Segmentation of Color Images Using Multiscale Clustering and Graph Theoretic Region Synthesis

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***Abstract*—A multiresolution color image segmentation approach is presented that incorporates the main principles of region-based segmentation and cluster-analysis approaches. The contribution of this paper may be divided into two parts. In the first part, a multiscale dissimilarity measure is proposed that makes use of a feature transformation operation to measure the interregion relations with respect to their proximity to the main clusters of the image. As a part of this process, an original approach is also presented to generate a multiscale representation of the image information using nonparametric clustering. In the second part, a graph theoretic algorithm is proposed to synthesize regions and produce the final segmentation results. The latter algorithm emerged from a brief analysis of fuzzy similarity relations in the context of clustering algorithms. This analysis indicates that the segmentation methods in general may be formulated sufficiently and concisely by means of similarity relations theory. The proposed scheme produces satisfying results and its efficiency is indicated by comparing it with: 1) the single scale version of dissimilarity measure and 2) several earlier graph theoretic merging approaches proposed in the literature. Finally, the multiscale processing and region-synthesis properties validate our method for applications, such as object recognition, image retrieval, and emulation of human visual perception.**

***Index Terms*—Clustering, graph theory, image segmentation.**

I. Introduction

IMAGE segmentation is an essential first step in low-level vision that is very significant for object recognition and tracking, image retrieval, face detection, and other computer-vision-related applications. Segmentation is primarily used to achieve a compact, object-based description of the image scene that preserves significant image information. In that respect, the input image is divided into a disjoint set of physically meaningful, quasi-homogeneous regions. The partition is made according to some perceptual attributes like color, boundary information, or a certain application-dependent region uniformity criterion. Very often, segmentation is required to be carried out in an unsupervised manner or to produce a hierarchical and multiscale representation of the image content. Frequently, some perceptual criteria need to be considered too, since humans usually evaluate the final results. The complexity of the image field and the increase in dimensionality introduced by color or multispectral components of images introduce additional difficulties in the segmentation task. It is, thus, no surprise that image segmentation has been an active area of research over so many years and that many different techniques have been proposed in literature [2], [3], [6], [9], [11]–[17], [22], [23], [25]–[30]. Among all these methods, several segmentation surveys [3], [17] have concluded that the most efficient algorithms may be classified into the categories of clustering and spatial-based approaches.

Clustering techniques were the ones that appeared earlier in the literature and were used in numerous applications [7], including image processing [5], [17], [20], [29]. Following the selection and calculation of the image features, usually based on color or texture, clustering operates on the feature space in order to capture the global characteristics of the image. Ignoring spatial information and using a specific distance measure, the feature samples are handled as vectors and the objective is to group them in compact but well-separated clusters. After the clustering process is completed, the data samples are mapped onto the image plane to produce the final regions. In the ideal case, the estimated clusters correspond to consistent and meaningful regions of the image. However, for the case of natural images, the data-clustering problem is quite complex and the literature of clustering algorithms is very rich [7]. The method known as K-Means and its fuzzy counterpart Fuzzy C-Means [1] are some of the most common techniques in the segmentation field. Based on the assumptions that the number of clusters is *a priori* known and the shape is approximately spherical, these algorithms converge to the final cluster centers. Another popular category of clustering algorithms recently employed for image segmentation applications are known as nonparametric clustering methods [4], [18], [20]. These algorithms attempt to locate the cluster centers based on the observation that significant features of the image correspond to high probability density areas of the feature space. Density is estimated using nonparametric techniques [18] and these methods are well suited for unsupervised clustering-based segmentation, where the number and shape of the data clusters is unknown [20]. Nevertheless, these algorithms imply increased computational cost due to the difficulty in locating the density peaks and assigning image data to the nearest peak. Clustering-based segmentation algorithms in general also have a serious drawback. Pixels from disconnected areas of the image can be grouped together, if there is an overlap in their feature space values. As a consequence, several noisy areas and incomplete region borders are produced in the segmentation results.

In the category of spatial-based methods, the segmentation algorithm is applied on the image plane and the connectivity information is retained. When an algorithm is based on region

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entities, the corresponding method is called region based. Representation using region elements is finding an increasing number of applications in computer vision. The Watershed algorithm [11]–[13], [27] is an attractive technique used extensively for region-based segmentation. According to this approach, the image is interpreted as a topographic relief and the Watershed algorithm is applied to the intensity or color gradient to track the region boundaries. Its popularity is based on the following basic advantages: it partitions the image into connected regions, produces one-pixel-width closed contours with accurate delineation, and retains the one to one correspondence relation between the gradient minima and the regions. The unavoidable disadvantage of Watershed is the so called oversegmentation effect, i.e., a very large number of rather small but quasi-homogenous regions is produced. A prefiltering—usually smoothing—operation might be applied to moderate this effect. Nevertheless, this operation reduces the edge precision and significant object boundaries may be eliminated after the Watershed algorithm is applied, since the gradient estimate does not have the same magnitude along the whole boundary. A possible solution to that problem would be to select markers in order to produce meaningful regions [13]; however, this implies a nonautomatic process. Another more efficient option is to apply a merging algorithm on these regions and produce the final partition. A merging scheme requires a region representation structure, calculation of region features and the interregion dissimilarity function, and, finally, the (merging) algorithm to produce the final regions. This region synthesis procedure is not simple though, as it represents a combinatorial optimization problem.

An efficient spatial representation of an oversegmented image is the region adjacency graph (RAG) structure [24]. Nodes of this graph represent regions, while edges contain the interregion dissimilarity relation. A usual region feature is the color estimate and, as graph edge metric is employed, the vector distance. This complex structure has to be simplified by successive merging steps between neighboring regions. Using the RAG, these merging operations are performed on a local scale and, unless guided by global image information, can lead to suboptimal solutions that correspond to erroneous segmentation results.

An interesting structure that emerges from the RAG and has been applied to spatial segmentation approaches was the minimal (or shortest) spanning tree. In the essential work of Morris *et al.* [15], several applications of the shortest spanning tree (SST) were presented. In [28], they were generalized for color images, and in [9], a fast version of the recursive SST (RSST) algorithm was proposed. Another interesting graph-based algorithm proposed in the literature is known as the graph cuts (Shi and Malik) [23]. According to that work, the image is segmented by minimizing a cost associated with cutting the graph into subgraphs. The degree of similarity between two sets can be computed as the total weight of removed edges. An additional approach is the binary partition tree [22], a hierarchical structure that can be used for filtering, retrieval, segmentation, and coding purposes. Furthermore, other approaches propose to operate in a varying manner (adaptively to different image regions [6]). Apart from that, some interesting graph theoretic approaches have been proposed for clustering algorithms too [7], [29].

Images in general have a hierarchical structure and it is well known that a multiple scale representation of image information is useful in many applications, mainly due to the multiscale nature of the human vision. Various multiple resolution segmentation structures have been proposed, such as the Quadtree, Pyramid, Wavelet, and Scale Space approaches. It was indicated that multiresolution schemes produce more efficient results than single resolution methods in several applications such as edge and blob detection [10], segmentation [12], [26], compression (Quadtree, Wavelet coding), etc. In the domain of segmentation, multiresolution schemes produce more efficient results than single scale approaches, and are suitable for estimating the scale of interest for a specific processing task, e.g., to find the localization scale in scale space approaches. A shortcoming of the spatial-based approaches is that the representation of multiscale information using the RAG structure and the linking between different scales is a computationally demanding process. In this case, clustering can be used advantageously, since it is relatively simple to be defined at different resolutions. Based on this idea, in [20], a multiresolution-based clustering approach was proposed to analyze the pixel data using parametric and nonparametric approaches.

Moreover, in [17] and [3], it was also concluded that fuzzy logic represents a flexible framework that manipulates ambiguity in knowledge, suitable for image analysis and segmentation applications in particular. It can incorporate the color and spatial uncertainty and guide the segmentation process. In the past, some fuzzy clustering algorithms [1], [16] were introduced that had a reasonable effect on several following works. Years later, several spatial segmentation methods were presented, such as fuzzy region growing [14], segmentation using fuzzy affinity relations [2], [25] that produced efficient results. In addition, the region dissimilarity function and the whole merging process can be directed by fuzzy rules as indicated in [12].

In this paper, a hybrid algorithm is proposed that combines the concepts of multiresolution fuzzy clustering and region-based graph segmentation to produce the final regions. Our intention is to introduce a method that incorporates the efficient analysis of global image characteristics and, especially at multiple resolutions, provided by the clustering algorithms, with the significant topological information of region-based graph representation using a merging algorithm. As a result, the contribution of this paper is the introduction of a multiresolution clustering scheme and an original graph theoretic segmentation method. The proposed scheme is outlined as follows.

The Watershed algorithm is routinely employed to produce the initial regions and the feature vectors are calculated over the Watershed regions that define the starting point of our method. The clusters formed by the initial region features are estimated via the Fuzzy C-Means (FCM) algorithm [1]. The latter uses, as initial conditions, the cluster validity given by nonparametric cluster analysis, i.e., mountain clustering [4]. The multiple resolutions are iteratively generated in the employed feature space by increasing the resolution parameter of the mountain-clustering process. The multiscale membership vectors produced by the FCM method are assigned to each Watershed region next, and a multiresolution dissimilarity relation is also defined that will be used in the subsequent merging stage.

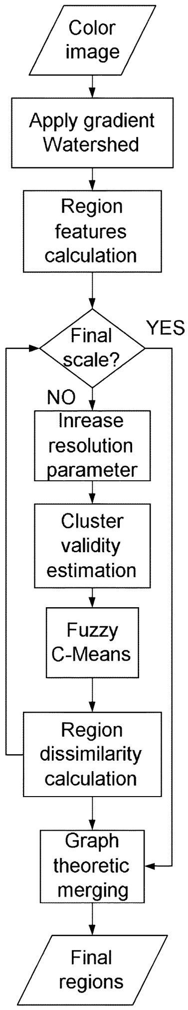


Fig. 1. Flowchart of the proposed algorithm.

The merging stage is analyzed in the second part of this paper. It is indicated that region-based segmentation may be described using fuzzy similarity relations [2], [21] and graph theory [15], [28]. In this framework, the main weaknesses of merging operations are explained and some existing graph theoretic segmentation approaches are interpreted according to our previous analysis and generalized for the case of region-based segmentation. Furthermore, a graph-theoretic segmentation scheme is originally proposed here to alleviate the main weakness of similarity relations and derive improved results. The outline of the proposed algorithm is also depicted in Fig. 1.

In the experimental part of this paper, some results are reported in order to: 1) indicate the efficiency of the proposed multiscale dissimilarity measure versus its single scale counterpart and 2) compare the proposed merging algorithm to previously reported graph theoretic approaches. In order to compare the computational efficiency, a theoretical approximation of the computational complexity is first carried out that is validated by experimental execution times as well. A discussion is also made, where it is pointed out that the proposed approach produces improved results with moderate computational complexity. Finally, some conclusions are drawn on our points of contribution and the applicability of this scheme.

II. Watershed Based Segmentation and Graph Representation

The Watershed transform, a reliable tool for image segmentation, is employed to produce the initial image partition. A significant advantage of Watershed segmentation and a reason behind its extended utilization is that boundaries on the image plane are always guaranteed to be connected and closed, and each gradient minimum corresponds to one region [13]. In order to prevent excessive oversegmentation and preserve the location of the edges, the original color image is filtered first by means of nonlinear diffusion using the algorithm proposed in [19]. According to this approach, an inhomogeneous process is employed that reduces the diffusivity at those locations, which have a larger likelihood to be edges. Nonlinear diffusion was originally proposed for intensity images (grayscale); however, it can be readily applied to color images by using Euclidean vector distances to estimate the edges, as employed in [12] and [26].

Following this smoothing operation, an edge-detection stage follows. Instead of the usual gradient magnitude operator, a minimal density-edge detector based on nonparametric density estimation is employed [5]. This method approximates the gradient magnitude more efficiently than traditional operators, such as Sobel and Prewitt. It is well known that the Watershed algorithm is applied to the intensity, or the color gradient image to carry out segmentation. Therefore, the method presented in [5] serves as the gradient magnitude estimation in this context. More precisely, the input signal is interpreted as a topographic relief, consisting of valleys (catchment basins) and ridges (Watershed lines). The final regions are formed using immersion simulations [27]. The implementation that is employed here, includes three stages, i.e., minima tracking, sorting, and flooding, and it uses the ordered queues structure [13] in the last two stages.

The outcome of this process is a label map that contains the Watershed regions, corresponding to the detected gradient minima and the contours of the regions. This map contains overcomplete information, i.e., numerous insignificant regions. This effect is called oversegmentation and has to be reduced, in order to produce meaningful segmentation results. An efficient approach is to synthesize the Watershed regions to form larger regions that correspond to objects of the image, or significant parts of them. This merging process is a combinatorial optimization problem of significant algorithmic complexity and several techniques have been proposed, as described in the introduction.

The Watershed regions are represented by a planar weighted RAG [24] $G = (V, E)$ that incorporates topological information of the image structure and region connectivity. The nodes $V = \{1, 2, \ldots, N\}$ of this graph are associated with the image regions, while the edges E represent the links between neighboring regions, i.e., $E \subset VxV$. The weight $W_{i,j}$ of an edge connecting two nodes V_i, V_j is a measure of dissimilarity between the corresponding regions. The majority of region-merging algorithms define this region dissimilarity metric as the distance between the two adjacent regions in an appropriately defined feature space. This parameter plays a decisive role in the overall performance of the complete process. In a graph structure, the notion of connectivity is also very important and facilitates the construction of consistent objects. From a different viewpoint, regions of the RAG correspond to samples of an overall image probability space. The graph edges indicate both the connectivity of the nodes and their distances to adjacent neighbors in the image plane. The whole RAG is embedded in a Euclidean feature space, while we can observe and manipulate the whole image on the spatial domain. Even so, by adopting this approach, we let the whole merging procedure, which has to be globally optimal, be guided by a local metric. In order to avoid this inconsistency, an alternative solution is provided in the next paragraphs.

III. Multiscale Dissimilarity Function

This section describes the proposed dissimilarity function and, it is indicated, that the two different approaches of spatial segmentation and clustering provide complementary information. In the following paragraphs, it is shown that the incorporation of topological and feature space information yields efficient results.

Our first consideration is related to the dimensionality and number of the feature vectors. Individual regions defined by the Watershed contours are quite homogeneous and their pixels tend to form compact clusters in the selected feature space. In general, several statistical attributes have appeared in the literature to define the feature space that were mainly based on intensity, color, texture or edge information. In this paper, the mean value estimate is selected as a reliable and practical feature. Thus, the mean color vectors are estimated over the Watershed partitioning and represent the corresponding regions in the employed color space. Clustering regions instead of pixels, reduces considerably the computational load of this stage, since a typical oversegmented 256×256 image has 65 536 pixels, however, it may contain as many as ~ 1000 Watershed regions.

In the feature space, Watershed regions are considered as samples of an unknown probability distribution. Dominant image features correspond to high probability density areas. In this domain, region connectivity constrains are relaxed and clustering operations are performed fast and efficiently. This space is well suited for extracting significant image features that are essential for efficient segmentation. Furthermore, a multiscale method may be defined by processing the existing data samples in several resolutions.

The different scales are generated in the feature space using non—parametric density estimation [4] to calculate the cluster validity. The FCM cluster-analysis method [1] is subsequently applied to each scale and assigns fuzzy membership vectors to the Watershed regions (Fig. 1).

A. Single Scale Dissimilarity Measure

The subtractive clustering approach [4] is used to estimate the number C of clusters formed by the resulting data set. It uses the notion of density estimators to calculate the density of the data samples and determine the number and the location of the most prominent cluster centers that will be provided as input to the subsequent FCM algorithm. These clusters denote the basic global features of the image that are considerably significant for the efficiency of the final segmentation result.

The process of the subtractive—or mountain—clustering method can be divided into three steps. In the first step the points of feature space are selected on which the potential function is calculated. In our case the potential function is calculated on the feature vectors i.e., the mean color vectors of Watershed regions. After that, the mountain function is estimated as follows: each sample point creates a potential function, which decreases exponentially with distance. Assuming a set of q points, $-q$ is equal to the number of initial regions-, the mountain probability density MPD on each point -or feature vector-P^k is estimated in its more simplified form as the sum of the contributions of all the remaining sample points

$$\mathrm{MPD}(P^k) = \sum_{i=1}^{q} e^{-\left[R\cdot d(P^k,P^i)\right]}. \tag{1}$$

In this equation, d represents the distance between the sample points P^k and P^i, which is usually the Euclidean distance. The exponential kernel is usually referred to as the potential function. The R variable represents the radium of each sample point that is the zone of contribution in the feature space. Bigger values of R reduce the clustering resolution, and produce fewer cluster centers. This variable is used to generate multiple scales in Section III-B.

In the following step, the data point of maximum density is designated as the first cluster center and removed from the set of data points. The mountain function is recalculated by subtracting the potential that is generated by the maximum point on the remaining data samples

$$\mathrm{MPD}\left(P_{l+1}^k\right) = \mathrm{MPD}\left(P_l^k\right) - \left(\mathrm{MPD}(P_l^*)^* \cdot e^{-\left[R\cdot d\left(P_l^k,P_l^*\right)\right]}\right) \tag{2}$$

where l symbolizes the iteration number, and P_l^* denotes the maximum point of iteration l. This operation is iterated until the lower threshold of potential values is reached. The lower threshold is usually set to 0.15, while the MPD variable ranges in $[0, 1]$. The previously extracted maxima represent the centers of prominent clusters and express the cluster validity. As a consequence, the number and location of maxima are employed as initial conditions in the subsequent fuzzy clustering algorithm.

The FCM clustering algorithm [1] is applied next to estimate the final cluster centers. Given the data set and the number C of clusters, this method converges to the final cluster centers and assigns C fuzzy membership values $\{\mu_{ik}, k = 1 \text{ to } C\}$, to each watershed region i. Therefore, this stage associates to each region i, which corresponds to the initial partitioning of the image, a vector $\tilde{A}i = \{\mu_{ik}, k = 1 \text{ to } C\}$ of length C. It should be mentioned that this operation actually defines a transformation from the employed feature space (color vectors) to a new domain constructed by the fuzzy membership values μ_{ik}.

The information conveyed by the vector $\tilde{A}i$ is utilized to develop a fuzzy dissimilarity relation. Among several standard inference methods [21], the sum of approaching degree represents an efficient and practical measure of *similarity*. In order to serve as a *dissimilarity* measure, the negation of it is used producing the expression in

$$\mathrm{FD}_{i,j} = \frac{\underset{k=1}{\overset{C}{\mathrm{MIN}}}(\mathrm{MAX}(\mu_{ik},\mu_{jk})) + \left\{1 - \left[\underset{k=1}{\overset{C}{\mathrm{MAX}}}(\mathrm{MIN}(\mu_{ik},\mu_{jk}))\right]\right\}}{2} \tag{3}$$

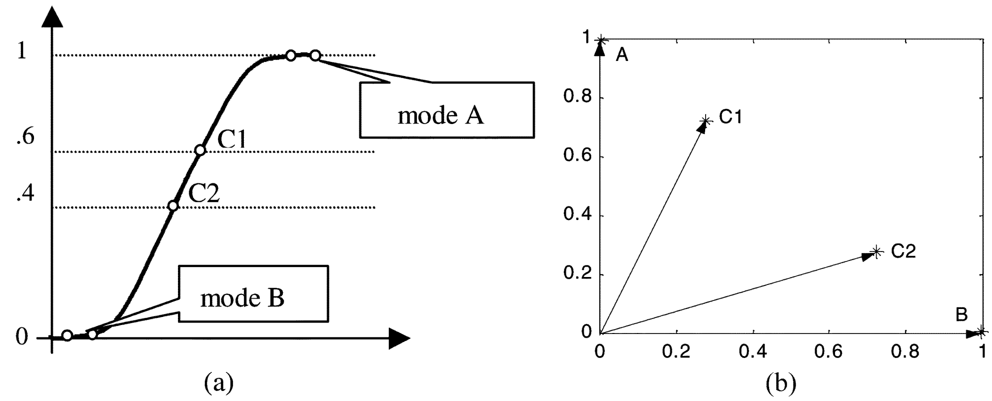


Fig. 2. (a) Points C_1 and C_2 with intermediate distance $d_{12} = 0.2$ appear to be very similar and the likelihood of false merging becomes high in this case. (b) The same points C_1 *and* C_2 take membership values $C_1 = (0.28, 0.72)$ and $C_2 = (0.72, 0.28)$ in the feature space with respect to clusters A and B. Now, they are well separated from each other and assigned to the correct clusters A(0,1) and B (1,0).

where μ_{ik} is the membership value of region i to the kth cluster as previously denoted, while MAX and MIN are the maximum and minimum operators, respectively. (See [21, Ch. 6] for more details on fuzzy arithmetic.)

At this point, it is worth noting the following comments on the proposed dissimilarity measure.

The dissimilarity function is actually defined in the domain of *membership values* μ_{ik}. This space has a dimensionality equal to the number C of clusters. In this space, the similarity of two regions in this space is defined by the vector $\tilde{A}i = \{\mu ik, k = 1 \text{ to } C\}$ associated with the image clusters. As a result, regions having the same distance in the feature space, but located at different positions with respect to the image clusters, differ significantly in the space of membership values. This usually happens when regions are located in the interval between the estimated image modes, however their feature distance is not close enough to be merged. This problem is resolved in the membership values domain. In order to illustrate this case, an example is given in Fig. 2(a) that presents a ramp in the feature space (one-dimensional case) with two data points C_1 and C_2 and two well-separated modes A and B that form the main clusters. The regions C_1 and C_2 are located close to modes A and B, respectively, while the distance between C_1 and C_2 is small. If the merging operation takes into account the interregion distance information only, C_1 and C_2 are considered to be very similar ($d = 0.2$) and are likely to be merged with high priority in the merging sequence. This operation produces the so-called chaining effect, which is a common problem of merging schemes. On the other hand, in the space of membership values [Fig. 2(b)], these vectors are significantly separated and properly *assigned* to the clusters–regions represented by the vectors A and B, respectively.

Apart from that, several variations of this procedure may be used. One possibility is to directly calculate the membership values μ_{ik} as the distances of the feature vectors from the detected cluster centers, derived from mountain clustering. Nevertheless, this would reasonably reduce the accuracy of the dissimilarity function calculation (3), since the mountain functions are calculated only over the data samples in order to avoid excessive computational cost and the cluster centers will necessarily be detected on some of those grid points. Although this approach

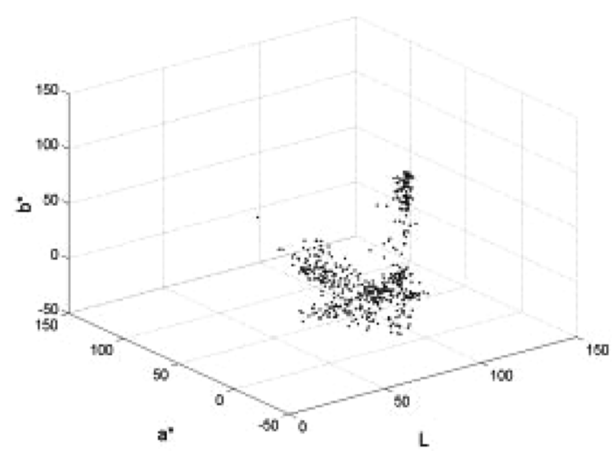


Fig. 3. Clusters formed by the mean values of Watershed regions (test image parrots).

is sufficient to estimate the population of cluster centers, the application of FCM is strongly recommended to converge to the final cluster centers with satisfactory accuracy.

Another consideration is that the mountain clustering may be omitted and the population of clusters may be given manually. However, there are three main pitfalls in this case: 1) the method becomes nonautomatic; 2) the user might not correctly evaluate the significant clusters of the image; and 3) the generation of multiple scales, which is the next step of our method, becomes a complicated and time consuming process, based on subjective human evaluation.

Concluding the above discussion, it should be emphasized that the dissimilarity between two regions is not based on their mutual distance, but is estimated using their relative distances from the detected cluster centers in the feature space. This single scale formulation is readily extended to develop an optimized method for multiscale processing in the following paragraphs.

B. Scale Generation

The previously described cluster-validity method can be used to produce different scales in the feature space. The evolution of the probability density *maxima* in this scale space provides information about the structure of the data. The different scales

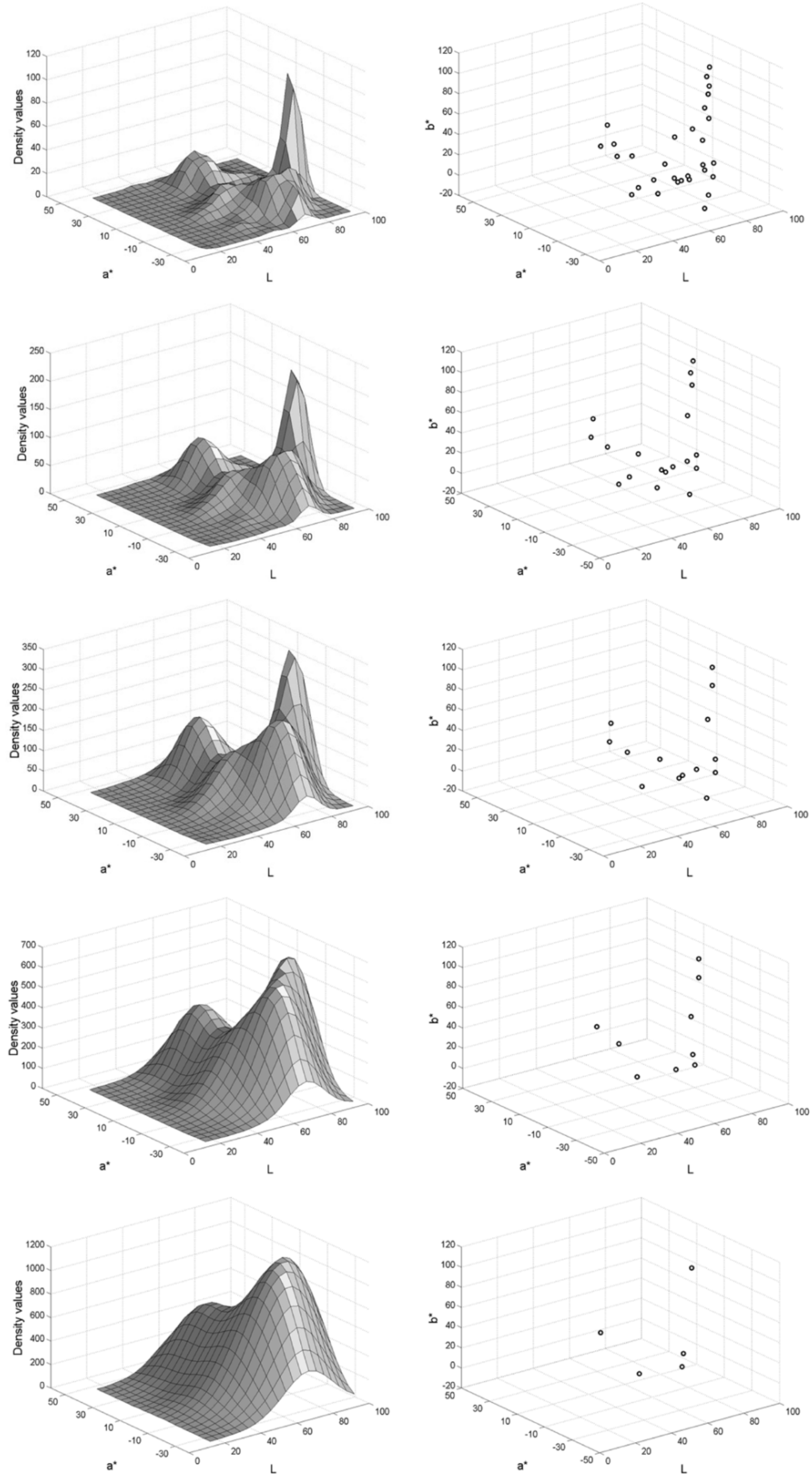


Fig. 4. Multiresolution density estimation for the test image parrots. The scale index increases from the top row downwards (see Table I). Left column: density values and cluster validity estimation calculated over the Watershed partitioning in the employed feature space. Right column: final location of the cluster centers produced by the FCM algorithm.

Fig. 5. Test image (left), Watershed result (33 regions) (middle) and the corresponding RAG representation.

TABLE I
EVOLUTION OF THE CLUSTER CENTERS POPULATION, AS A FUNCTION OF THE RESOLUTION PARAMETER (FIG. 4). EACH ROW OF FIG. 4 CORRESPONDS TO THE SAME ROW OF TABLE 1

RESOLUTION PARAMETER	**CLUSTER CENTERS**
0.1	30
0.15	18
0.2	14
0.3	9
0.4	5

may be produced by the resolution parameter of the density kernel function. As the resolution becomes less accurate, the resulting number of clusters is exponentially reduced [20]. Less accurate resolution, means bigger radii values for the density estimation kernel. As a result, in order to convert the scale sampling into a linear decreasing function, the different scales are produced using logarithmic sampling

$$R = -\frac{\ln\Big(-\big(\mathrm{msoc} + (\mathrm{mspc}\cdot s)\big)\Big)}{\beta}, \qquad s = 0, \ldots, N-1 \tag{4}$$

where R is the resolution parameter used in the subtractive clustering process, msoc is the multiscale offset coefficient, mspc denotes the multiscale product coefficient, s stands for the scale index, N is the number of scales, and β is a normalization constant, in our case, equal to 1. The msoc variable is used to select the initial scale and takes values in the range $(-1, 0)$, while mspc corresponds to the scale sampling density and its range is (0,1). Fig. 3 displays the data samples of Watershed regions produced by image parrots (the test image and the initial Watershed regions are depicted in Fig. 9, the third row, and the first and second columns, respectively). Fig. 4 illustrates the generation of multiple scales using nonparametric clustering and the cluster centers in the employed feature space. Table I contains the respective resolution parameter's value and the population of cluster centers for each scale of Fig. 4.

C. Multiscale Dissimilarity Measure

The multiscale dissimilarity calculation is completed by summation of the dissimilarity values across the different scales. This is described in

$$\mathrm{MFD}_{i,j} = \sum_{s=0}^{N-1} \mathrm{FD}_{i,j}^{s} \tag{5}$$

where MFD stands for multiscale feature dissimilarity, FD is the feature dissimilarity at the scale index denoted by s, which is calculated as in Section III-A. Variables i and j are the labels of the examined region pair in the oversegmented image and N is the total number of scales.

Considering the multiscale approach, our main objective is to estimate the evolution of the cluster centers with respect to the resolution of the nonparametric density estimation process. As previously mentioned, the cluster centers correspond to local maxima in the probability density domain and more clusters are detected for bigger values of the resolution parameter R. Since we have no clue about the most suitable resolution, a more robust approach is to estimate the dissimilarity measure over multiple resolutions. According to this approach, the information from different resolutions is taken into account in (5) to calculate the final dissimilarities. It should also be mentioned that in the presented method of scale generation, the scales are *not* produced as usual by means of Gaussian filtering [8] or anisotropic diffusion methods [19], [26], which are applied to the original image domain and are time consuming. Those methods also require a linking step in order to associate the regions across successive scales, which is a difficult process and remains an open research topic. Unlike these approaches, in the proposed method, the multiple scales are produced in the feature space by estimation of the density maxima evolution, therefore, the original image information and the initial Watershed regions remain unchanged. As a result, no linking between scales is needed, since the membership vectors of each scale are associated with the original Watershed regions.

Apart from that, the genericness of this approach enabled us to conduct experiments in several color spaces i.e., RGB, YCbCr, YUV, CIELab, and CIELuv. It was concluded that the last two spaces produced better results, and the CIELab was finally employed. This outcome is mainly attributed to the perceptual uniformity property that is critical both for the estimation of the edges prior to the Watershed operation and the feature distance calculation that is carried out in the classification-based dissimilarity estimation process as well. The Euclidean distance metric in the CIELab is also known as $\Delta E_{a,b}$ and represents a reliable expression of the color distance. In addition to that, the clusters formed in CIELab space are more compact and uniformly distributed than in other color spaces.

In this part of our paper, a multiscale dissimilarity criterion was presented that employs the principles of cluster analysis. The feature space is produced by calculating statistical estimates over the Watershed regions. The Watershed-partitioned image is represented in two domains: 1) in the feature space and 2) using a planar graph. The subject of Section IV will be the combination of spatial and feature space information in order to produce the final regions.

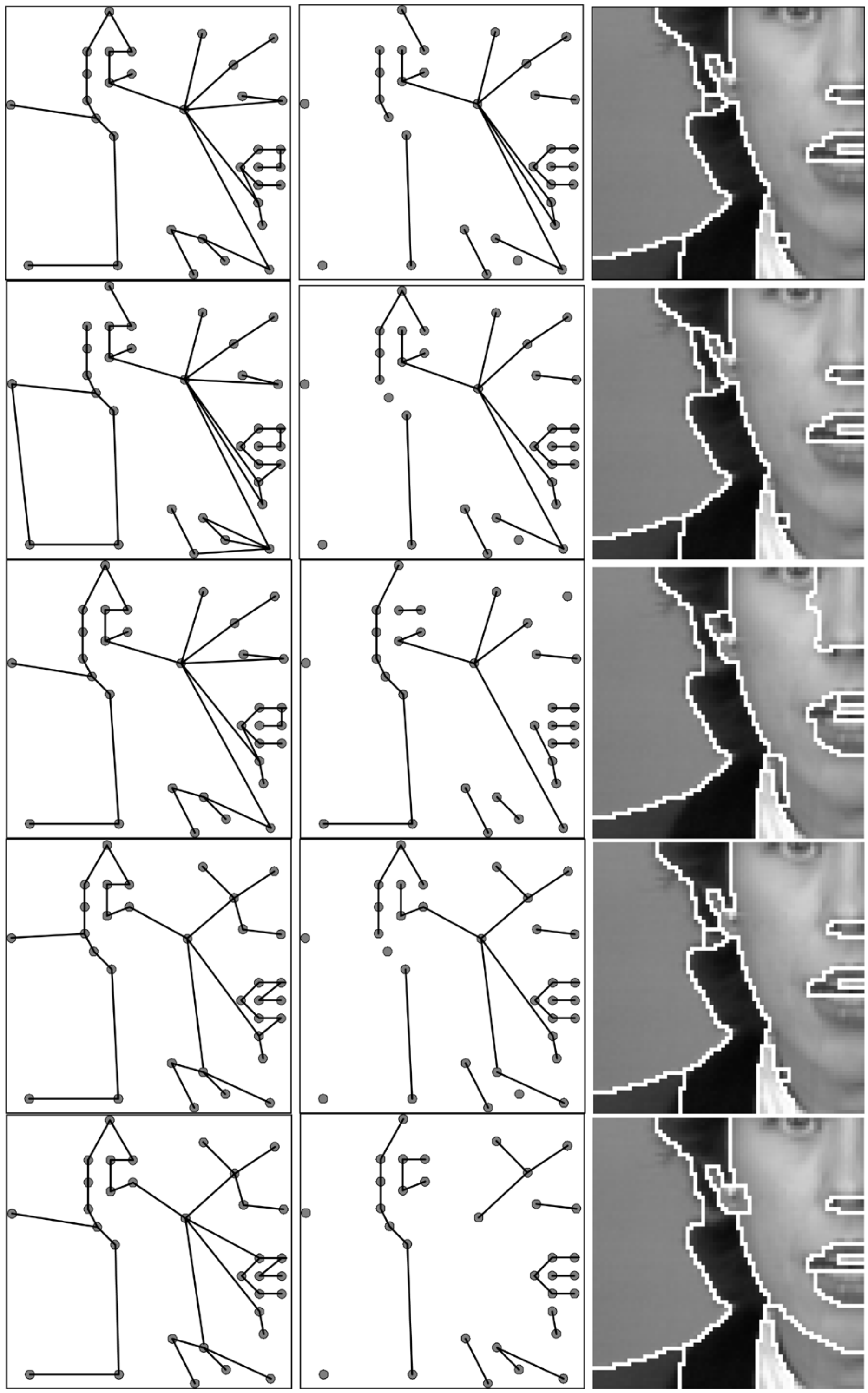


Fig. 6. First row: SST, thresholded SST (11 regions) and the corresponding region map. Second row: MCNG, thresholded MCNG (11 regions) and the corresponding region map. Third row: SST-minimax, thresholded SST-minimax (11 regions) and the corresponding region map. Fourth row: RSST, thresholded RSST (11 regions) and the corresponding region map. Fifth row: RAG-minimax, thresholded RAG-minimax (11 regions) and the corresponding region map.

IV. Final Partitioning Using Graph Structures

After the definition of the dissimilarity relation, the merging stage follows to form the final region map. In this paper, the problem of region-based segmentation is reformulated using the theory of *fuzzy similarity relations* [21]. A new merging algorithm emerges from this theoretical analysis, defined as the RAG-Minimax algorithm. The final segmentation is produced by applying lambda cuts to produce a crisp relation that embraces the similar regions.

As mentioned in the previous paragraphs, the image data may be represented using graphs. It is recognized that segmentation can be considered as a graph-partitioning problem; there have appeared several approaches in the literature to solve this problem, including the spanning trees [15], [28], graph cuts [23], and the binary partition tree [22]. The following paragraphs give the basic framework, according to which, fuzzy logic and graph theory principles are incorporated to derive the proposed method.

A. Fuzzy Similarity Relations Theory

Fuzzy logic theory provides a firm theoretical background for image segmentation. More precisely, image segmentation is a subset of fuzzy segmentation [21] and the latter can be defined using principles of fuzzy classification theory. In this paper, region-based segmentation approaches are represented by equivalence relations in the framework of fuzzy classification theory.

Let us define $[x_i] = \{x_j, |(x_i, x_j) \in \mathrm{ER}]$ as the equivalent class of x_i on a universe of data points, X. This class is contained in a special relation ER, known as equivalence relation. The equivalence relation is defined as a mathematical relation that possesses the properties of reflexivity, symmetry and transitivity

$$\text{Reflexivity}: \mu_{\mathrm{ER}}(x_i, x_i) = 1 \tag{6}$$

$$\text{Symmetry}: \mu_{\mathrm{ER}}(x_i, x_j) = \mu_{\mathrm{ER}}(x_j, x_i) \tag{7}$$

$$\begin{aligned} \text{Transitivity}: \mu_{\mathrm{ER}}(x_i, x_j) &= \lambda 1 \text{ and} \\ \mu_{\mathrm{ER}}(x_j, x_k) &= \lambda 2 \text{ then} \\ \mu_{\mathrm{ER}}(x_i, x_k) &= \lambda, \quad \lambda \geq \min(\lambda 1, \lambda 2). \end{aligned} \tag{8}$$

When only reflexivity and symmetry requirements are fulfilled, it is called a tolerance relation. The class produced by an equivalence relation is a set of all elements related to x_i that have the following properties [21]:

$$x_i \in [x_i], \quad (x_i, x_i) \in \mathrm{ER} \tag{9}$$

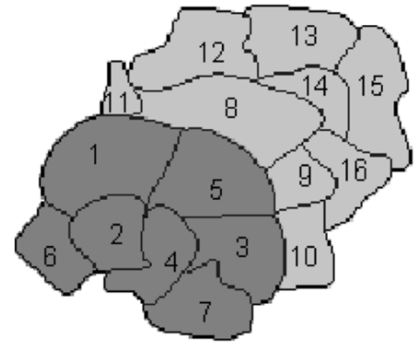
$$[x_i] \neq [x_j] \rightarrow [x_i] \cap [x_j] = 0 \tag{10}$$

$$\bigcup_{x_i \in X} [x_i] = X. \tag{11}$$

These properties are: 1) reflexivity; 2) that equivalent classes do not overlap; and 3) that the union of all equivalent classes exhausts the universe. It should be noted that the same formulation describes the basic requirements of region-based segmentation as well [17]. As a result, the context of region-based segmentation is explained as fuzzy classification using equivalence relations. In segmentation theory, the information of the image is classified into different regions using a (dis)similarity function, which actually defines a fuzzy (dis)similarity relation represented by a relation matrix [21]. The application of lambda cuts to the corresponding fuzzy relation matrix provides the (crisp) segmentation results.

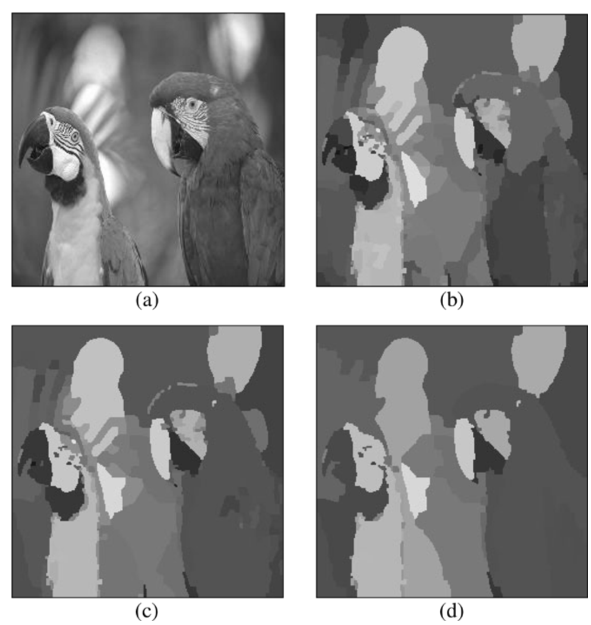
The main problem of segmentation is that the majority of dissimilarity functions used in the literature are tolerance and not equivalence relations, i.e., the transitivity property is not satisfied. This is mainly attributed to several quality degradations that take place during the digitization process (noise, quantization, limited resolution, blurring).

Several fuzzy segmentation algorithms have been proposed so far aiming at object recognition or complete segmentation using fuzzy affinity relations [2], [25] in an attempt to produce an equivalence relation. In [25], the notion of fuzzy connectedness for objects is introduced. Pixels from the region of interest (ROI) are linked through a connectedness path to all pixels of the image. By thresholding these links, region connectivity can be established. Their main drawback is that they do not use global information; their usefulness is, therefore, limited and they may be used in the place of thresholding operations for object extraction [2], [25].



Cost	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*
1	**0.15**	**0.32**	**0.28**	**0.17**	**0.26**	**0.3**	**0.29**	**0.31**	**0.28**
2	**0.23**	**0.21**	**0.23**	**0.15**	**0.2**	**0.19**	**0.24**	**0.27**	**0.26**
3	**0.12**	**0.08**	**0.14**	**0.25**	**0.22**	**0.32**	**0.23**	**0.19**	**0.21**
4	**0.23**	**0.29**	**0.26**	**0.28**	0.38	**0.2**	**0.18**	**0.22**	**0.24**
5	**0.09**	**0.12**	**0.16**	**0.14**	**0.21**	**0.19**	**0.24**	**0.27**	**0.25**
6	**0.22**	**0.25**	**0.23**	**0.18**	**0.17**	**0.21**	**0.24**	**0.27**	**0.2**
7	**0.21**	**0.18**	**0.23**	**0.3**	**0.24**	**0.27**	**0.19**	**0.25**	**0.22**

Fig. 7. Example of the dissimilarity calculation process in RAG-minimax algorithm. Subtree A includes the regions: 1, 2, 3, 4, 5, 6, 7 and subtree B: 8, 9, 10, 11, 12, 13, 14, 15, 16. The dissimilarity value between A and B is calculated as the maximum value of the partial dissimilarity estimates between the regions-members of subtrees. In this example the maximum dissimilarity value is produced by regions 4 and 12.



(a) (b) (c) (d)

Fig. 8. Hierarchical segmentation results of the proposed method. (a) Test image parrots and the merging hierarchy for (b) 300, (c) 150, and (d) 75 regions.

B. Graph Theoretic Merging Approaches

In previous paragraphs, it was noted that the RAG is a suitable structure for incorporating the interregion relation informa-

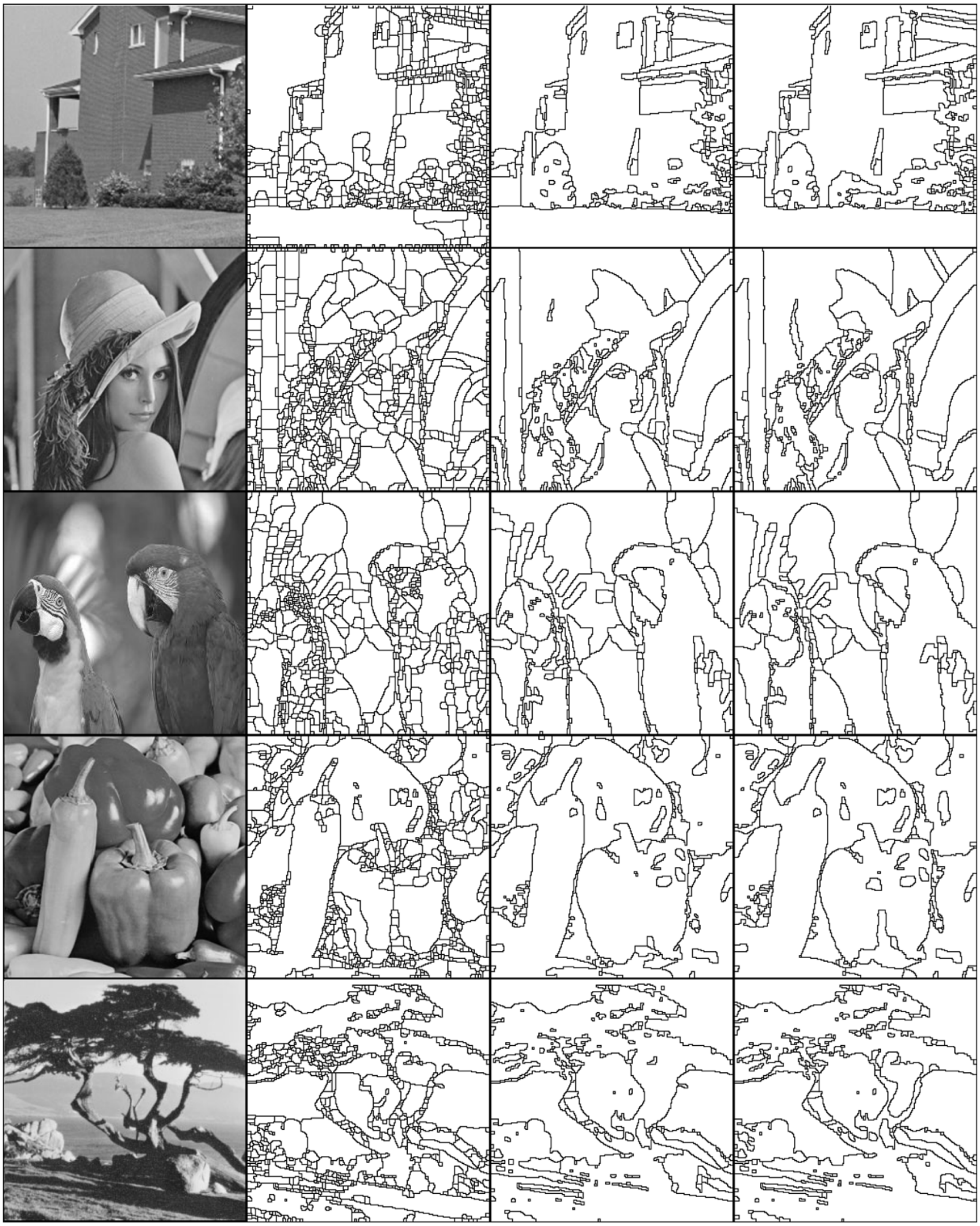


Fig. 9. Comparison between single and multiple scale versions. First column: original test images house, lena, parrots, peppers, tree. Second column: initial watershed regions. Third column: single scale results. Fourth column: multiscale results for the same number of final regions (see Table I).

tion. It is also well known [21] that graphs are used to represent fuzzy relations in the fuzzy clustering field. As a result, a correspondence between the region dissimilarity measure and a fuzzy (dis)similarity relation can be defined using graph theory. In this paragraph, some previously reported graph based segmentation methods are outlined. A novel graph based merging method is proposed in the last part of this paragraph that uses the fuzzy similarity relation theory to produce equivalence relations. In order to illustrate these algorithms, we use the example of Fig. 5 that displays a simplified example of the Watershed regions and the corresponding Region Adjacency Graph (33 regions). In addition, Fig. 6 contains the corresponding results of the examined approaches.

The SST is a well-known graph structure, initially proposed for pixel-based segmentation [15] and represents a reliable and fast merging scheme for region-based approaches. This is a tree structure that spans the RAG and contains the minimum cost links that do not form cycles. The final regions are produced by applying graph cuts on the SST and mapping the final tree onto the region map. Its main drawback is that as the number of required regions decreases, some false merging operations occur. This is mainly attributed to the fact that this structure

TABLE II
SINGLE- AND MULTI- SCALE SEGMENTATION RESULTS

Image	Initial Regions	Final Regions	Scale Version	YLGC	PSNR
House	648	180	*Single*	48.72	21.61
House	648	180	*Multi*	46.95	22.48
Lena	694	180	*Single*	41.5	21.71
Lena	694	180	*Multi*	38.15	22.18
Parrots	563	140	*Single*	57.9	20.51
Parrots	563	140	*Multi*	58.38	20.52
Peppers	609	140	*Single*	62.87	18.06
Peppers	609	140	*Multi*	57.3	18.53
Tree	679	180	*Single*	96.57	16.385
Tree	679	180	*Multi*	83.75	18

does not preserve the transitivity condition (see Section IV-A). In Fig. 6 (first row) is depicted the SST that results from the RAG of Fig. 5, the thesholded SST and the final regions (11 regions).

A previously presented graph-theoretic approach with acceptable results is the most coherent neighbor graph (MCNG) algorithm [11]. This is a subtractive nearest-neighbor finding technique that takes into account the spatial interregion relations as well. As indicated in [11], it normally produces better results than the SST without having to recalculate any features. The main pitfall of this method is the artificial contouring effect in the final segmentation results. Fig. 6, the second row displays the MCNG of Fig. 5, and the final segmentation result (11 regions).

A suboptimal solution for the region-based segmentation problem is provided by the SST-Minimax algorithm. This is a sophisticated graph-theoretic top–down approach that divides the initial SST into a forest that comprises of several subtree-regions by minimizing the maximum cost of the subtrees [15], [28]. The main advantage of this approach is that it produces good segmentation results, without having to recalculate region features. On the other hand, this is a suboptimal solution, since it operates on the SST and not on the complete RAG structure. An example of the SST-Minimax segmentation is illustrated in Fig. 6 (third row).

An efficient algorithm that was presented in [15] and employed for color images in [28] is the RSST. This algorithm was also generalized for our region-based case. According to this approach, the RAG nodes and links are updated after each merging operation. This approach preserves the transitivity property, and is considered to be a very efficient solution. However, it requires the recursive calculation of region and interregion features. Apart from being computationally demanding, this method is not feasible for several dissimilarity measures, for example multiscale approaches as the method proposed here. In Fig. 6 (fourth row), is displayed the RSST structure, the thresholded version and the final segmentation (11 regions).

The proposed merging algorithm—A transitivity preserving and computationally efficient merging algorithm is proposed here. This is a graph theoretic, bottom-up approach that preserves the transitivity property, and thus creates a fuzzy equivalence relation as defined in Section IV-A.

The initial regions are represented by subtrees that comprise a forest. The subtrees with minimum pairwise cost are iteratively merged to form equivalence classes and the merging costs are updated by examining the dissimilarity between the region-members of the examined subtrees and keeping the maximum values. This process is completed in the following steps.

```
1. Map the Watershed regions onto RAG.
2. Form a forest that comprises of N_initial
    subtrees.
3. Repeat until N_final subtrees are formed.
   4. Find the minimum cost link between
       subtrees.
   5. Merge the corresponding subtree-regions
       and reduce total population by 1.
   6. Calculate the new merging costs between
       the resulting subtree and its neighbors.
       For each pair of subtrees:
      7. Calculate the dissimilarity values of
          the regions-members between the
          examined subtrees.
      8. Find the maximum dissimilarity value.
      9. Assign the maximum value to the cost
          between the subtrees.
10. Map the final subtrees onto the region
     map.
```

In order to display the operation of the above algorithm, Fig. 7 depicts an example of two subtrees designated by different shades of gray. Each subtree consists of several regions that have been merged in previous iterations. The subtrees dissimilarity value is calculated by the maximum of the partial dissimilarities between the subtree regions–members. The final cost may, therefore, be determined by nonneighboring regions to preserve the transitivity property and produce equivalence classes. According to the theory of fuzzy similarity relations, a fuzzy equivalence relation is built and the final results are produced by applying lambda-cuts, i.e., hard thresholds, on the dissimilarity values and mapping the forest onto the region map. Fig. 8 shows the segmentation results of the proposed algorithm for variable amounts of final regions, indicating that RAG-Minimax produces effective segmentation in terms of hierarchy as well.

This Minimax operation is applied to the complete RAG structure of the image; therefore, the presented algorithm is denoted by RAG-Minimax. In Fig. 6 (fifth row) are displayed the results of the RAG-Minimax process for the example of Fig. 5. In this simplified case, it is obvious that the presented

Fig. 10. Comparison between different merging methods (Test images: house, lena, parrots, peppers, tree). First column: MCNG; Second column: SST; Third column: SST-minimax; and Fourth column: RAG-minimax results. The final segmentation is produced using the initial region map of Fig. 1, for the same number of final regions as displayed in Table II.

algorithm produces more accurate results than the other examined approaches. Another advantage is that it is suitable for multiscale dissimilarity measures as well. Besides that, the RAG-Minimax algorithm may operate as an autonomous segmentation method applied on pixel basis.

Considering the computational burden of the proposed algorithm, the initial Watershed segmentation stage requires approximately $O(N^2)$ computations, where N is the number of pixels. This cost is unavoidable for every segmentation algorithm. In the second stage, the order is about $O(k+e) + \{l \cdot [(2 \cdot O(e-1)) + O((e-l-2)^2/4)]\}$ computations for the RAG-Minimax method, where k is the number of regions, e is the number of graph edges, and l is the number of merging iterations. The complexity of SST and MCNG is about $O(k+e)+O(e\cdot\log(e))+k\cdot O(k-1)$, so these are well suited for applications of low complexity, but reduced quality requirements. SST-Minimax is a more elaborate algorithm, the complexity of which is estimated as $O(k+e)+O(e\cdot\log(e))+l\cdot\{O(k-1)+[(k-l-1)\cdot O(k-1)]\}$, which is considerably higher than that of SST and MCNG. On the other hand, the ap-

TABLE III
COMPARATIVE RESULTS OF DIFFERENT MERGING SCHEMES

Image	**Merging Approach**	**Final Regions**	**YLGC**	**PSNR**	**Ex. Time (Normalized)**
House	*MCNG*	140	52.58	21.86	1.65
House	*SST*	140	41.73	21.96	1.56
House	*SST-Minimax*	140	59.7	21.32	5.04
House	*RAG-Minimax*	140	41.71	22.63	2.21
Lena	*MCNG*	60	30.2	19.56	1.02
Lena	*SST*	60	39.23	16.28	1.03
Lena	*SST-Minimax*	60	34.41	20.36	5.87
Lena	*RAG-Minimax*	60	20.42	21.421	1.33
Parrots	*MCNG*	100	51.06	21.02	1
Parrots	*SST*	100	48.29	20.21	1.07
Parrots	*SST-Minimax*	100	61.44	20.51	3.61
Parrots	*RAG-Minimax*	100	49.07	20.744	1.25
Peppers	*MCNG*	60	55.08	17.82	1.05
Peppers	*SST*	60	51.71	15.27	1
Peppers	*SST-Minimax*	60	50.81	18.05	4.03
Peppers	*RAG-Minimax*	60	34.72	18.81	1.36
Tree	*MCNG*	80	76.79	17.28	1.14
Tree	*SST*	80	72.96	13.6	1.17
Tree	*SST-Minimax*	80	68.75	18.32	7.43
Tree	*RAG-Minimax*	80	55.16	18.2	1.52

proximate burden of RSST is $O(N^2)$. A faster version of RSST was proposed in [9], however, it cannot be implemented for region-based segmentation. The computational complexity for K means is $O(N^2/2)$, and for FCM $O(N^2)$ *for each iteration*. When these algorithms are applied to pixel entities, i.e., N is the number of pixels, the computational burden is significantly increased since: 1) the number of feature samples (pixels) is very large and 2) an order of 100 iterations is typically required for these algorithms to converge to an acceptable result.

In the following paragraphs, the presented method is tested more extensively for several natural images, and some comments are also made to evaluate the potential of our paper.

V. EXPERIMENTAL RESULTS AND DISCUSSION

The performance of the overall proposed scheme is assessed by examining the results of: 1) the multiscale dissimilarity measure and 2) the graph theoretic method that preserves transitivity in the merging stage.

In order to indicate its usefulness, the multiscale dissimilarity measure was compared to the single scale counterpart using the same number of initial and final regions and the SST algorithm to form the final regions. Fig. 9 and Table II contain the subjective and objective results, respectively. Fig. 9 depicts the original test images, the initial regions, and the final results using 1) the single scale dissimilarity function and 2) the multiscale approach. The corresponding objective results are reported in Table II. The segmentation efficiency is expressed by the segmentation cost proposed in [30], denoted here by YLGC and the peak signal-to-noise ratio criterion that is employed to measure the segmentation accuracy. The YLGC measure is expressed by the relation:

$$\mathrm{YLGC} = \sqrt{\frac{\mathrm{N_R}}{h \cdot w \cdot c}} \cdot \sum_{i=1}^{\mathrm{N_R}} \sigma i^2 \cdot \sqrt{\mathrm{card}}_i. \tag{12}$$

In this equation, h, w, and c are the height, width, and number of the image channels, respectively, N_R is the number of final regions, σ_i^2 is the color error over region i, and card_i is the number of pixels inside region i. This function expresses the tradeoff between the suppression of heterogeneity and preservation of details after merging. From these results, it becomes obvious that the multiscale approach produces more accurate segmentation results both from the objective (segmentation evaluation functions) and subjective (visual evaluation) viewpoints.

Furthermore, Fig. 10 and Table III contain the comparative results of the proposed graph theoretic algorithm RAG-Minimax and the previously reported approaches MCNG, SST, SST-Minimax using the same test images and initial partitions as in Fig. 9 and Table II. Here, it is concluded that the proposed scheme is more efficient than the other tested approaches combining improved segmentation quality and moderate complexity. The MCNG and SST approaches suffer from false merging operations, while the SST-Minimax is more effective, but more computationally complicated as well. In addition, SST-Minimax still produces less accurate segmentation results than RAG-Minimax, since it is applied on the limited data of SST and for that reason does not produce equivalence relations. Moreover, its implementation is rather complex, since it is a top–down algorithm. An effective approach is the RSST algorithm, which is also considered to be transitivity preserving, whereas it is not applicable to our multiscale dissimilarity measure, since it requires the recursive calculation of region features after each merging iteration. Furthermore, even the single scale version of this method is computationally demanding, according to our theoretical analysis. Considering the computational complexity, it should be noted that the experimental results are consistent with our theoretical approach too.

VI. Conclusion

A hybrid-segmentation scheme is proposed in this paper. The Watershed approach is applied to produce the initial oversegmented image and a second stage, known as the merging stage, is used to form the final regions. This stage consists of the dissimilarity calculation process and the merging algorithm, which represent the original points of our paper.

The dissimilarity calculation is carried out using a novel multiscale generation process in the feature space. A clustering approach based on nonparametric density estimation [4], known as subtractive clustering, is used to determine the population and location of the most prominent cluster centers at different resolutions. The FCM algorithm is subsequently employed to produce the membership vectors. The dissimilarity at each resolution is inferred using standard fuzzy arithmetic operations. The multiscale dissimilarity function takes into account the structure of clusters over multiple scales to evaluate the degree of dissimilarity. The result of this operation is the integration of the global cluster analysis results into the general region-based scheme.

A compact and generalized formulation of the segmentation process is also given using similarity relations theory. This analysis results in a new merging algorithm that develops a transitivity relation from tolerance relation using the spatial interconnection information. This may be regarded as a Minimax operation applied on the RAG structure. The RAG-Minimax algorithm represents a very efficient segmentation scheme. Moreover, a theoretical and experimental comparison of the computational order for these algorithms indicates the effectiveness of the proposed algorithm from the computational aspect too.

This method is expected to operate as an autonomous application to segment and detect objects. An interesting perspective is to make use of the multiscale processing algorithm and the perceptual characteristics of the graph theoretic scheme for object synthesis, to emulate the human visual perception process.

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