21 images were obtained from the Internet and uniformly darkened to demonstrate the performance of contrast enhancement. Two statistical performance measures are utilized to quantify the enhancement performances. The first one is the root-mean-square deviation (RMSD) [41-43] between the original and the enhanced image, as shown in Eq. (17).

$$\mathrm{RMSD} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left\|\mathbf{x}'_i - \mathbf{x}_i\right\|^2} \tag{17}$$

where $\mathbf{x}_i$ is the i^{th} pixel point of the original image and $\mathbf{x}'_i$ represents the i^{th} pixel point of the enhanced image. A large number of RMSD indicates that a large difference of pixel color is caused by the enhancement method. For an original photo with poor contrast, it is desired to obtain an enhanced photo with greater value of RMSD. On the other hand, a small amount of RMSD is desired for an original photo with good contrast.

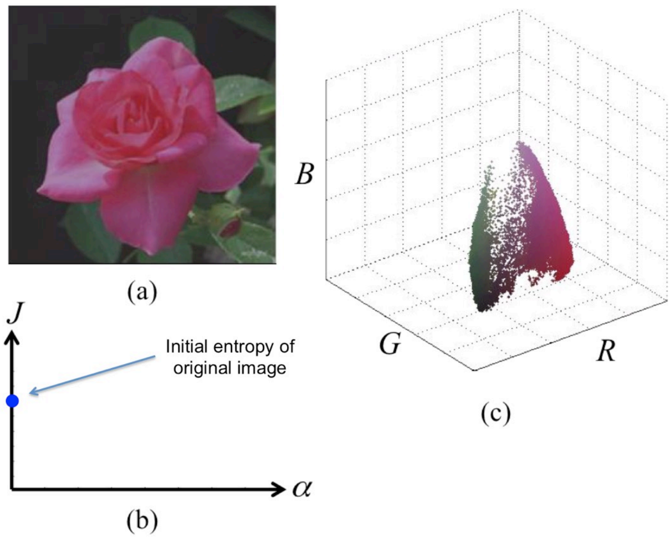


Fig. 3 Entropy of the rose image: (a) original image, (b) initial entropy, (c) initial pixel distribution.

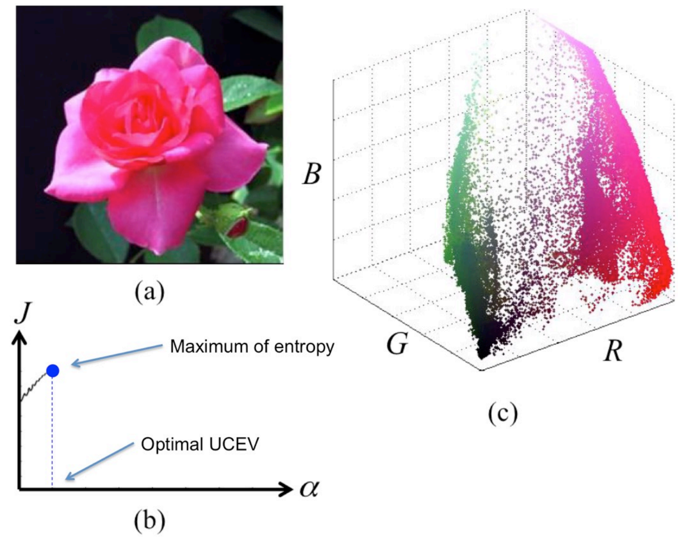


Fig. 4 Maximum entropy of the enhanced rose image: (a) enhanced image, (b) determination of optimal UCEV, (c) pixel distribution of the optimally enhanced image.

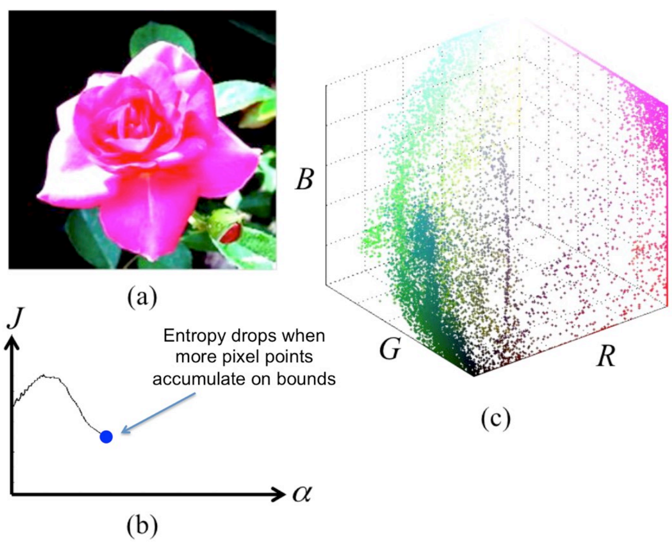


Fig. 5 Entropy of slightly over-enhanced rose image: (a) slightly over-enhanced image, (b) entropy drops as UCEV exceeds its optimal value, (c) accumulation of pixels is found on the bounds of the RGB color space.

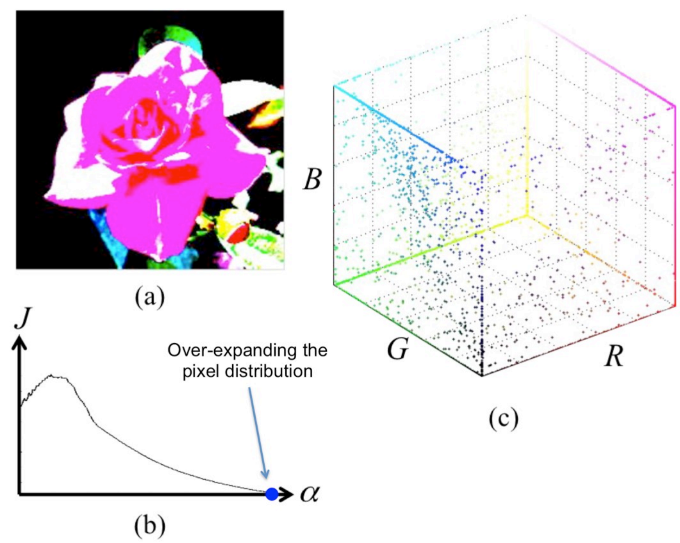


Fig. 6 Entropy of the excessively over-enhanced rose image: (a) excessively over-enhanced image, (b) entropy dramatically drops as UCEV becomes greater, (c) almost all pixel points are accumulated on the bounds of the RGB color space.

The second measurement for quantifying the performance of contrast enhancement is the root-mean-square contrast (RMSC), as shown in Eq. (18).

$$\mathrm{RMSC} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left\|\mathbf{x}'_i - \sum_{k=1}^{N}\mathbf{x}'_k\right\|^2} \tag{18}$$

Eq. (18) represents the difference between each pixel point in the enhanced photo. The measurement of RMSC does not depend on the spatial distribution of contrast in the image; therefore, it cannot be used to represent the local enhancement performance or the existence of artifacts. However, RMSC provides a global sense of the difference between the features and the background. A photo with larger RMSC is usually desired but a large measurement of RMSC may also represent a photo that is over-enhanced.

Table I shows the 21 original images and the enhanced images using both HE and the proposed FACE. The measurements of RMSC and RMSD are utilized to study the numerical performances of the enhanced images.

For all images, the values of RMSC are increased after contrast enhancements, i.e. RMSC of both HE-enhanced and FACE-enhanced images are larger than RMSC of the original image.

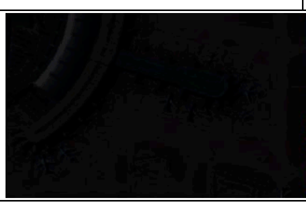
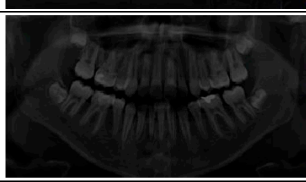
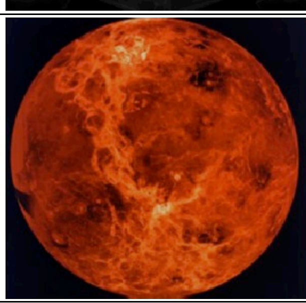
For the image Nos. 1-4, FACE delivers greater values of both RMSC and RMSD. Among these 4 cases, FACE not only provides greater enhancements to the original images (larger RMSD than HE) but also generates images with better contrast (larger RMSC than HE). Take image No. 3 as an example, many small features in the planet disappeared when HE was used; on the other hand, those features became clearer when FACE was used to enhance the image contrast. Furthermore, some artifacts appeared in the background when HE was used. The fuzzy clustering and enhancement in FACE kept the image free of artifacts during the enhancement process.

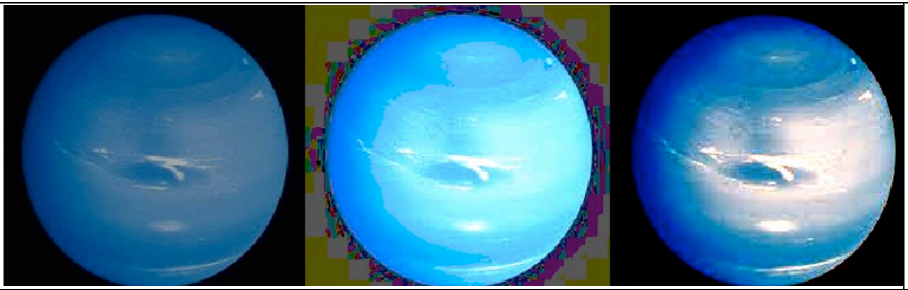
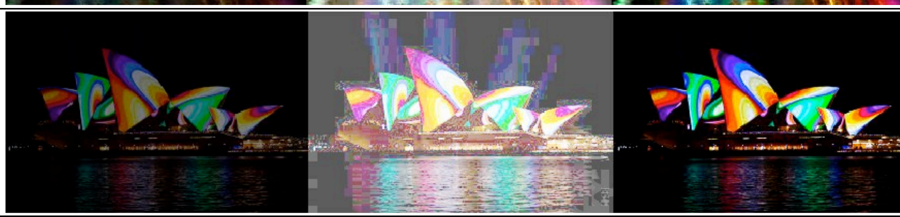
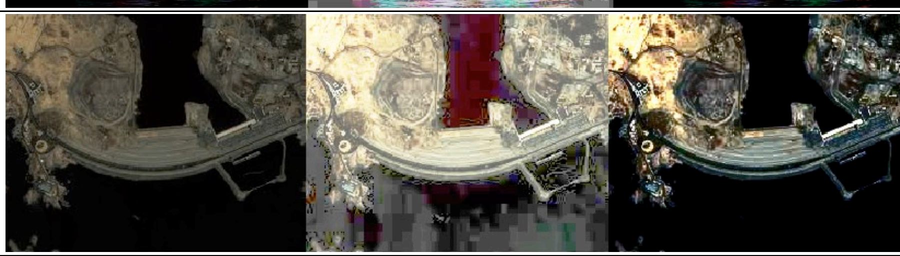
For the image Nos. 5-12, the FACE-enhanced images have greater values of RMSC but smaller values of RMSD when they are compared with the HE-enhanced ones. For these cases, HE generated greater amounts of color changes to the original images; however, some HE-enhanced images were over-enhanced. The background of HE-enhanced image No. 5 was too bright and many artifacts occurred. Similar issues can be seen in the HE-enhanced image Nos. 6 and 7. Some part of the image No. 8 was originally black and became red as enhanced by HE. FACE was capable of properly enhancing the image contrast without formations of artifacts.

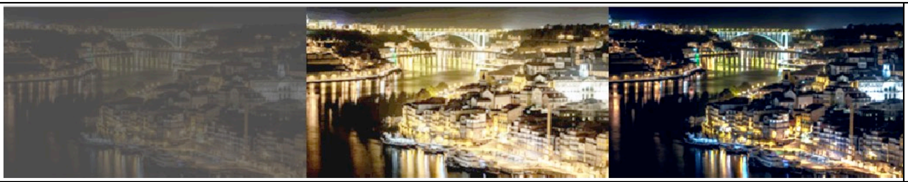
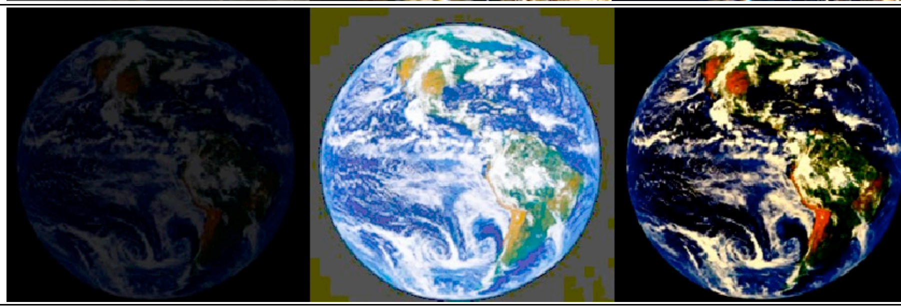
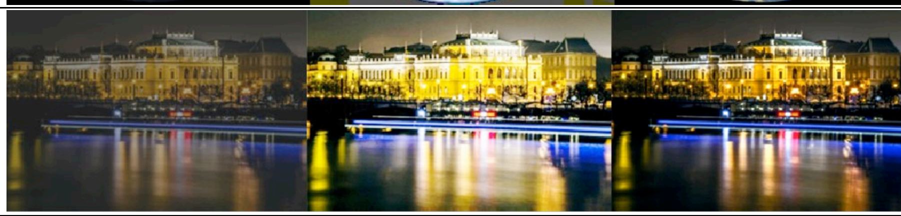
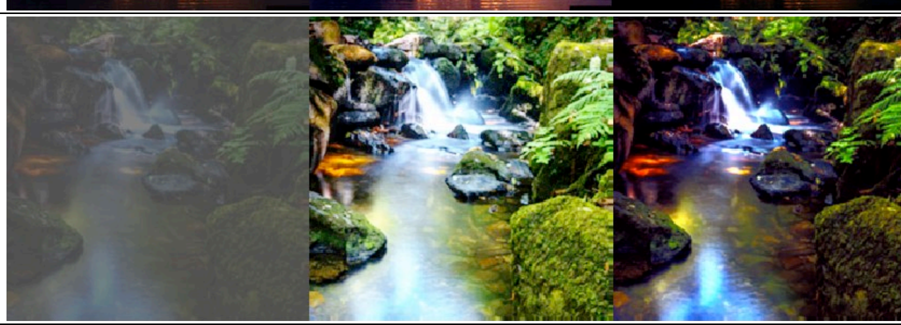
For the image Nos. 13-20, FACE provides lower values of both RMSC and RMSD. It is noted that FACE does not over-enhance the image contrast when the contrast of the original image is not poor. It's evident that FACE didn't modify the image Nos. 14-16 too much (RMSD much smaller than HE-enhanced ones). On the other hand, HE either overly changed the color in some parts of the images (e.g. background color of Nos. 14 and 20; grass of No. 15; color of sky in No. 16; ocean color in No. 18). FACE was able to keep the color tones of the original images and yet enhance the contrast of small features.

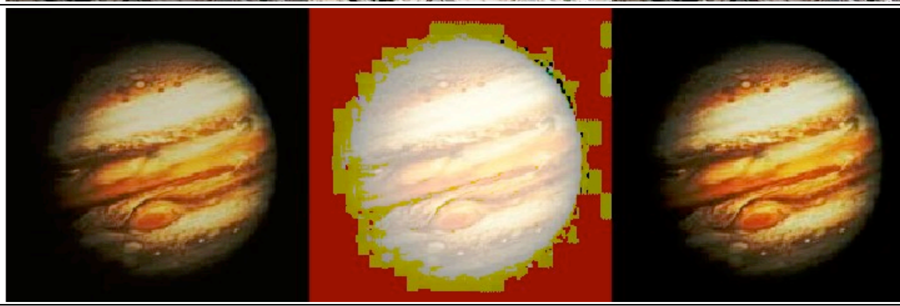
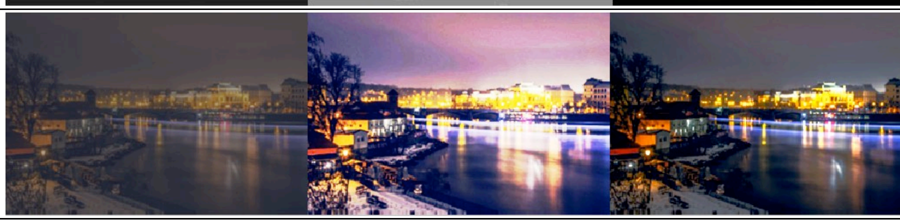
For the image No. 21, FACE delivers lower RMSC and greater RMSD than HE. However, the background color of the HE-enhanced image was overly changed and some small features disappeared as the image was over-enhanced by HE. FACE delivered a proper amount of contrast enhancement for this case.

TABLE I. RESULTS OF NUMERICAL EXAMPLES

No.	Original Image	HE-Enhanced Image	FACE-Enhanced Image	RMSC of Original Image; RMSC of HE-Enhanced Image; RMSC of FACE-Enhanced Image; RMSD of HE-Enhanced Image; RMSD of FACE-Enhanced Image;
1				8.5 125.4 221.8 203.3 224.7
2				23.4 129.0 217.7 128.2 140.0
3				74.7 112.9 246.3 98.8 173.6

4		82.7 136.1 262.3 146.5 189.1
5		123.3 134.1 141.7 92.7 19.9
6		48.3 124.6 159.4 190.8 120.8
7		54.7 93.4 113.0 226.5 160.1
8		69.1 119.1 187.7 147.6 131.8
9		13.0 123.5 196.5 242.2 231.6
10		12.9 129.8 216.3 246.0 243.7

11		16.0 116.5 120.9 123.4 109.9
12		25.3 119.2 180.1 237.8 158.7
13		46.3 128.7 110.1 123.9 65.1
14		66.3 131.0 74.8 186.4 19.7
15		71.7 129.5 102.8 94.1 50.0
16		50.0 118.0 98.0 151.9 50.0
17		19.7 130.4 110.4 125.2 102.5

18		74.9 133.4 111.6 141.8 37.6
19		102.4 137.0 107.8 165.9 12.6
20		39.7 262.4 192.8 205.2 161.0
21		29.5 123.0 104.5 143.9 176.7

V. CONCLUSIONS

This paper presented a novel method called Fuzzy Automatic Contrast Enhancement (FACE) to improve the photo quality. In our implementations, traditional methods based on histogram equalization (HE) may generate unwanted artifacts or excessive enhancements in images because the enhancements in ever color histogram were independent. The fuzzy clustering and enhancement procedures ensure dependent and smooth modifications of image color.

FACE first performs a fuzzy clustering in the CIELAB color space to group the pixels with similar colors together as the fuzziness of the clustering prevents distinct separation of pixel points. A universal contrast enhancement variable (UCEV) was optimized to find the maximal entropy of the image. The enhancement process was automatically completed without the needs of human-defined parameters. At the end, FACE delivered a more uncongested distribution of the image pixels with greater image contrast.

This paper also showed a series of tests of contrast enhancements. Twenty-one photos were obtained from the Internet and enhanced by both HE and FACE methods. The results showed that FACE was capable of properly enhancing the image contrast without generating local defects such as visual artifacts, excessive strengthening and over color change. HE can surely increase the room-mean-square contrast of the image but it sometimes excessively over-enhance the dark background, generates non-smooth artifacts in the dark area, or makes the small features disappear.

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