Region-Based Colour Image Segmentation: Control Parameters and Evaluation Functions

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Abstract

In this paper an original region-based segmentation technique for colour images is presented. This technique is based on the concepts of region growing without seeds and, in postprocessing process, on a small regions removal by region merging. Experimental results of proposed segmentation technique are reported. Selected heuristic functions for quantitative evaluation of segmentation results are reviewed. Problems with using evaluation functions for the choice of values of two control parameters are described.

1. Introduction

Colour image segmentation plays an important role in many applications. In the last decade first reviews of colour image segmentation techniques were published.[1,2,3] These techniques can be most often classified into following classes: pixel-based techniques, region-based techniques, edge-based techniques and physics-based techniques. Sometimes fuzzy techniques and neural networks techniques belong to separate classes. Additionally exist hybrid techniques that integrate elements of techniques from different classes.

Majority of colour segmentation techniques uses several control parameters, e.g. a number of clusters in clustering techniques or some values of thresholds in region-based segmentation. These parameters should be adjusted to obtain optimal image segmentation. The choice of values of parameters is non-trivial task. If quantitative evaluation function of segmentation results is applied then a choice of values of parameters is simpler.

This paper is organised as follows. Section 2 briefly describes a proposed segmentation technique. Section 3 reviews heuristic measures for quantitative evaluation of segmentation results. Section 4 shows some results of using evaluation functions for the choice of control parameters in the case of proposed segmentation technique. The conclusions are formulated in Section 5.

2. Segmentation Technique

Presented image segmentation technique works without defining the regions or pixels (seeds) needed to start the segmentation process. At the beginning each pixel has its own label i.e. the image consists of one-pixel regions. In the construction of the algorithm, the 4-neighbourhood system was used to increase the computational efficiency of the method. For the region growing process, the centroid linkage strategy is used. This strategy adds a pixel to a region if it is 4-connected to this region and has colour or gray scale value lying in a specified range around the mean value of an already constructed region. After the inclusion of a new pixel, the region's mean color value is being updated. For this updating, recurrent scheme can be applied.

In a first stage of the technique, a simple raster scan of the image pixels is employed: from left to right and from top to bottom. Next pass, in this two-stage technique, starts from the right bottom corner of the image. This pass permits additional merging of adjacent regions, which after the first pass possess features satisfying a predefined homogeneity criterion. Effective implementation of this segmentation technique requires the storing for each segmentation region the values of the mean region color, region size and the list of region pixels.

The segmentation results are strongly determined by a control parameter: threshold ***d***, which limits the value of homogeneity criterion e.g. in the case of RGB colour space:

$$\sqrt{(R-\overline{R})^2+(G-\overline{G})^2+(B-\overline{B})^2} \leq d \qquad (1)$$

or in the case of HSI colour space :

$$\sqrt{(I-\overline{I})^2+S^2+\overline{S}^2-2S\overline{S}\cos(H-\overline{H})} \leq d \qquad (2)$$

where current values relate to the tested pixel and mean values relate to a region. This technique, originally developed for color images works in different color spaces (RGB, HSI, CIELab etc.) and can be also applied for the segmentation of gray level images.

The segmented image can be further postprocessed by removing small regions that are usually not significant in further stages of image processing.[4] Small regions very often appear near object edges. Their colors are different from the color of the object and its background. Therefore these regions do not belong to object and background regions. Postprocessing needs additional third pass from the top left corner to the bottom right corner, whose aim is to remove the regions, which consist of a number of pixels smaller than a certain threshold. During this merging process each region with a number of pixels below a specified threshold ***A*** is merged into a region with a larger area if the homogeneity criterion is fulfilled. After the merging, a new mean color of region is calculated and the labels of pixels belonging to a region are modified. The use of flexible data structures known as linked lists[5] is very helpful in the merging process. The pre-selected size of removed regions ***A*** plays a role of second control parameter.

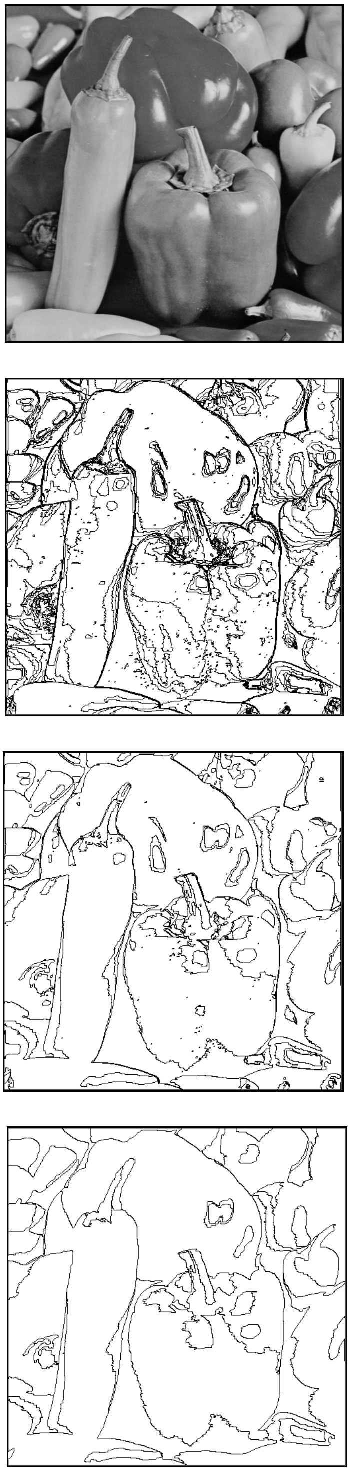

Figure 1. *Example of segmentation results in RGB colour space for image Peppers: (a) original image, (b) parameter value:* ***d****=30, (c) parameter value:* ***d****=60, (d) parameter values:* ***d****=60,* ***A****=500.*

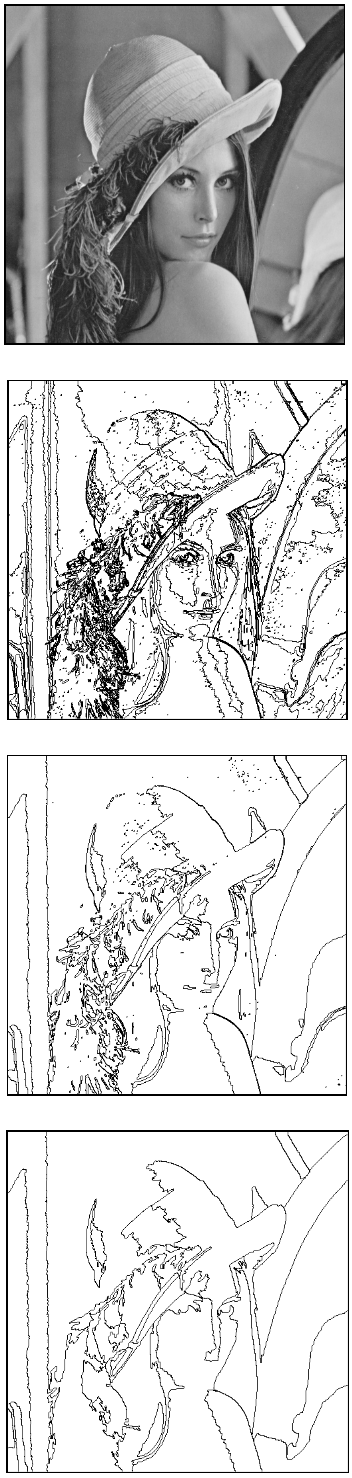

Figure 2. *Example of segmentation results in RGB colour space for image Lena: (a) original image, (b) parameter value:* ***d****=30, (c) parameter value:* ***d****=60, (d) parameter values:* ***d****=60,* ***A****=500.*

In the case of noisy images different filters can be applied as pre-processing tool for image segmentation. In Ref. 6 the performance of a new class of color image filters was visually evaluated and the number of regions served as a criterion of image segmentation quality.

Figures 1 and 2, show the segmentation results for popular test images. Fig.1b, 1c, 2b and 2c present results of two-pass segmentation without process of small regions removal. If a value of **d** is small then a number of regions is big (Fig.1b - 5177 regions, Fig.2b - 6956 regions, Fig.1c - 886 regions, Fig.2c - 1031 regions). This high numbers of regions can be decreased through additional removal regions smaller than ***A***. For **d**=60 and ***A***=500 pixels the segmented images have 48 regions (Peppers) and 31 regions (Lena) only (Fig.1d, 2d).

3. Evaluation Functions

In literature exist a few methods of quantitative evaluation of image segmentation results, which for lack of general image segmentation theory are necessary to practical applications. For example Liu and Yang[7] empirically defined following evaluation function:

$$F(I) = \frac{1}{1000(N \cdot M)} \sqrt{R} \sum_{i=1}^{R} \frac{e_i^2}{\sqrt{A_i}} \tag{3}$$

where: I is the segmented image, $N{\cdot}M$, size of the image, R, the number of regions in the segmented image, A_i, the area of pixels of the ith region, and e_i the colour error of region i. The colour error in RGB space is calculated as the sum of the Euclidean distances between colour components of pixels of region and components of average colour, which is an attribute of this region in the segmented image. The colour errors in different color space are not comparable and therefore are transformed back to the RGB space.

First term of equation (3) is a normalization factor, the second term penalizes results with too many regions (oversegmentation), the third term penalizes results with non-homogeneous regions. Last term is scaled by the area factor because the colour error is higher for large regions. The idea of using this kind of function can be formulate as: the lower the value of *F(I)*, the better is the segmentation result. More information about inspiration in building of this function is in Ref. 7. Evaluation function *F(I)* does not require any parameters or thresholds and conforms to the visual judgement.

Borsotti et al.8 have identified limitations of this evaluation function. In the case of many small regions in the segmented image (oversegmentation), the number of regions is large but the colour error of each region may be equal to zero and *F(I)* will be zero too, which means wrongly that segmentation results are very good. The best example of this situation is an image before segmentation: each pixel is one region. Therefore they modificated the function *F(I)*:

$$Q(I) = \frac{1}{1000\,(N \cdot M)} \sqrt{R} \sum_{i=1}^{R} \left[\frac{e_i^2}{1 + \log A_i} + \left(\frac{R(A_i)}{A_i} \right)^2 \right] \tag{4}$$

where: $R(A_i)$ is the number of regions having an area equal to A_i. Borsotti et al. used the function Q(I) for evaluation of segmentation results generated by clustering techniques. More detailed information about modificated function is presented in Ref. 8.

In the paper by Climent et al.[9] incorporated function *Q(I)* into their segmentation algorithm based on graph minimisation i.e. they used the evaluation function not for evaluating segmentation results, but for segmenting. Their algorithm, that does not require control parameters, find the segmented image adequate to minimal value of *Q*. Authors shown by using typical test images that this segmentation algorithm generates segmented images, which have a considerably lower value of function *Q* than other algorithms used in Ref. 8.

In some cases for controlling parameters of segmentation process the complex optimisation methods (e.g. evolutionary programming) were used.[10]

4. Choice of Values of Control Parameters

Experimental investigations of presented segmentation technique were performed using *Q* evaluation functions. The homogeneity criterion was established in RGB colour space. First tests proved that postprocessing stage is very effective. High value of *Q* function can be decreased through removal regions smaller than ***A***. In this case a colour error will increase, but the number of segmented regions will decrease more quickly.

Generally, we should minimise evaluation function *Q* for finding the values of control parameters ***d*** and ***A***. After testing over several colour images we could confirm that a global minimum of function of two variables ***d*** and **A** can be found nearly very low value of parameter ***d***. It means a low quality segmentation with minimal value of function Q or sometimes the oversegmentation. Why the minimum value of the function Q is situated in such point? Because the value of ***d*** is low, then the image is segmented into many small regions and its colour errors are low. During the postprocessing these small regions can be merged with few bigger regions and the number of regions in the image can dramatically decrease. The colour errors for new regions change insignificantly, because merged regions were small regions. Therefore the value of Q function can considerably decrease.

Good example are data obtained for image Peppers:

- without postprocessing: d = 0, A = 0, R = 250555, e_i = 0,00, Q = 2 702 218 442,5
- with postprocessing: d = 0, A = 10, R = 12704, e_i = 0,29, Q = 9,6.

In the case of presented segmentation technique the form of evaluation function Q, that is more complicated as in case of function F, do not protect us from disadvantages similar to drawbacks which have the function F (see Section 3). The solution of these troubles we can seek in limiting from below the value of parameter ***d*** during global minimum search. An other possiblity is to find a value of ***d*** that minimise the function Q in the case of segmenting without process of small regions removal and next to find a value of ***A***, that minimise the function Q in case of the whole segmentation process. This is a kind of sequential optimisation. In this way we can find "reasonably low" values of evaluation function Q and simultaneously a good quality segmentation.

Table 1. Control Parameters for Test Images

Name	Size	R	Q	**d**	**A**
Airplane	512×512	48	1166	35	600
Baboon	471×471	26	3345	60	2000
Girl	256×256	66	148	25	200
Hats	768×512	56	827	27	700
Lena	512×512	63	620	35	580
Lighthouse	768×512	24	4079	54	2100
Motocross	768×512	244	7198	49	240
Parrots	384×256	76	193	29	200
Peppers	512×512	203	645	29	200
Sailboats	512×768	75	1082	26	520

Table 1 shows "reasonably low" values of evaluation function and control parameters ***d*** and ***A*** for 10 typical test images. The function *Q* for tested images obtains these low values typically for ***d*** between 25 and 60. We can use the same values of parameters for segmentation of limited image class.

Conclusion

Visual evaluation of segmentation results is often used to assesment of segmentation process. In this paper the evaluation function Q was used for the choice of values two parameters. The problem of determination of their adequate values is not trivial. It was shown that the evaluation function checked on one class of segmentation techniques must be used very careful for segmentation technique from other class of techniques.

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