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Nonlinear Exposure Intensity Based Modification Histogram Equalization for Non-Uniform Illumination Image Enhancement

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ABSTRACT Non-uniform illumination image is often generated owing to various factors, such as an improper setting in the image acquisition device and absorption or reflectance of the objects that results in the existence of different exposure regions in the image. Although Histogram Equalization (HE) is well known and widely used in image enhancement, existing HE-based methods often generate washed-out effects and show unnatural appearance due to the over-enhancement phenomenon, which limits the capabilities of achieving illumination uniformity of an image. Therefore, this study proposes a modified HE method for non-uniform illumination image, namely Nonlinear Exposure Intensity-Based Modification Histogram Equalization (NEIMHE). The proposed NEIMHE method divides the non-uniform illumination image into five sub-regions and modifies the histogram of each sub-region by setting a nonlinear weight into their cumulative density function (CDF) of histogram in each sub-region. Each modified histogram is then equalized using modified HE equations that provide the intensity expansion and different intensity mapping directions for under-exposed and over-exposed sub-regions. A total of 354 non-uniform illuminated sample images were used to evaluate the performance of the proposed NEIMHE method, qualitatively and quantitatively. The proposed NEIMHE method was compared qualitatively with five state-of-the-art methods: Backlit, Adaptive Fuzzy Exposure Local Contrast Enhancement (AFELCE), Visual Contrast Enhancement Algorithm Based on Histogram Equalization (VCEA), Exposure Region-based Multi Histogram Equalization (ERMHE); and Exposure based Sub-Image Histogram Equalization (ESIHE). The proposed NEIMHE method produced an enhanced image with more uniform illumination, better preservation of image details, and high capability of maintaining image naturalness. Quantitatively, the proposed NEIMHE method achieved the highest scores in Discrete Entropy (DE), Measure of Enhancement (EME), Measure of Enhancement by Entropy (EMEE), and Peak Signal to Noise Ratio (PSNR); it attained second-best in Absolute Mean Brightness Error (AMBE) and Lightness Order Error (LOE). From both analyses, the proposed NEIMHE method has shown its capability of enhancing different exposure regions that exist in non-uniform illumination images.

INDEX TERMS Nonuniform illumination image, image enhancement, histogram equalization, nonlinear histogram modification, exposure regions.

I. INTRODUCTION

During image acquisition, light sources such as the sun, the moon and fluorescent light will radiate light to the object, which is then captured by the acquisition device sensor that produces an image. However, certain conditions either caused by the image acquisition device (i.e. inappropriate adjustment and limitation of the device properties) or by the condition of object itself (i.e. different absorption and reflection properties of the object on light irradiated) can result in uneven exposure to the object in an image [1], [2]. Hence, different illumination regions such as dark regions

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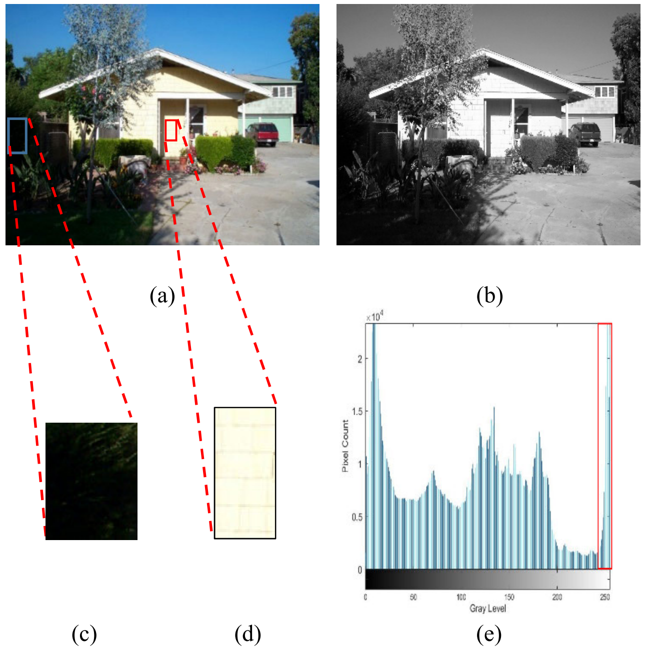

FIGURE 1. **Non-uniform illumination image (a) Original image (b) Greyscale image (c), (d) Degenerated details in UE and OE respectively (e) Its Grey level distribution histogram.**

(i.e. shadow region) and sometimes extreme bright regions (i.e. bright sky) could be observed in an image. In such condition, the image is said to have non-uniform illumination as shown in Fig. 1(a). Generally, the non-uniform illumination image suffers from extremely dark and/or extremely bright intensity regions termed as under-exposed (UE) and over-exposed (OE) regions, respectively. Based on Fig. 1(a), both UE and OE regions are not preferred in the image since the details in both regions are invisible and unobservable as shown by the magnified image in Fig. 1(c) and Fig. 1(d). These conditions affect visual evaluation, hence may lead to misinterpretation of information from the image and inaccuracies in subsequent processes in image analysis [2], [3]. On the other hand, there is a third region type exists in the image that has a good exposure and its details can be clearly seen by human visual system which is known as well-exposed (WE) region. The WE regions normally provide clear information, thus are preferable to be captured during image acquisition.

In order to improve the visual quality or interpretability of information in non-uniform illumination images for the sake of human viewers as well as to provide better input for subsequence image processing approaches, a proper enhancement process is needed. The main concern in non-uniform illumination image enhancement is to improve the uniformity of the image's illumination as well as restoring the degenerated details. Various enhancement methods have been published to address this concern, for instance histogram equalization [4]–[9], Retinex based algorithm [10]–[13], nonlinear mapping [3], [9], [14]–[16], and fuzzy transform [17]–[19]. Among the aforementioned methods, histogram based enhancement methods are commonly used in image enhancement due to their simplicity thus satisfy human visual system since they use luminance rather than color [20]. The most popular method in histogram based enhancement is histogram equalization (HE) that mapping the input gray level based on the probability of pixels' occurrences in each gray level.

Numerous HE works have shown excellent performance in enhancing the uniform illumination images, but only few works focused on enhancing non-uniform illumination images such as in [4] and [5]. The detailed review will be presented in Section II. There were HE-based enhancement methods proposed by previous researchers that combined between HE and another methods such as Retinex based and nonlinear mapping for the same purpose [6]–[9]. Method in [6] estimated the illumination and reflectance components of an image and divided the image into dark and bright regions using illumination component. Each region is then enhanced using specific approaches, which are different to each other. The enhanced images for both regions are then combined together and further enhanced using modified clipped HE. In the clipped HE method, the clip limit is set to be 50% of the total pixels. The remaining pixels above the clip limit is redistributed to both dark and bright regions. The clipped HE prevented over enhancement, thus ensures uniform shifting of input gray levels. The combination of the enhancers and clipped HE successfully produced more uniform illumination and better contrast image. In other works ([7], [8]), Tian and Cohen proposed two contrast enhancement methods that combined the global linear stretching and Contrast Limited Adaptive Histogram Equalization (CLAHE) in order to improve the contrast and reduce saturation in non-uniform illumination color image. Both proposed methods produced better contrast as a result of linear stretching and were able to preserve the details which was contributed by CLAHE. However, both methods did not consider noise amplification effects. In addition, method in [7] used optimization method that required complex computation, hence increase processing time. Nonlinear histogram modification was proposed in [9], where the images were modified using the modified image's luminance. The nonlinear properties were obtained by determination of pixel-wise threshold parameter that represent local luminance strength and assignment of different weightage on each bin based on Just-Noticable-Different theory. The color image was then reconstructed using original chromatic information and the modified luminance. In order to improve the details, local contrast was boosted via comparison between neighbors. This method produced vivid color and proper contrast. For all the abovementioned methods, the proposed method in [6] performed histogram equalization on the global histogram while methods in [7], [8], and [9] used local HE in the purpose of details enhancement.

As mentioned, a non-uniform illumination image consists of different types of exposure, therefore several researchers specifically considered the exposure conditions in their proposed enhancement methods. In general, the approaches used by those researchers applied different enhancement rates to different exposure types. For example, higher enhancement rate should be applied to UE or dark regions as compared to OE or bright regions. Thus, the original histogram of an image needs to be segmented into sub-histograms which represent the exposure types of the image before appropriate enhancement process is applied. Wharton *et al.* [4] first explored the exposure based HE technique in enhancing non-uniform illumination image by separating the original image into three different illumination regions and then equalized each region using conventional HE method. The idea of separating the image into different regions enable different enhancement rates to be applied to each sub-histogram. However, this method used the conventional HE which has limited enhancement rate control. In some cases, this issue has caused over enhancement in certain regions. This problem gave big impact to OE region where over-saturated region could be produced. The details could be washed-out. In order to prevent over-enhancement in each sub-histogram, Exposure Region-based Multi Histogram Equalization (ERMHE) considered entropy to obtain new thresholds that will be used to repartition the global histogram prior to HE process [5]. Similar to [4], this method, at first, segmented the histogram into three exposure regions named as UE, OE and WE region. Each sub-histogram is then repartitioned based on the optimum entropy determined for each sub-histogram. The re-allocation of the grey level range has been proven to prevent dominating bins from introducing unbalanced output gray levels range. HE was performed to each modified sub-histogram, which resulted in more uniform distribution of gray levels output. However, ERMHE introduced artefacts to the enhanced image. Since it only aimed to provide meaningful partition based on entropy, this method neglected to control the amount of grey level shifting, hence produced artefacts to the enhanced image. In addition, ERMHE was unable to reduce the high intensity of the OE region. The OE region is represented by high frequency bins that occasionally exist on the right end of the gray level histogram as shown by red rectangle in Fig. 1(d). The corresponding gray image is shown in Fig. 1(b). Similar to work in [4] that used the conventional HE to equalize the image, high intensity of the OE pixels as shown by red rectangle in Fig. 1(d) are unable to be reduced since the grey level shifting in the conventional HE was towards the right hand side. This conventional mapping resulted in over-enhancement of OE region, therefore was unable to enhance the details as well as to achieve uniformity of image illumination.

Motivated by those aforementioned problems, this paper aims to specifically enhance the UE, OE and WE regions by first considering the level of exposure in each region and then providing different and specific enhancement process to each region. It is believed to prevent over enhancement problem, over-saturated enhanced image, washed-out issue and existence of artefacts that experienced by the abovementioned HE based methods. The proposed method adopts histogram segmentation based on the actual exposure of the image as a first step. Then, a new HE-based contrast enhancement method will be introduced to perform different enhancement rate for each determined region. In order to prevent the over enhancement in each region, the proposed method will consider clipping process while nonlinear elements are introduced in equalization process to ensure the uniformity of image illumination. In addition, level of exposure of each region will be considered before nonlinear enhancement is applied to ensure the gray levels shifting is commensurate to the average exposure in the respective region.

II. RELATED WORKS

A. NON-UNIFORM ILLUMINATION IMAGE ENHANCEMENT METHODS

The inconsistent illumination produced in non-uniform illumination image has attracted many researchers to work on enhancement of the image. The existing enhancement works have produced enhanced images with more uniform illumination [3], [15], [18], clear details [16], [21], preserved naturalness [10], [11], [18], and suppressed noise [17]. These methods can be divided into several domains which are nonlinear mapping based algorithm, retinex based algorithm, fuzzy transformed based algorithm, and histogram based algorithm. Retinex based algorithm is inspired by Retinex theory which insists on the fact that the human perceived lightness is determined by its neighbor's relative lightness [22]. Thus, a difference between a pixel and its neighbors is used for renewing each pixels' strength in any color channels. Due to local comparisons of neighboring pixels, Retinex based algorithm can bring local luminance closer to correct values and effectively increase local contrast. Numerous image enhancement works have been done using this domain. The main difference among the Retinex-based methods lies on the technique used to decompose illumination and reflectance components of the image. This decomposition process is important to generate proper illumination and reflectance components for further enhancing the illumination component and also to avoid halo effect that normally occurs at the edge of an image.

Wang *et al.* [10] is the first researcher that used Retinex theory in enhancing non-uniform illumination image. They proposed image decomposition into reflectance and illumination using a bright-pass filter which determined the details and the naturalness of the image and at the same time limited the reflectance value to prevent over-enhancement [10]. Then, bi-log transformation was utilized to map the illumination in order to balance between details and naturalness. However, this method did not consider different levels of illumination, therefore it may introduce minor flickering in case the scenes vary with different degrees of illumination [10]. Shin *et al.* focused to preserve the naturalness, suppress halo effect around the edges, improve the contrast and brightness of non-uniform illumination images by proposing retinex based naturalness preservation method [11]. The image was decomposed into illumination and reflectance components using image gradient component which can suppress the artefacts around edges. The illumination was then enhanced using adaptive gamma correction to avoid over-enhancement. To further enhance the contrast, the proposed method adopted histogram based method by using specified mapping curve. However, this method failed to limit illumination range, therefore the illumination may be under estimated. Another illumination estimation algorithm was proposed by Gao *et al.* which was based on the edge-preserving filter [12]. This method preserved the naturalness of the image instead of exploits all constraints for another estimated illumination algorithm such as spatial smoothness, sharp edges on illumination boundaries, and limited range of illumination. In addition, the proposed method performed fast estimation by using box filter. The illumination was then enhanced using method proposed by [10]. The abovementioned Retinex based image enhancement methods, in some cases, produced poor ambiance due to the loss of illumination in order to boost the reflectance layer, hence resulted in extreme color distortion and unnaturalness in the enhanced image [13]. This problem happened due to the uncertainty in the boundary of image decomposition and illumination removal estimation.

In order to cater the uncertainty condition, fuzzy based image enhancement methods were studied. The fuzzy based system is based on fuzzy set theory that holds the principles of uncertainty, ambiguity, and vagueness [17]. Since non-uniform illumination images have no rigid boundaries between their dark and bright regions, fuzzy based system is useful in distinguishing these areas. Verma *et al.* [21] proposed enhancement method for high dynamic range color image using fuzzy logic. The method at first separated color image into three exposure regions named as UE, OE and mixed-exposed regions using exposure parameters. The luminance component of HSV color image in each region was then fuzzified using Gaussian membership function. Different sigmoid operators that emphasized on crossover points and intensification parameters were used to enhance the fuzzified luminance of UE and OE regions. These parameters were then optimized to get the enhanced image that can recover the degenerated details and produced visually pleasing image. Hasikin and Mat Isa [17] continued the idea of dividing the non-uniform illumination image into different exposure regions for further enhancing the image using fuzzy set theory. They proposed new parameter named as contrast factor which considered both global and local information to divide the image into bright and dark regions. Each determined region was then fuzzified separately using modified Gaussian membership function before the fuzzified image was enhanced using sigmoid function that consider local contrast of each region in order to preserve the details. By introducing the new parameter and associating local contrast during enhancement, the method was able to preserve brightness and details without amplifying existing noises. However, in some cases, the resultant images produced are low in contrast.

Reshmalakshmi and Sasikumar [18] implemented parametric fuzzy transform into luminance layer of LUV color space image. The parameters were obtained from the mean value of intensity, V channel of HSV color space image. In this method, RGB image was first converted to LUV and HSV color space. In order to enhance the details, a weighted V channel was implemented based on pixel neighborhood property. This method successfully enhanced the non-uniform illumination images and preserved the naturalness of the image at low computational cost. In [19], Mohammed Salih *et al.* enhanced the non-uniform illumination image locally and regionally using fuzzy logic approach. The image was first separated into three regions known as UE, OE and WE regions before each region was fuzzified using Gaussian membership function. The fuzzified image was then enhanced using different enhancement algorithms for each region. The specific enhancement algorithms however produced over-enhancement for some OE regions. In summary, most fuzzy based enhancement methods segmented the non-uniform illumination image into different exposure regions before fuzzification and enhancement processes were applied to the image. The fuzzified process that involves membership function indirectly contributed to different enhancement rate, hence can suppress noise.

Nonlinear mapping was also widely used in enhancing non-uniform illumination. This method mapped the image luminance nonlinearly in which UE region was lightened while OE region was dimmed, thus compressing the global dynamic range [9]. Wang *et al.* [3] applied the nonlinear modification method to image luminance using Symmetric Naka Rushton Formula (SNRF) to increase the luminance of UE pixels while decreasing the luminance of OE pixels. SNRF curve shaped as convex at the low luminance level while concave at the high luminance level with a control parameter for the adaptation of the two shapes. The UE and OE regions were determined locally using dynamic threshold value. To reconstruct the color image, the luminance and original chromaticity were combined together using exponential technique before local contrast was performed using local image exponential technique. Gupta and Agarwal [14] proposed modified sigmoid function on the base layer of luminance Y component of YCbCr image to enhance the contrast of dark region without affecting the mean brightness of the image and color information of bright region. The sigmoid function has specific inclination to consider the enhancement rate needed. Wang *et al.* [15] proposed the enhancement method that increased the intensity value in the excessive dark regions and reduced the intensity value in the excessive bright regions simultaneously as well as enhanced the details in both the dark and bright regions using bilateral Gamma Function. The non-uniform illumination panaromic image was first decomposed into illumination component and reflectance component using fast image guided filter due to its excellent edge-preserving capabilities and controlled computational complexity. Then, the illumination was corrected using bilateral gamma function that considered the distribution illumination characteristics in both dark and bright regions of the image which was determined by setting threshold value to 128. In [16], Xiong and Yang worked on improved gamma curve to correct the illumination adaptively in non-uniform illumination image. The illumination component extracted by multi-scale weighted filtering was enhanced by the dynamic gamma parameter that depends on the mean illumination of the image and the illumination of each pixel. This method overcame traditional gamma algorithm that unable to enhance the dark area, thus failed to properly enhance the details. Based on the literature review, as a conclusion, the nonlinear based image enhancement showed excellent performance in enhancing non-uniform illumination images. However, several methods (i.e. Luminance Based Sigmoid Function in [14], Adaptive Correction Algorithm Based On The Improved Bilateral Gamma Function in [15]) introduced predefined parameters that need to be predetermined and in some cases may not be well-suited to all types of images. In addition, a method such as in [15] required long processing time because of iteration processes to obtain the optimum parameters.

In order to reduce the constraints of the inappropriate value of predefined parameters in the abovementioned non-linear mapping methods, histogram based enhancement methods especially Histogram Equalization (HE) provide simplicity and effectiveness in enhancement. Several works on HE in enhancing non-uniform illumination image have been explained in previous section. Apart of HE, there are several enhancement works that suggested the addition of another processes after HE to be carried out to provide better enhancement performance. Visual Contrast Enhancement Algorithm Based on Histogram Equalization (VCEA) in [23] was proposed to improve image quality in consideration of the requirements of human visual perception. As HE resulted in overstretched especially in the low contrast image, VCEA adjusted the spaces between two adjacent gray level values by devising a space adjustment function using Just Noticeable Difference (JND) concept. In order to recover the lost details, compressed pixel recovery used free spaces to recover as many compressed gray values as possible in order to regain the lost features in JND image. Details texture enhancement was performed in the last stage to enhance the texture details in the image using gradient and space adjustment functions. The proposed method produced enhanced image with clear details and higher contrast in UE region. This work was extended in [24] with additional segmentation of image histogram into dark and bright regions at the beginning of the method using human visual perception element. However, the proposed method did not emphasize in controlling the enhancement in bright or OE regions, thus led to over-enhancement problem.

Due to the properties of non-uniform illumination image that consists of different exposure regions, it is important to enhance the image properly based on the actual exposure regions that appear in the image. In addition, the different enhancement rate of each region should also be emphasized, therefore level of exposure in each region must be considered during enhancement process. Lee *et. al.* proposed adaptively partitioned block-based contrast enhancement (Backlit) that performed contrast stretching based on the determined fuzzy-based exposure region [25]. This low computational complexity technique aimed to solve the over-saturation problem that occur in the conventional contrast stretching techniques. In Backlit, at first, the input image is partitioned into blocks and then each block is classified into different exposure regions known as dark, bright or ambiguous region using two threshold values that are computed using fuzzy C-means clustering (FCM). The ambiguous regions are then being partitioned and reclassified until the block is in 4×4 size. Then, guided filter is applied to the dark region and contrast stretching is performed in the dark region to increase the contrast of that region. The final enhanced image is generated by combining the contrast enhanced image and the original image with refined dark region. Table 1 summarizes the existing non-uniform illumination image enhancement methods (i.e. nonlinear mapping based, retinex based and fuzzy transformed based enhancement methods), which consider these two criteria (i.e. determination of different exposure regions and providing enhancement rate control in each region) to provide proper enhancement. Advantages and disadvantages of those methods are also tabulated. From the table, 8 out of 17 reviewed enhancement methods considered these two criterion in their works. The findings were promising. Unfortunately, these methods required manual predefined optimum parameters values, which is subjective and cause these methods to be inflexible yet unreliable to all type of images. For the other methods, which applied one or none of the criteria, although those methods were able to enhance the details and preserve the lightness, but several methods introduced over-enhancement such as in [4] and [18]. These limitations have motivated researchers to introduce histogram based enhancement methods especially the HE-based enhancement methods, which provided the simple yet reliable methods in enhancing the non-uniform illumination image.

B. HISTOGRAM EQUALIZATION BASED IMAGE ENHANCEMENT METHODS

Histogram modification, one of the popular approaches in image enhancement, maps or redistributes the original gray level of an image into new gray level to ensure a more uniform resultant histogram than the original histogram. This procedure, therefore, will increase the contrast of the image. The most well-known enhancement method that applies histogram modification is HE. Generally, HE has four main variants which are local HE, multi-histogram HE, histogram modification HE, and exposure intensity based HE. The conventional HE improves the contrast by flattening the input histogram using probability of each histogram bins and their cumulative value [26]. High probability pixels cause greater shift of a grey level while low probability pixels tend to accumulate to adjacent grey level. As a result, over enhancement

TABLE 1. Summary of existing non-uniform illumination enhancement methods.

Method	Considered criteria for enhancement process	Advantages	Limitations
NPEA [10]	Only enhancement rate control	• Preserve the lightness order • Enhance the details in the image	• May amplify noise • Needs longer processing time
ENR [11]	Only enhancement rate control	• Suppressed halo effect • Preserved naturalness • Provide low computational cost	• Produced redundant details in illumination [12]
NPNIE [12]	Only enhancement rate control	• Fast Implementation	• Inaccurate illumination estimation
AFIM [17]	Both different luminance region and enhancement rate control	• Preserve brightness and details without amplifying existing noises	• May produce low contrast image
FT [18]	None	• Preserved naturalness and details • Provide low computational cost	• May produce excessive contrast
AFELCE [19]	Both different luminance region and enhancement rate control	• Provide uniform illumination for two real case study images (underwater images and microscopic human sperm images)	• Produce over-enhancement in OE region
AENM [3]	Both different luminance region and enhancement rate control	• Produce good contrast and vivid color	• May generate overvivid images especially on warm color that exist in an image [5]
LBSF [14]	Both different luminance region and enhancement rate control	• Suppressed noise • Provide different level of enhancement in the darker region and brighter region	• Used fixed parameters that might not suitable for some particular images.
IBGF [15]	Both different luminance region and enhancement rate control	• Enhance details in both dark and bright regions effectively. • Reduce the intensity value in the bright regions.	• Used fixed parameters that might not suitable for some particular images.
AICUGC [16]	None	• Balance the uneven brightness of the image • Preserve the details of the image	• Used fixed parameters that might not suitable for some particular images.
HVSMHE [4]	Only different luminance region	• Provide controllable enhancement based on actual region exposure	• Caused over enhancement especially in high dominating bins
ERMHE [5]	Both different luminance region and enhancement rate control	• Produce more uniform illuminated image with better contrast • Preserved details	• Caused over enhancement especially in high dominating bins in OE region
Backlit [25]	Only different luminance region	• Produce brighter image which is suitable to UE image	• Produce block artifact between different exposure regions
BHMOSE [6]	Both different luminance region and enhancement rate control	• Improve local contrast • Preserve details • Reduce the effect of noise amplification	• Slight noise amplification
GLCAE [7]	Only enhancement rate control	• Produce better contrast • Preserve the details	• Undesirable noise in the dark regions of some non-uniform illumination images
COCC[8]	Only enhancement rate control	• Produce better contrast • Preserve the details	• Required complex computation
PWHMCR [9]	Both different luminance region and enhancement rate control	• Fast computational • Protecting smooth uniform areas • Provide effective enhancement for small dark, highly-bright regions and globally overexposed image	• Required complex computation

is produced which lead to loss of details in enhanced image. In order to preserve the details, local HE was proposed in which each pixel is allowed to adapt to its local pixel intensity distribution rather than global information [27]. Although this method successfully enhanced the details of image, but the computational time and complexity are also increased. In a non-uniform illumination image, local HE can also produce over enhancement and under enhancement in the extremely bright and dark regions respectively if the local neighborhood experienced these illumination regions [28].

In order to retain the local adaptability and contrast stretching, multi-histogram based HE was proposed. This method partitioned the input histogram into several segments and then the conventional HE was applied to each sub-histogram, hence provided local contrast stretching and adaptability compared to the conventional HE [4]. However, multi-histogram HE often produced high dominant components in a single sub-histogram due to the inappropriate threshold value that was used to segment the histogram. Hence, over enhancement might occur in the sub-histogram. In order to overcome the inappropriate histogram segmentation and a better consideration of image naturality, exposure intensity-based HE was proposed to provide proper exposure regions, therefore produced more accurate histogram segmentation [29]. As a solution to control the enhancement rate in each sub-histogram, histogram modification based HE was developed [30]. By modifying histogram bins, the enhancement rate can be controlled, therefore can prevent loss of details and over enhancement by amplifying the low dominating bins and maintaining the high dominating bins respectively. As this paper will introduce a new variant of HE methods by integrating the third and fourth type of HE variants (i.e., exposure intensity based HE and histogram modification based HE), the following review will focus on the state-of-the-art methods proposed under these two variants.

Exposure intensity based HE deals with certain exposure characteristics such as UE and OE regions for enhancing an image. The existing methods emphasized on exposure parameters to segment the histogram which was more proper than using the conventional histogram statistics such as mean, median etc. Singh and Kapoor [31] divided original image into UE and OE sub-histograms by using different exposure based intensity threshold. The sub-histograms were then clipped using average number of gray level occurrences before being equalized independently. Tang and Isa [29] also used the same exposure threshold as in [31] except the clipping method used mean and median values. These two methods provided enhancement only for two exposure regions, however in non-uniform illumination image, there is the third region that has good contrast and clear details known as WE region. Therefore, these methods often failed to be applied to the WE region, in which they tend to modify the contrast of WE region based on the enhancement designed for the two exposure regions, namely UE and OE regions. To solve this problem, Exposure Region-Based Multi-Histogram Equalization (ERMHE) was proposed [5]. This method segmented the histogram into three regions, which has been proven to provide more accurate image enhancement. However, in this method, enhancement rate control was less considered especially in the OE sub-histogram, which could possibly lead to over-saturated and washed-out problems.

Histogram modification based HE was proposed to eliminate the domination of higher histogram components in the image histogram. This method shortened the dominant histogram bins before applying the equalization process [32]. In conventional HE, the transformation function forced the gray levels in the lower bins to combine with the adjacent gray levels, therefore removed the details in the image. By limiting the pixels in the dominating histogram bins, the lower bins can have a chance to be separated. Reference [32] modified the accumulations in the histogram bins by shortening the histogram bins that have pixels accumulation higher than the mean of nonzero bins before equalized the global histogram. This method was able to preserve the small details in the image. In histogram modification based HE, power law transformation function was occasionally used after histogram clipping process. This process provided apparent enhancement control. Wang and Ward [33] controlled the increment of gray level in the middle region using power law transformation function. This method, at first, modified the histogram bins using three clipping levels; upper threshold, lower threshold and middle threshold. The clipped histogram avoided over enhancement at dominating bins. The power law index, r, controlled enhancement rate in which as r increases, more weight is put on the high dominating bins. Hence, this method provided an adequate space for enhancing low dominating bins by setting the index to be less than 1. However, this method required two manual control parameters which are the enhancement index, r and the upper clamping point. Recursive Separated Weighted Histogram Equalization (RSWHE) proposed in [30] also modified the sub-histograms using normalized power law function before equalized each weighted sub-histogram. This method segmented the global histogram into two or more sub-histograms recursively based on the mean or median of the image. This method effectively solved mean-shift problem, preserved the image brightness and enhanced the image contrast as well. However, RSWHE tended to introduce over enhancement to the OE region. Additionally, the user-defined selection of recursion level prevented RSWHE to yield optimal enhancement performance. Recursive weighted multi-plateau histogram equalization for image enhancement (RWMPHE) [34] extended the work in [30] by adding the histogram clipping process. The image histogram was split into more than two parts recursively based on mean or median values, therefore named as RWMPHE-M and RWMPHE-D, respectively. The bins were then clipped using six plateau limits based on the maximum peak value of the input image. Weighting module then modified the probability density of each sub-histogram

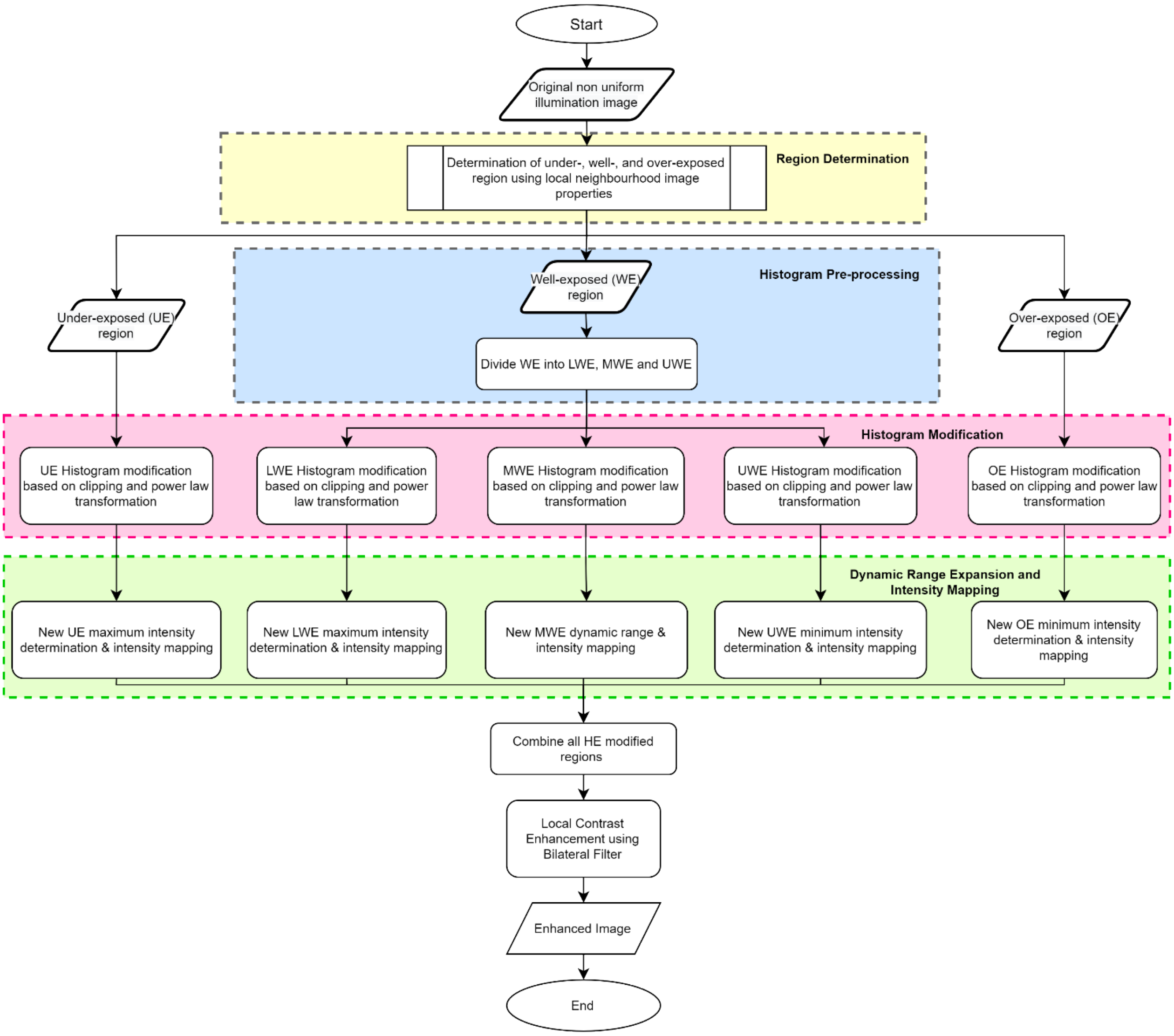

FIGURE 2. **Flow chart of the proposed NEIMHE method.**

using normalized power law. Lastly, HE was applied on each sub-histogram independently. This method produced image with better contrast due to combination of power law histogram modification and histogram clipping as the enhancement control. Both methods in [30] and [34] preserved the image mean brightness since the increment of number of histogram segmentation caused the output mean brightness to converge to the input mean brightness.

The abovementioned methods shared some common limitations in which these variants lack the element of image exposure during histogram segmentation. In order to apply these methods to the non-uniform illumination image that consists of different exposure regions, it seems unrealistic to segment the histogram using statistical method such as mean or median. Besides that, the abovementioned methods lack in controlling enhancement in high intensity region. The high intensity pixels in the enhanced image are maintained at the same intensity or slightly enhanced since the intensity is shifted towards the right-hand side of the histogram, resulting in over enhancement in the OE region. This condition will become worst if the high intensity region dominates the histogram that tends to overwhelm the overall enhancement of the image.

III. PROPOSED METHOD

Motivated by previous works discussed in Section II, (i.e., [3], [5], and [33]), this work will propose a new variant of HE method by, first, differentiating the input image into several exposure regions before histogram modification based HE is applied as nonlinear enhancement in order to provide different enhancement rates to each exposure region. The proposed method named as Nonlinear Exposure Intensity Modification Based Histogram Equalization (NEIMHE) adopts the combination of exposure intensity and histogram modification-based HE to enhance the image. Fig. 2 shows the flow chart of the proposed NEIMHE method. The proposed NEIMHE method uses exposure region determination method as introduced in [35] to divide the image into three exposure regions named as UE, OE, and WE region. Based on method in [35], the basic characteristics of an image such as intensity, entropy, and contrast were determined from locally defined non-overlapping windows to establish the decisive rules in classifying the exposure region. Based on the output of the method proposed in [35], the intensity range of the determined WE region distributes over the whole range of intensity levels, which is [0, L − 1] where L is the total number of intensities in WE regions. If one specific contrast enhancement method is applied to this WE region, the region is still being implemented by global contrast enhancement because the contrast enhancement method is applied to the whole range of intensity level (i.e. global region) and not to a specific range (i.e. local region). This is the limitation of the method proposed in [5] (i.e. which applied contrast enhancement process to UE, OE and WE regions detected by method in [35]), where, in some cases, the contrast of the WE regions is still low without details preservation. To reduce the problem, the proposed NEIMHE method will further divide the determined WE regions by [35] into three sub-regions named as lower well-exposed (LWE), mid well-exposed (MWE) and upper well-exposed (UWE) regions, before histogram of these three new sub-regions are generated. This pre-processing stage is done to allow difference enhancement rate to be applied to these WE sub-regions to allow implementation of local contrast enhancement. The intensity histograms of five regions (i.e. UE, OE, LWE, MWE, and UWE) are then modified by limiting their bins and applying the power law transformation function. This stage, as shown by a pink block in Fig. 2, provides different enhancement rates based on the average luminance in each exposure region. As a result, the original histograms are modified to nonlinear shape to facilitate the non-uniform intensity mapping to be performed in the third stage. The third stage of the proposed NEIMHE is a dynamic range expansion and intensity mapping in which the dynamic range of each region is expanded to certain values based on the average intensity of each region. Each region is then equalized using different HE equations (i.e. which is modified by the proposed NEIMHE method). Dynamic range expansion provides adequate space for the intensities shifting during contrast enhancement process, while different equalization process (i.e. different HE equations) controls the direction of intensity mapping in each exposure region either the original intensity is mapped to the higher intensity or to the lower intensity. The equalized images produced non-linear intensity shifting that caters different levels of exposure for different region. All five HE equalized regions (i.e. UE, OE, LWE, MWE and UWE regions) are then combined to generate an enhanced image. In order to further boost the local details in the enhanced image, local contrast boosting method adopted in [9] is performed in the last stage of the proposed method.

A. WE SUB-REGIONS DETERMINATION

As mentioned above, the proposed method uses three sub-images produced from method [35] that correspond to different exposure levels for further enhancement. These three sub-images contain local regions that are classified to have under-exposure, over-exposure, and well-exposure illumination. This approach is adopted in the proposed NEIMHE method in order to enable targeted enhancement to be done according to a predetermined level of exposure. As an example, areas that are too dark should be lightened while areas that are too bright should be slightly dimmed while WE areas only need a little enhancement or are maintained as the original regions. Since the input image is divided into three regions, therefore three histograms are generated (i.e. one histogram for each region). Compare to ERMHE in [5], which uses the mean of each exposure region to segment the original histogram, the proposed NEIMHE method constructs three new histograms by using information from each region. The UE histogram usually contains information about low-intensity pixels, while the OE histogram represents high-intensity pixels. The WE histogram stores information about the pixels throughout the entire range of image's intensity, which in many cases will overlap with the pixels in the UE and OE regions. Therefore, this histogram that experienced intensity overlapping needs to be pre-processed before enhancing the region. The pre-process involves dividing the WE histogram into three new sub-histograms, named as LWE, UWE, and MWE histograms as mentioned in the introduction of Section III. The separation is done to enable local contrast enhancement in these WE regions since these regions normally occupy wide dynamic range. By separating the region, difference enhancement rate can be applied to these WE sub-regions. The proposed dynamic ranges for LWE, MWE and UWE are tabulated in Table 2. Note that I_{LWE}, I_{MWE} and I_{UWE} are the intensities of LWE, MWE and UWE regions, respectively. I_{minWE}, I_{maxWE}, I_{maxUE} and I_{minOE} are the minimum intensity of WE region, maximum intensity of WE region, maximum intensity of UE region, and minimum intensity of OE region, respectively, which are obtained from [35].

TABLE 2. Proposed dynamic ranges for WE sub-regions.

WE Sub-regions	Intensity ranges
I_{LWE}	I_{minWE} to I_{maxUE}
I_{MWE}	$I_{maxUE} + 1$ to $I_{minOE} - 1$
I_{UWE}	I_{minOE} to I_{maxWE}

Consider the non-uniform illumination and the corresponding histogram in Fig. 3. After performing the exposure region determination process, the original histogram can be separated into three exposure region histograms (i.e. UE, WE, and OE) as shown in Fig. 3(a). WE histogram in Fig. 3(a) that comprises of the wide dynamic range is then further

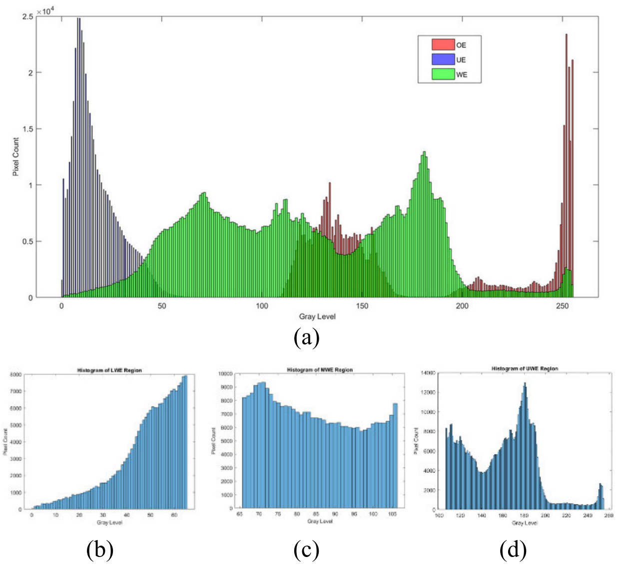

FIGURE 3. WE sub-regions determination process (a) Histogram of different exposure regions generated in [35] (b) Histogram of LWE region (c) Histogram of MWE region (d) Histogram of UWE region.

separated into three regions (i.e. LWE, MWE and UWE) as shown in Fig. 3(b)-(d) with the dynamic ranges of each region as stated in Table 2. Note that, after applying the abovementioned process, the proposed method constructs five histograms (i.e. UE, LWE, MWE, UWE, OE) in which the histogram modification process will be done separately in each histogram that will be further explained in the next section.

B. HISTOGRAM MODIFICATION

Histogram modification involves altering the histogram's natural properties such as the number of bin's pixels or indirect properties of histogram such as the cumulative sum of pixel's probability. In the proposed NEIMHE method, the conventional cumulative density function (CDF) is replaced by weighted CDF to perform controllable or adaptive enhancement level during the intensity mapping process. At first, for each sub-region, the number of pixels in each bin is limited to the average number of pixels of each sub-region. Then, the weighted CDF, CDF_{WR} is computed by associating power law transformation as represented in Eq. (1):

$$CDF_{WR}(k) = \begin{cases} \left(\sum_{i=1}^{k} PDF_R(i)\right)^r & \text{for } UE, LWE \\ \left(\sum_{i=k}^{K} PDF_R(i)\right)^r & \text{for } OE, UWE \\ \left(\sum_{i=1}^{k} PDF_R(i)\right) & \text{for } MWE \text{ and } I_{avg} < 128 \\ \left(\sum_{i=k}^{K} PDF_R(i)\right) & \text{for } MWE \text{ and } I_{avg} \geq 128 \end{cases} \quad (1)$$

where R is one of the five sub-regions defined in the previous step (i.e. UE, OE, LWE, MWE, and UWE), K is the total number of bins in each sub-region, r is a power-law index, k is the index of grey levels in each region, and I_{avg} is the average intensity of an image. $PDF_R(i)$ is the modified probability density function of each bin in sub-region R and is given by the ratio of average number of pixels of each sub-region, n_{avg} to the total pixels in each sub-region, n_T as stated in Eq. (2):

$$PDF_R(i) = \frac{n_{avg}}{n_T} \quad (2)$$

The power law index, r is devised to mimic the nonlinear pattern that represents the perception of brightness in the human visual system [36]. This power-law index, r is calculated by considering the average intensity of each sub-region and is given by Eq. (3):

$$r = \begin{cases} 0.5 + \left(\frac{I_{avgR} - I_{minR}}{I_{maxR} - I_{minR}}\right) \times 0.5 & \text{for } UE \text{ and } LWE \\ 0.5 + \left(\frac{I_{maxR} - I_{avgR}}{I_{maxR} - I_{minR}}\right) \times 0.5 & \text{for } OE \text{ and } UWE \end{cases} \quad (3)$$

where I_{avgR}, I_{minR} and , I_{maxR} are the average intensity, minimum intensity, and maximum intensity in each sub-region, respectively. In the proposed method, the level of exposure in each sub-region is considered to ensure that enhancement is done at the different and appropriate rates. The UE region with a lower average intensity needs to be enhanced at a higher rate than the UE region with higher average intensity. It is because theoretically the UE with lower average of intensity has lower visibility of image's details. As an example, consider two non-uniform illumination images namely *Sample1* and *Sample2* as shown in Fig. 4(a). The intensities of the UE region for *Sample1* distribute almost at the middle range of the histogram, while the intensities of the UE region for *Sample2* distribute to the left side of the histogram. The average of intensity of UE region for *Sample1* is higher than that of *Sample2*. In addition, the details in the UE region of *Sample2* are more difficult to be observed as compared to *Sample1*, which requires higher enhancement rate. An opposite scenario is to be applied for the OE region. The OE region with higher average of intensity should be enhanced at higher rate as compared to the OE region with lower average of intensity. Based on this explanation and information from Eq.(1) and Eq.(3), the relationship between the CDF, intensities' distribution and power law index, r, is illustrated in Fig. 5.

In the proposed NEIMHE method, the r index is limited from 0.5 to 1 in order to prevent the accumulation of the similar CDFs at the higher intensity of UE and LWE regions as well as lower intensity of OE and UWE regions. The similar CDFs tend to accumulate the pixels from different intensities into one intensity during intensity mapping process, hence will cause loss of details in the image. This nonlinear CDF also prevents the dominating bins in each region to have

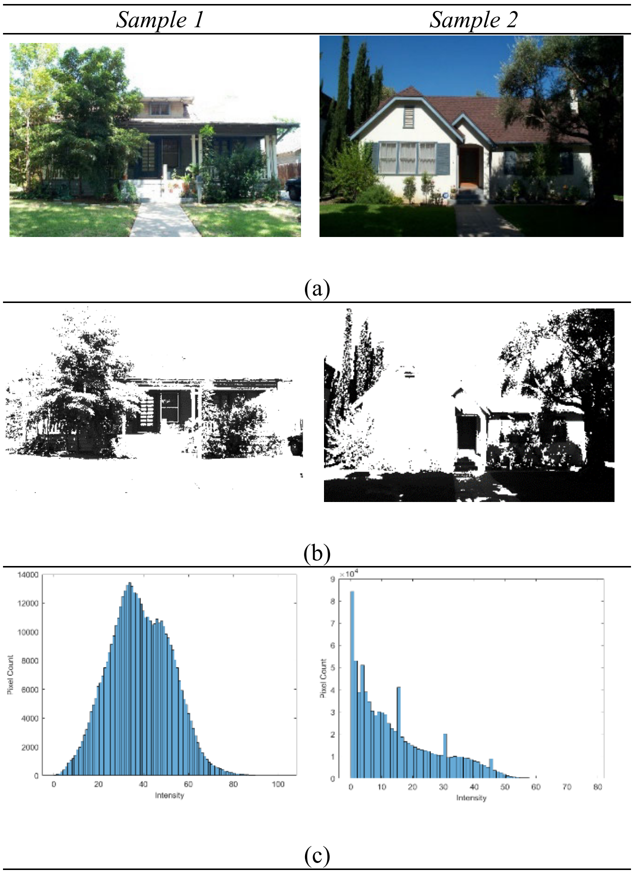

FIGURE 4. Examples of different UE histogram patterns produced by two different images (i.e. *Sample1* and *Sample 2*) (a) Original image (b) Detected UE region (c) Histogram of UE region.

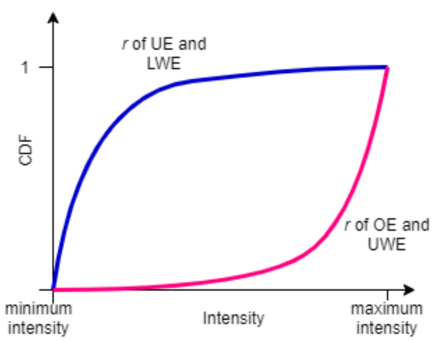

FIGURE 5. Effect of power-law index, *r* on CDF and image's intensities for different exposure regions.

greater intensity shifting during intensity mapping that indirectly will prevent over-enhancement from being occurred. In Eq.(1), note that the power-law index, r, is not applied to the MWE region since this region is considered to have proper exposure and only needs small enhancement that does not require the enhancement rate control. However, the calculation of CDF in MWE region considers the global mean of the image in order to provide more appropriate intensity mapping direction by taking into account the ideal average intensity of an image which is 128.

C. DYNAMIC RANGE EXPANSION AND INTENSITY MAPPING

As mentioned, histogram modification involves modifying the histogram bins into a nonlinear pattern to control the enhancement rate while the dynamic range expansion and intensity mapping process then transforms the nonlinear pattern bins into a certain intensity range. In most of the exposure based HE techniques, the original intensities in a region are mapped in the original dynamic range of the region; however, in the proposed method, the ranges of UE and OE regions are expanded to certain intensities based on a well-known photographic technique known as Zone System as proposed in [36]. This step is proposed to enable the pixels in the above-mentioned regions having sufficient spaces to be mapped. The expansion step also aims to prevent the accumulation of pixels in limited spaces, hence no improvement of intensities can be visualized. According to [24], the human visual system can discern a wide gap in the luminance range's bright and dark areas; thus, the proposed method expands the intensities of UE and OE regions to a new range using a new parameter named Control Exposure. This step is summarized in Eq. (4) and Eq. (5):

$$I_{newUE}(i) = \begin{cases} I_{minUE} + \left(\begin{pmatrix} I_{maxUE} + (51 - c_R) \\ -I_{\min UE} \end{pmatrix} \times CDF_{WR}(i) \right) & for\ c_R < 51 \\ I_{minUE} + \left(\begin{matrix} (I_{maxUE} - I_{minUE}) \\ \times CDF_{WR}(i) \end{matrix} \right) & for\ c_R \geq 51 \end{cases} \tag{4}$$

$$I_{new_{OE}}(i) = \begin{cases} I_{maxOE} - \left(\begin{pmatrix} I_{maxOE} - \\ (I_{minOE} - (c_R - 204) \end{pmatrix} \times CDF_{WR}(i) \right) & for\ c_R > 204 \\ I_{maxOE} - \left(\begin{matrix} (I_{maxOE} - I_{minOE}) \\ \times CDF_{WR}(i) \end{matrix} \right) & for\ c_R \leq 204 \end{cases} \tag{5}$$

where control exposure intensity for UE and OE region, c_R is given by Eq. (6):

$$c_R = \begin{cases} 0.5\,(I_{maxUE}) & for\ UE \\ I_{minOE} + (0.5\,(I_{maxOE} - I_{minOE})) & for\ OE \end{cases} \tag{6}$$

I_{minUE}, I_{maxUE}, are the minimum and maximum intensities of UE region, respectively, while I_{minOE}, I_{maxOE} are the minimum and maximum intensities of OE region, respectively. As shown in Eq. (4), the original dynamic range of UE is expanded to a certain range above the maximum intensity to allow more distributions of intensities if the control exposure is less than 51. While in Eq. (5) the original dynamic range is also expanded to a certain range below the minimum intensity of OE pixels if the control exposure is beyond 204. As mentioned above, values 51 and 204 are chosen by referring

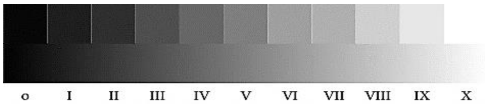

FIGURE 6. The 10 regions in the zone system [37].

to [37] in which the intensities that lied in Zone III to Zone VIII are considered to have appropriate exposure. Referring to the Zone system in [37], the grey levels of an image (0-255) are divided into ten zones (i.e. Zone I to Zone X), as shown in Fig. 6, therefore Zone III to Zone VIII consist of gray level 51 to 204.

By referring to Eq. (4), the new intensity values in the UE region will have the non-uniform shifts in which the gap between adjacent lower intensities being wider than the gap between adjacent higher intensities. As a result, in this exposure region, the darker region will be lightened more than the lighter region. Meanwhile, Eq. (5) shows that in the OE region, the gap between two adjacent intensities is larger at higher intensities. As a result, the area with the higher intensity in this OE histogram will have significantly reduced illumination compared to the area with less brightness (i.e. less intensity) located to the left of the histogram, which is adjacent to the WE intensities.

In order to enhance the WE region, the same hypothesis as used in enhancing the UE and OE are used for the enhancement of the LWE and UWE regions, respectively. However, control exposure, c_R is not applied to these processes. The mapping function for sub-regions in WE are shown in Eq.(7).

$$I_{newWE}(i) = \begin{cases} I_{minLWE} + \left(\begin{array}{l} (I_{newUEu} - I_{minLWE}) \\ \times CDF_{WR}(i) \end{array} \right) & \text{for } LWE \\ I_{maxUWE} - \left(\begin{array}{l} (I_{\max UE} - I_{newOEl}) \\ \times CDF_{WR} \\ (i) \end{array} \right) & \text{for } UWE \\ I_{newUEl} + \left(\begin{array}{l} (I_{newOEl} - I_{newUEl}) \\ \times CDF_{WR}(i) \end{array} \right) & \text{for } MWE \text{ and } I_{avg} \geq 128 \\ I_{newOEl} - \left(\begin{array}{l} (I_{newOEl} - I_{newUEu}) \\ \times CDF_{WR}(i) \end{array} \right) & \text{for } MWE \text{ and } I_{avg} < 128 \end{cases} \tag{7}$$

I_{minLWE} is minimum intensity of LWE region, I_{maxUWE} is maximum intensity of UWE region, I_{newUEu} and I_{newUEl} are minimum and maximum intensity of the modified UE region, respectively and I_{newOEl} is minimum intensity of the modified OE region. Eq. (7) shows the different direction of intensity mapping between LWE and UWE regions. Similar to the intensity mapping in the UE region, the intensity in LWE region is mapped by allocating wider gaps at the lower intensities compared to smaller gaps at the higher intensities of LWE pixels. In addition, the pixels in the LWE region are being mapped in the range of minimum intensity to the maximum intensity of the modified UE region produced by Eq. (4). The intensities in the UWE region, on the other hand, are mapped with wider gaps at higher-intensity pixels and smaller gaps at lower-intensity pixels. The minimum output intensity is the same as the minimum intensity of the mapped OE regions. For MWE region, the intensities are mapped in the range of the maximum output intensity of UE to the minimum output intensity of OE. Besides, the nonlinear mapping process is also done in this sub-region but at a minimum rate in which either the lower or higher intensities in MWE region will have wider displacement depending on the average intensity of the original image as shown in Eq. (7). The average intensity of the original image is compared with the average intensity of the ideally WE image which is 128 in order to determine intensity shifting direction of this MWE region either the original intensity is shifted to the right or left of the histogram. If the average intensity of the original image is less than 128, the intensities are shifted to the right where the pixels will have a higher intensity while if the average intensity of the original image is the opposite, the intensities will be shifted to the left where the initially brighter intensity will be reduced.

D. LOCAL CONTRAST BOOSTING

The image produced from histogram modification and equalization process that discussed in Section IIIB, and IIIC has lightened up low intensities and pulled down high intensities. This condition compresses the dynamic range, and sometimes the local contrast tends to be lost. In order to boost the local contrast, the proposed NEIMHE method adopted local contrast enhancement in [3], which aims to increase or decrease the intensity of a pixel by comparing with their neighboring pixels' intensities. Based on [3], a pixel's intensity will be increased if it is larger than its neighbors' intensities and will be decreased if it is smaller than its neighbors' intensities, as represented in Eq.(8):

$$I_{E\_R}(i,j) = \begin{cases} I_{new_R}(i,j)^{\left[\frac{BF * I_{new_R}(i,j)}{I_{new_R}(i,j)}\right]^2} & \text{if } I_{new_R}(i,j) \leq BF * I_{new_R} \\ 1 - \left(1 - I_{new_R}(i,j)\right)^{\left[\frac{1 - BF * I_{new_R}(i,j)}{1 - I_{new_R}(i,j)}\right]^2} & \text{otherwise} \end{cases} \tag{8}$$

where, I_{new_R} is the luminance nonlinear HE image produced from Section IIIB and Section IIIC and BF is a bilateral filter. The proposed method applies Eq.(8) into a luminance image in order to specifically boost the luminance compared to the method in [3] that applies the filter to each color channel.

IV. DATA SAMPLE AND ASSESSMENT METRICS

In order to evaluate the performance of the proposed method, 354 non-uniform illumination images consisting of scenery and face images are used. All images are taken from the California Institute of Technology database, namely Pasadena Houses 2000, and Faces 1999 (Front) packages [38]. These non-uniform illumination images are categorized into two types, namely close-up images and non-close-up images with 266 and 88 images, respectively. This study focuses on manipulating and applying HE variant methods on the grey level images and all processes are done in the spatial domain only. For assessment of the compatibility and capability of the proposed method, both qualitative and quantitative analyses are conducted.

Qualitative analysis is performed to assess the visual quality of the enhanced or resultant image. In this paper, the image is visually examined for contrast enhancement, detail preservation, and naturalness preservation. Each aspect will be supported by its respective quantitative measurement. In order to balance the subjective elements in the qualitative evaluation, quantitative analysis is conducted to analyze the enhanced image in terms of the widely used metrics. The existing work in enhancing non-uniform illumination, such as in [5] used Peak Signal to Noise Ratio (PSNR), Image Contrast Function (ICF), Discrete Entropy (DE), Absolute Mean Brightness Error (AMBE), and Average Score to evaluate the performance of HE based techniques. The work in [6] added two evaluation metrics named as a Measure of Enhancement (EME) and Natural Image Quality Evaluator (NIQE) to evaluate the enhancement in terms of local contrast and naturalness preservation, respectively. Another metrics known as a Measure of Entropy Enhancement (EMEE), which is an extension of EME, was used in [19] together with DE, ICF, EME, and Universal Image Quality Index (UIQI). In this study, only seven quantitative evaluation metrics are used which are ICF, EME, DE, EMEE, PSNR, AMBE and LOE. ICF and EME are used to evaluate the contrast of the output image in a global way and in the local region, respectively while DE and EMEE are used to evaluate the amount of the details appear in the image globally and in the local region, respectively. Meanwhile, PSNR, AMBE and LOE is used to evaluate the naturalness of the image in terms of noise presented, mean brightness change and additional light introduced to the enhanced image.

The contrast enhancement is analyzed by visually examining the global contrast and local contrast of the enhanced image. The global contrast is evaluated by globally visualized the levels of different brightness of the whole (overall) enhanced image. A resultant image with a good global contrast should provide clear visualized dark and bright regions, which is able, as an example, to differentiate between shadow regions (i.e. represented by dark regions) and sky regions (i.e. represented by bright regions). However, in some cases, with excessive global contrast enhancement implementation (i.e. having extreme dark and bright regions), non-uniform illumination resultant images could be still produced. As the proposed NEIMHE method is specifically designed to produce uniform illumination resultant images, the production of these extreme dark and bright regions should be avoided. Based on [6], the illumination uniformity is evaluated by inspecting the brightness difference between UE and OE regions in which the lower the differences, the better the illumination uniformity. In general, a good contrast enhancement method should be able to improve the global contrast with uniform illumination of resultant images. Meanwhile, the local contrast is evaluated locally especially in OE and UE regions to examine the performance of the enhancement applied to these extreme regions. Similar to global contrast enhancement, local contrast should be enhanced as well. Both global and local contrast visual evaluation is further associated with the corresponding quantitative measurements which are ICF and EME. ICF is used to evaluate contrast improvement in an image [5]. In mathematical, ICF is given by Eq. (9) which represents the gray level deviation across the whole image. In Eq. (9) W and H represent the width and the height of the image, respectively, and $Y(w, h)$ is the grey level value of an image at (w, h). With higher value of C, the image is said to have better contrast [6]. Indirectly, it also implies that more information is contained in the image. Normally, ICF is represented in dB as in Eq.(10):

$$C = \frac{1}{W \times H}\sum_{w=1}^{W}\sum_{h=1}^{H} Y^2(w, h) - \left|\frac{1}{W \times H}\sum_{w=1}^{W}\sum_{h=1}^{H} Y(w, h)\right|^2 \tag{9}$$

$$C_{dB} = 10\log_{10} C \tag{10}$$

In order to assess the enhancement locally, a measure of enhancement, EME is used. EME which is proposed by Agaian *et al.* [39], computes the ratio between the maximum and minimum intensities in the defined small blocks in an image as shown by Eq. (11):

$$EME = \frac{1}{k_1 k_2}\sum_{l=1}^{k_1}\sum_{k=1}^{k_2} 20\log\frac{I^w_{max;k,l}}{I^w_{min;k,l} + c} \tag{11}$$

where $k_1 k_2$ is the number of small blocks $w_{k,l}(i, j)$ in an image, $I^w_{max;k,l}$ and $I^w_{min;k,l}$ are the maximum and minimum intensity of $w_{k,l}(i, j)$, respectively. EME works by dividing the image into 16×16 blocks for evaluation. c is a small constant at the denominator that equals 0.001 to avoid divisions by 0. Since EME segments the image into numerous blocks that involve evaluating maximum and minimum intensities in each block, EME is suitable for measuring local contrast of the image. Higher EME indicates a greater local contrast of the enhanced image. Hence, to produce uniform illumination enhanced image, low ICF and high EME are intended.

One of the criteria of the enhanced image is the ability to preserve the details. In order to evaluate the detail preservation in the enhanced image, the image's critical parts (e.g., leaves, grass, and surface texture of walls) should successfully be magnified to inspect for the observable details in that region [6]. The resultant image with more observable details shows better detail preservation. The visual analysis will be further supported by measuring the DE and EMEE. DE measures the information content of the simple 8-bit image according to information theory [26]. The number of bits required to encode the pixel's intensity in an image is represented by entropy. An image can only achieve the maximum entropy value when the probability of each gray level is the same. As a result, the intensity of the pixels is equitably distributed across the gray levels in a histogram and the image can be interpreted to have more details. Therefore, a higher value of DE is desired to indicate an image provides more information or details [26]. However, it may also indicate the presence of noise [40], therefore visual assessment is vital to be conducted in order to assess the noise levels. Discrete Entropy is given by Eq. (12):

$$DE = -\sum_{l=0}^{L-1} p(l) .log_2(p(l)) \tag{12}$$

where $p(l)$ is PDF of a histogram and l is the gray levels exist in an image. DE normally measures the entropy globally, therefore to evaluate the entropy locally, EMEE is used. EMEE performs enhancement evaluation in small blocks and uses concept of entropy as shown by Eq. (13):

$$EMEE = \frac{1}{k_1k_2}\sum_{l=1}^{k_1}\sum_{k=1}^{k_2}\alpha\left(\frac{I^w_{max;k,l}}{I^w_{min;k,l}+c}\right)^{\alpha}\log\frac{I^w_{max;k,l}}{I^w_{min;k,l}+c} \tag{13}$$

where α is a constant and is equivalent to 0.8 as suggested by the authors in [39]. Higher EMEE indicates that the image has better quality [41]. Based on the above discussion, higher DE as well as higher EMEE are intended to indicate better details preservation.

Another aspect to be evaluated to analyze the performance of enhanced image is the naturalness of the enhanced image. The images' naturalness is evaluated by examining the brightness change between the enhanced image and the original image [10]. The global intensity of the enhanced image cannot significantly differ from the original image's global intensity. Besides that, based on [42], to indicate that the enhanced image preserves the naturalness of the original image, no light source should be introduced and no blocking effect should be amplified in the enhanced image. The enhanced image will be also visually examined to detect the presence of noise which would affect the naturalness of the enhanced image. In order to quantitively measure the naturalness preserved in the enhanced image, LOE, AMBE, and PSNR are calculated. LOE is used to measure lightness distortion of the enhanced image and is calculated by using Eq. (14):

$$LOE = \frac{1}{W*H}\sum_{w=1}^{W}\sum_{h=1}^{H} RD(w,h) \tag{14}$$

where RD is the relative order of lightness difference between original image and its enhanced image which is calculated as Eq. (15):

$$RD(x,y) = \sum_{w=1}^{W}\sum_{h=1}^{H}(U(L(x,y), L(w,h)) \oplus U(L_e(x,y), L_e(w,h))) \tag{15}$$

where W and H are the height and width of an image, $\oplus$ is exclusive OR operator and $U(x,y)$ is unit step function that returns 1 if $x > y$ and 0 for other conditions. Smaller LOE is desired to have better lightness order. Meanwhile, AMBE is computed by taking the difference of the mean brightness between the input image and the enhanced image as in Eq. (16). $M(I)$ and $M(O)$ are the mean brightness of the enhanced image and original image, which are given by Eq. (17) and (18), respectively:

$$AMBE = |M(I) - M(O)| \tag{16}$$

$$M(I) = \frac{1}{W\times H}\sum_{w=1}^{W}\sum_{h=1}^{H} I(w,h) \tag{17}$$

$$M(O) = \frac{1}{W\times H}\sum_{w=1}^{W}\sum_{h=1}^{H} O(w,h) \tag{18}$$

A small AMBE is desired since it represents a small or no difference on the mean brightness of original image [43]. Therefore, the brightness of the image is preserved. During image enhancement, the degradation of signal commonly occurs. To evaluate the degradation of enhanced image, Peak Signal to Noise Ratio (PSNR) is used. PSNR is calculated by the use of Mean Square Error (MSE) that shown in Eq. (19):

$$PSNR = 10\log_{10}\left(\frac{(Max(I_i))^2}{MSE}\right) \tag{19}$$

where $Max(I_i)$ is the maximum gray level value of the input image I_i. MSE is given by Eq. (20) which represents the mean intensities difference between output image and the input image. W and H are the height and width of the image, respectively, while $I_i(w,h)$ and $I_o(w,h)$ are the pixel's gray level of the input image and output image, respectively. Therefore, the smaller MSE is desired, indicating smaller differences between output and input images that represent less error or degradation in the enhanced image. Lower MSE then produces greater PSNR, hence better image quality [26].

$$MSE = \frac{1}{W\times H}\sum_{w=1}^{W}\sum_{h=1}^{H}[I_i(w,h) - I_o(w,h)]^2 \tag{20}$$

V. RESULTS AND DISCUSSION

This section presents and analyses the enhanced images produced by the proposed NEIMHE method. The images used in the analysis were split into two types, namely close-up and non-close-up images. The analyses examined the effects of the proposed NEIMHE method on the characteristics of the tested images, and compared the performance of the NEIMHE method with those of the state-of-the-art contrast enhancement methods. The chosen state-of-the-art methods for performance comparison are Backlit [25], Adaptive Fuzzy Exposure Local Contrast Enhancement (AFELCE) [19], Visual Contrast Enhancement Algorithm (VCEA) [23], Exposure Region-Based Multi Histogram Equalization (ERMHE) [5] and Exposure based Sub-Image Histogram Equalization (ESIHE) [31].

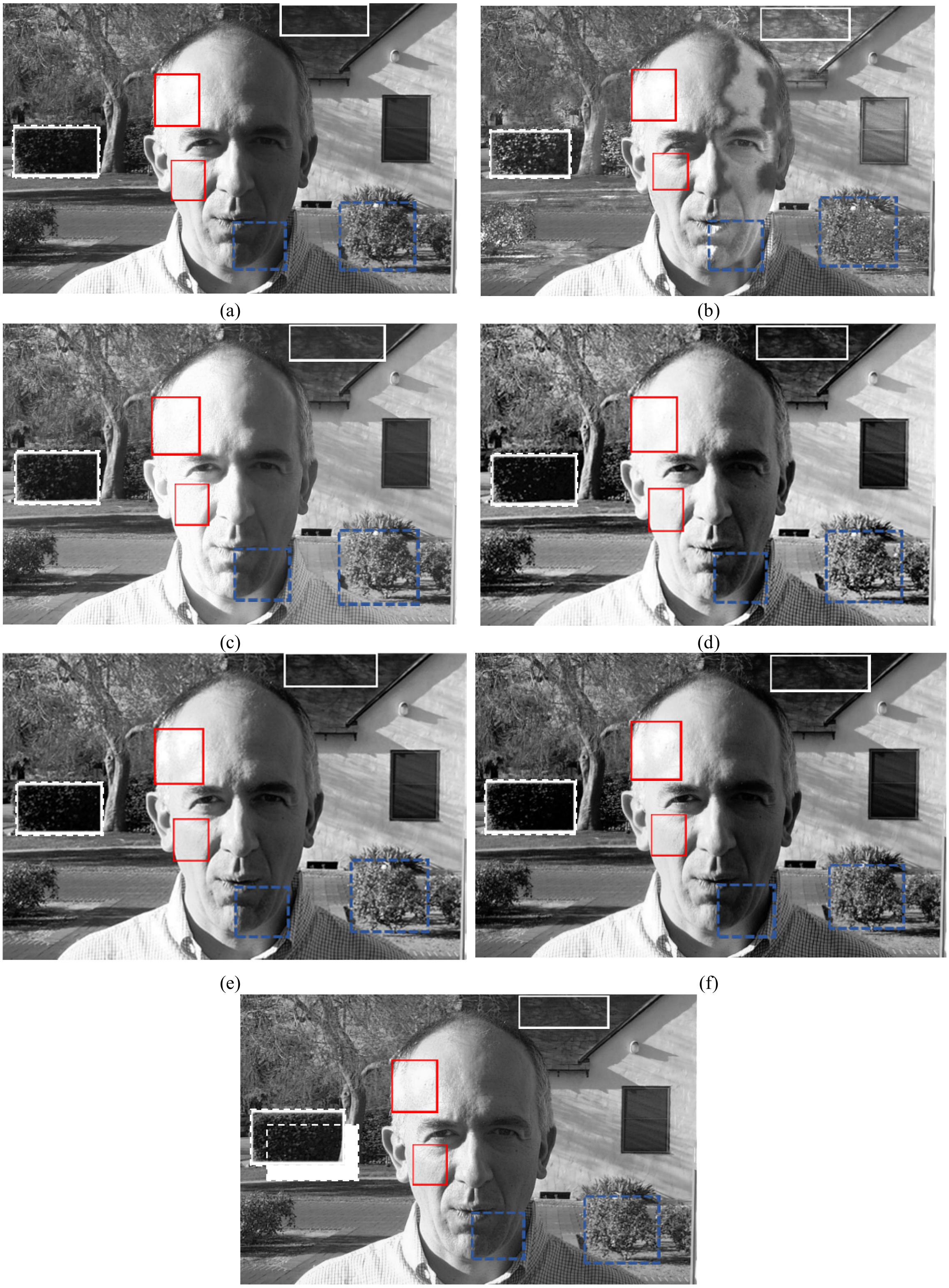
(a) (b) (c) (d) (e) (f) (g)

FIGURE 7. (a) Original *CloseUp1* image and resultant images produced by (b) Backlit (c) AFELCE (d) VCEA (e) ERMHE (f) ESIHE (g) proposed NEIMHE.

A. CLOSE-UP IMAGES

Fig. 7(a) shows an example of a non-uniform illumination close-up image, labelled as *CloseUp1*. The original *CloseUp1* image suffered from uneven or non-uniform illumination. The regions highlighted by the red rectangles in Fig. 7(a) have been irradiated with an excessive amount of light,

TABLE 3. Quantitative analysis results for CloseUp1 image.

Method	Quantitative Measurement						
	DE	EMEE	ICF	EME	AMBE	LOE	PSNR
Original Image	**7.77**	2.06	36.43	4.750			
Backlit	7.57	68.22	34.79	4.279	20.72	1094.61	16.27
AFELCE	7.48	66.02	36.44	3.918	19.52	**3.00**	20.14
VCEA	7.49	6.76	**37.59**	6.728	13.70	277.31	21.03
ERMHE	7.57	3087.14	36.54	9.003	2.48	281.23	**31.25**
ESIHE	7.63	3118.86	36.95	**11.11**	4.36	281.19	29.62
Proposed NEIMHE	7.74	**3250.29**	35.69	9.569	**2.46**	95.30	31.01

Values in bold indicate the best results, while underlined values indicate second-best results

representing OE regions. This excessive amount of light led to excessive bright regions, in which their details are invisible to the human eyes, e.g. the details of hair in the bigger red rectangle region. On the other hand, the white rectangle region in the same figure is overshadowed by tree branches; hence, producing dark shades that obscure the texture of the roof. This region is indicated as the UE region. The original image in Fig. 7(a) was enhanced using six different methods (i.e., Backlit, ALEFCE, VCEA, ERMHE, ESIHE and NEIMHE) and the enhanced images are illustrated in Fig. 7(b), (c), (d), (e), (f) and (g), respectively.

From the observation of the overall image's contrast, AFELCE, VCEA and ESIHE methods produced high contrast resultant images. However, these methods suffered from over-enhancement problems in the OE region that can be seen by the over-brightened regions, as highlighted by red rectangles in Fig. 7(c), Fig. 7(d) and Fig. 7(f). Meanwhile, VCEA and ESIHE failed to enhance the UE region, as the tree shade in the white rectangle region became darker, whereas the ALEFCE method maintained the original condition. Despite having high contrast enhanced images, which were supported by top three score for ICF values produced by VCEA, ESIHE and ALEFCE, the large brightness difference between the over-enhanced OE region and the under-enhanced UE regions showed that these methods have not been capable of generating uniform illumination. In order to further investigate the performance of the contrast enhancement, the local contrast of the enhanced image was visually examined, yet AFELCE failed to enhance the local contrast of the original image. As can be seen in Fig. 7(c), almost all regions highlighted by either a solid line or a dotted line rectangle, particularly the red rectangle regions, have low contrast. This led to the lowest EME produced by AFELCE. Meanwhile, VCEA and ESIHE enhanced the contrast of WE region, as shown by blue dotted rectangles in Fig. 7(d) and Fig. 7(f) respectively; therefore, VCEA and ESIHE scored higher EME than that of the original image. On the other hand, Backlit successfully brightened the UE region, as shown by the white rectangle area in Fig. 7(b). Therefore, the image appears brighter and uniform in illumination compared to the original image. More uniform illumination leads to a low global contrast of an image. This has been proven by the lowest ICF value, as recorded in Table 3. However, Backlit failed to produce better contrast in the local region, as evidenced by the blue dotted rectangle regions, where the plant and a portion of the jaw have low grey level variations as compared to the original image. As a result, the EME was relatively low.

ERMHE produced uniform illumination in the enhanced image, with a smaller brightness difference between the OE and UE regions than in the original image. ERMHE performed minimal intensity enhancement for the OE regions, while darkening the UE region, which could be observed by the dark shade of a tree branch in the white rectangle region, as shown in Fig. 7(e). As the UE region becomes darker than the original region, the global contrast of ERMHE becomes slightly higher than that of the original image. This is consistent with the higher ICF obtained by ERMHE compared to that of the original image. ERMHE failed to improve the local contrast in the OE region, as evidenced by the brighter and less intensity variations in the smaller red rectangle, as depicted in Fig. 7(e). This problem has been successfully solved by the proposed NEIMHE method, which produced more variations of intensities; thus, generating better contrast in the mentioned region as compared to other methods. By comparison, ERMHE was only able to produce good local contrast in the WE region (indicated by the smaller blue dotted rectangle), while the proposed NEIMHE method showed better local contrast for almost all regions. This was proven quantitatively by the lower EME score obtained by the ERMHE compared to the proposed NEIMHE method. The proposed NEIMHE method in Fig. 7(g) has also successfully dimmed the OE regions and brightened the UE regions. This is shown by the presence of more noticeable hair in the OE region, as highlighted by the large red rectangle, as well as the presence of only smaller patches of sunlight. Meanwhile, a weak shadow of the tree branches in the white rectangle region highlights the details of the enhanced UE region. In comparison to the original image, the enlightened UE regions and the dimmed OE regions produced slightly lower global contrast, resulting in a lower ICF than that of the original image, as tabulated in Table 3. Although the whole enhanced image has a low global contrast, the resultant image has shown a high local contrast, implying that the enhanced image produced by the proposed NEIMHE method has a more uniform global illumination and a higher local contrast.

For details preservation capability, AFELCE and VCEA failed to preserve the details in almost all OE regions and UE regions. This is confirmed by the invisible facial skin textures in the OE regions and less clear visible leaves in the UE region, as shown by the red rectangles and white dotted rectangle in Fig. 7(c) and Fig. 7(d), respectively. These outputs led to the lowest DE score produced by both methods. Both methods also failed to preserve the details in the local region, as shown by the small red rectangle in the same figures, in which the wrinkles below the left eye in the original image are invisible. Therefore, EMEE produced by VCEA and ALEFCE ranked as the bottom three amongst all tested methods. Backlit was only able to preserve the details in the UE region, as shown by the clearly seen leaves in the white dotted rectangle region in Fig. 7(b); thus, producing lower DE than that of the original image. Similar to Backlit, ERMHE and ESIHE were also able to preserve the details in most UE regions, but both methods failed to preserve the details in the OE region as shown by the invisible skin wrinkles in the small red rectangle. However, in the local WE region, as shown by the blue dotted rectangle, ERMHE and ESIHE were able to preserve the details as shown by the black spots that resemble the fine hairs which can be seen in the region. ERMHE and ESIHE scored lower DE than that of the original image, which show that the details of several regions (i.e., especially the OE regions) are washed out. However, both methods obtained a higher score in EMEE, where the details in the local regions can be better detected in comparison to those of the original image. Amongst all methods, the proposed NEIMHE method was able to preserve the details in all regions, including both OE and UE regions. This is shown by the visible wrinkles on the face in the small red rectangle OE region and the visible leaves in the white dotted rectangle, as depicted in Fig. 7(g). For the details in the local region, as shown in blue dotted rectangle area, the proposed NEIMHE also successfully retrieved the black spots. This is consistent with the second-best DE result and the highest EMEE score obtained by the proposed NEIMHE method. In conclusion, the proposed NEIMHE method better enhanced the details of the original image as compared to the other four tested methods.

The third important aspect in evaluating the quality of the enhanced image is the naturalness of the image. Backlit failed to preserve the naturalness of the image, as the enhanced intensity for UE and OE regions showed unnatural boundary artifacts between different exposure regions (i.e., OE and UE regions), as shown by the blue rectangles in Fig. 7(b). The enhanced image appears to be over-enhanced in the UE region that generates the discontinued effect; thus, eliminating several meaningful features of the original image. The enhanced image also generated noise, as indicated by the red oval in Fig. 7(b) which is further proven quantitatively by the lowest PSNR obtained. By looking at the image as a whole, Backlit-enhanced image is brighter compared to the original image, which shows that the light source is introduced in the enhanced image. The introduction of this light source is consistent with the highest value obtained for LOE and AMBE measurements, indicating that the lightness order error and the mean brightness between the enhanced image and the original image are large. Meanwhile, AFELCE produced a glowing effect on OE regions, as indicated by the red rectangles regions in Fig. 7(c); hence, producing an unnatural enhanced image. However, the UE region indicated by the white rectangle is almost similar in brightness with the original image. Since the lightness variation only occurred at the OE region, AFELCE obtained the lowest LOE, indicating that small lightness variations occurred in the enhanced image compared to the original image. The over-enhancement in OE regions caused the global image to appear brighter than the original image; hence, producing the largest AMBE, while the washed-out effect at OE regions, as shown by the loss of wrinkles in the small red rectangles, obtained a low PSNR. VCEA also produced an unnatural enhanced image, since this method over-enhanced the OE and UE regions, as shown by the brighter and darker regions in the red rectangles and white rectangles in Fig. 7(d), respectively; thus, producing a larger LOE than that of the AFELCE method. However, VCEA resultant image appears dimmer than that of ALEFCE and Backlit. This is shown by the lower AMBE obtained compared to those methods. VCEA also generated a washed-out effect in the same OE regions, as experienced by ALEFCE; hence, producing a low PSNR as that of the AFELCE. On the other hand, the proposed NEIMHE method, ERMHE and ESIHE produced almost similar global brightness and resembled the original brightness; therefore, these methods ranked the top AMBE score amongst other methods. Besides that, ESIHE, the proposed NEIMHE method and ERMHE prevented the washed-out effect; thus, obtaining the third-best, second-best and the highest PSNR score, respectively. However, the resultant image produced by the proposed NEIMHE method looks more natural compared to that of the ERMHE and ESIHE in terms of lightness order. NEIMHE successfully dimmed the OE regions and brightened the UE regions, as shown by the less bright regions in the red rectangles and the white rectangles in Fig. 7(g), respectively. Thus, lightness order error has been reduced compared to that of ERMHE and ESIHE, which minimally lightened the OE region but darkened the UE region, as shown by the similar regions mentioned above in Fig. 7(e) and Fig. 7(f), respectively. The lower lightness order contributed to a lower LOE for the proposed NEIMHE method. Even though ALEFCE scored the lowest in LOE, it still suffered from non-uniform illumination compared to the proposed NEIMHE which has solved the non-uniform illumination problem. Another example of enhancement result for close-up image is shown by Fig. 11 in Appendix. The results are similar to those of *CloseUp1* image. The findings favour the proposed NEIMHE method as the best method among all tested methods.

In order to provide more comparative results, Table 4 tabulates the average score of seven quantitative measurements produced by all tested enhancement methods.

TABLE 4. Average quantitative analysis results for 266 close-up images.

Quantitative Measurement	Proposed NEIMHE Method vs	Mean	p-value	
			Two-tailed test	One-tailed test
DE	Original Image	<u>7.43</u>	1.01 E-03	5.08 E-04
	Backlit	7.40	1.81 E-21	9.03 E-22
	AFELCE	6.91	1.09 E-47	5.46 E-48
	VCEA	7.14	7.37 E-89	3.68 E-89
	ERMHE	7.23	3.53 E-72	1.76 E-72
	ESIHE	7.15	1.9 E-79	9.48 E-80
	Proposed NEIMHE	**7.45**	N/A	N/A
EMEE	Original Image	2039.50	5.5 E-65	2.75 E-65
	Backlit	4374.51	1.11 E-47	5.53 E-48
	AFELCE	1217.32	5.55 E-65	2.78 E-65
	VCEA	2382.11	2.14 E-53	1.07 E-53
	ERMHE	<u>6968.56</u>	4.15 E-19	2.08 E-19
	ESIHE	2019.79	5.65 E-10	2.82 E-10
	Proposed NEIMHE	**11665.30**	N/A	N/A
ICF	Original Image	<u>37.80</u>	3.2 E-168	1
	Backlit	36.04	2.19 E-52	1.09 E-52
	AFELCE	**38.11**	1.28 E-85	1
	VCEA	37.38	1.17 E-82	1
	ERMHE	37.63	4.99 E-96	1
	ESIHE	37.28	1.36 E-60	1
	Proposed NEIMHE	37.02	N/A	N/A
EME	Original Image	20.72	3.85 E-81	1.92 E-81
	Backlit	20.63	3.09 E-79	1.55 E-79
	AFELCE	16.73	3.92 E-91	1.96 E-91
	VCEA	22.98	4.57 E-41	2.28 E-41
	ERMHE	<u>28.05</u>	2.32 E-11	1.16 E-11
	ESIHE	14.7	1.14 E-61	1
	Proposed NEIMHE	**33.78**	N/A	N/A
AMBE	Original Image	N/A	N/A	N/A
	Backlit	22.52	6.1 E-174	3 E-174
	AFELCE	18.99	1.8 E-109	8.8 E-110
	VCEA	16.70	1.51 E-56	7.56 E-57
	ERMHE	**2.03**	6.06 E-07	3.03 E-07
	ESIHE	10.00	2.75 E-14	1.38 E-14
	Proposed NEIMHE	<u>2.26</u>	N/A	N/A
LOE	Original Image	N/A	N/A	N/A
	Backlit	872.76	5.1 E-113	2.6 E-113
	AFELCE	**1.21**	2.24 E-25	1
	VCEA	390.15	9.52 E-64	4.76 E-64
	ERMHE	385.45	7.57 E-66	3.78 E-66
	ESIHE	377.24	2.64 E-65	1.32 E-65
	Proposed NEIMHE	<u>259.29</u>	N/A	N/A
PSNR	Original Image	N/A	N/A	N/A
	Backlit	15.23	5.6 E-190	2.8 E-190
	AFELCE	20.83	1.90 E-113	9.6 E-114
	VCEA	20.61	8.2 E-127	4.1 E-127
	ERMHE	<u>28.50</u>	0.50	N/A
	ESIHE	23.15	1.97 E-53	9.83 E-54
	Proposed NEIMHE	**29.67**	N/A	N/A

Values in bold indicate the best results, while underlined values indicate second-best results

All measurements were evaluated on 266 close-up images. In general, the higher DE, EMEE, ICF, EME, and PSNR are desired, indicating greater details preservation in a whole image, better details preservation in the local region, better global image contrast, better local image contrast, and less degradation, respectively. Meanwhile, low AMBE and LOE are desired to indicate that the enhanced image is better in preserving the mean brightness and naturalness of the original image, respectively. By observing the EME, EMEE, and DE scores in Table 4, AFELCE is seen to have produced the lowest score, since the method tends to combine adjacent intensities. This is proven by a visual observation of *CloseUp1* image, in which the enhanced image by AFELCE suffered from over-enhancement, especially on the OE regions. The proposed NEIMHE method was able to preserve a similar number of intensities held by the original image without great suppression of the original intensities. This is proven by the highest score obtained by the proposed method for DE, EMEE, and PSNR, compared to those of other methods. The minimal combination of original intensities into a single intensity in the enhanced image ensures that the proposed NEIMHE method was able to preserve the details, as shown by the highest score in DE and EMEE. Although producing a higher DE and EMEE might also represent the artefacts, the resultant *CloseUp1* image from the proposed method is less likely to generate the artefacts. This is further supported by the highest PSNR achieved by the proposed method. High PSNR values indicate that the proposed method was able to reduce image degradation of the original image. The second-best EME value achieved by the proposed method indicates that better contrast has been produced in the local region of the image. Although ESIHE obtained the best score in EME, however from visual evaluation, the proposed NEIMHE method able to produce the similar performance as ESIHE in terms of local contrast. Visual analysis for *CloseUp1* image as discussed above shows that the proposed enhancement steps introduced by the proposed NEIMHE method work individually in each exposure region, by successfully producing a significant change in the intensities of those regions, which indirectly contributes to the achievement of high EME values. In terms of AMBE, ERMHE produced the highest score, with only a slight change in the average overall intensity of the enhanced image compared to that of the original image. The proposed NEIMHE method also showed a good achievement that is almost similar to ERMHE in this measurement. In order to measure the preservation of naturalness, LOE was used, and AFELCE showed the best performance compared to other methods. This is because AFELCE does not provide much enhancement, especially in the UE region. Although the proposed NEIMHE method scored the second-best LOE, unlike ALEFCE, a visual analysis of *CloseUp1* image shows that the enhanced image produced by the proposed NEIMHE method is visually pleasing, even though ambiances of certain regions, especially in the UE and OE regions, are changed. In conclusion, based on the qualitative and quantitative analyses, the proposed NEIMHE method successfully outperformed the other tested state-of-the-art methods.

In order to statistically evaluated the performance of the proposed NEIMHE method, paired t-test is performed [44]. The paired t-test is performed for each quantitative measurement (i.e., DE, EMEE, ICF, EME, PSNR, AMBE, and LOE) between the proposed NEIMHE method and the comparison methods as well as the input image. There are two types of t-test that have been performed; two-tailed t-test and one-tailed t-test. In both tests, 0.05 significance level was adopted. The hypotheses for two-tailed t-test are stated as:

H_0 *:* There is no difference between the mean score of the proposed NEIMHE method and the mean score of the comparison method.

H_1 *:* There is a difference between the mean score of the proposed NEIMHE method and the mean score of the comparison method.

In this two-tailed test, the null hypothesis, H_0 is accepted if p-value is greater than 0.05. Otherwise, H_0 is rejected. If H_0 is rejected, one-tailed t-test will be performed by using two sets of hypotheses. The first set of hypothesis is used for evaluating DE, EMEE, ICF, EMEE and PSNR which is:

H_0 *:* The mean score of the proposed NEIMHE method is less than or equal to the mean score of the comparison method.

H_1 *:* The mean score of the proposed NEIMHE method is greater than the mean score of the comparison method.

Meanwhile, in order to evaluate AMBE and LOE, second set of hypotheses are used which stated as:

H_0 *:* The mean score of the proposed NEIMHE method is greater than or equal to the mean score of the comparison method.

H_1 *:* The mean score of the proposed NEIMHE method is less than the mean score of the comparison method.

Similar to the two-tailed test, for one tailed test, if p-value is greater than 0.05, then H_0 is accepted. Otherwise, H_0 is rejected.

Based on results in Table 4, for DE, EMEE, ICF, EME, LOE, and AMBE, the null hypothesis, H_0 is rejected at 0.05 level of confidence for the pairwise comparison between the proposed method and all comparison methods. In this case, the alternate hypothesis, H_1 is accepted i.e. the average score of the proposed NEIMHE method is statistically difference than average score of the other methods. In order to evaluate whether the proposed NEIMHE method performed better than other methods statistically, p-values of one-tailed test have been examined for each quantitative measurement. Based on Table 4, all p-values of DE, EMEE, and AMBE are less than 5 E-02 (or 0.05), therefore H_0 is rejected. These findings interpret that for DE, EMEE and AMBE the proposed NEIMHE method statistically outperform other methods including the original image. Additionally, the highest mean scores obtained by the proposed NEIMHE method for DE and EMEE demonstrated these findings, while for AMBE, even though the proposed NEIMHE method ranked second for the mean score, however statistically it performed better than ERMHE. Meanwhile, for ICF, H_0 for one-tailed test is accepted for all methods except Backlit which means that statistically the global contrast of the proposed NEIMHE method is not as good as original image, ALEFCE, ERMHE, VCEA and ESIHE enhanced image. However, visual evaluations as discussed previously shown that the proposed method produced more uniform illumination compared to other methods. For EME, H_0 of one-tailed test is accepted for pairwise comparison between the proposed NEIMHE method and ESIHE. This shows that statistically, ESIHE performed better than the proposed method in terms of EME although the average EME score of the proposed method is higher than ESIHE. For one-tailed test of LOE, the H_0 is also accepted for pairwise comparison between the proposed NEIMHE method and ALEFCE which indicate that statistically, ALEFCE performed better than the proposed NEIMHE method in naturalness. For other methods, p-values in Table 4 statistically shown that the proposed NEIMHE method has the best performance which are also supported by the average score obtained.

Meanwhile, for PSNR, the proposed method has significant mean with ERMHE since the p-value of two-tailed test is greater than 0.05. This indicate that statistically, there are no difference on the PSNR performance between the proposed NEIMHE method and ERMHE. Therefore, statistically the proposed NEIMHE method gives better PSNR performance than other methods except ERMHE as being indicated by the p-value of one-tailed test as shown in Table 4.

B. NON-CLOSE-UP IMAGES

Fig. 8(a) shows an example of a non-close-up image with non-uniform illumination. As shown by the red rectangles in Fig. 8(a), the house wall is irradiated by the sunlight that causes a loss of the wall texture; thus, these regions are categorised as OE regions. On the other hand, the house courtyard, as shown by the white rectangle are scattered by lighting obstacles during the image acquisition process; thus, creating a relatively dark region without details visibility. This region is the UE region. The magnified images of both UE and OE regions are shown in Fig. 9(a) and Fig. 10(a), respectively. All methods successfully lightened the UE region, as shown by the white rectangle in Fig. 9(b)-(g). However, Backlit over-enhanced this region, which is shown by the excessively bright courtyard. In the OE region, Backlit failed to reduce the brightness of the extreme illumination. The irradiated regions are maintained as in the original image. As a result, the Backlit resultant image looks brighter and low in contrast compared to the original image. This is further supported by the lowest ICF value obtained by Backlit, as tabulated in Table 5. However, most local regions specified in the Backlit image show better contrast than the original image, especially in the UE regions highlighted by the white rectangle. The plant and the grass in the courtyard are comprised of various intensities, which highlight the details compared to the original image, which is proven by the higher EME score than that of the original image. Similar to Backlit, ALEFCE failed to enhance OE regions; the OE region in Fig. 10(c) looks brighter than that of the original image. However, ALEFCE minimally brightened the UE region. This is shown by the brighter intensity produced in the white rectangle region. Therefore, the ICF value is almost similar to that of the original image. In local contrast evaluation, ALEFCE showed good local contrast but only in the UE region. However, since almost half of the image is in high intensity (i.e., region) on average, ALEFCE was unable to achieve a higher EME score compared to the original image. ERMHE, VCEA, ESIHE and the proposed NEIMHE method solved the unavailability of enhancement in OE regions faced by Backlit and ALEFCE. These methods successfully reduced the brightness of one of the OE regions, as shown in Fig. 10(d)-(g). However, VCEA, ERMHE and ESIHE showed inconsistent brightness changes in UE regions, where some parts of the grass in the courtyard are over-brightened, as shown in Fig. 8(d), Fig. 8(e), and Fig. 8(f), respectively. The proposed NEIMHE method was able to brighten the UE regions without introducing any over-enhancement problem. Since these four methods successfully brightened the UE regions, the ICF scores are lower than that of the original image, and the images looks more uniform compared to the resultant images produced by other methods. VCEA, ERMHE, ESIHE and the proposed NEIMHE method also provided a better local contrast both in OE and UE regions than that of other methods. This can be seen by various intensities produced in the highlighted UE regions in Fig. 8(d)-(g). However, in several WE regions, as shown by the blue dotted rectangle in Fig. 8(d) and Fig. 8(e), VCEA and ERMHE, respectively over-enhanced this region until the stairs are invisible. Meanwhile, ESIHE under enhanced the OE region in which the wall looks darker, therefore low in contrast. The proposed NEIMHE method produced better contrast in this WE region. This is further supported by the highest EME score in Table 5. In conclusion, the proposed NEIMHE method successfully brightened the UE regions, dimmed the OE regions, and preserved the WE regions so that the enhanced image looks more uniform in illumination.

The second criteria to be considered in evaluating image enhancement is the preservation of details. By looking at the image as a whole, ALEFCE lacked details preservation in the bright regions due to over-enhancement. Since half of the image is bright, the DE score obtained by ALEFCE is lower than that of the original image. However, ALEFCE produced better details preservation in the local UE region, as highlighted in Fig. 9(c). The leaves are observed to be more visible compared to the similar region of the original image in Fig. 9(a). In the OE region, this method failed to enhance the details, as illustrated in the Fig. 10(c), where the region looks similar to the original image. VCEA faced a similar problem in preserving the details in most OE regions, as well as in the WE region highlighted by the blue rectangle in Fig. 8(d). The illumination in both regions is over-dimmed until the details are washed out. However, in certain OE region, as shown in Fig. 10(d), the details of this local region

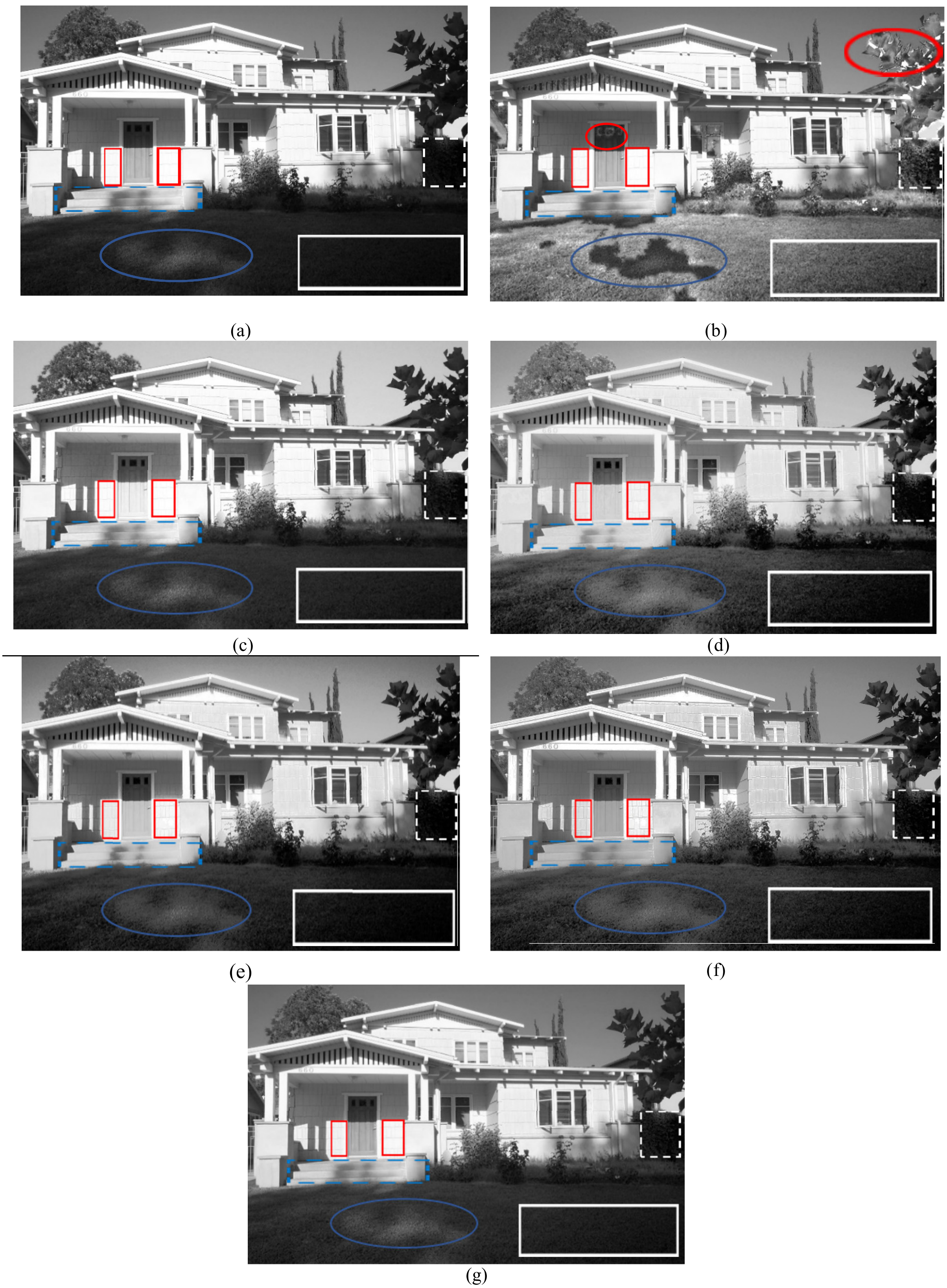

FIGURE 8. **(a) Original *NonCloseUp1* image and resultant images produced by (b) Backlit; (c) AFELCE; (d) VCEA; (e) ERMHE; (f) ESIHE; (g) proposed NEIMHE.**

TABLE 5. Quantitative analysis results for NonCloseUp1 image.

Image	Technique	Quantitative Measurement						
		DE	EMEE	ICF	EME	AMBE	LOE	PSNR
NoncloseUp1	Input	<u>7.45</u>	52.39	<u>38.21</u>	15.38			
	Backlit	7.42	370.33	36.11	15.86	31.70	787.28	13.29
	AFELCE	7.35	70.04	**38.41**	12.88	19.53	**0.40**	18.50
	VCEA	7.17	125.87	37.59	18.82	23.38	164.39	17.65
	ERMHE	7.16	<u>1173.14</u>	38.02	<u>25.48</u>	5.77	162.94	<u>24.38</u>
	ESIHE	7.15	588.35	36.80	11.58	**3.50**	163.09	22.40
	Proposed NEIMHE	**7.50**	**1234.69**	37.37	**25.79**	<u>4.70</u>	<u>105.60</u>	**27.82**

Values in bold indicate the best result, while underlined values indicate second-best results

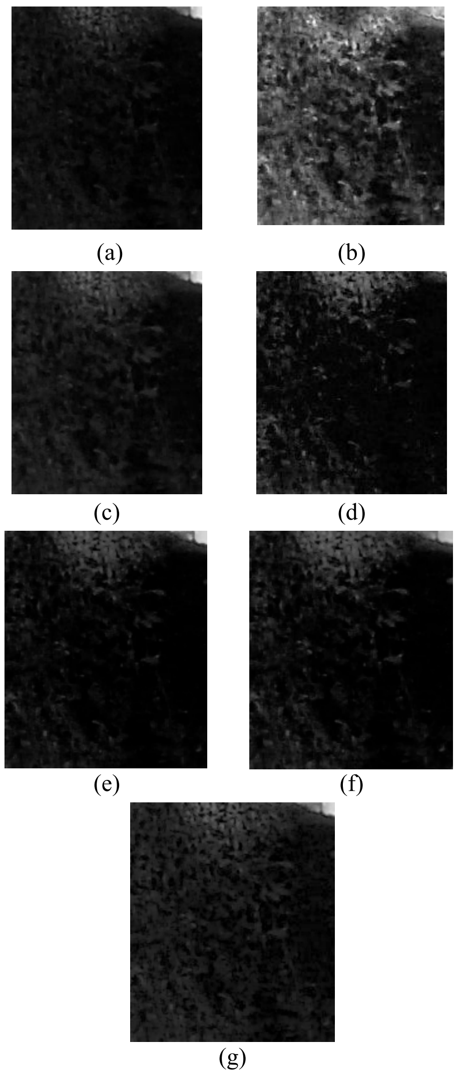

FIGURE 9. The magnified UE region of (a) original *NonCloseUp1* image and resultant images produced by (b) Backlit; (c) AFELCE; (d) VCEA; (e) ERMHE; (f) ESIHE; (g) proposed NEIMHE.

(i.e., divider between the bricks) are observable compared to those of the original image. In contrast, VCEA was unable to produce better contrast for the UE region where parts of the leaves in Fig. 9(d) are not clearly visible. These limitations are further proven with the obtainment of low EMEE and DE scores. On the other hand, Backlit was able to properly enhance the details of the UE regions, but not of the OE regions. This is shown by the clearly visible grass in the white rectangle region and invisible details in red rectangle region, respectively, as shown in Fig. 8(b). Similar findings were obtained by evaluating the details in magnified UE and OE regions, as shown by clearly visible leaves in Fig. 9(b) and invisible details in Fig. 10(b), respectively. As tabulated in Table 5, the average DE score obtained by Backlit, which is almost similar to the DE score of the original image, whereas a higher EMEE value further supports the findings that Backlit was able to preserve the details globally, as well as in the local region. The ability to enhance the details in the local region is also shown by ERMHE and ESIHE. As depicted in Fig. 10(e) and Fig. 10(f), the enhanced image was able to preserve details in certain OE regions, shown by the clearly visible wall bricks. However, in certain UE regions, both methods failed to preserve the details, as shown by several washed-out details in Fig. 9(e) and Fig. 9(f). In contrast, the proposed NEIMHE method was able to properly enhance the details in similar UE region, as shown in Fig. 9(g). The leaves are clearly visible compared to those in the original image and other enhanced images. The proposed NEIMHE method also successfully preserved the details in OE regions, as illustrated in Fig. 10(g). By visually examining the whole NEIMHE enhanced image, the details in the image are preserved better than in ERMHE. The details in OE, UE, and WE regions, represented by the blue dotted rectangle region, are still visible compared to those of ERMHE. The ability of the proposed NEIMHE to enhance details either of the local regions or generally of the whole image is measurably indicated by DE and EMEE values, which recorded the highest scores compared to other methods.

In image enhancement, the naturalness of the original image is desired to be preserved. In *NonCloseUp2* image, Backlit failed to preserve the naturalness of the original image. The enhanced Backlit image looks brighter, as an additional light source has been introduced. The highest score of LOE and AMBE supported the abovementioned additional light source problem produced by Backlit. Besides that, Backlit produced noise, as shown by the red ovals in Fig. 8(b), where unwanted white pixels appeared. Therefore, this method obtained the lowest score for PSNR.

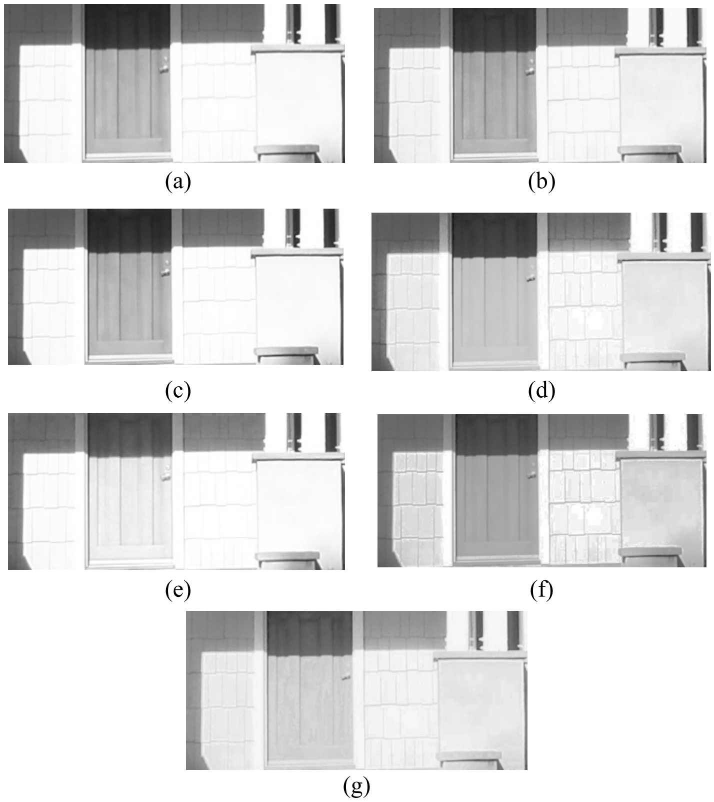

FIGURE 10. The magnified OE region of (a) original *NonCloseUp1* image and resultant images produced by (b) Backlit; (c) AFELCE; (d) VCEA; (e) ERMHE; (f) ESIHE; (g) proposed NEIMHE.

Meanwhile, VCEA produced brighter OE and WE regions, where the sky and the house become brighter. This affected the LOE and AMBE scores as high scores were recorded in both measurements. Similar to Backlit, VCEA produced noise as indicated by the blue oval region in Fig. 8(d), where the sunlight patch is becomes wider. Thus, the PSNR score for VCEA is low. ALEFCE showed better naturalness preservation compared to Backlit and VCEA. However, the sky region in Fig. 8(c) becomes slightly brighter; thus, producing a slightly brighter enhanced image compared to the original image. This is further proven by the lowest score obtained in LOE amongst all methods and a lower score in AMBE compared to VCEA and Backlit. In image degradation, the over-bright OE regions, as highlighted in Fig. 10(c), produced a washed-out effect that contributes to the low PSNR value. Similar to ALEFCE, ERMHE also produced slightly brighter sky and UE region; therefore, the enhanced image looks brighter than the original image, which produced a higher LOE than that of ALEFCE.

However, the slightly brighter intensities produced in the UE region contributed to the slightly higher mean brightness; thus, a lower AMBE score was obtained. ESIHE over-dimmed the OE region while brightened the UE region, therefore the mean brightness is low. Similar to VCEA, ERMHE and ESIHE produced noise as shown by the blue oval in Fig. 8(e) and Fig. 8(f), respectively. Besides that, the shades in the blue dotted rectangle in Fig. 8(e) and Fig. 8(f) are washed-out; hence, generating unnaturalness of the enhanced image. The proposed NEIMHE method produced an enhanced image without introducing noise and washed-out effect. This can be seen by the well-preserved sunlight region, represented by the blue oval in Fig. 8(g) which did not wash-out any WE neighbouring pixel. Therefore, the proposed NEIMHE method obtained the highest PSNR amongst those of other methods. Similar to ERMHE and ESIHE, the proposed NEIMHE method produced a slightly brighter UE region; therefore, the mean brightness of the enhanced image is slightly higher than that of the original image, contributing to the second best AMBE. Compare to ERMHE, no light source was introduced to the sky region; therefore, the proposed NEIMHE method produced more natural image than ERMHE and ESIHE. This is further supported by a lower LOE score than that of ERMHE and ESIHE. Fig. 12 in the Appendix shows another example of an enhanced result for a non-close-up image. The results are comparable to the *NonCloseUp1* image. The findings demonstrate that the proposed NEIMHE method is the best methods among all enhancement methods. In order to observe the performance of the proposed NEIMHE and state-of-the-art methods in enhancing non- close-up images, Table 6 tabulates the average score of seven quantitative measurements for 88 non-close-up images. The proposed

TABLE 6. Average quantitative analysis results for 88 non-close-up images.

Quantitative Measurement	Proposed NEIMHE Method vs	Mean	p-value	
			Two-tailed test	One-tailed test
DE	Original Image	7.53	0.18	N/A
	Backlit	7.49	1.31 E-14	6.54 E-15
	AFELCE	7.40	1.29 E-20	6.45 E-21
	VCEA	7.27	6.6 E-56	3.3 E-56
	ERMHE	7.36	5.31 E-44	2.65 E-44
	ESIHE	7.31	1.11 E-48	5.57 E-49
	Proposed NEIMHE	**7.56**	N/A	N/A
EMEE	Original Image	1075.91	1.97 E-30	9.48 E-31
	Backlit	1112.82	5.65 E-21	2.83 E-21
	AFELCE	613.18	4.84 E-30	2.42 E-30
	VCEA	1282.90	2.9 E-29	1.45 E-29
	ERMHE	2780.74	8.61 E-13	4.31 E-13
	ESIHE	2902.97	1.35 E-26	6.77 E-27
	Proposed NEIMHE	**4050.19**	N/A	N/A
ICF	Original Image	36.14	2.26 E-73	1
	Backlit	34.82	1.55 E-39	7.77 E-40
	AFELCE	36.19	3.39 E-21	1
	VCEA	**37.57**	0.04	0.98
	ERMHE	36.55	3.67 E-32	1
	ESIHE	36.66	2.51 E-04	0.99
	Proposed NEIMHE	35.35	N/A	N/A
EME	Original Image	6.55	2.87 E-40	1.43 E-40
	Backlit	5.98	1.39 E-36	6.95 E-37
	AFELCE	5.04	6.6 E-42	3.3 E-42
	VCEA	7.55	2.66 E-25	1.33 E-25
	ERMHE	8.86	1.59 E-07	7.95 E-08
	ESIHE	**17.09**	4.06 E-32	2.03 E-32
	Proposed NEIMHE	10.13	N/A	
AMBE	Original Image	N/A	N/A	N/A
	Backlit	16.81	4.09 E-45	2.04 E-45
	AFELCE	17.81	1.48 E-43	7.41 E-44
	VCEA	19.64	2.71 E-18	1.36 E-18
	ERMHE	**3.13**	0.62	N/A
	ESIHE	9.584	1.05 E-15	5.24 E-16
	Proposed NEIMHE	3.50	N/A	N/A
LOE	Original Image	N/A	N/A	N/A
	Backlit	852.31	1.44 E-40	7.22 E-41
	AFELCE	**2.64**	7.10 E-23	1
	VCEA	266.19	5.34 E-08	2.67 E-08
	ERMHE	265.39	8.10 E-08	4.05 E-08
	ESIHE	244.98	3.96 E-08	1.98 E-08
	Proposed NEIMHE	132.65	N/A	N/A
PSNR	Original Image	N/A	N/A	N/A
	Backlit	17.81	4.98 E-77	2.49 E-77
	AFELCE	21.69	8.5 E-47	4.25 E-47
	VCEA	19.57	8.62 E-37	4.31 E-37
	ERMHE	**29.03**	1.45 E-03	7.25 E-04
	ESIHE	23.83	4.77 E-33	2.39 E-33
	Proposed NEIMHE	28.11	N/A	N/A

Values in bold indicate the best result, while underlined values indicate second-best results

NEIMHE method scored the best performance in two measurements; DE, and EMEE. As mentioned in the introduction of this section, DE, and EMEE are related to the distribution of the greyscale, either globally as represented by DE, or in the local regions as represented by EMEE. Compared to the original image, the proposed NEIMHE method, which works based on region targeted enhancement, successfully generated the best DE score of 7.56. Based on Table 6, all methods show comparable performance in terms of DE; however, different performances can be seen in terms of EME and EMEE. In EME measurement, HE-based enhancement methods, i.e., VCEA, ERMHE, ESIHE and the proposed NEIMHE method, achieved better local contrast than that of the original image and other enhancement methods. Meanwhile, for EMEE, only AFELCE was unable to preserve the local entropy of the original image. This may be caused by the over-enhancement problem faced by ALEFCE. The proposed NEIMHE method scored the highest EMEE amongst other methods, where the score gap between the proposed NEIMHE method and the second-best method is quite big: about half of the score obtained by the proposed NEIMHE method. This finding shows that the proposed NEIMHE method successfully enhanced the local entropy of the image. The proposed NEIMHE method was also resilient against image degradation and the mean brightness shift of the image. This is shown by the comparable scores with ERMHE, which has the highest in PSNR and the lowest in AMBE. For AMBE measurement, the exposure based HE method, such as ERMHE, and the proposed NEIMHE method obtained good scores (i.e., lower scores), while other methods obtained higher scores; the gap between these two groups is very large. This shows that segmented enhancement based on exposure regions can control the mean brightness shift in of the image. However, the proposed NEIMHE method was unable to produce a low LOE score. Since two dominating regions (i.e., UE and OE regions) were enhanced (UE was brightened while OE was slightly dimmed), the original lightness order was impossible to attain. However, as long as the enhanced image shows appealing resultant images without apparent additional light sources, it can be concluded that the naturalness of the image is preserved.

To further analyse the performance of the proposed NEIMHE method on non-close-up images, simple statistical test has been performed as explained in Section V-A. The similar hypotheses are used either in two-tailed or one-tailed t-test as discussed in that section. Based on p-values of the two-tailed test in Table 6, H_0 is rejected for all pairwise comparisons on EMEE, ICF, EME, LOE and PSNR since all p-values obtained on those quantitative measurements are less than 5 E-02 (0.05). Therefore, it can be concluded that there are significant differences of performance in terms of EMEE, ICF, EME, LOE and PSNR between the proposed NEIMHE method and other methods. As being mentioned in Section V-A, in order to further compare the performance of the proposed NEIMHE method with other methods statistically, one-tailed t-test is performed. Based on p-values of one-tailed test on the abovementioned quantitative measurements (i.e. EMEE, EME, LOE and PSNR) in Table 6, H_0 for all pairwise comparisons on EMEE, EME and PSNR are accepted which indicate that statistically, the proposed NEIMHE method has better performance than all methods in terms of EMEE, EME and PSNR. For EME, although the proposed NEIMHE method ranked second-best in average score, however statistically the proposed NEIMHE method shows the best performance. While for LOE, H_0 is accepted only for pairwise comparison between the proposed NEIMHE method and ALEFCE which indicates that ALEFCE has better LOE performance than the proposed NEIMHE method, statistically. In other words, the proposed NEIMHE shows better LOE performance than other comparison methods (i.e Backlit, VCEA, ERMHE and ESIHE) except ALEFCE. This is also supported by the average score obtained as shown in Table 6 in which the proposed NEIMHE method ranked second-best for LOE. Meanwhile, the proposed NEIMHE method shows better ICF performance compared to Backlit, statistically. Nevertheless, the proposed NEIMHE method shows lower performance in statistically significant ICF evaluation when compared to other methods except the Backlit. However, based on visual evaluation for *NonCloseUp1,* the NEIMHE enhanced image as shown in Fig. 8(g) shows that even though ICF score is low, but the image looks more uniform in illumination and has appealing contrast.

In terms of DE and AMBE, H_0 is accepted for the pairwise comparison between the proposed NEIMHE method and original image as well as ERMHE, respectively. Therefore, statistically, DE performance between the proposed NEIMHE method and original image does not have significant difference. Similar finding is concluded for AMBE performance between the proposed NEIMHE method and ERMHE. As a conclusion, for both DE and AMBE, the proposed NEIMHE method gives better performance than other comparison methods except the original image for DE and ERMHE for AMBE as explained previously.

VI. CONCLUSION

This study proposed a HE-based method called Nonlinear Exposure Intensity Modification-Based HE (NEIMHE) for enhancing non-uniform illumination image. The main contributions of this method are the nonlinear histogram bin modification, and the exposure-based intensity mapping function. The non-uniform illumination image was enhanced individually in five different exposure sub-regions, namely UE, LWE, MWE, UWE, and OE regions. The nonlinear histogram bin modification put weight on the cumulative density function (CDF) in a nonlinear pattern based on each region's exposure level. These weighted CDFs helped to prevent over-enhancement and under-enhancement problems in each region, especially in the OE and UE regions respectively, compared to the conventional HE. The exposure-based intensity mapping functions extended the range of OE and

FIGURE 11. (a) Original *CloseUp2* image and resultant images produced by (b) Backlit (c) AFELCE (d) VCEA (e) ERMHE (f) ESIHE (g) proposed NEIMHE.

(a) (b) (c) (d) (e) (f) (g)

FIGURE 12. **(a) Original *NonCloseUp2* image and resultant images produced by (b) Backlit (c) AFELCE (d) VCEA (e) ERMHE (f) ESIHE (g) proposed NEIMHE.**

UE regions based on the Zone system. The functions provided different intensity mapping directions on UE and OE, in order to lighten or reduce the brightness, respectively. To preserve details, the proposed method integrated local contrast boosting for producing a uniform illumination and preserving details of the enhanced image. The performance of the proposed NEIMHE method in improving the enhancement of original non-uniform illumination images was studied qualitatively and quantitatively. It tested 266 close-up and 88 non-close-up non-uniform illumination images, while evaluation was performed against four existing non-uniform illumination image enhancement methods, i.e., Backlit, ERMHE, AFELCE, and VCEA. Unlike other existing methods, the proposed NEIMHE method produced enhanced images that are more uniform in illumination, preserving the image details, and maintaining the naturalness of the original image. The proposed NEIMHE method is helpful to solve non uniform illumination on the enhanced image of the existing enhancement methods (i.e. VCEA, ESIHE) by performing enhancement individually on the different exposure regions. Based on literature review, there are three methods that have been introduced the individual enhancement on each separate exposure region (i.e. Backlit, ALEFCE, ERMHE), however, these methods lacked of enhancement rate control on each exposure region, therefore they suffered from under enhancement or over enhancement problems. The amount of intensity shift is not controlled, that may produce artifacts as can be seen in ERMHE. As a solution, the proposed method solved the under and over enhancement problems by adopting the nonlinear HE to control the enhancement rate of each exposure region. A good visual performance of the proposed method was further supported quantitatively by the attainment of the highest scores in DE, PSNR, EME, and EMEE, with AMBE and LOE being second-best. From statistical analysis of the close-up images, the proposed NEIMHE method outperformed all comparison methods in all quantitative measurements except in some cases namely on ICF in which all methods except Backlit outperformed the proposed NEIMHE method. Meanwhile, ESIHE, ALEFCE and ERMHE also outperformed the proposed NEIMHE method on EME, LOE, and PSNR measurement, respectively. Similar to the statistical analysis of the close-up images, for non-close-up images, the proposed NEIMHE method also outperformed most of comparison methods on all quantitative measurements except on ICF, in which all methods except Backlit outperformed the proposed NEIMHE method. Besides that, the original image, ERMHE, and ALEFCE outperformed the proposed NEIMHE method in terms of DE, AMBE, and LOE, respectively. These findings prove that the proposed NEIMHE method: (i) produces enhanced images with high information contents, either on the whole image or on certain local regions in the image; (ii) prone to degradation; (iii) produced a better contrast in the local regions of the image; and (iv) preserved the mean brightness and naturalness of the original image.

FUTURE WORKS

NEIMHE used certain grey level ranges based on the WE region defined in the Zone System in order to map the intensity. Therefore, the fixed ranges may not suitable for some type of images such as underexposed image. In the future, the optimization method could be adopted in order to find the most suitable range for the dynamic range expansion of each exposure region (i.e. UE, LWE, WE, UWE, and OE). This optional method could also reduce under enhancement and over enhancement problem. The proposed NEIMHE method also sometimes generated slightly smaller dynamic range as compared to the original dynamic range. Therefore, contrast stretching can be considered to be done in order to maintain the original dynamic range after intensity mapping is performed. Besides that, the proposed method manipulates the grey image processing in order to perform the enhancement, as a result the final enhanced image is in a grey image. Therefore, colour image processing can be adopted further to obtain the colour enhanced image.

APPPENDIX

See Figures 11 and 12.

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