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 in order 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 to 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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A part o this paper was presented at EI2015 held in San Francisco.

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 age³, and for changes in race⁴. 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) by using facial photographs taken with different light sources. Guo and Sim² 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 in order to obtain feature values.

Typically, RGB values are used for processing facial images in order 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.^{5,6,7} 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 study⁸, 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 Section 2, we describe our approach in detail. In Section 2.1, we discuss the construction of a facial image database, and in Section 2.2, we obtain facial landmarks that represent facial structures, and how we transform facial images to that of an average face. In Section 2.3, we use independent component analysis⁵ to extract melanin and hemoglobin pigmentation from a single skin color image. In Section 2.4, we use multiresolution analysis to extract the gloss and asperities from surface reflectance components. In Section 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 Section 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 Section 3, we discuss our results and perform a subjective evaluation. In Section 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 Figure 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 1/3s - 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 Figure 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 parallel to each other. We sample facial images from the database: (a) with specular reflectance, and (b) without specular reflectance.



Fig. 1 Overview of imaging system





Fig. 2 Distribution of ages in the database



Fig. 3 Sample of captured images in the database: (a) with specular reflectance, and (b) without specular reflectance

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 Figure 4(a), and the shape of each face was transformed to match the average face in the database. Figure 4(b) and (c) show an average face and the normalized image after transforming the image shown in Figure 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 Figure 5(a), and this image without specular reflectance is shown in Figure 5(b). The specular reflectance component that was removed from Figure 5(a) to obtain Figure 5(b) is shown in Figure 5(c).







Fig. 4 Image processed by FUTON: (a) facial landmarks identified by yellow dots; (b) average face; (c) normalized image



Fig. 5 Removal of specular reflectance from an image: (a) with specular reflectance; (b) without specular reflectance; (c) specular reflectance component

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 skin color is reprojected onto each pigmentation density vector.

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







Fig. 7 The pigmentation components extracted by independent component analysis: (a) melanin component; (b) hemoglobin component; and (c) shading component

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 Section 2.2. The two-dimensional discrete wavelet transform is applied to the high-frequency components in order to average the individual variations. Figure 8 shows an overview of these processes.

The left image in Figure 9(a) shows a simple example of pixel values assumed for parts of the original image. The center image in Figure 9(a) shows an example of the diagonal high-frequency component that is applied to the two-dimensional discrete wavelet transform. When we average its high-frequency component in order 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 Figure 9(a). 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 Figure 9(b). The original images contain the information about the positive or negative sign of each pixel. The results of the multiresolution analysis are shown in Figure 10.



Fig. 8 Overview of proposed multiresolution analysis



(b)

Fig. 9 A simple example of the two-dimensional discrete wavelet transform applied to the high-frequency components: (a) conventional method; and (b) proposed method in which the absolute value is calculated



Fig. 10 The results of the proposed multiresolution analysis: (a) low-frequency component; (b) horizontal high-frequency component; (c) vertical high-frequency component; and (d) diagonal high-frequency component

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 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{x}_i which is defined by the principal component p_m and the weight vector w_{lm} as follows:

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

where M is the number of principal components used in the approximation, p_m is the *m*-th principal component, and w_{lm} is the weight for the *m*-th principal component, as shown in Figure 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 downsampled 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), 4,096 (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 Figures 12 through 14, respectively. Principal components representing variations in the facial structure are shown in Figure 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 lowfrequency, horizontal high-frequency, vertical high-frequency, and diagonal high-frequency components are shown in Figures 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 Figures 12-19 and the contribution rate of each principal components are shown in Figure 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 highfrequency components can be recognized as oblique fine lines, such as wrinkles on the cheeks.



Fig. 11 Overview of principal component analysis









0.0427

Fig. 14 The results of PCA: shading components



Fig. 15 The results of PCA: facial landmarks





Fig. 18 The results of PCA: vertical high-frequency components of surface reflectance



Fig. 19 The results of PCA: diagonal high-frequency components of surface reflectance



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; (h) diagonal high-frequency components of surface reflectance; (b) diagonal high-frequency components of surface reflectance; (h) diagonal high-frequency components diagonal high-frequenc

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, Figure 22 shows the results for the facial structure when the facial landmarks were changed, Figure 23 shows the reconstructed images after the low- and high-frequency components were changed, and Figure 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.



















Fig. 23 The results of the facial surface reflectance with age-related changes in the low-frequency, horizontal high-frequency, vertical high-frequency, and diagonal high-frequency components; apparent age: (a) 20s, (b) 50s, (c) 70s



Fig. 24 The results in the overall appearance with age-related changes in all components; apparent age: (a) 20s, (b) 50s, (c)70s

3 Discussion

In Figure 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 Figure 12 and the first principal component shown in Figure 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 Figure 14. In Figure 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 were simulated by modulating the first principal were simulated by modulating the the top of the eye is depressed by the modulation of the shadow component. These changes were simulated by modulating the first principal 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 Figure 15. Figure 24 shows more age-related

changes, such as sagging around the nasolabial fold and fine wrinkles. These changes are influenced by increases in the first and second principal components shown in Figure 16 and increases in the first principal component shown in Figures 17 to 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 Figure 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 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 Figure 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 40s to 70s, significant 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 have darker skin.

Categories	Reproduced Image						
	10	20	30	40	50	60	70
Only pigmentation distribution	-Ma	363	alla	- Ale	The second	26	
Only facial structure	and a	-Mar	-Mar	-M-	- Ale	- Ale	- AF
Only facial surface reflectance	-25-	-26-	-26-	(all all all all all all all all all all	-Mar	-25-	25
All components	-25-	-25-	26-	24-	Part -	Part -	2

Fig. 25 Evaluated images



Fig. 26 The results of subjective evaluation: The black bar indicates the standard error, and significant differences, as calculated a t-test (p = 0.05), are indicated.

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 by 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 two hours 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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Caption List

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

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

Fig. 7 The results of independent component analysis extracted pigmentation components : (a)

melanin component (b) hemoglobin component (c) shading component

Fig. 8 Overview of proposed multiresolution analysis

Fig. 9 The simple example applied two-dimentional 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

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

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 reflectance

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

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

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

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

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.