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Preferred Skin Color Reproduction Based on *Y*-Dependent Gaussian Modeling of Skin Color

Sung-Jin Kang, Oh-Yeol Kwon, and Sung-Il Chien
School of Electrical Engineering and Computer Science, Kyungpook National University, IR1-812, 1370 Sangyuk-dong, Buk-gu, Daegu, Korea 702-701
E-mail: sichien@ee.knu.ac.kr

Abstract. *The authors present a method of modeling skin color using three Gaussian distributions on (Y, u′,v′) chromaticity coordinates and transforming skin color pixels into preferred color zone. Elaborate modeling enables us to adaptively change degree of movement to reduce contour artifacts arising from transformation and to obtain more natural feeling in the transformed skin color domain. It is also shown that our method can achieve relatively fast operation without introducing an extra frame memory. © 2011 Society for Imaging Science and Technology.*
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INTRODUCTION

Observer's preference is one of important measures for evaluation of image quality and improvement of display equipments.[1,2] Preference indicates degree of satisfaction of an observer with respect to an image. Research for preferred reproduction of colors is mostly performed on colors of sky, grass, and skin.[3,4] Among these three colors, much emphasis is put on skin color because it occupies a relatively large region in reproduced video signals, and observers are more interested in facial skin than in other components. Thus, observers notice improvement of image quality much more when preferred skin color is reproduced preferably than they do for other components.

So far, much research on reproduction of preferred skin color has been performed.[5–8] Lee and Ha[5] proposed an algorithm reproducing preferred skin color by adjusting voltage intensity of video signals in an analog television. Yet this algorithm is not appropriate to current digital broadcasting systems, and coordinates of the preferred skin color in this algorithm are quite different from those proposed in recent research, so it seems difficult to apply it to actual digital imagery. A hue shift method proposed by Philips produces preferred skin color by shifting a hue to a preferred axis, but it does not consider saturation of skin color. Sanger et al.[6] proposed a technique of detecting facial regions and reproducing its preferred color from negative film. They can determine the chromaticity distributions of skin color for three races and their preferred distribution in (u',v') chromaticity coordinates. Yet their approach did not provide a detailed technique of transformation and did not address related issues such as artifact problems and computational expense. You et al.[7] proposed a preferred skin color reproduction method using an affine transform from detected skin color to preferred skin color in (u',v') chromaticity coordinates and introduced an erosion based technique to reduce contour artifacts. This method does not consider luminance Y of skin color pixels, which also affects visual impression of a skin color considerably. Kim et al.[8] modeled a preferred skin color region with a set of ellipses according to average luminance of skin color in (u',v') chromaticity coordinates. Although this method adjusts size of the preferred skin color region according to average luminance of the skin color region, it rather weakens the three-dimensional feeling of a face, since all detected skin colors are converted into a color region of elliptical shape regardless of Y variations.

In this article, skin color regions of an input image are converted into (Y, u',v') chromaticity coordinates and are classified into three skin regions according to Y value. Each classified skin color region is modeled by a two-dimensional (2-D) Gaussian density distribution in (u',v') chromaticity coordinates. By use of these three models, we define three representative skin color ellipses, which can cover most skin pixels, and three affine transform matrices are constructed to move input skin color pixels to the preferred skin color zone. Since skin color detection is not perfect, such transformation may generate contour artifacts around the skin color regions, which are visually quite irritating and thus, severely degrade quality of the resultant image. Although You et al.[7] introduced an erosion operation to avoid such artifacts, this operation is computationally expensive without an extra frame memory. Our proposed method adjusts amount of movement of skin colors adaptively for three skin ellipses depending on Y and area of the preferred skin ellipse in order to minimize such artifacts. At the same time, the proposed method can achieve relatively fast computation without extra frame memory because time-consuming erosion operations are no longer used.

SKIN COLOR DETECTION AND PREFERRED SKIN COLOR REPRODUCTION

RGB values of a facial image are converted into (Y, u',v') chromaticity coordinates, and skin color is detected in

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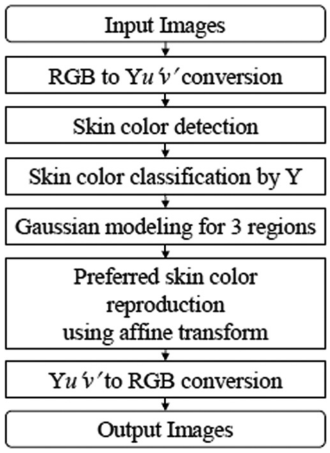


Figure 1. Overall block diagram of proposed method.

(Y, u', v') chromaticity coordinates. Then, skin color regions are classified into three skin color regions according to Y value. For each region, Gaussian modeling is performed and a preferred skin color is reproduced using an affine transform from Gaussian ellipses into a target ellipse. An overall diagram of preferred skin color reproduction based on an affine transform and three elliptical Gaussian models is shown in Figure 1.

Skin Color Region Detection

Skin color detection is a first step in reproduction of preferred skin color because robust skin color detection can guarantee good performance in color reproduction. To segment out skin color, we use a decision boundary in HSV color space, which is defined by

$$0^\circ \le H \le 50^\circ, \quad 0.1 \le S \le 0.68, \quad 0.35 \le V \le 1, \tag{1}$$

where the original level of S (saturation) is somewhat lowered in our case[9] in order to allow more bright pixels to be detected as skin colors, since our method is capable of dealing with bright or light skin colors. RGB values of input video sequences are transformed into CIE XYZ values by 3×3 transform matrix composed of NTSC phosphor and D65 standard white reference colors, and XYZ values are transformed into (Y, u', v') chromaticity coordinates by Eq. (2)[10]

$$u' = \frac{4X}{X + 15Y + 3Z}, \qquad v' = \frac{9Y}{X + 15Y + 3Z}. \tag{2}$$

Consequently, once RGB values of the input image are converted into (Y, u', v') chromaticity coordinates, pixels located inside the skin color detection gamut shown in Figure 2(a) are detected as skin colors; skin colors can be projected into (u', v') coordinates and their projected values are shown in Fig. 2(b). In this case, the decision boundary has quadrilateral shape.

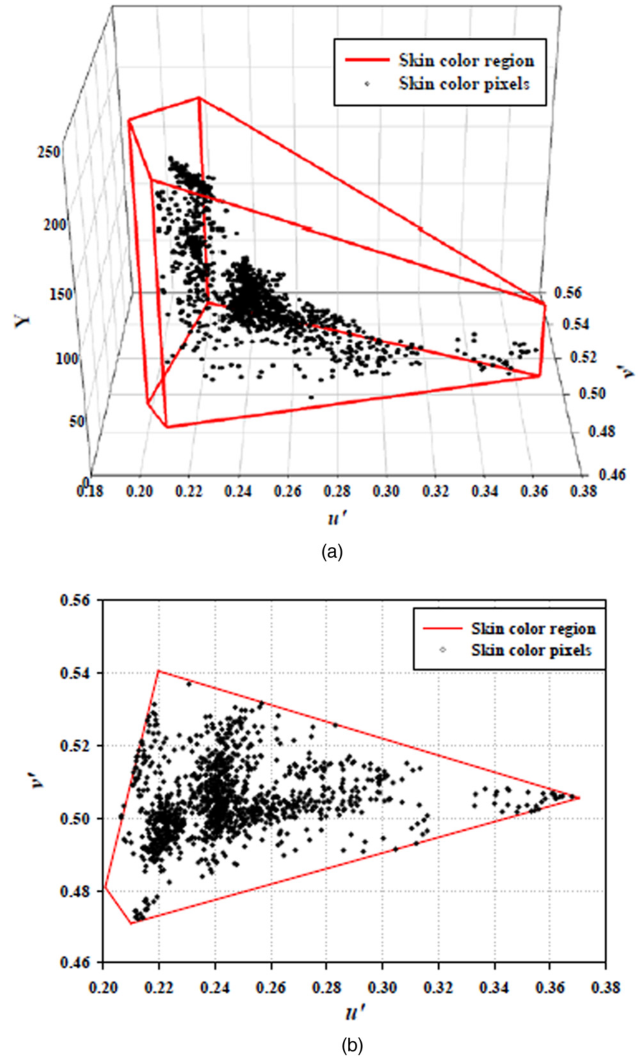


Figure 2. (a) Skin color detection gamut in (Y, u', v') chromaticity coordinates and (b) projected skin colors in (u', v') coordinates.

Y-Dependent Modeling of Skin Color Region

We gather sample points corresponding to skin color pixels from 100 images including bright and dark skin images. Here, a bright skin color means that its Y value is relatively high, while a dark skin means that its Y value is relatively low, without any implication of racial tendency in skin color. Next, we transform them into points in (Y, u', v') chromaticity coordinates. A typical distribution is displayed in Figure 3. Dark regions of skin color often appear in shadows on a face or neck and spread over most part of the detection region when projected to (u', v') chromaticity coordinates. As for this dark region, we are hardly aware of much change in color even if the color is transformed significantly in (u', v') coordinates when Y does not change. On the other hand, most skin color pixels that influence an observer's preference are mainly distributed on smaller parts of skin color regions with luminance values Y above a certain threshold. So far conventional methods[5–7] without consideration of Y have employed an elliptical Gaussian model in (u', v') chromaticity coordinates to reproduce

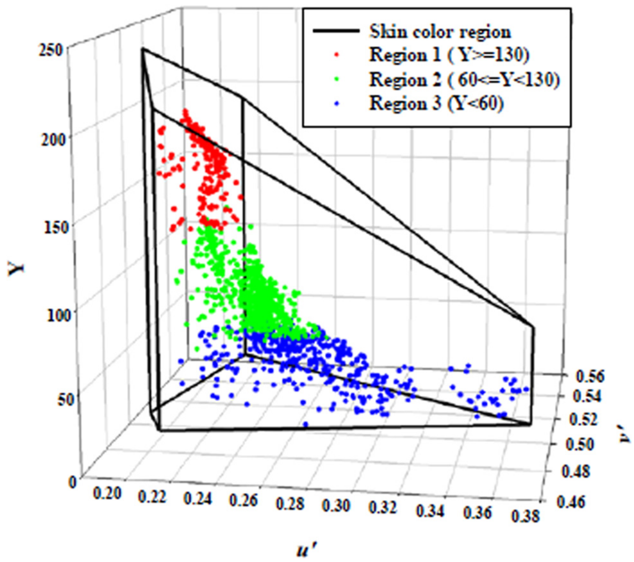


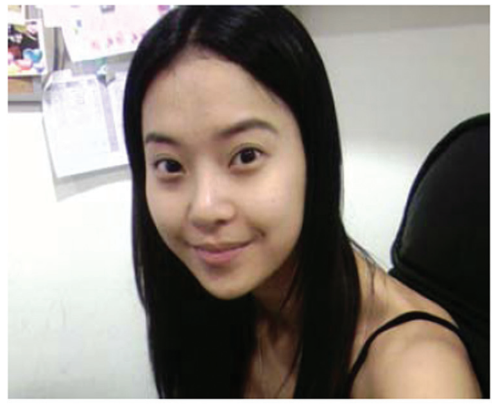
Figure 3. Distribution of skin color in (Y, u', v') chromaticity coordinates.

preferred skin color. This Gaussian ellipse covers most of the detection region in (u', v') chromaticity coordinates to include large dark regions of skin color. So when preferred skin color is reproduced by use of an affine transform from a Gaussian ellipse into a target ellipse, it is observed that the three-dimensional feeling of a face is sometimes weakened because skin color pixels that most influence an observer's preference are often located in a narrow region of (u', v') space. Thus, special treatment of influential skin color pixels with higher Y values is helpful to obtain the best performing transformation. Consequently, we propose to divide a skin color region into three color regions using Y, and preferred skin color is reproduced by performing elliptical Gaussian modeling of them individually and transforming each of them into a target ellipse, respectively. Here, most bright skin pixels also are treated independently because they are located near white color regions with highest Y values, and they are sometimes out of color gamut when transformed into the preferred skin color ellipse. Still, change in Y value is prone to introducing intolerable artifacts in the transformed image, which cannot be allowed. This artifact issue will be detailed later.

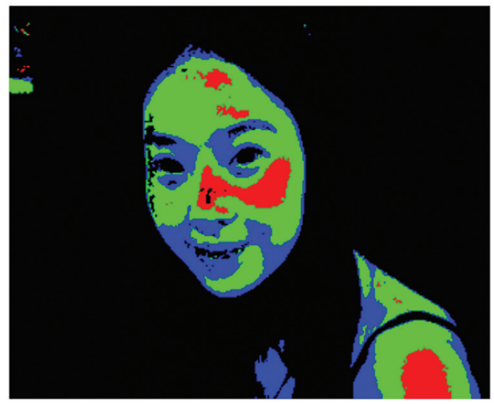
As shown in Fig. 3, skin color regions are classified into three types according to Y.

(1) When Y is larger than threshold level 130, the skin color region is classified into region 1 and is expressed as red in Fig. 3. It occupies a relatively narrow region on (u', v') space and its Y value changes almost vertically. As region 1 includes highlight regions of skin color, this region is considerably affected by illumination.

(2) When Y is between threshold levels of 130 and 60, skin color region is classified into region 2 and is expressed as green in Fig. 3. This region occupies a large part of a facial image and greatly influences an observer's preference.



(a)



(b)

Figure 4. Segmentation of skin color in image: (a) original image and (b) three regions of skin color classified by Y.

(3) When Y is smaller than threshold level 60, skin color region is classified into region 3 and is expressed as blue in Fig. 3. This region usually corresponds to shadows on a face or neck and is distributed widely inside the detection boundary. There is scarcely much change of Y in this region.

Adaptive thresholding of Y can be considered, but it is found through several experiments that the experimental result does not change much when thresholds have been changed slightly. A sample image segmented by two different thresholds is displayed in Figure 4.

Elliptical Gaussian Model for Skin Color Region

Detected pixels in each region are projected onto (u', v') chromaticity coordinates, where skin color pixels are modeled by two-dimensional Gaussian density distributions in (u', v') space, as given by Duda et al.[11] and Yang et al.[12]

$$p(\mathbf{x}) = \frac{1}{2\pi|\sum|^{1/2}} \exp\left(-\frac{1}{2}\lambda^2\right),$$
$$\lambda^2 = (\mathbf{x} - \mu)^t \sum^{-1} (\mathbf{x} - \mu). \tag{3}$$

Here, $\mathbf{x}$ is input vector defined by $\mathbf{x} = (u', v')^t$, μ is its mean vector, and Σ is its 2×2 covariance matrix.[7]

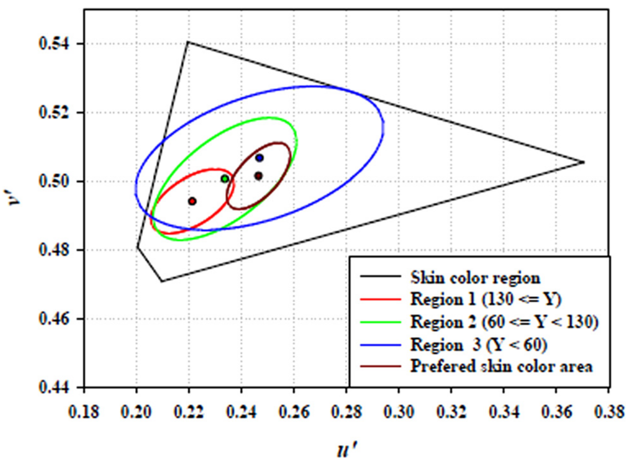


Figure 5. Three skin color ellipses and preferred skin color ellipse.

Mahalanobis distance λ is measured between $\mathbf{x}$ and μ. A set of points with constant λ constitutes an ellipse in 2-D space.[13] Probability that $\mathbf{x}$ will be within the ellipse is given by

$$\Pr\left[(\mathbf{x}-\mu)^t \sum^{-1}(\mathbf{x}-\mu) \le \chi^2\right] = 1-\alpha, \tag{4}$$

where α is called a significance level. The ellipse defined by

$$(\mathbf{x}-\mu)^t \sum^{-1}(\mathbf{x}-\mu) = \chi^2, \tag{5}$$

which is called a $(1-\alpha) \times 100\%$ prediction ellipse for a normal random vector with a given Chi square (χ^2) value. The relationship between χ^2 and α is available elsewhere.[14] For our case, α is determined to be 0.05 and a prediction ellipse of 95% is obtained, which means that with a probability of 0.95 skin colors will be located inside a given skin color ellipse.

Mahalanobis distance (λ) is obtained when mean $(\mu_{u'}, \mu_{v'})$ and variances ($\sigma_{u'}$, $\sigma_{v'}$, and $\sigma_{u'v'}$) are given by

$$\lambda^2 = \frac{1}{(1-\rho^2)}\left(\frac{(u'-\mu_{u'})^2}{\sigma_{u'}^2} + \frac{(v'-\mu_{v'})^2}{\sigma_{v'}^2} - \frac{2\rho(u'-\mu_{u'})(v'-\mu_{v'})}{\sigma_{u'}\sigma_{v'}}\right), \tag{6}$$

where ρ is defined as

$$\rho = \frac{\sigma_{u'v'}}{\sigma_{u'}\sigma_{v'}}. \tag{7}$$

Preferred Skin Color Reproduction Using Affine Transform

To reproduce preferred skin color, three affine transforms from three detected skin color ellipses modeling three segmented skin colors to the preferred skin color ellipse will be performed, and these ellipses are shown in Figure 5. So far definitive preferred skin color has not been agreed on by researchers, and we feel that the preferred skin color point given by Kim and Oh[1] is most suitable. Yet a different choice will produce a skin color of a different color tone, and thus, its choice should be determined by preference of viewers. Instead of a single center point, a preferred or target skin ellipse is often used to reduce artifacts due to transformation, and for this reason we adopt ellipse parameters such as rotation angle and lengths of major and minor axes proposed by Sanger et al.[6]

Let initial and preferred skin color values be (u'_S, v'_S) and (u'_P, v'_P), respectively; input skin color is converted to preferred skin color by Eq. (8)

$$[\,u'_P \quad v'_P \quad 1\,]^T = \mathbf{M}_T [\,u'_S \quad v'_S \quad 1\,]^T, \tag{8}$$

where $\mathbf{M}_T$ is the 3×3 matrix for skin color transformation, which is composed of five matrices as follows:[8]

$$\mathbf{M}_T = \mathbf{M}_{O\mathrm{Trans}}\mathbf{M}_{O\mathrm{Rot}}\mathbf{M}_{\mathrm{Sc}}\mathbf{M}_{I\mathrm{Rot}}\mathbf{M}_{I\mathrm{Trans}}. \tag{9}$$

Here, $\mathbf{M}_{I\mathrm{Trans}}$ is used to translate the center point of the detected skin color ellipse to the origin of coordinates, and $\mathbf{M}_{I\mathrm{Rot}}$ is a matrix that rotates detected skin colors so that the angle of its major axis becomes 0°. $\mathbf{M}_{\mathrm{Sc}}$ rescales the detected skin color ellipse to match the preferred skin color ellipse, and $\mathbf{M}_{O\mathrm{Rot}}$ is a rotation matrix, which aligns the major axis of ellipse parallel to that of the target ellipse. Finally, $\mathbf{M}_{O\mathrm{Trans}}$ displaces the skin color ellipse from the origin to the center point of the target ellipse. $\mathbf{M}_{\mathrm{Sc}}$ is defined by

$$\mathbf{M}_{\mathrm{Sc}} = \begin{pmatrix} \frac{A_P}{2} & -\frac{A_P}{2} & 0 \\ 0 & 0 & \frac{B_P}{2} \\ 1 & 1 & 1 \end{pmatrix} \begin{pmatrix} \frac{A_S}{2} & -\frac{A_S}{2} & 0 \\ 0 & 0 & \frac{B_S}{2} \\ 1 & 1 & 1 \end{pmatrix}^{-1}. \tag{10}$$

Here, A_P and B_P are lengths of major and minor axes of the preferred skin color ellipse, whereas A_S and B_S are those of the detected skin color ellipse, respectively.

Yet when a relatively large detected skin color ellipse is transformed into a small preferred skin color ellipse, three-dimensional feeling of a face may be weakened because several colors may be merged into a single color. This phenomenon is often observable in face images with dark or medium bright skin colors represented as regions 2 and 3 in Fig. 5. Therefore, we need to modify the original preferred ellipse proposed by Sanger, increasing its area by four times. If the area of a detected skin color ellipse is eight times larger than that of a preferred skin color ellipse, its area will become four times larger than original one by letting lengths of major and minor axes of the target ellipse be doubled, which is done by

$$\begin{aligned} A'_p &= 2A_p, \\ B'_p &= 2B_p. \end{aligned} \tag{11}$$

Once affine matrix $\mathbf{M}_T$ is constructed, each skin color will be moved to a new color by Eq. (8).

The next issue to be addressed is artifacts arising from such affine transforms, since contour lines are often found near boundaries between the corrected and uncorrected regions. A remedy for such a problem is to limit amount of movement of near-boundary pixels in order to minimize the resulting color variation.

Let the initial vector be $\mathbf{u} = (u', v', 1)^t$ and $\mathbf{M}_T\mathbf{u}$ be the new vector moved into the preferred skin color region. To avoid such artifacts, we use a new vector $\mathbf{u}'$ that is not fully moved but is located on a line between $\mathbf{u}$ and $\mathbf{M}_T\mathbf{u}$ and is given by

$$\begin{aligned}\mathbf{u}' &= \mathbf{u} + \alpha(\mathbf{M}_T\mathbf{u} - \mathbf{u}) \\ &= [\alpha\mathbf{M}_T + (1-\alpha)\mathbf{I}]\mathbf{u},\end{aligned} \tag{12}$$

where $0 < \alpha \leq 1$ and $\mathbf{I}$ is an identity matrix.

As a pixel of a skin color gets closer to the boundary, we decrease α. Therefore, we need to know how far a skin pixel is located from nearest boundaries, which is accomplished using an erosion operation as proposed by You et al.[7] Yet an erosion operation is quite time-consuming, especially when no extra frame memory is used. Our approach to this problem is the adaptive use of parameter α, which varies depending on the skin color regions classified by Y value. Our first observation is that the area of the preferred skin color ellipse can be enlarged four times compared to that shown in Fig. 5, as usually occurs for regions 2 and 3, and that the amount of movement becomes smaller because of this enlargement. For smaller Y values, a boundary artifact is less irritating to the human visual system, even if it occurs, as color movement in (u',v') space remains inside the color gamut, even if the amount of movement is large. Consequently, α is set to unity for region 3 and to 0.65 for region 2. As for bright pixels represented as region 1 in Fig. 5, a boundary artifact is quite noticeable, since Y has relatively large values. Yet the center point of region 1 is located furthest from that of the preferred ellipse and much movement in (u',v') space is expected though not be intended. Thus, the amount of movement needs be limited severely in order to avoid an artifact problem, and α is finally set to 0.2. Further discussion will be presented below, along with an example.

EXPERIMENTAL RESULTS AND DISCUSSION

For comparative evaluation of the proposed method, we included Sanger's method[6] as well as You's method.[7] Although Sanger et al. provided three elliptical distributions of three racial colors and three elliptical distributions of their preferred colors in (u',v') space, we used only Asian and Caucasoid distributions because detailed analysis of this method is beyond the scope of our study. At the same time, we used Kim's preferred color[1] as center point of the preferred ellipses to allow a fair comparison of this method with You's method and our proposed method, which use Kim's color as the preferred color. Sanger's method did not address any way of reducing transform artifacts. You et al. introduced an erosion operation to minimize such artifacts, whereby Y determined how far a pixel was located from a nearby boundary. Starting from a skin pixel, they checked eight neighbor pixels one by one until they encountered a nonskin pixel; this process was quite time-consuming and inefficient. Therefore, we have implemented a fast version of their algorithm using a grassfire transform algorithm,[15] which is very fast but requires additional frame memory. Adding this frame memory may sometimes be quite expensive when hardware implementation is needed. Experimental results for Sanger's, You's, and proposed methods are summarized in Figures 6–9.

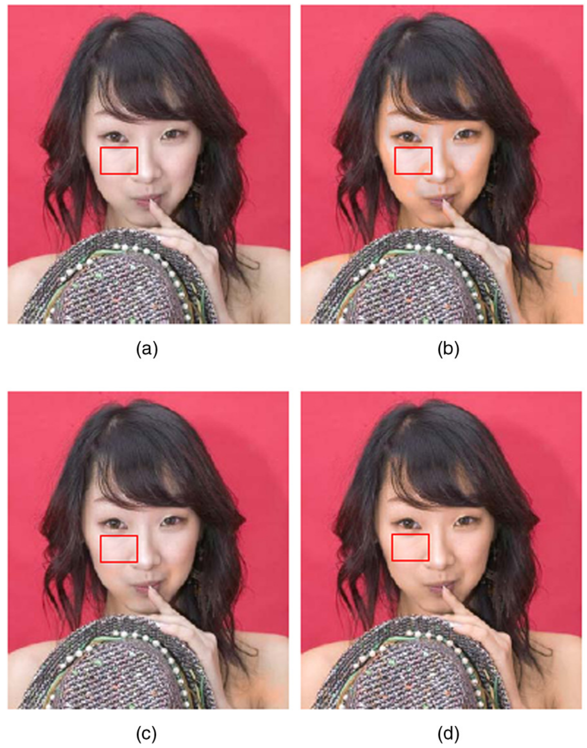
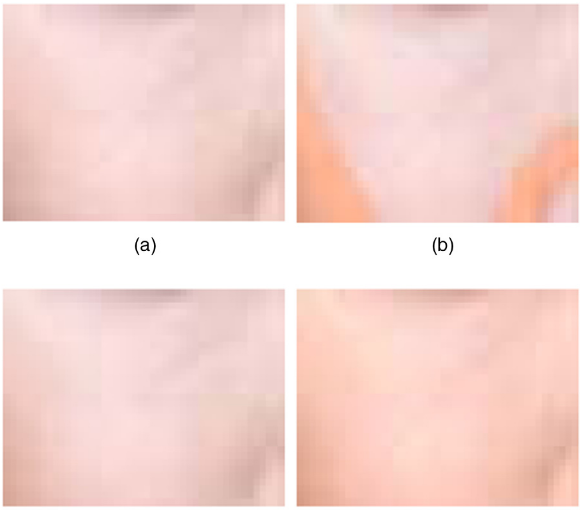


Figure 6. Experimental results for light skin color image: (a) original input image, (b) Sanger's method, (c) You's method with erosion operation, and (d) proposed method.

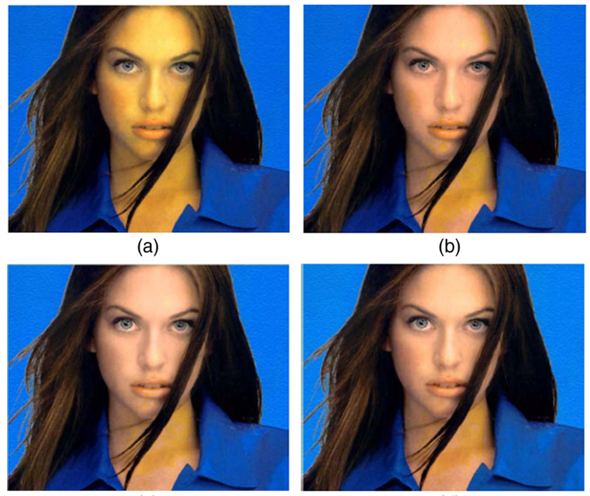
As our database, we gathered 100 portrait images including two ethnic groups, Caucasoid and Asian. Images with multiple faces can be considered but are not included in our database because face regions in this case are often so small that reproduction quality of the preferred color cannot be observed well, and thus, the images are not suitable for comparative study.

Fig. 6 shows reproduction results for preferred skin color for a sample image including bright skin color, and part of a face containing a bright cheek region is enlarged and shown in Fig. 7. As expected, Sanger's method generates many contour artifacts, as shown in Figs. 6(b) and 7(b). Such contours occur due to the fact that skin color detection is not perfect; color regions near a detected skin color boundary are split into skin and nonskin regions. Only designated skin regions will be mapped onto the preferred skin color region, while designated nonskin regions remain untouched. Therefore, color differences between



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

Figure 7. Enlarged image of rectangular part of Fig. 6: (a) original input image, (b) Sanger's method, (c) You's method with erosion operation, and (d) proposed method.



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

Figure 8. Experimental results for yellowish skin color tone image: (a) original input image, (b) Sanger's method, (c) You's method with erosion operation, and (d) proposed method.

near-boundary pixels, which are originally very small, become larger, leading to false contours in the transformed image. In contrast, You's method using an erosion operation as shown in Figs. 6(c) and 7(c) can remove most of contour artifacts. However, when we examine the enlarged image (Fig. 7(c)), the image transformed by You's method becomes similar to the original image because skin pixels near white regions, which are not detected as skin color, are scarcely moved in order to avoid artifacts. This excessive white color in the face leads to a somewhat unnatural feeling for the face.

Yet our proposed method allows more bright pixels to be detected as skin color and can isolate bright skin pixels labeled region 1 in Fig. 3, moving them into the preferred region without causing artifacts. As shown in Figs. 6(d) and 7(d), our proposed method can transform bright skin color into more natural skin color, thereby enhancing the three-dimensional feeling of a face. Especially, Figs. 6 and 7 are recommended to be seen on a color monitor, since artifacts are not observed well when the picture is printed in black-and-white on paper.

As shown in Fig. 8(a), skin color tone of the original image is distorted to a yellow tone with a little green tint. When we examine transformed images, most skin color pixels are well corrected except some artifacts found in a forehead, a nose, and a lip in Sanger's method; yellowish tone is still found in the neck because that part is not detected as skin color and remains uncorrected.

The original image of Fig. 9 has a reddish skin tone but its image quality is rather good on the whole. Transformed results seem to be of good quality for all methods. Although some difference in skin color tone can be observed depending upon methods used, it is hard to decide which result is better because preferred skin color tone can be different according to individual preferences.

Considering these three results and other results in our database, we believe that our proposed method is able to reproduce preferred skin colors well and give enhanced naturalness to images by decreasing contour artifacts and providing a three-dimensional feeling for a face.

One remaining issue is computational time involved in a reproduction process. An experiment is simulated in VISUAL C++ on a personal computer with Intel core2 duo central processing unit (CPU) of 3 GHz and 2 GB RAM. First, computation time for Sanger's method is normalized to unity and compared with those of other methods, with the understanding that CPU time depends directly on image size. Average computation time for Sanger's method is 47.5 ms. The relative computation time of You's original method using an erosion operation without an extra frame memory is 15.832 on average. When a modified operation with an extra frame memory is used to improve speed, average time is reduced significantly to 1.652. On the other hand, our proposed method, which does not need extra frame memory, requires relative computation time of 1.003 on average. This computation time is essentially the same as that of Sanger's method, but it is just 0.61 of that of You's modified method utilizing extra frame memory. Even though our proposed method requires three elliptical skin color models and respective affine transform operations, detected skin pixels are divided into three groups, and thus, overall computation time does not increase greatly compared with Sanger's method. Relative computation times are included in Table I.

CONCLUSION

Skin colors in (Y, u', v') color space have been divided into three groups according to Y values, each being modeled by a Gaussian distribution on (u', v') coordinates, whereby a characteristic ellipse has been defined to cover most skin colors with a probability of 0.95. Three affine transform matrices can be constructed to map input skin colors to the

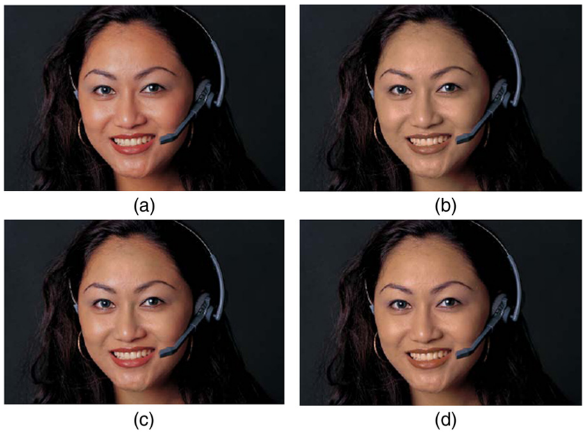


Figure 9. Experimental results for reddish skin color tone image: (a) original input image, (b) Sanger's method, (c) You's method with erosion operation, and (d) proposed method.

Table I. Relative CPU times with respect to Sanger's method.

Method	Average	Standard deviation
Sanger's method	1	0
You's method by using erosion operation without frame memory	15.832	1.416
You's method by using erosion operation with frame memory	1.652	0.158
Proposed method	1.003	0.004

preferred skin color zone, which is similarly modeled as a target ellipse. Because of the more elaborate *Y*-dependent Gaussian models, our proposed method can focus on the specific problems in reproduction occurring for specific ranges of *Y* values and can adaptively adjust the amount of movement in color space to minimize contour artifacts often arising from such transforms. Fast computation can also be achieved, since our proposed method can remove a time-consuming erosion operation introduced by You without employing extra frame memory.

ACKNOWLEDGMENTS
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