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Detection of Skin Pigmentation using Independent Component Analysis

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ABSTRACT

This paper presents an approach for detecting and measuring human skin pigmentation. In the proposed scheme, we extract a skin area by a Gaussian skin color model that is estimated from the statistical analysis of training images and remove tiny noises through the morphology processing. A skin area is decomposed into two components of hemoglobin and melanin by an independent component analysis (ICA) algorithm. Then, we calculate the intensities of hemoglobin and melanin by using the location histogram and determine the existence of skin pigmentation according to the global and local distribution of two intensities. Furthermore, we measure the area and density of the detected skin pigmentation. Experimental results verified that our scheme can both detect the skin pigmentation and measure the quantity of that and also our scheme takes less time because of the location histogram.

Key words: Pigmentation, ICA, Hemoglobin, Melanin, Location histogram

1. INTRODUCTION

Skin pigmentation refers to those areas of the skin which differs in color from regular skin. As the skin is the largest organ of human body, it is always being influenced by some internal and external factor and often reacts through modifying the constitutive pattern of pigmentation. So the skin appears different in color. The pigmentation not only affects the skin appearance but also signs serious diseases such as melanoma, basal cell carcinoma, and squamous cell carcinoma. Hence, the pigmentation detection is a very significant for medical area or skin care and cosmetology.

Melanin and hemoglobin are the two components that impart a wide variety of colors to skin. The amount of melanin causes the skin color to vary from pale yellow to reddish-brown to black. The red color is due to hemoglobin, the oxygen carrying pigment in red blood cells. The abnormal of melanin and hemoglobin gives cause for the appearance of pigmentation disorder. The visual examination is the basic way of the pigmentation detection and it can help clinician and beautician to detect the pigmentation. But this is subjective and non-quantitative. Therefore, the quantity measurement has been very required for the pigmentation detection.

Since the early 90s, the digital image analysis has been used to detect the pigmentation without contacting with the skin. The image analysis can not only extract only the pigmentation from background but also can measure the information of the

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pigmentation such as size and color density. Clawson et al. [1] proposed a vision-based approach that detects and quantifies the pigment asymmetry which can display the degree of skin lesions. Automatic induction and neural network model are able to evaluate the diagnostic capability and identify maximum correlation values of skin lesions Madasu et al. [2] extended the technique of Fuzzy Co-Clustering Algorithm for images (FCCI) for detecting blotches in skin lesions. They computed the texture features of blotches by the normalized entropy function, which are included as an additional parameter for multidimensional clustering. However, most of conventional schemes need a stable illumination environment for improving the detection accuracy or dermoscopy equipments for acquiring the skin images. In this paper, we introduce a technique for pigmentation detection that is robust to illumination and is applied to a broader range of uses without the dermoscopy equipments.

Unlike skin lesions, the pigmentation disorders affect outward appearance but they are not indicative of potential health risks in most cases. Many people use cosmetics to cover them for the sake of vanity. It is necessary to detect and analyze the pigmentation for evaluating objectively the efficacy of cosmetics or the medical treatment. Like skin lesion detection, the vision-based detection approach can not only precisely extract pigments from the skin area but can also measure the quantity of pigmentation [3-5].

In this paper, we present a new scheme for detecting and measuring the pigmentation. The pigmentation can be detected by the different of scales of pigmentation and normal skin. Our scheme proceeds in three steps; skin detection based on a Gaussian color model, pigment decomposition by an ICA algorithm, and the measurement of hemoglobin and melanin by 2D location histogram. We experimented with two tests for evaluating the performance of our scheme. The first is the adaptability test for achieving the high recognition rate under a variety of illumination conditions. The second is the measurement test for evaluating the cosmetic efficacy that covers pigmentation disorders. From the experimental results, we verified that the recognition rate was above 93 percent under most conditions while achieving an acceptable processing time and also our scheme is able to measure the cosmetic efficacy.

The organization of our paper is as follows: In Section II, we introduce the definition of skin pigmentation and the related works about general skin detection and pigmentation detection. In Section III, we explain our scheme for detecting and measuring the hemoglobin and melanin of skin pigmentation in detail. The results of two experimental tests are discussed and compared to previous work in Section IV. Finally, we conclude our paper and make mention of future work in Section V.

2. SKIN PIGMENTATION

Our scheme uses one component of color-space to measure the pigmentation, similar as the general color measuring methods. This section looks about the physiological structure and optical properties of skin briefly and then discuss about the significance of color components and how to measure them.

The color of human skin is basically formed from two components, melanin and hemoglobin. They exist in the epidermis and dermis of human skin as shown in Fig. 1. Melanin is produced by melanocytes that absorb and propagate visible light and darken our skin color. Light absorption levels depend on the unit-volume of melanin. This is the reason for skin color differences between Caucasians, Asians and African. Hemoglobin, which is another natural chromophore, is found in blood cells. It makes the skin be a reddish color. The skin color is mainly formed by melanin and hemoglobin. When melanin levels are abnormal, al-

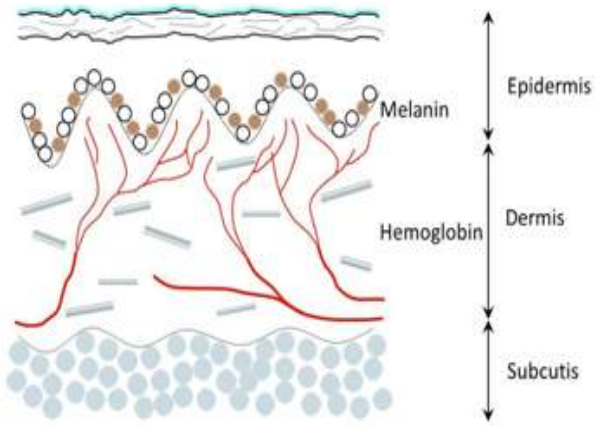


Fig. 1. Schematic cross-section of human skin tissue.

binism or melanoma could be diagnosed. When hemoglobin levels are abnormal, the skin may suffer injury or become erythematic. By the image analysis, two components can be decomposed from the normal skin and then the density and size of them can be quantified respectively.

Lu et al. [6] presented an approach for detecting the pigmentation by vision-based analysis. They segmented the skin region by a histogram-based Bayesian classifier and extracted components of melanin and hemoglobin based on an ICA algorithm. Then, they identified erythema regions by using a support vector machine (SVM) for melanin and hemoglobin. This scheme can detect well the pigmentation in low contrast images. But it takes a long time to process and it has limited adaptability under a variety of illumination conditions. Furthermore, this scheme does not quantify the pigmentation.

We present a new scheme for solving these problems in this paper. The skin segmentation and pigmentation detection can be thought of as image classification based on the color properties of three channels. But it may take more time. Therefore, our scheme utilizes two channels of CbCr to reduce computation time and memory capacity. Furthermore, our scheme decomposes the skin region into two components of hemoglobin and melanin by using an ICA algorithm. These processes lead to low processing time, especially for images with large resolution. Our scheme also measures the size or density of the pigmentation based on a location histogram.

3. PROPOSED PIGMENTATION DETECTION

The process of proposed pigmentation detection is shown in Fig. 2. Main features of our scheme are as follows. Firstly, our scheme uses the Gaussian skin color model and morphology (close) processing to segment skin area in the image. Two channels of Cb and Cr are selected to calculate the

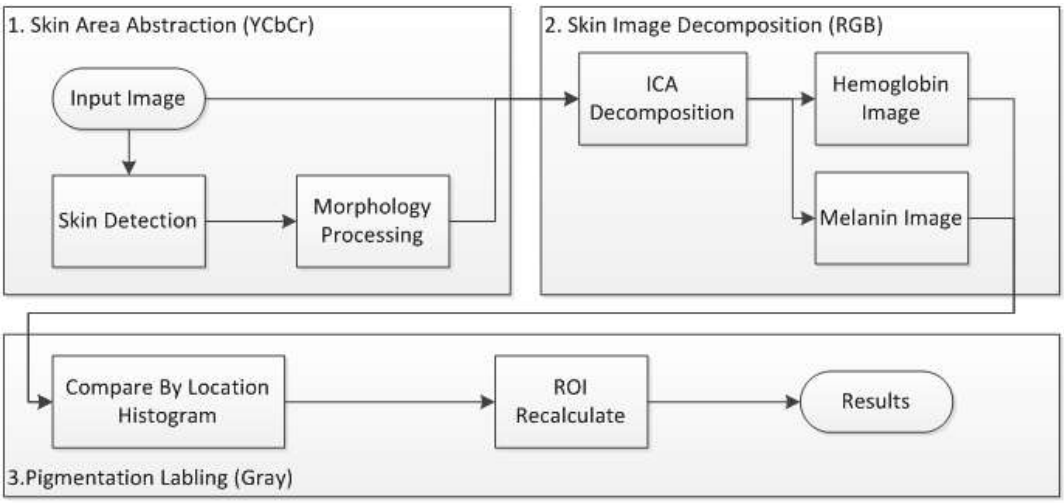


Fig. 2. Process of proposed pigmentation detection.

range of skin color. Secondly, our scheme uses an ICA algorithm to decompose the skin area into two parts of hemoglobin and melanin. Thirdly, our scheme uses the location histogram to measure the intensity of hemoglobin and melanin.

3.1 Skin Area Segment

3.1.1 CbCr channel

YCbCr is a common and important color space and it is a way of encoding RGB information. We obtain YCbCr color space from RGB color space as follows.

$$\begin{aligned} Y &= 0.229 \times R + 0.587 \times G + 0.114 \times B \\ Cr &= (R - Y) \times 0.713 + 128 \\ Cb &= (B - Y) \times 0.564 + 128 \end{aligned} \quad (1)$$

Generally and absolutely, it can find that color spaces of RGB and HIS are not good for color clustering algorithm, as shown in Fig. 3 but Cb and Cr spaces are good for clustering, as shown in Fig. 4. Our scheme designs the Gaussian skin color model in YCbCr space.

The different skin color has been mainly influenced by illumination, but a little influence from chromaticity. The illumination influences mainly

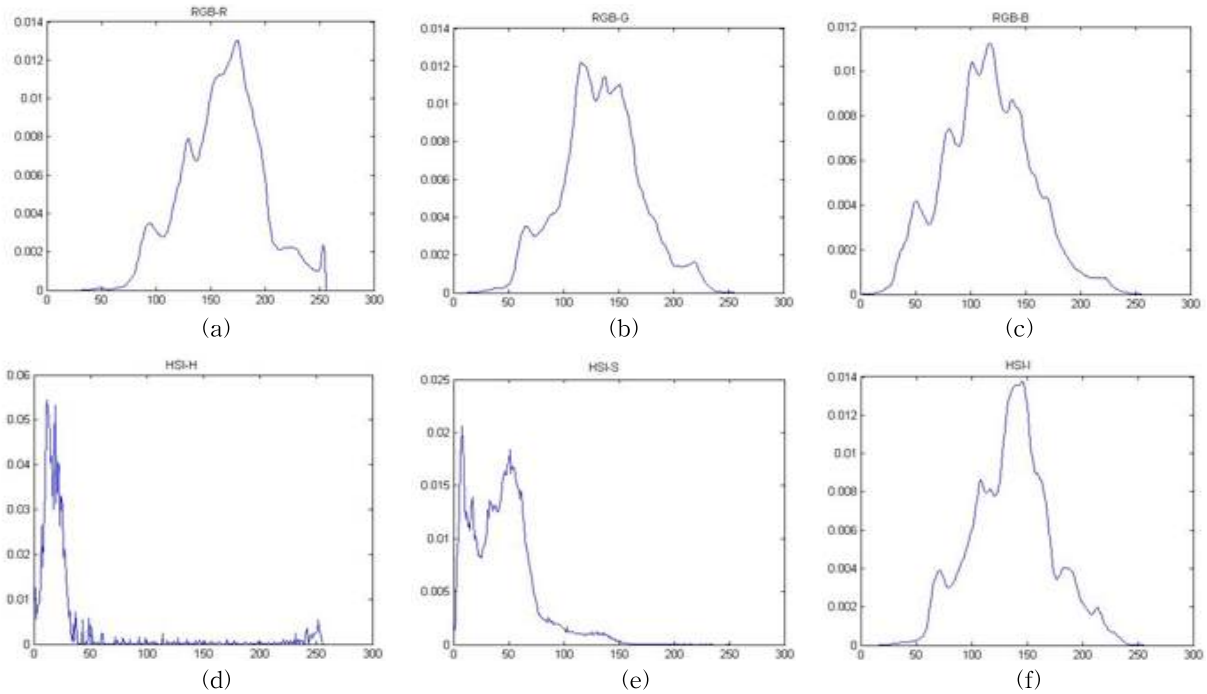


Fig. 3. Distributions of skin pixels in each channel; (a) R, (b) G, and (c) B channels in RGB space and (d) H, (e) S, and (f) I channels in HIS color space.

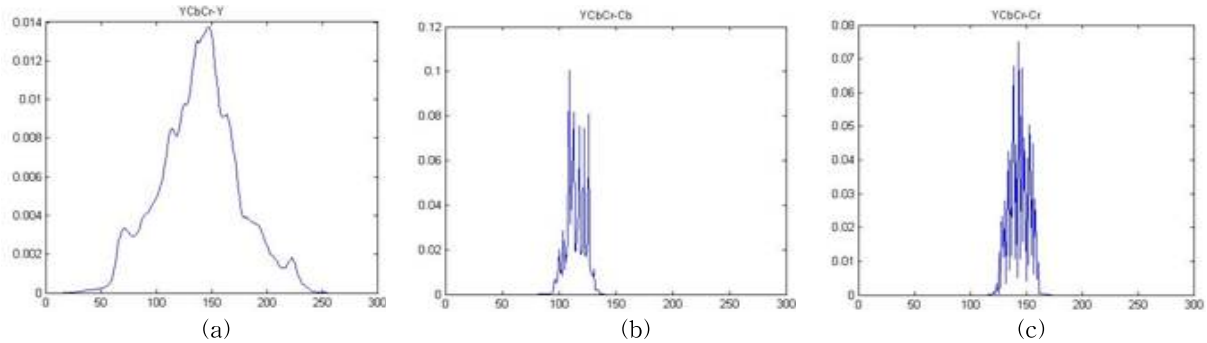


Fig. 4. Distributions of skin pixels in each channel; (a) Y, (b) Cb, (c) Cr channels.

on the skin color but the chromaticity little influences on it. This reasons that skin colors are closely distributed on chromaticity in YCbCr space although they are different. Therefore, our scheme uses the Gaussian distribution to describe the skin color in the CbCr channels [7,8]. We collect two hundreds of skin pictures that contain hand, arm, and face in a number of illumination environments and analyze color distributions of them for the Gaussian skin color model.

3.1.2 Gaussian skin color model

It is necessary to estimate the probability that a pixel belongs to skin areas. We get the similarity of skin by the distance from a center point of Gaussian distribution as follows.

$$P(CbCr) = \exp[-0.5(x-m)^T C^{-1}(x-m)] \quad (2)$$

m is the mean value of sample images and C is the covariance matrix.

$$x = (CbCr)^T,\ C = E[(x-m)(x-m)^T] \quad (3)$$

The 2D Gaussian model $G(m, V)$ of skin color can be expressed by

$$m = (\overline{Cb}\,\overline{Cr}),\ \overline{Cb} = \frac{1}{N}\sum_{i=1}^{N} Cb_i,\ \overline{Cr} = \frac{1}{N}\sum_{i=1}^{N} Cr_i, \quad (4)$$

$$V = \begin{pmatrix} \sigma_{CrCr} & \sigma_{CrCb} \\ \sigma_{CbCr} & \sigma_{CbCb} \end{pmatrix} \quad (5)$$

$\overline{Cr}$ and $\overline{Cb}$ are the mean values of Cr and Cb channels.

The Gaussian skin color model can be determined from a number of test skin pictures with experiments. Fig. 5 shows the Gaussian skin color model. Our scheme segments only the skin area from skin pictures and generates the binary image by the skin area and the non-skin area and then removes the noise area by the morphology processing.

3.2 Skin Decomposition

An ICA algorithm can extract the original signals from mixtures of many independent sources without a priori information on the sources. It can find the independent components by maximizing the statistical independence of the estimated components. Therefore, our scheme decomposes the skin area into two components of hemoglobin and melanin by an ICA algorithm, as shown in Fig. 6.

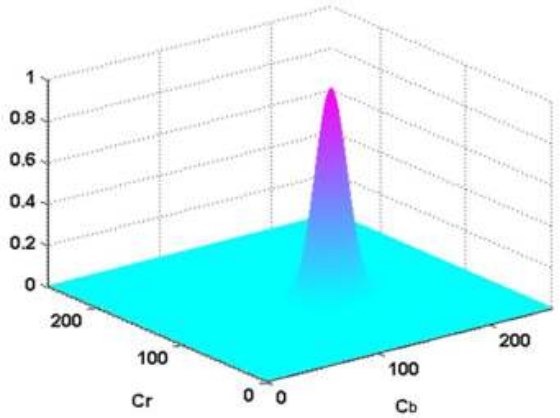


Fig. 5. Gaussian skin color model.

The analysis for skin color model is based on three assumptions. 1) The variations of colors in the skin are caused by two components: hemoglobin and melanin. 2) Quantities of them are independent to each other. 3) The observed color signals and the quantities of them keep the linearity in the optical density domain. Tsumura et al. [9] extracted components of hemoglobin and melanin from a human skin color image by using an ICA algorithm. Based on the linearity assumption, the skin color model in the optical density domain of RGB channels can be expressed by the color den-

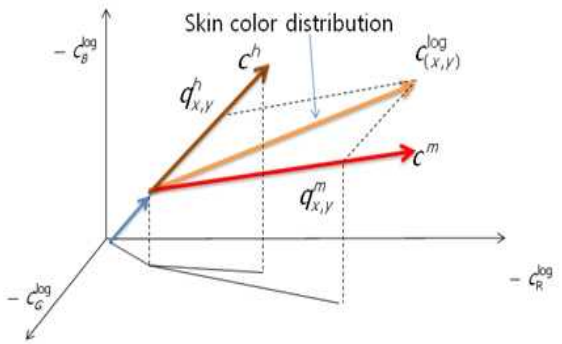


Fig. 6. Skin color model in the optical density domain of three channels.

sity vector $L_{x,y}$.

$$L_{x,y} = [-\log(r_{x,y}), -\log(g_{x,y}), -\log(b_{x,y})]^T \quad (6)$$

T represents the transposition and $r_{x,y}, g_{x,y}, b_{x,y}$ are pixel values in R,G,B channels of the skin color image. According to the first and second assumptions, $L_{x,y}$ can be rewritten by

$$L_{x,y} = c^m q^m_{x,y} + c^h q^h_{x,y} + \triangle \quad (7)$$

c^m and c^h are pure density vectors of melanin and hemoglobin. $q^m_{x,y}$ and $q^h_{x,y}$ are relative quantities of two pigments. $\triangle$ is a spatially stationary vector caused by other skin structure. An ICA algorithm is applied to estimate the relative quantities of two pigments. Therefore, the skin is decomposed as follows.

$$\begin{aligned} L'_{x,y} &= \tilde{C}(K[q^m_{x,y}, q^h_{x,y}]^T + jE) + j\triangle \\ [q^m_{x,y}, q^h_{x,y}] &= \widetilde{C^{-1}} L_{x,y} - E \\ E &= \min_{x,y}(\widetilde{C^{-1}} L_{x,y}) \end{aligned} \quad (8)$$

$L'_{x,y}$ is the synthesized skin color. $\tilde{C}$ is the estimated $[C^m, C^h]$. K and j are synthesis parameters. We set the synthesis parameters as K=diag[1,0], j=0 for melanin and K=diag[0,1], j=0 for hemoglobin.

From experiments, we know that if there are both hemoglobin and melanin in skin area, the distribution of melanin pigments will not get influence from haemoglobin pigments. Furthermore, we know that if pixels in skin area have low intensity, this area will be pigmented by melanin.

3.3 Pigmentation Measuring

3.3.1 Location histogram

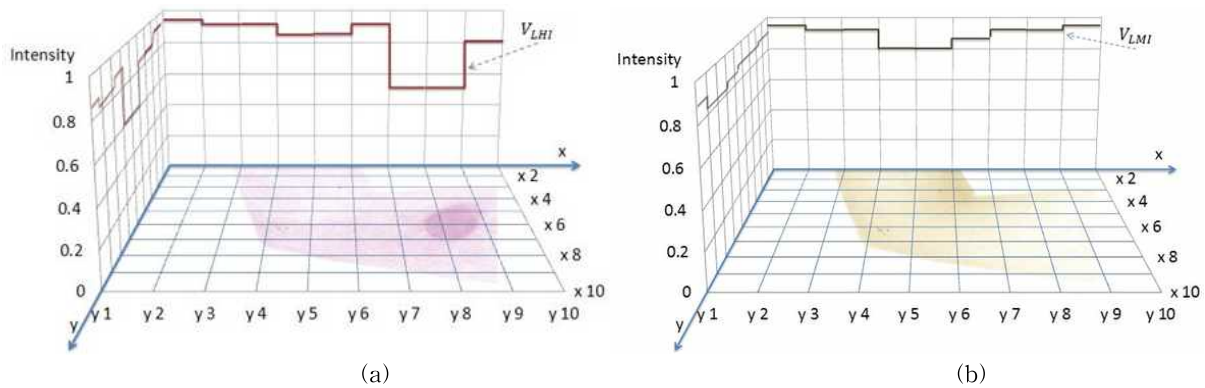
We design the location histogram to reflect the local distribution of two pigments and to identify the location of them. The location histogram can be defined on two axes of horizontal and vertical directions; 'X' and 'Y' [10]. Then we divide the skin area into a number of rectangular blocks and design two histograms on X axis and Y axis respectively. Fig. 7 shows location histograms of hemoglobin and melanin respectively. The block location can be known from the bin number of coordinates of skin areas. The representative value of block is the mean value of pixels that are included in this block.

We define two values of global ratio G and local ratio L. G is the ratio between the mean intensity of all hemoglobin pigments V_{WH} and that of all melanin pigments V_{WM}. L is the ratio between hemoglobin pigments V_{LH_i} and melanin pigments V_{LM_i} in a corresponding block.

$$G = \frac{V_{WH}}{V_{WM}}, \quad L = \frac{V_{LH_i}}{V_{LM_i}} \quad (9)$$

i is the index of a block. We determine a threshold th by G value and then compare local ratios L with th for estimating if there are pigments.

We compare hemoglobin and melanin pigments



(a) (b)

Fig. 7. Location histograms of (a) hemoglobin component and (b) melanin component.

by using two ratio values because human skin surface is not regular. In the same illuminations, some curved surfaces make different areas of skin have different intensities. But this effect usually appears in both hemoglobin area and melanin area at the same time. Therefore our scheme uses one ratio value to avoid this effect.

Additionally, the region of interest (ROI) must be considered to be recalculated. Our scheme uses the location histogram to detect the pigmentation. If the edge detection needs to be exact or there is not one pigment in skin area, any blocks will be falsely declared. Therefore, our scheme uses the same ratio value to recalculate ROI that is labeled by the last step. ROI is recalculated block by block.

3.3.2 Pigmentation quantification

Finally, our scheme quantifies the size of the pigmentation based the above location histogram. It can be represented by the number of pigmented blocks. Thus, the percentage of pigmentation area is the percentage of pigmented positive blocks. The intensity influence can be expressed by the standard deviation as follows.

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{10}$$

It measures the pigmented intensity how much different is around normal skin. Our scheme can use the above parameter to measure some areas that are taken before and after makeup to treatment.

4. EXPERIMENTAL RESULTS

Our scheme consists of main three steps; the skin area segmentation, skin decomposition, and pigmentation measurement. In the first step, the Gaussian skin color model $G(m, V)$ is designed by using two hundreds pictures of human skin. $G(m, V)$ is defined as

$$m = (\overline{Cb}, \overline{Cr}) = (117.4361, 156.5599), \tag{11}$$

$$V = \begin{pmatrix} \sigma_{CrCr} & \sigma_{CrCb} \\ \sigma_{CbCr} & \sigma_{CbCb} \end{pmatrix} = \begin{pmatrix} 160.1301, 12.1430 \\ 12.1430, 299.4574 \end{pmatrix} \tag{12}$$

We cluster the skin color according to the color distribution of Caucasian, Asian, and African, as shown in Fig. 8. These different color distributions of human race make the clustering range wide. Any skin color can be detected falsely to different human race in specific conditions. Furthermore, any skin color can be segmented to the non-skin area that looks like human skin. To decrease the false detection probability, we set the clustering

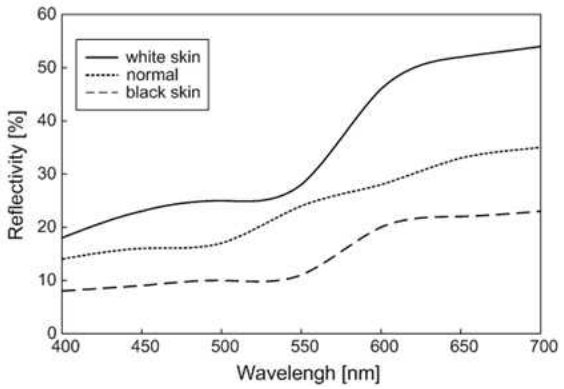


Fig. 8. The reflectivity of human race with white, medium, and black.

(a) (b)

Fig. 9. Example of skin area segmentation; (a) original image and (b) segmented image.

(a) (b) (c)

Fig. 10. (a) Original of human skin image and decomposed images to (b) melanin and (c) haemoglobin.

(a) (b) (c) (d)

Fig. 11. (a) Skin area with hemoglobin pigments, (b) detected hemoglobin pigments by 100x100 blocks, (c) skin area with melanin pigments, and (d) detected melanin pigments by 30x30 blocks.

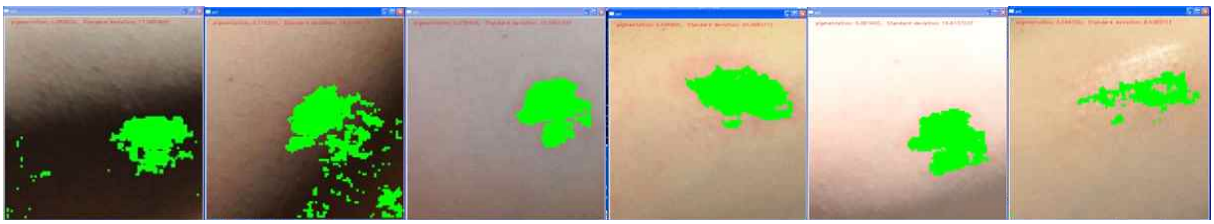


Fig. 12. Testing results in six illumination conditions.

range skin color according to human race. Fig. 9 shows an example of skin area segmentation. From this figure, we know that the skin area can be segmented with high accuracy.

The second step process the skin decomposition based on an ICA algorithm. Fig. 10 shows that segmented skin areas are decomposed into two components of haemoglobin and melanin. They are naturally detected from the same skin area. From these results, we know that the size and location of them are detected exactly. This makes the location histogram of the next step be accurate.

For the location histogram, we calculate histograms of decomposed components of hemoglobin and melanin on the horizontal and vertical axes. Our experiment found that the global ratio and local ratio in normal skin are similar $G \approx L$ but these ratios will be far away when the skin area contains red or black spot. Fig. 11 shows skin areas with hemoglobin pigments or melanin pigments and detected haemoglobin or melanin pigments on blocks.

Fig. 12 shows detected results in a number of illumination conditions, which are shadows of three types, light, sunshine, light reflection. Our scheme provides a way to detect haemoglobin and melanin pigments from a regular skin image and can effectively detect them as shown in Fig. 11 and Fig. 12. But our scheme should consider some problems. The first consideration is that any non-skin area that looks like human skin can be falsely segmented in the skin area segmentation. The second consideration is that the influence of illuminations must be minimized in the skin decomposition. Our scheme uses two ratios to minimize the influence of illuminations. Fig. 13 shows the pigment recognition rate of our scheme and Lu's scheme. From these results, we know that our scheme do recognize pigments better than Lu's scheme. When it is so dark shadow, as shown in the first example of

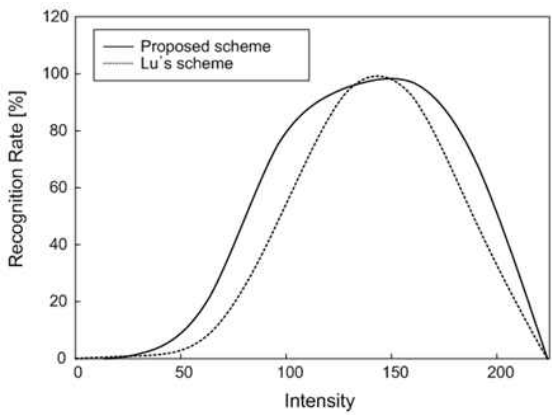


Fig. 13. Recognition rate of our scheme and conventional scheme.

Fig. 12, the intensity range is very limited. In this example, the shadow color looks like melanoma. We detected the shading component using the conventional method [11,12].

5. CONCLUSIONS

The paper presents an approach to detect and measure the human skin pigmentation. Our scheme designs a Gaussian skin color model by clustering skin color in CbCr channels and segments the skin are using this model. Then our scheme decomposes the skin area into two pigments of haemoglobin and melanin by using an ICA algorithm. Furthermore, our scheme introduces the location histogram for detecting the location and size of pigments. Experimental results verified that our scheme has a fast processing time and good detection performance in a number of illumination conditions. Our scheme has some problems to be improved; low detection accuracy in dark shadow and the trade-off relationship of an ICA algorithm between processing time and stability. They are our future works. Our scheme will improve the accuracy rate for detecting skin regions including background if conventional face detection algorithms [13,14] are used.

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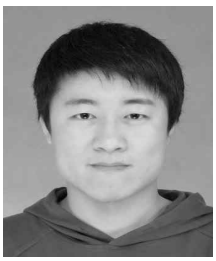

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