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REGULAR PAPER

Principal component analysis for surface reflection components and structure in facial images and synthesis of facial images for various ages

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Abstract In this paper, principal component analysis is applied to the distribution of pigmentation, surface reflectance, and landmarks in whole facial images to obtain feature values. The relationship between the obtained feature vectors and the age of the face is then estimated by multiple regression analysis so that facial images can be modulated for woman aged 10–70. In a previous study, we analyzed only the distribution of pigmentation, and the reproduced images appeared to be younger than the apparent age of the initial images. We believe that this happened because we did not modulate the facial structures and detailed surfaces, such as wrinkles. By considering landmarks and surface reflectance over the entire face, we were able to analyze the variation in the distributions of facial structures and fine asperity, and pigmentation. As a result, our method is able to appropriately modulate the appearance of a face so that it appears to be the correct age.

Keywords Principal component analysis · Surface reflectance · Wrinkle · Facial structure · Facial appearance

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1 Introduction

Compared to other body parts, the human face receives a lot of attention. When we observe facial structure, skin color, or skin type, we can obtain a lot of information about an individual, such as their individual features, race, age, sex, emotion, gender, and health. Small changes in features can result in large differences in the overall appearance. In this paper, the qualities and structures that remain constant over time will be called *physical features*, and those influenced by age or health will be called *psychological features*.

Recently, applications that change facial appearance have been put into practical use. Many people have a strong interest in the appearance of their face or skin, and applications that improve facial appearance are in high demand. For example, photo-retouching software can improve facial images to remove the appearance of pores or to make the skin color more uniform. However, conventional applications combine various simple retouching methods, such as those that smooth the skin coloring; they do not adequately consider physical or psychological features. For this reason, a facial image retouched by one of these applications will often have an appearance that is very different from the real face.

Facial appearances have been reconstructed or simulated by various methods in many studies. For example, changes in facial appearance have been simulated for the addition of makeup [1, 2], for changes in age [3], and for changes in race [4]. Some typical examples of simulation methods include the following. Scherbaum et al. [1] presented a method for computer-suggested makeup. They obtained detailed feature values (such as the three-dimensional structure, a normal map, subsurface scattering, specular and diffuse reflectance, and glossiness) using facial photographs taken with different light sources. Guo and Sim [2] proposed a digital makeup system in which makeup information was extracted from facial images with makeup already applied, and the extracted information was added to a facial image without makeup. Appropriate results for personal features could be obtained in all of these studies, because they used the person's own three-dimensional structure. With the Guo and Sim approach, however, large systems are required to obtain information, and it is not suited to practical use. On the other hand, Lantis et al. [3] proposed a framework that can be used to simulate the effects of aging on facial images; that is, it can be used to predict the appearance of a given individual in the future or in the past. In this method, the facial structure is changed by applying principal component analysis (PCA) and a genetic algorithm to landmarks obtained from monochrome images. Chalothorn et al. [4] extracted differences between Japanese and Thai people, and they applied PCA to skin texture and structure for the classification of race. PCA is used extensively for obtaining feature values because it is relatively easy to use. In this paper, we apply PCA to the distribution of pigmentation, surface reflectance, and facial landmarks in whole facial images to obtain feature values.

Typically, RGB values are used for processing facial images to obtain skin texture information. However, RGB values are dependent on the light source and characteristics of the camera, and they do not reflect the structures and properties of the skin. Skin color is primarily due to the presence of melanin and hemoglobin pigmentation, so Tsumura et al. [5–7] proposed a method that can extract the melanin and hemoglobin pigmentation from a single image; their method uses independent component analysis and is not affected by changes in the light source or the characteristics of the camera.

In a previous study [8], we applied PCA to whole facial images by extending the area of analysis, and we analyzed the unevenness of pigmentation. Additionally, we used multiple regression analysis to simulate faces with arbitrary psychological features; this was based on the relationship between the obtained principal components and the features. However, when we performed a subjective evaluation of the reproduced images, the faces in the reproductions were estimated to be younger than the estimated ages of the faces in the initial images. For example, in a reproduction, the estimated age of the face was 35.3 years old, whereas the estimated age of the initial face was in the eighties. We assumed that this happened because we did not modulate the facial structures and facial asperities, such as fine wrinkles.

In this paper, therefore, we apply PCA to landmarks that represent structures and surface reflectance components, as well as the distribution of pigmentation over whole facial images. We use the results to analyze the unevenness of pigmentation, the variations in the facial structure, and the asperity distribution for the goal to make practical applications that change facial appearance with considering physical or psychological features. In Sect. 2, we describe our approach in detail. In Sect. 2.1, we discuss the construction of a facial image database, and in Sect. 2.2, we obtain facial landmarks that represent facial structures, and how we transform facial images to that of an average face. In Sect. 2.3, we use independent component analysis [5] to extract melanin and hemoglobin pigmentation from a single skin color image. In Sect. 2.4, we use multiresolution analysis to extract the gloss and asperities from surface reflectance components. In Sect. 2.5, we describe the method we used to apply PCA to the distribution of pigmentation, facial landmarks, and surface reflectance components; and the method we used to analyze the principal component vectors of uneven pigmentation, variations in facial structure, and surface asperity distribution. In Sect. 2.6, after estimating the relationship between the principal components and the psychological features evaluated by multiple regression analysis, we simulate the appearance of a face with various arbitrary ages. In Sect. 3, we discuss our results and perform a subjective evaluation. In Sect. 4, we present our conclusions.

2 Approach

In this section, we present the method used to obtain the feature values of pigmentation unevenness, asperity distribution, and variations in the structures of an entire face; and the method used to simulate a face with arbitrary psychological features. The overview of the process is as follows.

Step 1. Construct a facial image database
Step 2. Obtain facial landmarks and transform facial images to match an average face
Step 3. Use independent component analysis to extract melanin and hemoglobin pigmentation
Step 4. Use multiresolution analysis to extract the gloss and asperities from the surface reflectance components
Step 5. Use PCA to analyze uneven pigmentation, variations in facial structures, and the distribution of asperity over the entire face
Step 6. Use multiple regression analysis and synthesized facial images to estimate the appearance of a face

In the next subsections, we will describe the details of the above processes.

2.1 Constructing a facial image database

We took photographs of women who ranged in age from 10 to 80 and constructed a database of these images. The number of subjects was 202. Their actual ages were included in the database as a psychological feature. Figure 1 shows an overview of the imaging system, and the distribution of ages in the database is shown in Fig. 2. In this imaging system, interference with the lighting conditions was prevented by blackout curtains. The light source comprised four fluorescent lights, which surrounded the camera. We took images using a digital camera (Nikon D3X) and used a chin support to prevent movement of the subject's face. The exposure time and F-number were 1/3 s–f/5.6 in capturing. In this setting, we captured only one image for each face. The setting of white balance was Preset d-4.0 which is defined Nikon digital camera. As shown in Fig. 1, four fluorescent lamps are located so as to surround the subject's face, and the entire face can considered to be taken with uniform brightness. Therefore, we did not perform the correction of unevenness of the illumination light in the pre-processing. We obtained facial images with specular reflectance by setting polarization filters in front of the camera and positioning the light sources parallel to each other. We also obtained facial images without specular reflectance by setting polarization filters in front of the camera and positioning the light sources perpendicular to each other. Figure 3 shows two sample facial images from the database: (a) with specular reflectance and (b) without specular reflectance.

2.2 Obtaining facial landmarks and transforming facial images to match an average face

From the images in the database, we obtained landmarks that represent facial structures. We then transformed the shape of the face to match that of an average face; this was done to remove the influence of individual facial shape when applying PCA, and thus to obtain a higher degree of accuracy. FUTON (Foolproof UTilities for Facial Image ManipulatiON System), which was developed by Mukaida et al. [9], was used to transform the facial images. FUTON supports the identification of landmarks in the facial structure, as shown in Fig. 4a, and the shape of each face was transformed to match the average face in the database. Figure 4b and c show an average face and the normalized image after transforming the image shown in Fig. 2. It can be seen that although the overall shape and structures were normalized, the skin texture information was maintained.

In addition, since the pigmentation properties of eyes and lips are different from those of skin, we removed these areas to prevent their having any influence on the extracted pigmentation. The eye and lip areas were removed after they were used to connect with similar landmarks of the average face. The specular reflectance of the facial image without eyes or lips is shown in Fig. 5a, and this image without specular reflectance is shown in Fig. 5b. The specular reflectance component that was removed from Fig. 5a to obtain Fig. 5b is shown in Fig. 5c.

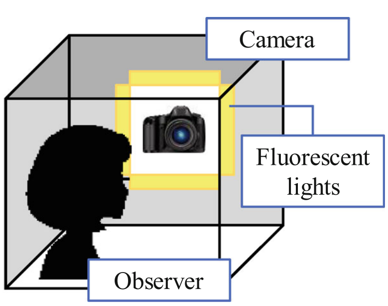


Fig. 1 Overview of imaging system

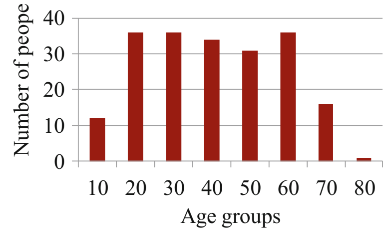


Fig. 2 Distribution of age in the database

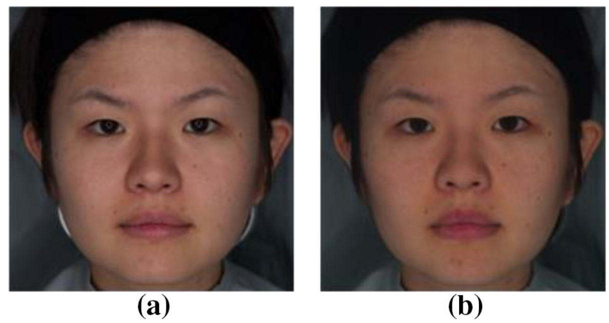


Fig. 3 Sample of captured image in the database: **a** with specular reflectance, **b** without specular reflectance

2.3 Extracting melanin and hemoglobin pigmentations

Figure 6 shows an overview of the use of independent component analysis to extract melanin and hemoglobin pigmentation. The pigmentation density vectors can be obtained by applying independent component analysis to samples of the skin color datasets plotted in RGB density space. When a new skin color is given, its vector is projected onto the skin color plane by varying the shading. The pigmentation densities are obtained when the projected

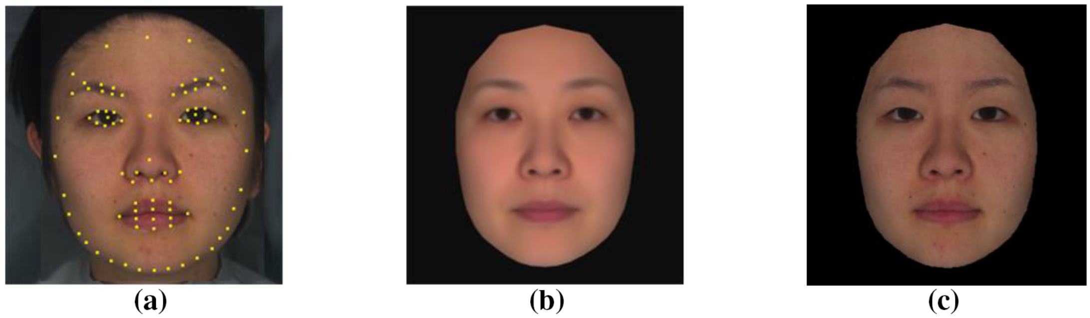


Fig. 4 Processed image by FUTON: **a** obtained facial landmarks, **b** average face, **c** samples of normalized image by morphing

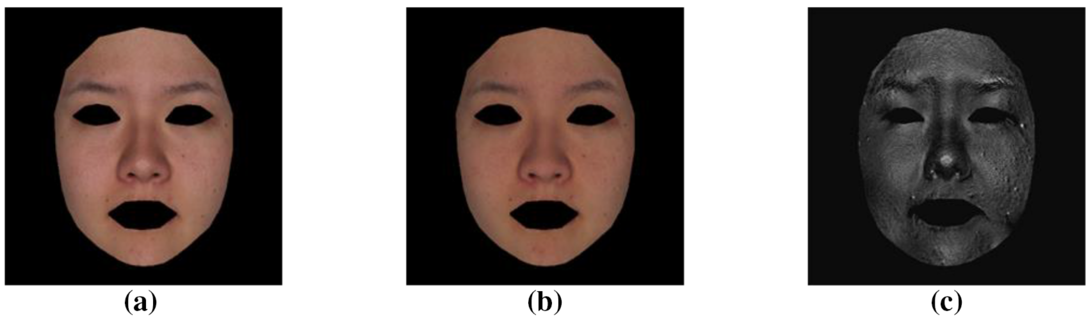


Fig. 5 Sample of image where unneeded area are removed: **a** with specular reflectance, **b** without specular reflectance, **c** surface reflectance component

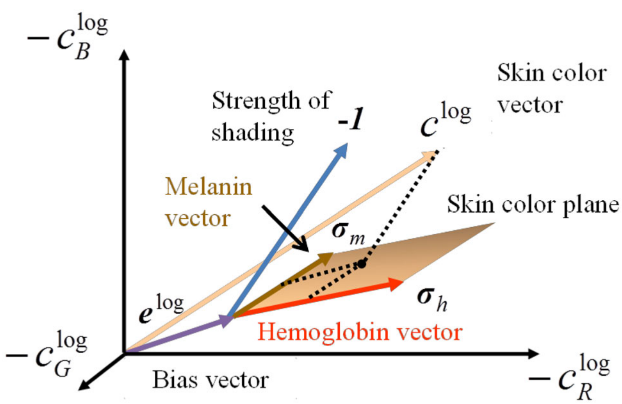


Fig. 6 Overview of independent component analysis

skin color is re-projected onto each pigmentation density vector.

Figure 7a and b, respectively, show the extracted melanin and hemoglobin pigmentations, and Fig. 7c shows the shading of the whole facial image shown in Fig. 5b. We can recognize the mole and pigmented spots from the melanin component shown in Fig. 7a. As an example, you can see that a mole on the left eyebrow is extracted in image of melanin component shown in Fig. 7a. Redness caused by pimples can be recognized from the hemoglobin component in Fig. 7b. The shading component in Fig. 7c can be used to recognize the facial shape. In this study, the features in each component were processed separately.

2.4 Extracting facial gloss and asperity distribution

We used multiresolution analysis to extract the facial gloss and asperity distribution from the surface reflectance components. A two-dimensional discrete wavelet transform was used in this analysis, and when applied to the images, it produced low-frequency and high-frequency components. There are three types of high-frequency components, which differ by the direction of the edge: horizontal, vertical, and diagonal. When the two-dimensional discrete wavelet transform is applied to the surface reflectance component, a generalized image of the face is obtained in the low-frequency component. The facial asperities can be obtained in the high-frequency components, but we note that these still contain characteristics of the individual, even after transformation to match the average face, as described in Sect. 2.2. The two-dimensional discrete wavelet transform is applied to the high-frequency components to average the individual variations. Figure 8 shows an overview of these processes.

The left image in Fig. 9a shows a simple example of pixel values assumed for parts of the original image. The center image in Fig. 9a shows an example of the diagonal high-frequency component that is applied to the two-dimensional

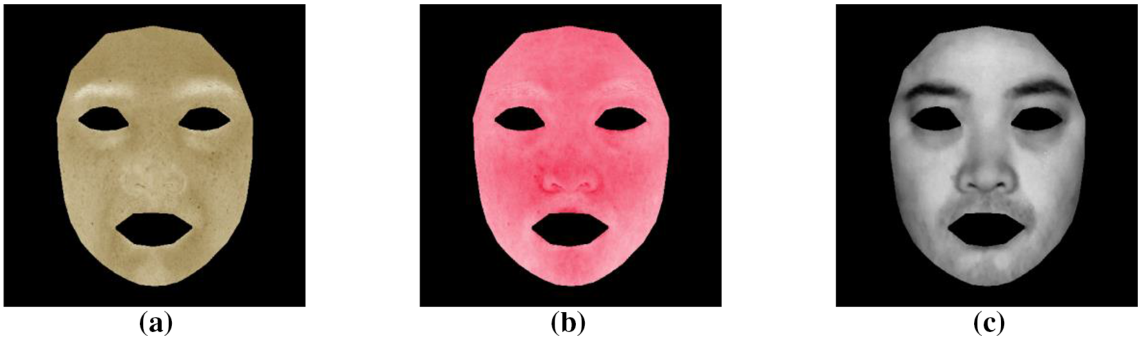


Fig. 7 The pigmentation components extracted by independent component analysis: **a** melanin component, **b** hemoglobin component, **c** shading component

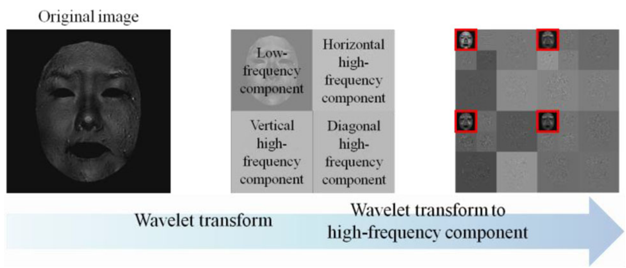


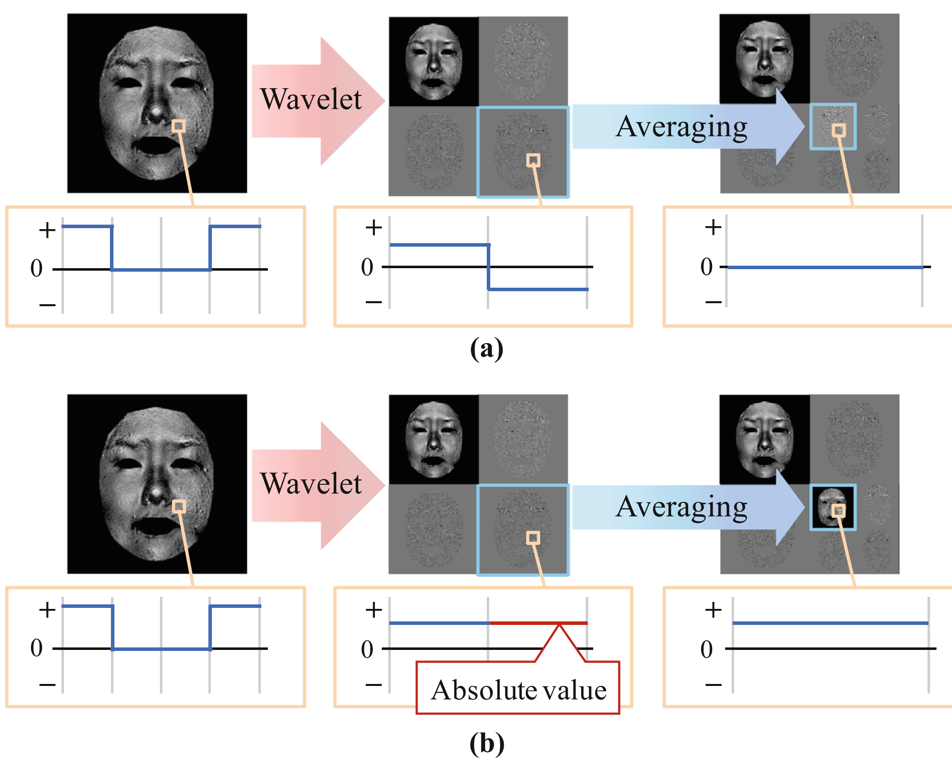
Fig. 8 Overview of proposed multiresolution analysis

discrete wavelet transform. When we average its high-frequency component to apply the two-dimensional discrete wavelet transform, sometimes the averaged pixel value can be zero, since they can have both positive and negative values; this is shown in the right-hand image in Fig. 9a. We saved the information about the asperity distribution and calculated the absolute values of the high-frequency components before using the two-dimensional discrete wavelet transform to find the average value, as shown in Fig. 9b. The original images contain the information about the positive or negative sign of each pixel. The results of the multiresolution analysis are shown in Fig. 10.

2.5 Analyzing the principal components of uneven pigmentation, facial structure, and asperity distribution in a color image

We obtained the feature values for uneven pigmentations, variations in facial structure, and asperity distribution by applying PCA to the pigmentation distribution, facial

Fig. 9 The simple example applied two-dimensional discrete wavelet transform to high-frequency components: **a** conventional method, **b** proposed method by calculating absolute value



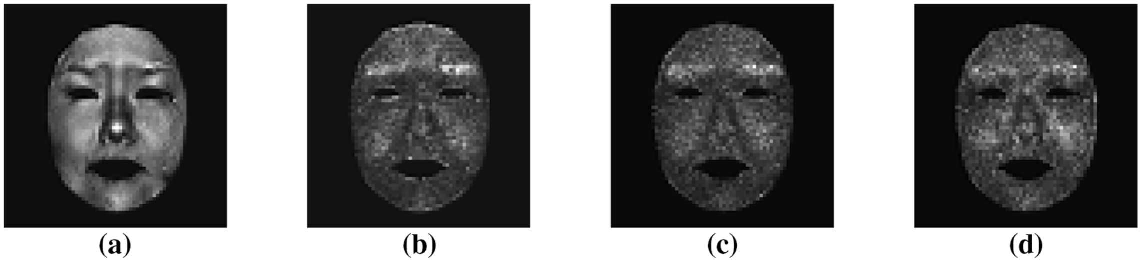


Fig. 10 The results of proposed multiresolution analysis: **a** low-frequency component, **b** horizontal high-frequency component, **c** vertical high-frequency component, **d** diagonal high-frequency component

landmarks, and frequency components of surface reflectance. PCA is a basic method of multivariate statistical analysis; it calculates the vector with maximum variance for an arbitrary data group and defines this first principal component as a new index. The second principal component is defined in such a way that it is perpendicular to the first principal component, and subsequent principal components are defined similarly. Following the PCA, the l-th n-dimensional vector x_{ln} in the dataset can be approximated by the vector $\hat{\boldsymbol{x}}_l$ which is defined by the principal component $\boldsymbol{p}_m$ and the weight vector $\boldsymbol{w}_{lm}$ as follows:

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

where M is the number of principal components used in the approximation, $\boldsymbol{p}_m$ is the m-th principal component, and $\boldsymbol{w}_{lm}$ is the weight for the m-th principal component, as shown in Fig. 11.

We applied PCA to a facial image that had 512 × 512 pixels in the pigmentation distribution and 64 × 64 pixels in the frequency components for surface reflectance (there are fewer pixels because these components were down-sampled by multiresolution analysis). We also applied PCA to the facial landmarks, which are represented by 91 points that are specified by rectangular coordinates and represent the facial structures. A single pixel was assigned to each element in the vector, and then each facial data point was assigned to one point each in 262,144 (512 × 512), 4096 (64 × 64), and 182 (91 × 2) dimensional spaces. Since 202 facial images were used, there were 202 points in each of these spaces.

From the PCA, we obtained 201 principal components for the pigmentation distributions and frequency components of surface reflectance. We also obtained 166 principal components for the facial landmarks. Examples of images based on the melanin, hemoglobin, and shading principle components are shown in Figs. 12 through 14, respectively. Principal components representing variations in the facial structure are shown in Fig. 15. The blue solid lines represent the structures in an average face, and the red solid lines represent variations relative to each landmark. Examples of the principal component images that were applied to the low-frequency, horizontal high-frequency, vertical high-frequency, and diagonal high-frequency components are shown in Figs. 16 through 19, respectively. The numbers at the top left of the images represent the number of principal components sorted by the contributions. The value of contribution rate is also written in the bottom of each figure in Figs. 12, 13, 14, 15, 16, 17, 18 and 19 and the contribution rate of each principal component are shown in Fig. 20. We can obtain principal components for the pigmentation distributions over the entire face. The sagging eyebrows, eyes, and jaw can be obtained from the principal components of the facial structure. The gloss can be obtained from the principal components of the low-frequency components, and the facial asperity distribution can be obtained from the principal components of the high-frequency components. In particular, the horizontal high-frequency components can be recognized as lateral fine lines, such as forehead wrinkles, and the vertical high-frequency components can be recognized as longitudinal fine lines, such as wrinkles around the mouth. Diagonal

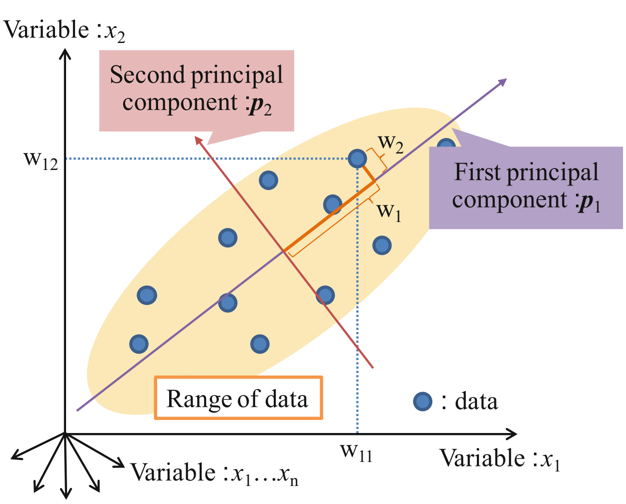


Fig. 11 Overview of the principal component analysis

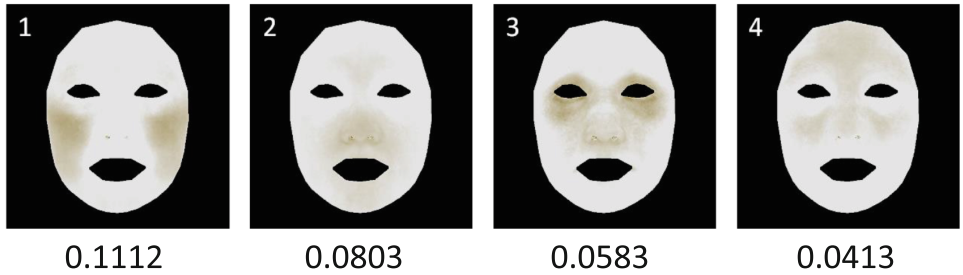


Fig. 12 The results of PCA in melanin components

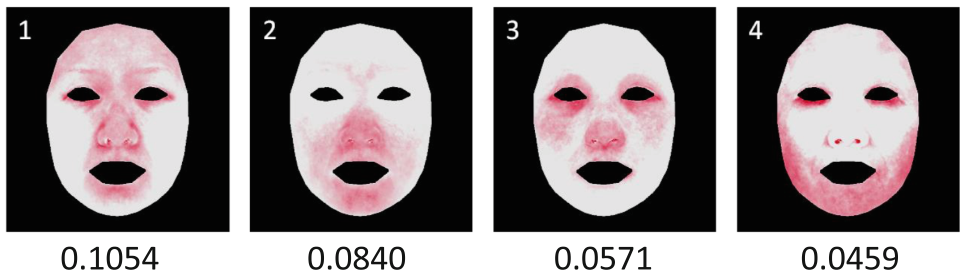


Fig. 13 The results of PCA in hemoglobin components

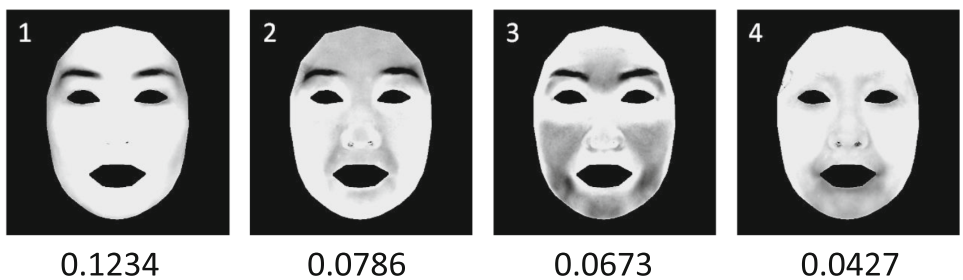


Fig. 14 The results of PCA in shading components

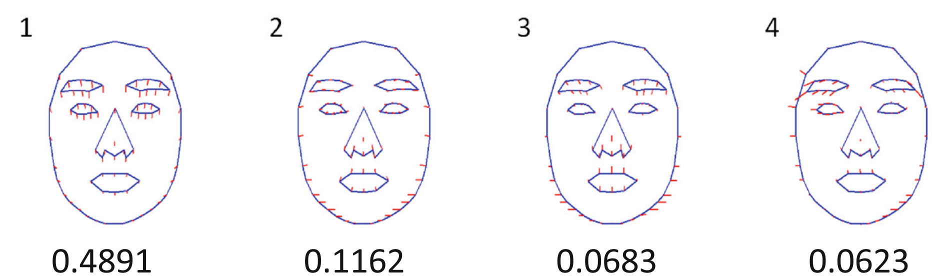


Fig. 15 The results of PCA in facial landmarks

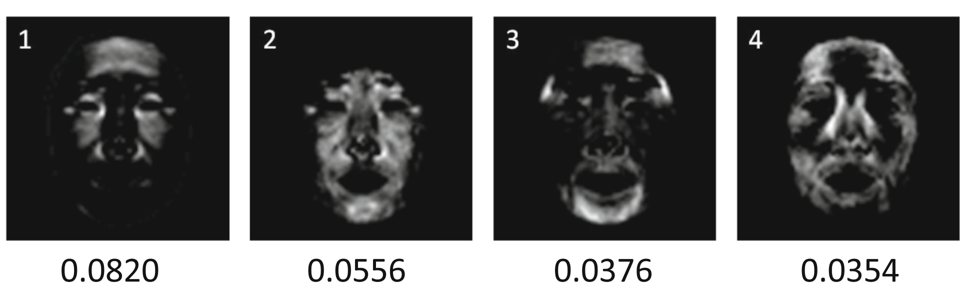


Fig. 16 The results of PCA in low-frequency component of surface reflectance

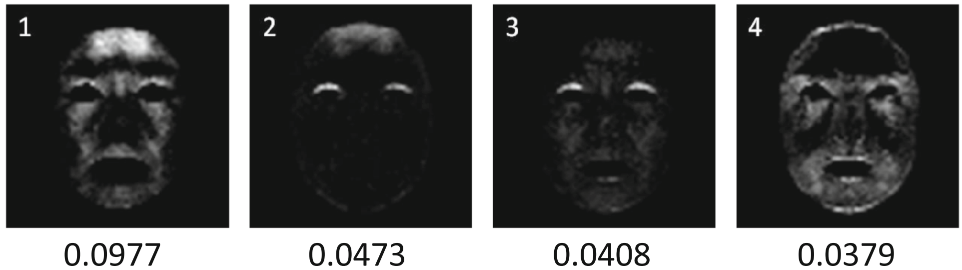


Fig. 17 The results of PCA in horizontal high-frequency component of surface reflectance

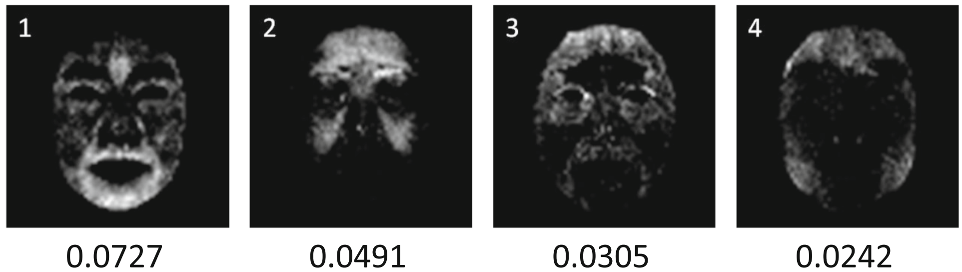


Fig. 18 The results of PCA in vertical high-frequency component of surface reflectance

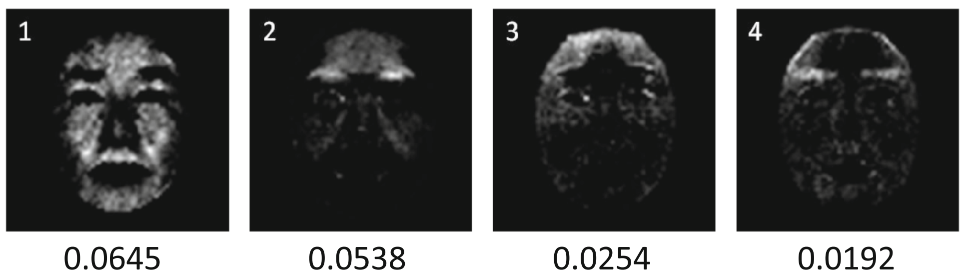


Fig. 19 The results of PCA in diagonal high-frequency component of surface reflectance

high-frequency components can be recognized as oblique fine lines, such as wrinkles on the cheeks.

2.6 Facial color image synthesis

We used multiple regression analysis to estimate the relationship between the feature values and the age as a psychological feature. After the weight of each principal component was modulated, based on the estimated relationship between the component and the age, the appearance of the face was simulated using the age-related changes. Figure 21 shows the reproduced images, in which the melanin, hemoglobin, and shading components were changed, Fig. 22 shows the results for the facial structure when the facial landmarks were changed, Fig. 23 shows the reconstructed images after the low- and high-frequency components were changed, and Fig. 24 shows the result when all of these components were changed. The regions of eyes, mouth and nose were pasted to the facial image without modulation.

3 Discussion

In Fig. 21, we can see age-related changes, such as the pigmented spots, redness of cheeks, and shape-included shading. The increase in the unevenness of the pigmentation on the cheeks and around the eyes was represented by modulating the first and third principal components that are shown in Fig. 12 and the first principal component shown in Fig. 13. Components other than the first and third principal component have low contribution ratios. Therefore, it is said that the image does not change significantly even if modulated. The age-related changes in shading were simulated by modulating the first principal component shown in Fig. 14. In Fig. 22, the influence on the age by the modulation of the shadow component is small compared with the pigment component. However, we found that the top of the eye is depressed by the modulation of the shadow component. These changes were simulated by modulating the first principal component shown in Fig. 15. Figure 24 shows more age-related changes, such

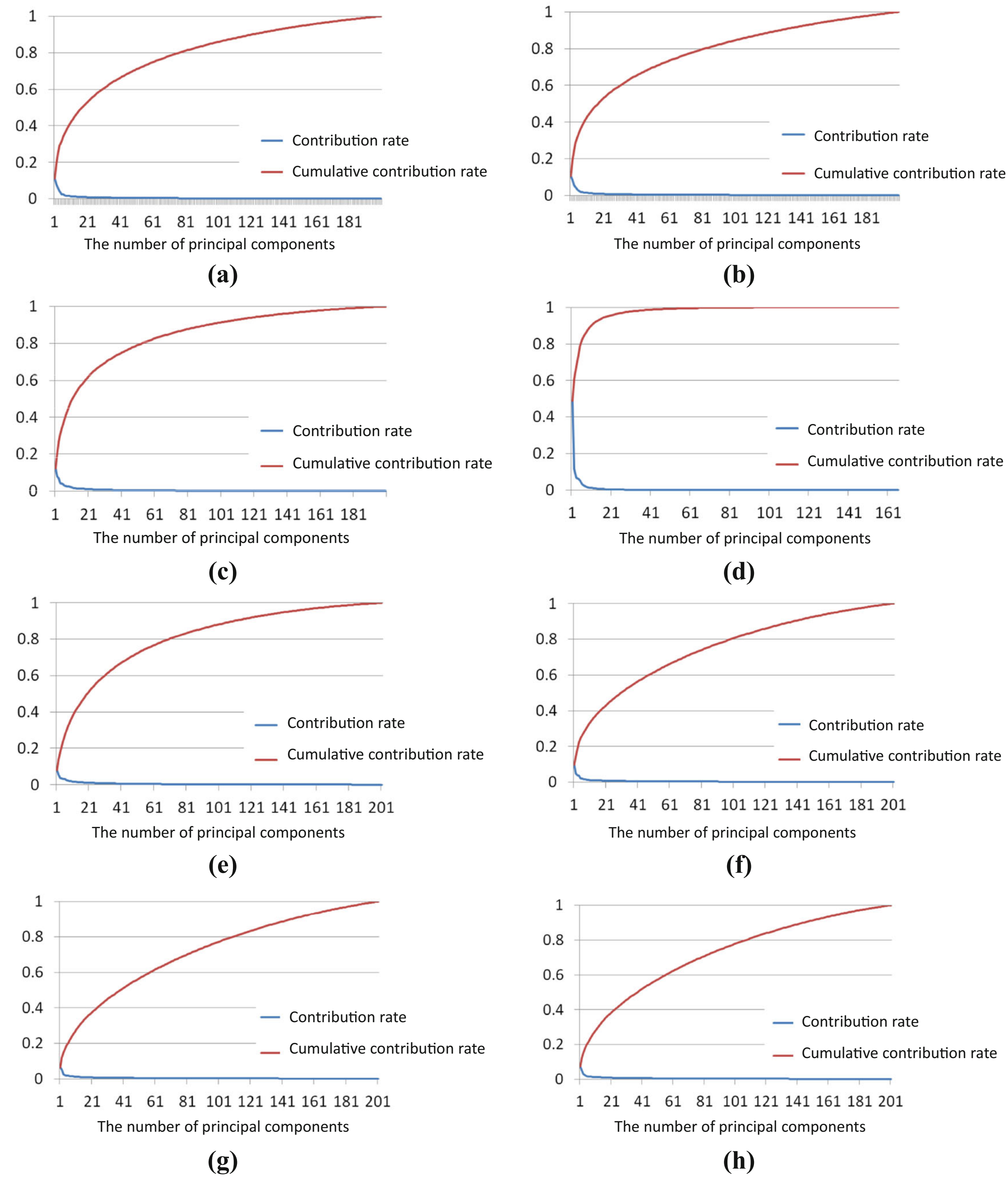
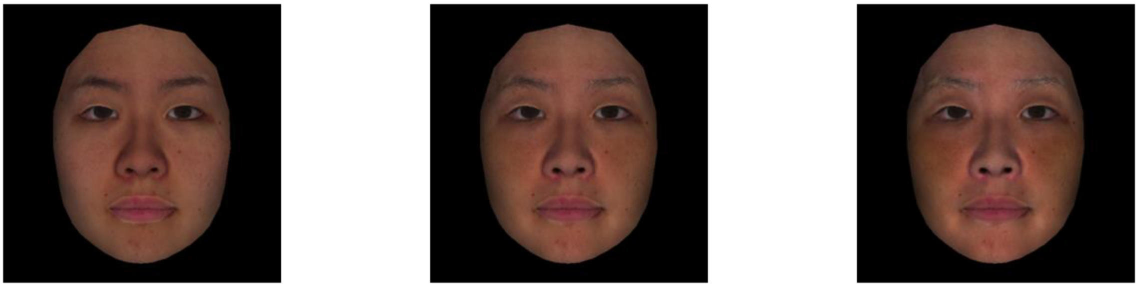


Fig. 20 Contribution rate of principal components: **a** melanin component; **b** hemoglobin component; **c** shading component; **d** facial landmarks; **e** low-frequency components of surface reflectance; **f** horizontal high-frequency components; **g** vertical high-frequency components of surface reflectance; **h** diagonal high-frequency components of surface reflectance

as sagging around the nasolabial fold and fine wrinkles. These changes are influenced by increases in the first and second principal components shown in Fig. 16 and increases in the first principal component shown in Figs. 17, 18 and 19.

In addition, we performed a subjective evaluation of the reproduced images. We evaluated 27 images, each of which was modified to appear in each of the age ranges (10s, 20s,…, 70s), and with each of four modifications; the results are shown in Fig. 25. The four modifications were changing only the pigmentation distribution; changing only the facial structure so that it was based on the 20s face; changing only the facial surface component so that it was based on the 20s face; and changing all components. The reproduced images were displayed randomly on a 21.3-inch display (RadiForce R22S, EIZO). The distance between the display and the observer was three times the height of the display. Each observer evaluated the age of



(a) (b) (c)

Fig. 21 The results of facial appearance by age-related changes in melanin component: **a** 20s, **b** 50s, **c** 70s

(a) (b) (c)

Fig. 22 The results of imaged facial structure by age-related changes in facial landmarks: **a** 20s, **b** 50s, **c** 70s

(a) (b) (c)

Fig. 23 The results of the appearance of facial surface reflectance by age-related changes in low-frequency component, horizontal high-frequency component, vertical high-frequency component and diagonal high-frequency component: **a** 20s, **b** 50s, **c** 70s

(a) (b) (c)

Fig. 24 The results of the appearance of a face by age-related changes in all components: **a** 20s, **b** 50s, **c** 70s

each of the reproduced images, placing them in one of the decadal categories. There were ten observers in their twenties. The results are shown in Fig. 26. The modulations of the facial components were appropriate for age-related changes from the perspective of physiology. Only the changes in the facial structure had a strong influence on the apparent age. However, for faces for which the original image showed a person in their 40–70s, significant

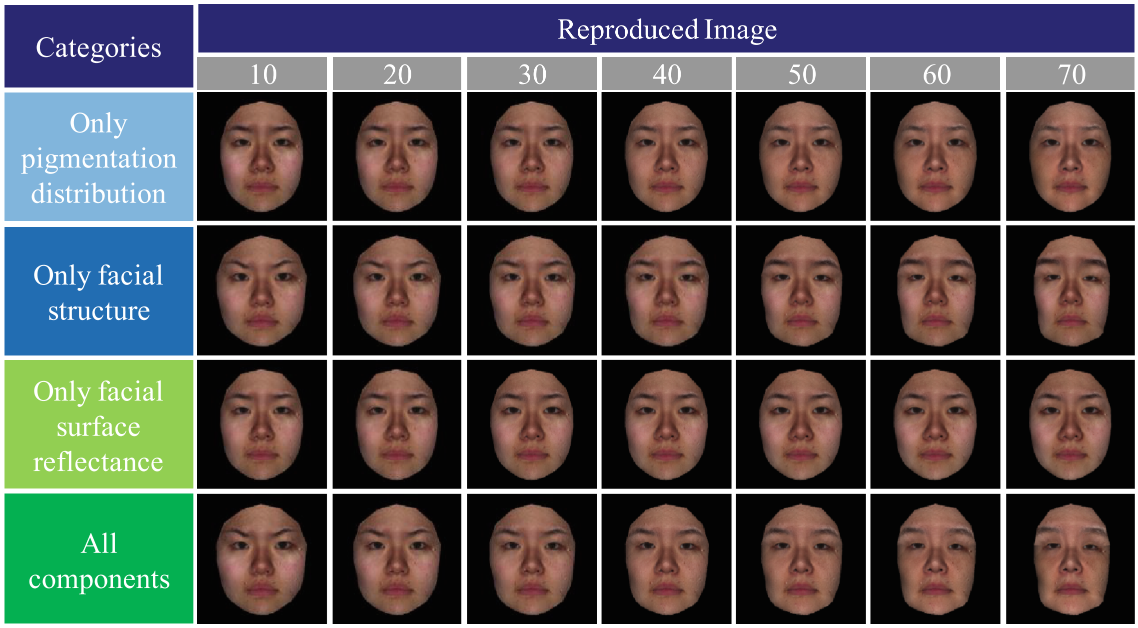


Fig. 25 Evaluated facial images

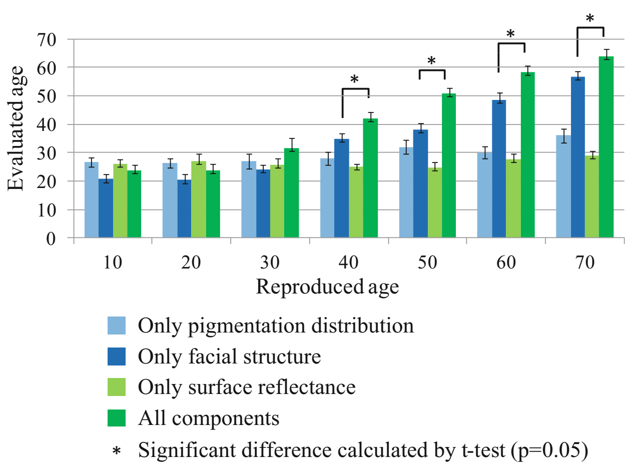


Fig. 26 The results performed subjected evaluation: *Error bar* is the standard error, significant difference calculated by *t* test ($p = 0.05$) are represented

differences were seen between the results for images in which only the facial structure was changed and those in which all components were changed. Therefore, we conclude that it is important for age-related changes to modulate the pigmentation distribution and facial surface reflectance component as well as the facial structure.

In this paper, we analyzed images in the face database which is only constructed by Japanese woman facial images. However, we consider that our analysis can be also applied into facial images where pigment components can be separated from facial images appropriately even if the facial image has darker skin.

4 Conclusion

In this study, we reproduced facial images with age-related changes to synthesize modulated pigmentation distributions, facial structure, and surface reflectance components. First, we constructed a database of facial images. These images were then normalized by transforming the shape of the face in the image to match that of the average face, which was obtained by averaging the landmarks that represent the facial structure. Next, we used independent component analysis to extract the pigmentation distribution from each image. The general gloss and asperity were extracted from surface reflectance components using multiresolution analysis. We applied PCA to the pigmentation distributions, facial landmarks, and frequency components of surface reflectance, and from this we obtained the feature values for variations in pigmentation, facial structure, and distributions of facial gloss and asperity. We used multiple regression analysis to estimate the relationship between these obtained feature values and the apparent age of the face. The weights of the principal components were modulated, based on these estimated relationships, and the simulated images were adjusted using these age-related changes. They were subjectively evaluated, and from the results, we concluded that the modulation of facial components is appropriate for age-related changes, from the perspective of physiology.

In this study, we used averaged age-related changes to modulate the facial images.

We could synthesize the facial images under arbitrary age from the original image. However, the accuracy of synthesis could not be evaluated in this paper, since do not have facial images of the same person of different ages. In our future work, we will prepare the facial images of the same person of different ages, and we will evaluate the accuracy of synthesis of facial images.

We also intend to categorize the obtained feature values based on the age-related changes observed in individuals. We also note that our method requires about 2 h of computer time in addition to various manual operations, and thus it is not ready for practical use; we intend to speed up and automate this system. We also need to perform the analysis of other factors about the facial appearances such as hair.

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