

# SEGMENTATION OF CLINICAL ENDOSCOPIC IMAGE BASED ON HOMOGENEITY AND HUE

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**Abstract-** A computer-assisted endoscopic analysis is intended and facilitates the diagnosis process. Segmentation of the image is an important step and a novel approach is proposed to segment clinical endoscopic images based on homogeneity and color feature hue. In the first stage, the regions are segmented using a peak-finding algorithm on a 2-D histogram of homogeneity and intensity values. In the second stage, histogram analysis of the color feature hue is performed to subdivide the segmented regions obtained from the first stage. The subdivisions of different segmented regions having similar CIE ( $L^* a^* b^*$ ) color measure are merged. The proposed scheme was evaluated on a database of clinical endoscopic images.

**Keywords-** clinical endoscopic image, color image segmentation, homogeneity, color space, region merging.

## I. INTRODUCTION

Minimally invasive endoscopic procedures are increasingly employed for diagnostic and surgical purposes in cases such as the gastrointestinal and respiratory ailments. An endoscopist, who analyzes the acquired images, performs these procedures. A computer-aided scheme will help considerably in the image analysis and quantitative characterization of abnormalities, thereby improving the overall efficiency of the diagnosis. A crucial step in such an automated diagnostic scheme is proper segmentation of the endoscopic images.

Color of an image carries much more information than the gray levels. In many pattern recognition and computer vision applications, the additional information provided by color can help in image analysis and provide better results than approaches using merely gray scale information.

The scales employed to differentiate pixels in a color image include uniform chromaticity scale (UCS), OHTA, and Hue, Saturation, and Intensity (HSI).

The UCS approximates human perceptions when a Euclidean distance measure in the ( $L^* a^* b^*$ ), and ( $L^* u^* v^*$ ) color spaces is used to differentiate between pixels compare to (R,G,B) and (X,Y,Z) color spaces. The UCS matches the sensitivity of human eye, and can mimic human perception.

OHTA color space was derived as a result of a search of completely statistically independent components on a representative sample of images. The OHTA components are good approximations of the results of the Karhunen-Loeve transformation, which is very good with respect to decorrelation of RGB components [3].

HSI uses psychological attributes instead of human perceptions to differentiate pixels. The perceptual color

space is used to capture the psychological attributes, and it usually described by Hue, Saturation, and Intensity (HSI). The hue is the attribute of color perception denoted by red, yellow, green, blue, and so on. Saturation is used to describe how pure a color is or how much white is added to a pure color. The intensity is a measure of total reflectance in the visible region of spectrum, and it is an achromatic component of color. Using HSI color space for color image segmentation has two advantages: (1) specifying and controlling color is more suitable for human perception than using the primary colors RGB; (2) it can control intensity and chromatic components more easily and independently [1].

The segmentation of the image is performed on the basis of one of the above scales using histogram analysis, edge detection, and statistical analysis.

X. Yang [2] developed a fuzzy logic based segmentation scheme in Hue, Saturation, and Intensity (HSI) color space. The segmentation was realized in two stages. In the first stage, a 3-D histogram of HSI color space was obtained. Using scale-space filter, a number of regions in 3-D HSI space were segmented. In the second stage, these regions were merged using fuzzy logic on the basis of their edge strength along the boundary, color similarity, and spatial connectivity between adjoining regions.

X.Y. Zue [3] developed two stages segmentation scheme in OHTA color space. The first stage is similar to that proposed by X. Yang [2]. In the second stage, the regions obtained in the first stage were merged using a Markov Random Field (MRF) model based multi-channel Bayesian segmentation technique. The HSI color space was segmented using three histogram parameters. An iterative method called Iterated Conditional Modes (ICM) and a simulated annealing are employed for merging. This proposed scheme is computationally intensive compare to [2].

In this paper, the segmentation is realized in two stages. In the first stage, the image is segmented using the homogeneity and intensity values of the pixels. In the second stage, sub-regions are obtained by differentiating the pixels on the basis of color feature hue measure. The sub-regions with similar color are then merged.

## II. METHODOLOGY

A 2-D histogram in the intensity-homogeneity domain is obtained. For each intensity value, the number of pixels with homogeneity value greater than a certain threshold value is computed. The image is segmented into regions by locating the relative minima of the histogram. These regions are

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further subdivided, and merged using color feature hue, and CIE (L\* a\* b\*) color space measure, respectively.

### A. Intensity and Homogeneity

Let (x,y) is the location of a pixel. The intensity, I, of the pixel (x,y) is computed as follows [7].

$$I(x, y) = 1/3(R(x, y) + G(x, y) + B(x, y)) \quad (1)$$

Suppose I(x, y) is the intensity of a pixel P(x, y) at the location (x,y) in an MxN image,  $w_{xy}^{(1)}$  is a size dxd window centered at (x,y) for the computation of variation,  $w_{xy}^{(2)}$  is a size txt window centered at (x,y) for the computation for discontinuity, d and t are odd integers greater than one. The windows  $w_{xy}^{(1)}$  and  $w_{xy}^{(2)}$  are considered as the local regions when calculating the homogeneity features.

The standard deviation of a pixel P(x, y) is

$$v(x, y) = \sqrt{\frac{1}{d^2} \sum_{p=x-(d-1)/2}^{x+(d-1)/2} \sum_{q=y-(d-1)/2}^{y+(d-1)/2} (I(p, q) - \mu(x, y))^2} \quad (2)$$

where  $0 \leq x, p \leq M-1, 0 \leq y, q \leq N-1$ .  $\mu(x, y)$  is the mean of the gray levels within window  $w_{xy}^{(1)}$  given by

$$\mu(x, y) = \frac{1}{d^2} \sum_{p=x-(d-1)/2}^{x+(d-1)/2} \sum_{q=y-(d-1)/2}^{y+(d-1)/2} I(p, q) \quad (3)$$

The discontinuity for pixel P(x, y) is described by edge value. There are many different edge operators: Sobel, Laplace, Canny, etc. Here as it is not required to find the exact locations of the edges, the Sobel operator is employed due to its simplicity, to calculate the discontinuity. The Sobel operator computes the magnitude of the gradient at location (x,y) using [7].

$$e(x, y) = \sqrt{G_x^2 + G_y^2} \quad (4)$$

where  $G_x$  and  $G_y$  are the components of the gradient in the x and y directions, respectively.

The standard deviation and discontinuity values are normalized in order to achieve computational consistency.

$$V(I(x, y)) = \frac{v(x, y)}{v_{\max}} \quad (5)$$

$$E(I(x, y)) = \frac{e(x, y)}{e_{\max}} \quad (6)$$

where  $v_{\max} = \max\{v(x, y)\}$ ,  $e_{\max} = \max\{e(x, y)\}$ ,  $0 \leq x \leq M-1, 0 \leq y \leq N-1$ .

The homogeneity is defined as [4]

$$H(I(x, y)) = 1 - E(I(x, y)) \times V(I(x, y)) \quad (7)$$

where  $0 \leq x \leq M-1, 0 \leq y \leq N-1$ .

The value of the homogeneity at each location of an image has a range from [0,1]. The more uniform the local region surrounding a pixel is, the larger the homogeneity value the pixel has.

### B. Segmentation from 2-D Histogram

The intensity I(x,y) and homogeneity H(x,y) are discretized with i-th value of intensity and j-th value of homogeneity denoted respectively by  $I_i$  and  $H_j$ . Define a set of  $R_{ij}$  given by

$$R_{ij} = \{P(x, y) | I(x, y) = I_i, H(x, y) = H_j\} \quad (8)$$

Let  $n_{ij}$  be the number of pixels in  $R_{ij}$ . A 2-D histogram is merely a plot of  $n_{ij}$  versus  $I_i$  and  $H_j$ . A 1-D histogram is obtained from the 2-D histogram as follows. Define a set of  $R_i$  given by

$$R_i = \{P(x, y) | I(x, y) = I_i, H(x, y) \geq \delta\} \quad (9)$$

where  $\delta$  is the threshold, and usually chosen close to the maximum value of the homogeneity, say  $\delta=0.95$ . Let  $n_i$  be the number of pixels in  $R_i$ . The 1-D histogram denoted by  $h(i)$  is a plot of  $n_i$  versus  $I_i$ . The relative maxima of this histogram are computed to obtain the segments using a peak-finding algorithm.

*The peak-finding algorithm:*

1. *Find all peaks:* Find the set of points corresponding to the local maximums of the histogram

$$P_0 = \{(i, h(i)) | h(i) > h(i-1) \& h(i) > h(i+1), 1 \leq i \leq 254\} \quad (10)$$

2. *Find significant peaks:* The points in set  $P_0$  form a new curve. On this new curve, repeat the operation of step 1. The result forms set  $P_1$ .

$$P_1 = \{(p_i, h(p_i)) | h(p_i) > h(p_{i-1}) \& h(p_i) > h(p_{i+1}), p_i \in P_0\} \quad (11)$$

All the points in set  $P_1$  are much more significant than the points in set  $P_0$  in determination of the peaks of the histogram.

3. *Thresholding:* includes three steps.

The first step is to remove small peaks. If a peak is too small compared to the biggest peak, then it is removed.

Suppose  $i_{\max}$  is the value of the highest peak satisfying  $h_{\max} = h(i_{\max})$ . For any peak  $j$ , if  $(h(j)/h_{\max}) < 0.05$ , then peak  $j$  is removed. The second step is to choose one peak if two peaks are too close. For two peaks  $h(p_1)$  and  $h(p_2)$ ,  $p_2 > p_1$ , if  $p_2 - p_1 \leq 15$ , then  $h = \max\{h(p_1), h(p_2)\}$ . Thus, the peak with the bigger value is chosen. The third step is to remove a peak if the valley between two peaks is not present. The presence or an absence of a valley is determined by calculating the average of the intensity values between the two peaks. The average value is computed over the pixels in the region between the peaks  $p_1$  and  $p_2$  as follows [4].

$$h_{\text{avg}} = \frac{\sum_{p_i=p_1}^{p_i=p_2} h(p_i)}{p_2 - p_1 + 1} \quad (12)$$

The valley between the two peaks is considered absent if the average value,  $h_{\text{avg}}$  is too big compared to the peaks. That is if

$$h_{\text{avg}} / ((h(p_1) + h(p_2)) / 2) > 0.75 \quad (13)$$

The smaller of the two peaks for which the valley is absent will not be considered.

This peak-finding algorithm locates the globally significant peaks of the histogram. After the peaks are found, the valleys are determined from the minimum between any two adjacent peaks. The valleys thus obtained serve as the boundaries for the segmentation in homogeneity domain.

Let  $v(k)$ ,  $k=1, 2, \dots, l$  be the intensity value of the valley. Using  $v(k)$  as the threshold value, the image is segmented as

$$S_I(k) = \{(x, y) \mid v(k-1) \leq I(x, y) \leq v(k)\}, k = 1, 2, \dots, l \quad (14)$$

#### C. Subdivision based on the Color Feature Hue

The Hue,  $H$ , of the pixel  $(x, y)$  is computed as follows [6].

$$H(x, y) = \arctan\left(\frac{\sqrt{3}(G(x, y) - B(x, y))}{(R(x, y) - G(x, y)) + (R(x, y) - B(x, y))}\right) \quad (15)$$

Procedure explained in the previous stage is adopted.

$$S_{IH}(i, j) = \{(x, y) \in S_I(i) \mid H_{th}(j) \leq H(x, y) \leq H_{th}(j+1)\} \\ i = 0, 1, 2, \dots, \ell - 1; \quad j = 0, 1, 2, \dots, \kappa - 1 \quad (16)$$

The given image is segmented into regions based on similar intensities and hues.

#### D. Merging the Subdivisions

The segments with different value of intensity and hue but having similar colors are merged. The measure of color is based on the recommendation of CIE. The CIE color system is obtained from the nonlinear transformation of three primary colors denoted as  $X$ ,  $Y$ , and  $Z$ , which are obtained from a linear combination of  $R$ ,  $G$ , and  $B$  values. The CIE color system has an ability to measure a small color difference compare to RGB. The CIE color values computed as follows.

Average  $R$ ,  $G$ , and  $B$  values are given to every pixel belonging to the same segment,  $S_{ij}$ .

$$\begin{aligned} R &= E[R(x, y)] \\ G &= E[G(x, y)] \\ B &= E[B(x, y)] \end{aligned}$$

where  $E[.]$  denotes average value computed over all pixels in the same segment  $S_{ij}$ . The  $X$ ,  $Y$ , and  $Z$  are computed as follows [6].

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.490 & 0.310 & 0.200 \\ 0.177 & 0.813 & 0.011 \\ 0.000 & 0.010 & 0.990 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (18)$$

Instead of using  $X$ ,  $Y$ , and  $Z$  color scheme, a color scheme, which possess more uniform perceptual properties, denoted  $L^*$ ,  $a^*$ , and  $b^*$  is employed.  $L^*$ ,  $a^*$ , and  $b^*$  is obtained through a nonlinear transformation on  $X$ ,  $Y$ , and  $Z$ , as follows [6].

$$L^* = 116 \left( \sqrt[3]{\frac{Y}{Y_0}} \right) - 16 \quad (19)$$

$$a^* = 500 \left[ \sqrt[3]{\frac{X}{X_0}} - \sqrt[3]{\frac{Y}{Y_0}} \right] \quad (20)$$

$$b^* = 200 \left[ \sqrt[3]{\frac{Y}{Y_0}} - \sqrt[3]{\frac{Z}{Z_0}} \right] \quad (21)$$

where  $(X_0, Y_0, Z_0)$  are XYZ values for the standard white.

The color difference between the any two pixels in the subdivisions  $i$ , and  $j$  are computed as using a Euclidean distance, given by

$$D_{ij} = \sqrt{(L_i - L_j)^2 + (a_i - a_j)^2 + (b_i - b_j)^2} \quad (22)$$

where  $(L_i, a_i, b_i)$  and  $(L_j, a_j, b_j)$  are the CIE  $(L^*, a^*, b^*)$  color representations for the pixels in the subdivisions  $i$ , and  $j$

respectively. There will be total of  $(k(k-1))/2$  such color distance measures. Note that all the pixels in the same subdivision will have the identical color value. The above Euclidean distance measure matches the sensitivity and perceptions of human eyes.

Based on this color scheme, the subdivisions  $S_{ij}$  with the similar color are merged using the Euclidean distance measures given by (22). Let  $k$  be the total number of subdivisions, which is also the total number of CIE color values.

Let  $\mu_d$  and  $\sigma_d$  be the average and the standard deviation respectively of the color differences between the  $k$  subdivisions. The mean and the standard deviation are given by

$$\mu_d = \frac{1}{n} \sum_i \sum_j D_{ij} \quad (23)$$

$$\sigma_d = \sqrt{\frac{1}{n} \sum_i \sum_j (D_{ij} - \mu_d)^2} \quad (24)$$

where:  $n = (k(k-1)/2)$  is the total number of,  $\mu_d$  is the mean of color differences, and  $D_{ij}$  is color difference between  $i$ , and  $j$  given by the equation (22).

The regions  $i$ , and  $j$  will be merged if

$$D_{ij} \leq Th \quad (25)$$

where

$$Th = \mu_d - \sigma_d \quad (26)$$

The segments  $\{S_{ij}\}$  having similar CIE color values are merged to form the final segment.

$$S_k = \bigcup_{i,j \in \kappa} S_{ij}, \quad k=1,2,\dots,K \quad (27)$$

where the index set  $\kappa$  is defined as

$$\kappa = \{i, j \mid D_{ij} \leq Th\} \quad (28)$$

### III. RESULTS AND DISCUSSION

The method proposed in this paper has been tested with 50 clinical endoscopic images. The original images are shown in Fig. 1 and the segmentation results are shown in Fig. 2. The proposed method can segment the image into regions, which can be used for further analysis on detecting the abnormality of the colon.



Fig. 1. Original Clinical Endoscopic Images



Fig. 2. Segmented Endoscopic Images

### IV. CONCLUSION

The proposed scheme segments the image based on homogeneity, color feature hue, and CIE color system. The segmentation algorithm is computationally efficient and may be implemented in real-time. The segmentation results on actual images were promising in diagnosing abnormalities, such as polyp, ulcers, and bleeding.

### REFERENCES

- [1] D. C. Tseng and C. H. Chang, "Color Segmentation Using Perceptual Attributes", *Pattern Recognition*, vol. III, pp. 228-231, 1992
- [2] X. Yang, S.M.Krishnan, K.L.Chan, "Color Image Segmentation Based on Fuzzy Rule-base Reasoning Applied to Colonoscopic Images", *Critical Reviews TM in Biomedical Engineering*, v 26 no 5&6, pp.346-347, 1998
- [3] X. Y. Zue, *Computerized Detection of Abnormalities in Endoscopic Oesophageal Images*, M.Eng Thesis, Nanyang Technological University, Singapore, 2000
- [4] H. D. Cheng and Y. Sun, "A Hierarchical Approach to Color Image Segmentation Using Homogeneity", *IEEE Transactions on Image Processing*, vol. 9, No. 12, December 2000
- [5] N. Pal and S. Pal, "A Review on Image Segmentation Techniques", *Pattern recognition*, vol. 26, no.9, pp.1277-1294, 1993
- [6] A. K. Jain, *Fundamental of digital image processing*, Prentice-Hall international edition, 1989
- [7] R. C. Gonzales and R. E. Woods, *Digital Image Processing*, Addison-Wesley Publishing Company, Inc., 1992