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Color-Texture Segmentation of Medical Images Based on Local Contrast Information

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***Abstract*-A novel color texture-based segmentation algorithm is proposed. Many powerful color segmentation algorithms such as JSEG (J-SEGmentation) suffer from over segmentation. An improved JSEG method called improved contrast JSEG (IC-JSEG) is developed to construct the contrast map to obtain the basic contours of the homogeneous regions in the image. A two serial type-based filtering and a noise-protected edge detector are adopted to remove the noise and enhance the edge strength to provide a better contrast map. Based on the combination of improved contrast map and the original J map in JSEG, seed growing-merging method is used to segment the image. Experiments on both natural color-texture images and color medical images show promising results.**

I. INTRODUCTION

Image segmentation is a core problem in image analysis and computer vision. In recent years, research work has been focused on color image segmentation since grayscale images can not satisfy the needs in many situations. Color image segmentation divides a color image into a set of disjointed regions which are homogeneous with respect to some properties consistent with human visual perception, such as colors or textures.

In this paper, we consider the problem of natural and medical image segmentation based on color and texture information. Many texture or color segmentation methods [1-6] have been proposed in the past couple of decades. Most of them were based on two basic properties of the pixels in relation to their local neighborhoods: discontinuity and similarity. Approaches based on discontinuity partition an image by detecting isolated points, lines, and edges, which were known as edge detection techniques. On the other hand, region based approaches including region growing, region splitting, region merging, and their combinations group similar pixels into different homogeneous regions. In order to get better segmentation result, new algorithms which integrated region and boundary information have been proposed over the last few years [7-9].

Texture, which usually represents inhomogeneous areas, contains more than one color pattern in the image. For this reason, it is difficult to rely entirely on color discrimination to describe homogeneous regions and edges. Deng and Manjunath proposed an unsupervised image segmentation method called JSEG which separated the segmentation process into two stages: color quantization and spatial segmentation [10]. However, because of the drawbacks in the design of J measure for boundary detection, the result often suffered from over segmentation. Chen proposed a contrast-based color image segmentation method [11], in which from 10 experimenters' subjective observations, they concluded that color contrast definition is roughly equivalent to the perceived color contrast and was weakly correlated to luminance/color levels. Although the segmentation results were better than that of JSEG to alleviate the over-segmentation problem, it did not consider images with complex textures. Using only one contrast threshold caused different homogeneous regions to merge into one.

Based on JSEG, we propose a new color image segmentation algorithm using a more effective homogeneity measure. Section 2 reviews the homogeneity measure defined by JSEG and points out the reason why over-segmentation occurs. Section 3 proposes a new contrast map based homogeneity measure to improve the JSEG measure quality. Comparative experiments are given in Section 4, and we conclude this paper in Section 5.

II. JSEG METHOD

As previously mentioned, JSEG divided segmentation process into two stages. Color quantization based on peer group filtering (PGF) and vector quantization were adopted by JSEG method to reduce the number of colors in the image. The result of color quantization formed a class map in which each pixel was represented by a color class label. Then based on the class map, spatial segmentation was performed.

Let Z be the set of all N data points in the class map, $z=(x,y), z\in Z$, and m be the mean. Suppose that Z has been classified into C classes, i.e. $Z_i, i=1,\cdots,C$ and the mean of the N_i data points of class Z_i is m_i. Moreover, we can calculate the total variance S_T for each class as

$$S_T=\sum_{z\in Z}\| z-m\|^2 \tag{1}$$

, and the variance between classes S_W.

$$S_W = \sum_{i=1}^{C} S_i = \sum_{i=1}^{C} \sum_{z \in Z_i} \| z - m_i \|^2 \tag{2}$$

The J measure is defined as

$$J = S_B / S_W = (S_T - S_W) / S_W \tag{3}$$

For each pixel, its corresponding J value was calculated over the local window centered on the pixel. Thus, a J-image was formed. In the JSEG method, J-image constructed at different scales corresponded to local homogeneities, which indicated potential boundary locations. The higher the local J value was, the more likely that the corresponding pixel was close to a region boundary.

The author calculated J values over the class map so that no color information of the pixels was considered. Fig.1 gives two simple class maps of this sort. In this example, "*", "o" and "+" indicate different classes of data points. Assuming the intensity value of Class "+" is much higher than that of Class "o", and Class "o" intensity value is slightly higher than Class "*". Note that class map (a) often occurs in the case of varying illumination such as a sunset sky. According to (1)-(3), we can calculate J values of the two patterns to be equal to 0.6. Perceptually, however, the edge in class-map (b) is sharper or has higher contrast than that of class-map (a). We concluded that J measure could only detect the boundaries, but failed to give the boundary strength, as shown in Fig. 1(b). We consider that this can explain to some extent why over-segmentation occurs using JSEG.

III. Segmentation based on improved contrast map (ICMap)

A. *Construct Contrast Map*

We propose a new color image segmentation approach that addresses the drawbacks of JSEG method. In [11], a subjective experiment was conducted to test the contrast definition that is roughly equivalent to the perceived color contrast and is weakly correlated to luminance/color levels. In this paper, we first converted the original image into CIE $L^*a^*b^*$ color space. The Euclidean distance between (L_1^*, a_1^*, b_1^*) and (L_2^*, a_2^*, b_2^*) defined as:

$$\Delta E_{c2c1} = \sqrt{(L_2^* - L_1^*)^2 + (a_2^* - a_1^*)^2 + (b_2^* - b_1^*)^2} \tag{4}$$

is approximately equivalent to the perceptual difference between these two colors [12].

For image $I(i,j)$, in the 3×3 window of pixel $p(i,j)$, we calculate its contrast by

$$\begin{aligned} contrast\ (i,j) = {} & \max(\Delta E_{p(i+m,j+n)p(i,j)}) \\ & - \min(\Delta E_{p(i+m,j+n)p(i,j)}) \\ & m = -1, 0, 1;\ \mathrm{n} = \text{-}1, 0, 1 \end{aligned} \tag{5}$$

We can construct a contrast map using (5). However, the contrast map is usually noisy and the noise will influence the final segmentation result.

B. *Improved Contrast Map*

In order to reduce the noise and enhance the boundary strength, we adopted a two serial types filtering and noise-protected edge detector [13] to improve the contrast map. Based on the 256-grayscale contrast map $C(x,y)$ which was quantized from $contrast(i,j)$, a two-step procedure was applied to the image channels in order to increase the effectiveness of the smoothing action. This procedure is defined by the following equations.

$$\begin{aligned} c^{(1)}(i,j) = {} & c^{(0)}(i,j) + \\ & \frac{1}{8} \sum_{m=-1}^{1} \sum_{n=-1,(m,n\neq(0,0))}^{1} \varsigma^{(1)}(c^{(0)}(i+m,j+n), c^{(0)}(i,j)) \end{aligned} \tag{6}$$

Fig.1. Two two-class maps with size 5×5 and "*", "o", "+" indicating three classes of data points.

$$c^{(2)}(i,j)=c^{(1)}(i,j)+\frac{1}{8}\sum_{m=-1}^{1}\sum_{n=-1,(m,n\neq(0,0))}^{1}\varsigma^{(2)}(c^{(1)}(i+m,j+n),c^{(1)}(i,j)) \tag{7}$$

where $\varsigma^{(p)}$ is a parameterized nonlinear function

$$\varsigma^{(p)}(u,v)=\begin{cases} u-v & |u-v|\le a^{(p)} \\ (\frac{3a^{(p)}-u+v}{2})sgm(u-v) & a^{(p)}<|u-v|\le 3a^{(p)} \\ 0 & |u-v|>3a^{(p)} \end{cases} \tag{8}$$

and $a^{(p)}$ is an integer $0<a^{(p)}<L$ ($L=256$ in our case). Small $a^{(p)}$ values preserve the fine details, and large values produce a strong noise cancellation [14].

The second step takes into account the differences between the pixel to be processed and its neighbors in a different way: if all these differences are very large, the pixel is (possibly) part of the boundary to be cancelled. It is briefly summarized as follows.

$$c^{(3)}(i,j)=c^{(2)}(i,j)-(L-1)\Delta(i,j) \tag{9}$$

where

$$\begin{aligned}\Delta(i,j) = MIN\ &\{\mu_{LA}(c^{(2)}(i,j),c^{(2)}(i+m,j+n))\} \\ -\ MIN\ &\{\mu_{LA}(c^{(2)}(i+m,j+n),c^{(2)}(i,j))\} \\ &m=-1,0,1;\ n=-1,0,1;(m,n)\neq(0,0)\end{aligned} \tag{10}$$

and $\mu_{LA}(u,v)$ denotes the membership function that describes the fuzzy relation:

$$\mu_{LA}(u,v)=\begin{cases}\frac{u-v}{L-1} & 0<u-v\le L-1 \\ 0 & u-v\le 0\end{cases} \tag{11}$$

In order to enhance the boundaries, the output of the color edge detector is given by the following relations:

$$ICMap(i,j)=(L-1)[1-MIN\{\mu_{SM}(B_1),\mu_{SM}(B_2)\}] \tag{12}$$

where concrete parameters information can be seen in [13]. This improved contrast map (ICMap) can reduce the noise and enhance the boundaries to a large extent.

C. A novel Measure Definition and Spatial Segmentation

We construct a new measure combining the ICMap and J measure in JSEG for color-texture segmentation. The proposed method is called IC-JSEG.

For an $M\times N$ image, ICMap is calculated according to (12) first. Then, the magnitude is normalized as following:

$$w_{IC}(i,j)=\frac{ICMap(i,j)}{ICMap_{\max}} \tag{13}$$

Where

$$ICMap_{\max}=\max\{ICMap(i,j)\} \quad (0\le i\le M-1, 0\le j\le N-1)$$

The J value (also normalized) of the local region is computed according to (1)-(3). Then the proposed novel measure is formed by weighting the J value with w_{IC}.

$$J_{IC}(i,j)=w_{IC}(i,j)\times J(i,j) \tag{14}$$

With the integration of ICMap, the J map can be strengthened to distinguish the edges from inner details.

Using the new J_{IC} measure, we can construct the J_{IC} -image, where J_{IC} values can be used to indicate interiors and boundaries of the regions. We also adopt the multi-scale segmentation scheme provided by JSEG. This scheme consists of three main operations: seed area determination, region growing, and region merging. Starting at a coarse initial scale, the following processes are performed repetitively in a multi-scale manner until all the pixels are classified.

(1). Seed area determination. A set of initial seed areas is determined to be the basis for region growing. Here, we set a threshold to find the seed areas: $T=\mu+\partial\sigma$, where μ and σ are the average and the standard deviation of the local J_{IC} values in the regions, respectively, and ∂ is a constant. Then pixels with J_{IC} values less than T are connected and considered as a seed.

(2). Seed growing. The new regions are grown from these seeds. Firstly, average the local J_{IC} values in the remaining unsegmented part of the regions and assign the pixels below the average to an adjacent seed. For the remaining pixels, calculate their local J_{IC} values and deal with them at next finer scale to more accurately locate the boundaries.

Region growing is followed by a region merging operation to give the final segmented image. The color histogram for each region is extracted where the quantized colors from the color quantization process are used as bins. The two regions with the minimum distance between their histograms are merged together and this process continues until a maximum threshold for the distance is reached.

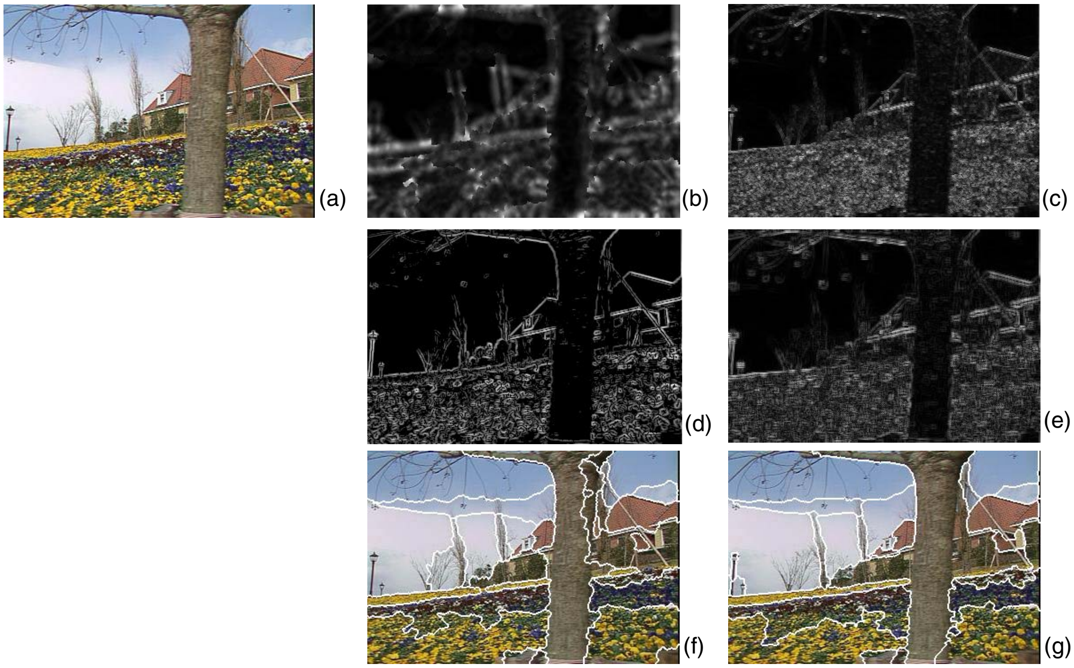


Fig. 2. (a) Original image (b) J map (c) Contrast Map (d) ICMap (e) J_{IC} map (f) JSEG segmentation result (g) result from the proposed segmentation method.

Fig. 2 (a) shows the garden image as the original image. Figs. 2 (b) and (c) are the J map and contrast map from the original JSEG method, respectively. Figs. 2 (d) and (e) are the improved contrast map and J map using the proposed method. Figs. 2 (f) and (g) show the segmentation results of JSEG and the proposed method.

IV. Experimental Results

We test the proposed algorithm on the natural color-texture images and three sets of medical images and compare it with JSEG method. No parameters are tuned on individual images in order to test the robustness of the algorithm. The same parameters are used in all the experiments: quantization parameter is 160, region merging threshold is 0.4, and other parameters are chosen automatically. Fig. 3 shows the segmentation comparison among JSEG, proposed method.

From Fig. 3, we can see that the performance of our proposed method is better than JSEG method. Using JSEG method the lawn and trees are split apart into many bits and pieces. On the contrary, our method keeps their integrity which is closer to human visual perception. Furthermore, for the mountains, lakes and churches, the proposed algorithm can preserve more homogeneous regions than that of JSEG method.

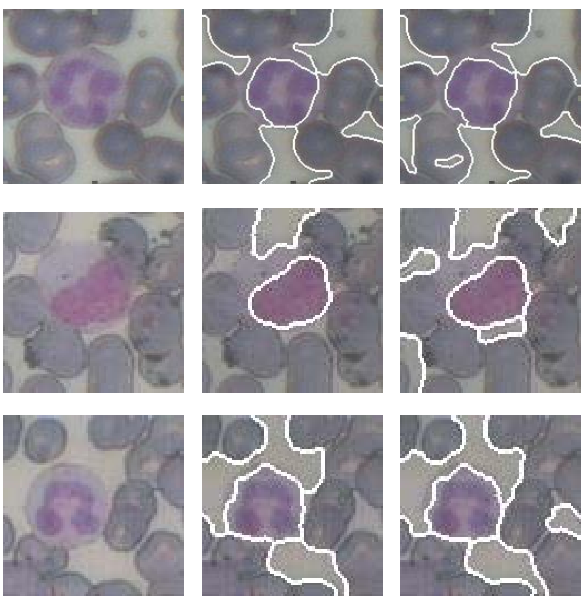
The proposed method is also applied to three color medical images to test its performance, as shown in Fig. 4. From these three cell color image groups, we can see that our method can detect more homogeneous regions than that of JSEG method. Since our method strengthens the edges to discriminate different homogeneous regions, it can detect the trivial homogeneous regions. Although our method segments the images into more regions, these segmented regions conform with human visual perception better and are not considered to be over-segmentations.

V. Conclusion

Color and texture are two most important factors in human visual perception. Many segmentation approaches use both of them to obtain homogeneous regions. In this paper, a new homogeneity measure for color-texture segmentation is proposed, which integrates textural homogeneity and edge information to overcome the drawbacks of JSEG method. After analyzing over-segmentation problem of the JSEG, method, we propose to use the contrast visual information to form the contrast map. We adopt the noise removal and edge enhancement strategies to construct the improved contrast map to form explicit outlines of the major objects in the image. Next, the improved contrast map (ICMap) and original J-map are combined to form a new J_{IC} map. Based on the new J_{IC} map we use seed growing-merging method to segment the image. The experiments performed on both natural and medical images show that the proposed method is robust for both and could match better with human segmentation than JSEG.

(a) (b) (c)

Fig. 3. Natural color-texture images: column (a) natural color-texture images, (b) results of JSEG method, and (c) results of the proposed method.



(a) (b) (c)

Fig. 4. Color medical images: column (a) cell images, (b) results of JSEG method, and (c) results of the proposed method.

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