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AUTOMATIC FACIAL SKIN DETECTION USING GAUSSIAN MIXTURE MODEL UNDER VARYING ILLUMINATION

Md. Foisal Hossain[1], Mousa Shamsi[2], Mohammad Reza Alsharif[1]
Reza A. Zoroofi[3] and Katsumi Yamashita[4]

[1]Department of Information Engineering
University of the Ryukyus
1-Senbaru, Nishihara, Okinawa 903-0213, Japan
foisalkuet@yahoo.com; asharif@ie.u-ryukyu.ac.jp

[2]Faculty of Electrical Engineering
Sahand University of Technology
New Sahand Town, Tabriz, Iran
mousa_shamsi@yahoo.com

[3]School of Electrical and Computer Engineering
University of Tehran
Tehran, Iran
zoroofi@ut.ac.ir

[4]Graduate School of Engineering
Osaka Prefecture University
1-1 Gakuen-cho, Nakaku, Sakai, Osaka 599-8531, Japan
yamashita@eis.osakafu-u.ac.jp

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Abstract. *Recently, skin detection methodologies based on skin-color information as a cue have gained much attention as skin-color provides computationally effective, robust information against rotations, scaling and partial occlusions. Skin detection using color information can be a challenging task as the skin appearance in images is affected by various factors such as illumination, background, camera characteristics and ethnicity. This paper presents a method of facial skin extraction by estimating varying illumination of the image and using Gaussian Mixture Model (GMM) of facial images. For illumination estimation, two skin models are used. One is under normal condition and the other is under bright illumination condition. If the estimated illumination is very far from the normal image, then the given image is illumination compensated and feeds again to Gaussian Mixture Model for segmentation, which automatically segments the skin portion. Experimental results on frontal and lateral color images show the efficiency of the proposed method compared with the conventional skin color segmentation method based on GMM. Experimental results show that this method is highly applicable for practical purpose such as surgical planning.*
Keywords: Facial skin detection, Gaussian mixture model, Varying illumination, Skin models

1. **Introduction.** Nowadays, facial skin detection has been an active research area for purposes, such as intelligent vision based human computer interaction, face tracking, face recognition, facial expression analysis, human emotion recognition system, content-based image retrieval (CBIR) systems and facial surgery. Recently, skin detection methodology based on skin-color information as a cue has gained much attention as skin color provides computationally effective information. Recent advances in Digital Human Technology with broad availability of high performance computer graphics have created a unique

opportunity to develop a novel set of applications meeting the demands of reconstructive and aesthetic plastic surgery. In this case, it is required to measure some standard linear and spatial facial features which are accepted by many surgeons.

A lot of algorithms in the above areas use a skin color detection algorithm as a post processing step to separate skin regions from the background of the image and treat the skin regions as candidate faces for detecting and tracking. Exact determination of facial features is highly required for surgical planning. However, most of the facial image processing methods assume that faces have been previously localized and identified within the image. A precise and reliable face detection, and segmentation technique is the key factor to improve the performance of these algorithms in face detection and tracking. A robust face detection technique is, therefore, a requirement to build fully automated systems that analyze facial information.

Many methods have been proposed to build a skin color model. Several color spaces have been utilized to label pixels as skin, including RGB, normalized RGB, HSV, YCbCr, YIQ, CIE XYZ and CIE LUV [1]. The YCbCr space represents color as luminance (Y) computed as a weighted sum of RGB values, and chrominance (Cb and Cr) computed by subtracting the luminance component from B and R values. The YCbCr space is one of the most popular choices for skin detection and has been used by Hsu et al. [2].

Several approaches have been proposed to detect skin color in varying illumination conditions [3-11]. In [3], the object's color distributions were modeled using Gaussian mixture model in hue saturation space. However, this method is applicable in highly constrained environment.

Quan et al. [4] have presented a skin-color extraction algorithm to detect human faces in color images based on Gaussian mixture model (GMM) of human skin color distribution. Morphological operations are used to refine the detected regions. However, this method has not presented any model for varying illumination effect.

Terrillon et al. [5] have human face detection in natural scenes at invariant moments. Zheng et al. [6] have presented an algorithm to improve the performance of skin detection algorithms using standard Gaussian model. Yoo et al. [9] state, since the face is generally oval in shape, pixels from an oval region on the face tracking results may be taken as training pixels. A limitation of such a constraint is that, if the training region includes non-skin pixels, the color model can adapt to non-skin color. Skin detectors based on histogram [12] have the expensive time constraint.

Most existing skin detection algorithms work well in a normal environment, but are not reliable in the case of unpredictable and drastically changing real-world environments. Under a drastic change of illumination, skin color shows up as too bright or too dark, or exists with highlight regions somewhere on the forehead or with shadow regions somewhere over the face. Even in varying colored lighting conditions, the colors that skin shows are very different from the original skin color. In this case, most existing skin detection algorithms detect fragmented skin which will seriously influence the performance of a face detecting and tracking algorithm based on face color.

Previously proposed color based approaches usually face problems in detecting robustly skin region in presence of varying lighting condition. Most of the research efforts on skin detection have focused on visible spectrum imaging. Skin color detection in visible spectrum can be a very challenging task as the skin color in an image is sensitive to various factors such as illumination, camera characteristics, ethnicity and individual characteristics. A change in the light source distribution and in the illumination level produces a change in the color of the skin in the image. The illumination variation is the most important problem among current skin detection systems that seriously degrades the performance. Even under the same illumination, the skin-color distribution for the same person differs from one camera to another. Skin color also varies from person to person belonging to different ethnic groups and from persons across different regions. Skin color also varies for individual characteristics such as age, sex and body parts.

In this paper, a method of facial skin detection using Gaussian mixture model and illumination estimation is presented. For illumination estimation, two skin models are used. One is under normal condition and the other is under high lighting condition. The method was applied on frontal and lateral color images and the results are compared with conventional skin color segmentation method based on GMM. The proposed method of facial skin detection can detect skin under normal environment as well as varying illumination condition. The percentage of correct skin detection by this method is higher than other methods. Also, the percentage of skin detected as non skin is lower than other methods. Experimental results ascertain the proposed method can detect skin more correctly than other method in different illumination condition which makes it highly applicable in plastic facial surgery.

The rest of the paper is organized in the following way. Section 2 describes about skin color modeling and segmentation based on GMM. Illumination estimation and compensation method is described in Section 3. The proposed method is given in Section 4. Section 5 shows some experimental results. Section 6 concludes the experiments and algorithms.

2. **Skin Color Modeling and Segmentation Based on GMM.** Although people from different ethnicities have different skin colors in appearance, experiments have shown that skin colors of individuals cluster closely in the color space, i.e., color appearances in human faces differ more in intensity than chrominance [13,14]. YCbCr color space is used to model skin color as it is suitable for real time application. Figure 1 represents the distribution of human skin color under normal illumination condition in YCbCr color space.

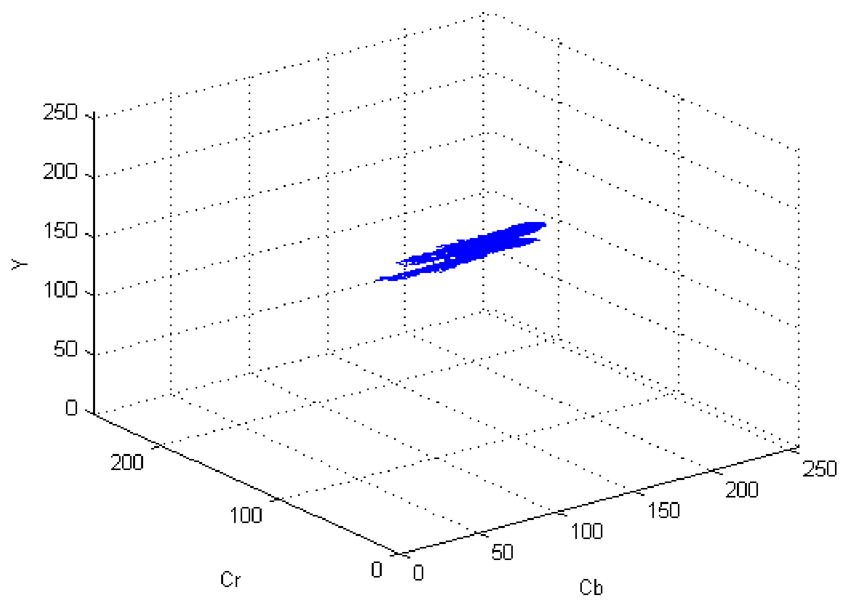

FIGURE 1. Skin color distribution under normal conditions in YCbCr color space

We have selected some pictures from internet with different ethnicities (e.g., Caucasian, Asian, African and dark skin types) under different varying illumination conditions and obtained the skin samples. One point for each skin samples are drawn in YCbCr color space according to the luminance and chrominance values of each skin samples. It can be observed from Figure 1 that although skin samples are taken from people of different ethnicities, the skin boundary for all falls within a specified region.

The distribution of skin color can be represented by a Gaussian model $G(\mu, \sum)$, with the mean by the following equation:

$$\mu = E(x) = (\bar{C}_b, \bar{C}_r)^T \tag{1}$$

where $x = (C_b, C_r)^T$ is the chrominance vector and the covariance is represented by the following equation:

$$\sum = E\left[(x-\mu)(x-\mu)^T\right] = \begin{bmatrix} \sigma_{cb,cb} & \sigma_{cb,cr} \\ \sigma_{cr,cb} & \sigma_{cr,cr} \end{bmatrix} \tag{2}$$

Skin model parameters are generated by manually selected skin regions. However, model parameters may vary for individually selecting data. Under changing illumination, the color of skin pixels have also changed and distributed outside of the skin color cluster according to the skin color model under normal conditions. In this case, conventional skin detection algorithm becomes unstable. The ability of a skin model adapting to illumination changes can be strengthened if the skin samples from unconstrained lighting conditions are modeled as separate skin models. So, each of the skin color sample sets is modeled as a Gaussian model which results two Gaussian skin models. The former one under normal conditions can be represented by $G_n(\mu_n, \sum_n)$, standing for the normal Gaussian skin model. The later one, obtained under special conditions, can be represented by $G_s(\mu_s, \sum_s)$, standing for the special skin model. The normal skin model is used as the ground truth model in skin detection whereas the special skin model is used to estimate the illumination.

To segment skin region, we have modeled the human facial color skin by GMM. The probability density function of this model will be as the following equation:

$$\begin{aligned} P(x|\theta) &= \sum_{i=1}^{k} \alpha_i P(x|i,\theta_i) \\ &= \sum_{i=1}^{k} \alpha_i \frac{1}{\sqrt{(2\pi)^d \left|\sum_i\right|}} \times \exp\left\{-\frac{1}{2}(x-\mu_i)^T \sum\nolimits_i^{-1} (x-\mu_i)\right\} \end{aligned} \tag{3}$$

where k is the number of classes in the mixture model, α_i is the weighting coefficient for each class, the parameter set $\sum_{i=1}^{k} \alpha_i = 1$, $\theta = \{\alpha_i, \mu_i, \sum_i\}_{i=1}^{k}$ is such that: $\alpha_i > 0$ and $\sum_i$ is a $d \times d$ positive definite matrix.

By assuming that the pixels in the image are independent, we have log likelihood function of the GMM as the following equation:

$$L(\theta) = \sum_{j=1}^{N} \sum_{i=1}^{K} \log\{\alpha_i P(x_j\,|i;\theta_i)\} P(i\,|x_j;\theta_i) \tag{4}$$

In case of Gaussian distribution this function becomes as follows:

$$\begin{aligned} L(\theta) = &\sum_{j=1}^{N} \sum_{i=1}^{K} \left\{ -\frac{1}{2}(x_j-\mu_i)^T \sum\nolimits_i^{-1} (x_j-\mu_i) \right. \\ &\left. -\frac{1}{2}\log\left((2\pi)^d \left|\sum\nolimits_i\right|\right) + \log(\alpha_i) \right\} P(i\,|x_j;\theta_i) \end{aligned} \tag{5}$$

where x_j is the value in jth pixel and N is number of image pixels.

We now can estimate the model parameters by the ML (Maximum Likelihood) estimation. In general, such a nonlinear maximization problem demands for iterative optimization methods like steepest descent or Newton method. EM (Expectation Maximization) is an alternative iterative optimization method for this particular problem, which offers a rather fast guaranteed convergence. Estimation of the model parameters by EM algorithm will be as the following equations [4,15,16]:

E step:

$$\alpha_i^{new} = \frac{1}{N}\sum_{j=1}^{N} P(i|x_j,\theta_i) \tag{6}$$

$$\mu_i^{new} = \frac{\sum_{j=1}^{N} x_j P\left(i|x_j,\theta_i\right)}{\sum_{j=1}^{N} P\left(i|x_j,\theta_i\right)} \tag{7}$$

$$\sum\nolimits_i^{new} = \frac{\sum_{j=1}^{N} P\left(i|x_j,\theta_i\right)\left(x_j-\mu_i^{new}\right)\left(x_j-\mu_i^{new}\right)^T}{\sum_{j=1}^{N} P\left(i|x_j,\theta_i\right)} \tag{8}$$

M step:

$$P\left(i|x_j,\theta_i\right) = \frac{P\left(x_j|i,\theta_i\right)\alpha_i}{\sum_{i=1}^{k}\alpha_i P\left(x_j|i,\theta_i\right)} \tag{9}$$

The first step in applying the EM algorithm is the initialization of the class parameters. This is done automatically by using *k-means* clustering.

3. **Illumination Estimation and Compensation Applied to GMM Based Skin Detection Algorithm.** To estimate the illumination condition four parameters of skin model are used. They are the chrominance component mean values μ and covariance Σ in the Gaussian distribution model, Standard deviation S of the chrominance components and luminance mean values $\bar{Y}$. The vector that characterizes the skin cluster center is defined as $v = (\bar{Y}, \mu)^T$. So, for normal model we have $v_n = (\bar{Y}_n, \mu_n)^T$ and for special model we have $v_s = (\bar{Y}_s, \mu_s)^T$. The detected skin color regions based on standard skin model is considered as known pixel P and represented by $v_p = (\bar{Y}_p, \mu_p)^T$. Then, the affects of illumination change on the chromaticity of skin pixels is determined and decided whether illumination compensation is needed or not [6].

Three distances related to P are determined as follows:

$$\begin{aligned} d_{pn} &= v_n - v_p = \left(\Delta\bar{Y}_{pn}, \Delta\mu_{pn}\right)^T \\ d_{ps} &= v_p - v_s = \left(\Delta\bar{Y}_{ps}, \Delta\mu_{ps}\right)^T \\ d_{ns} &= v_n - v_s = \left(\Delta\bar{Y}_{ns}, \Delta\mu_{ns}\right)^T \end{aligned} \tag{10}$$

If P is out of maximum inscribed circle of the standard skin model then the detected skin needs compensation. This can be represented as

$$\tilde{d}_{pn} > R \tag{11}$$

where R is the radius of the maximum inscribed circle of the standard skin cluster and $\tilde{d}_{pn}$ is the Euclidean distance between known pixel P and the normal skin cluster center on the chrominance plane [6].

$$\begin{aligned}\tilde{d}_{pn} &= |d_{pn}(C_b, C_r)| = \sqrt{d_{pn}^2(C_b) + d_{pn}^2(C_r)} \\ &= \sqrt{\Delta\mu_{pn}^2(C_b) + \Delta\mu_{pn}^2(C_r)}\end{aligned} \tag{12}$$

The adjusting values in the YCbCr color space are estimated using the distance d_{ns} of the two skin clusters. The adjusting factor is defined as the following equation:

$$\eta = (\eta_Y, \eta_{Cb}, \eta_{Cr})^T = \begin{bmatrix} 1 - d_{ns}(\bar{Y}) \times \omega \\ 1 + |d_{ns}(Cb)| \times \omega \\ 1 + |d_{ns}(Cr)| \times \omega \end{bmatrix} \tag{13}$$

where ω is the scale factor ($\omega = 1\%$) [6].

Finally, the adjusting vector of the chrominance pair components is defined as in the following equation. The illumination compensation of image is done based on this equation as described in more detail in [6].

$$\delta(C_b, C_r) = \eta(C_b, C_r) \cdot \Delta\mu_{pn} \tag{14}$$

Figure 2 shows the block diagram of the proposed method. At first RGB color space of the input image is converted to YCbCr color space. Then, Gaussian mixture model is applied to the converted image to extract the facial skin. The mean of the extracted skin pixels is the known value P. Then, illumination condition is estimated of the input image by measuring the position of P in the standard skin cluster region on the Cb-Cr chrominance plane. If P exceeds the radius of inscribed circle then illumination compensation is needed. Illumination compensation to the input image is done according to Equation (14). The illumination compensated image is feed to the Gaussian mixture model to segment the facial skin.

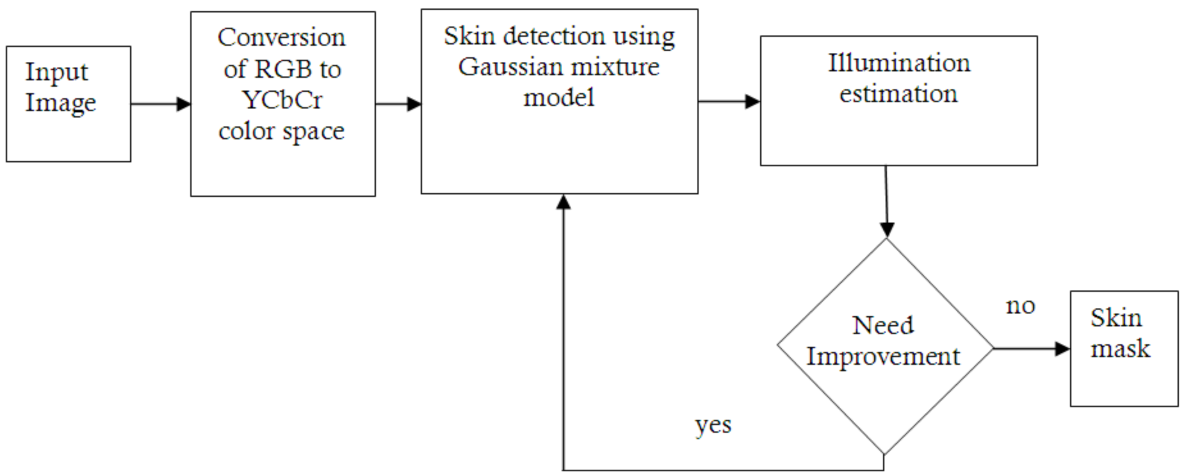

FIGURE 2. Block diagram of the proposed method

4. **Experimental Results.** To investigate the performance of the proposed method, experimental results are compared with conventional skin detection method based on GMM. For this purpose, we have used the frontal and lateral images of 50 persons as test images with different lighting condition. Figures 3 and 4 demonstrate some results of the proposed method on facial color images. We have assumed four classes with normal distribution in Gaussian mixture model. Figures 3(b) and 4(b) show the results obtained by

conventional skin detection method based on GMM. Figures 3(c) and 4(c) show the results obtained by the proposed method. Comparing these results we can see the proposed method performs better than conventional skin color segmentation method.

FIGURE 3. Skin color segmentation: (a) input frontal images, (b) the segmented images using conventional method and (c) the segmented images using the proposed method

Quantitative analysis has also been done to evaluate the performance of the proposed method. Four different metrics are used to evaluate the results of the facial skin detection algorithms like [6]. *SE* (skin error) is the number of skin pixels identified as non-skin, divided by the number manually segmented facial skin pixels. *NSE* (non-skin error) is the non skin pixels identified as skin, divided by the number manually segmented facial skin pixels. S is the percentage of skin pixels identified correctly. Based on the above mentioned parameters (SE, NSE and S), another two metrics are defined as follows:

$$M_E = \left(SE^2 + NSE^2\right)^{\frac{1}{2}} \tag{15}$$

$$M_S = \left(SE^2 + NSE^2 + (1-s)^2\right)^{\frac{1}{2}} \tag{16}$$

where M_E checks both kind of error, while M_S evaluates the skin detection results as a whole. Thus, we have five metrics values for all frontal and lateral facial images to indicate the skin detection performance of the proposed method.

Tables 1 and 2 show the performance of our proposed algorithm and conventional skin detection model based on GMM on frontal and profile images. Investigating Tables 1 and 2, it can be seen that the proposed algorithm achieves better performance on all images.

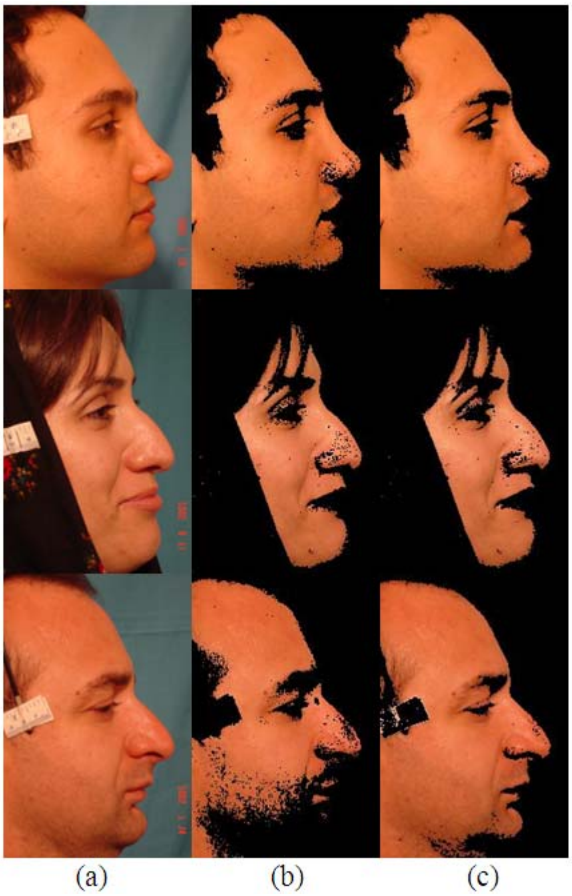

FIGURE 4. Skin color segmentation: (a) input lateral images, (b) the segmented images using conventional method and (c) the segmented images using the proposed method

TABLE 1. Skin detection performance from frontal images

	$\bar{S}\bar{E}$	$\bar{N}\bar{S}\bar{E}$	$\bar{S}$	$\bar{M}_E$	$\bar{M}_S$
Conventional Method	0.0716	0.0582	0.8602	0.1723	0.166
Proposed Method	0.0273	0.0327	0.9631	0.0564	0.097

TABLE 2. Skin detection performance from lateral images

	$\bar{S}\bar{E}$	$\bar{N}\bar{S}\bar{E}$	$\bar{S}$	$\bar{M}_E$	$\bar{M}_S$
Conventional Method	0.0824	0.0644	0.8510	0.1102	0.3104
Proposed Method	0.0251	0.0301	0.9592	0.0612	0.0718

Both average error ($\bar{S}\bar{E}, \bar{N}\bar{S}\bar{E}$) remain at low level, and the average correct decision ($\bar{S}$) are 0.9631 and 0.9592 for frontal and profile images, respectively.

As the experimental results shows that the proposed method of facial skin detection can detect skin most accurately than conventional method in varying illumination condition, the results of this method can be used to measure the necessary features for surgical planning in practical field more efficiently.

5. **Conclusion.** The varying illumination conditions have significant effect in facial skin color detection. In this paper, a method of skin detection based on Gaussian mixture model and illumination estimation using two skin models has been presented. Using two skin models for illumination estimation is suitable to cope with a complex illumination change. Based on this method an adaptive skin detection algorithm is presented. The key feature of this method is that it compensates the varying illumination effect and gives better skin detection performance under varying illumination. The advantages of this method includes better skin extraction under varying illumination condition, skin portion detection as non skin to be very low and non skin portion detection as skin to also be very low for all kinds of illumination. Experimental results ascertain that this method is highly applicable for facial surgical planning in practice.

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