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Strategies for image segmentation combining region and boundary information

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Abstract

Image segmentation has been, and still is, an important research area in Computer Vision, and hundreds of segmentation algorithms have been proposed in the last 30 years. However, elementary segmentation techniques based on either boundary or region information often fail to produce accurate segmentation results on their own. In the last few years, there has therefore been a trend towards algorithms that take advantage of their complementary nature. This paper reviews various segmentation proposals that integrate edge and region information and highlights different strategies and methods for fusing such information. The key objective is to point out the advantages and disadvantages of the various approaches, as well as to comment upon new and interesting ideas that perhaps have not been properly exploited.

Keywords: Image segmentation; Information fusion; Region detection; Edge detection

1. Introduction

One of the first and most important operations in image analysis and Computer Vision is segmentation (Rosenfeld and Kak, 1982; Haralick and Shapiro, 1992/1993). 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 certain properties, such as grey level, texture or colour. Applications range from industrial quality control to medicine, robot navigation, geophysical exploration, and military applications. In all these areas, the quality of the end result 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: Riseman and Arbib, 1977; Zucker, 1977; Fu and Mui, 1981; Haralick and Shapiro, 1985; Nevatia, 1986; Pal and Pal, 1993). Many segmentation methods are based on two basic properties of pixels in relation to their local neighbourhood: discontinuity and similarity. Pixel

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discontinuity gives rise to boundary-based methods, whereas pixel similarity gives rise to region-based methods.

Unfortunately, both boundary-based and region-based techniques often fail to produce accurate segmentation, although the locations where each method fails are not necessarily identical. In boundary-based methods, if an image is noisy or if its attributes differ by only a small amount between regions (and this occurs very commonly in natural scenarios), 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 very 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 whether or not a pixel should be aggregated 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 a failure to distinguish regions that would be small in comparison with the block size used. Furthermore reasonable initial seed points and stopping criteria are often difficult to choose in the absence of a priori information. Finally, as Salotti and Garbay (1992) noted, both approaches sometimes suffer from a lack of information due to the fact that they rely on the use of ill-defined hard thresholds that may lead to wrong decisions.

It is often difficult to obtain satisfactory results when using only one of these methods in the segmentation of complex pictures such as outdoor and natural images, which involve additional difficulties due to effects such as shading, highlights, non-uniform illumination or texture. By using the complementary nature of edge-based and region-based information, it is possible to reduce the problems that arise in each individual method. The trend towards integrating several techniques seems to be the best way forward. 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 Pavlidis and Liow (1990), while integration has long been a desirable goal, achieving this is not an easy task.

In recent years, numerous techniques for integrating region and boundary information have been proposed. One of the main features of these proposals is the timing of the integration: embedded in the region detection, or after both processes are completed (Falah et al., 1994).

- Embedded integration can be described as integration through the definition of new parameters or a new decision criterion for the segmentation. In the most common strategy, the edge information is extracted first, and this information is then used within the segmentation algorithm, which is mainly based on regions. A basic scheme of this method is shown in Fig. 1a. The additional information contributed by edge detection can be used to define new parameters or new decision criteria. For example, edge information can be used to define the seed points from which regions are grown. 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. However, we will mention later, there is a current trend which carries out the integration in reverse; i.e. by using region information within the boundary finding process.
- Post-processing integration is performed after both boundary-based and region-based techniques have been used to process the image. Edge and region information are extracted independently as a preliminary step, as shown in Fig. 1b. 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 to improve the initial results and to produce a more accurate segmentation.

Although many studies have been published on image segmentation, none of them focuses specifically on the integration of region and boundary information, which is the aim of this paper, in

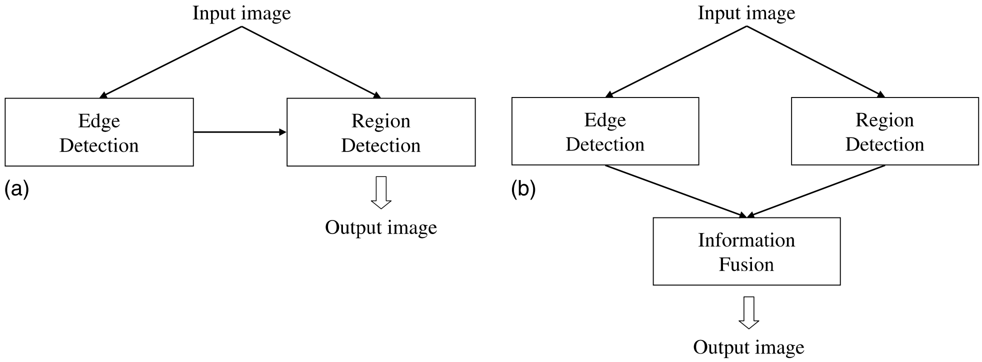

Fig. 1. Schemes of region and boundary integration strategies according to the timing of the integration: (a) Embedded integration and (b) post-processing integration.

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

The paper is structured as follows: Section 1 is concluded by related work, 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 Section 5.

1.1. Related work

A brief mention of the integration of region and boundary information for segmentation can be found in the introductory sections of several papers. For instance, Pavlidis and Liow (1990) introduce some earlier papers that emphasise the integration of such information. In 1994, Falah et al. (1994) 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 edge information to control or refine a region segmentation process. The other alternative (*embedded*) is to integrate edge detection and region extraction within the same process. The classification proposed by Falah, Bolon and Cocquerez has been adopted and discussed in this paper. Lemoigne and Tilton (1995) thinking about data fusion in general, identified two levels of fusion: pixel and symbol. A pixel-level integration between edges and regions assumes that the decision regarding integration is made individually for each pixel, while the symbol-level integration is performed on the basis of selected features, thereby simplifying the problem. Furthermore, they discuss embedded and post-processing strategies and present important arguments concerning the supposed superiority of the post-processing strategy. They argue that a posteriori fusion provides 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 using dynamic contours (snakes). Chan et al. (1996) 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 usually consists of using previously extracted edge information, 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 (Kittler and Illingworth, 1985), while the region's shape will depend on the particular growth chosen (Kohler, 1981). Some proposals try to use boundary information in order to avoid these problems. According to the way in which this information is used, it is possible to distinguish two trends:

(1) *Control of decision criterion*: edge information is included in the definition of the decision criterion which controls the growth of the region.
(2) *Seed placement guidance*: 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.

2.1. Control of decision criterion

The most common way to perform integration in the embedded strategy consists of incorporating edge information into the growing criterion of a region-based segmentation algorithm. The edge information is thus included in the definition of the decision criterion that controls the growth of the region.

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 truly different in terms of the decisions taken. For this reason, and in order to facilitate analysis of this approach, we shall discuss integration into these two types of algorithms in two separate subsections.

2.1.1. Integration in split-and-merge algorithms

Typical split-and-merge techniques (Fukada, 1980; Chen and Pavlidis, 1980) consist of two basic steps. First, the whole image is considered as one region. If this region does not satisfy a homogeneity criterion the region is split into four quadrants (sub-regions) and each quadrant is tested in the same way until every square region created in this way contains homogeneous pixels. Secondly, all adjacent regions with similar attributes may be merged according to other (or the same) criteria.

The homogeneity criterion is generally based on the chromatic features analysis of the region. When the intensity of the region's pixels has a sufficiently small standard deviation, the region is considered homogeneous. Moreover, the integration of edge information allows a new criterion to be defined: a region is considered homogeneous when it is totally free of contours. This concept can then substitute or be added to the traditional homogeneity criterion.

Bonnin et al. (1989) proposed a split-and-merge algorithm controlled by edge detection. The homogeneity criterion is fulfilled when there is no edge point in the region and the homogeneity intensity constraints are satisfied. This basic idea was also proposed in the work of Buvry et al. (1994), which incorporates a rule-based system in order to improve initial segmentation. Later, Buvry et al. (1997) reviewed their own work, and proposed a hierarchical region detection algorithm for stereovision applications.

Healey (1992) presented an algorithm for segmenting images of 3-D scenes, which uses the absence of edge pixels in the region as a homogeneity criterion. Furthermore, he considers the effects of edge detection mistakes (false positive and false negative) on the segmentation algorithm, and gives evidence that false negatives have more serious consequences, so the edge detector threshold should be set low enough to minimize their occurrence.

Other proposals include those by Bertolino and Montanvert (1996), an enrichment of segmentation by means of irregular pyramidal structure using edge information, or the algorithm described by Gevers and Smeulders (1997), which extends the possibilities of this integration, using edge information to decide how the partition of the region should be made or, in other words, where to split the region.

2.1.2. Integration in region growing algorithms

Region growing algorithms are based on the growth of a region whenever its interior is homogeneous according to certain features, such as intensity, colour or texture. This definition is broad enough to allow different variants to be analysed:

(1) *Region growing*: this embraces the traditional implementation of region growing based on the growth of a region by adding similar neighbours.
(2) *Watershed*: a watershed algorithm effects the growth by simulating a flooding process, which progressively covers the region.
(3) *Active region model* (*ARM*): considered to be a fusion of region growing with the techniques of active contour models (ACMs).

2.1.2.1. Region growing. Region growing (Zucker, 1976; Adams and Bischof, 1994) is one of the most simple and popular algorithms for region-based segmentation. Typically, the first step is choosing a starting point or seed pixel. The region then grows by adding neighbouring pixels that are similar, according to a certain homogeneity criterion, increasing the size of the region step-by-step. So, the homogeneity criterion has the function of determining whether or not a pixel belongs to the growing region.

The decision to merge is generally based only on the contrast between the current pixel and the region. However, it is not easy to decide when this difference is small (or large) enough to make a decision. The edge map provides an additional criterion in decisions. A scheme of this approach is shown in Fig. 2. The technique consists of determining whether or not the pixel under scrutiny is a contour pixel. Finding a contour means that the growth process has reached the boundary of the region. The pixel must therefore not be aggregated and the growth of the region finishes.

Xiaohan et al. (1992) proposed a homogeneity criterion consisting of the weighted sum of the contrast between the region and the pixel, and the value of the modulus of the gradient of the pixel. A low value of this function indicates the pixel's suitability for aggregation to the region. A similar proposal was suggested by Falah et al. (1994), where at each iteration, only pixels having low gradient values (below a certain threshold) are aggregated to the growing region. On the other hand, Gambotto (1993) suggested using edge information to stop the growing process. His proposal assumes that the gradient takes a high value over a large part of the region boundary. The iterative growing process is thus continued until the maximum of the average gradient computed over the region boundary is detected.

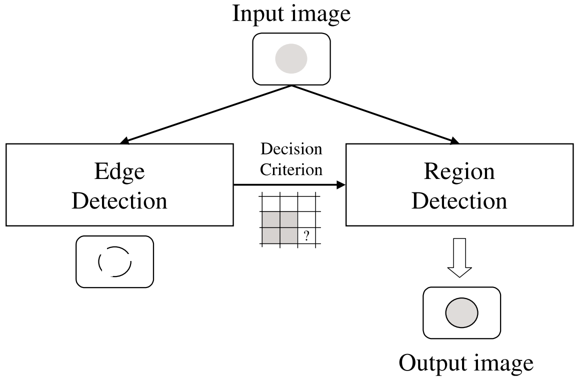

Fig. 2. A scheme of the control of decision criterion approach of the embedded integration strategy. Edge information is used in the decisions taken concerning the growth of the region.

The role of fuzzy logic: The fuzzy rule-based homogeneity criterion offers several advantages compared to ordinary feature aggregation methods and is worth mentioning. It does not take long to develop because a set of tools and methodologies already exists, and it is easy to modify or extend the system to meet the specific requirements of a certain application. Furthermore, it does not require a full knowledge of the process and can be understood intuitively because of its human-like semantics. It is also possible to include such linguistic concepts as shape, size and color, which are difficult to handle using most other mathematical methods.

Steudel and Glesner (1999), in a highly important work, carried out segmentation on the basis of a region-growing algorithm that uses a fuzzy rule-based system for the evaluation of the homogeneity criterion. The proposed homogeneity criterion is composed of a set of four fuzzy rules referring to the contrast, gradient, size and shape of regions. A similar method was proposed by Krishnan et al. (1994), who applied the integration of a fuzzy rule-based region growing and a fuzzy rule-based edge detection to colonoscopic images in order to identify closed-boundaries of intestinal lumen, in the diagnosis of colon abnormalities.

The role of fuzzy logic in segmentation techniques is becoming more important (Lambert and Carron, 1999; Pham and Prince, 1999) and integration techniques are the main stream of this tendency. This is mainly because these two methods (region and boundary based) are developed from complementary approaches and do not share a common measure. Hence, fuzzy logic offers the possibility of solving this problem, as it is especially suited for carrying out the fusion of diverse information (Moghaddamzadeh and Bourbakis, 1997; Kong and Kosko, 1992).

2.1.2.2. Watershed. Another algorithm based on the growth of the region from a seed pixel is the watershed transformation. Various definitions of watershed have been proposed in the literature for both digital and continuous spaces (Meyer and Beucher, 1990; Vincent and Soille, 1991). The typical watershed algorithm simulates a flooding process. An image is identified with a topographical surface in which the altitude of every point is generally equal to the gradient value of the corresponding pixel. Holes are then pierced in all regional minima of the relief (connected plateaus of constant altitude from which it is impossible to reach a location at lower altitude without having to climb). Sinking the whole surface slowly into a lake, water springs through the holes and progressively immerses the adjacent walls. To prevent intermingling of streams of water coming from different holes, a constraint is set up at the meeting points. Once the relief is completely covered by water, the set of obstacles depicts the watershed image (Bieniek and Moga, 2000).

Although watershed is usually considered as a region-based approach, De Smet et al. (1999) pointed out that the watershed transformation has proven to be a powerful basic segmentation tool that can hold the attributed properties of both edge detection and region growing techniques.

Nevertheless, the performance of a watershed-based image segmentation method depends largely on the algorithm used to compute the gradient. With a conventional gradient operator, watershed transformation produces an over-segmented result, with many irrelevant regions. A region merging algorithm must then be employed to merge these irrelevant regions, which requires a long computational time. Hence, recent studies focus on improving the gradient image in order to perform the watershed transformation. Wang (1997) proposed a multi-scale gradient algorithm based on morphological operators for watershed-based image segmentation, which has the goal of increasing the gradient value for blurred edges above those caused by noise and quantization error. Recently, Weickert (2001) studied the use of partial differential equations (PDEs) for preprocessing the image before segmentation. These PDE-based regularization techniques lead to simplified images where noise and unimportant fine-scale details have been removed.

2.1.2.3. Active region model. ACMs have emerged as an effective mechanism for segmenting and tracking object boundaries in images or image sequences. Central to the implementation of any ACM is the minimization of a function that describes the energy of the contour. This energy functional typically has two components: internal energy, which applies shape constraints to the model, and external energy, derived from the data to which the model is being applied. Since the original formulation in (Kass et al., 1987), many variations and improvements have been suggested. However, ACMs in general are sensitive to initial conditions.

Recently, some algorithms which combine the techniques of ACMs and region growing (Alexander and Buxton, 1997) have been developed. The external part of the ACM energy functional is replaced by a term derived from local region information. Points on the contour are allowed to expand or contract according to the match between local region information and a global model

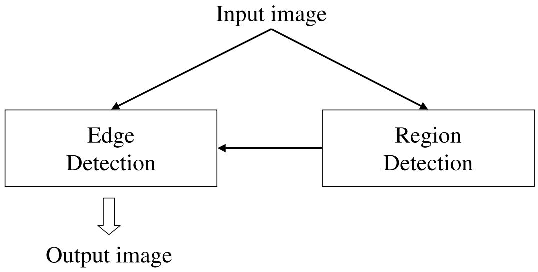

Fig. 3. Embedded integration by the ARM. Edge detection by the active contour model is influenced by the region information.

of the region derived from the initial configuration. The resulting ARM retains the desirable features of both techniques. The regularity of the contour can be controlled by the shape constraints in the energy functional. In addition, by examining local region information, boundary points are able to traverse large homogeneous areas of the image, providing the initial configuration with robustness. As shown in (Chakraborty et al., 1994) this integration could be considered as the incorporation of the region information into the boundary finding process using an active contour model (a scheme of this co-operation is shown in Fig. 3).

The origin of region-based energy functionals can be found in global optimization approaches based on energy functions. In these approaches to segmentation, an energy functional includes the desired properties of the resulting segmentation, such as smoothness within homogeneous regions and the preservation of boundaries between homogeneous regions. The minimum energy the functional can attain, given the observation, is chosen as the solution. However, it is often difficult to find their minima. Mumford and Shah (1985, 1989) and Shah et al. (1996) propose a piecewise constant energy, in which three things are kept as small as possible: (i) the difference between the image I and its simplified noiseless version J, (ii) the gradient of J where it is smooth and (iii) the length of the curve where J has discontinuities. This proposal has had a major influence on subsequent works on ARMs such as the "region competition" algorithm of Zhu and Yuille (1996), which incorporates a statistical criterion into the ideas discussed by Mumford and Shah.

The "anticipating snake" of Ronfard (1994), the "statistical snake" of Ivins and Porrill (Ivins and Porrill, 1995; Ivins, 1996), or the most recent proposal by Chesnaud et al. (1999) are other good examples of ARMs.

Moreover, there is a recent trend which combines the region information inside the active contour and the boundary information on the contour to define the energy functional. Hence, boundary and region information are cooperating in a coupled active contour model. The exemplary work on this approach is by Paragios and Deriche (1999a), where the texture segmentation is obtained by unifying region and boundary-based information as an improved Geodesic Active Contour Model (originally proposed by Caselles et al. (1997)). Initially, an off-line step is performed that creates multi-component probabilistic texture descriptors for the given set of texture patterns. The segmentation problem is then stated under an improved geodesic active contour model that aims to find the minimal length geodesic curve that best preserves high boundary probabilities, and creates regions that have maximum a posteriori segmentation probability with respect to the associated texture hypothesis. This proposal was used subsequently by the same authors to address the problem of tracking several non-rigid objects over a sequence of frames acquired from a static observer (Paragios and Deriche, 1999b). Moreover, its use has been analysed by Will et al. (2000) to further enhance the results of a proposed texture edge detector, which can generate precise maps of highly significant edge-probabilities for the ARM to produce satisfactory results.

Finally, we want to mention the work of Chakraborty, Duncan et al., which has undergone constant evolution in recent years, with the continuous flow of new ideas and updating of the techniques used, opening up new ways to perform the integration. In their last proposal (Chakrabory and Duncan, 1999), they suggest a method for integrating region segmentation and active contours 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 the results of both computational modules are improved through mutual information sharing.

Hence, both processes (edge and region detection) use the information from the co-operative process and the integration carried out is embedded in both segmentation techniques at the same time. The proposed algorithm 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-theory framework. The flow of information is restricted to passing only the results of the decisions among the modules. Thus, for any module, the results of the decisions of the other modules are used as priors, and players try to minimize their cost functions at each turn.

2.2. Seed placement guidance

One of the aspects that has a major influence on the result of a region-based segmentation is the placement of initial seed points. However, the typical region growing algorithm chooses them randomly or by using a set a priori direction of the image scan. In order to take a more reasonable decision, edge information can be used to decide the best position to place the seed.

It is generally accepted that the growth of a region has to start from within that region (see Benois and Barba (1992), Sinclair (1999)). The interior of the region is a representative zone and enables a correct sample of the region's characteristics to be obtained. The boundaries between regions must be avoided when choosing the seeds because they are unstable zones and not suitable for obtaining information about the region as a whole. This approach therefore uses the edge information to place the seeds in the interior of the regions. The seeds are launched in placements which are free of contours and, in some proposals, as far as possible from them. A scheme of this integration strategy is shown in Fig. 4.

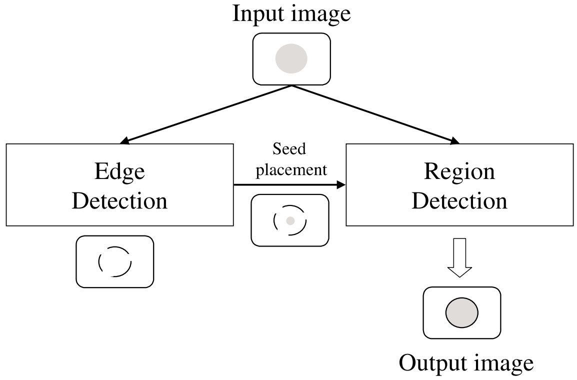

Fig. 4. A scheme of the seed placement guidance approach of the embedded integration strategy. Edge information enhances decisions regarding the most suitable position for the starting seed point of the region detection.

Edge information can also be used to establish 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. Edge-based segmentation enables this order to be decided, in some cases by simulating the order in which humans separate segments from each other in an image (from large to small) (Moghaddamzadeh and Bourbakis, 1997), or in other proposals, by giving the same opportunities of growing to all the regions (Cufí et al., 2000).

3. Post-processing integration

In contrast to the works analyzed so far, which follow an embedded strategy, post-processing strategies carry out a posteriori integration, i.e. after the segmentation of the image by region-based and boundary-based algorithms. Region and edge information is extracted in a preliminary step, and then the two are integrated. 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 of providing an accurate and meaningful segmentation. We have identified three different approaches for performing these tasks:

(1) *Over-segmentation*: this approach consists of using a segmentation method with parameters fixed specifically to obtain an over-segmented result. Additional information from other segmentation techniques is then used to eliminate

false boundaries that do not correspond with regions.

(2) *Boundary refinement*: this approach considers the region segmentation result as an initial approach, with well-defined regions, 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. This third set of techniques deals with the difficulty of establishing adequate stopping criteria and thresholds in region segmentation.

3.1. Over-segmentation

This approach emerged as a result of the difficulty in establishing an adequate homogeneity criterion for region growing. As Pavlidis and Liow (1990) suggested, the major reason that region growing produces false boundaries is that the definition of region uniformity is too strict, such 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 exactly match these requirements and do not generate false boundaries. They concluded that the results could be significantly improved by checking all the region boundaries that qualify as edges rather than attempting to fine tune the uniformity criteria.

The over-segmentation method begins by obtaining an over-segmented result, which is achieved by setting the parameters of the algorithm properly. This result is then compared with the result from the dual approach: each boundary is checked to find out if it is consistent in both results. When this correspondence does not exist, the boundary is considered false and is removed. In the end, only real boundaries are preserved. A basic scheme clarifying the ideas of this strategy is shown in Fig. 5.

The most common technique consists of obtaining the over-segmented result using a region-based algorithm. Every initial boundary is checked by analysing its coherence with the edge map,

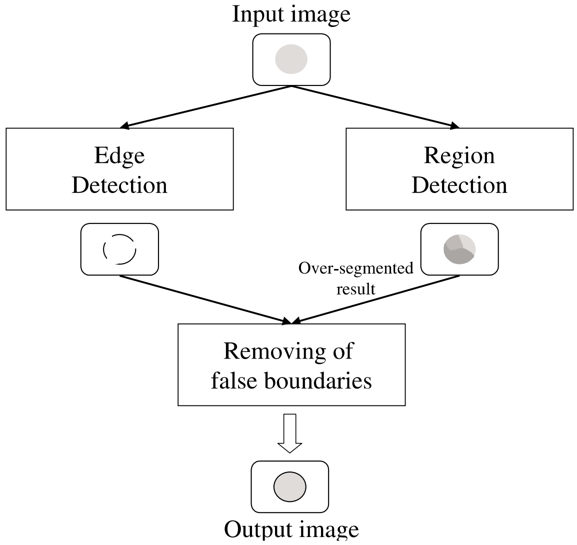

Fig. 5. A scheme of the over-segmentation approach to the post-processing integration strategy. The parameters of the region detection method are set to obtain an over-segmented result. Edge information is then used to eliminate false boundaries. This scheme can also be used starting from an over-segmented edge-based result, and using region information to distinguish between true and false boundaries.

where real boundaries must have high gradient values, while false boundaries have low values. An example of this method is the one proposed by Monga et al. (Gagalowicz and Monga, 1986; Wrobel and Monga, 1987), where two adjacent regions are merged if the average gradient on their boundary is lower than a fixed threshold. A similar work was presented by Pavlidis and Liow (1990), who include a criterion in the merging decision in order to eliminate the false boundaries that have resulted from the data structure used.

The technique can also be applied by starting from an over-segmented result obtained from a boundary-based approach (Philipp and Zamperoni, 1996; FjØrtoft et al., 1997). Region information then allows true and false contours to be distinguished. The boundaries are checked by analyzing the chromatic and textural characteristic on both sides of the contour. A real boundary borders on two regions, so it has different characteristics on each side. A good example of this is provided by Philipp and Zamperoni (1996), who suggest starting with a high-resolution edge extractor, and then, according to the texture characteristics of the extracted regions, deciding whether to suppress or prolong a boundary.

3.2. Boundary refinement

As we have already mentioned, region-based segmentation detects true regions very well, although, as is well known, the resultant sensitivity to noise causes the boundary of the extracted region to be highly irregular. This approach, which we have called boundary refinement, considers region-based segmentation as an initial 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 enables an initial result to be refined. Examples of this strategy are the works of Haddon and Boyce (1990), Chu and Aggarwal (1993) and Nair and Aggarwal (1996), or the most recent by Sato et al. (2000).

Nevertheless, we will consider two basic techniques used to refine the boundary of the regions:

(1) *Multiresolution*: this technique is based on analysis at different scales. A coarse initial segmentation is refined by increasing the resolution.
(2) *Boundary refinement by snakes*: this involves the integration of region information with dynamic contours, particularly snakes. The region boundary is refined by minimizing the energy of the snake.

3.2.1. Multiresolution

The multiresolution approach is a promising strategy for refining the boundary. The image is analyzed at different scales, using a pyramid or quadtree structure. The algorithm consists of an upward path which has the effect of smoothing or increasing class resolution, at the expense of a reduction in spatial resolution, and a downward path which attempts to regain the lost spatial resolution, while preserving the newly won class resolution. This multiresolution structure is then used, according to a coarse-to-fine strategy which assumes the invariance of region properties over a range of scales: those nodes in an estimate considered to be interior in a region are given the same class as their "fathers" at lower resolution. Specifically, a boundary region is defined at the coarsest level and then the candidate boundary is further refined at successively finer levels. As a result, the boundaries of the full image size are produced at the finest resolution. The scale-space model is also adopted by the edge-focusing approach to edge detection (Bergholm, 1987), where the edges are detected at a coarse scale and progressively refined through the examination of smaller scales. Starting with an edge map at a heavily smoothed scale eliminates the influence of noise on a gradient based detector. Good localization is also achieved by propagating edges from their initial rough location to their true location in the original unblurred image.

A key work in multiresolution strategy was developed by Spann and Wilson. Their strategy (Spann and Wilson, 1985) employs a quadtree method using classification at the top level of the tree, followed by boundary refinement. A non-parametric clustering algorithm (Spann and Wilson, 1990) is used to perform classification at the top level, yielding to an initial boundary, followed by downward boundary estimation to refine the result. A generalization of this work was applied to texture segmentation in (Wilson and Spann, 1988).

Hsu et al. (2000) described a texture segmentation algorithm, which uses a co-operative algorithm within the multiresolution Fourier transform (MFT) framework. The magnitude spectrum of the MFT is employed as feature space in which the texture boundaries are detected by means of the combination of boundary information and region properties. This information is propagated down to the next resolution in a multiresolution framework, whereby both the required boundary and region information are used successively until the finest spatial resolution is reached.

3.2.2. Boundary refinement by snakes

The snake method is known to solve boundary refinement 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 the optimization functions may therefore have many local optima. Consequently, active contours are, in general, sensitive to initial conditions and they are only truly 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 early works on dynamic contours, an expert was responsible for putting the snake close to an intended contour, and minimizing its energy carried it the rest of the way.

However, region segmentation could be the solution to the problem of where to initialize snakes. Proposals concerning 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. 6). First, a region growing with a seed point in the target region is performed, and its corresponding output is used for the initial contour of the dynamic contour model. Secondly, the initial contour is modified on the basis of energy minimization.

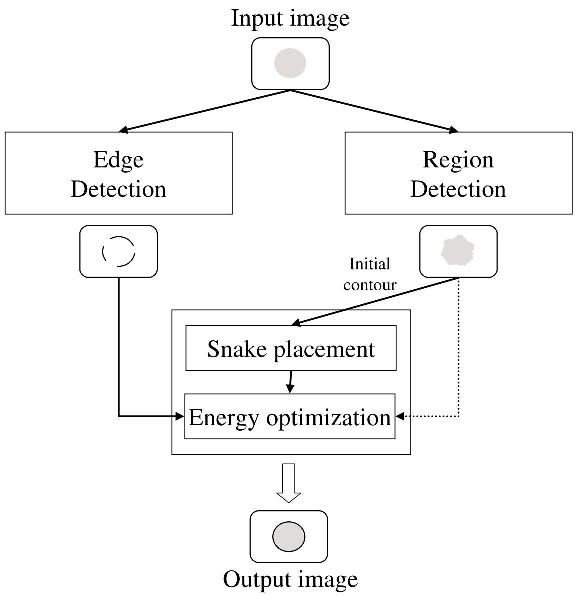

Fig. 6. A scheme of the boundary refinement approach of the post-processing strategy. Information from edge detection is used to refine the inaccurate boundaries obtained from the region detection. This process is generally carried out by placing a snake over the region. The energy minimization process then permits a precise boundary to be obtained.

Various works combining region detection and dynamic contours can be found in the literature (Chan et al., 1996; Vérard et al., 1996; Jang et al., 1997). Curiously, the results of all these techniques have been shown on magnetic resonance imaging (MRI) images, but this is not merely a coincidence. Accurate segmentation is critical for diagnosis in medical images, but in MRI images, it is very difficult to extract the contour that exactly matches the target region. Integrated methods seem to be a valid solution for achieving an accurate and consistent detection.

3.3. Selection–evaluation

In the absence of object or scene models or ground truth data, it is critical to have a criterion that enables the quality of a segmentation to be evaluated. Many 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 in a region segmentation algorithm, and then to use the evaluation function to choose the best result. The basic scheme of this approach is shown in Fig. 7. This strategy provides a solution to the traditional problems of region segmentation, such as defining an adequate stopping criterion or setting appropriate thresholds.

The evaluation function measures the quality of a region-based segmentation according to its consistency with the edge map. The best region segmentation is the one where the region boundaries correspond most closely to the contours.

Fua and Hanson (1987) developed a pioneering proposal in which high-level domain knowledge and edge-based techniques were used to select the best segmentation from a series of region-based segmented images. However, the majority of methods based on the selection approach have been developed in the last five years. Example algorithms have been suggested in the works of

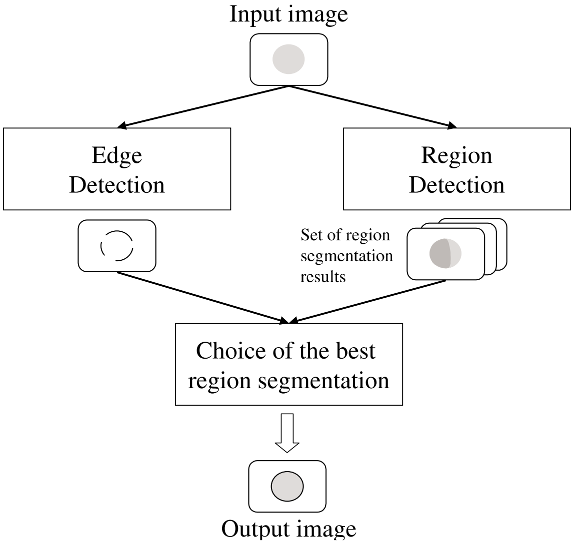

Fig. 7. A scheme of the selection–evaluation approach of the post-processing integration strategy. The edge information is used to evaluate the quality of a segmentation in order to choose the best segmentation from a set of region-based results.

Lemoigne and Tilton (1995), Hojjatoleslami and Kittler (1998), Siebert (1997) and Revol-Muller et al. (2000).

4. Summary

We have reviewed various segmentation proposals which integrate edge and region information and identified the various strategies and methods used to fuse such information. The aim of this summary is to point out the features and the essential differences of these approaches, as well as to discuss some questions that perhaps have not been properly considered.

Table 1 summarizes the different ways in which the integration of edge and region information is performed. The first column distinguishes the strategy according to the timing of the fusion: embedded or post-processing. The second column gives a name to the approach. 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, 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 a posteriori integration module tries to correct them. The key features that characterize and contrast the two strategies are:

- single algorithm and avoidance of errors (embedded integration)
- multiple algorithms and correction of errors (post-processing integration).

These two essential characteristics mean that these strategies produce notable differences. The first aspect to analyze is the complexity of both strategies. Embedded integration produces, in general, a more complex algorithm because it attempts not to commit errors or take wrong decisions. The post-processing strategy can be viewed as the set of many simple algorithms working in parallel which produce many wrong segmentation results. These errors are solved by a posteriori fusion module that works on these results. Post-processing complexity is therefore lower because the quantity of information to process decreases, as only the results are taken into consideration.

Another aspect worth analyzing is the independence of these integration strategies with respect to their implementation in the segmentation algorithm. The embedded strategy is strongly dependent, because it typically implies the design of a new algorithm, which incorporates the integration. Hence, any change in the integration procedure will imply the modification of the algorithm. On the other hand, the post-processing strategy gives rise to a more general approach because it is independent of the choice of algorithms for image segmentation. 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 (Lemoigne

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

Integration	Approach	Problem to solve	Objective	Procedure
Embedded	Control of decision criterion	The shape of the obtained region depends on the growth criterion chosen.	To include edge information, with or without color information, and 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.
	Seed placement guidance	The resulting region-based segmentation inevitably depends on the choice of the region's initial growth points.	Choosing reasonable starting points for region-based segmentation.	Edge information is used to choose a seed (or seeds) inside the region to start the growth.
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 an initial over-segmented result. Next, boundaries that do not exist (according to segmentation from a complementary approach) are removed.
	Boundary refinement	Region-based segmentation generates erroneous and highly irregular boundaries.	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, generally using either multiresolution analysis or snakes.
	Selection–evaluation	No criterion exists to evaluate 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 in terms of how the boundary corresponds with the edge information.

and Tilton, 1995) 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, we need to point out that the post-processing strategy is not 100% independent, and this, in fact, is its weak point. It is true that it is independent in terms of 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. Final segmentation will therefore inevitably depend, to a greater or lesser extent, on the initial results of the segmentation. An initial fault, e.g., the inappropriate selection of seeds in a region-growing algorithm, will be carried over into the entire segmentation process. A posteriori integration of edge information may not be able to overcome an error of this magnitude.

4.1. Open questions

Having reviewed the different proposals, we think that some questions still deserve special attention. First, there are important questions related to the evaluation of the approaches, since there is no common framework (nor generally accepted methodology) for evaluating segmentation. Secondly, there are certain tasks that are included in many of the reviewed proposals, such as contour or texture extraction, which are by themselves significant research topics.

(1) *Evaluating the different approaches*: Actually, it is not feasible to determine the best approach to segmentation that integrates boundary and region information. There are several reasons for this: the lack of a generally accepted and clear methodology for evaluating segmentation algorithms (Pal and Pal, 1993); the difficulty of obtaining and ground truthing sufficient real imagery (Vincken et al., 1997); or the fact that different segmentation algorithms differ in terms of the properties and objectives they try to satisfy and the image domain in which they are working (Haralick and Shapiro, 1985). However, the most important factor is probably the difficulty in implementing other people's algorithms due to the lack of necessary details (Yu et al., 1994). Obviously, unless a given segmentation algorithm is specifically implemented and tried out on the data to hand, it is very difficult to evaluate from the published results how well it will work for that data (Fu and Mui, 1981). As Hoover et al. (1996) indicated the comparative framework is itself a research issue, and although positive steps have been taken, a guiding philosophy for the design of such a framework is lacking.

(2) *Tasks*: The first thing to point out is the high number of very difficult tasks that are integral parts of the approaches we have reviewed, for example edge map extraction or thresholding, among others, which are themselves significant research topics. For instance, a serious difficulty appears when, as is usual, the most significant edges in the image are required. Extracting these is not an easy task and the process often includes many parameters: i.e. an adequate threshold that will result in a reliable binarization and the subsequent edge map. In this sense, the embedded proposals that directly use the gradient map as boundary information have an important advantage. Another question to consider is the lack of attention that, in general, the reviewed works devote to texture. Without this property, it is not possible to distinguish whether a high-magnitude gradient corresponds to a boundary between regions, or to a textured region. Regrettably, texture is generally forgotten in the different proposals of embedded integration, with specific exceptions which have been duly noted. As a consequence, the algorithms are not adapted to segmenting heavily 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 an over-segmented image must solve a non-trivial problem: What should the threshold be in order 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 may lead to an irrecoverable loss of boundaries. An initial mistake in such an algorithm could be a serious handicap for the a posteriori fusion, resulting in an under-segmented result. Moreover, the authenticity of the initial contours is generally checked under the assumption that real boundaries have high gradients. However, this assumption is not an indispensable characteristic of real boundaries and this leads to one of the most serious difficulties of the segmentation task. As described in Section 3.2, the aim of the boundary refinement approaches is to obtain reliable smooth boundaries. In order to achieve this, cooperation between region-based segmentation and snakes, which is the commonest 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 have a deficiency that is shared with the third set of post-processing methods: their exclusive attention to the boundary. Refining the result is reduced to the region boundary, so it is not possible to correct any other mistakes inside the region. The same problem is found in the selection–evaluation 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 that do not appear. In short, all these weak points of the post-processing integration reaffirm the previous assertion about the need for good initial segmentation results and the inability 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 that integrate region and boundary information. Special emphasis has been placed on the strategy used to carry out the integration process. A classification of cooperative segmentation techniques has been proposed, and we have described several algorithms, pointing out their specific features.

The lack of specific treatment of textured images has been noted, and it is one of the great problems of segmentation (Deng et al., 1999). If an image mainly contains homogeneous color regions, traditional methods of segmentation working in color spaces may be sufficient to attain reasonable results. However, some real images "suffer" from texture, for example, images corresponding to natural scenes, which have considerable variety of color and texture. Texture, therefore, undoubtedly has a pivotal role to play in image segmentation. However, there is now some new and promising research into the integration of color and texture (Mirmehdi and Petrou, 2000). An attempt to integrate complementary information from the image may follow; it seems reasonable to assume that a considerable improvement in segmentation will result from the fusion of color, texture and boundary information.

Segmentation techniques, in general, are still in need of considerable improvement. The techniques we have looked at still have some faults and there is, as yet, no perfect segmentation algorithm, something which is vital for the advancement of Computer Vision and its applications. However, integration of region and boundary information has brought improvements to previous results. Work in this field of research has generated numerous proposals in the last few years. This current interest encourages us to predict that further work and improvement of segmentation will be focussed on integrating algorithms as well as information.

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