

Color Image Segmentation Based on Adaptive Local Thresholds

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Abstract

The goal of still color image segmentation is to divide the image into homogeneous regions. Object extraction, object recognition and object-based compression are typical applications that use still segmentation as a low-level image processing. In this paper we present a new method for color image segmentation. The proposed algorithm divides the image into homogeneous regions by local thresholds. The number of thresholds and their values are adaptively derived by an automatic process, where local information is taken into consideration. First, the watershed algorithm is applied. Its results are used as an initialization for the next step, which is iterative merging process. During the iterative process regions are merged and local thresholds are derived. The thresholds are determined one-by-one at different times during the merging process. Every threshold is calculated by local information on any region and its surroundings. Any statistical information on the input images is not given. The algorithm is found to be reliable and robust to different kind of images.

Key words: Local thresholds, Image segmentation, Homogeneity, Splitting, Merging.

1. Introduction

Image segmentation partitions an image into non-overlapping regions. A region is defined as a homogeneous group of connected pixels with respect to a chosen property. There are several ways to define homogeneity of a region that are based on a particular objective in the segmentation process. For instance, it may be measured by color, gray levels, texture, motion, depth of layers, etc. Overlaps among regions are not permitted, thus, each pixel belongs only to a single region. Two neighboring regions should be merged if the new combined region is homogeneous. Consequently, each region is anticipated to be as large as possible under its certain characterization. Then, the total number of regions is reduced.

Since segmentation definition is informal, it is very difficult to propose a semantics to measure the quality of a given segmentation, unless the segmentation's goal is well defined. Image segmentation has a variety of purposes. For example, segmentation plays an important role in the field of video object extraction [1],[2],[3]. Since homogeneous regions correspondent to meaningful objects (which are mostly inhomogeneous), many of the video object extraction algorithms first partition the image into homogeneous regions, and then, in order to extract the moving object, the regions are merged according to temporal information of the sequence. In image compression [6],[7],[8], the input image is divided into regions that should be separately compressed since better compression is achieved as long as the regions are more homogeneous. Tracking systems that are region-based [9],[10],[11] utilize the information of the entire object's regions. They track the homogenous regions of the object by their color, luminance or texture. Then, a merging technique that is based on motion estimation is used in order to obtain the complete object in the next frame. Image segmentation is also used in object recognition systems [4],[5]. Many of these systems partition the object to be recognized into sub-regions and try to characterize each separately in order to simplify the matching process.

Automatic segmentation in still image has been investigated ([12],[13]) by many researchers from diverse fields of sciences. The existing segmentation methods can be divided into the following main approaches: *Histogram-based* methods, *boundary-based* methods, *region-based* methods, *hybrid-based* methods and *graph-based* techniques.

Histogram-Based methods: Most of the histogram based algorithms deal with gray level images, which are represented as one dimensional histogram. The range of intensities is assumed to be constant. The histogram is considered as being a probability density function

of a Gaussian and the segmentation problem is reformulated as a parameter estimation followed by pixel classification [13]. However, color images are usually represented by three-dimensional (3-D) bands as RGB or some transformation of RGB. Hence, selecting global thresholds in 3-D histograms is a difficult task. In order to deal with 3-D color histograms, some techniques [16], [17] were developed to project the 3-D color space onto 2-D or even 1-D surface, and analyze the obtained surface for the segmentation process. Other techniques [14],[15] transformed the 3-D histogram into a binary tree such that each node represents a different range for RGB key values. The number of the RGB points that are represented by each node is transformed to the key value of the node. Later, Cheng and Sun [18] extended the general 3-D histograms to homogeneous domain histogram. They defined homogeneity as a composition of two components: standard deviation and discontinuity of the intensities, and used the homogeneity histogram to detect uniform regions. Then, for any region the traditional histogram, based on Hue color feature, is constructed and histogram analysis is performed. However, most of the histogram based methods were found to fit specific images. These methods achieved reasonable performance when the input is characterized without noise and with small number of regions. Moreover, the number of potential segmentation classes in the image is usually assumed to be known beforehand.

Boundary-based methods: These methods search for pixels that lie on a region boundary (or at the boundary between two regions). These pixels are called edges [22]. An edge is characterized by a significant local change in image intensities. Edges are detected by looking at neighboring pixels. The basic assumption is that the change in pixels values between neighboring pixels inside a region is not as significant as the change in pixels values on the regions boundary. When the difference between two regions grows, the change becomes bigger and the edge becomes stronger. Sometimes weak edges should be detected as strong edges and in other times they should not. Consequently, not all the detected edges create closed curves, which are necessary to separate between regions. Therefore, some type of post/pre-processing techniques, such as [19],[20],[21] are required for grouping the detected edges into a connected surfaces to represent the region. In [23] an EdgeFlow method was presented that is based on the edge directions rather than the edge energy. They detected the regions boundaries by identifying a flow direction at each pixel location that point to the closest boundary. Then, it follows by detection of the locations that encounter two opposite directions of edge flow. However, the main drawback of many

boundary based methods is the over-segmentation result, which is not always correctly reflects the image nature.

Region-based methods: These methods gather similar pixels according to some homogeneity criteria [24],[25] and [26]. They are based on the assumption that pixels, which belong to the same homogeneous region, are more alike than pixels from different homogeneous regions. The split-and-merge or the region-growing techniques are examples for such method [27],[28],[30],[31],[32]. The region growing algorithm initially defines each pixel as a region. Then, it scans the image from left to right and from top to bottom and compares the current pixel with its neighboring regions that were already scanned. If the pixel is sufficiently similar to one of its adjacent regions it is added to that region. If it is not close enough to any of them, then it is still defined as a different region. On the contrary, the split-and-merge techniques [29] initially assume that the image is composed of one region. It splits inhomogeneous segment into four rectangular segments and merge four adjacent regions if they are found to be similar. When no region can split and no four adjacent regions can merge the algorithm is terminated. Two main drawbacks characterize these techniques. They are both strongly dependent on global pre-defined homogeneous criteria thresholds while the region growing technique depends also on initial segments, which is the first pixel/segment, that is first to be scanned and on the order of the process.

Hybrid-based methods: These methods improve the segmentation result by combining the above methods for segmentation. Many of the hybrid techniques combine the region-based method with the boundary-based method. Some used the combination of the histogram-based with the region-based methods. The hybrid technique for segmentation is very common since it relies on wide information as global (histogram) and local (regions and boundaries). An example of an hybrid technique was presented in [35], which integrated between regions based and boundary based methods. First a split-and-merge algorithm is performed in order to initially segment the image. Then, the contours of the obtained regions are refined using the edge information. Later, the watershed algorithm [33],[34] was presented. It begins with a boundary based method to get gradient magnitude. Then, regions are produced by a region growing technique. In [36], K. Haris *et al* presented a segmentation algorithm using the watershed algorithm [33] and regions merging. They applied the watershed transform to initial partition the image into primitive regions. The output of the watershed used as an input for hierarchical (bottom-up) region merging process, which produced the final segmentation.

Graph-Based technique: Special graph algorithms have been adopted for segmentation. These algorithms typically construct a graph in which the nodes represent the pixels in the image and arcs represent affinities between nearby pixels. The image is segmented by minimizing the weight, which is associated with cutting the graph into subgraphs. In a simpler version, the weight is the sum of the affinities across the cut [41]. Other versions normalize this weight by dividing it by the overall area of the segments [38] or by a measure derived from the affinities between nodes within the segments [39],[40]. Normalizing the weight of a cut prevents over-segmentation of the image. In [37] a fast, multiscale algorithm for image segmentation was introduced. The algorithm uses algebraic multigrid (AMG) solvers to find an approximate solution to normalized cut measures in time that is linear in the image size. It detects the segments by applying a process of recursive coarsening in which the same minimization problem is represented with fewer and fewer variables producing an irregular pyramid.

We propose a new method for still color image segmentation, which is based on adaptive automatic derivation of local thresholds through an iterative procedure, where local information is taken into consideration. The algorithm is composed of two main steps. Initially, the image is divided into a large number of regions using the application of watershed algorithm. The Region Adjacency Graph (RAG) is the data structure we use to represent the image partition. The second step is an iterative process, in which regions are merged and local thresholds are derived. The order in which the merging process takes place is based on Kruskal's algorithm [43] for finding minimum spanning tree in a graph. During the merging process we follow the changes of each region and save the changes of the regions characteristics. By analyzing these changes we identify where during the merging process each region becomes inhomogeneous. Then, local thresholds are derived. To cancel the merge that produces inhomogeneous region, all the merges are canceled one-by-one from the end until that merge is reached. The two regions, which this merge refers to, are identified as non-mergeable regions, and are considered as “final regions”. The algorithm neither assumes any given parameters nor any given thresholds. The number of thresholds and their values are known only when the process is terminated. The segmentation result is the partition of the image, which is obtained by the “final regions”.

The rest of the paper is organized as follows. Section 2 describes the proposed merging methodology and its relation to the minimum spanning tree algorithm. In section 3 we describe the core process that assigns local thresholds based on local consideration of each region. Section 4 presents all the steps of the segmentation algorithm and analyzes the

overall time complexity. Experimental results are given in section 5 and we conclude this paper in section 6.

2. Merging Methodology

The proposed algorithm pre-segments the image (section 2.1) using the watershed algorithm, which generates an over-segmentation output. Next a merging process is applied. The merging process deals with the following three issues: (i) the dissimilarity between regions (section 2.2), (ii) MST construction (section 2.4). (iii) computation of local thresholds (section 3)

2.1 Initial Segmentation Using the Watershed Algorithm

The input to the watershed algorithm is a gray-scale gradient image. Thus, we first convert our input (color image) I into a gray level image. Then, Canny edge detection [20] is applied to get its gradient magnitude image, denoted by I_G . The gradient image is considered as a topographic relief. Each pixel's value (gray level) stands for the evaluation at that point. The algorithm defines catchment basins and dams. Each catchment basin, which is associated with a minimum M is a set of connected pixels such that a drop of water falling from any pixel that belongs to this catchment basin, falling down until it reaches the minimum M . On its way down the drop passes only through pixels that belong to this catchment basin. Dams are watershed lines. They are pixels that separate different catchment basins. A drop falling from one side of a dam reaches the minimum of one catchment basin while a drop falling from its other side reaches the minimum of another catchment basin. Catchment basins and dams are illustrated in Figure 1.

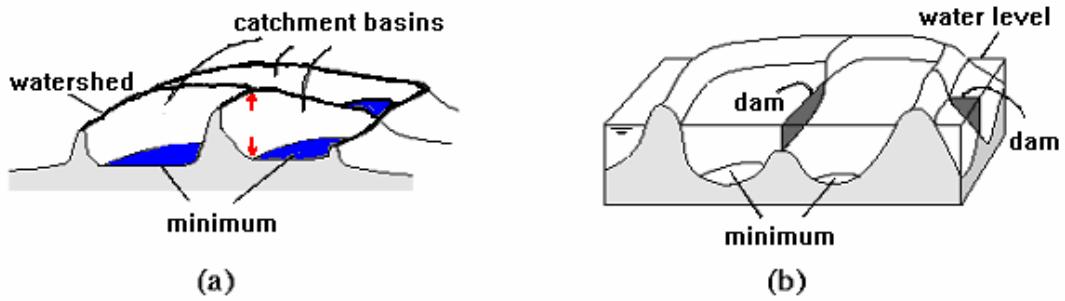


Figure 1: Catchment basins and dams. Low and height level pixels are illustrated by the lower and upper red arrows, respectively.

We apply the Vincent and Soille [33] version of the watershed algorithm, which is based on immersion simulation: the topographic surface is immersed from its lowest altitude until water reaches all pixels. The algorithm contains two steps: sorting and flooding. At the first step the pixels are sorted in an increasing order according to their intensities. Then, at the flooding step the pixels are scanned by the sorting order to construct catchment basins. Each catchment basin is assigned a different label. At a point where water comes from different catchment basins, dam is constructed. At the end of the process a tessellation of the image into catchment basins (by their labels) is produced. Figure 2 demonstrates the watershed result. Figure 2a is the input image. Figure 2b is its gray level image. The gradient image after applying Canny edge detector is shown in Figure 2c and the segmentation, that is generated by the watershed algorithm is shown in Figure 2c.

The output of the watershed algorithm is segmentation of I_G into a set of n non-overlapping regions. Since these regions are going to be merged during the next merging process we denote them by $R_i^{m_i}$, $i = 1, \dots, n$, $m_i = 1, \dots, M_i$, where n is the number of regions, and M_i is the number of merges of $R_i^{m_i}$ during the merging process. $R_i^0, i = 1, \dots, n$ is the set of initial regions, which is the output of the watershed algorithm before the iterative merging process of the second step starts.

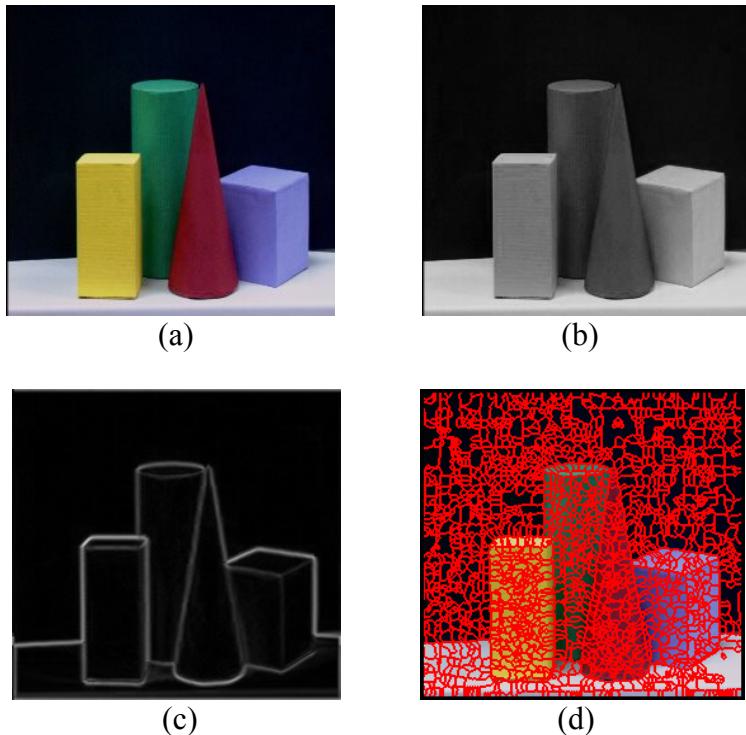


Figure 2:(a) The input color image. (b) Its gray-level image. (c) The gradient image after applying Canny edge-detector. (d) The segmentation result by the watershed algorithm.

2.2 Dissimilarity Measure between Regions

To determine the merging order dissimilarity function between any two neighboring regions, $R_i^{m_i}$ and $R_j^{m_j}$, denoted by $f(R_i^{m_i}, R_j^{m_j})$, is defined. The function is based on two components: color and edges. The Hue component of the HSV color space [42] is used for the color component since it less influenced by changes in illumination such as shade and shadow. The mean value of the hue component of a given region $R_i^{m_i}$ is denoted by $\mu_h(R_i^{m_i})$. The gradient magnitude is used as another source of local information for the second component. We denote by $\mu_G(R_i^{m_i}, R_j^{m_j})$ the mean gradient between $R_i^{m_i}$ and $R_j^{m_j}$, which is calculated from the gradients among the shared pixels between the two regions. The values of the pixels in I_G are used to get the magnitude of the gradients. Let B_{ij} be the set of pixels which are the boundary of $R_i^{m_i}$ and $R_j^{m_j}$. $\mu_G(R_i^{m_i}, R_j^{m_j})$ is defined as

$$\mu_G(R_i^{m_i}, R_j^{m_j}) = \frac{\sum_{(x,y) \in B_{ij}} I_G(x, y)}{|B_{ij}|} \quad (1)$$

where $|B_{ij}|$ denotes the number of pixels at B_{ij} . The dissimilarity function is defined as

$$f(R_i^{m_i}, R_j^{m_j}) = w_1 \cdot d(\mu_h(R_i^{m_i}), \mu_h(R_j^{m_j})) + w_2 \cdot \mu_G(R_i^{m_i}, R_j^{m_j}) \quad (2)$$

where $d(\mu_h(R_i^{m_i}), \mu_h(R_j^{m_j}))$ is the difference between the mean value of $R_i^{m_i}$ and the mean value of $R_j^{m_j}$

$$d(\mu_h(R_i^{m_i}), \mu_h(R_j^{m_j})) = \min\{|\mu_h(R_i^{m_i}) - \mu_h(R_j^{m_j})|, (360 - |\mu_h(R_i^{m_i}) - \mu_h(R_j^{m_j})|)\} \quad (3)$$

and w_1 and w_2 are predefined constant coefficients. The dissimilarity function is mostly based on the hue color space rather than the gradient magnitude, thus, $w_1 \gg w_2$. Based on experiments on different images w_1 and w_2 set to 0.8 and 0.2, respectively.

2.3 RAG Data Structure

The region adjacency graph (RAG) is the data structure that is being used to represent the partition of the image. The RAG that represents the set of regions $R_i^0, i = 1, \dots, n$ is an undirected graph $G = (V, E)$. $V = \{1, 2, \dots, n\}$ such that each region is represented by a node, and $e(i, j) \in E$ if $i, j \in V$ and the regions $R_i^{m_i}$ and $R_j^{m_j}$ are adjacent. Since the merging process is based on G , each edge is assigned a weight. The weight of an edge $e(i, j)$ is the value of $f(R_i^{m_i}, R_j^{m_j})$, calculated by Eq.(2). An example of an image that contains six regions with its corresponding RAG is shown in Figure 3. The six regions are represented by six nodes and the edges correspond to the neighboring list. For instance, the four edges that are connected to node 1, $e(1,2)$, $e(1,3)$, $e(1,4)$ and $e(1,5)$, represent its four adjacent regions: 2, 3, 4 and 5.

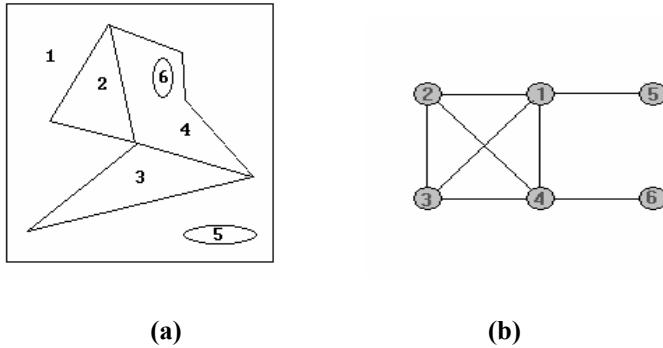


Figure 3: (a) Six partitions of the image and (b) its corresponding RAG.

2.4 On the Relation between MST and the Merging Process

The merging process is based on Kruskal's algorithm [43] for finding a minimum spanning tree (MST). Let $G = (V, E)$ be the RAG, which represents the initial segmentation of I where the weight of $e(i, j)$ is the value of $f(R_i^{m_i}, R_j^{m_j})$. A spanning tree of G is defined as a connected acyclic subgraph that spans all its nodes. Every spanning tree of G has $n - 1$ edges where $|V| = n$. When each edge has a weight, a minimum spanning tree is a spanning tree of G that has the lowest total weight of its edges measured as the sum of the weights of the edges in the spanning tree.

Kruskal's algorithm generates the minimum spanning tree, denoted as T , from scratch by adding one edge at a time. Initially, the edges of G are sorted in a non-decreasing order

of their weights. Then, the edges in the sorted list are examined one by one and checked whether adding the edge that is currently being examined creates a cycle with the edges that were already added to T . If it does not, it is added to T . Otherwise, it is discarded. The process is terminated when T contains $n-1$ edges. At the end of the process T is the minimum spanning tree of G . We apply Kruskal's algorithm on G while focusing on the process itself. The process that constructs the MST is the process that merges regions as described below:

- Adding $e(i,j)$ to T represents the merge of its two corresponding nodes (its two regions) $R_i^{m_i}$ and $R_j^{m_j}$.
- Adding the edge with the minimum weight one-by-one in an increasing order to T (using the sorted list) is equivalent to the merge of the two most similar regions.
- When an edge is rejected because it creates a cycle in T , no merge is performed because its two regions have already been merged into one region.
- At the end, when T spans all the nodes, all the regions were merged into one region, and the merging process is terminated.

Figure 4 is an example of a weighted graph G . The black thick edges in Figure 4b are the edges of its minimum spanning tree. After its edges were sorted, the MST construction, which represents a merging process, proceeds as follows: $e(4,6)$ with weight “10” is added first to T since it has the lowest weight among the edges in the sorted list, hence, R_4 and R_6 are merged. Second, $e(2,3)$ is added to T , hence, R_2 and R_3 are merged. The third edge is $e(3,4)$, hence, R_3 (that already merged with R_2) is merged with R_4 (that was already merged with R_6). The fourth edge is $e(1,5)$, hence, R_1 and R_5 are merged. $e(2,4)$ is examined next. Since $e(2,4)$ creates a cycle with $e(2,3)$ and $e(2,3)$ that have already been chosen to be in T , it is rejected. Discarding $e(2,4)$ means that no merge takes place since R_2, R_3, R_4 and R_6 have already been merged into one region. Next, $e(1,4)$ is added, hence, R_1 is merged with R_4 . Then, the construction of the minimum spanning tree is terminated since T contains five edges that span its six nodes. Hence, all the regions have been merged into one region and no further merge is possible.

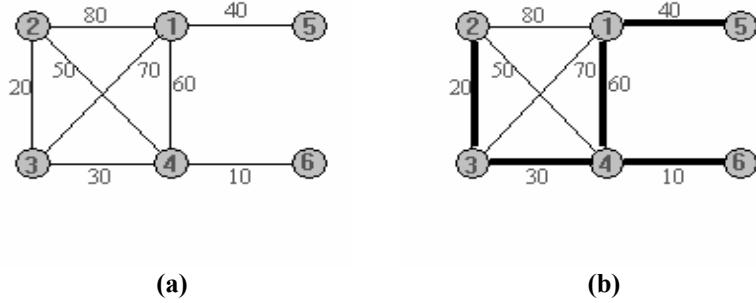


Figure 4: (a) The source graph. (b) Its minimum spanning tree is indicated by the black bold edges.

During the MST construction process T is not necessarily connected. Minimal forests may be created. Growing forests, and not only one tree, is equivalent to merging regions at different locations in the image. Not only one region may grow but many, unlike the traditional region-growing method where pixels or regions are scanned in a predefined order and the generated regions are emerged and expanded from one location.

After any merge of any two regions a new region is generated. As a result, there is new information about this region and its new surroundings while the previous information becomes irrelevant. Therefore, we have to follow the changes of the regions during the process and use the current updated information. Let $R_{ij}^{m_j} = R_i^{m_i} \cup R_j^{m_j}$ be the new region that is generated by the merge of $R_i^{m_i}$ with $R_j^{m_j}$ and let $N(R_{ij}^{m_j}) = N(R_i^{m_i}) \cup N(R_j^{m_j})$ be the neighbors of the new region $R_{ij}^{m_j}$, where $N(R_i^{m_i})$ is the neighboring regions of $R_i^{m_i}$. Then $f(R_{ij}^{m_j}, R_v^{m_v})$ for every $R_v^{m_v} \in N(R_{ij}^{m_j})$ is recomputed by the new modified information. Since the values of $f(R_{ij}^{m_j}, R_v^{m_v})$ for every $R_v^{m_v} \in N(R_{ij}^{m_j})$ are the weights of the corresponding edges in G , the edges and the sorted list have to be updated to include the new values after $f(R_{ij}^{m_j}, R_v^{m_v})$ has been updated.

Thus, the complete merging process is based on Kruskal's algorithm for MST construction with the following modification: When an edge, say $e(i, j)$, is added to T and T has less than $n - 1$ edges the sorted list is updated. $f(R_{ij}^{m_j}, R_v^{m_v})$ is calculated for any new region $R_{ij}^{m_j}$ and its neighbors, and then the weights of the edges

$\{e(i,k) \cup e(j,l) \mid R_i^{m_k} \in N(R_i^{m_i}), R_l^{m_l} \in N(R_j^{m_j}), k \neq j, l \neq i\}$ are updated. These are the edges that are connected to $R_i^{m_i}$ and the edges that are connected to $R_j^{m_j}$. Parallel edges may be generated during any merge. Two edges, $e(i,j)$ and $e(u,v)$, are considered to be parallel if $R_i^{m_i}$ already merged with $R_u^{m_u}$ (or with $R_v^{m_v}$) and $R_j^{m_j}$ already merged with $R_v^{m_v}$ (or with $R_u^{m_u}$, respectively). Since only one of the parallel edges may be added to T , one of the edges is assigned the cost of the dissimilarity function and the other is assigned " ∞ ". The edge, whose cost is assigned to be " ∞ ", is added to the end of the sorted list and will not be examined. Hence, " ∞ " indicates that no further consideration whether to add it to T is required. Figure 5 illustrates an updating process. When the first edge $e(4,6)$ is added to T , $e(3,4)$, $e(2,4)$ and $e(1,4)$ have to be updated. $f(R_1^{m_1}, R_4^{m_4})$, $f(R_2^{m_2}, R_4^{m_4})$ and $f(R_3^{m_3}, R_4^{m_4})$ are recalculated and the new values, "61", "50" and "28" are the new edge costs, respectively. $e(2,3)$ is the next edge with the minimum weight that is added to T . Four edges have to be updated: $e(2,1)$, $e(2,4)$, $e(3,1)$ and $e(3,4)$. Since $e(2,1)$ and $e(3,1)$ become parallel, we assign to one of them the new value "73" and the other edge is assumed to have " ∞ ". The same is done for $e(2,4)$ and $e(3,4)$. The weight of $e(3,4)$ is "42" and the weight of $e(2,4)$ is " ∞ ".

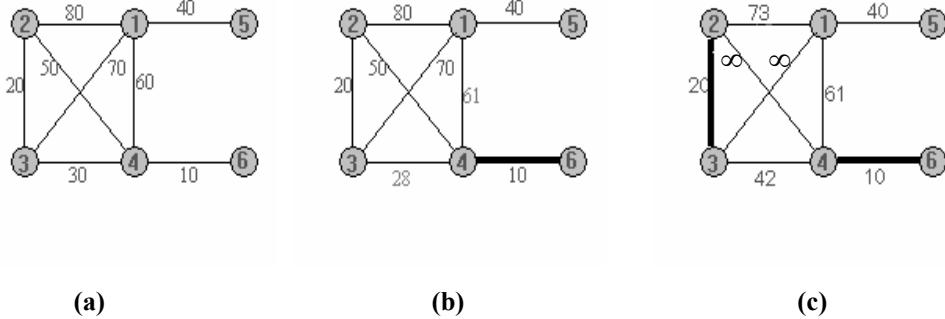


Figure 5: Updating edges during the application of the MST construction. (a) The source graph. (b) Adding $e(4,6)$ to T . (c) Adding $e(2,3)$ to T .

3. Finding Adaptive Local Thresholds

Although the description of the merging process is completed, it should be decided when the process has to be terminated. In other words, it is unknown how to determine which regions should not be merged and when. We describe here an automatic procedure that derives local thresholds by following the changes of each region during the application of the merging process. These thresholds will be the indication whether or not a certain region should be merged. Hence, these thresholds generate the final segmentation.

3.1 The Need for Local Information

Since we consider the segmentation process to be a local operation we can assume that not all the local merges will be terminated simultaneously. The use of one global threshold is insufficient because different regions are usually separated from their surroundings at different times during the process with different thresholds. However, there are some cases, where one global threshold is sufficient. The example in Figure 6 describes an exceptional situation where a good segmentation can be obtained by a single global threshold. This is possible since the image contains one object, which is homogenous in its colored texture, and so is its surrounding background. In this case, one threshold was used in the merging process. The process was terminated when the weight of the examined edge was higher than the chosen threshold, which was set to be 100. The segmentation result is demonstrated in Figure 6b. Since in most of the cases the image contains more than two homogenous regions, it is obvious that it is difficult to predict whether one global threshold can handle a given input image.

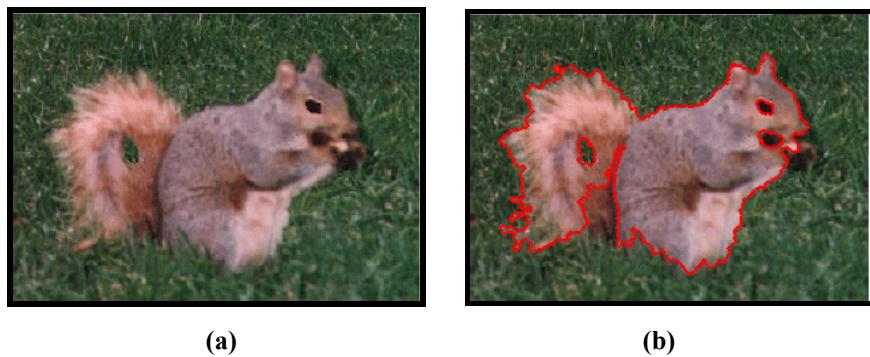


Figure 6: (a) The source image. (b) Segmentation result obtained by the global threshold 100.

Figure 7 illustrates the reason why local thresholds are needed instead of using one global threshold. Figure 7a is the source image. Figure 7b is the output of the watershed algorithm. Figure 7c is the result after using global threshold, $t=20$. Figure 7d is the result after using global threshold, $t=30$. In Figure 7c all the regions are homogenous and can grow. However, as the threshold increases to 30, regions such as the face and the sofa, which are considered visually as homogenous, are still over-segmented, while the region, which is indicated by the yellow arrow, is inhomogeneous. Thus, the construction of that region should be terminated at $t<30$ in order to prevent the merge of the two different homogenous regions: the man's jacket and the sofa.

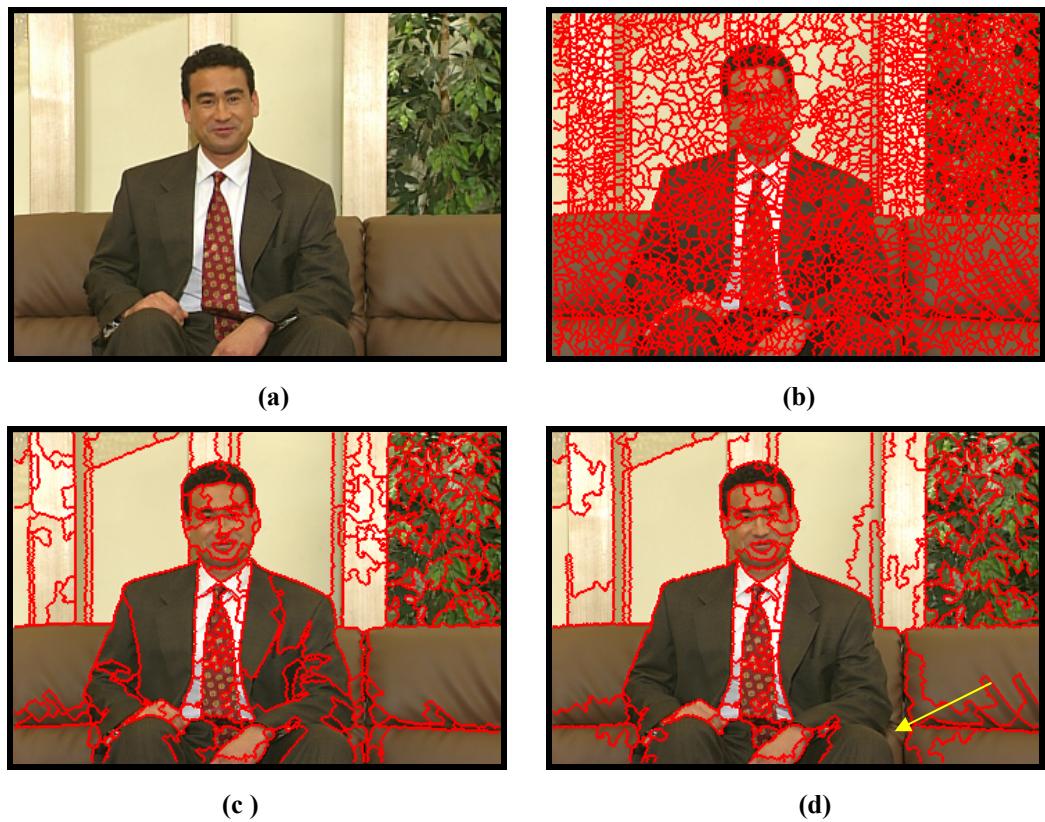


Figure 7: (a) Original input image. (b) After the application of the watershed algorithm. (c) After the completion of the merging process using one global threshold $t=20$. (d) After the merging process using one global threshold $t=30$.

The calculation of local thresholds will be based on local information, which is related to the regions and their surroundings, since regions are affected by their surroundings. The dependency between regions and their surroundings, which causes the same region in different surroundings to be visually different, can be simply demonstrated. In Figure 8a the yellow elliptic object is clearly seen and it is well separated from its background while the same yellow elliptic object with different background is almost invisible in Figure 8b.



Figure 8: The same bright elliptic object appears differently due to its different backgrounds.

3.2 Computation of a Local Adaptive Threshold

We present an automatic method that calculates adaptive local thresholds. The method is based on local properties of the regions during the merging process.

Proposition 1: *A significant change in the homogeneity of a given region occurs during a merge that generates inhomogeneous region. At this merge, local threshold is determined.*

The identification of homogeneity is mainly based on color space. We use the V component of the HSV color space to calculate the variance of the homogeneity of a given region. Let $\mu_v(R_i^{m_i})$ be the mean V value of $R_i^{m_i}$ and let $V(x, y)$ be the value of V in location (x, y) .

The variance of any region $R_i^{m_i} \ i = 1, \dots, n$ after its $m_i - th$ merge is defined as:

$$\sigma(R_i^{m_i}) = \frac{1}{|R_i^{m_i}|} \sqrt{\sum_{(x,y) \in R_i^{m_i}} (V(x, y) - \mu_v(R_i^{m_i}))^2} \quad (4)$$

where $|R_i^{m_i}|$ is the size of $R_i^{m_i}$. We define the change in the homogeneity of $R_i^{m_i}$ after the $m_i - th$ merge to be

$$\Delta\sigma(R_i^{m_i}) = |\sigma(R_i^{m_i}) - \sigma(R_i^{m_i-1})|. \quad (5)$$

Let J_i be the set of K_i local maximums of $\Delta\sigma(R_i^{m_i})$, $m_i = 1, \dots, M_i$.

$$J_i = \{(m_i, \Delta\sigma(R_i^{m_i})) | \Delta\sigma(R_i^{m_i}) > \Delta\sigma(R_i^{m_i-1}) \& \Delta\sigma(R_i^{m_i}) > \Delta\sigma(R_i^{m_i+1})\}. \quad (6)$$

Although no statistical information on the image is given, local information on any region $R_i^{m_i} \quad i = 1, \dots, n$ is obtained from $\Delta\sigma(R_i^{m_i})$. Since the variance is a measure for homogeneity, the merges in J_i represent significant transitions of $R_i^{m_i}$ during the merging process. Given that the merging process begins with over-segmentation of homogeneous regions and the regions are merged until one region is left, every region becomes inhomogeneous at a different merge operation. Hence, we argue that $R_i^{m_i}$ becomes inhomogeneous at the first local maximum in J_i that satisfies:

$$\Delta\sigma(R_i^{m_i}) > \beta \quad (7)$$

where β is the mean value of $\Delta\sigma(R_i^{m_i})$ at every $m_i \in J_i$ defined as

$$\beta = \frac{1}{K_i} \cdot \sum_{m_i \in J_i} \Delta\sigma(R_i^{m_i}). \quad (8)$$

Due to the unique behavior of $\Delta\sigma(R_i^{m_i})$ (see Figure 9) the definition of β enables to reject the local maximums that refer to the merges in which $R_i^{m_i}$ is still homogenous. The three plots in Figure 9 illustrate the behavior of $\Delta\sigma(R_i^{m_i})$ of three different regions of the man's shirt (Figure 7b), which reflects the changes in the homogeneity. The plots describe the values of $\Delta\sigma(R_i^{m_i})$ as a function of the number of the merges. The green arrow in each plot points to the first local maximum, among all the local maximums, that satisfies Eq. (7). In this merge, the shirt region is merged with another region (the bright background) and becomes inhomogeneous. Since these three regions were merged into one region, the values of the plots in Figure 9a and Figure 9b are equal from the fifth merge of Figure 9a and the first merge of Figure 9b. In addition, from the third merge of the region in Figure 9c and from the ninth merge of Figure 9b (or the 13th merge of Figure 9a) the values $\Delta\sigma(R_i^{m_i})$ of the plots in Figure 9c and in Figure 9b are equal. Moreover, the identification of the merge that generates inhomogeneous region, which is equal too, is independent on which region (among all the regions that compose the homogenous region, the man's shirt) we examine.

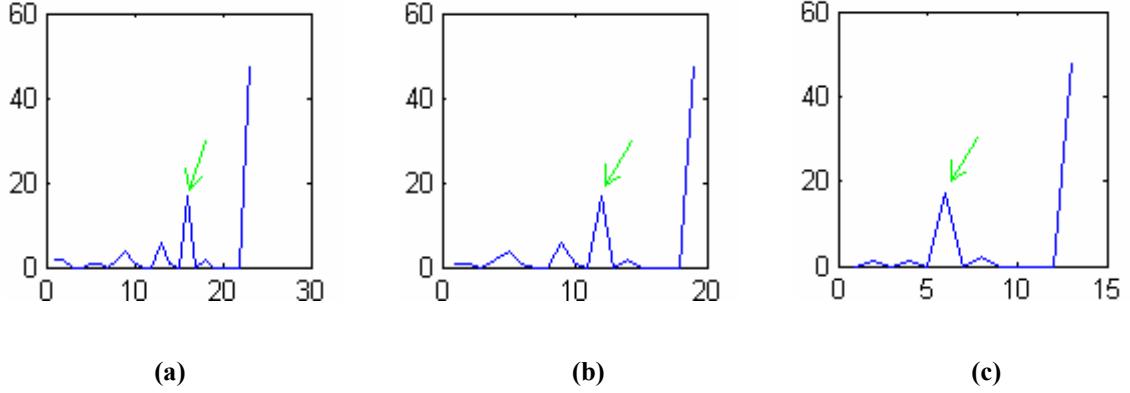


Figure 9: The representation of $\Delta\sigma(R_i^{m_i})$ of three different regions of the man's shirt (from Figure 7b). The x-axis is the number of merges m_i . The y-axis is $\Delta\sigma(R_i^{m_i})$. The green arrow in each plot points to the first local maximum that satisfies Eq.7, among all the local maximums, which indicates the merge where the region becomes inhomogeneous.

The merge that generates inhomogeneous region has to be canceled. Assume that $R_i^{m_i}$ and $R_j^{m_j}$ are the two regions that by their merge inhomogeneous region was generate. A local threshold is derived and its value is the value of $f(R_i^{m_i}, R_j^{m_j})$ of that merge. Because of the merge order any other merge of $R_i^{m_i}$ with any of its neighbors will generates inhomogeneous region. Therefore, this threshold prevents these two regions from being merged during the proceeding operations.

As was mentioned, an iterative process is applied in order to derive the thresholds. More precisely, any iteration obtains a single threshold. Let $s = 1, \dots, K$ be the index of the iterations number. K is currently unknown since the number of thresholds (iterations) is unknown. Let t_s be the threshold of the $s-th$ iteration and let mt_s be the merge that is associated with t_s . During the $s-th$ iteration regions are merged according to the merging process until one region is left (except from “final regions” that are discussed bellow). For every region $R_i^{m_i}$, $i = 1, \dots, n$ we get from that process a map L_i for every $m_i \in \{1, \dots, M_i\}$ to $m \in \{1, \dots, M\}$:

$$L_i : \{1, \dots, M_i\} \rightarrow \{1, \dots, M\} \quad i = 1, \dots, n \quad (9)$$

where M is the total number of merges in the current iteration. $L_i(m_i) = m$ means that the m_i-th merge of $R_i^{m_i}$ is its $m-th$ merge among all the M merges. For example, $m_i = 5$ and $L_i(m_i) = 27$ means that the fifth merge of R_i^5 is the $27-th$ merge among all the M

merges of all regions. For every region $R_i^{m_i}$ let $m'_i \in J_i$, be the first local maximum that satisfies Eq.(7). The mt_s merge of the current threshold is defined to be

$$mt_s = \min_{i=1,\dots,n} \{L_i(m'_i)\}. \quad (10)$$

At the $s-th$ iteration, t_s refers to the first merge among all the merges in the current iteration, that generates inhomogeneous region. If $R_i^{m_i}$ and $R_j^{m_j}$ are the two regions that were merged at the mt_s merge, the value of $f(R_i^{m_i}, R_j^{m_j})$ of that merge is assigned to be the value of t_s . Since t_s prevents the merge of $R_i^{m_i}$ and $R_j^{m_j}$, all the merges from the final merge to the mt_s merge have to be canceled one-by-one. This process is called a *regression process*, and it will be discussed in section 3.3. When the mt_s merge is reached and canceled during the regression process, $R_i^{m_i}$ and $R_j^{m_j}$ are marked as “final regions”, and denoted as R_i^* and R_j^* . They will remain unmerged. Hence, during the next iteration, the merging process proceeds and all the regions, except the “final regions”, are merged into one region, and the next threshold t_{s+1} will be derived. Given that R_i^* and R_j^* are final, all the edges in the sorted list are examined except the edges $\{e(k, m) | k = j \quad or \quad m = i\}$ that are immediately rejected, since adding the edge $e(k, m)$ to T means that either $R_i^{m_i}$ or $R_j^{m_j}$ are being merged. As a result, T at that point is not a tree but contains three forests: 1. R_i^* and its connected nodes. 2. R_j^* and its connected nodes. 3. All the others nodes. Note that T is a spanning forest such that by adding edges from $\{e(k, m) | k = j \quad or \quad m = i\}$ a minimum spanning tree is generated. The iterative process, which consists of merging process, derivation of local threshold and regression process, is terminated when no regions to be merged are left and all the regions are marked as “final regions”.

3.3 The Regression Process

During the regression process we remove edges from T . This is done in a reverse order to the order they were added: edges are removed from bottom to top. Adding $e(i, j)$ to T means that $R_i^{m_i}$ and $R_j^{m_j}$ are merged to create $R_{ij}^{m_j}$; removal of $e(i, j)$ from T means a split

of $R_{ij}^{m_{ji}}$ into two different regions $R_i^{m_i}$ and $R_j^{m_j}$. Hence, all the edges that were added to T are saved in the order they were added. We save these edges in a “merging tree” denoted by MT . The root of MT represents the single region that was obtained at the end of the merging process and all its leaves correspond to the nodes of G . At the beginning MT contains only leaves, and it is constructed from its leaves to the root. Each merge operation creates a new node. This node represents the ancestor of the two regions that were already merged. Figure 10 illustrates the MT construction, which is done in parallel to the construction of the MST of G (the corresponding graph is presented in Figure 5a). Figure 10a is the MT at the beginning of the merging process. Only the leaves that correspond to the nodes of G are included. The new node in Figure 10b, which points to its two descendants $R_4^{m_4}$ and $R_6^{m_6}$, was created when $e(4,6)$ (see Figure 5a) was added to T . The new node in Figure 10c, that points to its two descendants $R_2^{m_2}$ and $R_3^{m_3}$, was created when $e(2,3)$ was added to T . The final form of MT is presented in Figure 10d. MT is constructed by two operations:

- $\text{MTAdd}(e(i,j))$: Generates a new node $R_{ij}^{m_{ji}}$ which is the father of $R_i^{m_i}$ and $R_j^{m_j}$.
Saves $e(i,j)$.
Updates LastP: LastP points to $R_{ij}^{m_{ji}}$.
- $\text{MTLast}()$: Returns the node pointed by LastP and removes it from MT .

where LastP is a pointer to the last node that was generated and has to be updated when $\text{MTAdd}(e(i,j))$ or $\text{MTLast}()$ are invoked.

The operation $\text{MTAdd}(e(i,j))$ is invoked when $e(i,j)$ is added to T during the merging process. When the merging process is terminated MT is fully constructed and the regression process can be applied. Throughout the regression process, $\text{MTLast}()$ is called until it returns the region that corresponds to the current threshold. The region $R_{ij}^{m_{ji}}$, that returns by $\text{MTLast}()$, is split into its two descendants: $R_i^{m_i}$ and $R_j^{m_j}$ ($e(i,j)$ is removed from T). When $\text{MTLast}()$ returns a node that corresponds to the last threshold, the regression

process is terminated. Its two descendants are marked as "final regions". Since the regression process is applied in each iteration, MT is constructed in parallel to the merging process and it used in every regression process. When the iterative process is terminated, the unmerged nodes in MT represent the "final regions".

When the edge $e(i, j)$ is added to T , the set of edges $E_{i,j} = \{e(i,k) \cup e(j,p) \mid R_k^{m_k} \in N(R_i^{m_i}), R_p^{m_p} \in N(R_j^{m_j})\}$ is updated with the new weights of the edges. When $e(i, j)$ is removed from T , the weights of the edges in $E_{i,j}$ are reassigned with the original weights (which are the weights before $e(i, j)$ was added to T). Therefore, the reconstruction of G by the merge of $R_i^{m_i}$ and $R_j^{m_j}$ required that $E_{i,j}$ will be saved by MTAdd($e(i, j)$) procedure. Parallel edges, whose weights are " ∞ ", are not saved since they are not going to take part in any future merging procedures.

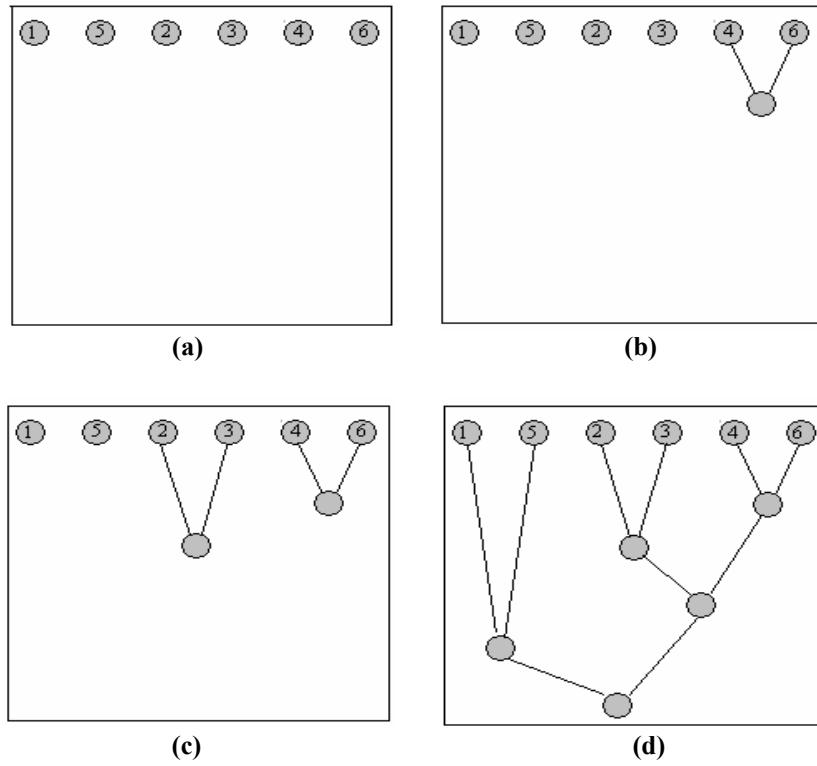


Figure 10: The MT construction process that corresponds to the MST construction of the graph in Figure 5a. (a) MT at the beginning. Only the leaves are included. The new node in (b), which points to its two descendants $R_4^{m_4}$ and $R_6^{m_6}$, was created when $e(4,6)$ (see Figure 5a) was added to T . The new node in (c), that points to its two descendants $R_2^{m_2}$ and $R_3^{m_3}$, was created when $e(2,3)$ was added to T . (d) The final MT .

3.4 From local thresholds to adaptive algorithm

The computation of local thresholds is an automatic process, which comes from the combination of local consideration and the proposed technique. As we have already mentioned, the number of thresholds is known only when the process is terminated. Using local information does not necessarily associate with automatic procedure. At [18] for example, local information is considered to define homogeneity histogram. Then, peak-finding algorithm is employed to identify the most significant peaks. Since it uses predefined constant thresholds, significant global peaks are detected. As a result the obtained regions are divided in the next step. The use of local information in every step of our proposed method is actually a study process of the image. The input to the merging process (the over-segmentation generated by the watershed algorithm) and the order of the merges (of minimum spanning tree construction) enable to investigate the growing regions: the information is saved, updated and examined. At any iteration, where single threshold is derived, a specific region is regarded. The final segmentation of this region is defined (by 'final region') while the examination process of the other regions of the image continues similarly. As a result, this automatic study process derives adaptive thresholds, which produce adaptive segmentation. Hence, the proposed algorithm is an adaptive algorithm. Since good results are obtained by adaptive algorithms our algorithm performs well on different kind of images; low contrast images (regions) are segmented (defined) as well as height contrast images (regions).

4. Implementation and Complexity

In this section we describe the flow of the algorithm followed by time complexity analysis.

4.1 Algorithmic Implementation

Notation:

I is the input color image, $s = 1, \dots, K$ is the index of the derived thresholds (set to 1). The set $R_i^{m_i}$, $i = 1, 2, \dots, n$, $m_i = 1, 2, \dots, M_i$, represent the regions during the merging process where M_i is the number of merges of the region $R_i^{m_i}$ of the current iteration. R_i^* , $i = 1, 2, \dots, n^*$ is the n^* "final regions", which is the algorithm output.

Process:

1. Apply Canny edge detector on the gray level image of I . Its output I_G is the image gradients.
2. Apply the watershed algorithm on I_G to get an initial partition of I . The set $R_i^0, i = 1, \dots, n$ are the image partition after the application of the watershed algorithm.
3. Construct a RAG, denoted by G , to represent the partition of I .
4. Merge regions:
 - a. Merge the regions into one region (except the “final regions”). The merging order is based on Kruskal’s MST algorithm, using the dissimilarity function $f(R_i^{m_i}, R_j^{m_j})$ (Eq.(2)).
 - b. Construct the “merging tree” denoted by MT .
 - c. For any region $R_i^{m_i}$ save the set J_i of K_i local maximums of $\Delta\sigma(R_i^{m_i})$, $m_i = 1, \dots, M_i$ that were calculated using Eq.(6). For every $m_i \in J_i$ save its $L_i(m_i)$.
5. Calculate the $s - th$ threshold :
 - a. For any region $R_i^{m_i}$ calculate β by Eq.(8) and then detect the first $m'_i \in J_i$ that satisfies Eq.(7).
 - b. For any region $R_i^{m_i}$ use the map L_i in Eq.(9) to detect the mt_s merge (defined by Eq.(10)), which is associated with the t_s threshold. Assume that $R_i^{m_i}$ and $R_j^{m_j}$ are the regions that correspond to t_s .
 - c. $t_s = f(R_j^{m_j}, R_i^{m_i})$.
6. Apply the regression process: remove all the merges from bottom to top, using the MT data structure, until the merge of $R_i^{m_i}$ and $R_j^{m_j}$, which is related to the last threshold, is reached.
7. $R_i^{m_i}$ and $R_j^{m_j}$ are defined as “final regions” and denoted by R_i^* and R_j^* , respectively.

8. If regions to be merged remain, set $s = s + 1$ and repeat step 4. Otherwise, terminate the process and let $R_i^*, i = 1, 2, \dots, n^*$ be the segmentation result.

4.2 Complexity Analysis

The overall time complexity of the algorithm is $O(N + K \cdot |E| \log |E|)$ where $|E|$ is the number of edges in G , N is the image size and K is the number of iterations. Next we analyze the complexity for the most expensive steps in the algorithm.

The time complexity of the watershed algorithm is linear in the image size N . A discussion on its complexity is given in [33]. Any iteration contains the merging process, the derivation of the current threshold and regression. The merging process takes $O(|E| \log |E|)$ operations, which is the sum of the following three procedures:

1. Sorting the edges of G requires $O(|E| \log |E|)$ operations.
2. Updating the sorted list requires $O(nC \log |E|)$ operations: If C is the maximum degree in G then, when an edge is added to T , $O(C)$ edges in the sorted list are updated. If the sorted list is implemented by a heap data structure, the update can be done in $O(C \log |E|)$ operations. Hence, for the worst case, which contains $n - 1$ merges we get $O(nC \log |E|)$ operations.
3. The construction of MT requires $O(nC)$ operations: Since $n - 1$ edges are added to T , MT is built in $n - 1$ operations. Each operation follows by adding a new node, which is done in $O(1)$ operations. Saving the edges of the merged regions requires $O(C)$ operations.

The total complexity of the above three procedures is $O(|E| \log |E| + nC \log |E| + nC)$. Since $|E| = O(nC)$ the complexity is $O(|E| \log |E|)$.

When the merging process is completed, the current threshold is derived in $O(n)$ operations: β is calculated in $O(n)$ operations, which is the number of regions that have been merged in the worst case (the first iteration). Then, for every region $R_i^{m_i}$ we scan all its merges to detect the merge $m_i \in J_i$ that is the first merge that satisfied Eq.(7). For the n

regions $O(n^2)$ operations are required. Finally, using Eq.(10) mt_s is derived in $O(n)$ operation. We reduce $O(n^2)$ to $O(n)$ as follows: For every region $R_i^{m_i}$ we save the set J_i and β value such that a direct access to $m_i \in J_i$ and its $\Delta\sigma(R_i^{m_i})$ takes $O(1)$ operations. In addition, we use an array of size M such that the $m-th$ entry, $m = 1, \dots, M$, represents the pair (m_i, m_j) , where $R_i^{m_i}$ and $R_j^{m_j}$ are the two regions that are merged such that $L_i(m_i) = m$ and $L_j(m_j) = m$. For example $m = 31$ and $(5,8)$ means that the $31-th$ merge among all the merges is the fifth merge of $R_i^{m_i}$ and is the eighth merge of $R_j^{m_j}$. Then, by one scan of this array mt_s is derived. Hence, it is un-necessary to find the first local maximum of every region that first satisfies Eq.(7). Since M in the worst case is $O(n)$, one scan of the array requires $O(n)$ operations.

In each step during the regression process the last new region is deleted from MT in $O(1)$ operations. Since the worst case demands a removal of $n-1$ previous merges and update of $O(C)$ edges (in the heap) during each step then, the total number of operations for the regression is $O(nC\log|E|)$. If the number of iterations is K , then the whole iterative process takes $O(K \cdot |E|\log|E|)$ operations. By adding to it the time complexity of the watershed transform, the overall complexity is $O(N + K \cdot |E|\log|E|)$. Some examples and further discussion on execution time are given at the experimental results section (section 5.2).

5. Experimental Results

5.1 Step-by-Step Execution of the Algorithm

Figure 11, Figure 13 and Figure 14 demonstrate step-by-step the intermediate results of the segmentation process. Different types of images with different homogenous areas were chosen in order to demonstrate the advantages of using local thresholds.

Figure 11 demonstrates step-by-step the results during the application of the algorithm on “Clair” video sequence (Figure 11a). Figure 11b is the over-segmentation generated by the application of the watersheds algorithm. Figure 11c shows the result after the detection of the first local threshold t_1 , which generates the “final regions” R_1^* and R_2^* . Figure 11d shows the result after finding the second threshold t_2 , that generates the regions R_3^* and R_4^* . Figure 11e, shows the result after finding t_3 that generates the regions R_5^* and R_6^* . The regions that are pointed by the red arrows in Figure 11e are not associated with any threshold. Since they are surrounded by “final regions” they remain unmerged.

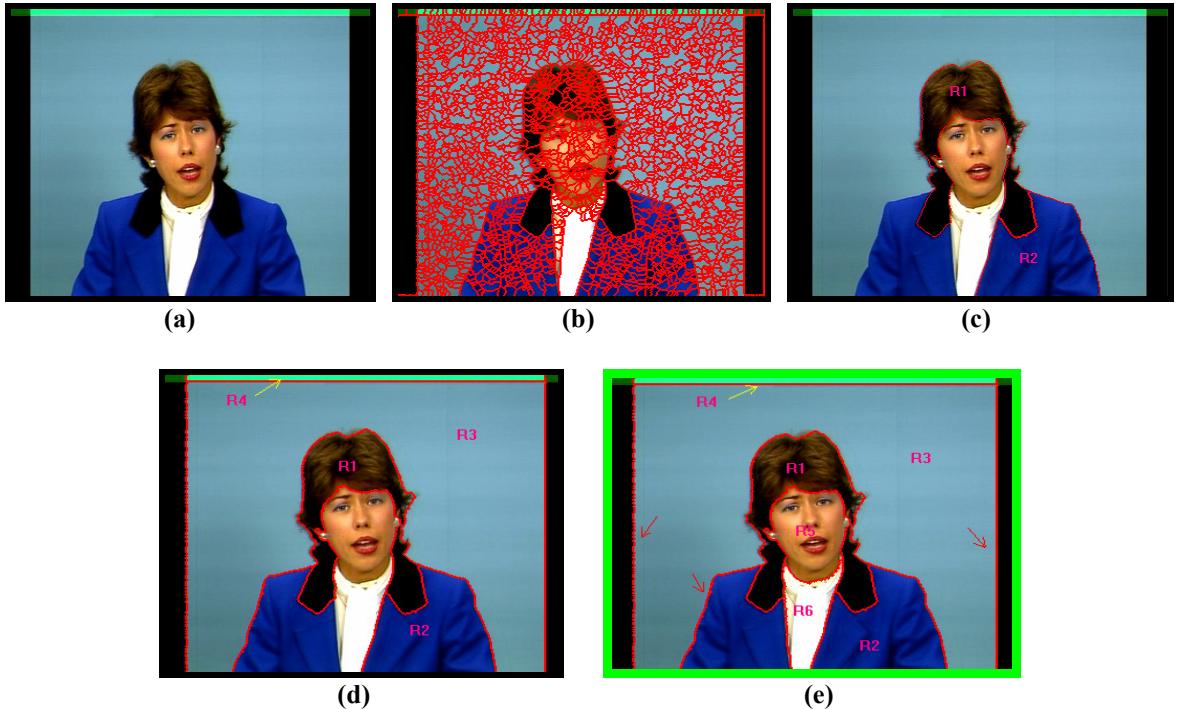


Figure 11: Intermediate results of the segmentation process on the input image(a). (e) represents the final segmentation output.

The values of $\Delta\sigma(R_i^{m_i})$ of the three regions, which are associated with the three thresholds (Figure 11), are represented by the three different plots in Figure 12. The green arrow in each plot points to the merge, from which the threshold is derived. This merge is the first that satisfies Eq.(7), among all the local maximums, that generates an inhomogeneous region. Since every threshold is derived in a different iteration, each plot represents the merges in different iteration.

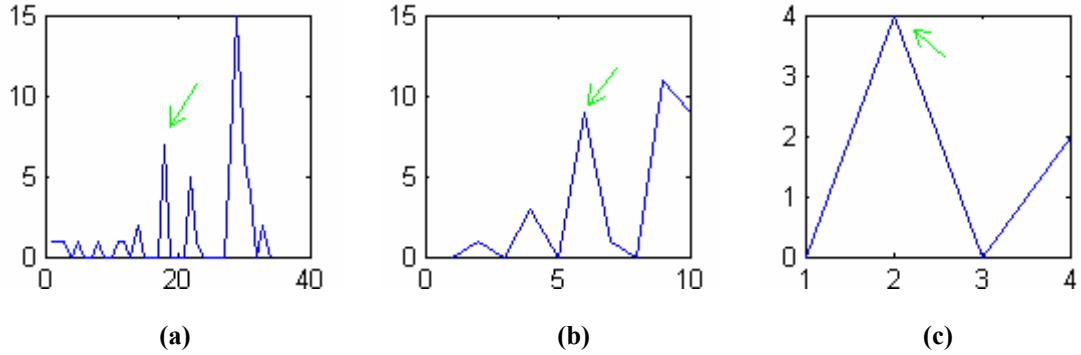


Figure 12: The values of $\Delta\sigma(R_i^{m_i})$ of the three regions, which are associated with the three thresholds (Figure 11). The x-axis is the number of merges m_i . The y-axis is $\Delta\sigma(R_i^{m_i})$. The green arrow in each plot points to the merge, from which the threshold is derived.

Figure 13 and Figure 14 demonstrate step-by-step the result of the segmentation process of two different images. The input images are Figure 13a and Figure 14a. The outputs from the algorithm (that are bounded by the green borders) are given by Figure 13f and Figure 14f. Figure 13a was segmented into 16 different regions. Figure 14a was segmented into 12 different regions. Note that not all the results from all the iterations are given. Only four arbitrary iterations were picked.

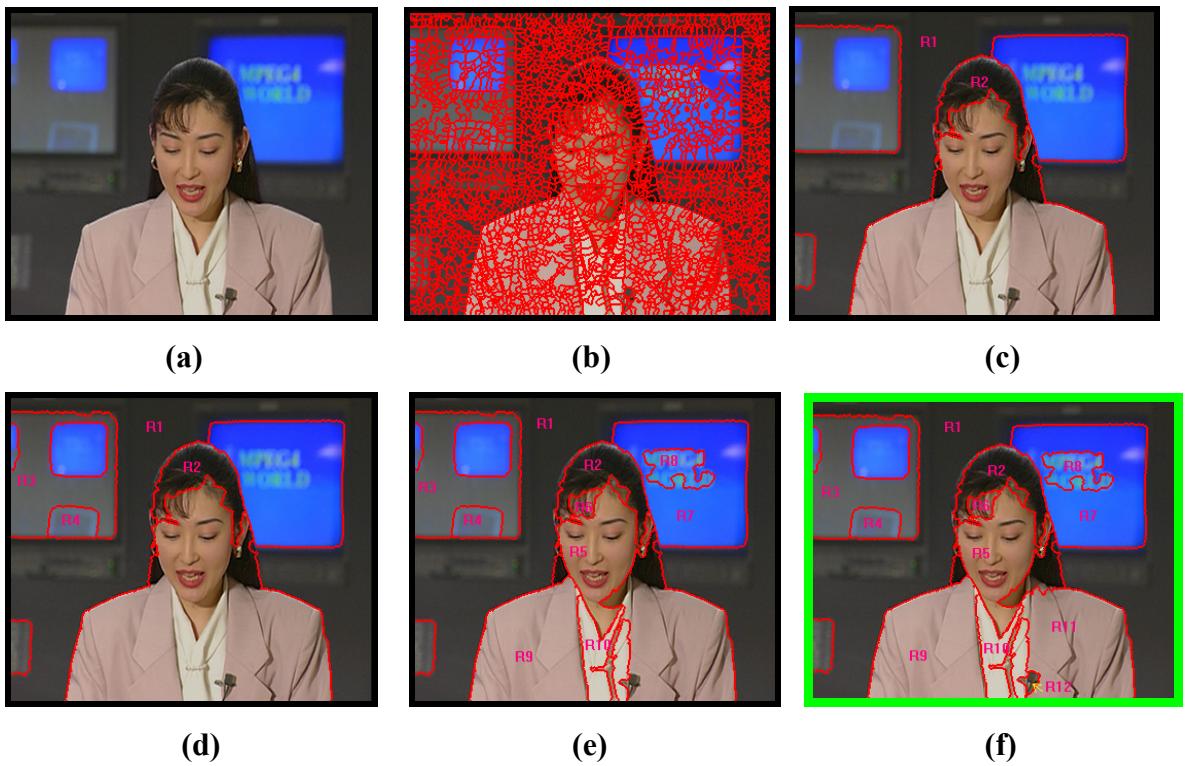


Figure 13: Step-by-step results of the segmentation process that operates on the input image (a). (e) is the final segmentation output.

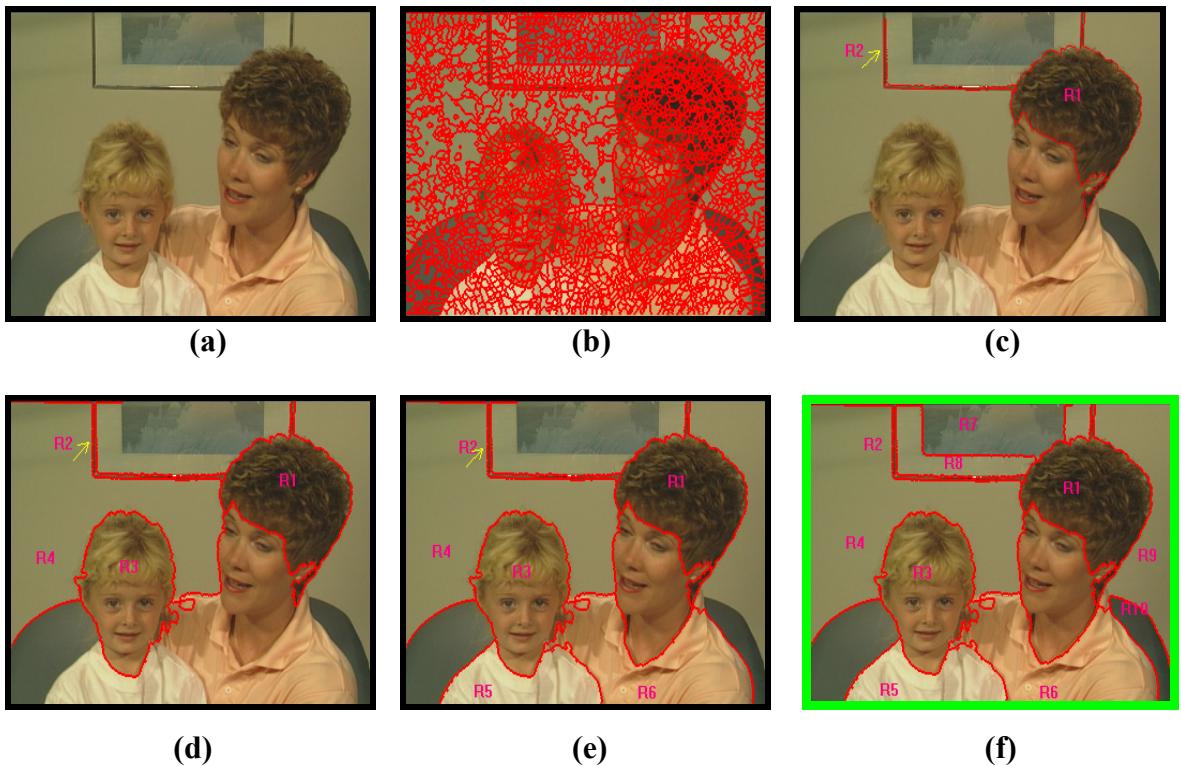


Figure 14: Step-by-step results of the segmentation process that operates on the input image (a). (e) is the final segmentation output.

5.2 Final Results

Segmentation results of variety of images are illustrated in Figure 15 and Figure 16. The images are characterized by different color homogeneity. Since the variance of the performance of the algorithm is low, images with low contrast regions are segmented as well as images with height contrast regions. The left images are the input and the right images are the final segmentation results.

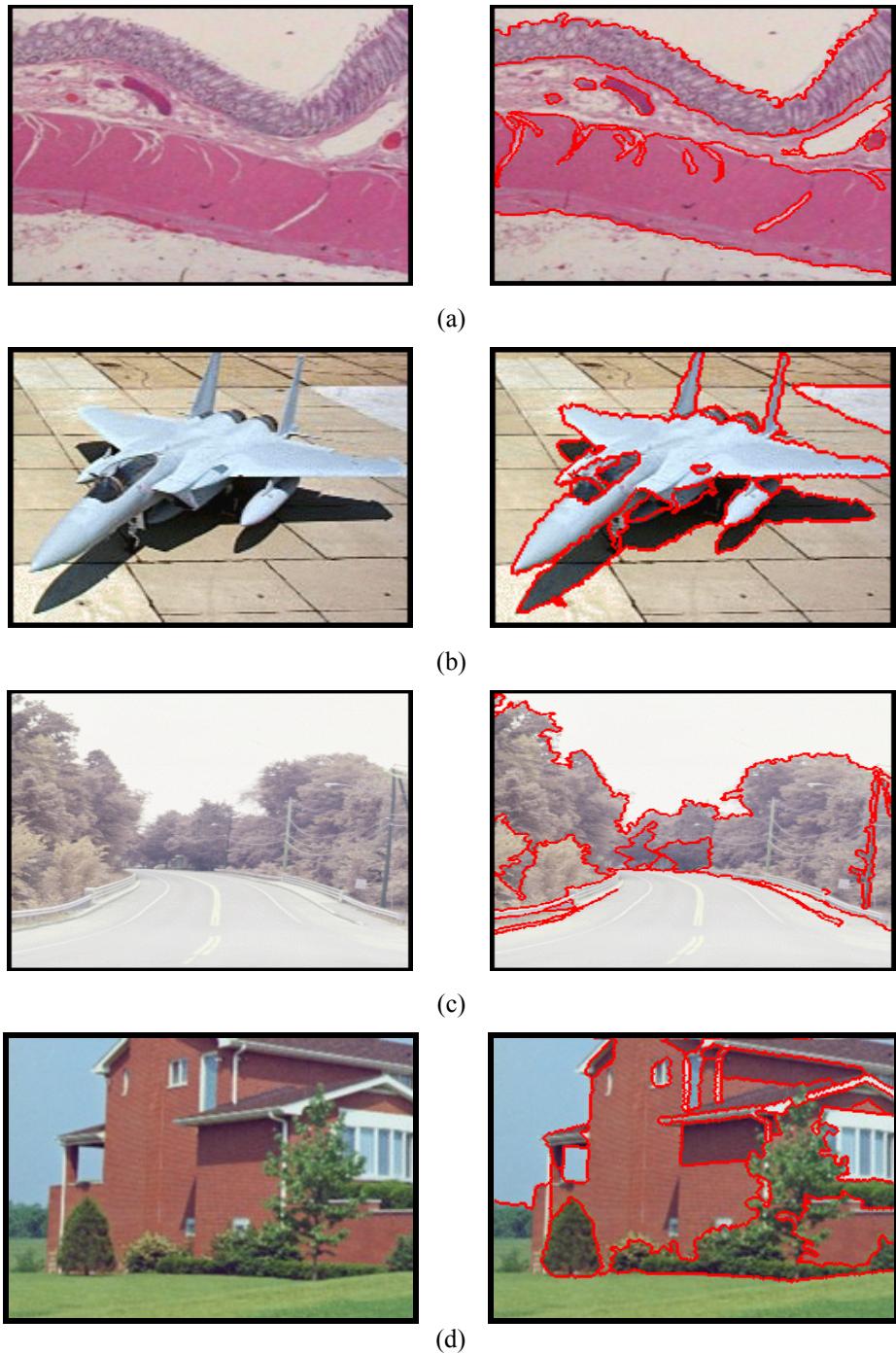


Figure 15: Final results after the application of the segmentation algorithm.

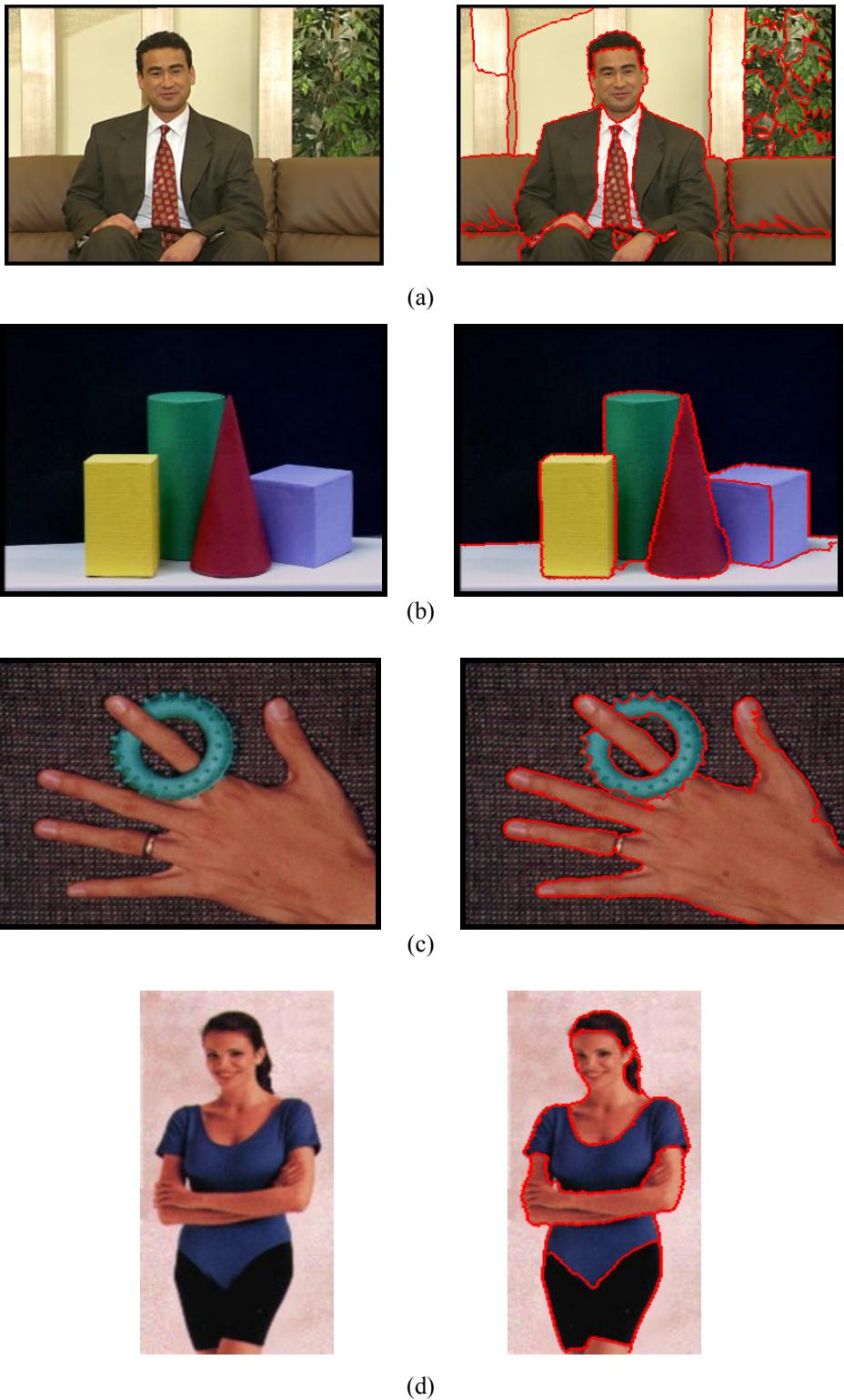


Figure 16: Final results after the application of the segmentation algorithm.

The proposed algorithm was implemented in *C++* programming language on a *Pentium 3* 800 MHz computer. Table 1 shows execution times (see complexity analysis in section 4.2) of the algorithm on different images (presented in this section) and the main variables of the

algorithm: the image size (N), the number of regions (n) that is generated by the watershed and the number of thresholds/iterations (K) of the main iterative process. The values of n are illustrated for the values of E , which is included at the complexity analysis, since $|E| = O(nC)$ and experimentally the average maximal value of C found to be 9. Note that although any threshold defines two 'final regions' the number of regions of the segmentation in any image is not necessary $2K$ due to the order in which final regions are generated. For example see the regions that are pointed by the red arrows in Figure 11e. Regarding the execution time of the algorithm, which depends also on the number of regions (n), the three plots in Figure 17 illustrate the number of regions at any iteration during the iterative process of three different images (Figure 16a, Figure 16c and Figure 16d). It is clear that the major reduction at the number of regions is accomplished by the first iteration. For example, in Figure 17a at the beginning of the iterative process the number of regions n is 1991. After the first iteration it reduces to 83, after the second iteration it reduces to 71 etc'. This is justified from the fact that the input to the iterative process is the over-segmentation generated by the watershed algorithm. Thus, the over segmentation is significantly reduced by the first iteration, while the number of regions is gradually decreased during the next iterations. As a result, among all the iterations, the execution time of the first iteration is affected by the over-segmentation.

Based on experiments on large number of different images the coefficients w_1 (for the color component) and w_2 (for the gradient magnitude component) of the dissimilarity function (Eq.(2)) set to 0.8 and 0.2, respectively. Since the thresholds derived adaptively, the segmentation result is not sensitive to w_1 and w_2 . Different values of w_1 and w_2 have an affect only on the growing regions during the merging process. However, as long as the regions grow and become homogenous (and the gradients become stronger) the differentiation between w_1 and w_2 is negligible since colors and gradients usually depend on each other. Figure 18 illustrates the growing region for three different values of w_1 and w_2 : $w_1=0.8$ and $w_2=0.2$, $w_1=0.2$ and $w_2=0.8$, and equal values, $w_1 = w_2 = 0.5$ (Figure 18b, Figure 18c and Figure 18d, respectively). The examples are taken from the first iteration, at some arbitrary step (when the first experiment is stopped at some random step the value of the dissimilarity function is exemplified and used for the next two cases). At the three cases some different regions exist; more regions caused by weak edges are generated as long as

w_2 increases. However, the same segmentation result (Figure 18e) is obtained at the three experiments.

| Image | image size (N) | N | (K) | total time (seconds) |
|-------------------|------------------|------|-----|----------------------|
| Figure 11a | 352×289 | 660 | 3 | 0.5461 |
| Figure 13a | 352×289 | 948 | 6 | 0.5214 |
| Figure 14a | 352×289 | 1544 | 5 | 0.6009 |
| Figure 15a | 256×242 | 1983 | 7 | 0.4257 |
| Figure 15b | 215×158 | 2002 | 7 | 0.2698 |
| Figure 15c | 256×256 | 2131 | 4 | 0.3586 |
| Figure 15d | 255×192 | 1383 | 8 | 0.3192 |
| Figure 16a | 375×267 | 1991 | 13 | 0.6342 |
| Figure 16b | 256×256 | 246 | 3 | 0.3584 |
| Figure 16c | 303×243 | 3755 | 2 | 0.6271 |
| Figure 16d | 116×261 | 545 | 3 | 0.1897 |

Table 1: Experimental results of different images: Image size (N), number of regions (n) generated by the watershed, the number of thresholds (K) and execution time.

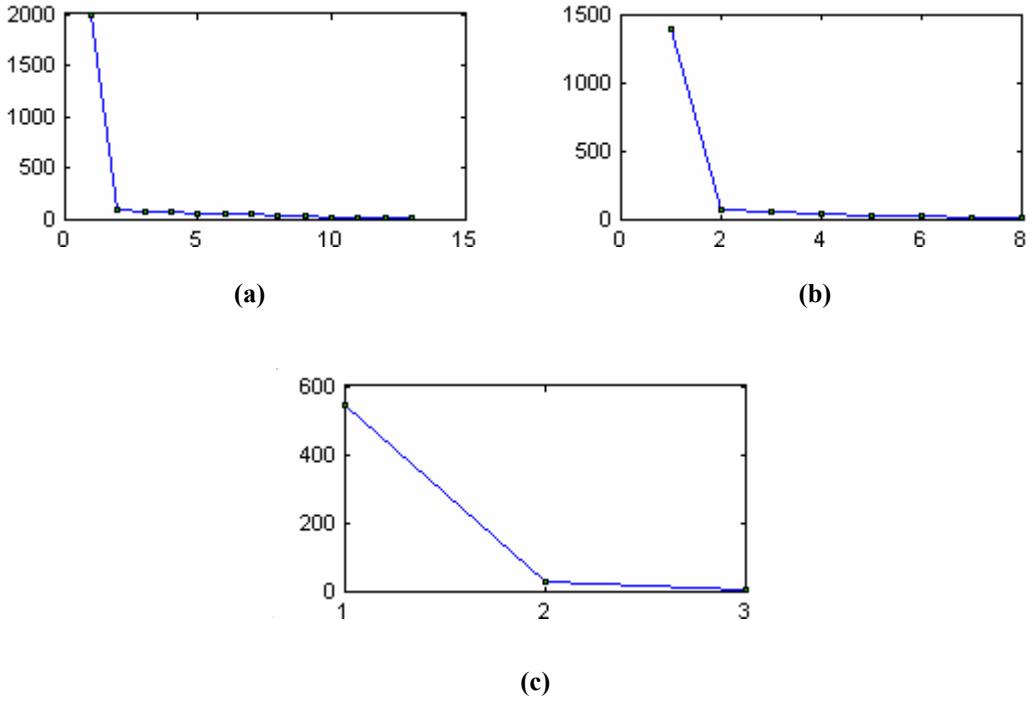


Figure 17: (a), (b) and (c) illustrate the number of regions (y-axis) after any iteration (x-axis) of three different images: Figure 16a, Figure 16c and Figure 16d, respectively. The major reduction at the number of regions, which is accomplished by the first iteration at all the examples, represents the reduction of the over segmentation.



Figure 18: The same segmentation (e) is obtained although different values for of w_1 and w_2 are used. The growing regions at the first iteration at some arbitrary step are illustrated: (a) the source image. (b) $w_1=0.8$ $w_2=0.2$ (c) $w_1=0.2$ $w_2=0.8$ (d) $w_1 = w_2 = 0.5$.

6. Conclusions

In this paper we propose a new approach to color image segmentation. The algorithm integrates edges and region-based techniques while local information is considered. The local consideration enables to derive local thresholds adaptively such that any threshold is associated with a specific region. As a result, the quality of the segmentation is improved. The algorithm is composed of two stages. In the first stage, the watershed algorithm is applied. Its segmentation result is represented by RAG data structure and is used as an initialization for the next stage. An iterative process that derives the thresholds is the second stage. Any iteration consists of a merging process, derivation of threshold and regression process. During the merging process attributes of homogeneity of each region are saved in order to identify when inhomogeneous regions are generated. Then a threshold, which is associated with the first merge that generates inhomogeneous region, is derived. The number of thresholds is automatically determined during the process, which is also automatically terminated. The output of the algorithm is the “final regions” that are determined by the thresholds. The algorithm is robust for large variety of color images.

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