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Analysis of relationship between wrinkle distribution and age based on the components of surface reflection by removing luminance unevenness on the face

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Abstract

In this paper, we perform multi-resolution analysis by using Wavelet transform for the components of surface reflection on faces in order to acquire features of wrinkles and fine asperities on the face. Also, by applying principal component analysis to the acquired trend of the wrinkles and the fine asperities, we analyze the relationship between the distribution of wrinkles and asperities, and actual age statistically. In the previous researches, components of facial surface reflection were directly used for multiresolution analysis, and it is considered that the acquired relationship was dependent on the luminance unevenness of lighting on the face. In this research, therefore, we propose to remove the luminance unevenness of the lighting on the face is transformed into uniform distribution by signal processing, and it contributes to the appropriate analysis to the component of surface reflection on the face.

1. Introduction

The human face is easy to receive much attention compared with other body parts. When we observe facial structure, skin color or skin type, many information can be obtained in their appearances such as sex, the human race, individual features, emotion, apparent age, and health condition. The features such as skin color or facial structures from human faces are called the physical features. In contrast, the features such as apparent age or health condition based on physical features are the extra-physical features. We call them psychological features in this paper. A slight change in our facial features makes significant differences in the appearance of faces. Therefore, especially in the beauty industry, a simulator that modulates the physical features of the face and reproduces an arbitrary appearance is required and put to practical use [1] [2]. The purpose of this simulator is to predict the effect of basic cosmetics and to reproduce the face with the effect of the make-up, so it is based on the physical features such as the face structure and skin condition of the subject. Thus, it becomes to be important to consider the actual ages and how many days the basic cosmetics are used. In general, a makeup simulator installed in a cosmetic department such as a department store measures the condition of the customer's skin, and by applying makeup on the computer to compensate the problem of skin color and facial appearance, the simulator can assist in proposing cosmetic products suitable for the customer.

Hirose *et al*. analyzed the distribution of facial pigment concentration which consists of the skin color, the component of surface reflection that represents the wrinkles and the fine asperities on the skin such as wrinkles, and the shape of the face [3]. Based on the analysis results, they simulated the modulation of the facial feature to reproduce any appearance of the face. They photographed facial images in a laboratory environment and constructed a facial image database, which is consisted of the components of surface reflection, components of internal reflection, facial landmarks, and the actual ages. Based on the database, they analyzed the relationship between components of the internal reflection consists of the skin color and its actual ages, and they synthesized the arbitrary skin color. Moreover, they analyzed the relationship between the components of surface reflection which represents the wrinkles and the fine asperities on the skin and its actual ages, and they synthesized the arbitrary the wrinkles and the fine asperities. Combined with these three components, as shown in Figure 1, the facial image was modulated to a face equivalent to the feature in any ages. In the previous study, the components of surface reflection were directly used for multiresolution analysis, but the components of the surface reflection depend on the shape of the face, and the face is strongly illuminated at heights parts such as the forehead, nose, and cheeks. As a result, the wrinkles and the fine asperities appeared the strong changes in only the strongly illuminated region. Figure 2 shows the result of Principal Component Analysis (PCA) for components of surface reflection with the conventional method. The color scale in Figure 2(a) is a jet color map of MATLAB [4], and shows the intensity and direction of the principal component vector. The detail of PCA is described in Section 3. As shown in Figure 2(b), there were some strong tendencies at high positions on the face such as the forehead, nose, and cheek within a limited range. In other words, it is considered that they analyzed biased the wrinkles and the fine asperities of the skin from a limited area of the face, and the result of the analysis was inappropriate.

In this research, therefore, the illumination unevenness of surface reflection is made uniform by the signal processing, and by applying the analysis method used in the previous research, we aim to analyze the appropriate relationship between the wrinkles and the fine asperities on the skin and the actual ages.

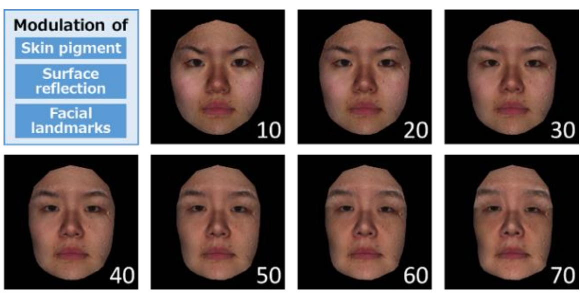
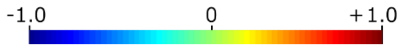
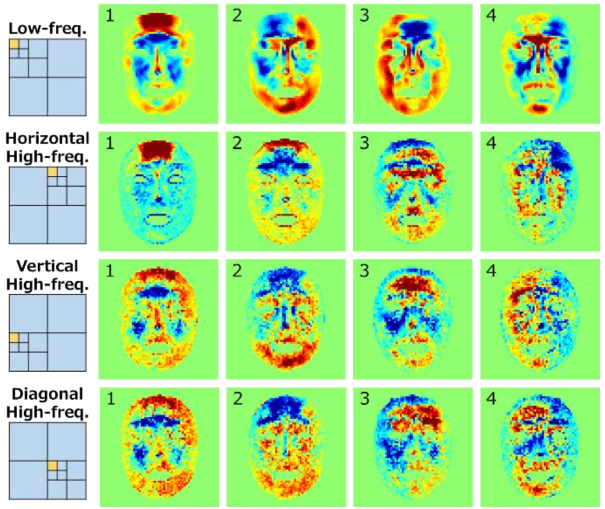


Figure 1. *The results of the aging appearances with appearance-related three components (Skin pigment, surface reflection, and facial landmarks).*



(a) Color scale



(b) The results of PCA in the conventional method

Figure 2. The result of Principal Component Analysis applied to each frequency component in conventional method: (a) Color scale which is shown intensity and direction of the principal component vector, (b) The results of PCA in the conventional method.

In this paper, Section 2 explains the construction of the facial database and our method to remove luminance unevenness of components of surface reflection (proposed method). Also, a multiresolution analysis, which is the conventional method is applied to the corrected surface reflection, and we acquire the frequency features depends on the direction. These are applied PCA in Section 3, and we obtain a relationship between its features and the actual ages in Section 4. The conclusions and future issues are described in Section 5.

2. Approach

This section shows the method to obtain feature values of the wrinkles and the fine asperities distributions on the skin surface and analyze the relationship between the features of the wrinkles and the fine asperities distributions in the whole face and the actual ages. The procedure of the process is as follows. In the next subsection, we describe the details of each process.

Step 1	Construction of the database of facial images
Step 2	Acquisition of facial landmarks, and morphing facial images to an average face
Step 3	Obtaining components of surface reflectance by subtraction processing
Step 4	Correction for the components of surface reflectance (Proposed method)
Step 5	Extracting facial glosses, wrinkles and asperities distributions by Multiresolution analysis
Step 6	Principal component analysis for the wrinkles and the fine asperities distributions in the whole face

2.1. Construction of the database of facial images

We constructed a database based on components of surface reflection, components of internal reflection, and the actual ages. First of all, we photographed 60 Japanese women's faces in a darkroom. As a light source, there were four fluorescent lights so that the lights surrounded the camera. The used camera was Nikon D2H. In order to prevent movement of the face, we used support for the neck and head, which was fixed on the backrest of a chair.

The ages of subjects were between 10 and 80 years old in 2015. We obtained facial images with and without specular reflectance by quickly setting polarization filters in front of the camera and the light sources mutually perpendicularly. The difference image between these two images means the surface reflection component, which expresses the gloss, the wrinkles, and the fine asperities of the whole face such as pores. Therefore, the components of surface reflection were used to acquire the features such as the wrinkles and the fine asperities. The actual surface reflection we used was obtained by taking the difference between the images with and without surface reflection after normalization processing of the facial image described later.

2.2. Acquisition of facial landmarks, and morphing facial images to an average face

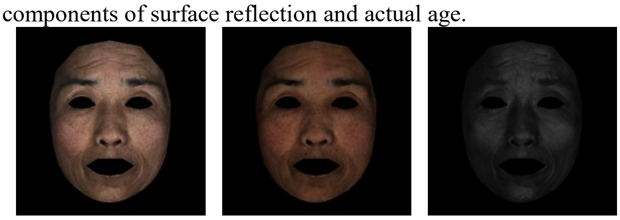
In this research, captured facial images were required to be normalized to remove influence caused by the variation of individual facial shapes in order to apply PCA accurately to the images later. For this reason, we used FUTON (Foolproof UTilities for facial image manipulatiON system), which is a systems to synthesis a facial image developed by Mukaida et al. [5]. Figures 3 (a) and 3 (b) show the results of applying normalization to the captured facial images as in the previous study [3]. Due to the limitations of the FUTON system, the image resolution was downsampled to 512 x 512.

2.3. Obtaining components of surface reflectance by subtraction processing

To obtain the component of surface reflection, subtraction processing was applied to Figure 3 (a) and 3 (b). The subtraction image has three channels (RGB). In order to reduce the data amount, the equation (1) is applied to extract the luminance component Y (YUV color space) from the RGB image. The extracted luminance component is shown in Figure 3 (c).

$$Y = 0.299R + 0.587G + 0.114B \quad (1)$$

By the above procedure, we acquired the components of surface reflection, and we constructed a database which consists of the components of surface reflection and actual age.



(a) (b) (c)

Figure 3. Normalized capture image: (a) Normalized facial image with specular light, (b) Normalized facial image without specular light, (c) Component of surface reflection image by subtracting (a) and (b).

2.4. Correction for the components of surface reflectance (Proposed method)

Based on the previous research, the multiresolution analysis will be applied in the next section to analyze the wrinkles and the fine asperities and wrinkles on the skin surface. The multiresolution analysis was a method to decompose an image in direction-dependent frequency features in horizontal, vertical and vertical directions by using Wavelet transform. If the intensity of the illumination onto the face is unevenness as shown in Figure. 3 (c), the pixel values will be changed by depending on the luminance unevenness. In this section, therefore, we propose a method to remove luminance unevenness of the surface reflection components by signal processing. 1) Smooth the component of surface reflection with arbitrary parameters. 2) Calculate a value which the original value is divided by the value of 1). As a result, it is possible to acquire the surface reflection in which the unevenness of the illumination light is removed. This procedure is shown in Figure 4 as a one-dimensional signal across the mouth of the surface reflection component in Fig. 3 (c). The result of applying the proposed method to Figure 3 (c) is shown in Figure 5. As shown Figure 3 (c), before the correction, the illumination lighted the forehead and cheeks of the face strongly, and the distribution of the wrinkles and the fine asperities on the skin surface was dependent on the luminance intensity distribution, but proposed method, as shown in Figure 5 was possible to obtain the wrinkles and the fine asperities not depending on the distribution of the luminance intensity. We acquired the corrected data of the surface reflection from which uneven lighting was removed by applying this process to the all surface reflection in the database.

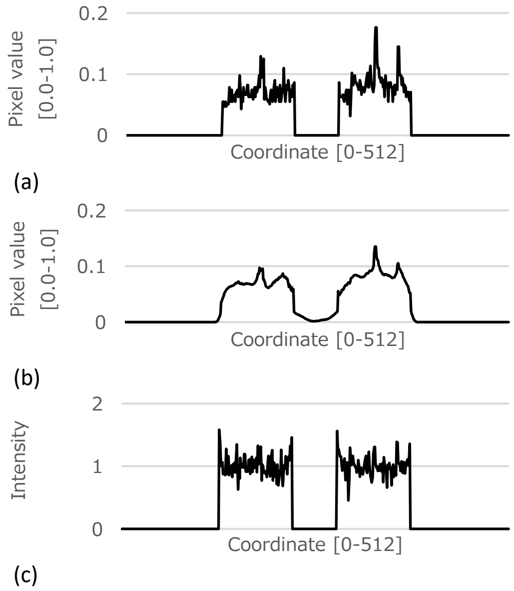


Figure 4. *Proposed method as a one-dimensional signal: (a) Original signal, a line of surface reflection shown in Figure 3 (c) in 400 rows, (b) Smoothed signal in any parameter, (c) A divided signal from (a) to (b).*

Figure 5. *The result of applying the proposed method to Figure 3 (c).*

2.5. Extracting facial glosses, wrinkles and asperities distributions by Multiresolution analysis

We extracted facial glosses and facial asperities distributions from components of surface reflectance by applying multiresolution analysis. Two-dimensional discrete wavelet transform was used in this analysis. By applying two-dimensional discrete wavelet transform to the images, a low-frequency component and three kinds of high-frequency components were obtained. Each high-frequency component has three directions, horizontal, vertical and diagonal. When we applied two-dimensional discrete wavelet transform to the components of surface reflectance, the general gross of face was obtained in the low-frequency component. The facial asperities can be obtained in the high-frequency components, but high-frequency components appeared included individual variations in spite of the correction described in section 3. In order to remove the individual variations, we applied two-dimensional discrete wavelet transform to the high-frequency components to average individual variations. Figure 6 shows an overview of this process.

The left image in Figure 7(a) shows an example representing the pixel values of the original image simply. The center image in Figure 7(a) is the example of obtained diagonal high-frequency components which was applied two-dimensional discrete wavelet transform to the original image at once. When we average its high-frequency component to apply two-dimensional discrete wavelet transform, sometimes averaged pixel value can be zero because the pixel values include both of positive values and negative values such as the right image shown in Figure 7(a). Then, we stored the signs of the values of the wrinkles and the fine asperities distributions by calculating absolute values of high-frequency components before averaging prior to applying two-dimensional discrete wavelet transform shown in Figure 7(b). Original images can be reconstructed to stored information on positive or negative values in all pixels. The results of the multiresolution analysis are shown in Figure 8

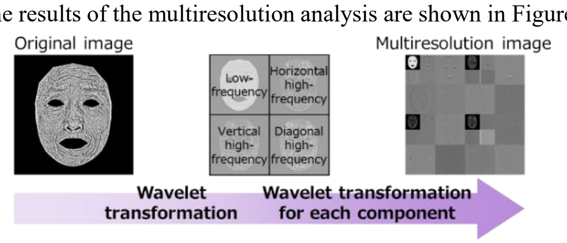


Figure 6. *Overview of conventional multiresolution analysis [2].*

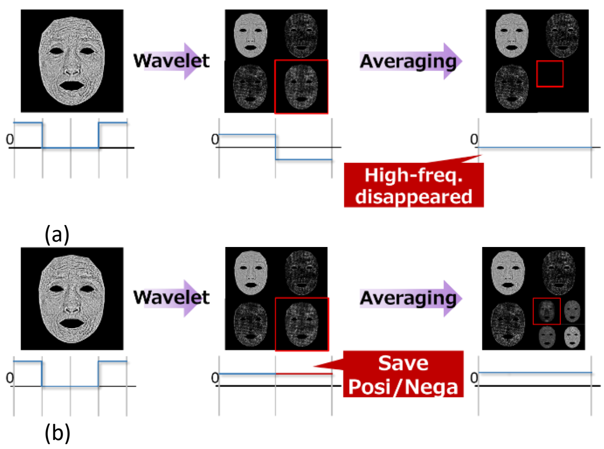


Figure 7. *The simple example applied two-dimensional discrete wavelet transform to high-frequency components: (a) General two-*

dimensional discrete Wavelet transformation, (b) The method by calculating an absolute value which was proposed by Toyota et al., [3].

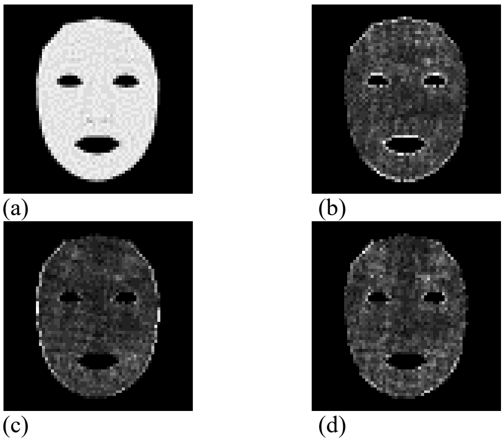


Figure 8. *The results of proposed multiresolution analysis: (a)low-frequency component, (b)horizontal high-frequency component, (c)vertical high-frequency component, (d)diagonal high-frequency component.*

2.6. Principal component analysis for the wrinkles and the fine asperities distributions in the whole face

In this subsection, we obtained feature values of facial wrinkles and asperities distributions by applying PCA to frequency components of surface reflectance. PCA is a primary method of multivariate statistical analysis. By applying PCA to data groups, we can obtain principal component vectors that indicate the direction in which the variance increases. Moreover, by reducing the dimension by PCA and observing the weight of the principal component vector (called principal component score), we can find that how much the feature of the principal component vector is included in its data. In this study, firstly we acquired principal component vectors in order to obtain the change tendency of the wrinkles and the fine asperities of the whole face. Next, we analyzed the correlation between age and principal component score. The results of PCA is explained in the next section.

3. Results of Principal Component Analysis

By applying principal component analysis to each frequency component, we analyzed the correlation between the distribution of each frequency component and actual age. The principal component vector images and their contribution rates obtained by PCA are described in Subsection 3.1. The relationship between the principal component score and the actual age are described in Subsection 3.2.

3.1. Principal component vector and Contribution ratio

We applied PCA to the facial image, which has 64×64 pixels representing the frequency components of the surface wrinkles and fine asperities because frequency components have been down-sampled by multiresolution analysis. The one pixel is assigned as one element in the vector, then the one facial data is assigned as the one point in 4,096(64×64) dimensional spaces respectively. The 60 facial images were used because we had 60 points in these dimensional spaces.

As a result, we obtained 59 principal components in frequency components of surface reflectance by PCA.

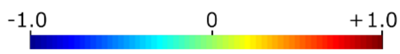
Figure. 10 shows the results of PCA applied to low-frequency components, horizontal high-frequency components, vertical high-frequency components and diagonal high-frequency components in the conventional and proposed method. Figure 10(a) shows the color bar which shows the intensity and direction of principal components vector. The numbers at the top left of the images represent the number of principal components sorted by the contribution rate. Table 1 shows the contribution of the 1st to 4th principal components, and Figure 11 shows the cumulative contribution of the principal components at each frequency. Being compared the conventional method shown in Figure 2 with the proposed method shown in Figure 10(b), it seems that the proposed method was able to extract features from the whole face without depending on the local area such as the forehead. Next, we focus on the results in the proposed method. We discuss the trend of the corrected frequency signal, which has mixed low frequency and high frequency such as noticeable wrinkles and fine unevenness.

In the low-frequency components, it was predicted that features of wrinkles appear which did not depend on direction. The output signals show the almost high frequency on the whole face. On the other hand, in characteristic features was seen only on the facial contour and around the nose. It is considered that low-frequency components appear in places where the contrast is clearly visible, regardless of individual differences. The contrast of the facial contour dues to the normalization process was described in Section 2.2. Therefore, it is thought that noticeable change in the luminance is easy to occur only around the nose.

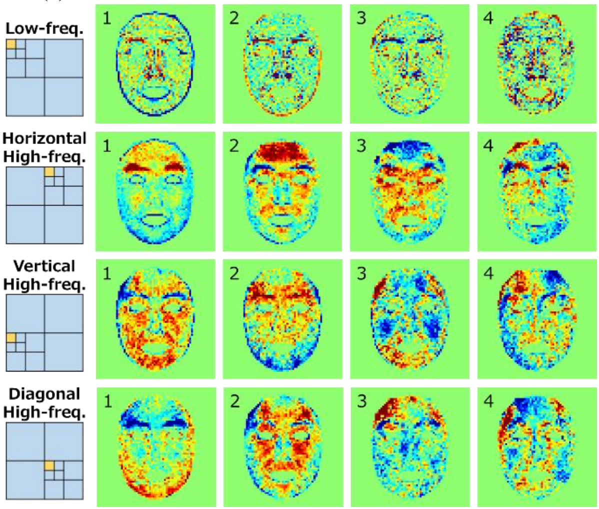
Next is the horizontal high-frequency component. Since it detects changes in the vertical direction, high-intensity principal components vectors appeared at the locations where horizontal lines are distributed. In fact, the second row in Fig. 10 (b) shows that individual difference of vertical changes appear strongly on the eyebrow, forehead, cheek, and so on. Observing the 1st to 3rd principal component, it is considered that there are many horizontal lines on the forehead, especially.

Next is the vertical high-frequency component. Since this detects changes in the horizontal direction, high-intensity principal components vectors appeared at the locations where vertical lines are distributed. In fact, the third row in Fig. 10 (b) shows that individual difference of vertical changes appear strongly on the cheeks around the mouth, and so on. Observing the 1st and 3rd principal component, it is considered that there are many vertical lines especially on the cheeks around the mouth.

The last is the vertical high-frequency component. Since this detects changes in the diagonal direction, high-intensity principal components vectors appeared at the locations where diagonal lines are distributed. In fact, the 1st and 2nd row in Fig. 10 (b) shows that individual difference of diagonal changes appear strongly on the cheeks around the mouth, and so on. Observing the 1st and 2nd principal component, it is considered that there are many diagonal lines especially on the cheeks around the mouth. The relationship and the trends between the actual ages and each component will be explained in the next section.



(a) Color scale



(b) The results of PCA in the proposed method

Figure 10. *The result of PCA applied to each frequency component in the proposed method: (a) Color scale which is shown intensity and direction of the principal component vector, (b) The results of PCA in the proposed method.*

	The 1st	The 2nd	The 3rd	The 4th
Low	0.0657	0.0453	0.0406	0.0375
Horizontal High	0.0914	0.0636	0.0440	0.0346
Vertical High	0.0560	0.0468	0.0374	0.0364
Diagonal High	0.0655	0.0519	0.0384	0.0344

Table 1. *Contribution ratio in each component of the surface wrinkles and fine asperities*

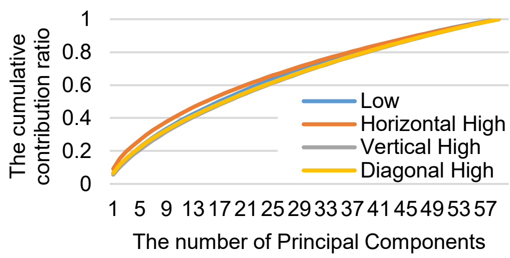


Figure 11. *The contribution ratio of PCA in each component of the surface wrinkles and fine asperities.*

3.2. Principal component score

We obtained principal component scores in each frequency components of surface reflectance. Figure 12 shows the principal components scores of each subject corresponding to the principal components of the respective frequency components shown in Figure 10 (c). Therefore, each Figure corresponds to the 1st, 2nd, 3rd, and 4th principal component from left to right. The horizontal axis shows the actual age (from the 20s to the 80s), and the vertical axis shows each principal component score. The straight line in the figure shows the regression line. Looking at these figures, we can find whether there is a correlation between principal components scores and actual ages or not.

First, regarding the low-frequency component shown in the first row of Figure 12, the tendency of change hardly appears as explained in the previous section. It can be seen that the nose around the first principal component which had a slight tendency to change, tended to increase with age. Therefore, we found that the luminance change is apt to occur around the nose with age from the low-frequency component.

Next, with regard to the horizontal high-frequency components shown in the second row of Figure 12, the first to third principal component vectors showed the tendency to change the luminance on the eyebrow, forehead, and cheek in the previous section. The 1st principal component shows that the individual difference in the change in luminance is the largest with regard to the eyebrows, but its correlation coefficient was only 0.0197 shown Table 1, so it is considered that there is almost no correlation between changes in luminance in the eyebrows and the actual age. The 2nd and 3rd principal component shows that the individual difference in the change in luminance was the largest with regard to the forehead and cheeks, and its correlation coefficient is 0.5793 and 0.5890, respectively. Thus, it was considered that there is a correlation between luminance changes in especially forehead and cheeks, and the actual age. Therefore, from the horizontal high-frequency components, we found that the luminance change in the horizontal direction is apt to occur on the forehead and cheeks with age.

Next, with regard to the vertical high-frequency components shown in the third row of Figure 12, especially the 1st principal component vectors showed the tendency to change the luminance on the cheeks around the mouth in the previous section, which its correlation coefficient is 0.5428. Thus, it is considered that there is a correlation between luminance changes especially on the cheeks around the mouth and the actual age. Therefore, from the vertical high-frequency components, we found that the luminance change in the vertical direction is apt to occur on the cheeks around the mouth with age.

Finally, with regard to the diagonal high-frequency components shown in the last row of Figure 12, the 1st and 2nd principal component vectors showed the tendency to change the luminance on the cheeks around the mouth in the previous section, which its correlation coefficient is 0.1195 and 0.6331, respectively. Thus, from the 2nd principal component scores, it is considered that there is a correlation between luminance changes especially on the cheeks around the mouth and the actual age. Therefore, from the diagonal high-frequency components, we found that the luminance change in the diagonal direction is apt to occur on the cheeks around the mouth with age.

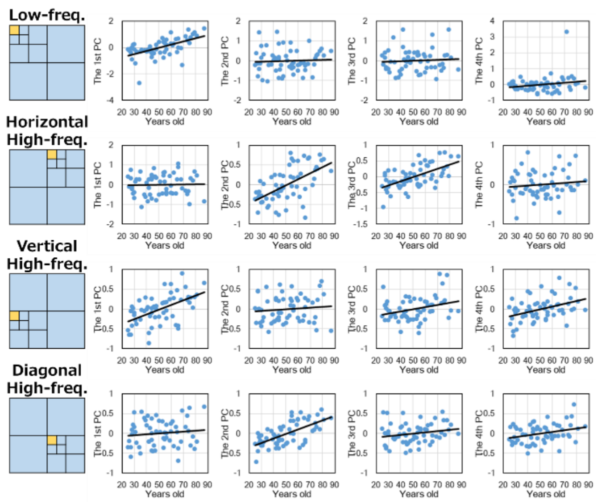


Figure 12. The principal component scores in each frequency components.

	The 1st	The 2nd	The 3rd	The 4th
Low	**0.5718**	0.0479	0.0719	0.2018
Horizontal High	0.0197	**0.5793**	**0.5890**	0.1201
Vertical High	**0.5428**	0.1051	0.3142	0.3966
Diagonal High	0.1195	**0.6331**	0.1974	0.2818

Table 1. Correlation coefficient of principal component in each frequency component

4. Discussion

In the previous section, the principal component analysis was performed, and feature value distributions with significant individual differences were obtained for frequency components in each direction. Also, by analyzing the relationship between age and principal component score, we obtained the trend of changes on the wrinkles and the fine asperities in the skin with aging. The tendencies of changes over the years are shown below.

Low-frequency component: The changes in the luminance around the nose appeared.

Horizontal high-frequency component: The changes in the luminance on the forehead increased.

Vertical high-frequency component: The changes in the luminance on the cheeks and around mouth increased.

Diagonal high-frequency component: The changes in the luminance on the cheeks and around the mouth increased.

The above results are discussed subjectively with the actual images whose ages are difference shown in Figure 13. Figure 13(a) shows the facial image whose age is 25 years old, and Figure 13(b) shows the 87 years old.

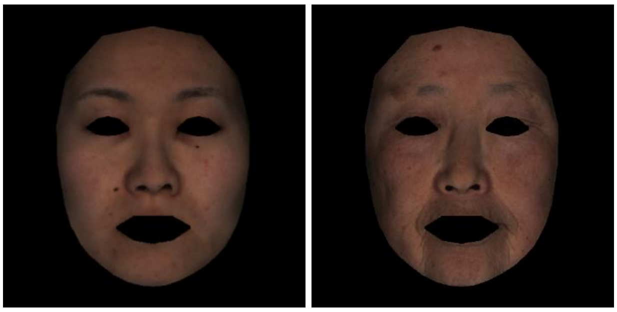
First, observing the luminance changes around the nose found from the low-frequency components, it can be seen that the wrinkles on the side of the nasal muscles of the elderly face are deeper than those of younger face.

Second, observing the luminance changes on the forehead from the horizontal high-frequency components, it can be seen that the wrinkles on the forehead of the old face are slightly deeper than the younger face. Since the 2nd principal component score of the subject shown in Figure 12 is located below the regression line, it can be seen that the subject is shown in Figure 13(b) has fewer forehead wrinkles concerning age. On the other hand, the other image which has high 2nd principal component scores can be seen deep wrinkles on the forehead.

Third, observing the luminance changes on the forehead from the vertical high-frequency components, it can be seen that the wrinkles on the cheeks and around the mouth of the old face are deeper than those of younger face. These wrinkles in the vertical direction which located on the bottom edge of the mouth is called marionette line [6].

Lastly, observing the luminance changes on the forehead from the diagonal high-frequency component, it can be seen that the wrinkles on the cheeks and around the mouth of the old face are deeper than those of younger face. These wrinkles in the diagonal direction which located on the edge of the mouth is called nasolabial fold [6].

In summary, by comparing the principal component score and the actual face image, it was found that the frequency of each face and the degree of wrinkles in each direction can be indexed by the principal component score.



(a) (b)

Figure 13. The facial image in different years old: (a) the youngest facial image (25 years old), (b) the oldest facial image (87 years old).

5. Conclusion

In this research, we constructed a facial image database of Japanese women consisting of 60 people and acquired the component of the wrinkles and the fine asperities which corrected the illumination difference of the surface reflection component by the proposed method. The acquired components were applied multi-resolution analysis in the same way as in the previous research, and feature values were obtained by frequency-resolving the skin's wrinkles and fine asperities in the horizontal, vertical, and diagonal directions. By applying principal component analysis to each frequency component, and analyzing the relationship between the principal component score and actual age, we found that the scores indicated the lateral and forehead wrinkles of the nasal muscles, the marionette line, and nasolabial fold with age. Furthermore, the proposed method makes it possible to compare the degree of wrinkles in each part by comparing the principal component scores.

In the future, we will modulate principal component scores and reconstruct surface reflection components by inverse transforming multiresolution analysis. Moreover, we plan to simulate the change of wrinkles by combining it with the internal reflection component that represents the skin color. In this study, face images were taken in a laboratory environment because it was necessary to obtain a fine surface reflection component using a polarizing filter. In the future, we plan to verify images taken in a robust environment closer to the actual scene by using a polarization camera.

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