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Pattern Recognition Letters 27 (2006) 1230–1238
Pattern Recognition Letters
www.elsevier.com/locate/patrec

A multiagent system approach for image segmentation using genetic algorithms and extremal optimization heuristics

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Available online 28 December 2005

Abstract

We propose a new distributed image segmentation algorithm structured as a multiagent system composed of a set of segmentation agents and a coordinator agent. Starting from its own initial image, each segmentation agent performs the iterated conditional modes method, known as ICM, in applications based on Markov random fields, to obtain a sub-optimal segmented image. The coordinator agent diversifies the initial images using the genetic crossover and mutation operators along with the extremal optimization local search. This combination increases the efficiency of our algorithm and ensures its convergence to an optimal segmentation as it is shown through some experimental results.

Keywords: Image segmentation; Markov random fields; Multiagent systems; Genetic algorithms; Extremal optimization

1. Introduction

The image segmentation process partitions the image into a set of disjoint regions (Haralick and Shapiro, 1985). Image segmentation has been subject to intensive research, that gave a number of segmentation algorithms, based on various techniques such as Markov random fields (MRF) (Geman and Geman, 1984; Besag, 1986; Dubes and Jain, 1989; Barker and Rayner, 2000; Dubes et al., 1990; Li, 2001; Zhu and Mumford, 1997, 1998) and Genetic algorithms (GA) (Andrey, 1999; Bhandarkar et al., 1994; Bhanu and Lee, 1994; Cagnoni et al., 1999; Mignotte et al., 2000).

The aim of this paper is to present a new distributed image segmentation algorithm, in which several techniques are carefully combined to achieve different tasks in the segmentation process. The algorithm is structured as a multiagent system (MAS) composed of a set of segmentation agents interconnected around a coordinator agent. Segmentation agents use the MRF based iterated conditional modes (ICM) method to accomplish their segmentation tasks. The coordinator agent combines the crossover and mutation genetic operators with the extremal optimization local search to provide new initial images for the segmentation agents. In the remaining of this paper, the proposed algorithm is referred to as MAS-GA. The following paragraphs give more details about ICM, GA, extremal optimization and MAS.

The simulated annealing (Kirkpatrick et al., 1983; Geman and Geman, 1984; Kato et al., 1992; Lakshmanan and Derin, 1989) and the Besag's ICM (Besag, 1986; Dubes and Jain, 1989; Dubes et al., 1990) are the two main MRF based algorithms used in this context. Starting with a sub-optimal configuration, the ICM maximizes the probability of the segmentation field by deterministically and iteratively changing pixel classifications. The ICM is computationally efficient (Dubes et al., 1990), but it strongly depends on the initialization. The simulated annealing

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doi:10.1016/j.patrec.2005.07.021

(Kirkpatrick et al., 1983) is inspired by simulation equilibrium behavior of large lattice-based systems. Theoretically, it always converges to the global optimum (Geman and Geman, 1984), but it remains a computationally intensive method of image segmentation compared to ICM (Dubes et al., 1990).

GAs have been used in image segmentation as robust optimization techniques. A GA transforms a population of individual objects, each with an associated fitness value, into a new generation of the population using the Darwinian principle of reproduction and *survival of the fittest* concept (Goldberg, 1989; Holland, 1975; Koza et al., 1995). A very interesting MRF model-based approach for image segmentation using GA, called selectionist relaxation, was presented by Andrey (1999); the initial image represents the environment and its regions, according to the segmentation criteria, as many ecological niches. Based on GA, each chromosome belongs to a species out of a number of distinct ones. This GA process leads distinct species to spread over different niches and the segmentation progressively emerges as a result of a relaxation process mainly driven by selection. In fact, GAs are among multi-point searching algorithms which suffer from the number of iterations required to find a solution. However, GAs are strong candidates for the future optimization tools on parallel computers. The island model is an excellent example of such GAs optimizations (Levine et al., 1996; Gordon et al., 1992; Lin et al., 1994).

Extremal optimization is a Local-Search algorithm that successively replaces extremely undesirable variables of a single sub-optimal solution with new, random ones (Boettcher and Percus, 2001). A fitness value λ_i is required for each variable i in the problem, in each iteration variables are ranked according to the value of their fitness. In image segmentation, variables represent image sites; the fitness of each site i can be seen as the local contribution of site i to the total fitness of the system (Boettcher and Percus, 1999). Combining GA and extremal optimization can accelerate the convergence towards the global optimum and improves the genetic search in the later stages of the evolution cycle (Elmihoub et al., 2004).

The MASs are distributed applications consisting of relatively independent modules called agents, which sometimes employ artificial intelligence techniques to accomplish complex operations (Ferber, 1999; Florea, 1998). Various applications of MASs have been proposed in computer vision and image segmentation (Rares et al., 1999; Bond and Gaser, 1988).

The rest of this paper is organized as follows: Section 2 presents fundamental concepts needed in this work. Section 3 describes the architecture of the proposed approach. Section 4 presents and discusses some experimental results. Conclusion and ideas for future extensions of this work are given in Section 5.

2. Related concepts

2.1. Image modeling using MRF

The MRF is a discrete stochastic process whose global properties are controlled by means of local ones. The Ising model highlights MRF and facilitates their use in different domains of application (Kindermann and Snell, 1980). In fact, the Ising model is the best known and the most used in MRF image segmentation (Andrey, 1999; Dubes et al., 1990).

An image $S = \{1, \ldots, t, \ldots, MN\}$ specifies the gray levels for all pixels in an MN-lattice ($MN = M \times N$), where t is called a site. The true image X is represented by a Gibbs random field and the observed image Y, obtained by adding Gaussian noise to the true image, is denoted by a MN-vector random variable (Dubes et al., 1990). Let $X = (X_1, \ldots, X_t, \ldots, X_{MN})$, $X_t \in \{1, \ldots, C\}$, where C is the number of clusters, and $Y = (Y_1, \ldots, Y_t, \ldots, Y_{MN})$, $Y_t \in \{0, \ldots, 255\}$. A neighborhood system $NS = \{N_i \subset S, i \in S\}$ is a subset collection N_i of S according to: (1) $i \notin N_i$ and (2) $j \in N_i \iff i \in N_j$. A clique is a subset $c \subset S$ for which any two elements are neighbors: $\forall r, t \in c$, $r \in N_t$.

The structure of the neighborhood system (see Fig. 1(a)) determines the MRF order. For a first order the neighborhood of a site consists of its four nearest neighbors. In a second order the neighborhood of a site consists of the eight nearest neighbors. The clique structures for a second order MRF are illustrated in Fig. 1(b). Let $X = (X_1, \ldots, X_t, \ldots, X_{MN}) \in \Omega$, where Ω is the set of all possible configurations. X is a MRF with respect to the neighborhood system if $\forall x \in \Omega : P(X = x) > 0$, and $\forall t \in S$, $\forall x \in \Omega$, $P(x_i/x_j, j \in S - \{i\}) = P(x_i/x_j, j \in N_i)$. $P(X = x) = \mathrm{e}^{-U(x)}/Z$ where $Z = \sum_{x \in \Omega} \mathrm{e}^{-U(x)}$ is the partition function and $U(x)$ is the energy function:

$$U(x) = \sum_{t=1}^{MN} \sum_{r \in N_t} \theta_r \delta(x_t, x_r) \tag{1}$$

where θ_r are the clique parameters, $\delta(a, b) = -1$ if $a = b$ and $\delta(a, b) = 1$ if $a \neq b$. $P(X = x)$, called the a-priori probability follows the Gibbs distribution.

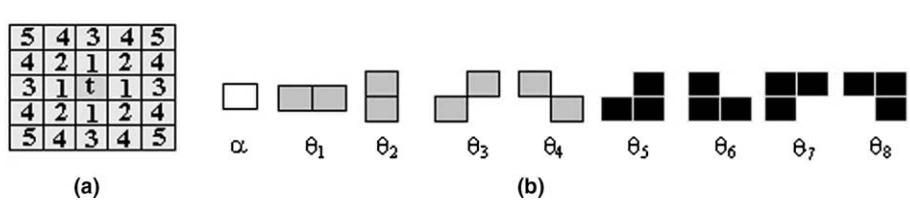

Fig. 1. (a) A neighborhood system, (b) cliques of the second-order neighborhoods.

We assume an isotropic second-order Ising model, so in Eq. (1), $\theta_1 = \theta_2 = \theta_3 = \theta_4 = \beta$. This model uses only cliques that contain not more than two sites having non-zero potentials. In this paper, a second-order model is used, so the number of clique types is four presented in gray (see Fig. 1(b)).

The a-posteriori probability $P(x/y) = \mathrm{e}^{-U(x/y)}/Z_y$ where Z_y is the normalization constant and $U(x/y)$ is the energy function (Kato et al., 1992) given in Eq. (2):

$$U(x/y) = \sum_{t=1}^{MN}\left[\ln\left(\sqrt{2\Pi}\sigma_{x_t}\right) + \frac{(y_t - \mu_{x_t})^2}{2\sigma_{x_t}^2} + \sum_{r\in N_t}(\beta\delta(x_t, x_r))\right] \tag{2}$$

where μ_{x_t} and $\sigma_{x_t}^2$ are the mean and the variance of the Gaussian noise respectively, and β is a parameter for controlling the homogeneity of the regions, as β increases the resulting regions become more homogenous. The image segmentation problem can then be seen as the problem of minimizing the energy function $U(x/y)$ of Eq. (2). The estimator that maximizes $P(x/y)$ is called the maximum a-posteriori.

2.2. Bak–Sneppen model

The science of self-organized criticality is a study of emergent complex behavior in physical and biological systems (Bak, 1996); the Bak–Sneppen model is one of the successful application of this science (Bak and Sneppen, 1993). In this Bak–Sneppen model, ℓ species are situated on a circle and each species has its own independent fitness, uniformly distributed on $[0, 1]$. At each cycle, the system is updated by locating the worst species corresponding to the smallest fitness and its two neighbors. These three species will have their fitness values replaced by independent uniform values in $[0, 1]$. Thereafter, each species is represented by a single quantity, its fitness measuring thus how well the species is adapted to its environment. After a sufficient number of iterations, the system reaches a preferable state, called self-organized criticality (Bak, 1996; Bak et al., 1987), in which most of species have a fitness value greater than a given threshold. Boettcher and Percus (1999) and Boettcher (2000, 2003) have used the Bak–Sneppen paradigm to define the extremal optimization.

3. The MAS-GA architecture

The MAS-GA for image segmentation is composed of k segmentation agents interconnected to a coordinator agent in a star topology, Fig. 2. Each segmentation agent uses ICM to segment an image from its own *initial image*, then sends this *initial image*, the *segmented image* and the *fitness value* of its maximum a-posteriori estimate to the coordinator agent. Thereafter, the coordinator agent receives the different *initial images* forming the *population*, the *segmented images* with their *fitness values*, saves the best of all the segmented images in a variable called *Best-Segmentation* with its fitness in a variable U^*, and then retransmits the new initial images to the segmentation agents after having applied genetic operators and extremal optimization.

3.1. Hybrid-genetic algorithm optimization

The MAS-GA attempts to find a best segmentation by genetically breeding the population of sub-optimal images over a series of generations used as an initial sub-optimal images by the segmentation agents.

3.1.1. Population and fitness

In the MAS-GA, the segmentation agent creates an initial population of individuals corresponding to the *initial images*, created from the observed image, first by using the K-means and second by perturbing randomly certain site labels. So, the *population* is a set of initial images. Let A be an individual of the population, a site label $A[i, j] \in \{1, 2, \ldots, C\}$ is considered as a *gene*, where

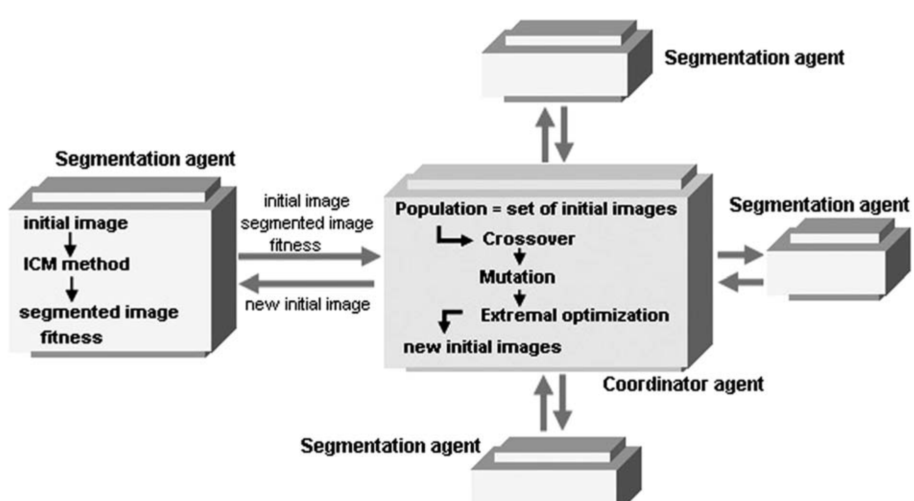

Fig. 2. The architecture of the MAS-GA for image segmentation.

$i \in \{1, \ldots, N\}$ and $j \in \{1, \ldots, M\}$. The *alphabet* corresponds to the label set $\{1, 2, \ldots, C\}$. Each individual is encoded as a *chromosome* called a *genotype*, and each chromosome is given a measure of *fitness* via the energy function given in Eq. (2). The fitness determines the chromosome ability to survive and to produce offspring.

Let I be a chromosome (sub-segmented image) and $i_1, i_2 \in \{1, \ldots, N\}$, $j_1, j_2 \in \{1, \ldots, M\}$, where $i_1 \leqslant i_2$ and $j_1 \leqslant j_2$. Let P be a part (rectangle) of the image I limited by the points (i_1, i_2) and (j_1, j_2) defined by $P = \{I_{i,j} \in I / i_1 \leqslant i \leqslant i_2, j_1 \leqslant j \leqslant j_2\}$. We can show that each part P of I is evaluated by the $U(P/y) = \sum_{i=i_1}^{i_2} \sum_{j=j_1}^{j_2} U(I_{i,j}/y)$, where y is the observed image. The selection process used in MAS-GA gives more chance of survival to the best individuals than to the worst ones; this increases the possibility of finding the best segmentation.

3.1.2. The crossover

The crossover operator combines pairs of parents to produce new offsprings (see Figs. 3 and 4) with a probability of 0.9. For each mating, the crossover positions are selected randomly. Each crossover position corresponds to a cut line and a cut column numbers of the parent images (see Fig. 3). Crossover performs important global exchanges. It cuts, in the same manner two initial images into rectangles and swaps them in order to produce two new initial images (see Fig. 3). In fact, the crossover diversifies the initial images used by the segmentation agents which attempts to overcome the problems of avoiding premature convergence and escaping local optima. Fig. 4 shows that the second offspring is better than the two parents. Indeed, this offspring inherits the best parts from its parents (the square and circle parts from the first parent, the triangle and the star from the second parent). This crossover offers all survival chances to one or some offsprings using the fitness values of the parent parts.

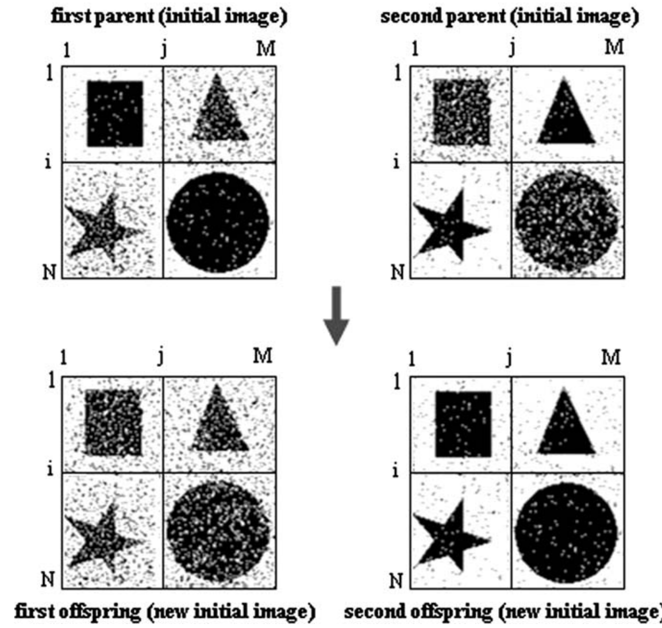

Fig. 4. The importance of the crossover in the improvement of the initial images.

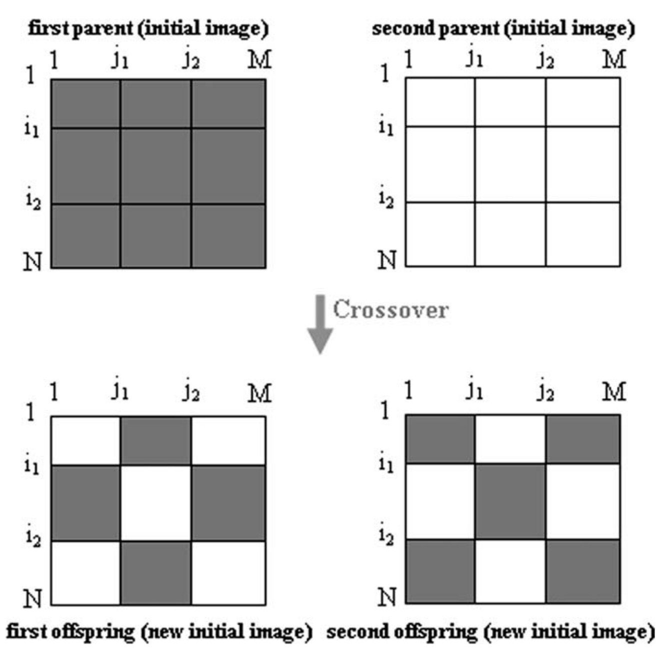

Fig. 3. Crossover of two parents gray and white reproduces two offsprings 'metisses'. i_1, i_2 are the cross line points j_1, j_2 are the cross column points.

3.1.3. The mutation

The mutation is a rare but extremely important event in GA, which insures that every segmentation can be reached by the system. When a site label is mutated, it is randomly selected and randomly replaced with another category from the set of labels (alphabet). Mutation modifies a single parent (initial image of the population) selected at random by modifying one or several genes (site labels) with a probability of 0.005. In Fig. 5 for example, two sites (i_1, j_1) and (i_2, j_2) have been randomly chosen; their labels have changed after the mutation operator is applied (see the right sub-figure).

3.1.4. The extremal optimization local search

In this section, we combine the MRF and Bak–Sneppen models to introduce a new image segmentation method. We consider site labels x_i as species and the image x as a

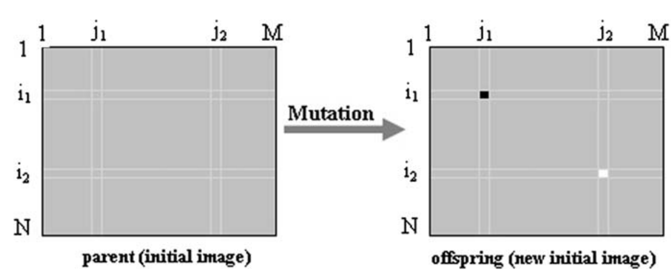

Fig. 5. Two sites mutation of an initial image.

lattice-system like Bak–Sneppen model. The fitness value of a species x_i is λ_i given by Eq. (3):

$$\lambda_i = P(x_i/x_j, j \in N_i) \tag{3}$$

At each update, the process modifies randomly several selected worst site labels. Moreover, any change in the fitness value of a species engenders a change in the fitness values of its neighboring species. After a sufficient number of steps, the species reorganize themselves in a set of categories, each one represents an image cluster. This co-evolution activity leads to chain reactions called *avalanches* (Boettcher and Percus, 1999, 2001; Boettcher, 2000), which are one of the keys especially relevant for optimizing highly disordered systems.

After applying genetic operators, the coordinator agent performs the extremal optimization on a sub-optimal configuration x, selected randomly, by repeating: first, evaluating site labels x_t of x according to the local fitness defined in Eq. (3). Second, ranking site labels x_t of x according to the following rule: classifying the *worst site label* having the weakest fitness value in the rank 1, and the *best site label* having the greatest fitness value is classed in the rank MN, i.e. find a permutation π of site labels x_t such that $\lambda_{\pi(1)} \leqslant \cdots \leqslant \lambda_{\pi(MN)}$, where $\pi(i) = j$ means that site j is of rank i, Line 4 of Table 1 is an example of such permutation. Third, selecting some worst site labels x_t according to the probability $p_s \propto s^{-\tau}$ (where s represents the rank of the site label and τ is the single fixed parameter) to be modified, i.e. while the rank is higher, site label has better chance to survive. Forth, saving the best configuration with its fitness. These steps are clearly shown in Algorithm 1.

Algorithm 1. Steps of the extremal optimization local search carried out by the coordinator agent.

(1) Select randomly an individual x among a current population. For each site t compute λ_t. Let $f = U(x/y)$, $x_{\text{best}} = x$, $F_{\text{best}} = f$ and iteration = 1.
(2) Find a permutation π of site labels x_t such that $\lambda_{\pi(1)} \leqslant \cdots \leqslant \lambda_{\pi(MN)}$.
Example: In Table 1, we suppose that $N = 2$ and $M = 3$. The site label x_2 is the worst site label and x_5 is the best site label.
(3) For $s = 1$ to MN do
- Compute $p_s \propto s^{-\tau}$ and generate a random number μ in $[0, 1]$.
- If $\mu \leqslant p_s$ then modify the label of the site $\pi(s)$.

Example: In Table 1, the extremal optimization algorithm replaces the labels of the sites $\pi(1)$, $\pi(2)$ and $\pi(4)$.
(4) For each site t compute λ_t of x_t. Set $f = U(x/y)$.
(5) If $f < F_{\text{best}}$ then $x_{\text{best}} = x$ and $F_{\text{best}} = f$.
(6) Iteration = Iteration + 1. If Iteration $\leqslant$ a given number of iterations then go to 2.
(7) Replace x with x_{best}.

Table 1
Selection and modification of the labels of sites $\pi(1)$, $\pi(2)$ and $\pi(4)$

Site i	$i = 1$	$i = 2$	$i = 3$	$i = 4$	$i = 5$	$i = 6$
Site label x_i	x_1	x_2	x_3	x_4	x_5	x_6
Fitness value λ_i	0.53	0.1	0.35	0.63	0.8	0.25
$\pi(i)$	2	6	3	1	4	5
p_i	0.5	0.27	0.13	0.05	0.03	0.02
$\mu(i)$	0.38	0.25	0.15	0.025	0.5	0.8

3.2. MAS-GA for image segmentation

Algorithm 2 shows how our MAS-GA operates, and gives its different steps. In this algorithm, agents cooperation is illustrated through the collective activity of the agents to enhance the quality of the initial images. The coordinator agent diversifies these sub-optimal images using crossover operator, mutation and extremal optimization. Semaphores are employed to solve potential conflicts during the coordination of agents activities.

The MAS-GA seems similar to the island model (Gordon et al., 1992; Lin et al., 1994; Levine et al., 1996), because it can be considered as a parallel GA. In the island model, the population is partitioned into few subpopulations called demes and a GA is executed per subpopulation.

Algorithm 2. Steps of the MAS-GA for image segmentation.

(1) **Initialization**: Each segmentation agent uses K-means procedure to create a sub-optimal image from the observed image and perturbs this sub-optimal image by modifying one or several site labels at random with a probability of 0.001.
(2) **Tasks of a segmentation agent**:
- performs ICM procedure using its own initial image,
- transmits a packet containing *initial image*, *segmented image* and *fitness value of the segmented image* to the coordinator agent.

(3) **Tasks of the coordinator agent**:
- receives different packets from the segmentation agents,
- saves the best of all the current segmentations in the *Current-Segmentation* variable with its fitness value in the W variable. If $W < U^*$ then Set *Best-Segmentation* = *Current-Segmentation* and $U^* = W$,
- performs the crossover on pairs of parents selected from the population,
- applies the mutation on one or several parents,
- applies the extremal optimization local search on a selected parent at random,
- transmits the new offsprings to the segmentation agents.

(4) **The cycle of the MAS-GA**: The system repeats the second and the third steps for a given number of iterations.

separately on different machines or processors. The migration operator allows 'metissage' of the different subpopulations and is supposed to mix good features that emerge locally in the different demes. However, in the MAS-GA, each segmentation agent accomplishes its own segmentation using ICM. In fact, the role of the segmentation agent can be modified and supplementary paradigms can be easily added. The MAS-GA population is composed of different initial images used by segmentation agents as starting points of the ICM method. Lin et al. (1994) describe several migration policies of the island model. Generally, the process replaces the worst k individuals of a deme by k different individuals coming from other populations, mostly the best individuals are copied. Whereas, in the MAS-GA the coordinator agent diversifies the initial configurations using genetic operators and extremal optimization.

4. Experimental results

In this section, we present some results of the MAS-GA compared to the ICM. Experiments were done on a Pentium 4 (2.66 GHz, 256 MB), using the Builder C++ 5.0 running under Windows XP. We have used a single value of $\beta = 1.5$ and $\tau = 2.3$ which are kept constant through all these experiments. The segmentation is evaluated by both energy function $U(x/y)$ and visual appearance. Table 2 summarizes the results (minimal values of the energy function and the number of iterations) of these experiments given by MAS-GA and ICM.

Fig. 6 shows a synthetic image containing different geometric drawings in three gray-tones. It can be seen that different regions are better segmented by MAS-GA than by ICM (see Table 2), despite the interference and the thinness of some regions.

In Fig. 7, the MAS-GA results are still better than the ICM results (see Table 2). Indeed, the MAS-GA extracts better the parts of the wheel and saves boundary length by linking the spokes with the rim of the wheel in spite of the degradation of the image. Fig. 7(g) presents the MAS-GA segmentation evolution for "characters t_i" experiment. At each MAS-GA iteration, we get the $u(x/y)/(MN)$ value of the best agent realizing the maximum a-posteriori estimate. This graph shows the intensification aspect of the MAS-GA which enables to the system to still at late run time seeking a new segmentations in the configuration space.

Fig. 8(a) shows a sonar image, adapted from Yao et al. (2000), representing a sandy sea floor with the cast shadow of a tyre. The two-class segmentation (see Fig. 8) shows again a better robustness of the MAS-GA against the speckle noise. The graph presented in Fig. 8(d) illustrates clearly that the MAS-GA intensifies the search and crosses barriers to finally accede to a good solution in the iteration 70. Whereas,

Table 2
Minimal values of energy functions and parameters

Experiment	Approach	$U(x^*/y)/MN$	Parameters and convergence
Fig. 6	ICM	−4.721	Convergence needs 10 iterations
	MAS-GA	−5.195	Segmentation agents = 10, iterations = 100
Fig. 7(b)	ICM	−4.12	Convergence needs 9 iterations
Fig. 7(c)	MAS-GA	−4.79	Segmentation agents = 8, iterations = 70
Fig. 7(e)	ICM	−2.79	Convergence needs 9 iterations
Fig. 7(f)	MAS-GA	−2.819	Segmentation agents = 10, iterations = 100
Fig. 8	ICM	−4.8093	Convergence needs 9 iterations
	MAS-GA	−6.00	Segmentation agents = 10, iterations = 100
Fig. 9	ICM	−4.3345	Convergence needs 9 iterations
	MAS-GA	−4.4652	Segmentation agents = 10, iterations = 80

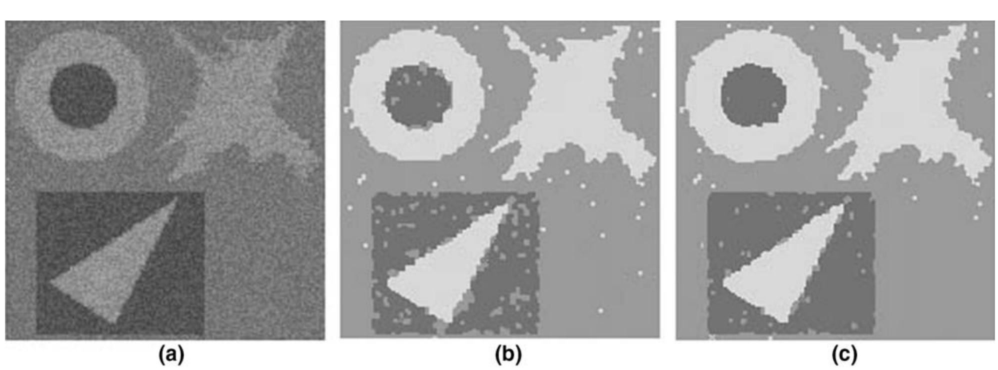

Fig. 6. Synthetic noisy image. (a) A noisy image, (b) ICM result, (c) MAS-GA result.

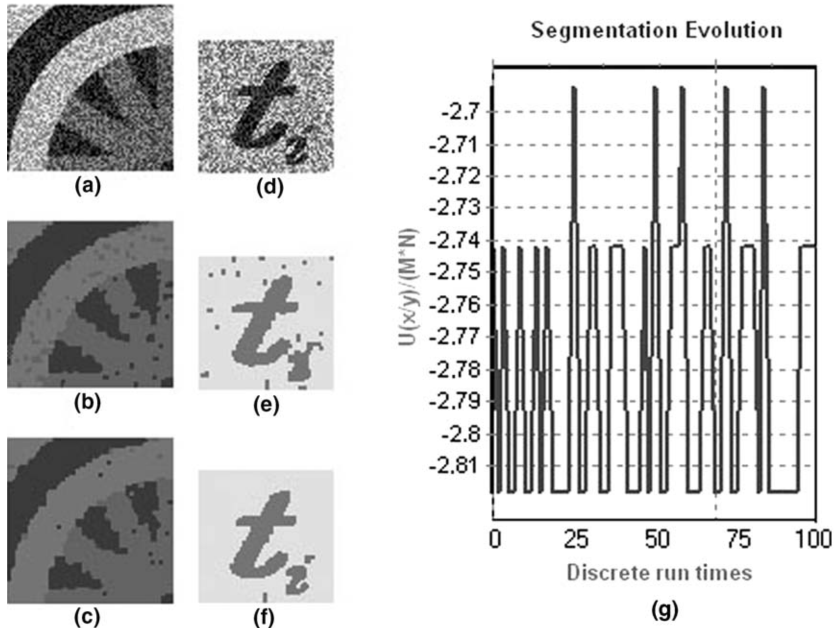

Fig. 7. (a) A noisy wheel image (80×80), (d) a noisy "characters t_i" (64×64), (b) and (e) ICM results, (c) and (f) MAS-GA results, (g) the graph of segmentation evolution of (f).

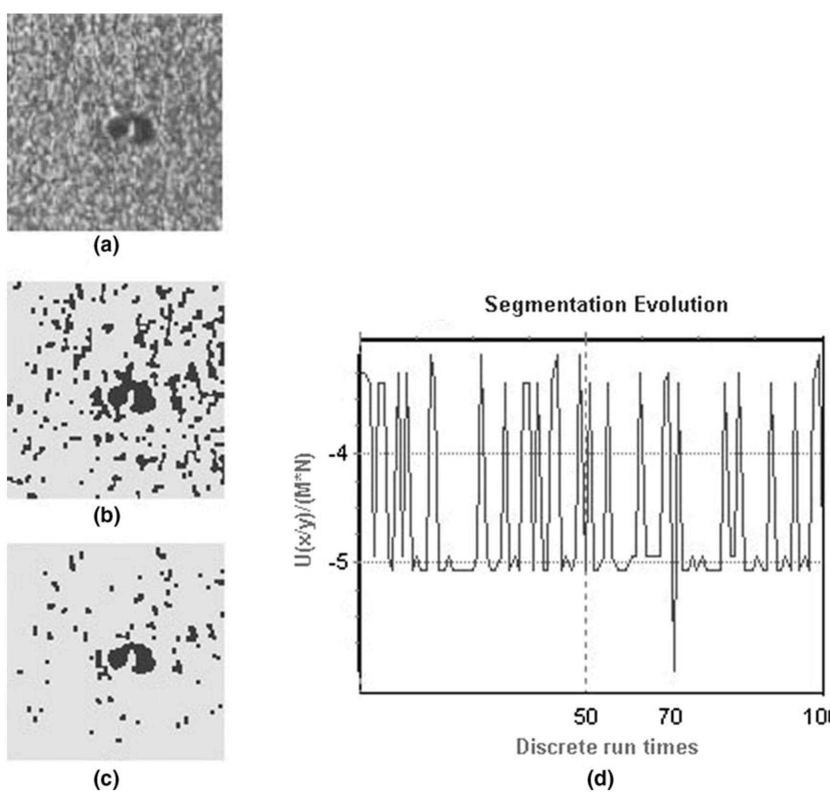

Fig. 8. MAS-GA application on a real image. (a) Real image, (b) ICM result, (c) MAS-GA result, (d) graph of the segmentation evolution.

ICM fails to enhance the quality of the segmentation, because the real image violates the assumed noise model. In the four-class segmentation of the natural scene of Fig. 9, we show that our MAS-GA decomposes the segmentation in great objects (mountains, sky, ...), while the ICM tries unsuccessfully to detail the segmentation.

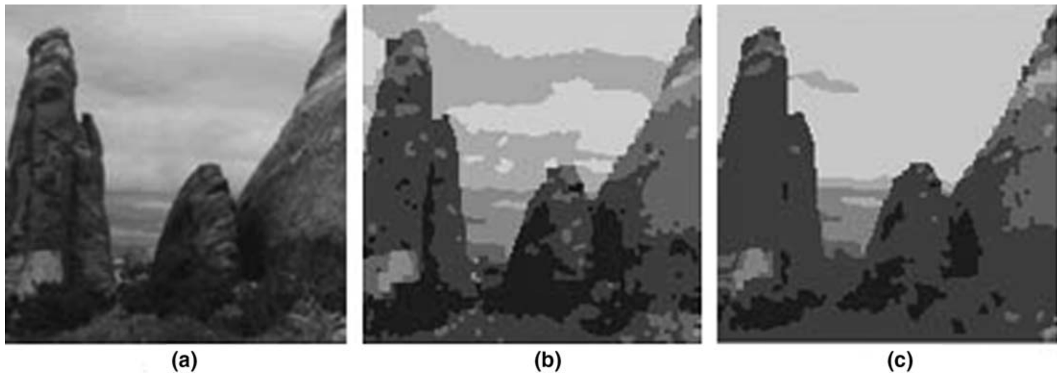

Fig. 9. MAS-GA application on a natural scene. (a) Observed image, (b) ICM result, (c) MAS-GA result.

5. Conclusion

In this paper, we have proposed a new framework for image segmentation based on MAS theory and a hybrid GA. According to this approach, each segmentation agent performs the ICM algorithm starting from its own sub-optimal image and returns the resulting segmented image to the coordinator agent. This latter diversifies these initial sub-optimal images by applying the hybrid genetic operators in order to produce new promising starting solutions which are refined once again by the segmentation agents. This competition/cooperation activity insures that this iterative process accedes to a good segmentation. In fact, the MAS-GA suggests a way to use genetic operators to provide pertinent initializations for segmentation agents.

As a distributed system, the MAS-GA contains a set of agents working together and can generate a flexible layout. Each initial image causes possible behavior of a segmentation agent. Genetic operators are then applied by the coordinator agent in order to improve the behavior performance of segmentation agents across the initial images. These autonomous agents provide modularity in which one agent does not need to have a precise knowledge of the internal structure of others in order to add a new behavior to the system. Both synthetic and real images have been used to assess the validity and performance of the approach. Experimental results are very encouraging which demonstrate the feasibility, the convergence and the robustness of the method.

The evaluation of segmentation results is an important step for any segmentation method. So, we propose to combine the fitness function evaluation with an expert evaluation (achieved through a visual judgement). We can then consider this expert as an agent integrated in the MAS-GA. This perspective may certainly improve and intensify the cooperation action. In addition, the proposed approach is very amenable to parallel implementation which can potentially result in great speed-ups over conventional optimization techniques.

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