Unsupervised Image Segmentation by Bayesian Discriminator Starting with K-means Classifier

Hiroaki Kotera and Takahiko Horiuchi
Department of Information and Image Sciences, Chiba University
Chiba, Japan

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. Once the colored objects are clearly segmented in a source and a destination image, they could be mutually interchanged from one to another. This paper proposes a setting method for initial seed points to improve the performance of Bayesian discriminator and introduces a new application to swap the scene colors.

Image Segmentation by Color Clustering

Figure1 illustrates the overview of unsupervised image segmentation process. First the image color distribution is analyzed in CIELAB space. Next the initial seed points located at the higher populations are extracted as a candid ate for the clustering centers. The location of seed points are corrected by ***k-means*** classifier. Then image segmentation by Bayesian discriminator is performed based on color clustering. Once the segmentation is successful, a region-based color transformation is possible between the different objects in different scenes.

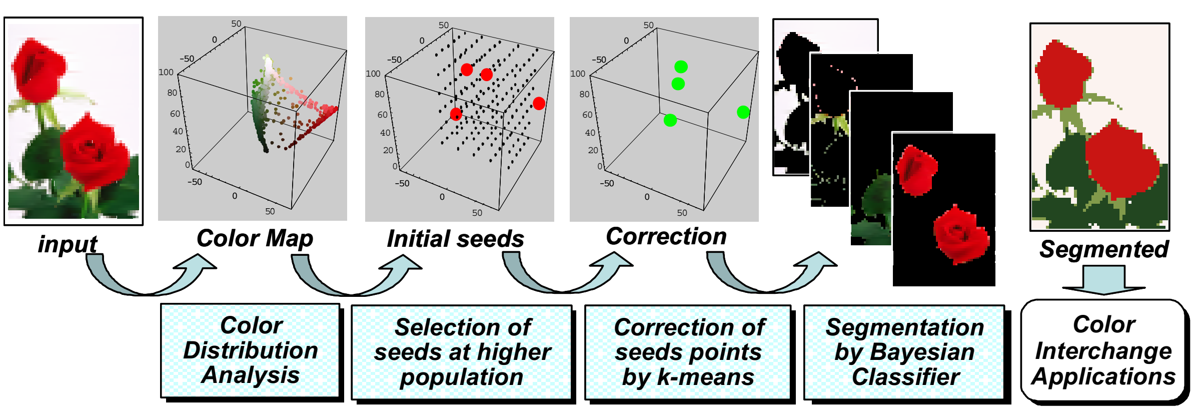

Figure 1. Overview of Unsupervised Color Image Segmentation

Bayesian Classifier with k-means Starter

Color Distance Measure

In the previous papers, we examined the following three typical color distance measures to discriminate the clustered color objects.

[1] Euclidean [2] Mahalanobis [3] Bayesian discriminator

Among them a well-known ***Bayesian*** discriminator worked best for many test samples.

Setting of Initial Seeds Points

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

A. Random

Obviously, a random setting of seed points resulted in the worst and unstable segmentation, because it is independent of image color distribution.

B. 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 the min-max color ranges of image color distribution.

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

$$\begin{aligned} \Delta\boldsymbol{L} &= [max\{L_n^*\} - min\{L_n^*\}]/m \\ \Delta\boldsymbol{a} &= [max\{a_n^*\} - min\{a_n^*\}]/m \\ \Delta\boldsymbol{b} &= [max\{b_n^*\} - min\{b_n^*\}]/m \end{aligned} \tag{1}$$

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

$$\boldsymbol{X_n} = [L_n^*, a_n^*, b_n^*]^t \;;\; n = 1 \sim N \tag{2}$$

$$\boldsymbol{\mu} = E\{\boldsymbol{X}\} = [\overline{L}^*, \overline{a}^*, \overline{b}^*]^t \tag{3}$$

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.

$$\begin{aligned} &\mu_{seed}(k) = E\{\boldsymbol{X_n}\} \\ &\quad for\ \boldsymbol{X_n} \in \boldsymbol{b_k}\ \ and\ P(1) \geq P(2) \geq P(3) \cdots P(K) \end{aligned} \tag{4}$$

These seed points are used as initial class centers for the color clustering in the next stage.

C. Correction for B by k-Means

Surely the method ***B*** sets a better initial class center than ***A*** depending on image color distribution, but $\mu_{seed}(k)$ 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 $\mu_{seed}(k)$.

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,

$$J = \sum_{k=1}^{K} \sum_{n \subseteq \boldsymbol{S}_k} \left| \boldsymbol{X}_n - \boldsymbol{\mu}_k \right|^2 \tag{5}$$

where μ_K is the geometric centroid of the data points in $\boldsymbol{S}_k$ First the initial seed points $\mu_{seed}(k)$ are assigned to $k=1\sim K$ classes, then the centroid is re-computed 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 by setting the initial seeds in random, here we applied this technique to relocate the initial seeds to the more reliable gravity centers in clusters.

3.2 Bayesian Classifier

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

$$\begin{aligned} {}_k d(Bayes) &= -log\{p(k)\} + \frac{1}{2} log\left(\left|{}_k\Sigma_X\right|\right) \\ &\quad + \frac{1}{2}\left(X - {}_k\mu\right)^t {}_k\Sigma_X^{-1}\left(X - {}_k\mu\right) \end{aligned} \tag{5}$$

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

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

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

$$\min\{{}_c d(\mathrm{Bayes})\}_{k=1\sim K} = {}_c d\,(\mathrm{Bayes}) \tag{6}$$

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.***

Interchange in Segmented Scene Colors

When the segmentation is successful, a flexible color transformation is possible for each individual cluster in attention. Reinhard et al[7] tried to transfer the scene color of one to another, where the total atmosphere of source scene was transferred to that of reference scene.

In our approach, individual object color is interchanged between a pair of source and target clusters in two different images. 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 in both source and target images. *Hotelling Transform* in ***PCA*** (*Principal Component Analysis*) projects a ***color*** vector ${}_k\boldsymbol{X}$ in class k into a vector ${}_k\boldsymbol{Y}$ in ***PC*** space as

$${}_k\boldsymbol{Y} = {}_k\boldsymbol{A}({}_k\boldsymbol{X} - {}_k\boldsymbol{\mu}) \tag{7}$$

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

$${}_k\boldsymbol{A} = \left[{}_k\boldsymbol{e}_1, {}_k\boldsymbol{e}_2, {}_k\boldsymbol{e}_3\right] \tag{8}$$

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

$${}_k\boldsymbol{\Sigma}_{\boldsymbol{Y}} = {}_k\boldsymbol{A}({}_k\boldsymbol{\Sigma}_{\boldsymbol{X}})_k\boldsymbol{A}^t = \begin{bmatrix} {}_k\lambda_1 & 0 & 0 \\ 0 & {}_k\lambda_2 & 0 \\ 0 & 0 & {}_k\lambda_3 \end{bmatrix} \tag{9}$$

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 ${}_{jk}\boldsymbol{S}$.

$$\begin{aligned} {}_k\boldsymbol{Y}_{DST} &= {}_k\boldsymbol{A}_{DST}({}_k\boldsymbol{X}_{DST} - {}_k\boldsymbol{\mu}_{DST}) \\ {}_j\boldsymbol{Y}_{ORG} &= {}_j\boldsymbol{A}_{ORG}({}_j\boldsymbol{X}_{ORG} - {}_j\boldsymbol{\mu}_{ORG}) \end{aligned} \tag{10}$$

$${}_k\boldsymbol{Y}_{DST} = {}_k\boldsymbol{S} \cdot {}_j\boldsymbol{Y}_{ORG} \tag{11}$$

$${}_{jk}\boldsymbol{S} = \begin{bmatrix} \sqrt{{}_k\lambda_{1DST} / {}_j\lambda_{1ORG}} & 0 & 0 \\ 0 & \sqrt{{}_k\lambda_{2DST} / {}_j\lambda_{2ORG}} & 0 \\ 0 & 0 & \sqrt{{}_k\lambda_{3DST} / {}_j\lambda_{3ORG}} \end{bmatrix} \tag{12}$$

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.

$${}_k\boldsymbol{X}_{DST} - {}_k\boldsymbol{\mu}_{DST} = {}_{jk}\boldsymbol{M}_C({}_j\boldsymbol{X}_{ORG} - {}_j\boldsymbol{\mu}_{ORG}) \tag{13}$$

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

$${}_{jk}\boldsymbol{M}_C = \left({}_k\boldsymbol{A}_{DST}^{-1}\right)\left({}_{jk}\boldsymbol{S}\right)\left({}_j\boldsymbol{A}_{ORG}\right) \tag{14}$$

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

First the performance of ***k-means Bayesian*** *classifier* is evaluated in comparison with normal ***Bayesian*** *classifier* without ***k-means***. Second, we tried to interchange the scene colors between two resemble images and to transfer a specified object color in source image into a different object color in target image.

Comparison in Color Classifiers

Figure 2 shows a segmentation result tested for image "***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, because they are placed at independent of image color distributions. 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 the normal ***Bayesian*** in second row. In conclusion, the proposed ***k-means Bayesian*** resulted in best performance.

Figure 3 shows another result for image ***"Mt. Fuji"***. In this sample, ***k-means Bayesian*** also worked excellent as compared with normal ***Bayesian***.

Interchange in Scene Colors

Proposed ***k-means Bayesian*** classifier is applied for extract the object areas from source and target scenes and a pair of color distributions in segmented clusters are interchanged from one to another. Fig.4 shows a tested primitive sample.

A ***red rose*** with ***dark green*** leaf is transformed into a ***pink rose*** with ***light green*** leaf and vice versa.

Conclusions

In this paper, we improved a conventional ***Bayesian*** *classifier* by coupling with a well-known ***k-means*** clustering method as a starter to set the initial seed points.

The crucial difference in normal and improved ***Bayesian***s 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 approach to object-to-object scene color interchange is challenged to open a new field of applications such as automatic creation or synthesis of scenes with similar atmosphere.

References

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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.

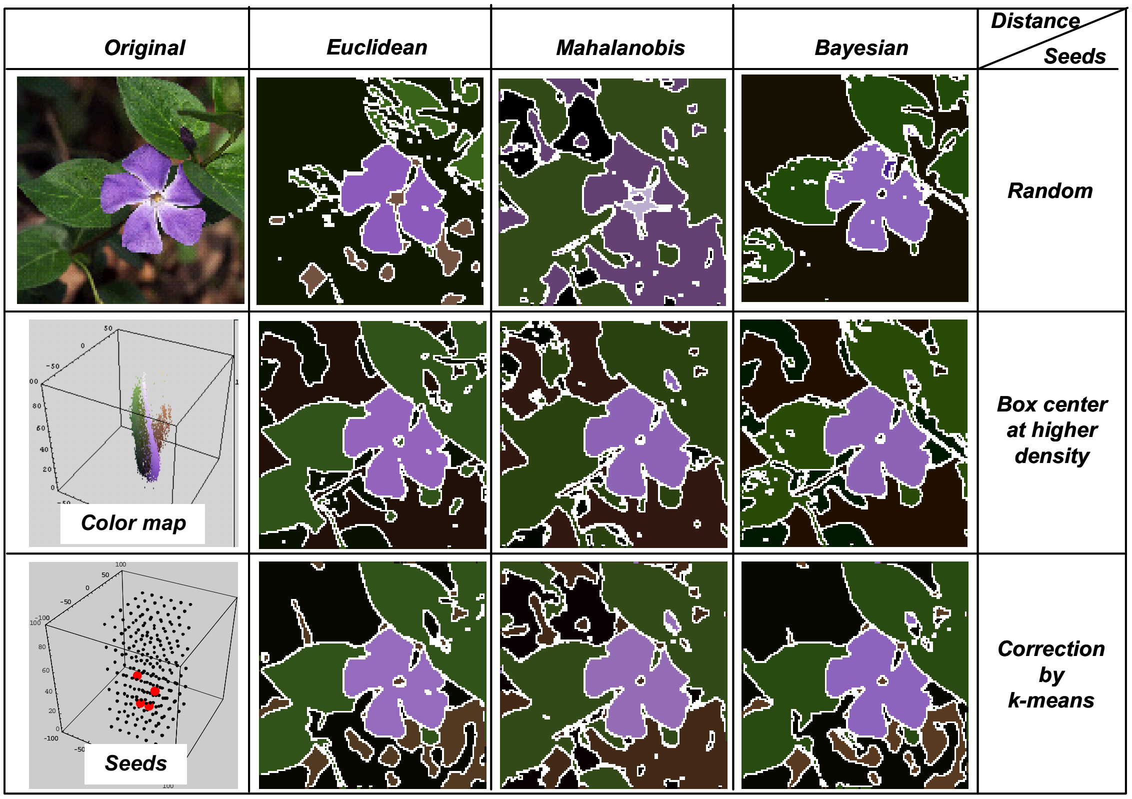

Figure 2. Comparison in image segmentations by color clustering methods

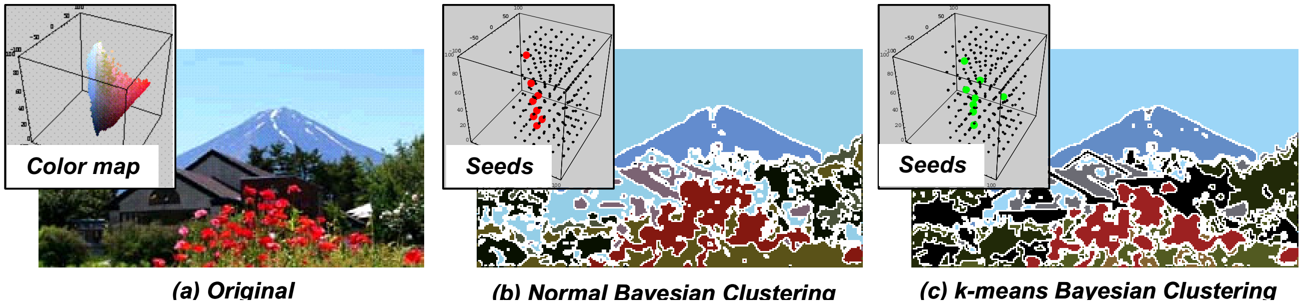

Figure 3. Comparison in segmentations by normal Bayesian and k-means Bayesian

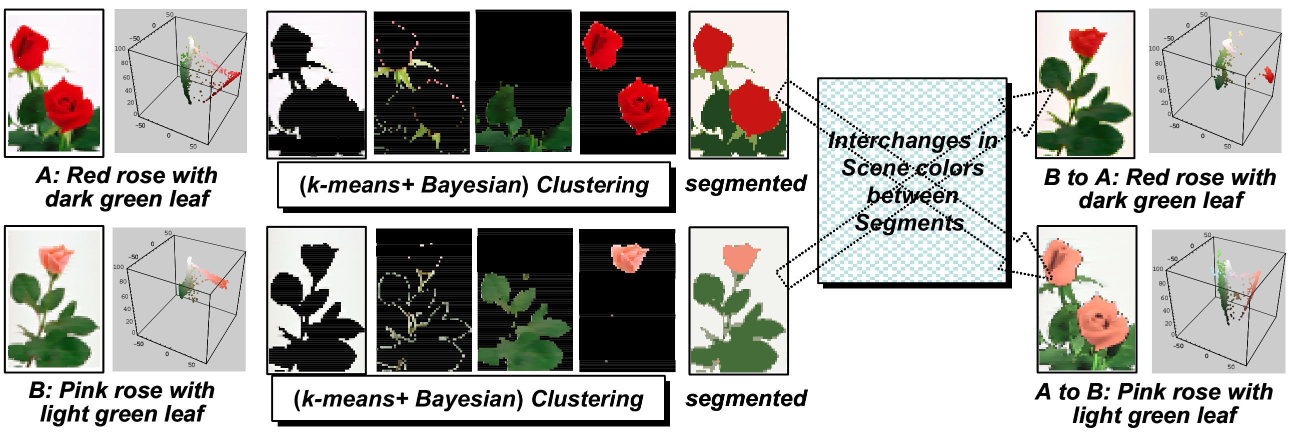

Figure 4. Application to scene color interchange