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Exposure Based Multi-Histogram Equalization Contrast Enhancement for Non-Uniform Illumination Images

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ABSTRACT Non-uniform illuminated images pose challenges in contrast enhancement due to the existence of different exposure region caused by uneven illumination. Although Histogram Equalization (HE) is a well-known method for contrast improvement, however, the existing HE-based enhancement methods for non-illumination often generated the unnatural images, introduced unwanted artifacts, and washed out effect because they do not utilize the information from the different exposure regions in performing equalization. Therefore, this study proposes a modified HE-based contrast enhancement technique for non-uniform illuminated images namely Exposure Region-Based Multi-Histogram Equalization (ERMHE). The ERMHE uses exposure region-based histogram segmentation thresholds to segment the original histogram into sub-histograms. With the thresholded sub-histograms, the ERMHE then uses an entropy-controlled gray level allocation scheme to allocate new output gray level range and to obtain new thresholds that will be used to repartition the histogram prior to HE process. A total of 154 non-uniform illuminated sample images are used to evaluate the application of the proposed ERMHE. By comparing ERMHE to four existing HE-based contrast enhancement namely, Global HE, Mean Preserving Bi-Histogram Equalization (BBHE), Dualistic Sub-Image Histogram Equalization (DSIHE), and Contrast Limited Adaptive Histogram Equalization (CLAHE), qualitatively, the ERMHE produces enhanced images with a natural appearance, appealing contrast, less degradation, and reasonable detail preservation. Quantitatively, the ERMHE achieves the highest peak signal-to-noise-ratio (PSNR), lowest Absolute Mean Brightness Error (AMBE), and second best in Discrete Entropy (DE) scores. From the analyses, the ERMHE has shown its capability in enhancing different exposure regions exist in non-uniform illuminated images.

INDEX TERMS Contrast enhancement, exposure regions, multi-histogram equalization, non-uniform illuminated image.

I. INTRODUCTION

An object can be visualized because of the light irradiated on it. Different kind of light sources such as sun light, moon light, fluorescent light and others have different illumination intensity. Yet, they can be blocked by non-fully transparent objects [1]. Hence, this phenomenon forms the non-uniform illumination on the object which then becomes the uneven illumination captured by the images. Apart from that, the camera properties, inappropriate focusing [2], as well as the absorption and reflection level of the object on light irradiated [3], can also contribute to the occurrence of non-uniform illumination in images. If an image has low contrast, its histogram is narrow in shape [4], however, due to the existence of different pixel frequency saturation across different pixel intensity in a single image, it creates different luminance exposure that form the non-uniform illuminated regions in the image as shown in Fig. 1. Conventionally, overexposed and underexposed regions are used to express pixels which exhibit extremely bright or dark intensity in the image respectively while those pixels which lie between the two are being classified as well-exposed regions.

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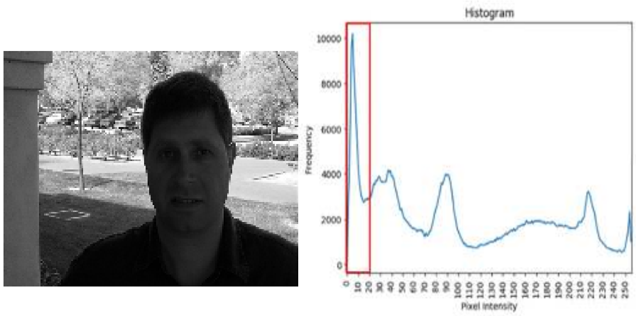


FIGURE 1. **Non-uniform illuminated image and its corresponding histogram. Highlighted in red shows saturation of pixel frequency across small range of pixel intensity that introduced uneven illumination.**

Contrast enhancement has been widely used in digital imagery to help improve visual perception for both human and machine vision in identifying the key features of an image. It is done by creating difference in luminance reflectance (contrast) by modifying the pixel intensity of the input image (enhancement) [5]. Nowadays, there are various state-of-the-art techniques that are used in enhancing the contrast of an image, for instance, histogram equalization, unshaped masking, gray-level grouping, wavelet transform, intensity pair distribution, and multiscale enhancement [4]. Among the aforementioned techniques, Histogram Equalization (HE) is one of the methods that is developed to satisfy human visual system which focuses on luminance rather than color information and is well known of its simplicity and effectiveness in contrast enhancement [4], [6]. There are various HE-based techniques that produced good performance for uniform brightness problem, however, there are only a few existing researches such as study done by [7] which focus on the application of HE for non-uniform illuminated images. Conventional Global HE (GHE), Local HE (LHE) and some other equivalent HE-based techniques do not help much in enhancing the contrast of non-uniform illuminated images. GHE is not suitable for non-uniform illuminated images as the images require different contrast-stretching ratio for different illumination regions identified in the image. LHE, on the other hand, enhances both target and background which causes over enhancement [4], [8]. Meanwhile, multi-histogram uses multiple sub-histograms to ensure no dominating component among segmented sub-histograms and uses dynamic range gray levels to eliminate the possibility of compression on low histogram component to preserve image's details. However, the segmented multi-histogram does not reflect the different exposure regions found in a non-uniform illuminated image.

It is difficult to strike a balance between underexposure and overexposure as both of them are contradicting to each other. If light enhancement is applied on the overall image, the underexposure part will be brighter while the overexposed part will be too bright or vice versa. It is also possible that certain images might contain both underexposed and overexposed regions where no single underexposed or overexposed enhancement can be applied directly to both regions to enhance the overall contrast [9]. Therefore, the aim of this research is to develop an exposure based multi-histogram equalization contrast enhancement method for non-uniform illuminated images. The idea is to adapt HE with information obtained from different types of exposure regions exist in an image. For instance, in this research, mean computed from each exposure region's histogram is used as the exposure information to partition the histogram into sub-histograms prior to the application of HE. With the information obtained from exposure region determination, this research aims to equalize the individual exposure regions better in order to preserve the details. The rest of this paper is organized as follows: Section II discusses some related work in HE-based contrast enhancement methods. Section III presents the proposed ERMHE in detail. Section IV highlights the data sample and the widely-used assessment metrics. Section V discusses the resultant image and performance comparison. Finally, Section VI outlines the conclusion and Section VII discusses the drawbacks & future work.

II. LITERATURE REVIEW ON PREVIOUS WORK

A. EXISTING APPLICATION OF CONTRAST ENHANCEMENT TECHNIQUE ON NON-UNIFORM ILLUMINATED IMAGES

There are several existing application of contrast enhancement techniques such as nonlinear mapping [1], retinex-based algorithm [10], fuzzy transformed-based [11], histogram-based [2] and HE-based [7] method that have been widely used in enhancing contrast of non-uniform illuminated images.

Adaptive enhancement for nonuniform illumination images via nonlinear mapping is proposed by [1]. With a low-pass filter estimated image luminance on the Y channel of YCbCr space, it uses local adaptive demarcation to segregate luminance image's underexposed from the overexposed region. This method has successfully preserved vivid color on images while retaining a moderate amount of details. However, it tends to generate overvivid images that do not preserve the naturalness of an image especially on warm color that exist in an image. Naturalness Preserved Non-uniform Illumination Estimation for Image Enhancement Based on Retinex is developed with the aim to estimate illumination effectively while preserving naturalness of an enhanced image [10]. According to [12], a filter is used to estimate illumination and reflectance which eventually used to smooth the image. This smoothed version image is acting as the illumination of most retinex-based method image enhancement. However, retinex-based image enhancement often requires to make up the effect of illumination on the image [12] where illumination estimation directly influences reflectance estimation. It also often results in poor ambiance due to the facts that it tends to remove illumination for better reflectance layer enhancement and results in severe color distortion and unnaturalness in the enhanced image [11]. This is due to the ambiguity in the decision boundary of image decomposition as well as in illumination removal estimation. In order to encounter the ambiguity and vagueness of retinex-based algorithm, fuzzy based method was used to enhance non-uniformly illuminated low contrast image. [11] introduced image illumination regularization algorithm on the value component of HSV space through the use of parametric fuzzy transform (pFT) in the luminance domain. By converting RGB images into LUV and HSV color space images, this algorithm is able to take advantages on luminance layer (L of LUV color space) and value layer (V of HSV color space) to decouple the original image into luminance and chrominance respectively to preserve image details better. This algorithm has successfully preserved the luminance, details, and color naturalness with unaltered hue and saturation layer of an input image.

There have been many researches that focus on using different channel of different color space in luminance estimation and enhancement for non-uniform illuminated images enhancement. But there are only a little research focusing on histogram-based non-uniform illumination enhancement. [2] introduced histogram-based image enhancement for non-uniform illuminated images. It consists of the dark enhancer which will be applied to darken the bright region while the bright enhancer will be used to brighten up dark region thus resulting in a more uniformly illuminated image. The proposed algorithm is capable of preserving the naturalness and image details as it enhances the given input image pixel by pixel through the enhancers. However, contrast is not just a simple representation from pixel intensity where dark region and bright region do not always reflect low contrast. Therefore, this method might tend to enhance good contrast region that may already exist in the dark and bright regions. This can be proven by the low score in contrast improvement analysis obtained in this study. Besides that, Bright ratio (BR) and Dark ratio (DR) are to be obtained manually as there is not clear indication on how both ratios are being computed. Meanwhile, [7] proposed a Human Visual System Based Multi-Histogram Equalization (HVSMHE) that utilizes human visual system-based thresholding techniques in order to correct the non-uniform brightness problem. This algorithm allows separation of the image according to the quality of illumination namely, over-illuminated, well illuminated, and under-illuminated before applying the traditional HE. By separating the image into different regions of illumination instead of simple pixel intensity thresholding [7] demonstrated the ability of their method to overcome bi-histogram and tri-histogram equalization inconsistency. However, it involves a lot of tedious manual measures computation in obtaining the human visual parameters such as computation of background intensity, gradient information and the parameter defined constants which involve complex mathematical operation. Since there are only a few researches that work on HE-based enhancement for non-uniform illuminated images and there is still a need of improvement for existing HE application on non-uniform illumination, these have motivated this study in discovering an alternative HE-based method in enhancing the contrast of non-uniform illuminated images.

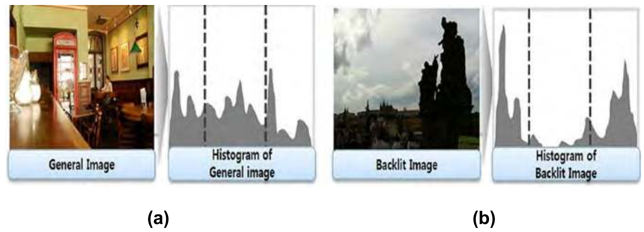


FIGURE 2. **(a) Uniform illuminated image and its histogram. (b) Backlit image and its histogram [13].**

B. ILLUMINATION REGION DETERMINATION

Illumination region determination is an important preprocessing stage in image enhancement as small range of intensity in a pre-determined region could help HE in effective quantitative measurement that ensures optimal enhancement [7]. In the effort of determining underexposed and overexposed regions in an image, [9] introduced an objective measure parameter called exposure and threshold a in identifying underexposed or overexposed region in an image. [9] found that pleasant image tends to have exposure value of 0.5. Based on (1), when the exposure is high, it gives low value of a indicating more gray levels is categorized as an overexposed region while when exposure is low, it gives a high value of a indicating more gray level is categorized as underexposed region. Then, it divides an image in the range of $[0, L-1]$ into two regions where $[0, a-1]$ for underexposed regions and $[a, L-1]$ for overexposed regions where L is the number of gray levels.

$$a = L \cdot (1 - exposure) \tag{1}$$

Similarly, Hasikin and Mat Isa (2015) also cluster an image into two regions, namely dark and bright regions through the use of adaptive fuzzy intensity measure (AFIM). Unlike exposure-based method by [9], this method uses statistical information of the histogram distribution instead of purely intensity only in computing the threshold. With the FIM computed threshold T, dark region is clustered in a range of $[0, T-1]$ whereas the bright region is clustered in a range of $[T, L-1]$. Both the exposure-based and AFIM method discussed above only classify an image into two regions, therefore it tends to classify the well-exposed pixels (pixels having proper and sufficient amount of lighting) to either overexposed or underexposed. Consequently, this has caused further enhancement to degrade the contrast of well-exposed region of an image.

[13], [14] introduce some techniques to solve the ambiguity due to uncategorized pixels that do not belong to any of the two regions. From Fig. 2, it can be seen that dark backlit region tends to have a narrow dynamic range of low intensity level compared to a normal illuminated image. [13] proposed adaptively partitioned blocks through Fuzzy C-means clustering (FCM) with two clustering which used to detect dark backlit and background regions of an image before enhancing the contrast of the identified dark regions. Input image is divided into a 64×64 non-overlapped blocks

FIGURE 3. Non-uniform illuminated images showing dark background and bright foreground.

where two optimal thresholds namely, c_1 and c_2 for dark and background regions respectively are generated. If the maximum brightness value in the block is less than c_1, that pixel is classified as dark block meanwhile if minimum brightness value in the block is larger than c_2, that pixel is classified as the bright block else it is classified as ambiguous block. The ambiguous regions are partitioned to further produce four sub-blocks which are then re-classified in the same manner until the size of the block becomes 4×4. However, as this method only considers intensity for region determination in backlit images, it is not applicable to non-uniform illuminated image. This is because non-uniform illuminated image as in Fig. 3 might have a dark background and bright object in the foreground where high brightness value does not readily represent the background as in backlit images. For instance, this method is only able to enhance the contrast of the identified dark regions but not the bright face region of Fig. 3.

Later, [14] proposed a rule-based region determination in identifying underexposed, well-exposed and overexposed regions of an image. Unlike FCM that only considers intensity in region classification, this method determines different regions according to three characteristics of local neighborhood namely, intensity, entropy and contrast. According to the intensity, entropy and contrast thresholds computed, a rule is defined such that if local entropy and local contrast of the block is higher than the entropy and contrast thresholds respectively, the block is a well-exposed region. Else, the region is to be defined as underexposed and overexposed region according to the intensity threshold. Compare to the aforementioned methods, this method is relatively simple and easy to be implemented yet it is able to determine three regions that consist of different illumination across the image. Besides that, this method considers not only the intensity but also the entropy and contrast to identify the regions more precisely.

C. COMPARISON OF HISTOGRAM EQUALIZATION BASED CONTRAST ENHANCEMENT

GHE improves overall contrast by stretching and flattening the dynamic range of the input histogram through probability density function (PDF) and cumulative density function (CDF). However, due to the nature of CDF, high occurrence pixel intensity usually causes the gray levels to be mapped apart from each other. Meanwhile, pixel intensities with low occurrence tend to accumulate and they are being compressed to gray level that is close to each other. Contrast is improved due to the huge difference exists between two different gray levels [15] but HE often over-enhances an image and causes saturation in small and visually important areas [16]. On top of that, there are also rounding error incurs during the quantization of the output gray level into integer values, mapping more than one input gray levels into the same output gray level which causes the loss of image details [17]. Indirectly, the unfair gray level allocation scheme and rounding errors have contributed to the washed-out appearance of an output image. Besides that, [18] also claimed that GHE tends to change the brightness of the input image due to the intensities saturation. All the undesirable characteristics of HE has led to poor enhancement of non-uniformly illuminated images.

LHE was developed in an effort to allow each pixel to adapt to its local pixel intensity distribution rather than global information [19]. It successfully improves overall contrast by enhancing every location of an image and proven its ability in preserving local details. LHE and its variants give better enhancement quality however at the expense of computational and time complexity [7]. Non-overlapped sub-block HE is targeted to speed up enhancement rate, however, it introduced a blocking effect to the image. Partially overlapped sub-block HE can eliminate the blocking effect while retaining the contrast enhancement rate as in block-overlapped HE with lower computation complexity. However, the computation of sub-block HE is still usually slower than the conventional HE [4]. Moreover, LHE often causes over enhancement or under enhancement in non-uniform illuminated image due to the facts that its local neighborhood who is also suffering from overexposure or underexposure. It tends to over enhanced the background and causes human eyes often fail to perceive the target due to the fact that local histogram equalization makes the background as clear as the target object [4].

In order to counter the limitation of GHE and LHE, Multi-histogram HE is used to retain the local adaptability of LHE and contrast stretching of GHE. Local adaptability is achieved by partitioning histogram into several segments to reduce the compression caused by global high frequency histogram portion. Meanwhile, it achieves local contrast stretching by applying conventional HE on each sub-histogram. [7] also emphasized the advantages of multi-histogram equalization as it provides an effective quantitative measure that ensures optimal enhancement as well as the capability of LHE. Promising review on aforementioned multi-histogram HE has encouraged the use of the multi-histogram concept in this study. However, multi-histogram HE faces the difficulty in finding the optimum threshold that is used to segment the histogram. If the optimum threshold is not found, multiple high dominant components might exist in a single sub-histogram which causes over-enhancement. Over-enhancement is introduced due to the lack of a mechanism to control the high dominant components enhancement rate. Moreover, conventional multi-histogram HE often does not readily adapt to or consider various exposure regions that exist in a non-uniform illuminated image.

Therefore, Histogram Modification-based HE is introduced to provide a way to control the dominating gray levels enhancement rate through histogram modification. By clipping or transforming the histogram bins, this method has effectively prevented loss of detail and eliminated the dominancy of high-frequency histogram bin that is overwhelming the enhancement [16], [17], [20]. In another word, it amplifies the enhancement of infrequent gray level bins. However, due to the modified histogram being capped at a certain threshold, the overall enhancement is less obvious compared to other HE category. This is because dominating gray levels of the modified histogram are now given a relatively smaller weightage when compare to the original histogram, thus smaller stretching and it results in little enhancement. Besides that, it is difficult to find the optimum parameter that gives a good balance in enhancing both high and low frequency histogram bins.

Exposure intensity-based HE has an advantage in enhancing images with certain exposure characteristics such as overexposed or underexposed images. This is because it uses an exposure parameter in determining the threshold in segmenting the histogram according to exposure regions found in an image, unlike multi-histogram HE which involves conventional histogram statistic such as mean, median and local extremum in determining the histogram partitioning threshold. However, existing exposure intensity-based HE methods [21] do not work best for images with more than one exposure regions. Although some methods are designed to provide enhancement for two exposure regions [22], they often failed to identify region with good contrast (well-exposed region). So, they tend to modify the contrast of well-exposed region according to the enhancement defined for the two exposure regions (underexposed and overexposed regions). Table 1 is constructed in order to provide a better summary regarding the pros and cons of the various category of HE discussed above.

D. COMPARISON OF MULTI-HISTOGRAM EQUALIZATION VARIANTS

Non-uniform illuminated image consists of non-uniform brightness problem due to the different exposure level found in the image. It possesses challenges in enhancement through the use of traditional HE because traditional HE only works best on images with uniform brightness [7]. In general, [7] also claimed that conventional HE and its variants such as Adaptive HE, DSIHE and RMSHE do not work best in correcting non-uniform illumination and shadows. As an alternative enhancement technique for non-uniform illuminated image, this study will focus on exposure region-based enhancement through the use of illumination region determination and multi-histogram HE.

The comparison in previous section discussed multi-histogram HE in general. Since the core of this study is originated from multi-histogram HE, pros and cons of each multi-histogram HE variants are further discussed. Bi-histogram uses a relatively simple measure such as mean,

TABLE 1. Summary of the strength and limitation on the different category of HE-based contrast enhancement method.

Category	Existing Method	Strength	Limitation
GHE	-	- Simple computation - Good enhancment on various type of images	- Limited contrast stretching ratio due to dominancy - Washed-out appearance - Cannot conserve the contrast and brightness of the original image. - Gray level quantization rounding error
LHE	- AHE [23][24] - CLAHE [25][26] - POSHE [6]	- Local adaptability - Details preservation	- Computational complexity - Unnatural image appearance - Caused over enhancement - Blocking effect
Multi-histogram HE	- BBHE [27] - DSIHE [15] - BHEMHB [28] - RMSHE [29] - RSIHE [30] - MVSIHE [31] - DHE [32] - BPDHE [18] - CEDHE [4] - EDSHE [33]	- Reduce the risk of compression on low frequency histogram portion - Optimal enhancement as in GHE	- Difficult in determining the optimum threshold for histogram segementation - Lack of control over the enhancment rate - Lack of exposure elements in threshold computation
Histogram modification-based HE	- MHE [17] - WTHE [16] - RSWHE [20]	- Take control of the enhancment rate - Amplify the enhancement on low-frequency histogram bin - Detail preservation	- Enhancment is limitted to the capped threshold - Enhancment is not obvious - Difficult in determining the optimum threshold parameter for histogram modification
Exposure intensity-base HE	- ESIHE [21] - BHEPL [22] - ABHE [22]	- Able to provide enhancement on images with certain exposure - Use of exposure parameters in histogram thresholding	- Do not work best on a single image with multiple exposures - Affect the contrast of the well-exposed region

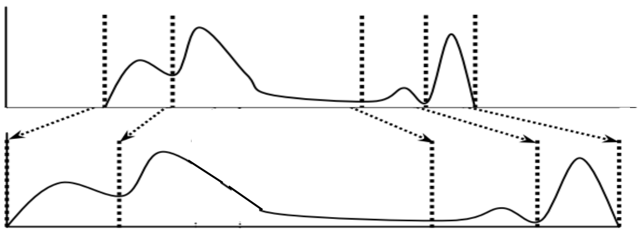


FIGURE 4. A fair sub-histogram expansion with dynamic gray level allocation [32].

entropy, and median [15], [27], [28] in deciding the threshold to segment the histogram, thus it is relatively simpler to be implemented compared to multi-histogram. But the histogram is only allowed to be segmented into two sub-histograms. For this reason, it inherits the dominancy issue from GHE if there are multiple dominating bins exist in each sub-histogram. Besides that, the dynamic range of gray level in the output image is limited to the way the input image dynamic range is allocated [18].

Multi-histogram is then proposed to reduce the dominancy of dominating bins over smaller bins in bi-histogram by allowing histogram to be partitioned into more than two sub-histograms. With more partitioned sub-histograms, Multi-histogram is able to preserve the local details in each sub-histogram better. However, it suffers from the limited dynamic range of gray level expansion issue as in bi-histogram. On top of that, it also introduces an issue where if too many sub-histograms are generated, no viable enhancement can be noticed [29]. Besides that, it also suffers in determining the optimum thresholds for histogram segmentation as they are depending on the gray level distribution of the histogram that varies across different images [17]. Moreover, the computation of threshold is usually more complicated than those in bi-histogram.

Inheriting the strength of Multi-histogram, Multi-histogram with dynamic gray level allocation scheme is used to tackle the limited dynamic gray level range expansion issue in bi-histogram and Multi-histogram. With dynamic gray level allocation scheme, each partitioned sub-histogram will be remapped accordingly to form the output histogram as in Fig. 4 [32]. This ensures even sub-histogram with small dynamic range will be expanded according to input dynamic gray level range and pixel intensity frequency for better contrast. While it is able to provide flexible and adaptive expansion of the dynamic range of gray level, Multi-histogram with dynamic gray level allocation scheme experiences similar limitations as in Multi-histogram where it has no viable enhancement if too many sub-histograms are generated and it also struggles in determining the optimum threshold for histogram segmentation.

All of the discussed Multi-histogram variants have some limitations in common. Firstly, these variants are lacking exposure-based element in histogram segmentation threshold computation. It is not feasible to apply the same threshold directly to non-uniform illuminated images that made up of different exposure regions as this will greatly affect how the histogram are being segmented and equalized. Second, these variants are lacking control over enhancement rate. Although optimum threshold is used in partitioning the histogram, high frequency histogram bins in non-uniform illuminated image's extremely bright and dark region will tend to overwhelm the overall enhancement in that particular sub-histogram.

TABLE 2. Comparison of different variants of multi-histogram HE corresponding to the existing method.

Multi-histogram variants	Existing Method	Strength	Limitation
Bi-histogram	- BBHE [27] - DSIHE [15] - BHEMHB [28]	- Simple computation - Easy to be implemented - Simple threshold computation	- Histogram segmentation is limited to two - Do not solve multiple dominating bins that exist in each sub-histogram - Limited dynamic range of gray level expansion
Multi-histogram	- RMSHE [29] - RSIHE [30] - MVSIHE [31]	- Reduced compression on smaller bins due to dominating bins - More than two sub-histograms to preserve more details locally	- Limited dynamic range of gray level expansion - No viable enhancement if too many sub-histogram is generated - Difficult to determine the optimum threshold for histogram segmentation
Multi-histogram with dynamic gray level allocation scheme	- DHE [32] - BPDHE [18] - CEDHE [4] - EDSHE [15]	- Flexible and adptive dynamic range of gray level expansion - Reduced compression on smaller bins due to dominating bins - More than two sub-histograms to preserve more details locally	- No viable enhancement if too many sub-histogram is generated - Difficult to determine the optimum threshold for histogram segmentation
All discussed Multi-histogram variants	- Not applicable	- Not applicable	- Lack of exposure elements in histogram segmentation threshold computation - Lack of control on enhancement rate

Table 2 provides a comparison summary of the advantages and disadvantages of Multi-histogram HE-based variants. It is clearly seen that there is no single method which is able to provide the perfect solution but it is more of a continuous improvement over another's limitation. Therefore, this study aims to discover an alternative to tackle the issue of lacking exposure elements in threshold computation in Multi-histogram based HE with dynamic gray level allocation scheme.

III. METHODOLOGY

Present work differs from [7] by attempting to use sample images pre-processed with the illumination region detection proposed by [14]. This method has an advantage in using only simple information such as intensity, entropy and contrast of an image within multiple locally defined non-overlapping windows to define the decisive rules in illumination region classification of a non-uniform illuminated image. With the illumination region determination, each pixel is classified into three sub-images namely, underexposed, well-exposed and overexposed. Fig. 5 shows that ERMHE consists of three stages namely, exposure region-based histogram segmentation threshold identification, entropy-controlled dynamic gray level range allocation scheme followed by histogram segmentation threshold redefinition and equalization. Each implementation of the building block is discussed in detail as follow.

A. EXPOSURE REGION-BASED HISTOGRAM SEGMENTATION THRESHOLD IDENTIFICATION

Implementation of ERMHE relies on the three sub-images generated from the original image according to the exposure regions determined by [14]. Fig. 6 shows the sub-images from one of the samples images. It can be seen that sub-images as in Fig. 6(b) and Fig. 6(c) consist only the underexposed and well-exposed pixels extracted from the original image respectively. Both images are being padded with white background (pixel intensity of 255). Meanwhile, Fig. 6(d) consists only over-exposed pixels of the original image padded with a black background (pixel intensity of 0). At this stage, ERMHE will consume the three sub-images provided as an input to construct three corresponding histograms. These sub-images padded backgrounds are excluded from the construction of sub-image's histogram (local histogram) since it does not contain any information regarding the original image. From Fig. 7, it can be seen that histogram of each sub-image consists only the particular exposure information which is independent of each other.

Let I_U, I_W, and I_O denote underexposed, well-exposed and overexposed sub-images and I_G denotes the original image. In ERMHE, the local threshold is identified as the mean of local histogram using (2), (3), and (4) given $H_{I_U}(i)$, $H_{I_W}(i)$, and $H_{I_O}(i)$ are histogram for underexposed, well-exposed and overexposed sub-images with its corresponding pixel gray level intensity i. So, there will be three thresholds denoted

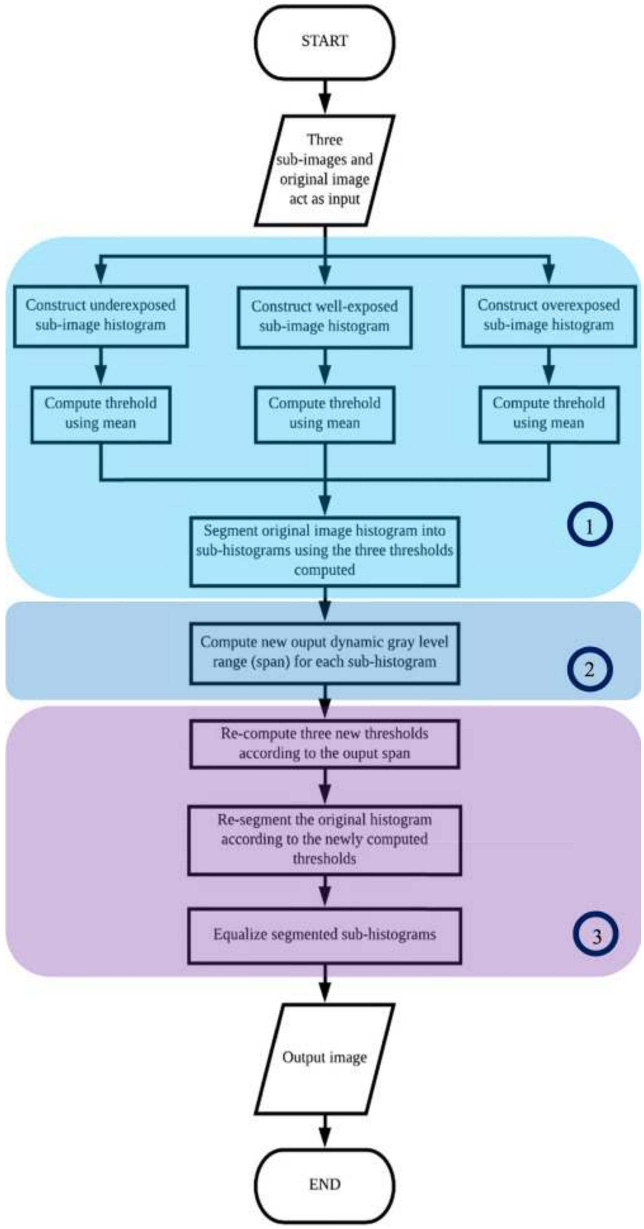


FIGURE 5. The flowchart illustrates the implementation of the proposed techniques. 1 denotes the exposure region-based histogram segmentation threshold identification, 2 denotes the entropy-controlled dynamic gray level range allocation scheme while 3 denotes the thresholds redefinition, histogram repartitioning and equalization.

as M_U, M_W, and M_O which representing mean of I_U, I_W, and I_O. With the thresholds identified from each sub-images exposure region, the global histogram is being segmented into 4 sub-histograms as in Fig. 8.

$$M_U = \frac{\sum_{i=0}^{254} H_{I_U}(i) \cdot i}{\sum_{i=0}^{254} H_{I_U}(i)} \tag{2}$$

$$M_W = \frac{\sum_{i=0}^{254} H_{I_W}(i) \cdot i}{\sum_{i=0}^{254} H_{I_W}(i)} \tag{3}$$

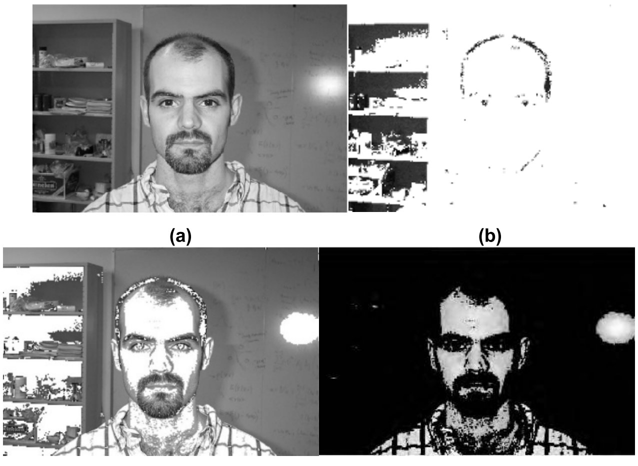


FIGURE 6. One of the sample images from closeup category showing (a) Original image, (b) Underexposed sub-image, (c) Well-exposed sub-image and (d) Overexposed sub-image.

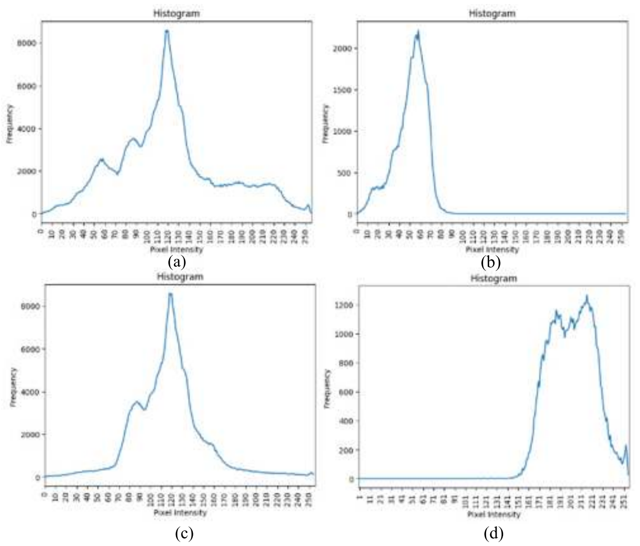


FIGURE 7. (a) is the histogram of Fig. 6(a). Meanwhile, (b), (c), and (d) are the histogram for sub-images in Fig. 6(b), Fig. 6(c), and Fig. 6(d) respectively.

$$M_O = \frac{\sum_{i=1}^{255} H_{I_O}(i) \cdot i}{\sum_{i=1}^{255} H_{I_O}(i)} \tag{4}$$

B. ENTROPY-CONTROLLED DYNAMIC GRAY LEVEL RANGE ALLOCATION SCHEME

Non-uniform illuminated images tend to have extremely bright or dark spot which causes the pixel intensity to accumulate across a narrow interval of gray levels as in sub-histogram G4 of Fig. 9. In order to improve the contrast, the spike must be flattened across a larger interval of gray levels.

Unlike other images, non-uniform illuminated image usually has extremely bright and dark spot usually takes both ends of the gray level range in the histogram, leaving no

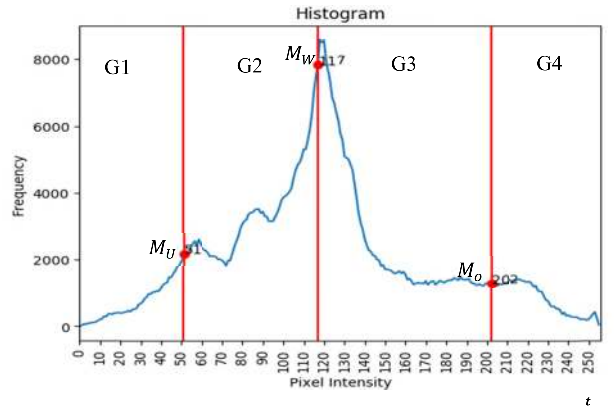


FIGURE 8. Segmented sub-histograms with G1 as the 1st sub-histogram, G2 as the 2nd sub-histogram, G3 as the 3rd sub-histogram, and G1 as the 4th sub-histogram.

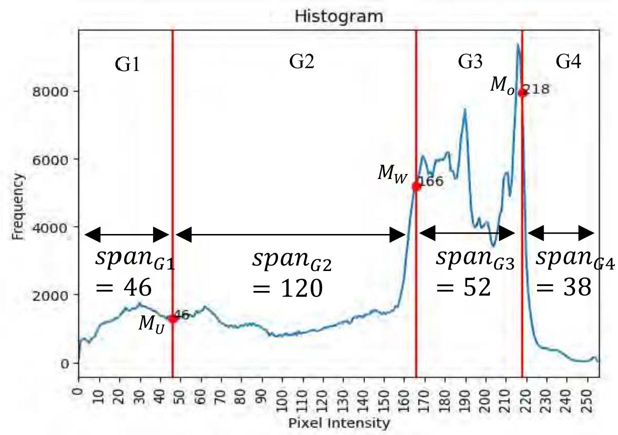


FIGURE 9. Histogram of the non-uniform illuminated input image which tends to have pixels saturate across a short gray level range (span).

readily available expansion gray level range to stretch the contrast of the spike. In this stage, ERMHE uses span, a weighting factor and range of each sub-histogram as in (5), (6) and (7) respectively in order to enlarge or narrow the output gray level range occupied by each sub-histogram where $span_i$ is the full extent of each i^{th} sub-histogram, $factor_i$ is a factor that used to control the $range_i$, $range_i$ is the allocated output gray level range for each i^{th} sub-histogram, i represents the current sub-histogram, $high_i$ and low_i are the highest and lowest brightness value in the current sub-histogram respectively, α is the entropy-controlled parameter computed as in (8), N_p and N are the non-zero bins and the total number of bins of the i^{th} sub-histogram respectively while L is the total gray levels.

$$span_i = high_i - low_i \tag{5}$$

$$factor_i = \alpha_i \times span_i \times \frac{N_p}{N} \tag{6}$$

$$range_i = (L-1) \times \frac{factor_i}{\sum_{k=1}^{n+1} factor_k} \tag{7}$$

TABLE 3. Entropy and entropy-controlled parameter, α of each sub-histogram in Fig. 9 according to (9) and (8) respectively.

Sub-histogram, k	G1	G2	G3	G4
$entropy_k$	5.45	6.78	5.66	3.69
α_k	0.18	0.15	0.18	0.27

$$\alpha_i = \frac{1}{E(H_i)} \tag{8}$$

$$E(H_i) = -\sum_{l=0}^{L-1} p_i(l) \cdot \log p_i(l) \tag{9}$$

According to (7, in order to find the remapped output gray level range, the total gray level $(L-1)$ is to be multiplied with an average factor that is computed according to (6). Meanwhile, (5) or span is defined as the difference between the highest brightness value and the lowest brightness value of the sub-histogram. ERMHE uses the same span and range computation used by [4] and [33] but with some modifications made to the factor computation. ERMHE introduces the use of an entropy-controlled parameter, α in factor computation to balance the gray level allocation between low frequency bins with large sub-histogram span (G2 of Fig. 9) and high frequency bins with small sub-histogram span (G4 of Fig. 9) of a non-uniform illuminated images. It is computed as in (8) where (9) or $E(H_i)$ is the entropy of the i^{th} sub-histogram and $p_i(l)$ is the PDF of the i^{th} sub-histogram across pixel intensity l.

Assuming that if a sub-histogram is having a larger number of low frequency non-zero bins across a large span (G2 of Fig. 9), the term $\frac{N_p}{N}$ makes sure that the sub-histogram would have enough output dynamic range for expansion. However, a sub-histogram might have a small number of high frequency non-zero bins across a narrow span (G4 of Fig. 9). It results in smaller $\frac{N_p}{N}$ and causes compression to that sub-histogram during gray level allocation. Therefore, ERMHE proposed the entropy-controlled parameter, α to counter the compression induced on G4. From (9), entropy is computed as PDF of a sub-histogram. It describes a histogram distribution where low entropy indicating concentrated and not uniformly distributed gray levels across the histogram and vice versa [34]. As shown in Table 3, sub-histogram G2 in Fig. 9 has the highest entropy indicating uniformly distributed gray levels and less dominating bins across the span. Meanwhile, sub-histogram G4 in Fig. 9 has the lowest entropy due to the huge difference in bin frequency on particular gray level across the narrow span. On the other hand, G1 and G3 sub-histograms has moderate entropy because they do not exhibit an extremely big difference in bin frequency across its own span. With α computed as the inverse of entropy, it allows little compression on the G2 output gray level range to allocate more output gray level range to G4 for greater expansion. Thus, allowing HE to stretch the contrast of G4 alike sub-histogram across a bigger range. In short, ERMHE computes the $span_i$, $factor_i$ and $range_i$ of the four sub-histograms which define the allocation of output gray level range for better contrast.

C. HISTOGRAM SEGMENTATION THRESHOLD REDEFINITION AND EQUALIZATION

With the range computed for each sub-histogram, ERMHE then performs Histogram Segmentation Threshold Redefinition and Equalization. Histogram segmentation threshold redefinition involves two components, namely thresholds re-computation and original histogram re-segmentation. In thresholds re-computation, ERMHE redefines the thresholds according to (10) where $range_{Gx}$ is the entropy-controlled dynamic gray level range allocated, x is an integer representing the sub-histogram, k is the number of thresholds while n is the total number of sub-histograms. Note that they are actually the cumulative sum of the ranges from sub-histogram G1 to G3. Meanwhile, in original histogram re-segmentation, the three thresholds are used to re-segment the original histogram as in Fig. 10(a) to generate new four sub-histograms as in Fig. 10(b).

$$M_k = \sum_{x=1}^{k} range_{Gx} \quad for\ k = 1, 2, \ldots, n-1 \tag{10}$$

Next, each new sub-histogram is to be equalized and mapped to generate the output histogram according to the range allocated. ERMHE applies conventional Histogram Equalization on each sub-histogram to enhance the original input image. The PDF of this four re-segmented sub-histograms are computed as in (11) while the CDF of these four sub-histograms is computed as in (12).

$$PDF = \begin{cases} P_{Gx}(i) = \dfrac{H_{I_G}(i)}{N_{Gx}}; & 0 \le i < M_x\ for\ x = 1 \\ P_{G_x}(i) = \dfrac{H_{I_G}(i)}{N_{G_x}}; & M_{x-1} \le i < M_x\ for\ 1 < x < n \\ P_{Gx}(i) = \dfrac{H_{I_G}(i)}{N_{G_x}}; & M_{x-1} \le i < L\ for\ x = n \end{cases} \tag{11}$$

$$CDF = \begin{cases} C_{Gx}(i) = \sum_{i=0}^{M_x-1} P_{Gx}(i); \\ \quad 0 \le i < M_x\ for\ x = 1 \\ C_{G_x}(i) = \sum_{i=M_{x-1}}^{M_x-1} P_{G_x}(i); \\ \quad M_{x-1} \le i < M_x\ for\ 1 < x < n \\ C_{Gx}(i) = \sum_{i=M_{x-1}}^{L-1} P_{Gx}(i); \\ \quad M_{x-1} \le i < L\ for\ x = n \end{cases} \tag{12}$$

where $C_{Gx}(i)$, $P_{Gx}(i)$ and N_{Gx} are the CDF, PDF and the total number of pixels of the x^{th} sub-histogram respectively, x is an integer representing the sub-histogram, $H_{I_G}(\mathrm{i})$ is the histogram for original image at intensity i, M_x is the redefined thresholds, n is the total number of sub-histograms, i is the pixel intensity while L is the total number of gray levels.

The transformation function can be defined as in (13). (14) is then used to map the gray level intensity of the original

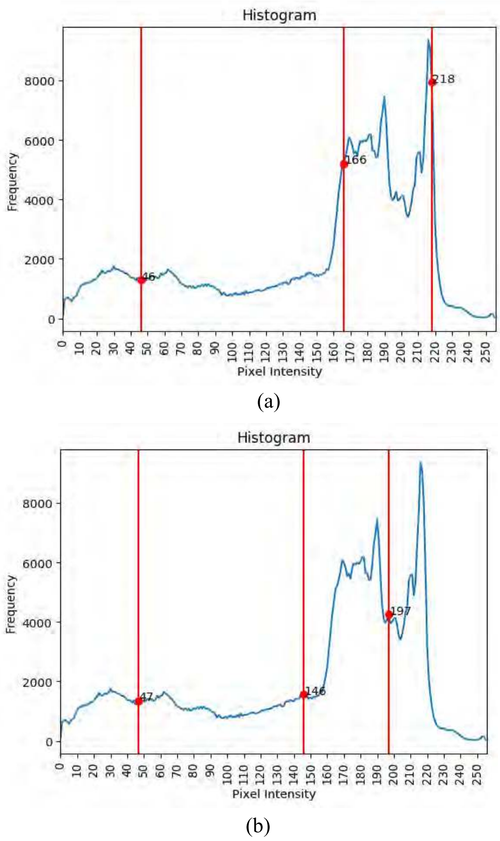


FIGURE 10. **(a) Original histogram before and (b) Original histogram after undergoing histogram segmentation threshold redefinition. M_1, M_2, and M_3 are the new three thresholds.**

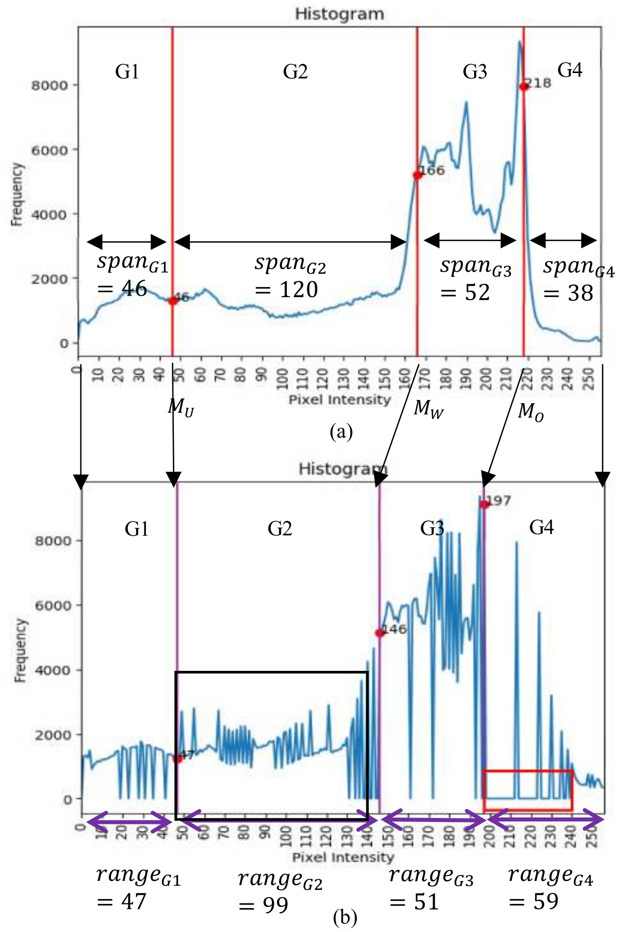


FIGURE 11. **Original input histogram and output histogram before threshold redefinition. (a) Original histogram. (b) The corresponding mapped and equalized output histogram.**

image to the corresponding output image's gray level intensity. As a result, through the computation of (11) to (14), ERMHE produces an enhanced output image with improved contrast and better image quality.

$$T_G(i) = \begin{cases} M_x \cdot C_{Gx}(i)\,; \\ \qquad 0 \leq i < M_x \; for \; x = 1 \\ M_{x-1} + (M_x - M_{x-1}) \cdot C_{Gx}(i)\,; \\ \qquad M_{x-1} \leq i < M_x \; for \; 1 < x < n \\ M_{x-1} + (L - M_{x-1}) \cdot C_{Gx}(i)\,; \\ \qquad M_{x-1} \leq i < L \; for \; x = n \end{cases} \tag{13}$$

where $T_G(i)$ is the transformation function, x is an integer representing the sub-histogram, M_x is the redefined thresholds, n is the total number of sub-histograms, i is the pixel intensity while L is the total number of gray levels.

$$S(x, y) = T_G\{f(x, y)\} \tag{14}$$

where $f(x, y)$ is the gray level intensity of input image at (x^{th}, y^{th}) pixel, $S(x, y)$ is the gray level intensity of output image at (x^{th}, y^{th}) pixel, and (x, y) is the pixel coordinate correspond to the image.

Comparing Fig. 11 and Fig. 12, the need for thresholds re-computation and histogram re-segmentation are to preserve the naturalness and details of the output image by avoiding a huge gap between the gray level of an output image and preventing mapping greater amount input gray levels to the same output gray levels respectively. It is done by allowing an equal amount of input gray level pixel intensities to be mapped to the allocated output gray level range. By using sub-histogram G4 of Fig. 12(a) as example, with histogram segmentation threshold redefinition, it now uses pixel intensities which lie within the 59 gray levels in the input sub-histogram G4 to map to the 59 gray levels at the output sub-histogram G4 as in Fig. 12(b). The mapping uses same amounts of gray levels in the input sub-histogram to reflect the gray levels in the output sub-histogram. Thus, threshold redefinition helps to reduce the interval between output gray levels during mapping and reducing the change in brightness value which helps in image naturalness preservation. As compared to Fig. 11(b), the spikes in the black box have also been reduced as shown in Fig. 12(b). This shows that threshold redefinition also prevents mapping of more input gray levels to the same output gray level due to the smaller output gray level range allocated. As a result, lesser output gray levels are missing, so it is able to retain details better.

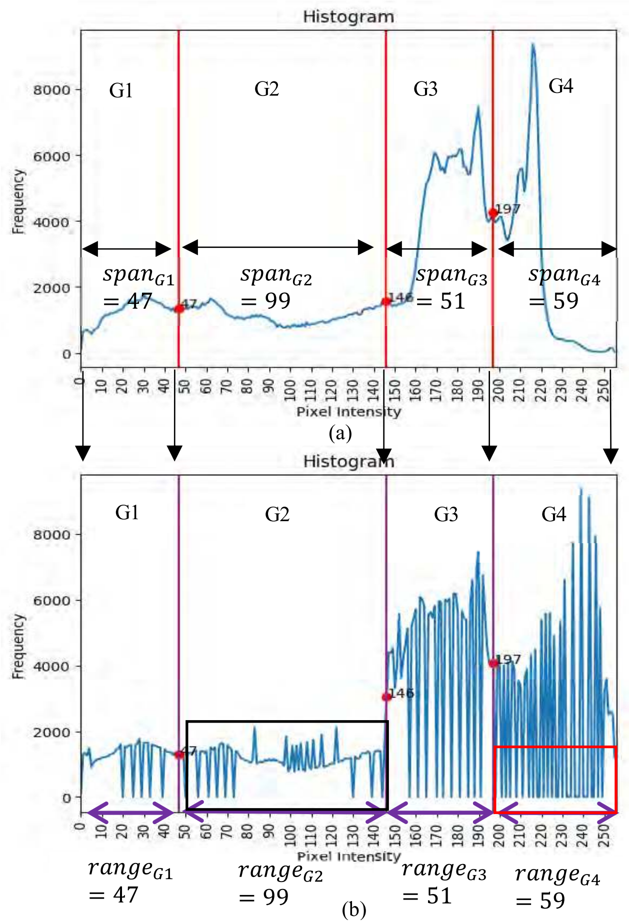


FIGURE 12. Original input histogram and output histogram after threshold redefinition. (a) Original histogram. (b) The corresponding mapped and equalized output histogram.

IV. DATA SAMPLE AND ASSESSMENT METRICS

A total of 154 sample images are used in this study. The images are made up of airplane, background, houses and portrait images which are taken from California Institute of Technology database namely Airplanes (Side), Background, Pasadena Houses 2000, and Faces 1999 (Front) packages (Computational vision at caltech, accessed 2018-6-30). These images are being classified into two categories namely closeup and non-closeup images with 60 and 94 samples respectively. For each sample image in each category, it is being pre-processed with exposure region determination proposed by [14] to generate three sub-images in grayscale. This study only focusses on grayscale images and application of HE solely in contrast enhancement on spatial domain only. In order to assess the robustness of the proposed method, both the qualitative and quantitative analyses are conducted.

A. QUALITATIVE ANALYSE

Qualitative analysis focusses on the evaluation of the visual quality of the resultant images. The resultant images are being inspected in term of judgement on over-enhancement, naturalness and contrast improvement. This subjective evaluation is important to ensure the results of enhancement give better contrast, pleasant looking appearance and are able to preserve the naturalness of the original image without introducing undesired artefacts [31]. The noise level of an image should be reduced or at least being maintained throughout the enhancement process. In short, visual assessment is an effective quality measure that used to judge the performance of a proposed method [31].

B. QUANTITATIVE ANALYSES

As the visual perception of the enhanced image varies from one individual to another, quantitative analysis is included to evaluate the enhanced image in term of the following widely-used metrics. In a comparative study, [19] uses quality measurement metrics such as Peak Signal to Noise Ratio (PSNR), Discrete Entropy (DE), and Absolute Mean Brightness Error (AMBE) to evaluate the performance of various HE-based techniques. [20], [28] and [31] also use similar assessment to evaluate the performance of their methods. In addition, Image Contrast Function (ICF) is also used by [2], [31], and [35] to measure the contrast improvement provided by their methods. Aforementioned metrics are used as the evaluation criteria in this study where the details of each metric are presented as follows.

1) PEAK SIGNAL TO NOISE RATIO (PSNR)

PSNR is a ratio used to measure the degree of degradation [19], [31], [36]. It can be computed according to (15) through the use of a Mean Square Error (MSE) [19]. According to (16), MSE is computed as the mean intensities difference between the input and output image. Therefore, the lower the MSE, the smaller the error or degradation experienced by the enhanced image as compared to the original image. Small MSE gives large PSNR, thus the greater the PSNR, the better the enhanced output image quality is [36]. [2] also claimed that PSNR also can be used to compare the noise level exists in an image where high PSNR denotes existing noise is not being amplified by the enhancement technique.

$$PSNR = 10\, log_{10}\left(\frac{(Max(I_i))^2}{MSE}\right) \tag{15}$$

where $(Max(I_i))^2$ is the maximum gray level intensity value of the input image and I_i represents the input image.

$$MSE = \frac{1}{MN}\sum\nolimits_{m=1}^{M}\sum\nolimits_{n=1}^{N}\left[I_i\,(m,n) - I_o\,(m,n)\right]^2 \tag{16}$$

where M and N represent the width and height of the image respectively while $I_i\,(m,n)$ and $I_o\,(m,n)$ is the pixel gray level of the input image and the output image at (m, n) respectively.

2) IMAGE CONTRAST FUNCTION (ICF)

On the other hand, ICF is used to evaluate the contrast improvement being achieved [2], [31], [35]. It is represented as in (17) by calculating the deviation of gray levels across the whole image. The greater the $C_{contrast}$ is, the better the contrast of output image as the difference between gray levels have appeared to be greater [35]. Besides that, high $C_{contrast}$ also implies that more information is contained in the enhanced image [31]. Meanwhile, (18) is just another representation of $C_{contrast}$ in the unit of decibel (dB).

$$C_{contrast} = \frac{1}{W \times H} \sum_{w=1}^{W} \sum_{h=1}^{H} Y^2(w,h) - \left| \frac{1}{W \times H} \sum_{w=1}^{W} \sum_{h=1}^{H} Y(w,h) \right|^2 \tag{17}$$

$$C^*_{contrast} = 10 log_{10} C_{contrast} \tag{18}$$

where W and H represent the width and height of the image respectively while $Y(w, h)$ is the pixel gray level of an image at (w, h).

3) DISCRETE ENTROPY (DE)

DE or entropy is used to represent the information content of the simple 8-bit image according to information theory [24]. With a defined source model such that source symbols representing the gray levels of an 8-bit image and the source alphabet are composed of 256 possible symbols, then the symbol probability which also known as PDF of a histogram can be used to compute entropy as in (19). Verbally, it is a measure of the richness of information in an image [31], [34], [36]. Entropy represents the number of bits that can be used to represent a pixel intensity of an image. Entropy value of 8 represents 8 bit or 256 levels are required to represent a pixel and an image only can achieve the maximum entropy value of 8 when $p(0) = p(1) = \cdots = p(L-1) = \frac{1}{L}$ where L is 256 gray levels. Thus, higher entropy value means that the pixel intensities are more uniform and fairly distribute across a wide range of gray level in a histogram which results in better details [34]. Therefore, high entropy value is desired to indicate a higher amount of information contained [2], [19], [34]. However, a high value in entropy may signify noise-enhancement [33], therefore visual inspection plays an important role in assessing noise level.

$$DE = -\sum_{l=0}^{L-1} p(l) \cdot log_2 (p(l)) \tag{19}$$

where $p(l)$ represent the PDF of a histogram and l is the gray levels exist in an image.

4) ABSOLUTE MEAN BRIGHTNESS ERROR (AMBE)

AMBE is used to evaluate the ability of the proposed method to preserve the image mean brightness [18], [19], [36]. It can be computed by taking the difference of the mean brightness between the input image and the enhanced image as in (20). Mean brightness of the input and enhanced output image can be calculated using (21) and (22) respectively. A small AMBE indicates that the mean brightness of the enhanced image is close or equal to the mean brightness of the input image and vice versa [19]. Therefore, a method is said to be able to preserve the mean brightness of the image if a small value of AMBE is obtained [31].

$$AMBE = |M(I) - M(O)| \tag{20}$$

$$M(I) = \frac{1}{WH} \sum_{w=1}^{W} \sum_{h=1}^{H} I(w,h) \tag{21}$$

$$M(O) = \frac{1}{WH} \sum_{w=1}^{W} \sum_{h=1}^{H} O(w,h) \tag{22}$$

where W and H represent the width and height of the image respectively while $M(I)$ and M(O) depict the overall mean intensity of input image and output image respectively.

5) AVERAGE SCORE

The average score of each assessment metrics in each category (closeup and non-closeup) is also computed as in (23). This is to provide a brief score summary across the tested sample images.

$$Average\ Score = \frac{1}{n} \sum_{i=1}^{n} Assessment\ Score_i \tag{23}$$

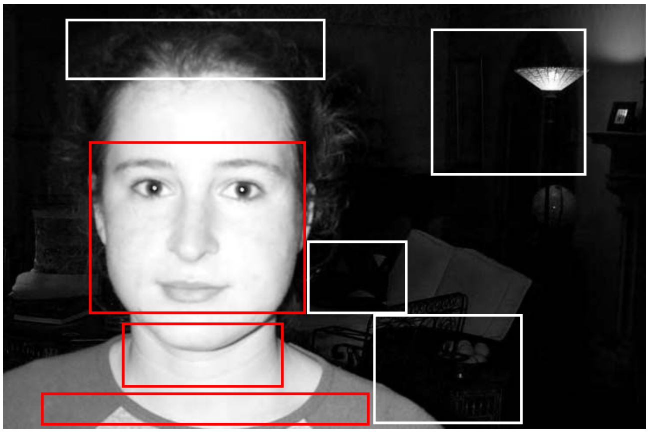
where Assessment Score is PSNR, ICF, AMBE and DE while n is the number of the sample image in each category.

V. RESULTANT IMAGE AND PERFORMANCE COMPARISON

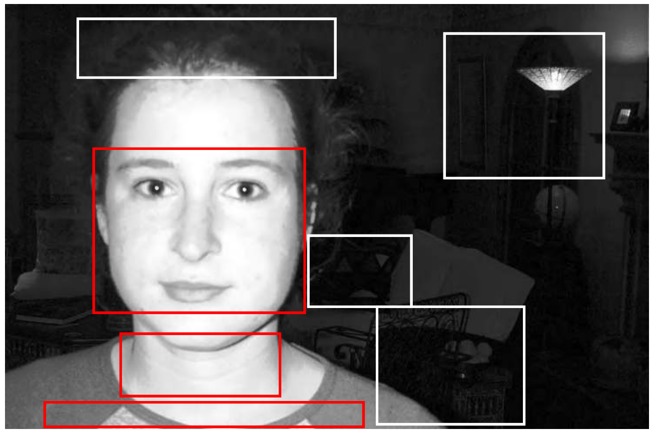
The resultant images of ERMHE are presented according to the two categories classified, namely closeup and non-closeup. In each category, the analysis focus on the characteristic of the selected non-uniform illuminated images, the enhancement provided by ERMHE and a comparison against existing state-of-the-art HE-based techniques qualitatively and quantitatively.

A. CLOSEUP SAMPLE IMAGES

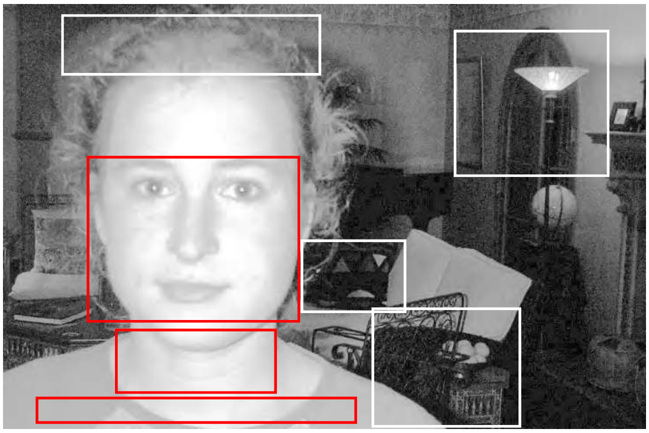
Fig. 13(a) shows the original image of CloseupSample1 with uneven illumination where the foreground is extremely bright meanwhile the background is essentially dark. Due to the drastic difference of brightness value between the two, there is a clear separation where human vision perceives as non-uniform illumination. This is due to concentration of pixel intensities rather than spreading across to give more balanced illumination hence poorer contrast. ERMHE enhancement in Fig. 13(b) results in a darkened face and brighten background with a clearer differentiation where the pixels of highlighted red and white rectangle regions stretched across gray level intensities locally without affecting each other. The hair can be distinguished better from the background. Meanwhile, at the foreground, the lips looked darker and the structure of the nose is better outlined. Although a better contrast is observed, ERMHE scored lower in ICF (38.39) compared to the original image (39.02). This is because ERMHE has its gray level representation stretch across the grayscale color tone resulting in smaller difference and smaller ICF score. GHE failed to achieve the locality of ERMHE as bright pixel get brighter and dark pixels get darken which introduce a large difference in brightness value and produces washed out effect as in Fig. 13(c). This is proven by the relatively higher AMBE score obtained by GHE. Both BBHE and DSIHE scored low in PSNR with 19.27 and 22.34 respectively indicating more degradation of image and amplification of noise



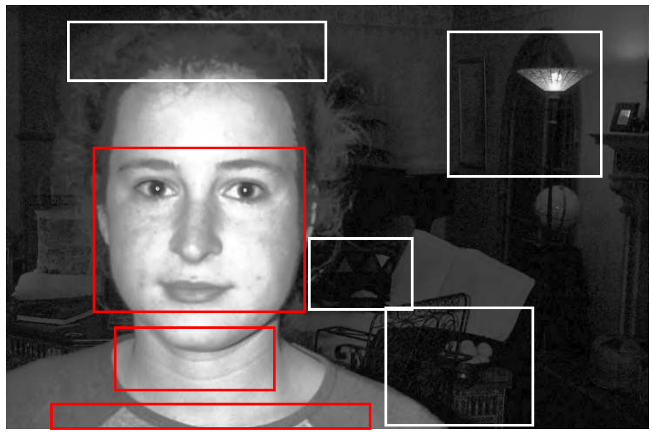
(a) Original. PSNR: ∞, ICF: 39.02, DE: 6.68, AMBE: 0.00



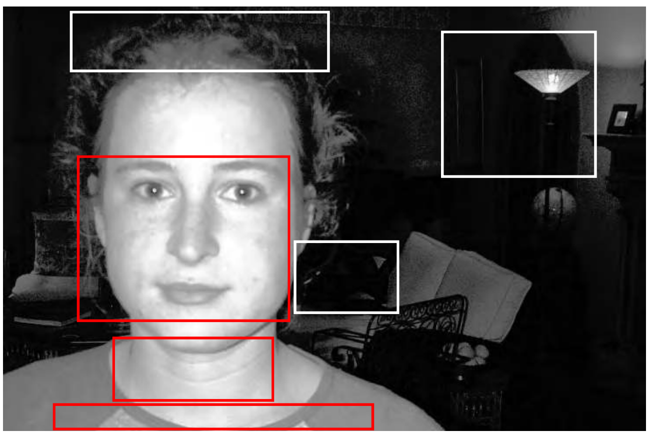
(b) ERMHE. PSNR: 27.38, ICF: 38.39, DE: 6.41, AMBE: 6.35



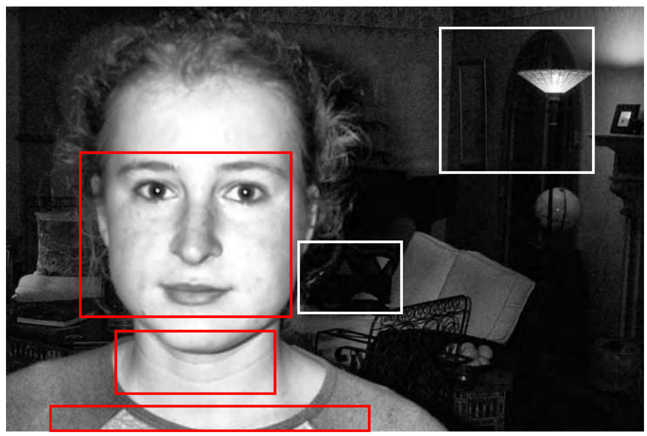
(c) GHE. PSNR: 10.68, ICF: 37.05, DE: 6.33, AMBE: 60.67



(d) BBHE. PSNR: 19.27, ICF: 36.63, DE: 6.41, AMBE: 6.31



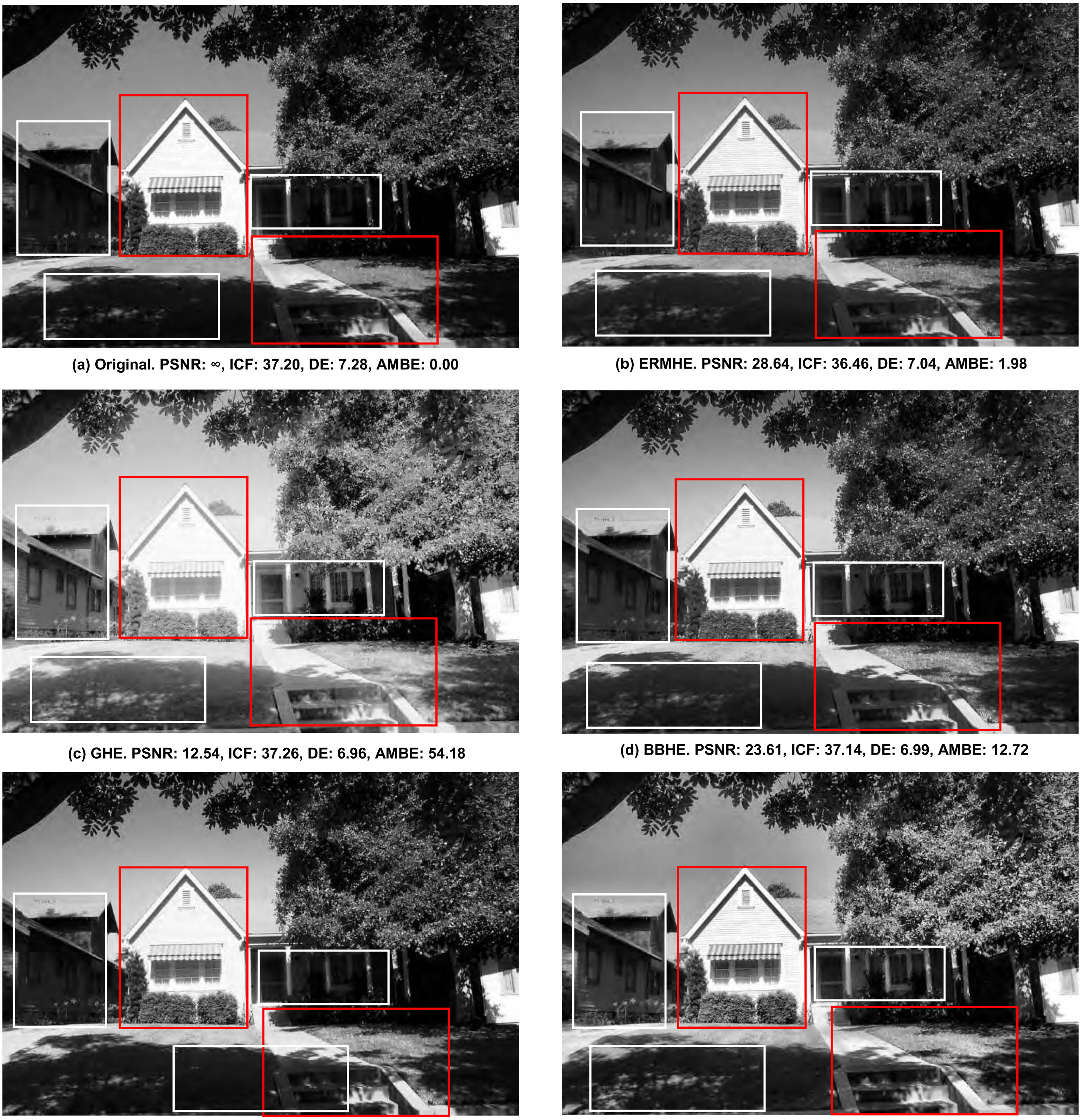
(e) DSIHE. PSNR: 22.34, ICF: 38.04, DE: 6.35, AMBE: 3.71



(f) CLAHE. PSNR: 20.61, ICF: 37.86, DE: 7.35, AMBE: 9.11

FIGURE 13. (a) Original image of CloseupSample1 and resultant images produced by (b) ERMHE, (c) GHE, (d) BBHE, (e) DSIHE and (f) CLAHE with metric scores (PSNR, ICF, DE and AMBE) computed for each image.

when compared to ERMHE with PSNR score of 27.38. For BBHE and DSIHE, from Fig. 13(d) and Fig. 13(e), notice that the hair has whitened and two distinct illuminations (black and white spot) can be observed at the face. In Fig. 13(f), although CLAHE produces the most uniform illumination across the face (foreground) against ERMHE, BBHE and DSIHE, but it suffers a lower PSNR score with 20.61 as compared to ERMHE with 27.38. This is because noise can be spotted near the wall with the hanging picture in the image enhanced by CLAHE. Overall, ERMHE possesses highest ICF with 38.39 among GHE (37.05), BBHE (36.63), DSIHE (38.04) and CLAHE (37.86). This is because the difference between gray levels of ERMHE appeared to be greater across the image globally, indicating better overall contrast.



(a) Original. PSNR: ∞, ICF: 37.20, DE: 7.28, AMBE: 0.00

(b) ERMHE. PSNR: 28.64, ICF: 36.46, DE: 7.04, AMBE: 1.98

(c) GHE. PSNR: 12.54, ICF: 37.26, DE: 6.96, AMBE: 54.18

(d) BBHE. PSNR: 23.61, ICF: 37.14, DE: 6.99, AMBE: 12.72

(e) DSIHE. PSNR: 25.30, ICF: 37.80, DE: 7.04, AMBE: 9.23

(f) CLAHE. PSNR: 18.62, ICF: 37.30, DE: 7.67, AMBE: 21.42

FIGURE 14. **(a) Original image of Non-CloseupSample1 and resultant images produced by (b) ERMHE, (c) GHE, (d) BBHE, (e) DSIHE and (f) CLAHE with metric scores (PSNR, ICF, DE and AMBE) computed for each image.**

In order to provide a more comparative result on all of the 60 closeup sample images involved, Table 4 gives the average of various assessment scores on the tested 60 sample images computed according to (23). Generally, by comparing to the original image, higher PSNR, ICF and DE is desired, indicating less degradation, more contrast and greater detail preservation respectively while lower AMBE indicates better brightness preservation.

Disregard the original image, ERMHE has the highest PSNR and lowest AMBE scores in overall. High PSNR score proves that ERMHE has smaller mean intensities differences and is able to maintain the noise level in an image. Whereas low AMBE convinces that ERMHE does not impose a great shift in the mean brightness of the enhanced image. When compared to the original image's ICF score of 35.82, ERMHE enhanced image has a higher ICF score of 36.39 denoting its

TABLE 4. Average of various assessment scores PSNR, ICF, DE and AMBE across 60 non-uniform illuminated closeup sample images tested.

Images\Assessment	PSNR	ICF	DE	AMBE
Original	∞	35.82	7.48	0.00
ERMHE	**28.51**	36.39	7.27	**3.83**
GHE	18.09	37.31	7.23	25.31
BBHE	23.05	37.15	7.26	7.28
DSIHE	22.04	**37.45**	7.25	8.26
CLAHE	19.71	35.72	**7.70**	10.31

ability in providing contrast improvement over the original image. Due to a smaller mean intensities' deviation and a lower change in brightness, ERMHE does not achieve high in contrast analysis (ICF score) as compared to GHE, BBHE and DSIHE. However, ERMHE did provide remarkable contrast in the CloseupSamples1 proven as in the qualitative analysis presented above. Besides that, ERMHE generates a natural looking image which reflects the original image better because it does not bleach or darken images due to over and under enhancement as produced by GHE, BBHE and DSIHE. Meanwhile, CLAHE has the highest DE which is proven by its ability in highlighting and preserving small details. However, ERMHE also shows its ability in preserving considerable details proven by its highest DE score of 7.27 among GHE, BBHE and DSIHE. ERMHE, GHE, BBHE and DSIHE has relatively lower entropy than CLAHE due to the nature of the enhanced images has a discrete plot of histogram as shown in Fig. 17 given in the Appendixes. Fig. 18 in Appendixes shows another instance of ERMHE resultant CloseupSample2 image.

B. NON-CLOSEUP SAMPLE IMAGES

From Non-CloseupSample1 as in Fig. 14(a), it can be observed that region highlighted in red rectangles such as the wall of the house and the pathway are a real eyesore for human vision with its high brightness. On the other hand, due to the blockage by non-transparent objects, it reduces light penetration and forming shadow that shaded the regions as highlighted in white rectangles. In Fig. 14(b), EHRME attempts to homogenize the illumination across all the highlighted regions. Within the red rectangles, it can be observed that EHRME reveals the outline of the wall and reduces brightness around the pathway, giving a warmer grayscale tone and offering comfortability to human vision. On the white rectangles, EHRME gives a light up effect that enlivens the objects under a shadow as shown by exposure of the windows on the neighboring house that was previously shaded. EHRME scores lower in ICF with 36.46 as compared to the original image's 37.20 because it tries to balance the intensity distribution and reduces the difference among neighboring intensities which define the contrast computation. GHE resultant image as in Fig. 14(c) has its shaded region enhanced but it also enhances regions that are suffering from bright radiation of the sunlight. The increment in intensities introduced by GHE has contributed to high AMBE score of 54.18 meanwhile the loss of details is proven by its low DE of 6.96. Fig. 14(e) shows DSIHE provides minor illumination improvement, the regions highlighted by red rectangles are still obscured by shadow whereas regions in white rectangle still exhibit vivid bright tone. Visually, ERMHE has a greater enhancement compared to GHE and DSIHE. In term of quality of the resultant images and change in brightness, ERMHE scores high in PSNR (28.64) which proven its resilient toward degradation and has a low AMBE score (1.98) denoting a small change in brightness compared to GHE and DSIHE. Meanwhile, BBHE expresses remarkable enhancement in Fig. 14(d), especially shaded regions as highlighted in white rectangles. But it does not work best as ERMHE does for red rectangle regions such as the pathway, grasses and wall of the house which still has a striking appearance. CLAHE resultant image in Fig. 14(f) on the other hand offers significant enhancement in all regions with high information content indicated by a DE score of 7.67 out of 8. Still, CLAHE experiences greater tone changes for instance the brightness of the tree and grass region highlighted in red have been altered while ERMHE enhanced image is still able to retain their originality. CLAHE overdoes and producing an unnatural looking image. This can be signified by the second highest AMBE score of 21.42 denoting that CLAHE suffers from great brightness shift when compared to a lower AMBE score of 1.98 achieved by ERMHE.

TABLE 5. Average of various assessment scores (PSNR, ICF, DE and AMBE) across 94 non-uniform illuminated non-closeup sample images tested.

Images\Assessment	PSNR	ICF	DE	AMBE
Original	∞	35.60	7.23	0.00
ERMHE	**27.08**	36.37	7.03	**5.86**
GHE	17.35	37.39	6.99	26.77
BBHE	21.34	37.19	7.01	9.81
DSIHE	20.65	**37.50**	7.01	11.09
CLAHE	20.32	35.78	**7.56**	11.90

In order to provide a more comparative result on all the 94 non-closeup sample images involved, Table 5 tabulates the average of various assessment scores on the tested 94 sample images computed according to (23). ERMHE has the highest PSNR score of 27.08 and the lowest AMBE score of 5.86 among others. This indicates that ERMHE is resilient toward degradation and shift in brightness across pixel intensities. ERMHE scores 36.37 in ICF which is lower than GHE, BBHE and DSIHE. However, in term of visual inspection, ERMHE has the best contrast improvement without affecting the quality and appearance of the resultant image. CLAHE has the highest information content with a DE of 7.56 but it suffers a trade-off in ICF score. It scores lower in ICF because more gray level is used to represent the information in the image rather than being discretized for contrast improvement. Though, a high value in entropy may signify noise-enhancement [33] as shown in Fig. 19(f) given in Appendixes. As compared to CLAHE and others techniques, ERMHE is able to preserve a considerable amount of details with a DE of 7.03 yet without compromising the contrast and noise level in the image. Therefore, ERMHE is still the preferred option

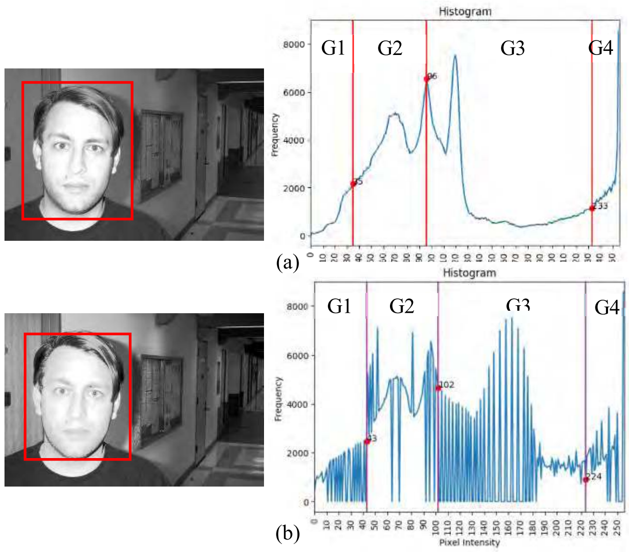


FIGURE 15. Non-uniform illuminated image with high brightness pixels accumulation. (a) Original image and (b) ERMHE resultant image.

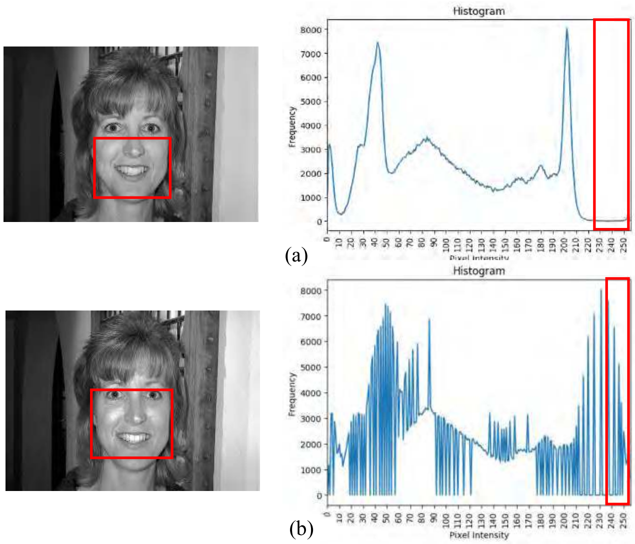


FIGURE 16. Resultant images with white patches introduced by ERMHE. (a) Original image and (b) ERMHE enhanced image with their respective histogram.

TABLE 6. Average computational time of 154 non-uniform illuminated sample images in seconds for ermhe, ghe, bbhe, dsihe & clahe.

Algorithms	ERMHE	GHE	BBHE	DSIHE	CLAHE
Time (s)	0.1316	0.0389	0.0394	0.0410	**0.0018**

in enhancing the contrast of the non-uniform illuminated image. Meanwhile, Fig. 19 in Appendixes shows another instance of ERMHE resultant Non-CloseupSample2 image.

C. COMPUTATIONAL PERFORMANCE

To evaluate the computational performance between ERMHE, GHE, BBHE, DSIHE and CLAHE, Table 6 is presented as the average (mean) computational time in seconds of all the 154 non-uniform illuminated sample images for each algorithm. Time is computed from the moment input image is fed until the resultant image is generated. From the table, it can be seen that CLAHE only takes 0.0018 seconds to complete the processing. This is due to the facts that an optimized OpenCV CLAHE library function is solely used in this study to ease data collection and comparison. Meanwhile, ERMHE, GHE, BBHE and DSIHE algorithms are self-implemented with the help of OpenCV look-up table transformation function. From the result, GHE, BBHE and DSIHE are ten times faster than the proposed ERMHE. This is because ERMHE involves multiple sub-images and consists of several processing stages while the nature of GHE computation is much simpler as well as BBHE and DSIHE computation are only involving different histogram segmentation thresholds such as mean and median. Although the proposed technique requires more processing time but in general the proposed technique produces better contrast enhancement performance qualitatively and quantitatively as compared to others.

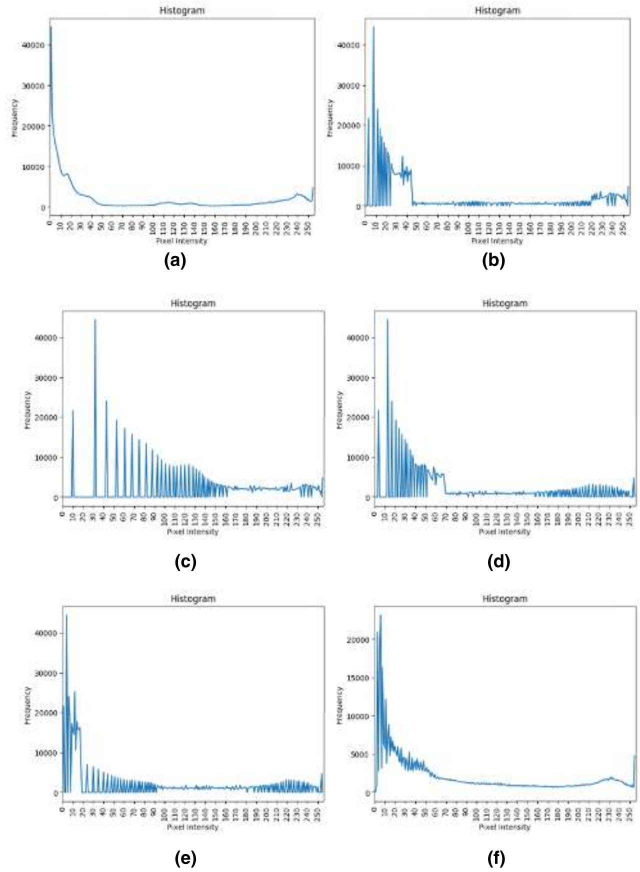


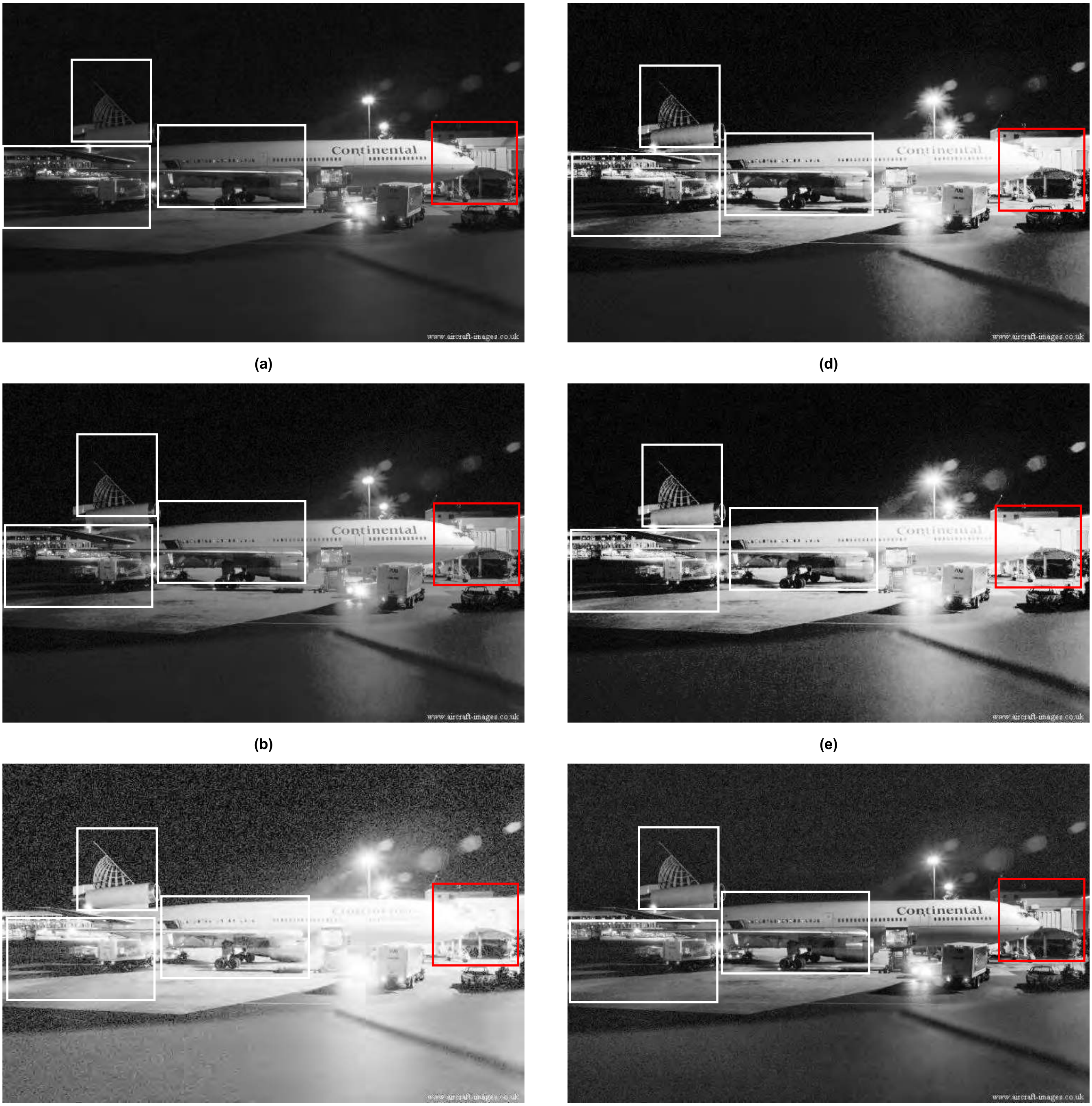
FIGURE 17. Histogram distribution of CloseupSample1 represented by (a) Original image and (b) ERMHE, (c) GHE, (d) BBHE, (e) DSIHE and (f) CLAHE resultant images.

VI. CONCLUSION

This study proposed a modified HE-based contrast enhancement namely Exposure Region-Based Multi-Histogram Equalization (ERMHE) for non-uniform illuminated image. The notable contribution of the proposed ERMHE is using

FIGURE 18. **(a) Original image of CloseupSample2 and resultant images produced by (b) ERMHE, (c) GHE, (d) BBHE, (e) DSIHE and (f) CLAHE with metric scores (PSNR, ICF, DE and AMBE) computed for each image.**

exposure region-based histogram segmentation threshold, entropy-controlled gray level allocation scheme and histogram repartitioning in enhancement. Exposure region determination has effectively isolated different exposure regions which facilitates the identification of exposure-based histogram partitioning thresholds locally in each region. This has indirectly involved the use of exposure element in threshold computation, unlike other HE methods that use non-exposure-based threshold which might end up using the same enhancement for different exposure regions found in the image. Meanwhile, the entropy-controlled gray level allocation scheme and histogram repartitioning had ensured fair and square output dynamic range distribution. ERMHE helps in preventing a bias distribution which eventually introduces unbalanced output gray levels range expansion and representation.



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

FIGURE 19. **(a) Original image of Non-CloseupSample2 and resultant images produced by (b) ERMHE, (c) GHE, (d) BBHE, (e) DSIHE and (f) CLAHE with metric scores (PSNR, ICF, DE and AMBE) computed for each image.**

Enhancement improvement of the proposed ERMHE is studied through qualitative and quantitative analyses. ERMHE are tested on 154 closeup and non-closeup non-uniform illuminated images where the results are being evaluated against various existing HE-based enhancement methods such as GHE, BBHE, DSIHE and CLAHE. In term of visual quality of the resultant images, GHE produces a bleached looking image as it tends to over enhance the uneven illumination globally. BBHE and DSIHE, on the other hand, produce an image with lower contrast where some of the details are hard to be seen. Meanwhile, CLAHE generates image with an unnatural appearance as it tends to amplify noise and introduce a greater amount of degradation. Unlike other existing methods, ERMHE can produce a more uniform illuminated image with better contrast without introducing undesired brightness and artefacts that affects the image appearance. The contribution provided by ERMHE is further supported by the quantitative analysis result which shows by the highest PSNR, lowest AMBE and the second highest DE score achieved. The achievement proves the ability of ERMHE in resisting degradation while preserving the brightness and detail in the image. The proposed ERMHE indeed has improved the overall illumination and contrast of non-uniform illuminated sample images with only a relatively small degree of degradation and change in mean intensity of the image.

VII. DRAWBACKS & FUTURE WORK

ERMHE does not work well for images with extremely high frequency histogram bins that accumulate in the same gray levels. ERMHE fails to provide a good contrast when there are many pixels that fall on the same brightness (gray level) as highlighted Fig. 15. By observing the histogram of ERMHE resultant image in Fig. 15(b), entropy-controlled dynamic gray level range allocation does expand the range of sub-histogram G4 for greater gray level expansion. But, due to the extremely high frequency histogram bins accumulate in sub-histogram G4 of Fig. 15(b), transformation function in (13) fails to spread the pixel intensities across the allocated gray level range resulting in no difference in gray level across the neighboring pixels. In order to prevent the mapping of the overlapping input gray levels to the same output gray levels, histogram modification can be done to clip the dominating pixel frequency to a threshold and re-distributes the clipped pixel counts across the histogram bins as in CLAHE. This can effectively spread the pixel intensities across a wider range of gray levels and resulting in larger CDF to give better contrast.

Secondly, resultant images of ERMHE have occasionally introduced white patches to the image such as around the forehead, the teeth and cheeks as shown in Fig. 16(b). This is because ERMHE does not control the enhancement by giving different weightage or emphasis on the stretching of sub-histograms and causes a change in the original histogram distribution. It attempts to flatten the histogram of the highlighted region by stretching too much across the gray levels, resulting in an increment of the pixel with bright intensity which altered the decreasing trend of the histogram as highlighted in Fig. 16. The increment is due to the cumulative sum that has been built up from previous histogram bins, thus end up mapping input gray level to a higher output gray level. Consequently, the resultant histogram no longer reflects the distribution of the original histogram. In order to control the enhancement rate of ERMHE, one should restrict the dynamic gray level range used by HE during enhancement. In each sub-histogram, the stretching of each sub-histograms in the allocated dedicated output range should be controlled in order to reflect the original histogram as close as possible. Besides that, the enhanced output histogram can also be modified so that it signifies the original histogram distribution as much as possible. This can be done by clipping the output histogram bin count to a reasonable threshold.

Currently, ERMHE performs HE enhancement on the segmented original histogram. In order to provide better contrast enhancement and detail preservation, HE can be applied separately on each sub-image to enhance each exposure regions individually. Next, the weighted average of each resultant sub-image can be computed to generate a final enhanced output image. Through the enhancement applied specifically to each sub-image, the contrast enhancement rate can be controlled better for different level of exposures found in the non-uniform illuminated image.

APPENDIXES

See Figures 17–19

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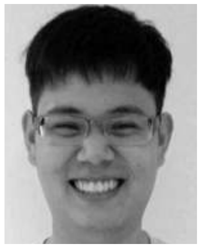

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