A Review on Image Segmentation Techniques Integrating Region and Boundary Information

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October 31, 2001

Abstract

Image segmentation is an important research area in computer vision and many segmentation methods have been proposed. However, elemental segmentation techniques based on boundary or region approaches often fail to produce accurate segmentation results. Hence, in the last few years, there has been a tendency towards the integration of both techniques in order to improve the results by taking into account the complementary nature of the edge and region information. Nevertheless, these techniques have not been summarized and classified until now and there is no survey focussing on the integration of region and boundary information. To overcome this deficiency, in this paper each of the major classes of image integrated segmentation techniques is defined, and several specific examples of each class of algorithm are described. Moreover, the overall performance of each proposal is analysed.

1 Introduction

One of the first and most important operations in image analysis and computer vision is segmentation [1, 2]. The aim of image segmentation is the domain-independent partition of the image into a set of regions, which are visually distinct and uniform with respect to some property, such as grey level, texture or colour. Segmentation can be considered the first step and key issue in object recognition, scene understanding and image understanding. Its application area varies from industrial quality control to medicine, robot navigation, geophysical exploration, military applications, etc. In all these areas, the quality of the final results depends largely on the quality of the segmentation.

The problem of segmentation has been, and still is, an important research field, and many segmentation methods have been proposed in the literature (see the surveys [3, 4, 5, 6, 7, 8]). In general, segmentation methods are based on two basic properties of the pixels in relation to their local neighbourhood: discontinuity and similarity. Methods that are based on some discontinuity property of the pixels are called boundary-based methods, whereas methods based on some similarity property are called region-based methods. More specifically,

- The boundary approach uses the postulate that abrupt changes occur with regard to the features of the pixels (e.g., abrupt changes in grey values) at the boundary between two regions. To find these positions there are two basic approaches: first- and second-order differentiation. In the first case, a gradient mask (Roberts [9] and Sobel [10] are well-known examples) is convolved with the image to obtain the gradient vector ∇f associated with each pixel. Edges are the places where the magnitude of the gradient vector $\|\nabla f\|$ is a local maximum along the direction of the gradient vector $\phi(\nabla f)$. For this purpose, the local value of the gradient magnitude must be compared with the values of the gradient estimated along this orientation and at unit distance on either side away from the pixel. After this process of non-maxima suppression takes place, the values of the gradient vectors that remain are thresholded, and only pixels with a gradient magnitude above the threshold are considered as edge pixels [11]. In the second-order derivative class, optimal edges (maxima of gradient magnitude) are found by searching for places where the second derivative is zero. The isotropic generalization of the second derivative to two dimensions is the Laplacian [12]. However, when gradient operators are applied to an image, the zeroes rarely fall exactly on a pixel. It is possible to isolate these zeroes by finding zero crossings: places where one pixel is positive and a neighbour is negative (or vice versa). Ideally, edges of images should correspond to boundaries of homogeneous objects and object surfaces.

- The region approach tries to isolate areas of images that are homogeneous according to a given set of characteristics. Candidate areas may be grown, shrunk, merged, split, created or destroyed during the segmentation process. There are two typical region-based segmentation algorithms: region-growing, and split-and-merge. Region growing [13, 14] is one of the most simple and popular algorithms and it starts by choosing a starting point or seed pixel. Then, the region grows by adding neighbouring pixels that are similar, according to a certain homogeneity criterion, increasing step by step the size of the region. Typical split-and-merge techniques [15, 16] consist of two basic steps. First, the whole image is considered as one region. If this region does not comply with a homogeneity criterion the region is split into four quadrants and each quadrant is tested in the same way until every square region created in this way contains homogeneous pixels. Next, in a second step, all adjacent regions with similar attributes may be merged following other criteria.

Unfortunately, both techniques, boundary-based and region-based, often fail to produce accurate segmentation, although the locations where they fail are not necessarily identical.

In boundary-based methods, if an image is noisy or if its region attributes differ by only a small amount between regions, characteristics very common in natural scenes, edge detection may result in spurious and broken edges. This is mainly due to the fact that they rely entirely on the local information available in the image; very few pixels are used to detect the desired features. Edge linking techniques can be employed to bridge short gaps in such a region boundary, although this is generally considered a really difficult task. Region-based methods always provide closed contour regions and make use of relatively large neighbourhoods in order to obtain sufficient information to decide the aggregation of a pixel into a region. Consequently, the region approach tends to sacrifice resolution and detail in the image to gain a sample large enough for the calculation of useful statistics for local properties. This can result in segmentation errors at the boundaries of the regions, and in failure to distinguish regions that would be small in comparison with the block size used. Further, in the absence of a priori information, reasonable starting seed points and stopping criteria are often difficult to choose. Finally, both approaches sometimes suffer from a lack of knowledge due to the fact that they rely on the use of ill defined hard thresholds that may lead to wrong decisions [17].

In the task of segmentation of some complex pictures, such as outdoor and natural images, it is often difficult to obtain satisfactory results using only one approach to image segmentation. Taking into account the complementary nature of the edge-based and region-based information, it is possible to alleviate the problems related to each of them considered separately. The tendency towards the integration of several techniques seems to be the best solution in order to produce better results. The difficulty lies in the fact that even though the two approaches yield complementary information, they involve conflicting and incommensurate objectives. Thus, as previously observed by [18], while integration has long been a desirable goal, achieving this is a non-trivial task.

In the last few years, numerous techniques of integrating region and boundary information have been proposed. One of the principal characteristics that permits classification of these approaches is the time of fusion: embedded in the region detection, or after both processes [19].

- Embedded integration can be described as integration through the definition of new parameters or a new decision criterion for the region-based segmentation. Firstly, the edge information is extracted, and this information is then used within the segmentation algorithm which is mainly based on regions. For example, edge information can be used to define the seed points from which regions are grown.

- Post-processing integration is performed after processing the image using the two different approaches (boundary-based and region-based techniques). Edge and region information are extracted independently in a preliminary step, and then integrated together.

Although many surveys on image segmentation have been published, as stated above, none of them focuses on the integration of region and boundary information. To overcome this deficiency, this paper discusses the most relevant segmentation techniques developed in recent years, which integrate region and boundary information. The remainder of this paper is structured as follows: a discussion of embedded and post-processing strategies and the related work, conclude the Introduction. Section 2 defines and classifies the different approaches to the embedded integration, while Section 3 analyses the proposals for the post-processing strategy. Section 4 summarizes the advantages and disadvantages of the various approaches. Finally, the results of our study are summarized in the Conclusions section.

1.1 Integration Techniques: Embedded versus Post-processing

Many cooperative methods have been developed in recent years, all of them with the common objective of improving the segmentation using integration. However, the fusion of boundary and region information has been tried using different approaches. The result is a set of techniques that contains very disparate tendencies. As many authors have proposed [19, 20], one of the main characteristics that allows classification of the integration techniques is the time of fusion. This concept refers to the moment during the segmentation process when the integration of the dual sets of information is performed. This property allows us to distinguish two basic groups among the integration proposals: embedded or post-processing.

The techniques based on embedded integration start with the extraction of the edge map. This information is then used in the region-detection algorithm, where the boundary information is combined with the region information to carry out the segmentation of the image. A basic scheme of this method is indicated in Fig. 1.a. The additional information contributed by the edge detection can be employed in the definition of new parameters or new decision criteria. The aim of this integration strategy is to use boundary information as the means of avoiding many of the common problems of region-based techniques.

On the other hand, the techniques based on post-processing integration extract edge and region information independently, as depicted in the scheme of Fig. 1.b. This preliminary step results in two segmented images obtained using the classical techniques of both approaches, so they probably have the typical faults that are generated by the use of a single isolated method. An a posteriori fusion process then tries to exploit the dual information in order to modify, or refine, the initial segmentation obtained by a single technique. The aim of this strategy is the improvement of the initial results and the production of a more accurate segmentation.

In the following, we give a description of several key approaches that we have classified as embedded or post-processing. Within the embedded methods we differentiate between those that used boundary information for seed placement purposes, and those that used this information to establish an appropriate decision criterion. Within the post-processing methods, we differentiate three different approaches: over-segmentation, boundary refinement, and selection evaluation. We discuss in depth each one of these approaches, as well as, in some cases, emphasize aspects related to the implementation of the methods (region-growing or split-and-merge), or the use of fuzzy logic, which has been considered in a number of proposals.

1.2 Related Work

Brief mention of the integration of region and boundary information for segmentation can be found in the introductory sections of several papers. As a first reference, Pavlidis and Liow [18] introduce some earlier papers that emphasize the integration of such information. In 1994 Falah, Bolon and Cocquerez [19] identified two basic strategies for achieving the integration of dual information, boundaries and regions. The first strategy (*post-processing*), is described as the use of the edge information to control or refine a region segmentation process. The other alternative (*embedded*), is to integrate edge detection and region extraction in the same process. The classification proposed by Falah, Bolon and Cocquerez has been adopted and discussed in this paper. On the other hand, Le Moigne and Tilton [20], thinking in the general case of data fusion, identified two levels of fusion: pixel and symbol. A pixel-level integration between edges and regions assumes that the decision for integration is made individually on each pixel, while the symbol-level integration is made based on selected features, thereby simplifying the problem. In the same paper, they discussed embedded and post-processing strategies and presented important arguments on the supposed superiority of the post-processing strategy. They argued that the a posteriori fusion gives a more general approach because, for the initial task, it can employ any type of boundary and region segmentation. A different point of view of integration of edge and region information for segmentation proposals consists of the use of dynamic contours (snakes). In this sense, Chan et al. [21] review different approaches, pointing out that integration is the way to decrease the limitations of traditional deformable contours.

2 Embedded Integration

The embedded integration strategy consists of using the edge information, previously extracted, within a region segmentation algorithm. It is well known that in most of the region-based segmentation algorithms, the manner in which initial regions are formed and the criteria for growing them are set a priori. Hence, the resulting segmentation will inevitably depend on the choice of initial region growth points [22], while the region's shape will depend on the particular growth chosen [23]. Some proposals try to use boundary information in order to avoid these problems. According to the manner in which this information is used, it is possible to distinguish two tendencies:

1) **Guidance of seed placement**: edge information is used as a guide in order to decide which is the most suitable position to place the seed (or seeds) of the region-growing process.

2) **Control of growing criteria**: edge information is included in the definition of the decision criterion which controls the growth of the region.

2.1 Guidance of Seed Placement

In 1992 Benois and Barba [24] presented a segmentation technique that combined contour detection and a split-and-merge procedure of region growing. In this work, the boundary information is used to choose the growing centres. More specifically, the original idea of the method is the placement of the seeds on the skeleton of non-closed regions obtained by edge detection. The technique starts with contour detection and extraction, according to the algorithm proposed in [25], which finds the most evident frontiers of homogeneous regions. The contours obtained as a result of this overall procedure are of high quality, but they are not always closed. Then, a region-growing procedure is used to close these regions and to obtain a more precise segmentation. Hence, in order to obtain a uniformly spread speed of region growing constrained by original contours, the growing centres should be chosen as far as possible from these contours. In order to do so, the algorithm chooses them on the skeleton defined by the set of the original contours. The skeleton is computed by the Rosenfeld method of local maxima distance. Finally the region-growing process is realized in the following steps: a splitting process that divides an initial image into homogeneous rectangular blocks, and then a merging process, grouping these blocks around growing centres to obtain final segments.

A similar work has been proposed recently by Sinclair [26] who presented an interesting integration segmentation algorithm. First, the Voronoi image generated from the edge image is used to derive the placement of the seeds. The intensity at each point in a Voronoi image is the distance to the closest edge. The peaks in the Voronoi image, reflecting the farthest points from the contours, are then used as seed points for region growing. In the growth, two criteria are used in order to attach unassigned pixels: the difference in colour between the candidate pixel and the boundary member pixel must be less than a set threshold, and the difference in colour between the candidate and the mean colour of the region must be less than a second, larger, threshold. In this sense, they take into account local and global region information for the aggregation of a new pixel to a region. This could be especially interesting for blurred regions. From another integration aspect, edges recovered from the image act as hard barriers through which regions are not allowed to grow. Figure 2 shows the images generated on the segmentation process, including the Voronoi image, which guide the placement of the region-growing centres.

Moghaddamzadeh and Bourbakis proposed in [27] an algorithm that uses edge detection to guide initialization of an a posteriori region-growing process. Actually, this work is not specifically oriented to the placement of the seeds for the a posteriori growing process, but is focussed on establishing a specific order for the processes of growing. As is well known, one of the disadvantages of the region-growing and merging processes is their inherently sequential nature. Hence, the final segmentation results depend on the order in which regions are grown or merged. The objective of this proposal is to simulate the order by which we humans separate segments from each other in an image; that is, from large to small. In order to achieve this, an edge detection technique is applied on the image to separate large and crisp segments from the rest. The threshold of the edge detection algorithm is fixed low enough to detect even the weakest edge pixels in order to separate regions from each other. Next, regions obtained (considering a region as a place closed by edges) are sequentially expanded, starting from the largest segment and finishing with the smallest. Expanding a segment refers to merging adjacent pixels with the segment, based on some conditions. Two fuzzy techniques are then proposed to expand the large segments and/or to find the smaller ones.

Another proposal which uses the edge information to initialize the seeds of a posteriori region growing, has been presented by Cufí et al. [28]. Just like the proposal of Moghaddamzadeh and Bourbakis, Cufí et al. take into account seed placement as well as the order by which the regions start the growing process. However, Moghaddamzadeh and Bourbakis give priority to the largest regions, whereas Cufi et al. prefer a concurrent growing, giving the same opportunities to the regions. The basic scheme of their technique is shown in Fig. 3, which begins by detecting the main contours of the image following the edge extraction algorithm discussed in [29]. For each one of the extracted contours, the algorithm places a set of growing centres at each side and along it. It is assumed that the whole set of seeds of one side of the contour belong to the same region. Then, these seeds are used as samples of the corresponding regions and analysed in the chromatic space in order to establish appropriate criteria for the posterior growing processes. The aim is to know a priori some characteristics of regions with the aim of adjusting the homogeneity criterion to the region's characteristics. Finally, the seeds simultaneously start a concurrent growth using the criterion established for each region, which is based on clustering analysis and convex hull construction.

2.2 Control of Growing Criterion

Another way to carry out the integration from an embedded strategy is to incorporate the edge information into the growing criterion of a region-based segmentation algorithm. Thus, the edge information is included in the definition of the decision criterion that controls the growth of the region.

As discussed in the Introduction, region-growing and split-and-merge are the typical region-based segmentation algorithms. Although both share the essential concept of homogeneity, the way they carry out the segmentation process is really different in the decisions taken. For this reason, and in order to facilitate the analysis of the surveyed algorithms, these two types of approach are presented in two different subsections.

2.2.1 Integration in Split-and-merge Algorithms

Bonnin and his colleagues proposed in [30] a region extraction based on a split-and-merge algorithm controlled by edge detection. The method includes boundary information into the homogeneity criterion of the regions to guide the region detection procedure. The criterion to decide the split of a region takes into account edge and intensity characteristics. More specifically, if there is no edge point on the patch and if the intensity homogeneity constraints are satisfied, then the region is stored; otherwise, the patch is divided into four sub-patches, and the process is recursively repeated. The homogeneity intensity criterion is rendered necessary because possible failures of the edge detector. After the split phase, the contours are thinned and chained into edges relative to the boundaries of the initial regions. Later, a final merging process takes into account edge information in order to solve possible over-segmentation problems. In this last step, two adjacent initial regions are merged only if there are no edges on the common boundary. The general structure of their method is depicted in Fig. 4, where it can be observed that edge information guides the split-and-merge procedure in both steps of the algorithm: first, to decide the split of a region, and finally in the merging phase to solve the possible over-segmentation.

The split-and-merge algorithm cooperating with an edge extractor was also proposed in the work of Buvry et al. [31]. The proposed algorithm follows the basic idea introduced by Bonnin, considering the edge segmentation in the step of merging. However, a rule-based system was added in order to improve the initial segmentation. A scheme of the proposed algorithm is illustrated in Fig. 5. They argued that the split-and-merge segmentation algorithm creates many horizontal or vertical boundaries without any physical meaning. In order to solve this problem the authors define a rule-based system dealing with this type of boundary. Specifically, the gradient mean of each boundary is used to decide if the boundary has really a physical reality.

In 1997, Buvry et al. reviewed the work presented in [31] and proposed a new hierarchical region detection algorithm for stereovision applications [32] taking into account the gradient image. The method yields a hierarchical coarse-to-fine segmentation where each region is validated by exploiting the gradient information. At each level of the segmentation process, a threshold is computed and the gradient image is binarized according to this threshold. Each closed area is labelled by applying a classical colouring process and defines a new region. Edge information is also used to determine if the split process is finished or if the next partition must be computed. So, in order to do that, a gradient histogram of all pixels belonging to the region is calculated and its characteristics (mean, maximum and entropy) are analysed.

A proposal of enriching the segmentation by irregular pyramidal structure by using edge information can be found in the work of Bertolino and Montanvert[33]. In the proposed algorithm, a graph of adjacent regions is computed and modified according to the edge map obtained from the original image. Each graph-edge[1] is weighted with a pair of values (r,c), which represent the number of region elements, and the contour elements in the common boundary of both regions respectively. Then, the algorithm goes through the graph and at each graph-edge decides whether to forbid or favour the fusion between adjacent regions.

The use of edge information in a split-and-merge algorithm may not only be reduced to the decision criterion. In this sense, Gevers and Smeulders [34] presented, in 1997, a new technique that extends the possibilities of this integration. Their proposal uses edge information to decide how the partition of the region should be made, or in other words, where to split the region. The idea is the adjustment of this decision to boundary information and to split the region following the edges contained in it. In reference to previous works, the authors affirmed that although the quad-tree scheme is simple to implement and computationally efficient, its major drawback is that the image tessellation process is unable to adapt the tessellation grid to the underlying structure of the image. For this reason they proposed to employ the incremental Delaunay triangulation competent of forming grid edges of arbitrary orientation and position. The tessellation grid, defined by the Delaunay triangulation, is adjusted to the semantics of the image data. In the splitting phase, if a global similarity criterion is not satisfied, pixels lying on image boundaries are determined using local difference measures and are used as new vertices to locally refine the tessellation grid.

2.2.2 Integration in Region-growing Algorithms

One of the first integrations of edge information into a region-growing algorithm can be found in the work of Xiaohan et al. [35], where edge information was included in the decision criterion. A classic region-growing algorithm generally only takes into account the contrast between the current pixel and the region in order to decide the merging of them. Xiaohan et al. proposed a region-growing technique that includes the gradient region in the homogeneity criterion to make this decision. The proposed combination of

[1] In order to avoid confusion, we have called graph-edge an edge that joins two nodes in a graph.

region-growing and gradient information can be expressed in the following formula

$$\begin{aligned} x(i,j) &= |X_a^N v - f(i,j)| \\ z(i,j) &= (1-\phi)x(i,j) + \phi G(i,j) \end{aligned} \tag{1}$$

where $X_a^N v$ is the average grey value of the region which is updated pixel by pixel. The contrast of the current pixel with respect to the region is denoted by $x(i,j)$. Parameter ϕ controls the weight of gradient, $G(i,j)$. Finally, the sum of the local and the global contrast is the final homogeneity measure, $z(i,j)$. Following this expression the proposed algorithm can be described using only two steps:

Step 1 If $z(i,j)$is less than a given threshold β, then the current pixel is merged into the region.

Step 2 else the local maximum of the gradients on a small neighbourhood of the current pixel is searched along the direction of region growing. The procedure stops at the pixel with the local gradient maximum.

The first step of the algorithm describes the growing of the region guided by the proposed homogeneity criterion. The second one tries to avoid the typical error of the region-based segmentation techniques; that is, the inaccuracy of the boundaries detected, by putting the result of the segmentation in coincidence with the edge map.

A similar integration proposal was suggested by Falah, Bolon and Cocquerez [19] in 1994. In this work the gradient information is included in the decision criterion to restrict the growth of regions. At each iteration, only pixels having low gradient values (below a certain threshold) are allowed to be aggregated to the growing region. Another interesting aspect of this work is the choice of the seeds for the process of region growing. This selection uses the redundancy between the results obtained by several region segmentations (with different thresholds and different directions of image scanning), with the aim to place the seeds in a proper position in which they have a high degree of certainty of belonging to an homogeneous region.

In 1992 Salotti and Garbay [17] developed a theoretical framework of an integrated segmentation system. The core of the problem of traditional segmentation methods, as denoted by the authors, relates to the autarchy of the methods and to the schedule of conditions that are defined with a priori assumptions. In order to solve this problem, major directives to control each decision are presented: to accumulate local information before taking difficult decisions; to use processes exploiting complementary information to cooperate successfully; to defer difficult decisions until more information is available; and finally, to enable easy context switches to ensure an opportunistic cooperation. The main idea of these directives is that each decision must be strongly controlled. This implies that a massive collaboration must be carried out, and that the segmentation task should not be necessarily achieved before the beginning of the high-level process. Finally, all these principles are used in a segmentation system with a region-growing process as main module. Pixels that seem difficult to classify because there is insufficient information for a sure decision, are given to an edge detection unit that has to respond whether they correspond to an edge, or not. The same directives were followed in an a posteriori work [36] that presents an edge-following technique which uses region-based information to compute adaptive thresholds. In such situations, where it is difficult to follow the high gradient, complementary information is requested and successfully obtained through the emergence of regions on both sides of the edge. A child edge process is then created with a threshold adapted to lower gradient values. Moreover, the authors introduce the adaptability of the aggregation criterion to the region's characteristics: several types of region are distinguished and defined. The region-growing method dynamically identifies the type of the analysed region, and a specific adapted criterion is used.

Fuzzy logic

A current trend in segmentation techniques that deserves special attention, is the use of fuzzy logic [37]. The role of fuzzy sets in segmentation techniques is becoming more important [38, 39] and the integration techniques are in the main stream of this tendency. In this sense, we want to emphasize a recent interest of researchers to incorporate fuzzy logic methods in integrated segmentation. This is mainly because these two methods are developed from complementary approaches and do not share a common measure. Hence, fuzzy logic offers the possibility to solve this problem, as it is especially suited to carry out the fusion of information of diverse nature [27, 40]. In the case of embedded integration of edge information into a region-growing procedure [41, 42], the fuzzy rule-based homogeneity criterion offers several advantages in contrast to ordinary feature aggregation methods. Among them is its short development time, due to the existing set of tools and methodologies for the development of fuzzy rule-based systems. An existing rule-based system can be easily modified or extended to meet the specific requirements of a certain application. Furthermore, it does not require a full knowledge of the process and it is intuitive to understand due to its human-like semantics. Additionally, it is possible to include such linguistic concepts as shape, size and colour, which are difficult to handle using most other mathematical methods.

A key work in using fuzzy logic was by Steudel and Glesner [41], where the segmentation is carried out on the basis of a region-growing algorithm that uses a fuzzy rule-based system for the evaluation of the homogeneity criterion. The authors affirmed that there are several negative points in just using the intensity difference for segmentation:

- over-segmentation of the image
- annoying false contours
- contours that are not sufficiently smooth

Therefore, new features are introduced into the rule-base of the fuzzy rule-based system, which result in a better and more robust partitioning of the image while maintaining a small and compact rule-base. The proposed homogeneity criterion is composed of a set of four fuzzy rules. The main criterion is the difference between the average intensity $\overline{A}$ of a region R_j and the pixel i_n under investigation. The corresponding fuzzy rule is

R1: IF DIFFERENCE IS SMALL
THEN HOMOGENEOUS
ELSE NOT_HOMOGENEOUS

Another quite important feature for the segmentation of regions is the gradient at the position of the pixel to be merged. A new pixel may be merged into a region R_j when the gradient at that location is `low`. On the other hand, when the gradient is `too high`, the pixel definitely does not belong to the region and should not be merged. In terms of a fuzzy rule

R2: IF GRADIENT IS LOW
THEN PROBABLY HOMOGENEOUS
ELSE NOT_HOMOGENEOUS

With this rule, an adjacent pixel i_n satisfies the premise of rule R2 with a degree of $\mu_{LOW}(GRADIENT(i_n))$. The two remaining rules are refereed to the size and the shape of regions, in order to avoid smallest regions, and to benefit compact regions with smooth contours. A complete scheme of this proposal is shown in Fig. 6.

Krishnan, Tan and Chan [42] describe a boundary extraction algorithm based on the integration of fuzzy rule-based region growing and fuzzy rule-based edge detection. The properties of homogeneity and edge information of each candidate along the search directions are evaluated and compared with the properties of the seed. Using the fuzzy output values of edge detection and a similarity measure of the candidate pixel, the test for the boundary pixel can be determined. This proposal was applied on colonoscopic images for the identification of closed-boundaries of intestinal lumen, to facilitate diagnosis of colon abnormalities.

Another proposal for the integration of boundary information into the region-growing process was presented by Gambotto in [43], where edge information was used to stop the growing process. The algorithm starts with the gradient image and an initial seed that must be located inside the connected region. Then, pixels that are adjacent to the region are iteratively merged if they satisfy a similarity criterion. A second criterion is used to stop this growth. They assume that the gradient takes a high value over a large part of the region boundary. Thus, growth termination is based on the average gradient, $F(n)$, computed over the region boundary following the expression

$$F(n) = \sum G(k,l)/P(n) \tag{2}$$

where $P(n)$ is the perimeter of the region R(n), and $G(k,l)$ is the value of the modulus of the gradient of pixels on the region boundary.

The iterative growing process is then continued until the maximum of the global contrast function, F, is detected. The authors point out that this cooperation between region growing and contour detection is in fact desirable because the assumption of homogeneous regions is usually too restrictive. Using this approach, a wider class of regions can be characterized than by smooth grey-level variations alone.

3 Post-processing Integration

In contrast to the works analysed up until this point, which follow an embedded strategy, the post-processing strategy carries out the integration a posteriori to the segmentation of the image by region-based and boundary-based algorithms. Region and edge information is extracted in a preliminary step, and then integrated together. Post-processing integration is based on fusing results from single segmentation methods attempting to combine the map of regions (generally with thick and inaccurate boundaries) and the map of edge outputs (generally with fine and sharp lines, but dislocated) with the aim to provide an accurate and meaningful segmentation. Most researchers agree on differentiating embedded from post-processing. We have identified different approaches for performing these tasks:

1) **Over-segmentation**: the approach consists of using a segmentation method with parameters specifically fixed to obtain an over-segmented result. Then, additional information from other segmentation techniques is used to eliminate false boundaries that do not correspond with regions.

2) **Boundary Refinement**: this approach considers the region segmentation result as a first approach, with regions well defined, but with inaccurate boundaries. Information from edge detection is used to refine region boundaries and to obtain a more precise result.

3) **Selection-Evaluation**: In this approach, edge information is used to evaluate the quality of different region-based segmentation results, with the aim of choosing the best. A third set of techniques deal with the difficulty of establishing adequate stopping criteria and thresholds in region segmentation.

3.1 Over-segmentation

This approach has emerged because of the difficulty of establishing an adequate homogeneity criterion for the region growing. As Pavlidis and Liow [18] suggested, the major reason that region growing produces false boundaries is that the definition of region uniformity is too strict, as when they insist on approximately constant brightness while in reality brightness may vary linearly within a region. It is very difficult to find uniformity criteria that match exactly these requirements and not generate false boundaries. Summarizing, they argued that the results can be significantly improved if all region boundaries qualified as edges are checked rather than attempting to fine-tune the uniformity criteria. A basic scheme is showed in Fig. 7.

A first proposal can be found in the work of Monga et al. [44, 45]. The algorithm starts with a region-growing or a split-and-merge procedure, where the parameters have been set up so that an over-segmented image results. Then the region merging process is controlled by edge information which helps to remove false contours generated by region segmentation. Every initial boundary is checked by analysing its coherence with the edge map, where real boundaries must have high gradient values, while low values correspond to false contours. According to this assumption, two adjacent regions are merged if the average gradient on their boundary is lower than a fixed threshold.

In 1992, Kong and Kosko [40] included fuzzy logic in the algorithm proposed by Monga et al. As Monga et al., Kong and Kosko computed gradient information that they called high-frequency characteristics h, to eliminate false contours.

$$h = \frac{|\text{high frequency components along the boundary}|}{\text{length of the boundary}} \tag{3}$$

For any boundary, if the high-frequency information h is `small`, the algorithm concludes the boundary is a false contour and it can be eliminated.

Another interesting work was presented by Pavlidis and Liow in [18]. The proposed algorithm shares the basic strategy of the previously described works, but the authors include a criterion in the merging decision in order to eliminate the false boundaries that have resulted from the data structure used. Starting from an over-segmented image, region boundaries are eliminated or modified on the basis of criteria that integrate contrast with boundary smoothness, and variation of the image gradient along the boundary, and a final criterion that penalizes the presence of artefacts reflecting the data structure used during the segmentation. For each boundary, a merit function is computed of the form

$$f_1(contrast) + \beta f_2(\text{segmentation artifacts}) \tag{4}$$

where boundaries with low values of that sum are candidates for elimination. Finally, the proposed algorithm ends up with a final step of contour refinement using snakes, which produces smoother contours.

Saber et al. proposed a segmentation algorithm [46] which uses a split-and-merge process to carry out the fusion of spatial edge information and regions resulting from adaptive Bayesian colour segmentation. The image is first segmented based on colour information only. Next, spatial edge locations are determined using the magnitude of the gradient of the three-channel image vector field, computed as described by Lee and Cok in [47]. In order to enforce the consistency of the colour segmentation map with colour edge locations, a split-and-merge procedure is proposed. In the first phase, colour segments that have at least one edge segment within their boundary will be split into multiple regions. The splitting is accomplished by first thresholding the gradient result, and then labelling all contiguous regions therein. Next, the merging criterion favours combining two regions if there is no significant edge between the region boundaries. A flowchart of the method is depicted in Fig. 8.

Using the same basic idea of starting from an over-segmented image, some authors have developed techniques that begin with edge detection to obtain over-segmentation results. The intention is the same as before: now, region information allows differentiation between true and false contours. Following this strategy, Philipp and Zamperoni [48] proposed to start with a high-resolution edge extractor, and then, according to the texture characteristics of the extracted regions, to decide whether to suppress or prolong a region. Derivative edge detectors, when employed at a high resolution, give long, rather isolated and well-localized contours in non-textured areas and numerous, short and close-spaced contours in textured areas. The former correspond to true edges in the image, because they are well localized and thin, so they must be preserved, and prolonged if possible. The latter ones must be suppressed if they are inside a textured region, but preserved and prolonged if they represent a piece of border. The feature used in this algorithm is the distance between textures on either side of the edge. To obtain texture information, two seeds are put on either side of the edge and start a recursive growing until N representative pixels are gathered. If the distance between textures is small, the edge is considered false and regions are merged. Otherwise, the contour is preserved and prolonged in order to maximize the distance on either side of the edge.

Fjortoft and Cabada [49] presented in 1997 another technique based on over-segmentation from edge detection, which was examined on SAR images. The authors discussed the key role of the threshold value to extract the possible edges from an edge strength map by thresholding. The chosen threshold is related to the probability of false alarm, i.e., the probability of detecting an edge in a zone of constant reflectivity. In order to detect all significant edges, a low threshold is set, accepting the detection of numerous false edges as well. The over-segmentation result provides, as the authors suggested, a good starting point for the merging process that eliminates false edges by merging regions. The merging step uses a Likelihood Ratio (LR) criterion to decide the homogeneity between adjacent regions and the consequent elimination of their boundary. That is LR is related to the probability that the two regions have the same reflectivity.

3.2 Boundary Refinement

As described above, region-based segmentation yields a good detection of true regions, although as is well known that the resultant sensitivity to noise causes the boundary of the extracted region to be highly irregular. This approach, which we have called result refinement, considers region-based segmentation as a first approximation to segmentation. Typically, a region-growing procedure is used to obtain an initial estimate of a target region, which is then combined with salient edge information to achieve a more accurate representation of the target boundary. As in the over-segmentation proposals, edge information permits refinement of an initial result.

An interesting example of boundary refinement can be found in the work of Haddon and Boyce [50], where they proposed a segmentation algorithm consisting of two stages: after an initial region segmentation, a posterior refinement of the generated regions is performed by means of a relaxation algorithm that uses the edge information to ensure local consistency of labelling. Nevertheless, the main characteristic of this work is the postulate that a co-occurrence matrix may be employed as a feature space, with clusters within the matrix being identified with the regions and boundaries of an image. This postulate is proven for nearest neighbour co-occurrence matrices derived from images whose regions satisfy Gaussian statistics; regions yield clusters on the main diagonal, and boundaries clusters off the main diagonal.

Chu and Aggarwal presented in [51] an algorithm which integrates multiple region segmentation and edge maps. The proposed algorithm allows multiple input maps and applies user-selected weights on various information sources. The first step consists of transforming all inputs to edge maps, then a maximum likelihood estimator provides initial solutions of edge positions and strengths from multiple inputs. An iterative procedure is then used to smooth the resultant edge patterns. Finally, regions are merged to ensure that every region has the required properties. The strength of this proposal is that the solution is a negotiated result of all input maps rather than a selection of them. More recently, Nair and Aggarwal [52] have made their initial proposal more sophisticated by stating the boundary refinement problem as a classification problem. Every point s on the region boundary must find its new location as a selection from a set of candidate edge element locations $\overline{z}$=z_j,j=0...n, where $z_0 = s$.

Using the Bayes decision rule, the algorithm chooses z_j as the new location if

$$p(s|z_j) \geq p(s|z_k)P(z_k) \quad \forall k \neq j, \tag{5}$$

where $p(s|z_j)$ represents the conditional density function of s given z_j, and $P(z_j)$ is the a priori probability of z. The a priori probability of each candidate location z_j is estimated as the proximity of the salient edge segment to which z_j belongs, to the boundary of the target region. Finally, the proposed algorithm tries to restore boundary segments by incorporating small parts of the target missed in the region segmentation; i.e., for each edge pixel at the site of a break in the boundary, tries to determine whether it is part of a salient edge. If it is, the complete edge segment can be incorporated into the boundary. A scheme of this proposal is indicated in Fig. 9.

A recent proposal on the boundary refinement approach was put forward by Sato et al. [53]. The objective of these authors is to obtain an accurate segmentation of 3D medical images for clinical applications. The proposed technique takes into account the gradients of the boundary and its neighbourhood and applies the gradient magnitude, based on a Sobel operator, for boundary improvement. The algorithm starts by successive steps of thresholding and ordinary region growing, which obtains a first segmentation of the region of interest. The highest gradient magnitude is expected at the boundary, so a growing process starts to find this optimal boundary. For each voxel (3D pixel) at a boundary, neighbourhoods of the voxel and outside the region are inspected by calculating their gradient magnitudes. If each of those voxels has a greater gradient magnitude than the boundary voxel, it is assigned to the next boundary region. This process is repeated recursively until no further boundary region can be created.

3.2.1 Boundary Refinement by Snakes

Although the above-mentioned proposals have contributed interesting results and new ideas, the most common way to refine the boundary consists of the integration of region information with dynamic contours, also called snakes. The concept of the snake was introduced by Kass et al. in [54]. A snake can be defined as an energy-minimizing spline guided by internal constraint forces and influenced by image forces. The image forces guide the snake towards salient image features such as lines, edges, and subjective contours. Representing the position of a snake parametrically by $v(s) = (x(s), y(s))$, its energy functional can be expressed as

$$E^*_{snake} = \int_0^1 [E_{int}(v(s)) + E_{ext}(v(s))]ds \quad (6)$$

where E_{int} represents the internal energy of the spline due to its elasticity and rigidity properties, and E_{ext} gives rise to the external constraint forces. The internal forces serve to impose a smoothness constraint, while the external energy guides the snake to image characteristics such as edges. Unlike most other techniques for finding salient contours, the snake model is active: it is always minimizing its energy functional and therefore exhibits dynamic behaviour. Due to the way the contour appears to slither while minimizing its energy, it is called a snake.

The snake method is known to solve such problems by locating the object boundary from an initial plan. However, snakes do not try to solve the entire problem of finding salient image contours. The high grey-level gradient of the image may be due to object boundaries as well as noise and object textures, and therefore the optimization functions may have many local optima. Consequently, in general, active contours are sensitive to initial conditions and they are only really effective when the initial position of the contour in the image is sufficiently close to the real boundary. For this reason, active contours rely on other mechanisms to place them somewhere near the desired contour. In first approximations to dynamic contours, an expert has been responsible for putting the snake close to an intended contour; its energy minimization carries it the rest of the way. The snake deforms itself into conformity with the nearest salient contour.

However, region segmentation could be the solution of the initialization problem of snakes. Proposals about integrated methods consist of using the region segmentation result as the initial contour of the snake. Here, the segmentation process is typically divided into two steps (see Fig. 10). First, a region growing with a seed point is performed in the target region, and its output is used for the initial contour of the dynamic contour model. Second, the initial contour is modified on the basis of energy minimization.

Different works can be found in the literature combining region detection and dynamic contours. In the work of Chan et al. [21], the greedy algorithm proposed by Williams [55] is used to find the minimum energy contour. This algorithm searches for the position of the minimum energy by adjusting each point on the contour during iteration to a lower energy position amongst its eight local neighbours. The result, although not always optimal, is comparable to that obtained by variational calculus methods and dynamic programming. The advantage is that their method is faster. Similar proposals can be found in the works of Vérard et al. [56] and Jang et al. [57]. Curiously, the results of all these techniques have been shown on Magnetic Resonance Imaging (MRI) images, but this is not a simple coincidence. Accurate segmentation is critical for diagnosis in medical images. However, it is very difficult to extract the contour that matches exactly the target region in MRI images. Integrated methods seem to be a valid solution to achieve an accurate and consistent detection.

In the sense of making maximum use of information and cooperation, there exists a set of techniques that do not limit region information to initialization of the snakes. Information supplied by region segmentation is also included in the snake, more specifically in its energy functional. This functional typically has two components: an internal energy component that applies shape constraints to the model, and an external energy derived from the data to which the model is being applied. In this approach, a term derived from region information is added to the external part of the energy functional. As a result, points on the contour are allowed to expand or contract according to the fit between contour and region information.

An exemplary work about these integration methods has been developed by Ivins and Porrill [58, 59]. In their implementation of the snake, the energy functional E is specified as

$$E = \frac{\alpha}{2} \oint_A \left| \frac{\delta \underline{u}}{\delta \lambda} \right|^2 d\lambda + \frac{\beta}{2} \oint_A \left| \frac{\delta^2 \underline{u}}{\delta \lambda^2} \right|^2 d\lambda - \rho \int_R \int G(I(x,y)) dx dy \tag{7}$$

The first two terms in equation 7 correspond, respectively, to the tension, and stiffness energy of the contour model, and together comprise the internal energy. The third term is the external energy derived from the image data. G is a goodness functional that returns a measure of the likelihood that the pixel, indexed by x and y in the image, is part of the region of interest. R is the interior of the contour, and α,β and ρ are parameters used to weigh these three energy terms. Thus, as the energy is minimized, the contour deforms to enclose as many pixels with positive goodness as possible while excluding those with negative goodness. This seed region serves two purposes: it is used as the initial configuration of the model, and also to construct a statistical model of the attributes (e.g., intensity, colour, texture) of the data comprising the region as a whole from which the goodness functional is derived. This implementation of the method has been a posteriori revised and modified by Alexander and Buxton [60], in order to be an effective solution to the problem of tracking the boundaries of country lanes in sequences of images from a camera mounted on an autonomous vehicle.

Another remarkable work, which is constantly evolving, has been carried out by Chakrabory et al. [61], who applied snakes in biomedical image analysis. The proposal uses a Fourier parameterisation to define the dynamic contour. It expresses a curve in terms of an orthonormal basis, which for most practical situations, is constrained to a limited number of harmonics. The curve is thus represented by a set of corresponding Fourier coefficients

$$p = (a_0, c_0, a_1, b_1, c_1, d_1, ...) \tag{8}$$

The objective function used is a function of conditional probability $P(p|I_g, I_r)$, or the probability of obtaining the p-contour given the region-classified image I_r and the image of the scalar magnitude of the grey-level gradient I_g. The function is the sum of three terms

$$M(p, I_g, I_r) = M_{prior}(p) + M_{gradient}(I_g, p) + M_{region}(I_r, p) \tag{9}$$

The first (prior) term biases the boundary toward a particular distribution of shapes generated from prior experience, while the second term in the equation (eq. 10), $M_{gradient}(I_g, p)$, depends on the coincidence of the parameterized boundary, with the image edges appearing as coherent features in the scalar gradient of the grey levels,

$$M_{gradient}(I_g, p) = \int_{C_p} I_g[x(p,t), y(p,t)]dt \tag{10}$$

such that the likelihood of p representing the true boundary is proportional to the sum of the gradient values of all points in C_p.

Finally, term $M_{region}(I_r, p)$ (eq. 11) measures the goodness of match of the contour with the perimeter of the segmented interior of the object. This method rewards the boundary that contains as much of the inside region and as little of the outside as possible. This function is evaluated by integrating over the area A_p bounded by the contour p, as expressed in

$$M_{region}(I_r, p) = \int\int_{A_p} I_r(x, y) dA \tag{11}$$

where pixels inside and outside A_p are set equal to $+1$ and -1, respectively. Stated that area integral must be evaluated many times, Chakraborty et al. describe an alternative and faster integration method based on Green's Theorem.

A recent proposal of Chakraborty and Duncan [62] emphasizes the necessity of integration. In this work, a method is proposed to integrate region segmentation and snakes using game theory in an effort to form a unified approach. The novelty of the method is that this is a bi-directional framework, whereby both computational modules improve their results through mutual information sharing. This consists of allowing the region and boundary modules to assume the roles of individual players who are trying to optimize their individual cost functions within a game-theoretic framework. The flow of information is restricted to passing only the results of the decisions between the modules. Thus, for any one of the modules, the results of the decisions of the other modules are used as priors, and players try to minimize their cost functions at each turn. The flow diagram for game-theoretic integration is showed in Fig. 11. The authors affirm that this makes it unnecessary to construct a giant objective function and optimize all the parameters simultaneously.

3.3 Selection

In the absence of object or scene models or ground truth data, it is critical to have a criterion that enables evaluation of the quality of a segmentation. In this sense, a set of proposals have used edge information to define an evaluation function that qualifies the quality of a region-based segmentation. The purpose is to achieve different results by changing parameters and thresholds on a region segmentation algorithm, and then to use the evaluation function to choose the best result. This strategy permits solution of the traditional problems of region segmentation, such as the definition of an adequate stopping criterion or the setting of appropriate thresholds. In 1986, Fua and Hanson [63] developed an algorithm that used edge information to evaluate region segmentation. In their proposal, high-level domain knowledge and edge-based techniques were used to select the best segmentation from a series of region-based segmented images. However, from this pioneer proposal the majority of methods based on the selection approach have been developed in the last five years, as is stated in the following.

In 1995, Le Moigne and Tilton [20] proposed choosing a stopping criterion for a region-growing procedure. This is adjusted locally to select the segmentation level that provides the best local match between edge features and region segmentation contours. Figure 12 shows a basic scheme of this proposal. Desired refined segmentation is defined as the region segmentation with minimum length boundaries including all edges extracted by the Canny edge detector and for which all contours include some edge pixels. The iteration of the region-growing process which minimizes the "Hausdorff distance" is chosen as the best iteration. The "Hausdorff distance" measures the distance between two binary images: the edge pixels obtained through Canny, A, and the boundary of the regions obtained through the region growing, B, and is computed as

$$H(A,B) = \frac{1}{2}[\max_{a \epsilon A} \min_{b \epsilon B} d(a,b) + \max_{b \epsilon B} \min_{a \epsilon A} d(a,b)] \tag{12}$$

where $d(a,b)$ is a point-to-point Euclidean distance. In summary, the distance is computed by finding, for each edge pixel, the closest region boundary pixel, and respectively for each region boundary pixel the closest edge pixel, and then computing the maxima and minima expressed in the equation.

Hojjatolestami and Kittler [64] presented a region-based segmentation which used gradient information to specify the boundary of a region. The method starts with a growing process which is stopped using the maximum possible size N of a region. Then, a reserve check on the relevant measurements is applied to detect the region boundary. Contrast and gradient are used as sequential discontinuity measurements derived by the region-growing process whose locally highest values identify the external boundary and the highest gradient boundary of each region, respectively. Contrast is defined as the difference between the average grey level of the region and the average of the current boundary, and is continuously calculated. The maximum contrast corresponds to the point where the process has started to grow into the background. Finally, the last maximum gradient measure, before the maximum contrast point, specifies the best boundary for the region.

Siebert [65] developed an interesting, simple and faster integration technique, where edge information is used to adjust the criterion function of a region-growing segmentation. For each seed the algorithm creates a whole family of segmentation results (with different criterion functions) and then, based on the local quality of the region's contour, picks the best one. To measure the segmentation quality, a metric that evaluates the strength of a contour is proposed. The contour strength $cs(R)$ of a region R is defined as the contrast between both sides of the boundary. More formally, the contour strength is expressed as the sum of the absolute differences between each pixel on the contour of a region and the pixels in the 4-neighbourhood of these contour points that are not part of the region. To calculate this parameter it is necessary to process a contour-following task, as well as several differences between integer numbers. As the authors remark, these operations are computationally inexpensive. Furthermore, the authors suggest that slightly improved results at higher computational costs can be expected if the contour strength is based on the gradient at each contour pixel rather than on the intensity difference.

A similar methodology can be found in a recent work of Revol-Muller et al. [66], where they have proposed a region-growing algorithm for the segmentation of medical three-dimensional images. As in the work described previously, the method consists of generating a region-growing sequence by increasing the criterion function at each step. An evaluation function estimates the quality of each segmented region and permits determination of the optimal threshold. This method is illustrated schematically in Fig. 13. The authors proposed different parameters based either on boundary or region criteria to be used as the evaluation function. Three choices are proposed based on boundary criteria: 1) the sum of contrasts of all transition couples (two neighbouring pixels located on either side of the boundary are called a transition couple), normalized by the total number of transition couples; 2) the sum of all standard deviations of members of the boundary and its neighbouring pixels not belonging to the segmented region, normalized by the total number of pixels belonging to the boundary; 3) the sum of transition levels of all transition couples normalized by total number of transition couples. Three alternate choices based on region criteria are proposed: 1) entropy, 2) inter-cluster variance and 3) inverse distance between the grey-level function of the original image and the mean of the region and its complement. Tests on 3D magnetic resonance images demonstrated that the proposed algorithm achieves better results than manual thresholding.

More ideas about the integration of different methods can be found in the work of Hibbard [67], where snakes are used to evaluate the quality of a segmentation result. The proposal is based on an iteratively region growing approach, where at each stage the region of interest grows following a deterministic criterion function based on a hierarchical classifier operating on texture features. At each stage, the optimal contour is determined using snakes. The optimal choice is the one that best satisfies the three conditions of the objective function proposed by Chakraborty et al. (see Section 3.2 and Eq. 9). The function proposed by Chakraborty is used in the method as a quality measure of the current segmentation and allows choice of which is the best segmentation between the set of iterations of the growing process. Finally, the resulting contour corresponds to the maximum over all of the iteratively computed contours.

4 Summary

The review of different segmentation proposals that integrate edge and region information has permitted the identification of different strategies and methods to fuse such information. The aim of this summary is to point out the advantages and disadvantages of these approaches, as well as remark upon new and interesting ideas that perhaps have not been properly exploited.

For the purpose of providing an overview of the presented methods, Table 1 summarizes the different ways to carry out the integration of edge and region information. The first column distinguishes the strategy according to the time of the fusion: embedded and post-processing. The second column identifies the approach used to carry out the segmentation. The next two columns describe the problem that the approach tries to solve and a description of the objective. Finally, the last column summarizes the procedure used to perform the segmentation task.

As described in Section 1.1, embedded and post-processing integration use different principles to perform the task of segmentation. Embedded integration is based on the design of a complex, or a superior, algorithm which uses region and edge information to avoid errors in segmentation. On the other hand, the post-processing strategy accepts faults in the elemental segmentation algorithms, but an a posteriori integration module tries to correct them. The key words that allow characterization and comparison of both strategies are:

- single algorithm and avoidance of errors by the embedded integration, and

- multiple algorithms and correction of errors by post-processing integration.

These two essential characteristics cause these strategies to exhibit outstanding differences. The first aspect to analyse is the complexity of both strategies. Embedded integration produces, in general, a more complex algorithm because, as derived from its definition, it endeavours not to commit errors or take wrong decisions. On the other hand, the post-processing strategy can be viewed as the set of many simple algorithms working in parallel producing many wrong segmentation results. The solution of these problems is moved to an a posteriori fusion module that works over these results. Therefore, post-processing complexity is lower because the quantity of information to process decreases, as only the results are taken into consideration.

Another aspect to analyse is the independence of these integration strategies as regards their implementation in the segmentation algorithm. In this sense, the embedded strategy is strongly dependent, because typically it implies the design of a new algorithm, which incorporates the integration internally. Hence, any change in the integration procedure will imply the modification of the algorithm. On the other hand, the post-processing strategy produces a more general approach because it is independent of the choice of algorithms to segment the image. The fusion of the information only takes into account the results of the segmentation algorithms, so the way they are obtained is not important, and it is possible to use any established algorithms. Some researchers [20] indicate that post-processing integration can also be viewed in a general data management framework, where all incoming data is processed on-line upon acquisition, producing basic features such as edges and regions.

However, it is necessary to remark that this independence assigned to the post-processing strategy is not complete, and this is the weak point of this approach. It is true that it is independent concerning the chosen method, but obviously if the results achieved by these algorithms are very poor, post-processing fails. It is undeniable that a posteriori fusion needs to work on a relatively good set of segmentation results. So, final segmentation will inevitably depend, to a larger or lesser extent, on the initial results of the segmentation. An initial fault, for example, is that inappropriate selection of seeds in a region-growing algorithm, will be carried over into the totality of the segmentation process. A posteriori integration of edge information may not be able to overcome an error of this magnitude.

4.1 Disadvantages of both strategies

Once a set of key proposals integrating edge and region information have been reviewed, it can be stated that it is not feasible to determine which is the best. First, this is because there is no generally accepted methodology in the field of computer vision which elucidates how to evaluate segmentation algorithms [68]. Second, because comparing different segmentation algorithms with each other is difficult, mainly because they differ in the properties and objectives they try to satisfy and the image domain in which they are working. In this sense, it is well known that there is no method available for all images, since requirements related to the images to be segmented are different; e.g., the requirements of 3D medical image analysis are very different from the outdoor colour images analysed by a road-following system.

In reference to the weak points of the approaches, a serious difficulty appears when it is required, as is usual, to obtain the most significant edges in the image. This process is not a trivial task: for example, the gradient map has some hardships as regards the choice of an adequate threshold to achieve a reliable binarization. In this sense, the embedded proposals that use the gradient map directly as boundary information have an important advantage. Another weak point to take into account is the lack of attention that, in general, the reviewed works devote to texture. Without this property, it is not possible to discern when a high-magnitude gradient corresponds to a boundary between regions, or if it is the response to a textured region. Regrettably, the texture is generally forgotten in the different proposals of embedded integration. As a consequence, the algorithms are not adapted to segment heavy textured areas, resulting in an over-segmentation of these regions. Segmentation techniques based on post-processing integration also suffer from some deficiencies. Those based on starting from an over-segmented image must solve a non-trivial problem: What should the threshold be to obtain an over-segmented result? It is well known that images have different characteristics, so this threshold cannot be a fixed value. An adequate threshold for one image may not be effective for others, and this can cause the irrecoverable loss of boundaries. An initial mistake in such algorithms could be a serious handicap for the a posteriori fusion, resulting in an under-segmented result. As described in Section 3.2, the aim of the boundary refinement approaches is to obtain reliable smooth boundaries. In order to achieve this, the cooperation between region-based segmentation and snakes, which is the most usual technique, is really a good choice. However, it should be stressed that the objective of these algorithms is, generally, to segment not a whole image, but individual objects from an image. Furthermore, these algorithms bear a deficiency that is shared with the third set of post-processing methods: their exclusive attention to the boundary. Result refinement is reduced to the region boundary, so it is not possible to correct other mistakes inside the region. The same problem is found in the selection approach, where the quality measure of a segmentation based on boundary information is exclusively based on the external boundary, and not on any inner contour lines caused by holes. For this reason, the regions extracted might contain holes. In summary, all these weak points of the post-processing integration, reaffirm the previous assertion about the necessity to have good initial segmentation results and the incapacity of the post-processing strategy to correct some initial mistakes.

5 Conclusions and further work

In this paper we have reviewed some key segmentation techniques, integrating region and boundary information. Special emphasis has been given to the strategy performed to carry out the integration process. In this sense, a classification of cooperative segmentation techniques has been proposed, and the paper has described several algorithms with the aim of pointing out their strengths and weaknesses.

The lack of a special treatment of textured images has been noticed, and it is one of the great problems of segmentation [69]. If an image mainly contains homogeneous colour regions, traditional methods of segmentation working in colour spaces can be sufficient to achieve reasonable results. However, some real images "suffer" from texture, for example, images corresponding to natural scenes which have considerable variety of colour and texture. Hence, undoubtedly, texture has a pivotal role to play in image segmentation. However, new and promising research has started in relation to the integration of colour and texture [70]. The intention of integrating complementary information from the image may follow; it seems reasonable to think that a considerable improvement in segmentation could result from the fusion of colour, texture and boundary information.

Concerning the strategies for the integration of edge and region information, it is obvious that there are still methods to be explored. In this sense, a hybrid strategy between embedded and post-processing may be a solution for some of the above mentioned typical weak points. A basic scheme of such an idea is presented in Fig. 14, where an algorithm based on an embedded strategy produces an initial result, which will be a posteriori refined by a post-processing fusion with boundary information. More specifically, the first step of this new proposal could consist of the extraction of edge and region information. In this sense, an embedded algorithm permits the adequate placement of the seeds in an optimal position, and a result with regions free of holes may be obtained. Then, a posteriori fusion with boundary information could refine the segmentation, improving the resulting boundaries. This proposal combines both strategies in a hybrid scheme that uses integration of information in all steps of segmentation with the aim to obtain a better segmentation result.

Segmentation techniques, in general, still require considerable improvement. Surveyed techniques still present some faults and there is no perfect segmentation algorithm, something which is a vital necessity for the advancement of computer vision and its applications. However, integration of region and boundary information has allowed the improvement of previous results. Note that the current work in this field of research has generated numerous proposals in the last few years. Thus, this current interest permits us to foresee that further work and improvement of segmentation will be focussed on the integration of algorithms and information.

Acknowledgements

This work has been partially developed thanks to the support of the Departament d'Universitats, Recerca i Societat de la Informació de la Generalitat de Catalunya.

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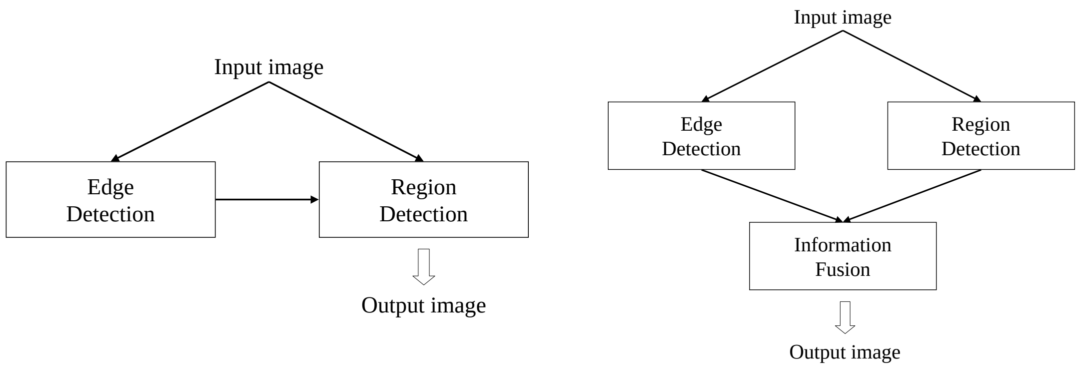

(a) (b)

Figure 1: Strategy schemes for region and boundary integration according to the time of the fusion: (a) Embedded integration; (b) Post-processing integration

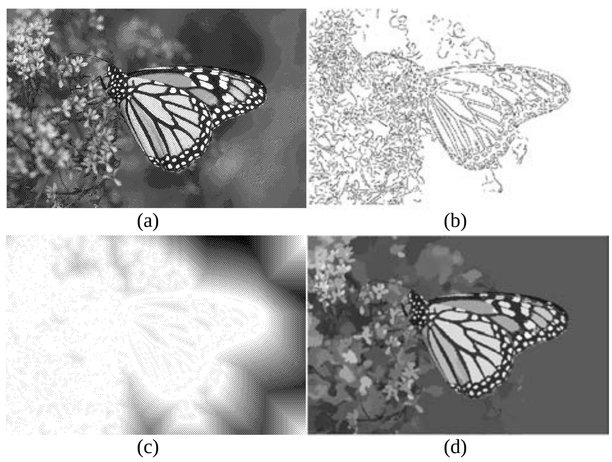

Figure 2: The Sinclair approach using the Voronoi image: (a) Original image; (b) Edges extracted from the original colour image; (c) Voronoi image computed from the edge image; (d) Final segmentation

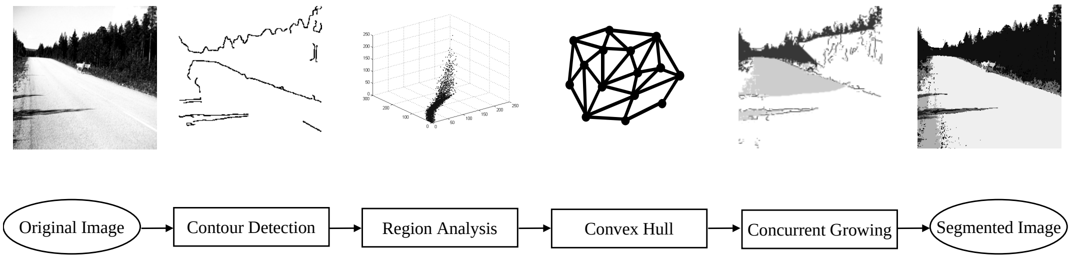

Figure 3: Scheme of the segmentation technique proposed by Cufí et al. The method is composed of four basic steps: 1) Main contour detection, 2) Analysis of the seeds, 3) Adjustment of the homogeneity criterion and 4) Concurrent region growing

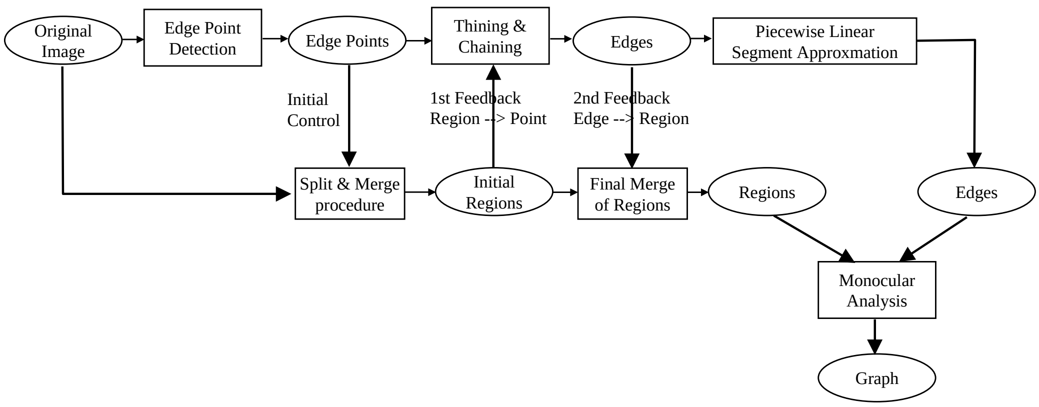

Figure 4: Scheme of the segmentation technique proposed by Bonnin et al. The edge information guides the split-and-merge procedure in both steps of the algorithm: first to decide the split of a region, and finally in the merging phase to solve the possible over-segmentation.

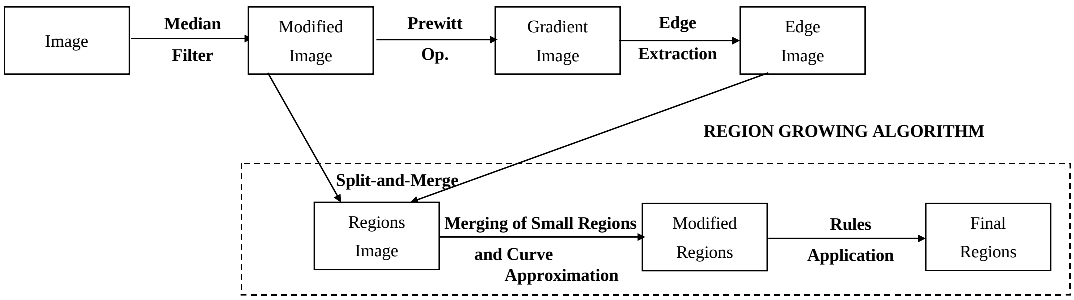

Figure 5: Segmentation technique proposed by Buvry et al. Edge information is used to guide the split-and-merge region segmentation. Finally, a set of rules improve the initial segmentation by removing boundaries without corresponding edge information.

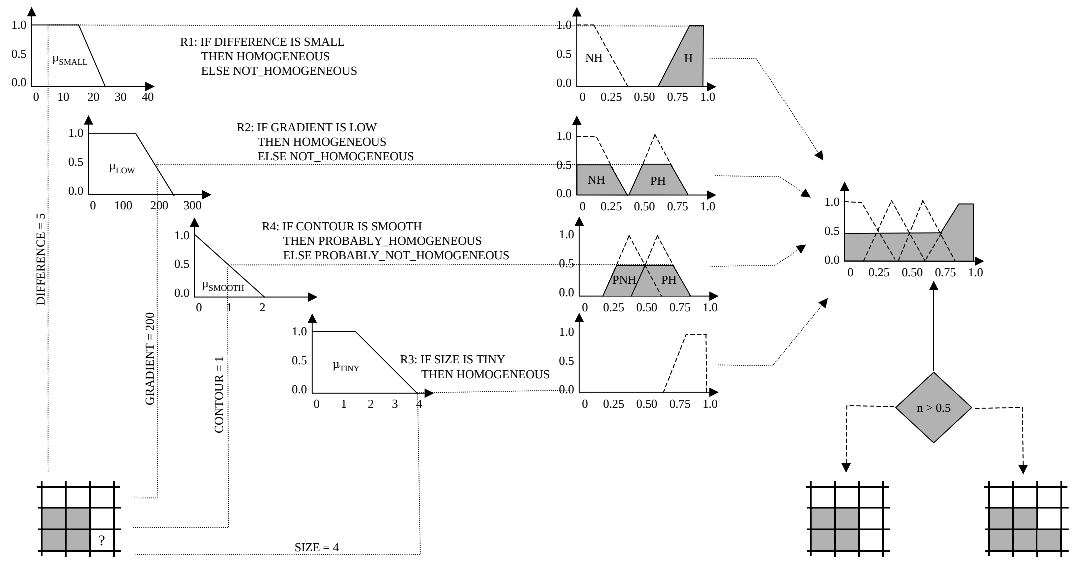

Figure 6: Fuzzy segmentation technique by Steudel and Glesner. The method is composed of a set of fuzzy rules corresponding to the main properties of the regions: intensity, gradient, shape and size. The united result of these rules indicates the desirability of aggregating a new pixel to the region. Reprinted from Pattern Recognition, vol. 32, no. 11, A. Steudel and M. Glesner, Fuzzy Segmented Image Coding Using Orthonormal Bases and Derivative Chain Coding, page 1830, ©1999, with permission from Elsevier Science.

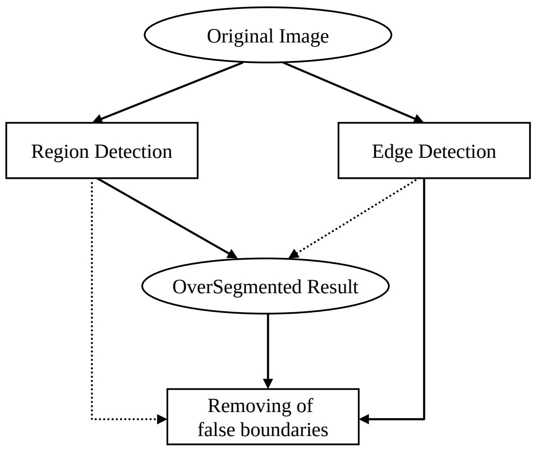

Figure 7: Scheme of post-processing integration method based on over-segmentation. First, thresholds are set to obtain an initial over-segmented result. Next, complementary information allows removal of false boundaries.

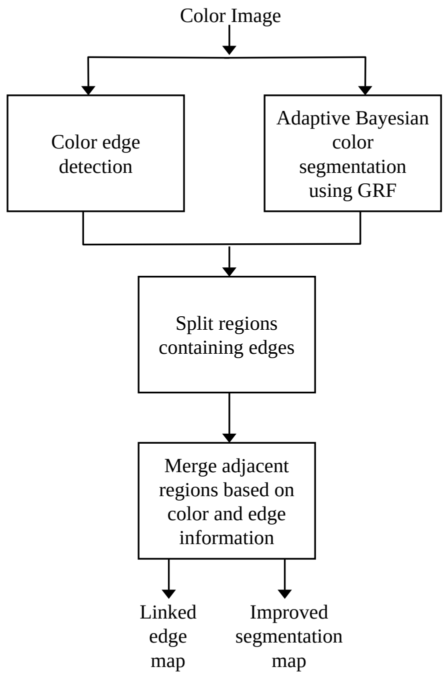

Figure 8: Flowchart of the method proposed by Saber, Tekalp and Bozdagi. First, an initial segmentation map is computed. Then, region labels are optimized by split-and-merge procedures to enforce consistency with the edge map. Reprinted from Image and Vision Computing, vol. 15, no. 10, E. Saber, A.M. Tekalp and G. Bozdagi, Fusion of Color and Edge Information for Improved Segmentation and Edge Linking, page 770, ©1997, with permission from Elsevier Science.

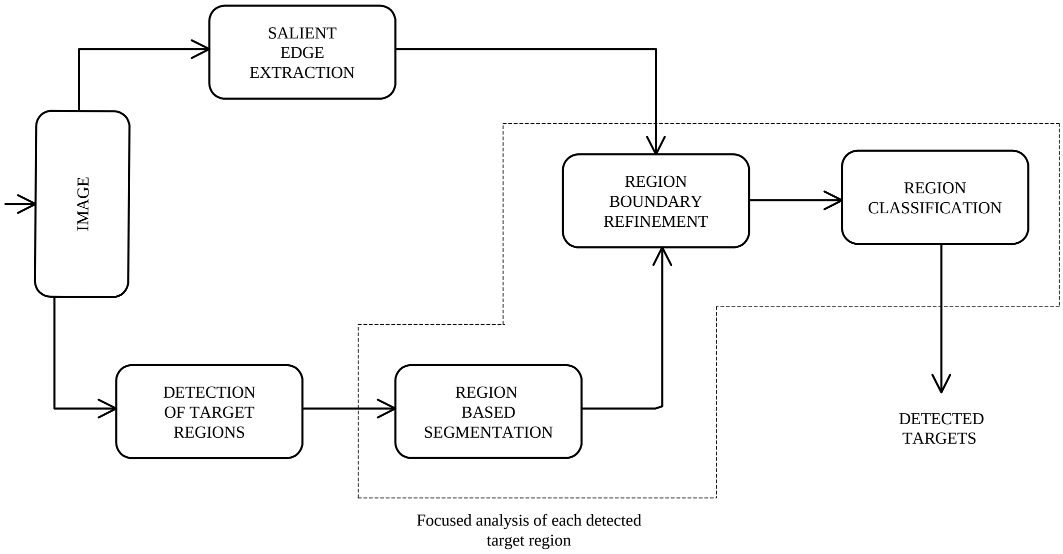

Figure 9: The general flow of the target segmentation paradigm proposed by Nair and Aggarwal. Boundary refinement from edge information is stated as a classification problem.

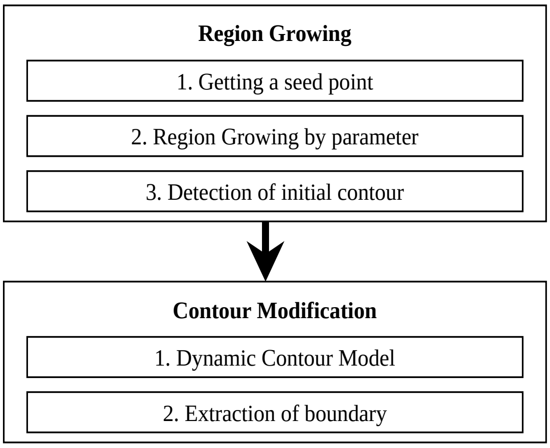

Figure 10: Block diagram of integration proposal using snakes. The region-based segmentation result is used to initialize the position of the dynamic contour. Next, energy minimization permits extraction of the accurate boundary of the target object.

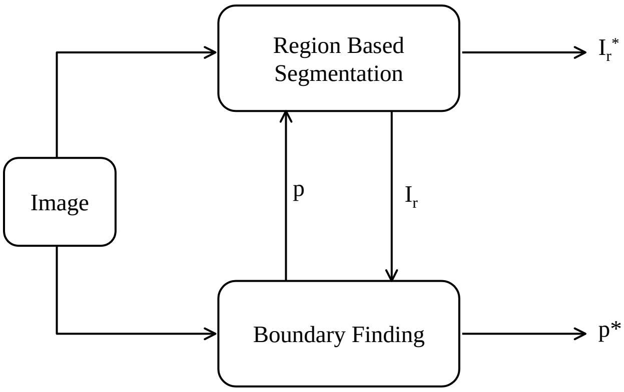

Figure 11: Flow diagram for game-theoretic integration of region-based segmentation and boundary finding proposed by Chakraborty and Duncan. The outputs of each of the modules feedback to each other after every decision-making step. The algorithm stops when none of the modules can improve their positions unilaterally. Reprinted from IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 21, no. 1, A. Chakraborty and J.S. Duncan, Game-Theoretic Integration for Image Segmentation, page 16, ©1999 IEEE.

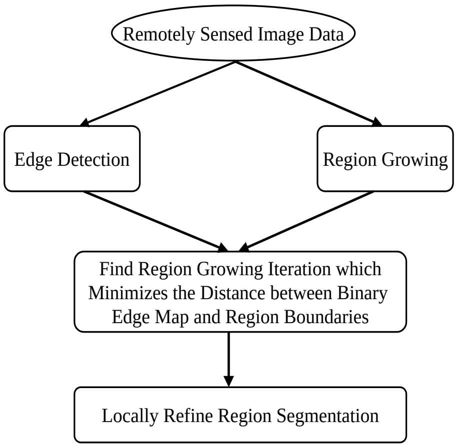

Figure 12: Outline of the edge/region integration algorithm proposed by Le Moigne and Tilton. Edge information is used to decide the best region-growing iteration that provides the best local match edge features and region boundaries. Reprinted from IEEE Transactions on GeoScience and Remote Sensing, vol. 33, no. 3, J. LeMoigne and J.C. Tilton, Refining Image Segmentation by Integration of Edge and Region Data, page 606, ©1995 IEEE.

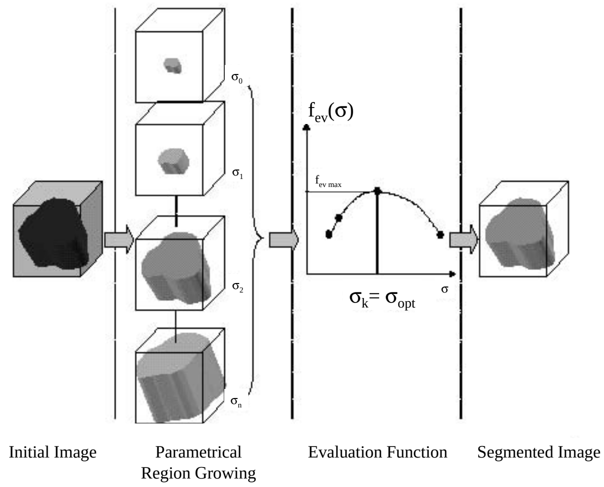

Figure 13: Scheme of the method proposed by Revol_Muller et al. A sequence of segmented regions is obtained by increasing the homogeneity threshold. Then, the evaluation function determines the optimal threshold automatically.

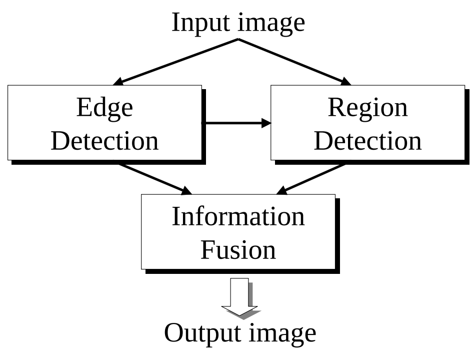

Figure 14: Hybrid strategy scheme to the region and boundary integration.

Table 1: Summary of approaches to image segmentation integrating region and boundary information

Integration	**Approach**	**Problem to Solve**	**Objective**	**Procedure**
Embedded	Seed placement	The resulting region-based segmentation inevitably depends on the choice of initial region growth points.	Choice of reasonable starting points for region-based segmentation.	Edge information is used to choose a seed (or some seeds) inside the region to start the growth.
	Decision Criterion	The obtained region's shape depends on the particular growth decision criterion chosen.	To have in account edge information, together or not with colour information, to decide about the homogeneity of a region.	A region is not homogeneous when there are edges inside. For this reason, a region cannot grow beyond an edge.
Post-processing	Over-Segmentation	Uniformity criteria are too strict and generate false boundaries in segmentation.	To remove false boundaries that do not coincide with additional information.	Thresholds are set to obtain a first over-segmented result. Next, boundaries that do not exist in the segmentation from a complementary approach are removed.
	Boundary Refinement	Region-based segmentation generates errors at boundaries and this is highly irregular.	To refine the result from region-based segmentation using edge information and arrive at a more accurate representation.	A region-based segmentation is used to get an initial estimate of the region. Next, the optimal boundary that coincides with edges is searched. This process is generally carried out using snakes.
	Selection	There is not a criterion to enable the evaluation of the quality of a segmentation.	To use edge information to carry out this evaluation in order to choose the best segmentation from a set of results.	The quality of a region segmentation is measured as the correspondence of the boundary with the edge information.