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

Kamal E. Melkemi [a,*], Mohamed Batouche [b], Sebti Foufou [c]

[a] Computer Science Department, University of Biskra, 07000 Biskra, Algeria
[b] LIRE Laboratory, University of Contantine, 25000 Constantine, Algeria
[c] LE2I Laboratory, University of Burgundy, UFR sciences, BP 47870, 21078 Dijon, Cedex, France

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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

* Corresponding author.
E-mail addresses: melkemi@mailcity.com (K.E. Melkemi), batouche@wissal.dz (M. Batouche), sfoufou@u-bourgogne.fr (S. Foufou).

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(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:

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

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.

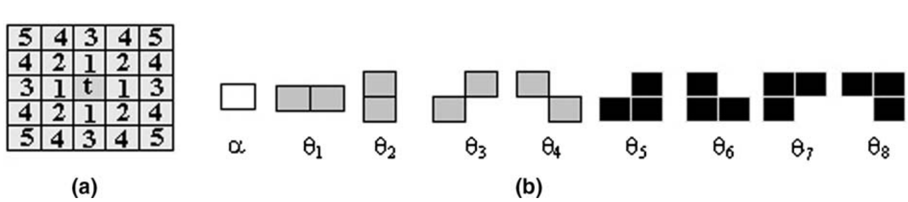

Fig. 1. (a) A neighborhood system, (b) cliques of the second-order neighborhoods.