Ant Colony System with local search for Markov Random Field Image Segmentation

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ABSTRACT

In this paper, we propose a new algorithm for image segmentation based on the Markov Random Field (MRF) and the Ant Colony Optimization (ACO) metaheuristic. The underlying idea is to take advantage from the ACO metaheuristic characteristics and the MRF theory to develop a novel agents-based approach to segment an image. The proposed algorithm is based on a population of simple agents which construct a candidate partition by a relaxation labeling with respect to the contextual constraints. The obtained results show the efficiency of the new algorithm and that it competes with other global stochastic optimization methods like Simulated annealing and Genetic algorithm.

1. INTRODUCTION

Image segmentation is a low level image processing task that aims at partitioning an image into meaningful regions so that each region groups contiguous pixels sharing similar attributes (intensity, color, etc.). Image segmentation 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 [13]. Among them, Markov random field (MRF) is one of the most frequently utilized techniques [1,3-4, 7, 9-11, 14]. The MRF based image segmentation method is a process seeking the optimal labeling of the image pixels. Due to its local characteristics, MRF allows the label selection of a pixel to be conditioned explicitly on the local interaction between the pixel and its neighbors within a well-defined neighborhood system without involving all the pixels of the image. The image is segmented by maximizing the a posteriori probability (MAP) of the labeling space given the image pixels. The MRF-MAP framework involves solving an energy maximization (or minimization) problem. However this maximization is combinatorial and the energy function is usually non convex and may exhibits many local minima in the solution space. As a result, many global optimization methods have been investigates as a solution to this combinatorial problem, such as the simulated annealing (SA) [9] and the genetic algorithm (GA) [1, 11].

Ant Colony Optimization (ACO) metaheuristic [12] is a recent population based approach inspired by the observation of real ants colony and based upon their collective foraging behavior. In ACO, solutions of the problem are constructed within a stochastic iterative process, by adding solution components to partial solutions. Each individual ant constructs a part of the solution using an artificial pheromone, which reflects its experience accumulated while solving the problem, and heuristic information dependent on the problem. In this paper, we propose an MRF image segmentation using the Ant Colony System (ACS) algorithm which is the best algorithm following the ACO. Our main motivation is that ACO metaheuristic has been successfully applied to several NP-hard combinatorial optimization problems and has been shown to be competitive against conventional global optimization methods like GA and SA [5]. The underlying idea is to take advantage from the ACO metaheuristic characteristics and the MRF theory to develop a novel agents-based approach to segment an image. The proposed ACS algorithm-based segmentation is a distributed algorithm based on a population of ants. Each ant constructs a candidate partition by assigning each pixel to the nearest class with respect to the contextual constraints. After some iterations, the best partition representing the optimum value of the objective function emerges. Experimental results show that the ACS-MRF based image segmentation yields good quality solution comparable to SA and GA.

Consequently and in order to be self-contained, the rest of the paper is organized as follows. Section 2 presents a brief review on image modeling using MRF. Section 3 describes ACO algorithm and the ACS version. Section 4 investigates the application of ACS for MRF based image segmentation. In section 5 we present the experimental results and finally a conclusion is drawn in section 6.

2. IMAGE MODELING USING MARKOV RANDOM FIELD

The MRF was introduced in image analysis by Geman and Geman [9]. MRF is a stochastic process in which spatial relations within the image are included in the labeling process through statistical dependence among neighboring pixels. The pixels of the image are indexed by a regular lattice $S=\{s_1,s_2,\ldots s_N\}$ and each pixel s is characterized by the gray level y_s from the set $Y=\{y_s \,/\, \forall s \in S\}$. The labeling of S is denoted by $X=\{x_s: x_s \in \Lambda, s \in S\}$ where x_s denotes the corresponding class label from the set of labels $\Lambda=\{0,..L-1\}$ of the pixel s. X is a particular realization of a random field X which is an MRF on S with respect to a neighboring system $N=\{N_s, s \in S\}$, where N_s is the set of pixels neighboring s.

The goal is to find the labeling $\hat{x}$ of the image, which is the estimation of the true but unknown labeling x^*. According to the MAP estimate [8] we have:

$$\hat{x}=\arg\max_{x \in X}\{P(X \mid Y)\}=\arg\max_{x \in X}\frac{P(Y \mid X).P(X)}{P(Y)} \tag{1}$$

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. We have:

$$P(Y|X)=\frac{1}{(2\pi)^{N/2}}Exp\left[-\sum_{s\in S}\left\{\frac{(y_s-\mu_{x_s})^2}{2\sigma_{x_s}^2}+\log(\sigma_{x_s})\right\}\right] \quad (2)$$

According to the Hammersley-Clifford theorem, the probability density of the prior model $P(X)$ is given by a Gibbs distribution with respect to the neighboring system N. $P(X)$ has de form:

$$P(X)=\frac{1}{Z}\exp\left\{-\sum_{c\in C}V_c(X)\right\} \quad (3)$$

Z is the normalization function, $V_c(X)$ is the potential function for clique c and C is 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 pair-site clique potentials of 8-neighborhood system, with the form $V(x_1,x_2)=-\beta$ if $x_1=x_2$ and 0 otherwise. β is a positive parameter and the larger β, the larger is the influence of the neighboring pixels.

According, (1) can be expressed by the following equation:

$$\hat{x}=\arg\min\left\{\sum_{s\in S}\frac{(y_s-\mu_{x_s})^2}{2\sigma_{x_s}^2}+\sum_{s\in S}\log\sigma_{x_s}+\sum_{c\in C}V_c(x)\right\} \quad (4)$$

3. ANT COLONY SYSTEM

Ant Colony Optimization (ACO) was initially introduced by Marco Dorigo in collaboration with Alberto Colorni and Vittorio Maniezzo [2, 6]. ACO is a population based approach attribute to Marco Dorigo [5, 12] 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. Ants smell pheromone and decide to follow the path with a high probability and thereby reinforce it with a further quantity of pheromone. 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 [5].

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. Ant is defined as a simple agent, which repeatedly constructs a candidate solution 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 [12]. The state transition rule depends on an artificial pheromone trail τ representing experience gathered by ants in previous iteration and a heuristic information η 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.

One of the best implementation of ACO has been Ant Colony System (ACS) [5] that introduced a particular use of pheromone trails. Pheromone trails are used for exploration and exploitation. Exploration allowed the construction of new solutions by making a probabilistic choice of the components of a solution: a higher probability is given to components with a strong pheromone trail. Exploitation is based on the choice of the components with a strong pheromone trail and a short cost. Also the pheromone is updated in two stages. A local pheromone updating rule is applied after an ant has built a candidate solution. Once all ants have built solutions, only the best solution is used to globally modify the pheromone trail.

4. ACS ALGORITHM FOR MRF IMAGE SEGMENTATION

In this paper, the segmentation problem is formalized as an optimization problem of the energy function within the MRF model based image segmentation. For this, we use the ACS algorithm. The main underlying idea of ACS-MRF algorithm is a cooperative search of the best class labels for image pixels by a population of artificial ants. Each ant iteratively assigns class labels to pixels with a probabilistic choice. For each pixel s, the ant applies a so-called random proportional state transition rule $p^k(s,l)$, that is, it probabilistically chooses the class label l to assign to the pixel s from the set of labels Λ. The transition probability $p^k(s,l)$ depends on the pheromone information $\tau(s,l)$ of the coupling (s,l), which gives an indication of how good it seems to assign to the pixel s the label l.

$$l=\begin{cases}\arg\max_{u\in\Lambda}\tau(s,u) & if\ q\le q_0\\ L & if\ q>q_0\end{cases} \quad (5)$$

L is a class label selected according to the transition probability given by:

$$p^k(s,l)=\frac{\tau(s,l)}{\sum_{u\in\Lambda}\tau(s,u)} \quad (6)$$

where $q\in[0,1]$ is a uniform random number, q_0 is a parameter in [0,1]. With probability q_0, the ant chooses to the pixel s the label l for which the pheromone trail $\tau(s,l)$ is highest (deterministic choice), while with probability $1-q_0$ it explores the search space.

After constructing its partition, an ant modify the amount of pheromone of the chosen couples (s,l) by applying the following local updating rule:

$$\tau(s,l)=(1-\rho).\tau(s,l)+\rho.\tau_0 \quad (7)$$

where ρ is a parameter in $]0,1[$, which represents the evaporation of the pheromone trail as in the behavior of the real ants and τ_0 is the initial pheromone value.

In order to improve the performance of ACS-MRF algorithm an additional local search is performed for each segmentation built by an ant. The local search algorithm start with a segmentation X found by an ant and will iteratively improve it using neighborhood search $N(X)$ and selection [8]. The neighborhood $N(X)$ is a set of candidates segmentation that can be reached from X by making small modifications on it. The modifications should perform local fine tuning towards a local optimum [8]. The most used search strategy is the steepest descent method which evaluated all the candidate partitions in the neighborhood and selects the one that minimize the objective function U. Let $U(x_s)$ the local energy of pixel s when assigning to it a class label, the sequential version of the local search algorithm is given in algorithm 1.

Algorithm 1 A local search algorithm

Let $X = \{x_s / s \in S\}$ the segmentation to improve
Repeat
For each $s \in S$ do
Find $x_s^{new} = \arg\min_{x_s \in \Lambda} U(x_s)$
If $x_s^{new} \neq x_s$ then
Set $x_s = x_s^{new}$
Until no improvement is possible
Return X^{new} as X

When all ants have built partitions, pheromone trails of couples (s, l) belonging to the global best solution found since the beginning of the algorithm, will increase with an amount, that is, function of the quality of this solution. The global update is done by applying the following global update rule.

$$\tau(s,l) = (1-\rho).\tau(s,l) + \rho.\Delta\tau(s,l) \tag{8}$$

Where

$$\Delta\tau(s,l) = \begin{cases} \dfrac{1}{U_{best}} & if\ (s,l) \in the\ best\ solution \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

U_{best} is the energy function of the best partition found since the start of the algorithm and is defined in Equation 4.

More formally, the general schema of our algorithm is as follow:

Algorithm 2. ACS for MAP-MRF image segmentation

/* Initialization phase*/
For each couple (s, l) set $\tau(s,l) := \tau_0$ End-for
Repeat
/* Construction of the solution */
For each ant do
Construct the candidate segmentation according to using the equation (5).
Apply a local pheromone updating rule according to equation (6).
End-for

/* local search */
Improve solutions by using the steepest descent method.

/* Global updating pheromone level */
Apply a global pheromone updating rule according to equations (7) and (8).
Until a maximum number of iterations.

5. EXPERIMENTAL RESULTS

To evaluate the performance of the proposed method, experiments were performed on cerebral magnetic resonance (MR) images. The most problems with the segmentation of MR images are due to the presence of noise and to the intensity inhomogeneities. Brain matter can generally be categorized as white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF). Assessing the performance of the image segmentation method is difficult when the ground truth is non-known. For this reason we used a computationally synthesized phantom available on the Brainweb site : http://www.bic.mni.mcgill.ca/brainweb/. The Brainweb site offers a large amount of different phantoms of MR brain images with different levels of noise and inhomogeneities (Fig1). Theses phantom images are labeled manually by a medical researcher and considered as the "ground truth" which is taken as a reference image and allows us to test the suggest algorithm.

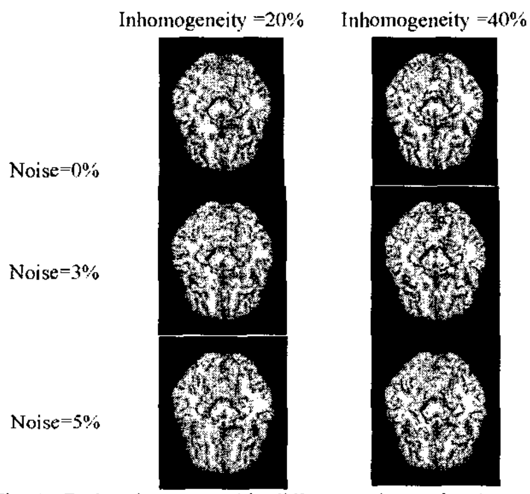

Fig 1. Brain phantoms with different values of noise and inhomogeneities.

Tests have been done on the Brainweb phantoms 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. The SA, GA and ACS-MRF have several parameters whose values are tabulated in Table 1.

Simulated annealing		Genetic algorithm		Ant colony system	
Parameters	Value	Parameters	Value	Parameters	Value
T_0	2	N	30	q_0	0.6
T_m	0.9	P_c	0.8	τ_0	0.001
N_i	100	P_m	0.01	ρ	0.9
N_{max}	3000	N_{max}	1000	N_{ants}	10
				N_{max}	2500

Table1. Parameters of the Simulated annealing, Genetic algorithm and Ant colony system algorithms. T_0: initial temperature, T_m : temperature multiplier, N_t : 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, τ_0: the initial pheromone trail, ρ : the pheromone decay parameter and N_{ants} : number of ants in the colony.

To validate the accuracy and reliability of the segmentation method, compared with the ground truth, we computed the Jaccard similarity, which measures the similarity of two sets as the ration of the size of their intersection divided by the size of their union. All results were obtained during 10 test runs and are tabulated in Table2.

		N= 0%		N = 3%		N = 5%	
		20%	40%	20%	40%	20%	40%
(1)	LCR	0.86	0.87	0.86	0.85	0.82	0.80
	GM	0.91	0.89	0.88	0.88	0.86	0.84
	WM	0.90	0.86	0.88	0.84	0.83	0.81
(2)	LCR	0.85	0.89	0.87	0.86	0.82	0.81
	GM	0.96	0.90	0.90	0.88	0.87	0.85
	WM	0.91	0.86	0.88	0.84	0.83	0.82
(3)	LCR	0.89	0.87	0.87	0.85	0.86	0.82
	GM	0.94	0.89	0.90	0.89	0.88	0.86
	WM	0.93	0.88	0.89	0.86	0.84	0.82

Table2. Performance comparison of the (1)SA, (2)GA and (3)ACS algorithms for segmentation of MR images.

6. CONCLUSION

In this paper we described a novel approach to image segmentation based on a cooperation between the Ant Colony System (ACS) algorithm which is the best algorithm following the Ant Colony Optimization and Markov Random Field. ACS-MRF algorithm is a distributed algorithm based on a population of ants. Each ant constructs a candidate partition using the pheromone information accumulated by the others ants. After some iterations, the best partition representing the optimum value of the posterior energy function emerges. A simple local search algorithm is used to improve the quality of the partition found by an ant and yielding a faster convergence of the algorithm. Experimental results show that the ACS-MRF based image segmentation is competitive with the other global optimization methods like SA and GA.

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