Principal component analysis for pigmentation distribution in whole facial image and prediction of the facial image in various ages

Saori Toyota[1)], Izumi Fujiwara[1)], Misa Hirose[1)], Nobutoshi Ojima[2)], Keiko Ogawa-Ochiai [3)], Norimichi Tsumura[1)]
1) Graduate School of Advanced Integration Science, Chiba University, CHIBA, JAPAN
2)Global R&D Beauty Creation, Kao Corporation, TOKYO, JAPAN
3) Clinic of Japanese-Oriental (Kampo) Medicine, Department of Otorhinolaryngology & Head and Neck Surgery, Kanazawa University Hospital KANAZAWA, JAPAN

Abstract

In this paper, we apply principal component analysis to pigmentation distribution in whole face and obtain feature values. Furthermore, we estimate the relationship between the obtained vectors and the ages and simulate the changes of women facial image from in her 20s to in her any age by multiple regression analysis. Human faces is the well-known part which receive a lot of attention in the body. Changing the small quantity of the features in faces make large differences in their appearance. The features which we can receive divide broadly into two categories. One is the physical feature such as skin condition and its shape, and another one is the psychological features such as the ages and the health. In the beauty industry it is required to synthesize the skin texture based on the two kinds of the feature values. Previous works remain in the analysis of the skin texture using small area. By morphing shape of facial images to that of average face and extending the analyzed area to whole face, our method can analyze pigmentation distribution in whole face and simulate appearance of face by changing the age.

1 Introduction

The face is the part that receives the most attention in our body. We can obtain many information in their appearance such as individual features, human races, ages, emotions, sex, and health conditions. Changing the small quantity of features make large differences in their appearance like that we can recognize health condition by changing their facial color.

Recently, applications which change appearance of faces are put into practical use and continue to be developed with the advance of technology in various fields. Women especially have a strong interest in appearance of their face or skin, then applications which improve facial appearance are required in the practical use. However, conventional applications improve appearance simply, and these applications do not consider personal features.

In the beauty industry, the applications which change facial appearances using facial images are also required to predict the facial image in various conditions. Some computer-suggested skin analysis is often applied. The computer measures skin information of moisture level or analyzes roughness of skin texture. Additionally, computer-suggested simulation which change facial appearance using facial images are used to simulate makeup or predict effect of basic skin care products. When users change their skin texture to made-up skin or texture which provided benefits by basic skin care products, they can get simulation results without makeup or use of product in long term. These application are expected to synthesize the skin texture physically or simulate skin color based on two kinds of feature values. One kind of the feature values is the physical features such as individual qualities and structures obtained from faces, the other kind of feature values is the psychological features such as ages and health conditions. The cosmetic simulator is one of the examples for the above application. The simulator can perform a digital makeup with the skin information of moisture level, textures, and so on. The simulator can give advices to customers when choosing cosmetics. This application has a lot of techniques such as obtaining, analyzing and synthesizing skin texture or facial structure information and estimating skin color changes.

In the previous methods, many researches simulate changes of facial appearance. For examples, the changes of facial appearance are simulated for makeup[1][2], various ages[3], and races[4]. In the following sentences, the typical examples of simulation methods are introduced. Scherbaum *et al.* provided computer-suggested makeup[1]. They obtained detailed feature values like 3D structure, diffuse reflectance, normal map, subsurface-scattering, specular and glossiness using facial photographs took by different light sources. Guo *et al.* also proposed a digital makeup system where makeup information is extracted from facial images that have already made up and the extracted information is added on the another facial image without makeup[2]. These research could obtain appropriate result for personal features, because they used personal 3D structure. In their system, however, large systems are required to obtain information and it is difficult to apply them into practical use. On the other hand, Lantis *et al.* proposed framework that can be used for simulating aging effects on new face images in order to predict how an individual might look like in the future or how subject used to look in the past[3]. In their method, facial structure is changed by applying principal component analysis (PCA) and genetic algorithm to landmarks which obtained from monochrome images. Chalothorn *et al.* extracted racial differences between Japanese and Thai [4]. They applied PCA to skin texture and structure based on classification such as race. PCA is used extensively as a method to obtain feature values comparatively easily. In this paper, PCA is applied for pigmentation distribution in whole facial image to obtain feature values.

In general case, the RGB values are used for processing facial image as skin texture information. However, RGB values depend on changes of light source or characteristics of the camera, and it does not consider skin structures and property. Skin color mainly consist of melanin and hemoglobin pigmentation. Tsumura *et al.* proposed the method to extract melanin pigmentation and hemoglobin pigmentation from a single skin color image by the independent component analysis [5][6]. Melanin and hemoglobin colors can be obtained without affected by the changes of light source or characteristics of the camera by independent component analysis.

Okaguchi *et al.* obtained hierarchical pigmentation distribution from the image pyramid analysis and set image histograms as feature values [7]. Furthermore they analyzed the principal vectors of skin unevenness by applying PCA to feature values in the histograms, and simulated the skin texture which has arbitrary psychological features based on multiple regression analysis between psychological features and the feature values in the histogram. This research showed skin texture which had uneven pigmentation can be synthesized physically with appropriate the skin appearance. However, this method is restricted to small skin areas for processing, and they cannot perform in whole face.

In this paper, therefore we apply PCA to whole facial images by extending the area of analysis and we analyze pigmentation unevenness in whole face. Additionally we simulate the facial texture which has arbitrary psychological features based on the relationship between obtained principal vectors and features vectors by multiple regression analysis.

In Section 2 we describe our approach. First we present constructing facial image database, and morphing facial images to average face in subsection 2.1. In subsection 2.2, we extract melanin and hemoglobin pigmentation from a single skin color image by the independent component analysis[5]. Next we describe the method to apply PCA into pigmentation distribution and the method to analyze principal vectors of uneven pigmentation in subsection 2.3. Finally we simulate appearance of face which has arbitrary ages after estimating the relationship between obtained principal vectors and feature values by multiple regression analysis in subsection 2.4. In Section 3, we discuss our results. In Section 4, we describe conclusion own research.

2 Approach

This section shows the method to obtain feature values of pigmentation unevenness in whole face and the method of simulate facial appearance which has arbitrary psychological features. The overview of the process is as follows.

Step 1. Constructing facial image database

Step 2. Morphing facial images to average face

Step 3. Extracting melanin and hemoglobin pigmentation by the independent component analysis

Step 4. Analyzing principal vectors of uneven pigmentation by PCA

Step 5. Estimating appearance of face by multiple regression analysis and synthesizing facial images

In the next subsection, we describe the details of the above processes.

2.1 Constructing facial image database

We took women photographs who are from 10's to 80's and constructed database. The number of subjects is 202. Figure 1 shows the overview of imaging system. In this imaging system, ambient light sources were unaffected by blackout curtains. The four fluorescent lights are set to make square as light source. We took images by Nikon D3X, and used chin support to prevent movement of face. We obtained facial image without specular reflectance by setting polarization filters in front of the camera and the light sources as to be perpendicular respectively. Figure 2 shows a sample of the captured facial image in the database. We obtained their age who in the database as psychological features in this paper. Distribution of age in the database are shown in Figure 3.

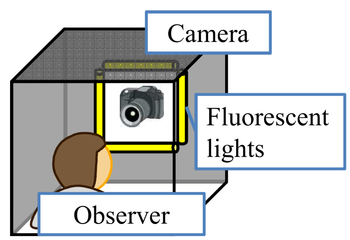


Figure 1 Over view of imaging system

Figure 2 Sample of captured image.

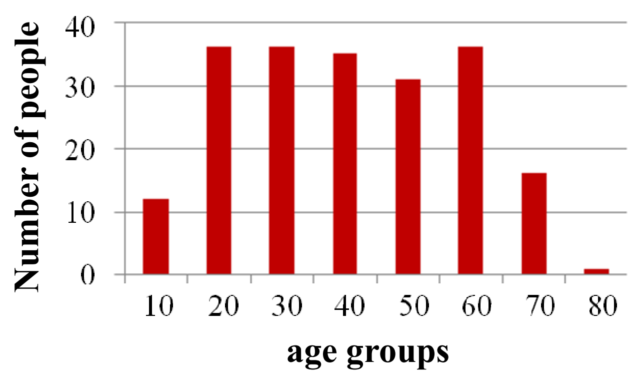
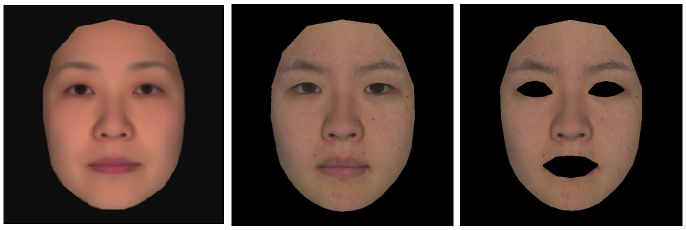


Figure 3 Distribution of age in the database

2.2 Morphing facial images to average face

We morphed shape of facial images into that of average face to remove the influence of individual facial shape in PCA for high degree of accuracy. Facial image synthesis system FUTON was used to morph facial images[8]. Each facial images were morphed to average face after created average facial image in the database. Figure 4(a),(b) shows average face and normalized image after morphing the image shown in Figure 2. It can be recognized that the image are normalized its structures with keeping its skin texture information. In addition, Since eyes and lips have different properties against pigmentation distribution of skins. we remove these area to prevent the influence when we apply PCA. The example of removed images is shown in Figure 4(c).



(a) (b) (c)

Figure 4 Processed image by FUTON: (a) average face, (b) Samples of normalized image by morphing, (c)Samples of image where unneeded area are removed

2.3 Extracting melanin and hemoglobin pigmentation

The human skin is constructed from two layers, epidermis layers and dermis layers. Epidermis layers mainly contains melanin pigmentation, and dermis layers mainly contains hemoglobin pigmentation. Entered incident light pass the epidermis and dermis, and light are emitted from surface of skin. Assuming that the Lambert-Beer law is satisfied in the skin layer for incident light, we can be considered that incident light is absorbed by the melanin and hemoglobin pigmentation, and changes of skin color depend on pigmentation distribution of these two pigmentation. In this case, the diffuse reflection can be written as follows:

$$L(x,y,\lambda) = \exp\{-\rho_m(x,y)\sigma_m(\lambda)l_m(\lambda) - \rho_h(x,y)\sigma_h(\lambda)l_h(\lambda)\}E(x,y,\lambda) \quad (1)$$

Lambert-Beer law is applicable by using the mean pass length of photons in the medium as depth of the medium. λ is wavelength, $E(x,y,\lambda)$ and $L(x,y,\lambda)$ are the incident spectral irradiance and reflected spectral radiance at position (x,y) on the surface. $\rho_m(x,y)$, $\rho_h(x,y)$, $\sigma_m(x,y)$, $\sigma_h(x,y)$ are the pigmentation densities and spectral cross-sections of melanin and hemoglobin, respectively. $l_m(\lambda)$ and $l_h(\lambda)$ are the mean pass length of photons in epidermis and dermis layers.

Surface reflection is removed by polarization in front of the camera and light source. Sensor response $c_i(i=R,G,B)$ from digital camera can be written in Equation (2):

$$\begin{aligned} c_i(x,y) &= \mathrm{k}\int L(x,y,\lambda)s_i(\lambda)d\lambda \\ &= \mathrm{k}\int \exp\{-\rho_m(x,y)\sigma_m(\lambda)l_m(\lambda) - \rho_h(x,y)\sigma_h(\lambda)l_h(\lambda)\}E(x,y,\lambda)s_i(\lambda)d\lambda \end{aligned} \quad (2)$$

where $s_i(\lambda)(i=R,G,B)$ is the spectral sensitivity of digital camera, and k is constant value determined from the gain of the camera. From the previous research by Dreaw et al. [9], we treat the sensitivities as delta function $s_i(\lambda)=\delta(\lambda-\lambda_i)$. Furthermore, we suppose the lighting environment is distant and that its spectrum does not vary with direction. Then irradiance can be written as $E(x,y,\lambda)=p(x,y)\bar{E}(\lambda)$, where $p(x,y)$ is shape-included shading variation. Therefore, Equation (2) can be simplified as follows:

$$c_i(x,y) = k\exp\{-\rho_m(x,y)\sigma_m(\lambda)l_m(\lambda) - \rho_h(x,y)\sigma_h(\lambda)l_h(\lambda)\}p(x,y)E(\lambda_i) \quad (3)$$

When we take the logarithm of Equation (3), following equation are obtained by vector and matrix formulation:

$$\boldsymbol{c}^{\log}(x,y) = -\rho_m(x,y)\boldsymbol{\sigma}_m - \rho_h(x,y)\boldsymbol{\sigma}_h + p^{\log}(x,y)\boldsymbol{1} + \boldsymbol{e}^{\log} \quad (4)$$

where,

$$\begin{aligned} &\boldsymbol{c}^{\log} = [\log(c_R(x,y)), \log(c_G(x,y)), \log(c_B(x,y))]^t, \\ &\boldsymbol{\sigma}_m = [\sigma_m(\lambda_R)l_m(\lambda_R), \sigma_m(\lambda_G)l_m(\lambda_G), \sigma_m(\lambda_B)l_m(\lambda_B)]^t, \\ &\boldsymbol{\sigma}_h = [\sigma_h(\lambda_R)l_h(\lambda_R), \sigma_h(\lambda_G)l_h(\lambda_G), \sigma_h(\lambda_B)l_h(\lambda_B)]^t, \\ &\boldsymbol{1} = [1,1,1]^t, \\ &\boldsymbol{e}^{log} = [\log(E(\lambda_R)), \log(E(\lambda_G)), \log(E(\lambda_B))] \\ &\boldsymbol{p}^{\log}(x,y) = \log(p(x,y)) + \log(k) \end{aligned}$$

are used to write Equation(4) in simple terms. Then the observed signals $\boldsymbol{v}^{\log}$ can be represented by the weighted linear combination of three vectors $\boldsymbol{\sigma}_m$, $\boldsymbol{\sigma}_h$ $\boldsymbol{1}$ with the bias vector $\boldsymbol{e}^{\log}$. Figure 5 shows overview of these process.

Figure 6(a) and (b) are the extracted melanin and hemoglobin pigmentation and (c) is shading in whole facial images shown in Figure 4(c). We can recognize the mole and pigmented spot from the melanin component images in Figure 6(a) and pimples from the hemoglobin component images in Figure 6(b). The shading component can be used to recognize the facial shape as in Figure 6(c). In this paper, the features in each components are processed respectively.

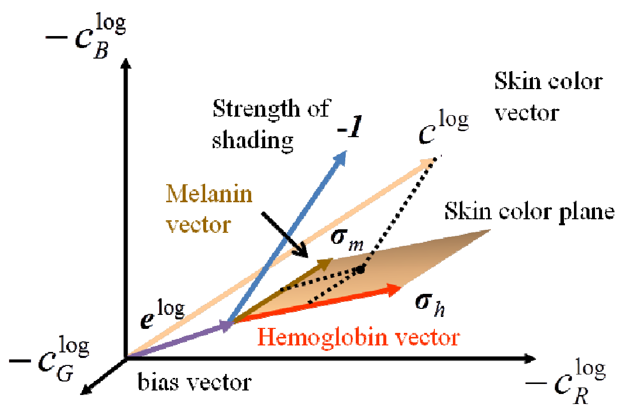


Figure 5 Overview of independent component analysis

(a) (b) (c)

Figure 6 The results of independent component analysis extracted pigmentation components: (a)melanin, (b) hemoglobin component, (c) shading

2.4 Analyzing principal vectors of uneven pigmentation

In this subsection, we describe the method to obtain feature values of uneven pigmentation in whole face by applying PCA to pigmentation distribution. PCA is a basic method of multivariate statistical analysis. This analysis calculates the maximum variance vector for the arbitrary data group, and defines the first principal component as a new index. Next the second principal component is defined in such a way that is perpendicular to the first principal component. This analysis continues in the next principal component. After PCA, n-dimentional l-th vector in dataset x_{ln} can be represented as the approximated vector $\hat{\boldsymbol{x}}_l$ which is defined by principal component vector $\boldsymbol{p}_m$ and weight value vector w_{lm} as follows:

$$\hat{\boldsymbol{x}}_l(x_{l1}, x_{l2}, \cdots, x_{ln}) = \sum_{m=1}^{M} w_{lm} \boldsymbol{p}_m \quad (5)$$

where M is the number of used principal component in approximation, $\boldsymbol{p}_m$ is the m-th principal component vector, and w_{lm} is the weight value for each m-th principal component as shown in Figure 7.

We applied PCA to the facial image which has 512×512 pixels. The one pixel is assigned as one elements in the vector, then the one facial image is assigned as the one point in 262144(512×512) dimensional spaces. The 202 facial images were used, then we had 202 points in 262144 dimensional spaces.

As a result by PCA, we obtained 201 principal components. The examples of principal component images which were applied to melanin components, hemoglobin components, and shading components are shown in Figure 8, Figure 9, and Figure 10. The numbers at the top left of the images represent the number of principal component sorted by the contribution rate. We could obtain principal components of pigmentation distribution in whole face.

2.5 Facial color image synthesis

We estimated the relationship between obtained feature values of pigmentation unevenness and ages as the psychological feature values by multiple regression analysis. After the weight of principal components were modulated based on estimated relationship, the appearance of face was simulated by age-related changes. Figure 11 show the images where melanin components are changed. Figure 12 show the images where hemoglobin components are changed. Figure 13 show the images where shading components are changed. Figure 14 show the image where all components are changed.

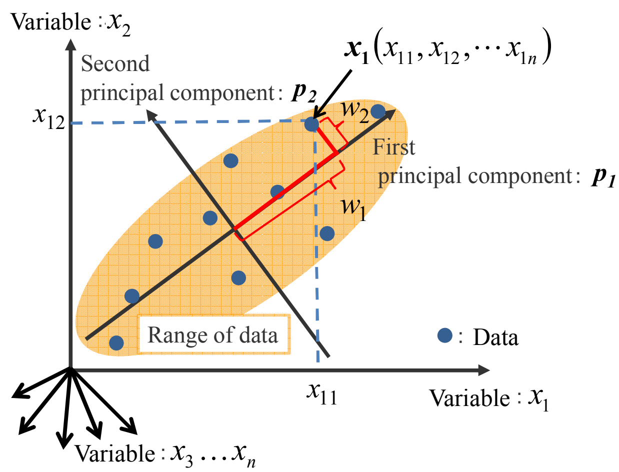


Figure 7 Overview of the principal component analysis

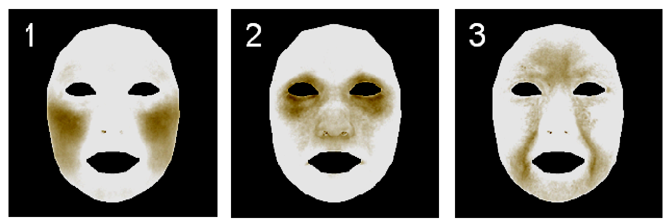


Figure 8 The results of PCA in melanin components

Figure 9 The results of PCA in hemoglobin components

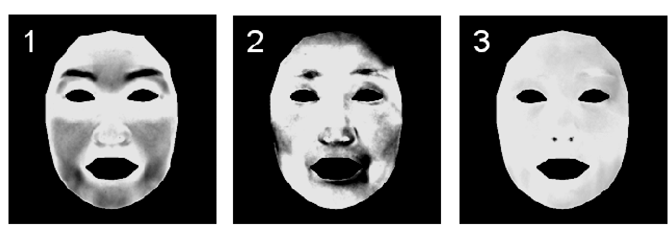
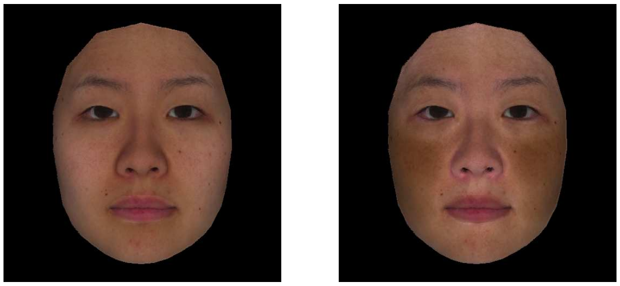
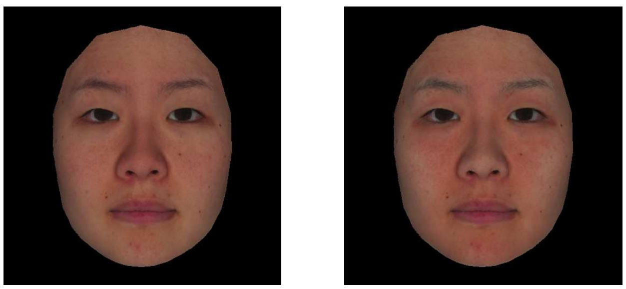


Figure 10 The results of PCA in shading components



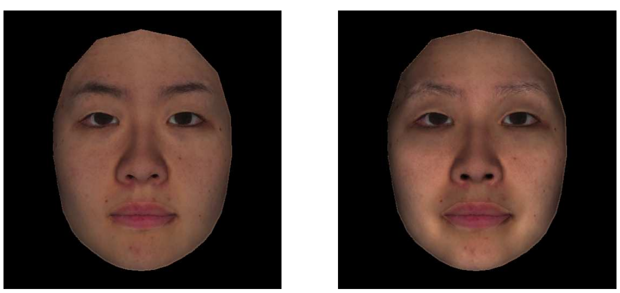
(a) (b)

Figure 11 The results of facial appearance by age-related changes in melanin component : (a) 10's, (b) 80's



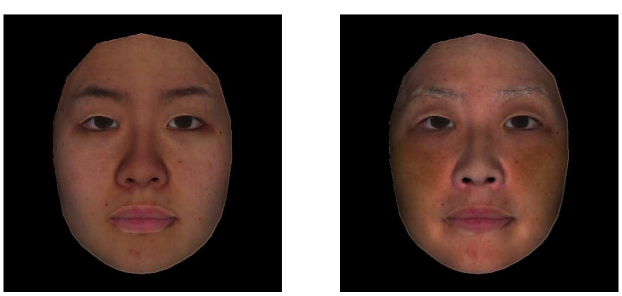
(a) (b)

Figure 12 The results of appearance of face by age-related changes in hemoglobin component : (a) 10's, (b) 80's



(a) (b)

Figure 13 The results of appearance of face by age-related changes in shading component : (a) 10's, (b) 80's



(a) (b)

Figure 14 The results of appearance of face by age-related changes in all components: (a) 10's, (b) 80's

3 Discussions

From Figure 11 to Figure 14, we can recognize age-related changes such as the pigmented spots, redness of cheeks, and shape-included shading. These images show that the melanin components and the shading components especially have a relationship with age-related changes. In the melanin components shown in Figure 11, increase of pigmentation unevenness on cheeks and pigmentation distribution around the eyes are represented by modulating the first and second principal components shown in Figure 8. In hemoglobin components changes show in Figure 12, the age-related changes are simulated mainly by the decrease of first principal component and increase of second principal component in Figure 9. In shading components changes shown in Figure 13, the age-related changes are simulated mainly by the modulation of first principal component in Figure 10. These changes are observed as shape-related changes such as hollows around the eyes and sagging of the jaw.

In addition, we performed subjective evaluation for reproduced images. The result show that the modulation of pigmentation distribution is appropriate for age-related changes from the perspective of physiology. However, the age in Figure 14(b) estimated by observers was 41.2 years old as against that the reproduced age is 80's. The reproduced images had the answers that they looked younger than reproduced age in many times. It is considered that this was happened, because we did not modulate the facial structures and detailed surfaces such as wrinkles. Lantis *et al.*[3] didn't consider pigmentation distribution and shading, but they got good results to modulate facial structure. Facial structure has critical factor for appearance of face and it needs to be taken into account in future works.

4 Conclusion

In this paper, we extracted melanin and hemoglobin pigmentation from a single skin color image by the independent component analysis. First, normalized facial images are obtained by morphing shape of facial images to that of average face. Next, we applied PCA to pigmentation distribution in whole face and obtained the feature values of uneven pigmentation. Then, we estimated relationship between the obtained feature values and ages by multiple regression analysis. After the weights of principal components were modulated based on estimated relationship, the appearance of face was simulated by age-related changes..

In future works, we will analyze feature values of the facial structure and the detailed surface and simulate appearance of face which has arbitrary psychological features more realistically. Furthermore, we need to explore generality of the feature values. In addition, our problem is to have about 30 minutes computing times and some manual operations. It is not practical to use and we will speed up and automate the systems.

Acknowledgement

This research is partly supported by JSPS Grants-in-Aid for Scientific Research (24560040)

References

[1] K Scherbaum and T Ritschel, *et al.* , "Computer-Suggested Facial Makeup," Computer Graphics Forum, vol.30, no.2, pp.485-492, 2011.

[2] D Guo, and T Sim, "Digital face makeup by example," Computer Vision and Pattern Recognition, pp. 73-79, (2009).

[3] A Lantis et al. , "Toward Automatic Simulation of Aging Effects on Face Images", IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, vol.24, No.4, April 2002.

[4] L Chalothorn, and M Akiba, *et al.*,"Extracted Facial Feature of Racial Closely Related Faces" The 2nd International Conference on Digital Image Processing,2010

[5] N Tsumura, H Haneishi, and Y Miyake, "Independent component analysis of skin color image," Journal of Optical Society of America A 16, 9, 2169-2176.

[6] N Tsumura, N Ojima, *et al.*, "Image-based skin color and texture analysis/synthesis by extracting hemoglobin and melanin information in the skin", ACM Transactions on Graphics (TOG), vol.22, pp.770-779, 2003.

[7] N Tsumura, S Okaguchi, *et al.*, "Real-time image-based control of skin melanin texture", ACM SIGGRAPH 2005 Sketches, pp.132, 2005.

[8] S Mukaida, M Kamachi *et al.* , "Facial image symthesis system: Futon -evaluation as tools for cognitive research on face processing-", IEICE Trans, Fundamentals, J85A(10):1126-1137,2002 (In Japanese)

[9] S Drew M, C Chen, D Hordley, and G Finlayson, "Sensor transforms for invariant image enhancement" In Proceeding of IS&T /SID's Tenth Color Imaging Conference, IS&T and SID, 325-330, 2002