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Evolutionary Region Growing for Image Segmentation

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Abstract

Image segmentation is important stage in image processing. Segmentation by region growing is a fast, simple and easy to implemented, but it suffers from three disadvantages: the threshold problem, initialization of germs, and the processing order of the neighboring pixels of germs. Evolutionary algorithms are particular methods for optimizing functions; they have a great ability to find the global optimum of a problem. In this paper, we used evolutionary algorithms to get over the three problems of region growing. We have proposed a segmentation method based on region growing and evolutionary algorithms. The proposed approach is validated on 1000 synthetic images (500 images with 2 regions and 500 images with 3 regions). Thus, our method is validated on five unsupervised evaluation criteria: Inter-region contrast Vinet criterion and compared with two methods: split and merge method and Kmeans algorithm. The results show the good performance of this approach.

INTRODUCTION

The segmentation is a very important stage in images and interpretation processing; there are many consistent methods available today for image segmentation, among these: there is the segmentation based on regions [3,17], segmentation based on pixel and segmentation based contour[7]. After many years of seeking the optimal method, the researchers understood that the ideal segmentation did not exist. Given an image, there are still several possible segmentations. A good segmentation method will be one that will arrive at a correct interpretation.

We are interested in this work to approach region and specifically the region growing. A region is a set of topologically related pixels and having similar attributes: gray levels, color, texture, movement [1, 2, 5].

Segmentation by region growing is very recognized, fast, simple and easy to implement, [2, 5,6] but it presents disadvantages: sensitive to the threshold, no global view of the problem, in practice, for different point of initialization (seeds) one gets different results, not very stable, sensitive to the order of course of the points and very sensitive to the noise.

Considering the great success of the strategies algorithms in the optimisations problems[14], we exploit them to get over three disadvantages of this algorithm. We have presented an algorithm of segmentation by evolutionary region growing.

In Section 2 image segmentation with *region growing* algorithm is presented. Section 3 gives an introduction to strategies algorithm. The evaluation criterion of segmentation is detailed in the next section. The proposed evolutionary algorithm for optimization of region growing is presented in section 5. In section 6, a validation of our approach is given; experimental results are obtained over 1000 synthetic images. Finally we give a conclusion.

REGION GROWING METHOD (RG)

The region growing algorithm is a method of segmentation based on the approach region, the principle of this algorithm is as follows [1, 2, 3]:

- We fix the points (seed) starting in the image. These points are called germs of regions searched.
- We fix a criterion of homogeneity (threshold) of the region searched for example, the grey level or texture criteria.
- For a recursive procedure (step by step), are included in the region all the points that satisfy the criterion related.

It is growing and the region as the criterion is met. The choice of starting points is the critical part of the algorithm. The growing stage will use a similarity measure to select the pixels to be agglomerated.

The growing stop when you cannot add more pixels without breaking homogeneity [1, 2, 3].

1. *Starting points (seeds)*

The choice of starting points or initialization is the critical part of the algorithm. Indeed, the growth stage will use a similarity measure based on a given threshold, to select the pixels to be agglomerated. If the starting point is located in a non-homogeneous, the similarity measure will produce large variations and growth will stop very soon.

2. *Region growing (growing)*

This step aims to grow a region by agglomerating neighboring pixels. The pixels are selected to maintain the homogeneity of the region. For this, we need to define an indicator of homogeneity. Neighboring pixels are added to the region of homogeneity if the indicator is true. Growth stops when you cannot add pixels without breaking the homogeneity [5, 6]. The choice of germs and the threshold can be either manually or automatically.

Several researchers have treated the problems of this method but these solutions are limited. The germs problem is treated by [12,16] is fixing the a priori threshold and finding germs. The threshold problem is treated by [17], have given it a priori germs point and automatically determine the optimal threshold by genetic algorithm.

This research does not provide a complete solution of the problems of the method of segmentation by region growing.

In this work we will determine the optimal germs and threshold automatically by evolutionary algorithm.

EVOLUTIONAY STRATEGIES

Evolutionary strategies (*ES*) are particular methods for optimizing functions. These techniques are based on the evolution of a *population* of solutions which under the action of some precise rules optimize a given behavior, which initially has been formulated by a given specified function called *fitness function* [15].

An *ES* algorithm manipulates a population of constant size. This population is formed by candidate points called *chromosomes*. Each of the chromosomes represents the coding of a potential solution to the problem to be solved, it is formed by a set of elements called genes, and these are reals [15].

At each iteration, called generation, is created a new population from its predecessor by applying the genetic operators: *selection* and mutation. The mutation operator perturbs with a Gaussian disturbance the chromosomes of the population in order to generate a new population permitting to further optimize the fitness function.

This procedure allows the algorithm to avoid the local optimums. The selection operator consists of constructing the population of the next generation. This generation is constituted by the pertinent individuals.

Figure 1 illustrates the different operations to be performed in a standard *ES* algorithm [9,15]:

```
Random generation of the initial population
Fitness evaluation of each chromosome
Repeat
    Select the parents
    Update the genes by mutation
    Select the next generation
    Fitness evaluation of each chromosome
Until Satisfying the stop criterion
```

Figure 1: Standard ES algorithm.

1. *Solving a problem by ES*

The application of ES to solve a problem requires to coding potential solutions to this problem by finite chains of bits to form chromosomes, to find a selective function allowing a good discrimination between chromosomes and to define genetic operators to be used [15].

EVALUATION OF A SEGMENTATION

There are a multitude of segmentation methods whose effectiveness is difficult to assess. Numerous works deal with the problem of the evaluation of a segmentation result [11, 19,22]. Zhang presents a possible classification of the evaluation criteria in three groups [23].

1. *Analytical methods*

The analytical methods which permit to characterize an algorithm in terms of principles, needs, complexity, convergency, stability,... without any reference to a concrete implementation of the algorithm or testing data[19].

2. *Supervised methods*

The supervised method evaluates the quality of a segmentation result by measuring its similarity to reference segmentation. They thus assess the quality of a segmentation result by using an a priori knowledge. This knowledge can be a segmentation result used as a reference which is called ground truth (GT) or some knowledge on the elements to recognize[11,19].

3. *Unsupervised methods*

The unsupervised method is based on unsupervised evaluation criteria for estimating the quality of a segmentation result from statistics calculated for each detected region. They which compute fitness metric on a segmentation result. And do not necessitate any knowledge on the segmented images to assess and their principles consist in an estimation of the quality of a segmentation result according to some statistics computed on each region, class, texture, fuzzy set... detected, mostly often by using a statistical point of view. In this work we have chosen to focus on criteria which assess region segmentation results because it is a complex problem. We study some unsupervised evaluation criteria. A criterion value close to 1 indicates a very good result of segmentation.

We selected, from the state of art [11, 19] for unsupervised evaluation criteria of gray level image segmentation results (into regions or classes) and one supervised criterion (Vinet criterion).

1) *Levine and Nazif's Inter-region contrast*

This criterion computes the sum of contrasts of the regions (R_i) balanced by their surfaces (A_i). The contrast of a region is defined from the existing contrasts with regions that are contiguous [18]:

$$C_{\text{inter}} = \frac{\sum_{R_i} A_i c_i}{\sum_{R_i} A_i} \tag{1}$$

Where $c_i = \sum_{R_j} \frac{l_{ij}|m_i - m_j|}{l_i(m_i + m_j)}$ (2)

m_i mean of the region R_i ; l_{ij}, length of the common border between R_i and R_j; l_i, perimeter of the region R_i.

The Inter criterion is recommended in the case of mixed images and for most textured ones (general case) [19].

1) Levine and Nazif 's intra-region uniformity

This criterion computes the sum of the normalized standard deviation of each region [18].

1) Levine and Nazif Intra-inter

Combination of intra-region and inter-region disparities this indicator combines similar versions of the Levine and Nazif inter-region and intra-region measures[18].

1) Borsotti's criterion (Borsotti)

This measure is based on the number, the surface and the variance of the regions[13].

$$BOR = \frac{\sqrt{N}}{1000 * A} \sum_{i=1}^{N} \left(\frac{\sum_{R_i} (f(s) - m_i)}{1 + \log A_i} + \frac{R(A_i)^2}{A_i^2} \right)$$

Where, m_i is the average value of the grey-levels in the region R_i, and $R(A_i)$ is the number of regions whose surface is equal to A_i.

Borsotti criterion is recommended in the case of uniformed images [13,19].

1) Zeboudj's contrast

Zeboudj [10] provides a measure based on the combined principles of maximum inter-regional contrast and minimum intra-region measured in the neighborhood of each pixel.

Denoting $W(s)$ a neighborhood of the pixel s, $I(s)$ the intensity of that pixel and L maximum intensity.

Contrast between two pixels s and t:

$$\mathrm{C(s,t)} = \frac{|I(s) - I(t)|}{\mathrm{L} - 1} \quad (4)$$

The external contrast and internal contrast of a region R_i and boundary F_i are defined respectively:

$$\mathrm{CI(i)} = \frac{1}{A_i} \sum_{s \in R_i} Max\{c(s,t), t \in W(s) \cap R_i\} \quad (5)$$

$$\mathrm{CE(i)} = \frac{1}{l_i} \sum_{s \in F_i} Max\{c(s,t), t \in W(s), t \notin R_i\} \quad (6)$$

Where l_i is the length of F_i and A_i is area of region R_i

The contrast of R_i is:

$$\mathrm{C(R_i)} = \begin{cases} 1 - \frac{CI(i)}{CE(i)} & if\ 0 < CI(i) < CE(i) \\ CE(i) & if\quad CI(i) = 0 \\ 0 & else \end{cases} \quad (7)$$

The global contrast is finally:

$$\mathrm{Zeboudj} = \frac{1}{A} \sum_i A_i C(R_i) \quad (8)$$

Zeboudj criterion is recommended in the case of uniformed images [19].

1) Rosenberger criterion

Rosenberger's criterion (Rosenberger) [11]: the originality of this criterion lies in its adaptive computation according to the type of region (uniform or textured). In the textured case, the dispersion of some textured parameters is used and in the uniform case, gray levels parameters are computed. Rosenberger criterion is recommended in the case of textured images [11].

1) Vinet criterion

Vinet's measure (Vinet): it is a supervised evaluation criterion. It computes the correct classification rate by comparing the result with a ground truth. Since we work in this study on a database composed of synthetic images, the Vinet's measure is used as a point of comparison[22].

1) Kmeans segmentation

The objects that are processed by the *Kmeans(KM)* algorithm are the pixels of the input image. The observation matrix in this case is formed by two columns which represent the attributes associated with each pixel of the image: the columns are associated with the Contrast and the Local Homogeneity. The size of the square window used must have an odd length (3 * 3, 5 * 5 ...). In this process each pixel is attributed to a specific class. The resulting image is segmented into C different regions where each region corresponds to a class [4].

1) Split and merge method

Split-and-merge segmentation (SP) is based on a quadtree partition of an image. It is sometimes called quadtree segmentation. This method starts at the root of the tree that represents the whole image. If it is found non-uniform (not homogeneous), then it is split into four son squares (the splitting process), and so on. If, in contrast, four son squares are homogeneous, they are merged as several connected components (the merging process). The node in the tree is a segmented node. This process continues recursively until no further splits or merges are possible [20,21].

REGION GROWING OPTIMIZATION BY EVOLUTIONARY STRATEGIES

1. *Proposed coding*

The proposed algorithm (ERG) consists of selecting among all of the possible partitions the optimal partition by maximizing a criterion for validating segmentation. This yields the optimal seeds $(P_s)_{1\leq s\leq C}$ and the optimal threshold S using in the region growing. Thus we suggest the real coding as:

$$chr = (P_{sj}, S_j)_{1\leq s\leq C, 1\leq j\leq N}\ , S\in[0,1[$$

$$= \left(P_{11}..P_{1N}P_{21}..P_{2N}..P_{s1}..P_{sN}..P_{C1}..P_{CN}\ , s\right) \qquad (12)$$

The *chr* chromosome is a real line vector of dimension $C\times N+1$. The genes $(g_{sj})_{1\leq j\leq N}$ are the coordinates x and y of P_s and the threshold :

$$P_s = (g_{sj})_{1\leq j\leq N} = (g_{s1}g_{s2}) = (x_s, y_s, S) \qquad (13)$$

2. *Constraint*

To avoid that the initial solutions be far away from the optimal solution, the coordinates of each point of departure should check the following conditions:

$$x_s \in [\min x_{i\ 1\leq i\leq m1}, \max x_{i\ 1\leq i\leq m1}],\qquad y_s \in [\min y_{j\,1\leq j\leq m2}, \max y_{j\,1\leq j\leq m2}] \qquad (14)$$

Where m_1 and m_2 are the dimensions of the image.

And the gray level of the original image in these germs are different. If we have two seeds (x_1, y_1) and (x_2, y_2), then

$(I(x_1, y_1) - I(x_2, y_2)) < variance(I)$, with I is the original image.

In the proposed algorithm, we discard any chromosome with a gene that does not satisfy this constraint. This gene, if any, is replaced by another one which complies with the constraint.

3. *Proposed fitness function*

Let *chr* be a chromosome of the population formed by the germs $(P_s) 1\leq s\leq C$, for computing the fitness function value associated with *chr*, we define the fitness function *F(chr)* which expresses the behavior to be optimized.

$$F(chr) = \sum_{i=1}^{C}\sum_{s=1}^{M} \left\| Moy_{Ri} - Ng_s \right\|^2 \qquad (15)$$

Where $MoyR_i$: mean of the current region

Ng_s : gray level of pixel P_s in the region R_i

M : number of pixels in the region R_i

The chromosome *chr* is optimal if $F(chr)$ is minimal.

4. *Evolutionary Region Growing (ERG)*

Figure 2 shows the different steps of the proposed algorithm ERG:

1. Fix :- The size of the population *maxpop*.
   - The number of region C in the image.
   - The maximum number of generation *maxgen*.
2. Generate randomly the population *Pop*
   $Pop = \{chr_1, .., chr_k, ..., chr_{maxpop}\}$
3. Verify for each *chr* of *Pop* the constraint.

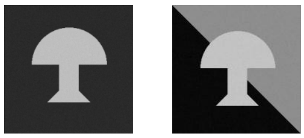
Repete

1. Region growing for each *chr* of *Pop*
2. Compute for each chr of Pop its fitness value CAR(chr).
3. Order the chromosomes *chr* in *Pop* from the best to the poor (*in an increasing order of F*).
4. Choose the best chromosomes *chr(replace the first chr by the last)*.
5. Determination of optimal *chr* and fitness value for this generation.
6. Mutation of all the chromosomes *chr* of *Pop* except the first one (*elitist technique*):$g^*_s = g_s + f_m \times N(0,1)$
7. Verify for each *chr* of *Pop* the constraint. **Until** *Nb_gen (Nombre of generation) > maxgen*

Figure 2: Proposed algorithm ERG.

RESULTS AND EVALUATIONS

In order to evaluate the performances of the proposed method ERG, we have considered a set of synthetic images including 5 subsets of images having respectively from 2 and 3 regions. The Figure 3 presents two examples of the ground truths used to create the images.



2 regions 3 regions

Figure 3: Examples of ground truths used for the creation of the synthetic set of images.

Thus, each subset has a fixed number of regions and is made up of 1000 images with a proportion of textures going from 0 to 100% by step of 25, these images are created as follows [8], table1:

Table 1: Information of the Data.

	Uniformed region	**Textured region**
Data1	100%	0%
Data2	75%	¨25%
Data3	50%	50%
Data4	25%	75%
Data5	0%	100%

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We used three segmentation methods: the proposed algorithm (ERG), Kmeans algorithm (KM) [4] and the split and merge algorithm (SP) [20,21]. In addition to these three segmentation results, an obvious synthetic segmentation result was added: the ground truth used to create the subset of synthetic images. This result is the best possible one.

Figure 4: presents an example of segmentation results obtained by using these methods on an image.

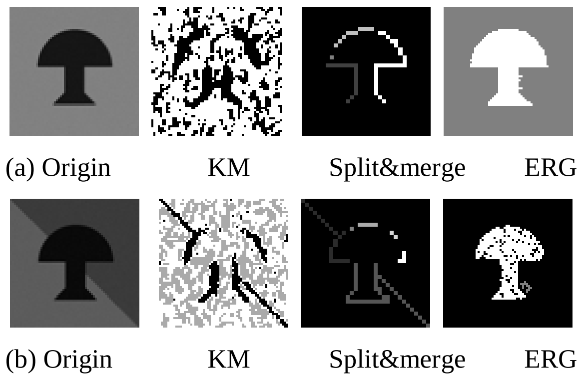

Figure 4: Segmentation results obtained by using these methods on an image. (a) two regions. (b) three regions.

The criteria used to evaluate these segmentation results bases were selected four criteria from those presented in paragraph 4.3: Intra Levine and Nazif Intra, Inter Levine and Nazif Inter[18], Borsotti Bor [13], Zeboudj Zeb [10] and Rosenberger Ros [11]. To simplify the comparison of criteria, they were normalized to evolve between 0 and 1, where 1 is optimum quality.

We calculated the evaluation criteria presented above based on segmentation results. We then have 1000 original images, 1000×3 results calculated segmentation and 2 ground truth using 4th result segmentation, a total of 4002 results of different segmentation.

Table 2: Result of image segmentation for 2 and 3 regions, with 3 méthods.

	Methods / Criteria	**ERG**	**KM**	**SP**
C=2	**Inter**	17,46	00,00	00,00
	Intra	09,36	03,90	16,03
	Zeboudj	50,26	00,02	00,00
	Rosenberger	50,19	42,31	35,08
C=3	**Inter**	19,05	00,54	00,00
	Intra	08,06	14,64	21,49
	Zeboudj	59,22	04,32	00,00
	Rosenberger	50,20	44,24	44,66

Table 2 illustrates the results of image segmentation by the three algorithms: our approach ERG, KM algorithm and SP algorithm, for two and three region(C=2 and C=3).

The proposed algorithm converges and gives the optimal chromosomes: threshold and germs. This gives the optimal segmentation. Table 3 and 4 show the values of each evaluation criterion. Its values are the sum of the values of evaluation criteria for all segmented images. The value of the criteria for the ERG result is much better than the other segmentation results KM and SP. On the contrary, the Intra's criterion has a bad value for this segmentation result. If we consider the results KM and SP, we see that the ERG segmentation result is again correctly preferred.

Figures 5 and 6 show that the criterion of Zeboudj is best, followed by the criterion of Rosenberger in the case of consistent data or slightly textured data1, data2 and data3, and this for both cases 2 and 3 regions. As against the textured data data4 and data5 criterion Rosenberger is the best followed by the criterion of Zeboudj. The results show that the proposed method gives ERG large values of all criteria: ROS, ZEB, Inter, Intra and Vinet, compared to other methods KM and SP.

The three algorithms were run several times and we noticed that the proposed algorithm ERG obtains each time the same result while the *KM* and split & merge obtains different results. We can conclude that the proposed algorithm is the most stable, it outperforms the *KM* and *SP* and it obtains good results. This confirms the good performance of the proposed method.

CONCLUSION

Region growing image segmentation shows some stability difficulties due to the threshold problem, the seeds and the processing order of the neighboring pixels of germs. We have proposed the evolutionary algorithm image segmentation in order to get over the three problems. The proposed approach has been validated on 1000 synthetic images and 6 evaluation criteria. The experimental results obtained show the good performance of this approach.

Table:3: Comparison of different segmentation results of an Data image by different evaluation criteria, with C=

C=2	Data1			Data2			Data3			Data4			Data5		
	ERG	KM	SP	ERG	KM	SP	ERG	KM	SP	ERG	KM	SP	ERG	KM	SP
Inter	24.45	0.00	0.00	19.29	0	0.00	22.95	0	0.00	10.78	0	0.00	9.83	0.00	0.00
Intra	2.64	8.06	20.87	8.13	4.86	14.38	7.23	2.71	14.98	15.72	2.12	15.29	13.07	1.74	14.61
Zeboudj	79.57	00.09	0	55.70	0	0	55.34	0	0	27.59	0	0	33.11	0.00	0
Rosenberger	50.17	50.12	27.65	50.19	44.12	30.23	50.22	39.09	31.8	50.18	40.10	44.13	50.17	38.10	41.59
Vinet	97.50	33.64	34.80	91.96	24.90	24.78	93.35	24.85	24.47	82.44	6.31	6.33	85.46	24.85	6.51

Table 4: Comparison of different segmentation results of an data image by different evaluation criteria with C=3.

C=3	Data1			Data2			Data3			Data4			Data5		
	ERG	KM	SP	ERG	KM	SP	ERG	KM	SP	ERG	KM	SP	ERG	KM	SP
Inter	23.07	2.72	0	22.74	0	0	17.79	0	0	16.98	0	0	14.68	0	0
Intra	03.98	29.94	28.46	06.10	17.50	23.22	08.99	10.95	17.37	10.54	8.01	19.26	10.71	6.81	19.15
Zeboudj	82.83	21.58	0	72.40	0	0	56.35	0	0	42.25	0	0	42.29	0	0
Rosenberger	50.20	50.13	40.17	50.20	42.62	39.79	50.20	41.64	43.41	50.19	46.16	49.71	50.19	40.64	50.23
Vinet	48.42	24.23	29.69	45.75	28.59	29.91	41.97	31.04	30.27	37.48	28.22	30.79	36.48	28.04	30.85

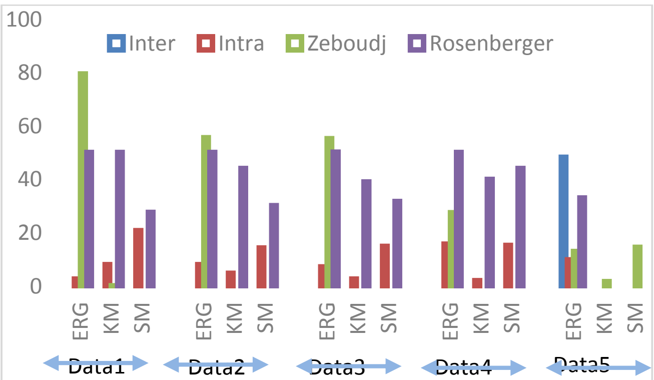

Figure 5: Segmentation results obtained by using these methods on an image with number of region equal 2.

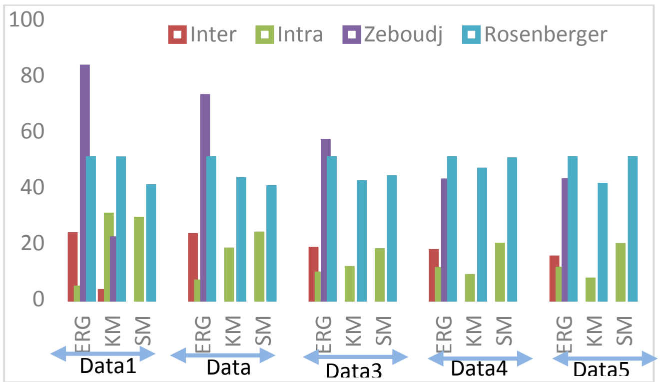

Figure 6: Segmentation results obtained by using these methods on an image with number of region equal 3.

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