Yet Another Survey on Image Segmentation: Region and Boundary Information Integration*

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Abstract. Image segmentation has been, and still is, a relevant research area in Computer Vision, and hundreds of segmentation algorithms have been proposed in the last 30 years. However, it is well known that elemental segmentation techniques based on boundary or region information often fail to produce accurate segmentation results. Hence, in the last few years, there has been a tendency towards algorithms which take advantage of the complementary nature of such information. This paper reviews different segmentation proposals which integrate edge and region information and highlights 7 different strategies and methods to fuse such information. In contrast with other surveys which only describe and compare qualitatively different approaches, this survey deals with a real quantitative comparison. In this sense, key methods have been programmed and their accuracy analyzed and compared using synthetic and real images. A discussion justified with experimental results is given and the code is available on Internet.

Keywords: grouping and segmentation, region based segmentation, boundary based segmentation, cooperative segmentation methods.

1 Introduction

One of the most important operations in Computer Vision is segmentation [1]. 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. The problem of segmentation has been, and still is, an important research field and many segmentation methods have been proposed in the literature (see surveys [2,3,4]). 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 [5]. With the aim of improving the segmentation

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process, a large number of new algorithms which integrate region and boundary information have been proposed over the last few years. Among other features, one of the main characteristics of these approaches is the time of fusion: embedded in the region detection or after both processes [6].

– Embedded integration can be described as integration through the definition of new parameters or a new decision criterion for segmentation. In the most habitual strategy, firstly, the edge information is extracted and 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. 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.
– 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. A posterior fusion process 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.

Although many surveys on image segmentation have been published, as stated above, none of them focus on the integration of region and boundary information. To overcome this lack, this paper discusses the most relevant segmentation techniques developed in recent years which integrate region and boundary information. Therefore, neither clustering methods nor texture segmentation have been included in this survey, stated they constitute a separated item. After analyzing more than 50 region-boundary cooperative algorithms, we have clearly identified 7 different strategies. First we distinguish between embedded and post-processing methods. Within the embedded methods we differentiate between those using boundary information for seed placement purposes, and those which use 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. After stating a classification, we discuss in depth each one of these approaches, emphasizing in some cases relevant aspects related to the implementation of the methods: for example, in the boundary refinement strategy, the use of snakes or multiresolution techniques. Finally, in order to compare the performance of the analyzed methods, we have implemented such algorithms, so a quantitative and qualitative evaluation of each strategy is given. Therefore, objective conclusions are provided.

The remainder of this paper is structured as follows: 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 discusses the methods analyzing the experimental results obtained by using synthetic and real data. Finally, the conclusions drawn from this study are summarized in Section 5.

2 Embedded Integration

The embedded integration strategy usually consists of using the edge information, previously extracted, within a region segmentation algorithm. It is well known that in most 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 particular growth chosen [7], as well as the choice of the initial region growth points [8]. Some recent 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. **Control of decision criterion**: edge information is included in the definition of the decision criterion which controls the growth of the region.
2. **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.

2.1 Control of Decision Criterion

The Region Growing and the 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 this approach, we have developed two different algorithms named A1 and A2 based on Split and Merge, and Region growing respectively.

A1: Split and Merge. Typical split and merge techniques [9] 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 (subregions) and each quadrant is tested in the same way; this process is recursively repeated until every square region created in this way contains homogeneous pixels. Next, in the second step, all adjacent regions with similar attributes may be merged following other (or the same) criteria. The criterion of homogeneity is generally based on the analysis of the chromatic characteristics of the region. A region with small standard deviation in the color of its members (pixels) is considered homogeneous. The integration of edge information allows adding to this criterion another term to take into account. So, a region is considered homogeneous when is totally free of contours.

A1 is an algorithm based on the ideas of Bonnin and his colleagues who proposed in [10] a region extraction based on a split and merge algorithm controlled by edge detection. 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 due to the 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.

A2: Region Growing. 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 implemented algorithm follows the strategy of a typical Region Growing: it is based on the growth of a region by adding similar neighbours. Region Growing [11] is one of the simplest and most popular algorithms for region based segmentation. 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 algorithm implemented A2, is based on the work of Xiaohan et al. [12], who 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 [13] 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.

2.2 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 [14,15]). 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, named A3, 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.

The algorithm proposed by Sinclair [15] has been taken as the basic reference for the implementation of A3. In this proposal, 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. Nevertheless, A3 avoids the necessity of extracting the edge image, which involves the difficult step of binarization, generating the Voronoi image directly from the gradient image.

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) [16], or in other proposals giving the same opportunities of growing to all the regions [17].

3 Post-processing Integration

In contrast to the works analysed up to 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 separately in a preliminary step, and then 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 specifically fixed to obtain an over-segmented result. Then additional information from other segmentation techniques is used to eliminate false boundaries which do not correspond with regions.
2. **Boundary Refinement**: this approach considers the region segmentation result as a first approach, with well defined regions, but inaccurate bound-

aries. 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 deal with the difficulty of establishing adequate stopping criteria and thresholds in region segmentation.

3.1 Over-Segmentation

This approach emerged due to the difficulty of establishing an adequate homogeneity criterion for region growing. As Pavlidis and Liow suggested [5], the major reason which explains why region growing produces so much 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 which exactly match 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.

The methodology of this approach starts with the obtention of an over-segmented result segmentation, which is achieved by properly setting the parameters of the algorithm. This result is then compared with the result from the dual approach: each boundary is checked to see if it is coherent in both results. When this correspondence does not exist the boundary is considered false and is removed. At the end, only real boundaries are preserved.

The implemented algorithm A4 follows the most habitual technique, which 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, where real boundaries must have high gradient values, while low values correspond to false contours. Concretely, A4 is based on the work of Gagalowicz and Monga [18], 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 [5], which includes a criterion in the merging decision in order to eliminate the false boundaries that have resulted from the data structure used.

On the other hand, it is also possible to carry out this approach starting with the over-segmented result obtained from a boundary based approach [19,20]. Then, region information allows differentiation between true and false contours. The boundaries are checked analyzing the chromatic and textural characteristic at both sides of the contour. A real boundary limits with two regions, so it has different characteristics on both sides. An exemplar work is that proposed by Philipp and Zamperoni [19], who proposed 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 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 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 [21], Chu and Aggarwal [22] or the most recent of Sato et al. [23]. 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.

A5: 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 A5 algorithm is based on the work of Spann and Wilson [24], 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 [25].

A6: 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, in the design of A6, 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.

The A6 algorithm is implemented following the ideas of Chan et al. [26], where 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. [27] and Jang et al. [28]. 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.

3.3 Selection-Evaluation

In the absence of object or scene models or ground truth data, it is critical to have a criterion which enables evaluation of the quality of a segmentation. In this sense, a set of proposals have used edge information to define an evaluation function which 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. The evaluation function measures the quality of a region based segmentation according to the coherence with the edge map. The best region segmentation is that in which the boundaries of the regions correspond in major measure to the contours.

The A7 algorithm is based on the work of Siebert [29] where edge information is used to adjust the criterion function of a region-growing segmentation. For each seed, A7 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. The contrast between both sides of the boundary is proposed as a measure of contour strength to evaluate the segmentation quality. 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 which are not part of the region. However, Siebert suggests 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. Hence, this second option has been the solution adopted in our implementation. Similar algorithms are proposed by Fua and Hanson [30] (a pioneer proposal), LeMoigne and Tilton [31], or Hojjatoleslami and Kittler [32].

4 Experimental Results

The methods surveyed (A1-A7) have been programmed and their accuracy analyzed over synthetic and real test images such as like the ones shown in figure 1.

The wide range of numerous and indeterminate characteristics of real images makes it very complicated to achieve an accurate comparison of the experimental results. As a rule, the segmentation results can only be judged either by using manually segmented images as reference, which implies a tedious and subjective task [33], or by visual comparison to the original images [4], or just applying quality measures corresponding to human intuition [34]. Hence, the use of carefully designed synthetic images appears to be a more suitable benchmark for an objective and quantitative evaluation of different segmentation algorithms [35]. Despite that suitability, the use of real images is also highly advisable as they provide useful results when realistic characteristics arise. Therefore, the algorithms evaluation has been performed jointly using real and synthetic images. The results obtained from the real ones have been evaluated by comparing them with manual segmentation, due to the subjective nature of the segmentation of real images. The set of synthetic images generated to test the algorithms follows the method proposed by Zhang [35], where the form of the objects of the images changes from a circle to an elongated ellipse. To make synthetic images more realistic, a $5x5$ 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. The noise samples have been generated with different variance parameters. On the other hand, 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.

4.1 The Evaluation Method

The evaluation of image segmentation is performed with several quantitative measures proposed by Huang and Dom [36]. Concretely, boundary-based and region-based performance evaluation schemes are proposed. The boundary-based approach evaluates segmentation in terms of both localization and shape accuracy of extracted regions, while the region-based approach assesses the segmentation quality in terms of both size and location of the segmented regions.

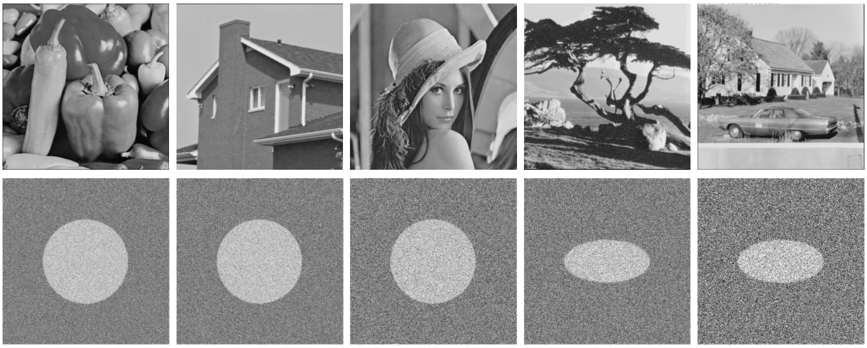

Fig. 1. A subset of the real and synthetic test images used in the trials.

Boundary-Based Evaluation. The boundary-based scheme is intended to evaluate segmentation quality in terms of the precision of the extracted region boundaries. Let B represent the boundary point set derived from the segmentation and G^B the boundary ground truth. Two distance distribution signatures are used, 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.

A distance distribution signature from a set B_1 to a set B_2 of boundary points, denoted by $D_{B_1}^{B_2}$, is a discrete function whose distribution characterizes the discrepancy, measured in distance, from B_1 and B_2. Define the distance from an arbitrary point x in set B_1 to B_2 as the minimum absolute distance from x to all the points in B_2, $d(x, B_2) = \min\{d_E(x, y)\}, \forall y \epsilon B_2$, where d_E denotes the Euclidean distance between points x and y. The discrepancy between B_1 and B_2 is described by the shape of the signature, which is commonly measured by its mean and standard deviation. As a rule, a $D_{B_1}^{B_2}$ with a near-zero mean and a small standard deviation indicates high quality of the image segmentation.

Region-Based Evaluation. The region-based scheme evaluates the segmentation accuracy in the number of regions, the locations and the sizes. Let the segmentation be S and the corresponding ground truth be G^S. The goal is to quantitatively describe the degree of mismatch between them.

Measures are based on the concept of directional Hamming distance from one segmentation $S_1 = \{R_1^1, R_1^2, \ldots R_1^n\}$ to another segmentation $S_2 = \{R_2^1, R_2^2, \ldots R_2^n\}$, denoted by $D_H(S_1 \Longrightarrow S_2)$. First, the correspondence between the labels of both segmentation results is established: each region R_2^i from S_2 is associated with a region R_1^j from S_1 such that $R_2^i \cap R_1^j$ is maximal. So, the directional Hamming distance from S_1 to S_2 is defined as:

$$D_H(S_1 \Longrightarrow S_2) = \sum{}_{R_2^i \epsilon S_2} \sum{}_{R_i^k \neq R_i^j, R_i^k \cap R_2^i \neq \emptyset} |R_2^i \cap R_1^k| \tag{1}$$

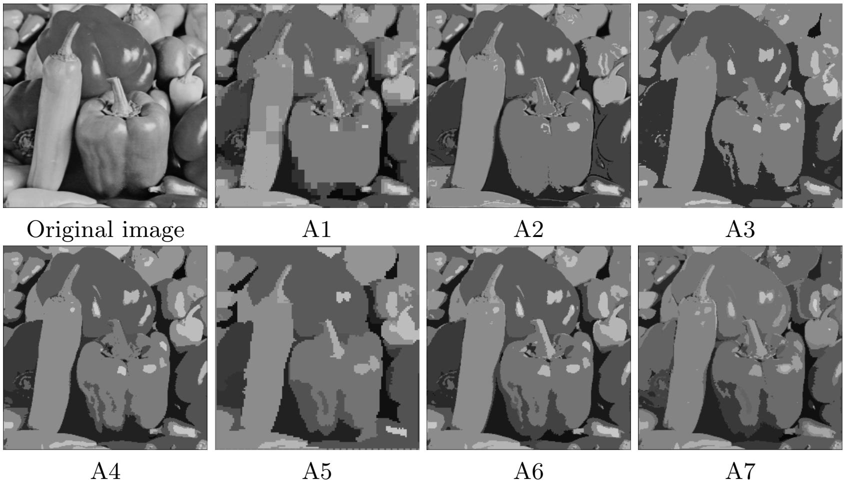

Fig. 2. Segmentation results over the peppers image. From top to bottom and left to right: original image and results when using the implemented algorithms (A1-A7).

where $|.|$ denote the size of a set. Therefore, $D_H(S_1 \Longrightarrow S_2)$ is the total area under the intersections between all $R_2^i \epsilon S_2$ and their non-maximal intersected regions from S_1.

A region-based performance measure based on normalized Hamming distance is defined as $p = 1 - \frac{D_H(S \Longrightarrow G^S) + D_H(G^S \Longrightarrow S)}{2 \times |S|}$, where $|S|$ is the image size and $p \epsilon [0, 1]$. The smaller the degree of mismatch, the closer the p is to one. Moreover, two types of errors are defined: missing rate e_R^m and false alarm rate E_R^f. The former indicates the percentage of the points in G^S being mistakenly segmented into the regions in S which are non-maximal with respect to the corresponding region G^S; while the latter describes the percentage of points in S falling into the regions of G^S which are non-maximal intersected with the region under consideration. We therefore have

$$e_R^m = \frac{D_H(S \Longrightarrow G^S)}{|S|}, \; and \; e_R^f = \frac{D_H(G^S \Longrightarrow S)}{|S|} \tag{2}$$

4.2 The Results

The implemented algorithms A1 to A7 have been applied to a set of 22 test images, including real and synthetic ones. Due to the limited space, we only show the detailed results of two images, while a summary of the results is provided for the remaining. A more complete report including the code, description and full details of the behaviour of each algorithm over the whole set of test images, can be accessed on `http://eia.udg.es/~xmunoz/seg.html`. The results obtained with the 7 algorithms over the peppers image are shown in figure 2. On the other hand, tables 1 and 2 show a set of quantitative results expressed in terms of the

Table 1. Segmentation results over synthetic test images. Performance of the 7 algorithms over the image 1(2nd row, 1st column), and the average of the results of the algorithms over 12 synthetic images.

Algorithm	Region-based			Boundary-based				Time
	e_R^m	e_R^f	p	μD_G^B	σD_G^B	μD_B^G	σD_B^G	
Circle Image Evaluation								
A1	0,0519	0,0333	0,9574	1,6030	1,9592	1,1899	2,2242	10,2500
A2	0,1273	0,0286	0,9221	1,2717	1,7487	2,0803	1,4658	0,3000
A3	0,0329	0,0048	0,9812	1,3423	2,0876	1,7654	1,3234	0,5200
A4	0,0106	0,0079	0,9907	0,8789	1,0762	0,9443	1,3240	0,2500
A5	0,0175	0,0338	0,9744	0,4125	0,7562	0,5601	0,7977	0,0800
A6	0,0812	0,0502	0,9343	0,2529	0,5737	0,3314	0,5992	7,7000
A7	0,0267	0,0217	0,9758	0,6318	1,4629	0,6338	1,4882	29,0500
Summary of Synthetic Images Evaluation								
A1	0,0453	0,0913	0,9317	1,1245	0,7015	1,0296	1,0449	41,2300
A2	0,2027	0,0111	0,8931	0,9547	0,6582	0,9654	0,8778	0,1800
A3	0,0590	0,0259	0,9576	1,0030	0,7083	0,9935	0,8435	0,3400
A4	0,0437	0,0203	0,9680	0,9601	1,0256	1,0054	1,1245	0,1100
A5	0,0343	0,0668	0,9495	0,4049	0,5067	0,7655	0,7713	0,0600
A6	0,0610	0,0602	0,9394	0,3345	0,5083	0,5459	0,6069	12,0200
A7	0,0587	0,0431	0,9491	0,9587	0,7632	1,1470	0,6103	25,0400

Table 2. Segmentation results over real test images. Performance of the 7 algorithms over the image 1(1st row, 1st column), and the average of the results of the algorithms over 10 real images.

Algorithm	Region-based			Boundary-based				Time
	e_R^m	e_R^f	p	μD_G^B	σD_G^B	μD_B^G	σD_B^G	
Peppers Image Evaluation								
A1	0,0232	0,0358	0,9705	1,1323	0,7800	1,1901	1,2118	34,2000
A2	0,1803	0,0138	0,9029	0,9745	0,8768	1,0399	1,0707	0,2100
A3	0,0266	0,0262	0,9736	0,9765	0,7721	1,8322	0,9057	0,2800
A4	0,0276	0,0262	0,9731	0,9357	1,0224	1,0099	1,0755	0,2100
A5	0,0175	0,0349	0,9738	0,8335	0,7605	0,8782	0,9114	0,0700
A6	0,1154	0,0419	0,9213	0,6515	0,7721	0,8322	0,9057	10,0300
A7	0,0884	0,0306	0,9405	0,8065	0,7862	1,0200	0,9057	24,0300
Summary of Real Images Evaluation								
A1	0,2080	0,0536	0,8692	3,8169	7,0020	4,9236	7,9250	9,0300
A2	0,1740	0,0446	0,8907	1,8285	1,2978	1,5440	3,1251	0,3600
A3	0,0665	0,0338	0,9499	2,1218	3,0183	2,1606	3,3891	0,4300
A4	0,0918	0,0125	0,9478	1,7327	3,1896	2,1238	4,2362	0,1900
A5	0,0749	0,0885	0,9183	0,6989	0,9687	0,4120	0,9826	0,0760
A6	0,1579	0,0448	0,8987	0,4354	0,5641	0,3457	0,5687	7,4500
A7	0,1677	0,0087	0,9118	0,8806	0,9918	1,4320	2,7155	31,6000

region and boundary evaluation parameters (described in section 4.1), as well as the execution time outlining the complexity of each algorithm.

Taking into account the quality of the results from a region-based scheme of evaluation, it will be noticed that the best results are reached by the A3 and A4 algorithms. Moreover, the importance of an appropriated placement of the starting seed points has been proved, which is generally forgotten or placed on a secondary priority in many region-based algorithms. On the other hand, the validity of the over-segmentation strategy has been proved by the good rates provided by the A4 algorithm. As a general rule, it will be noticed that the missing rate e_R^m is bigger than the false alarm rate e_R^f. This is mainly due to the presence of noise in images, which causes the appearance of holes inside the regions of the segmentation result. It can be easily avoided by either pre-processing the image with a smoothing filter, or post-processing by merging the smallest regions. The exception to this problem is the A5 algorithm (multiresolution strategy), where an initial coarse region segmentation is performed on lower resolution achieving the effect of smoothing.

The analysis of the segmentation results from a boundary-based scheme of evaluation yields the assumption that the boundary refinement strategy (A5 and A6 algorithms) is best. In fact, these results corroborate the expected ones stated that the obtention of a precise boundary is the main target for these methods. In this sense, the accuracy obtained by the A6 algorithm, which is based on the energy minimization of a snake, is remarkable.

The computational cost for each algorithm is another relevant feature to consider. After analyzing the experimental results, the high cost of A1 and A7 algorithms will be noticed. The reason of the high cost of A1 can be found in the recursive nature of its split and merge based algorithm. The “slowness” of A7 is due to the necessity of generating different region-based segmentation results in order to choose the best. So, finding a balance between the computational cost and the final accuracy of the results is mandatory. Nevertheless, both algorithms could be easily transported and executed over a parallel multiprocessor, which would considerably reduce the time of execution. In contrast, A6 does not have an excessively high cost. This can be easily explained when you consider that the placement of the snake from the region-based segmentation results allows initiation of the energy minimization very close to the final position. Hence, the suitable boundary is reached with few iterations.

5 Conclusions

The objective of this paper is a comparative survey of 7 of the most frequently used strategies to perform segmentation based on region and boundary information. The different methods have been programmed and their accuracy analyzed with real and synthetic images. Experimental results demonstrate that there is a strong similarity between the results obtained from synthetic and real images. The performance of the different algorithms over the set of synthetic images can be extrapolated to the results obtained over real ones, which seems to corroborate the remark made by Zhang [35], who noticed the convenience of using synthetic images in order to achieve an objective comparison of segmentation algorithms. Nevertheless, this statement can only be affirmed for the studied images and the studied algorithms.

The experimental results point out that, in general, post-processing algorithms give better results than embedded ones. Concretely, based on the region evaluation parameters, the algorithms A4 and A5 (post-processing) and A3 (embedded) are the ones which produce better results, while based on the boundary evaluation parameters, the algorithms A5 and A6 are the best. In conclusion, the best results were obtained with the Multiresolution strategy (algorithm A5) which provides the best performance according to the simplicity of the algorithm and the accuracy of the results. Further work is to validate these results over a wide set of different images, such as medical and satellite images.

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