Analyzing the individual relationship between habit of UV protection and melanin pigmentation based on the change of facial images for 7 years

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Abstract

In this paper, we obtain individual difference on variation of melanin component which greatly affect apparent age. We consider frequency of use for UV protection as the factor causing individual difference in aging. It is known that the exposure of UV rays produces melanin pigment in our skin, which promotes aging of a skin such as darkening and unevenness of a skin color. In our previous work, we applied principal component analysis (PCA) to skin color pigmentation distribution and obtained feature values. By changing feature values, we simulated the appearance of human face in arbitrary age. According to this, it is revealed that melanin component in around cheeks especially tends to increase with aging. However, in the previous method, averaged feature values are used for each ages in analysis, and individual difference should be considered at the next step of research. In this paper, we constructed database that have facial image taken in 2003 and 2010 where the same 77 people were subjective. The frequency of use for UV protection was also recorded as lifestyle habit. By applying the same analysis in the previous method, we obtained score shift from the data in 2003 and 2010. From these trends of the shift, we found that one-fourth people can get light-skinned face after 7 years if they use UV protection throughout the year.

1. Introduction

Human face receives a lot of attention in our body. We obtain many information from face, which are broadly divided into two kinds of feature values. One is called physical features such as skin condition or facial structure, and the other is called psychological features such as health condition or appearance of age. Facial appearance is largely depends on these two features.

People, especially, women have a strong interest in their appearance of face or skin. In the beauty industry, therefore, many kinds of cosmetics have been developed for improving these appearance, and the application which predict effect of these cosmetics are expected to be used in practical field. For example, there is a makeup simulator which can be used on the internet [1]. When you send a facial image to the server thorough the internet, facial landmarks are obtained to represent facial structure. The landmarks are key to judge impression of the face such as gentle and sweet. As a result, the server suggests some make-up that are suitable for user and simulates user's face with these make-up on the screen of the computer. This system make it possible to predict the effect of cosmetics anytime, anywhere at low cost and promote sales of cosmetics.

Moreover, there is a lot of research on simulation of facial appearance in recent years. For example, Scherbaum *et al.* obtained feature values from facial images photographed under various illumination environments. The obtained feature values are detailed features of human face like 3D structure, diffuse reflectance, normal map, subsurface-scattering, specular and glossiness. By using these feature values, they provided optimum makeup [2]. Guo *et al.* proposed digital make-up system as well. They extracted cosmetic component from an image of a face with make-up and apply the cosmetic component to another facial image [3]. These systems enabled us to get result suitable for individual. However, they require a large-scale photographic system to obtain detailed facial features, so it is difficult to put them to practical use. On the other hand, studies whose processes for obtaining features are simplified have been conducted for practical use. For example, PCA makes it easier to obtain feature values. Lantis *et al.* provided a framework for simulation of aging effects on facial image. By applying PCA to facial landmarks, they simulated facial structure in any age based on classification of age [4]. Suo *et al.* also predicted appearance of face for the long period by changing parts of face for the short period based on result of applying PCA to facial image database divided by parts or ages [5]. However, individual differences are not considered in this method.

As described above, we can obtain facial feature values relatively easily from information such as facial structure and skin texture by using PCA. Most of these researches directly analyze grayscale or RGB images. However, it is difficult to say that RGB colors consider skin layer structures properly because RGB colors are based on the device dependent color. For this reason, it is thought that we can analyze for face or skin more effectively by taking into account melanin and hemoglobin colors which is main components of skin color. Tsumura *et al.* proposed the technique to extract pigmentation distribution of melanin and hemoglobin from a single skin color image by applying independent component analysis (ICA) [6][7]. Melanin and hemoglobin color can be obtained regardless of light sources or characteristics of camera by ICA in their method.

Okaguchi et al. extracted hierarchical pigmentation distribution according to image pyramid analysis from the skin texture database and set image histograms as feature values of facial image [8]. They applied PCA to the feature values and obtained feature values of skin pigmentation. Melanin and hemoglobin are strongly correlated with psychological features such as age, sex, and race. They estimated relationship between feature values of skin pigmentation and skin texture by multiple regression analysis (MRA) and simulated skin texture having arbitrary psychological features. They analyzed only a small area of skin, on the other hand, Toyota *et al.* analyze pigmentation distribution in whole face. Toyota *et al.* obtained feature values of skin pigmentation in whole face by ICA and PCA and simulated appearance of face having arbitrary psychological features [9]. This method can perform to synthesize appearance of face considering the changes of the age. However, as a result of a subjective evaluation experiment by experts, there was large difference between age of synthesized images and evaluated results. For this reason, Hirose *et al.* analyze variation of facial landmarks representing facial structure and surface reflection component representing wrinkles and pores in addition to skin pigmentation distribution by PCA and MRA [10]. They succeeded to reduce the age difference of synthesized image and real images. Since this simulation is based on changing averaged features in the database with the same age, each synthesized image lost the individual characters. However, since the actual aging depends on individuals, it is expected to predict the appearance of face by considering the individual characters.

In this paper, therefore, we obtain individual difference on variation of melanin component which greatly affect apparent age. We consider frequency of use for UV protection as the factor causing individual difference in aging. We analyze change of melanin pigmentation of the same person in 7 years by PCA, and find relationship between habit of UV protection and melanin pigmentation.

2. Facial Image Database and Methods for Analysis

This section introduce constriction of facial image database for 7 years, and shows the method to obtain melanin pigmentation distribution in whole face and feature values of melanin component.

2.1. Construction of Facial Image Database

We constructed database from facial image, real age, and the frequency of use for UV protection. First of all, we took photographs of Japanese women faces whose age were between 10 and 80 in winter of 2003 and 2010. The number of subjects was 77, and each woman is the same person in 2003 and 2010. Thus, we obtained 154 facial images in total. Distribution of age in the database is shown in Fig. 1. We obtained age of each subject as psychological features. These photographs were taken in imaging system shown in Fig. 2. This imaging system was surrounded by blackout curtains in order to eliminate the effect of ambient light. As the light source, there were four fluorescent lights so that the lights surrounded the camera as shown in Fig. 2. The cameras we used were NikonD1 and NikonD2H; the former is used in 2003 and the latter in 2010. In order to prevent movement of face, we used the support for neck and head which was fixed on backrest of chair. We obtained facial image without specular reflectance by arranging polarization filters in front of the camera and the light sources mutually perpendicularly. There was difference in color tone between images taken in 2003 and those in 2010 due to using different camera. For this reason, we matched color tone of images taken in 2003 with those in 2010 by MRA.

Figure 3 shows a sample of the captured facial image. These captured facial images were required to be normalized in order to remove influence caused by variation of individual facial shapes on applying PCA accurately to images later. For this reason, we used FUTON (Foolproof UTilities for facial image manipulatiON system), which was facial image synthesis system developed by Mukaida *et* al.[11]. First, we obtained facial landmarks representing facial structure and extracted facial areas from captured facial images. Second, we morphed shape of facial images into an image of an average face which was made from facial images in database. As a result, we obtained normalized facial images while keeping individual skin texture information. The overview of this process is shown in Fig. 4.

Furthermore, we classified facial images in the database as to the frequency of use for UV protection in winter based on 3 grades: none-used, irregularly used, and constantly used. Figure 5 shows age distribution of the frequency of use for UV protection in the database. It is considered that those who use UV protection everyday in winter probably use it every day in other seasons. For this reason, we can regard them as people who protect their skin through the year. On the other hand, those who don't use UV protection in winter expose their skin to UV everyday at least in winter. Thus, two groups were established in this research. One was year-round use group consisted of 12 people who evaluated as constantly used both in 2003 and in 2010. The other was none-used for winter group consisted of 23 people who evaluated none-use both in 2003 and in 2010.

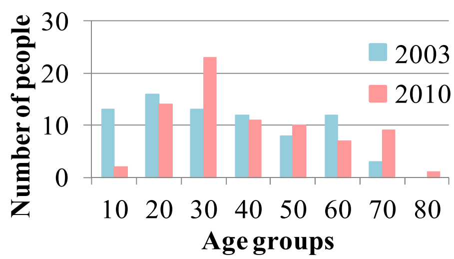


Figure 1 Distribution of age in the database.

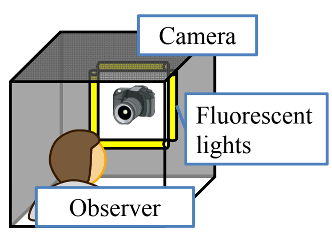


Figure 2 Overview of imaging system.

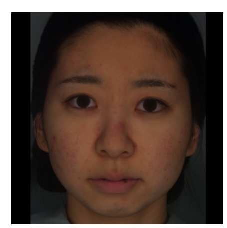


Figure 3 Sample of captured image.

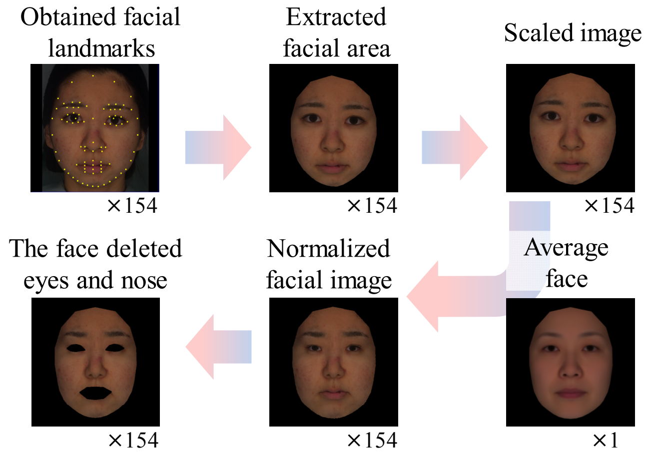


Figure 4 Overview of normalization process for facial images.

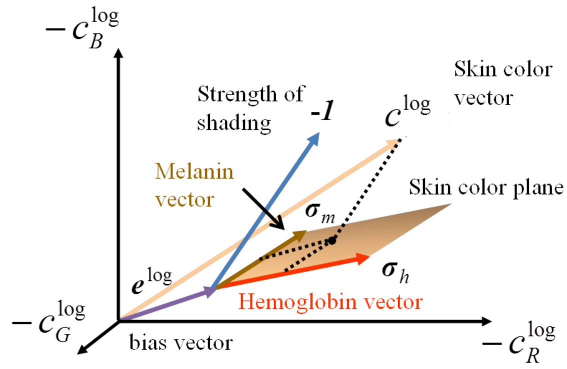


Figure 6 Overview of independent component analysis.

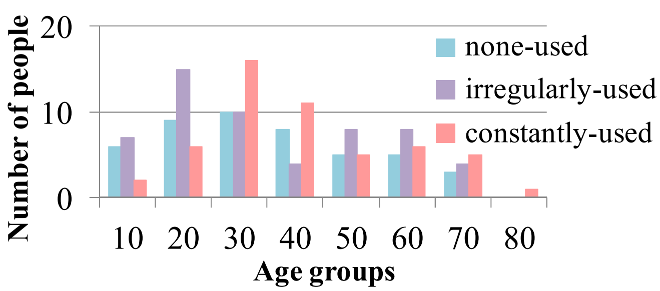


Figure 5 Age distribution of frequency of use for UV protection in the database.


(a) (b) (c)

Figure 7 The results of independent component analysis for extraction of pigmentation components: (a) melanin, (b) hemoglobin, (c) shading.

2.2. Extraction of Melanin Component by ICA

We extracted skin pigmentation distribution by ICA. The overview of process is shown in Fig. 6. Melanin and hemoglobin pigmentation density vectors can be estimated by applying ICA to the skin color of an arbitrary facial image in database, which is plotted in RGB density space. As a new skin color is given, its vector is projected onto the skin color plane in parallel with strength of shading vector. Melanin and hemoglobin pigmentation densities of the skin color are obtained by re-projecting onto each pigmentation density vector.

Figure 7 (a), (b) show a sample of the extracted melanin and hemoglobin pigmentations, and (c) shows the shading in the whole facial image. As you can see in Fig. 7 (a), the mole and pigmented spot can be obtained as melanin component. The redness caused by pimples can be seen in Fig. 6 (b), and the shadow caused by uneven facial features can be recognized in Fig. 7 (c). In this paper, we used melanin component for analysis because melanin pigmentation has high relativity with UV.

2.3. Analysis of Melanin Component by PCA

We obtained feature values of uneven pigmentations by applying PCA to melanin components of 154 facial images extracted in Section 2.2. PCA is a statistical method to grasp a tendency and features of data by multivariate analysis. This analysis calculates the linear sum of each variable in data group constructed from any variable, and defines a new index as the first component. The second component is defined in such a way that is perpendicular to the first component, and other components are defined similarly. The n-dimensional l-th vector in dataset x_{ln} can be represented as the approximated vector $\hat{x}_l$ as follows:

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

where M is the total number of principal components, w_{lm} is the weight value for each m-th principal component called as principal component score, and $\boldsymbol{p}_m$ is the m-th principal component vector, as shown in Fig. 8.

We applied PCA to melanin components whose size was 512 ×512 pixels. In this paper, we regarded one pixel as one variable. That is, a melanin component existed in 512×512-dimensional space. Therefore, 77 women's melanin components in 2003 and in 2010, 154 components in total, existed in 512×512-dimensional space.

As a result of PCA, we obtained 153 principal components of melanin pigmentation distribution. The examples of these are shown in Fig. 9. The numbers at the top left of the images represent the number of principal component sorted by the contribution rate. Melanin color pigmentation distribution in whole face could be obtained as the first principal component, that in around cheeks could be obtained as the second principal component, and that in around eyes could be recognized in the third principal component. Thus, we could obtain feature values of melanin component. It is noted that when principal component score is positive, the brown part in Fig. 9 changes as the increase of melanin components. It is also noted that when principal component score is negative, the white part in Fig. 9 changes as the decreased of melanin components.

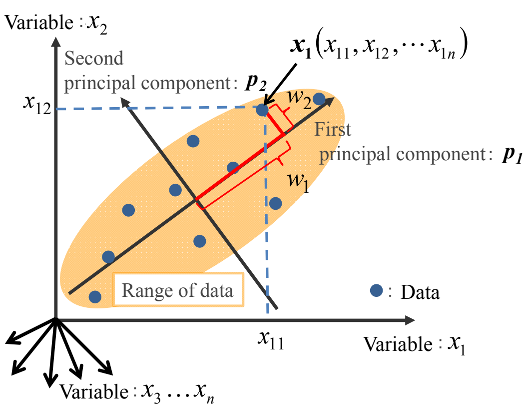


Figure 8 Overview of the principal component analysis in melanin component.

Figure 9 The results of PCA in melanin components.

3. Results to Show the Individual Difference in Principal Component Score

We obtained score shift of the first, second and third principal component in 7 years for each person. As shown in Fig. 10, according to consider individual score shift, we acquired new relationship between melanin component and age which had not been recognized in the previous study. After considering individual score shift, the inclination of lines changed from small one to large one. For this reason, we can conclude that there is large change in 7 years actually. Furthermore, we classified these individual variation by the frequency of use for UV protection in order to obtain the relationship between melanin component and UV protection. Figure 11, 12, and 13 show the result of acquisition of individual difference in score shift of the first, second, and third principal component score.

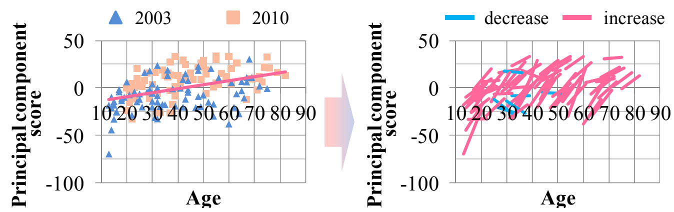
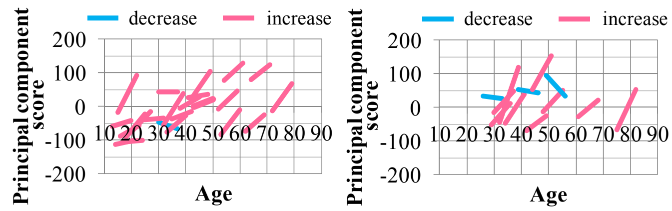
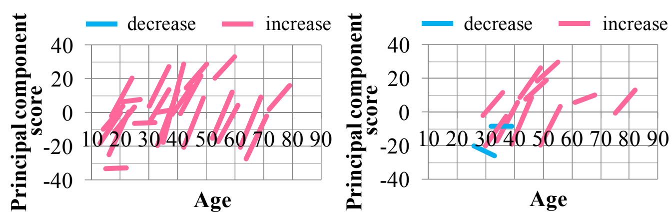


Figure 10 Appearance of new relationship between melanin component and age by considering individual shift of principal score



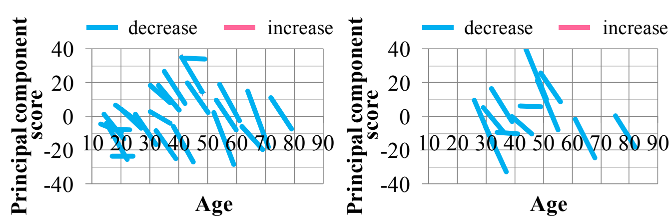
(a) (b)

Figure 11 The obtained results for shift of the first principal component score classified by frequency for use of UV protection: (a)none-use for winter group, (b) year-round use group



(a) (b)

Figure 12 The obtained results for shift of the second principal component score classified by frequency for use of UV protection: (a)none-use for winter group, (b) year-round use group



(a) (b)

Figure 13 The obtained results for shift of the third principal component score classified by frequency for use of UV protection: (a)none-use for winter group, (b) year-round use group

4. Discussion

Firstly, we discuss about the first principal component. From Fig. 11 (a), we can see that most principal component scores increase. Thus, darkening of skin is caused for almost all none-used for winter group. On the other hand, principal component score decrease for one out of four woman in year-round use group, as shown in Fig. 11 (b). This means that one-fourth people can get light-skinned face after 7 years if they use UV protection throughout the year. Moreover, it can be seen that there is higher correlation between age and principal component score of none-use for winter group, but that can be not found in year-round use group. Therefore, we can conclude that year-round use for UV protection decrease melanin pigmentation distribution in whole face and suppress age-related increase of melanin component. Secondly, we discuss about the second principal component. Figure 12 shows that the melanin component in around cheeks increase without regard to the frequency of use for UV protection. However, comparing the figures for those of score shift, we can recognize that each score shift of none-use for winter group is tend to be larger than that of year-round use group. Hence, it can be said that none-use for UV protection in winter causes darkening of cheeks partially and strong unevenness on cheeks. Finally, we discuss about the third principal component. From Fig. 13, we can see that all scores decrease, and most of them become negative. As described in Section 2.3, the white part in Fig. 9 (c) changes in color when principal component score is negative. For this reason, melanin component in around nose and mouth increase in 7 years regardless of UV protection and age.

5. Conclusion

In this paper, we applied PCA to melanin component of face in order to obtain feature values, and acquired individual difference in aging caused by frequency for use of UV protection. According to consider individual score shift from 2003 to 2010, we found new relationship between melanin component and age which had not been recognized in previous study. In our future works, we will analyze high-dimensional principal components and obtain relationship between UV protection and pigmented spot. Furthermore, we will predict the effect of UV protection by simulating facial appearance in arbitrary age based on the relationship between melanin component and UV protection.

Acknowledgement

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