Region-Boundary Cooperative Image Segmentation Based on Active Regions

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Abstract

An unsupervised approach to image segmentation which fuses different sources of information is presented. The proposed approach takes advantage of the combined use of 3 different strategies: an appropriated placement, the control of decision criterion, and the results refinement. The new algorithm uses the boundary information to initialize a set of active regions which compete for the pixels in order to segment the whole image. The method is implemented on a multiresolution representation which ensures noise robustness as well as computation efficiency. The accuracy of the segmentation results has been proven through an objective comparative evaluation of the method.

Keywords: image segmentation, region-based segmentation, boundary-based segmentation, active region model.

1 Introduction

Image segmentation is one of the most important processes of image analysis, understanding and interpretation [9]. Many segmentation methods are based on two basic properties of the pixels in relation to their local neighbourhood: discontinuity and similarity. Methods 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. Unfortunately, both techniques, boundary-based and region-based, often fail to produce accurate segmentation results.

Taking into account the complementary nature of the boundary-based and region-based information, it is possible to alleviate the problems related to each when considered separately. Although it is assumed that integration of both methods yields to get complementary information and, therefore, has long been a highly desirable goal [16], it becomes a non-trivial task due to the conflicts and incommensurate objectives it involves.

In this paper we propose a new segmentation method which combines different strategies to perform the integration: taking as a basis a previously developed segmentation algorithm [5], we have used the main contours of the image to adequately place the seeds in order to initialize the region models; then as these regions grow, they compete for the pixels of the image by using a decision criterion which ensures the homogeneity inside the region and the presence of edges at its boundary; finally, the method has been implemented on a multiresolution representation which allows us to refine the region boundaries from a coarse to a finer resolution.

The remainder of this paper is structured as follows: main strategies to perform the integration of region and boundary information are reviewed in Section 2. Section 3 describes the proposed segmentation technique, detailing the placement of the starting seeds and the growing of the active regions. The multiresolution representation is presented in Section 4, while experimental results proving the validity of our proposal appear in Section 5. Finally, conclusions are given in Section 6.

2 Related Work on Region-Boundary Integration

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. The tendency towards the integration of several techniques seems to be the best solution in order to produce better results. Hence, with the aim of improving the segmentation process, a large number of new algorithms which integrate region and boundary information have been proposed over the past few years.

The existing main strategies to integrate region and boundary information [4] rely on the processes of:

- **Guidance of seed placement:** boundary information is used in order to decide the most suitable position to place the seed of the region growing process.
- **Control of decision criterion:** the inclusion of edge information in the definition of the decision criterion which controls the growth of the region.
- **Boundary refinement:** boundary information is used to refine the inaccurate boundaries obtained by a region based segmentation

2.1 Guidance of Seed Placement

The placement of the initial seed points can be stated as a central issue on the obtained results of a region-based segmentation. Despite their importance, the traditional region growing algorithm chooses them randomly or using a set a priori direction of image scan. In order to make a more reasonable decision, edge information can be used to decide what is the most correct position in which to place the seed. It is generally accepted that the growth of a region has to start from inside it (see [1, 18]). The interior of the region is a representative zone and allows the obtention of a correct sample of the region's characteristics. On the other hand, it is necessary to avoid the boundaries between regions when choosing the seeds because they are unstable zones and not adequate to obtain information over the region. Therefore, this approach uses the edge information to place the seeds in the interior of the regions. The seeds are launched in placements free of contours and, in some proposals, as far as possible from them.

On the other hand, 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. The edge based segmentation allows for deciding this order, in some cases simulating the order by which humans separate segments from each other in an image (from large to small) [14], or in other proposals giving the same opportunities of growing to all the regions [5].

2.2 Control of Decision Criterion

Region growing algorithms are based on the growth of a region whenever its interior is homogeneous according to certain features as intensity, color or texture. The most traditional implementation starts by choosing a starting point called seed pixel. Then, the region grows by adding similar neighbouring pixels according to a certain homogeneity criterion, increasing step by step the size of the region. So, the homogeneity criterion has the function of deciding whether a pixel belongs to the growing region or not. The decision of merging is generally taken based only on the contrast between the evaluated pixel and the region. However, it is not easy to decide when this difference is small (or large) enough to take a decision. The edge map provides an additional criterion on that, such as the condition of contour pixel when deciding to aggregate it. The encounter of a contour signifies that the process of growing has reached the boundary of the region, so the pixel must not be aggregated and the growth of the region has finished.

The work of Xiaohan et al. [22] 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 convenience of aggregating the pixel to the region. A similar proposal was suggested by Kara et al. [6], 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 [7] proposed 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. Thus, the iterative growing process is continued until the maximum of the average gradient computed over the region boundary is detected.

Fuzzy logic becomes an interesting possibility to carry out the integration of edge information into the decision criterion. 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, and the facility 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 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 developed by Steudel and Glesner [19], who proposed to carry out the segmentation on the basis of a region growing algorithm that uses a fuzzy rule-based system composed of a set of four fuzzy rules refereed to the contrast, gradient, size and shape of regions. A similar work can be found in [13], where the integration of a fuzzy rule-based region growing and a fuzzy rule-based edge detection is applied on colonoscopic images for the identification of closed-boundaries of intestinal lumen, in order to facilitate diagnosis of colon abnormalities.

2.3 Boundary Refinement

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 boundary 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 here, the refinement of an initial result. Examples of this strategy are the works of Haddon and Boyce [8], Chu and Aggarwal [3] or the most recent of Sato et al. [17]. Nevertheless, two basic techniques can be considered as common ways to refine the boundary of the regions:

1. **Multiresolution**: this technique is based on the analysis at different scales. A coarse initial segmentation is refined by increasing the resolution.
2. **Boundary Refinement by Snakes**: another possibility is the integration of region information with dynamic contours, concretely snakes. The refinement of the region boundary is performed by the energy minimization of the snake.

2.3.1 Multiresolution

The multiresolution approach is an interesting strategy to carry out the refinement. The analysis operates on the image at different scales, using a pyramid or quadtree structure. The algorithm consists of an upward and a downward path; the former has the effect of smoothing or increasing the resolution in class space, at the expense of a reduction in spatial resolution, while the latter attempts to regain the lost spatial resolution, preserving the newly won class resolution. The assumption underlying this procedure is invariance across scales: those nodes in an estimate considered as interior to a region are given as the same class as their “fathers” at lower resolution.

The implemented algorithm is based on the work of Spann and Wilson [21], where the strategy uses a quadtree method using classification at the top level of the tree, followed by boundary refinement. A non-parametric clustering algorithm is used to perform classification at the top level, yielding an initial boundary, followed by downward boundary estimation to refine the result. A recent work following the same strategy can be found in [10].

2.3.2 Boundary Refinement by Snakes

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 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 is responsible for putting the snake close to an intended contour; its energy minimization carries it the rest of the way. However, region segmentation could be the solution of the initialization problem of 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: 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; Second, the initial contour is modified on the basis of energy minimization.

In the work of Chan et al. [2], the greedy algorithm 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 are the works of Vérard et al. [20] and Jang et al. [12]. Curiously, all these algorithms are tested on Magnetic Resonance Imaging (MRI) images, but this is not a mere coincidence. Accurate segmentation is critical for diagnosis in medical images. However, it is very difficult to extract the contour which exactly matches the target region in MRI images. Integrated methods seem to be a valid solution to achieve an accurate and consistent detection.

3 Active Region Segmentation

Our proposal combines these three strategies to perform the image segmentation. First, we use the main contours of the image to `adequately place the seeds` in order to initialize the region models. Then as these regions grow, they compete for the pixels of the image by using a `decision criterion` which ensures the homogeneity inside the region and the presence of edges at its boundary. Finally, the method has been implemented on a multiresolution representation which allows us to `refine the region boundaries` from a coarse to a finer resolution.

Recently, the concept of active regions as a way to combine the region and boundary information has been introduced. This model is a considerable extension on the active contour model since it incorporates region-based information with the aim of finding a partition where the interior and the exterior of the region preserve the desired image properties. The underlying idea is that the region moves through the image (shrinking or expanding) in order to contain a single, whole region. The competition algorithm proposed by Zhu and Yuille [24] and the geodesic active regions presented in Paragios and Deriche's work [15] are good examples of active region models.

The main contribution of our proposal is twofold:

- Unsupervised region initialization: the seeds which allow us to initialize the statistical measurements which model the region are automatically placed from the boundary information. Hence, it is not necessary user intervention or a previous learning phase.

- Integrated energy function: the energy function incorporates the homogeneity inside the region (region information) and the discontinuity at the contour (boundary information).

3.1 Initialization

To obtain a sample of each region large enough to model its homogeneity behaviour, initial seeds have to be placed completely inside the regions. Boundary information allows us to extract these positions in the "core" of the regions by looking for places far away from the contours. The seed placement is carried out according to the algorithm proposed in [5]. The method is based on the detection and extraction of the most relevant contours in the image characterized by an outstanding length within the global frame of the image and by any appreciable difference between the separated regions in chromatic and textural features. Further, seeds are placed in zones free of contours or, in other words, the "core" of the regions.

Each region is modeled by a Gaussian distribution, so the mean and the standard deviation, which are initialized from the seeds, describe the homogeneity region behaviour. Hence, the probability of a pixel (x, y) of belonging to a region characterized by (μ, σ) is

$$P_R((x,y)|(\mu,\sigma)) = \frac{1}{\sqrt{2\pi}\sigma}\exp\{-\frac{(I_{(x,y)}-\mu)^2}{2\sigma^2}\} \tag{1}$$

where $I_{(x,y)}$ is the intensity of the pixel (x, y). The background is treated as a single region having uniform probability distribution P_0.

3.2 Active Region Growing

The goal of image segmentation is to partition the image into subregions with homogeneous intensity (color or texture) properties in its interior and a high discontinuity with neighbouring regions in its boundary. With the aim of integrating both conditions in an optimal segmentation, the global energy is defined with two basic terms. Boundary term measures the probability that boundary pixels are really edge pixels. The probability of a given pixel (x, y) being at the real boundary is measured by $P_B((x, y))$, which can be considered as directly proportional to the value of the magnitude gradient of the pixel. Meanwhile, region term measures the homogeneity in the interior of the regions by the probability that these pixels belong to each corresponding region. As has been previously defined, $P_R((x, y)|(\mu, \sigma))$ measures the probability that a pixel (x, y) belongs to a region modeled by (μ, σ).

Some complementary definitions are required: let $\rho(R) = \{R_i : i\epsilon[0, N]\}$ be a partition of the image into $\{N + 1\}$ non-overlapping regions, where R_0 is the region corresponding to the background region. Let $\partial\rho(R) = \{\partial R_i : i\epsilon[1, N]\}$ be the region boundaries of the partition $\rho(R)$. The energy function is defined as

$$\begin{aligned} &E(\rho(R)) = \\ &(1-\alpha)\sum_{i=1}^{N} -\log P_B((x,y) : (x,y)\epsilon\partial R_i)) \\ &+\alpha\sum_{i=0}^{N} -\log P_R((x,y) : (x,y)\epsilon R_i|(\mu_i,\sigma_i)) \end{aligned} \tag{2}$$

where α is a model parameter weighing the two terms: boundary probability and region homogeneity. This function is then optimized by a region competition algorithm [24], which takes into account the neighbouring pixels to the current region boundaries $\partial\rho(R)$ to determine the next movement. Concretely, a region aggregates a neighbouring pixel when this new classification diminishes the energy of the segmentation.

Intuitively, all regions begin to move and grow, competing for the pixels of the image until an energy minimum is reached. When the minimization process finishes, if there is a background region R_0 not occupied by any seed regions, a new seed is placed in the background, and the energy minimization starts again.

4 MultiResolution Implementation

In order to further reduce the computational cost, a multiscale representation [21] is proposed which can be combined with the active region segmentation. Specifically, a pyramid of images at different scales is built upon the full resolution image. At lowest resolution level, the seeds are placed from the boundary information and start to compete for the image, obtaining a first segmentation result. 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. Specifically, a boundary region is defined at coarsest level and then, at successive levels, the pixels not classified as boundary are used to initialize and model the regions. Further, segmentation by active region is performed to refine the candidate boundary by a factor of two using the multiresolution structure. As a result, the boundaries of the full image size are produced at the finest resolution.

Furthermore, the use of a multiresolution representation allows us to avoid the over-segmentation problems produced by the presence of noise in images. An initial coarse region segmentation is performed on a lower resolution achieving the effect of smoothing. Hence, the use of a multiresolution technique ensures noise robustness as well as computation efficiency.

5 Experimental Results

The performance of our proposal has been analyzed over a set of 22 test images including synthetic and real ones. The set of 12 synthetic images has been generated following the method proposed by Zhang [23], where the form of the objects of the images changes from a circle to an elongated ellipse. To make synthetic images more realistic, a 5×5 average low-pass filter is applied to produce a smooth transition between objects and background. Then, a zero-mean Gaussian white noise is added to simulate noise effect. On the other hand, 10 selected real images are well-known standard test images extracted from the USC-SIPI image database (University of Southern California-Signal and Image Processing Institute). All test images are size 256×256 pixels. Figure 1 shows an example of segmentation with three images belonging to the trial set.

Figure 1: The segmentation results obtained over three images of the trial set.

In order to evaluate the results, we use the quality parameters (region-based and boundary-based) proposed by Huang and Dom [11]. The boundary-based approach evaluates segmentation in terms of both localization and shape accuracy of extracted regions. Two distance distribution signatures are used to measure the boundary quality, one from ground truth to the estimated, denoted by D_G^B, and the other from the estimated to ground truth, denoted by D_B^G. Instead, the region-based approach assesses the segmentation quality in terms of both size and location of the segmented regions. A region-based performance measure based on normalized Hamming distance is defined, p. Moreover, two types of errors are defined: missing rate e_R^m and false alarm rate e_R^f.

Furthermore, we have made a comparison of our proposal against other strategies to integrate region and boundary information. Thereby, we implemented the algorithms corresponding to the three previously described strategies. Concretely, our implementation of the `guidance of the seed placement` strategy (GSP) is based on proposal [5], while the `control of decision criterion` strategy (CDC) is based on [22], and the `boundary refinement` strategy (BR) on [21]. Table 1 shows the summarized results obtained for the three strategies; our proposal of active region segmentation (ARS), and our proposal implemented on a multiresolution representation (MARS).

Quantitative results successfully demonstrate the validity of our proposal. Although the active region segmentation (ARS) obtains useful results, the technique has some problems due to the presence of noise which causes an over-segmentation of the image and a relatively high computational cost. The implementation of this proposal on a multiresolution representation (MARS) solves these problems and achieves an optimal result.

6 Conclusions

A new strategy for image segmentation which integrates region and boundary information has been described. The algorithm uses boundary information in order to initialize, in an unsupervised way, a set of active regions, which later compete for the pixels minimizing an energy function which takes into account both region and boundary information. The method has been implemented on a multiresolution representation and has been tested on a set of synthetic and real images. The experimental results demonstrate the effectiveness of the

Table 1: Summarized segmentation results of main strategies and our proposal over a set of 12 synthetic and 10 real test images.

Strategy	**Region-based**			**Boundary-based**				**Time**
	e_R^m	e_R^f	p	μD_G^B	σD_G^B	μD_B^G	σD_B^G	
Summary of Synthetic Images Evaluation								
GSP	0,059	0,025	0,957	1,003	0,708	0,993	0,843	0,340
CDC	0,202	0,011	0,893	0,954	0,658	0,965	0,877	0,290
BR	0,034	0,066	0,949	0,404	0,506	0,765	0,771	0,120
ARS	0,089	0,015	0,947	0,480	0,312	0,563	0,688	6,251
MARS	0,030	0,015	0,977	0,475	0,580	0,560	0,341	0,980
Summary of Real Images Evaluation								
GSP	0,066	0,033	0,949	2,121	3,018	2,160	3,389	0,430
CDC	0,174	0,044	0,890	1,828	1,297	1,544	3,125	0,380
BR	0,074	0,088	0,918	0,698	0,968	0,412	0,982	0,176
ARS	0,106	0,033	0,929	0,711	0,528	0,344	0,886	8,132
MARS	0,038	0,032	0,964	0,730	0,711	0,320	0,641	1,256

proposed algorithm in estimating regions and their boundaries with high accuracy.

The algorithm can be directly adapted to perform color or texture segmentation assuming multivariable Gaussian distributions to model each region. In this sense, future extensions of this work are oriented to the integration of grey level, color and texture cues.

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