Bull. Soc. Photogr. Imag. Japan. (2019) Vol. 29 No. 2: 27–34

Original Paper

Analysis of the Relationship between Age and Wrinkle from Facial Images Corrected for Surface Reflection

Ikumi NOMURA*, Kaito IUCHI*, Mihiro UCHIDA*, Nobutoshi OJIMA**, Takeo IMAI**, Norimichi TSUMURA***

Abstract: We performed multi-resolution analysis using the wavelet transform on components of surface reflections from a facial image to identify wrinkles and fine asperities. Additionally, by applying principal component analysis, we statistically analyzed relationships between distributions of the wrinkles and surface asperities, and actual ages. In previous research, the components of facial surface reflection were calculated as for multi-resolution analysis, however, the uneven illuminance on the face affected the trend. Therefore, we proposed a method to transform the luminance unevenness of facial images into a uniform distribution using signal processing, which contributes to the appropriate analysis of the surface reflection components on the face. As a result, compared with previous research, we could analyze the lighting unevenness with less influence of bias and acquire the distribution tendency of wrinkles and fine asperities in each direction.

Key words: Facial image, Image processing, Wrinkles, Multi-resolution analysis, Principal Component Analysis (PCA)

1. Introduction

A human's face naturally receives the most attention compared with other body parts. When we observe the facial structure, skin color or skin type, information can be obtained, such as sex, race, individual features, emotion, apparent age, and health condition. Features, such as skin color or facial structures, are called physical features. In contrast, features such as apparent age, or health condition based on physical features, are extra-physical features and are identified as psychological features in this paper. A slight change in our facial features causes a significant difference in appearance. Therefore, especially in the beauty industry, a simulator that modulates the physical features of the face and reproduces an arbitrary appearance is required [1),2)]. The purpose of this simulator is to predict some effect of basic cosmetics and reproduce the face with the make-up; therefore, it is based on the physical features, such as the face structure and skin condition, of the subject. Thus, it becomes essential to consider the actual age of the subject, and how many days the basic cosmetics are used. In general, a makeup simulator installed in a cosmetic department, such as in a department store, measures the condition of the customer's skin. By applying makeup in the computer software to compensate for problems of skin color and facial appearance, the simulator can assist in proposing cosmetic products that suit the customer.

Hirose et al. analyzed skin and face components, and based on its results, they simulated the modulation of each feature to reproduce any appearance of the face [3)]. They photographed facial images in a laboratory environment and constructed a facial image database that consisted of the three components (surface reflection, components of internal reflection, facial landmarks) and the actual age. The tendency due to aging was able to be acquired by analyzing the three elements statistically, and then the facial image was simulated at any age by modulating features, as shown in Figure 1. The results of previous research are shown in Figure 2. The first line is the low-frequency component result, the second line is the horizontal high-frequency component result, the third line is the vertical high-frequency component result, and the fourth line is the diagonal high-frequency component. The distribution of the first to fifth

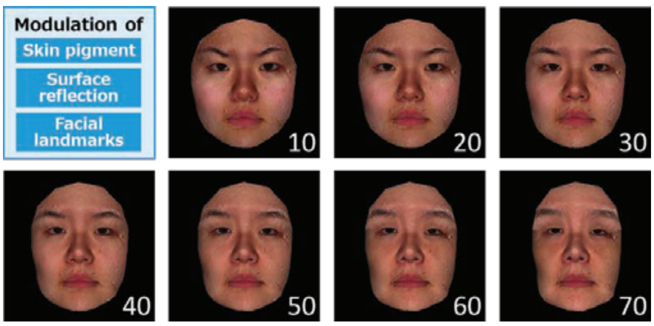


Figure 1 The results of aging simulation with three components related to appearance (skin pigment, surface reflection, and facial landmarks). * This figure is cited from Hirose et al. [3)]

Received 12th December 2019; Accepted 30th December 2019

*Graduate School of Science and Engineering, Ciba University; 1-33, Yayoi- cho, Inage-ku, Chiba-shi, Chiba 263-8522, Japan
**Kao Company, Ltd., 5-3-28 Kotobukicho, Odawara City, Kanagawa 250- 0002, Japan
***Graduate School of Engineering, Chiba University; 1-33, Yayoi-cho, Inage-ku, Chiba-shi, Chiba 263-8522, Japan

principal component vector are shown in order from the left. In particular, the surface reflection component represents fine asperities and wrinkles on the skin surface, so the age-based features appear prominently. In the previous research, according to the results of the statistical analysis shown in Figure 2, a strong tendency for aging appeared at prominent positions on the face, such as the forehead, nose, and cheeks. The component of the surface reflection depends on the shape of the face, and conspicuous parts such as the forehead, nose line, and chin tip, are more strongly illuminated. In other words, an illuminance difference throughout the face causes the wrinkles and fine asperities to appear noticeably in only the strongly illuminated region. That is, the analysis was biased to the wrinkles and fine asperities of the skin from a restricted area of the face, and it did not show an appropriate result of aging.

Therefore, in this paper, the illumination unevenness of the surface reflection was made uniform by signal processing, and feature maps of fine irregularities and wrinkles of the entire face were acquired. Then, by applying the analysis method used in the previous study, we aimed to analyze the appropriate relationship between wrinkles and fine asperities on the skin and actual age.

In this paper, Section 2 explains our approach, which consists of the construction of the database of facial images and the method to remove the luminance unevenness of components of the surface reflection (proposed method). Additionally, we acquired the frequency features depending on the direction by applying the multi-resolution analysis, which is the conventional method to correct surface reflection. Section 3 documents the use of Principal Component Analysis (PCA), and we obtained a relationship between its features and actual ages in Section 4. The conclusions and future issues are described in Section 5.

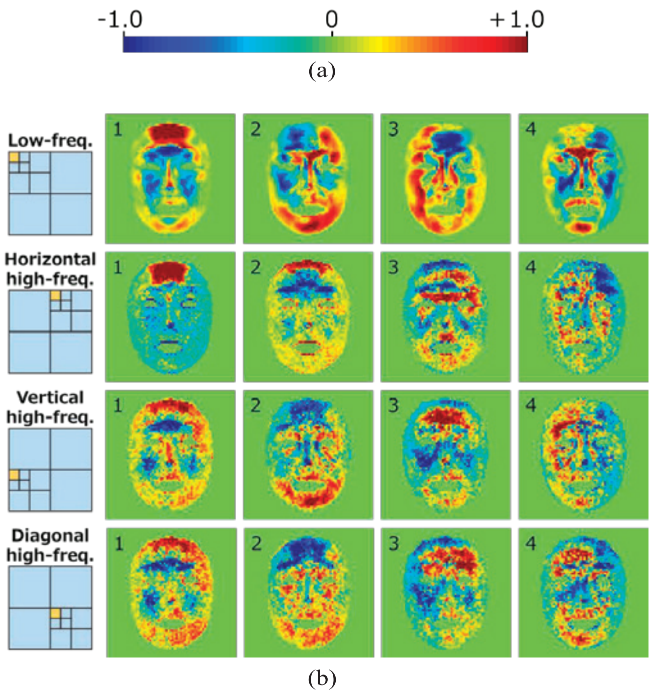


Figure 2 The result of PCA applied to each frequency component in the conventional method: (a) color scale, which is the intensity and direction of the principal component vector, and (b) the results of the PCA in the conventional method.

* This figure is cited from [3]

2. Approach

This section explains the procedure to obtain feature values of wrinkles and fine asperity distributions on the skin surface and analyze their relationship with respect to the whole face and actual age. The procedure of the process is shown in Table 1.

2.1 Construction of the database of facial images

We constructed a database based on components of surface reflection, components of internal reflection, and actual ages. First, we photographed 60 faces of Japanese women in a dark room. The experimental setup is shown in Figure 3. Blackout curtains surrounding the imaging system were used to eliminate the effect of ambient light. There were four fluorescent lights surrounding the camera

Table 1 Analysis procedure

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 asperity distributions by multi-resolution analysis
Step 6	Principal component analysis for the wrinkles and the distribution of fine asperities in the whole face

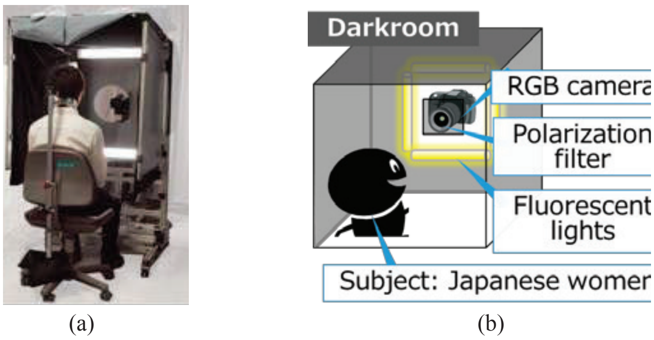


Figure 3 The experimental setup: (a) appearance of the imaging system and (b) overview of the imaging system.

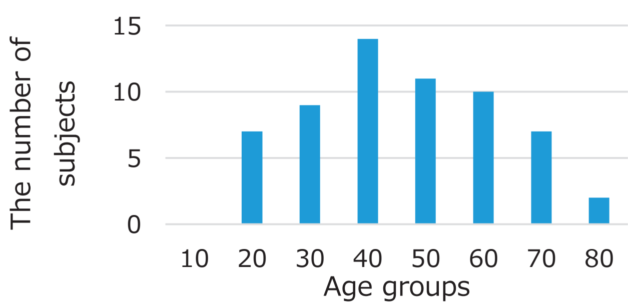


Figure 4 Age distribution of the subjects in this experiment image.

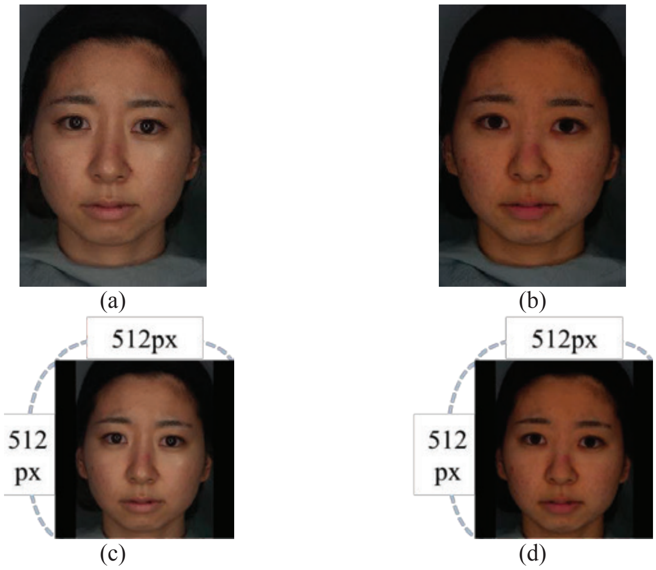


Figure 5 Examples of captured images and resized images: (a) a captured facial image with specular light, (b) captured facial image without specular light, (c) and (d) resized images from Figure 5 (a) and (b).

(Nikon D2H) for the light source. To prevent movement of the face, we used support for the neck and head that was fixed on a chair backrest.

The ages of the subjects were between 20 and 80 years old in 2015. The distribution of age in the database is shown in Figure 4.

Figure 5 (a) and (b) show examples of the captured images with and without specular reflectance. For the preprocessing of the next section, the captured images were resized to 512 * 512 resolution as shown in Figure 5 (c) and (d). Specular reflection on a captured image is removal by quickly setting polarization filters in front of the camera and light sources perpendicularly to each other. The image difference between these two images is the surface reflection component, which expresses the gloss, wrinkles and fine asperities of the whole face such as pores. Therefore, the components of surface reflection were used to acquire features such as wrinkles and fine asperities. The actual surface reflection used was obtained by calculating the difference between the images with and without surface reflection after the normalization processing of the facial image.

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

Facial images were normalized to remove influence caused by the variation of individual facial shapes for accurate application of PCA. For this reason, we used FUTON (Foolproof UTilities for facial image manipulatiON system), which is a system to synthesize facial images developed by Mukaida *et al.* [5]. First, facial landmarks representing the facial structure were obtained and facial areas were extracted. Second, we morphed the shapes of facial images into an image of an average face that was made from facial images in the database. As a result, we obtained normalized facial images that keep individual skin texture information. The overview of this process is shown in Figure 6. Figure 7 shows the results of applying the normalization to the captured facial images that are similar to Figure 5.

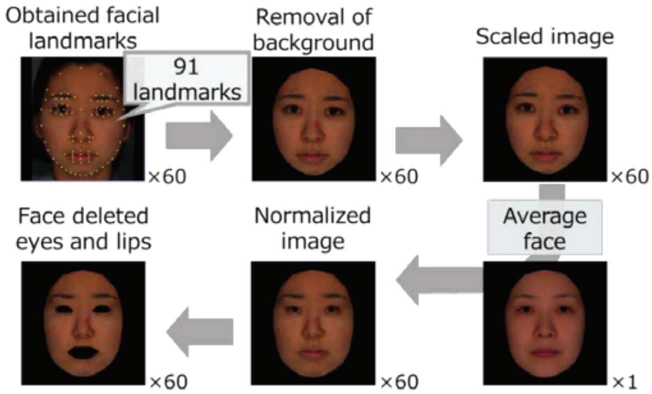


Figure 6 Overview of the normalization process for a facial image.

Figure 7

(a)is a transformed image from a facial image with surface reflection, and Figure 7

(b)is also a transformed image from a facial image without surface reflection.

2.3 Obtaining components of surface reflectance using a subtraction processing

Subtraction processing was applied to Figure 7 to obtain components of surface reflection. The subtraction image has three channels (RGB). In order to reduce the data amount, the luminance component Y (YUV color space) from the RGB image is given by

$$Y = 0.299R + 0.587G + 0.114B \tag{1}$$

where R, G, B is the pixel value from the original RGB image.

Figure 7 Normalized capture images: (a) facial image with specular light and (b) facial image without specular light.

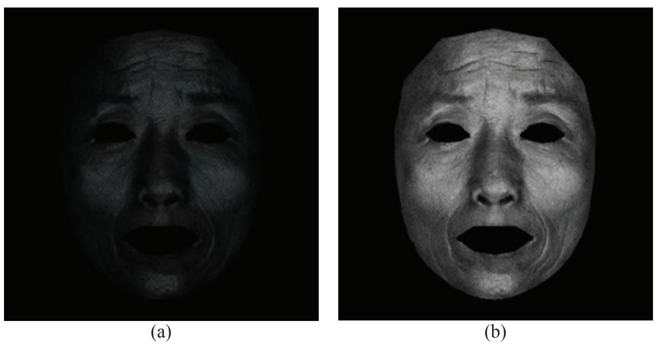


Figure 8 Components of surface reflection image by subtraction processing: (a) a result of subtraction between Figure 7 (a) and (b), and (b) an image after gamma correction for Figure 8 (a) for easy viewing.

The extracted luminance component is shown in Figure 8 (a), and then a gamma correction was applied to make it easier to see as shown in Figure 8 (b). By this process, the surface reflection component includes wrinkles and fine irregularities on the face. After the above procedure, we acquired the components of surface reflection and constructed a database with actual age.

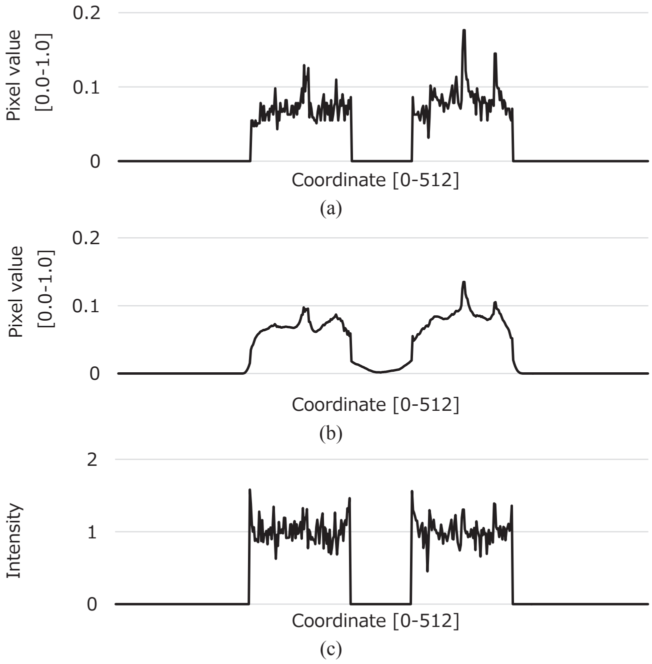


Figure 9 Proposed method as a one-dimensional signal: (a) original signal, a line of surface reflection shown in Figure 8 (a) in 400 rows, (b) smoothed signal in any parameter, (c) a divided signal from (a) to (b).

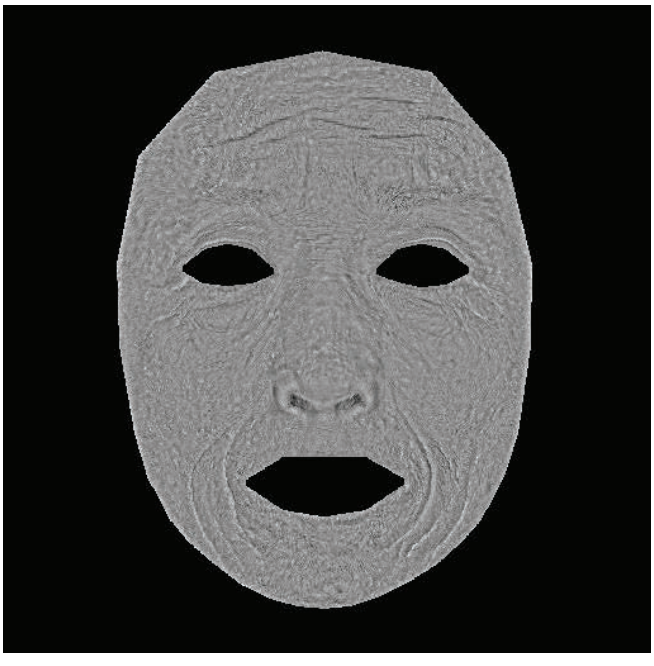


Figure 10 Results of applying the proposed method to the grayscale image of Figure 8 (a) which was converted by Equation (1).

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

Based on the previous research, a multi-resolution analysis was applied in the next section to analyze the wrinkles and fine asperities on the skin surface. The multi- resolution analysis was a method to decompose an image in direction-dependent frequency features in the horizontal and vertical directions using a wavelet transform. If the intensity of the illumination on the face was unevenness, as shown in Figure 8 (b), the pixel values were changed. Therefore, we proposed a method to remove the luminance unevenness of the surface reflection components by signal processing as the following procedure. 1) Smooth the component of surface reflection by bilateral filter with arbitrary parameters empirically. 2) Calculate a value in which the original value is divided by the value of 1). As a result, it was possible to acquire the surface reflection in which the unevenness of the illumination light is removed. This procedure is shown in Figure 9 as a one-dimensional signal. The result of applying the proposed method to Figure 8 (a) is shown in Figure 10. As shown in Figure 8 (a) and (b), before the correction, the illumination lit the forehead and cheeks of the face strongly, and the distribution of the wrinkles and fine asperities on the skin surface was dependent on the distribution of luminance intensity. Alternatively, the proposed method as shown in Figure 10 obtained wrinkles and fine asperities not dependent 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 all surface reflections in the database.

2.5 Extracting facial glosses and asperity distributions by a multi-resolution analysis

We used a multi-resolution analysis to extract facial glosses and facial asperity distributions from the surface reflectance components. A two-dimensional discrete wavelet transform was used in this analysis. By applying that transformation 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 a two-dimensional discrete wavelet transform to the components of the surface reflectance, the gross, i.e. the component of surface reflection on our faces, appears in the low-frequency component. The facial asperities can be obtained in the high-frequency components, but high- frequency components included individual variations, even after transformation to match the average face as described in Section 3. The two-dimensional discrete wavelet transform is applied to the high-frequency components to average the individual differences. Figure 11 shows an overview of these processes.

The left image in Figure 12 (a) shows an example of a result of the proposed method and its simple pixel values. The center image in Figure 12 (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 12 (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 12 (b). The original images contain information about the positive or negative sign of each pixel. The results of the multiresolution analysis are shown in Figure 13.

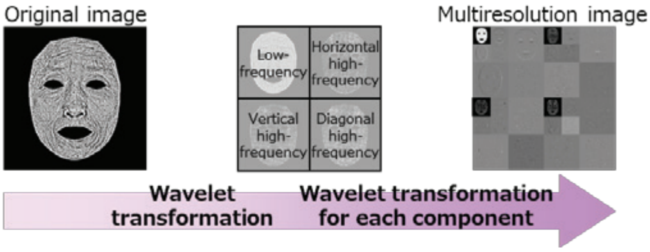
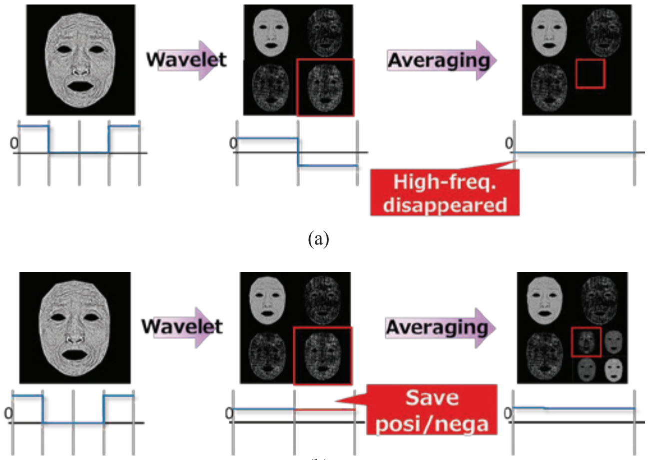


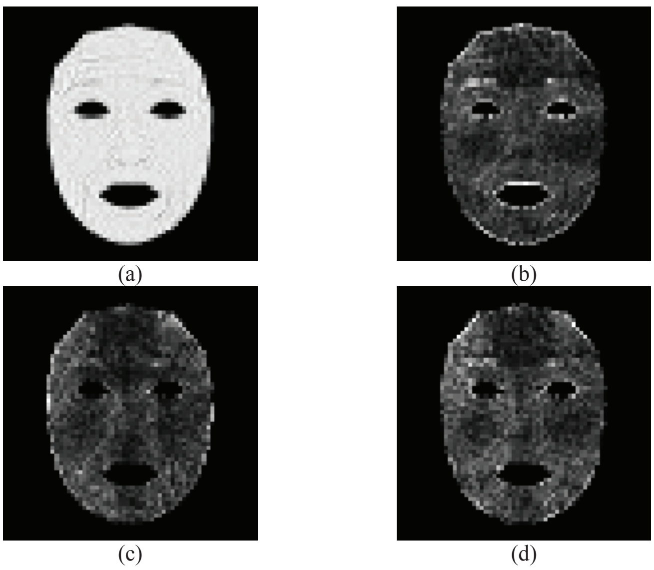
Figure 11 Overview of a conventional multi-resolution analysis [2].



(a)

(b)

Figure 12 Two-dimensional discrete wavelet transform of high-frequency components:
(a) general two-dimensional discrete wavelet transformation and
(b) the method by Hirose et al. [3] for calculating an absolute value.



(a) (b) (c) (d)

Figure 13 The results of the proposed multi-resolution analysis: (a) low-frequency, (b) horizontal high-frequency, (c) vertical high-frequency, and (d) diagonal high- frequency components.

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

In this subsection, we obtained feature values of facial wrinkles and asperity distributions by applying PCA to frequency components of the surface reflectance. PCA is a primary method to analyze statistically for multivariable. By applying PCA to data groups, we can obtain principal component vectors that indicate the direction in which the variance increases. The overview of PCA is shown in Figure 14.

The 1st principal component vector is first defined to maximize the variance of the data group. The 2nd principal component vector is defined in such a way that it is orthogonal to the 1st principal component vector. This analysis repeats up to the last principal component. By applying PCA, a n-dimensional l-th vector in a dataset x_{ln} can be represented as the approximated vector $\widehat{\boldsymbol{x}}_p$, which is defined by a principal component vector $\boldsymbol{P}_m$ and weight value vector w_{lm} as follows:

$$\widehat{\boldsymbol{x}}_l(x_{l1}, x_{l2}, x_{l3}, \cdots, x_{ln}) = \sum_{m=1}^{M} w_{lm} \boldsymbol{P}_m \tag{2}$$

PCA is able to approximately shrink the dimension by selecting an essential principal component vector. Additionally, based on the weight of the principal component vector (the principal component score), we can determine how much is included in the data. In this study, we first acquired principal component vectors to obtain the change tendency of wrinkles and fine asperities of the whole face. Next, we analyzed the correlation between age and the principal component score. The PCA results are explained in the next section.

3. Results of the Principal Component Analysis

By applying PCA to each frequency component, we analyzed the correlation between the distribution of each frequency component

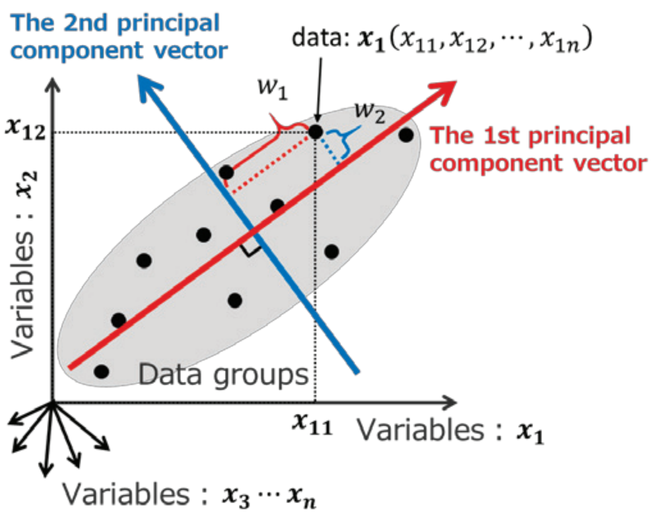


Figure 14 Overview of the PCA.

and actual age. The principal component vector images and their contribution rates are described in Subsection 3.1. The relationship between the principal component score and actual age is described in Subsection 3.2.

3.1 Principal component vector and contribution ratio

PCA was applied to the facial image, which has 64×64 pixels representing the frequency components of the surface wrinkles and fine asperities that were down- sampled by multi-resolution analysis. One pixel was assigned as one element in the vector, and then a single facial data was allocated as the one point in 4,096 (64×64) dimensional spaces, respectively. We had 60 points in these dimensional spaces because there are sixty facial images in our database.

Based on PCA, we obtained 59 principal components in the frequency components of surface reflectance.

Figure 15 (b) shows the results of PCA applied to low-frequency, horizontal high- frequency, vertical high-frequency and diagonal high-frequency components in the conventional and proposed method. Figure 15 (a) shows a color bar indicating the intensity and direction of the principal components vector. The numbers at the top left side of the images represent the number of principal components sorted by the contribution rate. Table 2 shows the contribution of the 1st to 4th principal components and Figure 16 shows the cumulative contribution of the principal components at each frequency. Comparing the conventional method in Figure 2 with the proposed method in Figure 15 (b), 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 that has mixed low and high frequencies such as noticeable

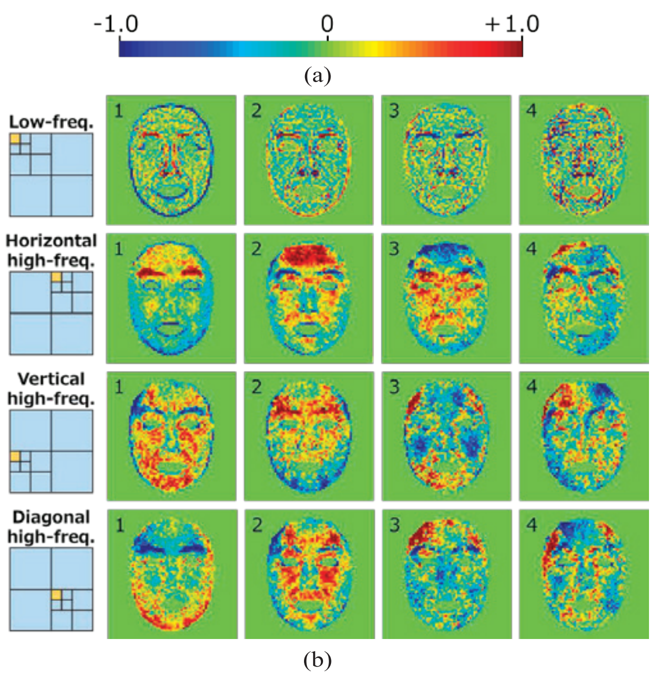


Figure 15 The results of PCA applied to each frequency component in the conventional method: (a) color scale that is shown in intensity and direction of the principal component vector and (b) the results of the PCA in the proposed method.

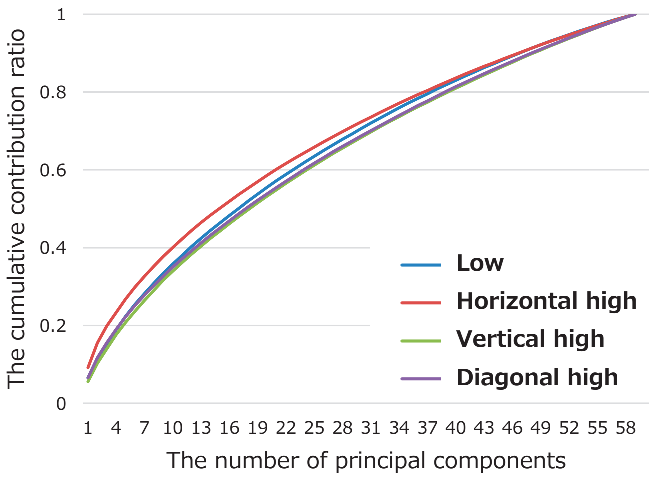


Figure 16 The contribution ratio of PCA in each component of the surface wrinkles and fine asperities.

wrinkles and fine unevenness.

In the low-frequency components, it was predicted that features of wrinkles appear that did not depend on the direction. The output signals show a nearly high frequency on the whole face. Alternatively, characteristic features were observed only on the facial contour and around the nose. It is considered that low-frequency components appear in places where the contrast is visible, regardless of individual differences. The contrast of the facial contour depends on the normalization process described in Section 2.2. Therefore, a noticeable change in the luminance easily occurs around the nose.

The horizontal high-frequency component detects changes in the vertical direction; as a result, the vectors appeared at the locations where horizontal lines were distributed. The second row in Figure 15 (b) shows that individual differences of vertical changes appear strongly on the eyebrow, forehead, cheek, and other prominent features. Reviewing the 1st to the 3rd principal component, it is considered that there are many horizontal lines, especially on the forehead.

The vertical high-frequency component detects changes in the horizontal direction; as a result, vectors appeared at the locations where vertical lines were distributed. The third row in Figure 15 (b) shows that individual differences of vertical changes appear strongly on the cheeks around the mouth, and so on. In a review of the 1st and 3rd principal component, there are many vertical lines especially on the cheeks around the mouth.

The vertical high-frequency component detects changes in the diagonal direction; as a result, the vectors appeared at the locations where diagonal lines were distributed. The 1st and 2nd row in Figure 15 (b) shows that individual differences of diagonal changes appear strongly on the cheeks around the mouth, and so on. Based on the 1st and 2nd principal components, it is considered that there are many diagonal lines especially on the cheeks around the mouth. The relationship and trends between the actual ages and each component are explained in the next section.

3.2 Principal component score

Figure 17 shows the principal component scores of each subject

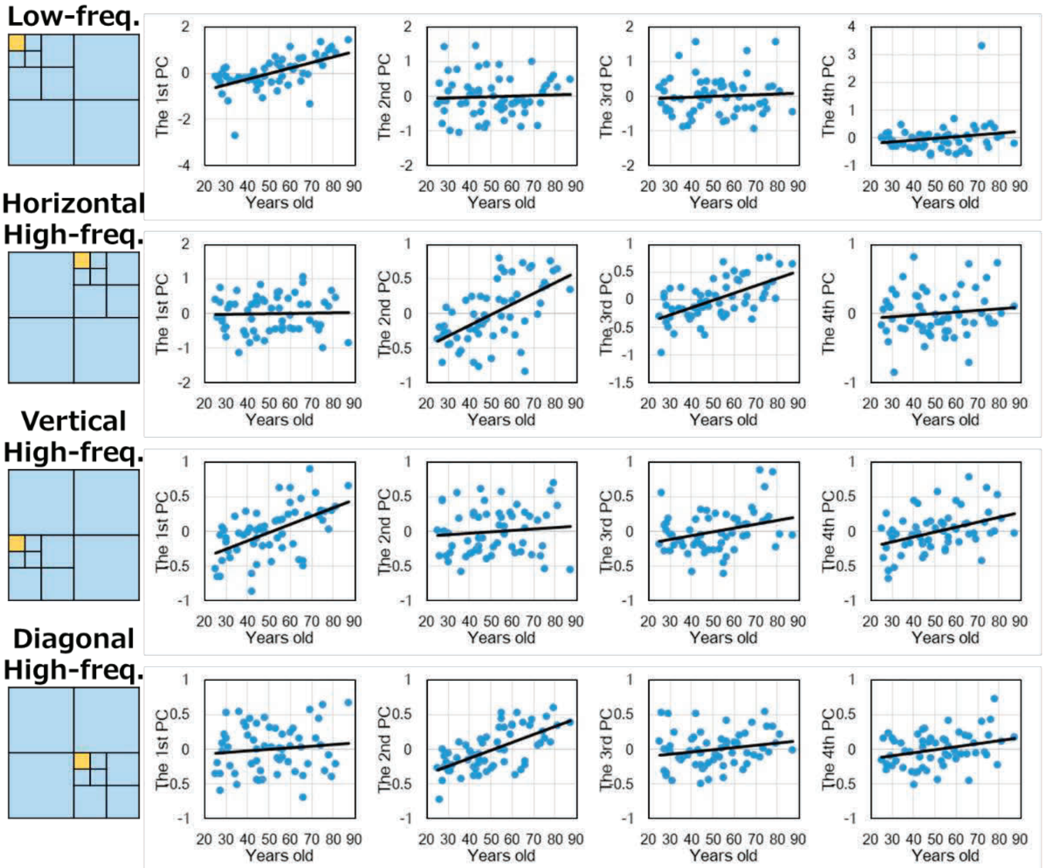


Figure 17 The principal component scores in each frequency component.

corresponding to the principal components of the respective frequency components shown in Figure 15 (b). Therefore, each figure corresponds to the 1st, 2nd, 3rd, and 4th principal components from left to right. The horizontal axis shows the actual age (from ages 20 to 90), and the vertical axis shows each principal component score. The straight line in the figure shows the regression line. Based on these figures, we can determine whether there are correlations between principal components scores and actual ages.

Regarding the low-frequency component shown in the first row of Figure 17, the tendency of change barely appears as previously explained. The nose around the 1st principal component, which had a slight tendency to change, tended to increase with age. Therefore, the luminance change was likely to occur around the nose with age from the low-frequency component.

The horizontal high-frequency components are shown in the second row of Figure 17. As previously demonstrated, the 1st to 3rd principal component vectors showed the tendency to change the luminance on the eyebrow, forehead, and cheek. The 1st principal component indicates that the individual difference in the change in luminance is the greatest around the eyebrows, but its correlation coefficient was only 0.0197 as shown in Table 2. Therefore, there is almost no correlation between changes in luminance in the eyebrows and actual age. The 2nd and 3rd principal component shows that the individual difference in the change in luminance was the largest around the forehead and cheeks, and its correlation coefficients were 0.5793 and 0.5890, respectively. Therefore, based on the horizontal high-frequency components, the luminance change in

Table 2 Contribution ratio in each component of the surface wrinkles and fine asperities

	1st	2nd	3rd	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

the horizontal direction was likely to occur on the forehead and cheeks with age.

Regarding the vertical high-frequency components shown in the third row of Figure 17, the 1st principal component vectors especially showed the tendency to change the luminance on the cheeks around the mouth, with a correlation coefficient of 0.5428. Therefore, based on the vertical high-frequency components, the luminance change in the vertical direction is likely to occur on the cheeks around the mouth with age.

Finally, regarding the diagonal high-frequency components shown in the last row of Figure 17, the 1st and 2nd principal component vectors showed the tendency to change the luminance on the cheeks around the mouth, resulting in a correlation coefficient of 0.1195 and 0.6331, respectively. Therefore, from a result of the 2nd principal component score of the diagonal high-frequency component, there is a correlation between the actual ages and the change in luminance on the cheek, especially around the mouth, and it can be considered that a change in luminance tends to occur in that areas.

4. Discussion

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

Low-frequency component: The luminance tends to change especially around the nose.

Horizontal high-frequency component: The luminance tends to change especially on the forehead.

Vertical high-frequency component: The luminance tends to change especially on the cheeks and around the mouth.

Diagonal high-frequency component: The luminance tends to change especially on the cheeks and around the mouth.

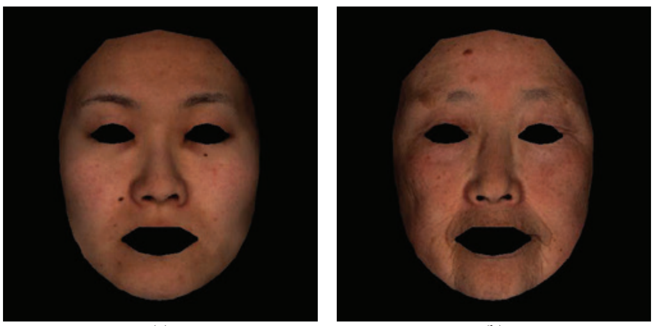
The above results are discussed subjectively using actual images of different ages shown in Figure 18. Figure 18 (a) shows the facial image of a 25-year-old and Figure 18 (b) shows an 87-year-old.

First, in Figure 18, the older face has deeper wrinkles in the nose than the younger face. This corresponds reasonably with the result of the low-frequency component, which is that the luminance depending on the facial gloss is likely to change at both sides of the nose, and the change is larger in the elderly than in the young.

Second, in Figure 18, the older face has slightly deeper wrinkles on the forehead than the younger face. Since the 2nd principal component score of the subject in the horizontal high- frequency shown in Figure 17 is below the regression line, the facial image shown in Figure 18 (b) has fewer forehead wrinkles for the age. In other words, there is a tendency that a deep wrinkle is seen on the forehead if the weight of the 2nd principle component in horizontal high frequency has high.

Third, in Figure 18, the older face has deeper wrinkles around the mouth than the younger face. These wrinkles in the vertical direction, located on the bottom edge of the mouth, are called the marionette line [6)].

Lastly, in Figure 18, the older face has deeper wrinkles on the cheeks and around the mouth than the younger face. These wrinkles in a diagonal direction, located on the edge of the mouth, are called a nasolabial fold [6)].



(a) (b)

Figure 18 The facial image of (a) a young woman (25 years old) and (b) older woman (87 years old).

In summary, by applying PCA to the components of noticeable wrinkles and fine asperities with corrected surface reflection components, an index representing the distribution of wrinkles on the face is acquired. Furthermore, the relationship between the actual age and its tendency was identified.

5. Conclusion

In this research, we constructed a facial image database of faces of 60 people and determined the component of wrinkles and fine asperities in which the illumination difference of the surface reflection component was corrected using the proposed method. The acquired components were subject to a multi-resolution analysis in the same way as in previous research, and feature values were obtained by resolving the frequency of the skin's wrinkles and fine asperities in the horizontal, vertical, and diagonal directions. Application of PCA to each frequency component and analysis of the relationship between the principal component score and actual age resulted in scores that identify the lateral and forehead wrinkles of the nasal muscles, the marionette line, and nasolabial fold with age. Moreover, the proposed method enabled us to compare different people or track changes of the same person by comparing principal component scores.

Reconstruction of surface reflection components is needed by an inverse transformation of multi- resolution analysis with modulated principal component scores. Moreover, we plan to simulate the change of wrinkles by combining it with the internal reflection component that represents skin color. Additionally, if we can detect lines from the image in which the proposed method was applied, as shown in Figure 10, the method is expected to efficiently analyze wrinkles without multi-resolution analysis and PCA. As a result, the proposed method produces an appropriate analysis of surface reflection components on faces.

References

1) Shiseido Company, Limited. “Taking skincare Hada Pasha", <http://hadapasha.shiseido.co.jp/>, (accessed on 26th December 2019).
2) J Perfect Corp.(n.d.), “Virtual make-up", <https://www.perfectcorp.com/business/products/virtual-makeup>, (accessed on 26th December 2019).
3) M. Hirose, S. Toyota, N. Ojima, K. Ogawa-Ochiai and N. Tsumura, “Principal component analysis for surface reflection components and structure in facial images and synthesis of facial images for various ages", Optical Review Volume 24, Issue 4, pp 517–528 (2017).
4) Jet colormap array – MATLAB jet, <https://www.mathworks.com/help/matlab/ref/jet.html>, (accessed on 21st August 2019).
5) S. Mukaida, M. Kamachi, M. Oda, T. Kato, S. Yoshikawa, S. Akamatsu, K. Chihara, “Facial Image Synthesis System: FUTON --Evaluation as Tools for Cognitive Research on Face Processing--", IEICE Trans, Fundamentals, J85A (10), 1126-1137, 2002 (In Japanese)
6) F. Meneghini, “Clinical Facial Analysis: Elements, Principles, Techniques", Springer, 2012, p. 167.