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

03CS6901 Seminar I

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C E R T I F I C A T E

This is to certify that, this report titled ***Local Neighbourhood Image Properties for Exposure Region Determination Method in Nonuniform Illumination Images*** is a bonafide record of the **03CS6901 Seminar I** presented on March 15, 2021 by

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First Semester M. Tech. Computer Science & Engineering (Image Processing)

scholar, under our guidance and supervision, in partial fulfillment of the requirements for the award of the degree, **M. Tech. Computer Science & Engineering (Image Processing)** of **APJ Abdul Kalam Technological University**.

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March 15, 2021

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Acknowledgments

I am greatly indebted to God Almighty for being the guiding light throughout with his abundant grace and blessings that strengthened me to do this endeavour with confidence.

I express my sincere thanks to **Dr. Jacob Thomas V.**, Principal, College of Engineering Chengannur for extending all the facilities required for doing my seminar. My heartfelt words of gratitude to **Dr. Smitha Dharan**, Professor and Head of Department of Computer Engineering, for providing constant support.

Now I express my gratitude to my seminar co-ordinator **Mr. Ahammed Siraj K K**, Associate Professor in Computer Engineering and my seminar guide **Ms. Syama S**, Assistant Professor in Computer Engineering for guiding me in my work and providing timely advices and valuable suggestions.

Shanu Joy.

Abstract

Image acquisition is the first step in Digital Image Processing. It is done by using image sensors. Image sensors are used in electronic devices which includes digital cameras, optical mouse devices, medical imaging equipment etc. During image acquisition, these sensors produces non-uniform illumination images. This image is characterised by different lightness values in certain regions in a digital image. This is formed due to several factors such as extreme environment light conditions, limitations in imaging devices, and the unsuitable exposure parameter settings of imaging devices. Information residing in this regions are hidden. So in order to extract those information, non-uniform image is needed to be converted to uniformly illuminated image. Enhancement technique is needed to be applied. But applying enhancement method with the same enhancement rate to the entire image can over enhance or under enhance resultant image. So before enhancement, exposure regions are needed to be determined. Then different enhancement rate can be applied to different regions separately. Existing methods that introduced region determination process failed to accurately determine exposure regions because those methods only consider intensity to determine the regions. For this problem, a new method used for the accurate detection of nonuniform illumination regions is proposed which considers three image attributes, namely, intensity, entropy and contrast, which are evaluated locally in detecting the regions. These three attributes are combined with a rule based method for the identification of illumination regions. Experimental results shows that proposed method is better than the current methods in terms of region determination capability.

Contents

Chapter 1

Introduction

Advancements in image processing have enabled the analysis of digital images in most computer vision applications, video surveillance, and biomedical engineering. Digital images are often low in quality and suffer from non-uniform illumination or brightness, loss of details, and poor contrast. These problems become critical when the foreground of interest is difficult to be distinguished from the background, which worsens the segmentation problem and allows false recognition and detection to occur. The human visual system has far larger dynamic ranges than most commercial cameras and video cameras. These devices have limited dynamic ranges; thus, recorded images obtained from these devices are usually non-homogeneous and low in contrast. Improper lighting condition and external disturbances, which worsen the problems, are inevitable during image acquisition.In this respect, most of the images acquired through commercial cameras and video cameras exhibit problems in non-uniform illumination and low contrast.

Nonuniform illumination image is a such kind of image which is 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 [2]. This image is characterised by different lightness values in certain regions in a digital image. 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 average luminance of the entire image, whereas the over-exposed region appears brighter [3]. The details in both regions cannot be seen or disappear in a nonuniform illumination image. Variation of intensity in both regions will be low. This results in low contrast areas.

Fig. 1 shows the examples of nonuniform illumination images. In fig. 1(a), over exposed region represented by red rectangle appears to washout the details. In fig.1(b), over exposed region represented by red rectangle is highly affected by sunlight, whereas the underexposed region represented by dotted red rectangle receives less sunlight. Microscopic image in fig. 1(c), with improper camera settings produced over exposed region represented by red rectangle and under exposed region represented by dotted rectangle. Both regions hide their

(a) (b) (c)

Figure 1: Examples of nonuniform illumination image. Coronary Cineangiograms image; (b) Scenery image; (c) Microscopic image.

details. This led to the inaccurate determination of the size or features of the object of interest. This properties of nonuniform illumination image cause inaccuracy during the segmentation process. So in order to retrieve hidden information, it is necessary to convert this image into uniformly illuminated images. For that purpose, first step is to determine different exposure regions in the image. Many researchers have contributed to the development of region determination and correction methods. Those techniques only considered intensity when determining the exposure regions. This limitation motivated to develop a new approach by which exposure regions are determined on basis of more than one property for the determination of precise regions. The overview of the proposed method is that, it focus on three image properties called local intensity, contrast and entropy of the image for the determination of exposure levels in a nonuniform illumination image.

Chapter 2

Literature survey

1. **A novel optimal fuzzy system for color image enhancement using bacterial foraging** [4], IEEE Trans. Instrum. Meas., vol. 58, no. 8, pp. 2867–2879, Aug. 2009.

   This model has the capability to determine under and over exposure regions from a non uniform illumination image. For determining these two regions, a simple threshold method was applied on the intensity value. This threshold value were set to 0.5 and 0.85 respectively. After determining regions, for correcting exposure, RGB color was converted to HSV color space. Direct enhancement on RGB color model is inappropriate for human visual system. So its necessary to convert it to Hue, Saturation and Intensity color space before enhancement. During enhancement, original color (Hue) of the image should not be disturbed and Saturation and intensity value should exceed maximum value. For the enhancement of under exposed region, parametric sigmoid function and for over exposed region, power law operator is used. But this method is subjective. It raises concern about inaccurate region determination, because each image is unique and applying fixed threshold value for all images is impossible. So its region determination is inaccurate.

2. **High dynamic range optimal fuzzy color image enhancement using artificial ant colony system**[5], Appl. Soft Comput., vol. 12, no. 1, pp. 394–404, Jan. 2012.

   Here determined under, over and mixed regions from image by using exposure criteria. It modified the fixed thresholding technique and calculated upper and lower threshold from the image itself using a pivot parameter. 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 be lie in the mixed region. Classification are done based on intensity value. Even though this method is an improved version of previous method, region classification is inaccurate. Because here only considers brightness as a factor for classifying regions. Variance of luminance and amount of information in certain region are not considered.

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

   Here divided the intensity of the nonuniform illumination image into two regions, namely, dark and bright. Here 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, introduced fuzzy intensity measure (FIM) to determine a threshold value that is more adaptive than the method in [4]. 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, is not defined in this method.

4. **Adaptively partitioned block-based contrast enhancement and its application to low light-level video surveillance**[7], SpringerPlus, vol. 4, no. 1, p. 431, Dec. 2015.

   Here 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 two main regions, namely, dark and background, 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.

5. **Adaptive fuzzy exposure local contrast enhancement**[8], IEEE Access, vol. 6, pp. 58794–58806, 2018.

Here 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 $\times$ 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. Enhanced each regions separately using fuzzy intensity measure enhancement. Even though this method performs better than other methods, here regions are classified by only using intensity. Amount of information and the variance of the luminance in a certain region are not considered. So, region misclassification occurs.

Chapter 3

Proposed system

Limitations in previous region determination methods motivated to develop a new approach by which exposure regions are determined on basis of more than one property for the determination of precise regions. Proposed method introduced entropy and contrast to integrate with the intensity for minimizing the misclassification problem especially on the well exposed region.
Entropy specifies amount of information in a certain region. and contrast specifies variance of the luminance in a certain region. These attributes can be used in measuring the details as well as detecting the well-exposed region in nonuniform illumination image.
Proposed method takes a color nonuniform illumination image of size R $\times$ C where R is the no. of rows and C is the no. of columns. It is then converted into Hue, Saturation, and Value (HSV) color model. The reason why RGB is converted to HSV is that HSV is good for object detection. Unlike RGB, HSV separates intensity of an image from its color information. Another color model called YCbCr also perform this separation. But HSV is often used because the code for converting RGB to HSV is widely available and can apply easily. For example, Matlab includes function rgbtohsv() for conversion. In order to conduct local processing, input image is needed to be divided into several blocks of size m $\times$ n.

3.1 Determination of Intensity Levels

In order to provide a simple and precise region determination based on the intensity, proposed method 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. The Value or intensity, V in HSV color model 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.

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

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

where V(i, j) is the intensity value at pixel position (i, j).
Two threshold points are determined to categorize the intensity of each block into three levels.

$$U_t = V_a + V_d \qquad Upper\ Threshold$$

$$L_t = V_a - V_d \qquad Lower\ Threshold$$

Mean of intensity in each m × n block, I is calculated. Then I is categorized into three different levels, low, medium and high, where the range of intensities for each level are defined in (3),

$$I = \begin{cases} I_{low} & if\ \ I < L_t \\ I_{middle} & if\ \ L_t \leq I \leq U_t \\ I_{high} & if\ \ I > U_t \end{cases} \tag{3}$$

3.2 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 [9]. It describes how much uncertainty or randomness occur in an image. High entropy specifies large amount of information lies in that particular region. This concept is adopted in proposed method for detecting the well-exposed region which must exhibit the richness in details. Entropy of each block sized m × n, E_{local} is calculated using Shannon's entropy. Shannon's entropy for each block X, with k grey levels $x_1, x_2, ..., x_k$ is defined as,

$$E_{local} = -\sum_{i=1}^{k} P_i log_2 P_i \tag{4}$$

where P_i represents the probability of grey level X_i . Then, the mean entropy of the entire image, E_a is calculated using (5) and becomes the reference value in dividing high and low entropy.

$$E_a = \frac{1}{N} \sum_{b=1}^{N} E_{local}(b) \tag{5}$$

where $E_{local}(b)$ is the entropy of a block sized m × n, and N is the number of blocks in an entire image. Subsequently, entropy is divided into two regions, low entropy and high entropy, based on the global mean entropy. It is represented in equation (6) as,

$$E = \begin{cases} E_{low} & if\ \ E_{local} < E_a \\ E_{high} & if\ \ E_{local} \geq E_a \end{cases} \tag{6}$$

3.3 Determination of Contrast Levels

In the proposed method, the contrast of an image has also been considered in determining the exposure regions. In general, contrast refers to the difference in luminance between an object and its surrounding region [10]. 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 [11]. This feature indicate that probably no or less details are found in the low contrast region compared to high contrast region. The contrast, Clocal of a local region m × n is calculated using (7):

$$C_{local} = \frac{1}{m \times n} \sum_{x=1}^{m} \sum_{y=1}^{n} G^2(x,y) - |\frac{1}{m \times n} \sum_{x=1}^{m} \sum_{y=1}^{n} G(x,y)|^2 \tag{7}$$

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). Mean of the local contrast of the entire image, C_a is calculated using (8):

$$C_a = \frac{1}{N} \sum_{b=1}^{N} C_{local}(b) \tag{8}$$

where $C_{local}(b)$ is the contrast of a block sized m× n, and N is the number of blocks in an entire image. Calculated contrast of each local region is then distinguished into two levels, namely, low contrast, C_{low} and high contrast, C_{high} using (9).

$$C = \begin{cases} C_{low} & if\ \ C_{local} < C_a \\ C_{high} & if\ \ C_{local} \geq C_a \end{cases} \tag{9}$$

3.4 Overall Region Determination

The final stage is conducted to categorise all blocks in the image to 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 3.1.

Input: Level of intensity - I for each block, Level of Entropy – E for each block, Level of contrast – C for each block

Output: Exposure Region, R

1. Input current block
2. If E and C are in high level, then R is well exposed
3. Else
4. If both E and C are in low level, or either E or C is in high level, then R is determined using equation (10)
5. Repeat step 1- 4 for m × n blocks
6. End

Table 3.1: Pseudocode for overall region determination.

Based on Table 3.1 the main idea that differentiates the proposed method with the existing ones is shown in step 2. 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 cases, this is not true. Because even though intensity is low or high, their is a chance that details might be clearly visible in those regions. So along with intensity, their amount of information contained and variance of luminance is also needed to be analysed. This is considered in step 2. Meanwhile, the entropy and the contrast can be both in low level or either one can be in high level. Based on the above mentioned situation, three cases can be created as follows:

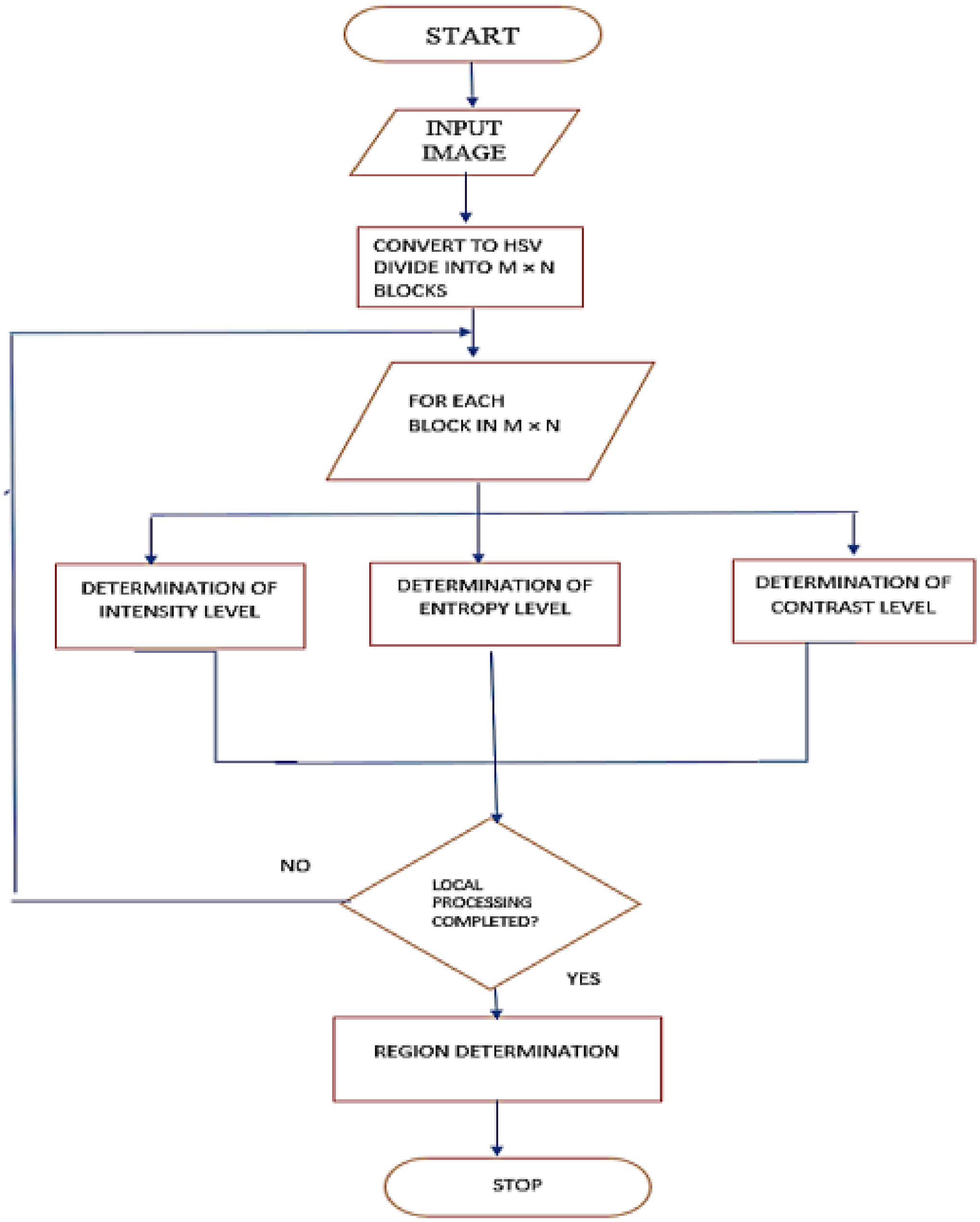
Case 1:The entropy (E_{low}) AND contrast are low (C_{low}).
Case 2:The entropy is low (E_{low}) AND contrast is high (C_{high}).
Case 3: The entropy is high (E_{high}) AND contrast is low (C_{low}).

For this case, the region will be determined based on the intensity. This is represented in (10).

$$R = \begin{cases} Under\ \ exposed & if\ \ I = I_{low} \\ Well\ \ exposed & if\ \ I = I_{medium} \\ Over\ \ exposed & if\ \ I = I_{high} \end{cases} \tag{10}$$

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.

Overall working of the proposed method is represented in this flowchart.



Chapter 4

Conclusions

4.1 Results

4.1.1 Dataset

In order to demonstrate the performance of the proposed approach, images are obtained from California Institute of Technology database [12]. 30 image are taken for performance evaluation. Evaluation is performed 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.

4.1.2 Results of the proposed method

Performance analysis is conducted using two stages. First stage focus on visual evaluation i.e., qualitative analysis. The region detection results obtained by the proposed method is compared with five methods named as AFELCE[8], Backlit[7], Exposure 3R [5], Exposure 2R [4] and FIM [6].

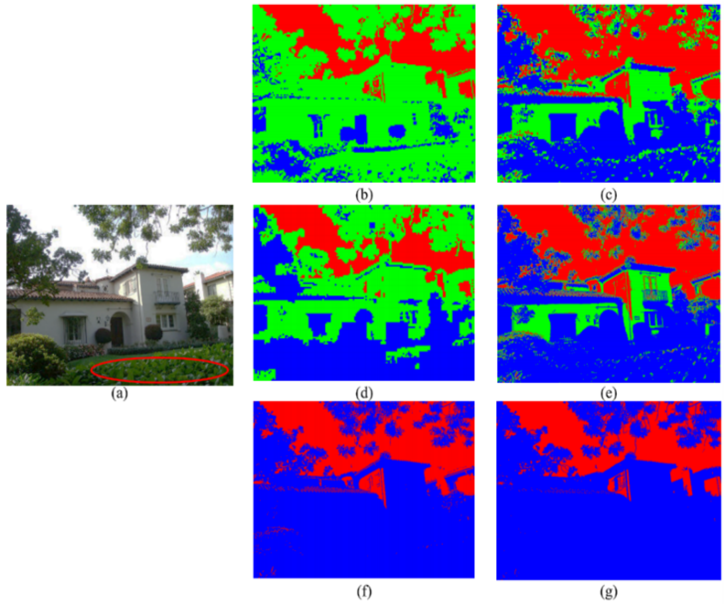


Figure 1: Resultant Images of Region Determination for Yard Image (a) Original Image; (b) Proposed Method (c) AFELCE (d) Backlit (e) Exposure 3R (f) Exposure 2R (g) FIM.

In fig 1, plants indicated by red oval is supposed to be classified as well exposed image. Because plant details are clearly visible. But based on intensity value, all 5 methods classified this as under exposed, while proposed method based on the Pseudocode determined its entropy and contrast as high. So regardless of intensity value, it accurately classified this part as well exposed region. As for detection of over exposed region, all methods correctly detected it by representing red color in the sky part. Misclassification for both under and well exposed are clearly visible in other five methods as compared with proposed method.

Fig. 2 shows the resultant images of region determination for House Balcony image. Referring to the original House Balcony image in Fig. 2(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 AFELCE and Exposure 3R detected wider over-exposed regions including the white pillar highlighted by black dotted rectangle in Fig. 2(c) and Fig. 2(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. 2(b) and Fig. 2(d) whereby the proposed method successfully detected only several parts of the plants that

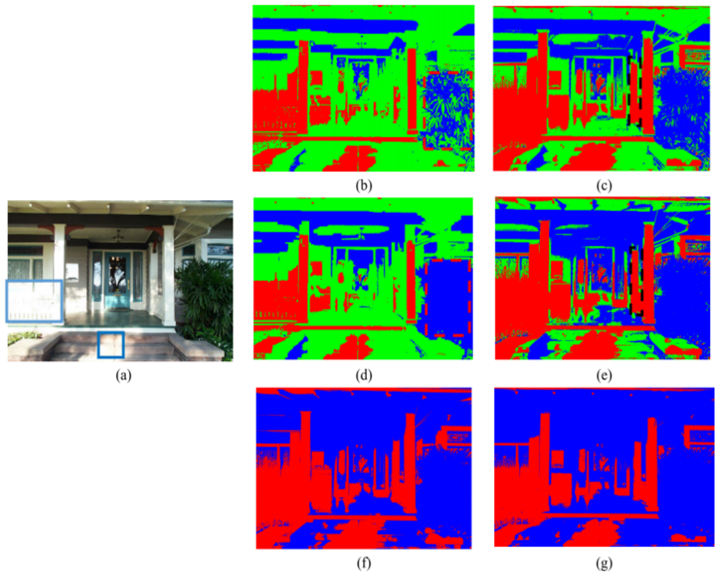


Figure 2: Resultant Images of Region Determination for House balcony image((a) Original Image; (b) Proposed Method (c) AFELCE (d) Backlit (e) Exposure 3R (f) Exposure 2R (g) FIM.

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

Figure 3 shows the region determination for woman image. The face shown by the red ovals in Fig. 3(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, AFELCE 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. 2(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.

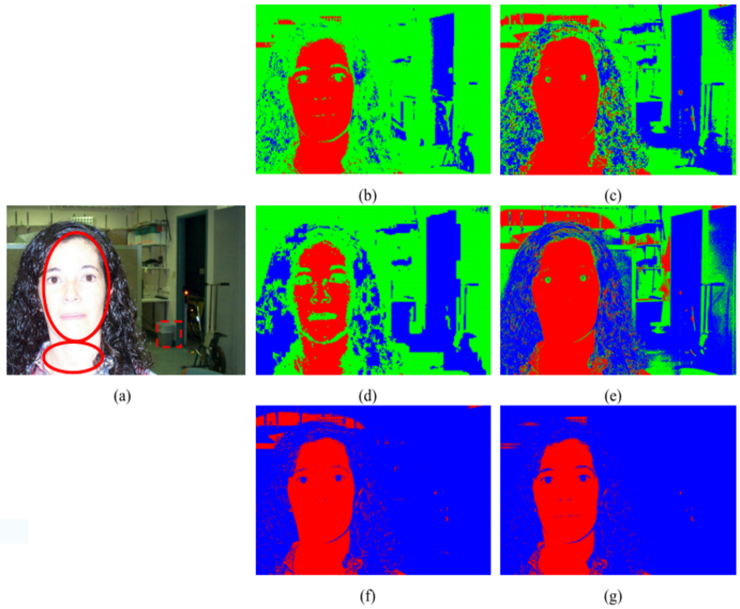


Figure 3: Resultant Images of Region Determination for woman image((a) Original Image; (b) Proposed Method (c) AFELCE (d) Backlit (e) Exposure 3R (f) Exposure 2R (g) FIM.

Based on the visual evaluation, proposed method exhibited better performance than the other methods. Visually, the proposed method has successfully detected almost all regions with high correct detection and 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.

After visual evaluation, next stage is subjective or quantitative evaluation. A survey is conducted and graded the resultant image based on quality scale in table 4.1.

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

Table 4.1: Comparison scale for subjective quality evaluation

By using the table 4.1, all 30 images are subjectively evaluated. Result is tabulated in table 4.2.

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

Table 4.2: Subjective evaluation result for region determination.
Value in the bold indicate highest average score

Observation on the results for all 30 images show that the proposed method outperforms the other methods for 24 out of 30 images. Average score obtained for proposed method after evaluating all 30 images is 3.83 which is also higher than other five methods. Thus the findings obtained in both analyses clearly show that the proposed method has successfully outperformed other methods.

4.2 Conclusions

The proposed method is an advanced one for the accurate detection of nonuniform illumination regions. The proposed framework considers three image attributes: 1) intensity, 2) entropy and 3) contrast. The method is validated using well known dataset taken from California Institute of Technology database. Experimental findings prove that the introduction of three new image characteristics significantly affect the determination of image regions into three classes, namely, over-exposed, well-exposed and under-exposed.

4.3 Future Scope and Suggestions

In future, the proposed model can be improved by using more image preprocessing method such as image enhancement to correct the classified exposure regions thereby converting non uniform illumination image into uniformly illuminated image. Different enhancement techniques with varying enhancement rates can be applied after the determination of various regions types.

By analysing the enhancement methods that are used in previous region determination techniques, most efficient among them is observed as Fuzzy intensity measure enhancement. So it can be used for correcting the classified regions.

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