Illumination Invariant Skin Color Segmentation

Ukil Yang, Bongjoe Kim and Kwanghoon Sohn
Biometric Engineering Research Center
Dept. of Electrical & Electronic Eng., Yonsei University
Seoul, South Korea
khsohn@yonsei.ac.kr

***Abstract*—Skin color segmentation takes a great attention in many vision-based methodologies. However, the performance of the segmentation is not stable because of color variations caused by various illumination conditions. In this paper, we propose a new skin color model for segmentation which is invariant to illumination variation. It is based on illumination-free color space which is defined on Lambertian surface. Through several experimental results, we confirm that the proposed skin color model is successfully applied to skin color segmentation under various illumination conditions.**

***Index Terms*—illumination-free color space, skin color model, skin color segmentation**

I. Introduction

Skin color segmentation techniques have been studied as pre-processing techniques for many vision-based methodologies such as face detection, hand detection, face recognition, sign language recognition, vision-based surveillance, target object tracking, etc. Especially, in a face detection system, methods based on skin color information have shown computational effectiveness and the robustness for rotation, scaling and partial occlusion problems[1].

A face detection system is usually used as a front-end process in face recognition systems. Facial regions are localized and extracted from the background. A good face detection system should extract and localize an unknown number of facial regions in a given still image or video regardless of acquisition environments, such as background, illumination, orientation, scale and partial occlusion. Skin color may provide effective and robust information to distinguish facial regions from the others in various acquisition environments.

Generally, the skin color in an image is sensitive to the following factors [2]:

• *Illumination conditions*: A change in the spectral distribution and the illumination level of light source (indoor, outdoor, highlights, shadows, color temperature of lights)

• *Camera characteristics*: The color reproduced by a CCD camera is dependent on not only the illumination conditions but also the spectral sensitivities of a camera sensor.

• *Ethnicity*: Skin color varies according to ethnic groups.

• *Individual characteristics*: Individual characteristics such as age, sex and body parts affect the skin color.

• *Other factors*: Different factors such as makeup, glasses, background colors, shadows and motion affect the skin color.

Among the above factors, '*Illumination conditions*' is the most important and difficult problem in skin color segmentation. Also, it may seriously deteriorate the performance of the system.

This paper proposes a new skin color model for skin color segmentation which is invariant to illumination variation. We model an image acquisition process based on Lambertian surface [3]. Then, the model is separated into a non-illumination term and an illumination term. Based on this model, we derive an illumination-free color space. Then, using the training images which are represented in the illumination-free color space, we construct a proposed skin color model. We applied the skin color model to Face Recognition Grand Challenge (FRGC) database to confirm the performance of skin color segmentation algorithm considering illumination conditions.

The remainder of the paper is organized as follows: Section II gives a brief description of an image acquisition model and ordinary skin color models. The proposed illumination-invariant skin color model is described in Section III. The experimental results of skin color segmentation are described in Sections IV. Finally, section V provides summary and conclusions.

II. Research Background

Generally, Skin color segmentation is considered as a two-class problem [2]. When a set of color pixels is given, the set is generally divided into two subsets (skin-color pixels or non-skin-color pixels) according to the probability distributions of skin color and non-skin color in any color space. That is, the process of skin color segmentation is performed as follows:

a. Constructing the probability distributions of skin color and non-skin color in the color space, which is given by a supervisor, using a training data set
b. Representing the color of input pixels in the given color space
c. Dividing and classifying the input pixels into the skin group or non-skin group according to the criterion based on the constructed probability distributions

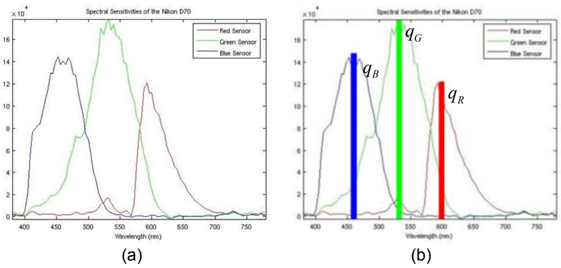

Figure 1. The example of the spectral sensitivities of a real camera: Measurement form (a) [7], approximation form (b)

Therefore, the performance of skin color segmentation is determined by the characteristics of skin color model on any color space which is used to represent the color of input pixels. In this section, we model an image acquisition process, and review the ordinary skin color model in sense of the image acquisition model.

A. Image acquisition model

An image acquisition process is modeled based on Lambertian surface as shown in Eq. (1) [6].

$$\begin{cases} \rho_R = \sigma \int E(\lambda) S(\lambda) Q_R(\lambda)\, d\lambda \\ \rho_G = \sigma \int E(\lambda) S(\lambda) Q_G(\lambda)\, d\lambda \\ \rho_B = \sigma \int E(\lambda) S(\lambda) Q_B(\lambda)\, d\lambda \end{cases} \tag{1}$$

where λ denotes a wavelength and ρ_R, ρ_G and ρ_B denote the RGB color values. The spectral power distribution of a light is denoted $E(\lambda)$, surface reflectance of an object is denoted $S(\lambda)$ and the spectral sensitivities of the RGB camera sensors are denoted $Q_R(\lambda)$, $Q_G(\lambda)$ and $Q_B(\lambda)$. σ is a constant factor which denotes the Lambertian shading term. It presents the angle between the surface normal and the illumination direction.

To derive the illumination factors of the RGB color values from Eq. (1), two assumptions are applied. First, the spectral sensitivities of the RGB camera sensors, $Q_R(\lambda)$, $Q_G(\lambda)$ and $Q_B(\lambda)$, must be delta functions. As shown in Fig. 1, the spectral sensitivity of each color sensor is not shown as a shape of delta function. However, because the RGB color values of a pixel, ρ_R, ρ_G and ρ_B, are the integral values for the all wavelengths, $Q_R(\lambda)$, $Q_G(\lambda)$ and $Q_B(\lambda)$ could be approximated to delta functions with a proper scaling factors, q_R, q_G and q_B. With the first assumption, Eq. (1) can be simplified as Eq. (2).

$$\begin{cases} Q_R(\lambda) \approx q_R \delta(\lambda - \lambda_R) \\ Q_G(\lambda) \approx q_G \delta(\lambda - \lambda_G) \\ Q_B(\lambda) \approx q_B \delta(\lambda - \lambda_B) \end{cases} \Rightarrow \begin{cases} \rho_R = \sigma E(\lambda_R) S(\lambda_R) q_R \\ \rho_G = \sigma E(\lambda_G) S(\lambda_G) q_G \\ \rho_B = \sigma E(\lambda_B) S(\lambda_B) q_B \end{cases} \tag{2}$$

Second, the spectral power distribution of a light, $E(\lambda)$, must be restricted to be the spectral power distribution of a black body presented by Planck's law [8]. As shown in Eq. (3), Planck's law describes the spectral power distribution at all wavelengths from a black body according to the temperature (T) variation of a black body. Moreover, when a color image is acquired in the ordinary illumination condition, Planck's law is approximated to Eq. (5). It is because the RGB camera sensors generally work in visible ray ($380\text{nm} \le \lambda \le 770\text{nm}$), as shown in Fig. 1, and the color temperature of natural illumination is below 10,000°K. That is, Eq. (2) is simplified as Eq. (6) with the second assumption.

$$E(\lambda) = \frac{2hc^2}{\lambda^5} \frac{1}{e^{\frac{hc}{\lambda k T}} - 1} = \frac{c_1}{\lambda^5} \frac{1}{e^{\frac{c_2}{\lambda T}} - 1} \tag{3}$$

where c, h and k are constants which denote the speed of a light, 3.8×10^8 (m/s), Planck constant, 6.626×10^{-34} (Js) and Boltmann constant, 1.380×10^{-23} (J/K). c_1 and c_2 are also constants which are defined as Eq. (4).

$$c_1 \triangleq 2hc^2,\ c_2 \triangleq \frac{hc}{k} \tag{4}$$

$$E(\lambda) = \frac{c_1}{\lambda^5} \frac{1}{e^{\frac{c_2}{\lambda T}} - 1} \approx \frac{c_1}{\lambda^5} e^{-\frac{c_2}{\lambda T}} \tag{5}$$

$$\begin{cases} \rho_R = \sigma \dfrac{c_1}{\lambda_R^5} e^{-\frac{c_2}{\lambda_R T}} S(\lambda_R) q_R \\ \rho_G = \sigma \dfrac{c_1}{\lambda_G^5} e^{-\frac{c_2}{\lambda_G T}} S(\lambda_G) q_G \\ \rho_B = \sigma \dfrac{c_1}{\lambda_B^5} e^{-\frac{c_2}{\lambda_B T}} S(\lambda_B) q_B \end{cases} \tag{6}$$

Consequently, when an object whose surface reflectance is $S(\lambda)$ is captured by a camera having the weighted delta spectral sensitivities in an illumination condition, $\frac{c_1}{\lambda^5} e^{-\frac{c_2}{\lambda T}}$, the RGB colors of the object are represented as ρ_R, ρ_G and ρ_B in an image by Eq. (6). That is, according to the image acquisition model, the color values of an image are determined by non-illumination terms ($S(\lambda)$: object characteristics and λ_R, λ_G, λ_B, q_R, q_G and q_B: camera characteristics) and illumination terms (T and σ).

B. Skin color models in ordinary color spaces

The choice of color space is the first step in skin color segmentation. Then, a skin color model is constructed based on the distributions of skin and non-skin colors in the color space. Skin color segmentation is performed based on the skin color model. Thus, a good color space for skin color segmentation should have the minimum overlap between the distributions of skin and non-skin colors. In addition, it should be robust against varying illumination conditions.

1) Basic color space

RGB is the most commonly used color space for storing and representing digital images. To reduce the dependence on lighting, the RGB color components are normalized by Eq. (7). It is normalized RGB color space (rgb).

$$r = \frac{R}{R+G+B},\ g = \frac{G}{R+G+B},\ b = \frac{B}{R+G+B} \tag{7}$$

Since the sum of these components is '1', the three components are reduced to two components without any loss of color information. According to the related researches [9-14], the differences in skin-color pixels due to lighting conditions and due to ethnicity can be greatly reduced in normalized RGB space. Also, the skin-color clusters in normalized RGB space have relatively lower variance than the corresponding clusters in RGB space. Hence, normalized RGB space is better than RGB space in skin color segmentation.

Some researchers have used color ratios such as R/G, B/G and R/B. Gomez et al. [15] selected different color components from various color spaces. They showed that the mixture of color components (E of YES space, the ratio R/G and H from HSV space) performed better than the existing color spaces. Also, the authors argue that this new mixture space is robust to various illumination conditions. Brand and Mason [16] have evaluated the performance of color ratios. They concluded that the combination of color ratios (R/G, R/B and G/B) provided a better response than the individual ratios.

To review the normalized RGB space and color ratio space in sense of the image acquisition model, Eq. (6) is applied to the normalized RGB space and color ratio space. As a result, Eq. (8) and Eq. (9) are derived.

$$\begin{cases} r = \dfrac{\lambda_R^{-5} e^{-\frac{c_2}{\lambda_R T}} S(\lambda_R) q_R}{\lambda_R^{-5} e^{-\frac{c_2}{\lambda_R T}} S(\lambda_R) q_R + \lambda_G^{-5} e^{-\frac{c_2}{\lambda_G T}} S(\lambda_G) q_G + \lambda_B^{-5} e^{-\frac{c_2}{\lambda_B T}} S(\lambda_B) q_B} \\ g = \dfrac{\lambda_R^{-5} e^{-\frac{c_2}{\lambda_R T}} S(\lambda_R) q_R}{\lambda_R^{-5} e^{-\frac{c_2}{\lambda_R T}} S(\lambda_R) q_R + \lambda_G^{-5} e^{-\frac{c_2}{\lambda_G T}} S(\lambda_G) q_G + \lambda_B^{-5} e^{-\frac{c_2}{\lambda_B T}} S(\lambda_B) q_B} \end{cases} \tag{8}$$

$$\frac{R}{G} = \frac{\lambda_R^{-5} e^{-\frac{c_2}{\lambda_R T}} S(\lambda_R) q_R}{\lambda_G^{-5} e^{-\frac{c_2}{\lambda_G T}} S(\lambda_G) q_G} = \frac{\lambda_R^{-5} S(\lambda_R) q_R}{\lambda_G^{-5} S(\lambda_G) q_G} e^{\frac{c_2}{T}\left(\frac{1}{\lambda_G} - \frac{1}{\lambda_R}\right)} \tag{9}$$

As shown in Eq. (8) and Eq. (9), in both color spaces, one of the illumination terms of the image acquisition model, which is 'T', is still remaining even if the other one, which is 'σ', is removed. Thus, the above two color spaces are still affected by the variation of illumination conditions.

2) Perceptual color space

Perceptual color space, such as HSI, HSV and HSL, attempt to describe perceptual color relationships more accurately than RGB. They represent a color with *Hue*, *Saturation* and *Intensity*. *Hue* is mainly used in skin color segmentation, because a color is conveniently represented in the hue. *Saturation* is typically used as a masking image in order to isolate further regions of interest in the image segmented by hue. Generally, *intensity* is not used because it carries no color information.

Perceptual color space is used in many researches [17-20], and it shows good performance in skin color segmentation. However, it is a problem that perceptual color space cannot be described directly by RGB color space, even if many non-linear transformations are proposed to map RGB into perceptual features.

To analyze the image acquisition model in perceptual color space, Eq. (6) is applied to a general hue transformation. As shown in Eq. (10), similar to the case of basic color space, one of the illumination terms of the image acquisition model, which is 'T', is still remaining. Thus, perceptual color space is also affected by the variation of illumination conditions.

$$Hue \propto \frac{\lambda_G^{-5} e^{-\frac{c_2}{\lambda_G T}} S(\lambda_G) q_G - \lambda_B^{-5} e^{-\frac{c_2}{\lambda_B T}} S(\lambda_B) q_B}{\lambda_R^{-5} e^{-\frac{c_2}{\lambda_R T}} S(\lambda_R) q_R - \lambda_G^{-5} e^{-\frac{c_2}{\lambda_G T}} S(\lambda_G) q_G} \tag{10}$$

3) Orthogonal color space

The orthogonal color spaces, such as YC_bC_r, YIQ and YUV, reduce the redundancy present in RGB color space and represent the color as statistically independent components. Especially, because the luminance and chrominance components of a color are explicitly separated, this space is good choice for skin color segmentation. Moreover, since the orthogonal color spaces are used as standard for image transmission systems, they are more efficient than any other color spaces in specific applications such as TV system. Accordingly, many researchers used the orthogonal color space or its modified color space [21-25] for skin color segmentation.

However, this color space represents color as *luminance* (Y) and *chrominance* (C_bC_r or IQ or UV) in sense of image compression. That is, the mean of chrominance in the orthogonal color space is slightly different from that of an object color. As shown in Eq. (11), because the components of the orthogonal color space are computed as a weighted sum of RGB values, any illumination term of the image acquisition model is not removed. Thus, orthogonal color space is also affected by the variation of illumination conditions.

$$V = \sigma c_1 \begin{pmatrix} \omega_R \times \lambda_R^{-5} e^{-\frac{c_2}{\lambda_R T}} S(\lambda_R) q_R \\ +\omega_G \times \lambda_G^{-5} e^{-\frac{c_2}{\lambda_G T}} S(\lambda_G) q_G \\ +\omega_B \times \lambda_B^{-5} e^{-\frac{c_2}{\lambda_B T}} S(\lambda_B) q_B \end{pmatrix} \quad (11)$$

where V denotes the value of *luminance* or *chrominance*, and ω_R, ω_G and ω_B denotes the proper weights.

III. Proposed Skin Color Model

A. Illumination-free color space

Illumination-free color space is derived from the image acquisition model described in section II-A. It is constructed by removing illumination terms, which are 'T' and 'σ', from Eq. (6). To remove the 'σ' term, RGB values are normalized with the geometric mean ($\sqrt[3]{RGB}$). Then, we take the natural logarithm to the normalized values, which is the pre-processing to remove the 'T' term, and we obtain Eq. (12). Since sum of these components is '0' ($\rho'_R + \rho'_G + \rho'_B = 0$), three components are reduced to two components without any loss of color information. In this paper, we used ρ'_R and ρ'_B to represent color information. Eq. (12) is represented as Eq. (13) in vector form for ρ'_R and ρ'_B.

$$\begin{cases} \ln\left(\frac{\rho_R}{\sqrt[3]{\rho_R\rho_G\rho_B}}\right) = \ln\left(\frac{\lambda_R^{-5}S(\lambda_R)q_R}{\sqrt[3]{\lambda_R^{-5}S(\lambda_R)q_R \times \lambda_G^{-5}S(\lambda_G)q_G \times \lambda_B^{-5}S(\lambda_B)q_B}}\right) \\ \qquad + \frac{c_2}{T}\left(\frac{(\lambda_R\lambda_G + \lambda_G\lambda_B + \lambda_B\lambda_R)}{3\lambda_R\lambda_G\lambda_B} - \frac{1}{\lambda_R}\right) \triangleq \rho'_R \\ \ln\left(\frac{\rho_G}{\sqrt[3]{\rho_R\rho_G\rho_B}}\right) = \ln\left(\frac{\lambda_G^{-5}S(\lambda_G)q_G}{\sqrt[3]{\lambda_R^{-5}S(\lambda_R)q_R \times \lambda_G^{-5}S(\lambda_G)q_G \times \lambda_B^{-5}S(\lambda_B)q_B}}\right) \\ \qquad + \frac{c_2}{T}\left(\frac{(\lambda_R\lambda_G + \lambda_G\lambda_B + \lambda_B\lambda_R)}{3\lambda_R\lambda_G\lambda_B} - \frac{1}{\lambda_G}\right) \triangleq \rho'_G \\ \ln\left(\frac{\rho_B}{\sqrt[3]{\rho_R\rho_G\rho_B}}\right) = \ln\left(\frac{\lambda_B^{-5}S(\lambda_B)q_B}{\sqrt[3]{\lambda_R^{-5}S(\lambda_R)q_R \times \lambda_G^{-5}S(\lambda_G)q_G \times \lambda_B^{-5}S(\lambda_B)q_B}}\right) \\ \qquad + \frac{c_2}{T}\left(\frac{(\lambda_R\lambda_G + \lambda_G\lambda_B + \lambda_B\lambda_R)}{3\lambda_R\lambda_G\lambda_B} - \frac{1}{\lambda_B}\right) \triangleq \rho'_B \end{cases} \quad (12)$$

As shown in Eq. (13), $\vec{\rho}$ is a color vector defined in the new color space represented by normalization and logarithm (NL space). The color vector is represented with two color vectors ($\vec{S}$ and $\vec{\lambda}$) and its weight ($\frac{c_2}{T}$). $\vec{S}$ and $\vec{\lambda}$ consist of non-illumination terms of the image acquisition model. However, $\frac{c_2}{T}$ consists of illumination terms of the image acquisition model. That is, the variation of illumination conditions only affects the weight. Consequently, illumination-free color space is defined by removing the $\frac{c_2}{T}$ term from Eq. (13).

$$\vec{\rho} = \vec{S} + \frac{c_2}{T}\vec{\lambda}$$

$$\vec{\rho} \triangleq \begin{bmatrix} \rho'_R \\ \rho'_B \end{bmatrix}, \qquad \vec{\lambda} \triangleq \begin{bmatrix} \frac{(\lambda_R\lambda_G + \lambda_G\lambda_B + \lambda_B\lambda_R)}{3\lambda_R\lambda_G\lambda_B} - \frac{1}{\lambda_R} \\ \frac{(\lambda_R\lambda_G + \lambda_G\lambda_B + \lambda_B\lambda_R)}{3\lambda_R\lambda_G\lambda_B} - \frac{1}{\lambda_B} \end{bmatrix} \quad (13)$$

$$\vec{S} \triangleq \begin{bmatrix} \ln\left(\frac{\lambda_R^{-5}S(\lambda_R)q_R}{\sqrt[3]{\lambda_R^{-5}S(\lambda_R)q_R \times \lambda_G^{-5}S(\lambda_G)q_G \times \lambda_B^{-5}S(\lambda_B)q_B}}\right) \\ \ln\left(\frac{\lambda_B^{-5}S(\lambda_B)q_B}{\sqrt[3]{\lambda_R^{-5}S(\lambda_R)q_R \times \lambda_G^{-5}S(\lambda_G)q_G \times \lambda_B^{-5}S(\lambda_B)q_B}}\right) \end{bmatrix}$$

B. Proposed skin color model

The proposed skin color model is constructed in illumination-free color space. To define illumination-free color space, the $\frac{c_2}{T}$ is removed from Eq. (13). In Eq. (13), $\vec{\rho}$ is calculated from RGB values of an acquired image. c_2 is a constant, and $\vec{S}$, $\vec{\lambda}$ and T are unknown variables, respectively. To remove the $\frac{c_2}{T}$, we apply an inner product with the orthonormal vector of $\vec{\lambda}$, which we denote $\vec{\lambda}^{\perp}$ ($\vec{\lambda} \cdot \vec{\lambda}^{\perp} = 0$ and $\left\|\vec{\lambda}^{\perp}\right\| = 1$), to Eq. (13). Then we obtain Eq. (14).

$$\begin{aligned} \vec{\rho} \cdot \vec{\lambda}^{\perp} &= \left(\vec{S} + \frac{c_2}{T}\vec{\lambda}\right) \cdot \vec{\lambda}^{\perp} \\ \vec{\rho} \cdot \vec{\lambda}^{\perp} &= \vec{S} \cdot \vec{\lambda}^{\perp} \end{aligned} \quad (14)$$

In Eq. (14), $\vec{S}$ and $\vec{\lambda}^{\perp}$ are still unknown variables. To extract the essential color information of an object ($\vec{S}$) from the acquired RGB values ($\vec{\rho}$) affected by illumination conditions based on Eq. (14), the $\vec{\lambda}^{\perp}$ should be empirically estimated with a training dataset. And the dataset to be used for estimation should be acquired in various illumination conditions for a same object with a same camera. Because $\vec{S}$ and $\vec{\lambda}^{\perp}$ are static for all $\vec{\rho}$ in the dataset, variance of $\vec{\rho} \cdot \vec{\lambda}^{\perp}$ is ideally '0'. In this paper, we estimated $\vec{\lambda}^{\perp}$ which minimizes variance of $\vec{\rho} \cdot \vec{\lambda}^{\perp}$ by computing Eq. (15).

$$\arg\min_{\vec{\lambda}^{\perp}} \left\{ \mathrm{var}\left[\vec{\rho}_i \cdot \vec{\lambda}^{\perp}\right] \right\} \quad (15)$$

where $\vec{\rho}_i$ denotes the color vector of the i^{th} data in the dataset. After setting $\vec{\rho}_i = \begin{bmatrix} x_i \\ y_i \end{bmatrix}$ and $\vec{\lambda}_{opt}^{\perp} = \begin{bmatrix} \frac{1}{\sqrt{1+\lambda^2}} & \frac{\lambda}{\sqrt{1+\lambda^2}} \end{bmatrix}^T$ which is an optimal solution of Eq. (15), $\vec{\lambda}_{opt}^{\perp}$ is derived from Eq. (15) and we obtain Eq. (16).

$$
\begin{aligned}
&\lambda = \frac{-B-\sqrt{B^2+4A^2}}{2A}\ \ (A \geq 0)\ \text{or}\ \lambda = \frac{-B+\sqrt{B^2+4A^2}}{2A}\ \ (A<0) \\
&A \triangleq \frac{1}{N}\sum x_i y_i - \left(\frac{1}{N}\sum x_i \times \frac{1}{N}\sum y_i\right) \qquad (16)\\
&B \triangleq \frac{1}{N}\left(\sum x_i^2 - \sum y_i^2\right) - \left\{\left(\frac{1}{N}\sum x_i\right)^2 - \left(\frac{1}{N}\sum y_i\right)^2\right\}
\end{aligned}
$$

where N denotes the size of a training dataset.

We constructed the proposed skin color model with FRGC database based on Eq. (12), Eq. (14) and Eq. (16). First, we manually cropped skin regions from the database. And the skin regions are represented in NL color space by Eq. (12). By using the represented color vectors, $\vec{\lambda}^{\perp}$ is estimated based on Eq. (16). Based on the estimated result, the skin regions are finally represented in illumination-free color space by Eq. (14). Then, the probability distribution of skin color is obtained using the skin color values of a training dataset in newly defined illumination-free color space. Lastly, we classify skin color and non-skin color based on Bayesian rule with the assumption which the probability distribution of non-skin color is uniformly distributed.

IV. Experimental Results

To compare the variation of skin color model according to '*illumination conditions*', we divided the database into three illumination groups as shown in Fig. 2. Then, we compared the probability distributions in every illumination group. Fig. 3 shows the probability distribution of skin color in normalized RGB color space, Fig. 4 and Fig. 5 show them in R/G, B/G color space and in illumination-free color space, respectively. In Fig. 3, group 1 and group 2 have the similar distribution, but group 3 has visibly different distribution with group 1 and group 2. That is, in normalized RGB color space, a proper skin color model according to illumination conditions should be used for skin color segmentation. In brief, the skin color model in normalized RGB color space is not robust to the variation of illumination conditions, and the variation may seriously deteriorate the performance of skin color segmentation. As shown in Fig. 4, the results in R/G, B/G space are similar to those in normalized RGB space. The skin color model in R/G, B/G color space is also affected by the variation of illumination conditions.

However, as shown in Fig. 5, the distribution ranges of group 1 and group 3 are included in the region of group 2 in illumination-free color space. It means that it is independent of variation of illumination conditions. Thus, we can construct the illumination invariant skin color model in illumination-free color space, and the variation of illumination conditions do not affected the performance of skin color segmentation based on the proposed skin color model.

For segmentation experiments, we divided FRGC database into training set and test set. In training set, the skin color regions are manually cropped. By using the cropped region, we calculated the $\vec{\lambda}^{\perp}$ based on Eq. (16). Then, we build the proposed skin color model in illumination-free color space

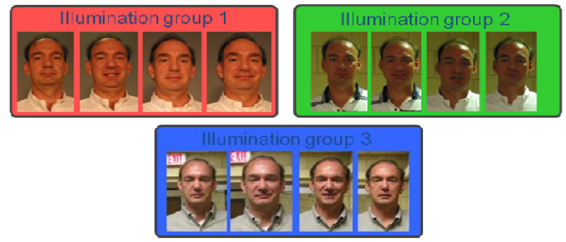

Fig. 2 Examples of illumination groups

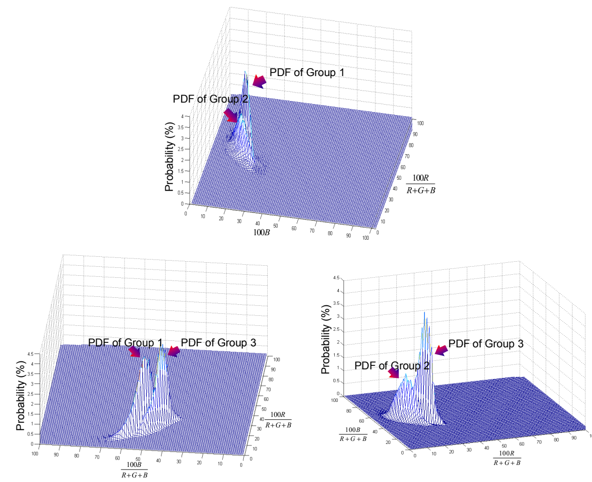

Figure 3. The probability distribution of skin color in normalized RGB space: Group1 vs. Group2 (up), Group1 vs. Group3 (left), Group2 vs. Group3 (right)

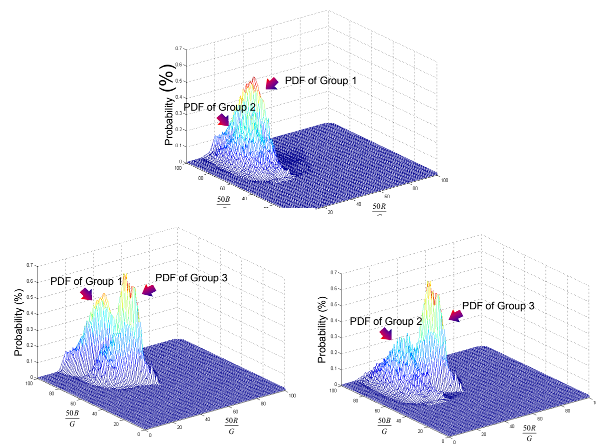

Figure 4. The probability distribution of skin color in R/G, B/G space: Group1 vs. Group2 (up), Group1 vs. Group3 (left), Group2 vs. Group3 (right)

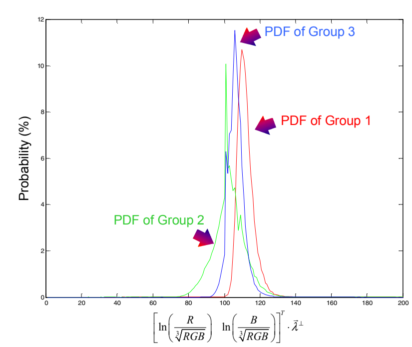

Figure 5. The probability distribution of skin color in illumination-free space

Figure 6. The results of skin color segmentation:
a data in illumination group 1 (up), a data in illumination group 2 (middle),
a data in illumination group 3 (bottom)

based on Bayesian rule with the assumption which the probability distribution of non-skin color is uniformly distributed. Finally, we test the skin color segmentation in the test set. Fig. 6 shows the segmentation results. From these results, we confirm that the proposed skin color model is robust to the variations of illumination conditions.

V. CONCLUSION

Skin color segmentation is an essential process in a lot of vision based tasks. However, it suffers from color variations caused by irregular illumination changes. In this paper, we have proposed the illumination invariant skin color model. To derive the skin color model, we model image acquisition process on Lambertian surface. Then, we divide the model into two parts such as illumination term and non-illumination term. We define illumination-free color space by removing the illumination term. We build the proposed skin color model in the illumination-free color space. Through several experiments, we confirmed that the proposed skin color model is robust to the variations of illumination conditions.

ACKNOWLEDGMENT

This work was supported by the Korea Science and Engineering Foundation (KOSEF) through the Biometrics Engineering Research Center (BERC) at Yonsei University. (R112002105070030(2008))

REFERENCES

[1] Ming-Hsuan Yang, David J. Kriegman, and Narendra Ahuja, “Detecting Faces in Images: A Survey,” IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 24, No. 1, pp. 34-58, 2002

[2] P. Kakumanu, S. Makrogiannis and N. Bourbakis, “A survey of skin-color modeling and detection methods,” Pattern Recognition, Vol. 40, No. 3, pp. 1106-1122, 2007

[3] B. K. Horn, ‘Robot Vision,’ MIT Press, 1986.

[4] P. Phillips, P. Flynn, T. Scruggs, K. Bowyer, J. Chang, K. Hoffman, J. Marques, J. Min and W. Worek, “Overview of the face recognition grand challenge,” Proceeding of Computer Vision and Pattern Recognition, pp. 947-954, 2005

[5] Prag Sharma and Richard B. Reilly, “A Colour Face Image Database for Benchmarking of Automatic Face Detection Algorithms,” Proceeding of EURASIP Conference focused on Video / Image Processing and Multimedia Communications, 2003

[6] Finlayson, G.D., Hordley, S.D., Cheng Lum and Drew, M.S., “On the removal of shadows from images,” IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 28, No. 1, pp. 59-68, 2006

[7] Moh Joan, Hon Mun Low, and Greg Wientjes, “Nikon D70 Characterization,” PSYCH 221 Final Projects, Stanford Center for Image Systems Engineering, 2006, http://ise.stanford.edu/class/psych221/projects/05/joanmoh/index.html

[8] G. Wyszecki and W. Stiles, ‘Color Science: Concepts and Methods 2nd edition,’ Quantitative Data and Formulas, New York: Wiley, 1982.

[9] J. Yang, W. Lu and A. Waibel, “Skin-color modeling and adaptation,” Proceeding of Asian Conference on Computer Vision, 1998.

[10] M.H. Yang and N. Ahuja, “Gaussian Mixture model for human skin color and its application in image and video databases,” Proceedings of SPIE: Conference on Storage and Retrieval for Image and Video Databases, pp. 458-466, 1999.

[11] L. M. Bergasa, M. Mazo, A. Gardel, M. A. Sotelo and L. Boquete, “Unsupervised and adaptive Gaussian skin-color model,” Image and Vision Computing, Vol. 18, No. 12, pp. 987-1003, 2000.

[12] N. Oliver, A. Pentland, F. Berard and Lafter, “Lips and face real time tracker,” Processing of Computer Vision and Pattern Recognition, 1997.

[13] N. Sebe, T. Cohen, T. S. Huang and T. Gevers, “Skin detection, a Bayesian network approach,” Processing of International Conference on Pattern Recognition, 2004.

[14] M. Soriano, J. B. M. Kauppi, S. Huovinen and M. Laaksonen, “Adaptive skin color modeling using the skin locus for selecting training pixels,” Pattern Recognition, Vol. 36, No. 3, pp. 681-690, 2003.

[15] G. Gomez, M. Sanchez and L. E. Sucar, “On selecting an appropriate colour space for skin detection,” Lecture Notes in Artificial Intelligence, vol. 2313, pp. 70-79, 2002.

[16] J. Brand and J. Mason, “A comparative assessment of three approaches to pixel level human skin-detection,” Processing of International Conference on Pattern Recognition, pp 1056-1059, 2000.

[17] C. Garcia and G. Tziritas, “Face detection using quantized skin color regions merging and wavelet packet analysis,” IEEE Transactions on Multimedia Vol. 1, No. 3, pp. 264-277, 1999.

[18] S. McKenna, S. Gong and Y. Raja, “Modeling facial colour and identity with Gaussian mixtures,” Pattern Recognition, Vol. 31, No. 12. pp. 1883-1892, 1998.

[19] K. Sobottka and I. Pitas, “A novel method for automatic face segmentation, facial feature extraction and tracking,” Signal Processing: Image Communication, Vol.12, No. 3, pp. 263-281, 1998.

[20] Y. Wang and B. Yuan, “A novel approach for human face detection from color images under complex background,” Pattern Recognition, Vol. 34, No. 10, pp. 1983-1992, 2001.

[21] R. L. Hsu, M. Abdel-Mottaleb and A. K. Jain, “Face detection in color images,” IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 24, No. 5, pp. 696-706, 2002.

[22] K. W. Wong, K. M. Lam and W. C. Siu, “A robust scheme for live detection of human faces in color images,” Signal Processing: Image Communication, Vol. 18, No. 2, pp. 103-114, 2003.

[23] Y. Dai and Y. Nakano, “Face-texture model based on SGLD and its application in face detection in a color scene,” Pattern Recognition, Vol. 29, No. 6, pp. 1007-1017, 1996.

[24] F. Marques and V. Vilaplana, “A morphological approach for segmentation and tracking of human face,” Processing of International Conference on Pattern Recognition, 2000.