A New Method of Color Image Segmentation Based on Intensity and Hue Clustering

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Abstract

A new method of color image segmentation is proposed in this paper. It's based on K-means algorithm in HSI space and has the advantage over those based on the RGB space. Both the hue and the intensity components are fully utilized. In the process of hue clustering, the special cyclic property of the hue component is taken into consideration. The paper gives the definition of the distance and the center in the hue space, based on which the hue-clustering algorithm is implemented. Utilized in medical image processing, the new method has got a good performance.

Keywords: *K-means algorithm, Color Image Segmentation, HSI Color Representation.*

1. Introduction

Image segmentation is a bottleneck for image processing and computer vision. Most segmentation algorithms only deal with gray scale images.[5] Some segmentation algorithms do deal with color images are based on the *RGB* color representation.[4] However, *RGB* representation does not coincide with the vision psychology of human eyes and there is high correlation among its three components, though it's convenient for display devices. Other color spaces have been considered in the literature.[6] In this paper, we propose a new algorithm segmenting color images in *HSI* space. *HSI* color representation is compatible with the vision psychology of human eyes,[3] and its three components are relatively independent.

The main thought is applying K-means algorithm[1] on color image segmentation. Both the hue and the intensity components of *HSI* are utilized. The special cyclic property of the hue component is taken into consideration and the hue-clustering algorithm is designed.

2. HSI Color Representation

In *HSI* color representation, the *I* component represents intensity. *H* component represents hue. *S* component represents saturation. To convert *RGB* representation to *HSI* representation, first compute: [3]

$$\begin{bmatrix} Y \\ C_1 \\ C_2 \end{bmatrix} = \begin{bmatrix} 1/3 & 1/3 & 1/3 \\ 1 & -1/2 & -1/2 \\ 0 & -\sqrt{3}/2 & \sqrt{3}/2 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (1)$$

Then *HSI* values can be given as:

$$I = Y,\ S = \sqrt{C_1^2 + C_2^2}$$

$$H = \begin{cases} Arc\cos(C_2 / S) & C_1 \geq 0 \\ 2\pi - Arc\cos(C_2 / S) & C_1 < 0 \end{cases} \quad (2)$$

One point worth noticing is that the *H* component is a value of angle and it displays a special cyclic property.

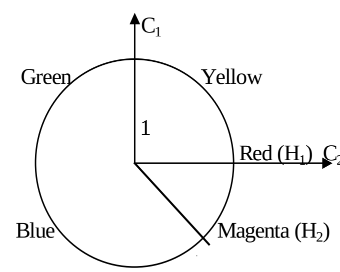


Fig 2.1 Distribution of hue values

As shown in the Fig 2.1, in the C_1-C_2 two-dimensional space, a point on the unit circle corresponds to one color. Starting from C_2 axis and going counterclockwise along the unit circle to another point on the unit circle, the positive angle ($\in [0, 2\pi)$) you experienced is just the hue value of the color. For $H_1 = 0$ (red) and $H_2 = 5\pi/3$ (Magenta), the difference of hue values are quite large ($H_2 - H_1 = 5\pi/3$). However, if we start from H_1 and go clockwise along the unit circle to H_2, the absolute value of the angle experienced ($-\pi/3$) is not that large since a shortcut is taken. This example demonstrates the effect of the cyclic property (with a period of 2π) of hue component.

3. Clustering in Hue Space

The cyclic property of the hue component is the most challenging aspect of color image segmentation based on the *HSI* space. To study color image segmentation, clustering in hue space must be first studied. In hue space, we should redefine the distance and the center, which are the basis of clustering algorithms. Considering the cyclic property of hue values, the following definition is given:

Definition 1: *The distance between two H values H_1 and H_2 is:*

$$d(H_1, H_2) = \begin{cases} |H_1 - H_2| & |H_1 - H_2| \le \pi \\ 2\pi - |H_1 - H_2| & |H_1 - H_2| > \pi \end{cases} \quad (3)$$

It's easy to verify that the definition satisfies three axioms of distance. Hue Space is defined as the set of all hue values $[0, 2\pi)$ with the above definition of distance.

From Fig.2.1, $d(H_1, H_2)$ is actually the length of the shorter arc between H_1 and H_2, and $0 \le d(H_1, H_2) \le \pi$. Similarly, we can give:

Definition 2: *The directed distance between two H values H_1 and H_2 is:*

$$\bar{d}(H_1, H_2) = \begin{cases} H_2 - H_1 & |H_2 - H_1| \le \pi \\ H_2 - H_1 - 2\pi & |H_2 - H_1| \ge \pi, H_2 \ge H_1 \\ 2\pi - (H_1 - H_2) & |H_2 - H_1| \ge \pi, H_1 \ge H_2 \end{cases} \quad (4)$$

Claim 1: $$|\bar{d}(H_1, H_2)| = d(H_1, H_2) \quad (5)$$

Unfortunately, the following vector addition property no longer holds:

$$\vec{d}(H_1, H_3) = \vec{d}(H_1, H_2) + \vec{d}(H_2, H_3)$$

For example, $H_1 = 0, H_2 = 2\pi/3, H_3 = 4\pi/3$. However under certain restrictions, it can be true:

Claim 2: *If* $|\vec{d}(H_1, H_2) + \vec{d}(H_2, H_3)| \le \pi$ *then*

$$\vec{d}(H_1, H_3) = \vec{d}(H_1, H_2) + \vec{d}(H_2, H_3) \quad (6)$$

Definition 3: *The interval $[H_1, H_2]$ determined by two hue values H_1 and H_2 in the hue space is a set of points in the hue space:*

If $|H_1 - H_2| \le \pi$

$$[H_1, H_2] = \{H \mid H_1 \le H \le H_2\}$$

if $|H_1 - H_2| \ge \pi$

$$[H_1, H_2] = \{H \mid \max(H_1, H_2) \le H \le 2\pi \mid 2\pi \le H \le \min(H_1, H_2)\} \quad (7)$$

And the midpoint H_M of the interval is defined as:

$$\bar{d}(H_1, H_M) = \bar{d}(H_M, H_2), \text{ And } H_M \in [H_1, H_2] \quad (8)$$

It's obvious that

$$H_M = \begin{cases} (H_1 + H_2)/2 & |H_1 - H_2| \le \pi \\ (H_1 + H_2)/2 - \pi & |H_1 - H_2| \ge \pi, (H_1 + H_2)/2 \ge \pi \\ (H_1 + H_2)/2 + \pi & |H_1 - H_2| \ge \pi, (H_1 + H_2)/2 \le \pi \end{cases} \quad (9)$$

Definition 4: *x_1, x_2, …… x_n are n points in the hue space. All the points fall within the interval $[H_1, H_2]$. The center point of x1, x_2, …… x_n are the point in hue space that satisfies:*

$$\sum_{i=1}^{n} \bar{d}(X_c, X_i) = 0 \text{ and } X_c \in [H_1, H_2] \quad (10)$$

The second condition in (10) is to prevent the ambiguity of the center point, or to ensure the center point falls within the interval $[H_1, H_2]$.

Theorem (Euclidean Theory in Hue Space): *x_1, x_2, …… x_n are n points in the hue space. All the points are within the interval [H1, H2]. The midpoint of [H1, H2] is H_M. The center point of x_1, x_2, …… x_n can be given by the following equation:*

$$X_C = H_M + \frac{1}{n} \sum_{i=1}^{n} \bar{d}(H_M, X_i) \quad (11)$$

Equation (11) is well known in Euclidean space. In Euclidean space H_M in equation (11) can be substituted by an arbitrary base point, and the proof relies on the vector addition property shown by equation (6). However in the hue space, the correctness of equation (6) is under certain conditions. So the concepts of interval and its midpoint are introduced. The center point should be computed by Equation (11) and the H_M in equation (11) can't be substituted by an arbitrary base point. Applying the new definition of distance and center to the K-means algorithm, we get the clustering algorithm in hue space.

4. Color Image Segmentation Based on the HSI Representation

Among the three components of *HSI* representation, the most important ones are *H* and *I*. Good color segmentation algorithms should consider both.[2] In some cases, because of the occlusion and the variation of the projected light intensity, the brightness of the same object surface is not uniform. However, the hue values determined by the reflective property of the object surface are relatively stable.[2] While in some other cases, the color intensities of different objects are more distinguishable among different objects. For an extreme example, if the input is a gray scale image that loses most color information, we must resort to the I component. Fuzzy membership function is used here to combine them.

Without loss of generality, suppose the number of classes in the images is 2 (object and background). Since components of *HSI* representation are relatively independent, hue image and intensity image can be treated separately before they are combined together. First compute the histogram of I component. Apply K-means clustering algorithm, obtain the centers of two classes I_{c1} and I_{c2}, and give the fuzzy membership functions of two classes accordingly (Fig 4.1).

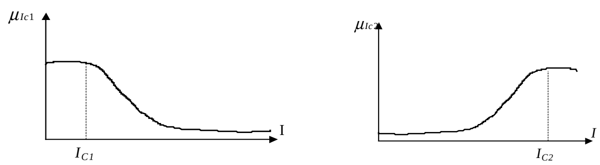


Fig 4.1 Member functions for intensity

Each pixel's grades of membership for each class can be given:

$$\mu_{Ic1}\big(I(x,y)\big)\ \ \mu_{Ic2}\big(I(x,y)\big)$$

where $I(x,y)$ is the I component of the pixel at (x,y). Usually these two values add up to 1.

Then compute the histogram of the H component. Apply K-means clustering algorithm in the hue space established in chapter 3. Obtain the center points of two classes H_{c1} and H_{c2}, and give the fuzzy membership functions of two classes accordingly (fig 4.2).

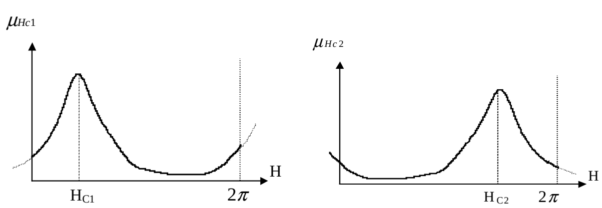


Fig 4.2 Member functions for hue

As can be seen, the cyclic property of the hue component has been taken into consideration. Hence each pixel's grades of membership for each class can be given:

$$\mu_{Hc1}\big(H(x,y)\big)\ \mu_{Hc2}\big(H(x,y)\big)$$

where $H(x,y)$ is the H component of the pixel at (x,y). Usually these two values add up to 1.

Thus, for each pixel in the image we have four grades of membership. Since the first two add up to 1 and the last two add up to 1, $\mu_{Ic1}\big(I(x,y)\big)$ and $\mu_{Hc1}\big(H(x,y)\big)$ are chosen to represent the overall color feature of the pixel, without loss of generality. Combine these two grades of membership to form a two-dimensional feature vector:

$$\bar{c} = \Big(\mu_{Ic1}\big(L(x,y)\big), \mu_{Hc1}\big(H(x,y)\big)\Big) \tag{14}$$

Apply K-means clustering algorithm on the above feature vector. We get the final result of color image segmentation.

5. Experiments

We test our color image segmentation algorithms in a Medical Image Processing System, a knowledge-based system processing medical slide images. One module of the system is to extract bone areas from noisy and varied color slide images. Color image segmentation is a critical step within this module. The segmentation task is challenging because the color distribution varies from image to image, due to the change of reagent.

Fig. 5.1 and Fig. 5.2 (attached to the end of the paper) give two experiment results. Fig.5.1 (a) is the original color image. Fig 5.1 (b) is the image of I component, while Fig 5.1 (c) is the image of H component. It's not difficult to observe that in the Intensity image bone areas are much clearer than that in the Hue image. Fig 5.1(d) shows the result of segmentation based on Hue image and Fig 5.1(e) shows the result of segmentation based on Hue and Intensity images. Both (d) and (e) are after some sort of knowledge-based post-processing.

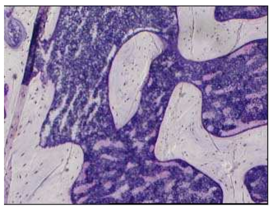
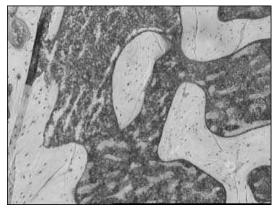
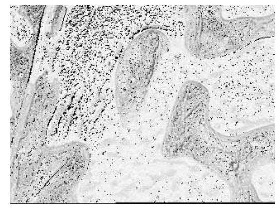
Fig 5.2 demonstrates a quite different example. Fig.5.2 (a) is the original color image. Fig 5.2 (b) is the image of I component, while Fig 5.2 (c) is the image of H component. It's easy to see that in the Intensity image, gray levels of pixels in bone areas (except on the boundary) are quite close to those in the background area. On the other hand, in the Hue image, pixels in bone areas are much more distinguishable. Fig 5.2(d) shows the result of segmentation based on Intensity image and Fig 5.2(e) shows the result of segmentation based on Hue and Intensity images. Both (d) and (e) are after some sort of knowledge-based post-processing.

As we can see, segmentation in terms of only one component might easily fail due to the variation of color distribution. Our algorithm, which combines both aspects, is quite robust.

6. References

1. Sing-Tze Bow, Pattern Recognition, Marcel Dekker Inc., 1984. (Chapter 1, 5).
2. K.P.Valavanis, J.Zhang and G.Paschos, A Total Color Difference Measure for Segmentation in Color Images, Journal of Intelligent and Robotic Systems, vol. 16, pp269-313, 1996

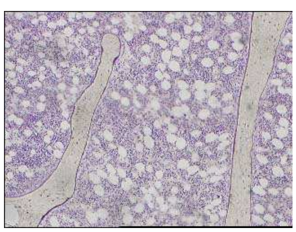
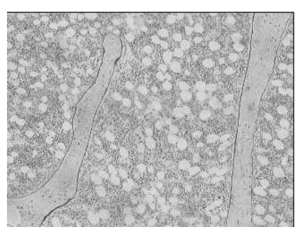
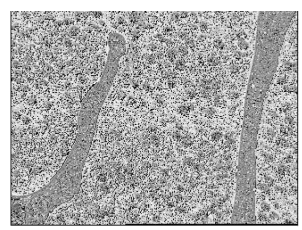
3. Thierry Carron, Patrick Lambert, Color Edge Detector Using Jointly Hue, Saturation and Intensity, International Conference on Image Processing '94, pp977-981.
4. A.Moghaddamzadeh and N.Bourbakis, A Fuzzy Region Growing Approach for Segmentation of Color Images, Pattern Recognition, vol. 30, No. 6, pp867- 881,1997.
5. N.R.Pal and S.K.Pal, A review on Image Segmentation Techniques, Pattern Recognition, vol. 26, No. 9, pp1277-1294,1993.
6. Uchiyama, T., and Arbib, M.A., Color Image Segmentation Using Competitive Learning, PAMI vol. 16, No. 12, pp. 1197-1206, 1994.

(a) Original color image **(b) Intensity image** **(c) Hue image**


(d) Segmentation by hue **(e) Segmentation by hue and intensity**

Fig 5.1 Color image segmentation – example 1

(a) Original color image **(b) Intensity image** **(c) Hue image**


(d) Segmentation by intensity **(e) Segmentation by hue and intensity**

Fig 5.2 Color image segmentation – example 2