A Region-based Automatic Scene Color Interchange

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Abstract

*This paper proposes a color interchange model between different objects in different scenes based on image segmentation. Proposed system is applied to preferred color reproduction, scene simulation, industrial design, etc. First, unsupervised image segmentation method in our previous paper is improved by coupling the **Bayesian** decision rule with **K-means** classifier as a starter for setting the initial seeds points. Here, we tested new methods for choosing the initial seeds points, such as, finding **the higher population density center** in color distribution or searching the mountain peaks in **color histogram**. Secondly we applied this model for automatic segmentation of key color areas in an image. After the segmentation, each segmented color area is projected onto **PC** (**Principal Component**) space and the paired segments are selected to transfer or mutually interchange the colors one to another between the corresponding pairs. Finally a color atmosphere in reference scene is transferred into a source scene by matching the **PC**s through the hue rotation and the variance scaling in **PC** axes between the corresponding paired segments. The paper introduces the experiments on typical applications to scene color change, scene-referred color correction, or flesh-tint reproduction for facial images.*

Introduction

Image segmentation has been used for various purposes. In our previous papers, we have reported an object-to-object color transform strategy based on color clustering for pleasant color reproduction.[1,2] However, it is difficult to separate a complicated object exactly from the image. Hence, its applications were limited to the color transforms where segmentation errors are not so striking, such as color correction or adjustment between the two images with color similarities. Recently, E. Reinhard et al[3] tried to transfer the scene color from one image to another using vision-based lαβ color space and M. Zhang et al[4] applied it to correct the color imbalance between the right and left image in a panoramic scene. Although lαβ is a visually de-correlated color space, its axes don't always match to the principal axes in the image and doesn't always work in stable.

This paper presents our approach to a color interchange between different objects in different scenes. A color image is composed of different objects distinguished from others that are distributed in clusters in 3D color space. Unsupervised image segmentation method in our previous paper combines the Bayesian decision rule with K-means classifier as a starter for setting the initial seeds points. Once the key color areas are clearly segmented from a source and a reference (target) image, their clustered colors could be mutually interchanged from one to another and vice versa. In our model, the color interchanges are done for their PC to be matched through each transform matrix which is mathematically derived for a pair of source and reference color clusters.

Scene Color Exchange Model

Figure 1 illustrates a system concept to interchange the major object colors between two different scenes with or without similarity.

Bayesian Classifier with K-means

In the proposed model, we combined a well-known ***Bayesian*** classifier with a popular ***K-means*** clustering method as illustrated in Figure 2.

Initial Seed Setting

To start an unsupervised color classifier for unknown image, any geometric centroid must be set in 3D color space as a seed point.

Setting at Higher Population Lattice Center

At first, we generated the regular lattice points inside the rectangular parallelepiped limited by min-max CIELAB coordinates for the image color distribution. Next, the body centers with higher density of color population are selected as a candidate for the initial seed points.

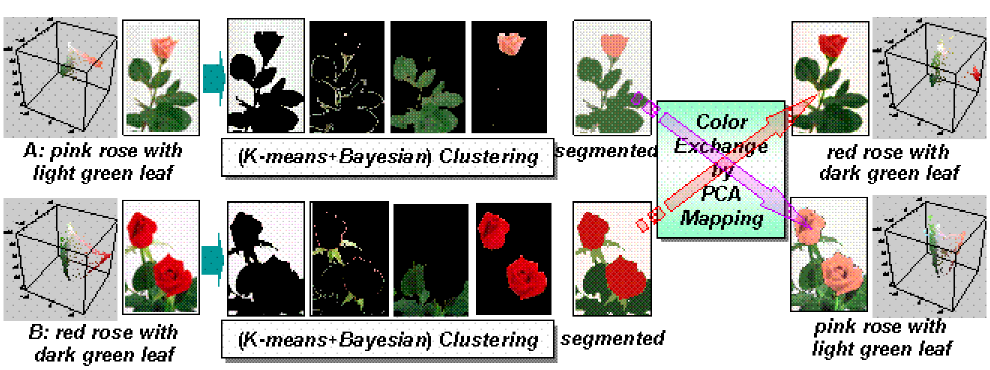


*Figure 1. Scene Color Interchange Model based-on **PC** Matching by Image Segmentation*

Setting at Peak of Color Histogram

Since the higher population body centers in regular lattice don't exactly reflect the true centers of wide-spread clusters, we analyzed the color histogram in CIELAB space and set the initial seeds at its mountain peaks. These peaks reflect a more reliable candidate than the above regular lattice center.

Correction of Seed Points by K-means

K-means clustering model introduced by *J. MacQueen* has been widely used as an unsupervised classifier. The locations of initial seed points are iteratively corrected by ***K-means*** and relocated at the more reliable centers of cluster.

Letting a CIELAB color vector $\boldsymbol{X}$ and a mean vector $\boldsymbol{\mu}$ be

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

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

where $E\{arg\}$ is the expected value of the argument and t denotes the transpose. ***K-means*** algorithm partitions (or clustering) N data points into K disjoint subsets $\boldsymbol{S}_j$ containing N_j data points so as to minimize the sum-of-squares criterion,

$$J = \sum_{k=1}^{K} \sum_{n \subseteq S_k} \left|\boldsymbol{X}_n - \boldsymbol{\mu}_k\right|^2 \tag{3}$$

where $\boldsymbol{X}_n$ is a vector representing the nth data point and μ_k is the geometric centroid of the data points in $\boldsymbol{S}_j$. In general, the algorithm does not achieve a global minimum of J over the assignments. Since the algorithm uses discrete assignment rather than a set of continuous parameters, the minimum cannot be properly called a local minimum. Despite these limitations, the algorithm is popularly used because of its ease in implementation. After the initial seed points are assigned to the K sets, then the centroid is re-computed for each cluster and the seed points are renewed. These two steps are continued until no further change in the assignment of the centroid.

Bayesian Classifier

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

$${}_k d(Bayes) = -\log\{p(k)\} + \frac{1}{2}\log\left(\left|{}_k\boldsymbol{\Sigma}_X\right|\right) + \frac{1}{2}\left(\boldsymbol{X} - {}_k\boldsymbol{\mu}\right)^t {}_k\boldsymbol{\Sigma}_X^{-1}\left(\boldsymbol{X} - {}_k\boldsymbol{\mu}\right) \tag{4}$$

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

Thus a color vector $\boldsymbol{X}$ is classified into class $k = c$, if

$$\min\left\{{}_c d(Bayes)\right\}_{k=1\sim K} = {}_c d(Bayes) \tag{5}$$

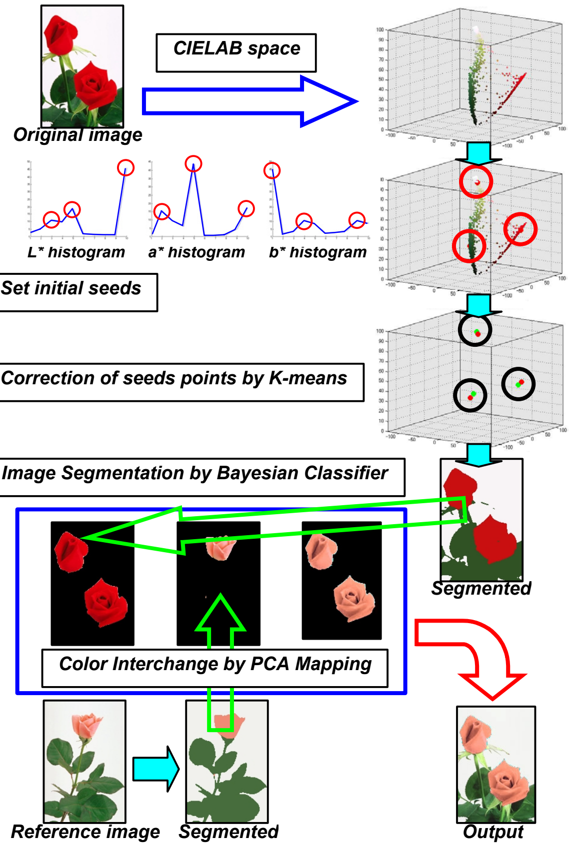


Figure 2. Flow Diagram of Proposed Algorithm

Removal of Boundary Noise by Median Filter

Though ***Bayesian*** classifier with ***K-means*** starter worked very well, isolated noises appear on the color boundaries caused by miss-classification. In order to remove these isolated noises, we applied Median filter after classification and obtained clear segmentation without noises.

Scene Color Interchange in Segments

When the segmentation is successful, ***PCA*** (***Principal Component Analysis***) is done and ***Hotelling Transform*** matrices are extracted in ***PC*** space. Finally, the color distribution of segmented object in a source image is transformed into that of corresponding target in a destination image. Thus the source object color looks to be interchanged with target color of destination.

Hotelling Transform projects a color vector ${}_k\boldsymbol{X}$ in class k into a vector ${}_k\boldsymbol{Y}$ in ***PC*** space as

$${}_k\boldsymbol{Y} = {}_k\boldsymbol{A}\left({}_k\boldsymbol{X} - {}_k\boldsymbol{\mu}\right) \tag{6}$$

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

$${}_k\boldsymbol{A} = \left[{}_k e_1, {}_k e_2, {}_k e_3\right] \tag{7}$$

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 ${}_k\Sigma_X$ given by

$$ {}_k\Sigma_Y = {}_kA\left({}_k\Sigma_X\right){}_kA^t = \begin{bmatrix} {}_k\lambda_1 & 0 & 0 \\ 0 & {}_k\lambda_2 & 0 \\ 0 & 0 & {}_k\lambda_3 \end{bmatrix} \tag{8} $$

The eigen values ${}_k\lambda_1$, ${}_k\lambda_2$, ${}_k\lambda_3$ denote the variances which mean the energy distributed in principal axes. Thus the color vectors in source image and destination image are mapped to the same ***PC*** space. Here in the projected ***PC*** space, the following equations are formed to make match a source vector ${}_kY_{ORG}$ in class k to a reference vector ${}_jY_{REF}$ in class j by applying a scaling matrix ${}_kS$.

$$ \begin{aligned} {}_kY_{ORG} &= {}_kA_{ORG\ k}\left({}_kX_{ORG} - {}_k\mu_{ORG}\right) \\ {}_jY_{REF} &= {}_jA_{REF}\left({}_jX_{REF} - {}_j\mu_{REF}\right) \end{aligned} \tag{9} $$

$$ {}_jY_{REF} = {}_{jk}S \cdot {}_kY_{ORG} \tag{10} $$

$$ {}_{jk}S = \begin{bmatrix} \sqrt{{}_j\lambda_{1REF} / {}_k\lambda_{1ORG}} & 0 & 0 \\ 0 & \sqrt{{}_j\lambda_{2REF} / {}_k\lambda_{2ORG}} & 0 \\ 0 & 0 & \sqrt{{}_j\lambda_{3REF} / {}_k\lambda_{3ORG}} \end{bmatrix} \tag{11} $$

Solving equations (9) and (10), we get the following relation between a source color ${}_kX_{ORG}$ and a reference color ${}_jX_{REF}$ in reference image which we want to interchange.

$$ {}_jX_{DST} - {}_j\mu_{REF} \cong {}_{jk}M_C\left({}_kX_{ORG} - {}_k\mu_{ORG}\right) \tag{12} $$

The matching matrix ${}_{jk}M_C$ is given by

$$ {}_{jk}M_C = \left({}_jA_{REF}^{-1}\right)\left({}_{jk}S\right)\left({}_kA_{ORG}\right) \tag{13} $$

When ${}_kA_{ORG}$ and ${}_jA_{REF}$ denote the eigen matrix for a source segment of class k and a reference segment of class j.

Experimental Results

Comparison of Regular Lattice and Color Histogram

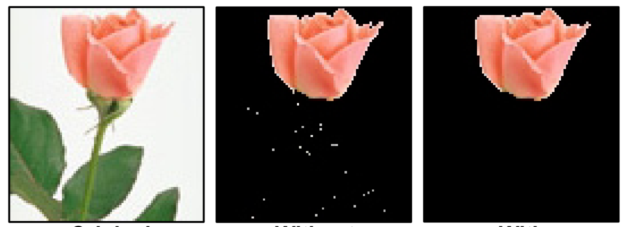
Figure 3 shows a segmentation result by setting initial seeds with regular lattice or with ***color histogram***. Of course, local optimal solutions by ***K-means*** are different according to the initial seeds points. The setting method by ***color histogram*** clearly worked better in this sample.

Median Filter Effect

The segmentation results with and without Median filter were compared each other. Figure 4 shows how the isolated noises are reduced by ***Median*** filter in the segmented object.

Original Image | ***Segmented Image by Regular Lattice*** | ***Segmented Image by Color Histogram***

*Figure 3. A segmented results image when Regular Lattice or **color histogram** were used for setting initial seeds points.*

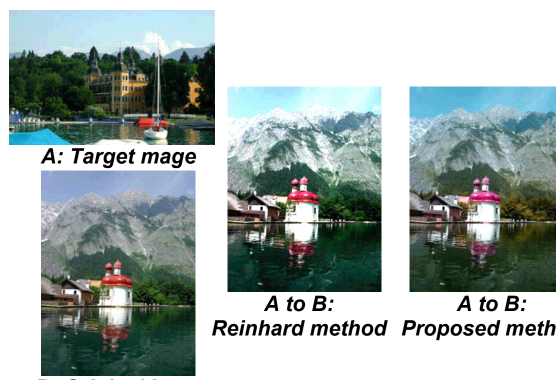


Original Image | ***Without Median Filter*** | ***With Median Filter***

Figure 4. Boundary noise reduction by Median filter

Total Color Interchange

The whole color atmospheres were interchanged between two scenes by applying our proposed algorithm without clustering (K = 1) (Figure 5).



A: Target mage

A to B: Reinhard method

A to B: Proposed method

B: Original Image

Figure 5. Comparison in total color interchange.

Color Interchange with Color Segmentation

Next we tried to interchange the segmented object colors between the different scenes. Figure 6 shows a result interchanged between two images of "pink rose" and "red rose". Two images look similar in colors but have isolated clusters, "*Total PC matching*" and "$l\alpha\beta$" models failed in the color interchange, because it's hard to manipulate as a single cluster. While the segmentation model worked best in comfortable color rendition. Figure 7 is another result, where the pictorial atmosphere of Gogh's "Café" is transferred into real scene "Castle". Theoretically our model reflect the color of "Café" more exactly than Reinhard's. However, which is comfortable will depend on the subjective impression by observers.

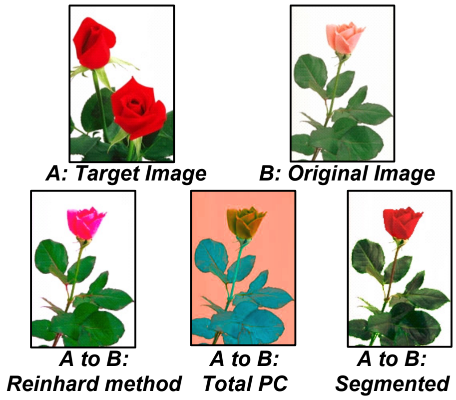


Figure 6. Improvement by color interchange with color segmentation.

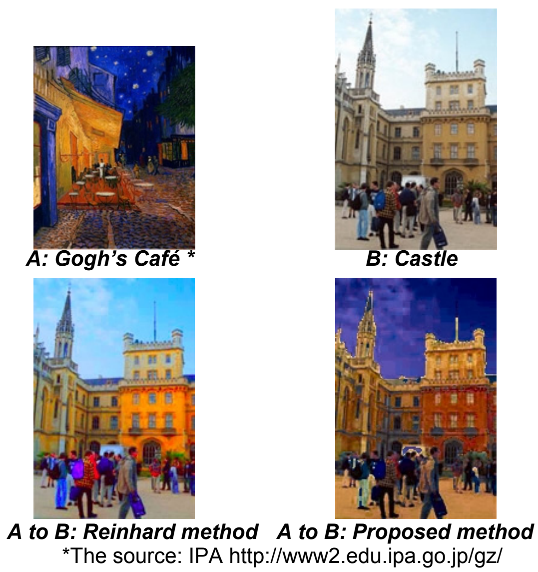


Figure 7. Comparison of Reinhard model and proposed model

Conclusion

This paper proposed a scene color transfer model by region-based ***PC matching*** in color clusters. Our basic ***PC matching*** model worked robust to transfer the total color atmosphere from one scene to another when manipulated as a single cluster. While local ***PC matching*** model by image segmentation worked effective for multi-clustered scenes to interchange their object colors between the different pair of clusters. Our model proved to be robust even for the two different scenes with color dissimilarity.

In conclusion, the paper is summarized as follows.

- Unsupervised Bayesian classifier was improved by coupling with K-means clustering.
- The proposed scene color transfer algorithm was tested for the different scenes and its validity in using PC space was verified.

Many problems are still left in practical use, for example, automatic selection of paired clusters to be interchanged is hard to solve logically for every kind of images. But the proposed approach would be a clue to a "*pleasant*" or "*comfortable*" color imaging applicable to scene simulation, industrial design, and/or computer graphics.

References

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Author Biography

Yoshifumi Matsusaki entered Department of Information and Image Sciences, Chiba University, Japan in 2001. Since 2004, he has been a Master student in Graduate School of Science and Technology of the same university. His current research interests include color image processing and its application to pleasant color imaging.