Future Iris Imaging with Advanced Fuzzified Histogram Equalization

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***Abstract*—Images captured under low lighting frequently exhibit low brightness, low contrast, and a small grayscale. These features can affect the individual's view and severely limit the performance of machine vision systems, particularly when data annotation is involved. Hence, the issues motivate this study to examine the effectiveness of advanced fuzzified histogram equalization for image enhancement. A comparative study was conducted based on the low lighting condition of iris images to evaluate three image enhancement methods: Advanced Fuzzified Histogram Equalization (AFHE), Contrast Limited Adaptive Histogram Equalization (CLAHE), and Fuzzy Contrast Enhancement (FCE) using the MIREIS dataset. The Gaussian membership functions (GMF) were modified accordingly to satisfy the suitable pixel intensity of the input iris images. The results were compared using the peak signal-to-noise ratio (PSNR) value, including the central processing unit (CPU) times. As a result, the AFHE showed a better PSNR value at 76.02db with faster CPU times at 4.04s compared to CLAHE and FCE. Although the PSNR value of HE is slightly lower than CLAHE (0.3%) and FCE (0.7%), AFHE improved the image's quality and brightness, which can help other researchers with the data annotation process. The performance of the proposed methods was validated by comparing them with state-of-the-art methods. The results demonstrated that AFHE, CLAHE, and FCE exceeded other HE, AHE, CLAHE, and hybrid HE using fuzzy approaches that employed PSNR metrics.**

***Keywords*—Image enhancement; fuzzy logic; histogram equalization; CLAHE; iris recognition**

I. Introduction

The quality of the images significantly influences the effectiveness of an iris recognition system. As such, it is crucial to enhance the image quality, especially when dealing with images captured in non-cooperative environments. The non-cooperative environment images provide low-quality data due to the rigidity condition during data acquisition [1]. The near-infrared illumination needed for iris recognition systems that allow for user identification additionally involves the users' cooperation to obtain a good-quality iris image, as these devices are not user-friendly [2]. These requirements impose an extra responsibility on the user to actively engage in the recognition process.

Current studies focus on detecting the iris when an iris image is acquired under varying lighting conditions and at a long distance. Poor quality images, mainly low lighting, reflection, occlusion, off-angle, and motion blur can further decrease iris pattern performance [3]. Nevertheless, when the distance between the iris and the device increases, the quality of the iris image decreases, and more illumination is necessary. Employing a visible light camera does not necessitate further illumination because the captured images present color data [4]. Iris recognition functionality can be integrated into an existing device or reduced to comply with these features.

A study has been conducted using a database comprising iris images captured at 4 to 8 meters with a high-resolution visible camera. The database includes low lighting, rotation, motion blur, and off-angle [5]. Another database contains an iris with face images captured with a visible light camera integrated into mobile devices [6]. The following processes must be followed to improve the quality of iris images: acquisition, enhancement, segmentation, feature extraction, and recognition. Image enhancement refers to converting the image intensity to create a new image and enhance the image quality. The key objectives of image enhancement are improving contrast, adjusting brightness, sharpening, color restoration, and noise reduction.

Various studies have proposed new enhancement methods based on histogram equalization (HE) [7], [8], [9], [10], [11]. By increasing the image's contrast through histogram stretching, HE can enhance the image's visual appeal [12]. The gray grouping approach underpins histogram stretching, which can be utilized for low-contrast and brightness images. It offers several benefits, including the fact that it is both simple and highly effective. While iris image enhancement technologies are generally efficient [13], they can lead to over-enhancing of the image if there is a prominent peak in the histogram [14]. In addition, HE tends to adjust the image's average brightness to the dynamic range's midpoint. This limitation renders the HE impractical in multiple technological applications.

This study is motivated by the crucial need for high-quality images in iris recognition systems, especially in challenging environments where image quality can be affected by factors like low lighting, reflections, occlusion, off-angle capture, and motion blur. Current methods frequently encounter challenges in retaining performance in these conditions, requiring the development of image enhancement methods to tackle these issues. While previous studies have investigated image enhancement methods such as HE, limitations such as over-enhancement and impractical brightness adjustments emphasize further investigation into more effective image enhancement methods for iris recognition systems.

The paper is structured as follows: Section II discusses the state-of-the-art image enhancement for iris recognition, and Section III presents a comprehensive explanation of the fuzzification process of advanced fuzzified histogram equalization (AFHE), contrast limited adaptive histogram equalization (CLAHE), and Fuzzy contrast enhancement (FCE). Section IV provides the experimental data and analysis, while Section V concludes this paper.

II. Related Works

Previous studies on iris image enhancement used images acquired from low lighting and NIR illumination to tackle image over-enhancing and brightness problems. A study in [12] employed HE to improve the visibility of iris images captured under low lighting conditions, aiming to determine the borders of the pupil area. This approach accomplished redistributing pixel intensities. Hence, the darkly pigmented iris reduced the HE outcome due to the low contrast ratio between the iris and pupil.

Maheshan et al. [15] employed HE and CLAHE methods for analyzing fuzzy sclera. In this study, HE aims to find the frequency of dark colors, which typically covers a range of zero to fifty pixels. Conversely, the CLAHE establishes a limit on contrast that provides a proportional adjustment of white balance for the image. Hassan et al. [1] conducted a comprehensive study on HE, CLAHE, and HE for iris images at varied distances and in visible wavelength illuminations. The study aims to improve iris segmentation and recognition performances.

A study in [16] introduced the CLAHE approach to enhance the performance of iris recognition in low contrast or low illumination conditions. It is an improved version of the adaptive histogram equalization (AHE) method initially developed by Zuiderveld [17]. This technique reduces potential noises in the image while enhancing contrast in grayscale images. A study in [18] presented an image enhancement method using HE to increase the quality of iris images for rubeosis iridis disease. The processes were divided into three image groups: low, medium, and high. The best results for the low contrast group enhanced by 50%; however, it can be reduced by 50% in the high contrast group.

An advanced recognition system in [19] proposed a Convolutional Neural Network (CNN) with HE and CLAHE to efficiently enhance and detect COVID-19 diseases in chest X-ray images. AlKhalid in [20] proposed the same model; CNN combined with HE and CLAHE using COVID-19 chest X-ray images for data expansion, transformation, and enhancement. Two layers of HE are applied to seven layers of data transformation; however, the study begins with a conceptual hashing algorithm to eliminate duplicate images. A study in [21] introduced CNN with HE and CLAHE to produce high-contrast tooth X-ray images. The proposed method created high-intensity data to visualize the tooth features, including the infection, inflammation, and nerve.

In study [22], Xiong et al. proposed a chaotic Pareto sparrow search algorithm (CPSSA) with CLAHE for iris augmentation. The CPSSA algorithm utilizes population-based iteration to search for specific clipping thresholds that meet the specified criteria, resulting in CLAHE generating a collection of iris images. A study in [23] applied HE and AHE to compare with Canny edge detection. The AHE aims to determine the iris patterns with high-contrast images. The Canny edge detection combined with HE produced a sharper, more structured image with less noise. On the other hand, the Canny edge detection method with AHE introduced more noise in the final images. However, these images exhibit more robust features than those obtained using conventional HE.

The enhancement method proposed by Chang et al. [24] eliminates the specular reflections from the iris image by applying the preprocessing method to the input image in three stages. The initial phase was applying the Gaussian filter method with a sigma value of 0.9. The second stage involved converting the ocular images from grayscale to binary using a threshold value of 0.18. Finally, the binary iris image was exposed to a Gaussian filter with a sigma value of 2, followed by a median filter to enhance the image's smoothness.

A study in [25] utilized fuzzy membership weighted functions to analyze image pixel values. With a triangle function, the fuzzy average and fuzzy median filters outperform the other four fuzzy filters in terms of filtering performance. Without using deep learning, these fuzzy techniques were employed to improve images. For instance, a one-pixel attack on an image can significantly change the prediction's outcome [26]. The resilience of neural networks can be enhanced by utilizing the fuzzified image enhancement in deep learning.

Orujov et al. [27] developed a contour detection algorithm using Mamdani (Type-2) fuzzy rules for blood vessel detection in retinal fundus images. It utilizes green channel data, Contrast-Limited Adaptive Histogram Equalization (CLAHE), and a median filter for background exclusion. The method achieved accuracies of 0.865, 0.939, and 0.950 on STARE, DRIVE, and ChaseDB datasets, respectively, demonstrating flexibility and comparable performance to existing methods, with potential for dynamic rule formulation in image processing systems.

Another study in [28] applied fuzzy average, fuzzy median, and Gaussian filters to preprocess iris images that had reflections on glasses and were occluded by eyelids and eyelashes. This preprocessing aimed to improve the out-of-bounds areas, enhance the noise ratios, and sharpen the edges of the iris images. However, the success rate remained poor, prompting the employment of morphological operations and other alternative preprocessing approaches.

This study proposed advanced fuzzified histogram equalization (AFHE) based on the modified Gaussian member functions to enhance the quality of low-lighting iris images, facilitating the data annotation process. The quality assessment of low-lighting iris images is evaluated based on the Peak Signal-to-Noise Ratio (PSNR) while optimizing the central processing unit (CPU) time. The proposed methods were compared with state-of-the-art methods to benchmark and validate the performance.

III. Materials and Method

This section discusses the materials used to implement the image enhancement methods. Fig. 1 illustrates the enhancement process that begins with data collection for iris images. The original image retains its dimensions without performing image resizing. The iris images are subjected to the image enhancement methods AFHE, CLAHE, and FCE, with equal distribution of intensities. Finally, the iris images are trained to achieve the PSNR values based on the implemented methods.

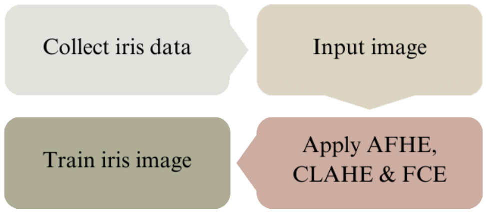

Fig. 1. Image enhancement system flow for AFHE, CLAHE, and FCE.

A. Dataset

This study employs 24 iris images from the Mobile Iris-Eye Computer Vision (MIREIS) dataset to test the image enhancement techniques for low lighting conditions as presented in Fig. 2. The iris images were captured using an iPhone 13 in early 2023 at the Universiti Teknologi Malaysia, Kuala Lumpur. The dataset focuses on the iris occlusions, motion blur, reflection, visible illuminations, and low-lighting conditions. Therefore, it is available for only several images in low-lighting conditions. The iris images are in standard exposure and RGB color space with the dimension of 2316 × 3088.

Fig. 2. Sample iris images from MIREIS dataset.

B. Fuzzification

Image enhancement with fuzzification involves the transformation of gray-level intensities of an image onto a fuzzy plane using membership functions. In addition to mapping the fuzzy plane back to the grayscale intensities of the images, the membership functions are changed to improve contrast. Increasing the weight of the gray levels closest to the image's mean gray level over those further from it aims to produce an image with higher contrast than the original.

Theoretically, fuzzy set theory provides a fresh perspective on image interpretation. An image with dimensions of size pixels and L distinct gray levels may be conceptualized as an array of fuzzy singletons. Each singleton represents a pixel, and its membership value indicates its brightness relative to a set of brightness levels, $I = 0, 1, 2, \ldots L - 1$ [29]. Eq. (1) presents the fuzzy theory utilized in image enhancement, where I_{xy} denotes the pixel intensity, (x, y), while μ_{xy} denotes its corresponding membership value.

$$FT = \bigcup_{x=1}^{X} \bigcup_{y=1}^{Y} \frac{\mu_{xy}}{I_{xy}} with \mu_{xy} \subseteq [0, 1] \tag{1}$$

The three phases of fuzzy image processing are membership functions, fuzzification, fuzzy inference system, and defuzzification. Fuzzification involves providing an image with one or more membership values based on intriguing features, such as sharpening, edginess, brightness, and similarity. Following the image transformation into fuzzification, the membership values are modified using an appropriate fuzzy method.

Defuzzification signifies a retransformation of the membership values into the gray-level plane. The grayscale levels must be blurred for the image histogram's location to handle grayscale uncertainty. It indicates that each gray level is given a certain degree of membership based on where it falls on the histogram. High membership values are generally given to bright pixels, and low membership values are assigned to black pixels.

C. Defuzzification

Contrary to fuzzification, image defuzzification converts a fuzzy image back into crisp values. The inverse transformation in Eq. (2) is calculated to produce the enhanced image, $I'(x, y)$, where T' represents the original inverse transformation, T, while $I'(x, y)$, represents the gray-level of the enhanced image.

$$I'(x, y) = T'(I(x, y)) = (\bigcup_{x=1}^{X} \bigcup_{y=1}^{Y} I(x, y) \times (L - 1) \tag{2}$$

D. Fuzzy Inference System

The fuzzy inference system comprises an expert's knowledge base, consisting of IF-THEN rules. The compositional rule establishes the mapping between fuzzy inputs and outputs, as presented in Fig. 3. The rules set in the proposed algorithms are as follows,

1) IF input is Very Dark THEN output is Extremely Dark
2) IF input is Dark THEN output is Very Dark
3) IF input is Slightly Dark THEN output is Dark
4) IF input is Slightly Bright THEN output is Bright
5) IF input is Bright THEN output is Very Bright
6) IF input is Very Bright THEN output is Extremely Bright

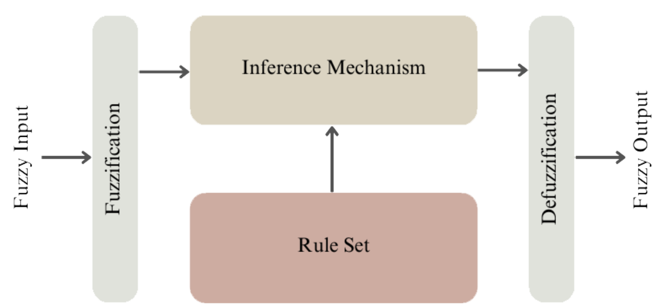

Fig. 3. The fuzzy inference system for this study.

This study involves eight rules for iris image enhancement, such as Extremely Dark (ED), Very Dark (VD), Dark (Da), Slightly Dark (SD), Slightly Bright (SB), Bright (Br), Very

Bright (VB), and Extremely Bright (EB). Fig. 4 illustrates the gray levels space derived from the membership functions for iris image enhancement. The rules are developed using the fuzzy sets specified in the gray levels ranging from [-50, 305] to [0, 255].

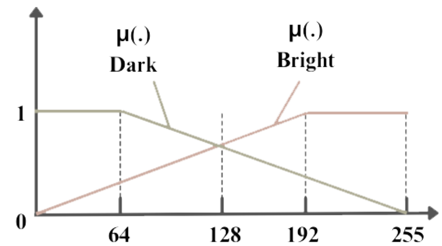

Fig. 4. The gray levels space based on the fuzzy sets.

E. Modified Gaussian Membership Functions

GMF comprises fuzzification, rule-based enhancement, and defuzzification. GMF quantifies the level to which pixel intensities belong to different iris regions. It transforms the initial data into a Gaussian distribution. The membership decreases as input values move further from the midpoint in positive and negative directions. The midpoint of the normal distribution, which is assigned to one, offers an optimal condition for the set.

Membership in the set decreases for input values, beginning at the midpoint and continuing until it diverges significantly from the optimal condition. At this point, it is deemed outside the set and is assigned zeros. The GMF can be computed in Eq. (3), where x is the input value of the GMF for set A, σ is the standard deviation, and c denotes the mean of the Gaussian function.

$$\mu_A(x;\sigma,c) = \exp\frac{-(x-c)^2}{2\sigma^2} \tag{3}$$

Following the fuzzification process, each intensity level, A, is assigned a corresponding fuzzy membership value $\mu(A)$ in the image. The attribute, such as bright or dark, is correlated with the intensity. The modification of GMF involves fine-tuning the fuzzy membership values assigned to each intensity level in the image. This modification enhances the image by increasing lighting on specific elements.

A function, $f(\mu(A))$, is selected to modify the membership values. This function varies according to the type of enhancement required. The modification function is applied to an individual's membership value. The modified value of intensity A, denoted as $f(\mu(A))$, is obtained by applying a function f on the original membership value $\mu(i)$. The function $f(\mu(A))$ affects membership values. An enhancement function can be:

$$f(\mu(A)) = \mu(A)^\gamma \tag{4}$$

The parameter γ determines the features of the enhancement:

- When γ is less than 1, the function extends the range of membership values, increasing contrast.
- When γ is greater than 1, the function compresses the membership values, reducing the contrast of specific intensity ranges.

Upon implementing this modification, the image's histogram receives a significant reshaping. The reshaping process is defined by fuzzy logic concepts and is characterized by a higher level of detail than conventional HE. The final stage in the procedure (distinct from the modification phase but essential for achieving the improvement) involves pairing these modified membership values with the corresponding pixel intensities.

F. Image Enhancement Methods

Image enhancement can be crucial due to poor image quality, including lighting, noise, high brightness or darkness levels, lack of sharpness, and blurriness. The image enhancement methods may reduce the analysis process that involves comprehensive image extraction. A low-quality image has distortions, such as an image that is not visible due to low lighting.

1) Advanced fuzzified histogram equalization: AFHE is an advanced approach used in image processing to boost brightness and improve the level of detail in images. The advanced version of the conventional HE method incorporates ideas of fuzzy logic. AFHE enables a more refined and situation-specific modification of image brightness in comparison to conventional HE. By transforming the original image into a uniform histogram, AFHE effectively improves the image's contrast. AFHE produces a significant global enhancement but may diminish the image's local details.

The AFHE provides the relationship in gray level and its corresponding frequency, which produces a gray image $G(i)$ as expressed in Eq. (5).

$$G(i) = \frac{n_i}{TN}, i = 0, 1, ..., L-1 \tag{5}$$

Let i represent the image's gray level, n_i be the number of pixels comprising gray level, and TN denotes the total number of pixels in the image. The histogram represents the probability distribution function of i. Eq. (6) expresses the HE, which can be accomplished based on $G(i)$.

$$h_k = Tf(r) = (L-1)\sum_{i=0}^{k} G(i) \tag{6}$$

Let the mapping function, $Tf(r)$, be denoted as h_k, and transform each pixel value k from the input image to h_k. L denotes the gray level of an output image. The histogram can receive a more even image intensity distribution with this modification. As a result, regions with lower local contrast can achieve higher contrast without compromising global contrast.

2) Contrast limited adaptive histogram equalization: CLAHE is a method for enhancing local contrast in an image. The image is acquired locally by forming some symmetrical grids, referred to as the region size. Three markers identify the image's regional structure: the corner region (CR) designates the areas in the image's corner, the border region (BR) designates the areas around the image that keeps the CR, and the inner region (IR) designates the remaining areas in the center.

CLAHE, which involves placing a boundary value on the histogram, can be used to solve the issue of excessive contrast enhancement. This limit value, which indicates a histogram's maximum height, is the clip limit. Eq. (7) defines how to compute a histogram's clip limit.

$$\beta = \frac{T}{L}(1 + \frac{\alpha}{100} S_{max}) \tag{7}$$

Let T denotes the pixel count of each block, and L indicates the block's gray level. While α is the clip factor and $Smax$ is the maximum slope.

3) Fuzzy contrast enhancement: The FCE aims to create dark pixels that are darker and bright pixels that are brighter to improve the image. Eq. (8) computes the FCE.

$$F \leftarrow h(x) + \sum_{x} \sum_{y} \mu_{F(x,y)'} \tag{8}$$

The FCE is an integer series, denoted as $h(x)$, where x ranges from 0 to $L - 1$. In this context, $h(x)$ represents the frequency at which gray levels within x occur. The fuzzy histogram is constructed by viewing the gray value $f(x, y)$ as a fuzzy number $\mu_{F(x,y)'}$. While $\mu_{F(x,y)}$ represents the fuzzy membership function. Fuzzy logic is more adept at managing values' imprecision than traditional crisp values. Thus, it yields a smooth histogram.

G. Performance Measurement

PSNR is a quantitative indicator that reflects how much an image's quality was reduced throughout the compression or processing processes. It measures the ratio between the maximum signal value and the amount of noise in the image using decibels (dB). This study employed PSNR to compare the quality differences between the original and enhanced images. Image quality is evaluated based on the PSNR value, which a higher PSNR value indicates a high-quality image.

The mean-squared error (MSE) is initially computed in Eq. (9) to obtain the PSNR, where I_1 is the enhanced iris image, I_2 is the original iris image, and X and Y are the numbers of rows and column in the input iris image.

$$MSE = \frac{\sum_{X \times Y} [I'(x, y) - I(x, y)]^2}{X \times Y} \tag{9}$$

Eq. (10) calculates the PSNR value, where Z represents the maximum variation in the data type of the input iris image. Z equals one if the input image is a double-precision floating-point; otherwise, Z is 255.

$$PSNR = 10 \log_{10} \frac{Z^2}{MSE} \tag{10}$$

IV. Result and Discussion

All experiments used Google Colaboratory to analyze the iris image enhancement methods: AFHE, CLAHE, and FCE. PSNR, a prevalent metric for assessing image quality, was employed to evaluate the efficacy of the iris image enhancement methods. This study also measures the total CPU times for each method to determine which image enhancement method works faster for 24 iris images. The relationship between the PSNR value and the CPU times shows the effectiveness of the image enhancement methods. Therefore, it can identify which image enhancement method works best for iris images.

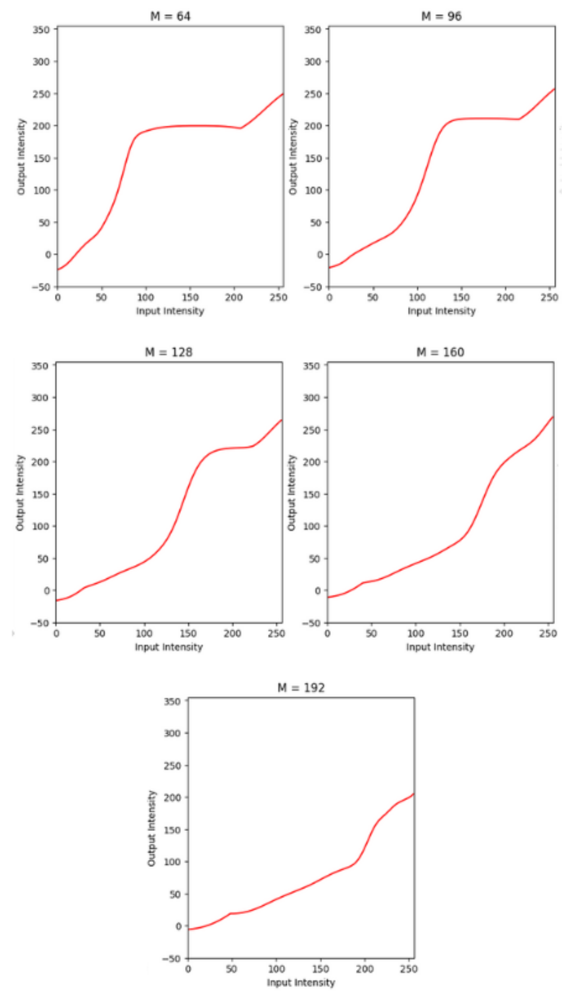

Fig. 5. The input and output intensity for $M = 64$, $M = 96$, $M = 128$, $M = 160$, and $M = 192$.

Fig. 5 shows the input and output intensities of 24 iris images to map the gray level. The range of the pixel intensity value is 64 for minimum input pixel intensity to 192 for maximum input pixel intensity. The gray level for the output pixel intensity increases for intensity values of 64, 96, and 128 at the middle of the block, while the intensity values of 160 and 192 slightly decrease but remain constant to enhance the image's brightness. The results highlight how the image enhancement methods improve the visibility and contrast of iris images, thereby rendering them more appropriate for iris recognition systems used in non-cooperative environments.

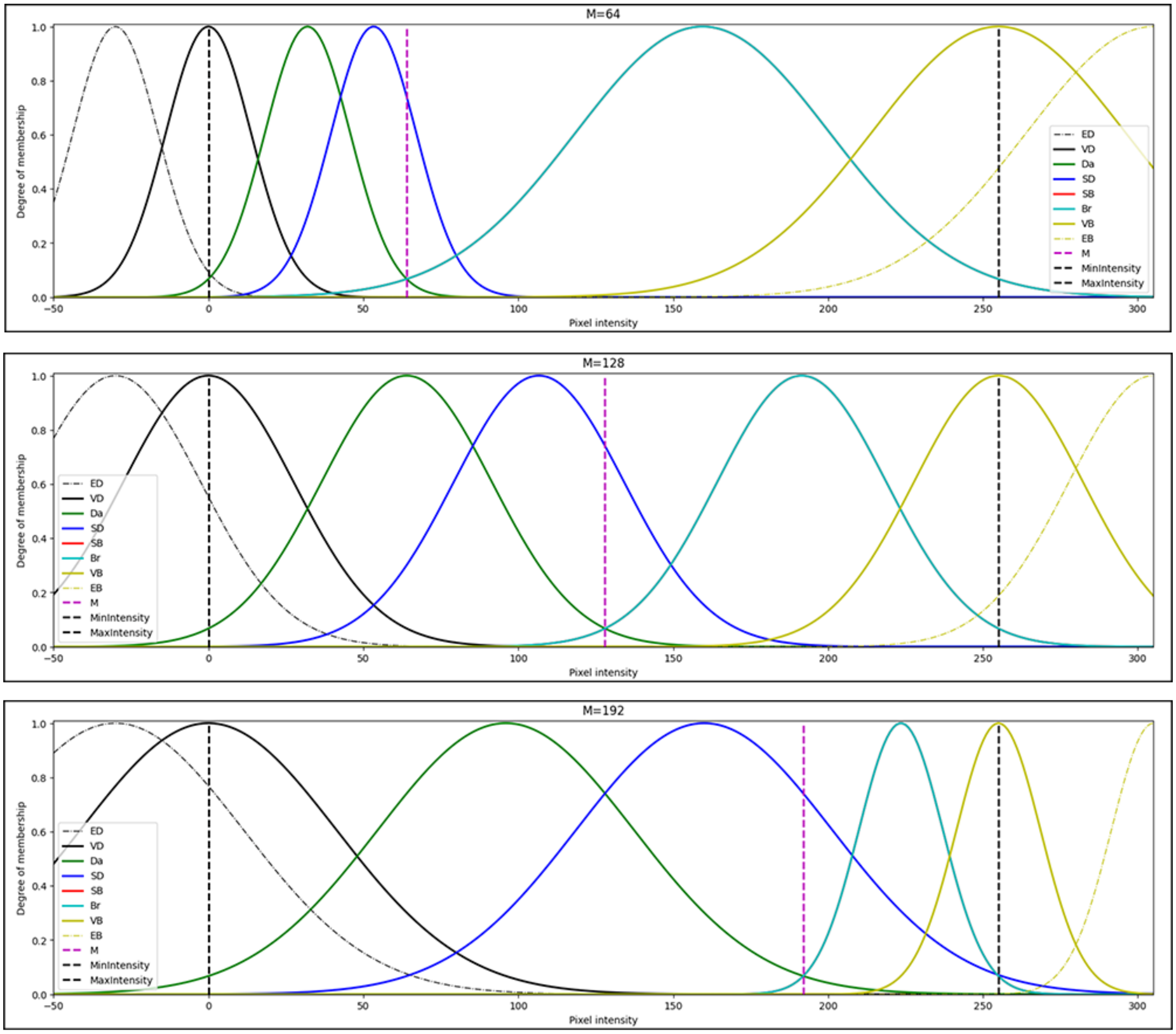

Fig. 6. The relationship between modified gaussian membership function, M and the pixel intensity based on the modified membership functions.

The fuzzy rule sets according to the IF-THEN rule were modified based on the input image. The maximum M used for iris images is six, while the minimum M is two. Fig. 6 demonstrates the relationship between the modified Gaussian membership functions and the pixel intensity based on the value in the selected membership functions, M. The image's brightness decreases and darkens when M equals 64. In addition, the pixel intensity also shows high contrast. The image becomes extremely bright when $M = 192$, with a maximum intensity between 192 and 255, respectively. Therefore, the image can contrast less to the $M = 64$. However, the high and low contrast is balanced when M is 128. The mid-range of the pixel intensity between 0 and 255 made the image not too dark and bright.

The analysis of the AFHE, CLAHE, and FCE depicted in Fig. 7 demonstrates that the image quality of AFHE outperforms those of CLAHE and FCE. The original images exhibit low lighting; hence, the enhanced images using AFHE preserves brightness better with low contrast. The AFHE could help the data annotation process for iris segmentation. CLAHE marginally brightens the image compared to AFHE; however, some areas continue to have high contrast, which makes the image slightly dark. Nevertheless, FCE demonstrates a significant difference in brightness levels, resulting in a darker appearance in some images. Some images merely enhance a low gray level, retaining the image in poor lighting.

Table I shows the experiment result of image enhancement methods (AFHE, CLAHE, and FCE) based on the PSNR. Enhanced image quality corresponds to a higher PSNR value. FCE has a higher PSNR value of 76.48db and longer CPU times at 13.9s. To be compared with AFHE, AFHE indicates the lowest PSNR value at 76.02db with faster CPU times at 4.04s. Although the PSNR value of HE is lower than CLAHE and FCE, it demonstrates better image quality, as depicted in Fig. 7, with faster CPU times.

AFHE enables more refined contrast enhancement, which is particularly beneficial in images with complex lighting settings or situations where simple histogram equalization can result in severe or insufficient enhancement. Fuzzy logic regulates

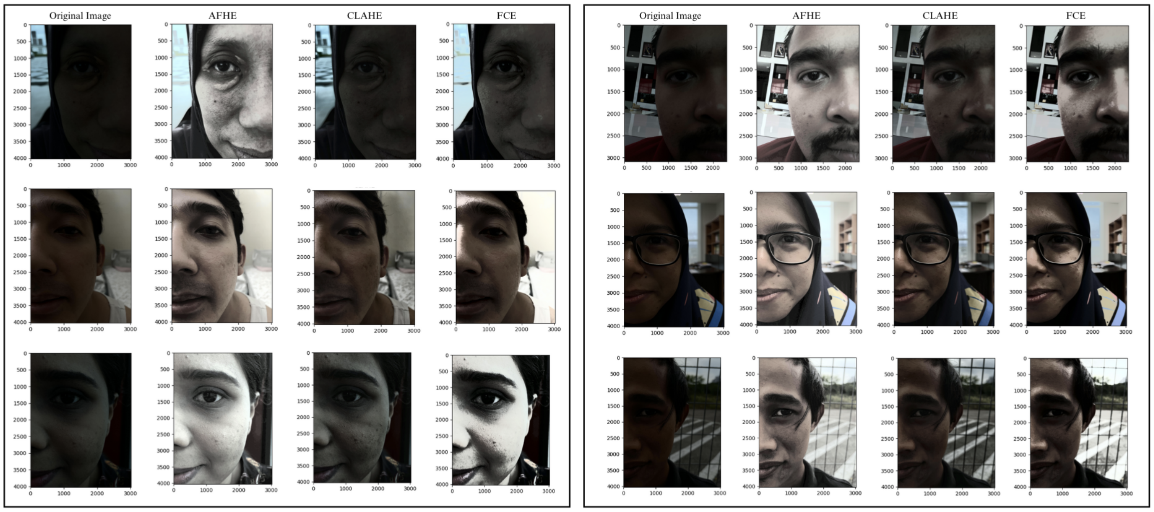

Fig. 7. Iris image enhancement results using AFHE, CLAHE, and FCE based on the low lighting conditions of original images.

TABLE I. Comparison of Iris Image Enhancement Methods with the PSNR Value

Enhancement Methods	PSNR (dB)	CPU Time (s)
AFHE	76.02	4.04
CLAHE	76.23	4.9
FCE	76.48	13.9

the enhancement, which helps retain details better and prevent errors frequently created by aggressive methods. Implementing fuzzy sets and rules enhances the method's adaptability to various image types and expected outcomes. Therefore, it can be concluded that AFHE is the best iris image enhancement method, followed by CLAHE and FCE, respectively, because AFHE preserves more brightness and provides a significant iris image quality.

The comparison with state-of-the-art methods is crucial for validating the effectiveness and benchmarking the performance of the proposed image enhancement techniques, namely AFHE, CLAHE, and FCE. Using PSNR as a measure evaluates the accuracy of the image enhancement in terms of pixel-level fidelity. The proposed approaches achieved higher PSNR values than existing state-of-the-art methods [1], [18], [23], as shown in Table II, indicating that AFHE, CLAHE, and FCE preserve image quality and reduce distortion throughout the enhancement process. PSNR is commonly employed to evaluate methods such as HE, CLAHE, and FCE that modify image brightness; however, it may not adequately measure perceptual quality or task performance. This limitation is highlighted by the accuracy results of previous studies in [15], [28], which demonstrate superior performance compared to AFHE, CLAHE, AHE, and FCE in terms of accuracy.

As different metrics may capture various aspects of image quality and utility, this inconsistency highlights the significance of employing multiple evaluation metrics to comprehensively evaluate the performance of image enhancement methods. Hence, while PSNR can indicate better pixel-level accuracy, accuracy metrics further explain enhanced images' perceptual quality and efficiency for specific applications. Further

TABLE II. Comparison with State-of-the-art Methods

Author	Method	Evaluation Metric	Result
[15]	HE-FCM	Accuracy	0.86
	CLAHE-FCM		0.91
[1]	HE	PSNR	14.725
	AHE		14.148
	CLAHE		17.459
[18]	HE	MSE	18.25
		PSNR	28.87
[23]	HE	PSNR	16.76
	AHE		16.95
[28]	Gaussian	Accuracy	89.2
	Triangular fuzzy average		87.4
	Triangular fuzzy median		88.4
	HE		83.4
	CLAHE		84.8
This study	**AFHE**	**PSNR**	**76.02**
	CLAHE		**76.23**
	FCE		**76.48**

research could explore the development of comprehensive evaluation frameworks that consider a range of metrics to provide a more holistic assessment of image enhancement methods. Additionally, investigating the factors contributing to inconsistency between PSNR and accuracy metrics could yield valuable information for further improving the performance of image enhancement methods, ultimately enhancing their utility in practical applications.

V. Conclusion

This study presented fuzzified image enhancement methods, AFHE, CLAHE, and FCE, to enhance the quality of iris images, specifically for data annotation. The iris images in the MIREIS dataset provide some images with low lighting conditions, creating a challenging process during data annotation. Based on the input iris images, the Gaussian membership functions were modified to the suitable intensity value. The GMF followed the rule set in the fuzzy inference system for the fuzzification and defuzzification process. The AFHE is the best fuzzified image enhancement method compared to CLAHE and FCE based on the PSNR value and CPU times. The findings of this study can assist other researchers in data annotation, particularly in non-cooperative environments when iris images contain low lighting conditions. This study only employed image enhancement methods to modify the iris image's contrast and lighting. However, these approaches cannot reduce the presence of reflections in the iris image.

VI. Future Work

Further work can be focused on extending the study to include reflections in iris images, which were not adequately reduced by the image enhancement methods. Studies could focus on developing methods to precisely reduce or eliminate reflections in iris images captured in non-cooperative environments with low lighting. Further improving the effectiveness of the AFHE, CLAHE, and FCE approaches in data annotation tasks might be examining their ability to work with iris images at different distances and angles. This could offer significant data concerning the methods' robustness and efficacy in various conditions.

Moreover, combining several image enhancement methods or employing machine learning for modifying parameters adaptively might improve the effectiveness and flexibility of image enhancement methods. The effectiveness and application of AFHE, CLAHE, and FCE in iris image enhancement would be further advanced by addressing these issues and investigating these potentials for enhancement. It can support the improvement of iris recognition systems in non-cooperative environments.

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