A GRAPH THEORY APPROACH FOR AUTOMATIC SEGMENTATION OF COLOR IMAGES

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ABSTRACT

A hybrid split and merge segmentation method for color images is presented in this work. It combines edge and region information to merge adjacent regions produced in the initial watershed-based segmentation stage. A novel technique is introduced to simplify the Region Adjacency Graph (RAG) structure and speed-up the merging process along with a merging termination criterion for automatic segmentation. The robustness of the proposed method has been experimentally verified and compared to other previously reported merging approaches.

1. INTRODUCTION

An automatic, color preserving segmentation approach is proposed. It comprises of two stages; the first one, based on watershed segmentation, produces the oversegmented image that contains numerous regions of little significance. The second stage employs a merging scheme to form the final regions.

Our contribution concerns the merging method that is the most important for the accuracy of final segmentation. It combines hierarchical graph clustering, the notion of dynamics of contours and perceptual features to merge the most similar regions of the initial segmentation stage. An approach is herein proposed to simplify the Region Adjacency Graph (RAG) structure and speed-up the merging process. The outcome of this operation is the Most Coherent Neighbor Graph (MCNG) that contains the merging sequence. The merging process is eventually terminated by means of a histogram thresholding method to derive an automatic segmentation scheme. The proposed approach was compared to other previously reported schemes to verify its efficiency.

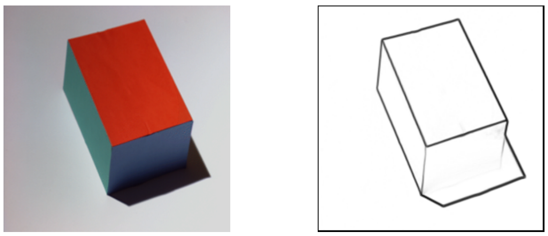
2. COLOR SPACE

Among several existing color spaces, the most common is the RGB. Here, each pixel is represented by the intensities of red, green and blue wavelengths as defined by the CIE committee. However, these three components are highly correlated and do not provide a separation between color and intensity information. The HSI (Hue Saturation and Intensity) color space allows an intuitive description of color and includes uncorrelated components. Nevertheless, the computation of the Hue component is non-linear and difficulties are subsequently introduced in the processing of it. The majority of the luminance-chrominance color spaces do not require a non-linear transformation of the RGB components and some of them are reasonably close to perceptual uniformity. The YC_BC_R, which we employed for this work, is such a color space. It separates the luminance information, i.e. the Y component, from the chromatic information, i.e. the C_R and C_B components.

3. INITIAL SEGMENTATION

In image segmentation, gradient-watersheds are often used to produce an initial partitioning of an image, where after some kind of post processing is performed to reduce the effect of oversegmentation inherent to watershed transformations [1]. The watershed is applied to the color gradient, which can be estimated in various ways. The gradient may be estimated either on each channel separately and combine their outcome or as a vector process. Shafarenko et al. [2] apply the waterfall hierarchical segmentation algorithm on a LUV gradient image, which is estimated using the Euclidean distance. A termination criterion is also applied to the merging process that is based on the topology of randomly textured images. In [3], the watershed is calculated on the di-Zenzo gradient and a hierarchical merging scheme is afterwards employed to reduce the oversegmentation. The hierarchy among the regions is obtained using the dynamics of contours [4].

In this work the inverse response of an edge detector is used as input for the watershed. The edge detector is based on the idea that the edges correspond to local density minima, i.e. boundaries of bi-modal density functions [1,5,6]. This is applied in the YC_BC_R color space as a vector process to retain both intensity and color edges. An example of the edge detector outcome is displayed in Figure 1.



(a) (b)

Figure 1. (a) The original image and (b) the inverse edge map using potential functions.

4. MERGING STAGE

4.1. Region Adjacency Graph Construction

Given the initial image segmentation, the well-known region adjacency graph G=(V,E) is constructed to describe the topology and inter-region relations of the image [7]. It consists of nodes V={1,2,...,N} and edges $E_{i,j}$ where i,j are node indices and $E \subset VxV$. Each node represents a specific region of the image, while the weight of the edges is indicative of the dissimilarity between two regions. It is highly significant in order to determine which regions will be merged. This dissimilarity is expressed by a merging cost function that includes some unary and binary features estimated over the initial regions.

4.1.1. Merging Cost Function

The features employed in this work utilize the region and contour information to measure the homogeneity of two adjacent regions. These are described as follows:

Relative Entropy (RE). To compare the Luminance histograms between two regions the relative entropy is employed. This feature is suitable for texture comparison between the examined regions:

$$RE_{i,j} = \sum_{k=0}^{255} \left[P_i(k) \cdot \log_{10}\left(\frac{P_i(k)}{P_j(k)}\right) + P_2(k) \cdot \log_{10}\left(\frac{P_j(k)}{P_i(k)}\right) \right] \quad (1)$$

P_r denotes the Luminance probability density function for region r and $RE_{i,,j}$ the relative entropy of the two distributions.

Dynamics of Contours (DOC). Due to the fact that the initial regions are derived from the application of watershed algorithm to the edge detectors output, the dynamics of contours [4] is employed as a measure of the contour saliency between two minima. In our case it is applied to measure the color contrast between two adjacent regions. The dynamics of contours is based on the idea of dynamics of minima. It takes into consideration the progress of the flooding process to estimate the color contrast between two adjacent regions that are represented by their minima in the topographic space. As a result the contrast between two adjacent regions is estimated by the most dominant minimum involved in the flooding chain.

Common Boundary Corner (CBC). The product of curvature and edge estimate of *the maximum curvature contour point* is employed to estimate the corner saliency [8] of the common boundary between two regions.

Common Boundary Sharpness (CBS). The sharpness of the contour is expressed by the sum of the edge estimate along the common boundary of the two regions, divided by the length of the common boundary.

The product of these variables provides the merging cost between two adjacent regions i.e. the edge weight of graph edge $E_{i,j}$:

$$E_{i,j} = RE_{i,j} \cdot DOC_{i,j} \cdot CBC_{i,j} \cdot CBS_{i,j} \cdot card_j \quad (2)$$

4.2. Most Coherent Neighbour Graph Construction

Several graph-theoretic approaches for image segmentation have been proposed in the past [9,10]. In this paper a one-dimensional graph is created denoted by MCNG to simplify the merging process. This graph contains the merging sequence derived from the most coherent neighbors of the regions. The MCNG is a 1D simplification of the directed RAG. It is a weighted graph that consists of nodes V_{MCN} and edges E_{MCN}, $G_{MCN}=(V_{MCN},E_{MCN})$. The nodes $V_{MCN} \equiv V$ represent the regions of the image. The edges of the MCNG are a subset of the RAG edges $E_{MCN} \subset E$. The destination node of each MCNG edge is the most coherent neighbour of its origin node. The edges of the MCNG are derived from the Region Adjacency Graph via the following steps:

1. *Scan the RAG from node 1 to N (i=1 to N).*
2. *For each node i of the RAG find the minimum weighted edge, denoted by $E_{i,j}$,* $E_{i,j} = \min_k(E_{i,k})$.
3. *Node j is the Most Coherent Neighbour of i. Add the corresponding edge to MCNG,* $E_{MCN} = E_{MCN} \cup \{E_{i,j}\}$.
4. *Remove $E_{i,j}$ from RAG.*
5. *Go to step 1.*

The edges of the MCNG are registered in a heap and sorted in increasing order according to their weight (merging cost). The nodes linked by the MCNG edges are subsequently merged and updated until the termination criterion is met. This is a hierarchical graph clustering method that does not require additional cost evaluation during the merging process and therefore can be executed faster than sequential merging methods. In Figure 3 a simple example of the transformation from RAG to MCNG is also displayed.

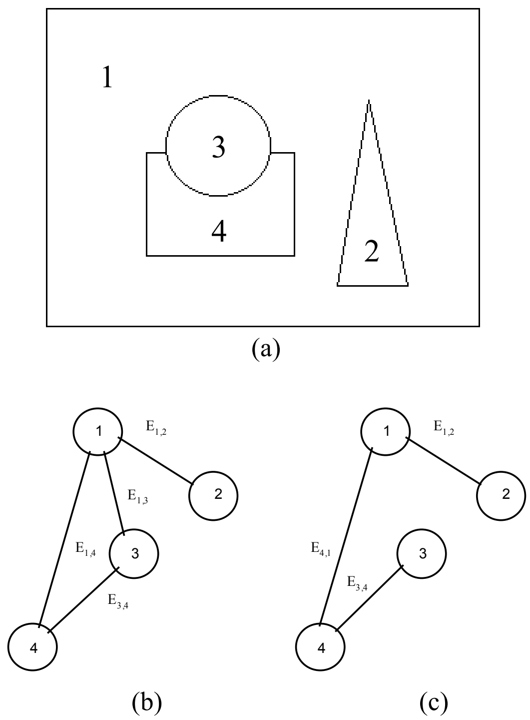


Figure 2. First Row: (a) Example of an initial region map. Second Row: (b) RAG of the initial partition and (c) the corresponding MCNG.

4.3. Merging Termination

After the merging sequence is determined, a termination criterion has to be defined to exclude the most dissimilar regions from being merged. Most of the works in the literature rely on some empirical thresholds that might vary between different images.

In the proposed scheme, the information of MCNG is exploited to define the termination point. In the beginning, the histogram of the pairwise costs is estimated. Due to the oversegmentation effect, most of the sorted MCNG edges are concentrated in small values. The histogram shape is therefore rapidly decreasing. After extensive experimentation it was concluded that the 5% of the histogram maximum value corresponds to the termination point of the merging sequence. Nevertheless, if no termination point was found (i.e. when slight oversegmentation occurs), the threshold is iteratively increased to 10, 20 and 40% of the histogram maximum value.

This method has proven to be robust regardless of the image type processed and the level of oversegmentation. Figure 3 contains the histograms of edge weights and the termination points for the test image 'Lena'.

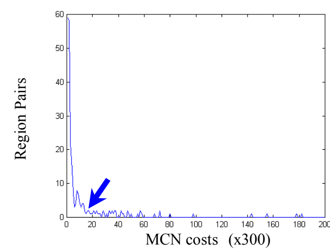


Figure 3. Histograms of MCN edge weights for image 'Lena'. The arrow indicates the merging termination point.

5. EXPERIMENTAL RESULTS

To evaluate the effectiveness of the proposed method (that we call RCFMCNG), it was compared to the conventional merging method applied to the sorted RAG edges (non-updating version) using i) the same dissimilarity function (denoted by RCFRAG) and ii) only the dynamics of contours (DOCRAG). The DOCRAG is also utilized in the merging process in [3] and [4].

The qualitative perspective is depicted in figures 4-7 for images 'woman', 'house', 'parrots' and 'tree'. The above approaches were evaluated quantitatively by means of the Mean Square Error (MSE) between the original image and the piecewise zero order approximation over the RGB components. In Table 1 some results are reported and the graph in figure 8 gives an illustrative overview.

From these results it is concluded that the proposed merging scheme yields regularly better visual results and lower MSE values than the other two approaches. The results of RCFRAG that are significantly worse than the two other approaches may be significantly refined, when the costs of the RAG are iteratively updated and sorted after each merging. Nevertheless, this operation results in a considerably higher computational complexity.

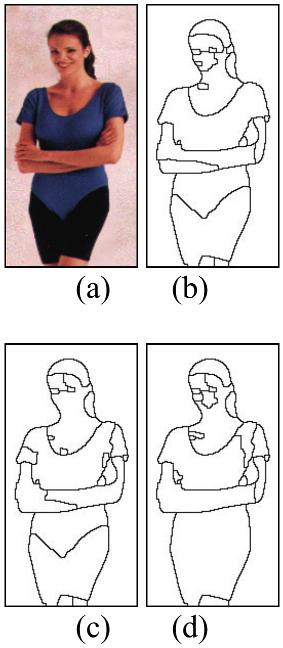


Figure 4. a) Test image 'Woman' and the final segmentation results (23 regions) of b) RCFMCNG, c) RCFRAG and d) DOCRAG approaches.

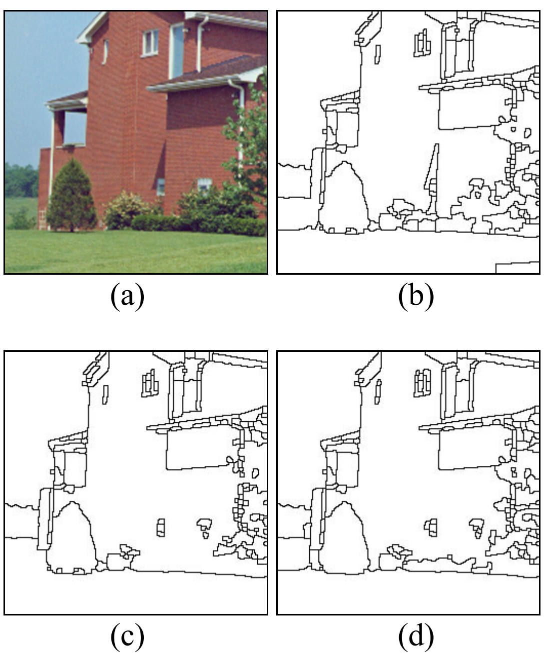


Figure 5. a) Test image 'House' and the final segmentation results (134 regions) of b) RCFMCNG, c) RCFRAG and d) DOCRAG approaches.

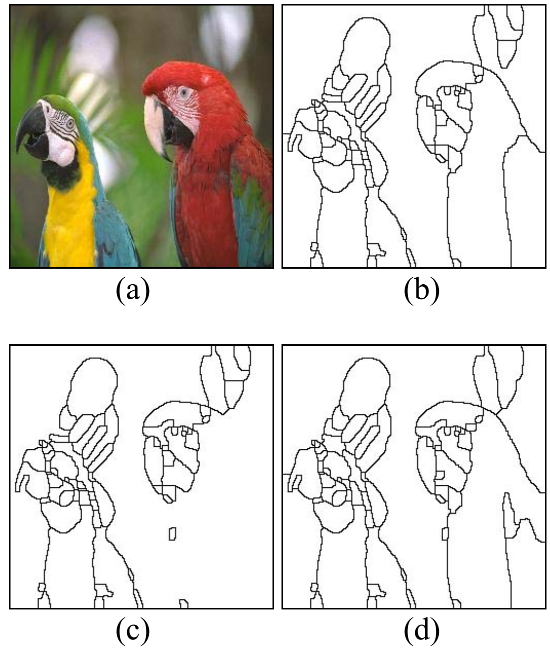


Figure 6. a) Test image 'Parrots' and the final segmentation results (68 regions) of b) RCFMCNG, c) RCFRAG and d) DOCRAG approaches.

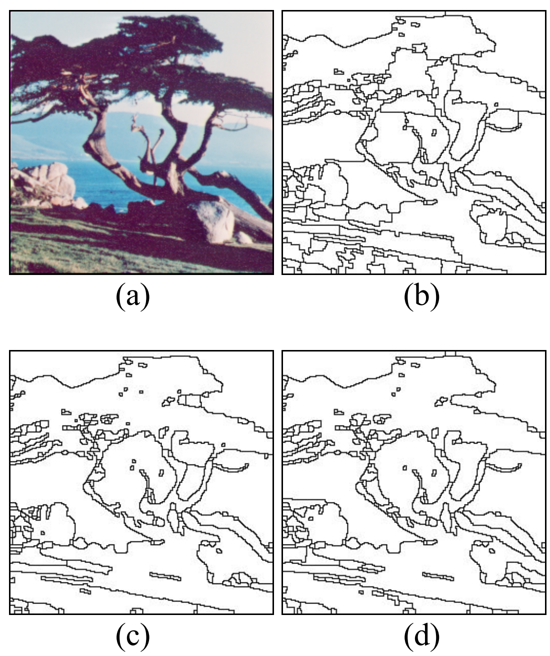


Figure 7. a) Test image 'Tree' and the final segmentation results (189 regions) of b) RCFMCNG, c) RCFRAG and d) DOCRAG approaches.

Table 1: Comparative Results in terms of Mean Square Error

IMAGE	FINAL REGIONS	RCFMCNG ($MSE.10^{-2}$)	RCFRAG ($MSE.10^{-2}$)	DOCRAG ($MSE.10^{-2}$)
Woman	23	6.252	6.3826	7.246
House	134	4.597	6.933	5.741
Parrots	68	8.921	13.351	9.239
Peppers	130	9.9083	23.5505	15.3109
Tree	189	9.6828	12.3595	10.4954
Lena	153	6.6834	11.5878	11.298
Boat	58	11.6413	36.2243	15.5597
Monarch	268	18.4502	20.3236	20.6063

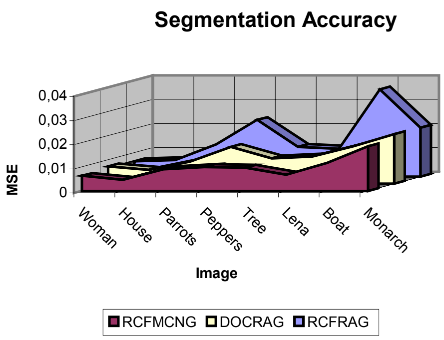


Figure 8. MSE graph of the three tested approaches.

6. CONCLUSIONS

A color segmentation method was presented in the reversible YC_BC_R space. It consists of two stages: initial segmentation and merging. Our interest is concentrated on the second stage and particularly, the selection of the merging sequence and the merging termination criterion. A simplified graph structure identified as the Most Coherent Neighbor Graph (MCNG) is introduced to speed up the merging process. A novel approach was presented to automatically determine the merging sequence based on the histogram information as well. The good performance of this method was experimentally verified on several color test images.

Our future objective is to include the proposed approach in a multiresolution scheme and to further investigate and refine the merging process.

7. ACKNOWLEDGEMENTS

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