Applied Soft Computing Journal 89 (2020) 106077

Contents lists available at ScienceDirect

Applied Soft Computing Journal

journal homepage: www.elsevier.com/locate/asoc

Fuzzy dissimilarity color histogram equalization for contrast enhancement and color correction

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ARTICLE INFO

Article history:
Received 31 May 2019
Received in revised form 30 October 2019
Accepted 5 January 2020
Available online 13 January 2020

Keywords:
Fuzzy dissimilarity
Adaptive histogram equalization
Gamma correction
Hue Deviation Index
Saturation

ABSTRACT

Many statistical histogram-based methods perform intensity transformation on gray levels in the statistical histogram. This may cause over-enhancement due to dominating portions of the histogram. Various methods tackle this problem by overwhelming the dominating portions and improving the inferior components. Though, this may change the natural appearances of the image and results in degraded visual quality. In order to attenuate such limitations, an efficient method called Fuzzy Dissimilarity Adaptive Histogram Equalization with Gamma Correction (FDAHE-GC) algorithm is proposed. In this work, a Fuzzy Dissimilarity Histogram (FDH) is obtained from the neighborhood characteristics of an intensity. An intensity mapping function, constructed from FDH is applied to enhance the contrast and natural characteristics of an image. Finally, the gamma correction is employed to enhance the dark regions. In order to tune the fine details and to improve visual appearance of an image, the proposed FDAHE-GC algorithm is applied to the intensity value of HSI space. The performance of the presented method is evaluated with different existing methods using image quality assessment tools such as entropy, Colorfulness (C), Hue Deviation Index (HDI), Saturation, Contrast Enhancement Factor (CEF) and Gradient (G). The investigational results tested on standard benchmark test images with visual inspection shows the superiority of the proposed FDAHE-GC algorithm.

1. Introduction

Numerous vision-based applications depend upon images with necessarily high contrast and colorfulness so that ample quantity of data is needed to exactly describe objects took from the image scene. This article helps to the tremendous growth in display technology and color imaging. The general interest in digital techniques for the improvement of color image quality has continually increased in the previous years. The applications towards color image enhancement are abundant. This can be traced back to, among other things, the ever-more-frequent use of color image processing methods in digital cameras, printing industry, mobile phone cameras, medical research and aerial image analysis. A further increase in the importance of color image enhancement techniques can be noted by the archiving of digital images and in the area of digital video. In several situations, an image is taken in extreme light conditions, like excessive bright or dark environmental conditions the result is low contrast, that produces a low dynamic range of intensities. Poor image capturing environments are typically unavoidable, however it will be compensated. Contrast enhancement (CE) plays a crucial role in enhancing the visual quality by varying the dynamic range of pixel intensity distribution for further processing and analysis by a computer vision system. The improvement of color image quality will be dispensed by converting an image from the primary color space (R—Red, G—Green and B—Blue) to the human perceptible domain (H—Hue, S—Saturation and I—Intensity). In this category of strategies, the hue is generally preserved for true reproduction of the image data. Improvement in saturation increase the richness of the objects in an image. Furthermore, in many cases, the intensity is deployed to produce an improved contrast that aids the mining of knowledge taken from the scene data.

In this situation, the Histogram Equalization (HE) technique becomes an important method for its simplicity in implementation [1]. The process of developing equalization algorithm still becomes a difficult task due to the fact that various images with a different amount of data contents. Many authors have recommended various CE techniques to boost the contrast of an image. For example, Bi-HE (BHE) is an extension of HE that divides a statistical histogram of an image based on mean intensity into two equal sub-histograms and it is equalized individually [2]. Minimum Mean Brightness Error BHE (MMBEBHE) is an improved version of BHE that divides a statistical histogram into two sub-histograms using Absolute Mean Brightness Error (AMBE) in order to preserve mean brightness [3]. Brightness Preserving Dynamic HE (BPDHE) splits the statistical histogram into different

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https://doi.org/10.1016/j.asoc.2020.106077
1568-4946/

sub-histograms and applies HE to every sub-histogram individually [4]. Fuzzy Logic and Histogram-based (FLH) algorithm have been proposed to boost the contrast of low illumination color images [5]. However, it fails to boost the contrast of dark images. An Optimal Gamma Correction and Weighted Sum (OGCWS) method is proposed to balance the performance of brightness preservation and contrast enhancement at the same time [6]. A pipelined approach called Averaging Histogram Equalization (AVHEQ) for image contrast enhancement is proposed [7]. It limits the artifact effect, frequently introduced by the equalization technique. Sometimes, this technique results in excessive enhancement. Histogram-based locality-preserving CE technique is introduced to solve an optimization problem by computing the intensity transformation with in the histogram of an original image [8]. Optimal profile compression and histogram equalization for color images is proposed, it encompasses a channel stretch, a HE, a magnitude compression and a maximize saturation operation [9]. However, the output of some bright images results with some minor artifacts. In order to boost the contrast and the fine details of non-smooth regions, a combined approach of 1-D and 2-D Histogram based method is proposed [10]. A combined approach called automatic Contrast-Limited Adaptive Histogram Equalization with Dual Gamma Correction (CLAHE-DGC) is implemented to enhance the contrast of an image by boosting its luminance value [11]. An Improved Adaptive Gamma Correction (IAGC) algorithm is developed to increase the brightness of distorted images [12]. Even though this technique consistently produces good CE outputs but fails to enhance the fine details. An adaptive RGB color enhancement technique based on logarithmic image processing is implemented to reduce color fading and to correct illumination in color images [13]. A Parametric Fuzzy Transform (PFT) is introduced to enhance the contrast of a color image by preserving fine details and naturalness [14]. In order to enhance the contrast of each region, a new approach called Adaptive Fuzzy Exposure Local Contrast Enhancement (AFELCE) is proposed by using definite algorithms for dissimilar regions [15]. Madasu Hanmandlu et al. implemented a Global Contrast Intensification operator (GINT) [16]. This operator has three parameters namely fuzzifier, crossover point and intensification parameter. These parameters are chosen in a way to improve the quality of color images. Entropy-based quality factor and fuzzy contrast-based quality factor are the visual factors defined to achieve the desired appearance of images. Mila Nikolova et al. implemented a color image enhancement method, in which hue of an input image is gets conserved and the range of the R, G, B channels is preserved in an optimal way [17]. This method uses an intensity transformation method in order to improve the quality of color images. Long Yu et al. proposed a contrast enhancement technique to improve the quality of color images using Just-Noticeable Difference (JND) transform and color constancy [18]. JND map is constructed using JND transform, this map characterizes the response of the human visual system. Color and contrast of an image gets optimized using generalized equalization model.

However, satisfactory results are found from the aforesaid CE techniques by adjusting the histograms. Histogram equalization-based approaches tend to improve the information content within the image still excessive enhancement often results with annoying artifacts. Moreover, the enhanced image obtained from the abovementioned methods might suffer from insufficient enrichment in contrast, preserving fine details, illumination, saturation and colorfulness. In order to improve the superiority of color images, encompassing contrast, perceptiveness and colorfulness, a novel method is proposed in this article. The proposed Fuzzy Dissimilarity Adaptive Histogram Equalization with Gamma Correction (FDAHE-GC) overcomes the above-mentioned limitations and yields better results in terms of its contrast, colorfulness, saturation and detail preservation.

2. Proposed work

The graphical abstract for the proposed method is displayed in Fig. 1. Consider an input color image $\mathrm{I}(p,\mathrm{q}) = \{\mathrm{R}(p,\mathrm{q}),\ \mathrm{G}(p,\mathrm{q}),\ \mathrm{B}(p,\mathrm{q})\}$ where {R, G, B} are the red, green and blue color spaces, (p,q) is the pixel co-ordinates, p = 1 to M, q =1 to N and M, N are the image width and height.

The colorfulness of an image can be improved by stretching the magnitude of every color channel. The magnitude stretching process enriches the color content by stretching the input color channels into their allowable maximum range. The stretched red color value is given as,

$$\mathrm{R}(\mathrm{p},\mathrm{q}) \leftarrow \frac{\mathrm{R}(p,\mathrm{q}) - \min\{\mathrm{R}(p,\mathrm{q})\}}{\max\{\mathrm{R}(p,\mathrm{q})\} - \min\{\mathrm{R}(p,\mathrm{q})\}} * 2^{L-1} \tag{1}$$

where, the minimum and maximum values gained over all pixels in an image are represented by min{.} and max{.} and L is the image bit depth whose values ranges from 0 to 255. Similarly, the same operation is used to stretch the green $\mathrm{G}(p,\mathrm{q})$ and blue $\mathrm{B}(p,\mathrm{q})$ channels. All color channels are converted to HSI color space after the process of magnitude stretching. To enhance the contrast, the intensity of the channel (I) is further processed. Using the transformation process mentioned in Eq. (2), the stretched RGB input image in RGB color space is converted into HSI color space.

$$[\mathrm{H}(p,\mathrm{q}),\ \mathrm{S}(p,\mathrm{q}),\ \mathrm{I}(p,\mathrm{q})] = \mathrm{T}_{\mathrm{RGB}}^{\mathrm{HSI}}[\mathrm{R}(p,\mathrm{q}),\ \mathrm{G}(p,\mathrm{q}),\ \mathrm{B}(p,\mathrm{q})] \tag{2}$$

where, $\mathrm{T}_{\mathrm{RGB}}^{\mathrm{HSI}}$ is the RGB-to-HSI color conversion process. While improving the channel intensity, H and S channel components can be conserved to enhance the image. In the HSI space, the intensity channel is given as

$$\mathrm{I}(p,\mathrm{q}) \leftarrow \frac{\{\mathrm{R}(p,\mathrm{q}) + \mathrm{G}(p,\mathrm{q}) + \mathrm{B}(p,\mathrm{q})\}}{3} \tag{3}$$

2.1. Fuzzy dissimilarity histogram

A Fuzzy property of intensity channel image is used to formulate Fuzzy Dissimilarity [19] Histogram (FDH). Let us consider an input image of which has a size of $M \times N$. *i.e.*,

$$I = \{I\ (p,q) |\, 0 \le p \le M-1, 0 \le q \le N-1\} \tag{4}$$

Here, $I(p,q) = s_k$ symbolizes the intensity of a pixel located at (p,q) where $k \in \{0,1,\ldots,L-1\}$ and a total number of intensity levels is represented as L. For each and every pixel in a 3×3 neighborhood, fuzzy neighborhood similarity is then calculated. At pixel location (p,q) by finding fuzzy neighborhood similarity in 3×3 neighborhood, Membership Function (MF) can be obtained and is given by,

$$\mu s\,(u,v) = \max\{1 - |I(p,y) - I(u,v)|/\sigma, 0\} \tag{5}$$

where, $u = p+i,\ v = q+j;\ i,j \in \{-1,0,1\}$ *and* σ is the Standard Deviation (SD) of the original image.

To create a "similar" fuzzy set, these fuzzy membership values of the neighboring pixels are used and is given by the fuzzy membership function Φ_{mfs}. The Membership function Φ_{mfs} is stated as a fuzzy similarity index and it is given by,

$$\Phi_{mfs}(p,q) = \left(\frac{1}{9}\right) \sum_{i=-1}^{1} \sum_{j=-1}^{1} \mu s\,(p+i, q+j) \tag{6}$$

A new dissimilar fuzzy set is obtained by taking the compliment of a fuzzy similarity index. The following equation gives the membership function of a new "dissimilar" fuzzy set.

$$\mu c\,(p,q) = \overline{\Phi_{mfs}}\,(p,q) \tag{7}$$

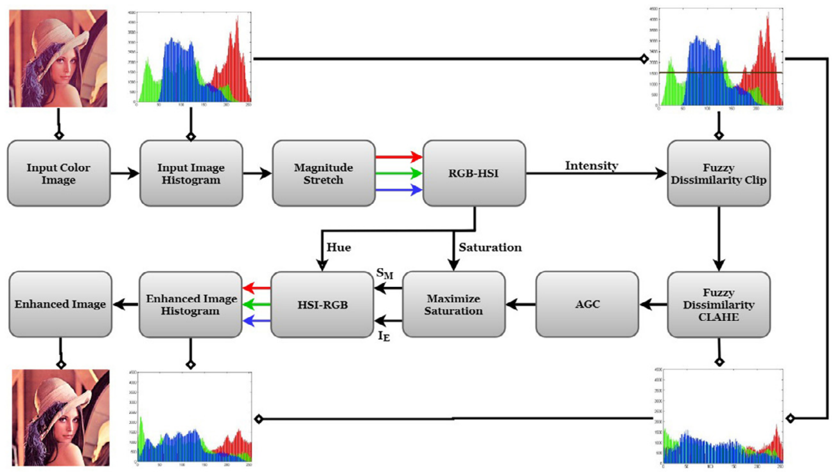

Fig. 1. Graphical abstract of proposed work.

The degree of the dissimilarity (contrast) of each pixel from its neighborhood pixel can be shown in the above equation. Fuzzy set "dissimilar" of each intensity level in an image is used to formulate a fuzzy dissimilarity histogram H_{fdh}.

$$H_{fdh} = \left\{h_{fdh}\left(s_k\right) | 0 \leq s_k \leq L-1\right\} \tag{8}$$

$$h_{fdh}\left(s_k\right) = \sum_{p=0}^{M-1}\sum_{q=0}^{N-1} \mu s_k(p, q) \tag{9}$$

$$\mu s_k\left(p, q\right) = \begin{cases} \mu c\left(p, q\right), & if\ I\left(p, q\right) = s_k \\ 0, & otherwise \end{cases} \tag{10}$$

The fuzzy dissimilarity histogram interprets for the contextual data present in the neighborhood of a pixel. It provides the average dissimilarity measure of each intensity level present in the given input image.

2.2. Fuzzy dissimilarity adaptive histogram equalization

To overcome the problem of excessive enhancement, the process of clipping in histogram has been tried by restricting its enhancement rate. Usage of pre-defined clip-limit in existing clipped histogram equalization methods has become the main disadvantage of it. The clip-limit is fixed and constant to all images. Hence, all the pixels inside the window region are equally affected. Clip limit is automatically selected by adaptive plateau histogram equalization, but it is not suitable for contrast enhancement.

The entropy and contrast measures in the input images are founded in order to calculate the fuzzy inference system based fuzzy dissimilarity clip.

$$Contrast\ (C) = \sum_{x,y=0}^{255} |x-y|^2\, P(x, y) \tag{11}$$

$$Entropy\ (E) = \sum_{x,y=0}^{255} P\left(x, y\right)\left(-\ln P\left(x, y\right)\right) \tag{12}$$

where, $P(x, y)$ denotes the probability of a possible outputs.

In image quality assessment, two important metrics are the entropy and contrast. To find the output fuzzy dissimilarity clip limit enhancement parameter (Δ), these two metrics inputs are being used by fuzzy interface system.

In this work, the input, $a_1 \in$ C (Contrast), $b_1 \in$ E (Entropy) and one output $o \in \Delta$. The fuzzy composition of C and E helps in tuning the value of Δ. Low (w_1), Medium (w_2) and High (w_3) are the fuzzy sets of C and Small (t_1) and Big (t_2) are the fuzzy sets of E. Using the standard database with ground truth, w_1, w_2, w_3, t_1, t_2 values have been fixed.

The fuzzy rules are formulated using triangular membership function for categorizing the fuzzy dissimilarity clip limit parameter into Fuzzy Dissimilarity Clip Limit Minimum (FDCL1) and Fuzzy Dissimilarity Clip Limit Maximum (FDCL2). Six rules have been generated to compute the fuzzy dissimilarity clip enhancement parameter. The membership degree of all rule outputs are formerly clipped and scaled are united into a single fuzzy set.

A set of fuzzy rules are formulated for selecting of fuzzy dissimilarity clip enhancement parameter automatically.

1. If C is Minimum and E is Minimum, then Δ is FDCL2.
2. If C is Medium and E is Minimum, then Δ is FDCL2.
3. If C is Minimum and E is Maximum, then Δ is FDCL2.
4. If C is Maximum and E is Minimum, then Δ is FDCL1.
5. If C is Medium and E is Maximum, then Δ is FDCL1.
6. If C is Maximum and E is Maximum, then Δ is FDCL1.

The fuzzy dissimilarity clip contrast enhancement parameter (Δ) lies in-between 0 and 1. By varying Δ, it is possible to achieve various levels of contrast enhancement. Based on contrast and entropy, an adaptive new fuzzy clip limit for an input image is formulated as,

$$Fuzzy\text{ dissimilarity }cliplimit = \left[\frac{\tau}{256}\right] + \left[.\Delta\left(\tau - \left[\frac{\tau}{256}\right]\right)\right] \tag{13}$$

where, $\Delta =$ fuzzy dissimilarity clip enhancement parameter.
[.] represents the truncation of value to the nearby integer value.
$\tau =$ number of pixels per tiles, and the number 256 represents the number of bins.

For a modified clipped histogram Mh_{fdh}, the Probability Density Function (PDF) is given by,

$$Mp_{fdh}\left(S_k\right) = \frac{Mh_{fdh}\left(s_k\right)}{\sum_{k=0}^{L-1} Mh_{fdh}\left(s_k\right)} \tag{14}$$

Its corresponding Cumulative Density Function (CDF) is calculated as,

$$Mc_{fdh}\left(S_k\right) = \sum_{j=0}^{k} Mp_{fdh}\left(S_j\right) \tag{15}$$

Using cumulative density function, intensity transformation function $T(x)$ is calculated and is given as

$$T(x) = X_0 + \left(X_{L-1} - X_0\right) Mc_{fdh}\left(S_k\right) \tag{16}$$

where, X_{L-1} represents the maximum gray level in an image.

The CE image obtained using fuzzy dissimilarity adaptive histogram equalization is given as,

$$Z(p,q) = T(x) = \left\{ Z(Mh_{fdh}(p,q)) \middle| \forall Mh_{fdh}(p,q) \in Mh_{fdh} \right\} \tag{17}$$

where, (p,q) are spatial coordinates of the pixel in the image.

2.3. Gamma correction and saturation maximization

In the proposed system, transformed enhanced pixel intensity is computed as

$$I_e(\mathrm{p,q}) = \mathrm{T}\{\mathrm{I}(\mathrm{p,q})\} = \mathrm{round}\left(\frac{\{\mathrm{Z}(\mathrm{p,q})\}}{Z_{\max}(\mathrm{p,q})}\right)^{\gamma} \tag{18}$$

Here, the gamma parameter [20] with cumulative density function (CDF) is calculated as,

$$\gamma = 1 - Mc_{fdh}(S_k) \tag{19}$$

Meanwhile, the saturation is

$$S(p,q) = 1 - \frac{3 \times min\{R(p,q), G(p,q), B(p,q)\}}{(R(p,q) + G(p,q) + B(p,q))} \tag{20}$$

Let the pixel of bright intensity is given by $I(p,q) \to (L-1)$ or particularly $R(p,q) \to (L-1), G(p,q) \to (L-1), B(p,q) \to (L-1)$, and the saturation is defined as

$$S(u,v) = 1 - \frac{min\{R(p,q), G(p,q), B(p,q)\}}{I(p,q)} \tag{21}$$

Here, numerator of the RHS (Right Hand Side) min $R(p,q)$, $G(p,q), B(p,q)$ tends to unity, consequently

$$S(p,q) \approx 1 - \frac{(L-1)}{(L-1)} \to 0 \tag{22}$$

A similar analysis can be carried out for low intensity pixels to reveal the de-saturation effect. Hence, de-saturation is essential in the equalization process if the intensities values are driven near the minimum and maximum value of the intensity range. A saturation maximization process is applied between the original image and the enhanced image saturation values to the image saturation after equalization. Then the equalized gray image should be embedded with the HSI components and then it is converted back to RGB color space. That is,

$$[R(p,q), G(p,q), B(p,q)]_e^T = T_{HSI}^{RGB}[H(p,q), S(p,q), I_e(p,q)]^T \tag{23}$$

And then again converted to HSI space to obtain $S_e(p,q)$. The maximization operation is invoked on the saturation $S_o(p,q)$ extracted from the input image. We have

$$S_m(p,q) = \max\{S_o(p,q), S_e(p,q)\} \tag{24}$$

The maximum saturation is then merged with the enhanced intensity and the hue space, then it is transformed back to the RGB space. The final enhanced image given by

$$[R(p,q), G(p,q), B(p,q)]_n^T = T_{HSI}^{RGB}[H(p,q), S_m(p,q), I_e(p,q)]^T \tag{25}$$

3. Experimental results and discussion

3.1. Objective measures

The quantitative measurements are presented to prove the performance of our proposed FDAHE-GC algorithm with other existing methods. The quantitative assessment tool includes the entropy, Colorfulness (C), Hue Deviation Index (HDI), Saturation (S), Contrast Enhancement Factor (CEF) and Gradient (G). The appropriate expressions for the above-mentioned measures are displayed in Eqs. (26)–(31)

$$CEF = \frac{\frac{1}{MN}\sum_{p=1}^{M}\sum_{q=1}^{N} I(p,q)\left[I(p,q) - \frac{1}{MN}\sum_{p=1}^{M}\sum_{q=1}^{N} I(p,q)\right]^2}{\frac{1}{MN}\sum_{p=1}^{M}\sum_{q=1}^{N} I(p,q)} \tag{26}$$

where M and N are the height and width of the image respectively.

$$Entropy = \sum_{k}^{n}(-p_k * log(p_k)) \tag{27}$$

where, p_k is the bins of the normalized histogram, in which i represents the total bin values and n is the greater entropy infers that fine details are improved.

$$G = \frac{1}{MN}\sum_{p=1}^{M}\sum_{p=1}^{N}(\Delta u^2 + \Delta v^2) \tag{28}$$

where, Δu *and* Δv denotes the changes in intensity values both in vertical and horizontal direction.

$$C = \sqrt{\sigma_x^2 + \sigma_y^2} + 0.3\sqrt{\mu_x^2 + \mu_y^2} \tag{29}$$

where, σ_x^2 and σ_y^2 are standard deviation and μ_x^2 and μ_y^2 are average values of $x = R - G$ and $y = \left(R + \frac{G}{2}\right) - B$ respectively.

$$S = \frac{1}{N}\sum_{p=1}^{M}\sum_{q=1}^{N} 1 - \frac{3min\{R(p,q), G(p,q), B(p,q)\}}{\sum(R(p,q), G(p,q), B(p,q))} \tag{30}$$

$$HDI = \left[\frac{1}{MN}\sum_{p=1}^{M}\sum_{q=1}^{N} min(|X(p,q) - Y(p,q)|, 1 - |X(p,q) - Y(p,q)|)\right] \times 100\% \tag{31}$$

where, $Y(p,q)$ is the transformed hue channel and $X(p,q)$ is the input hue channel of HSI color space.

3.2. Subjective analysis

To analyze the performance, the proposed method is compared with the other existing methods in terms of its visual perception.

Fig. 2 shows the simulation results on the image *parrot*, in which (a) indicates the input image to be enhanced, and (b) to (h) show the enhanced results produced by different CE algorithms. As shown in Fig. 2(b), though FLH attains high contrast, it experiences excessive enhancement in darker portions which makes to look much black. Fig. 2(c) shows that OGCWS method have little success in improving the contrast of the input parrot image and it also results in some darker regions. Fig. 2(d) using CLAHE-DGC shows a satisfactory balance between contrast enhancement and preserving brightness but still, the fine details are not tuned properly. Fig. 2(e) shows that the IAGC method suffers from the brightness degradation problem which makes an unpleasant look. Fig. 2(f) with the PFT method has only little marginal contrast enhancement over the input parrot image and also brightness preservation level is not too good. Fig. 2(g) with AFELCE method shows greater contrast over input image. Hence, it results in unwanted artifacts in some portions. Whereas, the proposed FDAHE-GC method, gives a clean and natural looking image without any distortion over the input image brightness

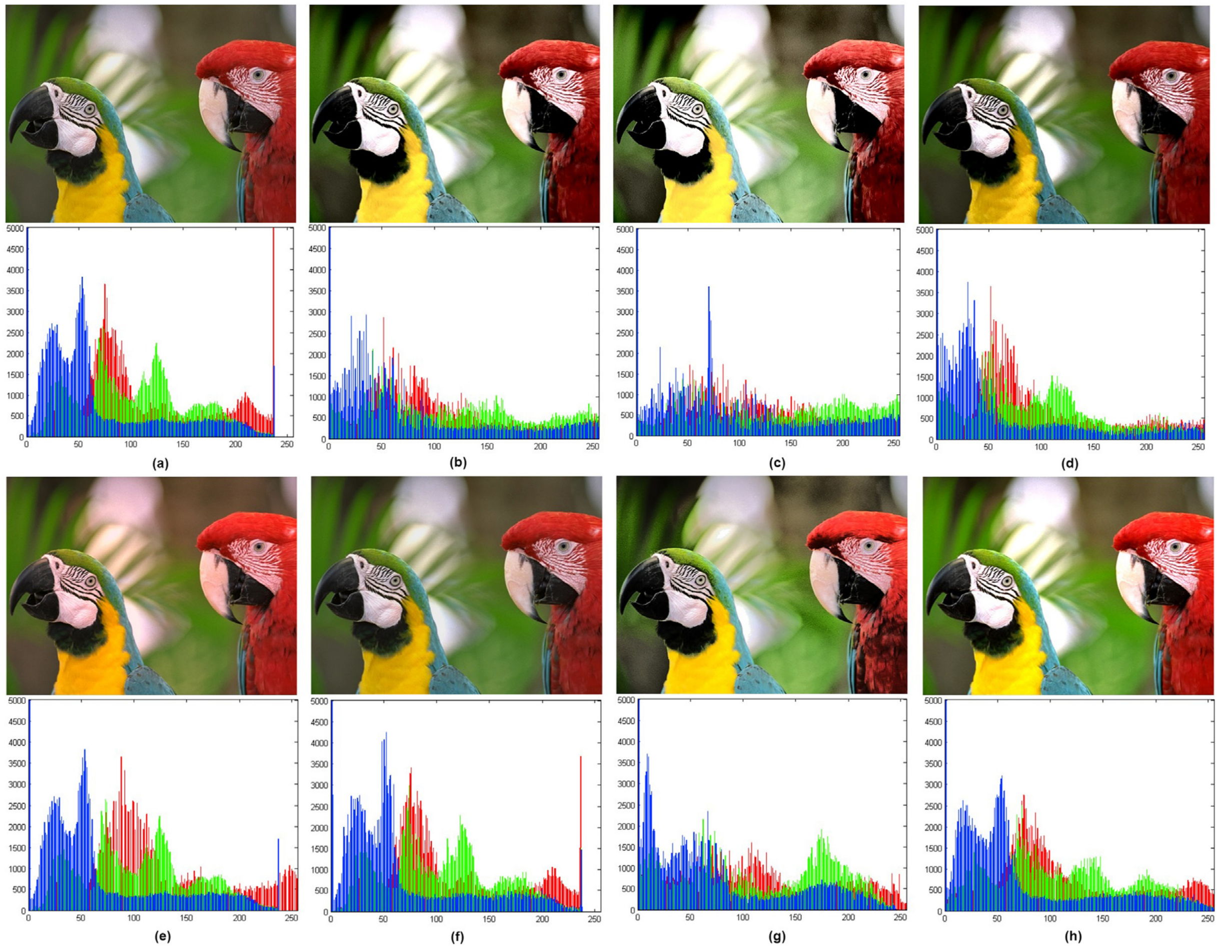

Fig. 2. Contrast enhancement results of the *parrot* image and its histogram. a. original image; b. FLH-ed image; c. OGCWS-ed image; d. CLAHE-DGC-ed image; e. IAGC-ed image; f. PET-ed image; g. AFELCE-ed image; h. FDAHE-GC-ed image.

level. Furthermore, the contrast of an image is enhanced with fine details of the image visible in all the regions. The statistical histogram plot in Fig. 2 for the proposed FDAHE-GC result confirms a close resemblance of the input statistical histogram with an extended dynamic range.

Fig. 3 displays the simulation results on the image *hats,* in which (a) indicates the input image to be enhanced, and (b) to (h) show the enhanced results produced by different CE algorithms.

Fig. 3(b) and (c) from FLH and OGCWS methods display over enhancement in bright areas, especially in the yellow hat. Therefore, it fails to produce naturalness. Results from CLAHE-DGC and AFELCE in Fig. 3(d) and (g) displays more dark portions more particularly in green hat. The improved contrast result of IAGC method as displayed in Fig. 3(e) is not significant.

Fig. 3(f) from PFT method is less-enhanced with concentrations of lower intensity values in an entire image. In contrast, the proposed FDAHE-GC method in Fig. 3(h) can balance the processes of brightness preservation, contrast improvement, perceptiveness, and color retrieval and also the edges in the objects are also sharpened by which each object in the images clearly shown.

In Fig. 4, another *lena* input color image is presented. Figs. from 4(b), (c) and (g) using FLH, OGCWS and AFELCE methods suffer from the same brightness degradation and excessive enhancement as found in the aforementioned test image. Contrast enhancement results from Fig. 4(d) using CLAHE-DGC causes too brighter portions especially in the hat of the lena image and it fails to produce a natural effect. Artifacts from contrast enhancement are evident from the outcomes of the IAGC method as shown in Fig. 4(e). Fig. 4(f) demonstrate that the contrast improvement gained by PFT method is rather weak and even invalid. Simulation results form our proposed FDAHE-GC algorithm has effectively boosted the contrast of color images without inviting any annoying artifacts, and the output of the proposed method is visually more consistent.

Fig. 5 illustrates the visual comparisons of contrast enhancement outputs by seven methods on *tower* image. Results from Fig. 5(b) and (c) using FLH and OGCWS method show that dimmer regions have become dimmer and fine details in the image are lost. The output from CLAHE-DGC in Fig. 5(d) leads poor-enhancement where the illumination is poor. It is noticed that simulation results from the IAGC method in Fig. 5(e) demonstrates that the quality of an image is not increased significantly and also the entire image gets polluted by annoying artifacts. It is observed from the Fig. 5(f) that, PET method alleviates the artifacts but contrast improvement is not acceptable. Results from AFELCE method in Fig. 5(g) gives good results both in the dim portions and bright portions. Though, the results attained by AFELCE algorithm are somewhat inferior to the proposed FDAHE-GC algorithm in terms of contrast enhancement. The proposed FDAHE-GC method attains good results with greater contrast and perceptiveness.

Fig. 6 displays the visual quality evaluation on the image *flower.* The outputs from the method FLH and OGCWS in Fig. 6(b) and (c) displays more improvement in brightness that diverges

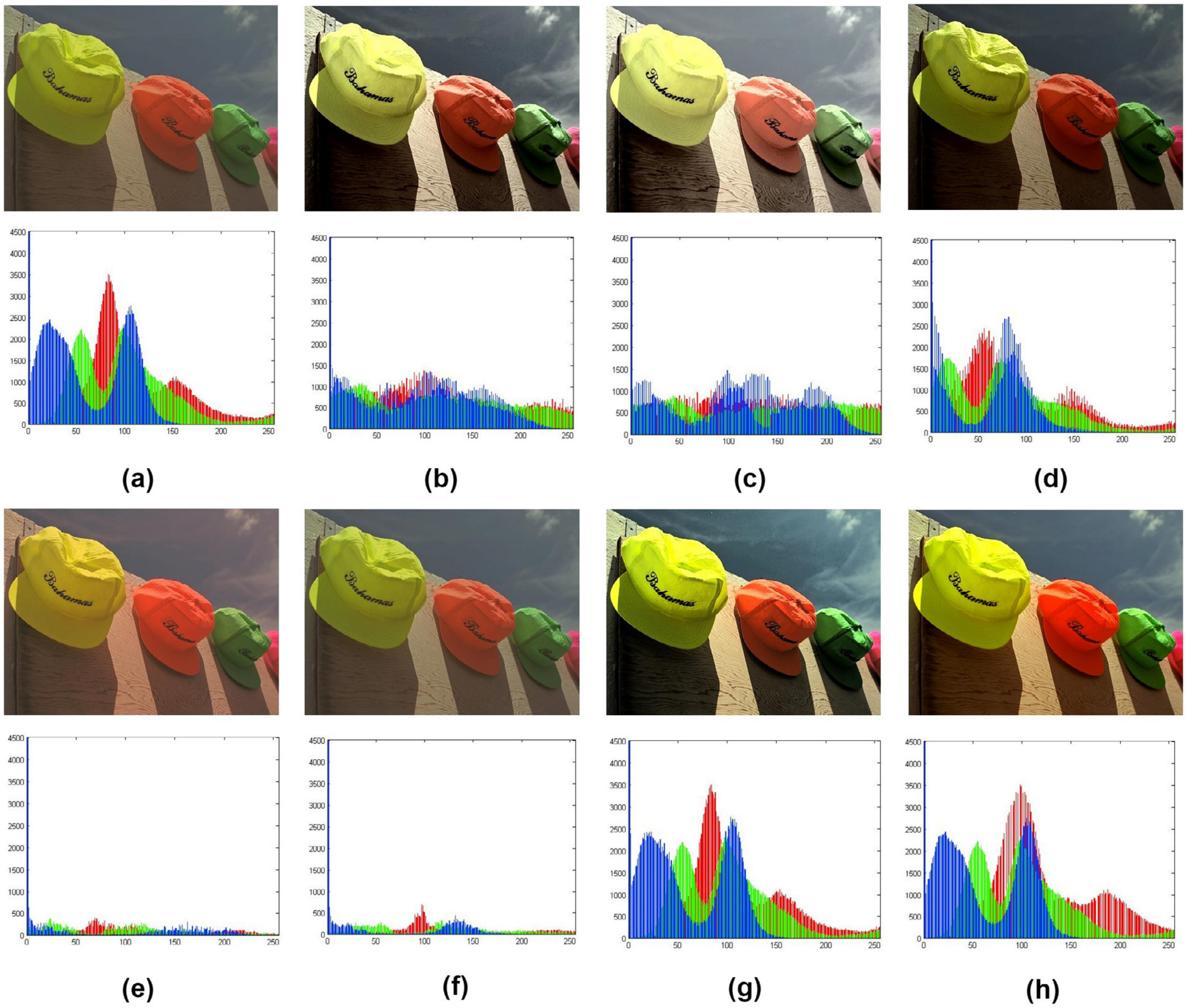

Fig. 3. Contrast enhancement results of the *hats* image. a. original image; b. FLH-ed image; c. OGCWS-ed image; d. CLAHE-DGC-ed image; e. IAGC-ed image; f. PET-ed image; g. AFELCE-ed image; h. FDAHE-GC-ed image.

from the input flower image. The output of CLAHE-DGC method shown in Fig. 6(d) does not show any improvement in contrast enhancement and it is very similar to original flower image. From Fig. 6(e), the IAGC method produces an image with undesirable noise in entire portions. From Fig. 6(f), it is noticed that fine details in some portions are lost to a greater extent after contrast enhancement by PET method. The output from AFELCE method in Fig. 6(g) shows a slight enhancement in dark portions and excessive enhancement in bright portions, which makes an image undesirable. A good contrast enhancement method must achieve stability between color distortion and contrast enhancement. Less color distortion should be invited while more contrast enhancement is gained. The proposed FDAHE-GC method can able to attain the comparative results when compared with all other existing methods.

Figs. 7 and 8 displays the visual quality evaluation on the *Raw image 1 and 2* taken from UCID database. Visually, it is noticed that the proposed algorithm can able to generate a better contrast image with natural look. The obtained output from the proposed method is illustrated in Figs. 7 and 8(h). It is perceived that image colors are brighter without incurring any unwanted visual artifacts as compared to resultant images from all other existing methods. Significant improvement in the contrast is found in all test images using proposed method.

3.3. Objective analysis

The quality of an image is assessed objectively using six different Image Quality Assessment (IQA) parameters namely entropy, Hue Deviation Index (HDI), Saturation (S), Colorfulness (C), Contrast Enhancement Factor (CEF) and Gradient (G). The Miscellaneous database consists of 14 color images which are used for experimentation. The sizes are 8 256 $\times$ 256 and 6 512 $\times$ 512.

Fig. 9 demonstrates the objective evaluation results for different images using the metric entropy. From Fig. 7, it is noticed that the proposed FDAHE-GC CE method is more consistent with greater entropy values and it enhances the richness of information in all the tested images. Greater entropy value indicates the richness of information present in the image.

Fig. 10 shows the objective evaluation results for different images using the metric HDI. The lower value of HDI indicates the less color deviation from the input color image suggesting best hue preservation. It is observed from Fig. 10 that, the proposed FDAHE-GC method attains low HDI value while compared to all other existing CE methods and it proves that hue is not significantly modified.

Fig. 11 shows the saturation values for different test images using the proposed and six other existing methods. The proposed FDAHE-GC method restricts the abrupt change in intensity values

Fig. 4. Contrast enhancement results of the *lena* Image. a. original image; b. FLH-ed image; c. OGCWS-ed image; d. CLAHE-DGC-ed image; e. IAGC-ed image; f. PET-ed image; g. AFELCE-ed image; h. FDAHE-GC-ed image.

Fig. 5. Contrast enhancement results of the *tower* image. a. original image; b. FLH-ed image; c. OGCWS-ed image; d. CLAHE-DGC-ed image; e. IAGC-ed image; f. PET-ed image; g. AFELCE-ed image; h. FDAHE-GC-ed image.

in the enhanced results and it maintains almost the same saturation values close to the input values when compared to other existing methods.

It is clear from Fig. 12 that, the proposed FDAHE-GC method produces the richest colorfulness value when compared with other techniques and hence the proposed FDAHE-GC method gains high natural color information from an input image.

It is observed from Fig. 13 that results of proposed FDAHE-GC method are better than other state of art methods in terms of contrast enhancement factor. This output displays that the proposed FDAHE-GC method will produce good results for most of the test images in terms of contrast balancing and uniformity.

Gradient metric measures the sharpness and mean value of all pixels. Greater gradient value is contained in high contrast image. The gradient metrics of the proposed FDAHE-GC technique is greater than all other existing methods under comparison in Fig. 14.

The average performance measures of proposed and other existing method for a set of 600 test images from standard database are illustrated in Tables 1–4. For experimentation, we considered 600 test images, from which 200 images from Computational and Subjective Image Quality (CSIQ) database (http://vision.eng.shizuoka.ac.jp/) [21], 330 images from Tampere Image Database (TID) (www.ponomarenko.info>tid2013) [22], 10 images from Miscellaneous (MISC) dataset (http://sipi.usc.edu/database/database.php?volume=misc) and 60 raw images from Uncompressed Color Image Dataset (UCID) (http://jasoncantarella.com/downloads/ucid.v2.tar.gz) [23]. The distortions considered are: Contrast change, change of color saturation, JPEG compression and JPEG 2000.

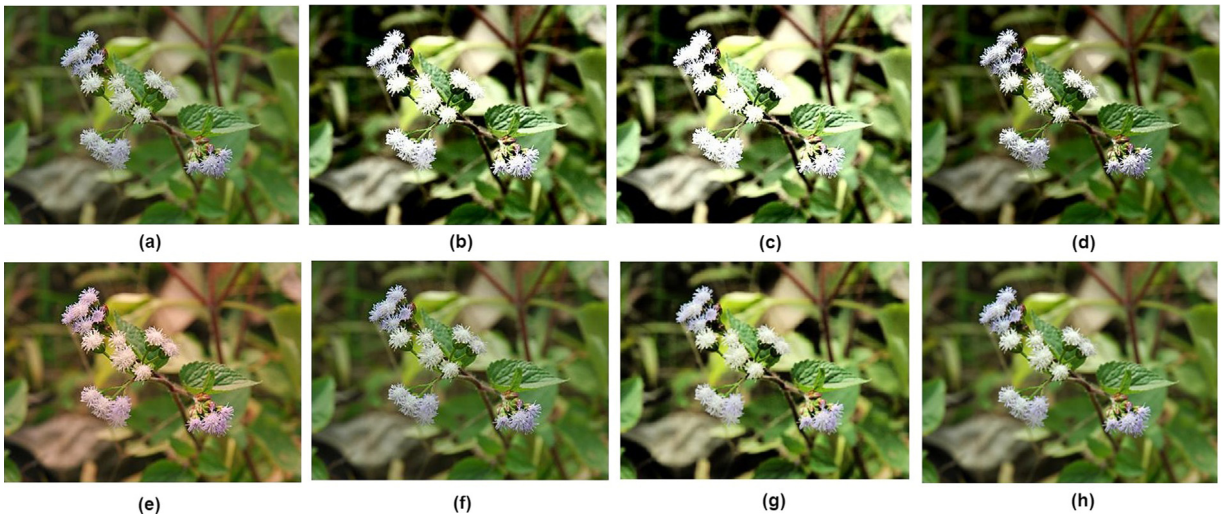

Fig. 6. Contrast enhancement results of the *flower* image. a. original image; b. FLH-ed image; c. OGCWS-ed image; d. CLAHE-DGC-ed image; e. IAGC-ed image; f. PET-ed image; g. AFELCE-ed image; h. FDAHE-GC-ed image.

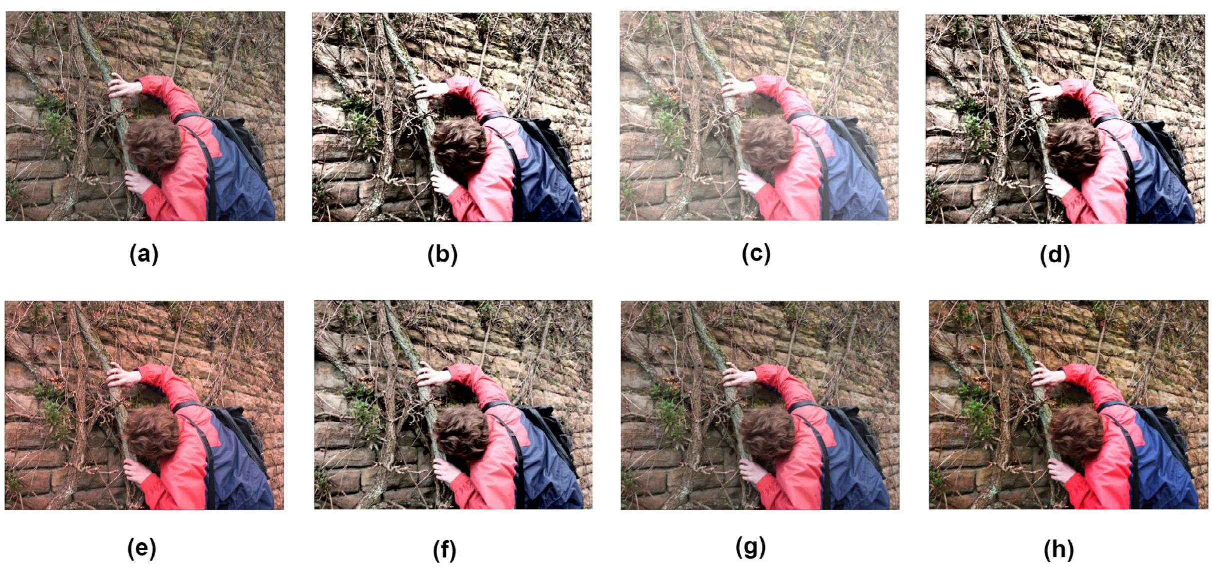

Fig. 7. Contrast enhancement results of the *Raw* image 1. a. original image; b. FLH-ed image; c. OGCWS-ed image; d. CLAHE-DGC-ed image; e. IAGC-ed image; f. PET-ed image; g. AFELCE-ed image; h. FDAHE-GC-ed image.

Table 1
Quantitative metric values obtained after applying various CE methods on MISC database.

Methods/Parameters	Original	FLH [4]	OGCWS [6]	CLAHE-DGC [11]	IAGC [12]	PET [14]	AFELCE [15]	FDAHE-GC
Entropy	5.9	5.65	5.80	5.72	5.79	5.65	5.81	**5.99**
HDI	3.98	5.037	6.095	4.617	4.137	4.557	5.295	**4.002**
Saturation	0.402	0.407	0.407	0.41	0.405	0.402	0.407	**0.42**
CEF	1.322	1.397	1.467	1.735	1.38	1.442	1.245	**2.327**
Gradient	0.035	0.035	0.038	0.035	0.039	0.04	0.042	**0.044**
Colorfulness	0.282	0.287	0.287	0.29	0.297	0.3	0.302	**0.307**
Computational time (s)	–	**0.023**	0.19	0.185	0.027	0.032	0.026	0.025

Table 2
Quantitative metric values obtained after applying various CE methods on CSIQ database.

Methods/Parameters	Original	FLH [4]	OGCWS [6]	CLAHE-DGC [11]	IAGC [12]	PET [14]	AFELCE [15]	FDAHE-GC
Entropy	6.7	6.5	6.56	6.56	6.56	6.63	6.65	**6.705**
HDI	4.17	6.31	6.22	5.21	4.935	2.88	7.33	**4.22**
Saturation	0.53	0.53	0.535	0.535	0.54	0.525	0.53	**0.54**
CEF	1.46	1.51	1.515	1.77	1.51	1.535	1.395	**2.455**
Gradient	0.033	0.034	0.041	0.033	0.042	0.041	0.042	**0.045**
Colorfulness	0.31	0.31	0.315	0.315	0.325	0.33	0.34	**0.35**
Computational time (s)	–	**0.024**	0.16	0.17	0.028	0.03	0.028	0.025

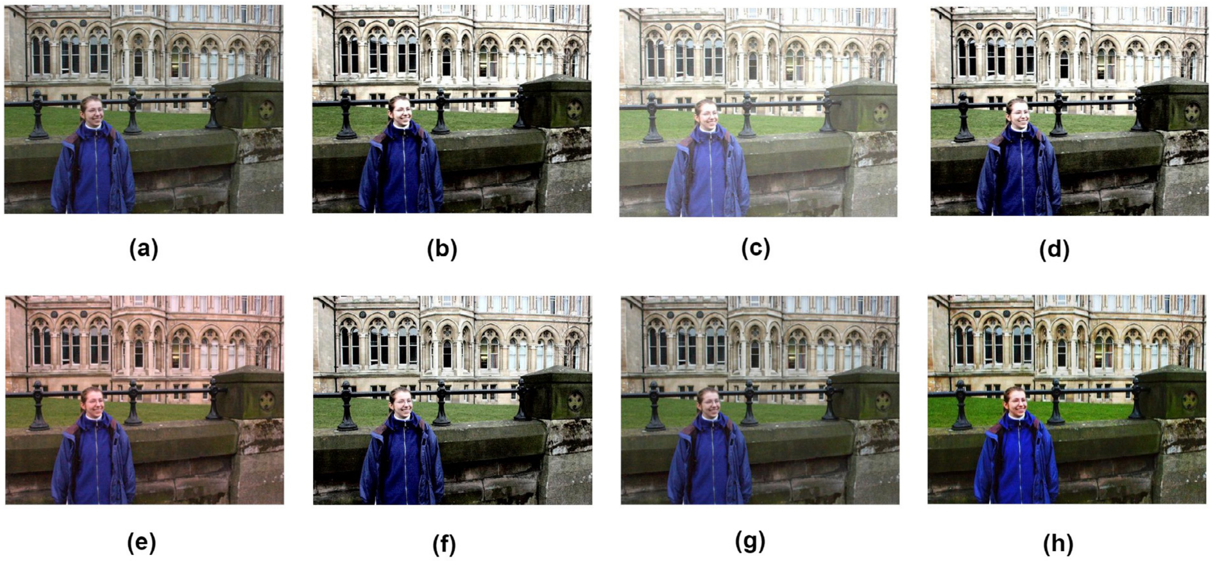

Fig. 8. Contrast enhancement results of the *Raw* image 2. a. original image; b. FLH-ed image; c. OGCWS-ed image; d. CLAHE-DGC-ed image; e. IAGC-ed image; f. PET-ed image; g. AFELCE-ed image; h. FDAHE-GC-ed image.

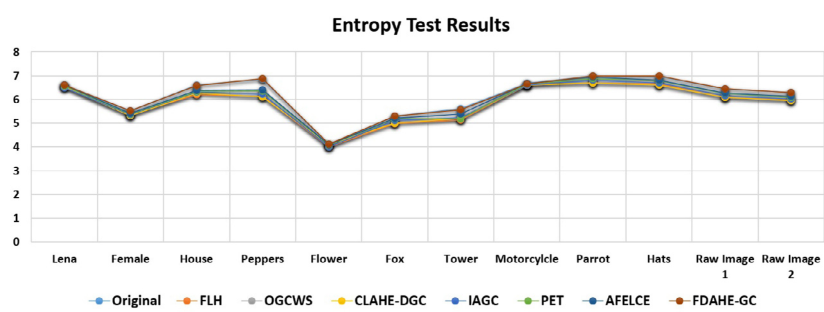

Fig. 9. Entropy test results.

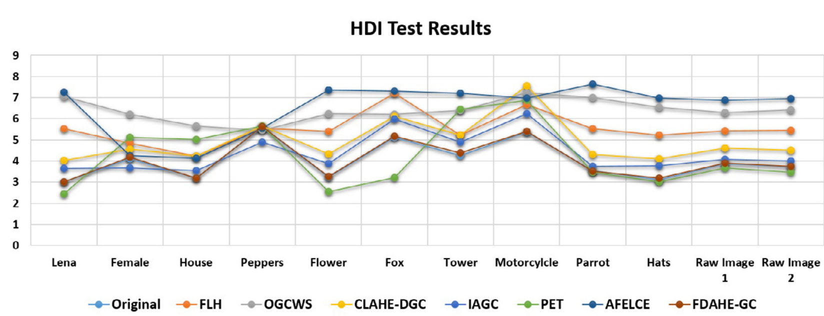

Fig. 10. HDI test results.

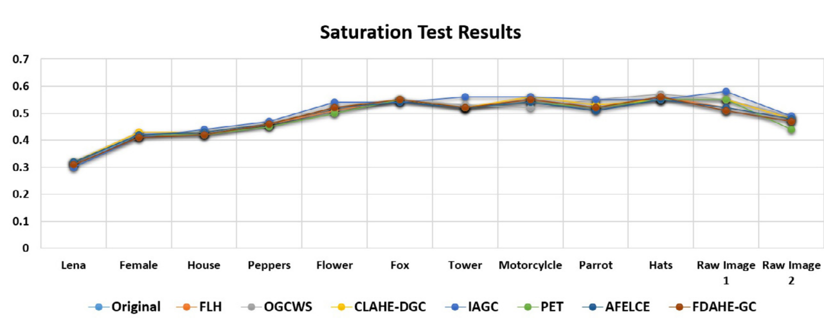

Fig. 11. Saturation test results.

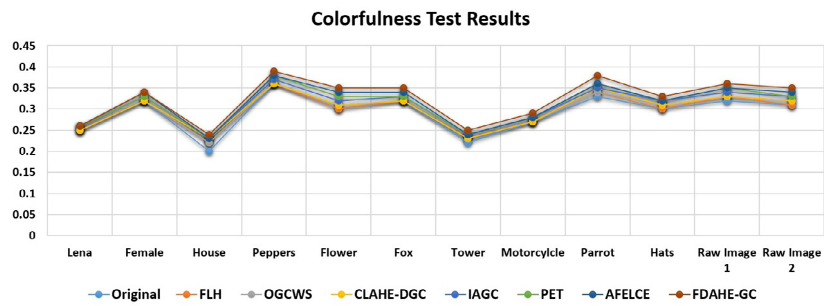

Fig. 12. Colorfulness test results.

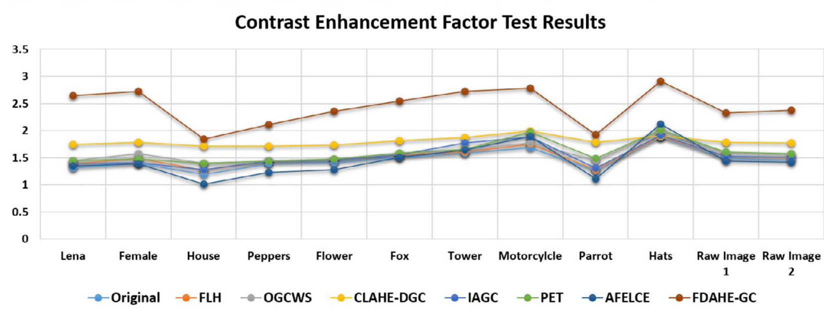

Fig. 13. Contrast enhancement factor test results.

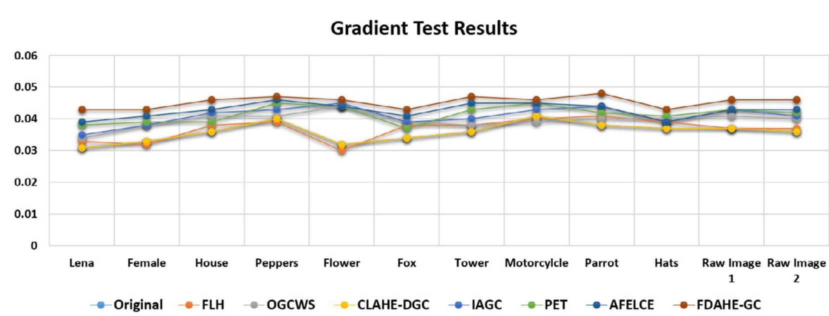

Fig. 14. Gradient test results.

Table 3
Quantitative metric values obtained after applying various CE methods on TID database.

Methods/Parameters	Original	FLH [4]	OGCWS [6]	CLAHE-DGC [11]	IAGC [12]	PET [14]	AFELCE [15]	FDAHE-GC
Entropy	6.962	6.88	6.812	6.78	6.842	6.782	6.857	**6.999**
HDI	4.072	5.66	6.792	5.3	4.66	4.947	7.21	**4.13**
Saturation	0.537	0.537	0.542	0.54	0.555	0.532	0.53	**0.55**
CEF	1.602	1.632	1.717	1.885	1.717	1.782	1.692	**2.582**
Gradient	0.038	0.039	0.039	0.038	0.041	0.042	0.043	**0.046**
Colorfulness	0.28	0.285	0.287	0.29	0.297	0.3	0.3	**0.312**
Computational time (s)	–	**0.026**	0.17	0.18	0.030	0.032	0.030	0.027

Table 4
Quantitative metric values obtained after applying various CE methods on UCID raw database.

Methods/Parameters	Original	FLH [4]	OGCWS [6]	CLAHE-DGC [11]	IAGC [12]	PET [14]	AFELCE [15]	FDAHE-GC
Entropy	6.554	6.285	6.301	6.301	6.333	6.392	6.436	**6.555**
HDI	4.074	5.669	6.369	5.042	4.577	4.128	6.612	**4.117**
Saturation	0.490	0.491	0.495	0.495	0.500	0.486	0.489	**0.503**
CEF	1.461	1.513	1.566	1.797	1.536	1.586	1.444	**2.455**
Gradient	0.035	0.036	0.039	0.035	0.041	0.041	0.042	**0.045**
Colorfulness	0.291	0.294	0.296	0.298	0.306	0.310	0.314	**0.323**
Computational time (s)	–	**0.031**	0.173	0.178	0.038	0.036	0.038	**0.031**

A good CE method has minimum computational complexity. In order to evaluate the computational complexity of our proposed method with other existing methods, PC codes were implemented in the Matlab 2013a platform run on a PC with Intel Core i3 2.2 GHz and 8 GB of RAM. As shown in Tables 1–4, the computational time of the proposed method for processing an image is 0.025 s as an average. All the existing method discussed in this work having greater computational time except FLH method. Moreover, FLH method having less computational time as compared to the proposed method and also its visual and objective results demonstrate that FLH method suffers with excessive enhancement, unwanted artifacts and perceptiveness. Overall, proposed FDAHE-GC attains superior contrast enhancement, colorfulness, saturation, detail preservation and perceptiveness against the existing methods with no artifacts at the cost of minimum computational complexity.

4. Conclusion

A fuzzy dissimilarity adaptive histogram equalization with gamma correction algorithm for color image enhancement is presented in this article. A number of novel color image enhancement algorithms were introduced, applied to consumer electronics and other applications. Proper color image enhancement algorithms have been designed based on perceptive and cognitive features without which it is impossible to produce an effective visualization. The expectation that the proposed technique can provide additional enhancement of color images, better data visualization, and preserving fine details was demonstrated by experimental results and evaluations. Extensive research is conducted on standard test images from the CSIQ, MISC, UCID and TID image datasets. It was shown through visual interpretation, and more importantly through testing with other existing methods, that newly developed proposed FDAHE-GC technique becomes a very valuable tools in increasing the contrast and fine details of poorly illuminated color images. A significant increase of HDI to 4.22, CEF to 2.455, gradient to 0.045 and colorfulness to 0.35 as compared with results from the existing methods and the original data. Experimental results show that proposed FDAHE-GC technique produce results more consistent and robust with the human and objective assessment.

Declaration of competing interest

No author associated with this paper has disclosed any potential or pertinent conflicts which may be perceived to have impending conflict with this work. For full disclosure statements refer to https://doi.org/10.1016/j.asoc.2020.106077.

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