Region-Edge Cooperation for Image Segmentation Using Game Theory

Omar Boudraa, Karima Benatchba

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Omar Boudraa[1] and Karima Benatchba[2]

[1,2] Doctoral School (STIC), High School of Computer Sciences (ESI),
Oued Smar, Algiers, Algeria
{o_boudraa,k_benatchba}@esi.dz

Abstract. Image segmentation is a central problem in image analysis. It consists of extracting objects from an image and separating between the background and the regions of interest. In the literature, there are mainly two dual approaches, namely the region-based segmentation and the edge-based segmentation. In this article, we propose to take advantage of Game theory in image segmentation by results fusion. Thus, the presented game is cooperative in a way that both players represented by the two segmentation modules (region-based and edge-based) try coalitionary to enhance the value of a common characteristic function. This is a variant of the parallel decision-making procedure based on Game theory proposed by Chakraborty and Duncan [1]. The involved pixels are those generated from the cooperation by results fusion between the edge detector (Active contour) and the region detector (Region growing) posing a decision-making problem. Adding or removing a pixel (to/from) the region of interest depends strongly on the value of the characteristic function. Then, and to study the effectiveness and noise robustness of our approach we proposed to generalize our experimentations, by applying this technique on a variety of images of different types taken mainly from two known test databases.

Keywords: Region-based segmentation, Edge-based segmentation, Region-edge cooperation, Game theory, Nash equilibrium.

1 Introduction

Image segmentation plays a key role in image analysis. In addition, it determines the quality of characteristics measures calculated later in image understanding process. However, there are mainly two dual approaches of segmentation. The edge-based segmentation approach that locates the boundaries of objects; and the region-based segmentation approach which partitions the image into a set of regions. Each region defines one or more connected objects.

In order to improve the results of each approach by trying to combine their own advantages, researchers have created what is called cooperative segmentation [2].

Game theory is a strong tool for analyzing situations, modeling and determining the best strategy(ies), often used in Economics and in a variety of domains. This theory proves interesting in this case given the principle of duality region-edge and the problem of antagonism between the two image segmentation approaches.

In our contribution, we propose to take advantage of Game theory in image segmentation by results fusion. It is to treat both types of segmentation, in a coalitionary way as two players exchanging information in "*Game Theory Integrator*" module to simultaneously improve their individual results.

This article consists of three sections. The first section presents general information on individual and cooperative techniques of image segmentation, its different forms and a bibliographical study on the integration of Game theory in image segmentation and its contribution. The second section details our contribution. While, the last section is devoted to experimentations, results and evaluation of the performance of our approach and its robustness to noise.

2   Around image segmentation and Game theory

2.1   Image segmentation

Segmentation is the partition of an image into a set of distinct regions (which do not overlap) and whose union is the whole image [3].

2.2   Image segmentation approaches

Image segmentation methods can be divided essentially into two categories which are based on two properties between neighboring pixels: *discontinuity* and *similarity*. The *discontinuity* is used by edge-based segmentation approach (boundary), while the *similarity* of pixels is used by region-based segmentation approach.

Edge approach.
The edge approach tries to identify changes between regions. In general, an edge element is a point of the image belonging to the boundary between two or more objects having different grayscale levels.

Derivate methods.
The derivate methods are most used to detect the pixels intensity transitions [4]. Overall, they can be classified into two big categories: *Gradient* approach that uses the first derivative and *Laplacian* approach that uses the second derivative.

Deformable models.
Segmentation algorithms based on deformable models have the advantage, compared to derivate methods that provide closed edges or surfaces [5]. These methods include: *Active contours* and *Level sets.*

Limitations of the edge-based segmentation.
Edge-based segmentation has some limitations and drawbacks such as the difficulty of identification and classification of parasite edges. In addition, the detected edges are not always closed. Nevertheless, the major weakness is that the edge-based segmentation does not give comprehensive information on the content of the image [6].

Region approach.

This approach consists in dividing the image into distinct regions [7]. In contrast to the edge approach, there methods are interested in the region content. The most common techniques for region-based segmentation are shown in the following.

Region growing.

Region growing technique is based primarily on the notion of seed. A seed is one pixel or set of pixels (region). From it, regions are constructed by aggregation of adjacent and homogeneous pixels (grayscale, color similarity...etc.) [7]. The Region growing process stops when all pixels have been processed (assigned to a region).

This technique is simple and quick to perform. In addition, it allows the object segmentation in complex topology [8]. Whereas, the choice of initial germs and homogeneity criterion is critical.

Region Splitting.

Region splitting technique involves image partitioning into homogeneous regions according to a given criterion. Its principle is to consider the image as the initial region, which then is divided into regions. The splitting process is repeated for each new region until homogeneous regions [9]. Its drawback is the *over-segmentation*.

Region Merging.

Region merging technique is a bottom-up method. Initially, each image pixel is considered as an elementary region. The method tents gradually to merge the related regions that satisfy a given predicate P [9].The process is repeated until the satisfaction of a stopping criterion (usually the visiting of the entire image) [10]. However, this method can introduce the *sub-segmentation* effect.

Region Splitting and Merging.

It is a hybrid method, in which, a splitting step is performed first. Its result is injected to the second process (merging similar regions) that corrects the possible effect of over-segmentation introduced by the splitting process.

Limitation of region-based segmentation.

Region-based segmentation has some disadvantages that we present below:

- The obtained regions do not always correspond to the objects in the image.
- The limits of the obtained regions are generally imprecise.
- The difficulty of identifying criteria for pixels aggregation or regions division.

Cooperative approach.

As we have seen previously, the region and the edge approaches have both advantages and disadvantages. Researchers have tried to take benefits from the strengths of both approaches and duality concepts between them and gave rise to what is called the cooperative segmentation. It combines the advantages of both solutions: *precision* and *speed* of edge-based segmentation*, boundary closures* and *density* of the extracted information of region-based segmentation [2].

Depending how to cooperate the both processes, the researchers proposed three different approaches: *Sequential cooperation*, *fusion results cooperation* and *mutual cooperation*.

Sequential cooperation.
The general principle of the sequential cooperation is one of the individual techniques is executed first. Its result is then exploited by the second technique [11].

Fusion results cooperation.
In fusion results cooperation, region-based and edge-based segmentation are executed in parallel and independently. Cooperation takes place at their respective results.

Mutual cooperation.
In mutual cooperation approach, different segmentation techniques are executed in parallel while mutually exchanging information.

2.3   About Game theory

Game theory is a formalism that aims to study the *planned*, *real* or *posteriori* justified behavior of agents deal with situations of *antagonism* (opposition), and seek to highlight *optimal* strategies [12]. It is based on the concept of game defined by a set of players (considered as rational agents), all the possible strategies for each player, and the gains specification of players for each combination of strategies [13].

Types of games.
The most popular types of games are:

- *Cooperative and non-cooperative games.*
- *Finite and infinite games.*
- *Synchronous and asynchronous games.*
- *Zero-sum games and non-zero-sum games.*
- *Complete information games and perfect information games.*

Nash equilibrium.
In 1950, *John Nash* has defined a stable interaction situation if no player has interest to change its strategy knowing strategies of others. The game becomes stable that no player can only change its strategy without weakening his own position [14].

Theoretically, it is said that a combination of strategies *s** is a Nash equilibrium if the following inequality is satisfied for each player *i* [14].

$$u_i(s_i^*, s_{-i}^*) \geq u_i(s_i, s_{-i}^*). \forall\, s_i \in S_i \tag{1}$$

More Clearly, if player *i* anticipates that the other players will choose the strategies associated with the combination of strategies s_{-i}^*, it can only maximize its gain *u* by choosing the strategy s_i^*.

2.4   Image segmentation and Game theory

Works on the matching between Game theory and image segmentation are not numerous. One possible reason is that Game theory is based primarily to satisfy economic needs. Whereas, the first published work is that of A. CHAKRABORTY et al. in 1999 [15, 1]. In this section, we will quote it with other work in this domain.

- Work of (A. CHAKRABORTY et al. in 1999) is an original and outstanding work that is based on a solid mathematical model integrating Game theory in image segmentation by mutual cooperation between the edge detector (Active contour) and the region detector (Markov Random Fields). It represents a reference work.
- (E. Cassel et al. in 2007) proposed a modified and simplified implementation of Chakraborty and Duncan approach [1]. This simplification involves removing the "Prior information about the form to segment" in the equation of the edge detector. The authors in [16] opted for the "Region growing" as region detector and the morphological operation "closure" for the edge detector.
- Even, (K. ROY et al. in 2010) have proposed an approach to iris and pupil segmentation based on Chakraborty and Duncan work [1]. However, this approach is suitable particularly on this special field of application. For this, they integrated pretreatments and post-treatments phases in their procedure. In this work, the "Region growing" and "Level sets" methods were used. [17]
- The last two works consist of two individual segmentation approaches (edge-based segmentation only). (B. IBRAGIMOV et al. in 2011) proposed a supervised algorithm based on Game theory and dynamic programming for the segmentation of lung fields [18], while (M. KALLEL et al. in 2013) proposed an approach based on Game theory to restore and segment simultaneously noisy images [19].

3   Cooperative segmentation approach using Game theory

Now, we present our approach. We propose segmentation by results fusion, suggesting a cooperative game where both players, represented by the two segmentation modules, try coalitionary to improve the value of a common characteristic function. This is mainly based on the work done by Chakraborty and Duncan [1]. This choice is based on the fact that their procedure is original, robust and has been proven mathematically. Indeed, Cassel et al [16] and Roy et al [17] works gives us the opportunity to suggest improvements and changes in the cost functions of this procedure.

3.1   Game formulation

Now, we define our game and detail its constituting elements, its type and nature.

Game components.
Following Chakraborty and Duncan procedure [1], the objective functions are:
For the *region-based segmentation module* (player 1),

$$F^1(p^1, p^2) = min_X \left[\sum_{i,j} [y_{i,j} - x_{i,j}]^2 + \lambda^2 \left(\sum_{i,j} (x_{i,j} - x_{i-1,j})^2 + \sum_{i,j} (x_{i,j} - x_{i,j+1})^2 \right) \right] + \alpha \left[\sum_{(i,j) \in A_p} (x_{i,j} - u)^2 + \sum_{(i,j) \in \overline{A_p}} (x_{i,j} - v)^2 \right]. \tag{2}$$

Where:

— $A_{\vec{p}}$ Corresponds to the set of points which lie inside the contour vector $\vec{p}$, while $\overline{A_{\vec{p}}}$ correspond to the points that lie outside it. Thus, $A_{\vec{p}} \cup \overline{A_{\vec{p}}} = \{(i,j)\,;\ 1 \le i \le M\,,\ 1 \le j \le N\}$ = Whole image.

— $u_{i,j}$ represents the information concerning the intensities of points inside the contour and $v_{i,j}$ for points outside.

Also, y is the intensity of the original image, x is the segmented image provided by p^1, u and v corresponds to the intensity mean value of the image on the inside (outside respectively) of the contour given by p^2. The first term attempts to minimize the difference between the values of the pixels intensities found in the region and to strengthen continuity. Whereas, the second term is trying to match between the region and the detected contour.

Whereas, the objective function of player 2 (*edge-based segmentation module*) is:

$$F^2(p^1, p^2) = arg\ max_{\vec{p}} [M_{gradient}(I_g, \vec{p}) + \beta M_{region}(I_r, \vec{p})] \tag{3}$$

Where $\vec{p}$ denotes the contour parameterization proposed by p^2, I_g is the gradient image, and I_r is the segmented region obtained by p^1. $M_{gradient}$ represents a correspondence measure (matching) between the gradient image I_g and the detected contour. While, M_{region} is a matching measure between the segmented region image I_r and the contour vector $\vec{p}$, β is its weight.

In our approach, we propose a new formula simplifying function F^2 by replacing:

- $M_{gradient}$ and M_{region} by Abdou and Pratt measure [4].
- Contour parameterization $\vec{p}$ by the constituent pixels of the Active contour.
- The gradient image I_g by *Canny* detector.
- The image of the segmented region I_r only by its boundary.

Finally, we proposed to unify the two cost functions above in one function F:

$$F = \frac{F_{i-1}^1(p^1, p^2) - F_i^1(p^1, p^2)}{F_{i-1}^1(p^1, p^2)} + \frac{F_i^2(p^1, p^2) - F_{i-1}^2(p^1, p^2)}{F_{i-1}^2(p^1, p^2)} \tag{4}$$

Adding or removing a pixel (to/from) the region of interest depends strongly on the improvement or deterioration of this function value. F_i^1 and F_i^2 represent the cost functions of the two segmentation modules, the index i determines whether the pixel i is taken into account or not (i-1 for no and i for yes).

Not only it takes into account the two cost functions, it also helps to normalize the rate of improvement or deterioration of each function because the variation of the function F^1 is almost always greater than those of F^2 as both are not commensurable.

Game type.
By inference, the proposed game is a: *Finite*, *Cooperative* and *Non-zero-sum* game.

3.2   Architecture of the adopted approach

We can summarize the organization of our system through a series of interactive modules for segmentation of an image. Each one is presented in the following:
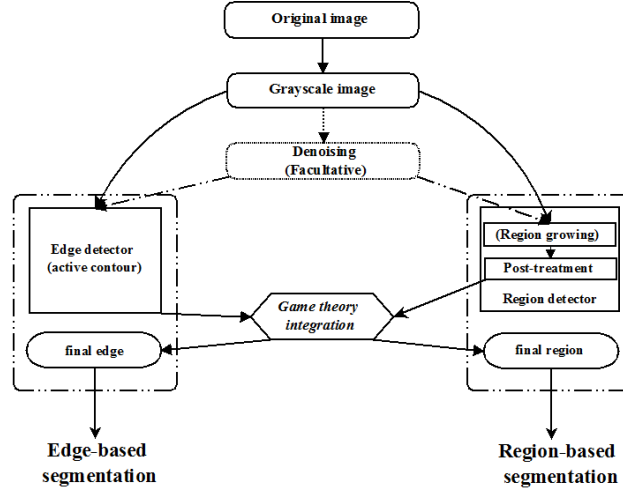

Fig. 1. Overview of the proposed system

Grayscale conversion.
This pretreatment is designed to simplify the image which makes easier the application of our procedures and comparisons; by reducing the amount of information.

Denoising.
It consists of an optional treatment, serving to smooth the image (blur effect), reduces noise (unwanted signals) and reduces detail in order to improve the image quality.

Region detector.
As a region detector module, we opted for the Region growing technique. The growing is through the aggregation of candidates' pixels similar to the initial germ of the region, while seeking to minimize the following cost function [16]:

$$E = \sum_{i,j}(y_{i,j} - x_{i,j})^2 + \lambda^2 \left(\sum_{i,j} \sum_{i_s,j_s}(x_{i,j} - x_{i_s,j_s})^2 \right) \tag{5}$$

Where i_s and j_s are the pixel neighborhood of the indices $x_{i,j}$ (in the classification image). The classification image (or segmentation) is initialized by the pixel intensity values in the image processed by the famous Otsu's thresholding technique [20]. That is applied to the grayscale image in order to overcome the problem of non-initialization of neighboring pixels that's not yet been processed.

In our case, and in order to reduce the number of calculations, we proposed at each iteration an estimation of the formula (5). We apply it only on the current pixel and its neighbors while following a *4-connected* neighborhood scheme.

Post-treatment.
In order to improve the detected region, any obtained agglomeration (non-significant small regions, holes and parasite pixels) that are located entirely within the region of interest are filled and aggregated to the pixels of the region.

Edge detector.
As edge detector, we have focused our choice on "Active contour" method. This choice is based on the fact that Active contours are closed and one-pixel thickness (i.e., they do not require post-treatments). However, we can remedy it major problem (not detecting of concave shapes) in the phase of Game theory integration.

In our implementation, thresholding image generated by the Otsu method [20] constitutes the input of the edge detector module. This Active contour is designed to fit the region in which the initial seed belongs.

Game theory integration.
After running the two detectors for a sufficient number of iterations, Game theory can take place in order to improve the results of the two detectors cooperatively.

The involved pixels are those generated through the cooperation by results fusion between the edge and region detectors posing a decision-making problem. Thus, we first address the list of pixels located inside the Active contour and which does not belong to the region of interest (considering first the nearest pixel to the region of interest) (see Fig. 2). At the end of each iteration, an update of the region and the edge configurations is made.

Adding or removing a pixel to the region of interest is highly depending of the improvement or deterioration of the function value defined in formula (4).
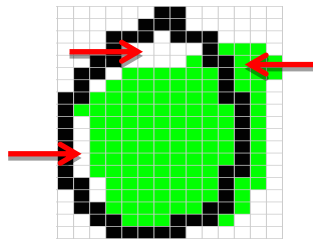

Fig. 2. Preliminary results and places where Game theory will be applied.

4   Experimental results

In this section, a summary of the tests and the obtained results is presented to demonstrate the effectiveness of our region-edge cooperation approach, we test it on a varie-

ty of different-kinds images (synthetic, real and medical: sane and added noise) from two known images databases ([21], [22] and a set of MRI-type medical images found on the Internet). Also, we compare the individual approach results (Region growing only) to those of the proposed cooperative approach.

To evaluate the segmentation results, We will use the following methodology. First, we start our tests on the proposed approach by fixing a few parameters and varying the other, in a guided and judicious manner. This allows us to adjust the parameters of the various modules and study their impact on segmentation quality. Then, we test our cooperative approach to all the images of the three benchmarks, while determining for each image the region of interest to extract.

Obtained results are therefor compared and evaluated using the following criterion:

— **Borsotti criterion:** Uniformity and contrast. 0 nearest value represents best result.
— **Zeboudj criterion:** Contrast intra-inter region. 1 nearest value represents best result.

The comparison is done using the criteria mean values.

After testing our cooperative approach to sane images (net), and to discuss its robustness to noise, we propose to evaluate the same image after adding artificial noise.

Fig. 3 shows the results of the individual methods implementation (Active contour and Region growing) and the proposed cooperative approach on a real image from the BCU database [22]. Visual analysis of this figure shows that the cooperative segmentation using Game theory improves in parallel manner the results therefor obtained by correcting lacunas generated by the individual methods, namely the poor detection of concave regions in the Active contours and excess pixels presented in the result of segmentation by Region growing technique.
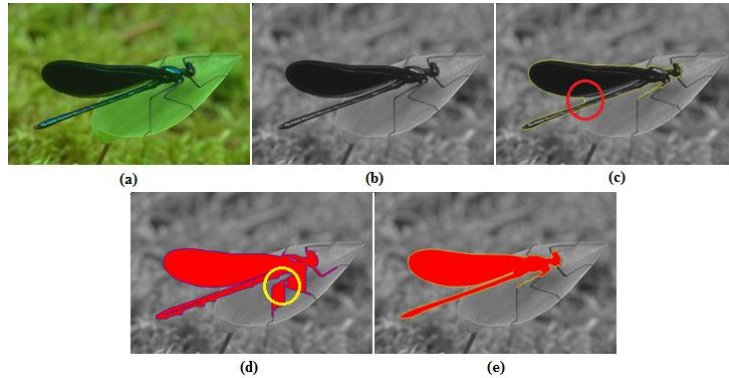

Fig. 3. Segmentation results of individual and cooperative approaches applied to a real image issued from the BCU database [22] (a) Original image (b) Grayscale image (c) Active Contour (d) Region growing (e) Image segmentation by region-edge cooperation using Game theory

4.1 Tests results on sane images

The analysis of the registered segmentations results in terms of *Borsotti* and *Zeboudj* global mean values, allows us to go out with the following consequences:

1. As shown in the histogram of Fig. 4, the mean value of *Borsotti* criterion remains good and more or less stable for the set of all images used in the tests in the case of individual segmentation (Region growing) and the case of the integration of Game theory in the image cooperative segmentation.

2. Whereas, we observe an improvement in *Zeboudj* criterion in the second compared to the first which shows the effectiveness of the approach and the contribution of Game theory in image segmentation field.
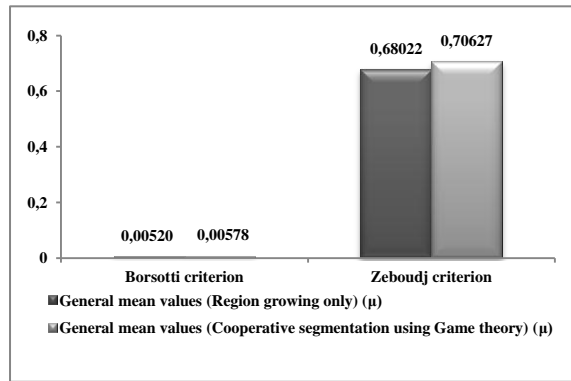

Fig. 4. General means values of Borsotti and Zeboudj criteria (without and with) integration of Game theory

4.2   Tests results on noisy images

In this section we perform the operation of adding noise to three test images of different natures (Image (a) (synthetic), Image (b) (real) and Image (c) (medical)) while varying the percentage of added noise from 5% to 25%, which is randomly distributed over the whole of each of these images. Knowing that a percentage of 25% means that half of the image corresponds to noise (25% of pepper type and 25% of salt type); this represents a high rate of parasites pixels. The results obtained are illustrated in Fig.5.

Qualitative visual comparison between the original image and the segmented images produced by this technique shows that:

1. The degree of robustness to noise differs from one image to another; the synthetic and medical images have both a good robustness against noise varying from 5% to 25%, in which the quality of regions of interest segmentation is inversely proportional to the percentage of noise.

2. The real image segmentation result is good for percentages of 5% and 10% of added noise. However, it becomes very bad (invalid) from 15% of added noise.

3. Areas affected by the deterioration are often the borders rather than the interior of the region of interest (it is clearly visualized in the images (b) and (c)).

4. Generally, the qualities of the segmentation results provided by our approach applied to all three test images are reliable for a percentage of noise strictly less to 15%. This proves the robustness of the implemented procedure to the added noise.
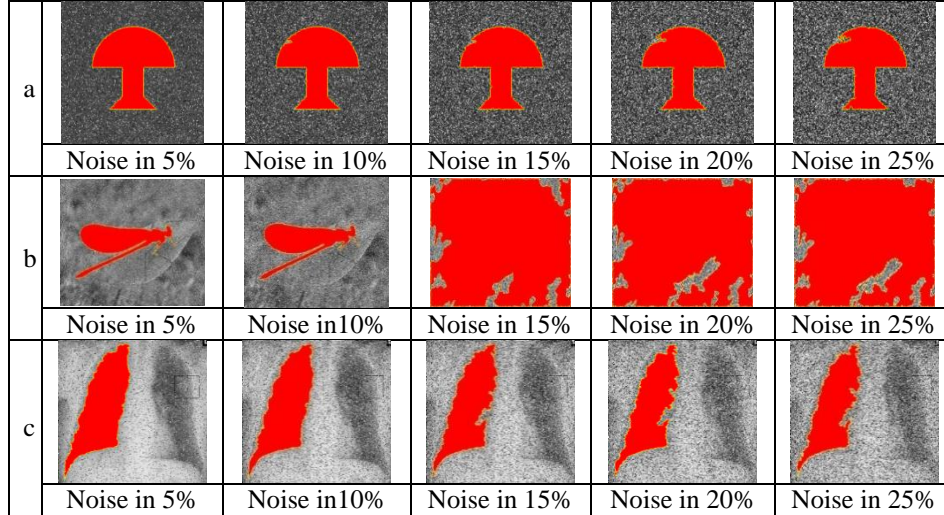
Fig. 5. Result of segmentation using a Game theory-based approach applied to different images after adding the salt and pepper noise (a) Synthetic image, (b) Real image, (c) Medical image

5 Conclusion and discussions

In this article, we studied the possibility of Game theory integrating in image segmentation by region-edge cooperation. Indeed, we proposed a modified and simplified version of the parallel decision-making procedure as described in the work of Chacraborty and Duncan [1]. Whereas, the proposed modification helps to make the game cooperative, so that both players try coalitionary to improve the value of a common characteristic function within a framework of segmentation by results fusion.

Provided performance indices either digital or visual showed its effectiveness and its robustness to poor conditions of the input image (specifically image noise problem). Nevertheless, our method has had some inconveniences to running as:

- Results are depending on optimizing of parameters number, which is relatively big.
- Calculation time is sometimes very high estimated at a few hours.
- Procedure and by its nature can detect a single region of interest at a time.

Many prospects may be cited, for any enrichment of our study. Among them:
- Improvements of the detection procedure for all the regions of the image.
- Proposing of other gaming models, such as the players are pixels or image objects.
- Proposing image segmentation by mutual cooperation.
- Find an automatic parameters adjustment to the input image characteristics.

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