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Multiscale roughness measure for color image segmentation

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ABSTRACT

Color image segmentation is always an important technique in image processing system. Highly precise segmentation with low computation complexity can be achieved through roughness measurement which approximate the color histogram based on rough set theory. However, due to the imprecise description of neighborhood similarity, the existing roughness measure tends to over-focus on the trivial homogeneous regions but is not accurate enough to measure the color homogeneity. This paper aims to construct a multiscale roughness measure through simulating the human vision. We apply the theories of linear scale-space and rough sets to generate the hierarchical roughness of color distribution under multiple scales. This multiscale roughness can tolerate the disturbance of trivial regions and also can provide the multilevel homogeneity representation in vision, which therefore produces precise and intuitive segmentation results. Furthermore, we propose roughness entropy for scale selection. The optimal scale for segmentation is decided by the entropy variation. The proposed method shows the encouraging performance in the experiments based on Berkeley segmentation database.

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1. Introduction

Image segmentation is an important pre-processing step in the areas of image analysis and image compression. It is a critical and essential component of image recognition system and usually determines the quality of the final result [9]. In segmentation, an image is partitioned into different non-overlapping homogeneous regions. The segmentation process can be formally defined as [34]: given a set of universally connected pixels of image F and a homogeneity predicate $P(\cdot)$, then segmentation is a partition of the set F into connected subsets or regions $(S_1, S_2, \ldots, S_n)$ such that $\cup_{i=1}^{n} S_i = F$ with $S_i \cap S_j = \emptyset,\ i \neq j$. The homogeneity predicate $P(S_i) = true$ for all regions, and $P(S_i \cup S_j) = false$, when $i \neq j,\ S_i$ and S_j are neighbors. The homogeneity of a region may be composed based on different criteria such as gray level, color or texture. Because color images can provide richer information than gray level images, color image segmentation attracts more and more attention.

The segmentation techniques for monochrome images can be extended to segment color images by using $R,\ G$ and B color components or their transformations (linear/non-linear) [3,47]. One important task of color image segmentation is to compress the colors in images. A digital color image has millions of different colors at the maximum. It can be concisely represented using only a small number of colors through segmentation. Different techniques in this research area can be roughly classified into histogram based [4,5,10,31,32], edge based [52,53], region based [2,49,54], clustering based [1,7,20,46], and combination of several techniques [6,15,17,25,26,30]. Any developed segmentation algorithm has its limitation and does

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not always produce good results for all kinds of images. The advantages and the limitations of these techniques have been discussed in [3,47].

The improvement of color image segmentation mainly focuses on the following aspects. First, color space should be constructed according to the specific applications. *RGB* space is suitable for color display, but not good for scene analysis because of the high correlation among the R, G, and B components. Although different color representations can be derived from either linear or non-linear transformations of *RGB* space (such as *YUV* and *HSI*), almost all color spaces have their respectively non-removable deficiencies [3,47]. The second issue is the dependence of different color components. Especially for the linear color space, image is usually segmented on each feature independently, which ignores the correlation between color components. The dependence between color components is helpful for further improving the segmentation quality. The last issue is synthesizing the statistical and spatial distributions of image color. Most traditional methods based on statistical information such as histogram do not consider the dependence of adjacent pixels. These methods have low computational complexity but the segmentation precision cannot be guaranteed. Other segmentation strategies using color spatial distribution such as region-based methods can achieve more precise results but usually cause computational complexity. This paper aims to combine statistical and spatial distributions but without increasing the computational complexity.

As a most widely used technique for color image segmentation, the histogram-based thresholding assumes that the homogeneous objects in image manifest themselves as clusters. The advantages of such methods are no need of priori information and the low computational complexity. But these methods only consider gray levels and do not take into account the spatial correlation of color in the real images. Through measuring the neighborhood similarity, Mohabey and Ray utilized the rough set theory to construct the histon concept [31]. Different from histogram, each bin of the histon is the pixel scale belonging to the corresponding intensity with uncertainty. Therefore histon and histogram can be respectively considered as the upper and lower approximations of color distribution from rough sets view. The segmentation based on histon utilizes the local correlation of color. But it pays little attention to the small homogeneous regions and leads to unsatisfactory results. Employing the boundary between two approximations, Mushrif and Ray then proposed the roughness measure to extract the homogeneous regions of color image [32]. The roughness index can effectively indicate the region homogeneity degree and avoid the disturbance of imbalanced color distribution. For image segmentation, it produces better performance than either histogram based methods or histon based methods.

However,due to the imprecise description of neighborhood similarity, the existing roughness measure tends to over-focus on the trivial homogeneous regions and is not accurate enough to represent the color homogeneity. The deficiency of this measurement will be further explained in Section 3. In this paper, we will use computer vision techniques to construct a precise and hierarchical roughness measurement for detecting the region homogeneity in color image. The main contributions of this paper are summarized as,

- Applying linear scale-space theory to construct the multiscale roughness for measuring the homogeneity in color image.
- With regard to the diversity of color distribution, designing the self-adaptive algorithms for thresholding and merging color.
- Proposing the roughness entropy for scale selection based on information variation.

As being discussed in other related work, this paper also adopts RGB color space as the case for image segmentation. The proposed method will compress the color space through image segmentation without reducing the image qualities.

This paper is organized as follows: Section 2 briefly reviews the related work. Section 3 describes the novel model of multiscale roughness for measuring the color region homogeneity. Section 4 investigates the information measurement of roughness and proposes the strategy of optimal scale selection. Section 5 introduces the segmentation method based on multiscale roughness with self-adaptive algorithms for thresholding feature and merging color. Section 6 presents the experimental results to validate the efficiency of the proposed method. The conclusion about our exploratory work is also given in the last section.

2. Related work

Rough set theory is a possibilistic approach to extract valuable patterns from information system at multiple granular levels. It is an effective tool for removing redundant attributes, finding interrelation among data components and dealing with vague, uncertain and imprecise information [36–38]. Besides the wide application in data mining and machine learning, rough set theory has been utilized into the areas of image analysis in recent years [29,35,58]. The image analysis based on rough sets usually focuses on similarity measure of pixel sets, hierarchical representation of image features and rules for classifying image contents. The related exploratory works actually offer us the new ways to analyze the information contained in digital images.

Hassanien applied rough set theory to analyze medical images. A hybrid scheme for detecting breast cancer was proposed based on fuzzy rough sets, in which rough sets were used to construct the concise rules for discriminating the regions whether cancer or non-cancer [11]. For diagnosing prostate cancer in ultrasound images, an image classification framework employing the wavelet and rough sets was also designed [33]. This framework uses rough sets to filter the wavelet-based features and construct rough confusion matrix to predict classification. A similar strategy combining rough sets and pulse coupled neural networks for analyzing ultrasound glaucoma images was presented in [8].

Ślęzak proposed a model of rough neural networks to represent some types of compound concepts. The rough neural networks was applied to the task of magnetic resonance image (MRI) analysis and used to label the MRI voxels with different tissue types [48]. Widz proposed another rough-set-based system to detect the voxels of partial volume effect (PVE) for MRI segmentation [56]. This approach uses reducts to produce the decision rules to correctly identify the PVE voxels from the low resolution magnetic resonance image, thus can form the basis of automated MRI segmentation algorithm.

Petrosino and Salvi presented C-sets for multi-scale image analysis based on the hybrid notion of rough fuzzy sets [42]. This novel set comes from the combination of two models of uncertainty like vagueness by handling rough sets and coarseness by handling fuzzy sets. Marrying characteristics of both rough sets and fuzzy sets, C-sets can represent pixel set approximation and further lead to fuzzy partition of image space.

Peters introduced an approach to analyze perceptual information systems in the context of near sets [12,13,41]. This work was motivated by an interest in discovering affinities between perceptual granules contained in images. Rather than traditional equivalence relation or tolerance relation, near sets consider various nearness relations which define coverings of sets of perceptual objects near each other. Near set theory provides a formal basis for the observation, comparison and classification of perceptual granules in information system.

Besides the image analysis tasks mentioned above, both clustering-based and histogram-based strategies employing rough sets were designed to segment color images. Schaefer et al. used a rough c-means clustering algorithm for image color quantisation [45]. This method aims at compressing the color in original image into a limited palette of distinct colors while guaranteeing the display quality of resulting image. In the rough clustering based segmentation, the cluster number, i.e. palette scale, should be predefined and the pixels located in cluster boundary need proper post processing.

Mohabey and Ray [31] proposed a histogram-based strategy for color image segmentation through inducing the concept of histon, which is a contour plotted on the top of the histogram. By investigating the spatial correlation of color distribution, histon utilizes a similar color sphere of a predefined radius around a pixel to define the neighborhood homogeneity. The base histogram was considered as the lower approximation and the histon as the upper approximation in rough-set theoretic sense. For segmentation, only the upper approximation was utilized and the histogram-based segmentation technique was applied on histon to threshold the color regions. This method does not take into account the boundary between two approximations and the induced segmentation over emphasizes the homogeneity of large scale pixel clusters.

To overcome the drawback of histon-based segmentation, Mushrif and Ray proposed a segmentation scheme that uses the roughness measure [32]. The roughness index at every intensity level is calculated from the approximation boundary. Index is large when the neighboring elements have the similar color or is small when the neighboring elements have the distinct color difference. Clearly, roughness will be very small in the boundary between heterogeneous objects and large in unified object region. Thus the roughness index can measure the region homogeneity and effectively avoid the disturbance caused by pixel scale imbalance. Through comparing with the histogram-based and histon-based approaches, the roughness measurement was demonstrated to achieve better segmentation results. However, this roughness measure just detects the color regions in fixed neighborhoods and does not quantify the neighborhood homogeneity, thus is not precise enough to obtain the delicate segmentation.

3. Multiscale roughness measure in color distribution

In this section, we propose a novel multilevel roughness measurement, in which scale-space theory is applied as a vision technique to construct more precise and intuitive representation of color homogeneity.

3.1. Model description and basic ideas

Mohabey and Ray first introduced the approximate representation of color distribution in rough-set theoretic sense. They constructed the statistics histon through measuring the color similarity of adjacent pixels. Histon is a contour plotted on the top of histogram and can be viewed as the extension of histogram with uncertainty. Thus the traditional histogram and histon are also defined as the lower and upper approximations of color distribution respectively. Moreover, Mushrif proposed a roughness measure utilizing the boundary between the two approximations. For an intensity on one color component, when the pixels of this value have similar color as their neighbors, the distinct lower and upper approximations will be formed. Thus the intensity on color component with the large approximation gap will have the property of roughness. Given a color image, the roughness index will be intuitively small in heterogeneous regions and large in homogeneous regions. The general roughness measure can be defined as [32]

$$\rho_i(l) = \frac{BN_i(l)}{\overline{H}_i(l)} = 1 - \frac{\underline{H}_i(l)}{\overline{H}_i(l)}, \quad 0 \leqslant l \leqslant L-1, \quad i = \{R, G, B\} \tag{1}$$

in which L is the intensity scale of color plane, $\underline{H}_i(l)$ and $\overline{H}_i(l)$ are the lower and upper approximations at intensity l in color plane i, $BN_i(l) = \overline{H}_i(l) - \underline{H}_i(l)$ is the boundary between two approximations.

The segmentations on histogram and histon are always sensitive to the pixel scale and tend to merge the small but significant regions into other segments. Employing the approximation boundary, the roughness index can effectively embody the region homogeneity and avoid the affection of pixel scale. Therefore the roughness-based segmentation usually performs better than the methods based on traditional histogram and histon, see Fig. 1. However, the existing roughness measurement still has the following deficiencies. First, this method just utilizes the standard eight neighbors to construct the upper approximation. It will be better to measure the local similarity in more flexible neighborhood. Under the settled template, existing roughness tends to over-embody the small regions, a trivial noisy point may obtain the roughness as much as a significant homogeneous region. Secondly, the neighborhoods where color difference is within a certain extent are mistakenly considered as the same homogeneity level, which leads to an inaccurate and single-level upper approximation. Thus the induced roughness can be viewed as the qualitative description of color homogeneity. A hierarchical model for further quantifying roughness should be given to represent the color homogeneity in more precise and intuitive way.

Aiming at the above problems, we expect to construct a quantitative and multilevel roughness through simulating the human vision. Scale-space theory as a vision technique [21,22,57] is applied into traditional roughness model to obtain the multiscale roughness for segmentation. Linear scale-space filtering is formed by convolving the specific field with the Gaussian kernel, thus the weighted average of neighborhood can be used to measure the region homogeneity. The improved homogeneity representation can be then utilized to construct the upper approximation and quantify the roughness index. With varying scales, the smoothing kernel actually induces a hierarchical approximate representation of color distribution and consequently leads to the multiscale roughness. Fig. 1 illustrates the segmentation results based on traditional roughness and multiscale roughness measure. We can see that in the segmented image of traditional roughness, the wall flecks and the hand shadow are set to the color of tennis table, while under a given scale, the segmentation based on multiscale

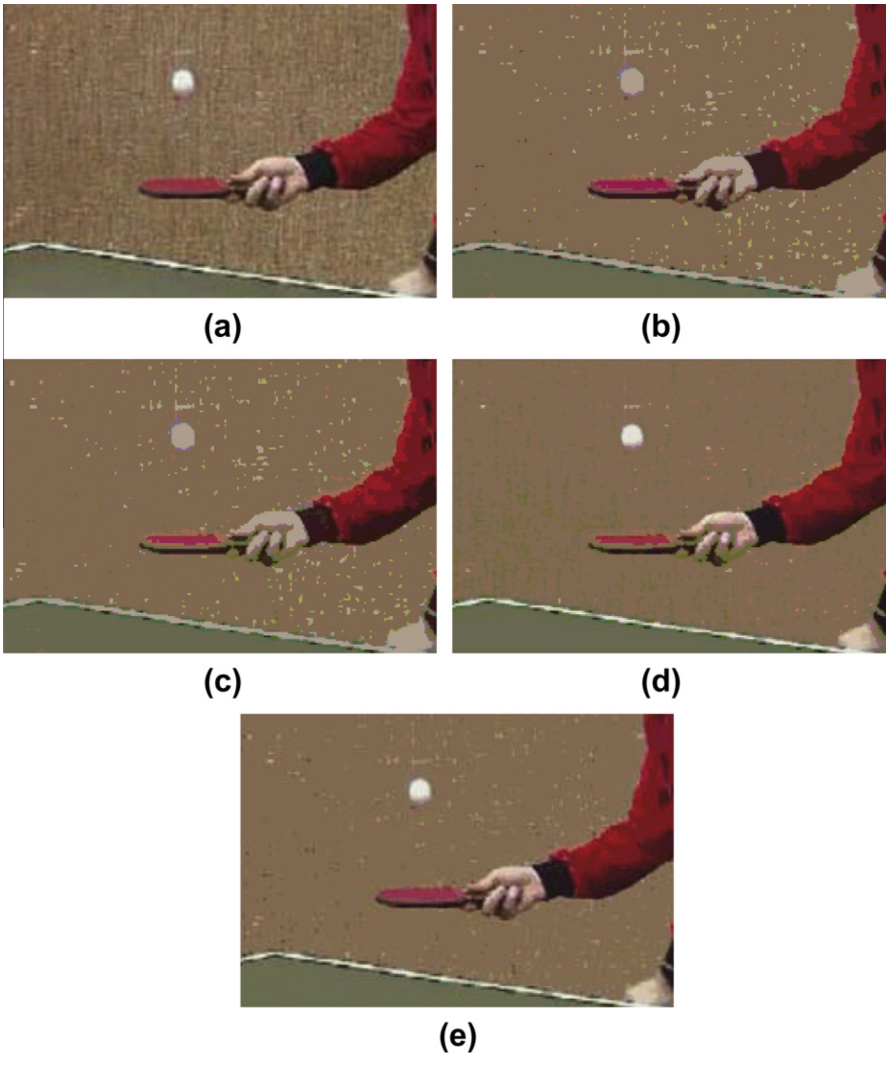

Fig. 1. (a) Original 'Table Tennis' image, (b–e) segmented images based on several kinds of statistics using the same thresholding strategy, (b) segmented image based on histogram, (c) segmented image based on histon, (d) segmented image based on traditional roughness, (e) segmented image based on multiscale roughness (scale $t = 0.5$).

roughness achieves more precise result. In the following sections, we will find other important properties of color roughness from the views of multiple scales.

3.2. Multiscale approximation of color distribution

In the next paragraphs, the linear scale-space technique will be utilized to construct the multiscale approximation of color distribution. Suppose F is an RGB image of size $M \times N$, consisting of three primary components, red R, green G, and blue B. The traditional histogram of image can be viewed as the lower approximation of color distribution.

Definition 1. The *lower approximation* of each color component is defined as

$$\underline{H}_i(l) = \sum_{m=1}^{M}\sum_{n=1}^{N}\delta(F(m,n,i) - l), \quad 0 \leqslant l \leqslant L-1, \quad i \in \{R,G,B\} \tag{2}$$

where $\delta(\cdot)$ is the impulse function and L is the intensity scale in each of the color components. Thus $\underline{H}_i(l)$ is the number of pixels having intensity l in color feature i, it is the accurate representation of color distribution at specific grey level.

Definition 2. Given a scale parameter t and a $P \times P$ neighborhood, the *linear scale-space representation* of image F is defined as

$$\begin{aligned} F^t &= \{F^t(i) | i \in \{R,G,B\}\}, \\ F^t(i) &= \{L^t(m,n,i) | 1 \leqslant m \leqslant M, 1 \leqslant n \leqslant N\} \end{aligned} \tag{3}$$

where $F^t(i)$ is the linear scale-space filtering of image F on color plane i. Let $F(m,n,i)$ be the intensity of pixel $F(m,n)$ on color i, $L^t(m,n,i)$ is the convolution of $F(m,n,i)$ with the t-scale Gaussian kernel covering the neighborhood of size $P \times P$, see Fig. 2. As introduced above, $L^t(m,n,i) = F(m,n,i) * g^t(m,n)$.

In a digital image, the linear scale-space filtering can be also understood as the weighted average of pixel intensities in the corresponding neighborhood of the reference point. The weight values are computed according to the distances between the neighboring points and the reference point. The closer a neighbor is to the central point, the more influence it will have in the neighborhood. Thus the scale-space representation can be used to measure the color difference between a central pixel and its around elements within a specific area.

Definition 3. Consider v_1, v_2 are color vectors in RGB space, the Euclidean *distance between the two vectors* is given by

$$d(v_1, v_2) = \sqrt{\sum_{i=R,G,B}(v_1(i) - v_2(i))^2} \tag{4}$$

For a pixel $F(m,n)$, suppose a scale t and $P \times P$ neighborhood, the color difference between $F(m,n)$ and its surrounding pixels in neighborhood can be defined as

$$d^t_{P\times P}(m,n) = d(F(m,n), F^t(m,n)) = \sqrt{\sum_{i=R,G,B}(F(m,n,i) - L^t(m,n,i))^2} \tag{5}$$

When the color difference of a neighborhood at specific position is within a limited range, the corresponding image region will be homogeneous. Homogeneity function is defined to measure the homogeneous degree based on the color difference in Eq. 5.

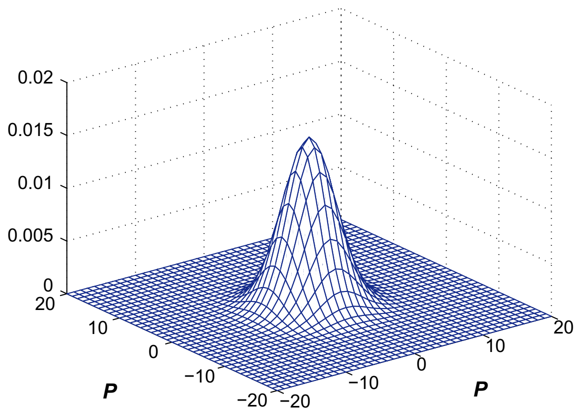

Fig. 2. Linear scale-space.

Definition 4. Suppose a pixel $F(m,n)$, under a given scale t, the homogeneous degree of $P \times P$ neighborhood relative to $F(m,n)$ is decided by the *homogeneity function* as follows.

$$s^t(m,n) = \begin{cases} 1 & d^t_{P\times P}(m,n) \leqslant r \\ \frac{1}{1+[2(d^t_{P\times P}(m,n)/r-1)]^3} & r < d^t_{P\times P}(m,n) \leqslant kr \\ 0 & kr < d^t_{P\times P}(m,n) \end{cases} \tag{6}$$

As shown in Fig. 3, $s^t(m,n)$ is a piecewise function of Gauchy distribution. Parameter r denotes the threshold of indistinguishable color difference. When $d^t_{P\times P}$ is less than the threshold r, the pixels in the neighborhood can be considered completely homogeneous. The homogeneous degree decreases smoothly as the color difference increases. The relative region is believed to be heterogeneous when color difference exceeds certain range. Considering the concrete cases of various color distribution, we assign r as one fifth of the median value among all distinct neighborhood differences in a image and set $k = 5$.

Definition 5. Depending on the homogeneity function as a similarity measurement of neighborhood, under the scale t, the *upper approximation* of each color component can now be constructed as

$$\overline{H}^t_i(l) = \sum_{m=1}^{M}\sum_{n=1}^{N}(1 + s^t(m,n))\delta(F(m,n,i) - l), \quad 0 \leqslant l \leqslant L-1, \quad i \in \{R,G,B\} \tag{7}$$

where $F(m,n,i)$ is the pixel's grey level of color component i, $\delta(\cdot)$ is the impulse function and L is the intensity scale. $\overline{H}^t_i(l)$ is the approximate representation of pixel distribution on color plane at lth intensity with uncertainty. Obviously, $\overline{H}^t_i(l) \geqslant \underline{H}^t_i(l)$.

Fig. 4 shows the homogeneous regions of the image 'Butterfly' with different scales. For the purpose of illustration, the homogeneous degree is scaled up from interval [0,1] to [0,255] in order to better show the homogeneity on a grey image. The bright regions in the images represent the homogeneous regions (the more bright, the more homogeneous). In contrast, the dark regions represent the heterogeneous regions. From Fig. 4, we can find that the homogeneous region in the image gradually shrinks with the increasing scales. At the initial scale level, the homogeneity of most objects in image can be well embodied and the heterogeneous regions are regarded as the edges to segment the different homogeneous areas. Under the coarse scales, the homogeneity of some regions disappears and the heterogeneous regions successively expand to ruin the homogeneous areas. This phenomena occurs especially on the small homogeneous region of objects with textural features such as leaves, petals and blocks of wings.

3.3. Multiscale roughness of color distribution

Depending on the upper approximations under different scales, the multiscale roughness can be obtained to reflect the region homogeneity. Because of the quantified local homogeneity and multiple scales, this improved roughness can be considered as the quantitative homogeneity measurement at multiple granular levels.

Definition 6. Given an *RGB* image F and a scale t, the *roughness* of each color component under the scale t is defined as

$$r^t_i(l) = 2 \times (1 - |\underline{H}_i(l)|/|\overline{H}^t_i(l)|), \quad 0 \leqslant l \leqslant L-1, \quad i \in \{R,G,B\} \tag{8}$$

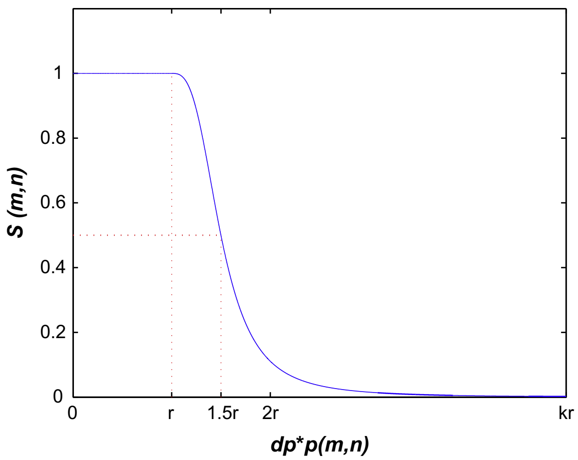

Fig. 3. Homogeneity function.

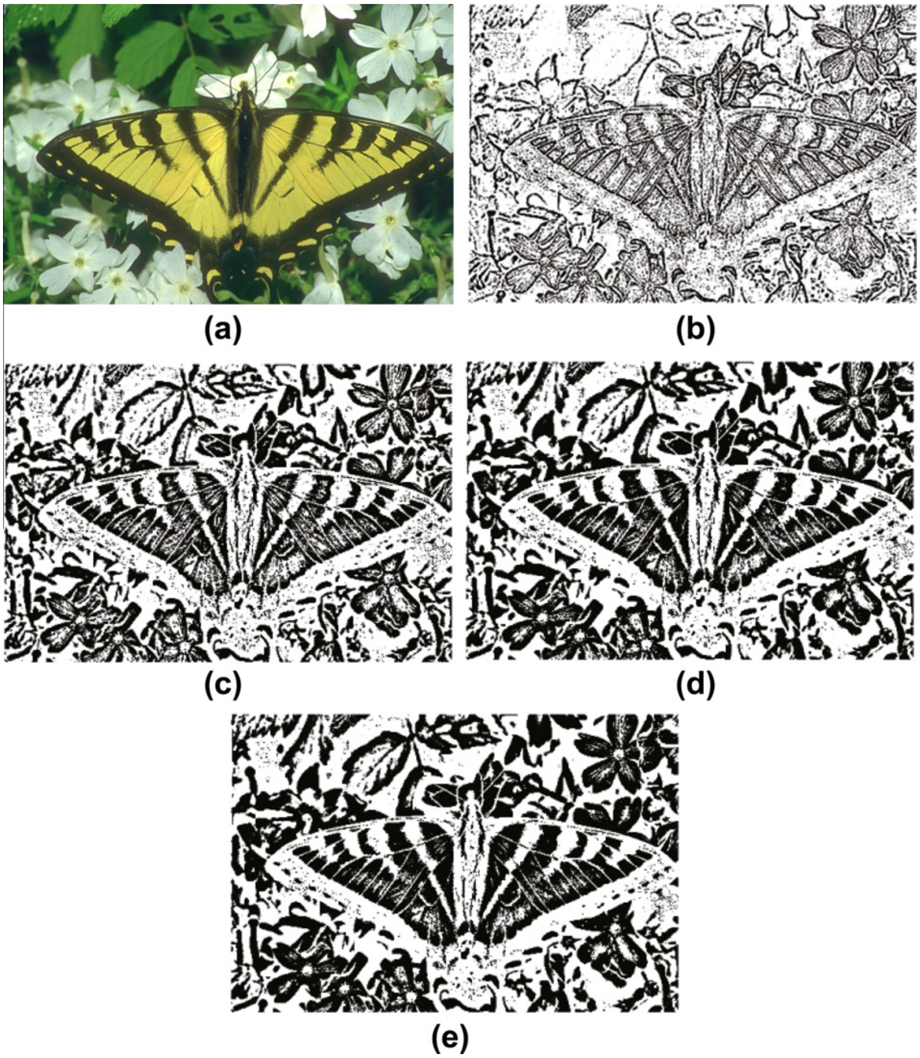

Fig. 4. Homogeneity distributions of image 'Butterfly' (a) original 'Butterfly' image, (b–e) homogeneous regions under different scales, (b) homogeneity under $t = 1$, (c) homogeneity under $t = 10$, (d) homogeneity under $t = 20$, (e) homogeneity under $t = 30$.

where L is the intensity scale, $\underline{H}_i(l)$ is the lower approximation and $\overline{H}_i^t(l)$ is the upper approximation at intensity l under the scale t. The constant '2' is used to map the roughness value into interval $[0,1]$ which will be consistent with the information measurement in next section.

Figs. 5 and 6 illustrate the upper approximation and roughness on Red color component of image 'Butterfly' under multiple scales. It is obvious that the local homogeneity and roughness at most intensities will be generally enhanced as the scale decreasing. Under the large scales, almost all surrounding pixels in the neighborhood will be considered for measuring the color difference. Even the pixels far from the central position still play an important role in computing the local homogeneity, which may lead to the improper high color difference on small homogenous regions. Therefore the roughness measure with large scales tends to exhibit the homogeneity of large areas in color image, and the homogeneity of small regions will be neglected. On the other hand, when we construct the region roughness by small scales, only the pixels near the central element can cause influence to homogeneity measuring. Thus the roughness under small scales can reflect the homogeneity of small regions effectively. However, too small scales can make almost all image regions having the property of roughness. In that case, the roughness measurement cannot give the precise representation of homogeneity. Thus it should be known that seeking an optimal scale is the key to measure the roughness of color distribution. The scale selection strategy will be further introduced in the following section.

As mentioned above, given a proper scale t, the multiscale roughness can represent the color distribution more precisely and intuitively. First, because the homogeneity is computed from the surrounding elements in neighborhood and the influences of surrounding pixels are weighted based on the distance to the central pixel (i.e. reference point), the approximation

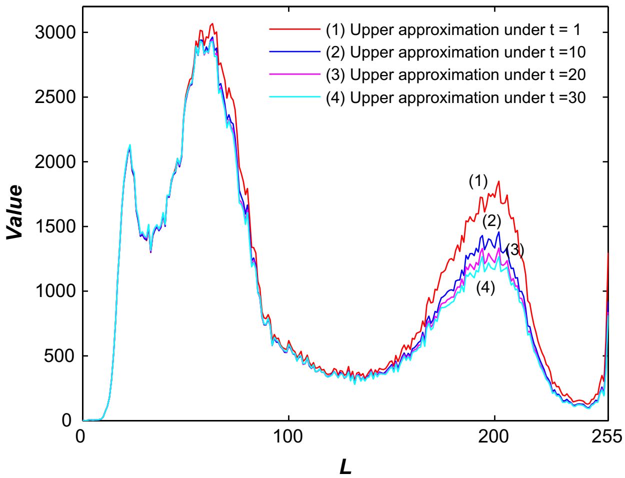

Fig. 5. Upper approximations.

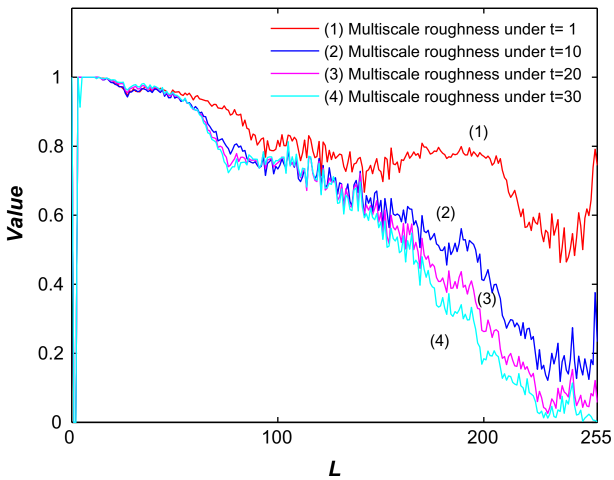

Fig. 6. Multiscale roughness.

induced from scale-space is more effective to represent the homogeneous regions and weaken the impact of noisy points. Secondly, besides the linear scale-space, the homogeneity function maps the local color difference into homogeneous degree, which can further quantify the roughness index. Finally, linear scale-space filtering can provide us an intuitive understanding on the roughness of color image. Like the human vision, multiscale roughness expresses the homogeneous regions from hierarchical views at different granular levels.

4. Scale selection

Choosing a proper scale is very important to construct the multiscale roughness for image segmentation. Different scales will determine how much detail of information will be acquired. In general, when the scale is too fine, too much redundant information will be shown. In contrast, when the scale is too rough, some important information may be lost.

4.1. Information measurement on multiscale roughness

Previous work usually investigated the information properties of scale-space in the form of entropies [27,50,51,55]. There are several kinds of entropies proposed based on statistical measurement and appearance features of multiscale images. Using histogram, Sporring applied the Shannon entropies in linear scale-space to perform scale selection in texture segmentation and showed the entropies' monotone behavior using thermodynamics concepts. Weickert proved the monotony of Shannon entropies in linear and non-linear diffusion scale-spaces. Besides studying the monotony and smoothness properties, Sporring and Weichert utilized the generalized entropy for global scale selection and size estimation [50,51]. Masaru proposed another information measurement based on Tsallis entropy, which is popular in physics. Moreover, relations between Renyi entropy and Tsallis entropy were elucidated to seek more natural information measurement in scale-spaces [27]. In addition to the entropies of statistical features, the entropies formed by visual traits was also designed. This kind of entropy uses the important structures embedded in multiscale images such as edges and vertexes to measure the information [55]. To sum up, the information measurement in scale-spaces should be chosen according to application requirements. Our aim is to find an effective tool for measuring the information represented by multiscale roughness.

Roughness, rough entropy, fuzziness and fuzzy entropy are major methods for measuring the uncertainty of data sets [14,16,18,19,28,39,43,44]. As per discussed in Section 3, each bin of roughness index represents the homogeneity degree at specific intensity. In another view, the roughness value also can be considered as the degree of an intensity on color component belonging to the homogeneity concept, like the membership in fuzzy sets. Thus we can measure the information contained in multiscale roughness in the form of classical fuzzy entropy.

Definition 7. Given an *RGB* image *F* and a scale *t*, the *roughness entropy* of *F* under the scale *t* is defined as the sum of roughness entropies of all color components.

$$H(F^t) = \sum_{i=R,G,B} H(F^t(i)),$$
$$H(F^t(i)) = \frac{-1}{Lln2}\sum_{l=1}^{L}[r_i^t(l)ln(r_i^t(l)) + (1-r_i^t(l))ln(1-r_i^t(l))] \tag{9}$$

in which $r_i^t(l)$ is the lth roughness index of color component i under scale t, L is the intensity scale.

The roughness entropy can effectively represent the distribution of homogeneity and heterogeneity in the view of information theory. With the different scales, the change of homogeneous regions will lead to the variance of roughness entropy. Therefore we can select the optimal scale for segmentation by investigating the roughness entropy variation.

4.2. Scale value estimation

Fig. 7 shows the change of roughness entropy, which is obtained based on all color images in the testing database. The changes of entropy can be approximately divided into two stages. In the first stage, the roughness entropy has a rapid growth from zero to the maximum. When the scale parameter is closed to zero, the scale is too small to make any color difference between the central pixel and the weighted average of neighborhood. This leads to a situation where almost all positions in image have the high degree of homogeneity. The corresponding roughness near the coordinate line of 1 represents little information of color distribution and zero entropy will be formed at the initial point. From the scale value of 0 to the scale value of 0.5, the entropy gradually increases and the region heterogeneity emerges. Because of the increase of heterogeneity, the redundant roughness will be removed, and the fluctuation of roughness index should become prominent. The distinct peaks and valleys of roughness index can further represent the homogeneous and heterogeneous regions and bring us more information for segmentation. In the second stage where the scale value is within the interval from 0.5 to the maximum, the roughness entropy experiences a smooth and slow variation. The excessively augmented scales may bring overmuch heterogeneity and reduce roughness index to zero, which result in the decay of roughness entropies. This stage indicates that

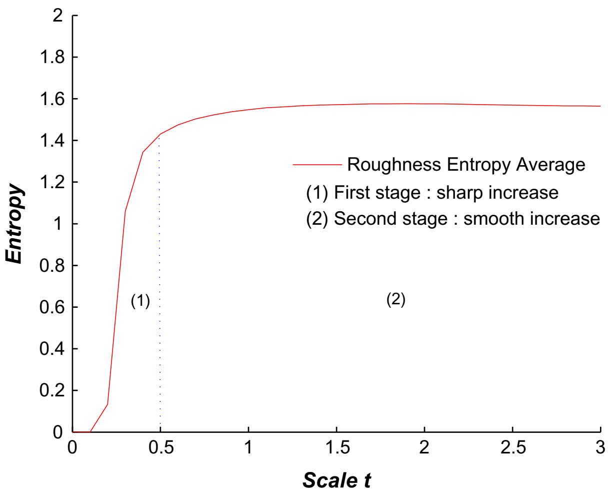

Fig. 7. Roughness entropy average.

the scales exceeding a specific rage cannot further improve the ability of roughness to represent the homogeneity distribution.

In this paper, we will find the optimal scale for segmentation in the interval where the roughness entropy has the rapid growth, because the roughness under these scales can offer us more information of homogeneity distribution. Fig. 8 shows the first derivative of Fig. 7. It is obvious that there is a sharp increase of entropy in the scale interval [0,0.5]. This indicates that a drastic variation of roughness entropy occurs around the scale 0.5. After the scale is larger than 0.5, the roughness entropy gradually transforms from rapid growth into smooth change. Therefore we set the optimal scale as 0.5 for segmentation. The experimental results in Section 6 will further confirm this strategy of scale selection.

5. Segmentation method

This paper proposes color (i.e. RGB) image segmentation based on multiscale roughness (*MSR* for short). The segmentation process is mainly divided into three stages. In the first stage, given a scale t, the approximations of each color component are computed, and then the roughness index under scale t is obtained using Eq. 8. For computing the multiscale roughness, we need to set two parameters. The first one is the size of the neighborhood, which is a window for scale-space filtering. A proper size is important to the quality of image segmentation. In this paper, $P = 20$ is set to construct the big enough template ($P \times P$) to detect the homogeneous regions. The second parameter is the adoptive scale. As introduced in Section 4, we suppose $t = 0.5$ for segmentation. In the second stage, significant peaks and valleys of roughness index are selected to determine the bands of each color component, and the initial image segmentation will be formed based on the determined color bands. The third stage involves color merging as the post processing. Because the bands obtained from the roughness peaks and valleys usually cause over-segmentation, the color region merging is necessary to reduce the redundant color, which will merge the similar small segments together.

5.1. Peak selection

Like the segmentation based on histogram, the significant peaks of roughness index always represent the color homogeneity at corresponding intensities. The correct peak selection is the key to achieve good segmentation results. The criterion used for selecting significant peaks is based on the peak height and the distance between adjacent peaks. Traditional methods usually set the fixed proportion of average index as the height threshold. However, because of the diversity of color distribution and especially the case caused by the fluctuated roughness, the fixed threshold is difficult to make accurate peak selection for different images. Too small threshold can cause many redundant bands on the color components, and over-large threshold may miss the important peaks for segmentation. Hence we design an algorithm using self-adaptive threshold to select the significant peaks to generate the color bands.

Algorithm 1. Peak selection using self-adaptive threshold

Input: Roughness index of a color component;
Output: Sequence of the selected significant peaks P;
Step 1. Produce all peaks of the roughness index, $P_k : P_{l_1}, P_{l_2}, \ldots, P_{l_k}$, in which l_i is the intensity level and $l_1 < l_2 \ldots < l_k$;
Step 2. Obtain the maximum and minimal peaks, $P_{max} = max\{P_{l_1}, P_{l_2}, \ldots, P_{l_k}\}, P_{min} = min\{P_{l_1}, P_{l_2}, \ldots, P_{l_k}\}$ and the mean value $\mu_m = (P_{max} + P_{min})/2$. Calculate the standard variance $\sigma_m = \sqrt{\sum_{i=1}^{k}(P_{l_i} - \mu_m)^2/k}$, set the peak height threshold $T_h = \mu_m - \sigma_m$;
Step 3. Select the significant peaks according to the height threshold T_h to form the peak sequence $P_h : P_{l_1}, P_{l_2}, \ldots, P_{l_k}$, set peak width threshold $T_w = 10$;
Step 4. Take turns to select adjacent peaks $P_{l_{h1}}$ and $P_{l_{h2}}$ in sequence P_h, suppose $l_{h1} < l_{h2}$, if $T_w > l_{h2} - l_{h1}$, choose the higher of the two peaks to insert into the peak sequence P;
Step 5. After filtering the peaks according to width threshold, return the peak sequence P.

After selecting the significant peaks, the valleys are obtained by finding the minimum values between every two adjacent peaks. According to the location of peaks and valleys, the bands of roughness on each color component are formed. The grey level of each band is set as the weighted average of all intensities within the band, and the weights are decided by the pixels in the relevant bands. Thus we can initially segment image according to the color bands.

5.2. Color region merging

Unlike the histogram based on pixel scales, roughness focuses on the region homogeneity, thus always generates more color bands than the traditional statistics. It is necessary to merge the region color in initially over segmented image. The merging process focuses on the colors of small regions and similar regions. When the pixel number of a color is less than

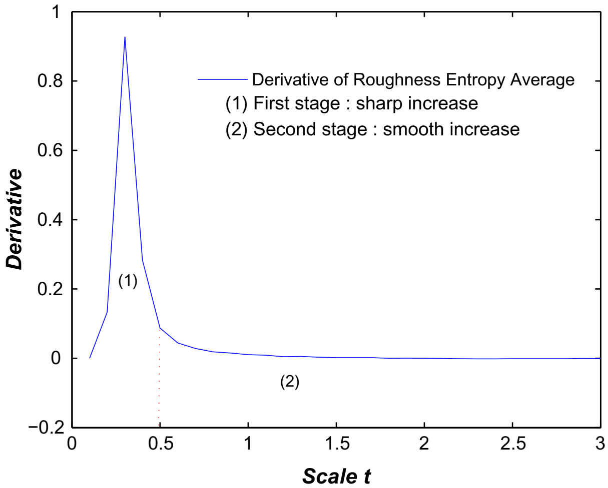

Fig. 8. Derivative of average entropy.

a predefined threshold (T_n can be set as 0.1 percent of the total number of pixels), the region of this color should be merged with the bigger region of the nearest color. Moreover, the regions that are very close in color space also should be merged into the same color cluster.

Given two regions $R_1,\ R_2$ in the initially segmented image, because the pixels in the same region will have the same color, we can define the distance between two regions in *RGB* space by predefined Eq. 4, and measure the region similarity according to the distance. Like the peak selection strategy, existing methods usually adopt fixed threshold to merge color region and neglect the diversity of color distribution. When image has the content of weak contrast, the small threshold can achieve good performance. However, in the case of strong contrast, the relatively big threshold may be more reasonable for merging color. Hence the judgment of region similarity should synthesize two factors, visual discernibility of color difference and characteristics of color distribution.

Suppose the image color is divided into M regions, the number of pairwise region differences is $N = C_M^2 = M(M-1)/2$, let n_i be the total number of pixels belonging to the ith color region after initial segmentation, the weighted average and variance of region differences are obtained by the equation.

$$d_\mu = \frac{\sum_{i=1}^{N} d_i * n_i}{\sum_{i=1}^{N} n_i}, \quad d_\sigma = \sqrt{\frac{\sum_{i=1}^{N}((d_i - d_\mu)^2 * n_i)}{\sum_{i=1}^{N} n_i}} \tag{10}$$

thus we can use d_μ and d_σ as the distribution characteristics to define the threshold for judging region similarity.

$$T_c = \begin{cases} d_\mu - d_\sigma & d_\mu \leqslant 50 \\ 50 * (1 - d_\sigma/d_\mu) & d_\mu > 50 \end{cases} \tag{11}$$

The piecewise function can avoid the improper threshold when d_μ exceeds a specific range. Considering the visual discernibility of color difference, set $T_v = 20$, we can obtain the final threshold of region similarity $T_s = max\{T_c, T_v\}$. The proposed algorithm merges the small and similar color regions successively.

Algorithm 2. Color region merging using self-adaptive threshold

Input: Sequence of color regions after initial segmentation $R_k : R_1, \ldots, R_k$;
Output: Sequence of color regions after region merging $R_m : R_1, \ldots, R_m$;
Step 1. Sort the sequence R_k by the region size (pixel number) ascendingly;
Step 2. Take every region R_i from the sequence R_k successively, if the scale of R_i is less than T_n, search the most similar region R_j of R_i from R_k. For R_i and R_j, merge the smaller one into the relatively bigger region, and then delete the small region from R_k;
Step 3. Check sequence R_k, if exists the region which scale is less than T_n, go to step 2;
Step 4. Obtain the region sequence R_s after merging the small regions, sort R_s ascendingly by region size;
Step 5. Take every region R_i from the sequence R_s successively, find the region R_j in sequence so that the color difference between R_i and R_j is less than T_s. For R_i and R_j, merge the smaller one into the other, and delete the smaller region from R_s;
Step 6. Check sequence R_s, if exists the region pair which color difference is less than T_s, go to Step5;
Step 7. Output the region sequence R_m after merging the similar regions.

Table 1
Information of illustrated color images.

Image name	Size	Component intensity			Color number
		Blue	Green	Red	
Bridge	481*321	256	255	256	761
Woman	481*321	234	236	237	701
Fruit	481*321	256	256	256	763
Old man	321*481	256	255	254	762

5.3. Complexity analysis

The efficiency of *MSR* segmentation mainly relies on the size of image. Given an RGB image F of pixel number n and intensity scale on each color component as L, the computational complexity is briefed as followings. At the first stage of computing the roughness, the computation on neighborhood difference under a given scale requires filtering the image on each color component, i.e. the calculation of $P \times P$ pixels in every neighborhood convolving with the Gaussian kernel, $O(3P^2n)$. Assuming the distance and homogeneity function as atomic operation, the computation of approximations has the complexity of $O(2n)$. Depending on two approximations, producing the roughness index on all color components needs $O(3L)$ operations.

At the stage of peak selection, given the number of initial peaks on every color component as k, the complexity of computing self adaptive threshold and selecting the significant peaks is $O(L + 4k)$. In the initial segmentation, every pixel is distributed into the corresponding color band and assigned the new value. This process needs about $O(3kn)$ operations. Because k is always far less than L, the complexity of initial segmentation can be considered as $O(3(L + kn))$.

In the post processing stage, supposing r_k and r_m are the color number after initial segmentation and after region merging ($r_k \geqslant r_m$) respectively, the complexity of computing the threshold for measuring region similarity and merging color is about $O(3r_k^2)$. Furthermore, the operation of readjusting color after merging has the complexity $O(3n(r_k - r_m))$. Summing up the operations in the three steps of *MSR*, the computational complexity of the whole segmentation process can be obtained by $O(3P^2n + 6L + 3(kn + r_k^2 + n(r_k - r_m)))$. Because the parameter of filtering window P is usually a relatively small integer, the method complexity is linearly dependent on the image size. Compared to the traditional roughness segmentation, the complexity of proposed method just increases by multiples of n calculations.

6. Experimental results and discussion

In our experiments, all testing images are collected from Berkeley segmentation database,[1] the illustrations exhibited in the following paragraphs are also chosen from these images. Table 1 shows the basic information of these illustrated color images. We expect to present the validity of proposed multiscale roughness measure and thresholding strategies, in order to validate the efficiency of *MSR* for segmentation.

6.1. Evaluation on peak selection strategy

The first work is to validate the efficiency of self-adaptive strategy for peak selection. In this experiment, we respectively adopt different fixed thresholds and self-adaptive threshold T_h as the peak height criteria. For the segmentation based on two kinds of roughness, Fig. 9 shows the influence of height thresholds to the segmented results. When the fixed threshold of the ratio of average roughness is set small, most peaks are selected to represent homogeneity and generate the exquisite segmentation. Although the small threshold can make the segmented result more close to the original image, too many feature bands will lead to much redundant color. As the height threshold increases, the band number and color scale in segmented image are gradually reduced. However, the improper large threshold may miss important peaks and cause the over-rough segmentation with the poor display quality. As indicated in Fig. 9 and Table 2, for both kinds of roughness, the segmentation based on self-adaptive peak selection can achieve precise result which is similar to the one when the fixed threshold is set small. In the meantime, the segmented color number is generally far less than that of the exquisitely segmented result. Considering the diversity of color distribution, the self-adaptive strategy can effectively improve the initial segmentation precision for most testing images (see Fig. 10).

From the segmentation based on two kinds of roughness, with different thresholds, we find the traditional roughness intends to make the segmented images over green, which results from the imprecise approximation of corresponding color component. Because scale-space filtering forms quantitative roughness to represent the region homogeneity, given a proper scale, the segmentation based on multiscale roughness achieves better results. Furthermore, we can also find the

[1] (http://www.eecs.berkeley.edu/Research/Projects/CS/vision/bsds).

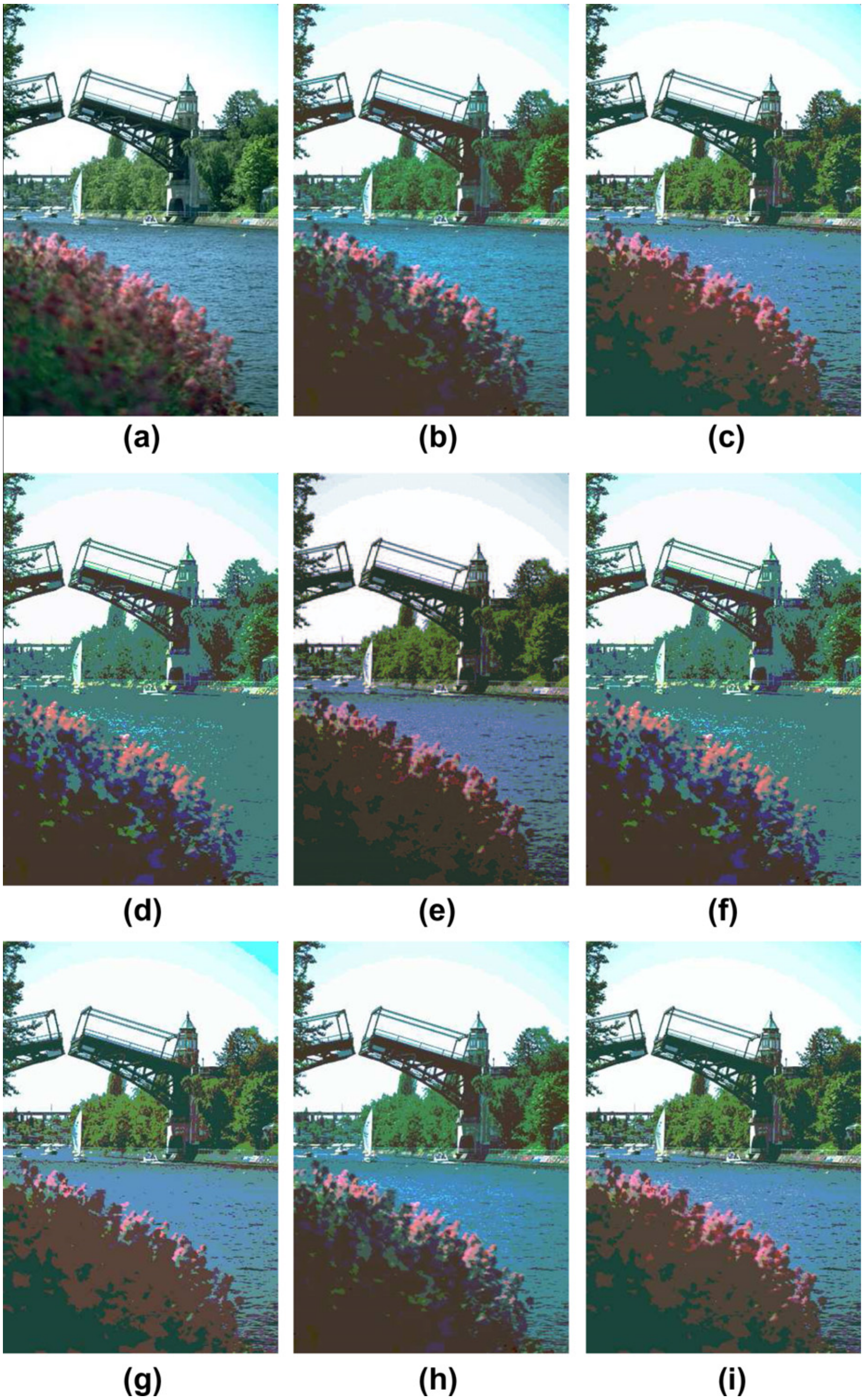

Fig. 9. (a) Original 'Bridge' image, (b, c) set $T_h = 0.2$ average roughness, segmented results from traditional roughness and multiscale roughness (t = 0.5), (d, e) $T_h = 0.8$ average roughness, segmented results from two kinds of roughness, (f, g) segmented results when T_h = average roughness, (h, i) segmented results when T_h = self-adaptive threshold.

segmentation based on multiscale roughness is more robust to the change of threshold than the traditional roughness. This indicates that the multiscale roughness can further focus on the distinct homogeneous regions and avoid the trivial noisy points' disturbing.

Table 2
Peak selection of image 'Bridge'.

Segmentation	Peak height	Blue band	Green band	Red band	Color number
Traditional roughness	0.2Average roughness	12	9	9	302
	0.8Average roughness	4	4	7	36
	Average roughness	4	4	7	36
	Self-adaptive threshold	6	6	8	94
Multiscale roughness	0.2Average roughness	6	7	10	163
	0.8Average roughness	5	4	9	74
	Average roughness	5	4	6	47
	Self-adaptive threshold	5	7	9	117

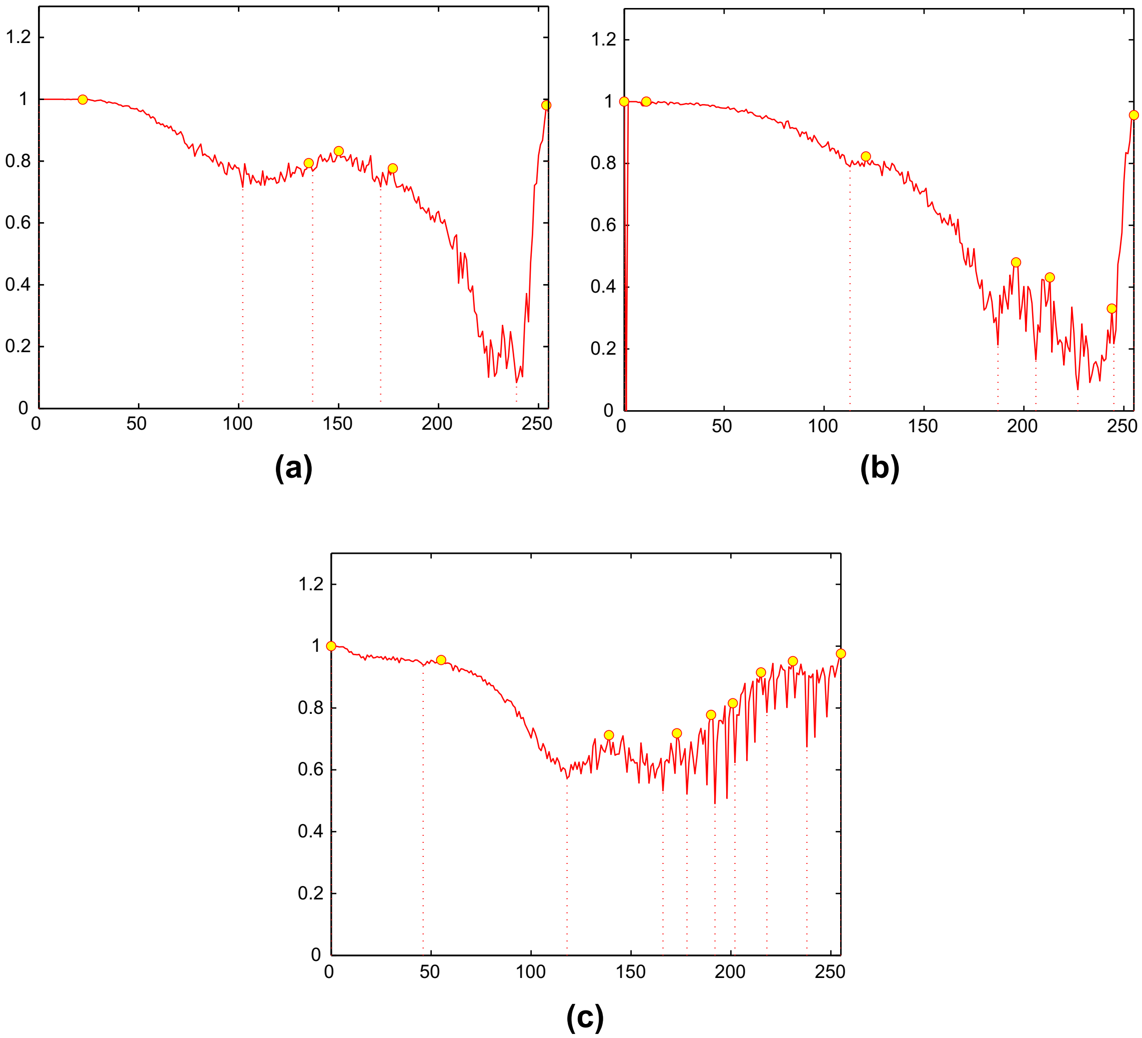

Fig. 10. (a) Bands and selected peaks of multiscale roughness on Blue component of image 'Bridge', (b) bands and selected peaks on Green component, (c) bands and selected peaks on Red component. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

6.2. Evaluation on roughness representation

This experiment tests the abilities of various statistics to represent the color homogeneity in image. Using the same thresholding strategy (self-adaptive threshold), Fig. 11 presents the segmentation results respectively induced from histogram, histon, traditional roughness and multiscale roughness. As introduced above, histogram is constructed only based on pixel

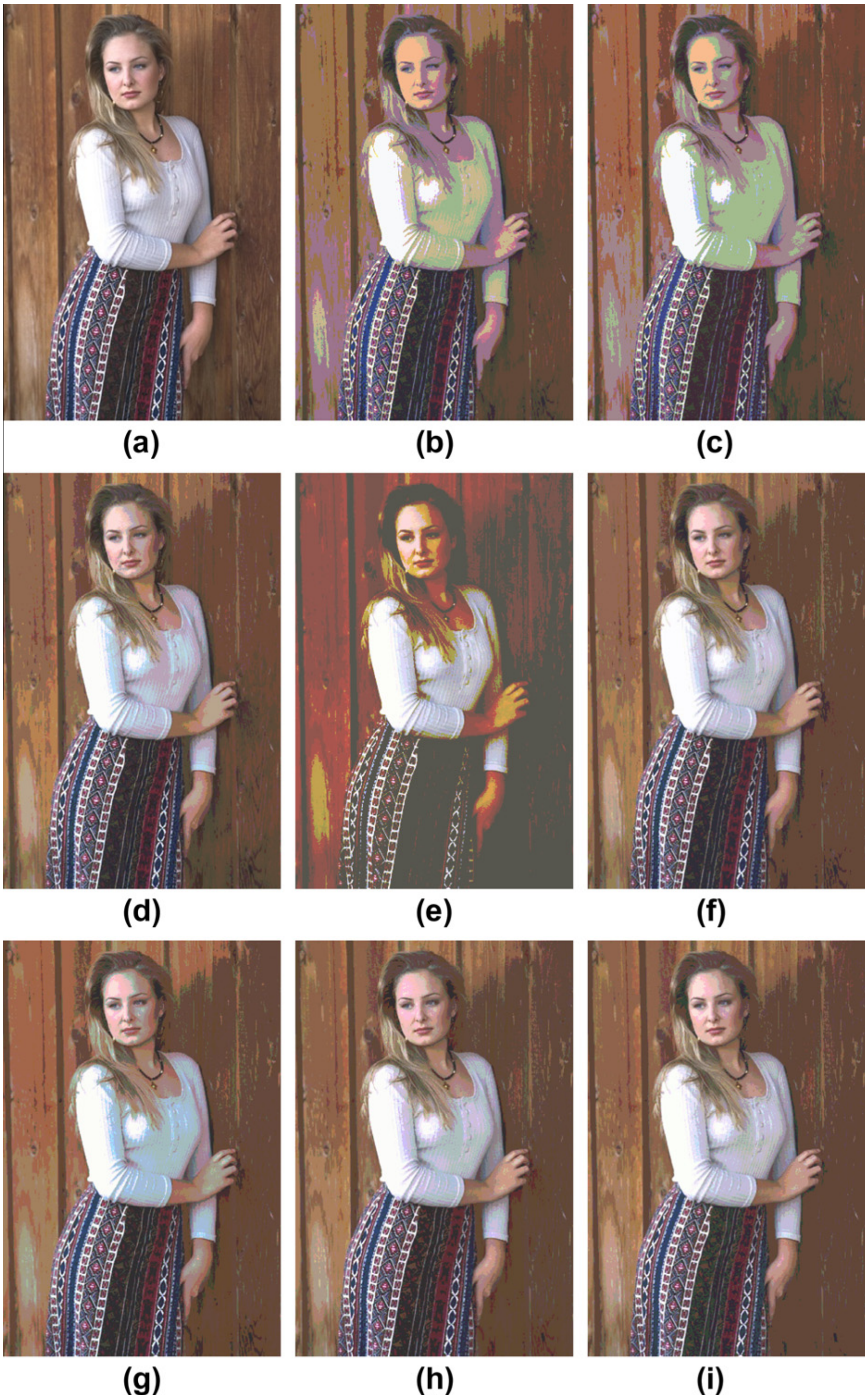

Fig. 11. (a) Original 'Woman' image, (b–i) adopting self-adaptive peak selection strategy, segmented results from various statistics, (b) segmented result from histogram, (c) segmented result from histon, (d) segmented result from traditional roughness, (e) segmented result from multiscale roughness when $t = 0.2$, (f) $t = 0.5$, (g) $t = 1$, (h) $t = 2$, (i) segmented result when $t = 5$.

counting, histon as an approximate representation of color distribution utilizes the spacial correlation but attaches overmuch importance to the homogeneity of large scale regions. Therefore, although the segmentations based on histogram and histon always produce less segmented bands and color number, they will lose many details of color homogeneity, especially for the small distinct regions, and generally lead to over rough segmented results, see Fig. 11b and c. Obviously, the

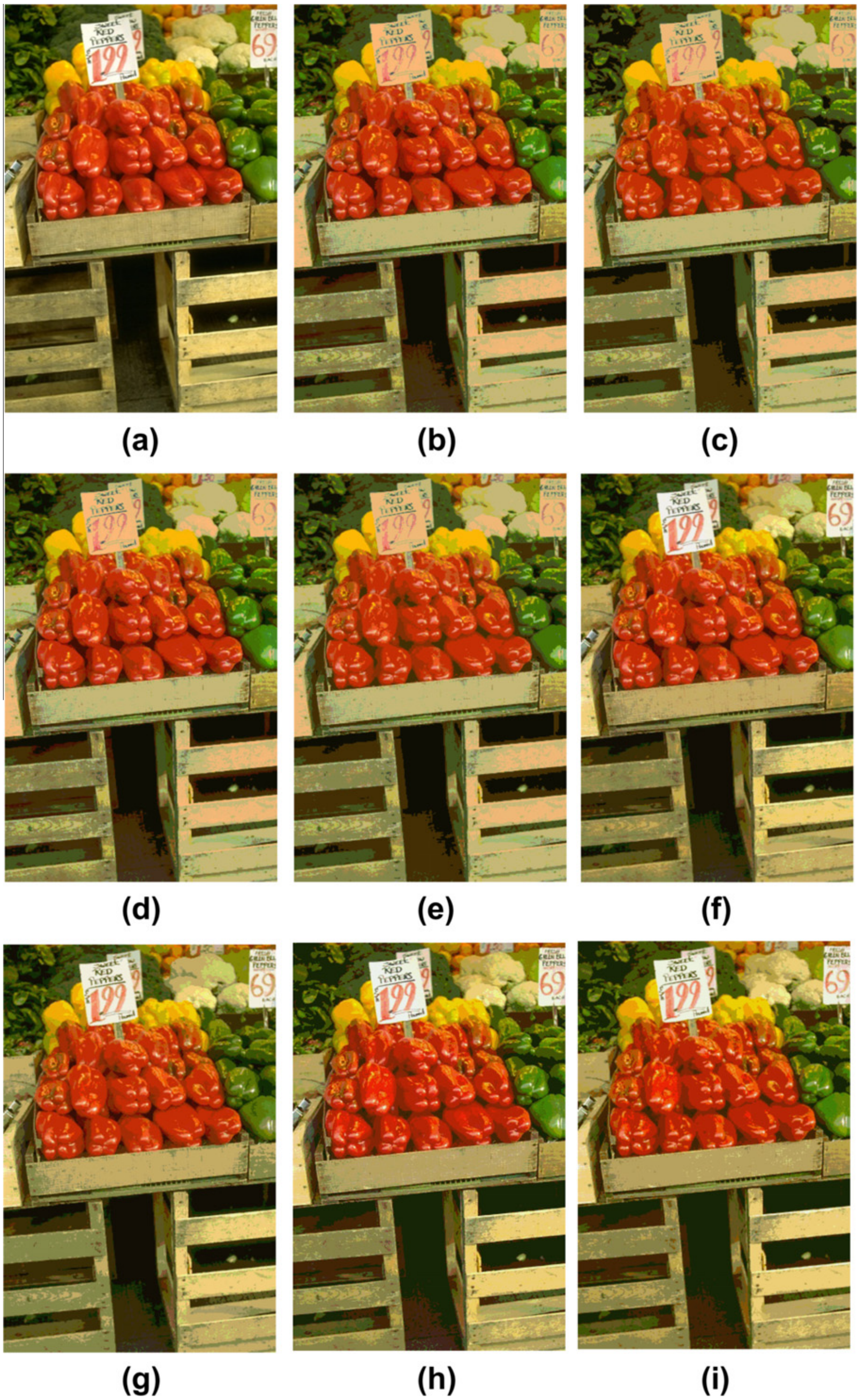

Fig. 12. (a) Original ‘Fruit’ image, (b, c) initially segmented result and the result after adaptive region merging based on histogram, (d, e) results of initial segmentation and after region merging based on histon, (f, g) results based on traditional roughness, (h, i) results based on multiscale roughness ($t = 0.5$).

segmentations based on roughness perform better than histogram and histon, which is because of taking the approximation boundary into account. Related works have also validated the superiority of roughness to the traditional statistics [32]. The segmentation based on roughness can effectively extract the homogeneous regions and avoid the influence of pixel scale.

However, due to the fixed neighborhood template and inaccurate approximation, the traditional roughness is still not precise and flexible enough to measure homogeneity inherent in color image. As illustrated in Fig. 11d, some areas of

Table 3
Segmented results of 'Woman' from various statistics.

Statistics	Blue band	Green band	Red band	Color number
Histogram	4	5	8	52
Histon	4	6	5	43
Traditional roughness	10	11	10	171
Multiscale roughness $t = 0.2$	4	8	9	93
Multiscale roughness $t = 0.5$	9	10	11	169
Multiscale roughness $t = 1$	11	10	9	144
Multiscale roughness $t = 2$	11	10	9	168
Multiscale roughness $t = 5$	9	10	9	154

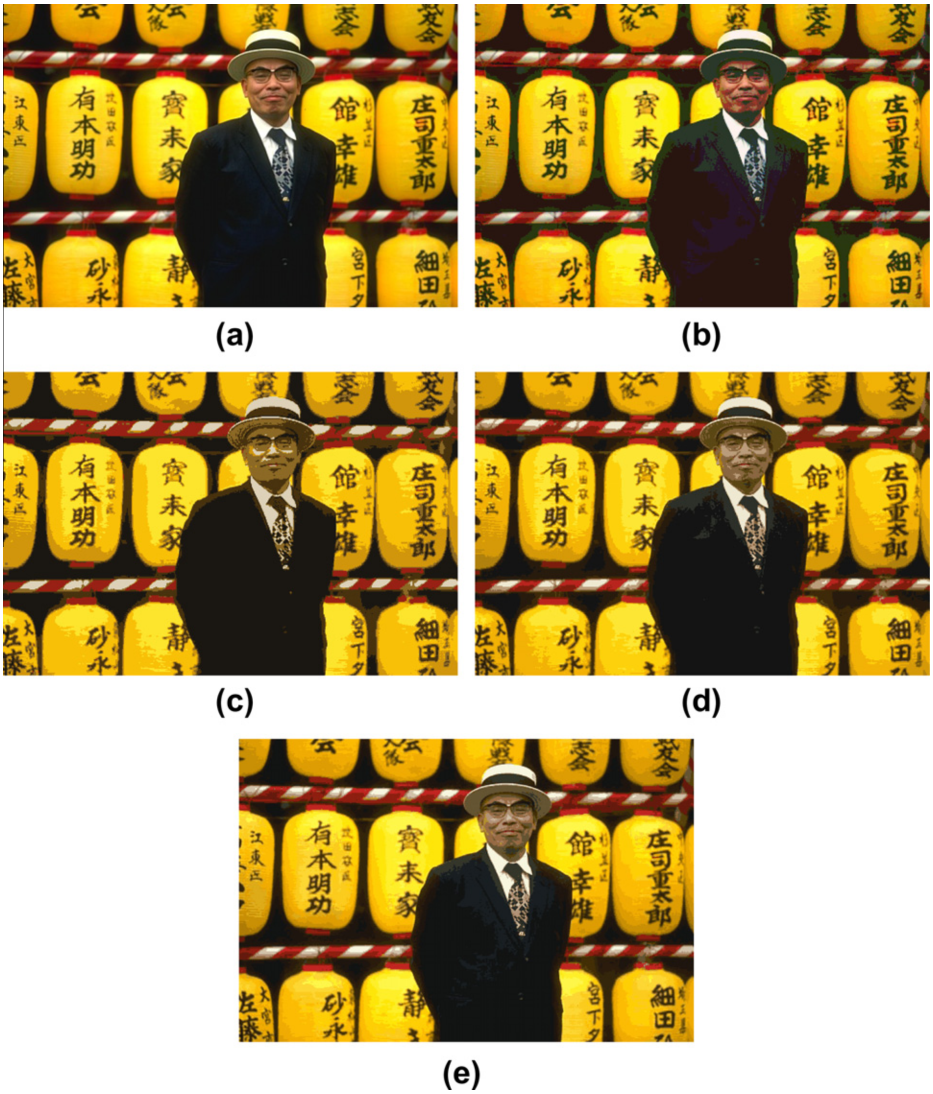

Fig. 13. (a) Original 'Old Man' image, (b) segmented image based on multiscale roughness ($t = 0.5$), (c-e) segmented images based on rough clustering with different K, (c) $K = 8$, (d) $K = 16$, (e) $K = 32$.

woman's face and clothes are segmented into the wrong colors. Fig. 11 presents the segmented images induced from multiscale roughness. Under too small scales, the multiscale roughness contains little information of homogeneity distribution and leads to poor segmentation. When the scale increases to 0.5, the information contained in roughness is greatly enriched

Table 4
Segmented results of ‘Fruit’ after region merging.

Statistics	Initial color number	Region similarity	Merged color number
Histogram	198	$T_s = 20$	53
		$T_s =$ adaptive threshold	39
Histon	163	$T_s = 20$	52
		$T_s =$ adaptive threshold	41
Traditional roughness	274	$T_s = 20$	62
		$T_s =$ adaptive threshold	55
Multiscale roughness	256	$T_s = 20$	80
		$T_s =$ adaptive threshold	42

because of the emergence of heterogeneity. Therefore the multiscale roughness can express more details about homogeneous regions and result in the precise segmented results. As the scale exceeds the specific extent, the ability of roughness to represent homogeneity is not enhanced. Thus the corresponding segmentations cannot be further improved. As shown in Fig. 11g–i, the gradually increasing scales do not improve the performance too much. Some regions of face and clothes are segmented more roughly than the scale of 0.5. This confirms our strategy to decide the optimal scale for segmentation (see Table 3).

6.3. Evaluation on region merging

Over segmentation based on roughness always produces redundant color, thus the post processing is necessary to merge the segmented color. In this experiment, we respectively adopt the self-adaptive threshold obtained from Algorithm 2 and the fixed threshold proposed in [32] to decide the region similarity and merge color region. Fig. 12 presents the segmentation results with/without the post-processing. Table 4 shows the number of color on the segmented images before and after merging.

As shown in Fig. 12 and Table 4, through merging process, the number of colors on the initially segmented images using various methods are greatly compressed while the display qualities are guaranteed. Furthermore, we find the self-adaptive similarity threshold can further reduce the color number in segmented results than fixed thresholds. Especially for the images with high color contrast, the self-adaptive strategy for region merging always has outstanding performances on various kinds of segmentations.

6.4. Comparison with rough clustering based segmentation

In [45], rough K-means clustering algorithm is used for segmenting color images. Segmentation process is viewed as a clustering problem where the task is to identify those clusters which may best represent the condensed colors in image. Rough K-means clustering algorithm utilizes two sets for each cluster, a lower and an upper approximation [23,40]. Through iterative adjustment of the cluster centers, the algorithm is expected to converge towards a good color palette. In this experiment, we compare the segmentation based on rough clustering with the one based on multiscale roughness measure. Fig. 13 shows the results obtained by both methods. It is seen that the quality of segmented image resulting from the roughness under the scale of 0.5, which has only 32 colors after region merging, is better than that of rough clustering with the various cluster numbers, i.e. $K = 8, 16, 32$. Comparing the roughness strategy, the following problems of rough K-means segmentation are revealed.

First, the quality of segmented image relies much on the clustering initialization. Rough K-means based segmentation needs an initialized parameter K as the number of condensed color in segmented image. Although K can be predefined as the size of fixed palette, the cluster number K will significantly influence the segmented results. See Fig. 13c–e, obviously the segmentation is too coarse with the small K and becomes fine with the large K. Thus it should be better to determine the optimal number of condensed color based on the specific color distribution of image. Moreover, for rough K-means, the clustering seeds are randomly selected from pixels, which may lead to the unstable segmented results. Second, for image segmentation, the pixels in the boundary of rough clusters have to be redistributed into a certain class. Therefore, the proper strategies for dealing with the uncertain pixels belonging to more than one color are necessary to improve the segmentation precision. Finally, the computational complexity of rough K-means algorithm is $O(iter \times K \times n)$ [24], in which n is the number of objects, K is the number of clusters and $iter$ is the number of iterations required to obtain stable centroid values. In practice, when the cluster number, i.e. expected condensed color number, is increased to guarantee the quality of segmented image, more iterations are generally required to achieve the clustering convergence due to the complex cluster boundaries. Therefore, unlike the roughness-based segmentation, the computational burden of segmentation based on rough clustering will clearly rise with K increasing.

Through testing and analyzing the segmented results of most color images in database, we demonstrate the multiscale roughness is precise and flexible to depict the color homogeneity. The self-adaptive strategies of selecting peaks and merging color can further improve the roughness-based segmentation precision. Furthermore, because the computational complexity of proposed method is linearly dependent on image size, the segmentation efficiency of *MSR* is generally acceptable.

7. Conclusion

In this paper, a multiscale roughness measure has been proposed for color image segmentation. Aiming at the problems of existing histogram-based methods, we apply the linear scale-space theory into the traditional roughness measure to construct the multilevel representation of color homogeneity. Given an appropriate scale, the multiscale roughness can tolerate the disturbance of trivial structures and form the precise segmentation. For scale selection, we propose the roughness entropy to measure the information contained in roughness, and then decide the optimal scale for segmentation according to the entropy variation. Furthermore, considering the diversity of color distribution, we design the self-adaptive strategies for thresholding bands and merging color. Experimental results have shown that the segmentation based on multiscale roughness performs well on the natural images in the testing database.

We also found several interesting issues remained in this exploratory work. The first one is about the scale-space representation of color image. Although the linear scale-space filtering can bring us the intuitive impression of color distribution on multiple visual levels, the increasing scales rarely cause color variation at the areas of small intensities, which will lead to the unbalanced changes of roughness at different grey levels as shown in Fig. 6. This means that the roughness with big scales tends to over focus on the homogeneity of dark areas. That is why the segmentation using relatively small scales can achieve better performance. The second issue is the scale selection. The proposed roughness entropy is an information measurement of roughness index from statistical view. The changing entropy reflects the homogeneity variation with varying scales. To the natural images with complex contents, this strategy is workable to depict the region homogeneity, whereas to other kinds of images, different strategies for deciding the optimal scale, such as visual feature detection or object size estimation, may be the better choice.

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