Illumination Normalization for Edge-Based Face Recognition Using the Fusion of RGB Normalization and Gamma Correction

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***Abstract*—In this paper, an illumination normalization technique for edge-based face recognition on face images with non-uniform illumination conditions, is proposed. The proposed illumination normalization technique fuses the merits of color (Red, Green and Blue) normalization (Nrgb) and gamma correction (GC) for color images. By the fusion of these methods the image becomes independent of the change in face images due to illumination direction. In that way, the presence of false edges in gradient faces is reduced. Experimental results on Georgia Tech Face database with illumination problem shows that the proposed technique improved significantly recognition accuracy in comparison to histogram equalization (HE), logarithm transform (LT) and gamma correction (GC).**

Keywords—RGB normalization; gamma color correction; edge-based face recognition, non-uniform illumination; illumination normalization.

I. INTRODUCTION

In face recognition, face images are mostly described using their intensity information. However, studies have shown that the edge information of an object is about the most significant regions of the object [1][2][3]. This capability of the edge information to represent the most significant details of an object makes it appropriate for describing a face image. Though edges of objects have been widely applied in object recognition [3-6], to the best of our knowledge, it is rarely explored in face recognition [1] [2] [7] and [8]. This might be due to the fact that edges are dependent on the degree of intensity changes in a given image.

The degree of intensity variation in face images can be dependent on the lighting conditions during image capture. For the face image acquired under uncontrolled illumination conditions, non-uniform illumination problem arises. Here and throughout this paper, non-uniform illumination is used to describe the image with regions of high intensity amidst other levels of intensity. The influence of non-uniform illumination, present challenges in edge-based face recognition task, in terms of edge information extraction. For such a task, where the variations in the faces of the same person due to illumination are larger than the variations between different person's identities [9], efficiently extracting the edge information about significant regions of the same faces becomes challenging. Another problem that can be a challenge in extracting useful information for the same person faces is the variations between the faces of the same person due to alterations by plastic surgery, which is introduced by Singh et al. [10]. When these two problems are combined, the edge-based face recognition performance might degrade. These variations present an open problem for the face recognition research community.

A plausible solution to the illumination problem and plastic surgery problem is to explore an option that preserves the features of the face so that the significant regions of the face and their shapes are intact. To explore such option two things must be taken into consideration, 1) illumination normalization approaches that correct for illumination problem and still retain the image feature properties, and 2) edge information extraction. In addressing 1) the illumination normalization approaches that correct the illumination problem and retain the features of the given image are the ideal techniques, some of which will be highlighted-on in the subsequent discussions.

The illumination correction approaches that correct for illumination problem and also retain the image feature characteristics in its original form are the illumination normalization approaches [11]. Some of the widely used methods, due to their simplicity, are the histogram equalization (HE) [12], gamma intensity correction (GC) [13] and the logarithm transform (LT) [14]. The HE is normally used to make an image have a uniform histogram to produce an optimal global contrast in the image. However, HE may make an image that has uneven illumination to be more uneven. The LT works best at shadow regions of a given image [15]. For the quotient image based techniques, it is known that they are dependent on the albedo (texture) [16]. Since the quotient image based techniques comprises of the ratio of albedo (texture) between a test face and a given face, edge information obtained from such techniques have the likelihood of containing many false edges [17]. The GC corrects the overall brightness of a face image to a pre-defined "canonical form", which fades away the effect of varying lighting. But, the GC is still affected by some level of directional lighting as pointed out by [18].

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We may note at this point that the problem of the GC is due to the direction of light source on the illuminated object. In most cases, the face images that are acquired and are available for face recognition task are color images. And studies have shown that illumination effect due to changes in light direction can be addressed in the color domain when the source color is known and constant over a scene [19][20]. According to Zickler et al. [19], Red, Green, and Blue (rgb) color space transformations can address the influence of the illumination direction on an image. This claim is also supported by the work of Finalyson et. al. [20]. In [20], it is highlighted that the rgb pixel triplet normalization reduces image dependencies on lighting geometry. Therefore, inspired by these studies the proposition of illumination normalization steps that take advantage of color domain normalization to improve the performance of edge based face recognition systems is desired.

To achieve the option where the features of the face is preserved in a compact manner that only represents the significant regions of the face and their various shapes, (1) and (2) stated above in the previous discussions must be addressed. In this paper, we propose an illumination normalization technique that uses series of steps to address the non-uniform illumination problem and still retain the shapes of significant face features, unimpaired. The proposed technique stems from the fusion of color normalization (red, green and blue (RGB) color space) and GC, called the rgb gamma encoding (rgbGE) illumination normalization technique. The idea behind the proposed technique is to be able to obtain gradient faces that are not responsive to illumination variations. The rest of this paper is organized as follows. In section II, a brief review of the human face reflectance model that explains the illumination problem and how it affects extraction of significant face features. In section III, the proposed illumination normalization technique, is presented. Section IV, the experimental results and discussions are given. Finally, conclusions are drawn in Section V.

II. THE REFLECTANCE MODEL

In this section, a brief review of the face reflectance model is firstly provided in a way that establishes a basis for presenting the proposed illumination normalization technique. Subsequently, we will present the reasoning behind the technique and the steps taken to arrive at the technique.

The light reflections from most surfaces are of two types, namely, the diffuse and specular reflections. The diffuse reflection defines the case where the incident light is reflected equally in all directions [21]. The diffuse reflectance component is often well-described by the Lambertian model [22]. The specular reflection for a smooth surface defines the case where the incident light is reflected in a mirror-like direction from the surface [23]. These reflections are often modelled using the Phong reflectance model [24]. The problem of illumination that we are interested in, in this paper is the problem due to illumination direction. An example of such problem is illustrated in Fig. 1, which shows faces with specularities.

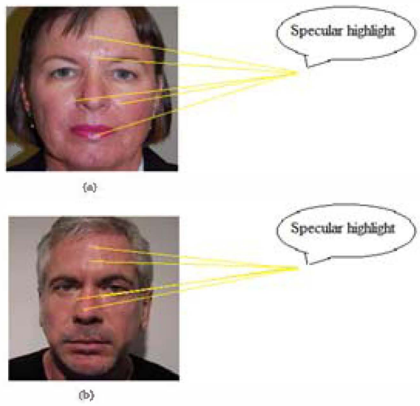


Fig.1. Face images showing (a) high level of specular highlight, (b) low level of specular highlight.

For a typical image captured using RGB camera sensor, we use the dichromatic reflection model defined by Shafer [25] to describe the reflectance properties of the face, which can affect edge information extraction. The model has the Lambertian term and the Phong's specular term. This model is given by:

$$I_k(c) = w_d(c) \int_w S^c(\lambda) E(\lambda) C_k(\lambda) d\lambda + w_s(c) \int_w E(\lambda) C_k(\lambda) d\lambda \qquad (1)$$

$$= w_d(c) D_k(c) + w_s(c) G_k \qquad (2)$$

where $D_k(c) = \int_w S^c(\lambda) E(\lambda) C_k(\lambda) d\lambda$, w_s and w_d are the specular term and diffuse terms of the incoming light, respectively. $G_k = \int_w E(\lambda) C_k(\lambda) d\lambda$, $I_k = \{I_r, I_g, I_b\}$ is the color vector of image intensity, λ is the wavelength of the light, $S^c(\lambda)$ is the spectral reflectance on a surface point c of spatial coordinates $\{x, y\}$. $E(\lambda)$ is the spectral power distribution of the incident light and $C_k(\lambda), k = r, g, b$ (chromaticity) is the spectral sensitivity of the sensor. The first part of the right hand side of (2) is the diffused component, while the second part is the specular component, for each color vector $\{r, g, b\}$ (2) is rewritten as:

$$I_k(c) = \begin{bmatrix} I_r(c) \\ I_g(c) \\ I_b(c) \end{bmatrix} = \begin{bmatrix} w_d(c) D_r(c) + w_s(c) G_r \\ w_d(c) D_g(c) + w_s(c) G_g \\ w_d(c) D_b(c) + w_s(c) G_b \end{bmatrix} \qquad (3)$$

To reduce/eliminate the dependency of $I_k(c)$ on the factors w_s, G_r, G_g and G_b (specular component) of the image, we combine the merits of rgb normalization and gamma correction discussed in Section I.

III. ILLUMINATION NORMALIZATION

A. RGB Normalization (Nrgb)

The RGB normalization is expressed as [26]:

$$\sigma_k(c) = \frac{I_k(c)}{I_r(c) + I_g(c) + I_b(c)}, \quad (4)$$

where $\sigma_k = \{\sigma_r, \sigma_g, \sigma_b\}$ for each color channel.

B. Gamma Correction (color)

Gamma correction is a nonlinear operation used to control the overall brightness of a given image. Gamma correction is defined as:

$$I_{output} = I_{input}^{\gamma} \quad (5)$$

where γ is gamma.

Usually, gamma value can be between the range $0 \le \gamma \ge 1$, the gamma value $\gamma \le 1$ is referred to as an encoding gamma, whereas the gamma value $\gamma \ge 1$ is a decoding gamma. Gamma encoding is used to maximize the use of bits as humans' perceive light and color [27]. Hence, the concept of the gamma encoding is adopted in this paper. For a colour image $I_k(c)$ acquired under non-uniform illumination, gamma correction is applied to the image pixel (RGB) values as:

$$I_{k,OUTPUT}(c) = I_{k,INPUT}^{\frac{1}{\gamma}}(c) \quad (6)$$

C. Fusion of Nrgb and GCC

The steps in the fusion of Nrgd and GC (color) are presented as follows.

Step 1: Normalize the pixel values using a predetermined gamma value $\gamma, \gamma < 1$. The gamma value is determined based on image intensity level. The value of the gamma is then applied to the color image I_k in order to gamma correct the overall image intensity, thus:

$$I'_G(c) = I_M(c)^{1/\gamma} \quad (7)$$

Step 2: Normalize the image pixel values in each color channels. The normalized is expressed as:

$$I'_{kN}(c) = \frac{I_k(c)}{I_M(c)}, \quad (r,g,b) \in k \quad (8)$$

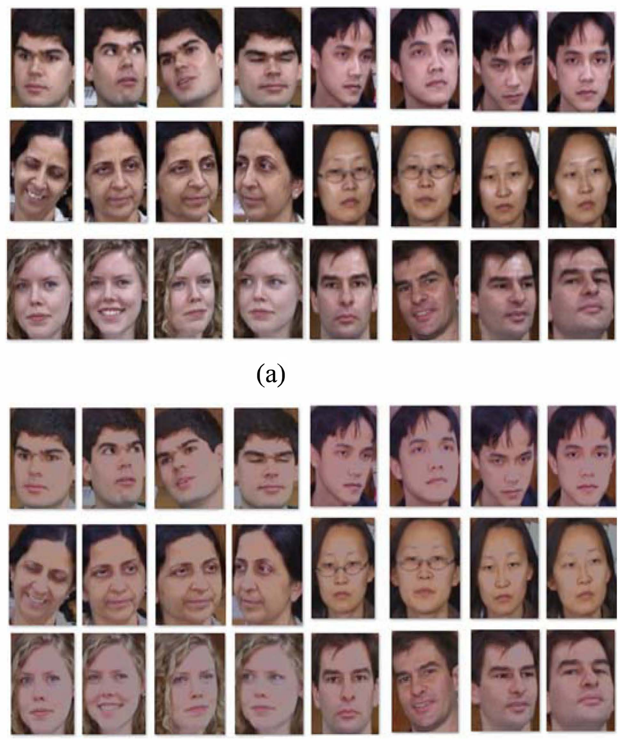
Hence:

$$I'_{rN}(c) = \frac{I_r(c)}{I_M(c)}, \quad I'_{gN}(c) = \frac{I_g(c)}{I_M(c)}, \quad I'_{bN}(c) = \frac{I_b(c)}{I_M(c)} \quad (9)$$

Step 3: Multiply each normalized color channel $\{I'_{rN}, I'_{gN}, I'_{bN}\}$ defined in (8) by the values of the image intensity obtained in (7). The fusion of the Nrgb and GCC is thus expressed as:

$$I'_k(c) = I'_{kN}(c)\, I'_G(c) \quad (10)$$

The result of Equation (10) for $\{I'_{rN}, I'_{gN}, I'_{bN}\}$, are further concatenated together to obtain the rgbGE normalized image. By the transformation in Equation (10), the illumination problem in terms of directional lighting effect on the face images is reduced. This can be seen in Fig. 2.



(a)

(b)

Fig.2. Normalized face images: (a) the original images, (b) the normalized images. Note that the figure is better viewed in color.

IV. ANALYSIS AND EXPERIMENTAL RESULTS

A. Analysis

We show the visual analysis of the edge information of rgbGE illumination normalized images in comparison with other well known illumination normalization methods on gradient faces for images of the same person.

As shown in Fig. 3. It can be observed that by normalizing the image illumination, significant amounts of non-uniform illumination are reduced. Therefore, only color and no luminance is specified. The HE normalized images for example, contains many false edges, which can increase the likelihood of miss matching a particular identity to another individual.

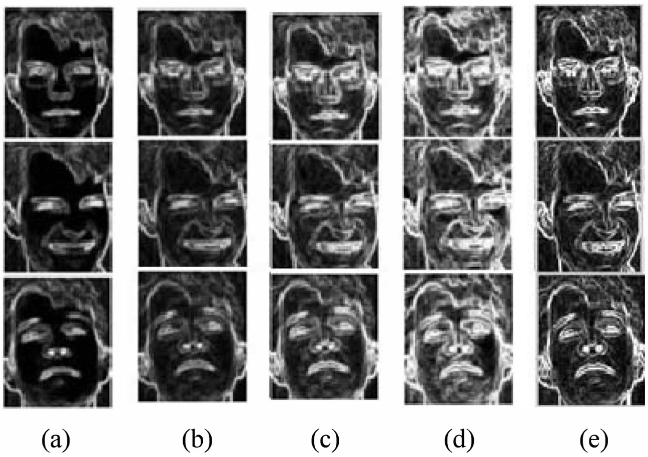


Fig3. Illustration of edge information for intra-faces with different illumination normalization techniques, (a) rgbGE, (b) LT, (c) without normalization, (d) HE, and (e) GC.

B. Experimental Setup

Here only the illumination problem highlighted in Section I is investigated. We evaluate the efficacy of the proposed rgbGE illumination normalization technique on the Georgia Tech face database [28]. The database contains 750 color images of 50 subjects, some of which where captured during different sessions. These images comprise of variations in illumination direction, scale, pose, and expression, see sample images in Fig. 2. The images were manually cropped, and resized to size 128-by-128 with no prior face alignment. The database is partitioned into training and testing sets. The number of training and test images is selected to resemble a real–time scenario where only one image per person is tested on a large database in which there exist numerous images of the same person. The gamma value used in the illumination correction is $\gamma = 0.75$, and is chosen based on image brightness.

For feature extraction on the normalized faces the gradient faces were extracted and then the Gabor descriptor is employed to emphasize on the individual gradient feature. For matching across the database, the cosine similarity measure is employed in the nearest neighbour search framework.

C. Experimental Results

The experimental results presented here, shows the Rank-1 face recognition result of the face recognition experiment on the color database GT. From the results in Fig. 4, it can be observed that the face recognition performance without correction and with LT performed at the same rate. This means that LT did not improve on the recognition of without correction face images. On the other hand, the recognition performances of without correction in comparison with HE and GC, showed

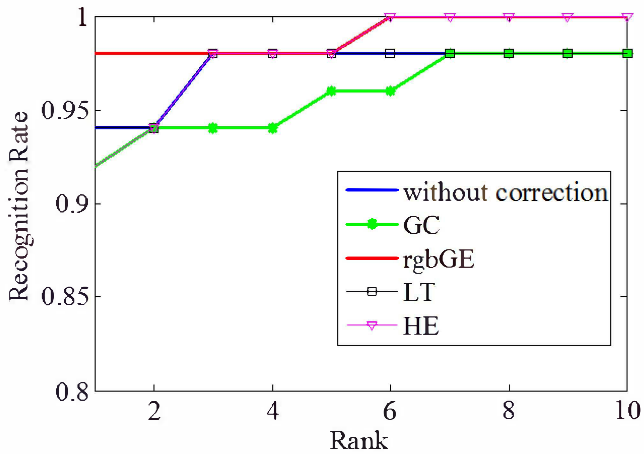


Fig.4. Recognition rate for EGM based face recognition method with different illumination normalization methods on GT database.

that HE and GC both degraded. In this case, such degradation may be associated with the false edges, which were more in comparison with no correction, as can be seen in Fig. 3. The recognition accuracy of the gradient faces with rgbGE normalization shows to significantly improve recognition of without correction by 4%. A recognition accuracy of 98%, 94%, 94%, 92% and 92% is achieved with rgbGE, LT, without correction, GC, HE, respectively.

V. CONCLUSION

In this paper, an illumination normalization technique is proposed for efficient edge information extraction. The proposed approach outperforms well known illumination normalization methods in terms of creating an image that is independent of illumination direction. The technique reduces the presence of false edges, which can be as a result of the presence of specularities and other illumination direction problem. In subsequent work, we will investigate the performance of the illumination normalization technique on other forms of illumination problem.

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