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Enhancement of the Low-Light Digital Image through the Fuzzy Local Binary Pattern Technique

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Abstract:- This paper proposes a new technique that improves a low-light image's contrast more effectively. First, the image has to be normalized with the help of the fuzzy normalization technique, to the fuzzy the image then the intensity of each pixel in the image is adjusted on the 3×3 neighborhood pixels according to a threshold value by using two fuzzy membership functions. Finally, the image is defuzzified to get an enhanced image. The proposed method is compared with the already existing enhancement methods, like histogram equalization (HE), contrast-limited adaptive histogram equalization (CLAHE), intuitionistic fuzzy sets (IFS), and interval-valued intuitionistic fuzzy sets (IVIFS). The resultant images are evaluated by the similarity measures, namely, Entropy, structural similarity index (SSIM), Pearson correlation coefficient (PCC), and feature similarity index measure (FSIM). The experimental results show that the proposed method gives a better enhancement when compared to other existing methods.

Keywords*:* Fuzzy set, Contrast enhancement, local binary pattern, linear contrast stretching operator, Entropy.

1. Introduction

Digital image processing is an algorithm and mathematical model to process and analyze digital images. The goal of digital image processing is to enhance the quality of images and extract meaningful information from images. A digital image is a finite number of elements, each of the elements has a particular value at a particular location and these elements are referred to as picture elements, image elements, and also pixels. There are many techniques used in image processing namely, image acquisition [1], image enhancement [2], image segmentation [3], morphological processing [4], object detection [5] and recognition, image restoration, and so on.

The low light enhancement provides numerous benefits across various applications, by making objects and features more discernible in low-light conditions [6]. This is crucial for security and surveillance systems while identifying objects. In medical imaging, enhanced low-light images, such as X-rays and MRIs lead to more accurate diagnostics [7]. Photography and videography also need improved image quality and reduced noise in low-light settings. Astronomical images such as, whereas remote sensing applications, like environmental monitoring and military reconnaissance, see improved imagery [8]. Forensic analysis relies on enhanced low-light images to uncover critical details during investigations [9].

Local Binary Pattern (LBP) is a visual descriptor used for texture classification in image processing. In this method, initially, the image is converted from a color image to a grayscale by analyzing a local neighborhood, typically a 3×3 window, around each pixel. Each neighboring pixel's intensity is compared to the center pixel's intensity. If the neighboring pixel's value is greater than or equal to the center pixel's value, it is assigned a value of 1; otherwise, it is assigned a value of 0 [10]. These binary values are concatenated to form a binary number, which is then converted to a decimal number representing the LBP value for the center pixel. This process is repeated for every pixel in the image, resulting in an LBP image.

Implementing LBP typically involves pre-processing steps like noise reduction and intensity normalization to improve performance. Histogram normalization and dimensionality reduction techniques like Principal Component Analysis can be applied to the resulting LBP histogram for further optimization. LBP is widely used in texture classification, face recognition, motion analysis, and medical image analysis. LBP is effective for various texture analysis applications. Rotation sensitivity, Rotation-Invariant LBP considers the minimum binary number obtained through circular bitwise shifts.

In texture classification, LBP distinguishes between different textures in industrial inspection [11], biomedical image analysis [12], and remote sensing [13]. In face recognition, LBP describes local facial textures, capturing fine details crucial for distinguishing between faces, often in combination with other descriptors and classifiers. For motion analysis, LBP can be extended to temporal data in videos, such as LBP from three orthogonal planes, capturing spatial and temporal texture changes [14].

In medical image analysis, LBP analyzes texture in MRI [15], CT [16], and ultrasound scans [17] that aid in diagnosis [17]. LBP is popular due to its simplicity and computational efficiency, making it robust for various texture analysis applications. Variations like uniform LBP, and multi-scale LBP enhance its capabilities by addressing rotation sensitivity, focusing on significant patterns, and capturing textures at multiple scales.

Uniform LBP focuses on patterns with at most two bitwise transitions, which are more significant in texture representation, reducing the dimensionality of the histogram. Multi-scale LBP captures texture information at multiple scales using different radii for LBP computation. Extended LBP (ELBP) involves larger neighborhoods to capture more spatial information [18], while three-dimensional LBP (3D LBP) extends the concept to three dimensions for volumetric data analysis [19].

Fuzzy enhancement methods can be adapted to different types of images and specific enhancement needs [20]. Fuzzy enhancement in image processing refers to techniques that utilize fuzzy principles to improve the quality or interpretability of images. These methods aim to handle the inherent uncertainty and imprecision in image data.

In the context of image processing, normal enhancement, and fuzzy enhancements refer to different techniques used to improve the quality or visibility of images. The fuzzy approach can produce smoother transitions and avoid over-enhancement. Fuzzy enhancement techniques are typically more adaptive and can provide better results in images with complex structures or noise, as they are designed to manage uncertainty and imprecision in image data.

Fuzzy enhancement techniques have been used to improve the quality of MRI, CT, ultrasound images, and more medical fields that have poor illumination. Enhanced images help radiologists detect abnormalities more accurately. Remote sensing, satellite, and aerial images often suffer from low contrast and noise [21].

Fuzzy enhancement improves the visibility of geographical features and environmental changes [22]. In recent days, cameras and photo-editing software have used fuzzy enhancement to improve image quality, particularly in low-light conditions. Security and surveillance enhancing video and image quality is needed in security cameras to identify objects and individuals more clearly [23]. Document and text image processing enhances scanned documents or text images for better readability and optical character recognition performance.

In this paper, a progressive method is introduced for enhancing the low-light image based on the fuzzy local binary pattern technique. The enhancement process commences with the normalization of the original image, establishing a consistent baseline for subsequent improvements. An enhancement and a linear contrast stretching membership operators are applied and two distinct output images are generated which inherit various aspects of the image data. These two images are then fused to create a single enhanced output, which is subsequently defuzzified to improve clarity and preserve essential tails. This comprehensive approach significantly enhances the visual qualityof low-light images.

The structure of this paper is as follows. Section 2 outlines the fundamental concepts of fuzzy sets (FSs) and HE. Section 3 details the proposed method's contrast enhancement algorithm. Section 4 provides an overviewof the evaluation metrics, and the conclusions are summarized in Section 5.

2. Preliminary ideas

This section outlines the basics of various methods of contrast enhancementin image processing.

2.1 Fuzzy set

In 1965, Lotfi A. Zadeh introduced the theory of fuzzy sets [24]. Let $X = x_1, x_2, \dots x_n$ be a non-empty finite set. A fuzzy set F of X can be defined as $F = \{< x, \mu_F(x) > | x \in X\}$, where $\mu_F(x): X \to [0,1]$ represents the membership degree x in X and the non-membership degree is $1 - \mu_F(x)$.

2.2 Contrast enhancement

Contrast enhancement techniques are used fundamentally in image processing, focusing on improving the visibility of details by adjusting contrast, brightness, and overall visual characteristics. Common methods include histogram equalization, which redistributes the intensity values of an image to create a more uniform histogram and enhance overall contrast.

Contrast stretching expands the range of intensity levels, effectively enhancing differences and making features more distinguishable. Brightness adjustment modifies the overall lightness or darkness of the image, improving visibility, and also sharpening emphasizes edges and fine details, making the image appear clearer and enhancing perceived contrast.

2.3 Histogram equalization (HE)

Histogram equalization is a technique in image processing that enhances the contrast of an image by redistributing the intensity values across the entire range of possible values. This process is particularly useful for images with poor contrast [25]. It improves the overall visibility of an image, making hidden details more apparent.

In some cases, this technique might over-enhance the image, resulting in unnatural or visually unpleasant results, types of histograms such as adaptive histogram equalization (AHE), and contrast limited adaptive histogram equalization (CLAHE) [26, 27].

2.4 Fuzzy Contrast Enhancement

In fuzzy image processing, each pixel in an image is assigned a membership value that indicates the degree to which the pixel belongs to a specific set, such as "dark", "gray" or "bright". Sets and their degrees of membership provide a more detailed and flexible representation of pixel values compared to crisp classifications. Commonly used membership functions include triangular, trapezoidal, Gaussian, and bell-shaped functions. Fuzzy enhancement techniques are used to improve image quality, which deals with reasoning that is approximate rather than fixed and can handle the uncertainty and imprecision in image data more effectively.

The choice of function affects the fuzziness and sensitivity of the enhancement process. Common fuzzy enhancement methods include namely, the fuzzy contrast enhancement method maps the intensity levels of an image to a fuzzy plane and adjusts the membership functions to enhance contrast. The result is an image with better visibility of details in both bright and dark areas. Fuzzy histogram equalization combines traditional histogram equalization with fuzzy technique to achieve better contrast enhancement.

3. Contrast enhancement algorithm of the proposed method

The steps of the proposed algorithm are as follows. The flowchart of the proposed mechanism is given in Figure 1.

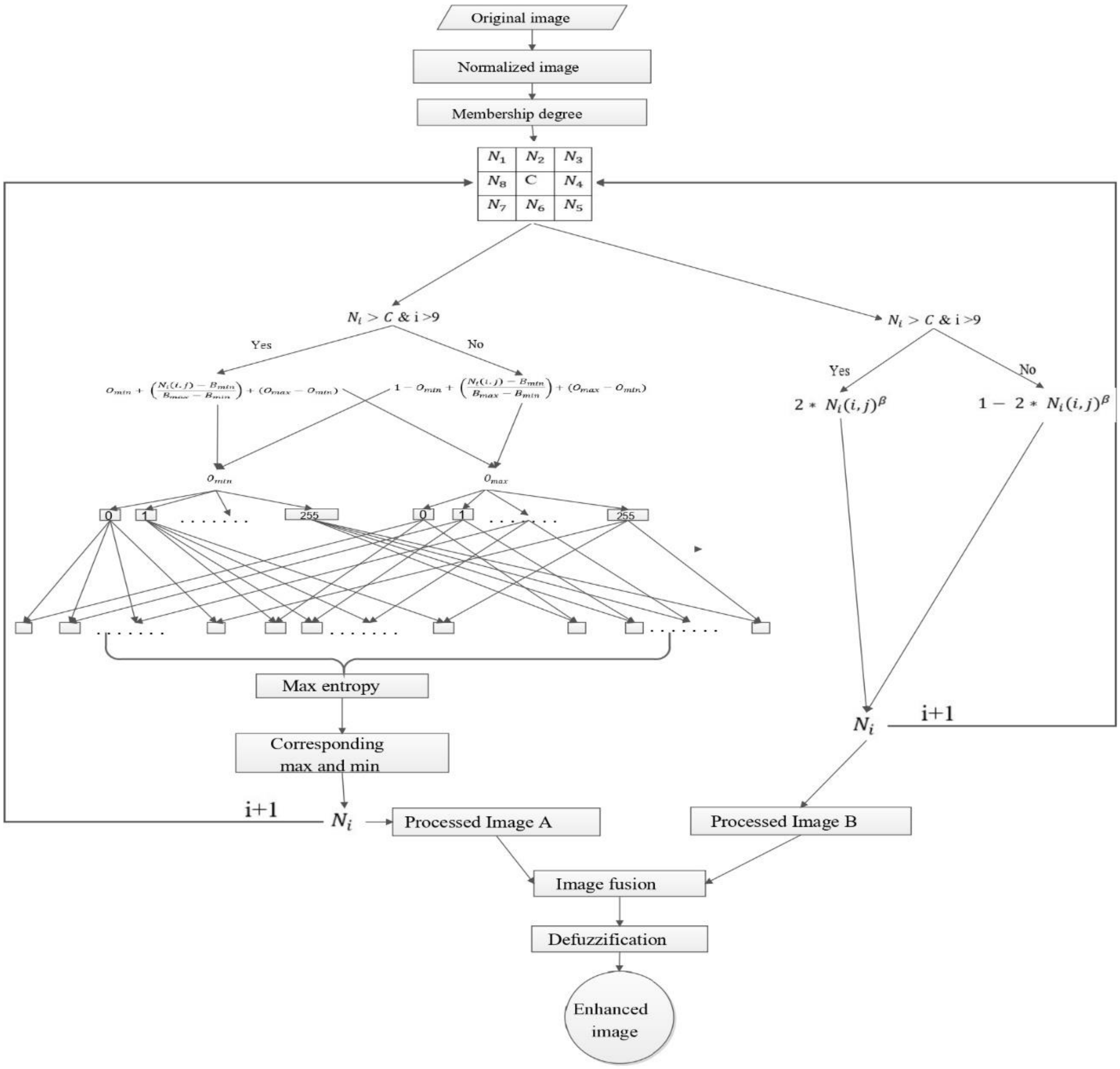

Figure 1: Flowchart of the Proposed Method

Step 1: Consider an input color image A with dimensions m×n, Figure 2.

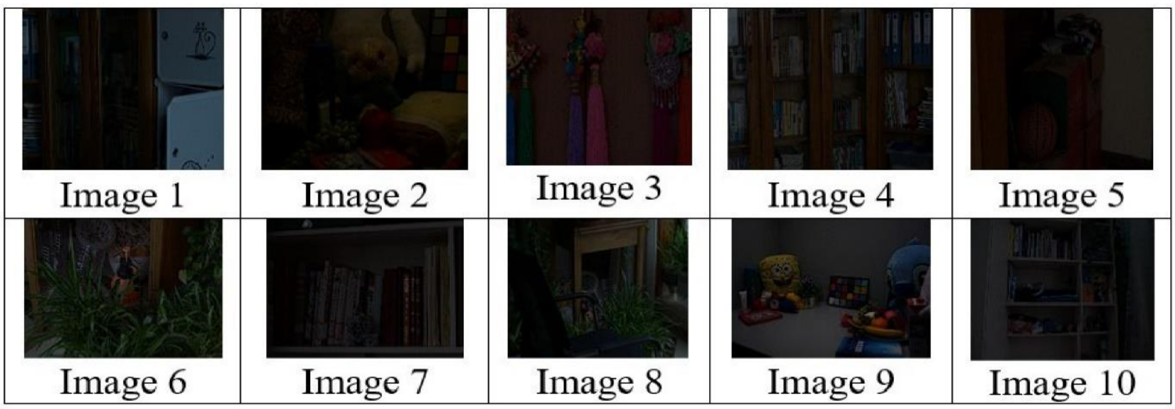

Figure 2: Low-light images

Figure 3: Ground truth images of the original images

Step 2: The original image A is converted into the fuzzy image F_A by using the following normalization function

$$\mu_A(i,j) = \frac{(A(i,j) - A_{min})}{(A_{max} - A_{min})}$$

where $\mu_A(i,j)$ represents a membership of the pixel value at the $(i,j)^{th}$ position and A_{min} and A_{max} are the minimum and maximum intensity values of image A, respectively. Non-membership degree of $A(i,j) = 1 - \mu_A(i,j)$.

Step 3: Consider a 3×3 matrix from the image A as follows:

N_1	N_2	N_3
N_8	C	N_4
N_7	N_6	N_5

where C is the center pixel value. The new contrast-enhanced value of pixel N_i of the 3×3 block is computed as

$$New\ N_i = \begin{cases} O_{min} + \left(\frac{N_i(i,j) - B_{min}}{B_{max} - B_{min}}\right) + (O_{max} - O_{min}), & \text{if } N_i \geq C \\ 1 - O_{min} + \left(\frac{N_i(i,j) - B_{min}}{B_{max} - B_{min}}\right) + (O_{max} - O_{min}), & \text{if } N_i < C \end{cases}$$

where N_i is the neighbourhood pixel, B_{max} and B_{min} are the maximum and minimum intensity values in the 3×3 block, $O_{min} \in [0, 255]$, and $O_{max} \in [0, 255]$. As a result, by changing O_{min} and O_{max} values, many enhanced image windows are obtained for each 3×3 block. The image block of maximum entropy is picked up as the final enhanced block. This operation is performed by sliding the 3×3 window over the image and the image is named as F_{Enh1}.

Step 4: Again consider the same 3×3 matrix as in step 2 from the image F_A as follows:

N_1	N_2	N_3
N_8	C	N_4
N_7	N_6	N_5

where C is the center pixel value and N_i represents the neighborhood pixel values. The new contrast-enhanced pixel value of pixel N_i of the 3×3 block is computed as

$$\text{New } Z_i = \begin{cases} 2^* N_i(i,j)^{\beta}, & \text{if } N_i \geq C \\ 1 - 2^* N_i(i,j)^{\beta}, & \text{if } N_i < C \end{cases}$$

where β is the contrast parameter. If the $\beta \geq 1$, affecting the brighter parts of the image, pulling them towards darkness. If the $\beta \leq 0.7$, as pixel intensities are stretched toward higher values, brightening even darker regions. This procedure is repeated for all the image block and enhanced image is named as F_{Enh2}.

Step 5: F_{Enh1} and F_{Enh2} are then combined through fusion to create the F_{Enh} enhanced final image.

Step 6: Finally, the enhanced image Enh is defuzzified by using the formula.

$$Enh(i,j) = F_{Enh}(i,j)(A_{max} - A_{min}) + A_{min}$$

4. Results and Discussion

This section deals with the performance analysis of the proposed method and the resultant analysis with the help of MATLAB (R 2017a) (64-bit) on a system running with Windows 11 pre (64-bit).

In the experimental section, the low light image dataset is obtained from the LOL dataset "https://daooshee.github.io/BMVC2018website/", 160 images are experimented. The results for only 10 images are presented in this paper. The proposed method is compared with the other existing methods namely, contrast-limited adaptive histogram equalization (CLAHE) [28], intuitionistic fuzzy set (IFS) [6], and interval-valued intuitionistic fuzzy sets (IVIFS) [6] these results are shown in Figure 4.

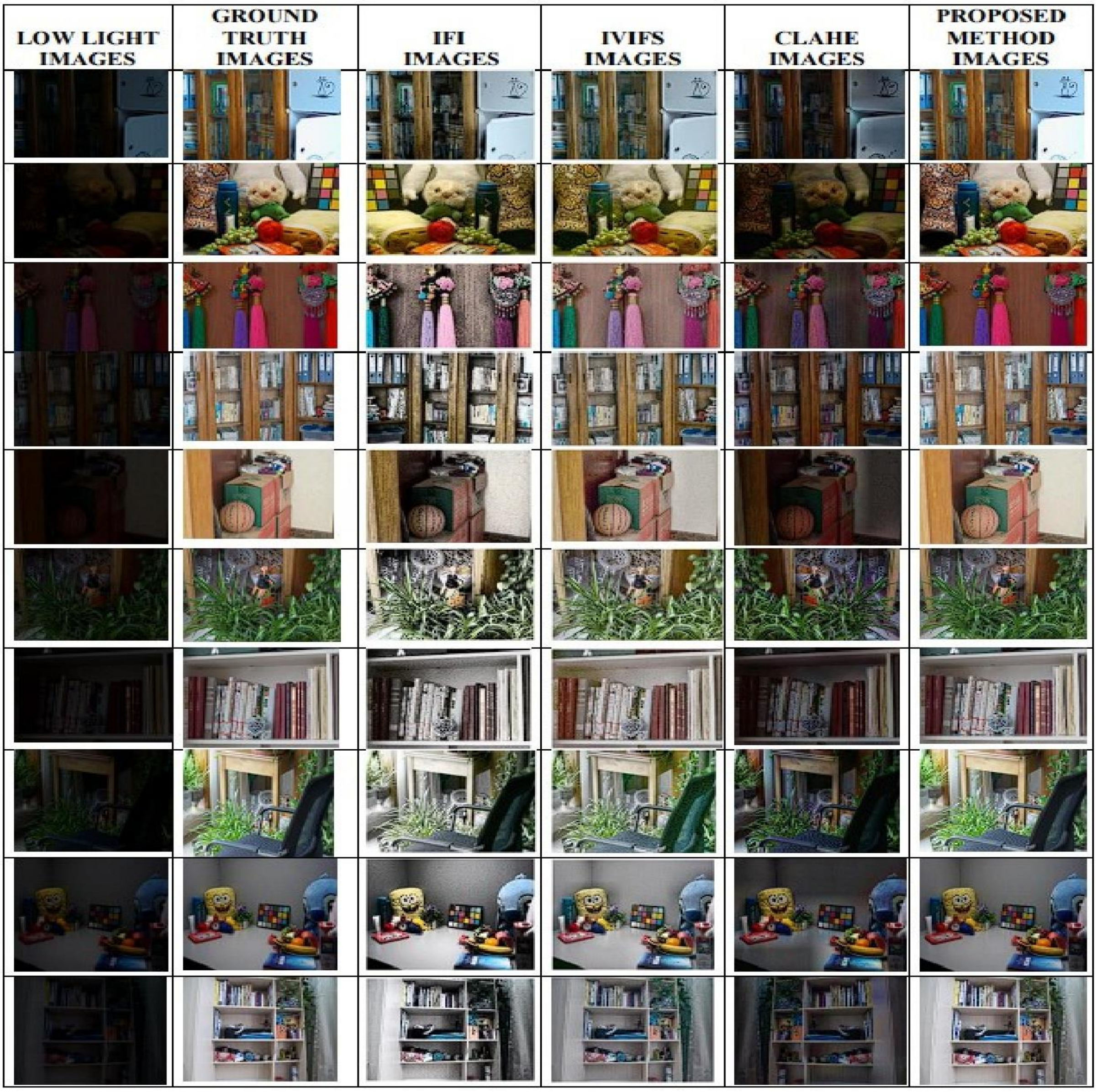

Figure 4: The improved low-light images are compared to different enhancing methods

4.1 Evaluation metrics

The quality of an image can be objectively assessed through various mathematical functions. A wide array of metrics is available to evaluate the enhancement of images, including entropy, the structural similarity index (SSIM), and others. The proposed method of this paper undergoes thoroughperformance analysis, yielding promising results that highlight their efficacy in enhancing image quality.

4.1.1 Entropy

Entropy measures the amount of information or randomness in an image[30]. The entropy of an image is defined using the probability distribution ofthe pixel values. For an image with a grayscale level i having a probability $q(i)$, the entropy can be calculated as

$$Entropy = \sum_{i=0}^{L-1} q(i) \log_2 q(i)$$

where $q(i)$is the probability of occurrence of the pixel intensity i, L is the number of possible intensity levels (e.g., 256 for an 8-bit grayscale image).

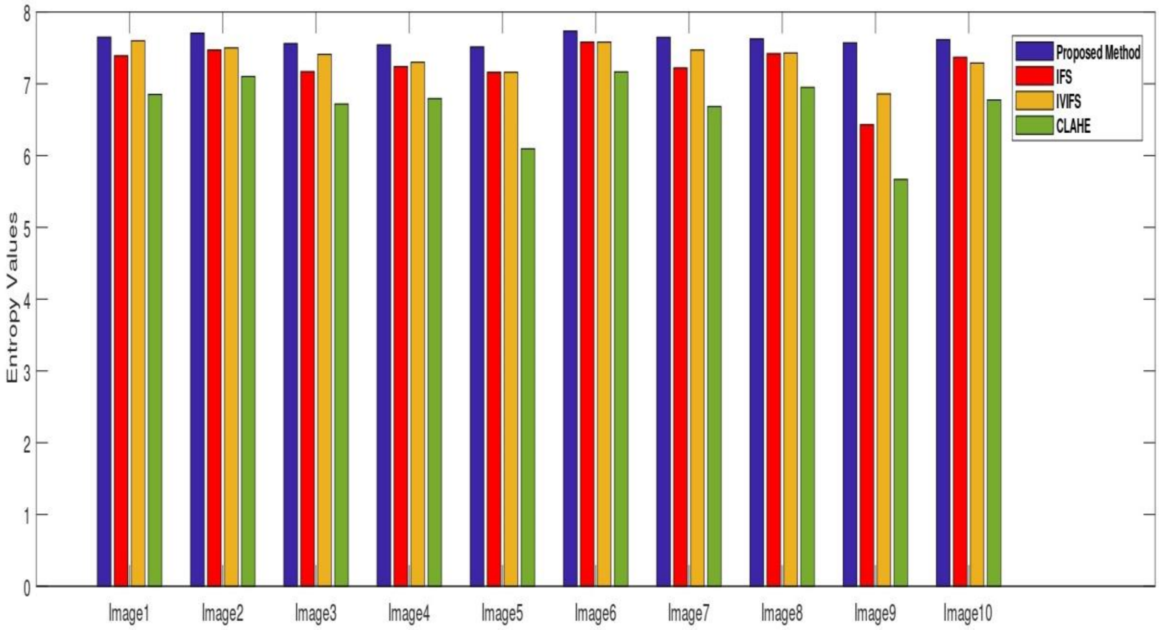

Figure 5: Evaluating enhanced image quality with entropy values

4.1.2 Structural Similarity Index (SSIM)

SSIM is a metric used to measure the similarity between two images. SSIM is a valuable measure of image enhancement SSIM values range from -1 to 1, where 1 indicates perfect symmetric [31]. A high SSIM value suggests that the enhancement process has successfully retained the image's structural details, contrast, and brightness, producing a result that is visually similar and of higher quality. The SSIM index between two images G and E is calculated as

$$SSIM(G,E) = \frac{((2\delta_G\delta_E + C_1)(2\alpha_{GE} + C_2))}{(\delta_G^2 + \delta_E^2 + C_1)(\alpha_G^2 + \alpha_E^2 + C_2)}$$

where G and E are the low-light image and enhanced image. δ_G and δ_E are the mean intensities of images G and E, respectively. α_G^2 and α_E^2 are the variances of G and E, $\alpha_{GE}$is the covariance between G and E.

C_1 and C_2 are small positive constants.

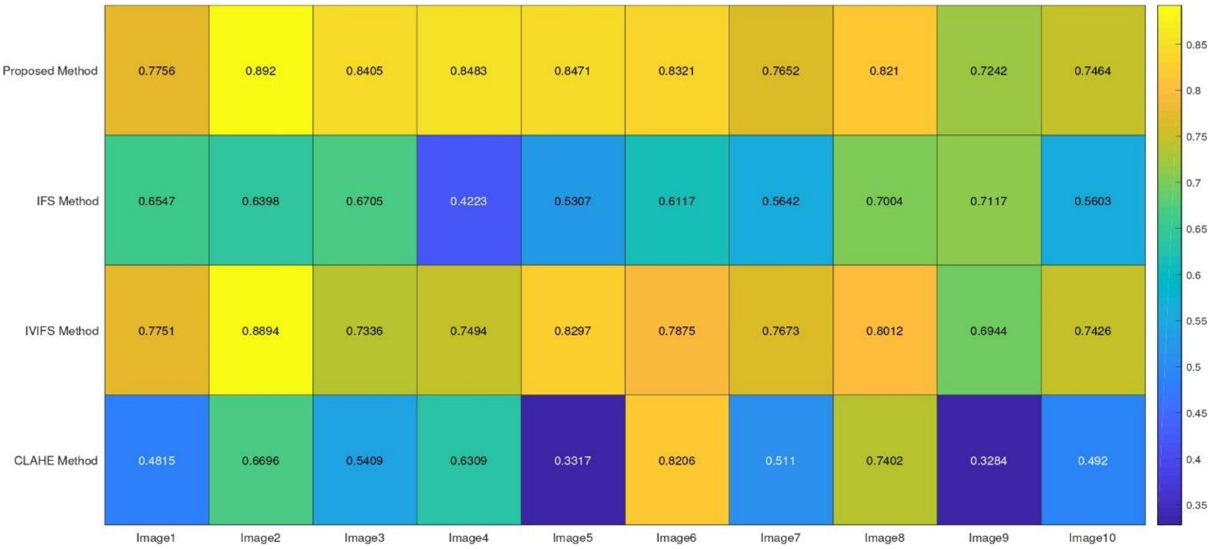

Figure 6: Evaluating enhanced image quality with SSIM values using heat map

4.1.3 Pearson Correlation Coefficient (PCC)

Pearson Correlation Coefficient is a measure of the linear correlation between two variables. It is used to assess the similarity between the original and enhanced images [32]. The PCC between two images can be calculated as

$$PCC(G,E) = \frac{\sum_{i=1}^{n}(G(i)-\bar{G})(E(i)-\bar{E})}{\sqrt{\sum_{i=1}^{n}(G(i)-\bar{G})^2}\sqrt{\sum_{i=1}^{n}(E(i)-\bar{E})^2}}$$

G and E are the pixel values of the low-light and enhanced images at position (i), respectively. $\bar{G}$ and $\bar{E}$ are the mean pixel values of the low-light and enhanced images, respectively. In image enhancement, PCC helps evaluate how well the enhanced image retains the characteristics of the original image. A higher PCC indicates that the enhanced image closely preserves the original's pixel distribution and relationships, which can be an indicator of effective enhancement.

Original Image	IFS	IVIFS	CLAHE	Proposed Method
Image 1	0.9456	0.9620	0.9134	**0.9568**
Image 2	0.8744	0.9441	0.9534	**0.9615**
Image 3	0.9503	0.9209	0.9378	**0.9744**
Image 4	0.6147	0.8494	0.8320	**0.9140**
Image 5	0.9228	0.9602	0.8518	**0.9710**
Image 6	0.8736	0.9209	0.9339	**0.9423**
Image 7	0.9440	0.9485	0.9258	**0.9496**
Image 8	0.9141	0.9476	0.7874	**0.9522**
Image 9	0.9275	0.9156	0.8724	**0.9361**
Image 10	**0.9422**	0.9149	0.8032	0.9405

Table 1: Evaluating enhanced image quality with PCC values

4.1.4 Feature Similarity Index Measure (FSIM)

Feature Similarity Index Measure (FSIM) is used in image processing to assess the similarity between two images. It is beneficial for evaluating the quality of images, especially in the context of image enhancement. It helps to compare the effectiveness of different image enhancement techniques by providing a quantitative measure of the improvement in image quality [33].

FSIM considers two key features: Phase congruency (PC): This reflects how well the structural information of an image is preserved. Gradient magnitude (GM): This measures how well the gradient (edge) information is preserved. Given two images, G (the original image) and E (the enhanced image), the FSIM is calculated as follows:

Calculate Similarity Measures:

Phase Congruency Similarity: $S_{PC}(x,y) = \frac{2\times PC_G(x,y)\times PC_E(x,y)+T_1}{PC_G(x,y)^2+PC_E(x,y)^2+T_1}$

Gradient Magnitude Similarity: $S_{GM}(x,y) = \frac{2\times GM_G(x,y)\times GM_E(x,y)+T_2}{GM_G(x,y)^2+GM_E(x,y)^2+T_2}$

where, $PC_G(x,y)$ is the PC for the original image, $PC_E(x,y)$ is the PC for the enhanced image $GM_G(x,y)$ is the GM for the original image, $GM_E(x,y)$ is the GM for the enhanced image and T_1 and T_2 are small constants to avoid division by zero.

The overall similarity measure at each pixel is given by:

$$S_L(x,y) = S_{PC}(x,y)^{\alpha} \times S_{GM}(x,y)^{\beta}$$

α and β are weighting factors, typically set to 1.

Finally, the FSIM for the entire image is computed as a weighted averageof the combined similarity measure over all pixels:

$$FSIM(G,E) = \frac{\sum_{x,y} S_L(x,y).W(x,y)}{\sum_{x,y} W(x,y)}$$

Here, W(x, y) is the combined phase congruency at pixel (x, y), calculated as:

$$W(x,y) = \max\left(PC_G(x,y), PC_E(x,y)\right)$$

Figure 5 demonstrates that the proposed method provides superior image enhancement compared to other methods, as reflected by its higher entropy values. These values indicate the method’s ability to retain more image details and improve information content, resulting in clearer and more detailed visual output than the other methods.

In Figure 6, one can see that the proposed method works better than other techniques for enhancing images, as indicated by its higher SSIM values. These values mean that the method keeps the original image’s structure and appearance while improving details effectively.

Table 1 demonstrates that the proposed method is more effective in enhancing images compared to other techniques, as shown by its higher PCC values except the image 10. These values indicate a stronger similarity between the enhanced and original images, the proposed method preserves important details while enhancing the overall image quality.

In Figure 7 indicates that the proposed method is better at enhancing images than other techniques, as shown by the higher FSIM values for 8 images. This means our method keeps important details, making the enhanced images look more like the original images.

5. Conclusion

The proposed technique introduces a highly effective approach to low-light image enhancement by integrating fuzzy normalization, neighborhood-based pixel intensity adjustment, and defuzzification. This method enhances image contrast while preserving fine details and minimizing noise, leading to clearer and more accurate visuals. This effectiveness is demonstrated by improved performance metrics, including higher entropy and FSIM, better SSIM, and stronger PCC, confirming its ability to produce superior image quality. The technique is particularly valuable for critical applications in surveillance, medical imaging, and photography, where enhanced clarity and detail are crucial, especially in low-light conditions. Its robust performance makes it a promising tool for improving image quality across various fields, setting a new standard for low-light image enhancement.

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