Canonical Correlation Analysis for long-term changes of facial images based on the frequency of UV protection, physical and psychological features

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Abstract

In this paper, we analyze the relationship between impression of facial skin and skin component distribution by applying Canonical Coefficient Analysis (CCA) to multiple physical and psychological features obtained from facial images. Based on the acquired relationship, we modulate the skin pigment features, and appearances of the face with arbitrary psychological features are reproduced. In our previous work, we applied Principal Component Analysis (PCA) to the melanin pigment variation of the facial skin, and we obtained individual differences in it occurring over 7 years. In the previous method, as the factor causing individual difference, we considered the frequency of UV protection. However, actual skin appearance is thought to depend on not only melanin but also several other factors. Therefore, in this study, we captured facial images of females aged from their 10s to 80s at intervals of 12 years, and we obtained not only physical but also psychological features. As physical features, melanin and hemoglobin pigment and shading distributions, and the frequency of UV protection for 12 years were obtained. Psychological features values were acquired as subjective evaluation. As a result of CCA on the physical features only, it was found that the whole face can be made lighter in appearance by performing UV protection every day continuously for 6 years or more. As a result on the both physical and psychological features, pigment features greatly affecting the impression of the skin and multiple skin aging patterns were obtained. According to this result, the pigment features were modulated, and facial appearances with arbitrary psychological features were reproduced.

1. Introduction

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

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

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

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

Toyota *et al*. obtained feature values of skin pigmentation of the whole face by ICA and PCA and simulated the appearance of face having arbitrary psychological features [8]. This method can synthesize the appearance of a face considering the changes due to age. However, as a result of a subjective evaluation experiment by experts, there was large difference between ages of synthesized images and the evaluated results. For this reason, Hirose *et al.* analyzed the variation of facial landmarks representing facial structure, and surface reflection component representing wrinkles and pores, in addition to skin pigmentation distribution by PCA and MRA [9]. They succeeded to reduce the age-difference between synthesized images and real images. Since this simulation was based on changing averaged features in a database with the same age, each synthesized image lost the individual characters. However, the actual aging depends on individuals, and it is expected to predict the appearance of face by considering the individual characters. Therefore, in a previous study, we considered the frequency of UV protection as the factor causing individual differences [10]. PCA was applied to the melanin pigmentation extracted from face image changes of same people for seven years. Compared with the principal component score changes of each person, it was found that the amounts of the melanin pigment in the whole facial skin and in the skin around the cheeks of those who don't perform UV protection tend to increase compared to those who use it every day for seven years. However, it seems that the appearance of the skin is influenced not only by melanin but also by several other factors.

In this paper, therefore, canonical coefficient analysis (CCA) is applied to multiple physical and psychological features, and the relationship between skin appearance and facial skin pigment is analyzed. Specifically, first of all, CCA is applied to physical features. In a previous study [10], only the melanin pigmentation was analyzed, but in this study, we perform CCA on the multiple skin pigment changes over 12 years and the frequency of UV protection over 12 years. By doing this, we analyze the influence of the frequency of UV protection in each year on skin pigment changes over 12 years. Next, in order to realize a face simulator, CCA is performed on the features of skin pigment, which are physical features, and on the subjective evaluation values of skin, which are psychological features. Thus, a relational expression between physical features and psychological features can be derived. By modulating the physical features based on this relational expression, reproductions of facial appearance with arbitrary psychological features are performed.

2. Construction of Facial Image Database

We constructed database from facial image, real age, and the frequency of UV protection. First of all, we captured photographs of Japanese women's faces whose ages were from 10s to 80s in 2003 and 2015. Note that those photos were photographed after washing their faces. The number of subjects was 86 in 2003 and 161 in 2015, in total, 247 facial images. Here, 60 women were same as who were photographed in 2003 and 2015. A total of 247 face images were used only for PCA, and 120 facial images of overlapped 60 persons who took in 2003 and 2015 were used for the next analysis. Breakdown of the number of subjects and distribution of age in the database are shown in Fig. 1. These photographs were taken using the imaging system shown in Fig. 2. This imaging system was surrounded by blackout curtains in order to eliminate the effect of ambient light. As a light source, there were four fluorescent lights so that the lights surrounded the camera as shown in Fig. 2.

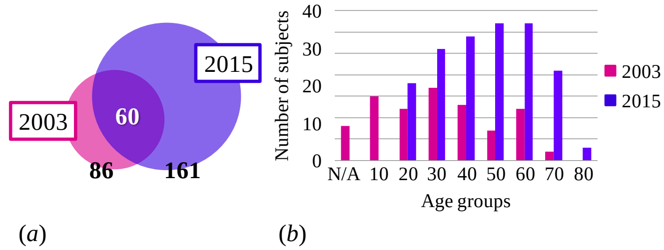


Figure 1. *Breakdown and Distribution of age of the database: (a) Breakdown of the number of subjects, (b) Distribution of age in the database*

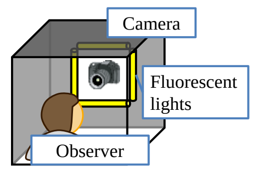


Figure 2. *Overview of imaging system*

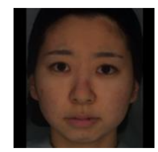


Figure 3. *Sample of captured image*

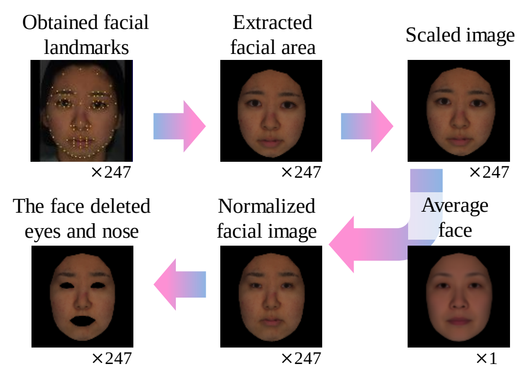


Figure 4. *Overview of normalization process for facial images*

The cameras used were Nikon D1 and Nikon D2H; the former was used in 2003 and the latter in 2015. In order to prevent movement of face, we used a support for the neck and head which was fixed on the backrest of a chair. We obtained facial image without specular reflectance by arranging polarization filters in front of the camera and the light sources mutually perpendicularly. There was difference in color tone between images taken in 2003 and those taken in 2015 due to using different cameras. In order to correct this, based on multiple regression analysis using color charts captured in each years, we calculated transformation function to convert pixels values from 2003 to 2015. We adapted the facial image, and the color tone of 2003 was matched to the 2015.

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

3. Acquisition of Features

This section introduces the acquisition of physical and psychological features. As the physical features, the frequency of UV protection and skin pigment distributions were obtained. The psychological features values were acquired by subjective evaluation.

3.1. The Frequency of UV Protection

The frequency of UV protection was obtained by a scale of 1 to 3 (1: Never, 2: Sometimes, 3: Daily) in winter of 2003 and 2010, and a scale of 1 to 6 (1: Daily during the past five years, 2: Daily in summer during the past five years, not in winter, 3: UV protection use period has been longer than non-use period during the past five years, 4: UV protection use period has been shorter than non-use period during the past five years, 5: Rarely during the past five years, 6: Others) in 2015. Figure 5 shows age distribution of frequency of UV protection use in the database. Note that the frequency of UV protection includes various methods such as sunscreen, hat, or parasol. Furthermore, how much the subjects reapply the sunscreen, or how long they stay in outside are not considered.

3.2. Skin Pigmentation Distribution

In order to estimate the melanin pigmentation from the face, we used the independent component analysis as shown below.

3.2.1. Extraction of Skin Pigmentation by ICA

Skin structure can be broadly divided into epidermis where the melanin pigment exists and dermis where hemoglobin pigment exists. Assuming that skin color depends on these two kinds of pigmentation density, the skin color vector can be represented by three vectors: melanin, hemoglobin, and shading, by using ICA and modified Lambert-Beer's rule [6][7]. Figures 6(a) and (b) show a sample of the extracted melanin and hemoglobin pigmentations, and (c) shows the shading in the whole facial image. As can be seen in Fig. 6(a), the mole and pigmented spot can be obtained as melanin component. The redness caused by pimples can be seen in Fig. 6(b), and the shadow caused by uneven facial features can be recognized in Fig. 6(c). In this study, we obtained melanin and hemoglobin pigmentation and shading components of facial skin by this method. However, in our previous work [6], we were possible to separate each component, it can be seen that the shading component is remaining around nose and mouth of Fig. 6(a) because of the limitation in an imaging system. Therefore, in this results, note that the melanin pigmentation distributions include a slight negative influence by shading component.

3.2.2. Acquiring Skin Pigmentation features by PCA

We obtained feature values of uneven pigmentations by applying PCA to melanin, hemoglobin, shading components of 247 facial images extracted in Section 3.2.1. PCA is a statistical method to grasp a tendency and features of data by multivariate analysis. This analysis calculates the linear sum of each variable in data group constructed from any variable, and defines a new index as the first component. The second component is defined in such a way that it is perpendicular (orthonormal) to the first component, and other components are defined similarly. The n-dimensional l-th vector in dataset can be represented as follows:

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

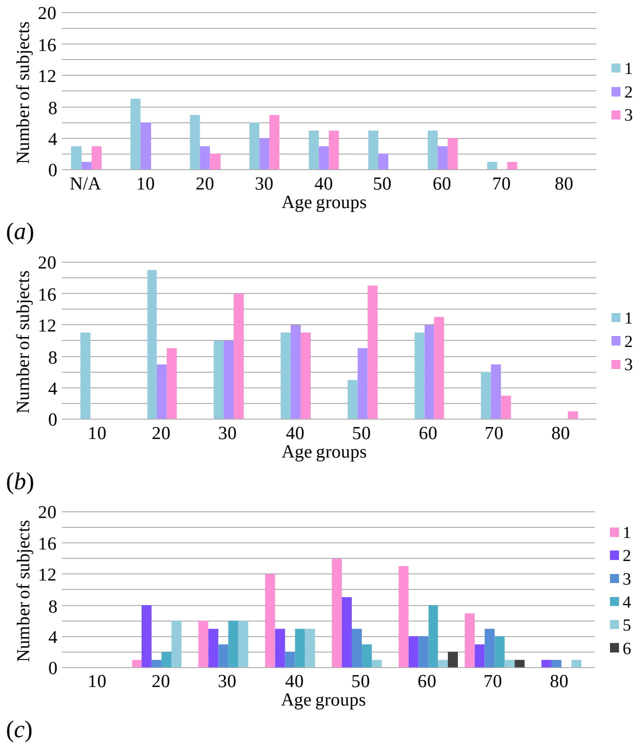


Figure 5. *Age distribution of the frequency of UV protection: (a) in 2003, (b) in 2010, (c) in 2015*

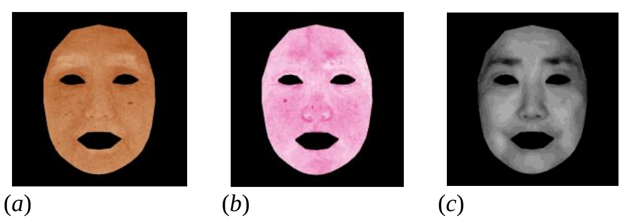


Figure 6. *The results of independent component analysis for extraction of pigmentation components: (a) melanin, (b) hemoglobin, (c) shading*

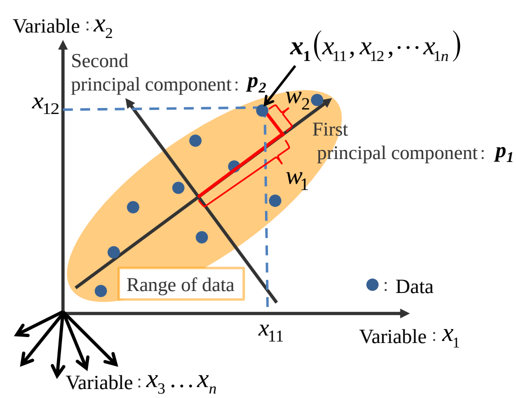


Figure 7. *Overview of principal component analysis*

where M (= n) is the total number of principal components, w_{lm} is the weight value for each m-th principal component called principal component score, and $\boldsymbol{p}_m$ is the m-th principal component vector, as shown in Fig. 7.

We applied PCA to melanin, hemoglobin, shading component images whose sizes were 512×512 pixels. In this paper, we regarded one pixel as one variable. That is, 247 women's melanin, hemoglobin, shading components existed in 512×512-dimensional space respectively. As a result of PCA, we obtained 246 principal components for each skin pigmentation component.

For example, compared between the principal component scores in 2003 and 2015 of the same person, we can obtain information on how the skin pigments components of that person have changed in 12 years. Also, compared the principal component scores of different subject, individual differences in skin pigments components can be acquired. In this study, principal component scores were used as physical features representing skin pigments.

3.3. Subjective Evaluation Value of Skin

Subjective evaluation experiments of skin were performed on face images taken in 2015. Three experts determined the evaluation values of total of 8 items: spots on the whole face, wrinkles on forehead, corner of the eyes, under the eyes and nasolabial grooves, sagging on the whole face, under the eyes and mouth corners. In this study, average values of three evaluation values were used for analysis as psychological features.

4. CCA for Multiple Features

In this section, we explain the method of canonical coefficient analysis (CCA) and the results of CCA on physical and psychological features.

4.1. The Method of CCA

CCA is a method of analyzing the relationship between multivariables by combining variables so that the correlation coefficients between the two variable groups is high. Let us consider the case where there are variable group $\boldsymbol{X} = \{\boldsymbol{X}_1, \cdots, \boldsymbol{X}_p\}$ and variable group $\boldsymbol{Y} = \{\boldsymbol{Y}_1, \cdots, \boldsymbol{Y}_q\}$, $(p < q)$. The canonical coefficients $\boldsymbol{A}$ and $\boldsymbol{B}$, which are weights, are set and synthesized so that the correlation coefficient $\boldsymbol{R}$ of the weighted linear sum $\boldsymbol{U}$ of the variable group $\boldsymbol{X}$ and the weighted linear sum $\boldsymbol{V}$ of the variable group $\boldsymbol{Y}$ becomes maximum. Interpretation of a canonical variable is performed by analyzing canonical loading which is a correlation coefficient between each variable constituting a variable group and a canonical variable. The overview of CCA is shown in Fig. 8.

4.2. CCA on Physical Features

In order to analyze the relationship between multiple skin pigments and the frequency of UV protection in each year, CCA was performed among physical features. In most cases, because it is sufficient to cover the cumulative contribution ratio (CCR) from 70 to 80%, the differences between the principal component scores of 2003 and 2015 of the 1st~8th principal components of melanin (CCR=0.7040) and the 1st~15th principal components of hemoglobin (CCR=0.7045), and the 1st~15th principal components of shading (CCR=0.7080), total of 38 variables were set as the variable group $\boldsymbol{X}$. As the variable group $\boldsymbol{Y}$, the frequency of UV protection in 2003, 2010, and 2015, in total, 3 variables were set. As a result of CCA on these groups, the 1st canonical variables $\boldsymbol{V}_1$ and $\boldsymbol{U}_1$ became significant. Here, $\boldsymbol{V}_1$ represents the 1st canonical variable of the variable group $\boldsymbol{Y}$, and $\boldsymbol{U}_1$ represents the 1st canonical variable of the variable group $\boldsymbol{X}$. Tables 1 and 2 show the canonical factor loadings

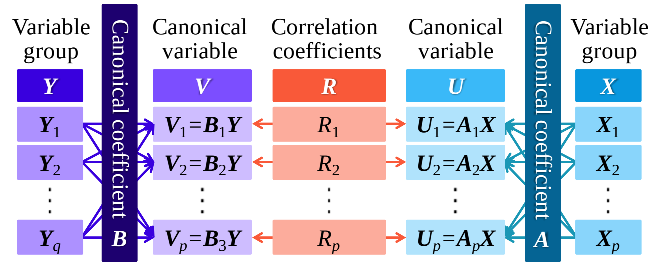
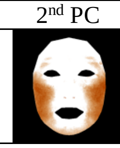
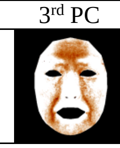
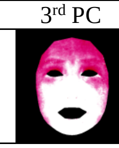


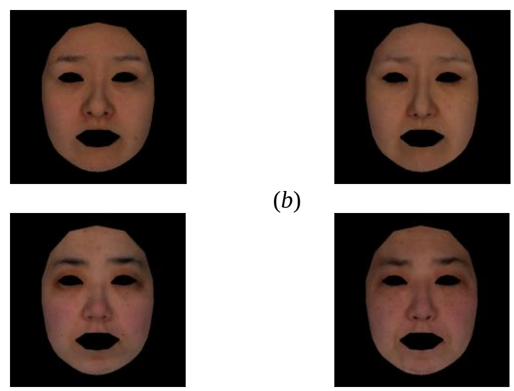
Figure 8. *Overview of canonical correlation analysis*

Table 1. Canonical Factor Loading of $\boldsymbol{V}_1$

Frequency of UV Protection Use		
In 2003	In 2010	In 2015
-0.855	-0.694	0.005

Table 2. Canonical Factor Loading of $\boldsymbol{U}_1$. Here, PC: principal component

Melanin			Hemoglobin
1st PC	2nd PC	3rd PC	3rd PC
			
0.2	0.2	0.3	0.3



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

Figure 9. *Actual 12-year changes of normalized face images whose $\boldsymbol{V}_1$ is: (a) smallest (taken in 2003), (b) smallest (taken in 2015), (c) largest (taken in 2003), (d) largest (taken in 2015)*

that means canonical correlation of $\boldsymbol{V}_1$ and $\boldsymbol{U}_1$, respectively. In Table 1, $\boldsymbol{V}_1$ has the largest negative correlation with the frequency of UV protection in 2003, the next largest correlation with that of 2010, and no correlation with that of 2015. That is, That is, person who didn't perform UV protection in the past tend to increase the value of $\boldsymbol{V}_1$. On the other hand, in Table 2, $\boldsymbol{U}_1$ has positive correlation with the variation of the melanin pigmentation on the whole face, cheeks, and forehead, and with the hemoglobin pigment of the forehead and around the eyes. That is, $\boldsymbol{U}_1$ becomes larger as these pigments components increase. Therefore, taken together, it can be said that the lower the frequencies of UV protection in 2003 and 2015 are, the more the amounts of melanin on the whole face, cheeks, and forehead, and hemoglobin of the forehead and around the eyes increase in 12 years. Actual 12-year changes of normalized face images whose $\boldsymbol{V}_1$ are smallest and largest are shown in Fig. 9. In Figs. 9(a) and (b), those who had a high frequency of UV protection in 2003 and 2010 had a lighter appearance of the whole face 12 years later. In contrast, in Figs. 9(c) and (d), for those who had a low frequency of UV protection use in 2003 and 2010, the whole face and cheeks had changed darker in 12 years.

4.3. CCA on Physical and Psychological Features

In order to reproduce the appearance of a face, CCA was performed on psychological features and physical features. Specifically, subjective evaluation values for 1 spot, 4 wrinkles, 3 sags, 8 variables in total were set as variable group $\boldsymbol{Y}$. As variable group $\boldsymbol{X}$, principal component scores in 2015 of the 1st ~ 8th principal components of melanin and the 1st ~ 15th principal components of hemoglobin, and the 1st~15th principal components of shading, total of 38 variables were set. As a result of CCA on these groups, the 1st, 2nd and 3rd canonical variables became significant. The canonical correlation coefficients of the 1st, 2nd and 3rd canonical variables were 0.93, 0.67 and 0.60, respectively. Let $\boldsymbol{V}$ be the canonical variable of the variable group $\boldsymbol{Y}$, and $\boldsymbol{U}$ the canonical variable of the variable group $\boldsymbol{X}$.

First, Tables 3 and 4 show particularly large canonical loadings of the 1st canonical variables $\boldsymbol{V}_1$ and $\boldsymbol{U}_1$. In Table 3, $\boldsymbol{V}_1$ has a high positive correlation with spots, wrinkles, and sagging. That is, the more conspicuous a person's spots, wrinkles and sag in her facial skin are, the larger $\boldsymbol{V}_1$ is. On the other hand, in Table 4, $\boldsymbol{U}_1$ has a positive correlation with the melanin pigmentation on the cheeks and the whole face, then it has also a positive correlation with shading on the whole face and around the mouth. That is, the stronger these pigments components are, the larger $\boldsymbol{U}_1$ is. Canonical correlation coefficient between $\boldsymbol{V}_1$ and $\boldsymbol{U}_1$ is 0.93. Therefore, it can be said that the melanin pigmentation on the cheeks and the whole face, and shading around the mouth are darker for people whose spots, wrinkles and sags are conspicuous. In this conclusion, note that we did not consider about shading on the whole face because it is relied on slight differences of the intensity of illumination.

Next, Tables 5 and 6 show particularly large canonical loadings of the 2nd canonical variables $\boldsymbol{V}_2$ and $\boldsymbol{U}_2$. In Table 5, $\boldsymbol{V}_2$ has a positive correlation with spots on the whole face but a negative correlation with sagging on the corners of the mouth. Additionally, the canonical loadings in other parts has a negative correlation too. As this results, we can found that the correlation among the melanin pigmentation such as spots, wrinkles and sags may be small, therefore it is suggested that these are independent each other. On the other hand, in Table 6, $\boldsymbol{U}_2$ has a positive correlation with the melanin pigmentation around eyes, nose ridge and cheeks, and hemoglobin of nose and cheeks. Variable $\boldsymbol{U}_2$ also has a negative correlation with melanin in the whole face. This means the stronger the melanin pigmentation is around the eyes, nose ridge and cheeks, and hemoglobin of nose and cheeks are, the larger $\boldsymbol{U}_2$ is, while the stronger the melanin pigmentation in the whole face is, the smaller $\boldsymbol{U}_2$ is. Canonical correlation coefficient of $\boldsymbol{V}_2$ and $\boldsymbol{U}_2$ is 0.67. Therefore, it may be said that people with conspicuous spots (that is positive $\boldsymbol{V}_2$) have strong melanin around the eyes, nose ridge and cheeks (that is positive $\boldsymbol{U}_2$), while people with conspicuous sagging on the corners of the mouth (that is negative $\boldsymbol{V}_2$) have strong the melanin pigmentation on the whole face (that is negative $\boldsymbol{U}_2$).

Lastly, let us consider the 3rd canonical variables. Tables 7 and 8 show particularly large canonical loadings of the 3rd canonical

Table 3. Canonical Loading of $\boldsymbol{V}_1$

Subjective Evaluation Value of Skin		
Age spots on whole face	Sagging on whole face	Wrinkles on the corners of the eyes
0.76	0.96	0.91

Table 4. Canonical Loading of $\boldsymbol{U}_1$. Here, PC: principal component

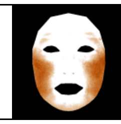
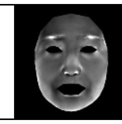
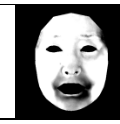
Melanin	Shading	
2nd PC	1st PC	6th PC
		
0.8	0.5	0.4

Table 5. Canonical Loading of $\boldsymbol{V}_2$

Subjective Evaluation Value of Skin	
Age spots on whole face	Sagging on mouth corners
0.62	-0.30

Table 6. Canonical Loading of $\boldsymbol{U}_2$. Here, PC: principal component

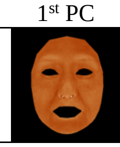
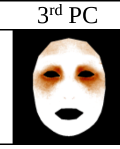
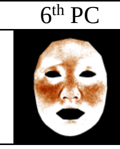
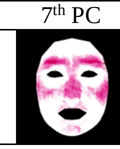
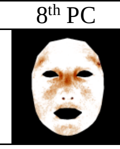
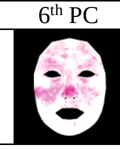
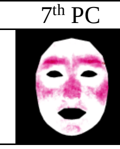
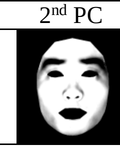
Melanin			Hemoglobin
1st PC	3rd PC	6th PC	7th PC
			
-0.4	0.3	0.3	0.4

Table 7. Canonical Loading of $\boldsymbol{V}_3$

Subjective Evaluation Value of Skin	
Wrinkles on corners of the eyes	Sagging on mouth corners
0.38	-0.21

Table 8. Canonical Loading of $\boldsymbol{U}_3$. Here, PC: principal component

Melanin	Hemoglobin		Shading
8th PC	6th PC	7th PC	2nd PC
			
-0.3	0.4	0.3	0.3

variables $\boldsymbol{V}_3$ and $\boldsymbol{U}_3$. As shown in Table 7, $\boldsymbol{V}_3$ has a positive correlation with wrinkles on the corners of the eyes and a negative correlation with sag on the mouth corners. On the other hand, in Table 8, $\boldsymbol{U}_3$ has a positive correlation with hemoglobin around the nose and cheeks, and shading around the eyebrows, the corners of the eye and around the mouth, and a negative correlation with the melanin pigmentation on the nose ridge and the inner corner of the eyes. Canonical correlation coefficient of $\boldsymbol{V}_3$ and $\boldsymbol{U}_3$ is 0.60. As these results, we found that the positions of wrinkle and sag where professionals evaluated were almost matched with the distribution of shading component.

In this way, by CCA on physical features and psychological features, skin pigments distribution corresponding to the subjective evaluation value of the skin could be acquired.

5. Reproduction of face with arbitrary psychological features

From the results of CCA shown in Section 4.3, the following relational expression is established:

$$(\boldsymbol{A}^{\mathrm{T}})^{+} \cdot diag([R_1, R_2, \cdots, R_7, R_8]) \cdot \boldsymbol{V}^{\mathrm{T}} = \boldsymbol{X}^{\mathrm{T}} \quad (2)$$

Here, $\boldsymbol{A}$ represents canonical coefficient for variable group $\boldsymbol{X}$, $\boldsymbol{R}$ represents canonical correlation coefficient, $\boldsymbol{V}$ represents canonical variable of variable group $\boldsymbol{Y}$, *diag* represents a diagonal matrix, + represents a pseudo-inverse matrix, and T represents a transposed matrix. From Equation (2), we obtained principal component score $\boldsymbol{X}$, and reproduced appearances of a face for arbitrary $\boldsymbol{V}_1$, $\boldsymbol{V}_2$, $\boldsymbol{V}_3$. The results reproduced so that $\boldsymbol{V}_1$, $\boldsymbol{V}_2$, and $\boldsymbol{V}_3$ are minimum and maximum are shown in Fig. 10. Reproduced images are emphasized by doubling the actual principal component score change in order to make them easy to see. In Fig. 10(a), color unevenness of the whole face is small, but in Fig. 10(b), cheeks are dark, shadows of the mouth corners and wrinkles of the corners of the eyes are conspicuous. Also, in Fig. 10(c), cheeks are whitish and there are sags in the mouth corners, whereas in Fig. 10(d), cheeks are dark and the sagging of the mouth corners is less noticeable than in Fig. 10(c). In Fig. 10(e), the shading of the corners of the mouth is dark. Figure 10(f) shows darker eyebrows and stronger wrinkles in the corners of the eyes than in Fig. 10(e). From the above, as a result of modulating the pigments distribution based on the results of CCA, we could reproduce the appearance of the skin almost similar to the examination.

6. Conclusion

In this study, Canonical Coefficient Analysis (CCA) was performed on multiple physical and psychological features, and the relation between skin appearance and skin pigments distribution was analyzed. As a result of CCA on physical features, skin pigments distribution affected by the frequency of UV protection was acquired. In addition, it is suggested that spots, wrinkles and sags are independent each other, however, for physical features, principal components of skin pigments greatly affect the appearance of skin color. Furthermore, based on this result, physical features were modulated, and appearances of a face with arbitrary psychological features were reproduced. In the future, I would like to define the scale shown the beauty of the skin and consider the correlation with the psychological feature value acquired in this paper. Also, we will examine and improve the estimation formula for reproducing the appearance of a face.

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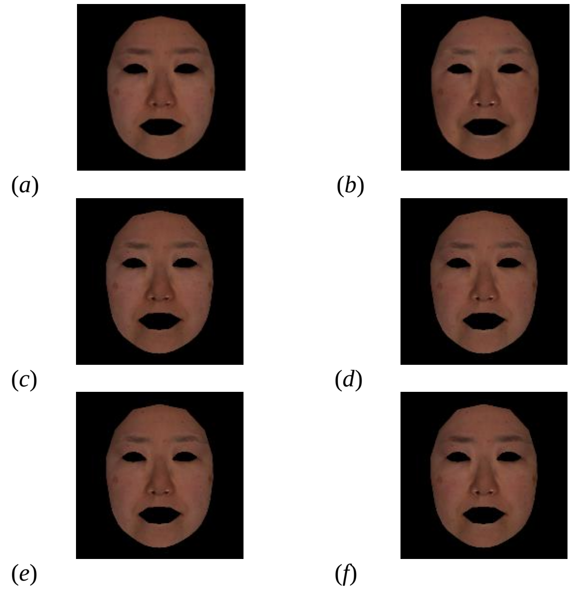

Figure 10. *The results of the appearance of a face in arbitrary psychological features : (a)* $\boldsymbol{V}_1$ *is smallest, (b)* $\boldsymbol{V}_1$ *is largest, (c)* $\boldsymbol{V}_2$ *is smallest, (d)* $\boldsymbol{V}_2$ *is largest, (e)* $\boldsymbol{V}_3$ *is smallest, (f)* $\boldsymbol{V}_3$ *is largest*

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