Local Neighbourhood Image Properties for Exposure Region Determination Method in Nonuniform Illumination Images

NOR HIDAYAH SAAD[1,2], NOR ASHIDI MAT ISA [1], AND ABDULLAH AMER MOHAMMED SALIH[1]

[1]Imaging and Intelligent System Research Team, School of Electrical and Electronic Engineering Campus, Universiti Sains Malaysia, Nibong Tebal 14300, Malaysia
[2]School of Microelectronic Engineering, Universiti Malaysia Perlis, Arau 02600, Malaysia

Corresponding author: Nor Ashidi Mat Isa (ashidi@usm.my)

ABSTRACT During image acquisition, nonuniform illumination regions are produced due to several factors, such as improper environment lighting and inappropriate capturing device setting. Applying contrast enhancement methods with the same enhancement concept to the whole image can over enhance or under enhance nonuniform illumination image. Thus, different and specific enhancement concepts should be applied to different regions in nonuniform illumination image. This concept requires identification of those different regions. Almost all existing methods that introduced the region determination process can only detect two different regions, namely, dark and bright, which inadequately represent the real exposure condition because the methods only consider intensity criteria to determine the regions. For this problem, a new method used for the accurate detection of nonuniform illumination regions is proposed. Different illumination levels affect not only the intensity but also the details in an image. Thus, three image attributes, namely, intensity, entropy and contrast, which are evaluated locally in detecting the regions, must be considered. For the detection to be on par with that in humans, the three attributes are combined with a rule-based method for the identification of illumination regions. Experimental results involving evaluation from research experts demonstrate that the proposed method qualitatively detects different illumination regions (i.e., over-exposed, well-exposed and under-exposed) in a nonuniform illumination image more accurate than the state-of-the-art methods.

INDEX TERMS Nonuniform illumination image, exposure region determination, image intensity, image entropy, image contrast.

I. INTRODUCTION

Nonuniform illumination image is characterised by different lightness values in certain regions in a digital image. It can be produced during image acquisition process due to several factors such as extreme environment light conditions, limitations in imaging devices, and the unsuitable exposure parameter settings of imaging devices [1]. Generally, different lightness values in a nonuniform illumination image can be categorised into three regions, namely, under-exposed, over-exposed and well-exposed regions. The under-exposed region is normally presented as a darker region relative to

The associate editor coordinating the review of this manuscript and approving it for publication was Jeon Gwanggil .

the average luminance of the entire image, whereas the over-exposed region appears brighter [2]. The details in both regions cannot be seen or disappear in a nonuniform illumination image. The low dynamic range of intensities in under-exposed and over-exposed regions produces low-contrast areas. Fig. 1 shows the examples of nonuniform illumination images. In Fig. 1(a), the over-exposed region (represented by a red rectangle in a bright region) appears to wash out the details. In Fig. 1(b), the over-exposed region (represented by a red rectangle) is highly affected by sunlight, whereas the under-exposed region (represented by a dotted red rectangle) received less sunlight. Both regions hide their details, such as the details of the tree in the over-exposed region and the section of the grass in the under-exposed
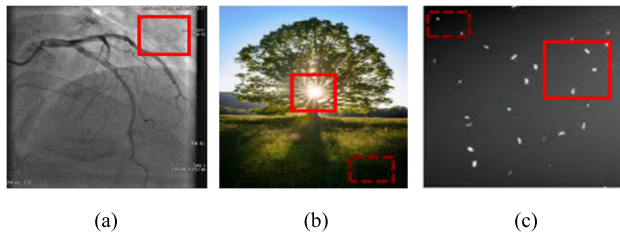
FIGURE 1. Examples of nonuniform illumination image. Coronary Cineangiograms image [3]; (b) Scenery image [4]; (c) Microscopic image [5].

region. The microscopic image in Fig. 1(c) with improper camera settings produced over-exposed region (represented by a red rectangle) and under-exposed region (represented by a dotted red rectangle), thereby leading to the inaccurate determination of the size or features of the object of interest.

The properties of nonuniform illumination image cause inaccuracy during the segmentation process. The intensities of the region of interest (ROI) and the background region can be similar because the intensity of a given object in a nonuniform illumination image varies owing to different lighting conditions. A segmentation process that is solely based on intensity value inaccurately segments the ROI into background regions. Therefore, enhancement should be applied to an acquired image, and the contrast and brightness of the images must be improved. However, existing contrast enhancement methods simultaneously enhance the contrast of the dark (under-exposed) and bright regions (over-exposed) with the same enhancement rate, thereby over enhancing the bright regions. As a result, the details in the bright regions often disappear. This problem occurs because of the illumination conditions or the exposure levels in the image are not determined before enhancement. To avoid this problem, different enhancement techniques with varying enhancement rates can be applied after various regions types are determined.

Most of the existing local contrast enhancement techniques do not focus on determining exposure levels or regions in images. Few techniques, such as in [6]–[15], divide a nonuniform illumination image into two regions on the basis of the intensity value of pixels in histogram and determine exposure levels. Meanwhile, the contrast enhancement technique in [16] added exposure levels into three regions on the basis of intensity value. Furthermore, exposure levels can be determined according to the illumination and reflection components of an image [17]–[19], and images are divided into two exposure regions, namely, dark and bright. These techniques consider only intensity when determining the exposure regions. This limitation motivates us to develop a new approach by which exposure regions are determined on basis of more than one property for the determination of precise regions. In this study, we focused on the local intensity, contrast and entropy of the image as the properties that contribute to the different exposure levels in a nonuniform illumination image.

II. RELATED WORKS

This section reviews the existing works related to the determination of exposure levels in nonuniform illumination images. Most of researches were focused on the determination of only one level of exposure either under-exposed or over-exposed region. Guo et al [10] created over-exposed map to detect the over-exposed regions based on intensity (L) and color features (C) of CIELAB colour space. Lee *et al.* [11] used a simple thresholding method based on the intensity level to classify over-exposed regions. However, this method showed lacks connectivity and the regions detected are scattered. Yoon *et al.* [12] developed a new over-exposed region detection method by thresholding the saturation value of the colour image. Based on the idea that human perception of over-exposed region does not depend solely on the intensity of the image, the subjective experiment on the characteristics of the saturation sensitivity of the human visual system were performed that resulted in formulation of a new function for determining the saturation threshold value that depends on the color and brightness of each pixel. Lee *et al.* [13] then proposed detection of over-exposed regions in image using regularized logistic regression (LR). Using this method, the characteristics of over-exposed regions are modelled as clusters rather than isolated pixels by both intensity and chrominance pixel values which resulted in detected regions with more spatially connected and perceptually accurate. Chung *et al.* [18] detected level of under-exposed region for poorly exposed images like night-time images and backlit images by adapting the Zone system used in photography. The image is decomposed into illumination and reflectance components before exposure levels are determined by those two parameters. For the methods mentioned above, they determined only one region which is under or over-exposed region.

Hanmandl *et al.* [8] determined under-exposed and over-exposed regions for low dynamic range input image by performing simple thresholding on the relative luminance of pixels. The thresholding values for under-exposed and over-exposed were fixed to 0.05 and 0.85, respectively. However, the thresholding values should be modified for different images. Therefore, this method is subjective and raises concerns about inaccurate region determination because each image is unique, and obtaining the same threshold value for all images is impossible. Hanmandlu *et al.* [8] introduced an objective measure called as exposure, which indicated the image's amount of exposure to light. Exposure is determined by calculating the single threshold value, which is the average of the grey level value of all the pixels in an image. Therefore, a pixel is under-exposed if the intensity value is lower than the corresponding threshold value or over-exposed when the intensity value is higher.

Hasikin and Isa [9] divided the intensity of the nonuniform illumination image into two regions, namely, dark and bright. They calculated the average grey level value of all the pixels in an image and the value is set as the fundamental measurement of region classification. Then, they introduced fuzzy

intensity measure (FIM) to determine a threshold value that is more adaptive than the method in [8]. FIM is determined by dividing the deviation grey level value with the average grey level value. If the intensity of a pixel is lower than the threshold value, then the pixel is classified as dark while in contrast the pixel is considered bright. However, this work raises the question of the presence of medium-class intensity on the pixels, that is, a combination of low (dark) and high (bright) intensities, which is not defined in this method.

Kim and Kim [14] detected the over or under-exposed regions using entropy-based metrics in which the differential of entropy is calculated through the fine-to-coarse transformation using a diffusion process. However, this method only considers the entropy calculation which found to have the inappropriate determination due to the intensity levels that are not considered.

Raju and Nair [15] categorised the nonuniform illumination image into two regions without mentioning their specific names. In this method, the RGB colour image is converted into hue, saturation and value (HSV) colour space, and the V component is used to determine the threshold value for the division of regions. This method functions on the basis of two important parameters, namely, M and K, where M is the average intensity value of the image that determine the threshold value, whereas K is the contrast intensification parameter for enhancement using a fuzzy-based method. The two regions are formed by using a threshold value, which divides the grey level value from 0 to M-1 in the first region and from M to 255 in another region. Although this method is simple and computationally fast, the number of regions defined is insufficient for proper enhancement.

To address the issue of insufficient number of regions defined, Verma *et al.* [20] continued their work in [8], in which they calculated the lower threshold [LT] and upper threshold [UT] to categorise the image into under-exposed, over-exposed and mixed regions by using exposure criteria as in [8]. A pivot parameter is introduced for the calculation of the lower and upper threshold values, and an initial value is set to the value of exposure which then is optimised using an artificial ant colony algorithm. The grey levels below the lower threshold value are classified as under-exposed region, and all grey levels above the upper threshold are categorised as the over-exposed region. The remaining pixels are assumed to lie in the mixed region.

Lee *et. al* [21] also addressed the insufficient number of regions by proposing the adaptive backlit region determination. The proposed method divided the input image into non-overlapped 64 × 64 blocks, and each block is subsequently classified into one of the three main regions, namely, dark, background, and bright, by using two optimal threshold values. The threshold values are calculated by using fuzzy C-means clustering method. However, this method misclassified the dark pixels inside the background regions into the class of backlit regions. Another limitation is this technique is only applicable to the detection of the dark region.

Salih *et al.* [16] developed a new method called adaptive local exposure-based region determination (ALEBRD) to classify the nonuniform illumination image into under-exposed, over-exposed and well-exposed regions. An RGB image is first converted into HSV space, where V channel is used for modification, and H and S are preserved. The image is divided into several blocks with size m × n for local processing. The fitness of each block is determined according to the difference between the intensity of the pixel and the average of local neighbourhood intensity. Then, the blocks are classified into their respective regions with a region determination parameter. The parameter that considers the maximum intensity and the fitness of each block served as threshold points for the division of the image into the three defined regions.

All these methods use intensity value to determine the exposure region. However, the intensity-based classification of regions does not reflect the luminance of the regions because intensity only considers the brightness level of an image. A region can be possibly detected correctly by using the details of the region, especially for a well-exposed scene. Many previous region determination methods failed to correctly identify well-exposed region as those methods only depend on intensity value. For better understanding, consider Fig. 2. There are two images processed by two previous region determination methods called as Exposure 3R [20] and ALEBRD [16]. Fig. 2(a) shows original images, while Fig. 2(b) and Fig. 2(c) represent the output images of Exposure 3R and ALEBRD respectively. The red, blue and green regions represent over-exposed, under-exposed and well-exposed regions respectively.
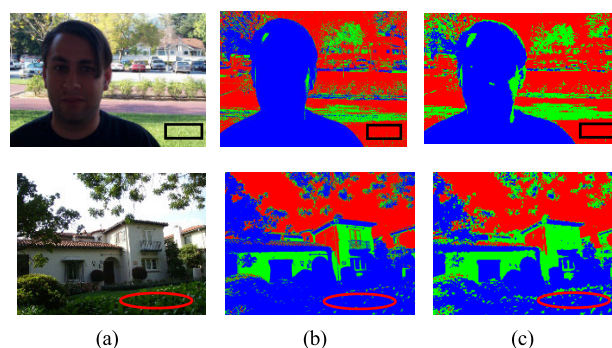

FIGURE 2. Region determination based on intensity. (a) Original image; (b) Region determination detected using exposure 3R [20]; (c) Region determination detected using ALEBRD [16].

For the first image as shown at the top row of Fig. 2, consider a region represented by black rectangle. It is a bright region and has high intensity. However, the details of grass are clearly seen. Based on human perception, over-exposed region refers to a region that is bright or too bright and the details of that region are lost and cannot be observed. Thus, this region should be classified as well-exposed region and not over-exposed region. But, both Exposure 3R and ALEBRD methods wrongly identify the region as

over-exposed region. This is the main limitation of region determination methods that only consider intensity value for determining the region type.

Region misclassification is also detected in the red oval region in Fig. 2(a). This region is a dark region, which has low intensity values. However, the details of the plants such as their shapes, and leaves are clearly seen. Thus, this region should be described as well-exposed region. Referring to Fig. 2(b) and (c), both Exposure 3R and ALEBRD methods wrongly determined the region as under-exposed region as shown by the blue pixels in the red oval region in both figures. The situations discussed above show the needs of considering another image attributes that can indicate the presence of details in the image. Therefore, in this work, we introduce entropy and contrast to integrate with the intensity for minimizing the misclassification problem especially on the well-exposed region. The entropy and contrast provide the amount of information and the variance of the luminance in a certain region respectively, therefore these attributes can be used in measuring the details as well as detecting the well-exposed region in nonuniform illumination image.

III. PROPOSED METHOD

A. DETERMINATION OF INTENSITY LEVELS

Many state-of-the-art techniques have been proposed to solve different region illumination detection issues. However, most of these techniques do not properly detect the regions and are designed to divide the image into two regions, namely, bright and dark. From related works, there are three methods that are dedicated to divide the image into more than two regions to represent the real exposure of an image which are Backlit [21], ALEBRD [16], and Exposure 3R [20]. These methods considered image intensity as a criterion to detect a region. As discussed in the previous section, Backlit divided the brightness histogram into three regions by using Fuzzy C Mean clustering, therefore this method suffered from complex computational while the Exposure 3R considered the average of global intensity of the image and one fixed value (0.1) to calculate the two threshold values globally, thus it is not adaptive and imprecise. In order to provide a simple and precise region determination based on the intensity, we introduced the new threshold values calculation based on the global and standard deviation of the intensity of the image which then will be used to evaluate the region in locally.

A colour image A with nonuniform illumination image of size $R \times C$, where R and C are the number of rows and columns in the image, respectively, is first converted into Hue, Saturation, and Value (HSV) color model. The Value or intensity, V is then considered in determining the local intensity of the region in which the average intensity of the entire image, V_a and the standard deviation intensity of the entire image, V_d are calculated by using (1) and (2), respectively.

$$V_a = \frac{1}{R \times C} \sum_{i=1}^{R} \sum_{j=1}^{C} V(i,j) \quad (1)$$

$$V_d = \sqrt{\frac{1}{R \times C} \sum_{i=1}^{R} \sum_{j=1}^{C} (V(i,j) - V_a)^2} \quad (2)$$

where $V(i,j)$ is the intensity value at pixel position (i,j).

Standard deviation is selected for calculating the upper and lower threshold values to express exact class statistical distributions since the dispersion of classes is proportional to the standard deviation rather than variance [22]. Then, the intensity, V values of the image are processed locally in $m \times n$ blocks, where the mean of intensity in each block, I is calculated. Two threshold points are determined to categorise the intensity of each block into three levels. The upper and lower threshold points are calculated by considering the average intensity and standard deviation intensity of the entire image, as shown in (3) and (4), respectively.

$$U_t = V_a + V_d \quad (3)$$
$$L_t = V_a - V_d \quad (4)$$

where U_t is the upper threshold point, and L_t L_t is the lower threshold point.

The mean luminance, of each block or named as intensity, I will then be categorised into three different levels, low, medium and high, where the range of intensities for each level are defined in (5):

$$Intensity, I = \begin{cases} I_{low} & if \ I < L_t \\ I_{medium} & if \ L_t \leq I \leq U_t \\ I_{high} & if \ I > U_t \end{cases} \quad (5)$$

where I_{low}, I_{medium} and I_{high} correspond to low, medium and high intensity, respectively.

In this work, it is being observed that by evaluating the local intensity of the pixels solely did not ensure the accurate detection of exposure regions. This problem is summarized in Fig. 3 where there are two regions as shown by the red and black rectangles in Fig. 3(a). Both regions have been assigned to have high intensity by using (5) as shown in Fig. 3(b). However, both regions have different patterns of gray scale distribution as shown in Fig. 3(c). The pixels intensity (in gray scale) distribution for the region highlighted by red rectangle shows most of the pixels accumulated at gray level 255. In contrast to region shown by black rectangle, the pixels intensity values are more scattered at various gray level values. However, the pixel distribution is dominant to the right side of the histogram indicating that the area is bright. Due to the existence of pixel distribution at each gray level value as shown by the histogram of black rectangle region in Fig. 3(c), it indicates that there are the significant details on the respective region to be considered. If only intensity is used to characterize a region, both red and black regions will be considered as a similar region although the details and contrast of black region are totally different as compared to red region. Therefore, in this work, entropy and contrast are proposed to be integrated with the intensity as these two attributes are known to best indicate the presence of details in a given space.
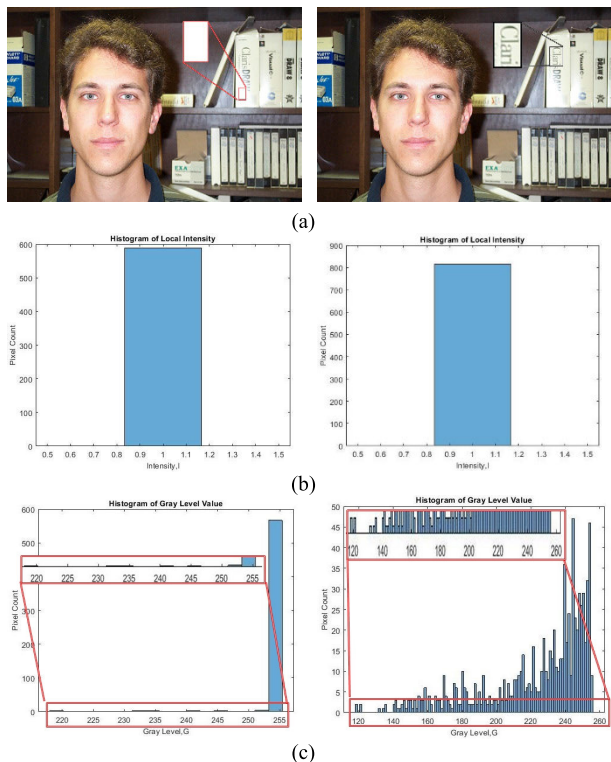
(a)

(b)

(c)

FIGURE 3. Analysis of intensity and gray level distribution on two difference exposure regions. (a) Original image (b) Histogram of region's intensity (c) Histogram of region's gray level.

B. DETERMINATION OF ENTROPY LEVELS

Entropy is the second image attribute included in determining illumination region. Entropy is a measure of image information content and is widely used in many image processing applications [23]. It describes how much uncertainty or randomness occur in an image. The Shannon's entropy, E for a discrete random variable X, which represents an image with k grey levels $\{x_1, x_2, \ldots, x_k\}$, is defined as [24]:

$$E = -\sum_{i=1}^{k} p_i \log_2 p_i \qquad (6)$$

where p_i represents the probability of grey level x_i.

Based on (6), for an 8-bit image, the histogram with uniform distribution as shown in Fig. 4 will have a maximum value of the entropy. This is because the probabilities of all pixels exist on each gray level are equal. The maximum entropy also indicates that the histogram uses all available dynamic range, i.e. the intensity in the range [0, 255]. In contrast, minimum entropy happens when the result is a certainty, for example all pixels lay on the same gray level. Therefore, the probability becomes 1, hence the entropy is zero. In image processing, discrete entropy refers as a measure of the number of bits required to encode image data [25]. A high entropy value indicates a high amount of information contained and vice versa [26]. Therefore, the amount of information relates with the details in an image, in which a high entropy value indicates more details exist in a region. This concept is
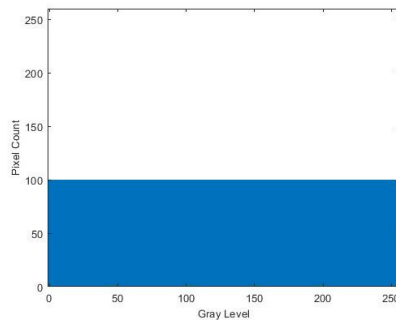

FIGURE 4. Histogram with uniform distribution.

adopted in this work for detecting the well-exposed region which must exhibit the richness in details.

In the proposed method, the entropy of each block sized $m \times n$, E_{local} is calculated using (6), where m is the number of rows, and n is number of columns. Then, the mean entropy of the entire image, E_a is calculated using (7) and becomes the reference value in dividing high and low entropy.

$$E_a = \frac{1}{N} \sum_{b=1}^{N} E_{local} (b) \qquad (7)$$

where $E_{local}(b)$ is the entropy of a block sized $m \times n$, and N is the number of blocks in an entire image. Subsequently, entropy is divided into two regions, low entropy (E_{low}) and high entropy (E_{high}), based on the global mean entropy (E_a). E_{low} covers local entropy value from 0 to $E_a - 1$, and E_{high} represents the local entropy values equal to or more than E_a. The output is summarised using (8).

$$Entropy, E = \begin{cases} E_{low} & if \ E_{local} < E_a \\ E_{high} & if \ E_{local} \geq E_a \end{cases} \qquad (8)$$

C. DETERMINATION OF CONTRAST LEVELS

In the proposed method, the contrast of an image has also been considered in determining the exposure regions. Contrast has been defined in many field of studies. In general, contrast refers to the difference in luminance between an object and its surrounding region [27]. In image processing, contrast indicates the division of grey levels in a region. A high contrast value indicates a large dynamic range of grey levels and presents remarkable contrast [28]. In Fig. 3(c), histogram on the left shows a region with low contrast compared to histogram on the right since the difference between the maximum and minimum intensities is smaller. It shows that less variation of gray level value found in this low contrast area. Indirectly, this feature indicate that probably no or less details are found in the low contrast region compared to high contrast region.

The contrast, C_{local} of a local region $m \times n$ is calculated using (9):

$$C_{local} = \frac{1}{m \times n} \sum_{x=1}^{m} \sum_{y=1}^{n} G^2(x, y) - \left| \frac{1}{m \times n} \sum_{x=1}^{m} \sum_{y=1}^{n} G(x, y) \right|^2 \qquad (9)$$

where m and n are the number of rows and columns of the local region in the image, respectively; and $G(x,y)$ is the grey level of the pixel at (x,y).

The mean of the local contrast of the entire image, C_a is calculated using (10):

$$C_a = \frac{1}{N} \sum_{b=1}^{N} C_{local} (b) \qquad (10)$$

where $C_{local}(b)$ is the contrast of a block sized $m \times n$, and N is the number of blocks in an entire image.

C_a divides the image into lower and upper contrast regions. The previously calculated contrast of each local region is then distinguished into two levels, namely, low contrast, C_{low} and high contrast, C_{high}. Equation (11) summarises the division of the upper and lower contrast.

$$Contrast, C = \begin{cases} C_{low} & if \ C_{local} < C_a \\ C_{high} & if \ C_{local} \geq C_a \end{cases} \qquad (11)$$

D. OVERALL REGION DETERMINATION

The final stage is conducted to categorise all blocks into one of the three previously defined regions based on the three previously determined properties. The algorithm to determine the final region is shown as pseudocode in Table 1. Based on Table 1 the main idea that differentiates the proposed method with the existing ones is shown in Line 4. This idea is generated based on the hypothesis that high entropy indicates that more details are found in the region, and vice versa. Similar to entropy, high contrast also shows the presence of significant changes in the grey value in the region and can also be relate to the details in the region. When the entropy and contrast are high, thereby showing the richness of details and significant grey value changes. Regardless of the intensity value, the block with these criteria will be classified as well-exposed region. In existing methods, if the region has low or high intensity values, then the region will be considered as an under-exposed or over-exposed region, respectively. In some

TABLE 1. Pseudocode for overall region determination.

Input : Level of Intensity, *I* for each pixel, Level of Entropy, *E* for each pixel, Level of Contrast, *C* for each pixel
Output : Exposure Region, *R*
1. Find the size of row's and column's pixels
2. Input the current pixels (row,column)
3. Repeat
4. IF *E* and *C* are in high level, then *R* is well-exposed.
5. ELSE
6. IF both *E* and *C* are in low level, or either *E* or *C* is in high level, then *R* is determined using Equation (12)
7. End

---

cases, this is not true as shown in Fig. 2. For both cases, both regions should be considered as well-exposed region.

Meanwhile, the entropy and the contrast can be both in low level or either one can be in high level. For this case, the region will be determined based on the intensity as shown in (12):

$$Exposure \ Region, R = \begin{cases} under \ exposed \ if \ I = I_{low} \\ well \ exposed \ if \ I = I_{medium} \\ over \ exposed \ if \ I = I_{high} \end{cases} \quad (12)$$

Based on the abovementioned situation, three cases can be created as follows:

Case 1: The entropy (E_{low}) AND contrast are low (C_{low}).

Case 2: The entropy is low (E_{low}) AND contrast is high (C_{high}).

Case 3: The entropy is high (E_{high}) AND contrast is low (C_{low}).

By referring to Case 1, the entropy and contrast are low, indicating the less/no details appear in the evaluated pixel and less/no significant changes of grey level value are detected in the pixel, respectively. This shows that both criteria have no significant effect during region determination. Therefore, the region is classified on the basis of intensity level. If the intensity level is low, then the region is categorised as under-exposed. When the intensity level is medium and high, the pixel is categorised as well-exposed and over-exposed, respectively. *Case 2* translates the condition of less/no details appear in the evaluated pixel (i.e., low entropy) combined with high/great significant changes of grey level value in the pixel (i.e., high contrast). Although the contrast is high, the details are not significantly detected. Thus, the pixel cannot be classified as well-exposed. For this case, the pixel is classified on the basis of intensity level. One possible pixel falls under these criteria is an edge. *Case 3* translates that more details appear in the pixel but less/no significant changes of grey level value. For this case, although the details of a region could be observed, their contrast is low and therefore cannot be considered as a well-exposed one. Thus, similar to *Case 2*, the region will be set on the basis of intensity level. Based on these three properties, the exposure region can be accurately determined.

IV. RESULT AND DISCUSSION

To demonstrate the effectiveness of the proposed method, we compare the region detection results obtained by the proposed method with five methods named as ALEBRD [16], Backlit [21], Exposure 3R [20], Exposure 2R [8] and FIM [9]. ALEBRD, Backlit and Exposure 3R produced three exposure regions known as under-exposed, over-exposed and well-exposed while FIM and Exposure 2R determined two exposure regions in an image known as under-exposed and over-exposed. In this study, the performance analysis comparison is conducted using two categories of a number of exposure region detected (three regions and two regions) due to the following reasons:
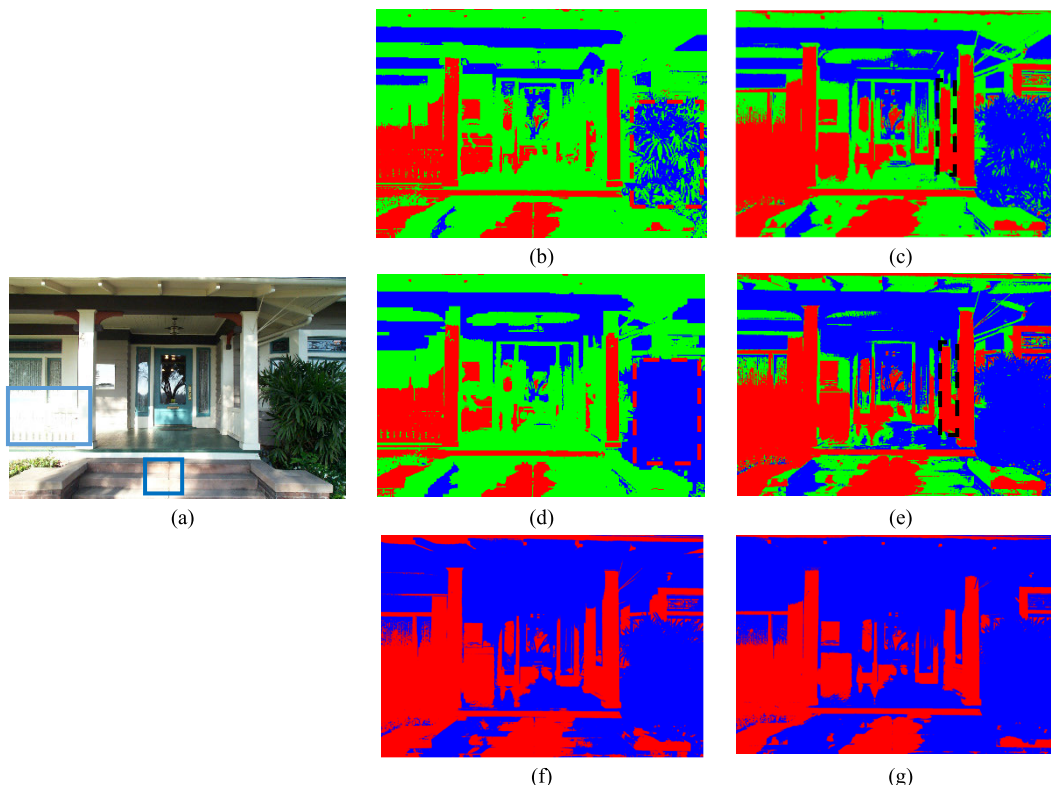
FIGURE 5. Resultant images of region determination for *House balcony image* (a) Original image; (b) Proposed method (c) ALEBRD (d) Backlit (e) Exposure 3R (f) Exposure 2R (g) FIM.

(i) ALEBRD, Backlit and Exposure 3R classified an image into three regions, namely, under-exposed, well-exposed and over-exposed, which are similar to the proposed one.

(ii) FIM and Exposure 2R are used to count on experts' opinion on number of exposure regions that should be good enough to be determined.

This work only consider a qualitative analysis for performance analysis. The literature review suggests that no standard quantitative analysis has been applied so far to evaluate the performance of region determination. All previous works only focused on visual evaluation. Each output image will be visually evaluated to identify any regions that are misclassified as other region types using this qualitative analysis. This procedure will be carried out in the first stage of performance analysis. Resultant images of the proposed method and all comparison methods will be placed side by side, and their performances will be visually compared and evaluated. In addition, a group of image processing experts will be asked to evaluate the resultant images to reduce the subjective element of evaluation. Their evaluation and comments will be analysed and presented. This survey is carried out in the second stage of performance evaluation. In this survey and analysis, ten experts with more than six years of experience in the image processing field were asked to assess the detection accuracy using the proposed and five state-of-the-art methods. Each expert will grade the resultant

TABLE 2. Comparison scale for subjective quality evaluation.

Grade Scale	Quality
1	Bad
2	Poor
3	Fair
4	Good
5	Excellent

images based on quality scale, as shown in Table 2 [12], [29]. 30 images obtained from the California Institute of Technology database [30] are used. The experts will perform their evaluation by using the same experimental environment where 30 original nonuniform illumination images, together with their corresponding region detection image are displayed using 14-inch diagonal HD BrightView LED-backlit Display. The brief background of ten experts took part in this assessment are summarized in Appendix I.

For the first step of performance evaluation, five images named as *House Balcony*, *Yard*, *Mansion*, *Woman*, and *Man*, have been applied using the proposed method, ALEBRD, Backlit, Exposure 3R, Exposure 2R and FIM. Resultant images for all methods are shown in Fig. 5, Fig. 6, Fig. 7, Fig. 8, and Fig. 9 respectively. For all resultant images, red colour pixels represent over-exposed region, while blue and green colour pixels indicate under-exposed and well-exposed
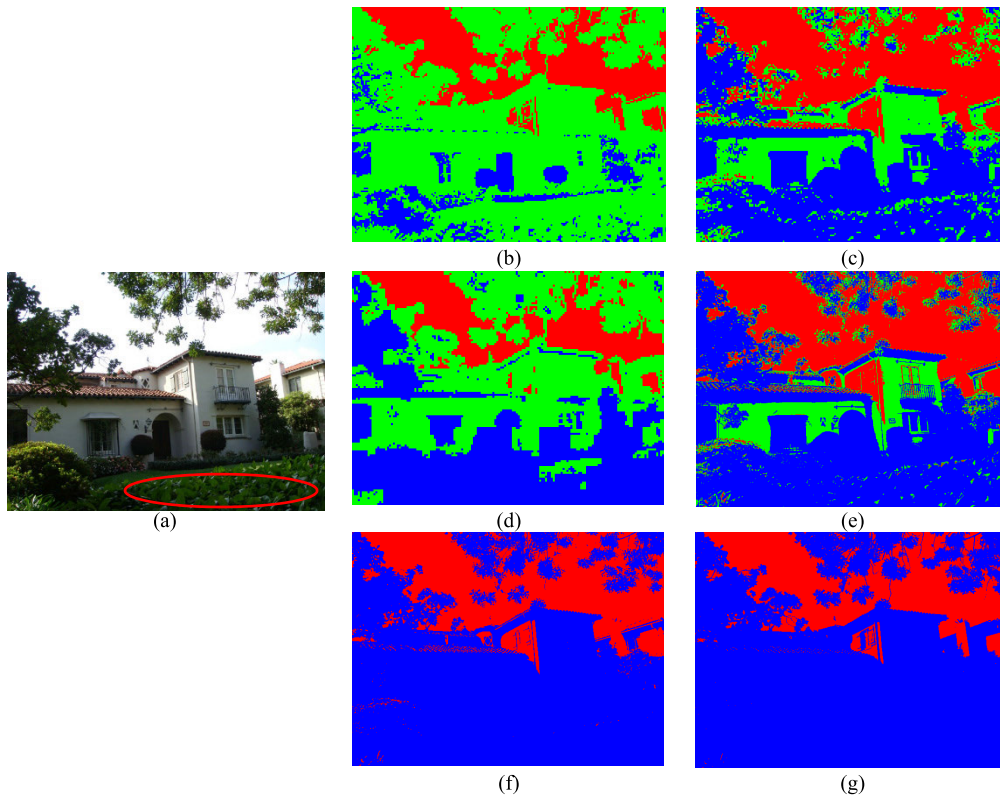
FIGURE 6. Resultant Images of Region Determination for *Yard* Image (a) Original Image; (b) Proposed Method (c) ALEBRD (d) Backlit (e) Exposure 3R (f) Exposure 2R (g) FIM.

region respectively. Fig. 5 shows the resultant images of region determination for *House Balcony* image. Referring to the original *House Balcony* image in Fig. 5(a), different illumination regions are produced in the image due to the effect of sunlight. Examples of the over-exposed regions are highlighted by blue rectangles in the same figure where details of small pillar and the stairs cannot be seen. The proposed method and Backlit detected almost similar over-exposed region while ALEBRD and Exposure 3R detected wider over-exposed regions including the white pillar highlighted by black dotted rectangle in Fig. 5(c) and Fig. 5(e) even though the region is not illuminated by the light, hence these methods misclassified the well-exposed region. The same misclassified result is also produced by Exposure 2R and FIM method whereby most of white colour regions are detected as over-exposed region. The main difference between the proposed method and Backlit is on the determination of under-exposed region. The proposed method detected less regions and able to detect more details regions compared to Backlit. It is shown by the red dashed rectangle area in Fig. 5(b) and Fig. 5(d) whereby the proposed method successfully detected only several parts of the plants that cannot be recognized by the shape and the change of luminance as under-exposed region, while the other parts of the plants (i.e. with clearly seen details) are correctly detected as well-exposed region. This region is correctly determined by the proposed method

since the proposed method considered entropy and contrast calculation in determining the details exist in that area.

The poor detection problem mentioned above also occurs in under-exposed detection region by Backlit for *Yard* image as shown in Fig. 6(d). In Fig. 6(b), the proposed method is able to detect under-exposed regions better than Backlit method (i.e. indicate by blue pixels). The plant as indicated by red oval in Fig. 6(a) is misclassified as under-exposed by Backlit method even though the details of the plants could be clearly seen. This situation can also be seen for under-exposed region determined by ALEBRD and Exposure 3R shown in Fig. 6 (c) and Fig. 6(e) respectively. Exposure 3R misclassified the well-exposed region (indicated by the red oval in Fig. 6(a) by over detected wider under-exposed area compared to ALEBRD since this method evaluated the pixels' intensity globally while ALEBRD evaluated the contrast of intensity value locally. As for detection of over-exposed region, all methods correctly detected the region.

The third tested image, *Mansion* as shown in Fig. 7 is another example of nonuniform illumination image with the effect of sunlight as the main factor of this phenomenon. The under-exposed regions can be observed inside the red rectangles in Fig. 7(a). All methods successfully detected similar under-exposed regions, including the one inside the red rectangle, however Exposure 3R over detected the under-exposed regions. This can be seen in the red oval area in Fig. 7(d) that
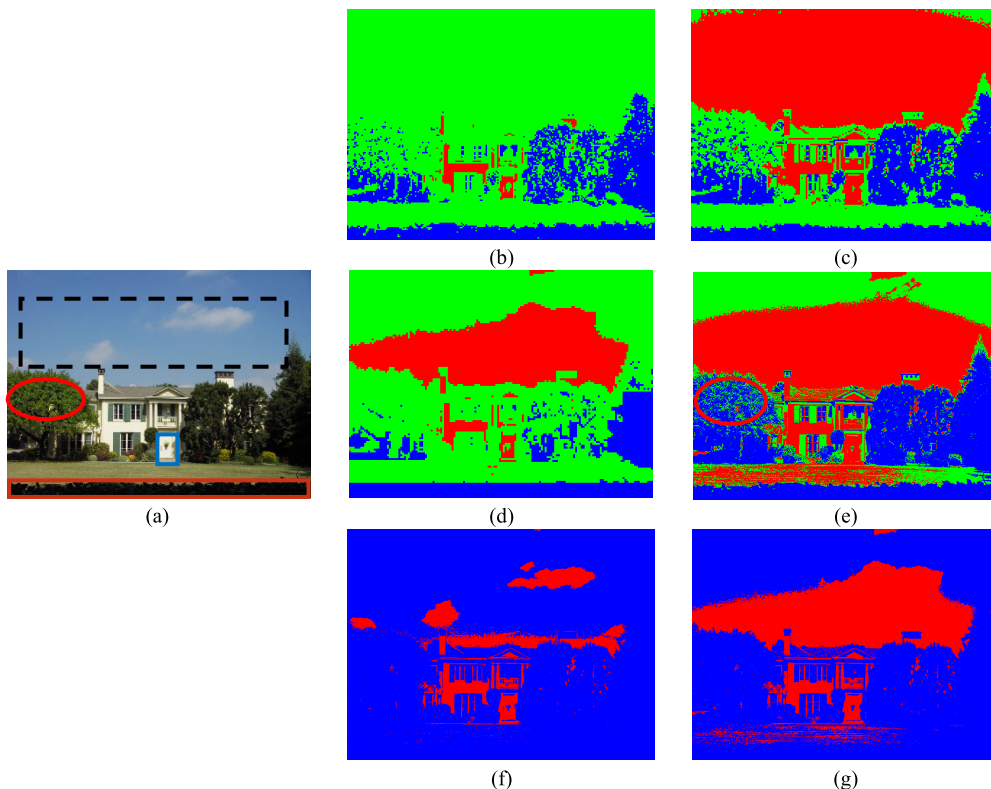
FIGURE 7. Resultant images of region determination for *mansion* image (a) Original image; (b) Proposed method (c) ALEBRD (d) Backlit (e) Exposure 3R (f) Exposure 2R (g) FIM.
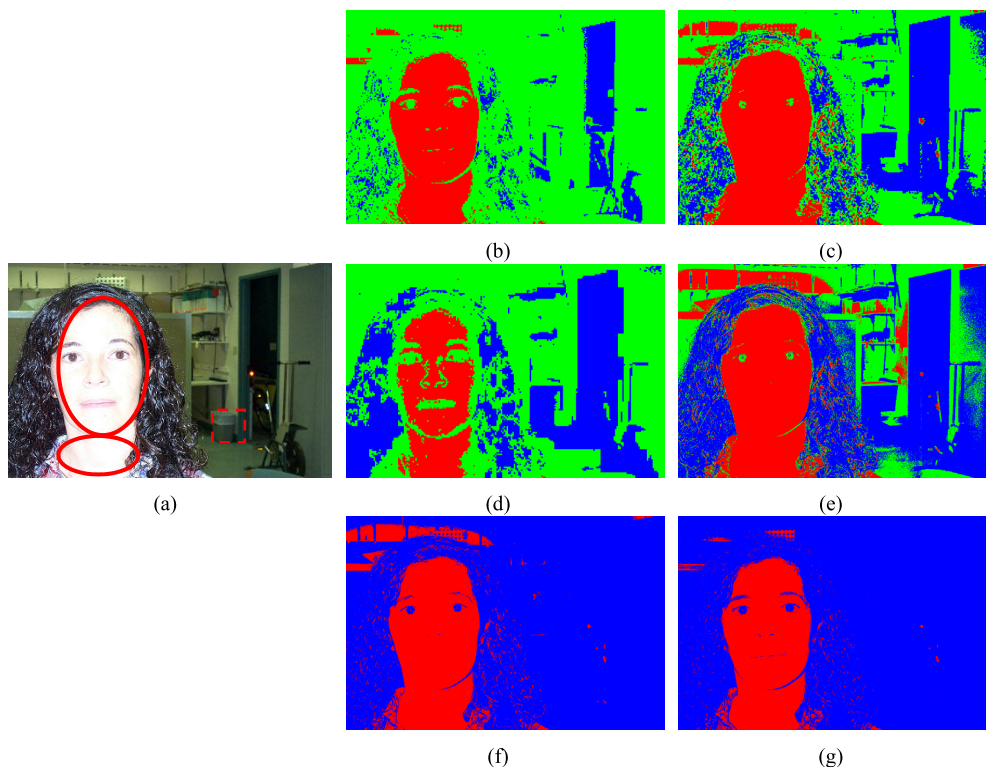

FIGURE 8. Resultant images of region determination for *woman* image (a) Original image; (b) Proposed method (c) ALEBRD (d) Backlit (e) Exposure 3R (f) Exposure 2R (g) FIM.

is misclassified as under-exposed region. Visually, the details of leaves of the tree in the similar area in Fig. 7(a) can be seen, therefore the region is considered as well-exposed region. For

determination of over-exposed region, all methods correctly detected the over-exposed regions, as highlighted by the blue rectangle. The main difference between region detected by
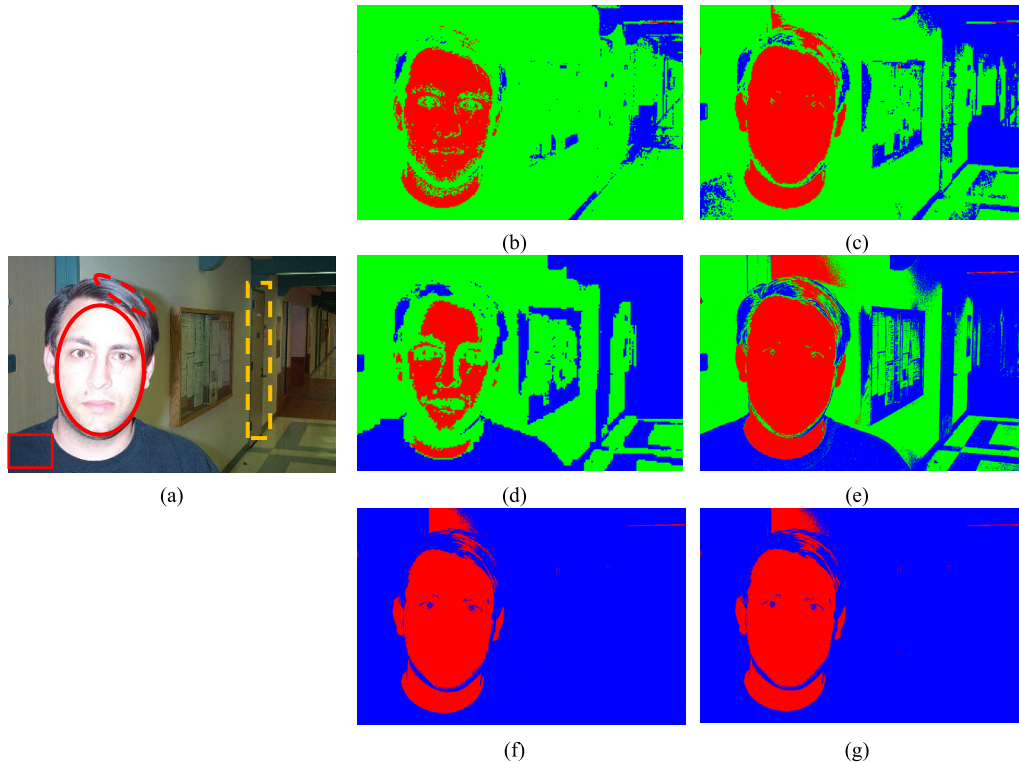
FIGURE 9. Resultant images of region determination for *man* image (a) Original image; (b) Proposed method (c) ALEBRD (d) Backlit (e) Exposure 3R (f) Exposure 2R (g) FIM.

the proposed method and other methods in this image is indicated in the determination of the sky region as represented by black dotted rectangle in Fig. 7(a). This region has high contrast and the details of clouds can be clearly observed. Thus, this region is considered as a well-exposed region. However, all methods except the proposed method failed to detect the well-exposed region (e.g., the sky region as represented by black dotted rectangle). This region has been wrongly detected as an over-exposed region by ALEBRD, Backlit, and Exposure 3R. Visually, the proposed method has successfully prevented the over detection problem and produced high percentage of correct determination of well-exposed region.

Fig. 8 and Fig. 9 are the examples of nonuniform illumination close up images of a human's face named as *Woman* and *Man* respectively. The face shown by the red ovals in Fig. 8(a) was illuminated with the extreme light conditions that produced the over-exposed regions. The proposed method and Backlit produced good over-exposed determination and they detected almost similar over-exposed region. However, ALEBRD and Exposure 3R over detected the over-exposed region in which both methods misclassified the woman's shirt which is determined as well-exposed region since the pattern on the shirt that can clearly be seen. The over detection problem also happened for the under-exposed region determination by all methods except the proposed method. The misclassified regions is highlighted by red dotted square

in Fig. 8(a) in which the dustbin that in the original dark grey colour is wrongly recognized as under-exposed region. The proposed method successfully recognized the region as well-exposed region since the basket's details could be observed (i.e it is partly covered by the plastic). Therefore, the proposed method produced the most accurate exposure region determination without causing over detection problem.

For *Man* image, all methods successfully detected red oval region in Fig. 9(a) as the over-exposed region. However, the proposed method and Backlit failed to detect the illuminated hair as over-exposed region while ALEBRD, Exposure 3R, exposure 2R and FIM successfully determined this region. This is due to the region in visual was partially and unclearly illuminated, thus the proposed method is unable to detect the region. In other hand, the proposed method detected well-exposed region better as compared to the other methods. This is proved by the dark blue shirt region shown by red rectangle in Fig. 9(a) which was misclassified as under-exposed by Backlit and Exposure 3R and there is small misclassified region detected in the same area by ALEBRD. In addition, these three methods also misclassified the well-exposed regions as indicated by yellow dotted rectangle in Fig. 9(a). As the doorknob can be seen, therefore the region is determined as well-exposed region. Based on the visual evaluation, the proposed method produced high percentage of correct region determination of well-exposed region.

TABLE 3. Subjective evaluation result for region determination.

Images	Quality Score					
	Proposed Method	ALEBRD	Backlit	Exposure 3R	Exposure 2R	FIM
House Balcony	**4.10**	2.90	3.60	2.90	1.40	1.40
Yard	**4.00**	3.40	3.50	3.40	1.20	1.20
Mansion	**4.10**	2.70	3.60	2.70	1.10	1.10
Woman	**4.18**	3.55	3.91	2.36	1.18	1.09
Man	**4.10**	3.40	3.70	3.30	1.10	1.20
Image 1	**3.85**	2.92	3.62	1.92	1.15	1.08
Image 2	**3.64**	3.55	3.36	2.73	1.18	1.18
Image 3	3.30	**4.00**	3.00	3.20	1.20	1.00
Image 4	**4.10**	**4.10**	3.80	2.90	1.20	1.20
Image 5	**3.80**	3.60	**3.80**	3.50	1.20	1.20
Image 6	**3.90**	3.70	**3.90**	2.00	1.10	1.10
Image 7	**3.50**	3.30	**3.50**	3.00	1.20	1.00
Image 8	**3.80**	**3.80**	3.60	3.10	1.20	1.20
Image 9	3.40	3.20	3.40	**3.50**	1.10	1.00
Image 10	**4.10**	3.90	**4.10**	2.40	1.20	1.20
Image 11	**3.70**	3.40	3.50	2.50	1.10	1.10
Image 12	**3.80**	3.60	3.70	2.90	1.20	1.20
Image 13	3.60	**3.80**	3.40	3.10	1.10	1.00
Image 14	**3.90**	3.80	3.40	3.60	1.20	1.20
Image 15	3.80	**3.80**	3.50	3.30	1.20	1.20
Image 16	**3.70**	3.40	**3.70**	3.00	1.10	1.10
Image 17	3.60	**3.80**	3.60	3.20	1.10	1.10
Image 18	**3.70**	**3.70**	**3.70**	3.40	1.10	1.10
Image 19	**3.90**	3.70	3.60	3.00	1.10	1.10
Image 20	**3.90**	3.70	3.60	3.30	1.20	1.10
Image 21	3.90	3.40	**4.00**	2.90	1.40	1.40
Image 22	**3.90**	3.40	**3.90**	3.30	1.20	1.20
Image 23	**3.90**	3.40	3.60	3.10	1.10	1.10
Image 24	**3.80**	3.60	3.60	3.20	1.30	1.30
Image 25	3.80	**3.90**	3.50	3.00	1.10	1.10
Average Score	**3.83**	3.55	3.62	2.99	1.17	1.15

Note : The value in bold indicate highest average score

In addition to these five images, the resultant images produced by all methods for 25 other images could be observed in Appendix II. The resultant images clearly show that the proposed method exhibited better performance than the other methods. Visually, the proposed method has successfully detected almost all regions with high correct detection and

TABLE 4. Background of experts took part in visual assessment.

Expert's Name	Position	Specialization	Years of Experience
Siti Noraini Sulaiman, Assoc. Prof.	Associate Professor / Researcher	Biomedical Engineering, Medical Image Processing, Image Processing	16
Wan Azani Mustafa, Mr.	Lecturer / Researcher	Image processing and analysis	12
Azah Kamilah Draman, Assoc. Prof.	Associate Professor / Researcher	Pattern Analysis and Recognition, Image Processing	20
Ahmad Shahrizan Abdul Ghani, Dr.	Senior Lecturer / Researcher	Image Processing	7
Nor Rizuan Mat Noor, Dr.	Senior Lecturer / Researcher	Image Processing	10
Samsul Setumin, Dr.	Senior Lecturer / Researcher	Image Processing	6
Abdul Jalil Radman, Dr.	Researcher	Image Processing	14
Ahmad Husni Mohd. Shapri, Dr.	Senior Lecturer / Researcher	Image Processing	12
Salina Asi, Dr.	Senior Lecturer / Researcher	Image Processing	8
Mohd. Fauzi Alias, Mr.	Lecturer / Researcher	Image Processing	10

less percentage of misclassification problem. This analysis proves that the introduction of more image characteristics (i.e., entropy and contrast) has successfully reduced the wrong determination of different illumination regions faced by state-of-the-art methods.

The result for the second stage, survey and evaluation by ten image processing experts are tabulated in Table 3. The results represent the average grades for 30 images evaluated by all ten experts. All ten experts preferred the proposed method as the best region determination method amongst other method. They agreed that the proposed method can detect more correct region types with less misclassification problem. From Table 3, the average grades obtained for five images discussed above are between good and excellent quality (i.e., 4.10, 4.00, 4.10, 4.18 and 4.10) as compared with another methods, which are between fair and good quality (i.e., 3.60, 3.50, 3.60, 3.91 and 3.70). Observation on the results for all 30 images show that the proposed method outperforms the other methods for 24 out of 30 images. Out of these 24 images, the proposed method shows high improvement in terms of average quality score as compared with other methods for three images, namely, *House Balcony*, *Mansion* and *Yard*. For another six images, although another methods scored better than the proposed method by the ten experts, the difference of average quality score for thus six images is small and could be neglected.

We extend the analysis of the score obtained from the second stage using box plot. Fig. 10 summarizes average scores collected from the second stage for 30 nonuniform illumination images as box plots. The boxes span from the first to the third quartile, referred to as Q1 and Q3, and the whiskers show the maximum and minimum values in the range of
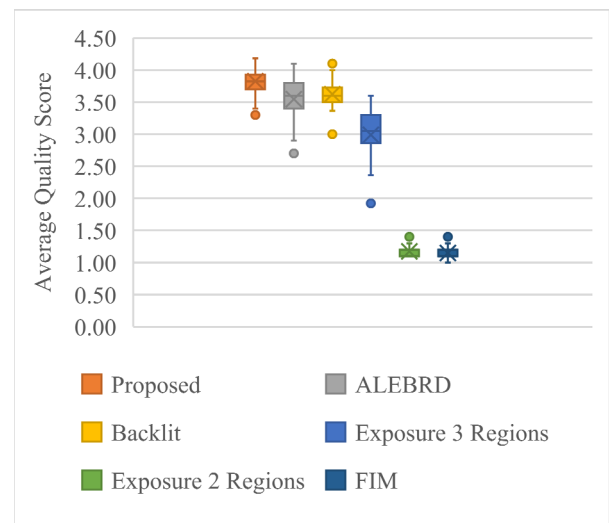

FIGURE 10. Box plot analysis for region determination.

$[Q1-1.5(Q3-Q1), Q3+1.5(Q3-Q1)]$. The band inside the boxes indicates the median, i.e., the second quartile Q2, and the crosses denote the average value while the dot indicate the outlier. From Fig. 10, it can be seen that the proposed method has the highest maximum and the highest median for average score compared to other methods. From Fig. 10 and Table 3, the proposed method gained the highest average score of the average quality score (scores were taken average from 10 experts) while Exposure2R and FIM gained the lowest score amongst the methods.

Therefore, both analyses show that the proposed method outperforms the other methods for this second stage evaluation. As conclusion, the findings obtained in both analyses
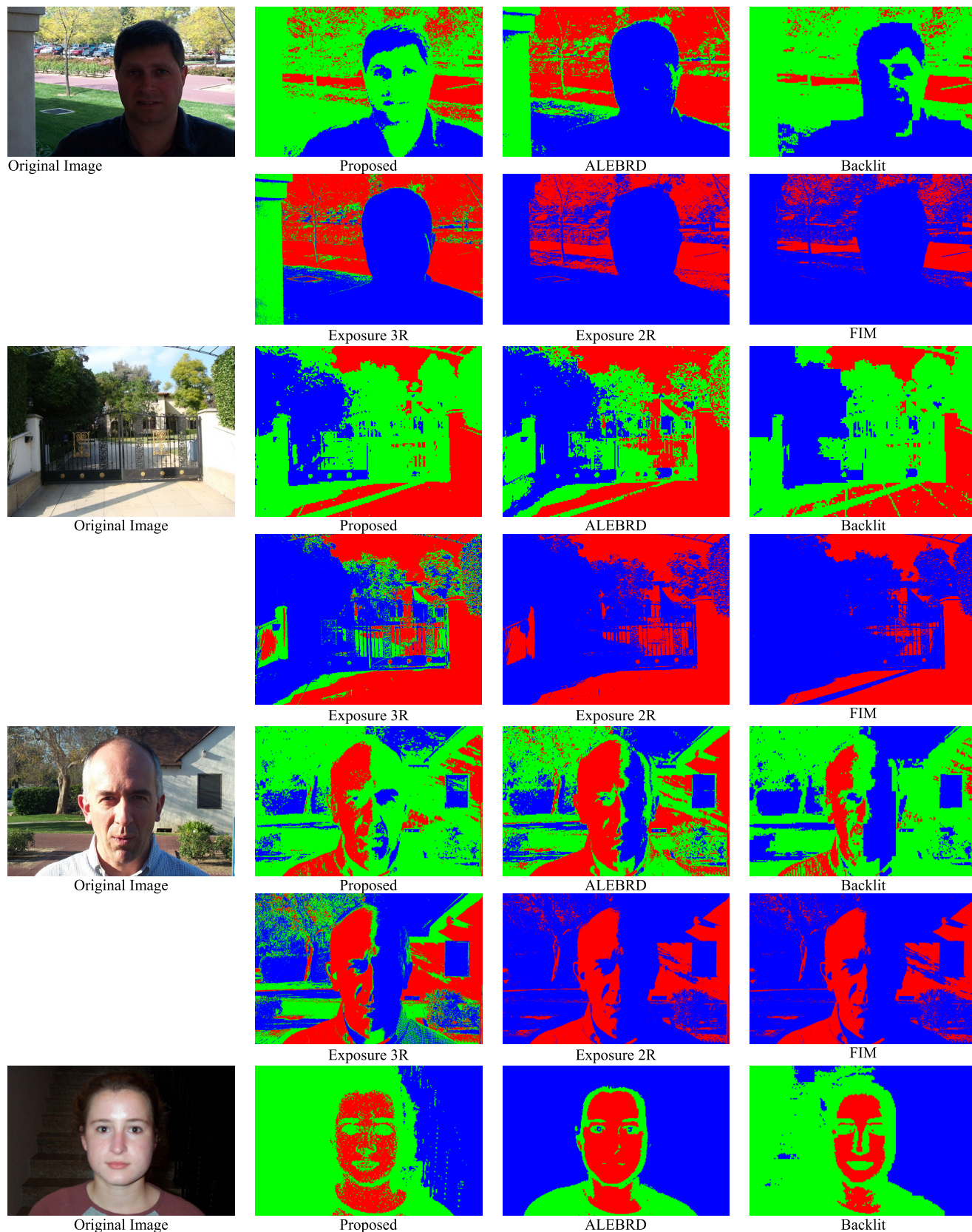
FIGURE 11. Resultant images of exposure region determination using proposed method and state-of-the-art methods.
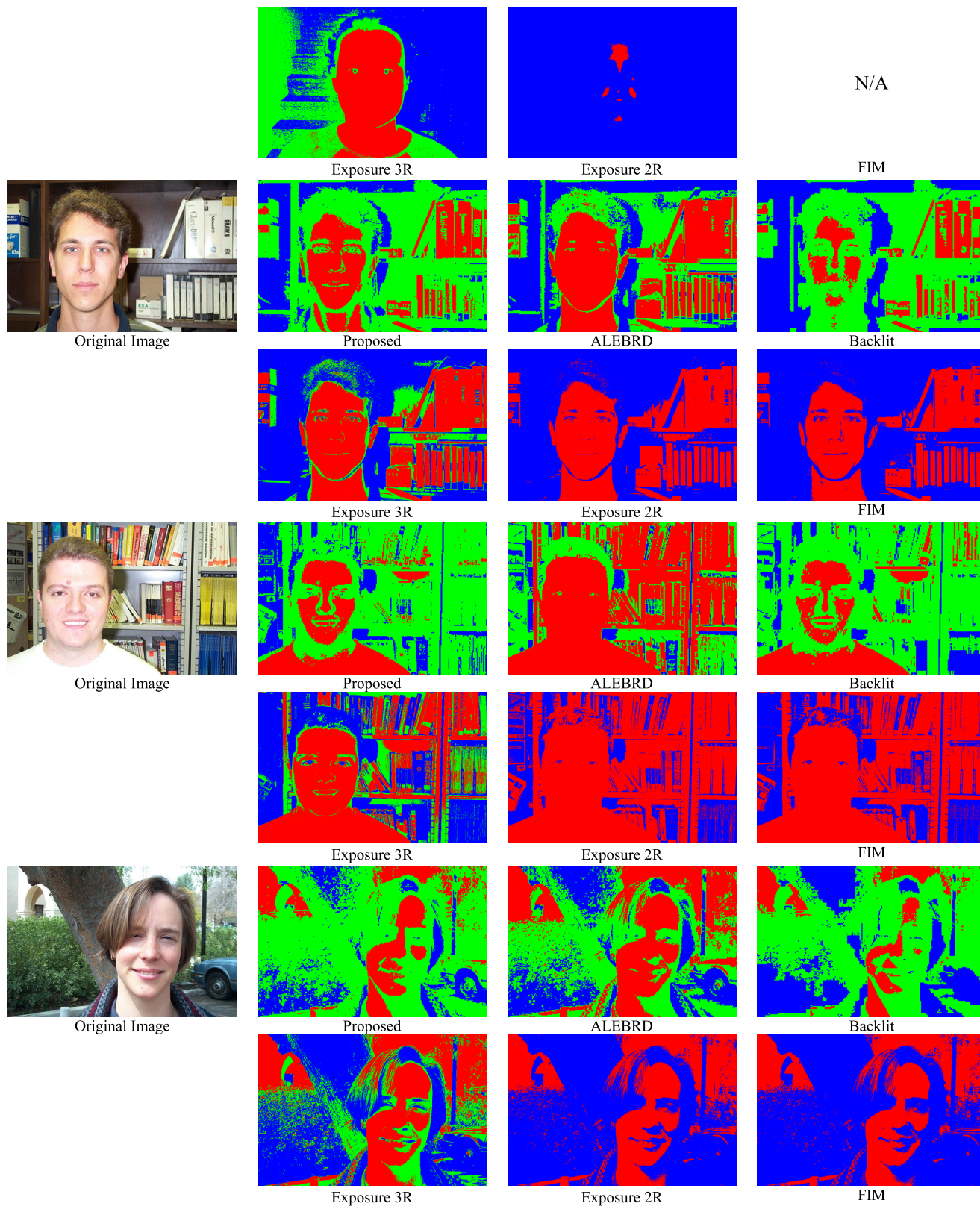
FIGURE 11. *(Continued.)* Resultant images of exposure region determination using proposed method and state-of-the-art methods.
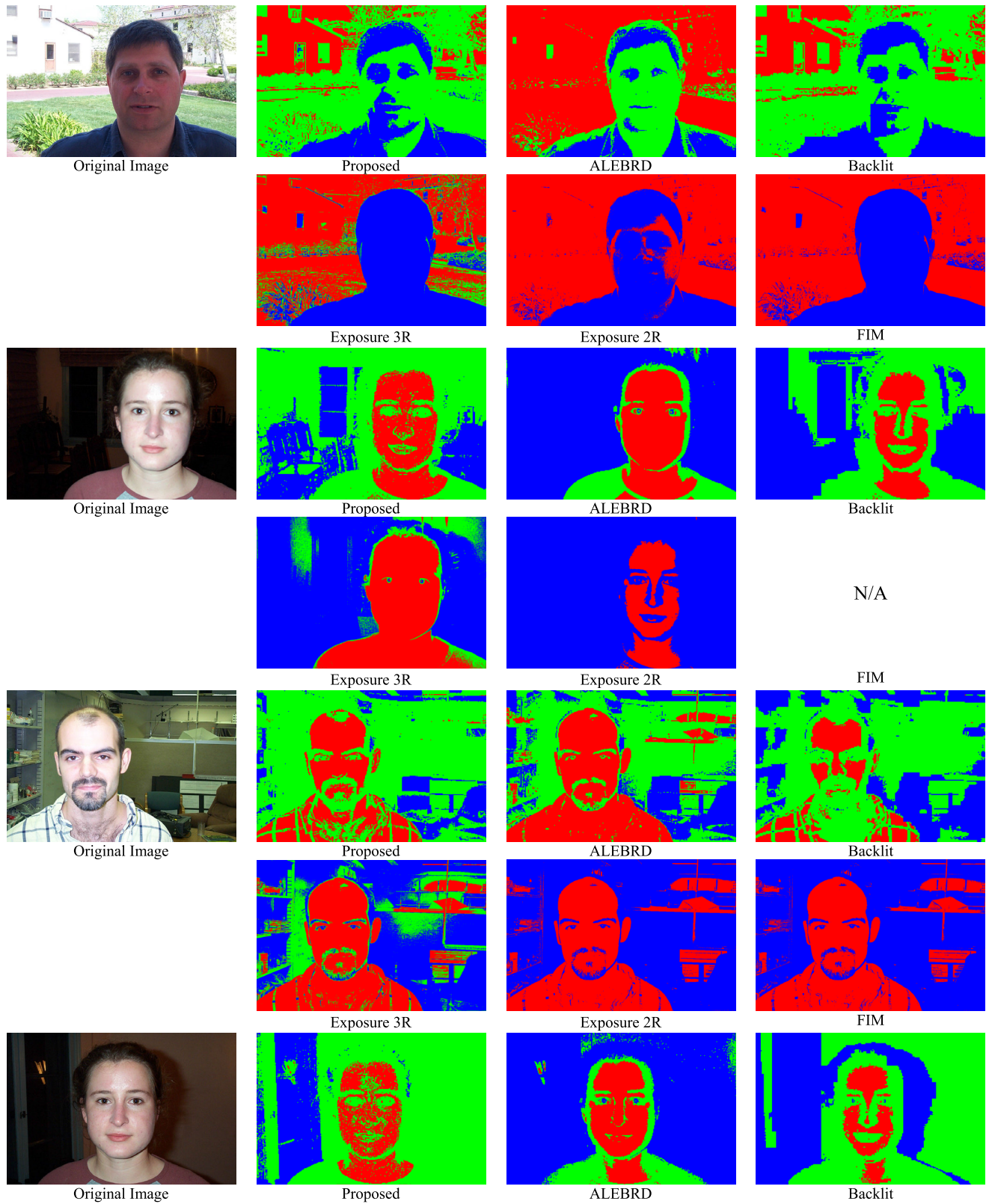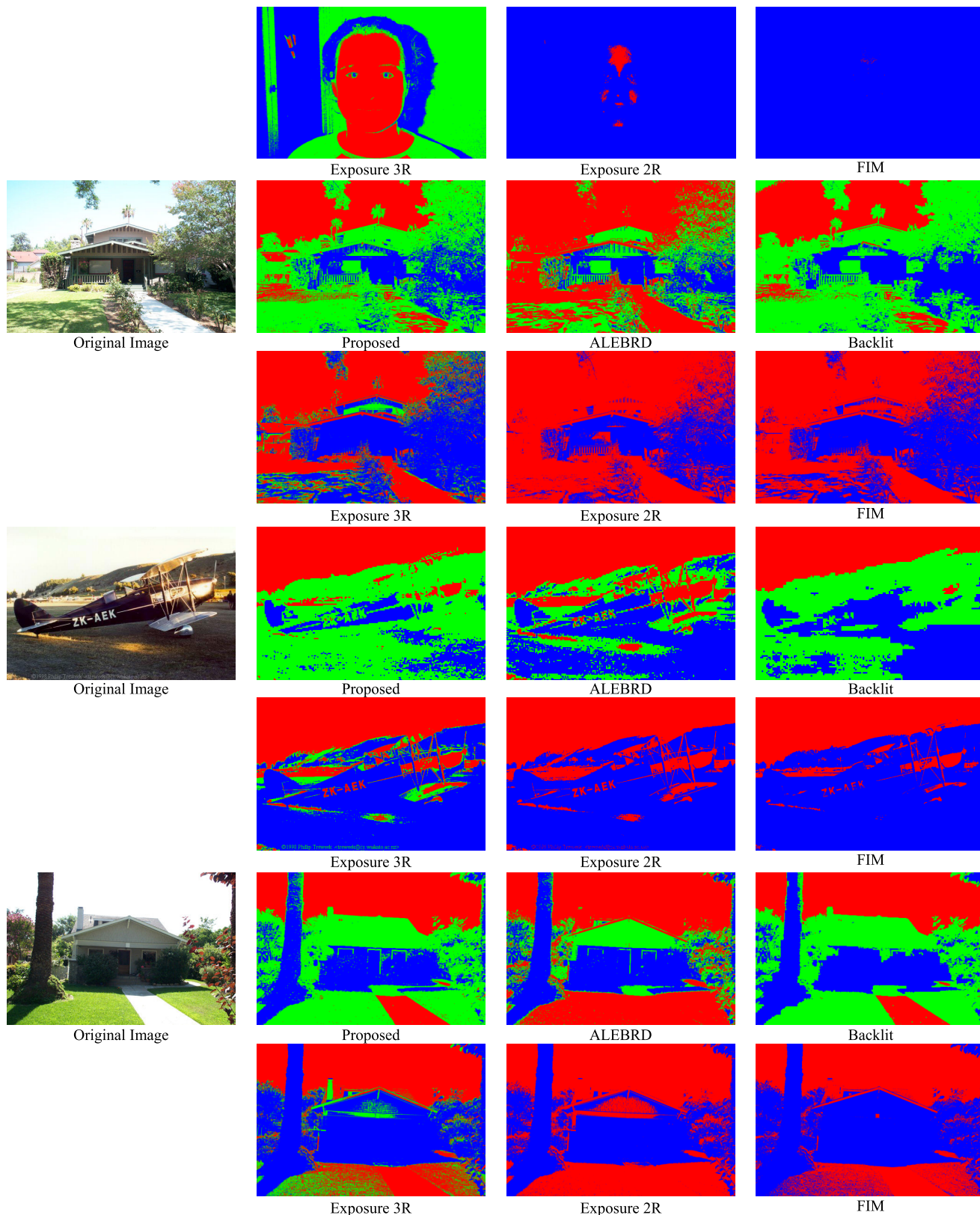
FIGURE 11. *(Continued.)* Resultant images of exposure region determination using proposed method and state-of-the-art methods.

FIGURE 11. *(Continued.)* Resultant images of exposure region determination using proposed method and state-of-the-art methods.
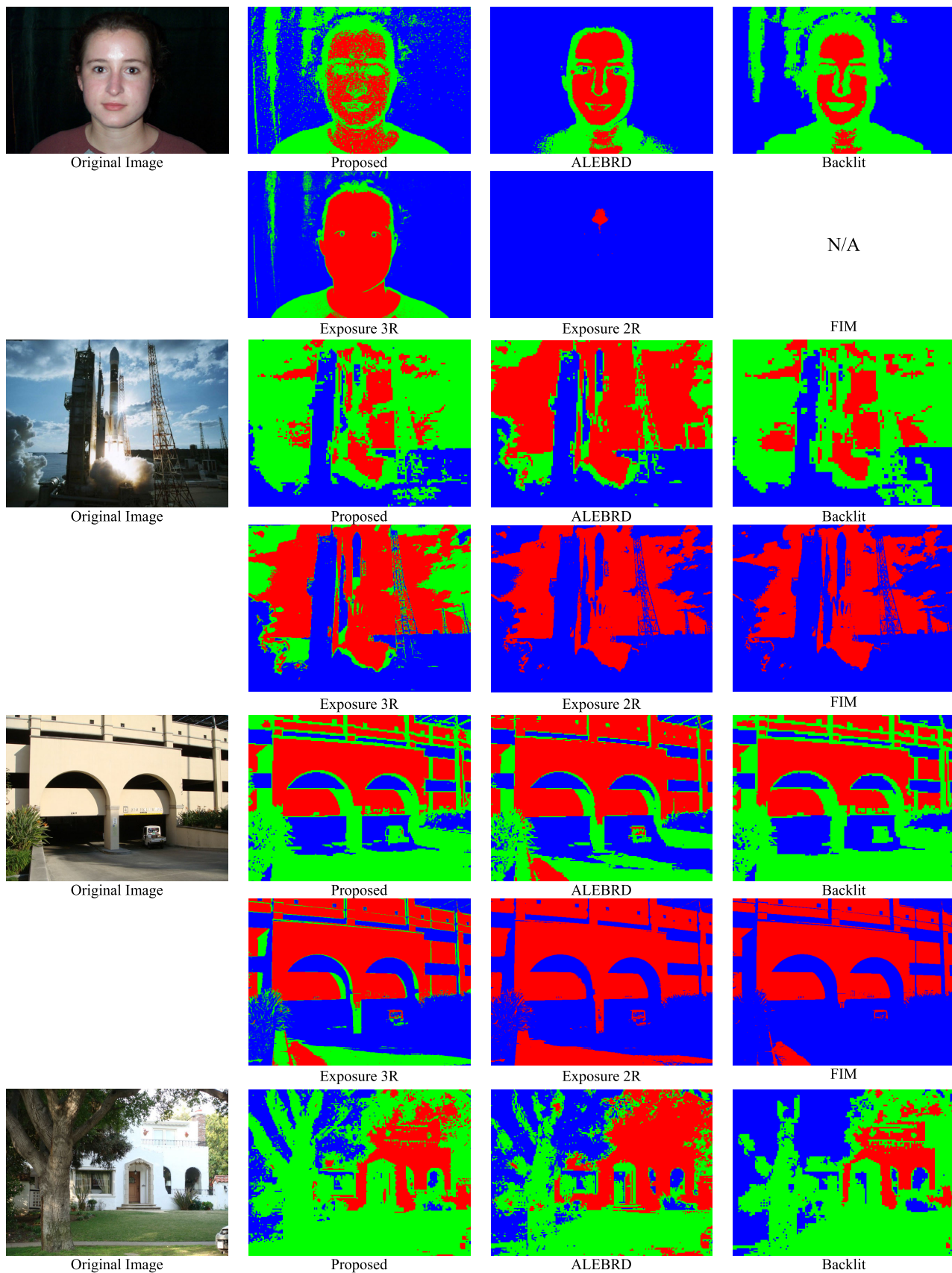
FIGURE 11. *(Continued.)* Resultant images of exposure region determination using proposed method and state-of-the-art methods.

FIGURE 11. *(Continued.)* Resultant images of exposure region determination using proposed method and state-of-the-art methods.

FIGURE 11. *(Continued.)* Resultant images of exposure region determination using proposed method and state-of-the-art methods.
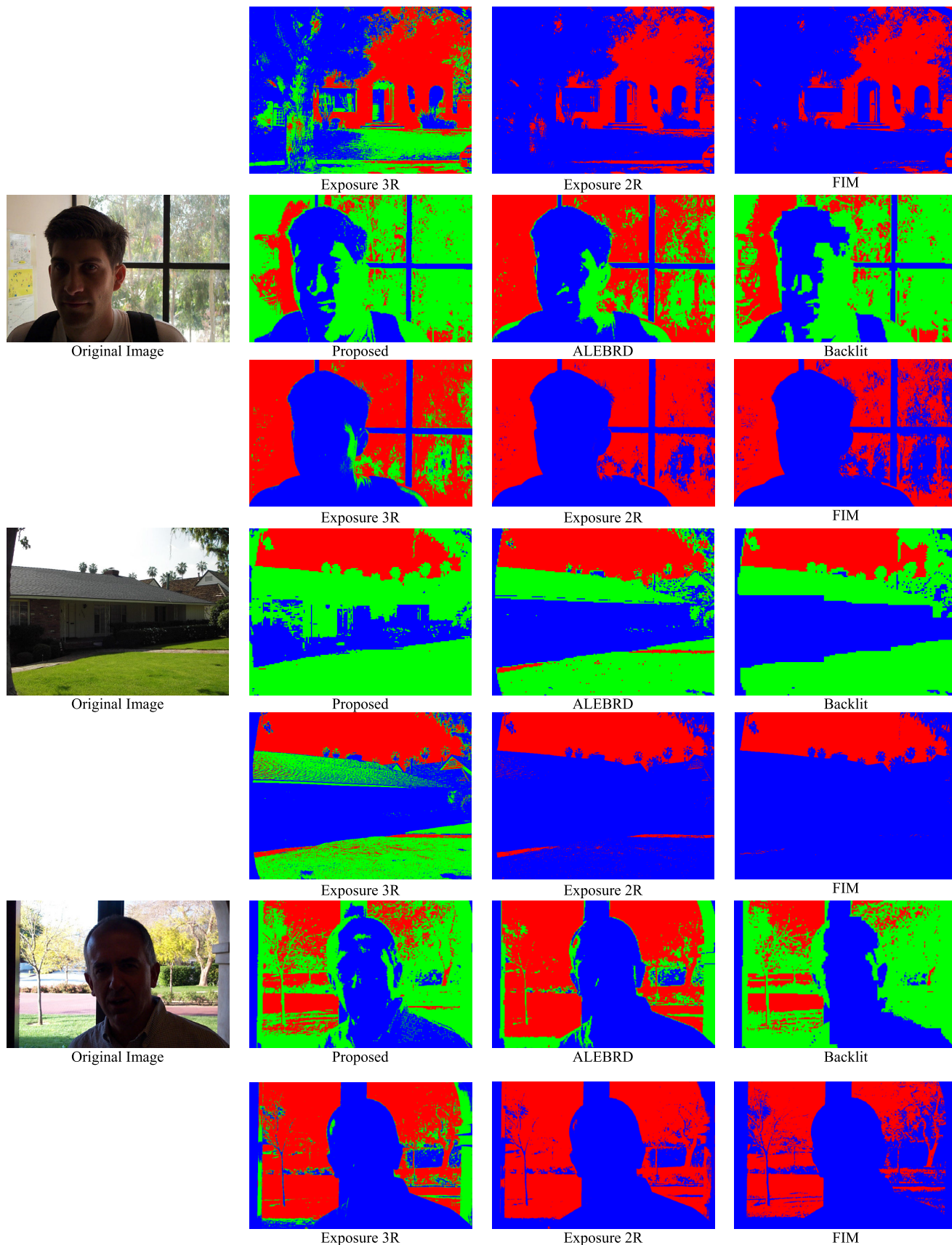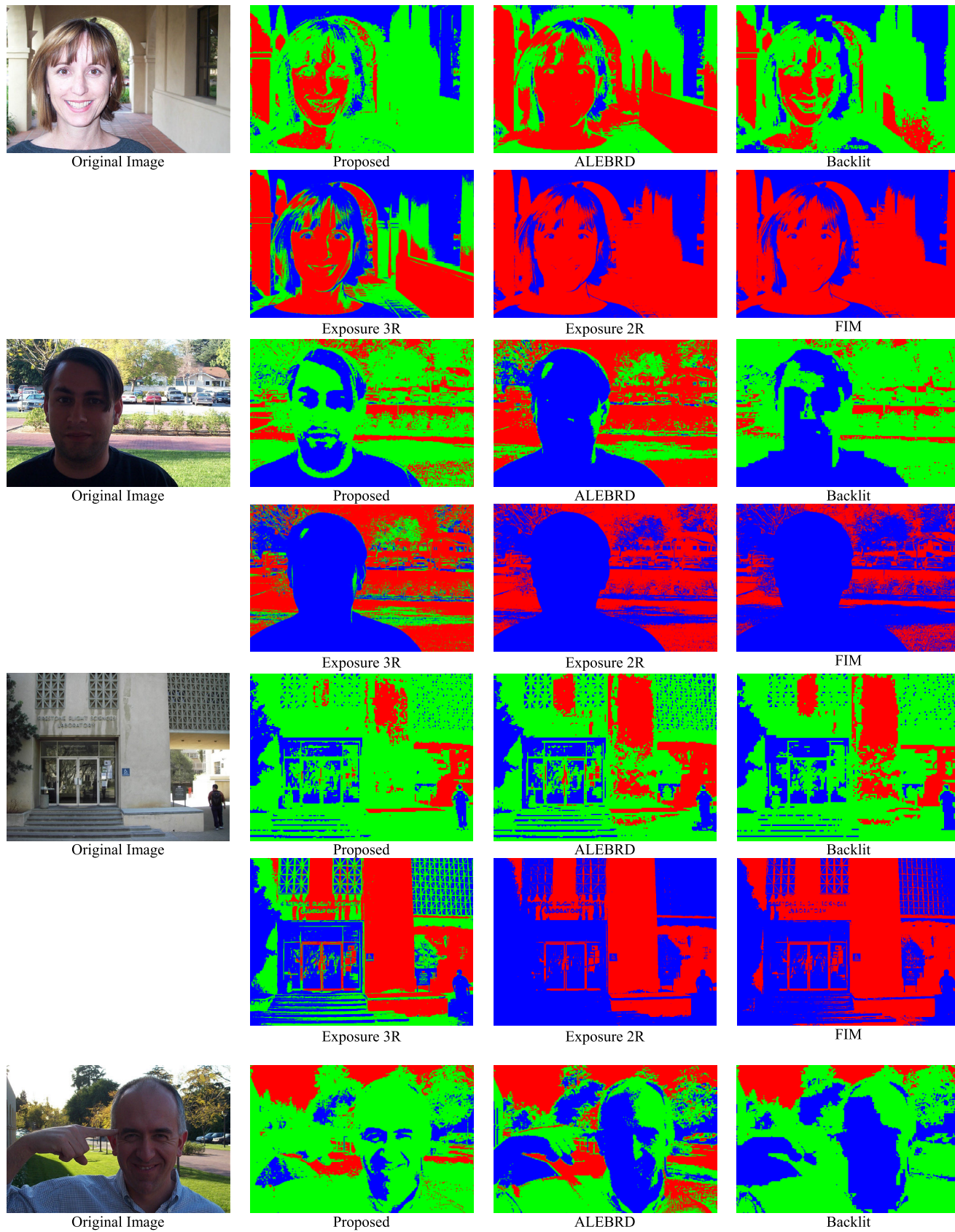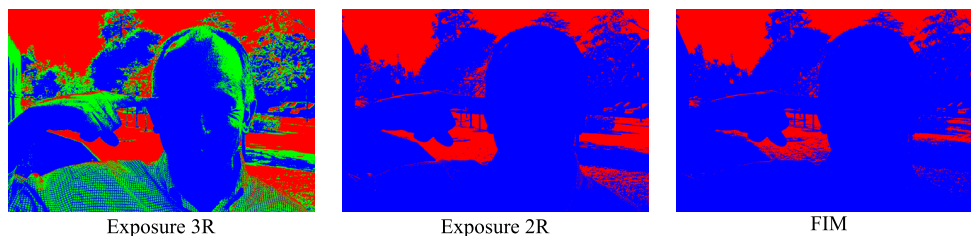
| Exposure 3R | Exposure 2R | FIM |

FIGURE 11. *(Continued.)* Resultant images of exposure region determination using proposed method and state-of-the-art methods.

clearly show that the proposed method has successfully outperformed other methods. Indirectly, these findings prove that the introduction of three new image characteristics (i.e., intensity, entropy and contrast) significantly affect the determination of image regions into three classes, namely, over-exposed, well-exposed and under-exposed.

V. CONCLUSION

This study explains the importance of determining the different areas of illumination to the enhancement of nonuniform illumination images. Most determination methods divide the regions of nonuniform illumination images into bright and dark illuminated areas except three methods that divide the image into three regions which are ALEBRD, Exposure 3R and Backlit. However, these methods only focused on the intensity level to differentiate the area of illumination, therefore led to insufficient of pixels information that resulted in the inaccurately determined regions. The proposed method addresses this problem by considering two other image attributes, namely, contrast and entropy. All attributes are determined in the local area. The experimental results show that the proposed method qualitatively produced better results than the other techniques. Additionally, according to the survey results, experts agree and support that the proposed method is better than the current methods in terms of region determination capability.

APPENDIXES
APPENDIX I
See Table 4.

APPENDIX II
See Figure 11.

REFERENCES

[1] Q.-C. Tian and L. D. Cohen, "Global and local contrast adaptive enhancement for non-uniform illumination color images," in *Proc. IEEE Int. Conf. Comput. Vis. Workshops (ICCVW)*, Oct. 2017, pp. 3023–3030.

[2] L. Hou, H. Ji, and Z. Shen, "Recovering over-/underexposed regions in photographs," *SIAM J. Imag. Sci.*, vol. 6, no. 4, pp. 2213–2235, Jan. 2013.

[3] K. A. S. H. Kulathilake, L. Ranthunga, G. Constantine, and N. A. Abdullah, "Hierarchical region based template matching technique for global motion reduction of coronary cineangiograms," *Int. J. Comput. Theory Eng.*, vol. 7, no. 2, pp. 156–161, 2015.

[4] G. Biderman, T. Cooper, M. Hill, L. Keimig, and C. Nicholson. *2017 Solar Eclipse Guide, National Parks at Night*. Accessed: Sep. 1, 2018. [Online]. Available: http://www.nationalparksatnight.com/2017-solar-eclipse-guide-here-comes-the-sun

[5] E. Priya, S. Srinivasan, and S. Ramakrishnan, "Retrospective non-uniform illumination correction techniques in images of tuberculosis," *Microsc. MicroAnal.*, vol. 20, no. 5, pp. 1382–1391, Oct. 2014.

[6] K. R. Bhutani and A. Battou, "An application of fuzzy relations to image enhancement," *Pattern Recognit. Lett.*, vol. 16, no. 9, pp. 901–909, Sep. 1995.

[7] L. Wang, L. Wei, K. Zhou, B. Guo, and H.-Y. Shum, "High dynamic range image hallucination," in *Proc. 18th Eurograph. Conf. Rendering Techn.*, 2007, pp. 321–326.

[8] M. Hanmandlu, O. P. Verma, N. K. Kumar, and M. Kulkarni, "A novel optimal fuzzy system for color image enhancement using bacterial foraging," *IEEE Trans. Instrum. Meas.*, vol. 58, no. 8, pp. 2867–2879, Aug. 2009.

[9] K. Hasikin and N. A. M. Isa, "Adaptive fuzzy intensity measure enhancement technique for non-uniform illumination and low-contrast images," *Signal, Image Video Process.*, vol. 9, no. 6, pp. 1419–1442, Sep. 2015.

[10] D. Guo, Y. Cheng, S. Zhuo, and T. Sim, "Correcting over-exposure in photographs," in *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, vol. 1, Jun. 2010, pp. 515–521.

[11] D.-H. Lee, Y.-J. Yoon, S.-J. Kang, and S.-J. Ko, "Correction of the over-exposed region in digital color image," *IEEE Trans. Consum. Electron.*, vol. 60, no. 2, pp. 173–178, May 2014.

[12] Y.-J. Yoon, K.-Y. Byun, D.-H. Lee, S.-W. Jung, and S.-J. Ko, "A new human perception-based over-exposure detection method for color images," *Sensors*, vol. 14, no. 9, pp. 17159–17173, 2014.

[13] S. Lee, H. Lee, P. Abbeel, and A. Y. Ng, "On over-exposed region detection with regularized logistic regression," in *Proc. 10th Int. Conf. Ubi-Media Comput. Workshops (Ubi-Media)*, 2017, pp. 1–6.

[14] J. Kim and A. Kim, "Light condition invariant visual SLAM via entropy based image fusion," in *Proc. 14th Int. Conf. Ubiquitous Robots Ambient Intell. (URAI)*, Jun. 2017, pp. 529–533.

[15] G. Raju and M. S. Nair, "A fast and efficient color image enhancement method based on fuzzy-logic and histogram," *AEU-Int. J. Electron. Commun.*, vol. 68, no. 3, pp. 237–243, Mar. 2014.

[16] A. A. M. Salih, K. Hasikin, and N. A. M. Isa, "Adaptive fuzzy exposure local contrast enhancement," *IEEE Access*, vol. 6, pp. 58794–58806, 2018.

[17] T. L. Kong and N. A. M. Isa, "Bi-histogram modification method for non-uniform illumination and low-contrast images," *Multimedia Tools Appl.*, vol. 77, no. 7, pp. 8955–8978, Apr. 2018.

[18] C.-J. Chung, W.-Y. Chou, and C.-W. Lin, "Under-exposed image enhancement using exposure compensation," in *Proc. 13th Int. Conf. ITS Telecommun. (ITST)*, Nov. 2013, pp. 204–209.

[19] S. Wang, J. Zheng, H.-M. Hu, and B. Li, "Naturalness preserved enhancement algorithm for non-uniform illumination images," *IEEE Trans. Image Process.*, vol. 22, no. 9, pp. 3538–3548, Sep. 2013.

[20] O. P. Verma, P. Kumar, M. Hanmandlu, and S. Chhabra, "High dynamic range optimal fuzzy color image enhancement using artificial ant colony system," *Appl. Soft Comput.*, vol. 12, no. 1, pp. 394–404, Jan. 2012.

[21] S. Lee, N. Kim, and J. Paik, "Adaptively partitioned block-based contrast enhancement and its application to low light-level video surveillance," *SpringerPlus*, vol. 4, no. 1, p. 431, Dec. 2015.

[22] J.-M. Sung, D.-C. Kim, B.-Y. Choi, and Y.-H. Ha, "Image thresholding using standard deviation," *Proc. SPIE*, vol. 9024, Mar. 2014, Art. no. 90240R.

[23] D.-Y. Tsai, Y. Lee, and E. Matsuyama, "Information entropy measure for evaluation of image quality," *J. Digit. Imag.*, vol. 21, no. 3, pp. 338–347, Sep. 2008.

[24] C. E. Shannon, "A mathematical theory of communication," *Bell Syst. Tech. J.*, vol. 27, no. 3, pp. 379–423, 1948. Accessed: Aug. 28, 2018. [Online]. Available: http://cm.bell-labs.com/cm/ms/what/shannonday/shannon1948.pdf

[25] Z. Ye, H. Mohamadian, S.-S. Pang, and S. Iyengar, "Image contrast enhancement and quantitative measuring of information flow," in *Proc. 6th WSEAS Int. Conf. Inf. Secur. Priv.*, 2007, pp. 172–177.

[26] M. T. Rahman, N. Kehtarnavaz, and Q. R. Razlighi, "Using image entropy maximum for auto exposure," *J. Electron. Imag.*, vol. 20, no. 1, 2011, Art. no. 013007.

[27] H. D. Cheng, M. Xue, and X. J. Shi, "Contrast enhancement based on a novel homogeneity measurement," *Pattern Recognit.*, vol. 36, no. 11, pp. 2687–2697, Nov. 2003.

[28] T. L. Kong and N. A. M. Isa, "Enhancer-based contrast enhancement technique for non-uniform illumination and low-contrast images," *Multimedia Tools Appl.*, vol. 76, no. 12, pp. 14305–14326, Jun. 2017.

[29] *Methodology for the Subjective Assessment of the Quality of Television Pictures*, Int. Telecommun. Union, Geneva, Switzerland, 2012.

[30] *Computational Vision at Caltech Data Sets*. Accessed: Aug. 1, 2018. [Online]. Available: http://www.vision.caltech.edu/archive.html

NOR ASHIDI MAT ISA received the B.Eng. degree (Hons.) in electrical and electronic engineering from Universiti Sains Malaysia (USM), in 1999, and the Ph.D. degree in electronic engineering (majoring in image processing and artificial neural network), in 2003. He is currently a Professor and the Deputy Dean (Academic, Career, and International) with the School of Electrical and Electronic Engineering, USM. His research interests include intelligent systems, image processing, neural networks, biomedical engineering, intelligent diagnostic systems, and algorithm.

NOR HIDAYAH SAAD received the B.Eng. degree in electronic engineering and the M.Sc. degree in electronic system design engineering from Universiti Sains Malaysia, in 2006 and 2010, respectively, where she is currently pursuing the Ph.D. degree. She is also a member of the Imaging and Intelligent System Research Group, Universiti Sains Malaysia. Since 2011, she has been a Lecturer with Universiti Malaysia Perlis. Her research interests include computer vision, image processing, and pattern recognition.

ABDULLAH AMER MOHAMMED SALIH received the B.S. Eng. degree in software engineering from Al-Mansour University College, Baghdad, Iraq, in 2008, and the master's degree in electrical computer engineering from Universiti Sains Malaysia, in 2014, and the Ph.D. degree in electronic engineering (major in image processing and computer vision) from Universiti Sains Malaysia, in 2018.

• • •