Ant Colonies For MRF-Based Image Segmentation

Salima Ouadfel$^{1,2}$, Mohamed Batouche$^2$ and Said Talhi$^1$

$^1$ Computer Science Department, University of Batna.

souadfel@wissal.dz

s_talhi@yahoo.fr

$^2$ Computer Vision Group, LIRE Laboratory, University of Constantine

batouche@wissal.dz

Résumé: This paper presents HACSEG, a new ant algorithm for the image segmentation based on the Markov Random Field (MRF) and a modified version of the Ant Colony System algorithm coupled with a local search. HACSEG algorithm differs from other ant algorithms proposed for image segmentation, in the way that each artificial ant is associated with a particular partition that is modified using pheromone trails and heuristic information unlike to build a completely new partition using an iterative constructive process. The new partitions found by ants are then optimized using a local search algorithm. Pheromone trails are updated according to the quality of the partitions found by the best ant. A diversification phase is also used to diversify the search. The experimental results presented outperforms those obtained with other methods.


1 Introduction

Image segmentation is a low-level image processing task in a vision system. It has been the subject of intensive research, and a wide variety of image segmentation techniques have been reported in the literature. A good review of these methods can be found in (Pal & al, 1993). Among them, Markov random field (MRF) is one of the most frequently utilized techniques (Andrey & al, 1998), (Chellappa & al, 1993), (Chen & al, 1995), (Kato, 1994), (Kervrann & al, 1995), (Panjwani & al, 1995). MRF has been shown to be quite successful for image segmentation because of its ability to characterize spatial relations among image pixels by conditional probability over small neighborhoods of pixels. The image is segmented by maximizing the a posteriori probability (MAP) of the labeling space given the image data (Li, 1995). Within this framework, the segmentation process is expressed as the problem of finding the optimum value of an energy function (Lin & al, 1993), (Panjwani & al, 1995). This is combinatorial optimization problem because of the large search space. Moreover, the energy function is usually non-convex and exhibits many local minima in the solution space.

As a result, techniques such as iterated conditional method (ICM) (Besag, 1986), simulated annealing (SA) (Geman & al, 1984), (Hu & al, 1992), (Gunnels & al, 1994) and genetic algorithm (GA) (Andrey & al, 1998), (Kim & al, 1998), Huang & al, 1995) has been often used as solution for this computational complexity.

Ant Colony Optimization (ACO) metaheuristic (Dorigo & al, 1999), (Maniezzo & al, 2001) is a multi-agent metaheuristic for combinatorial optimization and other problems. It is inspired by the capability of real ants to find the shortest path between their nest and a food source. In ACO, a colony of artificial ants build new solutions of the problem within a stochastic iterative process, by adding solution components to partial solutions using a combination of heuristic information and an artificial pheromone trail. The pheromone trail is reinforced according to the quality of the solutions built by the ants.

In previous works (Ouadfel & al, 2003a), (Ouadfel & al, 2003b), we have proposed ACS-MRF, a MRF model based image segmentation using a hybrid ant colony system algorithm. In this paper, we investigate the capability of HACSEG, a new ant algorithm for
image segmentation, that differ in (1) manipulation of solutions, (2) the way pheromone is exploited and laid, (3) the use of a heuristic information to guide ants and (4) the introduction of a diversification phase to diversify the search in the solutions space. Experimental results show that the HACSEG obtained good quality segmentation results and outperforms ACS-MRF and others methods.

The paper is organized as follows. Section 2 presents a brief review on image modeling using MRF. Section 3 describes ACO paradigm. Section 4 presents HACSEG for MRF based image segmentation. In section 5 we present the experimental results and we compare HACSEG with other heuristics. Finally a conclusion is drawn in section 6.

2 Image segmentation using Markov Random Field

The MRF was introduced in image analysis by Geman and Geman (Geman & al, 1984). MRF is a stochastic process in which spatial relations within the image are included in the labeling process through statistical dependence among neighboring pixels. Let \( Y=\{y_s/ \forall s \in S\} \) designate an observation field defined on a rectangular lattice \( S \). Let the label field \( X=\{X_s/ \forall s \in S\} \) defined on \( S \) and the set of labels \( \Lambda=\{0,...,L-1\} \) of the pixel \( s \). Realization of fields \( Y \) and \( X \) will be denoted by \( y=\{y_s/ \forall s \in S\} \) and \( x=\{x_s/ \forall s \in S\} \). \( (X, Y) \) is a Markov random field on \( S \) with respect to a neighboring system \( N=\{N_s, \forall s \in S\} \), where \( N_s \) is the set of pixels neighboring \( s \).

Our goal is to find the best estimated \( \hat{x} \) for \( x \) given \( y \). According to the Maximum A Posteriori (MAP), criterion \( x \) is obtained by minimizing the global energy function \( U(y,x) \).

\[
\hat{x} = \arg\min_x U(y,x)
\]  

(1)

If we make the assumption that the image data are conditional independent and that \( Y \) is obtained by adding an identical independently distributed (i.i.d.) Gaussian noise, and according to the Hammersley-Clifford theorem (Besag, 1986) the energy \( U(y,x) \) is formulated as follows (Ouadfel & al, 2003b):

\[
U(x) = \left\{ \sum_{c \in C} \left( \frac{\log|c|}{2\sigma_{x_c}} \right)^2 + \sum_{s \in S} \log(\sigma_{x_s}) + \sum_{c \in C} V_c(x) \right\}
\]  

(2)

where

- \( \mu_{x_c} \) : the mean value of the cluster \( x_c \)
- \( \sigma_{x_s} \) : the deviation value of the cluster \( x_s \)
- \( V_c(x) \) : the potential function for clique \( c \)
- \( C \) : the set of all cliques over the image.

A clique is a set of pixels that are neighboring of one another. In this paper we consider only the pairwise clique potentials of 8-neighborhood system, with the form \( V_c(x, y) = -\beta \) if \( x = y \) and 0 otherwise. \( \beta \) is a positive parameter and the larger \( \beta \), the larger is the influence of the neighboring pixels.

Minimization of the global energy function, is hard optimization problem because the number of possible label configurations is generally very large and moreover, the energy function may contains local minima (Li, 1995).

3 Ant Colony Optimization

Ant Colony Optimization (ACO) is a population based approach attribute to Marco Dorigo in collaboration with Alberto Colomn and Vittorio Maniezzo (Dorigo & al, 1991), (Bonabeau & al, 1999) and inspired by the foraging behavior of ant colonies concerning in particular how they can find shortest paths between food sources and their nest without using visual cues. Ants foraging for food lay down quantities of a volatile chemical substance named pheromone, marking their path that it follows. It has been observed that the more ants use a particular path, the more pheromone is deposited on that path and the more it becomes attractive and thereby reinforces it with a further quantity of pheromone. The process is thus characterized by a positive feedback loop where the probability that an ant chooses a path increases with the number of ants choosing the path at previous times and with the strong of the pheromone concentration laid on it (Dorigo & al, 1997a).

Consider the experimental setting shown in Figure 1. If an obstacle is suddenly placed on an established path leading to a food source, ants will initially go right or left in a seemingly random manner, but those choosing the side that is in fact shorter will reach the food more quickly and will make the return journey more often. The pheromone on the shorter path will therefore be more strongly reinforced and will eventually become the preferred route for the stream of ants.

![Figure 1. Ants facing an obstacle](image-url)
This indirect cooperation and stigmergetic communication has been used to solve difficult discrete combinatorial problems with a new paradigm Ant Colony Optimization (ACO). Figure 2 presents the generic ACO algorithm. The fundamental approach underlying ACO is an iterative process in which a population of artificial ants collectively search for good quality solutions to discrete combinatorial optimization problems. During each iteration, ants repeatedly construct candidate solutions by adding components to a partial solution. Partial solutions are seen as the states and the ant moves from one state to another to a more complete partial solution according to a probabilistic state transition rule (Maniezzo & al, 2001). The state transition rule depends on an artificial pheromone trail representing experience gathered by ants in previous iterations and a heuristic information that represent a priori information of the given problem. Once all ants have built a solution, pheromone trails are updated and the amount of pheromone deposited is a function of the quality of the solution constructed. The goal of this update process is the increasing the probability of choosing the moves that were part of good solutions, while decreasing all others.

1- Initialization of the pheromone trails
2- For Imax iteration repeat
   a. For each Ant repeat
      i. Solution construction using the pheromone trails and the heuristic information
      ii. Update the pheromone trails

Figure. 2. A generic ACO algorithm

The first ant algorithm, called Ant System (AS) was proposed by Dorigo and applied to the traveling salesman problem (TSP) (Dorigo & al, 1991), (Dorigo & al, 1997b). Since, the basic AS algorithm was further improved concerning the transition rule, the pheromone trail updating and the use of a local search, leading to more elaborate variants ants algorithms that were experimented on a broad range of hard combinatorial optimization problems including quadratic assignment (Maniezzo & al, 1994), (Taillard & al, 1997), (Gambardella & al, 1999), graph-coloring (Costa & al, 1997), (Bertelle & al, 2003), vehicle routing (Bullnheimer & al, 1997), telecommunication networks (Di Caro & al, 1998) and sequential ordering (Gambardella & al, 1997), solving the maximum clique (Solnon & al, 2004), clustering (Trjeos & al, 2004), image processing domain (Ramos & al, 2002), (Ouadfel & al, 2003a), (Ouadfel & al, 2003b), (Meshoul & al, 2003).

4 Ant Colonies For Image Segmentation

In this paper, the segmentation problem is formalized as an optimization problem of the energy function. For this, we use a new ant algorithm HACSEG. HACSEG is a hybridization of a modified version of Ant Colony System (ACS) with a local search method.

In HACSEG, each individual ant is associated with a particular partition and it uses pheromone trails and heuristic information to perform modifications on pixels’s labels, in the spirit of a neighborhood search, unlike (Ouadfel & al, 2003a) that uses pheromone trail information to construct a complete partition. During each iteration, the ant k will modify its partition $x_k$ by performing partition swapping in the following way: first a pixel $s$ is chosen at random, then another pixel $s'$ from its immediate neighbourhood $N_s$ is selected to be labelled with the same label as $s$, using a local heuristic information and the pheromone trails. The new partitions found by ants are then optimised using a local search algorithm. Pheromone trails are then updated according to the quality of the partitions found by the best ant. A diversification phase is also introduced when partitions seem not to be improving any more. It consists of a re-initialisation of both the pheromone trail matrix and the solutions associated to the ants (Gambardella & al, 1999).

To apply ACO algorithm to our problem, the following steps have to be taken: (1) The definition of the problem solution; (2) The choice of a suitable representation for artificial pheromone; (3) Assigning a heuristic preference to generated solutions at each time step (i.e., select new components by the ants); (4) Defining of the solution modification procedure.

Problem solution representation
For the problem considered in this study, the solution is given by the best partition $x^\ast$, which corresponds to a correct labeling of image pixels with respect to the contextual constrains.

Artificial Pheromone trail
The artificial pheromone trail is numeric information encoded as a matrix of dimension $(N, M)$ where $N$ is the number of image pixels and $M=8$ if we consider only the 8-neighborhood. Each element of the matrix $\tau(s, j)$ represents the amount of artificial pheromone associated to the corresponding pair and indicated the degree of desirability of setting the two pixels in the same class in a solution, and made available by previous attempts of other ants.

Heuristic function
An important feature of an ACO implementation is the choice of a good heuristic, which will be used in combination with the pheromone information to build solutions. It guides the ants’ probabilistic solution construction/modification with problem specific knowledge. In the case of this study, the heuristic function $\eta$ should measure the degree of similarity between two pixels. Therefore, the ant decides to label two pixels with the same label using the correlation
between intensity patterns in a local neighborhood of the two pixels. The heuristic function values are computed from the linear correlation coefficient \( corr \), once for all pixels in a preprocessing step and are recorded in a matrix of dimension \((N, M)\), where \( N \) is the dimension of the image and \( M=8 \) if we consider only the 8-neighborhood. The values of the heuristic function \( \eta \) are normalized to the range \([0,1]\) and are computed as follows:

\[
\eta(s,s') = \frac{corr(s,s') + 1}{2}
\]

(3)

where \( corr(s,s') \) represents the linear correlation coefficient between a neighborhood around the pixel \( s \) and a neighborhood around the pixel \( s' \).

The different steps of HACSEG algorithm are detailed below:

1. Generate \( K \) random partitions \( x^k \);
2. Associate each partition \( x^k \) to one ant;
3. Initialize the pheromone trail matrix;
4. Compute the heuristic function values;
5. For max_iterations repeat
   a. For each ant \( k=1,\ldots,K \) do
      i. Modify the partition \( x^k \);
      ii. Apply a local search to the modified partition;
   b. Record the global best solution

\[
x^{gb} = \min_{k=1,\ldots,K} \left( U(x^k) \right)
\]

c. Update the pheromone trails;
6. If a number of iterations applied without amelioration of \( x^{gb} \) then apply Diversification.

Figure 3. HACSEG algorithm for image segmentation

In the following, we present into details our implementation of HACSEG algorithm, step by step.

**Initialization of partitions**

Initially, we associate each ant \( k \) with a randomly chosen partition \( x^k \) such that each pixel \( s \) is given a random label from the set \( \Lambda \). Theses partitions are then optimized using ICM algorithm.

**Pheromone trail initialization**

From the \( K \) partitions generated in the previous phase, we record the global best partition \( x^{gb} = \min_{k=1,\ldots,K} \left( U(x^k) \right) \). For each pair \((s, s')\), \( s,s' \in N_s \), we have \( k=\text{chosen} \) to set \( \tau(s,s') := \tau_0 \) and \( \tau_0 = \frac{1}{(N \cdot U(x^{gb}))} \), where \( N \) is the number of image pixels.

**Modification of the partitions**

During each iteration, the ants will modify their partitions using the pheromone trails and heuristic information by moving pixels from one class to another. \( N/2 \) moves are applied as follows. First a pixel \( s \) is selected at random, next another pixel \( s' \) from its immediate neighbors \( N_s \) is selected to be assigned to the same class as the pixel \( s \), with two different policies: with a probability \( q_0 \), ant exploits the information contained in the pheromone trail and heuristic information, while with probability \( (1-q_0) \), ant explores the solution space.

More precisely, let \( q \) a random number uniformly distributed in \([0,1]\) and \( q_0 \) a fixed probability. If ant \( k \) has selected pixel \( s \) with \( \chi^k = l \), we have:

- If \( q \leq q_0 \), then pixel \( s' \in N_s \) is chosen such as:

\[
\eta(s,s') \cdot \tau^k(s,s') \text{ is maximum}
\]

(4)

- Otherwise pixel \( s' \) is chosen with the probability :

\[
P(s,s') = \frac{\eta(s,s') \cdot \tau^k(s,s')}{\sum_{j \in N_s} \eta(s,j) \cdot \tau^k(s,j)}
\]

(5)

where

- \( \eta(s,s') \) is the local heuristic between the two pixels \( s \) and \( s' \).
- \( \tau^k(s,s') \) is the desirability to assign the pixels \( s \) and \( s' \) to the same class in the new partition of ant \( k \).

Parameter \( q_0 \) allows to modulate the degree of exploration \((q_0 = 0)\) versus exploitation \((q_0 = 1)\) and to choose whether to concentrate the search of the algorithm on the best solutions (greedy search) or to explore the search space.

**Pheromone trail update**

In HACSEG, as in (Ouadfel & al, 2003a) the update of the pheromone trails is done only by the best ant with the best quality found since the beginning of the algorithm. First, all the values contained in the pheromone trail are reduced using the evaporation process (as in the real ants) according to the rule.

\[
\tau(s,s') = (1-\rho) \cdot \tau(s,s')
\]

(6)

where \( 0 < \rho < 1 \) is the evaporation parameter which has an influence on the exploratory behaviour of ants. A value of \( \rho \) close to 0 implies that the influence of the pheromone will be efficient a long time, while a value of \( \rho \) close to 1 implies a high degree of evaporation and so the algorithm takes longer to find good solutions.
In the second phase, only the globally best ant, the one that constructed the clustering with the minimum energy function defined in Eq (2) from the beginning of the algorithm, is allowed to update the pheromone trails using the following update formula
\[
\tau(s, s') = \tau(s, s') + \rho \Delta \tau(s, s')
\] (7)

where
\[
\Delta \tau(s, s') = \begin{cases} 
\frac{1}{U(x^{gb})} & \text{if } (s, s') \in x^{gb} \\
0 & \text{otherwise}
\end{cases}
\] (8)

**Local search**

Local search has shown to be effective to solve large optimization problems. Adding local search to ant algorithms yields a faster convergence of the algorithm and an earlier detection of high quality solutions. The basic idea is to construct a complete labeling and then iteratively refine it by applying a neighborhood examination with an improving strategy.

For each ant solution, we use a simple iterative improvement local search that starting from an initial solution iteratively generates a better solution from its neighborhood. The neighborhood for a current clustering \(x\) is the set of candidate clustering \(N(x)\) that can be reached from \(x\) by making small modifications on the labels of pixels. Iterative improvement has been implemented using the first improvement, i.e., the first improving move found is accepted. For each solution \(x\), we evaluate the neighboring candidates solutions and the first \(x' \in N(x)\) for which \(U(x') < U(x)\) is selected. The neighborhood of a solution is defined by a set of solutions that can be obtained by exchanging the labels of two pixels (Franti & al, 2000).

**Diversification**

If \(x^{gb}\), the best global partition has not been improved during a number of iterations which indicates that the search is stuck or has prematurely converged the diversification step is started in order to diversify the search. The pheromone trails are completely re-initialised: All the values of the pheromone trail matrix are set to the same value. and new partitions are generated for \(k - 1\) ants expect for the \(k^{\text{me}}\) ant for which we associate the best global partition \(x^{gb}\). A matrix \(F_{\text{Freq}}, (F_{\text{Freq}}(s, s'), s \in S, s' \in N_r)\) is used to store the number of times each pair \((s, s')\) has been incorporated into the ant solutions. During the diversification phase, we have used assignments that have not been incorporated into ants’solutions frequently to generate new partitions.

**5 Experimental Results**

HACSEG is compared with the previous algorithm presented in [Ouadfel & al, 2003a] which is also based on ant colonies, and with other methods based on genetic algorithm and simulated annealing. For the comparison, we use cerebral magnetic resonance (MR) images with different levels of noise and inhomogeneities (Figure. 3.) and real images considered in (Ouadfel & al, 2003A).

**MR images**

Brain matter can generally be categorized as white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF). Tests have been done on the computationally synthesized Brainweb phantoms available on the site Brainweb: http://www.bic.mni.mcgill.ca/brainweb/, containing 0, 3 and 5% of noise and have an inhomogeneity of 20, or 40%, to compare the following segmentation algorithms: (1) SA, (2) GA, (3)ACS-MRF, (4) HACSEG

<table>
<thead>
<tr>
<th>Inhomogeneity</th>
<th>Inhomogeneity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Noise=0%</td>
<td></td>
</tr>
<tr>
<td>Noise=3%</td>
<td></td>
</tr>
<tr>
<td>Noise=5%</td>
<td></td>
</tr>
</tbody>
</table>

**Figure. 3. Brain phantoms with different values of noise and inhomogeneities.**

The parameters of SA GA and ACS-MRF are directly taken form (Ouadfel & al, 2003a). The parameters of HACSEG are set identical to ACS-MRF and are tabulated in table 1

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(T_0)</td>
<td>2</td>
</tr>
</tbody>
</table>
Table 1. Parameters of the Simulated annealing, Genetic algorithm, ACS-MRF and HACSEG algorithms.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>SA</td>
<td>$T_0$</td>
<td>0.9</td>
</tr>
<tr>
<td></td>
<td>$T_m$</td>
<td>0.9</td>
</tr>
<tr>
<td></td>
<td>$N_i$</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>$N_{max}$</td>
<td>3000</td>
</tr>
<tr>
<td>GA</td>
<td>$N$</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td>$P_c$</td>
<td>0.8</td>
</tr>
<tr>
<td></td>
<td>$P_m$</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>$N_{max}$</td>
<td>1000</td>
</tr>
<tr>
<td>ACS-MRF</td>
<td>$Q_0$</td>
<td>0.6</td>
</tr>
<tr>
<td></td>
<td>$\alpha$</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>$\rho$</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>$N_{ants}$</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>$N_{max}$</td>
<td>2500</td>
</tr>
<tr>
<td>HACSEG</td>
<td>$Q_0$</td>
<td>0.6</td>
</tr>
<tr>
<td></td>
<td>$\gamma$</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>$\beta$</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>$\rho$</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>$N_{ants}$</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>$N_{max}$</td>
<td>2500</td>
</tr>
</tbody>
</table>

where $T_0$: initial temperature, $T_m$: temperature multiplier, $N_i$: number of iterations after which temperature is reduced, $N_{max}$: maximum number of iterations allowed, $N$: the population size, $P_c$: crossover probability, $P_m$: mutation probability, $q_0$: parameter with determine the relative importance of exploitation versus exploration, $\rho, \alpha$: the pheromone decay parameters, $\beta$: the relative importance of pheromone trails, $\gamma$: the relative importance of the heuristic function, and $N_{ants}$: number of ants.

To validate the accuracy and reliability of the segmentation method, compared with the ground truth, we computed the Jaccard similarity. The Jaccard similarity measures the similarity of two sets as the ration of the size of their intersection divided by the size of their union. Let $V^g_k$ and $V^s_k$ denotes the total number of pixels labeled into a cluster $k$ in the ground truth (g) and the obtained segmentation (s). For cluster $k$ the Jaccard similarity $J^k(g,s)$ is defined by

$$J^k(g,s) = \frac{|V^g_k \cap V^s_k|}{|V^g_k \cup V^s_k|}$$

A good segmentation is obtained when $J^k(g,s)$ is near 1 which means that the cluster $k$ is well detected.

Table 2. Performance comparison of the (1) SA, (2) GA, (3) ACS-MRF, (4) HACSEG algorithms for segmentation of MR images.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>20%</th>
<th>40%</th>
<th>20%</th>
<th>40%</th>
<th>20%</th>
<th>40%</th>
</tr>
</thead>
<tbody>
<tr>
<td>LCR</td>
<td>0.86</td>
<td>0.86</td>
<td>0.86</td>
<td>0.86</td>
<td>0.82</td>
<td>0.80</td>
</tr>
<tr>
<td>WM</td>
<td>0.90</td>
<td>0.88</td>
<td>0.88</td>
<td>0.88</td>
<td>0.86</td>
<td>0.84</td>
</tr>
<tr>
<td>GM</td>
<td>0.96</td>
<td>0.90</td>
<td>0.88</td>
<td>0.88</td>
<td>0.87</td>
<td>0.85</td>
</tr>
<tr>
<td>WM</td>
<td>0.91</td>
<td>0.86</td>
<td>0.88</td>
<td>0.84</td>
<td>0.83</td>
<td>0.81</td>
</tr>
<tr>
<td>LCR</td>
<td>0.85</td>
<td>0.89</td>
<td>0.87</td>
<td>0.86</td>
<td>0.82</td>
<td>0.81</td>
</tr>
<tr>
<td>GM</td>
<td>0.96</td>
<td>0.90</td>
<td>0.90</td>
<td>0.90</td>
<td>0.87</td>
<td>0.85</td>
</tr>
<tr>
<td>WM</td>
<td>0.91</td>
<td>0.86</td>
<td>0.88</td>
<td>0.84</td>
<td>0.83</td>
<td>0.82</td>
</tr>
<tr>
<td>LCR</td>
<td>0.95</td>
<td>0.91</td>
<td>0.91</td>
<td>0.90</td>
<td>0.88</td>
<td>0.87</td>
</tr>
<tr>
<td>WM</td>
<td>0.94</td>
<td>0.89</td>
<td>0.91</td>
<td>0.87</td>
<td>0.85</td>
<td>0.83</td>
</tr>
</tbody>
</table>

It is clear that the new algorithm HACSEG outperforms others algorithms and finds better results.

Real images.

HACSEG algorithm has been applied to two gray level real world images representing a muscle cell image and a house image, presented in Figure 4.

![Real images](image link)

Figure 4. Real world images. a) muscle cells image, b) a house image.

To quantitatively evaluate the quality of the segmentations, without need to a ground truth, we use a simplified version of the Borsotti-measure (Borsotti & al, 1998), which was defined as follows:

$$Q(I) = \frac{1}{1000(N)} \sqrt{R \sum_{k=1}^{R} \frac{\sigma_k^2}{\sqrt{A_k}}}$$

where:

- $I$: image to be segmented;
- $N$: size of the image;
- $R$: number of clusters in the segmented image;
\( A_k \) : area, or the number of pixels of the \( k \text{th} \) cluster;

\( e_k \) : gray level error of cluster \( k \).

\( e_k \) is defined as sum of the square of the Euclidean distances between the gray level intensity of pixels in cluster \( k \) and the average gray level intensity of cluster \( k \) in the segmented image.

The first term of Eq. (10) is a normalization factor. The smallest the value of \( Q(I) \), the better the segmentation results were. Table 2 summarize the results obtained from SA, GA, ACS-MRF and ACSEG algorithms.

<table>
<thead>
<tr>
<th>Images</th>
<th>(a)</th>
<th>(b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SA</td>
<td>1.130</td>
<td>0.980</td>
</tr>
<tr>
<td>GA</td>
<td>1.128</td>
<td>0.950</td>
</tr>
<tr>
<td>ACS-MRF</td>
<td>1.128</td>
<td>0.9486</td>
</tr>
<tr>
<td>HACSEG</td>
<td>1.1272</td>
<td>0.9473</td>
</tr>
</tbody>
</table>

**Table 2**: Borsotti & al. Measure \( Q \) comparison for real images (a) and (b)

As we can see, HACSEG obtained good quality segmentation results.

### 6 Conclusion

In this paper we have described HACSEG, a new ant algorithm for image segmentation based on a modified version of the Ant Colony System (ACS) algorithm coupled with a local search. Instead of building a new partition each time, the ant algorithm starts with a number of random partitions. Each partition is first optimized and then associated with one ant, which applies a given number of local moves to pixels. The moves are chosen according to the pheromone trails and heuristic information. A simple local search algorithm is used to improve the quality of the partition found by each ant and yielding a faster convergence of the algorithm. Experimental results show a noticeable increase in performance compared to ACS-MRF algorithm and other global optimization methods like SA and GA.

### Références


