Adaptive Fuzzy Exposure Local Contrast Enhancement

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ABSTRACT Numerous factors, such as illumination condition, can affect image quality. Local contrast enhancement is an approach for improving the local visibility detail of an image by increasing the contrast in local regions. Recently, researchers have shown an interest in solving the non-uniform illumination issues. However, all the studies failed to improve the contrast of the non-uniform illumination and low-contrast images locally and regionally by individually focusing on each region and improving its contrast. The contrast of each region will be enhanced using a new local contrast enhancement technique called adaptive fuzzy exposure local contrast enhancement (AFELCE). The proposed AFELCE method is specifically designed to enhance the contrast by using specific algorithms for different regions. The proposed AFELCE technique successfully improves the contrast of 300 low-contrast and non-uniform illumination images taken from three different databases, namely, standard, underwater (UW), and microscopic human sperm (MHS) images. The proposed AFELCE outperforms the state-of-the-art methods in terms of quality and quantity. Qualitatively, the proposed AFELCE method has successfully enhanced the contrast of the images by producing more uniform illumination images with high contrast than the other methods. Quantitatively, the proposed AFELCE method produces the highest average of entropy (E), measurement of enhancement (EME), and universal image quality index (UIQI) for the standard image database, with values of 7.582, 42.75, and 0.94, respectively. Similar results are obtained for the UW image database, where the proposed method produces the highest average of E, EME, and UIQI values with 7.124, 41.13, and 0.89, respectively. For the MHS image database, AFELCE produces the highest values for E and EME, with values of 7.602 and 42.51, respectively.

INDEX TERMS contrast enhancement, fuzzy logic, over-exposed, under-exposed, and well-exposed.

I. INTRODUCTION Numerous factors, such as illumination condition, can affect image quality. A poor illumination condition during image acquisition will produce a non-uniform illumination image [1]. This situation occurs commonly at night time (Lin and Shi, 2014), in microscopic images [2], and in a complex industrial environment [3] and in complex industrial environment [4]. In a non-uniform illumination image, a monochrome object might contain different levels of intensity due to light transition. The differences in the intensity level will cause difficulties to the subsequent processes of analysis, such as segmentation [5], [6]. Segmentation is based on either the discontinuity or similarity principle. The discontinuity principle extracts the regions that differ in properties, such as intensity, color, texture, or other image statistics; whereas the similarity principle groups the pixels on the basis of common properties to extract coherent regions [7]. However, non-uniform illumination causes the intensity of a given object to vary, which will render the segmentation a difficult task. Therefore, the enhancement of non-uniform illumination image is necessary to simplify segmentation.

Non-uniform illumination is one of the challenges in face recognition applications because of the difference in the illumination condition that will cause dramatic changes in face appearance [8]. Such non-uniform illumination problem is also occurred in microscopic images. It affects the captured image by removing important information from the image when the gray levels of objects are the same as the gray level of the background. Thus, the illumination condition of images must be improved to address the non-uniform illumination problems in digital imaging applications.
In addition to the non-uniform illumination issue, digital images also suffer from low contrast. In low-contrast images, a large number of pixels are spread within a small portion of an available intensity range [9]. These images are generated because the variation of scene brightness is considerably smaller than the dynamic range of the camera [10]. Several underlying reasons explain such low-contrast images, including the inferior quality imaging device; inadequate imaging method; and even adverse external conditions, such as haze, rain, and fog [11]. In brief, most of the non-uniform illuminated images encounter the problem of low contrast.

Image enhancement is one of the significant and difficult steps in digital image processing that contributes to visually appealing fields. However, it does not raise the built-in information contents of an image [7], [12]. Image enhancement is a process of manipulating an image by modifying its attributes to produce a more suitable and meaningful result than the original image for a specific task and a human viewer [13]. Performing image enhancement aims to improve the interpretability or perception of information in images for human viewers and provide better input for other automated image processing approaches, such as segmentation, detection, and recognition [13]–[15]. The images after executing image enhancement are transformed into a suitable representation of the subtle details and without undesirable deterioration. They are also improved in terms of visual appearance and image clarity. Moreover, less ambiguity exists among the different regions of the image, and the original image becomes conducive for computer processing [16], [17].

The limitation of the acquisition devices; transmission through a noisy channel and faulty memory locations in hardware [18]–[20], insufficient lighting during image capturing [21] or the adverse external condition during image acquisition, such as atmospheric disturbances [22]–[24] are regarded as the main causes of poor-quality image. Because of these cases, the image may suffer from poor contrast, noises [25], loss of information [26], poor illumination [27], blurring and incorrect color balance [28]. Generating an image with low contrast and noise result in difficulty in clearly extracting considerable key features from the original image, thereby producing wrong information in the system operation [29].

Therefore, enhancing the contrast, removing the noise, and reducing the blurring of the original image are necessary to increase image quality. For color images, image enhancement is required to obtain sharp details, rich color, and good visual effects without shifting the color by processing luminance and color information.

II. LITERATURE REVIEW

This section discuss about the state-of-the-art techniques for the non-uniform illumination and low contrast images that are based on Fuzzy logic image enhancement.

The fuzzy-rule-based system (FRBS) is a technique that is closely related to human knowledge. It incorporates human intuitions that are nonlinear in nature, where recognizing a precise or crisp condition is difficult. A set of conditions are defined on the pixels, and such conditions form the preceding part of the IF-THEN rules. They are related to the gray-level centered pixel and its neighborhood. The pixel to be enhanced is transformed by the consequent part of the rule. The FRBS makes soft decisions on each condition, aggregates the decision made, and finally makes a decision on the basis of aggregation.

[30] proposed a method of fuzzy if-then rules in combining smoothing and sharpening to enhance an image. By implementing this approach, [30] could effectively model the conflicting tasks that normally occur in low-contrast and non-uniform illumination images. Another example of the fuzzy rule-based application is presented in [31] study, which employed the concept of rule-based application on smoothing. Different filter classes are devised on the basis of compatibility with the neighborhood pixels. Although the FRBS is closely related to human’s intuition in enhancing the image, this method still suffers from high computational time and difficulty in generating a fuzzy rule. The consequent part of the rule will only be executed if the prior rule is accomplished. Thus, this technique is difficult to perform in real-time applications.

[32] proposed fuzzy adaptive contrast enhancement (FACE), which applies fuzzy inference system with five fuzzy if-then rules, to enable an adaptive specification of the contrast gain on the basis of the local activity around each pixel in the image. This algorithm specifies the maximum allowable contrast gain value to reduce over enhancement artifacts and distortion in the image. FACE has advantages in noise suppression and increases the sharpness of the image. Its disadvantages are represented by the limited level of contrast enhancement and the deficient improvement of illumination of the image. [33] proposed the application of fuzzy set theory in histogram equalization, namely, fuzzy logic-based histogram equalization (FHE). First, the fuzzy histogram is computed using fuzzy set theory to enhance the non-uniform illumination image. Then, it is separated on the basis of the median value of the original image before independently equalizing them using the FHE approach. The researchers claimed that the algorithm could preserve image brightness and improve the local contrast of the original image. However, detail preservation still has room for improvement because certain details are washed out during the remapping process of the intensity level of the image.

[34], [35] proposed the adaptive fuzzy contrast factor enhancement (AFCFE). Specifically, they introduced a new parameter called the contrast factor that provided information on the difference between the intensity values in the local neighborhood. First, the image was fuzzified and separated into two regions by using the threshold value derived from the contrast factor. Then, the membership function is modified using a sigmoid function before being defuzzified to obtain the enhanced image. This method had produced better PSNR and entropy (E) than FHE; however, it requires longer processing time and produces images with a lower level of contrast.
[36] proposed image contrast enhancement in spatial domain using the fuzzy logic to define the pixel intensity level transformation function from a set of locally stretched pixel intensity. The transformation function was applied to color space images and the results with the cubic spline interpolation method. This technique focused on using a triangular membership function by setting the minimum and maximum crisp value to be compatible with the triangular membership function. This technique successfully stretched the image contrast and produced promising output result on the basis of the output values of the root mean square for the contrast of the actual image. Moreover, it utilized a triangular membership function, which is suitable only for under-exposed images, to increase the image contrast. However, it is not suitable for other images, such as low-contrast and non-uniform illumination images [36].

[37] proposed the fuzzy contextual contrast enhancement (FCCE) technique. It introduces a fuzzy contrast factor of each pixel, which is termed as the fuzzy dissimilarity histogram (FDH). A cumulative distribution function is formed with the normalized value of FDH and used as a transfer function to obtain the contrast enhancement image. The algorithm gives good contrast enhancement and preserves the natural characteristic of the image. The fuzzy membership function is involved to provide good contextual intensity transfer function. The overall algorithm is referred as the FCCE algorithm. This algorithm efficiently enhances the global and local image contrast [37]. In using such technique, the output images do not fall into over- or under-enhancement problem. Quantitative output results indicate that this technique delivers the best entropy results and the second best EME results. However, the visual analysis of the output images shows that this technique fails to overcome the under-exposed region enhancement. The well-exposed regions turned out to be under-exposed, whereas the under-exposed regions turned out to be dark, and the over-exposed regions turned out to be bright.

III. THE PROPOSED METHOD

Although numerous state-of-the-art techniques have been proposed to solve the non-uniform illumination issue, most of these techniques are not robust. These techniques are specially designed to solve a specific problem or enhance certain characteristics of a given image. A robust technique should be able to enhance the images with various illumination conditions. These techniques have tradeoffs in certain aspects to maximize the enhancement or solve the problems. For example, the exposure technique performs well in illumination correction but has a drawback of noise amplification. AFCEFE also performs well in the illumination correction. However, this technique has a weakness in terms of its insignificant contrast enhancement [34]. The aforementioned problems faced by the non-uniform illumination and low-contrast images have motivated the development of a good image enhancement algorithm for the non-uniform illumination and low-contrast images in this study. Thus, this study proposes a new contrast enhancement technique called adaptive fuzzy exposure local contrast enhancement (AFELCE). The proposed AFELCE is specifically designed to reduce the problem of non-uniform illumination and low-contrast images by applying different enhancement processes to different types of region in the image. Figure 2 shows the flowchart of the proposed AFELCE.

FIGURE 2. The flowchart of Adaptive Fuzzy Exposure Local Contrast Enhancement method.

The main steps of the proposed method AFELCE start with the input non-uniform illumination image, where the input image will be classified into three main regions (i.e., over-, well-, and under-exposed) using the ALEBRD technique. The regions are transferred from the spatial domain to the fuzzy domain by fuzzifying each region. A modified fuzzy membership function is applied on each region individually to fuzzify that region before each region is defuzzified to attain the enhanced image. Each region is enhanced individually by applying three different nonlinear contrast enhancements. Then, the proposed AFELCE will combine the three enhanced regions to produce the resultant image. Qualitative and quantitative analyses are performed on the output image. The entire procedure is repeated until a satisfying result is reached. The procedure is stopped when the output image produced an enhanced image with detail preservation (qualitative observation) and the UIQI reaches almost 1 (which indicate the best enhanced image). UIQI has been chose as quantitative stopping criteria since it counts loss of correlation, luminance.
distortion, and contrast distortion. The detailed process of each stage is explained in the subsequent section.

A. FUZZY BASED CONTRAST ENHANCEMENT

The image information to be processed is occasionally uncertain and ambiguous for several image processing applications, including contrast enhancement. For example, the question of whether a pixel should be darker or brighter than the original gray-level is of concern in the realm of the fuzzy contrast enhancement approach. In image processing, certain objective criteria of the quality are usually defined to ascertain the sufficiency of the results. For example, the image quality is considered good if a low amount of fuzziness is present, thereby indicating that the contrast is high. However, a human observer may not perceive these objective results because human judgment is subjective; thus, different people would have different judgments of image quality. These fuzzy-based image processing techniques offer a tool that associates a degree of belongingness to a particular property domain using the membership function. Region fuzzification is separately performed on each region. Therefore, the modified Gaussian membership function (GMF) is modified to address the individual region type. The modified GMF for under-exposed region is:

\[
\mu(i_{xy}) = \frac{1}{Y_{ij,\text{max}} - e^{\frac{-(Y_{ij,\text{max}} - \overline{Y}_{i,j} + \psi(i_{xy}))^2}{2\sigma^2_{hu}}}} \quad \text{for } i_{xy} < a_i
\]

where \(Y_{ij,\text{max}}\) is the maximum intensity, and \(\overline{Y}_{i,j}\) is the local average intensity of the ith block of the under-exposed region. \(Y_{ij}\) is the intensity of the jth block in the range of \(i_{xy} < a_i\). \(\sigma^2_{hu}\) is the fuzzifier function of the under-exposed region, which can be expressed as:

\[
q^2_{hu} = \beta \frac{\sum_{k=0}^{L-1} (Y_{ij,\text{max},w} - a_l)^4 p(i_{xy},w)}{\sum_{k=0}^{L-1} (Y_{ij,\text{max},w} - a_l)^2 p(i_{xy},w)}
\]

where \(a_l\) is the standard deviation of intensity of the entire image, and \(p(i_{xy},w)\) is the histogram of the under-exposed region.

The mirror function of the aforementioned GMF is utilized to fuzzify the well-exposed region of the image for the range \(i_{xy} \leq a_i \leq i_{xy}\) as follows:

\[
\mu(i_{xy}) = \frac{1}{Y_{ij,\text{max}} - e^{\frac{-(Y_{ij,\text{max}} - \overline{Y}_{i,j} - \psi(i_{xy}))^2}{2\sigma^2_{hw}}}} \quad \text{for } i_{xy} \leq a_i \leq i_{xy}
\]

where \(Y_{ij,\text{min}}\) is the minimum intensity of \(Y_{ij}\), where \(Y_{ij}\) is the intensity of jth block in the range of \(i_{xy} \leq a_i \leq i_{xy}\). \(q^2_{hw}\) is the fuzzifier function in the well-exposed region, which is denoted as

\[
q^2_{hw} = \beta \frac{\sum_{k=0}^{L-1} (Y_{ij,\text{max},w} - a_l)^4 p(i_{xy},w)}{\sum_{k=0}^{L-1} (Y_{ij,\text{max},w} - a_l)^2 p(i_{xy},w)}
\]

where \(p(i_{xy},w)\) is the histogram of the well-exposed region. The modified GMF for the over-exposed region is expressed as

\[
\mu(i_{xy}) = e^{\frac{-(Y_{ij,\text{max}} - \overline{Y}_{i,j} - \psi(i_{xy}))^2}{2\sigma^2_{ho}} - Y_{ij,\text{min}}} \quad \text{for } i_{xy} \geq a_i
\]
\[ q_{ho}^2 = \beta \left( \frac{\sum_{i=0}^{i=x-1} \left( (V_{f,\text{max,}0}-\sigma_l)^4 p(i,x,y) \right)}{\sum_{i=0}^{i=x} \left( (V_{f,\text{max,}0}-\sigma_l)^4 p(i,x,y) \right)} \right) \]  

\[ p(i,x,y,0) \text{ is the histogram of the over-exposed region.} \]

\[ f_{\text{enh}}(x,y)_u = \mu x_u(i,x,y), \quad \text{for } i,x < a_i \]

\[ f_{\text{enh}}(x,y)_w = \mu x_w(i,x,y), \quad \text{for } i,x \leq a_i \leq i,x \]

\[ f_{\text{enh}}(x,y)_o = \mu x_o(i,x,y), \quad \text{for } i,x \geq a_i \]

where \( \mu x_u(i,x,y), \mu x_w(i,x,y), \) and \( \mu x_o(i,x,y) \) are the defuzzified under-, well-, and over- regions, respectively. These three defuzzified output regions are represented as \( f_{\text{enh}}(x,y)_u \) for the new output of the under-exposed region, \( f_{\text{enh}}(x,y)_w \) is the defuzzified output for the well-exposed region, and \( f_{\text{enh}}(x,y)_o \) is the defuzzified output for the over-exposed region.

\[ \text{B. DEFUZZIFICATION} \]

After obtaining the modified GMF, defuzzification is then applied to all regions, as shown follows:

\[ f_{\text{enh}}(x,y)_o = \mu x_o(i,x,y), \quad \text{for } i,x \geq a_i \]

where \( \mu x_u(i,x,y), \mu x_w(i,x,y), \) and \( \mu x_o(i,x,y) \) are the defuzzified under-, well-, and over- regions, respectively. These three defuzzified output regions are represented as \( f_{\text{enh}}(x,y)_u \) for the new output of the under-exposed region, \( f_{\text{enh}}(x,y)_w \) is the defuzzified output for the well-exposed region, and \( f_{\text{enh}}(x,y)_o \) is the defuzzified output for the over-exposed region.

\[ \text{C. CONTRAST REGION ENHANCEMENT} \]

Given that this study intends to develop a contrast enhancement technique that will be applied to different types of images, such as UW and microscopic images, enhancement of contrast for different images requires different techniques as well. Therefore, nonlinear contrast enhancement techniques are selected to enhance each region separately instead of using linear contrast enhancement technique. The linear contrast enhancement technique globally improves the entire image contrast, which is not suitable in enhancing the contrast of specific regions of interest of the image. On the basis of the previous output from Section B, all the new regions [i.e., \( f_{\text{enh}}(x,y)_u, f_{\text{enh}}(x,y)_w, \) and \( f_{\text{enh}}(x,y)_o \)] are enhanced, as discussed in this section.

To enhance those three regions, three techniques, namely, nonlinear under-exposed contrast enhancement technique, nonlinear well-exposed contrast enhancement technique, and nonlinear over-exposed contrast enhancement technique, are introduced. The equation for the proposed nonlinear under-exposed region contrast enhancement technique is

\[ f_{\text{u,enh,}i}(x,y) = (L-1) \left[ 1 - e^{\frac{-f_{\text{enh}}(x,y)_u-f_{\text{enh}}(x,y)_u,\text{min}}{255\phi}} \right] \]  

\[ \text{where } f_{\text{u,enh,}i}(x,y) \text{ is the new intensity value of the pixels for the under-exposed region; } f_{\text{enh}}(x,y)_u \text{ is the intensity value of the pixels in the under-exposed region; } f_{\text{enh}}(x,y)_u,\text{min} \text{ and } f_{\text{enh}}(x,y)_u,\text{max} \text{ are the minimum and maximum intensity values of the pixels for } f_{\text{enh}}(x,y)_u, \text{ respectively; and } \beta \text{ is a constant parameter for the contrast adjustment of the under-exposed region intensities. The constant parameter } \beta \text{ is in the range of } 0.01-1, \text{ with an increment of } 0.01. \]

In (10) can also be simplified into:

\[ f_{\text{u,enh,}i}(x,y) = (L-1) \left[ 1 - e^{\frac{-f_{\text{enh}}(x,y)_u-f_{\text{enh}}(x,y)_u,\text{min}}{255\phi}} \right] \]  

The proposed nonlinear under-exposed region contrast enhancement technique stretches out the intensity distribution of the entire histogram of the region nonlinearly by compressing the portion of pixels situated on the left of the intensity scale and expanding the portion of pixels located on the right of the intensity scale.

The equation for the proposed nonlinear over-exposed region contrast enhancement technique is

\[ f_{\text{o,enh,}i}(x,y) = (L-1) \left[ e^{\frac{f_{\text{enh}}(x,y)_\text{,max}-f_{\text{enh}}(x,y)_\text{,min}}{255\phi}} \right] \]  

\[ \text{where } f_{\text{o,enh,}i}(x,y) \text{ is the new intensity value of the pixel for the over-exposed region; } f_{\text{enh}}(x,y)_\text{,max} \text{ is the intensity value of the pixel in the over-exposed region; } \phi \text{ is the constant parameter for contrast adjustment of the over-exposed region intensities in the range of } 0.01-1, \text{ with an increment of } 0.01. \]

A smaller value of \( \phi \) indicates that the bright region becomes brighter and the contrast of that region also increases. In (12) can also be further simplified into

\[ f_{\text{o,enh,}i}(x,y) = (L-1) \left[ e^{\frac{f_{\text{enh}}(x,y)_\text{,max}-f_{\text{enh}}(x,y)_\text{,min}}{255\phi}} \right] \]

The proposed nonlinear over-exposed region contrast enhancement technique also nonlinearly stretches out the intensity distribution of the entire histogram of the region. However, it is performed by expanding the portion of pixels situated on the left of the intensity scale and compressing the portion of pixels located on the right of the intensity scale. Hence, the contrast of the under-exposed region is increased, whereas the contrast of the over-exposed region is decreased.

To enhance the nonlinear well-exposed region, integration of contrast enhancement techniques for under- and over-exposed regions is proposed in this study. This integration leads to (13).

\[ f_{\text{w,enh,}i}(x,y) = (L-1) \left[ e^{\frac{f_{\text{enh}}(x,y)_\text{,min}-f_{\text{enh}}(x,y)_\text{,max}}{255\phi}} \right] \]

Once the contrast of the pixels of the three regions (i.e., over-, under-, and well-exposed) are enhanced, the regions \( f_{\text{u,enh,}i}(x,y), f_{\text{o,enh,}i}(x,y), \) and \( f_{\text{w,enh,}i}(x,y) \) are combined to
produce the final enhanced image with suitable contrast and uniform illumination called \( f_{\text{enh},i}(x,y) \), as shown as follows:

\[
f_{\text{enh},i}(x,y) = (f_{u,\text{enh},i}(x,y) + f_{w,\text{enh},i}(x,y) + f_{o,\text{enh},i}(x,y))
\]  

(14)

**D. QUANTITATIVE ANALYSIS**

The compatibility of the proposed ALEBRD is evaluated on the basis of the qualitative analysis. No ground truth images exist in classifying the images into three different regions. Thus, qualitative analysis is employed to test and evaluate the capability of the proposed AFELCE method. Five quantitative evaluations are utilized in this study, namely, E [38], measure of enhancement (EME) [39], measure of enhancement by entropy (EMEE), contrast improvement analysis (C) [40] and universal image quality index (UIQI) [41].

As introduced by Shannon and Weaver, (1948), E is utilized to evaluate the number of details in the image. Images with high value of E imply that they contain further detail information. E of an image is calculated as follows:

\[
E = - \sum_{i=0}^{l-1} p(Y_i) \times \log_2 p(Y_i)
\]

(15)

where \( p(Y_i) \) is the probability of enhanced grey levels \( Y_i \). EME proposed by Agaian et al., (2000) is also utilized to determine the average ratio of maximum and minimum intensities, as expressed as follows:

\[
EME = \frac{1}{k_1 \times k_2} \sum_{l=1}^{k_1} \sum_{k=1}^{k_2} 20 \log \left( \frac{l_{\text{max},k,l}}{l_{\text{min},k,l}} \right)
\]

(16)

where the image is divided into \( k_1 \times k_2 \) blocks, \( l_{\text{min},i,j} \) is the minimum intensity of each block and \( c \) is a small constant which is equal to 0.0001 to avoid dividing the number by 0. EME divides an image into numerous blocks, which is similar to the idea of AHE. Therefore, EME is suitable for measuring the local contrast of images. EMEE [42] is an extension of EME. As stated by Agaian et al. (2007), for certain circumstances, EME shows a characteristic of range dependent which changes itself based on the maximum and minimum range. Therefore, as a measurement of enhancement which is based on the concept of entropy, EMEE was introduced. For the new image quality index, EMEE is given by (17). The high value of EMEE indicates the better image quality.

\[
EMEE = \frac{1}{k_1 \times k_2} \sum_{l=1}^{k_1} \sum_{k=1}^{k_2} \alpha \left( \frac{l_{\text{max},k,l}}{l_{\text{min},k,l}} \right) ^{\alpha} \log \left( \frac{l_{\text{max},k,l}}{l_{\text{min},k,l}} \right)
\]

(17)

Contrast improvement analysis, C calculates the deviation of gray levels. A higher value of C indicates a larger dynamic range of grey levels and better overall contrast. C was computed in decibels (dB) as given by (18):

\[
C = 10 \log_{10} \left[ \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{k=1}^{N} \left( f_{\text{enh},i}(x,y) \right) ^2 \right] - \left[ \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} f_{\text{enh},i}(x,y) \right] ^2
\]

(18)

where \( f_{\text{enh},i}(x,y) \) is the grey level of the pixel at \((x, y)\).

The universal image quality index was used to calculate and applicable to non-uniform illumination and low contrast images. The quality index is defined by modelling any image distortion as a combination of three factors: loss of correlation, luminance distortion, and contrast distortion. The universal quality index is mathematically defined by (19):

\[
X = [x_i | i = 1, 2, ..., N] \text{ and } Y = [y_i | i = 1, 2, ..., N]
\]

(19)

where \( X \) is the original image and the \( Y \) is the test image. The proposed quality image index is defined as:

\[
Q = \frac{4 \sigma_{xy} \bar{x} \bar{y}}{(\sigma_x^2 + \sigma_y^2)(\bar{x})^2 + (\bar{y})^2}
\]

\[
\bar{x} = \frac{1}{N} \sum_{i=1}^{N} x_i, \quad \bar{y} = \frac{1}{N} \sum_{i=1}^{N} y_i,
\]

\[
\sigma_x^2 = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \bar{x})^2, \quad \sigma_y^2 = \frac{1}{N-1} \sum_{i=1}^{N} (y_i - \bar{y})^2.
\]

\[
\sigma_{xy} = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \bar{x})(y_i - \bar{y})
\]

(20)

The dynamic range of \( Q \) is \([-1, 1]\). The best value is 1 which is achieved if and only if \( x_i = y_i \) for all \( i = 1, 2, ..., N \). The lowest value of -1 occurs when \( y_i = 2x_i - x_i \) for all \( i = 1, 2, ..., N \). The definition of \( Q \) is a product of three components.

**III. RESULTS AND DISCUSSION**

This section focuses on the results for the second proposed technique, namely, AFELCE. This technique aims to solve the major issue of the low-contrast and non-uniform illumination images by applying different local contrast enhancement approaches to each region. The proposed AFELCE method is also applied to three different image databases (i.e., standard, UW, and microscopic human sperm (MHS) images).

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**FIGURE 1.** Gaussian membership function for the three regions.
Qualitative and quantitative analyses are employed to evaluate the resultant images. The qualitative evaluation is based on the visual observation using the human naked eyes. For the quantitative analysis, six quantitative parameters are assigned to evaluate the enhanced images. These parameters are E, EME, EMEE, C, and UIQI. Qualitative and quantitative analyses are selected to evaluate the performance of the proposed AFELCE with other state-of-the-art methods (i.e., Multi Scale Retinex Color Restoration (MSRCR) [43], Exposure [44], and Fuzzy Intensity Measurement (FIM) [45] methods). The MSRCR method was proposed to solve the gray world assumption which would cause a greyish output image with a certain color dominant enhances the overall regions of the image, while the Exposure method set a single threshold parameter to determine the regions of the image, the FIM method overcome the limitation of the Exposure method by dividing the image into two regions through a new threshold T which is more adaptive as compared to the Exposure method. Yet, the FIM method divides the image only into two regions (i.e. under- and over-exposed) which is still unable to identify the well-exposed region.

A. RESULTS OF CONTRAST ENHANCEMENT FOR STANDARD IMAGES

Figure 3 shows the results of the enhanced standard image named (i.e., NASA rocket image). As shown in Figure 3(b), the resultant image produced by the MSRCR method suffers from over-saturation. Most of the regions are over-enhanced by the MSRCR method, which can be observed in the regions highlighted by the rectangles. Generally, the MSRCR method visually fails to avoid over-saturation. Over-saturation can be observed as highlighted by the rectangles in Figure 3(b). Meanwhile, the exposure method can only enhance certain regions [as represented by the rectangles in the NASA rocket in Figure 3(c)], whereas other regions are not enhanced (as highlighted by the circles). Among the tested state-of-the-art methods, the FIM method shows the best performance. It can reduce the over-enhanced regions and produce uniform illumination resultant images. This problem can also be observed in other resultant images, as highlighted by the regular shapes in Figure 3(d). Among the tested methods, the proposed AFELCE method produces the best resultant images. It can produce uniform illumination resultant images. On the basis of all resultant images produced by the proposed AFELCE method, the illumination of these images is uniform. Less regions appear, which are under- or over-exposed. Therefore, the proposed AFELCE method can enhance images better than the other state-of-the-art methods by producing output images with more uniform illumination and higher contrast.

The good qualitative analysis obtained by the proposed AFELCE methods is supported by the quantitative analysis, as tabulated in Table 1. From the table, the proposed AFELCE has produced the highest E value images and the second-best E value for (i) image. This finding shows that the proposed AFELCE produces the best visual observation as previously mentioned, high entropy related to high intensity, and uniformity contrast of the resultant images. The AFELCE method has also produced the best results for E and EMEE analyses. AFELCE obtains the highest and the second highest values for E and EMEE values, respectively. This result shows that the proposed method can produce better results for images in terms of uniformity and contrast balancing. The resultant images become clearer than their original counterparts. The best quantitative results obtained by the proposed AFELCE method can be observed from the UIQI analysis. The proposed AFELCE method has produced either the best or the second-best results of the UIQI analysis for all the tested images. This finding shows that the AFELCE method can produce the highest quality output images in terms of image quality and balance contrast than the other state-of-the-art methods. In addition, the proposed AFELCE method has produced promising results for an average of 100 images for the quantitative analysis. It has produced the best results for E, EME, and UIQI, with values of 7.582, 42.75, and 0.94, respectively, and the second-best results for C, as shown in Table 2. This finding further proves that the proposed AFELCE method has outperformed the other state-of-the-art methods in enhancing non-uniform illumination and low-contrast standard images.

Therefore, qualitative and quantitative analyses prove that the proposed AFELCE method has successfully outperformed the other state-of-the-art methods by producing more uniform illumination resultant images with high contrast. The following two sub-sections will present the results for the UW and the MHS images.

B. RESULTS OF CONTRAST ENHANCEMENT FOR UNDERWATER IMAGES

This section presents the results of contrast enhancement produced by the proposed AFELCE method and the three state-of-the-art methods (i.e., MSRCR, exposure method, and FIM) for the UW image database. Figure 4 shows the results for the enhanced UW image. As shown in Figure 4(b), the resultant image produced by the MSRCR method suffers from over-saturation. As highlighted by the rectangles, the MSRCR method has over-enhanced several regions. The details in these regions are difficult to observe. For the exposure method, the performance of the contrast enhancement is limited. It can only enhance certain regions, as represented by the rectangles in the UW image shown in Figure 4(c), whereas other regions are not enhanced, as highlighted by the circles. In addition, over-enhanced images can be observed in UW1 image, as highlighted by the rectangles in Figure 4(c). The resultant images produced by the exposure method generally remains in the form of non-uniform illumination.

Among the tested methods, the proposed AFELCE method has produced the best resultant images. It can produce better uniform illumination resultant images than the other state-of-the-art methods. On the basis of all the resultant images, which are produced by the proposed AFELCE method, the
illumination of these images is more uniform than the state-of-the-art methods. Less regions appear, which are under- or over-exposed. For example, the texture of sand in UW1 image and the UW (i.e., Figure 4(e)) can be observed more clearly than the other resultant images. Therefore, the proposed AFELCE method has been proven to have better capability in enhancing images than the other state-of-the-art methods by producing output images with more uniform illumination and higher contrast.

As shown in Table 1, the proposed AFELCE has produced the highest UIQI value. This finding shows that for the proposed AFELCE, the UIQI results match the previously mentioned visual observation, with high UIQI related to high quality image of the resultant images. The proposed AFELCE has also produced the highest EME image. In addition, the proposed AFELCE method has produced promising results for average qualitative analysis, as shown in Table 3. It has produced the best results for E, EME, and UIQI, with values 7.124, 41.31, and 0.89, respectively. This finding once again shows that the proposed AFELCE method is the best approach for contrast enhancement of non-uniform illumination and low-contrast UW images.

Therefore, qualitative and quantitative analyses have proven that the proposed AFELCE method has successfully outperformed the other state-of-the-art methods for UW images. Similar to the standard image results, the MSRCR and exposure method failed to produce uniform output images. By contrast, FIM has over-enhanced the over-exposed regions and consequently lead to over-saturation. However, the proposed AFELCE methods have successfully overcome all the aforementioned issues and produced the best uniform output images.

C. RESULTS OF CONTRAST ENHANCEMENT FOR MICROSCOPIC HUMAN SPERM IMAGES

This section tests another type of non-uniform illumination and low-contrast image. MHS image database is used to test the capability of the proposed AFELCE and compare the output resultant images with the state-of-the-art methods (i.e., MSRCR, exposure method, and FIM). Five random MHS images are selected from 100 tested images. Figure 5 shows the results for the enhanced MHS image. As shown in Figure 5(b), the resultant image produced by the MSRCR method suffers from over-saturation. Most of the regions are over-enhanced by the MSRCR method, as highlighted by the rectangles in the figure.

For the exposure method, the contrast enhancement is limited. It enhances only certain regions, as represented by the rectangles in the MHS images in Figure 5(c), whereas other regions are not enhanced, as highlighted by the circles.

Generally, the resultant images produced by the exposure method remain in the form of non-uniform illumination. Among the tested state-of-the-art methods, the FIM method shows the best performance. It can reduce the over-enhanced regions and produce uniform illumination resultant images. This finding can be observed in all the images, as shown in Figure 5(d). However, over-enhanced regions can still be observed. For example, the FIM method has over-enhanced certain regions in Figure 5(d), as highlighted by the rectangles.

Among the tested methods, the proposed AFELCE method has produced the best resultant images. It can produce more uniform illumination resultant images than those of the other state-of-the-art methods.

On the basis of all resultant images produced by the proposed AFELCE method, the illumination of these images is more uniform than the state-of-the-art methods. In conclusion, the proposed AFELCE method can enhance images better than the other state-of-the-art methods by producing output images with more uniform illumination and higher contrast. The good qualitative analysis obtained by the proposed AFELCE method is supported by the quantitative analysis, as tabulated in Table 1. From the table, the proposed AFELCE method has produced the highest E value. This promising result supports the visual observation of the proposed AFELCE than the other state-of-the-art methods. AFELCE has obtained the highest and second-highest values for E and EME values. This result shows that the proposed method can produce better results for image enhancement and that the resultant images becomes clearer than their original counterparts. The best quantitative results obtained by the proposed AFELCE method can be observed from the analysis of E value. This analysis shows that the AFELCE method, where high E refers to image information.

The proposed AFELCE method has also produced promising results for average quantitative analysis. It has produced the best results for E and EME, with values of 7.602 and 42.51, respectively, and the second-best results for C and UIQI, with values of 24.032 and 0.72, respectively, as shown in Table 4. This finding further proves that the proposed AFELCE method outperforms the other state-of-the-art methods in enhancing non-uniform illumination and low-contrast MHS images.

Therefore, qualitative and quantitative analyses have proven that the proposed AFELCE method has successfully outperformed the other state-of-the-art methods. The MSRCR and the exposure method have failed to produce uniform output images, whereas the FIM has failed to enhance the over-exposed regions. However, the proposed AFELCE methods have successfully overcome all the aforementioned issues and produced the best uniform output images.

VI. CONCLUSION

This study proposes a new a fuzzy-based contrast enhancement technique to enhance each region individually. The technique is called AFELCE. This technique employs a modified GMF as its main tool in the fuzzification process. After implementing the defuzzification process, three different nonlinear contrast enhancement approaches (i.e., nonlinear under-exposed contrast enhancement, nonlinear well-exposed contrast enhancement, and nonlinear over-exposed contrast enhancement techniques) are applied to under-, well-, and over-exposed regions, respectively. The resultant enhancement image is then obtained by recombining these three regions. The proposed AFLECE technique has
successfully enhanced low-contrast and non-uniform illumination images by having the best qualitative and quantitative image analyses than the MSRCR, exposure method, and FIM. The proposed AFELCE method has also successfully preserved the image details by individually applying the local contrast enhancement on each region.

In addition to standard images, the proposed AFELCE method is applied to two real-case studies, namely, UW, and MHS images. From the results obtained, the proposed method has a high level of robustness by providing uniform illumination and high-contrast resultant images. The AFELCE method has outperformed the other state-of-the-art methods quantitatively (i.e., in terms of E, EME, EMEE, C, and UIQI values) and qualitatively.
FIGURE 3. Results of contrast enhancement for standard images, NASA rocket: (a) Input image, (b) MSRCR method, (c) Exposure method, (d) FIM method and (e) AFELCE proposed method.
FIGURE 4. Results of contrast enhancement for standard images, UW image 1: (a) Input image, (b) MSRCR method, (c) Exposure method, (d) FIM method and (e) AFELCE proposed method.
FIGURE 5. Results of contrast enhancement for standard images, MHS image 1: (a) Input image, (b) MSRCR method, (c) Exposure method, (d) FIM method and (e) AFELCE proposed method.
### TABLE I

**Quantitative Results for the Standard Images Database in Figures 3 to 5**

<table>
<thead>
<tr>
<th>Method</th>
<th>E</th>
<th>EME</th>
<th>EMEE</th>
<th>C</th>
<th>UIQI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input</td>
<td>6.871</td>
<td>15.743</td>
<td>8.958</td>
<td>23.34</td>
<td>0.2667</td>
</tr>
<tr>
<td>MSRCR</td>
<td>6.410</td>
<td>4.876</td>
<td>6.0802</td>
<td>21.52</td>
<td>0.2239</td>
</tr>
<tr>
<td>Exposure</td>
<td>6.867</td>
<td>16.274</td>
<td>8.916</td>
<td>24.06</td>
<td>0.2508</td>
</tr>
<tr>
<td>Nasa rocket</td>
<td>FIM</td>
<td>6.884</td>
<td>32.524</td>
<td>8.926</td>
<td>24.048</td>
</tr>
<tr>
<td>AFELCE</td>
<td>7.003</td>
<td>26.315</td>
<td>8.947</td>
<td>24.025</td>
<td>0.2724</td>
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<tr>
<td>Input</td>
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<td>77.862</td>
<td>1.679</td>
<td>13.14</td>
<td>0.0084</td>
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<td>MSRCR</td>
<td>6.863</td>
<td>113.327</td>
<td>1.791</td>
<td>49.15</td>
<td>0.5676</td>
</tr>
<tr>
<td>Exposure</td>
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<td>148.007</td>
<td>1.552</td>
<td>54.92</td>
<td>0.7335</td>
</tr>
<tr>
<td>UW</td>
<td>FIM</td>
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<td>120.493</td>
<td>1.456</td>
<td>28.93</td>
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<tr>
<td>AFELCE</td>
<td>7.641</td>
<td>78.055</td>
<td>1.133</td>
<td>52.48</td>
<td>0.9374</td>
</tr>
<tr>
<td>Input</td>
<td>5.912</td>
<td>6.386</td>
<td>0.417</td>
<td>7.26</td>
<td>0.3214</td>
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<td>MSRCR</td>
<td>4.737</td>
<td>33.836</td>
<td>7.947</td>
<td>12.78</td>
<td>0.4668</td>
</tr>
<tr>
<td>Exposure</td>
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<td>10.566</td>
<td>1.980</td>
<td>21.80</td>
<td>0.8470</td>
</tr>
<tr>
<td>MHS</td>
<td>FIM</td>
<td>6.299</td>
<td>6.127</td>
<td>0.370</td>
<td>16.84</td>
</tr>
<tr>
<td>AFELCE</td>
<td>6.865</td>
<td>20.302</td>
<td>34.277</td>
<td>15.76</td>
<td>0.8352</td>
</tr>
</tbody>
</table>
### TABLE II
**AVERAGE VALUES OF QUANTITATIVE ANALYSIS OF STANDARD IMAGES IN TERMS OF E, EME, EMEE, C AND UIQI BETWEEN THE COMPARED STATE-OF-THE-ART WITH THE PROPOSED AFELCE METHODS FOR 100 STANDARD IMAGES.**

<table>
<thead>
<tr>
<th>Method</th>
<th>E</th>
<th>EME</th>
<th>EMEE</th>
<th>C</th>
<th>UIQI</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSRCR</td>
<td>5.649</td>
<td>21.83</td>
<td>1.645</td>
<td>23.874</td>
<td>0.67</td>
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<tr>
<td>Exposure</td>
<td>7.017</td>
<td>28.93</td>
<td>1.073</td>
<td>24.093</td>
<td>0.72</td>
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<td>FIM</td>
<td>6.518</td>
<td>28.31</td>
<td><strong>4.712</strong></td>
<td><strong>24.153</strong></td>
<td><strong>0.91</strong></td>
</tr>
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<td>AFELCE</td>
<td><strong>7.582</strong></td>
<td><strong>42.75</strong></td>
<td><strong>4.184</strong></td>
<td><strong>24.122</strong></td>
<td><strong>0.94</strong></td>
</tr>
</tbody>
</table>

### TABLE III
**AVERAGE VALUES OF QUANTITATIVE ANALYSIS OF UNDERWATER IMAGES IN TERMS OF E, EME, EMEE, C AND UIQI BETWEEN THE COMPARED STATE-OF-THE-ART WITH THE PROPOSED AFELCE METHODS FOR 100 UNDERWATER IMAGES.**

<table>
<thead>
<tr>
<th>Method</th>
<th>E</th>
<th>EME</th>
<th>EMEE</th>
<th>C</th>
<th>UIQI</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSRCR</td>
<td>5.712</td>
<td>24.15</td>
<td><strong>3.354</strong></td>
<td>23.016</td>
<td>0.62</td>
</tr>
<tr>
<td>Exposure</td>
<td>7.112</td>
<td>25.96</td>
<td>2.763</td>
<td>24.061</td>
<td>0.69</td>
</tr>
<tr>
<td>FIM</td>
<td>7.092</td>
<td>23.86</td>
<td>1.975</td>
<td><strong>24.098</strong></td>
<td><strong>0.78</strong></td>
</tr>
<tr>
<td>AFELCE</td>
<td><strong>7.124</strong></td>
<td><strong>41.13</strong></td>
<td>1.796</td>
<td>24.047</td>
<td><strong>0.89</strong></td>
</tr>
<tr>
<td>Method</td>
<td>E</td>
<td>EME</td>
<td>EMEE</td>
<td>C</td>
<td>UIQI</td>
</tr>
<tr>
<td>--------</td>
<td>-----</td>
<td>------</td>
<td>------</td>
<td>-----</td>
<td>------</td>
</tr>
<tr>
<td>MSRCR</td>
<td>7.011</td>
<td>23.82</td>
<td>5.871</td>
<td>23.071</td>
<td>0.64</td>
</tr>
<tr>
<td>Exposure</td>
<td>7.476</td>
<td>21.74</td>
<td>4.848</td>
<td>24.003</td>
<td>0.70</td>
</tr>
<tr>
<td>FIM</td>
<td>7.531</td>
<td>22.44</td>
<td>7.361</td>
<td>24.059</td>
<td>0.75</td>
</tr>
<tr>
<td>AFELCE</td>
<td><strong>7.602</strong></td>
<td><strong>42.51</strong></td>
<td><strong>3.673</strong></td>
<td><strong>24.032</strong></td>
<td><strong>0.72</strong></td>
</tr>
</tbody>
</table>

### REFERENCES AND FOOTNOTES

#### A. REFERENCES


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