Automated Hierarchical Image Segmentation Based on Merging of Quadrilaterals

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Abstract: - This paper proposes a quadrilateral-based and automated hierarchical segmentation method, in which quadrilaterals are first constructed from an edge map, where neighboring quadrilaterals with similar features of interest are then merged together in a hierarchical mode to form regions. When evaluated qualitatively and quantitatively, the proposed method outperforms three traditional and commonly-used techniques, namely, K-means clustering, seeded region growing and quadrilateral-based segmentation. It is shown by experimental results that our proposed method is robust in both recovering missed important regions while preventing unnecessary over-segmentation, and offers an efficient description of the segmented objects conducive to content-based applications.

Key-Words: - Object representations, Quadrilateral-based segmentation, Hierarchical merging, Feature of interest, Color, Area

1 Introduction

The availability of digital video content has increased tremendously in recent years. Rapid advances in the related technology have contributed to an amazing growth in the amount of multimedia content [8]. So the recognition of meaningful objects from visual data, which is usually termed as image segmentation, holds a more significant position in many content-based applications. As the demand for object-based multimedia services continues to increase, more sophisticated analysis techniques are in need, thus the problem of image segmentation has received considerable attention in the literature [2].

Despite the fact that image segmentation has been intensively studied in the past and considerable research and progress have been made in segmenting objects, the robustness and generality of such algorithms on a large variety of image data have not been fully exploited [7]. Most real images are rich in color and texture features, and this fact makes it very difficult to recognize objects in an image accurately. Two typical problems in image segmentation process are: (1) *over-segmentation*: an object is partitioned into multiple regions after the segmentation; and (2) *under-segmentation*: multiple objects are represented by a single region after segmentation [5]. In a previous work [3], a quadrilateral-based segmentation (QBS) concept was introduced. The concept is built upon a network of quadrilaterals to represent regions. This concept offers an efficient data reduction, which produces fewer regions than some classical methods, thus over-segmentation can be removed efficiently.

Although this quadrilateral-based segmentation (QBS) method has good performance, it also has some drawbacks. One the problem is that it overshoots the over-segmentation issue, leading to the missing of some important regions. So we are motivated to revisit this segmentation method and aim at resolving this problem. In particular, we concentrate on recovering some important regions which are missed out by using the previous method, without inducing over-segmentation. In this paper, we propose a new quadrilateral-based and automated hierarchical segmentation method. To illustrate the good performance of our proposed method, we compare it both qualitatively and quantitatively with three existing well-known methods: K-means clustering (KMC) [4], seeded region growing (SRG) [1], and quadrilateral-based segmentation (QBS) [3]. Experimental results have also confirmed that our proposed segmentation method has the best performance among these methods, and is robust in recovering missed important regions while preventing over-segmentation.

This paper is organized as follows: Section 2 gives the generalized quadrilateral-based segmentation framework, Section 3 details the automated hierarchical merging algorithm of quadrilaterals, while Section 4 presents the experiment results, and Section 5 concludes the whole paper.

2 Generalized Quadrilateral-Based Segmentation Framework

This quadrilateral-based segmentation (QBS) framework mainly consists of three modules, which is shown in Fig.1. We will describe the idea of each module in following sub-sections.

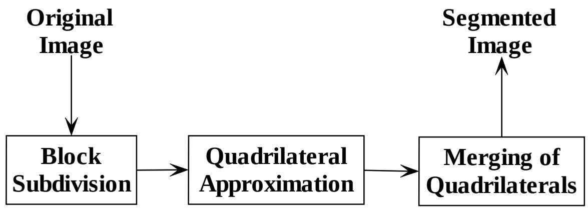


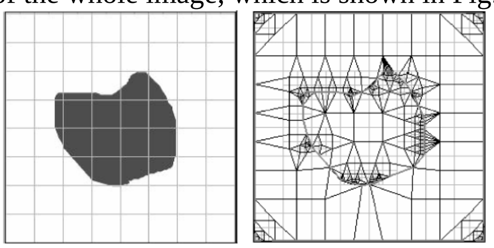
Fig.1 Block diagram of segmentation framework

2.1 Block Subdivision

The concept of *block subdivision* is to subdivide the whole image into a network of blocks of different sizes to produce the vertices of quadrilaterals. In essence, the whole image is first divided into a set of non-overlapping blocks. Then Sobel operator [9] is applied to obtain the gradient distribution of the whole image. A correlation criteria [3] is then applied on each block to judge whether initial blocks of the image should be further subdivided into four equal sub-blocks. Each block is subdivided until all blocks could satisfy the correlation criteria, thus the input image is divided into a network of blocks of different sizes.

2.2 Quadrilateral Approximation

We use a feature point to represent each of these resulted blocks. Then a network of quadrilaterals can be constructed by connecting feature points of adjacent blocks. We adopt the four connectivity scheme here, where each feature point only connects to the feature points of its top, left, bottom, and right blocks. The above scheme can be used to build a network of quadrilaterals that approximates an edge map of the whole image, which is shown in Fig.2.



(a) (b)

Fig.2 (a) Original image. (b) Quadrilaterals approximated for the image.

2.3 Merging of Quadrilaterals

Regions are obtained from merging neighboring quadrilaterals with similar features of interest. We define two quadrilaterals with a common edge are *neighboring quadrilaterals*. The algorithm of merging quadrilaterals, which will be described in the next section, derives from the idea of hierarchical merging, in which similar neighboring quadrilaterals are merged. We propose new merging criteria for comparing similarities of neighboring quadrilaterals.

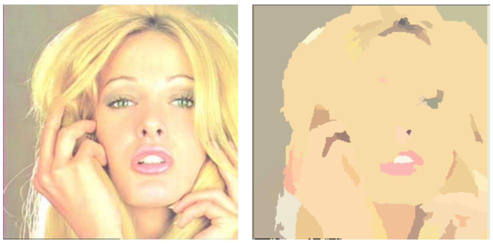
3 Automated Hierarchical Merging Algorithm of Quadrilaterals

In this section, we will further discuss the automated hierarchical merging algorithm operated on the quadrilateral structure (described in Section 2). The main idea of the algorithm is to merge neighboring quadrilaterals according to their similarity. We will firstly introduce the features of interest for measuring the similarity of quadrilaterals, then we will explain our merging criteria, followed by the merging algorithm will be described.

3.1 Features of Interest for Merging

We consider two kinds of features for measuring the similarity between neighboring quadrilaterals. The first kind of feature is color. In particular, we represent the color values of the quadrilaterals in the RGB color space, as it is found that RGB produces least noisy segmentation with reasonable number of regions in most cases [6]. The second kind of feature is area. Besides the color feature, we also consider sizes of quadrilaterals during the merging process.

In the previous method QBS, we only consider the color feature for merging. Fig.3 shows the segmented image and the boundary map of the face of a lady by QBS. When the features of the face are examined, we note that the top boundary of the lip and the boundary between the face and the right hair are missed. Because the color differences of the neighboring quadrilaterals at both sides of those boundaries are not large enough, these neighboring quadrilaterals are merged together. But besides color feature, we find that the size of the neighboring quadrilaterals is also an important feature when considering merging. In a real image, a region with a large area should be more *reserved*. Another observation is that a small-size region should possibly be more reserved if it is a neighbor of a large-size region than a small-size region. So in our new segmentation method, we consider color feature and area feature together. It can be shown experimentally that, in our merging algorithm, combining color and area features together could produce better segmentation results than some traditional and commonly-used segmentation methods.



(a) (b)

Fig.3 (a) Original image.
(b) Segmented image by QBS.

3.2 Merging Criteria

We first evaluate each color value average of the pixels within each quadrilateral. Let $M_R(Q)$, $M_G(Q)$, $M_B(Q)$ denote the average values of the Red, Green and Blue color component of the pixels within the quadrilateral Q, respectively. The color difference between two quadrilaterals Q and Q' is defined as:

$$\begin{aligned} D_C(Q,Q') &= (M_R(Q)-M_R(Q'))^2 \\ &+ (M_G(Q)-M_G(Q'))^2 \\ &+ (M_B(Q)-M_B(Q'))^2 \end{aligned} \quad (1)$$

In the previous quadrilateral-based segmentation (QBS) method, $D_C(Q,Q')$ is used as the merging criterion criteria. As mentioned in section 3.1, in our new segmentation method, we consider the area feature together with color feature. We produce a new merging criteria by assigning each pair of neighboring quadrilaterals a composite feature. Let $A(Q)$ and $A(Q')$ denote the areas of the numbers of pixels in Q and Q', respectively. The composite feature of each pair of neighboring quadrilaterals is defined as:

$$f(Q,Q') = \sqrt{\sqrt{A(Q)+A(Q')} * D_C(Q,Q')} \quad (2)$$

Intuitively, two small neighboring quadrilaterals should more readily be merged together than two large ones because of the smaller quadrilaterals introduce less errors than the larger ones based of two factors, their relative sizes and also the quadratic effects of the errors. That is the reason why the double square-root is used in the formula for the composite features. Thus, two large neighboring quadrilaterals will only be merged together if the pixel color values in the quadrilaterals are more homogeneity and uniform.

To determine whether two neighboring quadrilaterals are mergeable, we check whether the value of the composite feature is below a threshold ε. If the color difference between two neighboring quadrilaterals is below ε, these two quadrilaterals can be merged together. It should be noted that, the threshold ε is not determined by users, but algorithmically calculated based on the K-means clustering algorithm with K=2 for setting the threshold [3].

3.3 Merging Algorithm

The merging algorithm is operated in a hierarchical mode. Fig.4 shows the block diagram. In the previous method, there is only a single stage of merging quadrilaterals, while in our new method, there are two stages of merging quadrilaterals and intermediate regions, respectively.

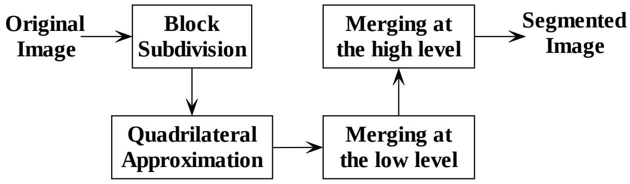


Fig.4 Block diagram of new segmentation method

During the merging of the quadrilaterals at the low level, the similarity of two quadrilaterals is measured by means of Equation (2) and the merging is performed according to the order of the $f(Q,Q')$ values (more similar quadrilaterals or regions are merged first). We divide all pairs of merge-able quadrilaterals into three cases, with different operations for each case. Suppose Q and Q' are two merge-able quadrilaterals in each pair. Let $L(Q)$ denote the region label of quadrilateral Q. $L(Q)>0$ means Q is labeled, while $L(Q)=0$ means Q is not labeled. We describe three cases and corresponding operation as follow:

Case 1: $L(Q)=0$ and $L(Q')=0$

Operation 1: Assigning Q and Q' a new region label, and increasing the total region number by 1;

Case 2: $L(Q)>0$ and $L(Q')=0$

Operation 2: Assigning Q' the same region label as Q;

Case 3: $L(Q)>0$ and $L(Q')>0$ and $L(Q)\neq L(Q')$

Operation 3: When both regions are already labeled, without loss of generality, modifying either region label to the other region label, and updating the region label of all the quadrilaterals in the region with the modified region label.

After the merging at the low level, we continue with the merging at the high level to produce better segmentation results. We regard each region as a quadrilateral in the low level merging, and similarly apply the merging algorithm and criteria on regions. The difference is, for the high level merging, only the third case will be considered. By repeating the merging operation iteratively, we could efficiently reduce over-segmentation. We have applied this segmentation method on many testing cases and observed that, for most of testing images, it is usually sufficient to iteratively merge intermediate regions twice for producing good segmentation results.

4 Experiment

To evaluate how well our proposed segmentation method performs, we compare its performance with the previous methods: the quadrilateral-based segmentation method, QBS [3], and two other segmentation methods, SRG [1] and KMC [4].

Both qualitative assessment and quantitative evaluation are used as the basis of comparison. For the quantitative evaluation, there are many different evaluation methods and they have been extensively studied by Zhang [10]. The one proposed by Liu and Yang [6] is adopted in our work because it is a parameter-free objective evaluation method without requiring a reference image. However, it should be noted that this evaluation gives merely a broad and general indication, where qualitative assessment should not be undervalued. The evaluation function L is defined as [6]:

$$L(I) = \frac{\sqrt{N_r}}{1000(MN)} \sum_{i=0}^{Nr-1} \frac{e_i^2}{\sqrt{A_i}} \qquad (3)$$

where I is the input image, N_r is the number of segmented regions in I, A_i is the number of pixels in the region R_i, M and N are the width and height of I, and e_i^2 is the color error of region R_i, which is defined as the sum of Euclidean distance of the color vector between I and the corresponding segmented image for each pixel in the region. According to [6], a smaller L means better performance. The qualitative assessment is mainly based on two criteria: the content correctness of segmented regions and the reasonable number of resultant regions.

We have tested the proposed segmentation method on many images, including portrait images and scene images. Here, we demonstrate the segmentation results of three testing images to explain the improvement of our segmentation method. Three testing images, namely "girl", "house" and "Lenna", are shown in Fig.5. In the "house" image, the similar color feature of the roof and the background sky, and the complicated texture feature of the tree around the house present some challenges in segmentation. The "girl" and "Lenna" are both color portrait images which introduce some difficulties in segmentation since the small important regions in the face need to be extracted correctly. The textured regions in both images are also difficult to handle in the segmentation process.

Table 1 shows the best objective performance (L), whereas Fig.6, 7, and 8 depict the corresponding segmented images with L. As depicted in Table 1, we could know our proposed method has the best performance among all these several methods since our proposed method gives the smallest L value for all the testing images. When the number of regions is concerned, our proposed segmentation method also gives the smallest number of regions for all the test images. This shows that our method is more conducive for content-based applications, as smaller number of regions means less computation power is required.

(a) (b) (c)

Fig.5 (a) "girl" image. (b) "house" image. (c) "Lenna" image.

TABLE 1
Smallest L Obtained and the Corresponding Number of Regions (R) Obtained from Each Method

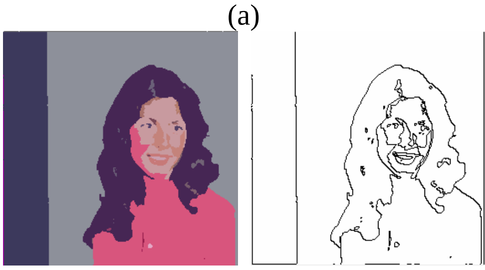
	KMC	SRG	QBS	Proposed
"girl"				
L	3.800518	0.603596	0.230985	0.160423
R	576	74	57	50
"house"				
L	6.479949	4.833943	0.997979	0.638300
R	1247	884	154	132
"Lenna"				
L	4.383851	2.350082	0.406771	0.270748
R	377	132	104	92

From the qualitative assessment viewpoint, let us observe the boundary map and region segmentation results in Fig.6, 7, and 8. In Fig.6, for KMC, the girl is described correctly by segmentation. But we could also see from the boundary map that over-segmentation exists notably in the region of eye, mouth, shirt, etc. The large number of regions also indicates this problem. For SRG, we could see the girl in the segmented image, but some under-segmentation exists since the neck even with some part of the face is merged with the shirt. For QBS, we could efficiently represent the image by fewer regions. But the reduction of over-segmentation also induces the missing of some important parts in the face region which makes the segmented image difficult for understanding. As for our proposed method, we could recover those important regions, while keeping even fewer regions than QBS. The only problem might be the small over-segmented regions existing at the boundary of the hair part.

In Fig.7, for KMC and SRG, we could obtain correct information of the original image from the segmentation result, but both methods have serious over-segmentation problem. It can be easily spotted in the part of the tree and the roof, which have many over-segmented tiny regions. For QBS, over-segmentation problem has been efficiently removed. But at the same time, under-segmentation problem can also be observed. In particular, the top boundary of the roof is missing, which makes the house difficult to be recognized. For our proposed method, we recover the important boundary of the roof to make the house recognizable and we also further remove the over-segmentation, such as in the part of the car, thus we could decrease the number of regions. The only problem might be some part of the tree being merged together with the roof at the right side.

In Fig.8, for KMC, Lenna could be recognized from the segmented image, but many tiny over-segmented regions exist in the textured region of the hat part. Another problem is some part of the top boundary of the hat is missed since of the hat being merged together with some background region. For SRG, the over-segmentation problem in the textured region is efficiently removed. But we also cannot keep a continuous boundary at the top of the hat. Compared with the original image, the feather part of the hat and the left hair part are merged together with the back part of the girl. For QBS, over-segmentation has been further removed. But some segmented regions are missed, such as lip and the hole in the top-right background region. Our proposed method is superior to QBS in the way that the missed regions have been recovered, while the number of regions has been further decreased.


(a)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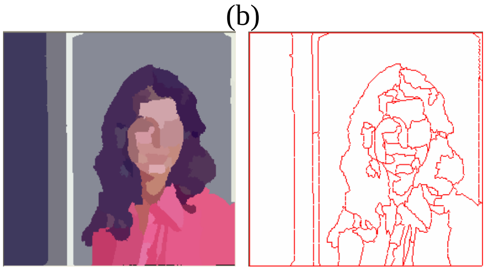

(c)

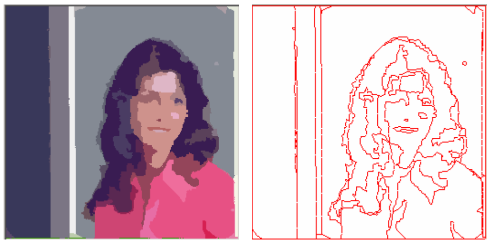
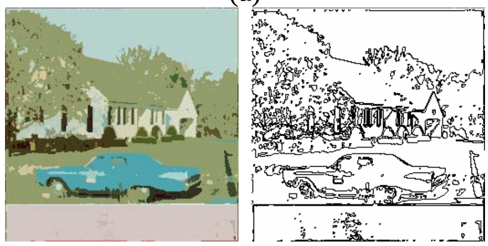

(d)

Fig.6 Segmented images and region maps of “girl” according to smallest L.
(a) KMC. (b) SRG. (c) QBS. (d) Proposed.


(a)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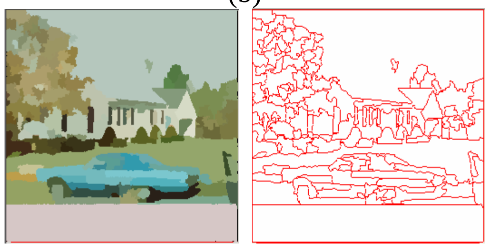

(c)

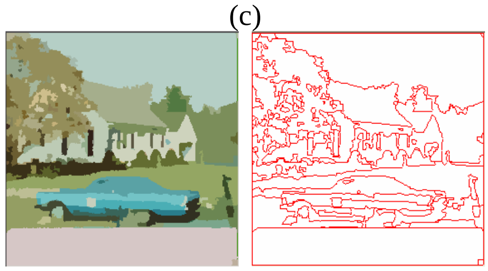
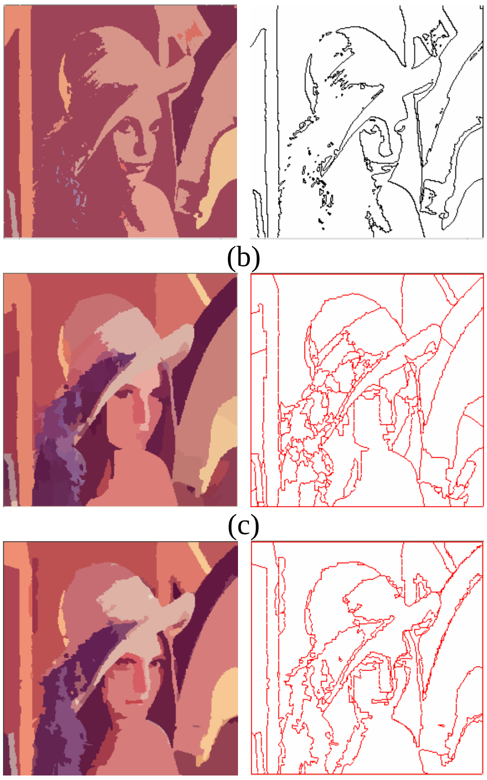

(d)

Fig.7 Segmented images and region maps of “house” according to smallest L.
(a) KMC. (b) SRG. (c) QBS. (d) Proposed.


(a)



(b)

(c)

(d)

Fig.8 Segmented images and region maps of "Lenna" according to smallest L.
(a) KMC. (b) SRG. (c) QBS. (d) Proposed.

5 Conclusion

We have proposed a new quadrilateral and automated hierarchical segmentation method. Our proposed method outperforms the three commonly-used methods, quadrilateral-based segmentation (QBS) [3], seeded region growing (SRG) [1], and K-means clustering (KMC) [4], and compares favorably, both qualitatively and quantitatively against these methods. Compared with KMC and SRG, the proposed method could obtain much less regions and effectively remove over-segmentation. When compared with QBS, under the precondition of effectively removing over-segmentation, our proposed method could recover some important regions which are missed out in QBS. Based on this result, our proposed method should be more suitable for applications such as content-based indexing and retrieval. We have shown qualitatively and quantitatively that this idea leads a correct direction for improving current segmentation results and we have also demonstrated that this framework enables us to develop better segmentation methods. Our future work will mainly concentrate on investigating the impact of different features of interest. We aim at searching more proper feature for measuring the similarity between neighboring quadrilaterals so that we could further improve our current segmentation method.

Acknowledgments

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References:

[1] R. Adams and L. Bischof, "Seeded Region Growing", *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 16, no. 6, pp. 641-647, Jun. 1994.

[2] M. Cheriet, J. N. Said, and C. Y. Suen, "A Recursive Thresholding Technique for Image Segmentation", *IEEE Trans. Image Processing*, vol. 7, no. 6, pp. 918-921, Jun. 1998.

[3] H. Y. Chung, N. H. C. Yung, and P. Y. S. Cheung, "An Efficient Parameterless Quadrilateral-Based Image Segmentation Method", *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol.27, no. 8, pp. 1446-1458, Aug. 2005.

[4] J.A. Hartigan, *Clustering Algorithms*. John Wiley Sons, 1975.

[5] X. Y. Jiang, "An Adaptive Contour Closure Algorithm and Its Experimental Evaluation", *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 22, no. 11, pp. 1252-1265, Nov. 2000.

[6] J. Liu and Y. H. Yang, "Multiresolution Color Image Segmentation", *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol.16, no. 7, pp. 689-700, Jul. 1994.

[7] W. Y. Ma and B. S. Manjunath, "Edge Flow: A Technique for Boundary Detection and Image Segmentation", *IEEE Trans. Image Processing*, vol. 9, no. 8, pp. 1375-1388, Aug. 2000.

[8] M. R. Naphade, I. V. Kozintsev, and T. S. Huang, "A Factor Graph Framework for Semantic Video Indexing", *IEEE Trans. Circuits and Systems for Video Technology*, vol. 12, no. 1, pp. 40-52, Jan. 2002.

[9] J. Russ. *The Image Processing Handbook*. Boca Raton, FL: CRC Press, 1999.

[10] Y. J. Zhang, "A Survey of Evaluation Methods for Image Segmentation", *Pattern Recognition*, vol. 29, no. 8, pp. 1335-1346, 1996.