Roughness Approach to Color Image Segmentation through Smoothing Local Difference

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Abstract. Aiming at the problems of histogram-based thresholding, rough set theory is applied to construct the roughness measure for segmenting color image. However, the extant roughness measure is a qualitative description of neighborhood similarity and tends to over focus on the trivial homogeneity. An improved roughness measure is proposed in this paper. The novel roughness is computed from smoothed local differences and quantified homogeneity, thus can form the accurate representation of homogeneous regions. The experimental results indicate that the segmentation based on improved roughness has good performances on most testing images.

Keywords: Color image segmentation, rough sets, local difference.

1 Introduction

The main task of color image segmentation is to partition an image into different homogenous regions depending on the color properties of pixels [1]. Considering the segmentation purpose, some methods focus on the object detection, for which the different objects contained in the color image are expected to be separated and recognized, while the other segmentations target at compressing image color, through which the image that may have upmost millions of different colors can be concisely represented using only a small number of ones. Moreover, according to different technical or theoretical backgrounds, most existing color image segmentation methods can be roughly classified into the approaches as histogram based [2], edge based [15], region based, clustering based [3,11,12], and combination of several techniques [6,13]. The characteristics of the related methods have been detailedly introduced and discussed in [1]. As the most popular segmentation technique, the histogram thresholding has the advantages of low computational complexity and no requirement of priory information, but its

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precision can not always be guaranteed. Therefore the histogram based method was improved from different views.

For synthesizing the color spatial distribution and feature dependency, rough set theory [9,10,4] was induced to extend the traditional histogram into various statistics for image segmentation. Mohabey and Ray constructed a concept histon [7], each bin of the histon is the pixel scale belonging to the corresponding intensity with uncertainty. Histon and histogram can be respectively considered as the upper and lower approximate representations of color distribution from rough sets view. Because the segmentation based on histon pays little attention to the small homogeneous regions, Mushrif then proposed the roughness measure to extract the homogeneous regions in color image by employing the boundary between two approximations [8]. It is indicated that the roughness index can effectively represent the color homogeneity and avoid the disturbance of pixel scale for segmentation.

However, according to the extant roughness, trivial noisy point and significant homogeneous region may have the same roughness, but they actually own different importance for segmentation in vision. Thus the roughness measure tends to over focus the homogeneity of small regions and is still not precise and flexible enough. Aiming at the problems, we expect to further quantify the neighborhood homogeneity and improve the roughness measure for color image segmentation. Like the segmentation based on traditional roughness, our method also focuses on color compression. The perceptually close color in image will be combined through segmenting the pixels into multiple homogenous regions. The main contributions of this paper are as follows.

- Proposing an improved roughness measure in LUV color space to precisely depict region homogeneity. This roughness is computed through smoothing the local color differences with linear scale-space filtering.

This paper is organized as follows: In Section 2, the improved roughness methodology for measuring homogeneity of color distribution is briefly introduced. Section 3 presents the experimental results to validate the method efficiency. The work conclusion is given in the last section.

2 Quantitative Roughness Measurement

2.1 Representing Local Consistency

Our method uses the smoothed matrix of neighborhood difference to represent the local consistency of color distribution. The multilevel neighborhood differences are obtained by linear scale space filtering, also known as Gaussian smoothing [5]. The color difference at rougher level will present more intuitive local homogeneity and weaken noise interference. The smoothed difference matrix is defined as follows to represent the local consistency of color distribution.

Definition 1. *Given a LUV image F of size $M \times N$, for a pixel $P : F(i,j)$, $1 \le i \le M$, $1 \le j \le N$, its color difference in 3×3 neighborhood is defined as*

$$D(i,j) = d_P^{3\times 3} = \sum\nolimits_{Q \in NB_P^{3\times 3}} d(P,Q) \tag{1}$$

where $d(P,Q)$ is the color difference between pixel P and Q, $NB_P^{3\times 3}$ is the pixel set of adjacent eight neighbors of P. $d(P,Q)$ can be calculated using the Euclidean distance of LUV coordinates of P and Q.

$$d(P,Q) = \sqrt{(L_P - L_Q)^2 + (U_P - U_Q)^2 + (V_P - V_Q)^2} \tag{2}$$

We can further define the neighborhood difference matrix D of color image F as

$$D = \{D(i,j) | 1 \le i \le M, 1 \le j \le N\} \tag{3}$$

Definition 2. *For $M \times N$ neighborhood difference matrix D, given a scale t and $R \times R$ template that denotes local area, $3 < R \ll \max\{M,N\}$, the smoothed difference matrix is the convolution of D with the t-scale Gaussian kernel.*

$$D^t = D * g^t = \{D^t(i,j)\} = \{D(i,j) * g_{i,j}^t\}, \quad 1 \le i \le M, 1 \le j \le N \tag{4}$$

where $*$ is the convolution operator, $g_{i,j}^t$ is the Gaussian kernel covering $R \times R$ template of center (i,j), each element of the kernel is computed as $g^t(x,y) = (1/2\pi t)e^{-(x^2+y^2)/2t}$.

Referring to the scale-space theory[5], the smoothed difference matrixes actually offer us a multilevel observation of local consistency of image color distribution. In view of scale-space, the optimal local consistency representation relies on the smoothing scale. According to the abundant experimental results, we set scale $t = 1$, under this scale, the noisy heterogeneity can be effectively filtered out while the significant region boundaries are guaranteed.

2.2 Roughness Measure of Color Distribution

Based on LUV histogram and quantified neighborhood homogeneity, the approximate representations of color distribution can be defined. The histograms on three primary components are certain pixel counting thus viewed as the lower approximation $\underline{H}_i$, $i \in \{L,U,V\}$. The histogram can be extended to upper approximation with neighborhood homogeneity to describe the local consistency of color distribution. Utilizing the boundary between two approximations which denotes uncertainty, the roughness under specific scale can be constructed according to rough set theory.

Definition 3. *Given a color image F and a scale t, D^t is the corresponding neighborhood difference matrix. For a pixel $F(m,n)$, the homogeneous degree of the $R \times R$ area centering on $F(m,n)$ is decided by the homogeneity function as*

$$h^t(m,n) = \begin{cases} 1 & D^t(m,n) \le r \\ \frac{1}{1+[0.5\times(D^t(m,n)/r-1)]^4} & r \le D^t(m,n) \le kr \\ 0 & kr \le D^t(m,n) \end{cases} \tag{5}$$

$h^t(m,n)$ is a typical membership function in fuzzy set theory to map local color difference into homogeneous degree [0, 1]. Parameter r denotes the threshold of indistinguishable color difference. The homogeneous degree is reduced smoothly as local color difference increasing. Considering the concrete cases of various color distribution, we assign r as a half of median value among all distinct neighborhood differences and set k big enough for precisely quantifying homogeneity.

Definition 4. *Given a color image F and its smoothed difference matrix under scale t, combining neighborhood homogeneity into histogram, the upper approximation of color component i is constructed as*

$$\overline{H}_i^t(l) = \sum\nolimits_{m=1}^{M} \sum\nolimits_{n=1}^{N} (1 + h^t(m,n))\sigma(F(m,n,i) \in bin_i^l), \quad 1 \le l \le N_i^b \tag{6}$$

where $h^t(m,n)$ is the homogeneous degree of $R \times R$ neighborhood centering $F(m,n)$ under scale t, N_i^b is the number of bins on component i. Obviously, $\overline{H}_i^t(l) \ge \underline{H}_i(l)$, the added part represents the uncertainty of surrounding pixels belonging to the lth intensity of color feature i. All $\overline{H}_i^t(l)$, $i \in \{L,U,V\}$ form the upper approximation of color distribution under scale t.

Definition 5. *Given a LUV color image F, the roughness of each color component under the scale t is defined as*

$$r_i^t(l) = 2 * (1 - |\underline{H}_i(l)|/|\overline{H}_i^t(l)|), \quad 1 \le l \le N_i^b, \quad i \in \{L,U,V\} \tag{7}$$

where N_i^b is the number of bins, i.e. intensity scale, on component i. For the lth intensity on component i, $\underline{H}_i(l)$, $\overline{H}_i^t(l)$ are the lower and upper approximations under scale t. The constant is a factor to map the roughness value into [0,1].

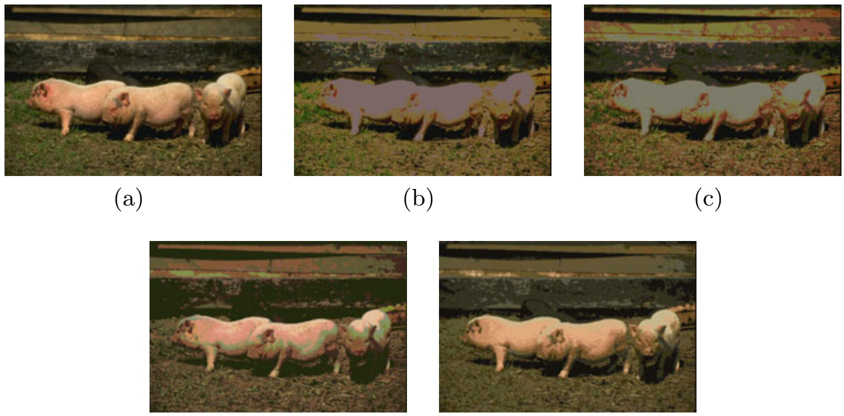
Because the linear scale-space kernel filters out the trivial homogeneity and the fuzzy membership function quantifies the neighborhood homogeneity, the improved roughness can depict region homogeneity more precisely. The further validation can be seen in experiment section.

3 Experimentation and Validation

In our experiments, all testing images are collected from Berkeley segmentation database [14]. Because of the limited space, here we just illustrate limited testing results. Considering both color compression and segmentation accuracy, we utilize the criteria proposed in Ref.[6] to evaluate the performances of segmentation methods, the evaluation function is empirically defined as

$$E(F) = \frac{1}{1000(N \times M)} \sqrt{S} \sum_{i=1}^{S} \frac{e_i^2}{\sqrt{|C_i|}} \tag{8}$$

where F is the segmented image, $N \times M$ is the image size, and S is the number of color of segmented image, while C_i and e_i are, respectively, the ith segmented



(a) (b) (c) (d) (e)

Fig. 1. (a) Color image 'Pigs', (b, c, d) segmented results based on histogram, histon and traditional roughness, (e) segmented image based on improved roughness

color and the segmented color error caused by C_i. Obviously, the smaller the value of $E(F)$, the better the segmentation result should be.

Given some testing images, Fig.1 illustrate their segmentation based on histogram, histon, traditional roughness, and improved roughness. Table 1 presents the corresponding information of segmented results, which involves segmented color number and segmentation evaluation, C_n and C_{nm} denote the numbers of initially segmented colors and merged colors, E_v is the segmentation quality evaluation.

Table 1. Segmented results based on various statistics

Images	Histogram		Histon		Roughness			Improved Roughness		
	C_n	E_v	C_n	E_v	C_n	C_{nm}	E_v	C_n	C_{nm}	E_v
Table tennis	47	0.070	47	0.069	111	30	0.034	388	32	0.035
Butterfly	71	0.082	88	0.077	119	28	0.035	327	32	0.034
Corn	68	0.202	63	0.180	86	25	0.076	451	32	0.066
House	116	0.127	115	0.100	160	45	0.038	752	16	0.033
Pigs	78	0.147	62	0.113	61	16	0.026	400	16	0.019
Basket	47	0.130	44	0.143	24	19	0.087	340	16	0.022
Horse	34	0.037	25	0.031	57	18	0.018	312	16	0.016
Lion	41	0.039	44	0.023	104	13	0.009	377	16	0.007

As shown above, the segmentation method based on improved roughness generally performs better than the methods based on histogram, histon and extant roughness measure. Experimental results indicate that the smoothed local differences can effectively restrain the disturbance of noisy or trivial points, and form the delicate color segmentation. Setting the merged color number as palette scales of 16 and 32, the colors of initially segmented image are further compressed while the segmentation quality being guaranteed.

4 Conclusion

Although the roughness measure can lead to fine color segmentation comparing with the traditional histogram-based methods, the extant roughness tends to be influenced by noisy points and is not accurate enough to present the homogenous regions. In this paper, an improved roughness measure is proposed based on the smoothed local differences, which can effectively restrain the noise interference to form the exquisite representation of color homogeneity. The experimental results have shown the proposed measure has good performances on most testing images.

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