International Journal of Computer Applications (0975 – 8887)
Volume 72– No.3, May 2013

Estimation of Skin Moisture and Elasticity from Facial Image by using Kernel Ridge Regression

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ABSTRACT
Various assessment characteristics have been used to evaluate the physiological condition of the skin, including skin moisture, elasticity, oil, and color. This often requires specific pieces of equipment such as a microscope. Although everyday evaluations may be needed to maintain skin condition, a particular piece of equipment may not be suitable for daily use. In this paper, it was proposed that a method to estimate skin moisture and elasticity from a facial image shot by a typical camera. The facial image's RGB, HSV, and YCrCb components were extracted as the explanatory variables for kernel ridge regression (KRR). In general processing, one color space is often adopted for a single purpose. In this research, some of the color components of various color spaces were selectively combined as explanatory variables for KRR. To select suitable explanatory variables, the sequential feature selection (SFS) method was applied. As a result, the correlation coefficient between the estimated and measured skin moisture values was 0.35. These results showed that skin moisture estimation using the facial image was insufficient. In contrast, the correlation coefficient between the estimated and measured skin elasticity values was 0.72, indicating that the skin elasticity estimation was successful.

General Terms
Data mining

Keywords
Skin moisture and elasticity, Facial image, **Kernel ridge regression**

1. INTRODUCTION
The physiological condition of the skin is generally evaluated based on its moisture, elasticity, oil, and color [1]. It is important to evaluate a skin's condition using physiological assessments of variables such as skin moisture or elasticity to maintain its health and beauty. This allows us (especially women) to select the most suitable cosmetics or skin care solutions depending on our skin condition. Additionally, these assessments are a very reliable way to objectively evaluate the effectiveness of some cosmetics or supplements. If users objectively determine that their cosmetics or skin care solutions are unproductive, they can substitute them with more suitable ones.

In previous researches, the evaluations of physiological assessments have been performed using various measuring instruments. For example, VISIA, produced by CANFIELD, could detect invisible flecks in a UV-image. In another study [2], a UV-image was obtained by VISIA and used as one of the clinical indices. In another instance, Takeyama et al. found skin dullness in a microscope image and quantified and classified the dullness level using a neural network algorithm [3]. Skin moisture can also be measured using several methods. A typical example is the capacitance method. On the other hand, Suh et al. attempted to estimate skin moisture using an FT near-infrared (NIR) spectrometer [4]. In the measurement of skin elasticity,a dermal torque meter (DTM 310) can be introduced, which measures the rapid elastic deformation with the application of torque. This is used in many investigations [5].

These approaches are effective for skin condition evaluations. However, they are not necessarily suitable for daily use because each requires a particular piece of equipment that is generally only used in a laboratory, clinic, or esthetic salon. However, everyday-evaluations are ideal for maintaining the skin's condition because it is very labile. Therefore, it would be desirable if evaluation could be performed using a standard digital camera, which anyone can easily obtain. However, no method to estimate skin condition using a standard digital camera has yet been presented. If this approach can be achieved, several new practical applications can be developed. For example, ifa facial image is shot using a smart phone's camera, skin condition can be assessed using a smart phone application.

This paper focuses on skin moisture and elasticity, and a method is proposed to estimate these from a facial image shot using a standard digital camera.

2. Facial color and experiment

2.1 Facial color and skin condition
It is well-known that the skin's moisture content and elasticity decrease with age. Further, it has been reported that skin color also changes with age [6, 7]. Inoue et al. measured the bare skin color of 639 female subjects between the ages of 17 and 69 using a spectrophotometer (CM-1000) [6]. This research revealed that aging shifted the skin tone from red to yellow and decreased skin lightness.

As presented above, aging decreases the skin's moisture content and elasticity, implying a correlation between skin moisture, elasticity, and skin color. A decrease in the skin's moisture content and elasticity can definitely be caused, not only by aging, but also by the environment, lifestyle, and physical conditions. However, if the skin color is also affected by elements other than aging, the skin's condition might be able to be estimated by evaluating its color. Thus, elasticity of facial skinare attempted to be estimated using the pixel values of a facial image.

2.2 Experiment

Experiments to obtain facial images and quantitative values of facial skin moisture and elasticity were conducted. The subjects were 20 Japanese, 16 men and four women, aged 21 to 37. Before the experiments, the subjects washed their faces to diminish the effects of makeup or milky lotion. The experiment began five minutes after they washed their faces. Moreover, the experiments were performed in a room with no windows to eliminate the influence of external light and simplify the experimental conditions. The only light source was fluorescent.

The facial images were shot using the iPod touch4's rear camera (960 × 720 pixels) and were saved in the JPEG format. In some researches on the evaluation of skin color, a polarized light (PL) filter has often been used to obtain radical skin color images (e.g., [8]). In this research, a circular-PL (C-PL) filter, produced by Izawaopt, was attached to the iPod's rear camera.

After the photo shoot, the facial skin moisture and elasticity were measured using the Triplesense device produced by MORITEX. This device uses electrostatic capacitance, ultrasonic oscillation, and optical sensors to measure skin moisture, elasticity, and amount of oil, respectively. Each condition is expressed in an arbitrary unit (a.u.) ranging from 0 to 99.

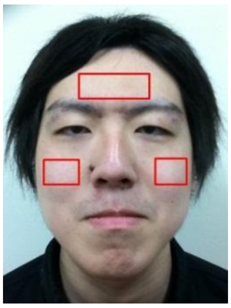

Figure 1 Measurement areas for skin moisture and elasticity.

The measurement areas were the brow and the left and right cheeks, as seen enclosed by squares in Figure 1. The measurements were repeated five or more times for each area. The position of the sensor was changed little-by-little inside the square because repetitive measurements may affect the elasticity of facial skin.

The mean value of skin moisture was 38.3 (SD: 13.2) a.u., and that of skin elasticity was 80.0 (SD: 13.0) a.u. In a later estimation, the skin moisture or elasticity value, as an objective variable for a regression, was computed as the median value of five or more measurements in one area (the standard deviation of five or more measured values was 10 a.u. on average for skin elasticity and approximately 5.5 a.u. for skin moisture).

In this research, skin oil was not treated because most of the skin oil values were 0 a.u. as a result of face washing.

2.3 Color space

In general image processing, the color components of one color space such as "RGB" or "HSV" are often used for a single purpose. In this research, the RGB color components were first adopted to estimate skin condition. However, as will become apparent below, this estimation using only the RGB color components was not accurate enough (the evaluation results using only RGB will be shown in 4.2). Thus, we attempted to adopt other color spaces and investigated the best combination of color components of various color spaces to estimate skin moisture and elasticity. Actually, there are numerous color spaces with similar characteristics. However, in this research, we focused on the following three representative color spaces, which are often used in image processing.

- RGB: In this color space, colors are composed of three primary elements: red (R), green (G), and blue (B). Each component ranges from 0 to 255.
- HSV: This color space is nonlinearly transformed from the RGB space. Colors are composed of hue (H), saturation (S), and lightness (V). S indicates the purity of the hue is in terms of a white reference and is related to the dullness of the color. When maximum and minimum values of RGB components are described as *MAX* and *MIN*, respectively, the HSV components are computed using Eqs. 1-3. H ranges from 0.0 to 360.0, and S and V range from 0.0 to 1.0.

$$H = \begin{cases} 60 \times \frac{G-B}{MAX-MIN} + 0, & if\ MAX = R \\ 60 \times \frac{B-R}{MAX-MIN} + 120, & if\ MAX = G \\ 60 \times \frac{R-G}{MAX-MIN} + 240, & if\ MAX = B \end{cases} \quad (1)$$

(if$H$< 0, H += 360),

$$S = \frac{MAX-MIN}{MAX} \quad (2)$$

$$V = MAX/255 \quad (3)$$

- YCrCb: Colors are specified in terms of luminance (Y), and (Cr) and (Cb) are the red-difference and blue-difference chroma components, respectively. The transformation between YCrCb and RGB is performed using Eq. 4.

$$\begin{pmatrix} Y \\ Cr \\ Cb \end{pmatrix} = \begin{pmatrix} 0.299 & 0.587 & 0.114 \\ 0.500 & -0.419 & -0.081 \\ -0.169 & -0.332 & 0.500 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix} \quad (4)$$

2.4 Correlation between facial skin color and skin condition

The medians of the pixel values described in 2.3 were extracted from the areas enclosed in the squares shown in Figure 1. The number of data points was 3 × 20 = 60. (The measurement positions were the brow, left cheek, and right cheek, and the number of subjects was 20. These color component extractions did not cause closed-set evaluations in the later learning and test steps because the skin condition was different in each facial area.)

To consider the feasibility of making estimations from facial images, the correlation coefficients between the skin moisture and elasticity values and each pixel value were computed. The results are shown in Table 1.

If a correlation coefficient > 0.330104 (N = 60), the null hypothesis of decorrelation can be rejected. Table 1 shows that R, G, B, V, and Y did not decorrelate with skin elasticity (marked with *). However, the null hypothesis of the decorrelation between the skin moisture and pixel values could not be rejected.

Table 1 Correlation coefficients between pixel values and skin moisture, elasticity.

Margin	Moisture	Elasticity
R	0.11	0.49*
G	0.0056	0.44*
B	0.83	0.39*
H	0.19	0.077
S	0.12	-0.063
V	0.12	0.47*
Y	0.048	0.45*
Cr	0.24	0.020
Cb	0.12	-0.079

3. Facial color and experiment

Table 1 shows that the skin moisture and pixel values in some color spaces were not correlated. In contrast, the skin elasticity and pixel values were correlated, but did not highly correlate. These results show that the skin moisture and elasticity cannot be estimated using a simple method like linear regression. In this paper, it is proposed that the use of the support vector machine (SVM) [9, 10] to estimate facial skin moisture and elasticity using the explanatory variables of some color spaces.

SVM is a linear classifier or regression in the feature space mapped by nonlinear transformation. In SVM, a kernel function realizes an implicit mapping of the input data into a high dimensional feature space, which is defined as a dot product in the feature space and does not require knowledge on the types of features that are being used. This idea was proposed by Vapnik [10].

In this paper, a kernel-based ridge regression method is proposed to estimate skin moisture and elasticity.

As mentioned previously, we propose to adopt the selectively combined color components of various color spaces. Selections are input into the kernel-based ridge regression as explanatory variables. To select suitable explanatory variables, the sequential feature selection (SFS) method [11] is applied. These algorithms will be described in 3.1 and 3.2.

3.1 Kernel ridge regression

Kernel ridge regression (KRR) is a ridge regression method based on some kernel matrices, and it can also be derived from the modified least squares method [12].

Suppose that $(x_1, y_1), \cdots, (x_T, y_T)$ is a training set, where T is the number of examples, $x_t \in \mathbb{R}^n$ are n-dimensional vectors, $y_t \in \mathbb{R}$,and t =1,…,T. A general linear function is defined as $y = w \cdot x$, where $w \in \mathbb{R}$. In the least square method, $w = w_0$ is solved, which minimizes the objective function (Eq. 5).

$$L_T(w) = \sum_{t=1}^{T} (y_t - w \cdot x_t)^2 (5)$$

When a new sample x is input, the predicted label is computed as $w_0 \cdot x$.

The ridge regression replaces Eq. 5 with Eq. 6.

$$\lambda \|\boldsymbol{w}\|^2 + \sum_{t=1}^{T} (y_t - \boldsymbol{w} \cdot \boldsymbol{x}_t)^2 (6)$$

where λ is a fixed positive constant. This optimization problem can be re-expressed as follows:

$$\lambda \|\boldsymbol{w}\|^2 + \sum_{t=1}^{T} \xi_t^2 \ (7)$$

subject to

$$y_t - \boldsymbol{w} \cdot \boldsymbol{x}_t = \xi_t, t = 1, \ldots, T. \qquad (8)$$

To solve Eq. 7 under the constraints in Eq. 8, the Lagrangian(Eq. 9) is introduced.

$$L(\boldsymbol{w}, \boldsymbol{\xi}, \boldsymbol{\alpha}) = \lambda \|\boldsymbol{w}\|^2 + \sum_{t=1}^{T} \xi_t^2 + \sum_{t=1}^{T} \alpha_t (y_t - \boldsymbol{w} \cdot \boldsymbol{x}_t - \xi_t) \qquad (9)$$

Eq. 9 is differentiated with respect to w and ξ_t, and assuming stationary conditions, Eqs. 10 and 11 are obtained.

$$\boldsymbol{w} = \frac{1}{2\lambda} \sum_{t=1}^{T} \alpha_t x_t \ (10)$$

$$\xi_t = \frac{\alpha_t}{2} \ (11)$$

By substituting the obtained values w and ξ_t into Eq. 9, we obtain Eq. 12.

$$W(\boldsymbol{\alpha}) = -\frac{1}{4\lambda}\sum_{s,t=1}^{T}\alpha_s\alpha_t(\boldsymbol{x}_s\cdot\boldsymbol{x}_t) - \frac{1}{4}\sum_{t=1}^{T}\alpha_t^2 + \sum_{t=1}^{T}y_t\alpha_t (12)$$

Furthermore, this equation can be re-written into a vector form as follows:

$$W(\boldsymbol{\alpha}) = \boldsymbol{y}'\boldsymbol{\alpha} - \frac{1}{4\lambda}\boldsymbol{\alpha}'\boldsymbol{K}\boldsymbol{\alpha} - \frac{1}{4}\boldsymbol{\alpha}'\boldsymbol{\alpha}. \quad (13)$$

Denoting $\boldsymbol{K}$ as the $T \times T$matrix of dot products.

Eq. 13 is differentiated with respect to $\boldsymbol{\alpha}$, and supposing stationary conditions, we obtain the condition

$$-\frac{1}{2\lambda}\boldsymbol{K}\boldsymbol{\alpha} - \frac{1}{2}\boldsymbol{\alpha} + \boldsymbol{y} = 0. \quad (14)$$

Eq. 14 is equivalent to

$$\boldsymbol{\alpha} = 2\lambda(\boldsymbol{K} + \lambda\boldsymbol{I})^{-1}\mathbf{y}. \quad (15)$$

Therefore, a prediction $f(\boldsymbol{x})$ of a new unlabeled example $\boldsymbol{x}$ is

$$f(\boldsymbol{x}) = \boldsymbol{w}\cdot\boldsymbol{x} = \boldsymbol{y}'(\boldsymbol{K} + \lambda\boldsymbol{I})^{-1}\boldsymbol{k} (16)$$

where $\boldsymbol{k}$ is the vector whose elements are $k_t = \boldsymbol{x}_t\cdot\boldsymbol{x}$, $t = 1, \ldots, T$.

If one wants to construct the linear regression in some feature space, $\boldsymbol{K}$ can be replaced with the kernel matrix $\boldsymbol{K}_{s,t} = K(\boldsymbol{x}_s, \boldsymbol{x}_t)$, and $\boldsymbol{k}$ can be re-written into the vector whose elements are $k_t = K(\boldsymbol{x}_t\cdot\boldsymbol{x})$. (In this research, *f*(*x*) is the estimated value of skin moisture or elasticity, and *y* is the measured one. *xt* represents input variables such as RGB, HSV, and YCrCb, and *x* is the learning one.)

A kernel function, $K(\boldsymbol{x}_s, \boldsymbol{x}_t)$, calculates the dot product of two vectors, x_s, x_t, in a given feature mapping, which are realized with several forms [13]. In this research, the following polynomial kernel (Eq. 17) was empirically selected.

$$K(\boldsymbol{x}_t, \boldsymbol{x}) = (\boldsymbol{x}_t\cdot\boldsymbol{x} + 1)^2 \ (17)$$

3.2 Selection of explanatory variables

Here, a method to select suitable explanatory variables from among the RGB, HSV, and YCrCb color spaces is described. (An “explanatory variable” is also called a “feature,” but “feature” is used only in explanations of SVM to avoid confusion. In this paper, the input variables for SVM are uniformly called “explanatory variables.”)

In most cases, the selection of explanatory variables is performed with dual aims. One is to avoid the curse of dimensionality and reduce the complexity of the classification or estimation process. Another is to select the best subset to increase the accuracy of the classification or regression. In this research, the former is inconsequential, because only nine explanatory variables are used. Thus, the selection of the explanatory variables is performed only to increase the estimation accuracy.

In this research, the SFS method is proposed. SFS is performed according to the following steps.

I. SFS starts with an evaluation of the accuracy of the estimation for each single explanatory variable, selecting the best one.

II. Then, SFS is performed using two explanatory variables at a time, the one that maximized the accuracy in the first iteration and each of the other variables from the remaining explanatory variable subsets, selecting the pair with the highest accuracy.

III. SFS evaluates three explanatory variable subsets, the two that were determined in the previous two steps, and another selected from the remaining subsets.

IV. The procedures described in steps I–III are repeated with four and more explanatory variables.

Based on these steps, evaluations are performed 9! times. Generally, the estimation accuracy peaks when the number of selected explanatory variables exceeds a sufficient number. Therefore, we can determine the best explanatory variable subsets that give the maximum accuracy in the SFS procedure. Note that the above-described accuracy is determined as the average absolute value of the difference between the estimated skin moisture or elasticity and the actual value.

4. Evaluation and results

In this paper, a KRR-based method is proposed to estimate skin moisture and elasticity from a facial image's pixel values: RGB, HSV, and YCrCb. First, the results of the RGB-based estimation will be shown in 4.2. The effectiveness of selectively combining color components will be shown in 4.4.

4.1 Evaluation method

Initially, one data set is selected as evaluation data from the 60 datasets. The remaining 59 are regarded as learning sets, and the skin moisture and elasticity are estimated. Next, another data set that has not been selected as evaluation data is selected as the new evaluation data, and the skin condition values are estimated with the remaining 59 learning sets. This same selection and estimation procedure is repeated 60 times, and 60 sets of estimated skin moisture and elasticity values are computed.

The evaluation indices are the average absolute values of the difference (prediction error) between the estimated skin moisture and elasticity values and the actual values, along with the correlation coefficient between the estimated and measured values.

4.2 Results of estimations using only RGB color components

First it is shown that the estimated skin moisture and elasticity results using the three RBG color components. The estimations were based on the KRR method. Table 2 shows the means of the correlation coefficients and prediction error differences between the measured and estimated values. This table shows that the estimated values of skin moisture were not correlated with the measured ones, whereas the estimated values of skin elasticity were correlated with the measured ones, but did not have a high correlation.

Table 2 Selected explanatory variables and order: moisture

Selected Order	1	2	3	4	5	6	7	8	9
Selected Explanatory Variable	H	R	S	Cb	V	Cr	B	Y	G

Table 3 Selected explanatory variables and order: elasticity

Selected Order	1	2	3	4	5	6	7	8	9
Selected Explanatory Variable	R	S	Cr	H	V	Y	G	B	Cb

Table 3 The average absolute value of difference and standard deviation between estimated and measured values of skin moisture, elasticity

Number of explanatory variable	1	2	3	4	5	6	7	8	9
Moisture	9.6 (8.6)	9.5 (8.2)	9.4 (8.3)	9.8 (7.8)	10 (8.1)	11 (9.0)	12 (10)	12 (10)	15 (12)
Elasticity	8.4 (6.5)	8.2 (6.6)	6.9 (5.9)	7.0 (6.0)	7.1 (6.0)	7.2 (5.9)	8.5 (6.6)	10 (8.0)	14 (13)

4.3 Results of estimations using single color component in different color space

As described in 4.2, the skin moisture and elasticity estimations using only the RGB color components were insufficient. Thus,the color components described in 2.3 is adopted as explanatory variables. Remarkably, the nine color components described in 2.3 can be selectively combined to estimate the skin condition even though the color spaces of these components are different. Suitable color components will be selected using the SFS method, which will be presented in 4.4. As a preliminary, the results of estimations using a single color component are shown. Tables 3 and 4 show the correlation coefficients and prediction errors between the measured values of skin moisture and elasticity and estimations calculated using a single color component.

Tables 2-4 show that the prediction errors of the estimations computed using the RGB components were smaller than those of most of the estimations calculated using a single component in both the skin moisture and elasticity estimations.

4.4 Results of estimations using color components selected with SFS method

As for the skin moisture estimation, the maximum correlation coefficient between the estimated and measured values was 0.35 (Figure 2), which is higher than most of the absolute correlation coefficients shown in Tables 2 and 3 (although the maximum absolute correlation coefficient was 0.53 when the single explanatory variable was a blue color component, the prediction error was insufficient). This shows that these were correlated but did not have a high correlation. No linearity between the estimated and measured values of skin moisture can be seen in the scatter diagrams of Figure 4, even with the maximum correlation coefficient (Figure 4 (d)). The minimum prediction error difference for the estimated skin moisture values was 9.4 a.u. when three explanatory variables, H, R, and S, were selected (Tables 5 and 7). As described in 2.2, the standard deviation in the values measured with Triplesense was 5.5 a.u. on average in one measurement area. Taking this result into consideration, it is concluded that the skin moisture estimation was insufficient because the prediction error for the skin moisture value exceeded the measurement variability for skin moisture.

In the skin elasticity estimation, the maximum correlation coefficient between the estimated and measured values was 0.72 (Figure 3), which exceeded those shown in Tables 2 and 4. Figure 5 shows that to an extent, linearity between the estimated and measured values of skin elasticity could be seen in these scatter diagrams. The prediction error difference between the estimated and measured values of skin elasticity was 6.9 a.u. for the maximum correlation coefficient, 0.72. This result indicates that there is a degree of accuracy in the skin elasticity estimation because this prediction error did not exceed the measurement variability for the skin elasticity, 10 a.u.

In both the skin moisture and elasticity estimations, the correlation coefficients and prediction errors of the estimations computed using the best SFS selections were better than those of the estimations computed using the three RGB components (see Tables 2 and 7, and Figures 2 and 3), which indicates that selectively combining color components based on the SFS method could be effective, especially in the estimation of skin elasticity. In addition, the results shown in

Tables 3-6 show that SFS did not select explanatory variables in the ascending order of the prediction error of the estimations using a single color component. Although the color components of one color space are not utilized with those of other color spaces in general image processing, as previously mentioned, these results indicate that combining the selected color components of various color spaces must have a physical basis.

The most commonly selected color components, which yielded the maximum correlation coefficients or minimum prediction error between the estimated and measured values, were R and S for both skin moisture and elasticity (Tables 5 and 6). As described above, aging shifts the skin tone from red to yellow, which is consistent with the fact that R was selected as a suitable explanatory variable in our study. Table 1 also shows a somewhat higher correlation between the values of R and skin elasticity. These results imply that a change in skin condition caused by several elements other than aging also contributes to skin color. In addition, Cr, which can be calculated as $0.731 \times (\mathrm{R} - \mathrm{Y})$ and corresponds to a red tinge, was an upper selection in the estimation of skin elasticity. These results suggest that red is an effective color component for the estimation of skin elasticity. Although S was also selected as a suitable explanatory variable by SFS, Table 1 shows decorrelation between S and skin moisture and elasticity. This result implies that S cannot accomplish anything alone but can be effective in combination with other pixel values.

In this research, skin moisture estimations were not sufficiently effective. Meanwhile, skin elasticity values were successfully calculated from facial images. In the future, to increase the accuracy of the estimations, it needs to consider other explanatory variables, including some components in other color spaces and some morphological aspects such as a facial outline. In terms of methodological aspects, a more suitable kernel function based on a mapping to the known feature space should be generated, which may be considered using the effective explanatory variables selected in this research. Moreover, we will attempt to estimate skin moisture and elasticity from facial images without the C-PL filter for practical realization.

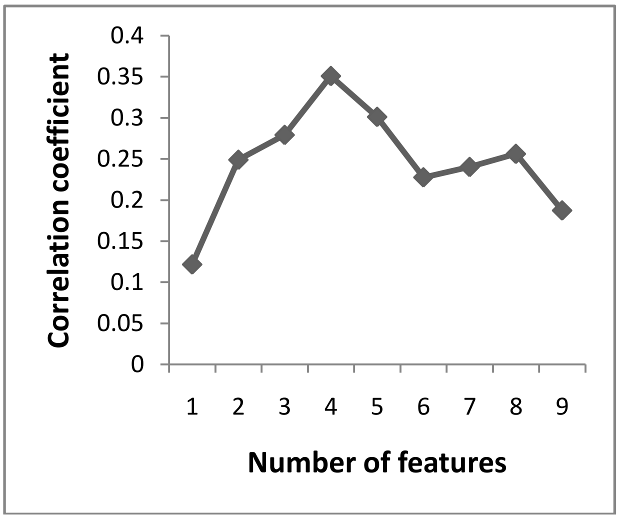

Figure 2 Correlation coefficients between pixel values and skin moisture values

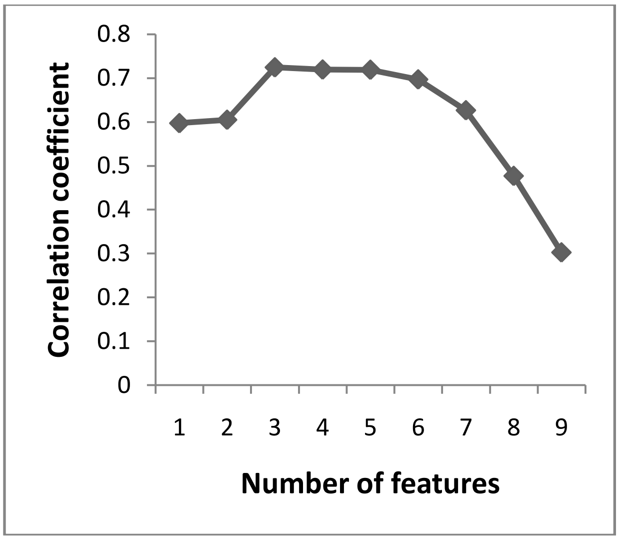

Figure 3 Correlation coefficients between pixel values and skin elasticity values

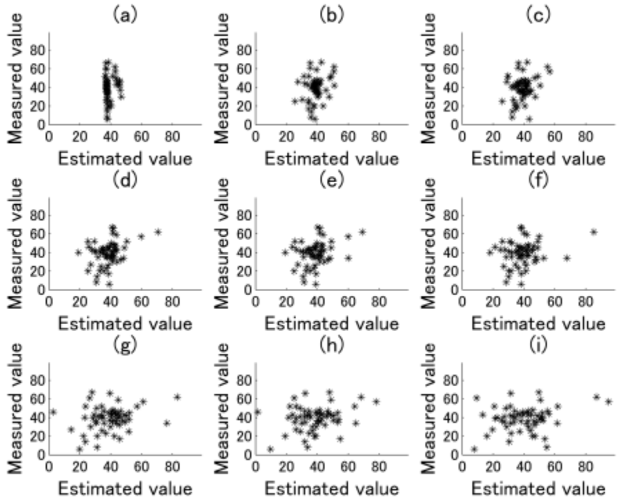

Figure 4 Scatter diagrams for estimated and measured values of skin moisture

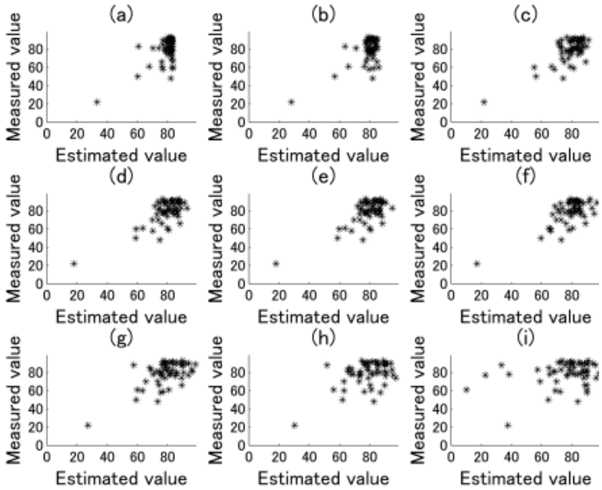

Figure 5 Scatter diagrams for estimated and measured values of skin elasticity

5. Conclusion

In this paper, the KRR method, which was a linear regression in the feature space mapped by nonlinear transformation, was proposed to estimate facial skin moisture and elasticity from pixel values. The actual skin moisture and elasticity were measured using a Triplesense device.

In general image processing, one color space such as RGB is often used for a single purpose. However, color components from various color spaces were adopted as explanatory variables for KRR. To select suitable explanatory variables, the SFS method was proposed.

In the SFS procedure, R and S were selected as suitable explanatory variables for both the skin moisture and elasticity estimations. In addition, the correlation coefficients and prediction errors of the SFS-based estimations were better than those of estimations computed using only the RGB color components.

As a result, the skin moisture estimation was insufficient, but the skin elasticity was successfully estimated from the pixel values.

In the future, more suitable explanatory variables and the kernel function should be considered.

6. Acknowledgments

The authors would like to thank Dr. Ryoko Futami for his advice and comments. In addition, we would like to express our gratitude to the members of Dr. Futami's Lab for their help with our experiments.

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