# A relationship between the use of UV protection and melanin pigmentation identified from changes in individual facial images over 12 years

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Is it feasible that the chemicals present in the natural dyes and colours of both plants and insects, which in the past have been exploited for their colour, could exhibit other properties that in the future will be understood and exploited for the health and wellbeing of mankind? The melanin component of skin pigmentation in the face greatly affects perceived age. In this study, we have analysed individual differences in how the melanin component changes with time. We consider the frequency of use of ultraviolet light (UV) protection as a factor causing individual difference in aging. It is known that melanin is produced in human skin in response to exposure to UV, which promotes aging effects such as darkening and unevenness of skin colour. In our previous work, we applied principal component analysis (PCA) to the distribution of facial skin colour and obtained feature values that quantitatively describe it. By changing these feature values, we simulated the appearance of a human face of arbitrary age. Accordingly, we found that the melanin component around the cheeks especially tends to increase with age. However, only the averaged feature values were used for each age in this analysis. In the present study, we take the next step of considering individual differences. We constructed a database of facial images taken in 2003 and 2015, including 60 subjects photographed in both years. Subjects' frequency of UV protection use was also recorded. By applying the same analysis as our previous study, we obtained PCA scores that describe the changes in individuals' faces from 2003 and 2015. From trends in these data, we found that people can brighten their whole face after 12 years if they use UV protection throughout the year.

## Introduction

The human face is the part of the body that receives the most attention. We obtain much information from the face, which is broadly conveyed in two types of features, physical and psychological. Physical features include skin condition and facial structure, while psychological features include the appearance of health and age. Facial appearance largely depends on these two types of features.

People, especially women, often have a strong interest in the appearance of their face and skin. In the beauty industry, therefore, many kinds of cosmetics have been developed for improving facial appearance. Applications which predict the effect of these cosmetics are expected to be useful to consumers. For example, there is a make-up simulator that can be used on the internet [1]. When one sends a facial image to the server, the simulator obtains facial landmarks representing facial structure. These landmarks are keys to judging viewers' subjective impression of the face, such as 'gentle' and 'sweet'. As a result, the server suggests make-up options that are suitable for the user and simulates an image of the user's face with this make-up applied. This system makes it possible to predict the effect of cosmetics anytime, anywhere, at low cost, and thereby promotes sales.

There has been much research on the 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 values described features of the human face such as three-dimensional structure, diffuse reflectance, normal map, subsurface-scattering, specularity and glossiness. By using these feature values, the authors provided an algorithm for determining optimal make-up [2]. Guo *et al.* have proposed a digital make-up system as well. They extracted the cosmetic component from an image of a face with make-up, and applied this cosmetic component to another facial image [3]. These systems enable one to get a result customised for an individual. However, they require a large-scale photographic system to obtain detailed facial features, and so it is difficult to put them into practical, everyday use. On the other hand, processes for obtaining facial features that are simplified for practical use have also been studied. 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 facial images. By applying PCA to facial landmarks, they simulated facial structure at any age based on classification by age [4]. Suo *et al.* also predicted the changing appearance of faces over long periods from changes to parts of the face over short periods based on the result of applying PCA to a facial image database divided by parts or ages [5]. However, differences between individuals are not considered in this method.

As described above, PCA can be used to obtain facial feature values from information such as facial structure and skin texture relatively easily. Most previous research has directly analysed greyscale or red–green–blue (RGB) images. However, it is not certain that RGB colours consider skin layer structures properly, because RGB colours are device-dependent. For this reason, it is thought that the face or skin can be analysed more effectively by taking into account melanin and haemoglobin colours, which are the main components of skin colour. Tsumura *et al.* proposed a technique to extract the pigmentation distribution of melanin and haemoglobin from a single colour image of skin by applying independent component analysis (ICA) [6-7]. Melanin and haemoglobin colour can be obtained using this method regardless of the light source or characteristics of the camera employed.

Okaguchi *et al.* extracted hierarchical pigmentation distributions from a skin texture database by pyramid image analysis, and took image histograms as feature values for facial images [8]. They applied PCA to these feature values and obtained feature values for skin pigmentation. Melanin and haemoglobin are strongly correlated with psychological features such as age, sex and race. The authors estimated the relationship between skin pigmentation feature values and skin texture by multiple regression analysis (MRA) and simulated skin texture having arbitrary psychological features. They analysed only a small area of skin; on the other hand, Toyota *et al.* analysed pigmentation distribution in the whole face. Toyota *et al.* obtained skin pigmentation feature values for the whole face using ICA and PCA, and simulated the appearance of a face having arbitrary psychological features [9]. This method can be used to synthesise the appearance of a face considering the changes associated with aging. However, following subjective evaluation by experts, there was large difference between the

nominal age of the synthesised images and the evaluated results. For this reason, Hirose *et al.* analysed the variation of facial landmarks representing facial structure and surface reflection components representing wrinkles and pores, in addition to skin pigmentation distribution, using PCA and MRA [10]. They succeeded in reducing the age difference between synthesised and real images. Since this simulation was based on changes to averaged features of faces in the database with the same age, individual characteristics were lost from each synthesised image. However, the actual aging process varies between individuals, and it is expected that individual characteristics will need to be considered to accurately predict the appearance of a face.

In this study, therefore, we obtained individual differences in variation of the melanin component, which greatly affects apparent age. We considered how frequently protection against ultraviolet light (UV) was used as a factor causing individual differences in aging. We analysed changes in melanin pigmentation of the same person over 12 years by PCA, and found a relationship between the use of UV protection and melanin pigmentation.

## Facial image database and methods of analysis

This section describes the construction of a facial image database, and the methods used to obtain melanin pigmentation distributions for the whole face and feature values for the melanin component.

### *Construction of the facial image database*

We constructed a database containing facial images, real ages, and the frequencies of UV protection use. We photographed the faces of Japanese women whose ages were between 10 and 80 years, in the winters of 2003 and 2015. The number of subjects was 86 in 2003 and 161 in 2015, in total, 247 facial images. Sixty of the 161 women photographed in 2015 had also been photographed in 2003. A breakdown of the number of subjects and the distributions of ages in the database are shown in Figure 1. All 247 images were used for finding the principal components in the later sub-section (Analysis of the melanin component by PCA). Only the 60 subjects included in both the 2003 and 2015 databases were analysed for individual differences in the next section.
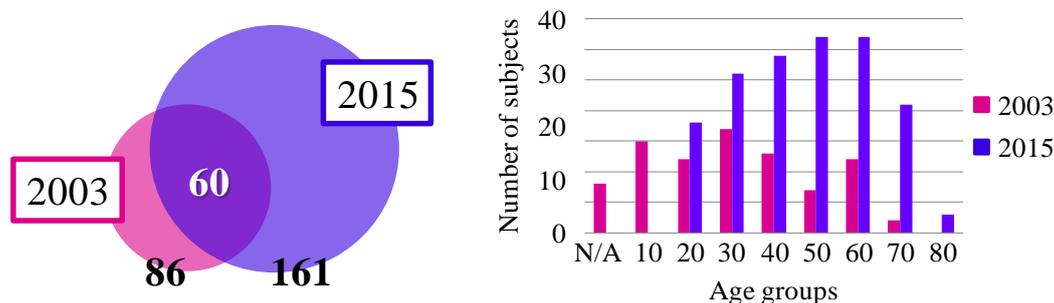


*Figure 1: Summary of data in the database: breakdown of the numbers of subjects entered in different years (left) and distribution of subjects' ages (right).*

The photographs were taken using the imaging system shown in Figure 2. It was surrounded by blackout curtains to eliminate the effects of ambient light. The light source was four fluorescent lamps surrounding the camera, as shown in Figure 2. The camera was a Nikon D1 or Nikon D2H; the former was used in 2003 and the latter in 2015. In order to prevent movement of the face, we used a support for the neck and head, which was fixed to the backrest of the chair. We obtained facial images without

specular reflectance by arranging mutually perpendicularly polarisation filters in front of the camera and the light sources. There was difference in colour tone between images taken in 2003 and in 2015, caused by the use of different cameras. For this reason, we used MRA to match the colour tone of images taken in 2003 with those from 2015.
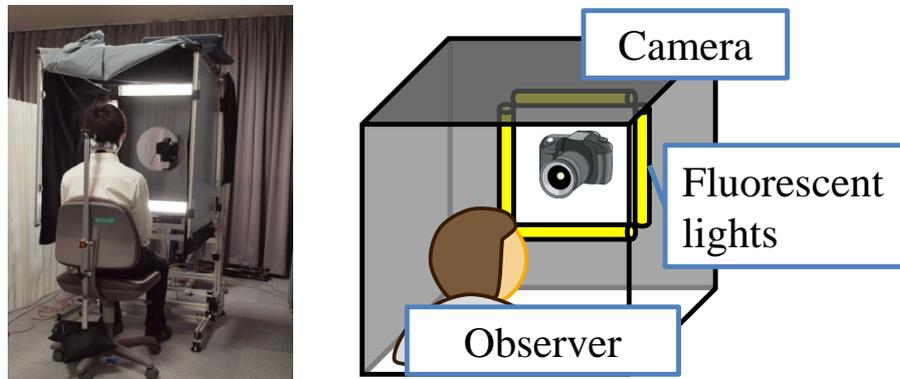


*Figure 2: Overview of the imaging system used.*

Figure 3 shows an example of the captured facial images. These images needed to be normalised in order to remove the influence of variation in individual facial shapes when subsequently applying PCA. For this purpose, we used FUTON (Fool-proof 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 each captured image. Second, we morphed the shape of the facial images to match that of an average face in the database. As a result, we obtained normalised facial images while keeping individual skin texture information. An overview of this process is shown in Figure 4.
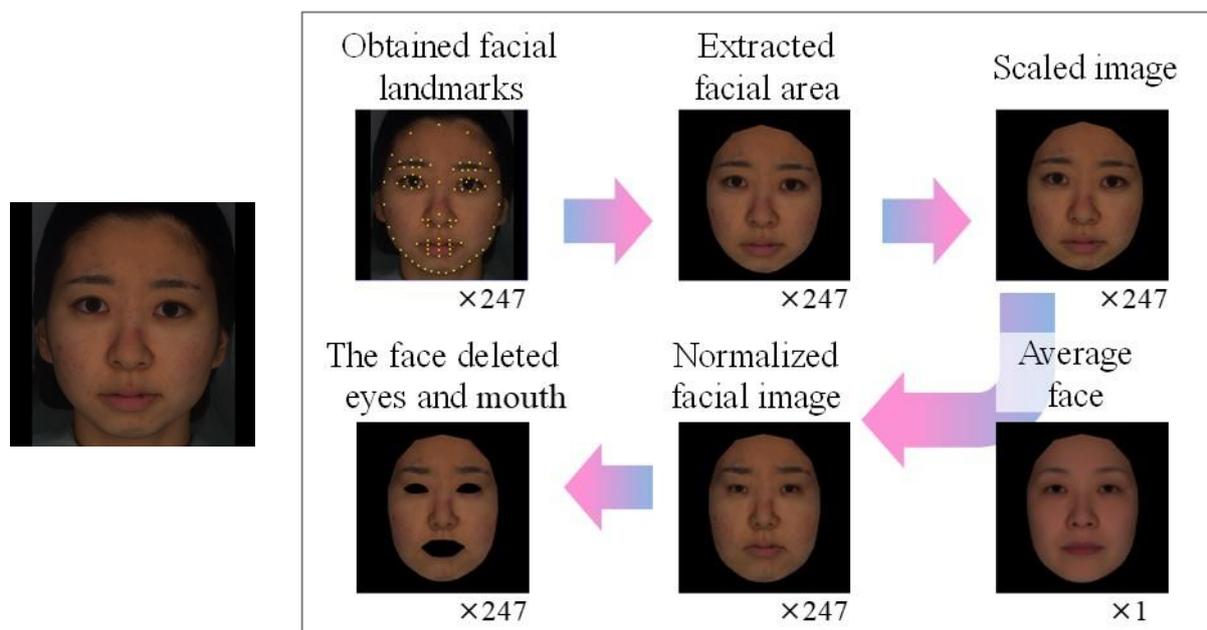


*Figure 3 (left): Example of a captured image.*
*Figure 4 (right): Overview of normalisation process for facial images by Fool-proof UTilities for facial image manipulatiON system (FUTON) [11].*

We classified facial images in the database according to the frequency of UV protection use by each subject. Frequencies were determined using a three-tiered evaluation (1: Never, 2: Sometimes, 3: Daily) in the winters of 2003 and 2010, and a six-tiered evaluation (1: Daily in the last five years, 2: Daily in the summer for the last five years, not in the winter, 3: The usage period was longer than the non-usage period in the last five years, 4: The usage period was shorter than the non-usage period in the last five years, 5: Rarely in the last five years, 6: Other) in 2015. Figure 5 shows the age distributions of frequencies of UV protection use.

Two groups of subjects can be discerned from these data. One group did not use UV protection in the winter, consisting of 10 people who answered '1: Never' both in 2003 and in 2010, and '2: Daily in the summer for the last five years, not in the winter' or '5: Rarely in the last five years' in 2015. The other group used UV protection throughout the year, consisting of 9 people who answered '3: Daily' both in 2003 and in 2010, and '1: Daily in the last five years' in 2015. Figure 6 shows the age distributions of these two groups.
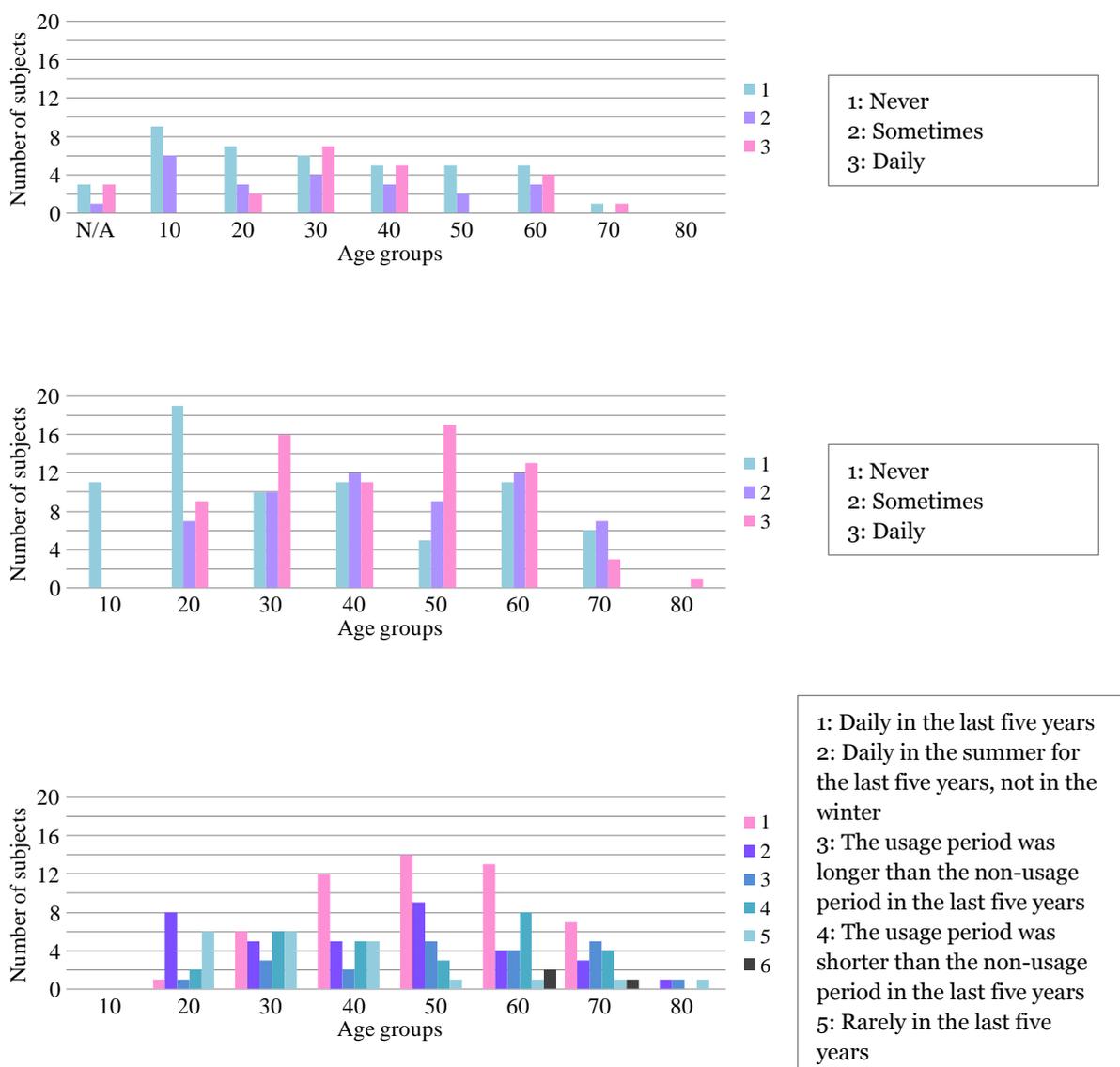


*Figure 5: Age distributions of the frequency of UV protection use in 2003 (top), 2010 (middle) and 2015 (bottom).*

*Figure 6: Age distributions of the group not using UV care protection in the winter (left), and the group using UV care protection throughout the year (right).*

### Extraction of the melanin component by ICA

We extracted the skin pigmentation distributions by ICA [6]. An overview of the process is shown in Figure 7. Melanin and haemoglobin pigmentation density vectors could be estimated by applying ICA to the skin colour of an arbitrary facial image in the database, and were plotted in RGB density space. For each new skin colour, its vector was projected onto the skin colour plane in parallel with the strength-of-shading vector. Melanin and haemoglobin pigmentation densities were then obtained by re-projection onto each pigmentation density vector.
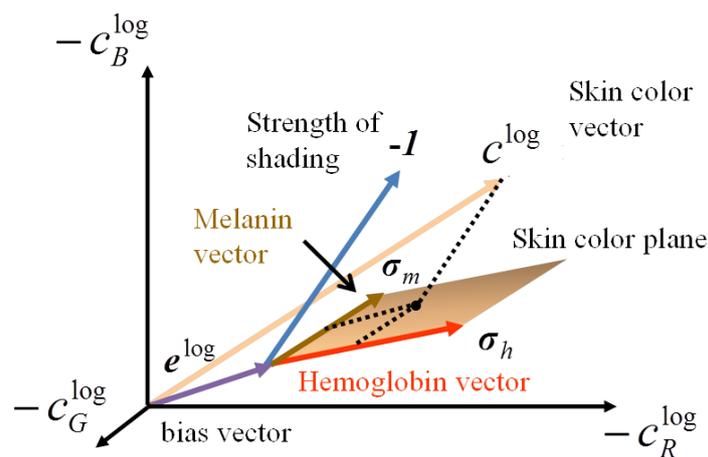


*Figure 7: Overview of independent component analysis.*

Figures 8(a) and 8(b) show an example of the extracted melanin and haemoglobin pigmentation, and Figure 8(c) shows shading in the whole facial image.



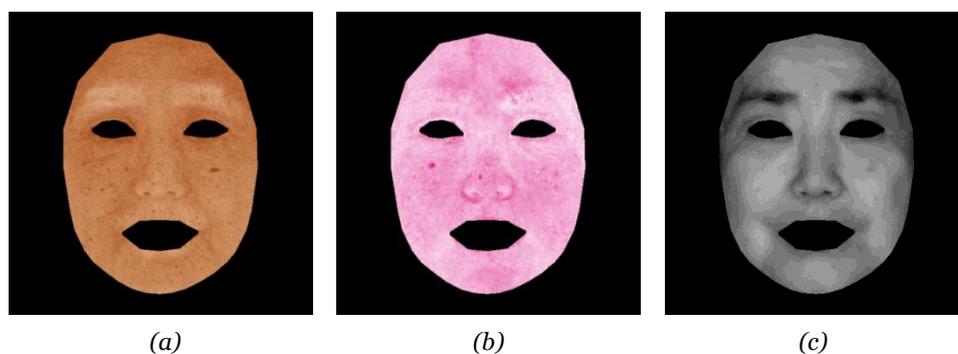|                    (a)                    |                    (b)                    |                    (c)                    |

*Figure 8: Results of independent component analysis for the extraction of three pigmentation components: (a) melanin, (b) haemoglobin and (c) shading.*

Close-ups of the cheek area in Figures 8(a) and 8(b) are shown in Figure 9. A pigmented spot can be recognised in the melanin component images in Figures 8(a) and 9(a). Pimples can be seen in the haemoglobin component images in Figures 8(b) and 9(b). The shading component can be used to characterise facial shape, as in Figure 8(c). In this study, we used the melanin component for analysis because melanin pigmentation has a high correlation with UV exposure. PCA was applied to all pixels of the whole image, to compare the spatial distribution of melanin components in the face.
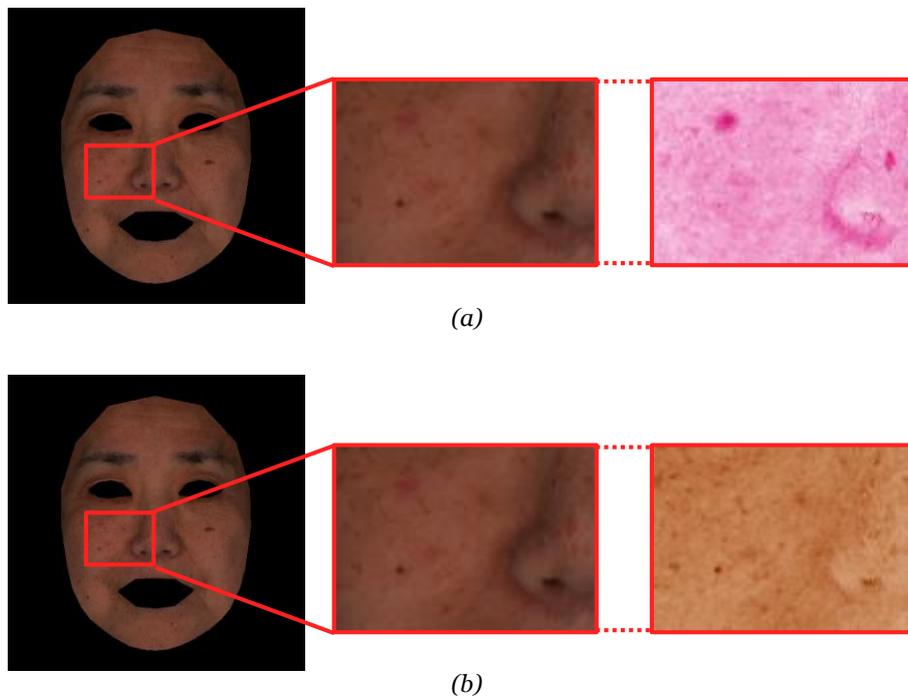


*(a)*



*(b)*

*Figure 9: Close-up images of results the extracted pigmentation components shown in Figure 8: (a) the cheek area, of melanin component and (b) the same cheek area, of haemoglobin component.*

### Analysis of the melanin component by PCA

We obtained feature values for uneven pigmentation by applying PCA to the melanin components of the 247 facial images extracted in the above subsection. PCA is a statistical method used to discern trends and features of data by multivariate analysis. It calculates the linear sum of each variable for each point in a data group, and defines a new index as the first component. The second component is defined in such a way that it is perpendicular to the first component, and other components are defined similarly. The $n$-dimensional $l$-th vector in a dataset can be represented as an approximated vector as follows:

$$\hat{\mathbf{x}}_l\left(x_{l1}, x_{l2}, \cdots, x_{ln}\right) = \sum_{m=1}^{M} w_{lm} \boldsymbol{p}_m \qquad (1)$$

where $M$ is the total number of principal components, $w_{lm}$ is the weight value for the $m$-th principal component, called the principal component score, and $\boldsymbol{p}_m$ is the $m$-th principal component vector.

Figure 10 shows an overview of the PCA of melanin components of the facial images. Since the number of pixels in the melanin images was 512×512, then each melanin image could be described by one data vector in 512×512 -dimensional space (that is, we regarded one pixel as one variable). In this study, we had 247 such data vectors. We applied PCA to these data vectors to find the first principal

component vector, such that the variance of the data vectors projected onto the principal component vector is maximised. The second principal component vector is then determined as the perpendicular vector which gives the maximum variance when data vectors excluding the first principal component are projected onto it. The vector describing a melanin image can be approximated by the weighted linear combination of the first two principal component vectors, if the contribution ratio for the two principal component vectors to the melanin image vectors is high enough. Therefore, the extracted principal component vectors and their weighting scores can be used to effectively analyse the very-high-dimensional data using a small number of variables.

Since there were 247 data vectors for subject's melanin components in this study, we could obtain 246 principal components of their melanin pigmentation distribution. The first two of these are shown in Figure 11. When the principal component score is positive, the brown parts in Figure 11 expand to reflect increased melanin. When the principal component score is negative, the white parts expand to reflect decreased melanin. The melanin pigmentation distribution in the whole face could be obtained as the first principal component (contribution rate = 0.557). The first principal component likely represents the whole face because the distribution of melanin mainly increases uniformly with aging. The melanin pigmentation distribution around the cheeks could be obtained as the second principal component (contribution rate = 0.041). It is noteworthy that the first principal component describes melanin pigmentation for the whole face, while the second principal component describes pigmentation only in the cheek area. Thus, we could obtain distinct feature values for the melanin component of the facial images.
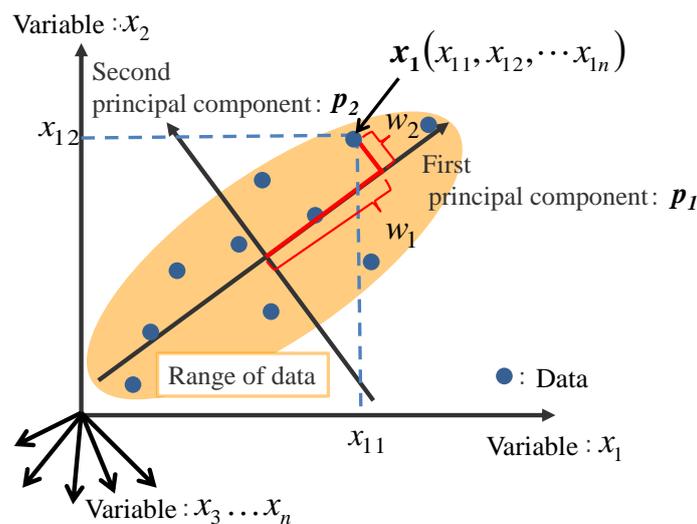


*Figure 10: Overview of the principal component analysis in of the melanin component (*n = *number of pixels in the image; other variables as defined in the text).*



*Figure 11: Results of PCA principal component analysis in of the melanin components: the first principal component (left) and the second principal component (right).*

## Results showing individual differences in principal component scores

We obtained changes in the first and second principal component scores over 12 years for each subject. Figure 12 shows the relationship between the first principal component score and age for the study group as a whole (left panel) and for each individual (right panel). The magenta line in the left panel represents a linear regression (correlation coefficient = 0.28, p < 0.01), in which individual differences were not taken into account. The lines in the right panel are drawn between the data points collected in 2003 and in 2015 for each individual. The results illustrate a new relationship between the melanin component and age which can only be seen by considering changes in individual scores, and which had not been recognised in previous studies (represented by the left panel). The slope of the regression line in the left panel is small compared with the slopes of the lines in the right panel. The small slope in the regression line can be considered to represent the average of the individual differences shown in the right panel. Thus, there are large but variable changes over 12 years which can be identified when the data are analysed with consideration of individual differences, but which cancel each other out when the data are pooled.

Furthermore, we analysed individual variation in subjects categorised according to their frequency of UV protection use, in order to examine the relationship between the melanin component of facial images and UV protection. Figures 13 and 14 show the changes in individual first and second principal component scores for subjects that did not use UV protection in the winter and those that used UV protection throughout the year.
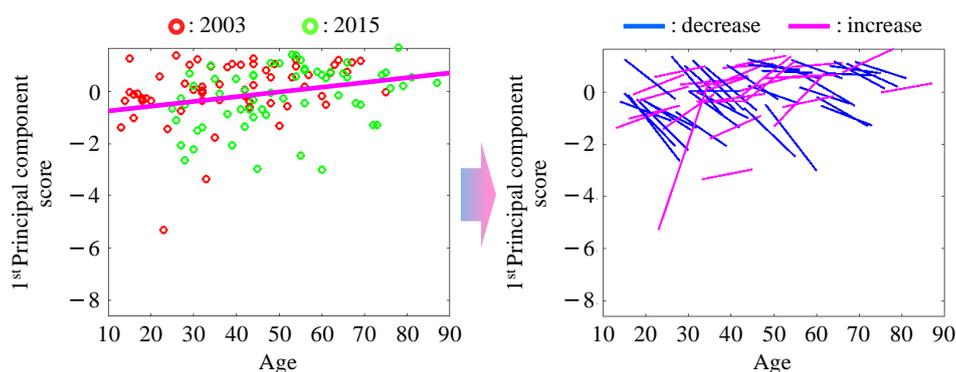


*Figure 12: Relationship between the first principal component score and age: linear regression of all data, not taking individual differences into account (left), and individual changes from 2003 to 2015 (right). Appearance of new relationship between melanin component and age by considering individual shift of principal score.*

## Discussion

Firstly, we discuss the first principal component. From Figure 13(a), it can be seen that the first principal component scores of five people not using UV protection in the winter increased and those of the remaining five people decreased. In particular, the scores of subjects in their teens and twenties tended to decrease over 12 years. Thus, darkening of the whole facial skin was a consequence for half this group of not using UV protection in the winter. In contrast, the first principal component scores decreased among all subjects except for one using UV protection throughout the year, as shown in Figure 13(b). This indicates that people can brighten their whole facial skin after 12 years, regardless of age, if they use UV protection throughout the year. Statistical analysis showed that, in the winter non-use group (average age: 37.4 years; age range: teens to sixties in 2003) there was no significant change

(two-tailed t-test, p-value = 0.33) in the first principal component over 12 years, while in the year-round use group (average age: 41.8 years; age range: twenties to sixties in 2003) there was a decreasing trend (two-tailed *t*-test, *p*-value = 0.063). Therefore, we can conclude that year-round use of UV protection has the potential to decrease melanin pigmentation over the whole face.

Secondly, we discuss the second principal component. Focusing on decreases in these scores, there were more people with a declining score in the winter non-use group than the year-round use group, as shown in Figure 14. From Figure 14(a), it can be seen that winter non-use women whose scores declined were mostly teenagers in 2003. On the other hand, Figure 14(b) shows that the only year-round use woman whose score decreased was in her sixties. Similarly, focusing on increases in the second principal component scores, scores for the group not using UV protection in the winter increased by approximately 20 units, while those for the group using UV protection throughout the year increased by approximately 10 units, except for one woman. Hence, it can be concluded that a partial darkening of the cheeks and an unevenness of cheek colour are caused by advancing age, but year-round use of UV protection suppresses these effects. When analysed by *t*-tests, scores in both groups showed significant increases over 12 years (*p*-value = 0.026 and 0.031, respectively). However, the year-round use group showed smaller increases than the winter non-use group.
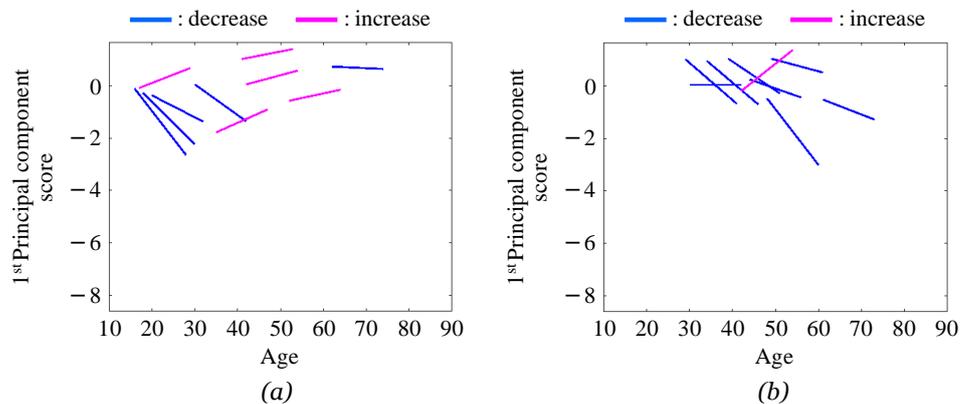


*Figure 13: Relationship between the first principal component score and age for subjects classified categorised according to their frequency for use of UV protection use: (a) the winter non-use group, (b) the year-round use group doing UV care throughout the year.*
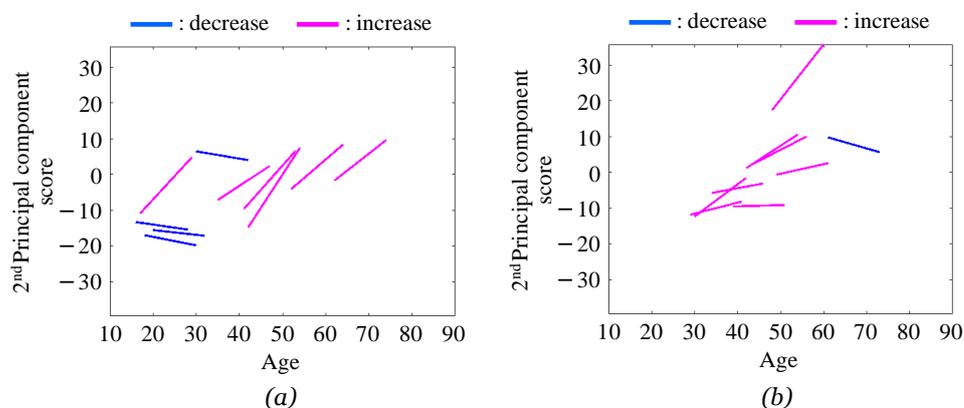


*Figure 14: The obtained results for variation in Relationship between the second principal component score and age for subjects classified categorised according to their frequency for use of UV protection use: (a) the winter non-use group, (b) the year-round use group doing UV care throughout the year.*

## Conclusions

In this study, we applied PCA to the melanin component of facial images and discovered individual differences in aging associated with the frequency of UV protection use. By considering individual changes in principal component scores over 12 years, we found a new relationship between the melanin component and age, which had not been recognised in previous studies. In future work, we will attempt to predict the effect of UV protection by simulating facial appearance at arbitrary ages based on the relationship between the melanin component and UV protection.

## Acknowledgements

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