Automatic Interchange in Scene Colors by Image Segmentation

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Abstract

Image segmentation is a first step to vision system and used as a pre-processing for many applications such as pattern recognition, image classification, picture coding or target tracking. In the previous papers, we reported an unsupervised image segmentation method based on ***Bayesian*** classifier and applied it to object-to-object color transformation. Although ***Bayesian*** decision rule is a robust tool to classify the objects statistically with the minimum error in average, it needs to preset some appropriate class centers before starting the classifier. The location of initial seed points much influences the segmentation accuracy. This paper discusses a better way to set the initial seeds and reports the ***Bayesian*** discriminator works better when coupled with ***k-means*** classifier for correcting the location of seed points. In addition, the paper introduces a new application of proposed model into scene color interchanges between segmented objects.

Introduction

Image segmentation is a low-level image processing task that aims at partitioning an image into homogeneous regions. How region homogeneity is defined depends on the application. A great number of works have developed the segmentation methods according to various criteria such as gray, color, texture, or shape.

In the previous works, we reported an object-to-object color transformation strategy based on image segmentation.[1-5]

Since the perfect segmentation is impossible in practice, our applications have been limited to a color transformation such as color correction, color matching or gamut mapping between two objects with color similarity, where the segmentation errors are not so striking.

However, the more accurate segmentation is necessary for a color transformation between two objects with color dissimilarity. When the segmentation is successful, a flexible color transformation is possible for each individual cluster in attention. Once the colored objects are clearly segmented in a source and a destination image, their colors could be mutually interchanged from one to another. This paper proposes a new approach to interchange the object colors between different scenes with the improvement in color clustering method.

Scene Color Interchange Models

Welsh et al, proposed a color transferring method from one image to another in their colorization algorithm for monochrome image.[7] Reinhard et al tried to transfer the scene color of one to another by scaling the color distributions on the three major axes in the vision-based $l\alpha\beta$ color space.[8] These approaches are addressed to transfer the total atmosphere of source scene to that of reference target scene.

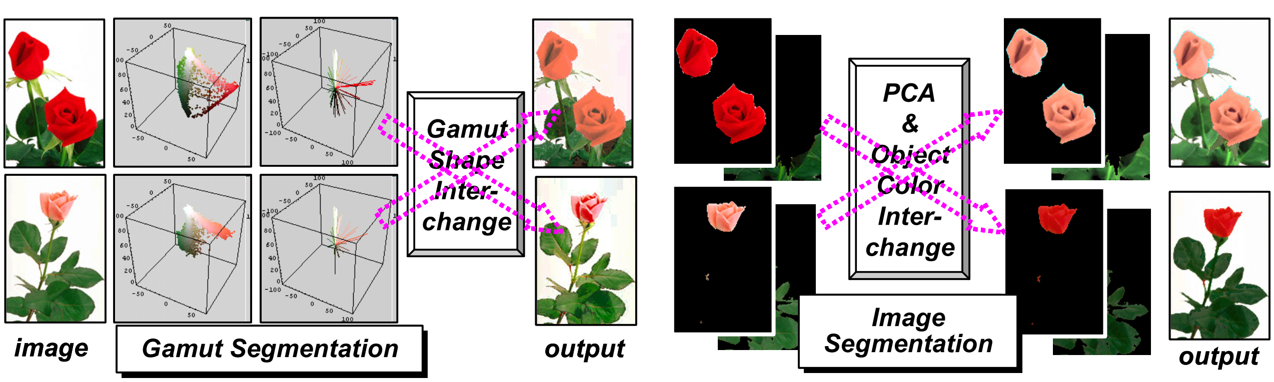

Figure 1. A concept of scene color interchange

In this paper, we propose a new approach to scene color interchange based on the image segmentation. Here the two types of color interchange models are discussed.

Model A: Total color interchange between scenes

Model B: Local color interchange between objects

Figure 1 illustrates a system concept to interchange the scene colors between two different images.

Total Color Interchange Model by Gamut Segmentation

First, we tried to transfer the color distribution of source image onto that of destination image by applying a gamut mapping technique, where the gamut shape of source image is deformed by a ratio of source vs. destination in the segmented radial color vectors.

Letting a color vector be $\boldsymbol{X}_i = [L_i^*, a_i^*, b_i^*] (i = 1 \sim n)$, a radial distance is measured from the gamut center $\boldsymbol{\mu}_0 = [L_0^*, a_0^*, b_0^*]$

$$r_i = \|\boldsymbol{X}_i - \boldsymbol{\mu}_0\| = \left[\left(L_i^* - L_0^*\right)^2 + \left(a_i^* - a_0^*\right)^2 + \left(b_i^* - b_0^*\right)^2\right]^{1/2} \tag{1}$$

The polar angle of each vector in CIELAB is defined by

$$\theta_i = tan^{-1}\left[\frac{b_i^* - b_0^*}{a_i^* - a_0^*}\right]; \quad 0 \le \theta_i \le 2\pi \tag{2}$$

$$\varphi_i = (\pi/2) + tan^{-1}\left(\frac{L_i^* - L_0^*}{\left\{\left(a_i^* - a_0^*\right)^2 + \left(b_i^* - b_0^*\right)^2\right\}^{1/2}}\right); \ 0 \le \varphi_i \le \pi \tag{3}$$

Here, the gamut surface is formed by picking up the points with the maximum radial distance in every segments divided by (*Δθ, Δφ*) as shown in Fig. 2.

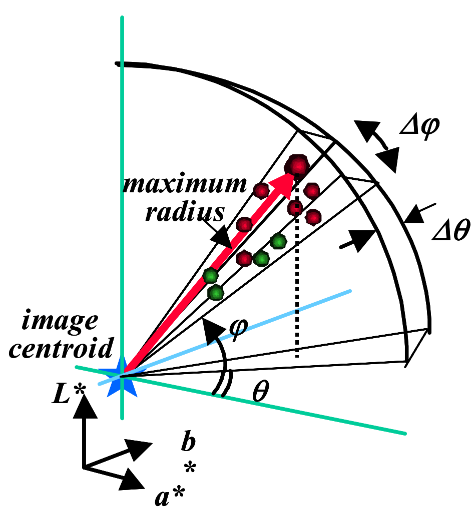

Figure 2. Segmentation of image gamut in Polar coordinate

To transfer the gamut shape from one image to another, the following two gamut modulation methods are applied to the divided segments.

Model A: Gamut Modulation by Maximum Radial Vector

The image gamut is defined by a set of maximum radial vectors, what we call gamut matrix $\boldsymbol{R}_{gamut}$ as

$$\begin{aligned} &\boldsymbol{R}_{gamut} = [R_{jk}] = [max\{r_i\}] \ ; \quad 1 \le i \le n \\ &\quad for \ (j-1)\Delta\theta \le \theta_j \le j\Delta\theta \ \ and \ \ (k-1)\Delta\varphi \le \varphi_k \le k\Delta\varphi \\ &\quad \Delta\theta = 2\pi / M \ ; \ 1 \le j \le M \\ &\quad \Delta\varphi = \pi / N \ \ ; \ 1 \le k \le N \end{aligned} \tag{4}$$

A most simple way to map the source gamut to the destination is to rescale a source color vector ${}_S\boldsymbol{X}_{i,jk}$ of pixel *i* in the segment *jk* by the source vs. destination ratio of radial elements existing in the same radial segment.
The modified source color vector ${}_S\hat{\boldsymbol{X}}_{i,jk}$ is given by

$${}_S\hat{\boldsymbol{X}}_{i,jk} = \left({}_D R_{jk} / {}_S R_{jk}\right)\left({}_S\boldsymbol{X}_{i,jk} - \boldsymbol{\mu}_0\right) + \boldsymbol{\mu}_0 \tag{5}$$

Where, ${}_S R_{jk}$ and ${}_D R_{jk}$ are the source and destination elements in the same segment *jk* of gamut matrix $\boldsymbol{R}_{gamut}$.

Model B: Gamut Modulation by Mean Vector and Variance

Since the ***Model A*** rescales the source gamut only by the ratio of maximum radial vectors in each segment, it doesn't reflect the statistical characteristics inside the gamut. Another ***Model B*** improves ***Model A***, which rescales the source color vector using the mean CIELAB vector and the variance of radial distances as follows.

$${}_S\hat{\boldsymbol{X}}_{i,jk} = \left({}_D\sigma_{jk} / {}_S\sigma_{jk}\right)\left({}_S\boldsymbol{X}_{i,jk} - {}_S\boldsymbol{\mu}_{jk}\right) + {}_D\boldsymbol{\mu}_{jk} \tag{6}$$

where, ${}_S\boldsymbol{\mu}_{jk}$ and ${}_D\boldsymbol{\mu}_{jk}$ denote the mean color vectors of source ${}_S\boldsymbol{X}_{i,jk}$ and destination ${}_D\boldsymbol{X}_{i,jk}$ respectively. Also, ${}_S\sigma_{jk}$ and ${}_D\sigma_{jk}$ are the standard deviations of source and destination radial distances in the same segment *jk* defined by

$$\begin{aligned} {}_S\sigma_{jk} &= \sqrt{\frac{1}{{}_S n_{jk}}\sum_{i=1}^{{}_S n_{jk}}\left({}_S r_{i,jk} - {}_S\bar{r}_{jk}\right)^2}, \quad {}_S\bar{r}_{jk} = \frac{1}{{}_S n_{jk}}\sum_{i=1}^{{}_S n_{jk}} {}_S r_{i,jk} \\ {}_D\sigma_{jk} &= \sqrt{\frac{1}{{}_D n_{jk}}\sum_{i=1}^{{}_D n_{jk}}\left({}_D r_{i,jk} - {}_S\bar{r}_{jk}\right)^2}, \quad {}_D\bar{r}_{jk} = \frac{1}{{}_D n_{jk}}\sum_{i=1}^{{}_D n_{jk}} {}_D r_{i,jk} \end{aligned} \tag{7}$$

Where, ${}_S n_{jk}$ and ${}_D n_{jk}$ denote the number of source and destination pixels included in the segment *jk*.

Local Color Interchange Model by Region-based Image Segmentation

In our gamut segmentation model, a total color atmosphere of source scene is changed reflecting that of destination, but can't transform individual object color. Figure 3 illustrates a local color interchange model based on an unsupervised image segmentation process. First the initial seed points are placed at the higher color populations as a candidate for the clustering centers. Next, the locations of seed points are corrected by ***k-means*** classifier. Then the image is segmented by Bayesian classifier based on maximum likelihood theorem. Once the segmentation is successful, a region-based color transformation is possible between the different objects in different scenes.

Bayesian Classifier with k-means Starter

In the previous papers, we reported a well-known ***Bayesian*** discriminator worked well to segment the clustered color objects. However, an improvement in setting the initial seed points is left for the better segmentation.

Setting of Initial Seeds Points

To start an unsupervised color classifier for unknown image, any geometric centroid must be set as the initial class center. Here we tested the following three methods for placing K number of initial seed points in 3D CIELAB space.

[*Random*]

A random setting of seed points resulted in unstable segmentation, because it is independent of image.

[*Box center at Higher Pixel Density*]

To select the more reliable seed points depending on image, we generated $M=m^3$ pieces of rectangular boxes surrounded by the regular lattice points inside of image color gamut.

The image color distribution is partitioned by a unit box with the size of $\Delta a \times \Delta b \times \Delta L$

$$\begin{aligned} \Delta \boldsymbol{L} &= [max\{L_n^*\} - min\{L_n^*\}]/m \\ \Delta \boldsymbol{a} &= [max\{a_n^*\} - min\{a_n^*\}]/m \\ \Delta \boldsymbol{b} &= [max\{b_n^*\} - min\{b_n^*\}]/m \end{aligned} \tag{8}$$

Let a color vector be $\boldsymbol{X}_n$ for n-th data point and $\boldsymbol{\mu}$ for the mean vector in CIELAB.

$$\boldsymbol{X_n} = [L_n^*, a_n^*, b_n^*]^t \;; n = 1 \sim N \tag{9}$$

$$\boldsymbol{\mu} = E\{\boldsymbol{X}\} = [\overline{L}^*, \overline{a}^*, \overline{b}^*]^t \tag{10}$$

Here, we count up the pixel population $P(k)$ existing inside the each box $\boldsymbol{b}_k$; $k=1\sim M$. Next, K body centers with higher color population are selected as a candidate of seeds points.

$$\begin{aligned} &\boldsymbol{\mu}_{seed}(k) = E\{\boldsymbol{X_n}\} \\ &\quad for\ \boldsymbol{X_n} \in \boldsymbol{b_k}\ \ and\ P(1) \geq P(2) \geq P(3) \cdots P(K) \end{aligned} \tag{11}$$

[*Correction for Box center by k-means*]

Surely the method ***B*** sets a better initial class center than ***A*** depending on image color distribution, but $\boldsymbol{\mu}_{seed}(k)$ isn't placed at the center of each cluster but placed at each body center in uniformly divided unit box. In order to place these candidates at the right position, ***k-means*** clustering method was introduced to make correction for the selected $\boldsymbol{\mu}_{seed}(k)$.

k-means algorithm partitions (or clustering) N data points into K disjoint subsets $\boldsymbol{S_k}$ containing N_k data points so as to minimize the sum-of-squares criterion,

$$J = \sum_{k=1}^{K} \sum_{n \subseteq \boldsymbol{S}_k} \left| \boldsymbol{X}_n - \boldsymbol{\mu}_k \right|^2 \tag{12}$$

Where $\boldsymbol{\mu}_K$ is the geometric centroid of the data points in $\boldsymbol{S}_k$ First the initial seed points $\boldsymbol{\mu}_{seed}(k)$ are assigned to $k=1\sim K$ classes, then the centroid is recomputed after clustering and the seed points are renewed. The renewal is continued until no further change occurs in the centroid by iteration.

Although ***k-means*** is used as unsupervised classifier, here we applied this technique to relocate the initial seeds to the more reliable gravity centers in clusters.

Bayesian Classifier

According to the ***Bayesian*** decision rule, the maximum likelihood is obtained when the following quadratic discrimination function[6] is minimized for k.

$$\begin{aligned} {}_k d(Bayes) = &-log\{p(k)\} + \frac{1}{2} log\left(\left|{}_k\Sigma_X\right|\right) \\ &+ \frac{1}{2}\left(X - {}_k\mu\right)^t {}_k\Sigma_X^{-1}\left(X - {}_k\mu\right) \end{aligned} \tag{13}$$

p(k) : occurrence probability of class *k*

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

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

$$min\{{}_c d(Bayes)\}_{k=1\sim K} = {}_c d\,(Bayes) \tag{14}$$

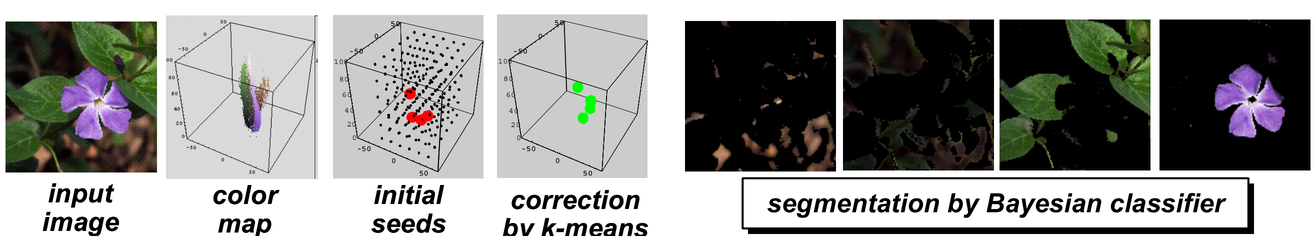

Figure 3. Unsupervised image segmentation process based on ***k-means Bayesian classifier***

Bayesian classifier is expected to work better when coupled with ***k-means*** clustering for setting the initial seed points. Here we call the coupled model as ***k-means Bayesian*.**

Model C: Local Color Interchange in Segmented Objects

Model C interchanges the segmented object colors in source and target clusters. Here we applied object-to-object color matching algorithm[5] in ***PC*** (Principal Component) space.

First, ***PC*** s are extracted from the segmented color areas. Hotelling Transform projects a color vector $_k\boldsymbol{X}$ in class k into a vector $_k\boldsymbol{Y}$ in ***PC*** space as

$$_k\boldsymbol{Y} = {}_k\boldsymbol{A}({}_k\boldsymbol{X} - {}_k\boldsymbol{\mu}) \tag{15}$$

The matrix $_k\boldsymbol{A}$ is formed by the eigen vectors $\{_ke_1, {}_ke_2, {}_ke_3\}$ of covariance matrix $_k\boldsymbol{\Sigma}_X$ as

$$_k\boldsymbol{A} = [{}_k\boldsymbol{e}_1, {}_k\boldsymbol{e}_2, {}_k\boldsymbol{e}_3] \tag{16}$$

The covariance matrix $_k\boldsymbol{\Sigma}_Y$ of $\{_k\boldsymbol{Y}\}$ is diagonalized in terms of $_k\boldsymbol{A}$ and $_k\boldsymbol{\Sigma}_X$ whose elements are the eigen values as

$$_k\boldsymbol{\Sigma}_{\boldsymbol{Y}} = {}_k\boldsymbol{A}({}_k\boldsymbol{\Sigma}_{\boldsymbol{X}})\,{}_k\boldsymbol{A}^t = \begin{bmatrix} {}_k\lambda_1 & 0 & 0 \\ 0 & {}_k\lambda_2 & 0 \\ 0 & 0 & {}_k\lambda_3 \end{bmatrix} \tag{17}$$

Thus the color vectors in source and target images are mapped to the same ***PC*** space and the following equations are formed to make match a ***source*** vector $_j\boldsymbol{Y}_{ORG}$ in class j to a ***target*** vector $_k\boldsymbol{Y}_{DST}$ in class k through a scaling matrix $_{jk}\boldsymbol{S}$.

$$\begin{aligned} {}_k\boldsymbol{Y}_{DST} &= {}_k\boldsymbol{A}_{DST}({}_k\boldsymbol{X}_{DST} - {}_k\boldsymbol{\mu}_{DST}) \\ {}_j\boldsymbol{Y}_{ORG} &= {}_j\boldsymbol{A}_{ORG}({}_j\boldsymbol{X}_{ORG} - {}_j\boldsymbol{\mu}_{ORG}) \end{aligned} \tag{18}$$

$$_k\boldsymbol{Y}_{DST} = {}_k\boldsymbol{S} \cdot {}_j\boldsymbol{Y}_{ORG} \tag{19}$$

$$_{jk}\boldsymbol{S} = \begin{bmatrix} \sqrt{{}_k\lambda_{1DST}/{}_j\lambda_{1ORG}} & 0 & 0 \\ 0 & \sqrt{{}_k\lambda_{2DST}/{}_j\lambda_{2ORG}} & 0 \\ 0 & 0 & \sqrt{{}_k\lambda_{3DST}/{}_j\lambda_{3ORG}} \end{bmatrix} \tag{20}$$

Solving (10) and (11), we get the following relation between a source color $_j\boldsymbol{X}_{ORG}$ and a target color $_k\boldsymbol{X}_{DST}$ which we want to interchange.

$$_k\boldsymbol{X}_{DST} - {}_k\boldsymbol{\mu}_{DST} = {}_{jk}\boldsymbol{M}_C({}_j\boldsymbol{X}_{ORG} - {}_j\boldsymbol{\mu}_{ORG}) \tag{21}$$

The matching matrix $_{jk}\boldsymbol{M}_C$ is given by

$$_{jk}\boldsymbol{M}_C = ({}_k\boldsymbol{A}_{DST}^{-1})({}_{jk}\boldsymbol{S})({}_j\boldsymbol{A}_{ORG}) \tag{22}$$

where $_j\boldsymbol{A}_{ORG}$ and $_k\boldsymbol{A}_{DST}$ denote the eigen matrix for a ***source*** segment of class j and a ***target*** segment of class k.

Experimental Results

Total Color Interchange by Gamut Segmentation

First, the total color interchange Model A and Model B are compared with Reinhard's model. A color atmosphere of test image "red rose with dark green leaves" is interchanged with that of "pink rose with light green leaves" in Fig. 4(a). Figure 4(b), 4(c) and 4(d) show the interchanged results by $l\alpha\beta$ Reinhard, Model A and Model B. Although "pink" petal is transformed into "reddish" and "red" petal into "pinkish", and also "light green" leaf into "dark green" or vice versa, $l\alpha\beta$ and Model A didn't work well in this image. On the other hand, the proposed Model B succeeded in the mutual transfer of colors in total. Figure 4(e) shows an example of maximum radial vectors by gamut segmentation. In our model, the resultant color appearance is influenced by the division number of gamut. The optimal gamut segmentation depends on image and is a key factor left in future work.

Local Color Interchange Between Segmented Objects

Next, the local color interchange ***Model C*** is tested.

To begin with, the performance of ***k-means Bayesian*** *classifier* is evaluated in comparison with normal ***Bayesian*** *classifier* without ***k-means***.

Figure 5 shows a segmentation result for "*daily flower*". The nine classifiers by the combinations of three color distance measures and three types of initial seed points are compared one another. All images are segmented to $K=4$ classes. As clearly shown in the top row, random seeds didn't give any stable results. In comparison with the results in 1st, 2nd and 3rd columns, ***Bayesian*** is better than ***Euclidean*** or ***Mahalanobis*** and ***k-means Bayesian*** in third row obviously works better than *normal Bayesian* in second row.

The proposed ***k-means Bayesian*** worked best and was applied to ***Model C***. Figure 6 shows the result for the same image in Fig. 4. As clearly different from the total color interchange models, ***Model C*** interchanges the scene colors between two different segmented objects.

A red rose with dark green leaves is transformed into a pink rose with light green leaves and vice versa. This model has an advantage of flexibility in object-to-object color interchange but has a disadvantage of difficulty in one-to-one correspondence to be interchanged for K classes of objects.

In Fig. 6, $K = 4$ pairs of segments could be automatically corresponded by choosing the closest partner with minimum color difference ΔE^*_{ab}, because the two rose images are a pair with color similarity.

Figure 7 shows another interchange sample for two different "building" images with color dissimilarity. In this sample, the color interchange pairs of objects are manually decided. Although we haven't any definitive solution for automatic selection of interchange pairs at present, the different pairs of object colors are flexibly interchanged between two different building images.

Conclusions

We proposed two different scene color interchange models of "total" and "local". The former is provided with Model A and Model B based on Gamut Segmentation and the latter with Model C based on Image Segmentation. In "local" interchange model, we introduced k-means Bayesian classifier by coupling a normal Bayesian with a well-known k-means clustering. The crucial difference in normal and improved Bayesians lies in whether the "initial seeds" are re-located or not with or without k-means preprocessor. Although the process speed a little bit goes down, the segmentation accuracy is much improved. In addition, an object-to-object scene color interchange is challenged to open a new field of applications such as automatic creation or synthesis of images with similar atmospheres.

Acknowledgement

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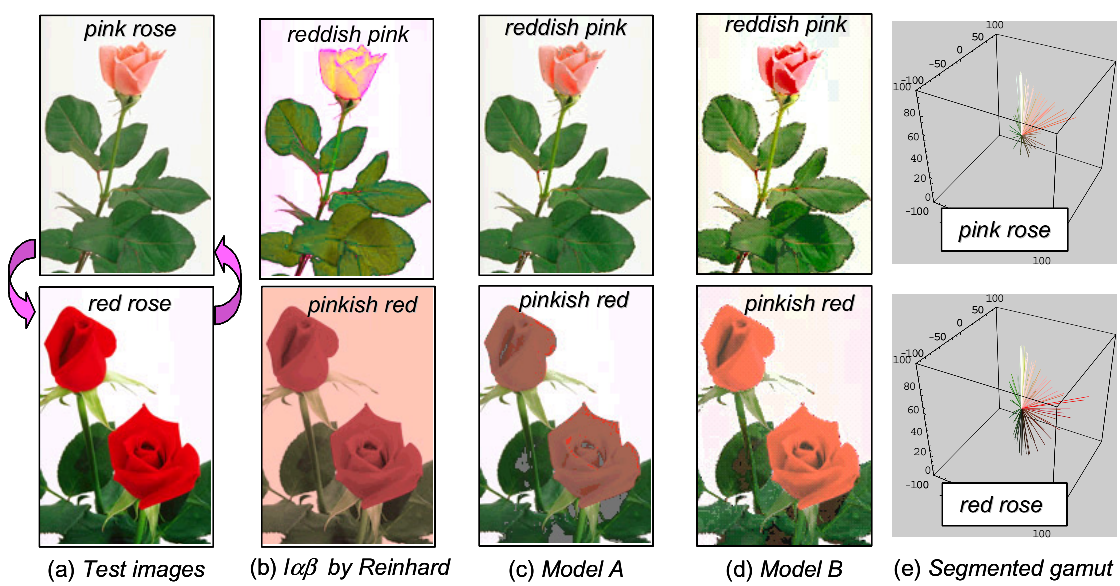

Figure 4. Examples of total scene color interchange by image gamut segmentation1 model

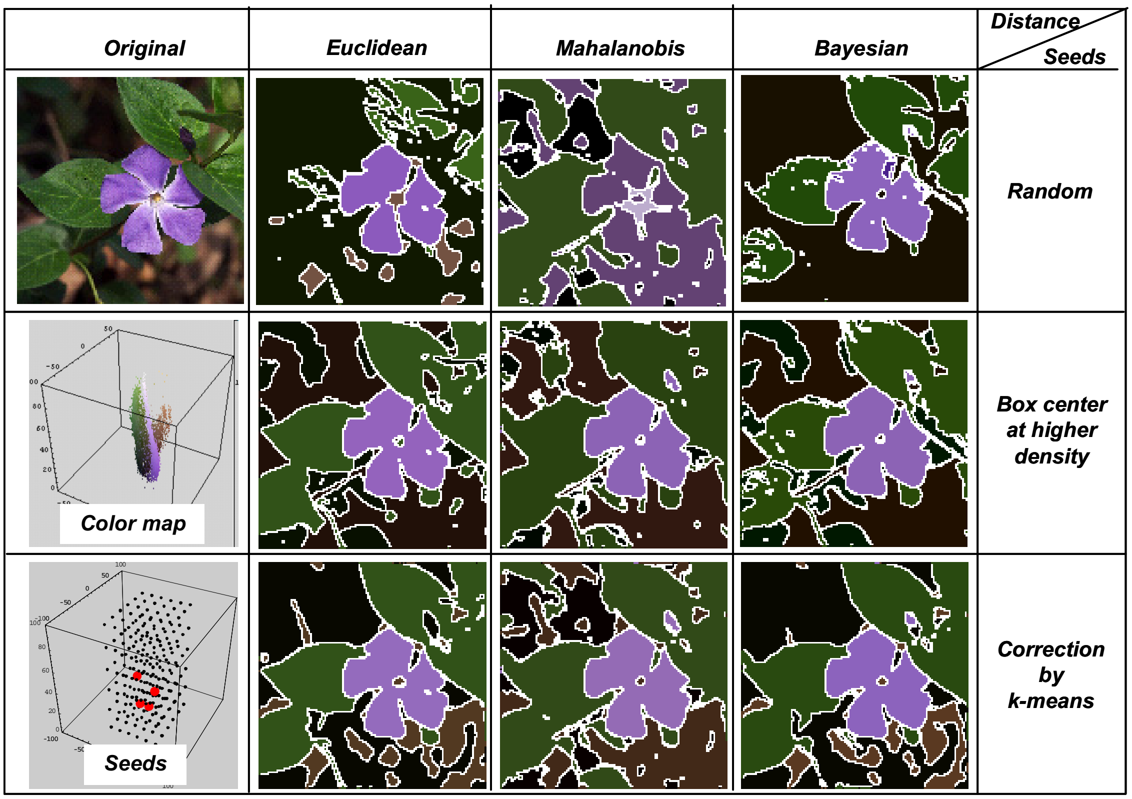

Figure 5. Comparison in image segmentations by color clustering method.

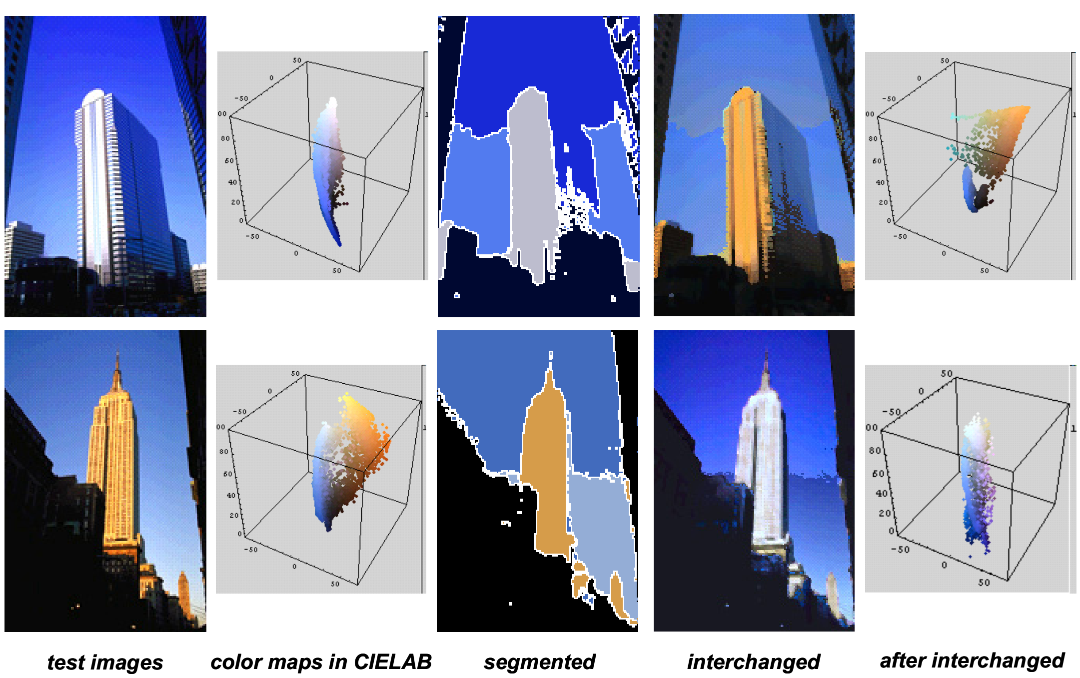

Figure 6. Results in local scene color interchanges for images with color similarity by ***Model C***

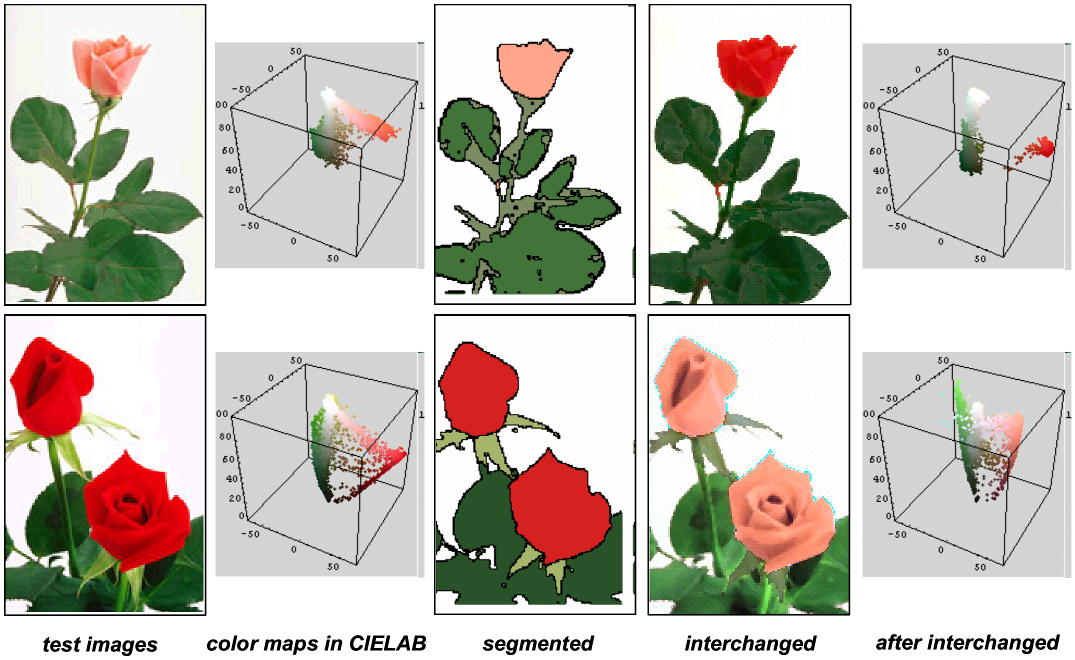

*Figure 7. Results in local scene color interchanges for images with color dissimilarity by **Model C***

Biography

Hiroaki Kotera received his B.S degree from Nagoya Inst. Tech. and Doctorate from University of Tokyo. He joined Matsushita Electric Industrial Co in 1963. Since 1973, he was working in digital image processing at Matsushita Res. Inst. Tokyo, Inc. In 1996, he moved to Chiba University. He is a professor at Dept. Information and Image Sciences. He received Johann Gutenberg prize from SID in 1995 and journal awards from IS&T in 1993, from IIEEJ in 1990 and 2000, and from ISJ in 2003. He is a Fellow of IS&T.