Comfortable Color Conversion using Image Segmentation

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Abstract

This paper presents a color transformation algorithm into the preferred colors extracted from the reference image. Key color objects areas are separated from original image by the image segmentation method using color distance measures in CIELAB space and the filtering considering local information. Each object color is transformed for its principal component (PC) to be matched to the corresponding reference color what we feel to be preferable. The color conversion into preferred reference color is performed by 3 x 3 matrix derived by PCA. Finally the preferred image is obtained by merging these key color areas into other remaining areas. The paper introduces the experimental results on the transformation for memorial colors such as skin color, green grass, and blue sky. extracted from different reference image and discusses the reduction of segmentation errors.

Introduction

Preferred color reproduction by Hunt classified to 6th category or color-preference reproduction by Fairchild re-classified to 5th objective is an eternal goal to present one's intents,, where the image need not to be faithful to the original but to be pleasant for clients. We proposed object-to-object color matching method by image segmentation, mainly applied to automatic color correction for digital color prints. In this paper, the same strategy is extended to transform the unwanted objects' colors to the preferred ones to approach to the preferred color rendition. Here, the key color areas such as skin color or green grass are separated from original image and matched to the trained reference colors to be preferred.

System Concept

First, the original image is segmented into major key color regions by statistical distance measures between the color clusters distributed in CIELAB space. Next, the segmentation errors on the region boundaries are removed by local spatial filtering in chromatic plane. Finally the segmented key colors are transformed into the previously trained preferred references, for their ellipsoidal shapes formed by PCs to be matched to those of reference colors.

Image Segmentation

In our previous papers, three color distance measures, Euclidian distance, Mahalanobis distance, and maximum likelihood function based on Bayesian decision rule, were introduced to the image segmentation. Among them, Bayesian decision rule mostly worked well, however, the segmentation errors in the mixed colored areas or the boundaries of the clusters arose as isolated noises or third wrong colors after color transformation.

In this paper, we propose a new color distance scale that can separate the ambiguous color clusters more clearly dependent to the image color distributions, and also apply the error correction spatial filter to remove the noisy pixels on chromatic plane.

A New Focal Distance Measure for Image Segmentation

Assuming the statistical probability ellipse in the two-dimensional first and second PC axes, a new focal color distance to the center of class k ellipsoid is approximately measured by

$${}_k d_f = \left\| X - {}_k f_+ \right\| + \left\| X - {}_k f_- \right\| \tag{1}$$

Where, ${}_k d_f$ means the averaging sum of Euclidian distance from two co-focuses ${}_k f_+$ and ${}_k f_-$ for the class k ellipse. The co-focal points are given by

$${}_k f_\pm = {}_k M \pm (\sqrt{{}_k P_1^2 - {}_k P_2^2}) \cdot {}_k e_1 \tag{2}$$

Where ${}_k M$ represents the mean vector for the class k, and ${}_k e_1$ is the eigen vector of the first PC.

$${}_k P_1 = \sqrt{{}_k \lambda_1} \Big/ 2\beta \tag{3}$$

$${}_k P_2 = \sqrt{{}_k \lambda_2} \Big/ 2\beta \tag{4}$$

Where, ${}_k\lambda_1$ and ${}_k\lambda_2$ are the first and second eigen values which represent the variances in the long and short axes of the ellipse, and β denotes a threshold.

Spatial Filtering for Segmentation Noise Reduction

Segmentation error arises as an isolated noise on the boundaries or as the third wrong colors in the mixture of two or more color clusters segmentation.

Taking the local spatial information into account by referring the surrounding pixels, the isolated noise pixels are removed by local filter. Here the class number at the center pixel in attention, is replaced by the class number that has the highest frequency in the 3 × 3 matrix elements as shown Figure.1. Each figure in the element shows class number and the bold figure represents the class number after filtering as shown in a sample of Figure 2.

Figure 3 summarizes the proposed image segmentation procedure.

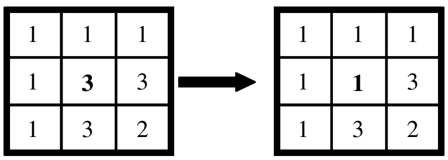


Figure 1. Spatial filter for noise reduction

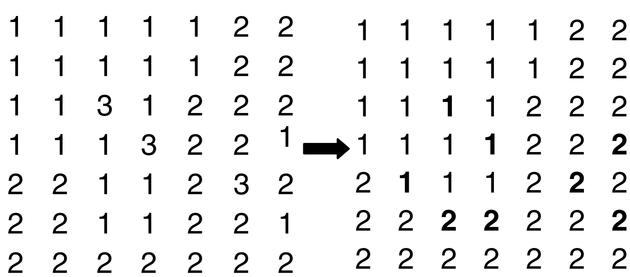


Figure 2. Correction of segmentation errors by spatial filter

Comfortable Color Conversion

Comfortable Reference Colors

In the simulation experiments, the four major key colors were tested to transform to the preferred reference colors. The preferred target colors are trained from the natural pictures including skin color, bluish sky, greenish grass, and reddish flower.

The statistical PC parameters, such as the mean vector, the variance-covariance matrix, its eigen vector, and eigen value, were collected and trained from the images with comfortable color distributions in CIELAB space. These reference colors were selected through subjective assessment for the candidate images including comfortable key colors.

In the table 1, the key colors simply called skin, blue, green and red, represent typical "skin color for young Japanese lady", "clear blue sky", "refreshing green lawn" and "brilliant reddish flower", respectively.

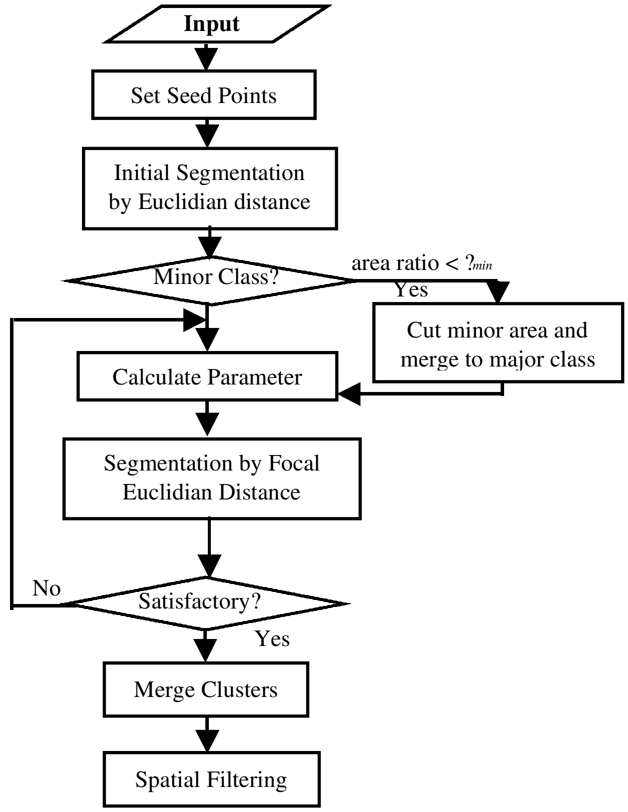


Figure 3. Segmentation Algorithm

Table 1. Assessment Term

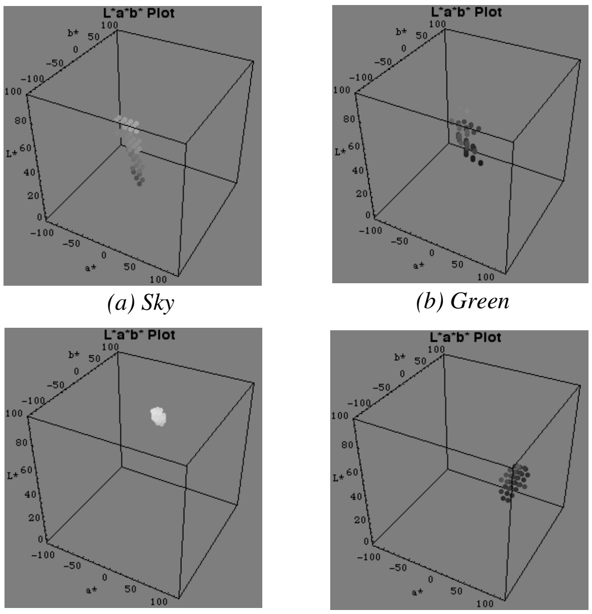
Key Colors	Assessment term
Skin	Skin for Japanese Lady
Blue	Clear Blue Sky
Green	Refreshing Green Lawn
Red	Brilliant Red Flower

Table 2. Assessment Measure

Measure	Excellent	Good	Fine	Poor	Bad
Point	+3	+2	+1	0	-1

As an assessment measure, we used "excellent" which has the highest point +3, and "bad" which has the worst -1. The above assessment was done by 10 observers, and the statistical ensembles were taken.

The CIELAB distributions of trained reference colors are shown in Figure 4.



(a) Sky *(b) Green*

(c) Skin *(d) Red*

Figure 4.Distribution of trained comfortable colors in CIELAB

Color Conversion

In each segmented color region *k* in the original image, the PCs are calculated by Hotelling transform. An original color vector kX is transformed into vector kY by the projection onto PC space as follows.

$$ {}_kY = {}_kA({}_kX - {}_kM) \tag{5} $$

Where ${}_kM$ denotes the mean vector and transformation matrix and ${}_kA$ is given by

$$ {}_kA = [{}_ke_1, {}_ke_2, {}_ke_3]^t \tag{6} $$

Here, ${}_ke_i$ denotes the eigen vector for the *i*-th PC.

The color transform matrix ${}_kC$ is determined to satisfy the following equation,

$$ {}_kX_{comf} - M_{comf} = {}_kC({}_kX_{org} - {}_kM_{org}) \tag{7} $$

where subscripts *org* and *comf* denote original and comfortable colors respectively.

We can employ the equation (8), because the Hotelling transformation works to project these two color vectors of original and comfortable into the same PC space.

$$ {}_kY_{trans} = {}_kS\,{}_kY_{org} = {}_kY_{comf} \tag{8} $$

where subscript *trans* denotes transformed image, and ${}_kS$ denotes a scaling matrix,

$$ {}_kS = \begin{bmatrix} \sqrt{r_1} & 0 & 0 \\ 0 & \sqrt{r_2} & 0 \\ 0 & 0 & \sqrt{r_3} \end{bmatrix} \tag{9} $$

${}_kS$ is a diagonal matrix whose elements are given by

$$ r_i = {}_k\lambda_{n\,comf} \Big/ {}_k\lambda_{n\,org} \quad (n = 1,2,3) \tag{10} $$

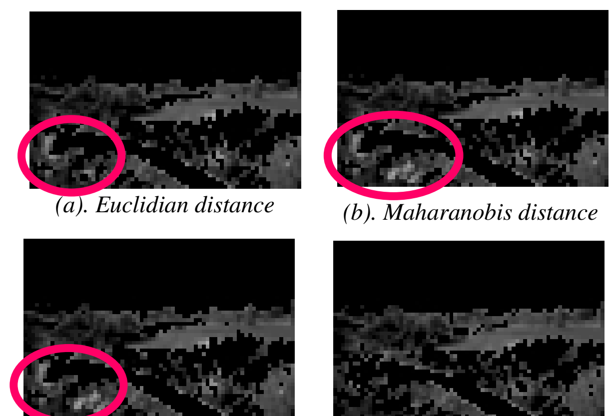
Finally, the transform matrix ${}_kC$ is calculated as

$$ {}_kC = (A_{comf}^{-1})({}_kS)(A_{org}) \tag{11} $$

The transform matrix kC works to match the statistical distributions for segmented original key colors to those of preferred references described by PC ellipsoids.

Experimental Results

First, the image segmentation performance by proposed new focal distance measure was compared with that by Euclid distance, Mahalanobis distance and the maximum likelihood function.



(a). Euclidian distance *(b). Maharanobis distance*

(c). Bayesian decision *(e). Focal distance*

Figure 5. Segmentation Images

Figure 5 shows a segmented example. The specified green key color areas are extracted by applying the above four different distance measures. As clearly observed in this sample, the proposed new focal distance measure resulted in the best. For other images, it mostly worked well.

Secondly, the preferred color transformation experiments were evaluated for the following five choices of matching types.

(b): center, (c): PC axes direction, (d): center and PC axes direction, (e): PC axes direction and dispersion. (f): center, PC axes direction and dispersion.

An example of transformed images is shown in Fig. 6.

The results by (c): PC axes direction matching or by (e): PC axes direction and dispersion matching, didn't give the comfortable rendition, because the matching in the cluster center is most important. In this sample, (d): center and PC axes direction matching and (f): center, PC axes direction and dispersion matching resulted in the better color appearance. In our opinion tests, all of the principal component matching by type (e) brought the most comfortable color rendition.

(a) Original Image

(b). Center

(c). Axes

(d). Center, Axes

(e). Axes, Dispersion

(f). Center, Axes, Dispersion

Figure (6) Transformed Images

Conclusions

A newly proposed focal distance measure resulted in the better image segmentation with less confusion in ambiguous cluster boundaries reducing the miss-segmentations. Furthermore, the isolated noisy pixels were removed by using simple spatial filter.

This paper challenged to the comfortable color transformation by two key technologies, that is, by “ image segmentation” and by “color matching in PC space”. However, it is too difficult to extract the key color areas from the given image automatically, because they are dependent on the image contents. Learning process with teacher or interactive selection of key colors on screen will be a practical solution to this problem.

After the success in image segmentation, proposed PC matching method worked well for the PCs of segmented key colors to be automatically matched to those of preferred reference colors.

In this matching process, how to prepare the trained reference color samples is a key point. Sometimes, if the trained samples have small standard deviations, the transformed image happens to be de-saturated, because the scaling matrix works to compress the chroma components or colorfulness.

Future works should be continued to improve the segmentation accuracy by taking the local spatial correlations into account and also to develop the advanced training method for reference colors through psychophysical evaluation experiments.

Reference

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Biography

Mitsunori Suzuki graduated from Department of Image Science, Faculty of Engineering, Chiba University, Japan in 2000. He is a student at Graduate school of Science and Technology, Chiba University. His research interests include image segmentation, color image processing and pattern recognition.