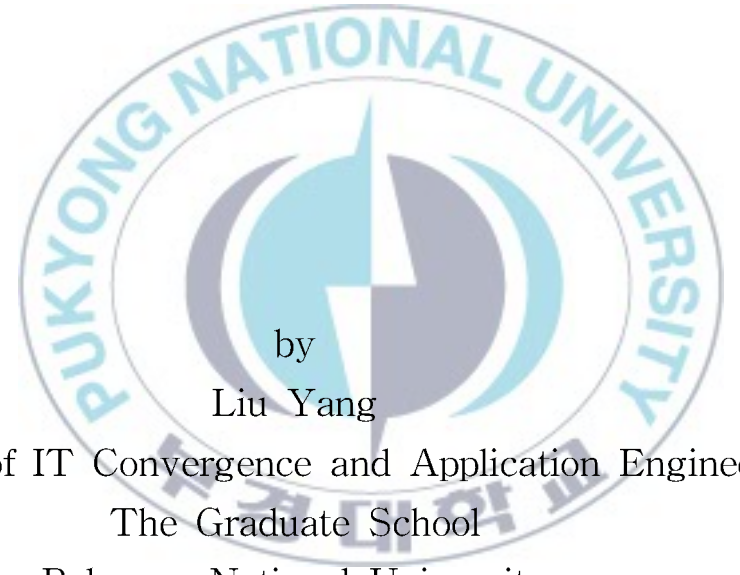
Thesis for the Degree of Master of Engineering

Skin Pigmentation Detection and Measurement based on ICA Algorithm



by
Liu Yang
Department of IT Convergence and Application Engineering
The Graduate School
Pukyong National University

August 2012

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ICA 알고리즘 기반 피부 색소침착 검출과 측정

Advisor: Prof. Ki-Ryong Kwon

by

Liu Yang

A thesis submitted in partial fulfillment of the requirements
for the degree of Master of Engineering

in Department of IT Convergence and Application Engineering, The Graduate School,
Pukyong National University

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Liu Yang

Approved by:

(Chairman) Young-Bong Kim

(Member) Mok-Dong Chung

(Member) Ki-Ryong Kwon

August 24, 2012

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Liu Yang

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요　　약

인간의 피부색은 멜라민, 헤모글로빈 및 카로틴 등의 여러 색소에 많이 영향을 받는다. 이들 색소들은 피부를 구성하고 있는 여러 계층들에 독립적으로 분포되어 있으며, 군집형태로 자리 잡고 있다. 인간들은 피부에 손상을 입거나 건강이 나빠지면 피부 색소 생산에 영향을 끼치며,

피부 색소침착은 작게는 인간의 외모에 영향을 주는 것 뿐 만 아니라, 크게는 인간의 건강에도 영향을 준다. 그렇기 때문에 피부 색소침착을 검출하는 것은 인간의 건강을 진단하는데 있어 아주 중요한 역할을 하며, 정확한 검출은 피부 질환 환자들의 빠른 치유에도 많은 도움이 된다. 또한, 피부 색소침착 검출 기술은 의료 응용 분야나 미용 및 화장품의 질을 평가하는 기준을 주기도 한다.

본 논문에서는 ICA 알고리즘 기반의 피부 색소침착 검출과 측정 기법을 제안한다. 제안하는 기법에서는 YCbCr 칼라 공간에서 가우시안 피부 색상 모델을 이용하여 피부 영역을 검출한 후 모폴로지 처리를 통해 잡음을 제거한다. 그 후, ICA 알고리즘을 이용하여 피부영역으로부터 헤모글로빈과 멜라닌 성분을 분리하고 2차원 국부 히스토그램을 통해 두 성분의 국부, 전역 강도와 위치, 크기들을 계산한다. 이러한 과정을 거친 두 성분의 국부적, 전역 강도 비교를 통해 피부 색소 장애 여부를 판단하게 된다.

피부 색소 계량화를 위해 본 논문에서는 색소 영역 백분율과 이미지의 표준 편차 인자값을 사용한다.

제안한 기법의 성능 평가를 위하여, 우리는 다양한 조도 환경에 변화에 따른 실험과 피부의 잡티를 감추는 여러 화장품에 대해 실험을 하였다. 실험 결과, 조도 변화에 강인한 것을 확인할 수 있었으며, 피부의 잡티를 감추는 화장품들의 질을 평가하는 기준을 마련할 수 있음을 확인할 수 있었다.

Skin Pigmentation Detection and Measurement based on ICA Algorithm

Liu Yang

Department of IT Convergence and Application Engineering, The Graduate School,
Pukyong National University

Abstract

Skin color of human is combined by the color which is from the melanin, hemoglobin and carotene etc. They are different distribution in different areas and crowd. When our skin become damaged or unhealthy, it affects skin pigmentation production.

skin pigmentation not only influence people's looks, some skin pigmentation disease will affect people's health. Skin pigmentation detection is very important in the skin disease diagnosis. Accurate detection is the premise of the fast cure skin disease. In evaluating the efficacy of medical hairdressing and cosmetic, skin pigmentation detection is also a important basis.

This paper presents an approach for detecting and measuring the skin pigmentation of human based on independent component analysis (ICA) algorithm. In the proposed scheme, we extract the skin area by using Gaussian skin color model in YCbCr color space and remove some noises by the morphology processing. Next, we decompose the skin area into two components: hemoglobin and melanin, by ICA algorithm and calculate local and global intensities, locations, and sizes of the two components by the 2D location histogram. Then we determine the existence of skin pigmentation disorders by comparing local and global intensities of them. And we give two parameters pigmentation area percentage and image standard deviation for the skin pigmentation quantification.

We tested our scheme with images in several different illumination conditions and also tested it on several cosmetic covering performances. As our expected,

experimental results of our scheme has better illumination adaptability and processing time than the conventional scheme. And our scheme also can be used to measure the vision-based evaluation of cosmetic covers by the parameters

Ⅰ. Introduction

Skin pigmentation is the area of our skin which part has different color from regular skin. As the largest organ of our body that is always influenced by some internal and external factors, the skin often reacts to those through modifying the constitutive pigmentation pattern. Then our skin will appear different color. When the body produces either too much or too little melanin, the skin pigmentation disorders occurs. There may be blotch, uneven areas, brown patches or spots. Additionally, uneven pigmentation affects many people, regardless of ethnic background or skin color. Melanin is the mainly determinant of our skin color. It can be found in hair, the iris of the eyes and brain. In most of cases, our skin possess a similar concentration of melanin. the melanin in some individuals and ethnic crowd more or less frequently express the melanin producing genes. If there is very little or no melanin in people's bodies, It's a condition named albinism.

Hemoglobin is another part of our skin color. It can disappear on finger pressure, while purple or bleeding in the skin and hemoglobin pigmentation do not. Hemoglobin pigmentation can be caused by infection, message, electrical treatment, acne medication, allergies, exercise, sunburn, etc. any of which can cause the capillaries to dilate or broke, resulting in redness. So some pigmentation is the reflection of disease or itself is the disease. That is not only affect people's appearance, even affect people's health.

Most of skin pigmentation detection is through the diagnosis of clinician or beautician. It's subjective and nonquantitative. In recent years people develop with the color measurement instrument to detect the skin pigmentation. A basic detection way of them is the visual examination for

solving this difficulty problem. Researches presented the vision-based detection of skin lesions in dermoscopy images for the diagnosis of them such as melanoma and other pigmented lesions [1],[2]. These algorithms focus on diagnosing and treating skin lesions from a medical standpoint. But optical instruments are more expensive, and the probe of color measurement instrument has great influence on the effects.

From 1987, people start to use the digital image analysis system to detect skin pigmentation. Image analysis not directly contact with skin. It's safe. Using the image processing technology can not only segment skin pigmentation from background, but also can calculate some character information of the skin pigmentation. But the image analysis system demand the image is high.

Unlike skin lesions, skin pigmentation disorders affects the outward appearance and they are not indicative of some potential health risks in most cases. Many people use the cosmetic to cover them for beauty. Skin pigmentation is necessary to detect and analyze for objectively evaluating the efficacy of cosmetic or skin medical treatment. Like skin lesion detection, the vision-based detection approach can not only precisely segment pigmented area from skin area but also calculate a quantity of pigmentation by any measurements [3].

In this paper, we propose a scheme to detect and measure hemoglobin and melanin of skin pigmentation in regular digital images. Our scheme proceeds on three steps: skin detection based on Gaussian skin color model, pigmentation decomposition by ICA algorithm, and detection and analysis of hemoglobin and melanin by 2D location histogram. We experimented two tests for evaluating the performance of our scheme. The first is for the adaptability in various illumination conditions. The second is for the measurement of the cosmetic efficacy to cover pigmentation disorders. From experimental results, we verified that our scheme has a good performance on two tests. The recognition rate can achieve 93

percentage in most conditions, meanwhile we got an acceptable processing time.

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

Ⅱ. Skin Pigmentation

2.1 Skin Optical Properties

As general color measurement methods, the proposed scheme uses one component of color space to measure the skin pigmentation. The color components have what kind of significance and how to measure them, we need to know more about the physiology structure and optical properties of our skin. Figure 1 illustrates the biological characteristics and how they affect the propagation and absorption of light [4]. Skin tissues can be divided into stratum corneum, epidermis, papillary dermis, reticular dermis and subcutis, from the outside to inside.

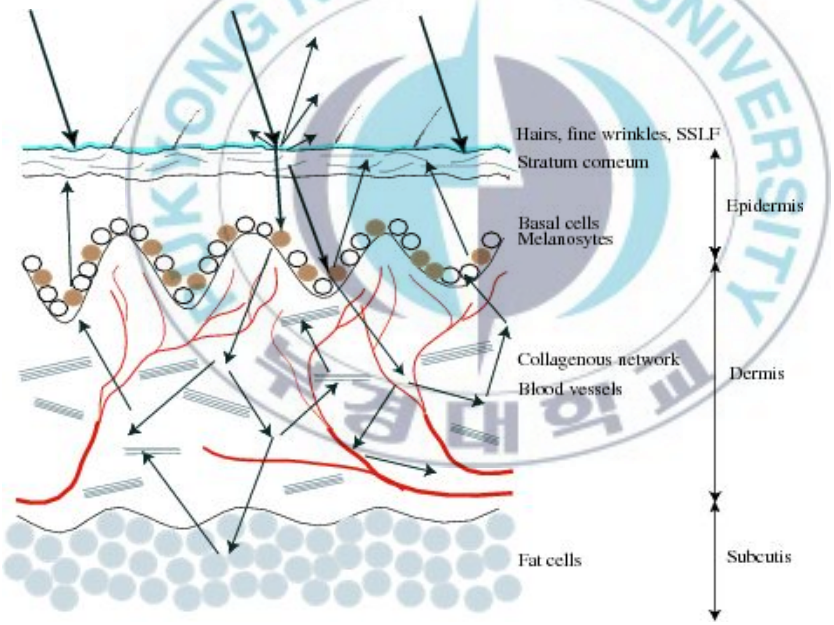


Figure 1. Schematic cross-section of human skin tissues

The outermost stratum is corneum which is a stratified structure of

approximately 0.01-0.02mm thick. This stratum is composed of mainly dead cells. This tissue gets low light absorption with the amount of transmitted light being relatively uniform in the range of visible spectrum.

The epidermis is 0.027~0.15 mm thick. The absorption ability comes mostly from a natural pigment which is called melanin. The absorption spectrum of melanin, as shown in figure 2, occurs highly around shorter wavelengths. Melanin is produced by melanocytes, which are found in the basal layer of the epidermis, and it absorbs and propagates visible light in the epidermis. The light absorption level depends on how many unit volume melanosomes in the epidermis. There are many types of melanin with differing proportions and bounding patterns of their components molecules. Both eumelanin and pheomelanin are found in human skin. Especially eumelanin is the most abundant melanin in humans.

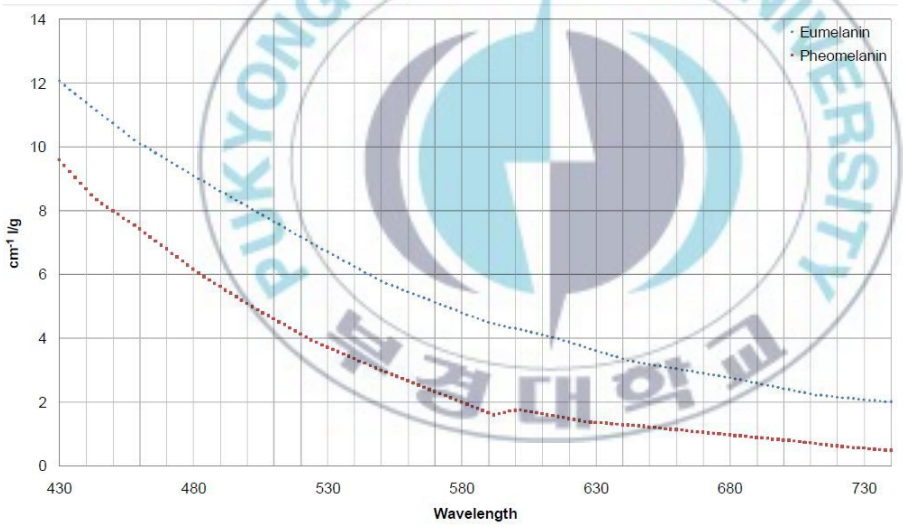


Figure 2. Absorption spectra of pheomelanin(red) and eumelanin(blue) which are common form of melanin.

The next stratum dermis is a 0.6-3.0mm thick structure which also propagates and absorbs light. It consists of the papillary dermis and the reticular dermis that are primarily composed of dense, irregular connective

tissue with nerves and blood vessels. In the blood cells we find another natural chromophore, hemglobin, which contain oxy-hemoglobin and deoxy-hemoglobin. The volume fraction of blood in tissue can be approximately in the 0.2~7% range. They absorb light and give blood red color. And the absorption spectra of hemoglobin depend on the visible light wavelength as figure 3. Another two blood pigments are bilirubin and beta carotene in the dermis, which provide the yellowish or olive tint to our skin. The absorption spectrum of them is shown in figure 4.

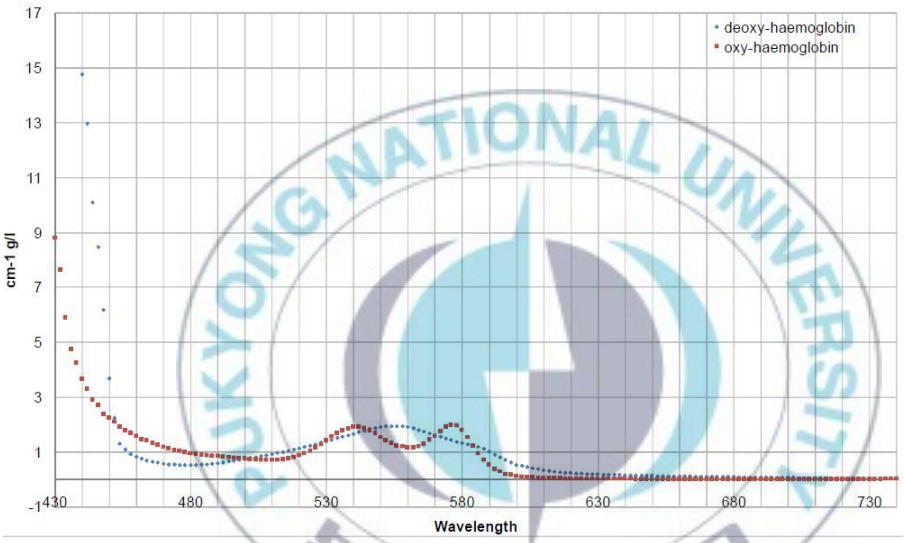


Figure 3. Absorption spectrum of hemoglobin.

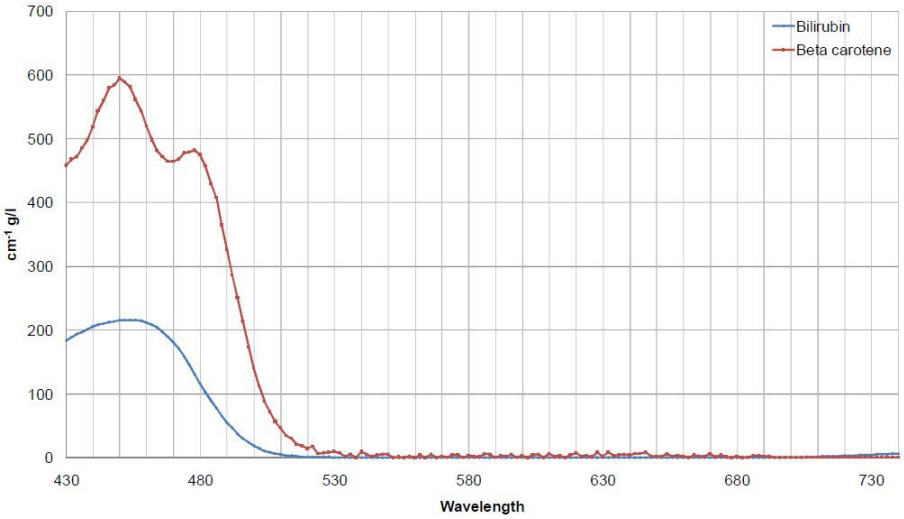


Figure 4. Absorption spectrum of bilirubin and beta carotene.

The subcutis is usually not considered part of the skin. It's a subcutaneous adipose tissue with a negligible absorption of light in the visible spectrum range. This layer consists primarily of white fat deposits and loose connective tissue. Because of loose connective tissue and white fat deposits, most of the visible light is reflected back to the upper layers when it reaches this tissue.

These absorption spectrums show that most of light is absorbed by skin around the short wavelength of spectrum. and according to those figures we can find a simple tendency of our skin color is that will be R>G>B in RGB color space. And the different components of our skin is independent to absorb light. Skin color is caused by mainly melanin and hemoglobin which are found in epidermis and dermis respectively. They can be appeared in certain ranges in the visible spectrum. And also they are causes of skin pigmentation. Therefore, melanin and hemoglobin are main components that we will have to detect for measuring the skin pigmentation.

2.2 Skin Detection Method

About the skin detection algorithm, the most simple and obvious characteristic of our skin is color or texture. Fotouhi [5] show us a way using contourlet-based texture analysis for the skin area detection. A pixel-based boosted skin detection method is used to recognize skin pixels. The skin texture features are used in the contourlet texture coefficients for improving the detect performance. For the candidate skin pixels in all subimages are selected and the feature vector of each patch is extracted. Multilayer perceptron is utilized to learn features and classify the input images.

On the other hand, as in paper [6], Zhengming proposed a scheme. That uses an image pixel skipping process instead of testing each pixel to label it as skin or non-skin. In addition to, motived by the efficient of Hsu's approach [7], a r-g color space based skin detection algorithm is developed. Author S. Kherchaoui [8] combine both a statistical model of skin color and geometrical face characteristics for face detection. The presented system contains two parts. One consists in skin color detection by using a statistical method, based on a Gaussian mixture model in the CbCr color space. The other part is about the detected candidate skin regions to select those corresponding to faces.

Most of skin detection methods use a relative mature algorithm that uses the color clustering combined Gaussian mixture model. The differences among these methods are color space and additional algorithm for improving the detect performance. They have shown that their methods are effective way for skin detection under some limitations, which are stable illumination and simple background. Without these limitations, the probability of false detections will be high. Therefore, we cluster skin pixels based on YCbCr color space and minimize the illumination influence and also classify different skin colors according to human intuitive.

2.3 Pigmentation Detection Method

Nugroho [9] developed image analysis of skin pigmentation for classification and quantification of eumelanin and pheomelanin types in skin. The proposed model is based on Monte Carlo simulation of light and skin. A model is developed by using collected data from clinical study. That clinical study involving hundreds participants with three different skin Images is conducted. In this paper, the inverse type of model is applied to extract the information of melanin and concentration reported. The proposed approach provides an effective characterization of skin layers to determine melanin types.

As the approach in [10], madasu extend the technique 'Fuzzy Co-Clustering Algorithm for images (FCCI)' by inclusion of texture features as a clustering parameter for detecting blotches in skin lesions based on color information. The algorithm is further improvised by adding the texture features computed from the normalized entropy function as an additional parameter for multidimensional clustering.

In Paper Clawson [11] proposed an algorithm for the detection of color asymmetry, the scheme is proposed for visual display and quantification color asymmetry. Automatic induction and neural network are brought in to evaluate the features diagnostic capability and identify those maximum correlation value. The results show that the features quantifying possible regression region are most indicative of color asymmetry.

In the most of pigmentation detection papers, the main application is for medical diagnosis. In order to get accurate and comparable results, Most of schemes need a stable illumination environment and some professional dermoscopy equipments for acquiring the skin images. The disadvantage is the limitations of application and expensive instruments. As an improvement, we propose an approach which has the illumination

robust quality, but not depend on the expensive professional equipments. Let our skin pigmentation scheme has more widespread uses.

Ⅲ. Proposed Skin Pigmentation Detection

3.1 Overview

The proposed scheme of skin pigmentation detection consists of three steps, as shown in figure 5. The first step is the skin region and non-skin region dispartment. In this step, Gaussian skin color model is used to segment skin region in the original image and the clustering range of skin color is calculated by CbCr components because YCbCr color space is effective in clustering and mininmizing the illumination influence. We use a binary image to label the skin area and the rest background, and process the image by a morphology (close) processing. Then we can use this processed image as a mask to segment original image. The final image will only contain the skin area.

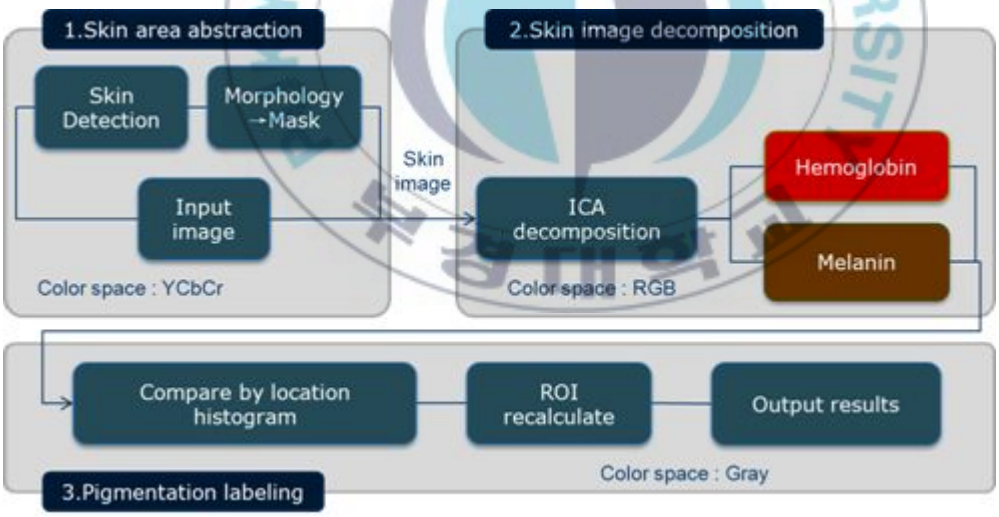


Figure 5. Proposed scheme of skin pigmentation.

In section Ⅱ we process the skin image by independent component

analysis (ICA) algorithm. Through the ICA algorithm, the preprocessing image will be decomposed into two parts: hemoglobin and melanin images which are only contain their respective color components. Meanwhile the melanin and hemoglobin pigmentation will be only showed in their own image. We can find their intensity will be different from the normal region.

In section Ⅲ we use the location histogram to calculate intensity of previous two pictures, and use these two intensity values to make a ratio. We call the whole image intensity ratio as G (global) value and the intensity ratio in each bin as L (local) value. We bring in the ratio value of the intensity to detect pigmentation for avoiding the illumination influence. We are according to the difference between the G value and L value to determine the existence of skin pigmentation, the skin pigmentation area will be estimated by the ratio value and a experience threshold. After that the bins which contain the skin pigmentation will be labeled. After that we use the same kernel to recalculate the candidate labeled region to enhance accuracy. Finally we get the skin pigmentation area ratio and standard deviation, two dimension parameters for the skin pigmentation quantification.

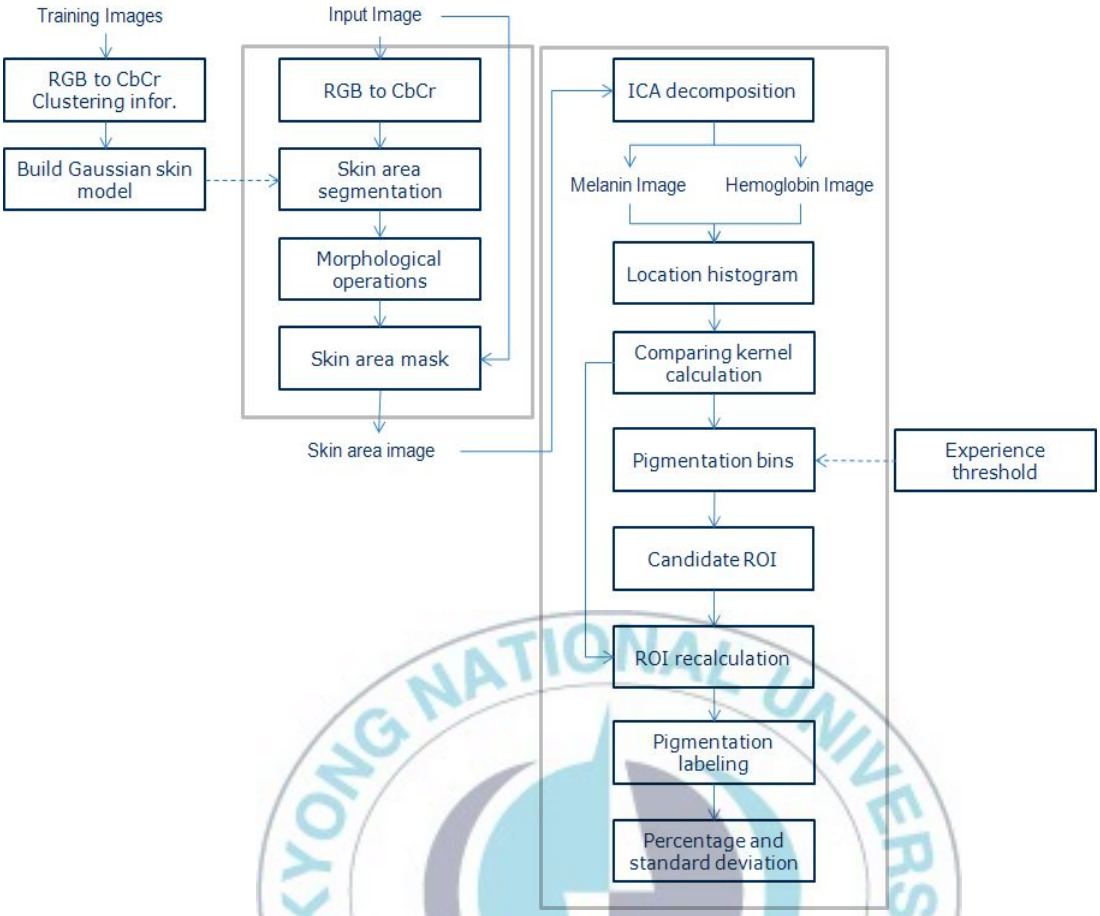


Figure 6. Detail process of the proposed skin pigmentation detection.

3.2 Skin Region Segmentation

Many researchers have presented methods for the detection and segmentation of skin area [12]-[14], which most of methods extract features of skin color pixel based on various color space models. We tested the performance of skin color clustering using various color spaces models and we found that CbCr components in YCbCr color space produce the best clustering performance. The proposed scheme segments an input image to the skin region and non-skin region by Gaussian color model in YCbCr color space.

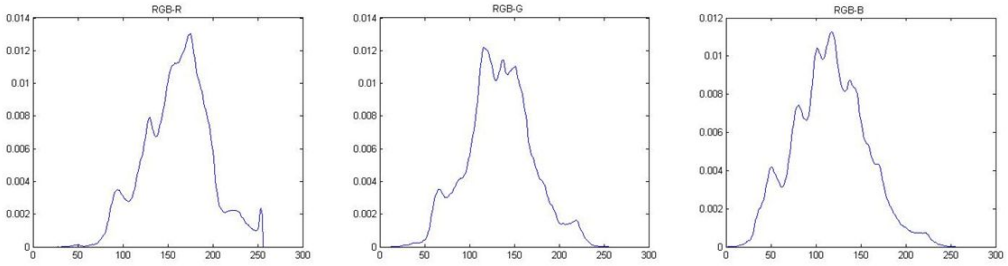
As figure 6, we try to use the training images as a prior information to make a mask for segmentation. The training images and the input image will be all converted to YCbCr color space. But we select the Cb, Cr components to segement the image. We collect two hundred pictures which only contain skin area pixels as the training images. The training image pixels distribution information will be calculated in YCbCr color space. Then according to these information we build the Gaussian skin color model. We use the Gaussian skin color model to estimate where contain the skin color pixels in the input image. Then in the image the skin color area will be labeled by white color, and the rest background area will be labeled by black. For removing some tiny noise area. we try to use a morphological operation (close). Then a skin mask is done for segmenting the input image. We use the mask to segment the original image. Finally the input image will only contain the skin area, and keep its original color space.

1) YCbCr Color Space

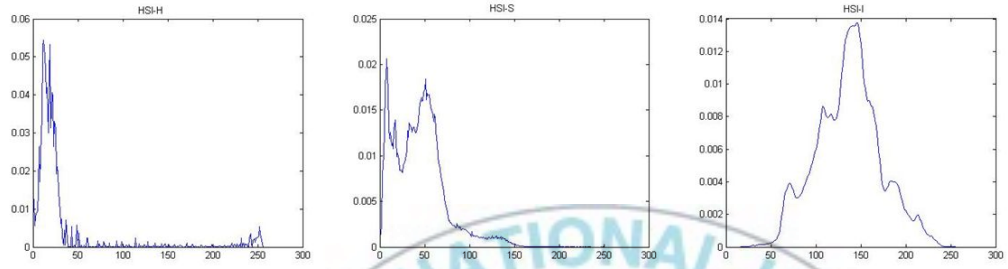
YCbCr is a common and important color space. It is not an absolute color space; it is a way of encoding RGB information. Therefore a value expresse d as YCbCr is predictable only if standard RGB primary chromaticities are used. And the values of YCbCr can be calculated from RGB as following:

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

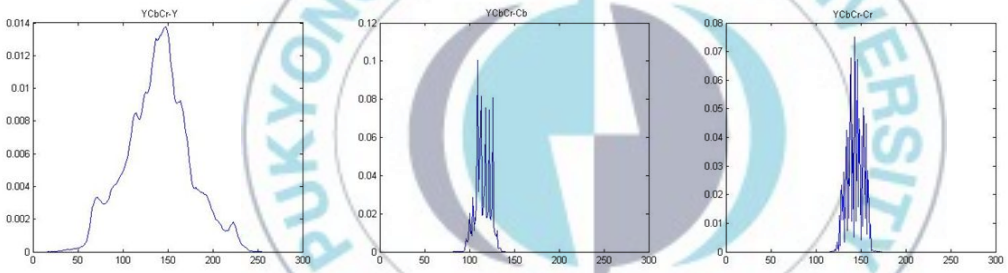
We compared the clustering performance of color spaces of HSI, RGB, and YCbCr etc. with two hundreds skin images which contain hands, arms or faces in regular day light. From the figure 7 (a)(b), we can see the pixels color distribution is not good for using clustering algorithm in RGB and HIS etc. color space. But in figure 7 (c), we can find the Cb, Cr from YCbCr color space have the best clustering performance, because of the most narrow range of the histogram. So we will build the Gaussian skin color model in YCbCr color space. On the other hand according to the statistic information, it has a wide distribution on illumination channel. So we only select a two dimension color space CbCr [15][16].



(a)



(b)



(c)

Figure 7. Histograms of (a) R,G,B channels, (b) H,S,I channels, and (c) Y,Cb,Cr channels.

2) Gaussian Skin Color Model

From the pixels intensity distribution statistical figure, we can find the pixels distribution is close to the Gaussian distribution as shown in figure 7(c). So we build the Gaussian skin color model according to that statistical information. We compute the skin similarity $P(CbCr)$, which means the probability that a pixel belongs to skin region, by using the distance from a center of Gaussian distribution. The skin color similarity image area is labelled by the model. In the other word, we can calculate the probability of pixels, that how much they belong to skin areas. And according to experience we give threshold of probability to distinguish the skin area from the background. And the formula of the similarity as following:

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

In the formula, m is the mean value of all the pixels of sample images. C is the covariance matrix.

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

The 2D Gaussian model G(m,V) of skin color distribution is also can be expressed as:

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

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

The $\overline{Cr}, \overline{Cb}$ are the mean values of Cr, Cb. V is the covariance matrix.

After that we finish the Gaussian skin color model building as figure 8. The new skin image can be input for segmentation. We convert the input image to YCbCr color space for measuring the similarity in the Gaussian skin color model. We calculate the Mahalanobis distance between input pixel location and the Gaussian model center. Then we need to select an appropriate threshold based on skin color statistic value of the skin image samples. Then we can know how much the probability of each pixel can be a skin pixel which is from new input skin image.

After we estimate the pixels if they belong to skin area, we transform input image to a binary image as a mask. We use white to denote the skin area part, and black to denote the rest background part. Here a Morphology processing (close) is used to remove the small noise area from the binary image. Finally we can use the mask to segment the original skin image. This session results are showed step by step like figure 9.

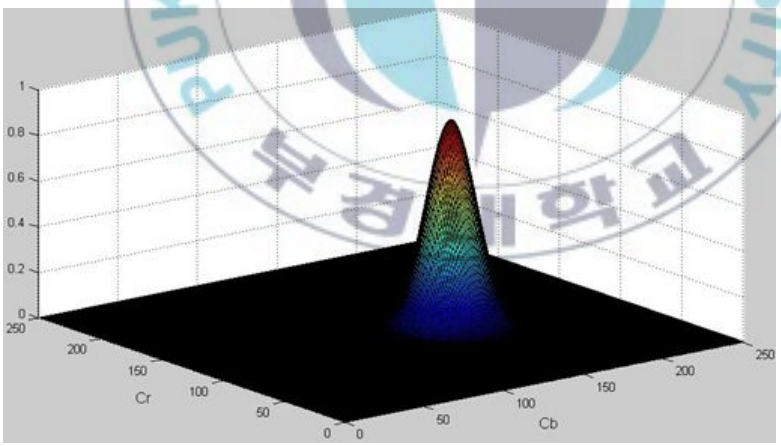


Figure 8. Gaussian skin color model

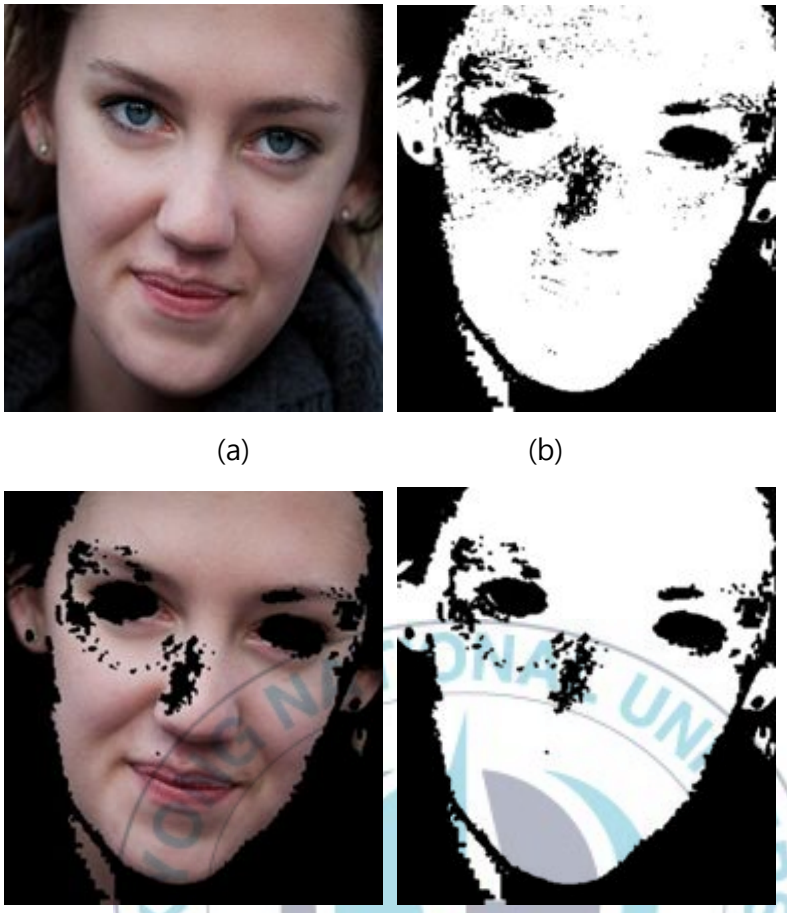


Figure 9. Examples of (a) an original image, (b) binary skin mask generated by Gaussian skin color model, (c) an image improved by morphology operators, and (d) final binary skin mask.

3.3 Skin Image Decomposition

1) ICA Decomposition

Independent component analysis (ICA) is a kind of new signal processing algorithm since 1990s. It is a method which can find out the hidden factors or component from the multidimensional statistics data. From linear transformation and linear space perspective, the source signals which are independent non-Gaussian signals can be seen as linear space based signals. The observed signal is a linear combination of the source signals. ICA is an algorithm which can estimate the basic structure of the data space or source signals from the observed signal when source signals and linear transformation are unknown.

ICA on its early stage primarily deals with blind separation issues like the "cocktail party problem". In the 1990s, J. Herault and C. Jutten [17] put forward the basic conception of ICA from the research of blind source separation (BSS). In 1995 A. J. Bell and J. Sejnowski [18] reinterpret the Blind Separation issue from the perspective of information system, and put forward the randomly graded decrease of Infomix ICA, the starting point of the ICA study peak. Hereafter, S. Amari with his research group did a lot of relative work in the calculation theory study. In the following ICA research system some young scholars, such as T. W. Lee, and A. Hyvarinen [19]-[21] did outstanding contributions in the field.

At present the ICA research work can be roughly divided into two categories, one is the basic theory and algorithm ICA, the basic theory part contains the basic model of linear and nonlinear ICA, signal mixing with the time delay, convolution sum condition, the ICA with noise, the instability source problem, etc. The algorithm part can be divided into iterative estimation methods based on information theory criteria and algebraic methods based on statistical, two mainly categories. In principle,

all of them use are using the independence of the source signal and non-Gaussian. And many scholars put forward a series of estimation algorithm, like FastICA algorithm, infomax algorithm, maximum likelihood estimation algorithm, the second order cumulant and fourth-order cumulants etc. high order cumulants method.

It is common that there exist some correlations among the different features of the samples, so one shall use some appropriate feature extraction method to get the most suitable features. In the progress of establishing a pattern recognition system, feature selection and feature extraction are the core jobs due to they are closely related to the design of classifying algorithms and are the main factors affected the performance of designed classifiers.

One of the major work of this paper lies in using a feature extraction method—Independent Component Analysis (ICA). The principle of independent component analysis algorithm is to find the mutual independent underlying components, to extract the independent original signals according to the analysis of the statistical relationships among the multidimensional observed data. Features extraction by ICA mainly aims at natural images processing. We try to bring in ICA algorithm to solve the skin pigmentation detection. As the previous introduction human skin color is cause of haemoglobin and melanin. These two components and some intensity composite our skin color. So we use an algorithm to decompose these two color components. That algorithm is Independent component analysis.

The spatial distributions of hemoglobin and melanin in skin image are separated by independent component analysis. The ICA algorithm can extract the original signals form mixtures of many independent sources without a priori information on the sources and process of the mixture. ICA finds the independent skin color components by maximizing the statistical independence of the estimated components. It can be calculate

by a neural network algorithm. We may also choose one or many ways to define independence, and this choice governs the form of the ICA algorithm. The independent component analysis is based on three assumptions, for human skin color model: 1) spatial variation of color in the skin is caused by two components: hemoglobin and melanin. 2) Their quantities are independent to each other. 3) The linearity holds among the quantities and the observed color signals in the optical density domain.

Tsumura et al. [22] extracted the hemoglobin and melanin images from a human skin color image by ICA algorithm. Base on the linearity assumption, in the optical density domain of RGB three channels we know the skin color model can be expressed as following:

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

Where T represents transposition, $L_{x,y}$ is color density vector on image coordinate, $r_{x,y}, g_{x,y}, b_{x,y}$ are the pixel values in red, green and blue channels of the skin color image on the image coordinate respectively.

The skin color density vector can be transformed by using the haemoglobin and melanin component to express. As shown in figure 12. So the skin color density vector also can be expressed as:

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

Where 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 the pigments; $\triangle$ is a spatially stationary vector caused by other skin structure. Principal component analysis (PCA) is used to extract the two-dimensional plane. Here about the measure the independence of independent component, we used the Burel's independence evaluation value [23] to obtain the minimizing value

for element of vector. The minimization is performed by quasi-Newton implementation using the Matlab toolbox [24]. ICA is applied to estimate the relative quantities. Skin is decomposed as:

$$L'_{x,y} = \widetilde{C}\left(K\left[q^m_{x,y}, q^h_{x,y}\right]^T + jE\right) + j\triangle, \tag{8}$$

where $\left[q^m_{x,y}, q^h_{x,y}\right] = \widetilde{C}^{-1}L_{x,y} - E$ and $E = \min_{x,y}\left(\widetilde{C}^{-1}L_{x,y}\right)$

In the formula, $L'_{x,y}$ is the synthesized skin color. $\widetilde{C}$ is the estimated $\left[q^m_{x,y}, q^h_{x,y}\right]$. *T* represents transposition. *K* and *j* are synthesis parameters. In our case, we set the synthesis parameters as $K = diag\,[1,0]$, $j = 0$ and $K = diag\,[0,1]$, $j = 0$ to get the melanin and hemoglobin components image.

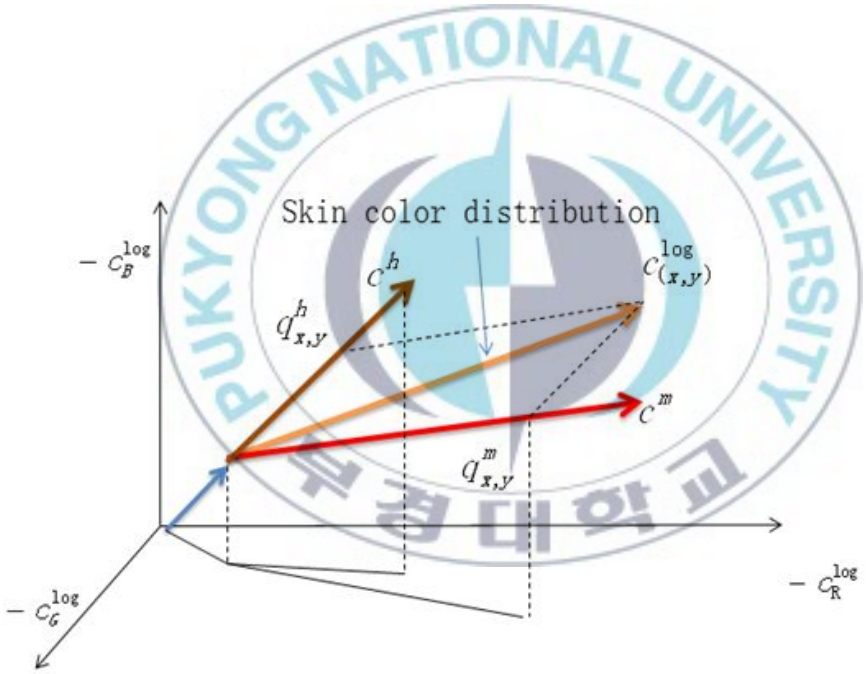


Figure 10. Skin color model in the optical density domain of three channels.

Though the ICA algorithm, original skin image is decomposed into

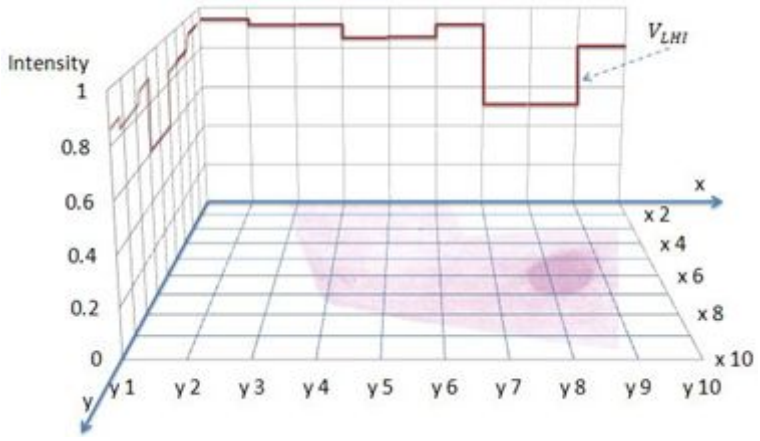
hemoglobin and melanin component images. From result images we can find if there is hemoglobin or melanin pigmentation in image, for example in the melanin component image intensity distribution will not get influence from hemoglobin component. If the pixels have lower intensity, that means there is pigmentation area in this melanin component image.

3.4 Skin Pigmentation Labelling

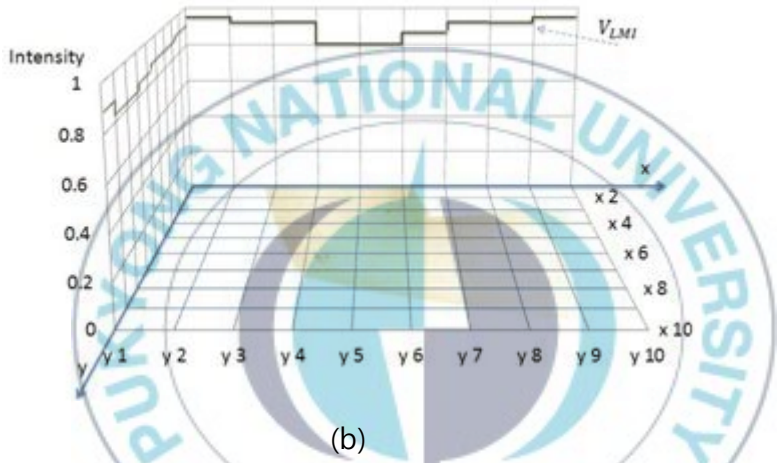
1) Location Histogram

In statistic histogram is a chart representation showing a visual impression of the distribution of data. It is a two dimensional statistics charts, its two coordinates are statistical sample and a corresponding measurement of the sample's attribute. In the image processing, a common application is the grayscale histogram. It's a grayscale function, describe the pixels number which is in this grayscale of the image. The horizontal of the coordinate is gray level, the vertical is the frequency of occurrence (pixels number) of image.

We propose the location histogram that reflects the space distribution of pixels. The location histogram has three axes of x,y,z. Z axis defines the intensity of pixels and X and Y axes define the spatial location of pixels in an image. We divide an image into a number of bins (blocks) and generate two histograms of X and Y axes respectively. Each bin is allocated to the mean intensity of pixels in a corresponding bin. The number of bins affects the intensity distribution of pixels [25]. Generally, the normal skin has more high intensity than the surrounding but the skin pigmentation has low intensity. This property can be used for detecting the skin pigmentation. We use the number of bins to control our simulation with accuracy.



(a)



(b)

Figure 11. Location histograms of (a) hemoglobin region and (b) melanin region.

Figure 11 shows location histograms of hemoglobin and melanin regions, which an image is divided into the blocks with the square number of bin. The intensity of block can be known from the matching bin value. Two histograms of X and Y axes are defined as follows.

$$h_x(i) = \frac{\int_{(i-1)\triangle}^{i\triangle} f(x,y)dy}{xy/n}, \quad h_y(j) = \frac{\int_{(j-1)\triangle}^{j\triangle} f(x,y)dx}{xy/n} \tag{9}$$

where i,j are the index of bin in the histogram and x,y are 2D position of pixels. $f(x,y)$ is the intensity of pixels, n is the number of bins. After computing the intensities of all bins, we make the global ratio, G, and the local ratio, L. Thus, G is the ratio of the mean-intensity of hemoglobin values to the mean-intensity of melanin values. And L is the local ratio of hemoglobin value of each bin to the matching melanin's.

$$G = \frac{V_{WH}}{V_{WM}}, \quad L = \frac{V_{LHi}}{V_{LMi}} \tag{10}$$

where i is the index of bins. We set the threshold depending on G and compare it with L to determine the pigmentation

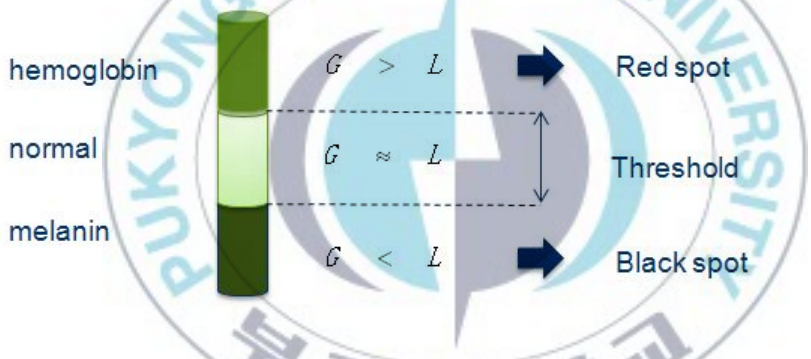


Figure 12. Distinction model of skin pigmentation.

we distinguish the different skin pigmentation from normal skin though the model in figure 12. For example, there is a hemoglobin skin pigmentation in the image, after the image decomposition the difference of intensity will obviously appear on the hemoglobin component image, but not in the melanin image. So intensity of the bin which contains the skin pigmentation in the hemoglobin will smaller than the global mean value. But intensity value of the matching bin which is in the melanin

component is similar to the melanin global, because the melanin component image doesn't contain the influence from the skin pigmentation. So we can complete the skin pigmentation by the above model.

2) Accuracy Enhancement

We compare hemoglobin and melanin images by using a ratio value. That's because human skin surface is always not a plane. In a same illumination environment, curved surface makes the different area of our skin will appear different intensity. And our skin also exist more of less secretions, it also causes the intensity distribution uneven. Then even in a same illumination environment, the different area of our skin will appear different intensity, as figure 13. But this effect usually appears at same time on both hemoglobin and melanin image. So we try to use a ratio value to avoid this influence.

Figure 13. The intensity of skin is not uniform under constant illumination because of the curve of face.

Another improved part is the interest of region recalculation block by block. we use the location histogram to detect the pigmentation. One of the benefits is that is a simple two dimensions space parameter make the processing and calculate faster. But if there is not only one skin pigmentation region on the image, there are some blocks will be falsely labeled. Location histogram labelling will be insufficient. So we will use same ratio value to recalculate the interest of region which is label by last step. During this process, the interest of region will be recalculated block

by block. Then we can keep the correct labeled block and remove the "false positive" one.

3) Pigmentation Quantification

After the detection, we can measure the skin pigmentation characteristic based on the location histogram information. About the size of skin pigmentation area it can be expressed by using the number of the skin pigmentation positive blocks percentage. The percentage of skin pigmentation area is about equal to positive blocks percentage. The number of bins is bigger, the accuracy is better. About the pigmentation color degree, we select a statistical parameter standard deviation to measure it. The standard deviation shows how much variation or 'dispersion' exists from the average. A low standard deviation indicates that the data points tend to be very close to the mean, whereas high standard deviation indicates that the data points are spread out over a large range of values. In our case the pixels intensity is the data points. the standard deviation shows how much different of the intensity between skin pigmentation pixels and the image mean value. Even the results will be affected by illumination and the percentage of the skin pigmentation area in the image. The standard deviation still can reflect the intensity difference between the skin pigmentation and the pixels which is around it. So the standard deviation can be expressed as following.

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^2} \tag{11}$$

where x is the intensity of pixels, $\bar{x}$ is the mean intensity value of whole image, N is the number of pixels.

Though the detection processing, we can know the skin pigmentation is

caused by melanin or hemoglobin, we only use one mainly influence component image to calculate the standard deviation. Then we can measure different skin pigmentation with the area percentage and standard deviation parameters. As we used this parameter to measure some images which are taken before and after makeup or treatment from the same place for judging their performance.

IV. Experimental Result and Analysis

4.1 Experimental Conditions

As the previous contents, we know the program can be briefly divided into three parts: skin area segmentation, image decomposition and histogram comparison. At the first stage the Gaussian model design is according to the values which are from the skin value cluster in the CbCr color model. As a priori information of this part, we collect two hundreds pictures of human skin. Those contain the parts from people's hands, arm, and face in different illumination environment. It's a mainly influencing factor. And our priori values as following:

$$M = (\overline{Cb}, \overline{Cr}) = (117.4361, 156.5599) \tag{12}$$

$$V = \begin{pmatrix} \sigma_{CrCr} & \sigma_{CrCb} \\ \sigma_{CbCr} & \sigma_{CbCb} \end{pmatrix} = \begin{pmatrix} 160.1301, & 12.1430 \\ 12.1430, & 229.4574 \end{pmatrix} \tag{13}$$

According to the statistical information as shown in figure 14, if we combine different kinds of skin color together, that makes cluster value width range. It will raise the possibility of detecting different kind color skin, but meanwhile program would also segment the background area which looks like human skin color. So we try to give different range value to different skin set to get the segmentation accuracy.

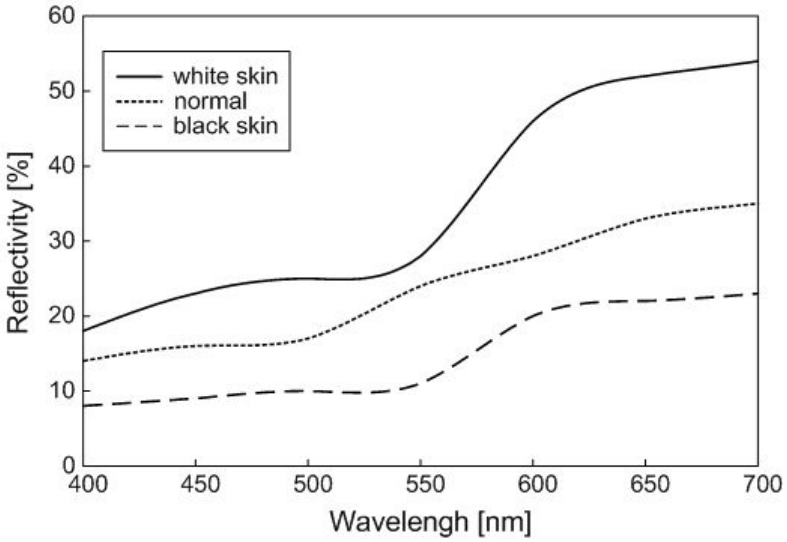


Figure 14. The reflectivity of three kinds of skin colors; white, normal, and black.

The image decomposition part is processed by ICA. As we expected the original skin image has been decomposed into hemoglobin component and melanin component as the figure 15. The two component images are extracted from one image. So the size and location of the skin pigmentation of those two images will be exactly match. This makes that the next stage histogram operation has a good accuracy by splitting the histogram into more bins.

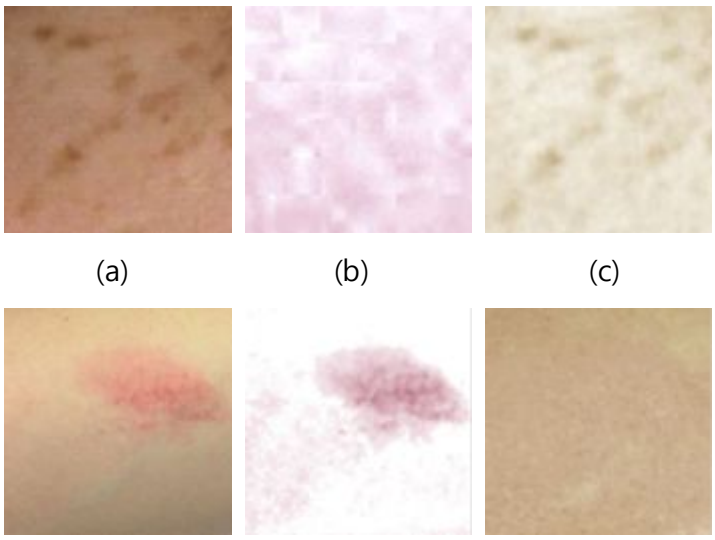
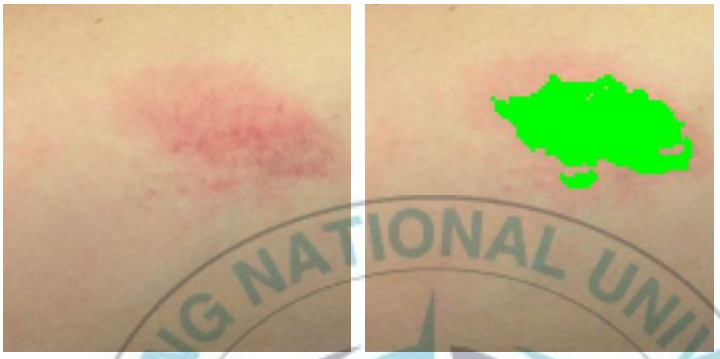


Figure 15. Results of skin pigmentation decomposition; (a) a skin region with black spot, (b) hemoglobin and (c) melanin components of black spot and (d) a skin region with red spot, (e) hemoglobin and (f) melanin components of red spot.

On the next step, we calculate the histogram value along the horizontal and vertical of the two images, then compared the matching values of bins to the global and local ratios in equation 10. From our experiment, we can see that normal skin ratio value is almost in a range around global ratio value, but if which bin contains a red or black spot, the ratio will be far away from this range. We use this feature to detect the block which contains skin pigmentation. The skin pigmentation is labelled as figure 16.

(a) (b)



(c) (d)

Figure 16. (a) a skin region with black spot and (b) a detected region with 30 by 30 numbers of bins, (c) a skin region with red spot and (b) a detected region with 100 by 100 numbers of bins.

4.2 Testing Results

1) Illumination Testing

For testing adaptability of program we acquired six kinds' pictures like figure 17 in different illumination environments. There are 60 images in our database. That contains in a single light source shadow, in multi light sources shadow, in the sun, with specular reflection etc. We test series images which are from low intensity to high. About picture shoot equipment we use digital camera Nikon D90, and white balance setting is auto.

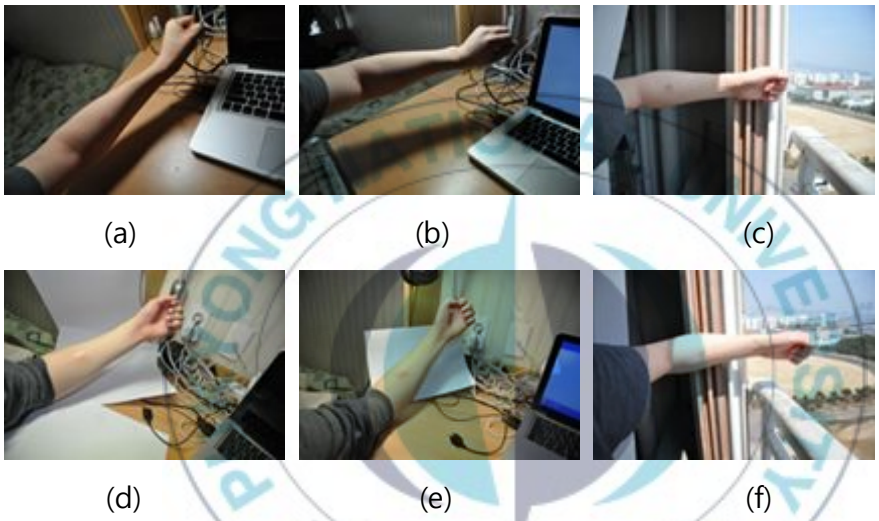
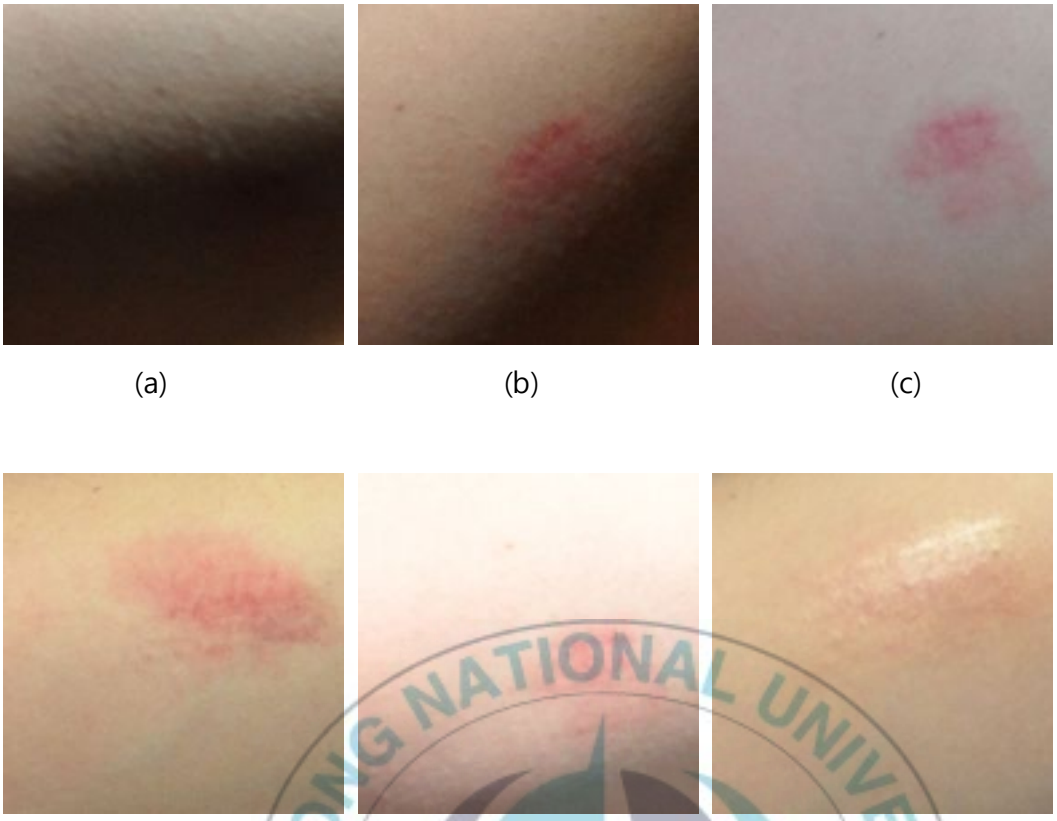


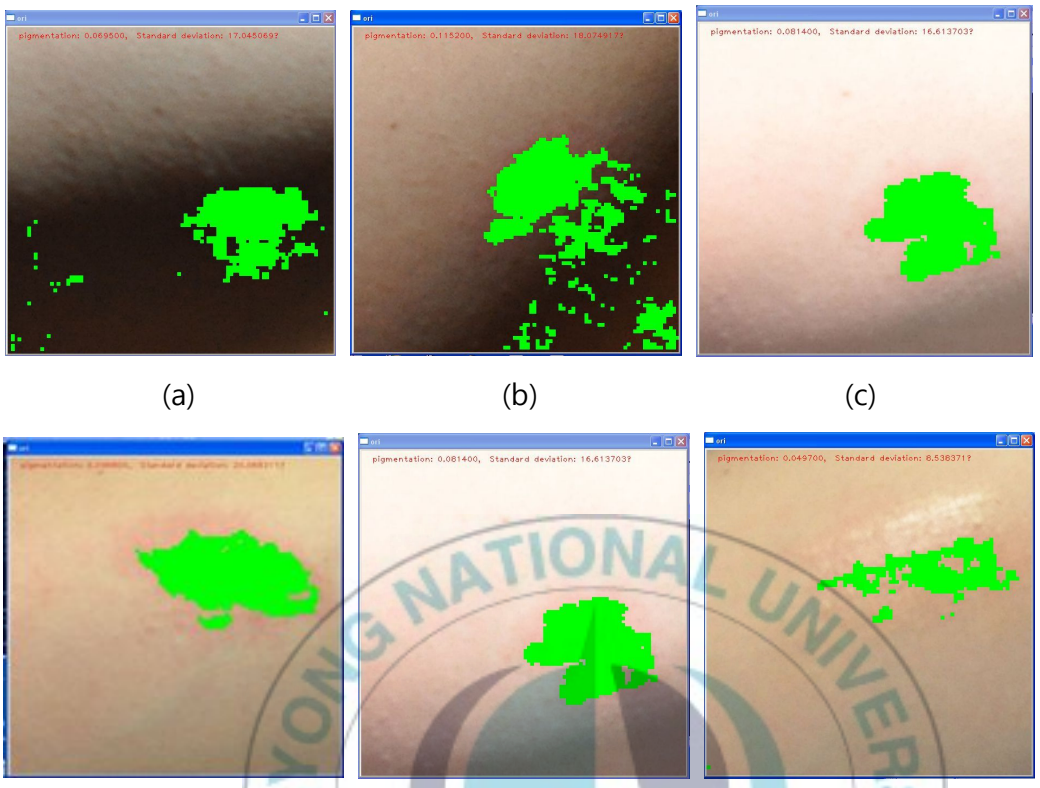
Figure 17. (a)-(f) Testing images obtained from Nikon D90 in difference illuminations.



(a) (b) (c)

(d) (e) (f)

Figure 18. (a)-(f) Tested images of pigmentations (a) in dark shadow, (b) in medium shadow, (c) in light shadow, (d) in light, (e) in the sun, and (f) specular.



(a) (b) (c)

(d) (e) (f)

Figure 19. (a)-(f) Detected results with the green part, which is labeled as skin pigmentation area and two parameters of the percentage of pigmentation area and the standard deviation.

Our tested images were under very common conditions in real-life, as shown in figure 18 and the detected results on these images are shown in figure 19. We used the green mask to label the skin pigmentation and output two quantities, which are the percentage of skin pigmentation area and the standard deviation. The results of two quantities are shown in table 1.

Table 1. Detected results under six kinds of illuminations.

	Dark shadow	Medium shadow	Light shadow	Lights	Sun	Specular
Detected area	6.95%	11.52%	7.54%	9.68%	8.14%	4.97%
Standard deviation	17.04	18.07	15.54	20.07	16.61	8.54
Error rate	22.85%	52.79%	1.28%	0%	1.19%	48.7%

From the results we can see the program has a certain light adaptability, the calculation error is very little. But we can also find in some extreme illumination environment, the results is far away from the true value.

2) Cosmetic Testing

That our scheme can apply to an important application is the evaluation of the cosmetic covering, which is one of purpose of our paper. We select three different brands cosmetic, all of them have covering skin pigmentation function. We applied about 0.05 [ml] of cosmetics to all of skin pigmentation areas and then measured quantities of skin pigmentation. We compared these after-makeup images with the normal skin region and the skin pigmentation region. Table 2 shows the detected results for three cosmetic products. We estimate the performance of the cosmetic covering according to the standard deviation. Our results verified that the color of cosmetic covering can be more close to human skin color.

Table 2. Detected results for three cosmetic covering.

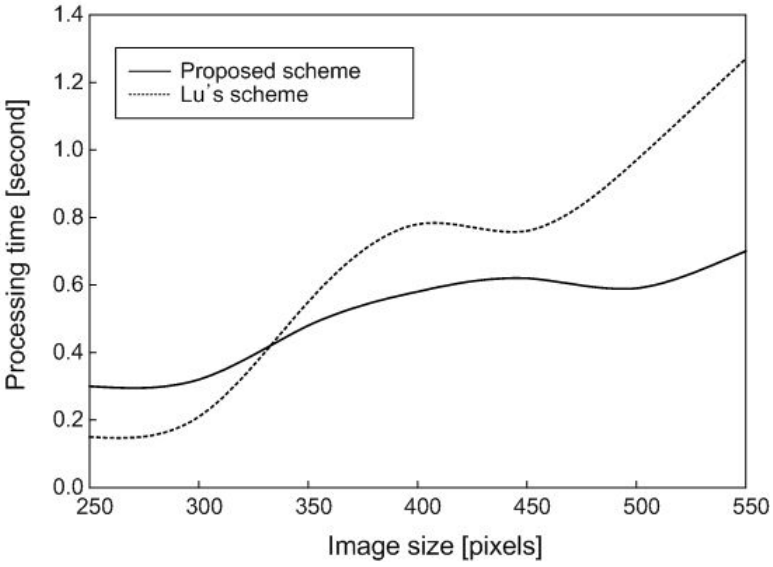
	Skin without pigmenta-tion	Skin with pigmenta-tion	Testing sample.1	Testing sample.2	Testing sample.3
Brand & item			Hera. Age away primer base	Meemoa. blemish cover balm	Etude House. BB magic cream
Detected area	0.00%	9.68%	0.12%	0.00%	0.15%
Standard deviation	7.61	20.07	9.17	7.72	8.98

From the table, we can see that the after-makeup images have less region of skin pigmentation. And according to the standard deviation value, we find the sample 2 has the smallest chromatic difference. This value is close to the surrounding normal skin. So we think that the sample 2 has the best performance.

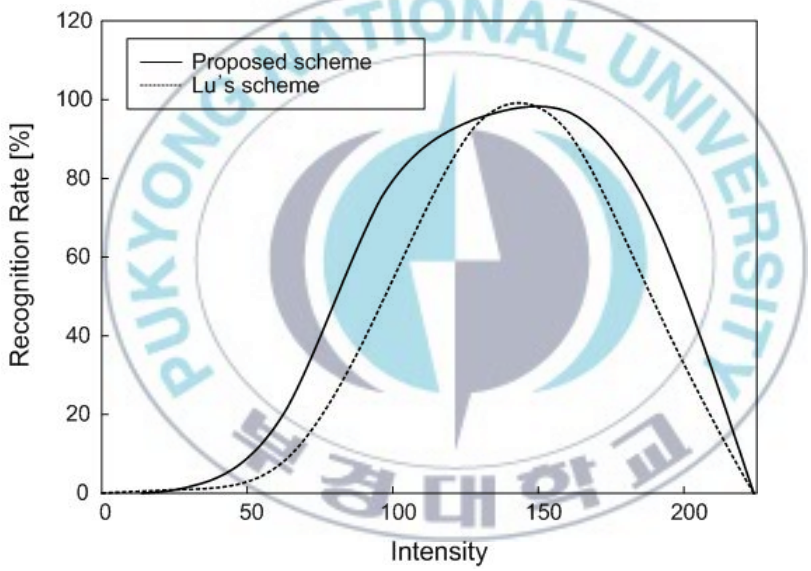
4.3 Performance Comparison

We compared our approach with paper [26]. The reference paper gives a way to segment skin pigmentation from digital images. It mainly contains three processing parts: first a skin region is detected with a histogram-based Bayesian classifier. Next the extracted skin image is represented in terms of melanin and hemoglobin components based on ICA. At last a trained Support Vector Machine (SVM) is applied to identify erythema areas using feature attributes from hemoglobin and melanin component images. That has the capability of segmenting the low contrast images and a good detection ratio. But it needs a long time for processing, and has limited adaptability for different illumination environment.

Thus we proposed our approach to solve them. The skin segmentation and pigmentation detection can be thought of as the image classification based on color properties of three channels. The essence of color space characteristic is three dimensional. Calculation is more complex and need more time. So in our scheme we try to project the three dimensions onto a low dimension vector space to reduce compute capacity requirement. For example, on the skin segmentation stage we remove the 'Y' element from the YCbCr color space. And on the skin pigmentation detection stage, the skin image is also decomposed into two dimensions the hemoglobin and melanin by ICA. And these processing does save processing time especially with the large images as figure 20. Meanwhile we bring statistical characteristic parameter to measure the size and density of the skin pigmentation base on the location histogram information. These make the program to use less time but more intuitive to describe the skin images.



(a)



(b)

Figure 20. Performance comparison of (a) processing times and (b) recognition rates

This approach provides a way to detect human skin pigmentation from a regular digital image. It can effectively detect the skin pigmentation from the digital image. But there are also some disadvantages. In the skin

segmentation step, the programming will be wrong to segment the area which is look like people skin on the background. And another is on the skin decomposition stage. We try to use a ratio value to avoid the illumination influence. But program will make some false label. Especially when there are shadows in the result, because the shadow color is like the melanoma. To solve this problem, we extracted the shading component like as [27],[28].

V. Conclusion and Future Works

The paper presented a scheme to detect the human skin pigmentation from a digital image. We use the skin color clustering in the YCbCr color model to build a Gaussian skin color model. After that we use this model to segment the skin area from the background of the image. Next we decompose the skin image into hemoglobin and melanin images by ICA algorithm. We bring in the location histogram to calculate the intensity of pixels, and we compare the global ratio value and the local ratio value which are computed by intensity value to determine if it is pigmentation. Meanwhile there are also some little processing steps for the programming can have a better performance. In our testing phase the programming perform a good processing time and detection rate in most cases. The program also has a shortage that it needs to improve the robustness for some special cases like dark shadow. And another part improvement is we can try to use different ICA estimate algorithm which is faster and stable. At last through the experiment proves our scheme is an effective way for the human skin pigmentation detection.

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Acknowledgements

I would like to express my sincere gratitude to all the people who have helped me to finish this paper. Without their help, I would not accomplish this thesis such successfully.

Firstly, I would like to give my thanks to my advisor, Professor Ki-Ryong Kwon, who has offered me his profound knowledge and devoted attention during my two years study. He is not only my supervisor who gives me many valuable suggestions through the whole postgraduate study, But also he act like an earnest friend who enlighten me how to brave the harsh time. I feel all the thanking sound pale to appreciate his endless help and care what he has given to me. All I can give back is my constant devotion in my future study. At the same time I would like to thank my another advisor Professor Suk-Hwan Lee, who has extensive knowledge. I very appreciate what he did during the past two years. And he read through all my rough paper and give me a very detail review.

There are also some people who must be mentioned. Doctor Teak-Yong Seung and Bong-Joo Jang who are the leaders of our MCSP laboratory. They gave me lots of useful advice on my korean life, They really make it so easy. Doctor Jun-Hee Kim our laboratory's female predecessor. She is really nice to me. And master Dae-Yeop Im is my closest friend. He is my korean life assistant and private translator. He is the people who I have talked the most. I am really happy that he is in our laboratory, Without him some thing would make me feel inconvenient. Master Xiao-Jiao Huo is another female who is from the same country like me. She also help a lot when I just came to Korea. So here I must sincerely say thank you to the above mentioned people.

During my two years graduate study life I have gotten lots of help and knowledge from the people in our laboratory. I feel very happy to be with them, The time when I live with them will be my unforgettable memory though my life. Thank my respectable professors and classmates for their support and encouragement.


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