MVA2000 IAPR Workshop on Machine Vision Applications, Nov. 28–30, 2000, The University of Tokyo, Japan

3—1

Comparison of Color Space Models Based on Human Color Classification and Image Segmentation

Keiko Takahashi† Masaki Matsuura† Takahiro Sugiyama‡ Keiichi Abe†‡
†Graduate School of Science and Engineering
‡Department of Computer Science, Faculty of Information
Shizuoka University *

Abstract

In this paper we compared color space models based on human color perception. For this purpose, we made two experiments to see how human subjects classify color pixels in color images. In the first experiment, subjects classify color pixels without seeing the image. In the second experiment, the subjects segment the images into regions considered to be of similar colors, seeing the images. We define three criteria, two of which are based on the color classification and segmentation made by humans, for comparison of eleven color space models. As a conclusion, we found that L*u*v* and L*a*b* color models are most closer to human color perception.

1 Introduction

In color image segmentation based on clustering methods, segmentation results vary according to color space model used. There is, however, no guideline for selecting the color space model.

In our earlier work[1] we compared eight color models from the viewpoint of using them in the ISODATA clustering method for color image segmentation. However, the problem of choosing an appropriate color model arises not only in segmentation of images. By generalizing the problem, we would like to find color space(s) close to human color perception. We compare eleven color space models based on the results of pixel color classification and region segmentation performed by human subjects.

2 Color spaces for comparison

The following eleven color space models are compared.

- RGB color space
- HSV color spaces:
  Smith model[2], Joblove model[3], Tenenbaum model[4], New HSV model 1, New HSV model 2[5]

*Address: 3-5-1 Johoku, Hamamatsu, Shizuoka, 432-8011 Japan. E-mail: keiko@cs.inf.shizuoka.ac.jp

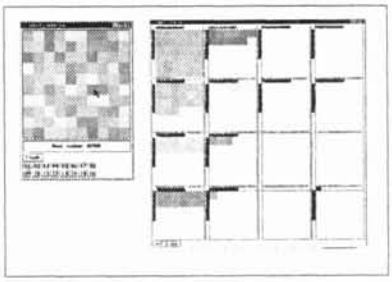

Figure 1: A tool for color pixel classification

- Uniform lightness and chromaticness systems[6]:
  L*u*v* model, L*a*b* model
- Linear transformation models:
  Opponent color axes model[7], YIQ model, YES model[8]

3 Experiments on color pixel classification and region segmentation by humans

3.1 Experiment on pixel classification based on color only by humans

We made two experiments to see how human subjects classify color pixels in a color image. In the first one, subjects are asked to classify color pixels without knowing its position or neighbors' colors in the image.

A tool used for the experiment is shown in Figure 1. On the left a set of pixels selected randomly one after another from the image are shown. The subject must classify them into the bins on the right. The criterion for classification is left to the subjects. As many as bins needed can be used. This process is repeated for all the pixels in the images and the result of the classification is obtained. As stated above the subjects classify pixels based on their colors, without knowing the original images.

Five subjects carried out this experiment. The time required for classification of pixels in an image is about two weeks, three hours a day, in average.

3.2 Experiment of segmentation by humans

In the second experiment the subjects are asked to segment the images into the regions considered to be of similar colors by seeing the images. Thus in this experiment man-made results of region segmentation of the image are produced. Moreover, each region is assigned to one of the color sets, which is considered as a similar color. Three subjects performed this experiment. It took about three hours in average per image.

3.3 Making standard color classification results and standard segmentation results

The color classification results and the segmentation results differ from subjects to subjects, so we would like to integrate into one result, respectively, by collecting common set of color classes (i.e., pixels or regions) from the individual subject's result.

Figure 2 shows inclusion relations among color sets made by two subjects. Color sets specified by each subject rarely cross over the boundaries made by common bigger groups of color sets. Thus the heart of the process is finding such a common group of color sets. The standard color classication results are made by the following two steps:

1. From the inclusion relations among all subjects' color sets, those which can be considered as in the same group are chosen, to make a cluster in standard classication results.

2. Which pixels belong to each cluster are decided.

We applied the above procedure to both human color classication result and human segmentation result.

At the first step, if a color set of a subject's result is included in a color set of another subject's result with a higher percentage than a specified threshold, these color sets are merged to form a cluster. The threshold for inclusion percentage is lowered from a large value less and less. When the percentage of the pixels not belonging to any clusters becomes less than 10 %, the current inclusion threshold and the results are adopted. At this time under the above condition of color set inclusion, the largest number of clusters are generated. This processing is iterated for all color sets of all subjects' results and the clusters of the standard result are derived by merging the color sets in this way. In case of making the standard segmented result, we substitute pixel sets for the color sets in the above procedure.

The next step is to assign the pixels to the clusters of the standard classification result or the standard segmentation result derived in the preceding step. The pixels classified into the same cluster by more than a half of the subjects, belong to that cluster, and the pixels not belonging to any cluster are labeled as unclassified pixels.

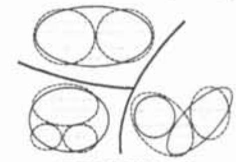

Figure 2: Example of inclusion relation among color sets

4 Criteria for comparison of color models

We compare eleven color models using Munsell color chart, standard classification results and standard segmentation results.

For a color model to be close to human color perception, 1) the distances between colors should be nearly equal for an equidistantly arranged color set in human perception, 2) the colors that humans regard as similar should gather densely and compactly, 3) two color sets that humans regard different should be sufficiently apart. Therefore, we define the following three criteria.

1. Uniform distances between adjacent colors
2. Concentration of clusters
3. Separability between clusters

We measure item 1 using the Munsell color chart and items 2 and 3 using standard classification results and standard segmentation results.

We define the uniformity of color arrangement by the normalized standard deviation U of distances between adjacent colors, i.e.,

$$U = \frac{\sigma_D}{\sqrt[3]{V}}, \qquad (1)$$

where σ_D is calculated by the following equation and V is the volume of the color space in consideration. For the volumes of color models are different, we need the normalization by the volume of the color space.

$$\sigma_D = \sqrt{\sum_{i,j} \frac{d^2(P_i\ ,P_j)}{N_m}}, \qquad (2)$$

where the summation is made over all pairs of adjacent colors $(i,\ j)$, N_m is the number of those pairs and $d(P_i\ ,P_j)$ is the Euclidean distance between the points representing color i and color j in the specified color space.

For checking the uniformity of color spaces we used the Munsell color chart, which is supposed to have an equidistant arrangement of colors from the human perceptual view. We first calculated (R,G,B)

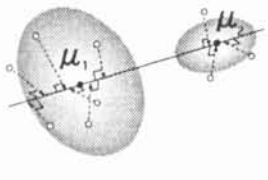

Figure 3: Calculating the separability

value from the (x, y, Yc) value associated with each Munsell color sample and converted it to the value in each specific color space.

A set of pixels which humans regard as the same color should gather tightly in the color space. We measure the degree of concentration of clusters by

$$C = \sum_{i=1}^{N} \sigma_i^3 / V, \tag{3}$$

where N is the number of clusters and σ_i is the standard deviation of cluster i in the color space, which is calculated by

$$\sigma_i = \sqrt{\sum_{k=1}^{n_i} \frac{d^2(\boldsymbol{\mu}_i, \boldsymbol{p}_{ik})}{n_i}}. \tag{4}$$

Here n_i is the number of pixels belonging to cluster i, $d(\boldsymbol{\mu}_i, \boldsymbol{p}_{ik})$ is the Euclidean distance between the center $\boldsymbol{\mu}_i$ of cluster i and the color $\boldsymbol{p}_{ik}$ of the k-th pixel belonging to cluster i.

We borrow a measure from the discriminant analysis for the degree of separability.

The color features of pixels are projected on the straight line passing through the centers of the two clusters in consideration, to reduce three dimensions into one dimension (see Figure 3).

The degree of separability η is defined as follows:

$$\eta = \frac{\omega_1 \omega_2 (\mu_1 - \mu_2)^2}{\sigma^2}, \tag{5}$$

where w_1, w_2 are occurrence probabilities of clusters 1 and 2, respectively, and σ^2 is the total variance over two clusters, calculated by

$$\sigma^2 = \omega_1 \omega_2 (\mu_1 - \mu_2)^2 + (\omega_1 \sigma_1^2 + \omega_2 \sigma_2^2), \tag{6}$$

where μ_1, μ_2 are the averages in clusters 1 and 2, and σ_1^2, σ_2^2 are the variances within clusters 1 and 2, respectively. When the number of pixels contained in each cluster does not differ so much, η is a good measure for separability. If the numbers of pixels in two clusters are quite different, the total σ^2 is pulled to the variance (σ_1^2 or σ_2^2) of the larger cluster. In this case η dose not show the degree of separability appropriately. In real images, such a case often occurs. We balance the populations of the two clusters as if $\omega_1 = \omega_2$ and calculate η to obtain a better degree of separability.

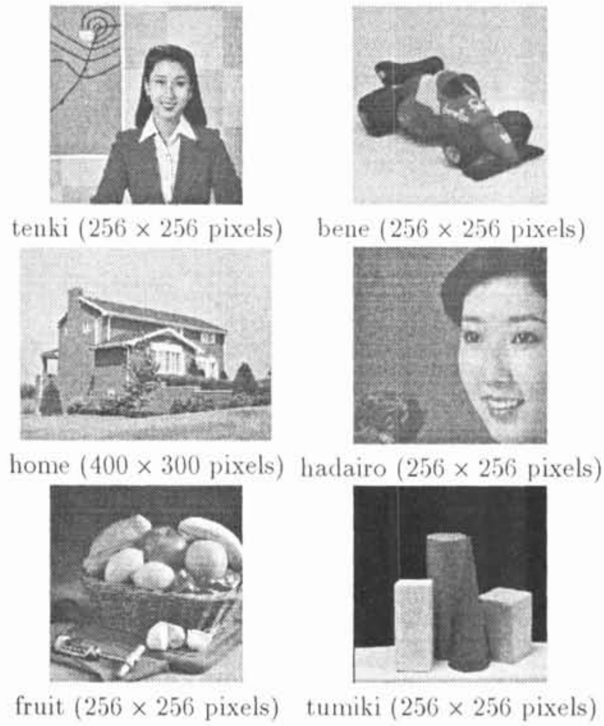

Figure 4: Input images

The degree of separability is measured for each pair of clusters. The degree of separability for a whole image is defined as the geometric mean of the degrees of separability over all pairs of clusters. The reason for using the geometric mean is if there are poor separations for one or more pairs of clusters, the separability of the segmentation as a whole should be low.

5 Experimental Results

5.1 Standard classification results and standard segmentation results

The color images used in this study are shown in Figure 4.

Figure 5 shows the standard classification results produced by the procedure in 3.3 from the classification results of five subjects. The stability of standard classification results was examined by comparing the results with the one produced from the classification results of four subjects (i.e., one subject excluded). As a consequence the standard classification result of 'fruit' image was found unstable. For this reason it was removed from the evaluation of color space models.

Figure 6 shows standard segmentation results made from the segmentation results of three subjects. The stability of each segmentation result was also investigated and there was no problem in their stability.

5.2 Comparative evaluation of color space models

Uniform distances between adjacent colors

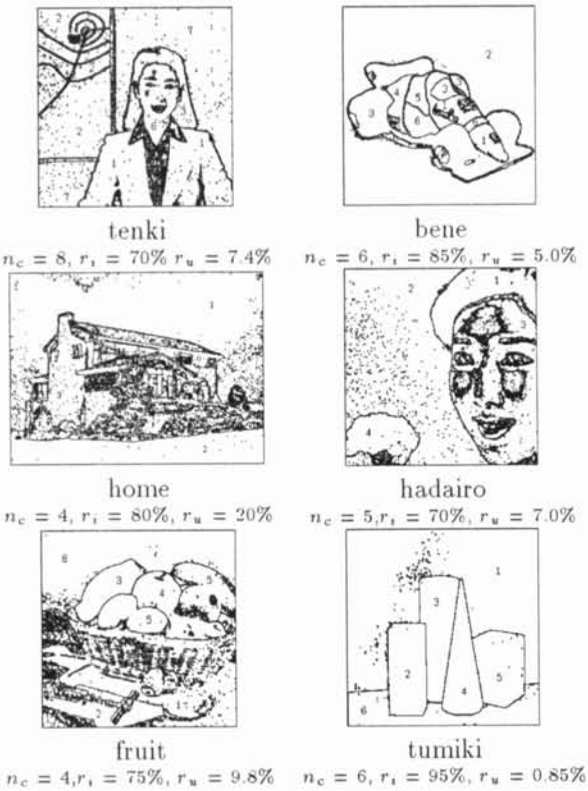

Figure 5: Standard classification results
n_c: the number of clusters
r_i: threshold for inclusion relation
r_u: percentage of unclassified pixels

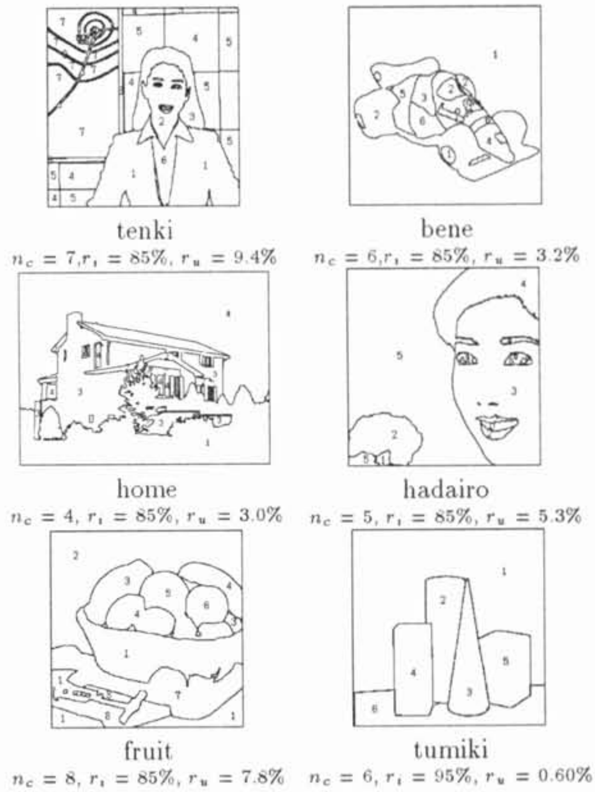

Figure 6: Standard segmentation results
n_c, r_i, r_u: the same as in Figure 5

The uniformity of color arrangement in three directions (hue, saturation, value) using Munsell color chart is shown in Figure 7. The smaller the value is, the better the color space is. L*a*b* model is the best and Joblove model follows next. The opponent color axes model and RGB color space are the worst.

Concentration of clusters

Figures 8 and 9 show the concentration of clusters for the standard classification results and for the standard segmentation results, respectively. The smaller the value is, the better the color space is. Both two graphs show a similar tendency. L*a*b* model is the best and Joblove model is the second. RGB color space, the opponent color axes model, YES, and YIQ models show poor concentration.

Separability between clusters

Figures 10 and 11 show normalized geometric mean of η, which is calculated by dividing each value of geometric mean of η by the best (biggest) value among the values for 11 color models. Figure 10 is for the standard classification results and Figure 11 is for the standard segmentation results.

There is a small difference of the performances between two results. L*u*v* model shows the best separability for the standard classification results, while Smith model shows the best for the standard segmentation results. Smith model, New HSV model 1, New HSV model 2, L*u*v* model and L*a*b* model show good separability in both results. RGB color space and linear transformation models have poor separability.

Table 1 summarizes the three kinds of evaluations. Scores in each column are normalized by the best score among 11 color models. The smaller the value is, the better the color space is.

We see from Table 1 that on the whole L*a*b* and L*u*v* models are close to human color perception, while RGB color space and linear transformation models are quite different from it.

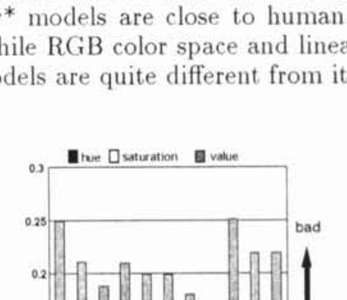

Figure 7: Uniformity of color arrangement

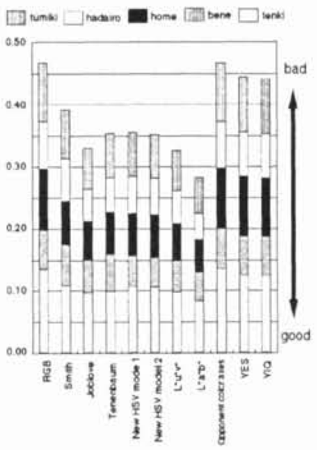

Figure 8: Concentration for standard classification results

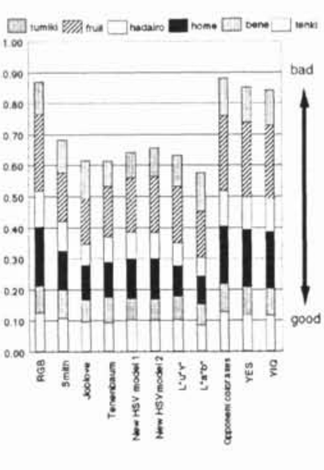

Figure 9: Concentration for standard segmentation results

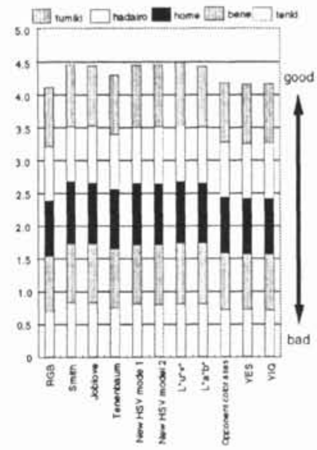

Figure 10: Normalized geometric mean of η for standard classification results

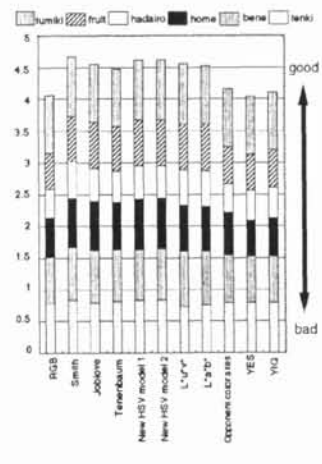

Figure 11: Normalized geometric mean of η for standard segmentation results

Acknowledgements

This work was supported in part by the Grant-in-Aid-for Scientific Research (C) 11680385 of the Ministry of Education, Science, Sports and Culture.

References

[1] K. Takahashi and K. Abe, "Color image segmentation using ISODATA clustering method," the Trans. of IEICE, D-II, pp.751–762, 1999 (in Japanese).

[2] A. R. Smith, "Color gamut transform pairs," Computer Graphics, vol.12, pp.12–19, 1978.

[3] G. H. Joblove and D. Greenberg, "Color spaces for computer graphics," Computer Graphics, vol.12, pp.20–27, 1978.

[4] J. M. Tenenbaum et al., "An interactive facility for scene analysis research," Technical Note 87, Artificial Intelligence Center, Stanford Research Institute, 1974.

[5] D. Yagi, K. Abe and H. Nakatani, "Segmentation of color aerial photographs using HSV color models," Proc.MVA'92, pp.367–370, 1992.

[6] G. W. Tou and W. S. Stiles, "Color Science," John Wiley & Sons, 1982.

[7] P. Lennie and M. D'Zmura, "Mechanisms of color vision," CRC Crit. Rev. Neurobiol, vol.3, pp.333–400, 1988.

[8] Xerox color encoding standards, Technical Report, Xerox Systems Institute, Sunnyvale, CA, 1989.

[9] K. Takahashi, T. Sugiyama and K. Abe, "Region Segmentation of Color Images Based on Clustering Method with Image Space Information," In Proc. of ACCV2000, vol.1, pp.216–221, 2000.

Table 1: Summary of evaluation of color space models

	arrangement	concentration		separability	
		classification	segmentation	classification	segmentation
RGB	1.56	1.53	1.46	1.09	1.17
Smith	1.32	1.28	1.23	1.01	1.00
Joblove	1.18	1.13	1.10	1.01	1.03
Tenenbaum	1.31	1.25	1.06	1.04	1.05
New HSV model 1	1.25	1.13	1.10	1.01	1.02
New HSV model 2	1.24	1.12	1.11	1.01	1.02
L*u*v*	1.13	1.08	1.06	1.00	1.03
L*a*b*	1.00	1.00	1.00	1.01	1.03
Opponent color axes	1.58	1.53	1.50	1.07	1.14
YES	1.37	1.44	1.43	1.08	1.17
YIQ	1.37	1.43	1.42	1.08	1.15