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Analysis of human perception of facial skin radiance by means of image histogram parameters of surface and subsurface reflections from the skin

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Background: The appearance of the skin is the result of complicated light–skin interactions involving surface and subsurface reflections. Radiant skin is a complicated attribute but is important for skin beauty. The aim of the present study was to achieve an understanding of the association between human perceptions of skin radiance and image histogram parameters from technically recorded images of surface and subsurface reflections.
Methods: Facial images of 45 subjects were evaluated visually by 30 respondents and were also computer analyzed in terms of their image histogram parameters. A partial least squares regression model was created to explain visual perceptions in terms of the image histogram parameters.
Results: Visual perceptions of subsurface reflections can be explained in terms of the mean from the subsurface reflection image histogram, and visual perceptions of surface reflections can be explained in terms of the standard deviation (SD) and skewness from the surface reflection image histogram. Skin radiance can be explained in terms of the mean from the subsurface reflection and the SD from the surface reflection.
Conclusion: To acquire skin radiance, a surface reflection component that makes the skin look shiny and a subsurface reflection component that is in line with skin fairness are both needed. A balance of these features provides the origin of skin radiance.

Key words: skin radiance – surface reflection – subsurface reflection – image analysis – PLS regression modeling

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Of all the attributes associated with skin beauty that women desire, radiance is perhaps the most nebulous. Radiance, as an optical parameter defined by physics, can be measured in terms of the amount of light that is emitted from a particular object, such as a light source. If we apply this definition to skin radiance, then skin that reflects more incident light should look more radiant. However, skin radiance as perceived by consumers is not necessarily defined in this way. Skin radiance is a psychophysical parameter that involves quite complicated surface and internal qualities of the skin (1), and it involves more than simply the quantity of light that is reflected from the skin. People often mention that radiant skin appears to have an internal glow. They distinguish radiant skin from shiny skin, from which they believe that most light is reflected from the surface of the skin. These views suggest that people have the ability to perceive the depth of the reflection from the skin and to use this as a basis for their perception of skin radiance. Does this ability really exist?

Even though people can tell whether incident light appears to be reflected from the surface or from the inside of the skin, this does not provide direct proof that the human vision system is capable of capturing reflected light from various depths within the skin. The skin consists of a series of very thin layers, and human eyesight is insufficiently sensitive to recognize differences in depth of the order of micromillimeters. It would more make sense to consider that human vision perceives surface and subsurface reflections from the skin by capturing other features of the reflected light from the skin. Motoyoshi et al. (2) have reported that visual perceptions of surface qualities, such as the glossiness of a sculpture, can be explained in terms of simple parameters of the image histogram, such as its skewness. They created artificial images of a sculpture that appeared matte or glossy and they analyzed the histograms of these images. They pointed out that a small area of brightness against a dark background creates a perception of glossiness, and this can be described in terms of the skewness parameter. Their study was based on a normal image consisting of both of surface and subsurface reflections.

We thought that it would be quite interesting to apply Motoyoshi's analysis to images of facial skin. We split a normal image of a face into surface reflection and subsurface reflection components by using a specialized system for image capture and analysis, and we analyzed the images by means of their image histogram parameters. In addition to the image histogram analysis, the facial images were evaluated by human eyes for perceptions of radiance, surface reflections, and subsurface reflections. We developed a mathematical regression model of the human perceptions by using the image histogram parameters. This model will help us to understand what sort of characteristics in the image are related to the perception of skin radiance as well as to examine whether human perceptions of surface and subsurface reflections from the skin actually concur with technically measurable components of surface or subsurface reflections.

Materials and Methods

Subjects and respondents

We refer to the people who appeared in the stimulus image as the 'subjects' and those who evaluated the images as the 'respondents'. There were 45 healthy female subjects aged 34–54 [mean age = 45.9; standard deviation (SD) = 6.0]. There were 30 other female respondents [mean age = 37.3; SD = 4.5]. These were naive respondents who were untrained in evaluating skin appearances before their enrollment in the study and were therefore representative of female consumers.

Face-imaging system

Facial images (stimuli) were captured by using a system for whole-face image capture and analysis, named SAMBA (3), which is manufactured by Bossa Nova Technologies (Los Angeles, CA, USA). The principle of measurement by SAMBA relies on the polarization imaging technique (4). The SAMBA system consists of illumination units equipped with linear polarizing filters and a high-resolution digital camera equipped with a liquid-crystal polarizer, the polarization angle of which can be electronically flipped from the direction parallel (P) to the plane of polarization of the polarizing filters on the illumination units to one that is at 90° to this direction, referred to as the crossed (C) orientation. When the two polarization filters are oriented in parallel, both the surface and subsurface reflection are present in the resulting image (P-image; Fig. 1). However, when the two polarization filters are oriented in the crossed position, surface reflections are excluded, and only the subsurface reflections are present in the crossed image (C-image; Fig. 1). By subtracting corresponding pixels in the C-image from those in the P-image, a surface reflection image (S-image; Fig. 1) can be extracted technically. In this way, technical surface reflection and subsurface reflection images were obtained.

Stimuli and visual evaluation methodology

The stimuli consisted of facial images of 45 subjects captured by using the SAMBA system. For visual evaluation, full-color P-images were used. Two facial images of each subject were captured with a 4-week interval and prepared for evaluation. Over the 4-week interval, the subjects were instructed to use designated facial moisturizers in place of their regular regimens. The perceptions of the 30 respondents of surface reflection, subsurface reflection, and skin radiance of the two images presented side by side in a pairwise manner on a color-corrected monitor (CLC202p; Totoku Electric Co. Ltd, Tokyo, Japan) were recorded. We adopt a system of comparison grading rather than an absolute grading for each pair of images, because comparison of the pair of images excludes subject-oriented facial characteristics, such as the morphological facial shape or skin color, from the evaluation because the respondent can focus on the differences in the optical features of the face. Furthermore, we have no reference (guidance scale) for judgment of the three attributes we examined, and for assigning an absolute

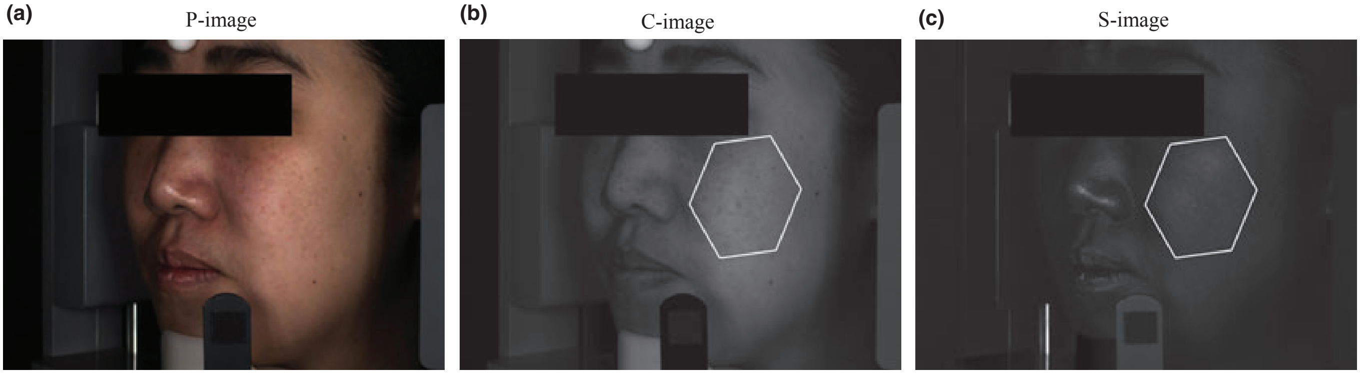

Fig. 1. SAMBA *P-image (a), C-image (b), and S-Image (c). The P-image (colored) was used for the visual evaluation of perceived surface reflection, perceived subsurface reflection, and perceived skin radiance. The C-image (gray scale) and the S-image (gray scale) were used in the image histogram analyses of the subsurface and surface reflection components from the skin, respectively. The hexagonal area in the C-image and S-image corresponds to the region of interest (ROI) used for the image histogram analysis. The ROI was chosen to include the visibly brightest part and to avoid shadows on the cheek.*

grading score for these perceptions is more difficult psychologically than assigning comparative differences between pairs of images.

The images of the 45 subjects appeared on the monitor in random order. In each visual evaluation session, the respondent viewed the 45 pairs of images and replied to each of the three questions given below for each pair of images.

(1) Which image do you think has more skin radiance?
(2) Which image do you think shows reflections from the skin's surface?
(3) Which image do you think shows reflections from inside the skin?

To complete the evaluation for all three questions, three rounds of sessions were conducted using the same image pairs. The respondents were instructed to evaluate the skin on the cheek, because this is an area that was amenable to computer-based image analysis. The respondents were asked to select the appropriate image in reply to the question and to give a score corresponding to their degree of agreement according to the four ratings given below:

4: Definitely
3: Moderately
2: Slightly
1: Maybe

Even if they thought there was no difference between the two images, they were forced to choose one or the other and to ascribe a rating of 1 in this case. In other cases, the choice of the rating relied on their perceptual scale. The evaluation scores were automatically recorded by the computerized system. A positive score was recorded when the later image (captured at week 4) was chosen whereas a negative score was recorded when the earlier image (captured at week 0) was chosen. Therefore, if there was no difference between the two images and the respondents were forced to choose rating of 1, the respondents' choices should be split in half into the later or earlier image and the average from the 30 respondents was resulting in zero score that means no difference between the two images. The data corresponding to the answers to the three questions are denoted Y1, Y2, and Y3, respectively, as shown in Fig. 2.

Image histogram parameters

The S-image (which included only surface reflections from the skin) generated by image processing with SAMBA and the C-image (which included only subsurface reflections from the skin) were used in the analysis of the image histogram parameters. Before the image analysis, these images were converted into gray-scale images. A designated hexagonal region was cropped from each of the images so that the hot spot on the cheek (the visibly brightest area) was included in the analysis (Fig. 1). The image histogram summarizes the distribution of the signals in the pixels in the cropped region. Landy (5) mentions that human eyesight is sensitive to at least three statistics (mean, variance, and skewness) of the histogram, and we therefore chose these three image histogram parameters for our analysis. The correspondence

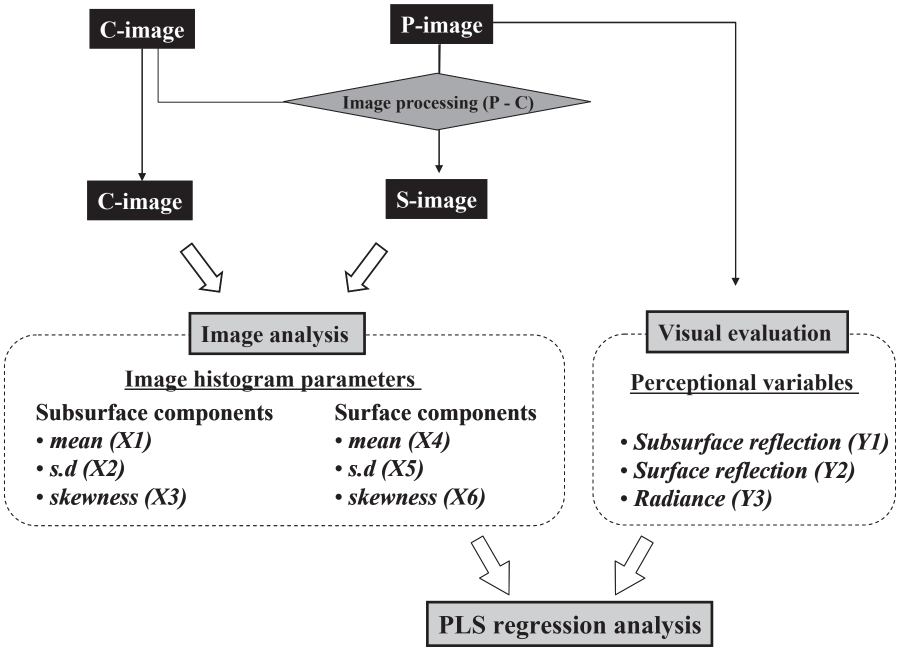

Fig. 2. A flowchart for the study. P-images and C-images captured by using an image-capture system (SAMBA) were analyzed with a computer-based image-analysis algorithm and by human eyes in the visual evaluation. The image analysis gave six objective variables (X1–X6) for subsurface and surface reflections. The visual evaluation gave three subjective variables (Y1–Y3) for the subsurface reflection, surface reflection, and skin radiance, respectively. Partial least squares regression analysis was performed to create a model that links the subjective variables with the objective variables.

between these image histogram parameters and the appearance perceived by humans is shown in Fig. 3. The mean, SD, and skewness were calculated for each of the surface reflection and subsurface reflection images, so that we had six parameters in total. These were denoted X1 through X6, respectively, as shown in Fig. 2.

Partial least squares regression modeling

We used partial least squares (PLS) regression analysis, as implement on JMP 8.0.2 software (SAS Institute Inc., Cary, NC, USA), to analyze the association between the respondents' perceptions and the image histogram parameters. We chose PLS regression analysis because the independent variables were correlated with each other and problems of multicollinearity would occur if a multiple regression was performed directly (6). Among the benefits of PLS regression analysis are that it can deal with multiple responses and that it can yield values of the variable importance projection (VIP) that can serve an index for the statistical importance of the independent variables in the final model. If a variable has a small coefficient and small VIP value, it is a candidate for deletion from the model. Wold et al. (7) considers a value of < 0.8 to be a small VIP value. In the first round of PLS regression analysis, all six technical parameters were included in creating the model. VIP values of the technical parameters were then checked and those with a value of < 0.8 were excluded from the model. A second round of PLS regression analysis was then performed for the variables with a VIP value of more than 0.8. This process was repeated until all the technical variables that remained in the regression model had VIP values of more than 0.8. When we reached this final model, we examined the centralized coefficient to describe the contribution of each technical parameter to the perceived optical skin features.

Results

In the first round of PLS regression analysis, three image histogram parameters had VIP values in excess of 0.8 (Table 1). These three parameters were the mean of the subsurface reflection (X1), the SD of the surface reflection (X5), and the skewness of the surface reflection (X6). We then performed a second round of PLS regression analysis with these three technical variables and we confirmed that the VIP parameters for all three parameters were more

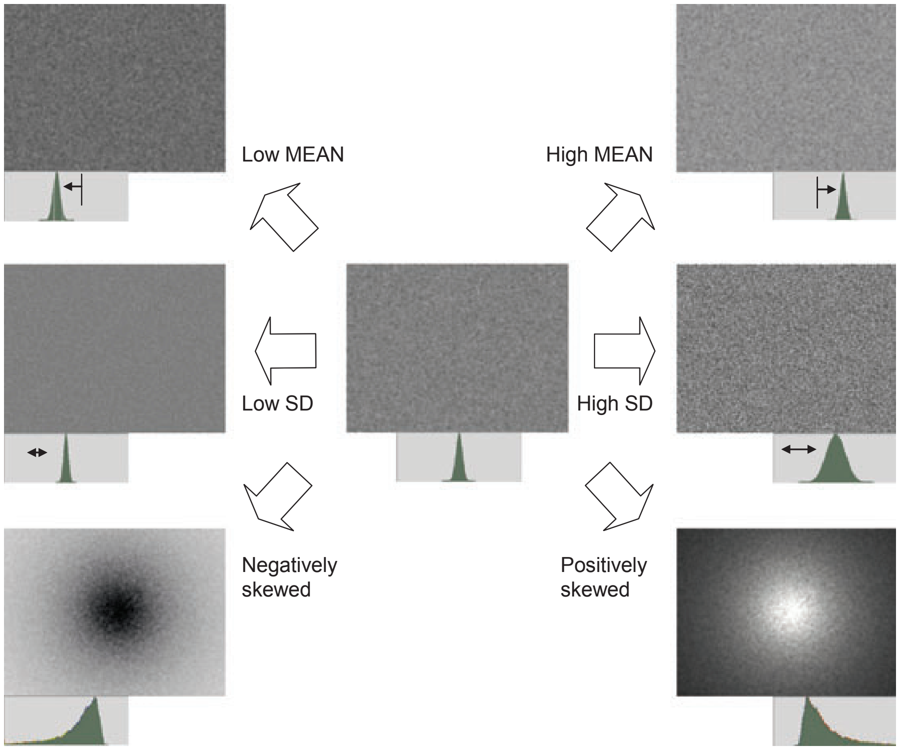

Fig. 3. Concept of the image histogram and the image histogram parameters (mean, standard deviation, skewness) illustrated by synthesized images. The image histogram is a chart showing a distribution of the pixel values in the image. These images are prepared to explain the concept of image histogram analyses by simulating the appearances that appears to the skin. This chart shows how the image histogram parameters are changed when the images look different.

than 0.8 (Table 1). We therefore adopted the centralized coefficients obtained from the second-round PLS regression analysis as a final model consisting of one subsurface reflection parameter and two surface reflection parameters. The resulting coefficients are summarized in Table 2. The centralized coefficient obtained by PLS regression analysis indicates the contribution of each image histogram parameter to the visual perception attributes. The perceived subsurface reflection (Y1) corresponds mainly to the mean of the subsurface reflection component, as the coefficient was 0.744 whereas the contributions from the surface reflection components were 0.177 and 0.013, respectively. The perceived surface reflection (Y2) can be explained in terms of the two surface reflection components, the coefficients for which were greater (0.512 and 0.420) than that for the subsurface reflection component (0.273) and the contribution from these two surface reflection components was almost equal. To explain the perception of skin radiance, however, the mean of the subsurface reflection and one of the surface reflection components (SD) were needed, as the centralized coefficients for these two parameters (0.466 and 0.417) were more weighted than that of the skewness of the surface reflection (0.291).

Discussion

The first objective of our study was to examine the correspondence between human perceptions of surface and subsurface reflections from the skin and technical measurements of the surface and subsurface reflections from the skin. The second objective of our study was to develop a mathematical regression model of the perceived skin radiance in terms of the parameters of the technical surface and subsurface reflection image histogram. To address these objectives, we used PLS regression analysis. Consumer perceptions of subsurface reflection can be mostly explained in terms of the mean from the image histogram for subsurface reflections from the skin, whereas consumer perceptions of surface reflections can be well explained in terms of two parameters of the image histogram (the SD and skewness) for surface reflection from the skin. These results show that the consumers' perceived depth of light reflection is

TABLE 1. VIP values for the first and second rounds of PLS regression analysis. In the first round of PLS analysis, the VIP values for three parameters (X1, X5, and X6) exceeded 0.8, the criterion for inclusion in the second round of analysis. These three parameters all remained after a second round of analysis and were adopted as the final model

Image histogram parameters	VIP value in round 1 of the PLS analysis	VIP value in round 2 of the PLS analysis
Mean of subsurface reflection (X1)	1.391	1.102
SD of subsurface reflection (X2)	0.781	n/a
Skewness of subsurface reflection (X3)	0.122	n/a
Mean of surface reflection (X4)	0.650	n/a
SD of surface reflection (X5)	1.497	1.080
Skewness of surface reflection (X6)	1.228	0.904

VIP, variable importance projection; PLS, partial least squares; SD, standard deviation.

TABLE 2. Model coefficients for centralized data. The size of the coefficient describes the contribution of each of the image histogram parameters in the model against the corresponding perception. For example, the model equation for perceived radiance (Y1) can be described as Y1 = 0.466*X1 + 0.417*X5 + 0.291*X6

	Centralized coefficients for image histogram parameters		
Reflection profile	Mean of subsurface reflection (X1)	SD of surface reflection (X5)	Skewness of surface reflection (X6)
Perceived subsurface reflection (Y1)	0.714	0.177	0.013
Perceived surface reflection (Y2)	0.273	0.512	0.420
Perceived radiance (Y3)	0.466	0.417	0.291

SD, standard deviation.

actually associated with the characteristics of light reflection from different depths within the skin, but what consumers use to recognize these attributes are the two-dimensional descriptive statistics of the images rather than the actual depths. The mean of the image histogram describes the average brightness of the measured region, and this represents the intensity of reflected light captured in the image. The intensity of light from the inside of the skin is determined by the density of chromophores such as melanin or hemoglobin in the skin, so that the mean from the image histogram for subsurface reflections indicates the overall skin tone or color. This suggests that people perceive fairer skin as showing more internal reflection. On the other hand, the SD and skewness of the image histogram represent the characteristics of the spatial distribution of the reflective light in the measured region. The association between the skewness and the perception of the surface reflection is in line with the findings of Motoyoshi et al. (2), who showed that a bright area surrounded by a dark region provides a perception that the light is coming from the surface of the skin. Our research suggests that the SD of the surface reflection is also involved in the recognition of skin surface reflection in addition to the skewness.

Next, we created a model of skin radiance in terms of the parameters in the image histogram corresponding to surface reflection and subsurface reflection. The coefficients of the model showed perceived skin radiance has to be explained in terms of the subsurface reflection and one of the surface reflection components from the skin. In the consumer's mind, skin radiance, a desired skin-beauty attribute, is associated more with subsurface reflections, and surface reflections are connected more with skin shine, which is often considered to be detrimental to skin beauty. This may appear to be contradicting the PLS regression model but consumers actually describe the appearance of skin that does not show any surface reflection as being matte and lacking radiance or shine. Our PLS regression model is explaining these complicated consumer perceptions. The perception of superficial reflection is simply described by the surface reflection components (the SD and skewness) from the skin whereas the perception of skin radiance involves a well-balanced mixture of the characteristics of tone/color (subsurface reflection) and half of surface reflection components (the SD) that is also involved in the perception of superficial reflection. This indicates why skin radiance has remained an intangible quality for a long time and it is difficult to differentiate from skin shine: the perception of skin radiance shares its visual quality partially with the perception of skin shine and also involves skin color/tone elements. If we simply increase surface reflection by applying a reflective agent such as a moisturizer, the face may acquire a quality of skin radiance but at the same time it can also add a quality of skin shine. Therefore, to achieve the improvement of skin radiance, addition of subsurface reflection is surely required and on top of that, a careful control of surface reflection components is needed.

Conclusion

Visual perceptions of surface reflection, subsurface reflection, and skin radiance are associated with the image histogram parameters. Consumers perceive subsurface reflections on the basis of the mean statistics of the image and they perceive surface reflections on the basis of the distributive statistics (SD and skewness) of the images. The perception of skin radiance involves a mixture of both types of reflection.

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