TEXTURE-BASED COLOR IMAGE SEGMENTATION USING LOCAL CONTRAST INFORMATION

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Abstract

A novel texture-based segmentation algorithm for color images is proposed in this paper. Many powerful color image segmentation algorithms such as J-Segmentation (JSEG)suffer from over segmentation. Analysis of undesirable results from JSEG segmentation has led to the development of an improved JSEG method called *improved contrast JSEG*, or IC-JSEG. The proposed method first constructs a contrast map to obtain the basic contours of the homogeneous regions in the image. Filtering is applied to remove noise and enhance the strength of edges found by a noise-protected edge detector. A seed growing-merging method uses both the improved contrast map and the original J-map constructed by JSEG to segment the image. Experiments on natural color-texture images and color medical images show improved results.

Keywords: color image segmentation, local contrast information, JSEG, contrast map, improved contrast JSEG

1 Introduction

Image segmentation is a fundamental problem in image analysis and computer vision. In recent years research has focused on the segmentation of color images, since grayscale images can not satisfy the needs in many application domains. 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 image segmentation based on color and texture information. Many texture or segmentation methods have been proposed in the literature, including [1] [3] [4] [8] [9] [10] [11] [15]. Most of these are 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. These are known as edge detection techniques. Similarity-based approaches group similar pixels into different homogenous regions; common methods include region growing, region splitting, region merging. More recently, new algorithms have been proposed that improve the accuracy of segmentation by integrating region and boundary information [7] [6] [16].

Image texture, by definition, refers to the variation of color patterns within the image. Image regions with high levels of texture are typically nonhomogenous. For this reason, it is difficult to rely entirely on color discrimination to identify both homogeneous regions and the boundaries or edges between those regions. In [5], the JSEG method is proposed for the unsupervised segmentation of color images. In JSEG, colors are first quantized and then images are spatially segmented. In practice, the boundary detection used by JSEG often produces results that exhibit *over-segmentation*, in which homogenous regions are unnecessarily and undesirably split into smaller subregions.

In [2], a contrast-based color image segmentation method is proposed. Based on the subjective observations of ten participants, the authors concluded that perceived color contrast is weakly correlated with luminance and color levels, as encoded in the CIE $L^*a^*b^*$ color space. Although their segmentation results are better than those of the original JSEG method with respect to over-segmentation, the algorithm does not consider images with complex textures. Because the algorithm uses a single threshold for contrast, it often merges different regions – themselves each homogenous – into a single region, resulting in under-segmentation.

In this paper, we propose a new algorithm based on JSEG for the segmentation of color images. Key to the new approach is a more effective measure of region homogeneity. Section 2 reviews the homogeneity measure defined by JSEG and discusses why it causes over-segmentation. Section 3 describes the new contrast map-based measure of homogeneity, and Section 4 presents experimental results that demonstrate the superiority of the new algorithm. Finally, we offer conclusions in Section 5.

2 JSEG Method

The JSEG segmentation algorithm begins by reducing the colors in the image through quantization based on peer group filtering (PGF) and vector quantization. The result of color quantization is a *class-map* which logically associates the label of a color class with each pixel belonging to the class. The spatial segmentation that follows as the second step in JSEG is based on the information in the class-map. The following notation and discussion are based on [5].

Let Z be the set of all (x, y) image pixels contained in a particular class-map. Suppose that Z has been classified into C classes, $Z_i, i = 1, \ldots, C$. Define m to be the spatial mean of all points in Z, and denote the spatial mean of pixels in Z_i as m_i. The total variance of all points in Z is given by

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

We can compute the total variance of points belonging to the same class as

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

A measure of the distribution of color classes is then given by

$$J = \frac{(S_T - S_W)}{S_W}. \tag{3}$$

The JSEG algorithm continues by computing, for each pixel, a J value over a small window centered at that pixel. This results in a *J-image* or *J-map* with corresponding pixel values defined by local J values. The J-images constructed at different scales specify local homogeneities, which in turn indicate potential boundary locations. The higher the local J value is, the more likely that the associated pixel is close to a region boundary.

In [5], J values are calculated over the class-map so that color or intensity information of the original pixels is not considered. Fig. 1 shows two simple class-maps with similarly shaped regions. In this example, the labels “1”, “2” and “3” correspond to different classifications of data points. As can be seen, the intensity value of Class 3 is much higher than that of Class 2, while Class 2’s intensity value is just slightly higher than that of Class 1. Despite the intensity differences, Equations (1)-(3) produce identical J values (0.6) for both two class-maps. Perceptually, the edge between Class 2 and Class 3 is sharper and has higher contrast than the edge between Classes 1 and 2. This example shows that the J measure can be used to detect boundaries, but the measure does not reflect the boundary strength. This illustrates one cause of over-segmentation in JSEG results.

Figure 1. Two similar class-maps calculated with a 5×5 window size. Labels indicate pixel classification in Class 1, 2, or 3.

3 Improved Contrast JSEG

3.1 Contrast Map Construction

We propose a new color image segmentation approach that addresses the limitations of the JSEG method. Our approach is based on the conclusion in [2] that color contrast is weakly correlated with luminance and color levels. We assume that the original image has first been converted to the CIE $L^*a^*b^*$ color space. For two colors representations within that color space, $c1 = (L_1^* a_1^* b_1^*)$ and $c2 = (L_2^* a_2^* b_2^*)$, the Euclidean distance between $c1$ and $c2$ is defined by

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

This measure of distance approximates the perceptual difference between two colors [14].

For pixel $p(i, j)$ in image $I(i, j)$, the contrast can be calculated from the 3×3 surrounding window using the Euclidean distance in CIE $L^*a^*b^*$ color space as

$$contrast(i,j) = \text{MAX}\left\{\Delta E_{p(i+m,j+n)p(i,j)}\right\} - \text{MIN}\left\{\Delta E_{p(i+m,j+n)p(i,j)}\right\},$$
$$m \in \{-1,0,1\}, n \in \{-1,0,1\} \qquad (5)$$

However, the contrast map constructed using values obtained from Equation (5) is usually noisy, and the noise negatively affects the final segmentation result.

3.2 Improved Contrast Map (ICMap

Our approach improves the contrast map by reducing the noise and enhancing the boundary strength using a filter proposed in [13]. Based on a 256-grayscale contrast map, quantized from *contrast*(i, j), a two-step procedure is applied to the image channels in order to increase the effectiveness of the smoothing operation. The first step of this procedure is defined by the following equations.

$$c^{(1)}(i,j) = c^{(0)}(i,j) + \frac{1}{8}\sum_{m=-1}^{1}\sum_{\substack{n=-1,\\(m,n)\neq(0,0)}}^{1} \varsigma^{(1)}(c^{(0)}(i+m,j+n), c^{(0)}(i,j)) \qquad (6)$$

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

where $\varsigma^{(p)}$ is the parameterized nonlinear function given by

$$\varsigma^{(p)}(u,v) = \begin{cases} u - v & : \quad |u-v| \leq a^{(p)} \\ \left(\dfrac{3a^{(p)} - u + v}{2}\right) sgm(u-v) & : \quad a^{(p)} < |u-v| \leq 3a^{(p)} \\ 0 & : \quad |u-v| > 3a^{(p)} \end{cases} \qquad (8)$$

and $a^{(p)}$ is an integer such that $0 < a^{(p)} < L$. (In this case $L = 256$.) In the filter, small $a^{(p)}$ values preserve the fine details, and large values produce a strong noise cancellation [12].

The second step of Russo's filter [13] takes into account the differences between the pixel to be processed and its neighboring pixels in a slightly different way: if all these differences are very large, the pixel is (possibly) part of a boundary that may be considered noise and may be cancelled. (Real boundaries will be enhanced in a future step.) This step is briefly summarized as follows.

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

where

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

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

$$\mu_{LA}(u,v) = \begin{cases} \dfrac{u-v}{L-1} & : \quad 0 < u - v \leq L-1 \\ 0 & : \quad u - v \leq 0 \end{cases} \tag{11}$$

To enhance the boundaries after image filtering, the output of the color edge detector is given by

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

where μ_{SM} is the membership function for another fuzzy set, and B_1 and B_2 are Euclidean distances between averages of selected color vectors. (See [13] for a detailed explanation.)

This improved contrast map (ICMap) reduces noise and enhances the boundaries to a large extent.

3.3 A Novel Measure Definition and Spatial Segmentation

A new measure combining the ICMap and J measure in JSEG can be constructed for color texture-based segmentation. The proposed new method is called IC-JSEG. For an M×N image, ICMap is first calculated according to Equation (5), and then improved according to Equation (12). At this point, the magnitude is normalized as follows:

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

where

$$ICMap_{max} = \text{MAX}\left\{ICMap(i,j)\right\}, \quad 0 \leq i \leq M-1, 0 \leq j \leq N-1. \tag{14}$$

The J value (also normalized) of the local region is computed according to Equations (1)-(3). Then the proposed measure is formed by weighting the J as follows: W_{IC}.

$$J_{IC}(i, j) = w_{IC}(i, j) \cdot J(i, j). \tag{15}$$

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 construct a J_{IC} image or map, where pixel values can be used to indicate the interior and boundary of the region. We also adopt the multi-scale segmentation scheme provided by JSEG, consisting 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. First, a threshold is set to find the seed areas: $T = \mu + \delta\sigma$, where μ and σ are the average and the standard deviation of the local J_{IC} values in the regions, respectively, and δ 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 the seed regions selected in Step 1. First, the the local J_{IC} values in the remaining unsegmented part of the regions are averaged. Then, pixels with values below that average are assigned to an adjacent seed. For the remaining pixels, their local J_{IC} values are calculated. They will be dealt with at the 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 the color histogram bins. The two regions with the minimum distance between their histograms are merged together and this process continues until a maximum distance threshold is reached.

Fig. 2(a) illustrates the effects of applying the new IC-JSEG algorithm to the “Garden” image. Image (a) in the figure shows the original image, and (b) and (c) show the J map and contrast map from the original JSEG method, respectively. Figs. 2(d) and (e) represent the improved contrast map and J map using the IC-JSEG algorithm. Figs. 2(f) and (g) show the final segmented images using JSEG and IC-JSEG respectively.

(a) (b) (c)

(d) (e)

(f) (g)

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

4 Experimental Results

The proposed algorithm was applied to a set of natural color images with varying textures and to a set of medical images, and the results were compared with segmentation results of the original JSEG algorithm. To test the overall robustness of the algorithm, our experiments did not include any fine-tuning of parameters for individual images. Parameters common to both JSEG and IC-JSEG were set to identical values for the experiments shown. Fig. 3 shows the segmentation results obtained by the JSEG and IC-JSEG methods.

From Fig. 3, we can see that the results obtained from the proposed IC-JSEG method are better than those obtained using the original JSEG method. With JSEG, the lawn and trees are split apart into many small regions. In contrast, IC-JSEG keeps them as an integral part which more closely matches human visual perception. Furthermore, for the mountain, lake, buildings, and

(a) (b) (c)

Figure 3. (a) Original natural color-texture images, (b) Results of JSEG method, (c) Results of the proposed method.

so forth, IC-JSEG preserves more homogeneous regions than does JSEG.

The new IC-JSEG method was also applied to three color medical images to test its performance, as shown in Fig. 4. From the results of these colored cell images, we can see that IC-JSEG detects more homogeneous regions than the JSEG method does. Since the IC-JSEG method strengthens edges to discriminate different homogeneous regions, it can also detect trivial homogeneous regions. Although IC-JSEG segments the images into more regions, these segmented regions conform more closely to human visual perception, and they are not considered to be evidence of over-segmentation.

(a) (b) (c)

Figure 4. (a) Original natural color-texture images, (b) Results of JSEG method, (c) Results of the proposed method.

5 Conclusion

Color and texture are critical factors in human visual perception. Many segmentation approaches use both factors to obtain homogeneous regions for segmentation. In this paper, a new measure of homogeneity is proposed for segmentation based on color texture. The measure integrates textural homogeneity and edge information to overcome the drawbacks of the JSEG method on which our overall algorithm is based. After analyzing the over-segmentation problem of the JSEG method, we proposed the use of contrast visual information to form a contrast map. We adopted noise removal and edge enhancement strategies to construct an improved contrast map to form explicit outlines of 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 a seed growing-merging method to segment the image. Experiments performed on both natural and medical images show that the proposed method is robust for both and produces segmented images that better match human perception than the original JSEG method.

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References

[1] Chang, T., Kuo, C.-C.J. 1993, *Texture analysis and classification with tree-structured wavelet transform*, IEEE Transactions on Image Processing, Vol. 2, No. 4, pp. 429-441.

[2] Chen, H.C., Chien. W.J., Wang S.J., 2004, *Contrast-based color image segmentation*, IEEE Signal Processing Letters, Vol. 11, No. 7, pp. 641-644.

[3] Comaniciu, D., Meer, P., 1997, *Robust analysis of feature spaces: color image segmentation*, IEEE Int. Conf. on Computer Vision and Pattern Recognition, San Juan, Puerto Rico, pp. 750-755.

[4] Comaniciu, D., Meer, P., 2002, *Mean shift: a robust approach toward feature space analysis*, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 24, No. 5, pp. 603-619.

[5] Deng, Y., Manjunath, B.S., 2001, *Unsupervised segmentation of color-texture regions in images and video*, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 23, No. 8, pp. 800-810.

[6] Fan, J., Yau, D.K.Y., Elmagarmid, A.K., Aref, W.G., 2001, *Automatic image segmentation by integrating color-edge extraction and seeded region growing*, IEEE Transactions on Image Processing, Vol. 10, No. 10, pp. 1454-1466.

[7] Freixenet, J., Muñoz, X., Raba, D., Marti, J., Cufi, X., 2002, *Yet another survey on image segmentation: region and boundary information integration*, Proc. 7th European Conference on Computer Vision – Part III, Copenhagen, Denmark, pp. 408-422.

[8] Luo, J., Gray, R.T., Lee, H.C., 1998, *Incorporation of derivative priors in adaptive Bayesian color image segmentation*, IEEE Int. Conf. on Image Processing, Chicago, IL, pp. 780-784.

[9] Luo, Q., Khoshgoftaar, T.M., 2006, *Unsupervised multiscale color image segmentation based on MDL principle*, IEEE Transactions on Image Processing, Vol. 15, No. 9, pp. 2755-2761.

[10] Pappas, T.N., 1992, *An adaptive clustering algorithm for image segmentation*, IEEE Transactions on Signal Processing, Vol. 40, No. 4, pp. 901-914.

[11] Randen, T., Husoy, J.H. 1999, *Texture segmentation using filters with optimized energy separation*, IEEE Transactions on Image Processing, Vol. 8, No. 4, pp. 571-582.

[12] Russo, F., 2003, *A method for estimation and filtering of Gaussian noise in images*, IEEE Transactions on Instrumentation and Measurement, Vol. 52, No. 4, pp. 1148-1154.

[13] Russo, F., Lazzari, A., 2005, *Color edge detection in presence of Gaussian noise using nonlinear prefiltering*, IEEE Transactions on Instrumentation and Measurement, Vol. 54, No. 1, pp. 352-358.

[14] Ruzon M.A., Tomasi, C., 2001, *Edge, junction, and corner detection using color distributions*, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 23, No. 11, pp. 1281-1295.

[15] Unser, M., 1995, *Texture classification and segmentation using wavelet frames*, IEEE Transactions on Image Processing, Vol. 4, No. 11, pp. 1549-1560.

[16] Xu, J., Shi, P.F., 2003, *Natural color image segmentation*, Proc. IEEE Int. Conf. Image Processing, Vol. 1, Barcelona, Spain, pp. 973-976.