# Independent component analysis of skin color image

**Norimichi Tsumura, Hideaki Haneishi, and Yoichi Miyake**

Department of Information and Image Science, Chiba University
1-33, Yayoi-cho, Inage-ku, Chiba 263-8522, JAPAN
Telephone: +81-43-290-3262 FAX: +81-43-290-3262
E-mail: tsumura@ics.tj.chiba-u.ac.jp

The spatial distributions of melanin and hemoglobin in human skin are separated by independent component analysis of skin color image. The analysis is based on the skin color model with assumptions; (1) spatial variation of color in the skin is caused by two pigments; melanin and hemoglobin, (2) their quantities are mutually independent spatially, (3) the linearity holds among the quantities and observed color signals in the optical density domain. The results of the separation agree well with the physiological knowledge. The separated components are synthesized to simulate the various facial color images by changing the quantities of the separated two pigments.

## 1. INTRODUCTION_

Skin color reproduction may be considered the most important problem for color reproduction of color film and color television systems[Hunt, 1995 #14]. With the recent progress of various imaging systems[Imai, 1996 #15; Yokoyama, 1997 #16; Hanarahan, 1993 #17; Yamaguchi, 1997 #9] such as multi-media, computer graphic and telemedicine systems, the skin color becomes increasingly important for communication, image reproduction on hardcopy and softcopy, medical diagnosis, cosmetic development and so on.

Human skin is the turbid media with multi-layered structure[Gemert, 1989 #12; Anderson, 1981 #13]. Various pigments such as melanin and hemoglobin are contained in the media. The slight changes of the structure and pigment construction produce rich skin color variation[Edwards, 1939 #18]. Therefore, it is necessary to analyze the skin color based on the structure and pigment construction in reproducing and diagnosing the various skin colors.

In this paper, the spatial distributions of melanin and hemoglobin in skin are separated by independent component analysis of skin color image. The independent component analysis(ICA) is a technique that extracts the original signals from mixtures of many independent sources without a priori information on the sources and the process of the mixture. The ICA has been applied to the various problems such as array processing, communication, medical signal processing, and speech processing[Karhunen, 1997 #10]. In the field of color image processing, Inoue et al.[Inoue, 1996 #28] proposed a technique to separate each pigment from compound color images. Their research is reviewed in Section 2 in this paper. However, they could not obtain any practical result, since they assumed the linearity among the quantities of pigments and observed color signals in the

intensity domain. In the intensity domain, generally, this linearity will not hold in practical applications. We improve their technique by processing the color signals in the density domain, and apply it to the skin color image. Moreover, we apply the result of the analysis to the separation and synthesis of a facial color image.

In Section 2, we review the independent component analysis for application to the color image separation, which is proposed in Ref. [Inoue, 1996 #28] In Section 3, the skin color is modeled based on the two pigments; melanin and hemoglobin in optical density domain. The result of the independent component analysis for skin color images is shown in Section 4. In Section 5, separated and synthesized facial color images are shown.

## 2. INDEPENDENT COMPONENT ANALYSIS

The ICA is a technique that extracts the original signals from mixtures of many independent sources without a priori information on the sources and the process of the mixture. To apply the ICA to color image separation, Inoue et al. considered that quantities of the pigments which construct the color are the original signals from independent sources, observed color signals are mixtures, pure color signals of the pigments indicate the process of the mixture of quantities[Inoue, 1996 #28] In this section, this technique is described based on the Ref. [Inoue, 1996 #28]

Simplifying the description, we assume that the media is constructed by two pigments and that it is captured by an imaging system with two color channels. This simplification does not prevent the generalization of the problem except when the number of pigments is larger than the number of channels. This is discussed later in this section.

Let $x_{l,m}(1)$ and $x_{l,m}(2)$ denote the quantity of the two pigments on the coordinate ($l$,$m$) in the digital color image, $\boldsymbol{a}(1)$ and $\boldsymbol{a}(2)$ denote

pure color vectors of the two pigments per unit quantity, respectively. Inoue at al. assumed $\boldsymbol{a}(1)$ and $\boldsymbol{a}(2)$ are different from each other. They also assumed the compound color vector $\boldsymbol{e}_{l,m}$ on the image coordinate (*l*,*m*) can be calculated by the linear combination of pure color vectors with the quantities of $x_{l,m}(1)$ and $x_{l,m}(2)$ as

$$\boldsymbol{e}_{l,m} = x_{l,m}(1)\boldsymbol{a}(1) + x_{l,m}(2)\boldsymbol{a}(2). \qquad (1)$$

Each element of the color vector indicates the pixel value of each channel. Denote now by $\mathrm{A} = [\boldsymbol{a}(1), \boldsymbol{a}(2)]$ the constant 2 x 2 mixing matrix whose column vectors are pure color vectors, and by $\boldsymbol{x}_{l,m} = [x_{l,m}(1), x_{l,m}(2)]^{\mathrm{t}}$ the quantity vector on the image coordinate (*l*,*m*). We can write the signal model in vector and matrix form as follows:

$$\boldsymbol{e}_{l,m} = \mathrm{A}\,\boldsymbol{x}_{l,m}. \qquad (2)$$

Inoue et al. also assumed that the elements $x_{l,m}(1)$ and $x_{l,m}(2)$ of the quantity vector are mutually independent for the image coordinate (*l*,*m*). Figures 1(a) and (b) show the process of the mixture and an example of probability density distribution of $x_{l,m}(1)$ and $x_{l,m}(2)$ that are mutually independent. Figure 1(c) shows the probability density distribution of $e_{l,m}(1)$ and $e_{l,m}(2)$ in the image, which are elements of compound color vector $\boldsymbol{e}_{l,m}$. It should be noted that the observed color signals $e_{l,m}(1)$ and $e_{l,m}(2)$ are not mutually independent. In Fig. 1(c), pure color vectors $\boldsymbol{a}(1)$ and $\boldsymbol{a}(2)$ are also shown to illustrate the relationship among the parameters.

By applying the ICA to the compound color vectors in the image, the relative quantity and pure color vector of each pigment are extracted without a priori information on the quantity and color vector under the

assumption that quantities of pigments are mutually independent for the image coordinate. Let us define the following equation using the separating matrix H and separated vector $\boldsymbol{s}_{l,m}$ as shown in Fig. 1(a).

$$\boldsymbol{s}_{l,m} = \mathrm{H}\,\boldsymbol{e}_{l,m}, \tag{3}$$

$$\mathrm{H} = [\boldsymbol{h}(1), \boldsymbol{h}(2)],$$

$$\boldsymbol{s}_{l,m} = [s_{l,m}(1), s_{l,m}(2)]^t$$

where $\boldsymbol{h}(1)$ and $\boldsymbol{h}(2)$ are separating vectors. By finding the appropriate separating matrix H, we can extract the mutually independent signals $s_{l,m}(1)$ and $s_{l,m}(2)$ from the compound color vectors in the image. Many methods are proposed to find the separating matrix H(for example [Burel, 1992 #6; Hyvärinen, 1997 #4; Jutten, 1991 #1; Karhunen, 1997 #5; Yang, 1997 #3]), such as using learning ability of artificial neural network[Karhunen, 1997 #5], optimization techniques based on fixed point method[Hyvärinen, 1997 #4].

The extracted independent signals $s_{l,m}(1)$ and $s_{l,m}(2)$ may correspond to $x_{l,m}(2)$ and $x_{l,m}(1)$, respectively, and it is impossible to determine the absolute quantities $x_{l,m}(1)$ and $x_{l,m}(2)$ without an additional assumption. Therefore the extracted independent vector $\boldsymbol{s}_{l,m}$ is given by

$$\boldsymbol{s}_{l,m} = \mathrm{R}\Lambda\,\boldsymbol{x}_{l,m}, \tag{4}$$

where R is the permutation matrix that may substitute the elements of the vector each other, $\Lambda$ is the diagonal matrix to relate the absolute

quantities to relative qualities. Substituting Eqs. (2) and (3) into Eq. (4) gives

$$\mathrm{HA}\,\boldsymbol{x}_{l,m} = \mathrm{R}\Lambda\,\boldsymbol{x}_{l,m}. \qquad (5)$$

Taking Eq. (5) in the arbitrary quantity vector, the matrix HA should be equal to the matrix RΣ, and the mixing matrix A is calculated by using the inverse matrix of H as follows:

$$\mathrm{A} = \mathrm{H}^{-1}\mathrm{R}\Lambda\ . \qquad (6)$$

Note that what we can obtain by the ICA are relative quantities and directions of compound color vectors. In our application of color image separation and synthesis, however, the absolute values are not required.

If the number of pigments is larger than the number of channels, it is impossible to extract the independent components caused by reduction of the signals. On the other hand, if the number of pigments is smaller than the number of channels, it is possible to make the number of channels equal to the number of pigments by using the principal component analysis[Karhunen, 1997 #5]. This technique is also used in our analysis.

## 3. SKIN COLOR MODEL

Schematic model of human skin is shown in Fig. 2 with plane parallel epidermal and dermal layers. The epidermal and dermal layers are the turbid media. Various pigments such as melanin, hemoglobin, bilirubin, and β-carotene are contained in the layers, especially melanin and hemoglobin are dominantly contained in the epidermal and dermal layer, respectively.

Figure 3(a) shows skin color image with 64 x 64 pixels used for the ICA. The image is extracted from the forehead of the facial image with 300 x 450 pixels taken by HDTV camera(Nikon HQ1500C) with 1920 x 1035 pixels. The facial image is shown in Fig. 3(b), the extracted area is surrounded by a white square. The subject was not wearing makeup and lipstick. Each pixel of these color images has three channels; red, green and blue. Let $r_{l,m}$, $g_{l,m}$, $b_{l,m}$ be the pixel values in red, green and blue channels of the skin color image on the image coordinate ($l$,$m$), respectively.

Analyzing the above skin color, we made four assumptions on skin color. First, the Lambert-Beer law or modified Lambert-Beer law[Hiraoka, 1993 #21] holds in the reflected light among the quantities and observed color signals. Second, spectral distribution of the skin is not abrupt in the sensitive spectral range of each channel in the imaging system. Third, the spatial variations of color in the skin are caused by two pigments; melanin and hemoglobin. Fourth, these quantities are mutually independent spatially.

The first assumption assures the linearity among the observed color signals and pure color signals of pigments in the spectral density domain. In the optical density domain of three channels; $-\log(r_{l,m})$, $-\log(g_{l,m})$ and $-\log(b_{l,m})$ , the linearity is assured by including the second assumption. This is because that the signal value of the each channel is obtained by the integration of spectral intensity with respect to wavelength in the sensitive spectral range of each channel in the imaging system, and the integration can be approximated as a product of the intensity at a wavelength by a constant, if the spectral distribution of the skin is approximated as flat in the sensitive spectral range. On the basis of the linearity and the third assumption, the color in skin image is modeled as Fig. 4 in the optical density domain of three channels. It is seen that the

three densities of skin color are distributed on the two dimensional plane spanned by pure color vectors of melanin and hemoglobin. Denote by $\boldsymbol{c}_{l,m}$ color density vector on image coordinate ($l$,$m$) as

$$\boldsymbol{c}_{l,m} = \left[-\log(r_{l,m}), -\log(g_{l,m}), -\log(b_{l,m})\right]^t, \quad (7)$$

where $[\cdot]^t$ represents transposition. According to the skin color model shown in Fig. 4, the color density vector of skin can be expressed by

$$\boldsymbol{c}_{l,m} = q_{l,m}(1)\boldsymbol{c}(1) + q_{l,m}(2)\boldsymbol{c}(2) + \boldsymbol{c}(3), \quad (8)$$

where $\boldsymbol{c}(1)$ and $\boldsymbol{c}(2)$ are pure density vectors of hemoglobin and melanin (or melanin and hemoglobin), $q_{l,m}(1)$ and $q_{l,m}(2)$ are relative quantities of the pigments respectively, $\boldsymbol{c}(3)$ is spatially stationary vector caused by other pigments and skin structure. The vectors $\boldsymbol{c}(1)$ and $\boldsymbol{c}(2)$ are normalized as $\|\boldsymbol{c}(1)\| = \|\boldsymbol{c}(2)\| = 1$, where $\|\cdot\|$ is the operation of Euclidean norm. Equation (8) is written in vector and matrix form using the pure color density matrix $\mathrm{C} = [\boldsymbol{c}(1), \boldsymbol{c}(2)]$ and quantity vector $\boldsymbol{q}_{l,m} = [q_{l,m}(1), q_{l,m}(2)]^t$ as

$$\boldsymbol{c}_{l,m} = \mathrm{C}\,\boldsymbol{q}_{l,m} + \boldsymbol{c}(3) \quad (9)$$

It is easily understood that the ICA described in Section 2 can be applied in the two dimensional plane spanned by $\boldsymbol{c}(1)$ and $\boldsymbol{c}(2)$ to estimate the quantity vector $\boldsymbol{q}_{l,m}$ from color density vectors $\boldsymbol{c}_{l,m}$. Principal component analysis(PCA) is used to extract the two-dimensional plane. Figure 5 shows the relationship between the number of principal components used and cumulative contribution ratio. The values of three channels can be adequately described by using the two principal ergeformat and EMBacy of 99.3%. Let denote the first, second and third principal component vectors as $\boldsymbol{p}(1)$, $\boldsymbol{p}(2)$ and $\boldsymbol{p}(3)$,

third principal component vectors as $\boldsymbol{p}(1)$, $\boldsymbol{p}(2)$ and $\boldsymbol{p}(3)$, respectively. It is noted that $\boldsymbol{p}(1)$, $\boldsymbol{p}(2)$ will span the two dimensional space spanned by $\boldsymbol{c}(1)$ and $\boldsymbol{c}(2)$.

Here define the projection matrix $\mathrm{PP}^{\mathrm{t}} = [\boldsymbol{p}(1), \boldsymbol{p}(2)][\boldsymbol{p}(1), \boldsymbol{p}(2)]^{\mathrm{t}}$ onto the two dimensional space spanned by $\boldsymbol{c}(1)$ and $\boldsymbol{c}(2)$. Based on the projection, the color density vector $\boldsymbol{c}_{l,m}$ can be divided into two components as follows:

$$\boldsymbol{c}_{l,m} = \mathrm{P}\ \mathrm{P}^{\mathrm{t}}\boldsymbol{c}_{l,m} + (\mathrm{I}\text{-}\mathrm{P}\ \mathrm{P}^{\mathrm{t}})\ \boldsymbol{c}_{l,m}, \qquad (10)$$

where matrix $\mathrm{I}$ denotes an identity matrix. The first term indicates the component in the two dimensional subspace spanned by $\boldsymbol{c}(1)$ and $\boldsymbol{c}(2)$ or $\boldsymbol{p}_1$ and $\boldsymbol{p}_2$. The second term indicates the component in the one dimensional subspace which is spanned by $\boldsymbol{p}_3$. Substituting Eq. (9) into Eq. (10), it is shown in Eq. (11) that the second term is independent of the quantities $\boldsymbol{q}_{l,m}$ .

$$\boldsymbol{c}_{l,m} = \mathrm{P}\ \mathrm{P}^{\mathrm{t}}\{\mathrm{C}\,\boldsymbol{q}_{l,m} + \boldsymbol{c}(3)\} + (\mathrm{I}\text{-}\mathrm{P}\ \mathrm{P}^{\mathrm{t}})\ \boldsymbol{c}(3). \quad (11)$$

## 4. SKIN COLOR IMAGE SEPARATION

The skin color model proposed in Section 3 is used to extract the unknown color density matrix $\mathrm{C}$ and unknown relative quantity vectors $\boldsymbol{q}_{l,m}$. The flowchart of the extraction is shown in Fig. 6 with the computation in Section 3.

Let us define the score vector $\boldsymbol{w}_{l,m}$ in the first term of Eq. (11) as

$$\boldsymbol{w}_{l,m} = \mathrm{P}^{\mathrm{t}}\{\mathrm{C}\,\boldsymbol{q}_{l,m} + \boldsymbol{c}(3)\} \qquad (12)$$

Equation (12) is rewritten as

$$\boldsymbol{w}_{l,m} = \mathrm{P}^{\mathrm{t}}\mathrm{C}\ \boldsymbol{q}'_{l,m}, \qquad (13)$$

where

$$\boldsymbol{q}'_{l,m} = \boldsymbol{q}_{l,m} + (\mathrm{P}^{\mathrm{t}}\mathrm{C})^{-1}\mathrm{P}^{\mathrm{t}}\boldsymbol{c}(3). \qquad (14)$$

Making the task of ICA easier[Karhunen, 1997 #5], the elements in score vector $\boldsymbol{w}_{l,m}$ were made zero mean by subtracting the mean vector $\overline{\boldsymbol{w}}$, and made unit variance by multiplying the inverse square root of the 2 x 2 diagonal matrix $\mathrm{D} = \mathrm{diag}[\lambda(1), \lambda(2)]$, where $\lambda(1)$ and $\lambda(2)$ denote the eigenvalues for the first and second principal components respectively. The whitened vector denoted by $\boldsymbol{e}_{l,m}$ is written as

$$\boldsymbol{e}_{l,m} = \mathrm{D}^{-1/2}(\mathrm{P}^{\mathrm{t}}\mathrm{C}\ \boldsymbol{q}'_{l,m} - \overline{\boldsymbol{w}}). \qquad (15)$$

Equation (15) is rewritten as

$$\boldsymbol{e}_{l,m} = \mathrm{D}^{-1/2}\mathrm{P}^{\mathrm{t}}\mathrm{C}\ \boldsymbol{x}_{l,m}, \qquad (16)$$

where

$$\boldsymbol{x}_{l,m} = \boldsymbol{q}'_{l,m} - (\mathrm{P}^{\mathrm{t}}\mathrm{C})^{-1}\overline{\boldsymbol{w}}. \qquad (17)$$

Here, we define the $A = \mathrm{D}^{-1/2}\mathrm{P}^{\mathrm{t}}\mathrm{C}$, then we get Eq. (18) that is as same as Eq. (2).

$$\boldsymbol{e}_{l,m} = \mathrm{A}\,\boldsymbol{x}_{l,m} \qquad (18)$$

The whitened vector $\boldsymbol{e}_{l,m}$ is considered as the compound color vector in Eq. (2) , and the vector $\boldsymbol{x}_{l,m}$ in Eq. (18) as the quantity vector in Eq. (2). The separation matrix $\mathrm{H}$ is obtained by the ICA for the normalized vectors $\boldsymbol{e}_{l,m}$, and the mixing matrix is calculated by Eq. (6). Substituting the $A = \mathrm{D}^{-1/2}\mathrm{P}^{\mathrm{t}}\mathrm{C}$ into the Eq. (6) and solving for the color matrix C, the estimated matrix $\tilde{C}$ of pure color densities is calculated as,

$$\tilde{C} = (\mathrm{D}^{-1/2}\mathrm{P}^{\mathrm{t}})^{-1}\mathrm{H}^{-1}R\Lambda \ . \qquad (19)$$

The diagonal matrix $\Lambda$ was decided to normalize the matrix $\tilde{C}$ as $\|\boldsymbol{c}(1)\| = \|\boldsymbol{c}(2)\| = 1$, permutation matrix R was an identity matrix in this paper.

Each element of separation matrix H was obtained by minimizing the Burel's independence evaluation value[Burel, 1992 #6] for the elements of vector $\boldsymbol{s}_{l,m}$. The independence evaluation value ranges from 0 to 1, and if the value is 0, the signals are mutually independent. The minimization is performed by quasi-Newton implementation using the MATLAB tool box[Garce, 1992 #8]. Figures 7(a) and (b) show the distribution of observed signals $e_{l,m}(1)$ and $e_{l,m}(2)$, and resultant signals $s_{l,m}(1)$ and $s_{l,m}(2)$ respectively. The independence evaluation value for the observed signals and resultant signals were 0.2414 and 0.0081, respectively. We can conclude that $s_{l,m}(1)$ and $s_{l,m}(2)$ are fairly independent of each other from the independence evaluation value of 0.0081[Burel, 1992 #6], therefore melanin and hemoglobin were distributed independently in the skin color image.

The quantity vector is estimated by using the estimated pure color matrix $\tilde{C}$ . Replacing the color matrix C with the estimated matrix $\tilde{C}$ in Eq. (9), and solving for quantity vector $\boldsymbol{q}_{l,m}$, the estimated quantity vector $\tilde{\boldsymbol{q}}_{l,m}$ is given by

$$\tilde{\boldsymbol{q}}_{l,m} = \tilde{\mathrm{C}}^{+}\boldsymbol{c}_{l,m} - \boldsymbol{b}, \qquad (20)$$

where $\tilde{\mathrm{C}}^{+}$ is the Moore-Penrose's generalized inverse matrix of $\tilde{\mathrm{C}}$, and $\boldsymbol{b}$ is defined by $\tilde{\mathrm{C}}^{+}\boldsymbol{c}(3)$. The vector $\boldsymbol{c}(3)$ is unknown, therefore, we assumed that the smallest value of each element in $\boldsymbol{q}_{l,m}$ in skin image is zero, then $\boldsymbol{b}$ is calculated by

$$\boldsymbol{b} = \min_{l,m}(\tilde{\mathrm{C}}^{+}\boldsymbol{c}_{l,m}), \qquad (21)$$

where $\min_{l,m}(\boldsymbol{x})$ produces the smallest element of the vector $\boldsymbol{x}$ in the image and gives them in vector form.

According to the above analysis, the color separation and synthesis equation is written by

$$\boldsymbol{c'}_{l,m} = \tilde{\mathrm{C}}\{K(\tilde{\mathrm{C}}^{+}\boldsymbol{c}_{l,m} - \boldsymbol{b}) + j\boldsymbol{b}\} + j(\mathrm{I}\text{-}\mathrm{P}\,\mathrm{P}^{\mathrm{t}})\,\boldsymbol{c}_{l,m}, \qquad (22)$$

where $\boldsymbol{c'}_{l,m}$ is the synthesized color, $K$ is the diagonal matrix to change the quantities of pigments $\boldsymbol{q}_{l,m}(=\tilde{\mathrm{C}}^{+}\boldsymbol{c}_{l,m} - \boldsymbol{b})$, $j$ is the value to change quantities of stationary color vector $\boldsymbol{c}(3)$. We call the $K$ and $j$ synthesis parameters.

Figures 8 (a) and (b) show the separated two independent components; first and second independent components, respectively. We set the synthesis parameters as $K = \mathrm{diag}[1,0]$ and $j = 0$ in Fig. 8(a), $K = \mathrm{diag}[0,1]$ and $j = 0$ in Fig. 8(b). It is assumed that the first and second independent components are caused by hemoglobin and melanin, respectively, since the pimples are seen in the first independent component and not seen in the second independent component.

## 4. FACIAL COLOR IMAGE SEPARATION AND SYNTHESIS

The main variations of the facial color are caused by the quantity variation of the hemoglobin and melanin. It is possible to simulate the facial color variation by synthesizing the separated two components with the increase or decrease of each separated quantity.

We applied the color separation and synthesis equation Eq. (22) to the facial image shown in Fig. 3(b). The coefficients of the equation were obtained by analyzing the skin color image shown in Fig. 3(a). Figures 9 (a) and (b) show separated two images corresponding to the first and second independent components, respectively. We set the synthesis parameters as $K = \mathrm{diag}[1,0]$ and $j = 0$ in Fig. 9(a), $K = \mathrm{diag}[0,1]$ and $j = 0$ in Fig. 9(b). Note that there is a little melanin at the lip region in Fig. 9(b). This result agrees well with the physiological knowledge. However, the region of hair is mistakenly separated into the region of hemoglobin. We considered that skin model does not hold in the hair.

Figures 10(a), (b), (c), and (d) show simulated results of facial color variation based on the independent component. We set the synthesis parameters as $K = \mathrm{diag}[2,1]$ and $j = 1$ in Fig. 10(a), $K = \mathrm{diag}[3,1]$ and $j = 1$ in Fig. 10(b), $K = \mathrm{diag}[1,2]$ and $j = 1$ in Fig.10(c), $K = \mathrm{diag}[1,3]$ and $j = 1$ in Fig. 2(d). If the estimated quantity at a certain point is smaller than the corresponding element of $\boldsymbol{b}$ in Eq.(22), the parameters are set as $K = \mathrm{diag}[1,1]$ and $j = 1$ to hold the image quality in the regions of hair, background and so on. It is seen in Fig. 10(a) that the pimples are enhanced by the increase of the hemoglobin, and in Fig. 10(b) the whole facial color becomes flushed, as if the lady is in the high temperature room. It is seen in Figs 10(d) and (e) that the facial colors become more brownish, as if the lady got a suntan. It is also seen that the highlights were emphasized relatively in the synthesized image in Fig. 10.

This is because we assumed that the smallest value of each quantity in skin image is zero in Eq. (21). The highlights were caused by the geometry of environmental illuminant in Fig. 2(b).

## 5. CONCLUSION AND DISCUSSION

The skin and facial color image were separated into two images by independent component analysis in optical density domain of three color channels. We believe that the images correspond to distributions of the melanin and hemoglobin, respectively, because the result of separation agreed well with the physiological knowledge. The separated components were synthesized to simulate the various facial color images by changing the quantities of the separated two pigments.

Many assumptions were made in the analysis; (1)linearity among the quantities and observed color signals in the optical density domain, (2)spatial color variation caused by only two pigments, (3)spatial independence of the two pigments, (4) zero quantity in a certain point of the skin image. From the results of PCA and ICA, we can conclude that the linearity, the spatial color variation, and the spatial independence were confirmed in our experiments. In applying this technique to various parts of the body, however, it will be necessary to consider the violation of these assumptions depending on the area of skin image, skin structure, skin condition and so on. In addition to the above assumptions, we have assumed implicitly that pure color vectors of pigments will not change spatially. However, hemoglobin has two types of state; Oxy-hemoglobin($HbO_2$) and Deoxy-hemoglobin(Hb). The spectral absorptions are different from each other, and ratio between $HbO_2$ and Hb will change spatially in a large area of skin image or in the area of skin diseases[Dwyer, 1997 #20]. Applying this technique to such images, the ICA for the skin

color images should be improved by using artificial neural network that is adaptive to the fluctuation of the system.

The values of three color channels are dependent on the imaging device. Therefore, it was impossible to discuss the separated colors directly in this paper. The proposing techniques should be applied to calibrated image or spectral reflectance image.

In the synthesis of facial color, the quantities of pigments are simply changed doubled and tripled in this paper. Various image processing techniques will give rich variations of facial color image, and knowledge of physiological phenomenon will help the techniques to reproduce the realistic variation of facial color.

## ACKNOWLEDGMENTS

A part of this research was supported by Photographic Research Fund of Konica Imaging Foundation.

## REFERENCES

3. Y. Yokoyama, N. Tsumura, H. Haneishi, Y. Miyake, J. Hayashi and M. Saito, "A new color management system based on human perception and its application to recording and reproduction of art printing," IS&T/SID's 5th Color Imaging Conference, Color Science, Systems and Appl. 169-172 (Scottsdale, Arizona, November 17-20, 1997).

4. P. Hanarahan and W. Krueger, "Reflection from layered surfaces due to subsurface scattering," Proc. SIGGRAPH 93 165-174 (Anaheim, California, 1-6 Augest, 1993).

9. J. Karhunen, A. Hyvarinen, R. Vigário, J. Hurri and E. Oja, "Applications of neural blind separation to signal and image processing," Proceedings of IEEE International Conference on Acoustics, Speech, and Signal Processing **1**, 131-134 (Munich, Germany, April 21-24, 1997).

10. T. Inoue, Y. Fujii, K. Itoh and Y. Ichioka, "Independent component analysis for a small number of elements in high-dimensional space," Japan Optics '95 Extended abstracts, 105-106 (Tokyo, September 20-22, 1995).

**Figure Captions**

Fig. 1 Mixture and separation of independent signals; (a) flow of the signals, (b) an example of probability density distribution of $x_{l,m}(1)$ and $x_{l,m}(2)$, (c) $e_{l,m}(1)$ and $e_{l,m}(2)$, and (d) $s_{l,m}(1)$ and $s_{l,m}(2)$.

Fig. 2 Schematic model of human skin with plane parallel epidermal and dermal layers

Fig. 3 The analyzed color images; (a)skin color image with 64 x 64 pixels, (b)facial image color image with 1920 x 1035 pixels. The skin color image is extracted from the forehead of the facial image. The extracted area is surrounded by white square.

Fig. 4 Skin color model in the optical density domain of three channels

Fig. 5 Relationship between the number of principal components used and cumulative contribution ratio in skin colors of three channels.

Fig. 6 Flowchart of the preprocessing and independent component analysis for skin color image

Fig. 7 Distribution of (a) observed signals $e_{l,m}(1)$, $e_{l,m}(2)$, and (b) separated signals $s_{l,m}(1)$, $s_{l,m}(2)$.

Fig. 8 Separated two independent components of the skin color image; (a) first and (b) second independent components. The synthesis

parameters are set as (a) $K = \mathrm{diag}[1,0]$ and $j = 0$ , (b) $K = \mathrm{diag}[0,1]$ and $j = 0$ .

Fig. 9 Separated two images corresponding to (a) first and (b)second independent components. Synthesis parameters are set as (a) $K = \mathrm{diag}[1,0]$ and $j = 0$ in , (b) $K = \mathrm{diag}[0,1]$ and $j = 0$.

Fig. 10 Simulated images of facial color variation based on the independent component. The synthesis parameters are set as (a) $K = \mathrm{diag}[2,1]$ and $j = 1$ , (b) $K = \mathrm{diag}[3,1]$ and $j = 1$ , (c) $K = \mathrm{diag}[1,2]$ and $j = 1$, (d) $K = \mathrm{diag}[1,3]$ and $j = 1$.