Object-Oriented Color Matching by Image Clustering

Hiroaki Kotera, Teturo Morimoto and Ryoichi Saito
Department of Information and Image Sciences, Chiba University, Japan

Abstract

An object-oriented color matching strategy depending on the image contents is proposed. Pictorial color image is segmented into different object areas with clustered color distributions. Euclidian or Mahalanobis color distance measures, and Bayesian decision rule based on maximum likelihood theory, are introduced to the segmentation. After the objects' segmentation, each clustered pixels are projected onto principal component space by Hotelling transform and the color mappings are performed for the principal components to be matched in between the individual objects of original and printed images.

Introduction

A variety of color mapping technologies have been developed. Usually the color transformations are performed independent of the image contents and a single color mapping matrix is often applied to transform all pixels. While the color image is composed of different colored objects where the different matrices should be applied for better reproduction.

This paper proposes an object-to-object color mapping strategy. Here the different mapping matrices are extracted depending on the objects' color distributions and applied to corresponding each colored object area. The proposed method is intended to be applied to automatic color correction, selective color adjustment, and/or color enhancement.

Basic System

Figure 1 shows the conceptual model of object-oriented color matching system. In this system, both an original image and its uncorrected printed image are captured through digital camera or color scanner. We used a flat bed scanner and inkjet printer in experiments. First, the images are segmented into plural numbers of clustered objects. RGB color data are transformed to CIELAB space and the clustered LAB values are automatically segmented into several key color areas dominant in given image. After the segmentation, each clustered pixels are projected onto principal component space by Hotelling transform. Finally, the object to object color mappings are performed between the original image and the printed image or displayed image on screen. Here the color mappings are done for principal components to be matched in between the individual objects of original and printed image. Otherwise, the PCA matching matrices may be determined to be matched to the preferred colors trained beforehand such as skin colors or blue sky.

In Fig.1, the system works to correct the printed colors automatically to match with that of original in each object area. Here the different color correction matrices are extracted corresponding to each segmented object area. Basically PCA matching applies 3 x 3 matrices just as linear color masking. However, the color clustering and color correction processes are independent. Then, if the higher accuracy color correction is required, conventional non-linear color masking matrices may be applied in the individual object area separately.

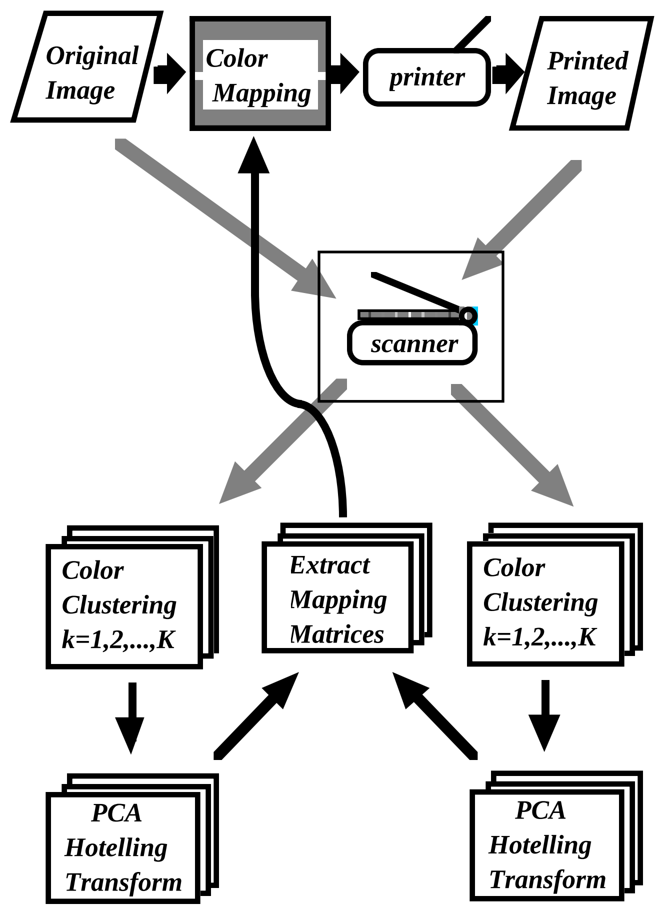


Figure 1. Conceptual model of object-to object color matching

Object Clustering

The first step is to segment the whole image into colored objects. For example, the boys image shown in Fig.2 includes the several key colors such as red shirt, green shirt, bluish back, and skin colors. They are distributed with clustering in 3-D CIELAB color space. Here the three types of classifiers are tested to separate these key colors, that is

[1] Euclidian color distance
[2] Mahalanobis color distance
[3] Bayesian decision rule

The LAB components in each color cluster are assumed to be approximately distributed in an ellipsoid.

Letting a CIELAB color vector X and the mean vector μ be

$$\boldsymbol{X}=[L^*,\ a^*,\ b^*]^t \tag{1}$$

$$\mu=E\{\boldsymbol{X}\}=[\ \overline{L}^*,\ \overline{a}^*,\ \overline{b}^*]^t \tag{2}$$

where *E{arg}* is the expected value of the argument and t denotes the transpose.

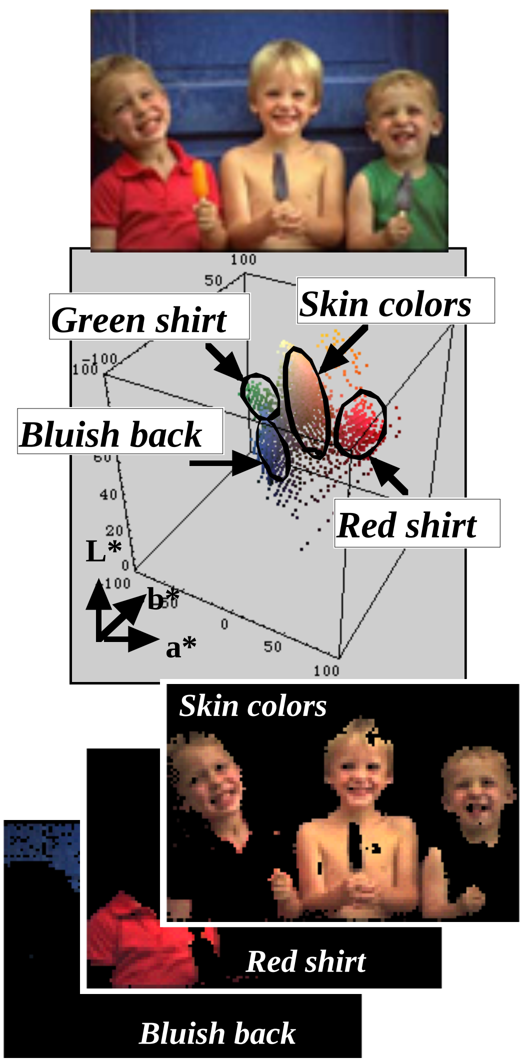


Figure 2. Clustered color distributions and segmented images

Euclidian and Mahalanobis color distances between a color vector of pixel i and the mean vector ${}_K\mu$ of class k are defined by

$${}_kd(Euclid)=\|\boldsymbol{X}-{}_k\mu\|=\{(L^*-{}_k\overline{L^*})^2+(a-{}_k\overline{a^*})^2+(b-{}_k\overline{b^*})^2\}^{1/2} \tag{3}$$

$${}_kd(Mahalanobis)=\{(\boldsymbol{X}-{}_k\mu)^t\,{}_k\Sigma_X^{-1}(\boldsymbol{X}-{}_k\mu)\}^{1/2} \tag{4}$$

where ${}_\kappa\Sigma$ denotes covariance matrix for class k given by

$${}_k\Sigma_X=E\{({}_k\boldsymbol{X}-{}_k\mu)({}_k\boldsymbol{X}-{}_k\mu)^t\} \tag{5}$$

Mahalanobis distance is a well known statistical measure assuming the multi-dimensional gaussian distribution.

On the other hand, the maximum likelihood classifier is also used to minimize the classification errors in average. According to the Bayesian decision rule, the maximum likelihood is obtained when the following discrimination function is minimized for k.

$${}_kd(Bayes)=-log\{p(k)\}+\frac{1}{2}log(|{}_k\Sigma_X|)+\frac{1}{2}(\boldsymbol{X}-{}_k\mu)^t\,{}_k\Sigma_X^{-1}(\boldsymbol{X}-{}_k\mu) \tag{6}$$

where *p(k)* means the occurrence probability of class k.

Thus a color vector X is classified into class $k=c$, if

$$min\{{}_kd(method)\}_{k=1\sim K}={}_cd(method) \tag{7}$$

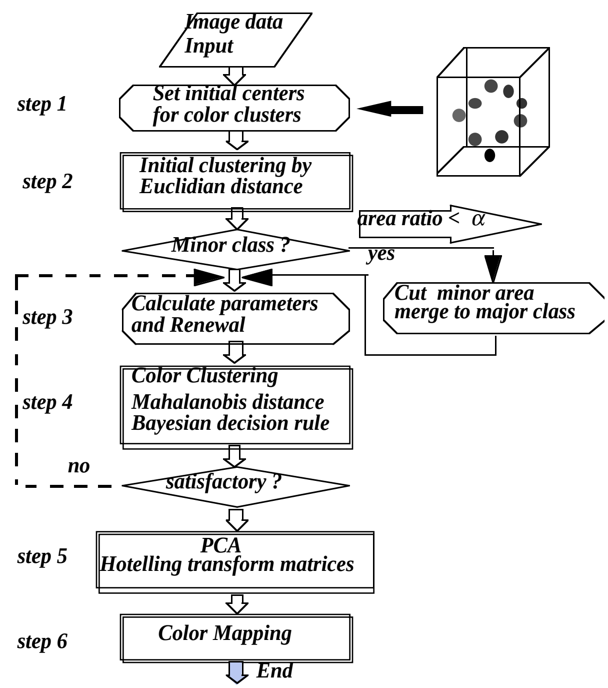


Figure 3. Flow diagram of color matching process

Fig. 3 illustrates the color matching procedures. In order to achieve full automatic color matchings, the clustering should be performed without teacher. To start the classifier, the center of class k, that is, mean vector μ must be given. In the **step 1**, 3^3=27 or 4^3=64 color centers have been initially set distributed inside the printer gamut. Next, Mahalanobis and Bayesian classifiers need statistical parameters such as covariance matrices Σ or prior probability $p(k)$, while Euclidian distance need not these parameters. Then, in the **step 2**, the Euclidian distance classifier was applied for initial clustering. Once the image is segmented, the parameters necessary for Mahalanobis or Bayesian classifiers are calculated in **step 3**, and the clustering is performed in **step 4**. When the clustering is successful, PCA is done and Hotelling transform matrices are extracted in **step 5**. In the final step 6, color corrections are executed to make match the colors in between the clustered objects. On the way from step 2 into step 3, we have cut off the minor classes with small areas less than threshold value a_{min} and merged into major classes, thus the key color areas dominant in the image have been extracted.

4. Color Matching by Hotelling transform

To make match the principal components, a color vector ${}_kX$ in class k is transformed into vector ${}_kY$ by Hotelling transform and projected onto principal component space as

$$ {}_k\boldsymbol{Y} = {}_k\boldsymbol{A}\,({}_k\boldsymbol{X} - {}_k\mu) \tag{8} $$

The matrix ${}_kA$ is formed by the eigen vectors $\{{}_ke_1, {}_ke_2, {}_ke_3\}$ of covariance matrix ${}_k\Sigma_X$ as

$$ {}_k\boldsymbol{A} = \left[{}_k\boldsymbol{e}_1\ {}_k\boldsymbol{e}_2\ {}_k\boldsymbol{e}_3\right]^t \tag{9} $$

The covariance matrix ${}_k\Sigma_Y$ of $\{{}_kY\}$ is diagonalized in terms of ${}_kA$ and ${}_k\Sigma_X$, whose elements are the eigen values of ${}_k\Sigma_X$ as

$$ {}_k\Sigma_Y = {}_k\boldsymbol{A}\,({}_k\Sigma_X)\,{}_k\boldsymbol{A}^t = \begin{bmatrix} {}_k\lambda_1 & 0 & 0 \\ 0 & {}_k\lambda_2 & 0 \\ 0 & 0 & {}_k\lambda_3 \end{bmatrix} \tag{10} $$

The eigen values ${}_k\lambda_1 \geq {}_k\lambda_2 \geq {}_k\lambda_3$ denote the variances which mean the energy distributed in principal axes. Thus the color vectors in original image and printed image are mapped to the same principal components space. Then the transformed vector ${}_kY_{ORG}$ and ${}_kY_{PRT}$ are matched by applying the scaling matrix ${}_kS$. ${}_kS$ is a diagonal matrix whose elements are given by eigen values' ratio between original and print.

Letting the transformed images be $\{{}_kY_{ORG}\}$ for original and $\{{}_kY_{PRT}\}$ for printed, the scaling matrix ${}_kS$ is applied to $\{{}_kY_{PRT}\}$ resulting in the corrected color vector $\{{}_kY_{COR}\}$ to estimate the original color vector $\{{}_kX_{ORG}\}$ as follows.

$$ \begin{aligned} {}_k\boldsymbol{Y}_{ORG} &= {}_k\boldsymbol{A}_{ORG}({}_k\boldsymbol{X}_{ORG} - {}_k\mu_{ORG}) \\ {}_k\boldsymbol{Y}_{PRT} &= {}_k\boldsymbol{A}_{PRT}({}_k\boldsymbol{X}_{PRT} - {}_k\mu_{PRT}) \end{aligned} \tag{11} $$

$$ {}_k\boldsymbol{Y}_{COR} = {}_k\boldsymbol{S}\,{}_k\boldsymbol{Y}_{PRT} = {}_k\hat{\boldsymbol{Y}}_{ORG} = {}_k\boldsymbol{A}_{ORG}({}_k\hat{\boldsymbol{X}}_{ORG} - {}_k\hat{\mu}_{ORG}) \tag{12} $$

$$ {}_k\boldsymbol{S} = \begin{bmatrix} \sqrt{{}_k\lambda_{1ORG}/{}_k\lambda_{1PRT}} & 0 & 0 \\ 0 & \sqrt{{}_k\lambda_{2ORG}/{}_k\lambda_{2PRT}} & 0 \\ 0 & 0 & \sqrt{{}_k\lambda_{3ORG}/{}_k\lambda_{3PRT}} \end{bmatrix} \tag{13} $$

Solving these equations, we get the following relation between the original color and the printed color.

$$ {}_k\hat{\boldsymbol{X}}_{ORG} - \hat{\mu}_{ORG} = {}_k\boldsymbol{M}_C({}_k\boldsymbol{X}_{PRT} - \mu_{PRT}) \tag{14} $$

The correction matrix ${}_kM_C$ is given by

$$ {}_k\boldsymbol{M}_C = (\boldsymbol{A}_{ORG}^{-1})({}_k\boldsymbol{S})(\boldsymbol{A}_{PRT}) \tag{15} $$

This means that the original data should be pre-corrected by matrix ${}_kM_C$ for the resultant print colors to be matched with the original colors.

5. Experiments

The color matching experiments have been done for pictorial images including facial objects. An output image from inkjet color printer is re-scanned by a flat bed scanner and the digitized *RGB* data are transformed into $L^*a^*b^*$ values. Next, both the original $\{L^*, a^*, b^*\}_{ORG}$ and the printed $\{L^*, a^*, b^*\}_{PRT}$ data are segmented into several key color areas using three types of classifier mentioned above.

Fig. 4 shows an example of clustered results in a lady image by : (a) Euclid distance and (b) Bayesian decision rule. This sample includes ambiguous colors different from boys image and was segmented into $K=6$ colored areas by adjusting the thresholding area ratio α_{min};

#1 : whitish pink, #2 : greyish pink, #3 : pinkish skin,

#4 : yellowish pink, #5 : pink flower, #6 : yellow flower

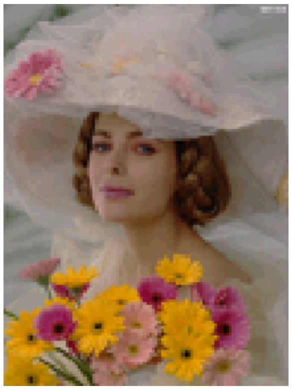
In general, Bayesian decision rule as statistical classifier works well to separate these ambiguous colored areas, while Euclidian distance is fit to separate the cleared color areas.

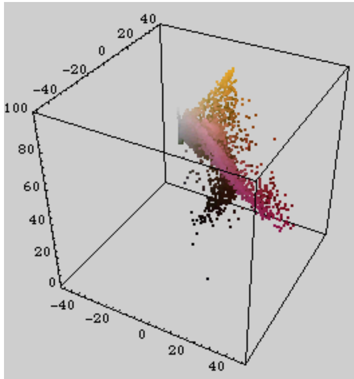
Here, totally *6* sets of color correction matrices $\{{}_kM_C\}$ are obtained and used for color matching in individual area.

Fig. 5 shows the color matching results for #3: pinkish skin. In this sample, although the printed image was obtained through default CMS(Color Management System), the reproduced colors were still unsatisfactory. In Fig.5, the pinkish skin area(most in face) is separated by Bayesian classifier and the color maps in (a*-b*) plane are given in (a) :original, (b) : printed, and (c) : corrected. As clearly shown, the hue angle, the central chromaticity coordinate, and the variances in (c) are well corrected to match with (a).

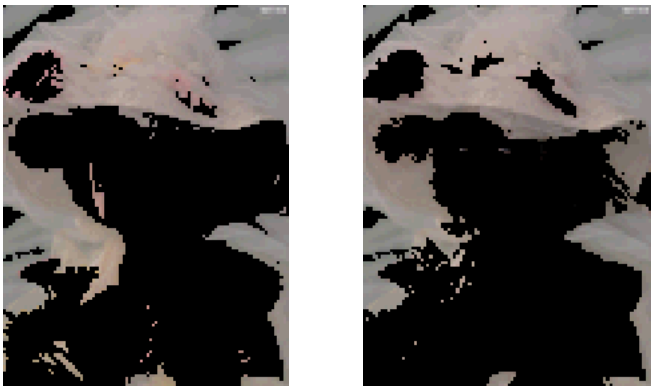
The following matrix was obtained for correcting the $\{[{}_kL_i^*, {}_ka_i^*, {}_kb_i^*]^t\}_{PRT}$ vectors in #3 : pinkish skin colors.

$$ {}_kM_C(pinkish\,skin) = \begin{bmatrix} 1.22407, & 0.33012, & -0.11311 \\ -0.71906, & 1.13148, & -0.08469 \\ 0.10522 & 0.13672, & 1.20664 \end{bmatrix} \tag{16} $$



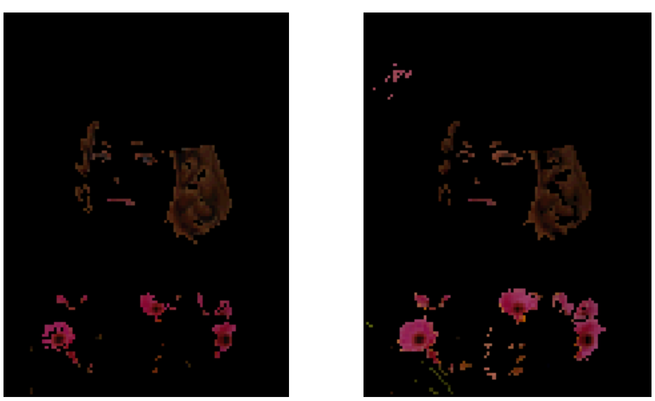


(a) original image (b) color distributions in CIELAB



#1 : whitish pink

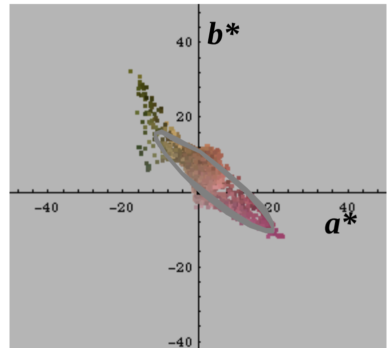
#3 : pinkish skin



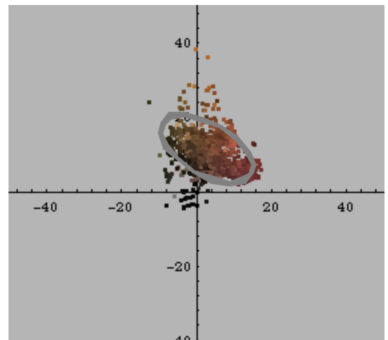
#5 : pink flower

(c) Left : Euclid (d) Right : Baysian

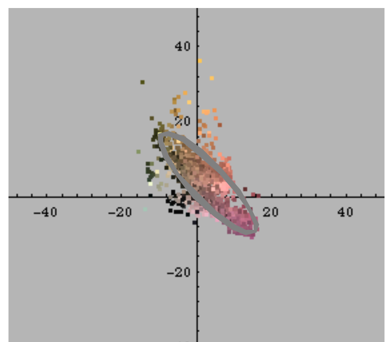
Figure 4. Segmented results by classifier



(a) original pinkish skin



(b) printed pinkish skin



(c) corrected pinkish skin

Figure 5 Correction in skin colors by PCA matching

6. Discussion and Conclusions

The clustering is successful or not plays an important role in the proposed system. Here the well-known statistical pattern recognition techniques are introduced to classify the individual object colored areas. In practice, the following difficulties should be overcome.

[1] Initial mean vectors as a representative of class k should be well set up without teacher.
[2] The number of clusters should be equal and the same object color areas are to be extracted between the original and the printed images keeping one to one correspondence.
[3] Classification errors should be suppressed not to generate noisy images in the reproduction.

Requirement [1] will need a learning process to find the center of the cluster. Requirement [2] has been easily realized by extracting the same pixel area from the printed image referring to the each clustered area in the original or vice versa. There the clustering is done only for either original image or printed image. The wrong clustering may cause the fatal defects in color correction.

A process to refuse the clustering and/or to remove the wrong pixels in classification error is necessary and now under development for requirement [3].

Acknowledgment

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