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Image Segmentation Using Probability Density Estimation

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Abstract

The image recognition is an important technology for analyzing the content from the image data. As the basic process, it is necessary to do image segmentation for the image recognition. Human-beings unconsciously does this process, but it is difficult for the computer. To improve the accuracy of the image recognition, an optimal region segmentation technique is needed. In this paper, we propose a new region segmentation technique. To reflect human-beings' sensory perception, we use the HSI color space. And we consider the HSI histograms to be the probability density function. We approximate the probability density function by using the HSI histogram and kernel density estimation for clustering. At last, we superimpose those results and obtain the final output. As the result of the simulation, the effectiveness of our proposed method is confirmed.

Keywords: Image Segmentation, HSI color space, kernel density estimation

1 Introduction

In recent years, a huge amount of image data has been accumulated in the computer by a rapid spread of the digital camera and the Internet. There are systems which retrieve the images according to the keyword from image database. To search an image data by keyword, the correspondence of between the keyword and the image data have to be correct. Human-beings can add proper information to image data. However, for enormous image data, the work is difficult only by human power. Thus, the technology of the image recognition with the computer is necessary.

The image recognition system extracts the outline of the objects to separate from background, and analyzes what the object is. Human-beings unconsciously does this process. However, it is difficult and complex for the computer. Therefore, to improve the accuracy of the image recognition, an optimal region segmentation technique is important. The recognition system equal to by human-beings is preferable. Therefore, to obtain optimal region segmentation, human-like quality is requested.

Here, we introduce some clustering methods of the region segmentation. K-means algorithm is a famous clustering method. However, there is a problem that it is necessary to give a number of clusters and center values of initial clusters beforehand. Then we can not automatically obtain the optimal number of clusters. By using ISODATA method, we can decide an effective number of clusters automatically within the range from half to twice of selected number of clusters. However, to use this method, we have to decide not only initial clusters but also many parameters beforehand.

In this paper, we propose a new image segmentation technique for solving these problems. We expect that the optimal image segmentation can be obtained by reflecting human-beings' sensory perception to the computer. To use human-beings' sensory perception, we converted the RGB color space into the HSI color space. In considering the probability density function of HSI histograms, we find characteristics of the image. The probability density function is approximated by using the HSI histogram and the kernel density estimation. We divide the cluster of hue, saturation and intensity based on the probability density function. And we superimpose three division result, we can obtain the final output. As a result of the comparison with the conventional method, the effectiveness of the proposal method is confirmed. The comparison image is an result by the method[1]. The image which we used is the global standard images

2 Image segmentation method

This chapter introduces the process of the proposal method for image segmentation. We write down about a flow of the proposal method here.

Step.1: Convert the RGB color space to the HSI color space.

Step.2: By using kernel density estimation, get smooth approximation of the probability density function.

Step.3: Get borders of characteristic from each histogram and divide regions.

Step.4: Superimpose divided regions.

Step.5: Reduce some small regions and obtain the final output.

In the following descriptions, we introduce the details of each step.

Figure 1: Input image "**Pepper** "

2.1 The HSI color space

K-means method is used as clustering technique for the image segmentation. In many case this method uses the RBG color space. But when we judge the difference of similar colors, we do not always accord with Euclid distance of the colors. We adopt the HSI color space. The HSI color space is near to human-beings' sensory perception. We adopt the HSI6 pyramid color model in conversion equation from the RBG color space[2] to the HSI color space.

$$I = \max(r, g, b) \tag{1}$$

$$S = \frac{I - \min(r, g, b)}{I} \tag{2}$$

$$H = \begin{cases} 60(1 + b - g) & \cdots \quad (if \quad r = I) \\ 60(3 + r - b) & \cdots \quad (if \quad g = I) \\ 60(5 + g - r) & \cdots \quad (if \quad b = I) \end{cases} \tag{3}$$

where r, g, and b are the normalized values of R, G and B. The range of the each H, S and I becomes $0 \le H \le 360$, $0 \le S \le 1.0$ and $0 \le I \le 1.0$ respectively. The HSI color space has high independence nature of each attribute in comparison with RGB color space. The following figures are histograms of saturation and hue.

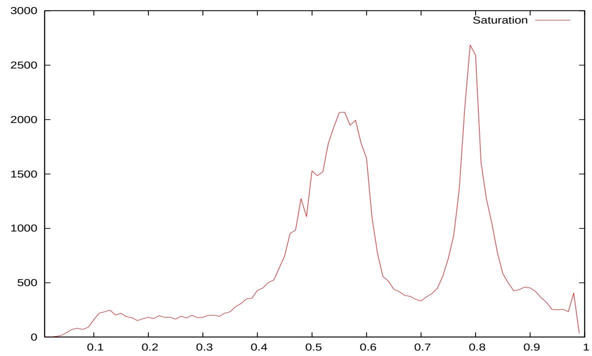

Figure 3: Saturation histogram

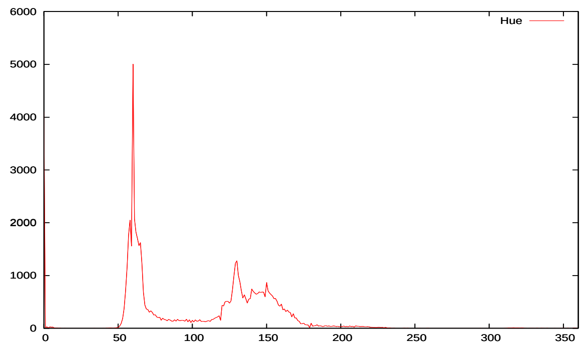

Figure 4: Hue histogram

2.2 Kernel Density Estimation

Like **Figure 3**, obtained histograms have a lot of ups and downs. When we consider such histograms in the probability density function, it is difficult to find the optimal border of clusters. To find the optimal border of clusters and to approximate the probability density function, we use kernel density estimation. This technique performs an approximation of the probability density function by the following equation from obtained data.

$$p(x) = \frac{1}{2nh} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \tag{4}$$

where $p(x)$, n, h and K are the probability density function, data, band width and kernel function respectively. To get more smooth approximation, we use the variable kernel density estimation. This technique uses neighboring density of each data point to obtain a smooth approximation. Thus, this technique uses a different value for band width corresponding to each data point. In the following, we show the equations of the band width and the probability density function finding again.

$$h_i = \frac{c}{\sqrt{p(x_i)}} \tag{5}$$

$$\tilde{p}(x) = \frac{1}{2n}\sum_{i=1}^{n}\frac{1}{h_i}K\left(\frac{x-x_i}{h_i}\right) \tag{6}$$

where $\tilde{p}(x)$ is the new probability density function. Here, h=2, c=1. The histogram of hue is extreme in comparison with the histograms of saturation and intensity. Thus, this work applies to only saturation and intensity.

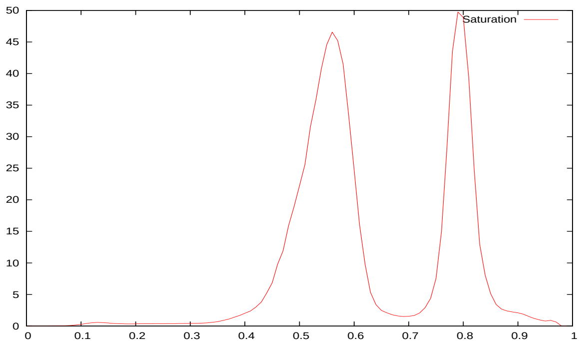

Figure 5: Saturation histogram after kernel density estimation

2.3 Clustering

With each probability density function of obtained hue, saturation and intensity, we divide there regions by using the mode method. This technique is expressed by following inequalities.

$$z_1 < t < z_2 \tag{7}$$

$$\frac{p(t)}{\min\{p(z_1), p(z_2)\}} < \theta_1 \tag{8}$$

where z_1, z_2 are peaks of the histograms. t is a border of clusters. Here, threshold θ_1 is set 0.5. When t is set in the deepest valley between two peaks and holds above inequalities, t is judged as a border.

2.4 Merge region

To obtain the final output, we superimpose results of hue, saturation and intensity. We compare a certain two points and gather it up to one region if they belong to the same cluster in hue, saturation and intensity. If even one is a different cluster among three attributes, it is judged as a different cluster.

2.5 Reduction of small region

We reduce some small region from the obtain region. At first we calculate the mean value of saturation and intensity of every region. We compare each mean value by Euclid distance. If it is smaller than 0.05, we go to the next step. At last, the results of cluster in hue are the same cluster, we superimpose the two regions.

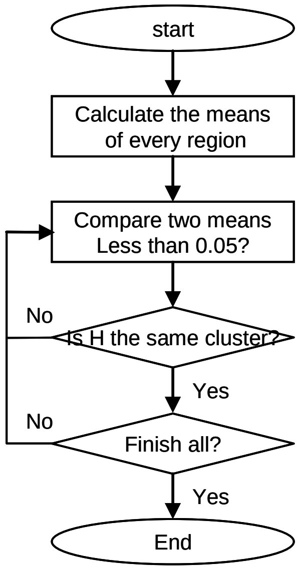

Figure 6: Flow chart of reduction method

4. Results

Figure 7 is a result by the method[1], and **Figure** 8 is a result by the proposal method. As can be seen, proposal method has less number of small regions than conventional method. In the same way, we simulated it about image "Parrots". In comparison with Figure 10, Figure 11 has a clear outline.

Figure 7: Output image by the conventional method

Figure 8: Output image by the proposal method

Figure 9: Input image "Parrots"

Figure 10: Output image by the conventional method

Figure 11: Output image by the proposal method

5 Conclusion

We performed image segmentation which was near to human-beings' sensory perception. In simulation of the image "Pepper", the proposal method reduces some small regions in the object. In simulation of the image "Parrots", the proposal method (see Figure 11) reduces some small regions of the part of the leaf. However, small regions increase in the part of the feather. In the future work, we will try to reduce of small regions more. And the examination of the threshold in mode method is necessary.

Reference

[1] D. Comaniciu and P. Meer, "Mean Shift: A Robust Approach toward Feature Space Abalysis," IEEE Transactions on pattern analysis and machine intelligence, Vol. 24, No. 5, pp. 603-609, 2002

[2] M. Takagi and H. Shimoda, "A Handbook of Image Analysis [Revised Edition]," pp. 1187-1196, University of Tokyo Press, 2004