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A Distributed Hybrid Genetic Algorithm for MRF-based for Image Segmentation Using Multiagent System

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Abstract: In this study we propose a new hybrid Island model-based approach for image segmentation structured on MAS. The general purpose of this distributed approach is to diversify a set of starting images using a GA for parallel ICM processes. This Island-MAS is composed of a set of Island-agents. Each one performs ICM starting from its own initial image. We show how cooperating Island-Agents are able to estimate the labels field and find the MAP estimate. Cooperation between Island-gents is performed by exchanging good initial images through a migration strategy. The efficiency of this Island-MAS is shown through some experimental results.

Key words: Image segmentation, MRF, multiagent systems, genetic algorithms, distributed evolutionary algorithms

INTRODUCTION

The image segmentation[1] process partitions the image into a set of disjoint homogenous regions. We are interested here to a segmentation based on MRF model[2-9]. We cite the two main algorithms: the Besag's Iterated Conditional Modes[2] and the Simulated Annealing (SA)[3]. 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[4] but it strongly depends on the initialization. However, the SA[5] is inspired by simulation equilibrium behavior of large lattice-based systems. Theoretically, it always converges to the global optimum[2], but it remains a computationally intensive method for the image segmentation compared to ICM[4]. Other image segmentation approaches using Genetic Algorithms (Gas) heuristics are reported[10,11]. Also, various applications of Multi Agent Systems (MAS)[12] have been proposed in computer vision and image segmentation[10,11].

In this study we propose a new hybrid Island MultiAgent System for image segmentation (Island-MAS) composed of a set of agents called Island-agents.

Island strategies have been suggested as an improvement for Evolutionary Algorithms (EAs) for many problem types and they are well documented[14,15].

This Island-MAS can be considered as a distributed hybrid GA in which a population of good initial images is divided into smaller subpopulations called demes and GA is executed on each subpopulation separately followed by ICM started on its judged good offspring (initial image). The main reason of the popularity of such model is that it can be readily implemented in parallel computers like for example distributed memory MIMD computers.

The number of evaluations and execution time are potentially reduced thanks to the Island-agents research which is separated in several areas from space of problem state.

In the initialization of the Island-MAS, each Island-agent creates an individual corresponding to an initial sub-optimal image. This latter is created from the observed image using K-means followed by a random perturbation. Then, each Island-agent performs ICM starting from its own initial image which will be transmitted thereafter to the other Island-agents. Thus, each Island-agent will have the whole of initial images of the other Island-agents forming a deme.

At each cycle of evolution of the Island-MAS, each Island-agent:

- Receives individuals (initial images) from the different Island-agents,
- Performs a GA on current deme, performs a crossover on peers of parents and performs a mutation on one or several individual.
- Performs ICM starting from the judged good offspring,
- Updates the best segmented image.
- Transmits this new initial image to the different Island-agents for another segmentation process.

The island topology, when migration occurs, and the synchronization among the Island-agents, must be defined in a migration policy.

The proposed Island-MAS replaces the previous k individuals of a deme by the same number of the judged good individuals coming from other different Island-agents. Thus, at each cycle, the demes contain the same individuals but the result of the genetic process will be different for each Island-agent.

As a coordination model, the Island-agents interact and cooperate to achieve their local segmentations and then a global segmentation.

The result of this cooperation is a sequence of new sub-optimal images used as input images by the ICMs of the Island-agents in order to obtain the best segmentation.

RELATED CONCEPTS

An image specifies the gray levels for all pixels in an MN-lattice. We note S= {1,..,t,..,MN} where t is called site. The gray levels belong to the set A= {0,..., G-1} where G is the number of gray level in the image.

We consider the perfect (true) image is represented by the vector random variable $X = (X_1, .., X_{MxN})$. A discrete Gibbs random field models this vector. Each site labels X_t belongs to the set of labels {1,..,C} where C is the number of categories. The observed image is denoted by the MN-vector random variable $Y = (Y_1,..,Y_{MxN})$. We suppose that Y is the result of adding noise process to the true image[2, 4]. In this study, we assume that this noise process is a Gaussian noise.

A neighborhood system $N = (N_i \subset S, i \in S)$ is collection subset N_i of S according the following conditions:

$$i \notin N_i \text{ and } 2\ j \notin N_i \Leftrightarrow i \in N_j \quad (1)$$

A clique is a subset $c \subset S$ for which any two elements are neighbours: $\forall\, r,t \in c,\ r \in N_t$.

Let a random field $X = (X_1,...,X_{MN})$. As usual, $(X_1=x_1,..,X_{MN}=x_{MN})$ is abbreviated X=x. Let Ω be the set of all possible configurations:

$$\Omega=\{x=(x_1,..,x_i,..,x_{MN}),\ x_i \in\{1,..,C\}\}.$$

X is an MRF with respect to N if:

- for all $x \in \Omega$: $P(X=x) > 0$.
- for every $t \in S$ and $x \in \Omega$:

$$P(x_i/x_j, j \neq i)=P(x_i/x_j, j \in N_i)$$

X is a MRF on S with respect to a neighborhood system N if and only if its distribution P(X=x) is a Gibbs distribution defined by: $P(X=x) = \exp(-U(x))/ Z$, where the normalization constant

$$Z = \sum_{\chi \in \Omega} \exp(-U(\chi))$$

and U(x) is the energy function given by:

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

where θ_r re the clique parameters and δ(a,b) =-1 if a=b, 1 if a≠b. P(X=x) is called the a-priori probability.

We have adopted the Ising model. This model is homogeneous (=strictly stationary) and isotropic (=rotationally invariant)[11]. This model used only those cliques that contain no more than 2 sites having non-zero potentials.

In this study adopt the approach of computing the MAP estimate of the perfect image given the degraded image. The posterior probability P(x/y) follows a Gibbs distribution given by:
$P(x/y) = e^{-U(x/y)}/Z_y$
where Z_y is the normalization constant and U(x/y) is the energy function. In this study , U(x/y) given as follows:

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

where β is a positive model parameter controlling the homogeneity of the image regions and μ_{x_t} and $\sigma_{x_t}^2$ are the mean and the variance of the Gaussian model.

THE ISLAND-MAS ARCHITECTURE

In the Island-MAS, we carefully combine ICM with Island Model in a MAS framework to define a new distributed GA[16-18] for image segmentation.

We can consider an agent as a computer system capable of autonomous actions in some environment[12] and a MAS as a set of agents cooperating, coordinating, etc. with each other. This type of approach is a distributed application consisting of relatively independent modules called agents which sometimes use artificial intelligence techniques for doing complex operations[19].

The general principle of an island strategy is a set of EA on small populations, which evolves independently from generations instead of evolving into one large population. Within each deme, a standard sequential EA is executed between migration phases, which occurs in order to share genetic material between populations.

In present MAS, each Island-agent disposes of a set of initial images coming from different Island-agents. These initial images are diversified by using Island-agent

GA. Then, the Island-agent selects a good offspring for an ICM segmentation. Thus, the Island-agents attempt to share genetic material of a set of good starting images in order to achieve a better segmentation thereafter. In fact, the Island-MAS attempts in an intensified manner to find good or better segmentation by genetically breeding of subpopulations of pertinent initial images over series of new generations of initial images.

The genetic operators the population and fitness: In the Island-MAS, the Island-agents create randomly an initial image, extracted from the observed image using K-means and then a random perturbation. The initial images constitute our population.

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 $i \in \{1,\ldots,N\}$ 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 evaluated with 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 $i_1 \leq i_2$ and $j_1 \leq j_2$. 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 : We can show that each part P of I is evaluated by the $U(P/y)=\Sigma_{i=i1..i2} (\Sigma_{j=j1..j2} U(I_{i,j}/y))$, where y is the observed image. The selection process used in Island-MAS gives more chance of survival to the best individuals than to the worst ones, which increases the possibility of finding the best segmentation. The genetic operation of reproduction is based on the Darwinian principle of reproduction and survival of the fittest[20,21].
The crossover: Crossover combines the genetic material of two parent chromosomes to produce an offspring. Indeed, the crossover operator combines peer of parents, corresponding to the initial images, to produce new offsprings. These offsprings are the new initial images which can be used by the Island-agents (Fig. 1). The crossover is performed with a probability of 0.95. For each mating, the crossover positions are selected randomly as numbers of lines and numbers of columns (Fig. I).
The mutation: is a rare but extremely important event in GA. When a site label is mutated, it is randomly selected and replaced by another category from the set of labels (alphabet) using a random perturbation: In our approach, we perform a mutation (Fig. 2) on site labels selected randomly with a probability of 0.005.

The result of these genetic operations is a sequence of new generations of sub-optimal images used as initial discrete data by the Island-agents, permitting thus to produce a new generation of segmented images.
$P=\{I_{i,j} \in I \,/\, i_1 \leq i \leq i_2 \,,\, j_1 \leq j \leq j_2\}$

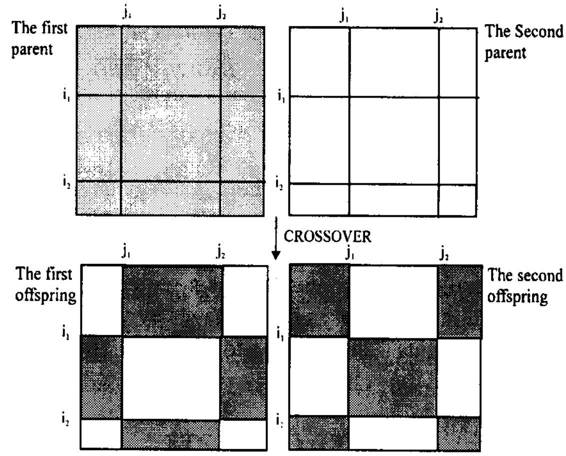

Fig.1: The two parents represent the initial sub-optimal images and the two offspring are also the new initial sub-optimal images. i_1 and i_2 are the cross line points, j_1 and j_2 are the cross column points

The island-MAS architecture: Because agents exist and perform their activities in a society, the coordination among agents is essential for achieving the goals and acting in a coherent manner. This coordination may imply cooperation and in this case the agent society works to achieve a best segmentation as a common goal, but may also imply competition with Island-agents having divergent goals results of the difference of initial images.

We can say that there is cooperation in our Island-MAS (Fig. 3) because the agents contract in a common action after identifying a common goal. The cooperation strategy guides Island-agent interactions towards the improvement of their collective performance by exchanging parts of their sub-optimal images thanks to this migration strategy, the Island-agents exchange the judged good individuals (initial images) selected among the offsprings. Each Island-agent will contain a deme represented by the current good individuals (initial sub-optimal images).

In the Island strategy presented with a fully-connected topology (Fig. 4), within each deme, a standard sequential EA is executed on a set of initial images. However, each Island-Agent performs GA on a deme in order to produce a new better initial image which will be used thereafter as an input discrete data by the ICM process. In fact, the Island-MAS shares genetic material between initial images in order to produce good initializations.

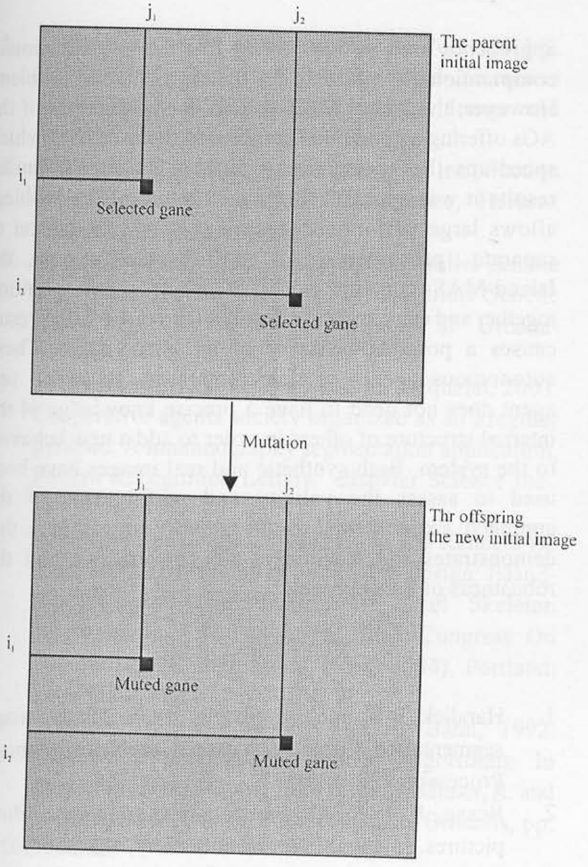

Fig. 2: Two sites mutation of an initial image. (i_1,j_1) and (i_2, j_2) are the two site-mutation

The algorithm: The description of the Island-MAS

- In the initialization of the Island-MAS, each Island-agent:
- creates an individual corresponding to an initial sub-optimal image created from the observed image using K-means followed by a random perturbation;
- performs ICM starting from its own initial image,
- transmit this initial image, to the other Island-agents for defining the initial deme.
- In the evolution cycle of the Island-MAS, each Island-agent:
- receives individuals (initial images) from the different Island-agents.
- performs a GA on a deme: performs a crossover on peers of parents and performs a mutation on one or several individual,
- performs ICM starting from the judged good offspring (initial image).
- updates the best segmented image with its fitness,

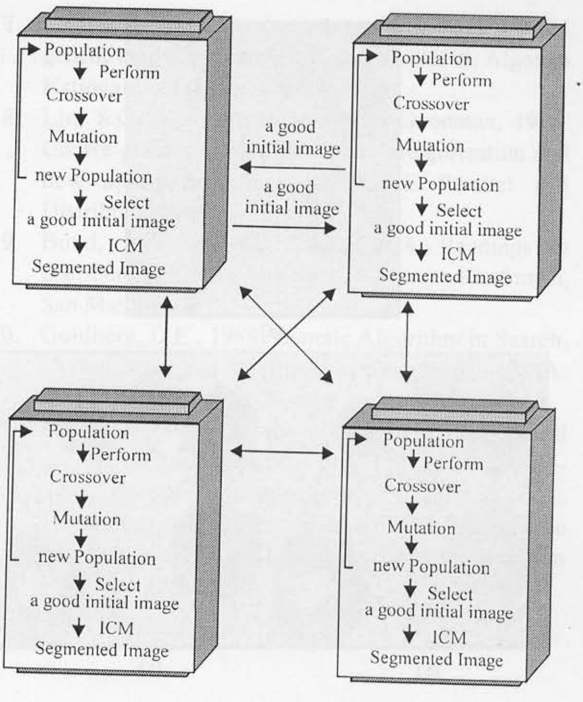

Fig. 3: Communication network of the Island-MAS

- transmits this new better initial image to the different Island-agents for another segmentation process.
- The Island-MAS output: The process cmputes the best segmented images of the Island-agents.

IMPLEMENTATION AND EXPERIMENT RESULTS

We present both synthetic and real results of the Island-MAS compared with the ICM. We assume an isotropic second-order Ising model, so in Equation (1), $\theta_1=\theta_2=\theta_3=\theta_4=\beta$. We have used one value of β which is kept constant through each segmentation process. The segmentation is evaluated by both visual examination and energy function. The observed y is the same starting discrete data for all the two algorithms given with the maximum likelihood estimate of the segmentation. These experiments were performed on a Pentium P_4, CPU 2.66 GHz with 128 Mo of RAM. In the Fig. 4, we have experienced our approach on a real noisy real scene that represented a number of bolts. The segmentation in two classes of this image demonstrates clearly the stability of our approach compared to the ICM and the Island-MAS extract segments better than ICM.

In Fig. 5, The Island-MAS 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.

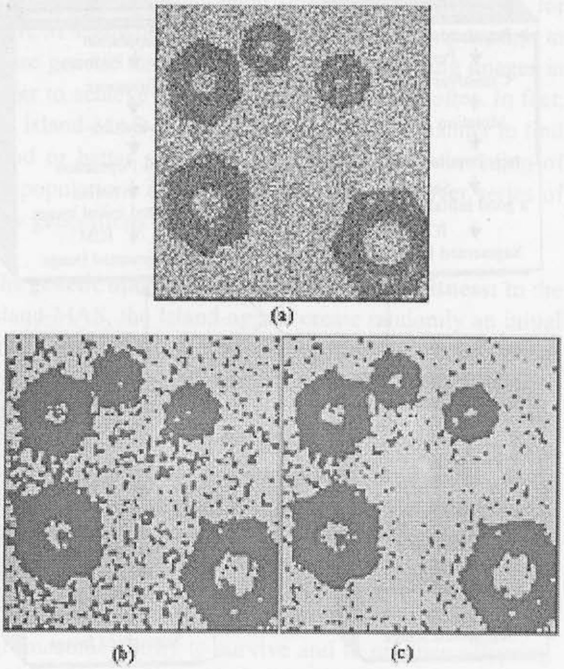

Fig. 4: A Two-class segmentations of noisy Real scene: a Noisy image (Observed image); b ICM segmentations; c Island-MAS segmentations

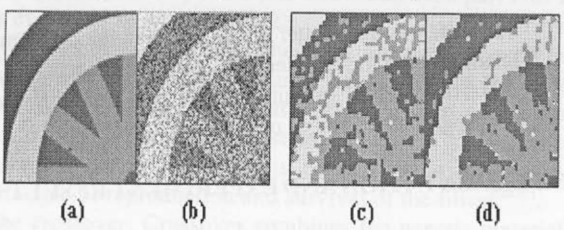

Fig. 5: A three-class segmentation of 64* 64 noisy synthetic scene: a True image: b Noisy image (Observed image): c ICM segmentation: d Island-MAS segmentation

CONCLUSIONS

We have introduced a new distributed GA approach for image segmentation using a MAS. This distributed hybrid GA allows the exchange of good genetic material and thus improves the quality of the initial images. The competition/cooperation activity of the different agents is achieved through a sequence of exchanging of best initial images between Island-agents after applying crossovers and mutations on subpopulations separately what intensifies and insures that this process accedes to a good segmentation. Also, the migration is a trigger effective for evolutionary changes. In fact, this Island-MAS suggests how to combine GA for providing pertinent initial images for ICMs. The classical stochastic approaches used in this context like SA and GA remain computationally intensive for the segmentation problem. However, the Island-MAS gathers the advantages of the AGs offering a good initialization and those of ICM which speed-ups the segmentation process. From the timing results it was apparent that the structure of the problem allows large performance gains as it is split out on to separate processors. As a distributed system, the Island-MAS contains a set of Island-agents working together and can generate a flexible layout. Each EA result causes a possible behavior of an Island-agent. 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; this demonstrates the feasibility, the convergence and the robustness of the approach.

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