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Low light enhancement algorithm for color images using intuitionistic fuzzy sets with histogram equalization

J. Reegan Jebadass[1] · P. Balasubramaniam[1]

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Abstract

In this work, a new fuzzy logic-based algorithm is proposed for the enhancement of low light color images. A generalization of a fuzzy set known as an intuitionistic fuzzy set (IFS) is used in this paper, which expresses the evidence of the support, opposition, and hesitation simultaneously. To generate non-membership degrees, Yager's generating function is used. Again entropy formula is used to generate non-membership degrees for improving the quality of the enhanced image derived by the proposed method. In the experimental section, the proposed method is compared with other existing methods like histogram equalization, contrast limited adaptive histogram equalization, histogram specification approach, discrete cosine transform coefficient, brightness preserving dynamic fuzzy histogram equalization, and intuitionistic fuzzy image. The experimental results revealed that the proposed method gives better results than the other existing methods. Performances are evaluated using entropy and structural similarity index. A comparative analysis of the quality of enhanced images shows that the proposed method performs better than several existing methods.

Keywords Histogram equalization · Image enhancement · Intuitionistic fuzzy sets

1 Introduction

With the latest technologies, Digital images are considered to be one of the most important methods of recording and representing information [23]. Mobile phones and digital cameras have acquired the technology of photography. Image processing is a field of study that implements a few steps in the input images to make a few changes to the output images and turn them into useful images. When image acquisition, bad lightning, adverse

✉ P. Balasubramaniam
balugru@gmail.com

J. Reegan Jebadass
reeganmail@gmail.com

1 Department of Mathematics, The Gandhigram Rural Institute (Deemed to be University), Gandhigram-624 302, Tamil Nadu, India

environmental conditions, an unfavorable environment, and negligence when image acquisition can affect the quality of the image. For reasons like these, there are some practical issues with handling images. In today's modern world, digital image processing has made a huge impact in solving such problems. The main reason for this is the rapid development of home electronics, medical field research, image analysis in a submarine, etc. So, low light and low contrast images are enhanced by computer vision and pattern recognition. Over the past few decades, histogram equalization (HE), fuzzy logic-based methods, etc. have played a significant role in improving images taken in low light. Many HE-based methods [1, 9, 12–14, 16, 17] have been proposed to enhance the quality of an image for better visual perception. Yussof et al. [30] used contrast limited adaptive histogram equalization (CLAHE) technique to derive the enhanced image from a combination of outputs performed on the RGB color model and hue, saturation, value (HSV) color model that was done through the euclidean norm. In the medical field, to cope with the problem of poor contrast in medical images, Wadhwa et al. [28] presented a method based on morphological transforms to improve the quality of the images. Zhuang et al. [32] developed a novel edge-preserving filtering retinex algorithm for single underwater image enhancement. In recent days the technology has improved from 2D images to 3D data [10, 18, 29]. Panetta et al. [22] introduced a new technique for contrast enhancement for color images called histogram shifting with alpha rooting.

Fuzzy set theory has the best ability to deal with uncertain areas in digital image processing. Zadeh [31] proposed the theory in 1965; since then, it is widely used in various fields, especially in digital image processing. Hanmandlu et al. [11] introduced a global contrast escalation operator (GINT), which contains three variables, intensification parameter, fuzzifier, and the crossover point, to enhance the color images. In 2009, Nair et al. [20] evaluated the conventional contrast enhancement techniques known as the recent Gray-level ensemble method and ambiguous logic method to find out what is suitable for automatic variation enhancement for ocean satellite images obtained from various sensors. In 2013, a novel fuzzy-based and histogram-based algorithm for enhancing low-intensity color images have been proposed by Raju et al. [25]. The algorithm is fast compared to standard and other new enhancement algorithms based on two important variables: M and K. Here, M is the average intensity value of the given image, which is calculated from the histogram, and K is the contrast escalation variable. Furthermore, current methods for image enhancement are based on transformational domain methods, which may introduce color artifacts and reduce the intensity of input remote sensing images. Sharma et al. [26] introduced a modified approach that can enhance the contrast in digital images efficiently by using a modified blur-based development algorithm to overcome this problem.

Sometimes the membership function of fuzzy sets cannot simultaneously represent evidence of support, opposition, and reluctance. To overcome this problem, Atanassov [2] introduced the higher version of fuzzy sets known as intuitionistic fuzzy sets ($IFSs$). In 1996, Burillo and Bustins [6] defined the distance between intuitionistic fuzzy sets, and they gave a definitive definition of intuitionistic fuzzy entropy and a theorem that characterizes it. Nowadays, several intuitionistic fuzzy c-means clustering algorithm methods have been introduced in [3, 5, 8, 27] by using intuitionistic fuzzy entropy.

Images captured in low light have low brightness, low contrast, relatively high noise, and artifacts. That captured low-light images seriously affects the visual experience, which leads to a significant decline in image quality and leads to difficulty in distinguishing details with the normal eye and tough in carrying out subsequent image processing. The above problem is critical to many vision tasks because computer vision algorithms like image denoising, image fusion, image restoration, image segmentation are primarily designed to accommodate high-quality inputs. So it is tough to process the low light images without enhancing them. The objective of image enhancement is to bring out hidden details and increase the contrast and the quality of an image. In the history of image enhancement, histogram equalization has received the most attention because of its intuitive implementation quality and high efficiency. However, histogram equalization in image enhancement technologies largely does not consider the fuzziness of the image but changes the contrast of the whole image or suppresses the noise, thus, often suppress the noise and weaken the detail of the image. The standard process of this method is to re-map the grayscale of the low illumination image and approximate the resulting histogram uniform distribution. This standard process assumes that the image quality will be the same in all areas, and a unique grayscale mapping will provide a similar improvement over all parts of the image. However, when the distribution of grayscale shifts from one region to another, this assumption is not valid, resulting in an unnatural appearance and fading appearance in images. To overcome this problem, a new fuzzy-based enhancement algorithm is proposed here. The original crisp image is first converted into a fuzzy image. However, when a crisp image is converted to a fuzzy image, its intensity values only change from 0-255 to 0-1. Nevertheless, there will be no change in the image's visualization. The fuzzy image again transformed into an intuitionistic fuzzy image to fix this shortcoming. The intuitionistic fuzzy image resolves the fading appearance of the given low-light image. Finally, one can get an enhanced image after applying the histogram equalization. In this manuscript, we introduce a new image enhancement technique for low light color images. A new feature of the proposed method is the determination of the degree of hesitation in Yager's intuitionistic fuzzy generator system.

This manuscript is arranged as follows. Section 2 outlines the initial stages of the intuitionistic fuzzy set (IFS). Section 3 discusses intuitionistic fuzzy images using Yager's intuitionistic fuzzy generator with histogram equalization. Section 4 demonstrates the experimental results of the proposed work. Finally, the decision is made in Section 5.

2 Preliminaries

2.1 Fuzzy sets (FSs)

Let $S = \{s_1, s_2, ..., s_n\}$ be a non-empty set. Define a fuzzy set B of S as

$$B = \{(s, \mu_B(s))\, |s \in S\} \tag{1}$$

where $\mu_B(s) : S \to [0, 1]$ represent the degree of membership of s in S.

2.2 Concept of intuitionistic fuzzy set

To create both member and non-member functions, Atanasov [2] introduced a new version of the fuzzy sets, called the IFS. An intuitionistic fuzzy set A in S, can be expressed as:

$$A = \{(s, \mu_A(s), \nu_A(s)) \mid s \in S\} \tag{2}$$

where $\mu_A(s) \to [0, 1], \nu_A(s) \to [0, 1]$ are the belongingness and non belongingness degrees of an element s in the set A with the condition $0 \le \mu_A(s) + \nu_A(s) \le 1$ when $\nu_A(s) = 1 - \mu_A(s)$ for every s in set A, then the set A becomes an intuitionistic fuzzy set.

Again Atanasov introduced a degree of hesitation $\pi_A(s)$ for all IFS and it is expressed as

$$\pi_A(s) = 1 - \mu_A(s) - \nu_A(s) \tag{3}$$

clearly $0 \leq \pi_A(s) \leq 1$. Because of the hesitation degree, the membership values are lies between $[\mu_A(s), \mu_A(s) + \pi_A(s)]$

2.3 Construction of intuitionistic fuzzy sets

Let $\Psi(S) : [0, 1] \rightarrow [0, 1]$ be an increasing, and decreasing continuous function and intuitionistic fuzzy generator if

$\Psi(s) \leq (1 - s)$ for all $s \in [0, 1]$ and $\Psi(0) \leq 1$ and $\Psi(1) \leq 0$

For more details one can refer [5, 7, 27] and references therein. In this manuscript, an intuitionistic fuzzy generator is constructed from Yager's generating function [6]. The fuzzy generator function is expressed as

$$\text{Ņ}(\mu_A(s)) = h^{-1}(h(1) - h(\mu_A(s))) \tag{4}$$

where $h(\cdot)$ is an increasing function and $h : [0, 1] \rightarrow [0, 1]$.

Yager's class can be generated by using the following function in the above equation (4) as follows:

$$h(s) = s^{\beta} \tag{5}$$

So, Yager's intuitionistic fuzzy generator can be expressed as:

$\text{Ņ}(s) = (1 - s^{\beta})^{1/\beta}, \beta > 0$ where $\text{Ņ}(1) = 0, \text{Ņ}(0) = 1$. Here $\text{Ņ}(s)$ are calculated by Yager's generating function. Hence, one can obtain the following IFS:
$A^{IFS} = \left\{\left(s, \mu_A(s), (1 - \mu_A(s)^{\beta})^{1/\beta}\right) | s \in S\right\}$ and the hesitation degree is:

$$\pi_A(s) = 1 - \mu_A(s) - (1 - \mu_A(s)^{\beta})^{1/\beta} \tag{6}$$

Also

$$\mu_A(s) = 1 - \pi_A(s) - (1 - \mu_A(s)^{\beta})^{1/\beta} \tag{7}$$

Remark 1 If $\mu_A(s) + \nu_A(s) = 1$ then $\pi_A(s) = 0$. Suppose if $\mu_A(s) + \nu_A(s) < 1$ then the hesitation value $\pi_A(s) > 0$. Intuitionistic fuzzy generator has been utilized to obtain the value of $\pi_A(s) > 0$.

2.4 Histogram equalization

Increasing the contrast of a low-contrast image involves distributing the pixel values of an image more evenly across the range of allowable values. An alternate approach is known as histogram equalization, which is entirely automatic, extremely simple to implement, and parameter-free.

Histogram equalization first converts the probability density function (captured by the normalized histogram) to a cumulative distribution function (CDF) by computing the running sum of the histogram:

$$\bar{c}[\rho] = \sum_{k=0}^{\rho} \bar{h}[k], \rho = 0, 1, ..., 255$$

where ρ are gray levels of the histogram. $\bar{c}$ is the running sum of the histogram. $\bar{h}$ is a floating-point value.

The running sum can be computed efficiently by initializing the first element of the array according to $\bar{c}[0] = \bar{h}[0]$ and then updating $\bar{c}[\rho] = \bar{c}[\rho - 1] + \bar{h}[\rho]$ for each gray level ρ. Once the CDF has been computed, a pixel with gray level ρ is simply transformed to $\rho' = Round(255 \cdot \bar{c}[\rho])$. Note that since the integral of a probability density function (PDF) is always 1, the CDF always evaluates to 1 at the largest value, and thus $\bar{c}[255] = 1$. As a result, the output ρ' is in the range from 0 to 255 as desired.

HE stretches the dynamic range of an image and enhances image contrast. The same argument can also be applied to color images by separating the RGB channels and applying the algorithm individually. However, it also tries to change the brightness of an image with an unnatural contrast magnification. For further details, one can refer [1].

3 Proposed fuzzy based method

3.1 Fuzzy image (*FI*)

An image I of $M \times N$ dimension is considered as an array of fuzzy singletons. An intuitionistic fuzzy set A in S, whose support is defined as $supp(A) = \{s \in S \mid \mu_A(s) > 0\}$ for further information, see [21]. The source image I is fuzzified by using the following expression [4]

$$\mu_A(I(i,j)) = \frac{\xi_{ij} - \xi_{min}}{\xi_{max} - \xi_{min}}, 1 \le i \le M, 1 \le j \le N. \tag{8}$$

where ξ_{ij} is the intensity value of $(i, j)th$ pixel. ξ_{max} and ξ_{min} denote the maximum and minimum intensity value of the image I, respectively.

3.2 Intuitionistic fuzzy image (*IFI*)

Using Yager's intuitionistic fuzzy generator, $\pi_A(s)$ is constructed using equation (6). From (6) and (8), we can construct an Intuitionistic fuzzy image as

$$IFI = \frac{\xi_{ij} - \xi_{min}}{\xi_{max} - \xi_{min}} + \pi_A(s) \tag{9}$$

where $\pi_A(s) = 1 - \mu_A(s) - (1 - \mu_A(s)^{\beta})^{1/\beta}, \beta > 0$

$$i.e \qquad IFI = \mu_A(I(i,j)) + \pi_A(s) \tag{10}$$

for all $i = 1, 2, ..., m$ and $j = 1, 2, ..., n$

3.3 Estimation of β

β value for equation (6) is calculated using entropy value described in section 4.1.1 as shown in Fig. 2. First, the β values are calculated from 0.1 to 1, each of which is calculated by the entropy value. The amount of β that gives the most entropy to them that is, the maximum entropy value, is taken as the selected value. These β values are different for different images.

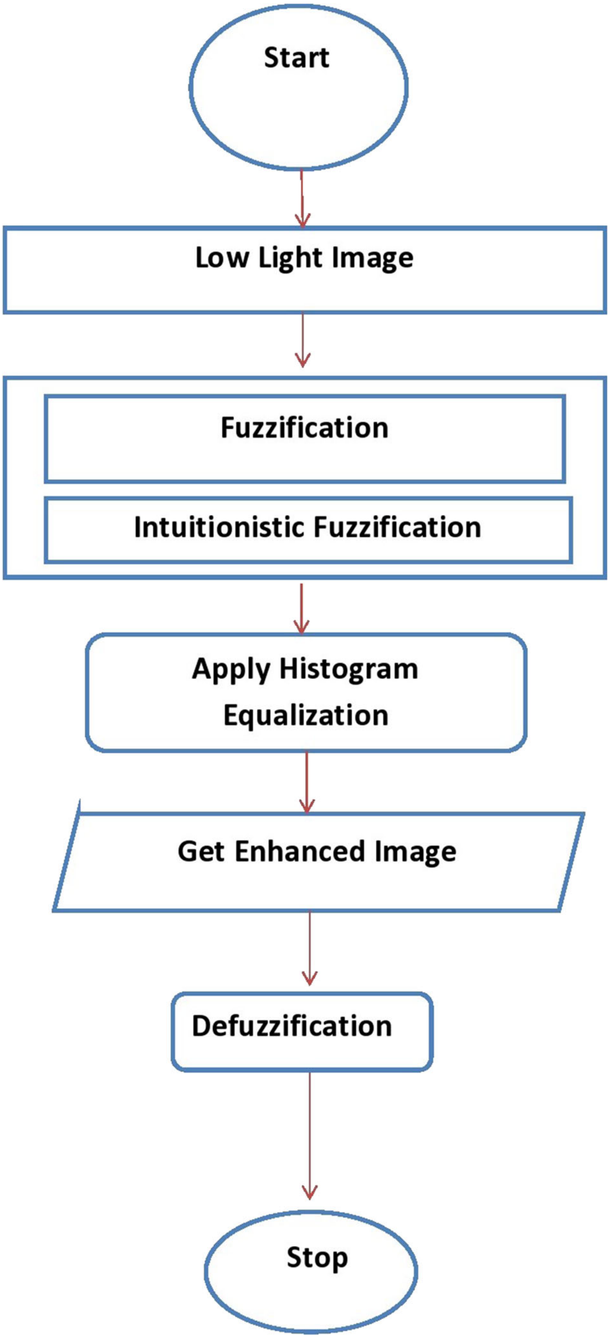

Fig. 1 Flow chart of the proposed algorithm

3.4 Defuzzification

Defuzzification is the process of representing a fuzzy set with a crisp number. The same argument is suitable for fuzzified images. For further information on defuzzification, refer [4] and for defuzzification of intuitionistic fuzzy sets refer [15, 24]. The crisp image derived from the fuzzified image becomes the following expression,

$$\xi_{ij} = FI(\xi_{max} - \xi_{min}) + \xi_{min} \tag{11}$$

Hence to defuzzify the intuitionistic fuzzy image, the expression becomes

$$\xi_{ij} = (IFI)(\xi_{max} - \xi_{min}) + (\xi_{min}) - \pi_A(s)(\xi_{max} - \xi_{min}). \tag{12}$$

3.5 Proposed algorithm

Step 1: Take a color image I which is taken in low light of size n $(= M \times N)$.

Step 2: Find fuzzy image $\mu(I(i, j))$ for the given original image I by using the expression $\mu_A(I(i, j)) = \frac{\xi_{ij} - \xi_{min}}{\xi_{max} - \xi_{min}}$. where ξ_{ij} is the intensity value of $(i, j)th$ pixel. ξ_{max} and ξ_{min} denote the maximum and minimum intensity value of the image I, respectively.

Step 3: Calculate β value as described in section 3.3 to find non-membership degree $(1 - \mu_A(s)^\beta)^{1/\beta}$ for $\mu_A(I(i, j))$ by using Yager's generating function as discribed in section 2.3.

Step 4: Find hesitation degree for $\mu_A(I(i, j))$ by using the expression $\pi_A(s) = 1 - \mu_A(s) - (1 - \mu_A(s)^\beta)^{1/\beta}$.

Step 5: Construct intuitionistic fuzzy image $IFI(i, j)$ from $\mu_A(I(i, j))$ by using the expression $IFI = \mu_A(I(i, j)) + \pi_A(s)$.

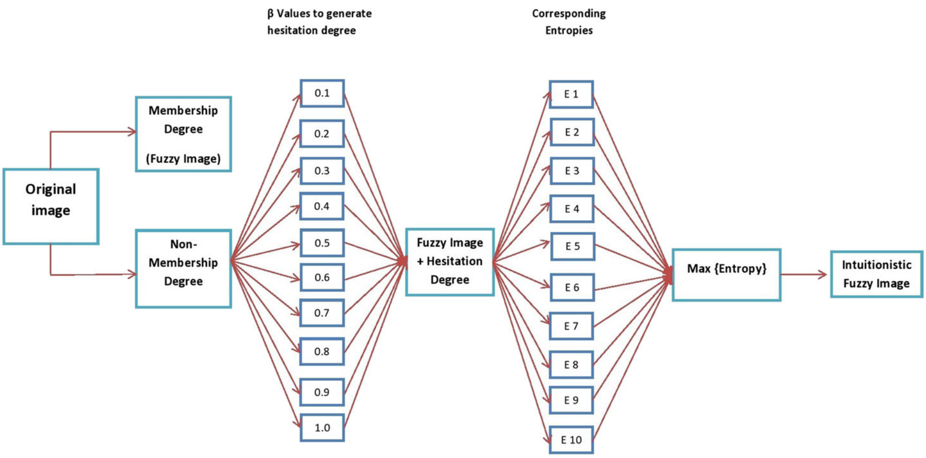

Fig. 2 Generation of intuitionistic fuzzy image

Step 6: Apply histogram equalization as described in section 2.4 for IFI to get the enhanced intuitionistic fuzzy image IFI_1.

Step 7: Finally defuzzy the enhanced image by mapping an intuitionistic fuzzy image to a crisp image $i.e$ $IFI_1 \rightarrow I$ to get the proposed enhanced image by using the expression $\xi_{ij} = (((IFI)(\xi_{max} - \xi_{min})) + \xi_{min}) - \pi_A(s)(\xi_{max} - \xi_{min})$.

4 Experimental result and analysis

An experiment is performed under the following environment. The machine CPU is an Intel (R) Core (TM) i7-9700 processor that works with a fundamental frequency of 3.00GHz

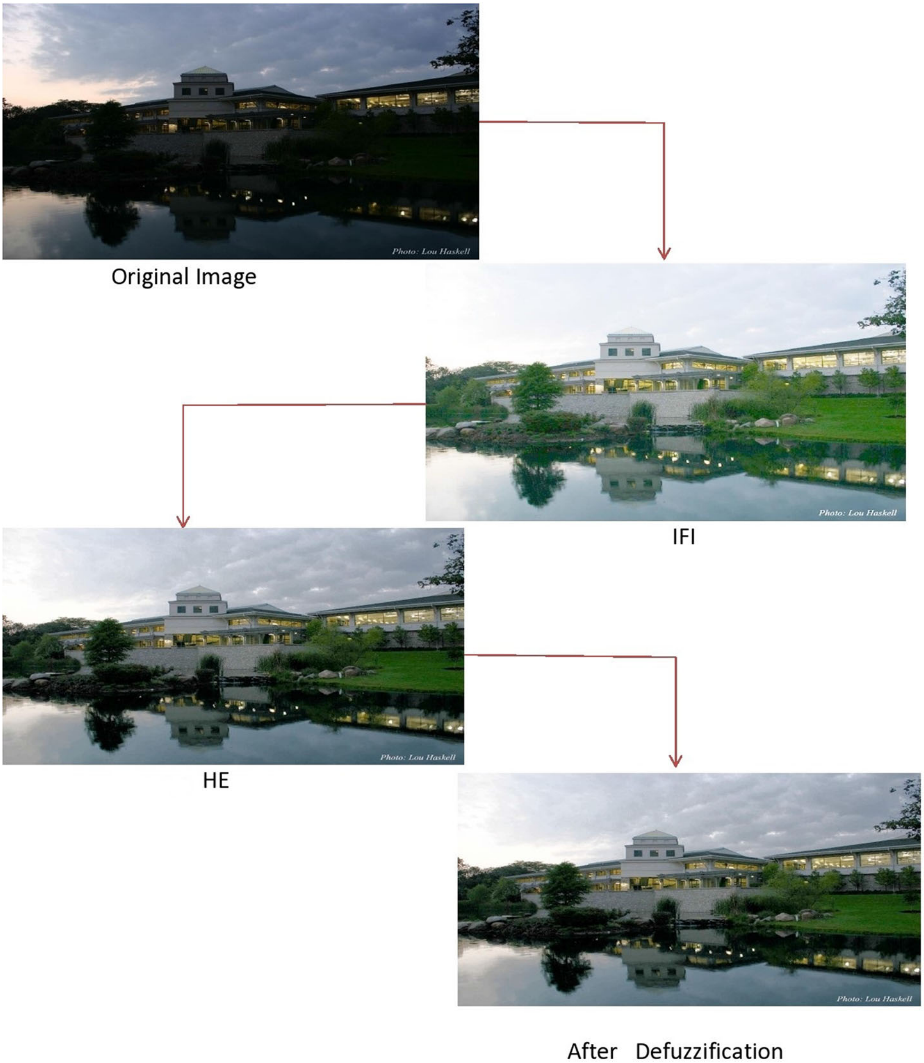

Fig. 3 Schematic diagram of the proposed method

Quad-Core technology. The hard disk is 2TB, and RAM is 16 GB installed with the Windows 10 Pro operating system's ultimate version. The experimental setup is run over the MATLAB R2018b by using the image processing toolbox.

Experimental tests are executed on 150 images which are taken from low light paired dataset (LOL) ("https://daooshee.github.io/BMVC2018website/"). The flow chart of the proposed algorithm is given in Fig. 1. The generation of the IFI is given in Fig. 2. The schematic diagram of the proposed method is given in Fig. 3. Figure 4 illustrates the original images and their corresponding enhanced images with their corresponding β values. In Fig. 5, the first column stands for original images. The second column stands for low light images tested by the histogram equalization method. Third, fourth, fifth, sixth, seventh, and finally eighth are tested by CLAHE, HSA, DCT, BPDFHE, IFI, and the proposed method. One can visualize that the proposed method gives better results than other existing literature.

4.1 Performance analysis

The quality of an image can be objectively measured using mathematical functions. There are many mathematical functions or measures to evaluate the quality of improved images, such as entropy and the structural similarity index, Etc. The method proposed in each performance analysis yields good results.

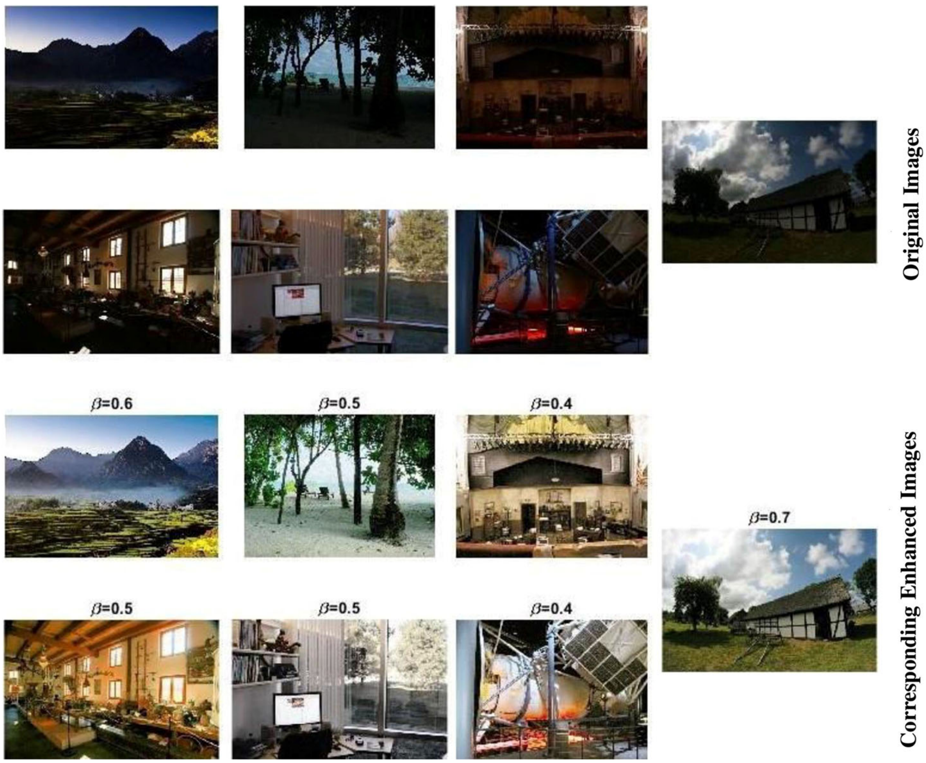

Fig. 4 Original and enhanced images with their corresponding β values

4.1.1 Entropy

Here Shannon entropy with maximum information is used to measure the quality of an image. Images with high entropy have the best quality of the image. Expression of entropy value is

$$E = -\sum_{i=1}^{m}\sum_{j=1}^{n} P(i, j) log P(i, j) \tag{13}$$

Where i and j represent two different gray-levels of the pictures, P refers to the number of co-appearance of gray-levels i and j.

In Table 1, The entropy values for the enhanced images have been discussed in Table 1. Moreover, researchers well know that images with maximum entropy values have the best quality images; for instance, see [19]. The table values that the proposed method gives good quality in images. The histogram output of entropy values for the low light images is given in Fig. 6.

4.1.2 Structural similarity index (*SSIM*)

The structural similarity index measure between images o and e is followed by

$$SSIM(o, e) = \frac{(2\bar{\mu}_o\bar{\mu}_e + c_1)(2\sigma_{oe} + c_2)}{(\bar{\mu}_o^2 + \bar{\mu}_e^2 + c_1)(\sigma_o^2 + \sigma_e^2 + c_2)} \tag{14}$$

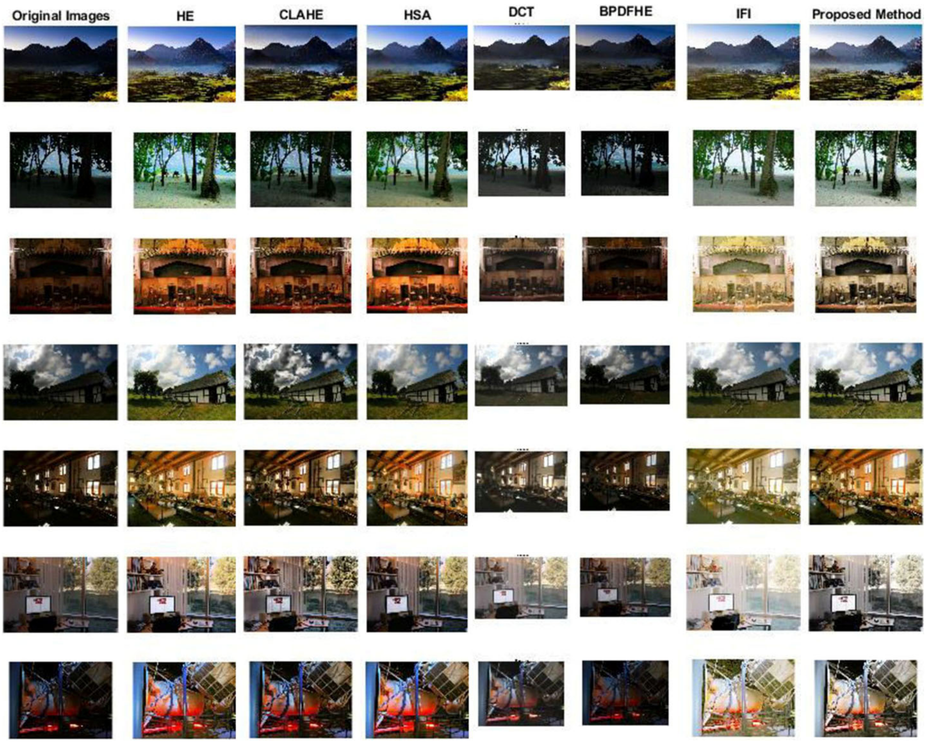

Fig. 5 The enhanced output of the low light images comparing with various methods

Table 1 Performance measures using entropy values for images in Fig. 5

S.No	Original Image	HE	CLAHE	HSA	DCT	BPDFHE	IFI	Proposed Method
1	6.7788	7.7688	7.3237	7.4441	5.9907	6.0589	7.7923	**7.8814**
2	5.8645	7.7727	6.9559	7.5346	5.5737	5.2861	7.6631	**7.8896**
3	6.1405	7.6190	7.1635	7.3837	5.5899	5.1726	7.7566	**7.9280**
4	7.1100	7.8978	7.5463	7.5258	5.7096	5.3446	7.7906	**7.9391**
5	6.2592	7.6774	7.1431	7.4802	5.3419	4.9642	**7.7895**	7.6673
6	7.2201	7.8910	7.6725	7.5686	5.8405	5.4514	7.2428	**7.9475**
7	6.1372	7.7255	7.2180	7.4559	5.5933	5.1131	7.8379	**7.9221**

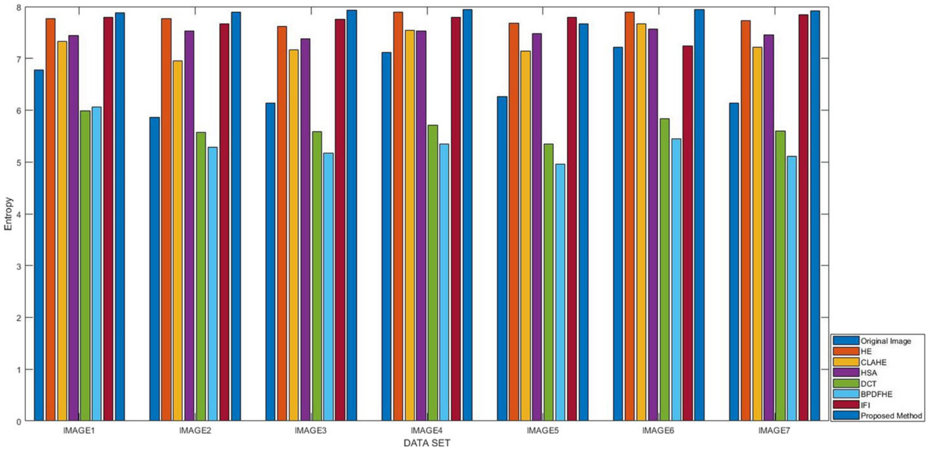

Fig. 6 Histogram output of entropy values for Fig. 5

Table 2 Performance measures using SSIM values for images in Fig. 5

S.No	HE	CLAHE	HSA	DCT	BPDFHE	IFI	Proposed Method
1	0.4508	0.6576	0.5390	0.7526	0.8846	0.4243	0.4196
2	0.2345	0.5771	0.3377	0.6617	0.9093	0.2214	0.2072
3	0.3068	0.5335	0.3617	0.7200	0.9587	0.1788	0.2770
4	0.4668	0.6125	0.6593	0.7722	0.9811	0.5943	0.4713
5	0.3113	0.6174	0.3868	0.7276	0.9192	0.2591	0.3113
6	0.7457	0.7013	0.8615	0.8489	0.9689	0.5316	0.6703
7	0.2785	0.5166	0.3759	0.7153	0.9432	0.2041	0.2712

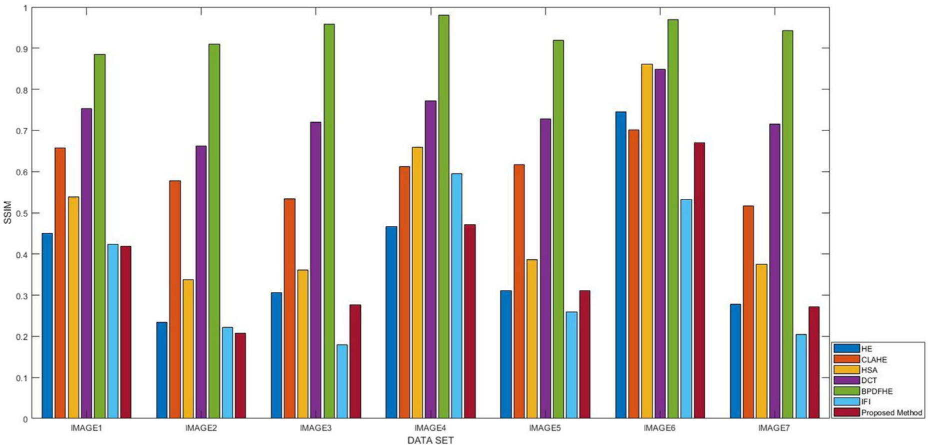

Fig. 7 Histogram output of SSIM values for Fig. 5

where c_1 and c_2 are positive constants. o and e represent original and enhanced images. $\bar{\mu}_o$ and $\bar{\mu}_e$ depict the mean intensities of o and e respectively. σ_{oe} represents the covariance of o and e. σ_o^2 and σ_e^2 are the variance of o and e respectively.

In Table 2, the SSIM values [15] for the enhanced images are discussed. If the two images have the same quality, the SSIM values will be 1; otherwise, 0. Figure 7 displays the histogram output for SSIM values between the low light images and the enhanced images. We can easily identify that the original images and the proposed enhanced images are neither close to 1 nor close to 0, which proves that the enhanced image does not lose its originality.

5 Conclusion and future direction

This study proposes an efficient intuitionistic fuzzy-based color image enhancement method. During the experimental section, the proposed method has been compared with other existing methods such as HE, CLAHE, HSA, DCT, BPDFHE, and IFI. The comparative analysis has been made by entropy and SSIM; it was decided that the proposed method provides best in most cases based on quantitative and qualitative improvement. The proposed method is more suitable for low light enhancement for color images than other existing methods. In the future, this proposed fuzzy set ideas will be extended to analyse 2D images to 3D images. The proposed method will be utilized to study the video enhancement techniques.

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