## Research Article

# Optimization-Based Image Segmentation by Genetic Algorithms

**S. Chabrier,[1] C. Rosenberger,[2] B. Emile,[3] and H. Laurent[3]**

[1] *Laboratoire Terre-Océan, Université de la Polynésie Francaise, B.P. 6570, 98702 Faa'a, Tahiti, Polynésie Française, France*
[2] *Laboratoire GREYC, ENSICAEN-Université de Caen-CNRS, 6 Boulevard du Maréchal Juin, 14050 Caen cedex, France*
[3] *Institut PRISME, ENSI de Bourges-Université d'Orléans, 88 Boulevard Lahitolle, 18020 Bourges cedex, France*

Correspondence should be addressed to H. Laurent, helene.laurent@ensi-bourges.fr

Many works in the literature focus on the definition of evaluation metrics and criteria that enable to quantify the performance of an image processing algorithm. These evaluation criteria can be used to define new image processing algorithms by optimizing them. In this paper, we propose a general scheme to segment images by a genetic algorithm. The developed method uses an evaluation criterion which quantifies the quality of an image segmentation result. The proposed segmentation method can integrate a local ground truth when it is available in order to set the desired level of precision of the final result. A genetic algorithm is then used in order to determine the best combination of information extracted by the selected criterion. Then, we show that this approach can either be applied for gray-levels or multicomponents images in a supervised context or in an unsupervised one. Last, we show the efficiency of the proposed method through some experimental results on several gray-levels and multicomponents images.

## 1. INTRODUCTION

Segmentation is an essential step in image processing since it conditions the quality of the resulting interpretation. Lots of approaches have been proposed and a dense literature is available [1–4]. In order to extract as much information as possible from an environment, multicomponents images can be used. In the last decade, multicomponents images segmentation has received a great deal of attention for remote sensing and industrial applications because it significantly improves the discrimination and the recognition capabilities compared with gray-levels images segmentation methods. To process these images, there are two types of segmentation methods: the scalar and the vectorial approaches. The first one consists in merging the segmentation result of each band [2, 5, 6]. The second one tries to generalize the classical segmentation process of one-component images [7].

Some works have applied genetic algorithms (GA) to image processing [8] and to segmentation particularly [9–12]. As segmentation can be seen as a process which finds out the optimal regions partition of an image according to a criterion, GA are well adapted to achieve this goal. Indeed, GA are particularly efficient when the search space is really important and when the criterion to optimize is numerically complicated which is always the case in image processing. The main advantages of using GA for segmentation lie in their ability to determine the optimal number of regions of a segmentation result or to choose some features such as the size of the analysis window or some heuristic thresholds.

The GA proposed by Holland [13] are a general-purpose global optimization technique based on randomized search. They incorporate some aspects of iterative algorithm. A genetic algorithm is based on the idea that natural evolution is a search process that optimizes the structures it generates. An interesting characteristic of GA is their high efficiency for difficult search problems without being stuck in local extremum. In a GA, a population of individuals, described by some chromosomes, is iteratively updated by applying operators of selection, mutation, and crossover to solve the problem. Each individual is evaluated by a fitness function that controls the population evolution in order to optimize it.

Bhanu and Lee [9] used GA to optimize the parameters of a segmentation method under various conditions of image acquisition. Another illustration of the interest of GA for image segmentation is given by Yoshimura and Oe [14]. They combined GA and Kohonen's self-organizing map for the
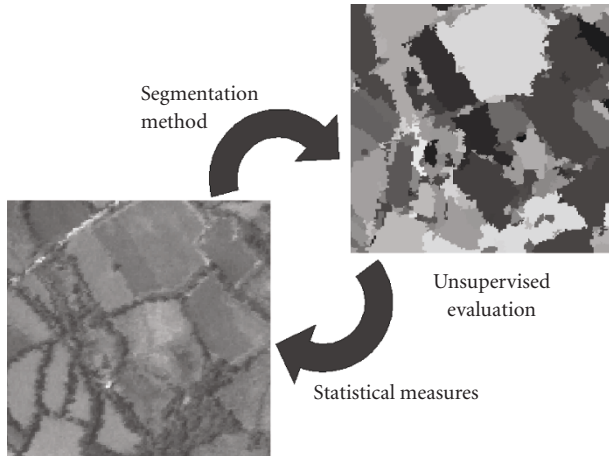
FIGURE 1: Principle of unsupervised evaluation criteria of an image segmentation result.

clustering of textured images. The fuzzy C-means algorithm was used to generate a fine segmentation result. Andrey [15] suggested an original approach as no objective fitness function is needed to evaluate segmentation results. Li and Chiao [16] proposed a genetic algorithm dedicated to texture images where the fitness function is based on texture features similarity. Melkemi et al. [17] use genetic algorithms to combine different segmentation results obtained by different agents. A recent work proposed by Lai and Chang uses a fitness function that can be considered as an evaluation criterion in a hierarchical process [18]. No study of the used fitness function has been done in order to quantify its reliability.

The most important components of the proposed methods concern both the modelling of the problem with GA and the definition of the fitness function. GA can be used to find out the optimal label of each pixel, to determine the optimal parameters of a segmentation method (number of regions, e.g.), or to merge regions of a fine segmentation result. Concerning the fitness function, it can be an unsupervised quantitative measure of a segmentation result or a supervised one using some a priori knowledge.

In this paper, we deal with a general scheme for gray-levels and multicomponents image segmentation that involves a GA. GA is used here as an optimization method for the optimal combination of segmentation results whose quality is quantified through an evaluation criterion. We define a general scheme to define segmentation methods by optimization. Note that we try in this paper to evaluate the reliability of the fitness functions we used in our method.

We illustrate the proposed method by defining different types of fitness functions in Section 2. The first one uses the value of an unsupervised evaluation criterion computed on a segmentation result. The second one uses a semisupervised evaluation criterion by taking into account a local ground truth when it is available. The last one shows the generalization for multicomponents images. In Section 3, we describe the optimization process with GA. We show the efficiency of the proposed method through experimental results on

gray-levels and multicomponents images in Section 4. In Section 5, we conclude and give some perspectives.

## 2. FITNESS FUNCTIONS

The developed method consists in looking for the optimal combination of segmentation results by taking into account an evaluation criterion and by using a genetic algorithm. We define in the following subsections some evaluation criteria for different purposes concerning the segmentation process.

### 2.1. Evaluation principles

Numerous works deal with the problem of the evaluation of a segmentation result [19, 20]. Zhang [21] presents a possible classification of the evaluation criteria in three groups:

  (i) the "analytical methods" which permit to characterize an algorithm in terms of principles, needs, complexity, convergency, stability, and so forth, without any reference to a concrete implementation of the algorithm or testing data,

 (ii) the "empirical goodness methods" also called unsupervised criteria which compute a fitness metric on a segmentation result. They 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 or fuzzy set detected, mostly often by using a statistical point of view (see Figure 1),

(iii) the "empirical discrepancy methods" also called supervised criteria which compute some measures of dissimilarity between a segmentation result and the desired segmentation result (see Figure 2). 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.

Our center of interest is to evaluate the quality of a segmentation result, thus the analytical criteria are not studied in this paper. Moreover, we have chosen for this study to focus on criteria which assess region segmentation results because it is a complex problem. In the next section, we study some unsupervised evaluation criteria.

### 2.2. Unsupervised evaluation

Unsupervised evaluation criteria give an information on the coherence of a segmentation result quality. The main objective of a previous work presented in [22] was to determine the supervised evaluation criterion, within a selection of criteria from the literature, having the best behavior in comparison with human experts judgement. To achieve this goal, two main steps have been realized. The first one concerns the ranking of segmentation results of some images by human experts. The second one concerns

TABLE 1: Value of the SRCC$_{\text{Vinet}}$ of each criterion of the comparative study.

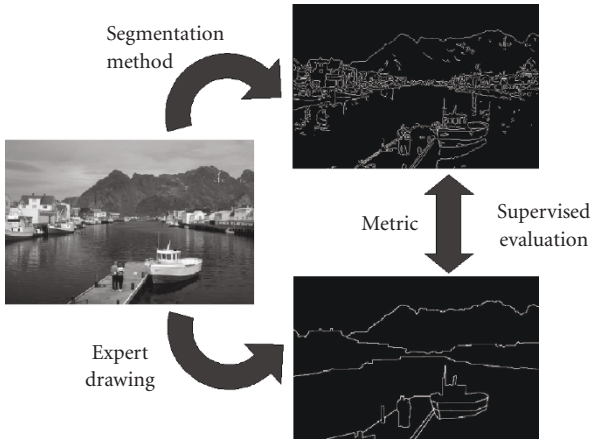| Criteria | Inter | Rosenberger | Zeboudj | Intra-inter | Intra | Borsotti |
|---|---|---|---|---|---|---|
| Overall SRCC$_{\text{Vinet}}$ | **66.09**% | 57.75% | 49.40% | 36.62% | 31.32% | 24.53% |
| Uniform SRCC$_{\text{Vinet}}$ | 73.72% | 50.70% | **88.45**% | 65.97% | 52.18% | 65.73% |
| Mixed SRCC$_{\text{Vinet}}$ | **71.83**% | 55.80% | 54.51% | 32.21% | 33.51% | 29.21% |
| Textured SRCC$_{\text{Vinet}}$ | **74.61**% | 64.98% | 32.23% | 23.46% | 20.01% | 11.10% |
| Textured2 SRCC$_{\text{Vinet}}$ | 33.62% | **61.33**% | 15.12% | 32.27% | 15.68% | 11.20% |



FIGURE 2: Principle of supervised evaluation criteria of an image segmentation result.

the creation of a similarity measure able to compare the evaluation behavior of the experts and of a criterion to study. Thus, a similarity rate of correct comparison criterion (SRCC) has been defined [22]. It computes the similarity of judgment given by an evaluation criterion and an expert. From this study, the Vinet's criterion has been determined as the one with the best behavior according to the human experts.

In the following part of this paper, we briefly present the results of a comparative study of unsupervised evaluation criteria [23] by using the Vinet's criterion as a reference in the case of synthetic images for which the ground truth is well known.

A set of synthetic images including 14 subsets of images having, respectively, from 2 to 15 classes was created. Figure 3 presents some examples of the ground truths used to create the images. Thus, each subset has a fixed number of classes and is made up of 600 images with a proportion of textures going from 0 to 100% by step of 25%. Figure 4 presents some examples of synthetic images created by using this process.

We used three segmentation methods: the Fuzzy C Means method (FCM) [24], a relaxation of this segmentation result and the mean shift algorithm (EDISON) [25]. 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 5 presents an example of segmentation results obtained by using these methods on an image (the number of classes is supposed to be known for the segmentation method).

We selected, from the state of art [21, 26], six unsupervised evaluation criteria of gray level image segmentation results into regions or classes.

(i) Zeboudj's contrast (Zeboudj) [27]: this measure takes into account the internal and external contrasts of the regions measured in the neighborhood of each pixel.

(ii) Levine and Nazif's interclass contrast (Inter) [28]: this criterion computes the sum of contrasts of the regions balanced by their surfaces.

(iii) Levine and Nazif's intraclass uniformity (Intra) [28]: this criterion computes the sum of the normalized standard deviation of each region.

(iv) Combination of intraclass and interclass disparities (Intra-inter) [28]: this indicator combines similar versions of the Levine and Nazif interclass and intraclass measures.

(v) Borsotti's criterion (Borsotti) [29]: this measure is based on the number, the surface, and the variance of the regions.

(vi) Rosenberger's criterion (Rosenberger) [26]: 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.

The Vinet's criterion [30] proved to be the closest one to the human judgement with a similarity rate of correct comparison (SRCC) of 86% in the supervised case [22]. This criterion was thus selected as our reference and was computed on the whole set of segmentation results obtained on the images set (the associated ground truth is always available because we use synthetic images). The similarity rate of correct comparison with the Vinet's criterion (SRCC$_{\text{Vinet}}$) was computed for the different criteria on different images subsets. The objective was to compare the classification of the various segmentation results for each image by the unsupervised evaluation criteria and the one established by the Vinet's criterion. The results were computed on the whole images set (overall SRCC$_{\text{Vinet}}$) and on images subsets considering only uniform images (Uniform SRCC$_{\text{Vinet}}$), only textured images (Textured SRCC$_{\text{Vinet}}$), uniform and textured images (Mixed SRCC$_{\text{Vinet}}$), and textured images with similar mean gray level between all the regions (Textured2 SRCC$_{\text{Vinet}}$). The results are presented in Table 1.

In the case of completely uniform images, the Zeboudj's criterion proves to be the most efficient with a SRCC$_{\text{Vinet}}$

| 3 classes | 6 classes | 9 classes | 11 classes | 14 classes |

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



| 3 classes | 6 classes | 9 classes | 11 classes | 14 classes |

FIGURE 4: Examples of synthetic images from the images set.



| Original image | FCM | FCM + relaxation | EDISON | Ground truth |

FIGURE 5: Example of an image with 6 classes and its segmentation results with paired gray levels.
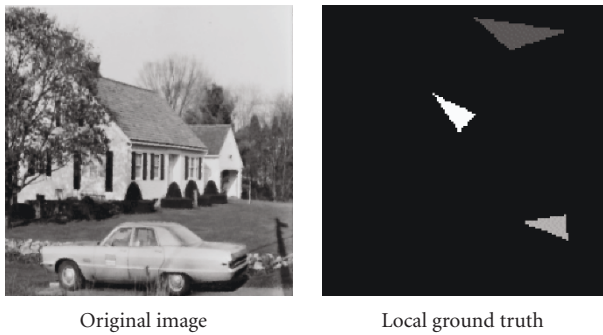


| Original image | Local ground truth |

FIGURE 6: Example of a local ground truth: 3 sets are defined meaning that pixels in these regions should belong in the same class.

superior to 88%. The Inter criterion is recommended in the case of mixed images and for most textured ones. It has a mean SRCC$_{\text{Vinet}}$ of more than 71% on the images sets corresponding to these cases. Finally, the Rosenberger's criterion is the only discriminating criterion for the study of segmentation results of images having textured classes with the same average of gray levels with a SRCC$_{\text{Vinet}}$ of more

than 61%. If one takes into account the whole images set, the Inter criterion appears to be the most efficient but presents a SRCC$_{\text{Vinet}}$ of only 66%.

### 2.3. Supervised evaluation

In order to define the level of precision of the segmentation result, we can use a local ground truth. A local ground truth is defined as a small set of pixels with a known class. It is used in the optimization process by computing the correct classification rate (Vinet's measure) on each cluster of the local ground truth. An example of a local ground truth is given in Figure 6. In this case, we set some examples of regions in an image.

We call GT the local ground truth used in our method. Given a segmentation result, we can compute the correct classification rate for each cluster of GT. We define the following criterion,

$$R(I^s, \text{GT}) = \frac{1}{\text{NbGT}} \sum_{i=1}^{\text{Nbclass}} \text{Rate}(C_i), \qquad (1)$$

where NbGT is the number of pixels in GT. The value Rate($C_i$) is the correct classification rate for the cluster

$C_i$. The correct classification rate for each pixel of GT is integrated into this criterion. The higher this value is, the more the result corresponds to the needed level of precision. If Nbclass equals to zero, the segmentation process will be unsupervised. The local ground truth can be seen as local constraints set by a user. The $R(I^s, GT)$ term evaluates the adequation of the segmentation result to GT (that means that all the clusters of GT in the final segmentation result must be as homogeneous as possible).

A new criterion can be defined by taking into account some constraints on the level of precision of the segmentation result

$$\text{SCR}(I^s, GT) = \text{CR}(I^s) + R(I^s, GT), \qquad (2)$$

where $\text{CR}(I^s, GT)$ is one of the unsupervised criteria detailed in Section 2.2. The $\text{SCR}(I^s, GT)$ criterion is a semisupervised one.

### 2.4. Generalization to the multicomponents case

We define in this section the generalization of an unsupervised evaluation criterion for multicomponents images. The objective is to evaluate different segmentation results (obtained by using different parameters) by combining the values of an evaluation criterion by considering each band.

Three simple fusion methods are used: the minimum, the maximum, and the average value of the criterion computed on each band. In order to compare the different evaluation methods in the multicomponents case, we used 20 synthetic images with 5 components. Each image is segmented with the MLBG method (K-means for the segmentation of multicomponents images) [31] using 32 different parameter settings. Vinet's measure is used again as an objective function and allows us to sort each segmentation result. For each unsupervised evaluation method, each fusion method gives a sorting of the 32 segmentation results for each image. So judged, the best evaluation method associated with the best fusion process is the one corresponding to the best sorting which means that it is the most similar to the Vinet's measure for the 20 images. To compare two sorting of segmentation results, we take into consideration the sum of each difference between the position in the sorting obtained by using the Vinet's measure and an other evaluation criterion.

Table 2 shows that there is no fundamental difference between the three fusion operators (mean, minimum, maximum). The best evaluation criterion in the multicomponents case, in sense of our approach, is the Rosenberger's criterion with the fusion method based on the mean.

We applied this criterion in the multicomponents case. Figure 7 presents three segmentation results of an MRI image with 4 bands obtained by the MLBG method with different parameters (windows size and others). The Rosenberger's criterion associated with mean fusion can sort the different segmentation results. The presented result 3 is defined as the best one (criterion: 0.731), before result 2 (criterion: 0.66), and finally result 1 (criterion: 0.649). This sorting of these segmentation results is difficult to validate with the visual perception even if the last result seems to be more precise.

Table 2: Distance between criteria and Vinet with 3 fusion approaches.

|  | Mean | Minimum | Maximum |
|---|---|---|---|
| Zeboudj | 187 | 187 | 170 |
| Inter | 137 | 143 | 121 |
| Intra | 187 | 187 | 187 |
| Intra-inter | 209 | 209 | 209 |
| Borsotti | 149 | 145 | 149 |
| Rosenberger | **51** | 52 | 56 |

## 3. OPTIMIZATION METHOD: A GENETIC ALGORITHM

Genetic algorithms determine the optimal value of a criterion by simulating the evolution of a population until survival of best fitted individuals [32]. The survivors are individuals obtained by crossing-over, mutation, and selection of individuals from the previous generation. We think that GA is a good candidate to find out the optimal combination of segmentation results for two main reasons. The first one is due to the fact that an evaluation criterion is not very easy to differentiate. GA is an optimization method that does not necessitate to differentiate the fitness function but only to evaluate it. Second, if the population is enough important considering the size of the search space, we have good guarantees that we will reach the optimal value of the fitness.

A genetic algorithm is defined by considering five essential data:

(1) *genotype*: the segmentation result of an image $I$ is considered as an individual described by the class of each pixel,

(2) *initial population*: a set of individuals characterized by their genotypes. It is composed of the segmentation results to combine,

(3) *fitness function*: this function enables us to quantify the fitness of an individual to the environment by considering its genotype. The evaluation criteria described in the previous sections can be used as a fitness function in the unsupervised case or in and in the semisupervised cases,

(4) *operators on genotypes*: they define alterations on genotypes in order to make the population evolve during generations. Three types of operators are used:

(a) individual mutation: individual's genes are modified in order to be better adapted to the environment. We use the nonuniform mutation process which randomly selects one chromosome $x_i$, and sets it as equal to a nonuniform random number,

$$x_i' = \begin{cases} x_i + (b_i - x_i) f(G) & \text{if } r_1 < 0.5, \\ x_i - (x_i + a_i) f(G) & \text{if } r_1 \geq 0.5, \end{cases} \qquad (3)$$

Band 1                    Band 2                    Band 3                    Band 4



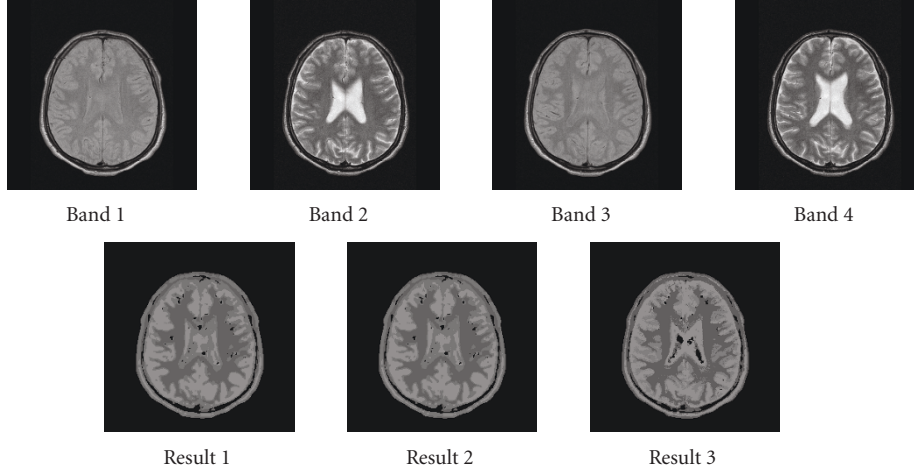Result 1                  Result 2                  Result 3

FIGURE 7: Three segmentation results of a MRI image with 4 bands.

where

$$f(G) = \left( r_2 \left( 1 - \frac{G}{G_{\max}} \right) \right)^b$$

$r_1, r_2$ : numbers in the interval $[0, 1]$

$a_i, b_i$ : lower and upper bound of

chromosome $x_i$

$G$ : the current generation

$G_{\max}$ : the maximum number of generations

$b$ : a shape parameter

$$(4)$$

(b) selection of an individual: individuals that are not adapted to the environment do not survive to the next generation. We used the normalized geometric ranking selection method which defines a probability $P_i$ for each individual $i$ to be selected as follows:

$$P_i = \frac{q(1-q)^{r-1}}{1 - (1-q)^n},$$

$$(5)$$

where

$q$ : the probability of selecting the best

individual

$r$ : the rank of individual, where 1          $(6)$

is the best

$n$ : the size of the population

(c) crossing-over: two individuals can reproduce by combining their genes. We use the arithmetic crossover which produces two complementary linear combinations of the parents;

$$\begin{aligned} X' &= aX + (1-a)Y, \\ Y' &= (1-a)X + aY, \end{aligned}$$

$$(7)$$

where

$X, Y$ : genotype of parents

$a$ : a number in the interval $[0, 1]$

$X', Y'$ : genotype of the linear combinations

of the parents

$$(8)$$

(5) *stopping criterion*: this criterion allows to stop the evolution of the population. We can consider the stability of the standard deviation of the evaluation criterion of the population or set a maximal number of iterations (we used the second one with the number of iterations equal to 1000).

Given these five information, the execution of the genetic algorithm is carried out in four steps:

(1) definition of the initial population (segmentation results) and computation of the fitness function (evaluation criterion) of each individual,

(2) mutation and crossing-over of individuals,

(3) selection of individuals,

(4) evaluation of individuals in the population,

(5) back to Step 2 if the stopping criterion is not satisfied.

## 4. EXPERIMENTAL RESULTS

In this paper, we show the results of two types of experiments. First, we use the previously presented method to segment gray levels images by combining several segmentation results. Second, we present some genetic segmentation results of multispectral images. These images were acquired with a CASI (Compact Airborne Spectrographic Imager).

For all the following experimental results, we set the value of the selection probability to 8%, the crossing-over probability to 60% and the mutation probability to 5%. The unsupervised evaluation criterion we use in this paper is the Rosenberger's one because of the presence of textures in test images.
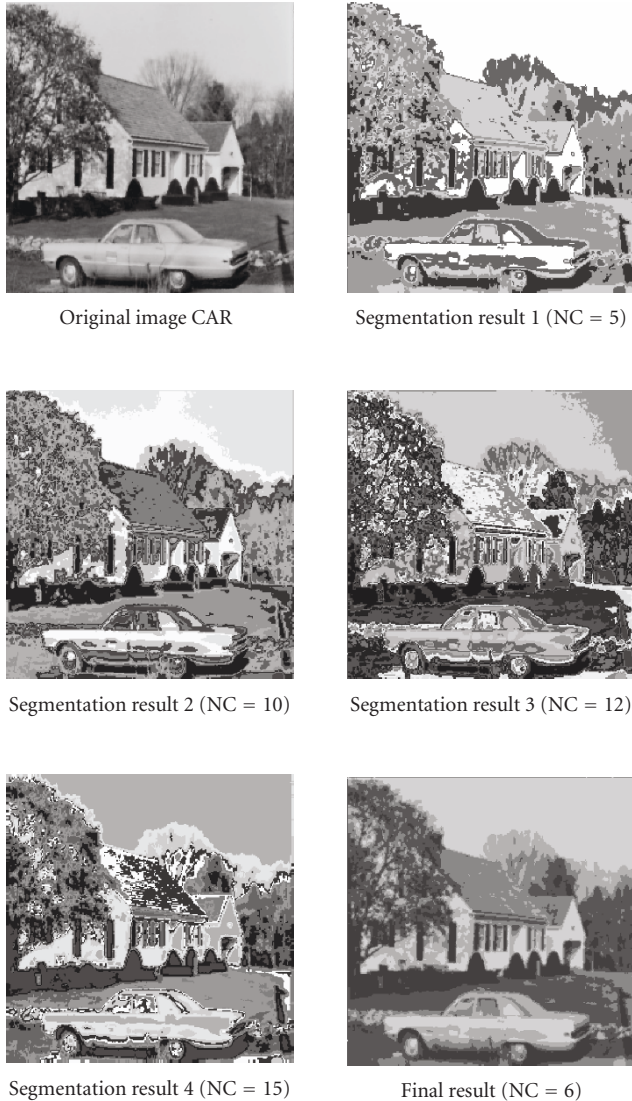
Original image CAR

Segmentation result 1 (NC = 5)



CAR image

Result

(a)

(b)



Segmentation result 2 (NC = 10)

Segmentation result 3 (NC = 12)



AERIAL image

Result

(c)

(d)

FIGURE 9: Supervised segmentation results of two gray-levels images.



Segmentation result 4 (NC = 15)

Final result (NC = 6)

FIGURE 8: Unsupervised segmentation result of image CAR.

### 4.1. Genetic segmentation of gray levels images

First of all, we show the unsupervised genetic segmentation result of one gray levels image called CAR (see Figure 8). This image was segmented using the K-means algorithm with mean and variance as attributes with different numbers of clusters NC (5, 10, 12, 15) which constitutes the initial population for the GA. In this case, the genotype of an individual is a vector of size 262144 (the size of each image is $512 \times 512$ pixels). A gene corresponds to the label of each pixel in the considered segmentation result. Final result shows the efficiency of the proposed method. If we look at the tree in left of the CAR image, we see that this textured region is not oversegmented like in the segmentation results we used in the initial population. An important point is that we did not specify in this experiment the number of clusters we wanted. It has been automatically determined (NC = 6).

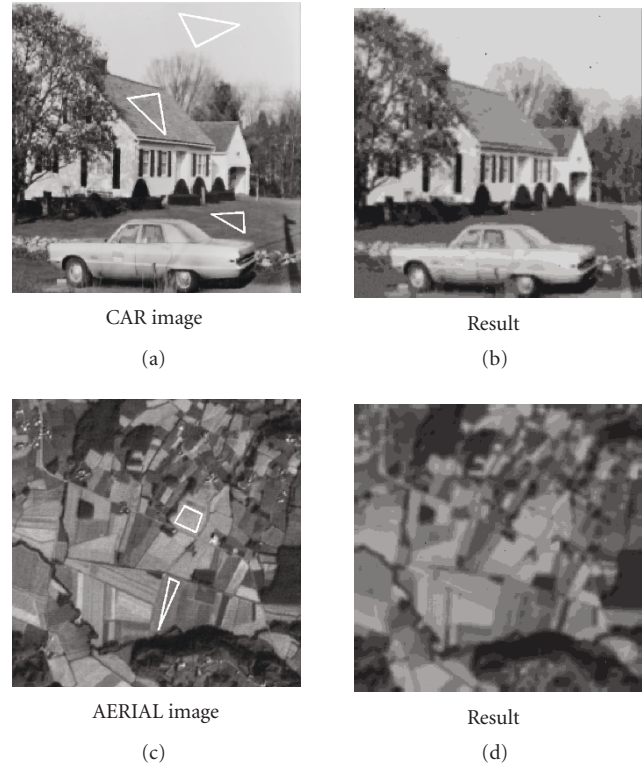Table 3 gives some statistics about the GA for the previous segmentation result. We show here the ability

of the GA to determine the best individual with a few iterations. The value of the evaluation criterion of the best segmentation result significantly increases. Note that we obtain a good stability of the results for different executions of this algorithm after 100 iterations.

We also present the supervised segmentation results of two images by using the developed method (see Figure 9). We define, for each original image, a local ground truth in order to obtain a precise segmentation result. The local ground truth defines some regions which must be present in the final result. As for example, we define three regions in Figure 9(a) and two in Figure 9(c), so we want in the final result that pixels in these regions belong to the same class. As we can see in the segmentation result (Figure 9(b)), the sky is represented by a single cluster as the roof of the house and the major part of the grass. For the image (c) of Figure 9, we select some fields in order to make the interpretation of the culture inside each field easier.

The initial population is composed of segmentation results obtained by using the K-means algorithm with mean and variance as attributes with different numbers of clusters (5, 10, 12, 15). Segmentation results are visually correct.

Table 4 gives the values of several optimized criteria. The $\underline{D}$ and $\overline{D}$ correspond to intermediate values used to compute the Rosenberger's criterion [26]. The $\underline{D}$ computes the global intraregion disparity and has to be close to zero (computation of the disparity of statistics inside the regions). The second one computes the global interregion disparity $\overline{D}$ and must have as high value as possible. Value CR corresponds
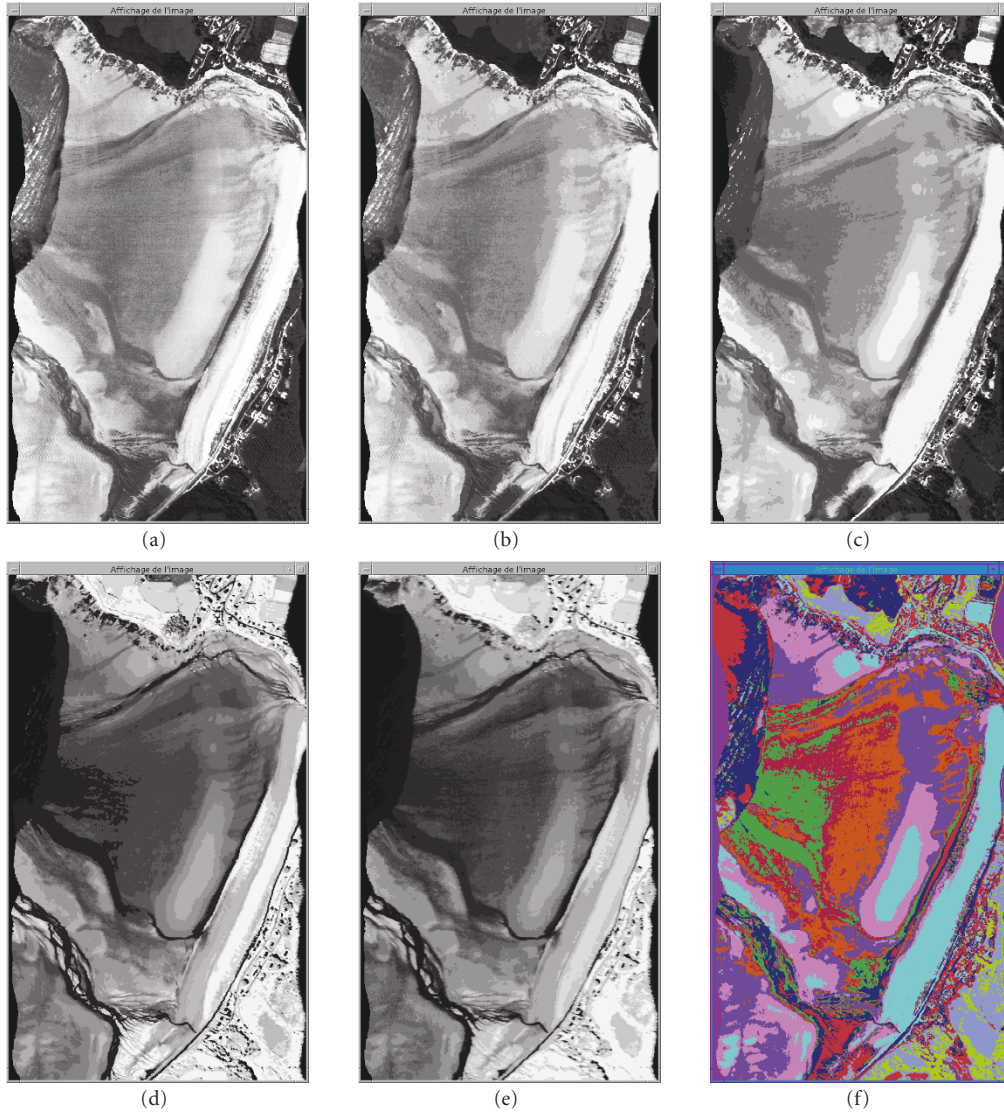
FIGURE 10: Unsupervised segmentation result of a CASI multispectral image, (a) image component 1, (b)–(e) segmentation results of components 1, 6, 7, and 9, (f) final segmentation result of the multicomponents image by merging with the proposed method the segmentation result of each component.



Band A1            Band A9            Local ground truth        Segmentation result
(a)                (b)                (c)                       (d)

Band B1            Band B9            Local ground truth        Segmentation result
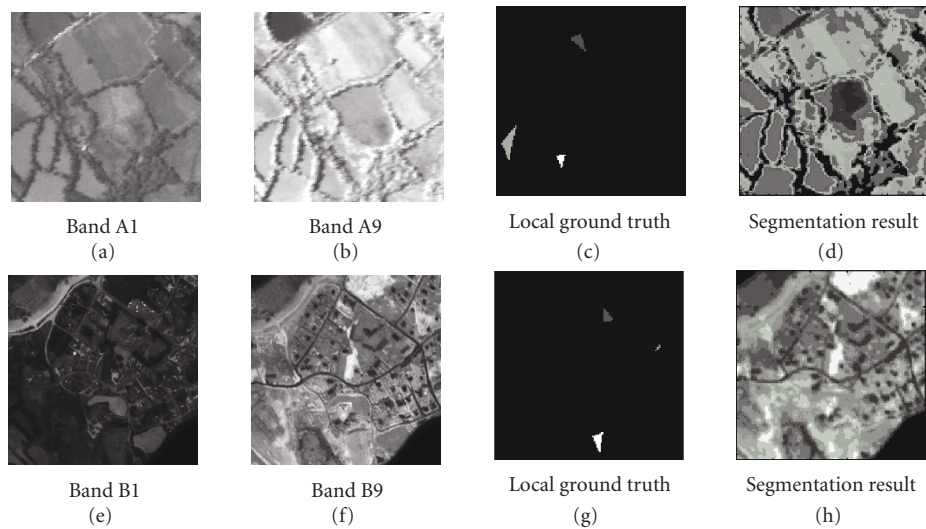(e)                (f)                (g)                       (h)

FIGURE 11: Supervised segmentation results of two CASI multicomponents images.

TABLE 3: Statistics for the initial and final population for the image CAR.

|  | Information | Image CAR |
|---|---|---|
| Initial population | Average value of criterion CR | 0.1827 |
|  | Highest value of criterion CR | 0.1844 |
|  | Lowest value of criterion CR | 0.1809 |
|  | Standard deviation of criterion CR | 0.010 |
| Final population | Average value of criterion CR | 0.1986 |
|  | Highest value of criterion CR | 0.1986 |
|  | Lowest value of criterion CR | 0.1986 |
|  | Standard deviation of criterion CR | 5.2e-08 |

to the unsupervised criterion which quantifies the global quality of a segmentation result (Rosenberger's criterion). Finally, the last criterion gives the correct classification rate if we only consider the local ground truth. One can notice that the values of each criterion are coherent. The correct classification rate has a high value which shows the ability of the proposed method to fit the level of precision of a segmentation result.

We compared the supervised approach and the unsupervised one by segmenting the same image AERIAL. The evaluation results are detailed in Table 5. These results show that the evaluation criterion CR is higher in the unsupervised case. This reveals the ability of the unsupervised approach to determine the optimal value of CR while the use of a ground truth allows us to match the level of precision of the segmentation result.

### 4.2. Genetic segmentation of multispectral images

In this section, we present the unsupervised segmentation result of a multispectral image composed of 9 bands (wavelength in nm: 551.1, 571.5, 600.9, 636.5, 677.7, 696.5, 715.4, 749.5, 799.9) using the proposed method (see Figure 10). Each component of this image was also segmented using the K-means algorithm with mean and variance as attributes. The final result is correct and combine well information from each component. The application for this image was to compute the biomass of algae lying on the beach. The use of multispectral data provides us a better discrimination of algae by taking account visible and also near infrared information. As for example, the white square detected in the segmentation result in Figure 10(c) on the top right is present in the final result while it was not really visible in Figure 10(d).

We present also the supervised segmentation result of two multispectral images with a similar protocol. We show the two most different components of these images (which correspond to components 1 and 9). We define for each original image a local ground truth in order to obtain a precise segmentation result. For Figure 11(a), the local ground truth corresponds to Figure 11(c). We select 2 types of field and an area corresponding to some hedges. Each component brings an additional piece of information, the problem for these images is to take them into account in the final result. As we can see in Figures 11(d) and

TABLE 4: Values of the evaluation criterion for results of Figure 9.

| Final result | $\underline{D}(I^s)$ | $\overline{D}(I^s)$ | $CR(I^s)$ | $R(I^s, GT)$ |
|---|---|---|---|---|
| CAR | 0.0045 | 0.3321 | 0.1638 | 98.4% |
| AERIAL | 0.0040 | 0.2803 | 0.138 | 93.6% |

TABLE 5: Values of the evaluation criterion by using the supervised and unsupervised approaches to segment AERIAL.

| Method | $\underline{D}(I^s)$ | $\overline{D}(I^s)$ | $CR(I^s)$ | $R(I^s, GT)$ |
|---|---|---|---|---|
| Supervised | 0.004 | 0.2803 | 0.138 | 93.6% |
| Unsupervised | 0.003 | 0.448 | 0.225 | — |

11(h), the segmentation results are visually correct and correctly integrate additional information from the different components. As for example, the dark region in the center of the segmentation result (d) is correctly detected while it is not visible in the component A9 (but visible in A1).

## 5. CONCLUSION AND PERSPECTIVES

Many works in the literature focus on the definition of evaluation metrics that enable to quantify the performance of an image processing algorithm. These evaluation criteria can be used to define new image processing algorithms by optimizing them. Genetic algorithms can be used for this application.

In this paper, we focused on the interest of genetic algorithms for image segmentation. We showed that this kind of approach can be applied either for gray-levels or multicomponents images. The developed method uses the ability of GA to solve optimization problems with a large search space (label of each pixel of an image). The developed method can also integrate some a priori knowledge (such as a local ground truth) if it is available. Its efficiency was illustrated through some experimental results on several CASI multispectral images.

Prospects for this work concern first of all the definition of some new fitness functions in order to define edge segmentation methods. Second, some a priori knowledge such as specific shapes characteristics could be included in the defintion of new fitness functions in order to facilate the localization of some particular objects in an image.

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