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FUNCTIONAL SELF-COORDINATION OF AUTONOMOUS MOBILE AGENTS: AN OPTIMIZED FORAGING MECHANISM

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The self-organized activity of a team of autonomous mobile agents is modeled based on their capabilities to perform a random walk, recognize and move different "objects". The emergent behavior is a distributed sorting and clustering based entirely on local information processing. Theoretically derived optimum memory weighting function is based on intermediate steady-states assumption. Computational optimization of the angular second-moment agrees with theoretical results.

Key words: mobile agents, swarm intelligence, self-organizing systems

1. INTRODUCTION

Recent surveys identified a growing interest in swarm intelligence applications in the last two decades. One explanation resides is that some tasks are inherently too complex or impossible for a single robot to perform. On the other hand, a swarm of simple robots may also be more flexible without the need to reprogram the robots, and more reliable and fault-tolerant because one or several robots may fail without impairing task completion. Swarm intelligence models can, at least partially, describe the collective activities of social insects, include the formation of trail networks and foraging patterns in many ant species [4,6,7], rhythmical patterns of activity in ants (Leptothorax) [3], thermoregulation in clusters of bees, the piling of dead bodies by ants (Pheidole) [5], larval sorting by ants (Leptothorax) [5], or the dynamics of colony development in wasps (Polistes) [11]. Self-organization has also been applied to the modeling of the social organization, including hierarchical differentiation [10,17], division of labor [16,17], and age (or temporal) polyethism [18].

The present study focuses mainly on searching and collecting "food-items" in a foraging area and sort them in disjoint piles. A theoretical expression for the time-dependent memory radius, *r*, for the functional self-organization process [1,8,13,14,15] was derived. The optimization procedure is based on intermediate steady states assumption and its validity was numerically tested using the angular second-moment feature as aggregation degree [9].

2. THE MECHANISM OF STOCHASTIC FUNCTIONAL SELF-ORGANIZATION BASED ON MEMORY-WEIGHTED MODEL

Our model is based on the following assumptions: (1) The environment is a two-dimensional periodic lattice with N_x x N_y sites. The periodic lattice (torus) was considered in order to eliminate the finite size effects. (2) The lattice sites are occupied by objects denoted by letters *a, b, c…* and so forth. A free site is occupied by a ϕ-type object. (3) The agents, called robot-like-ant (RLA), move randomly through the lattice. Anytime the RLAs transport an object. The carried object might be of ϕ-type and, therefore, the robot move freely. (4) When a robot moves to a given site it must decide if there are conditions to put down the carrying object and to pick up the existing one. The swapping condition writes $f_\alpha \geq f_\beta$, where f_α is the weighted frequency of the carried α-type object and f_β is the corresponding weighted frequency of the encountered β-type object. Walking through the lattice, every RLA records in its memory register the object-types encountered. By analyzing its content, the RLA extracts information about the spatial arrangement of the objects. Every object-type is characterized by a binary string $s_{\alpha,\tau}: u_{\alpha,1}\, u_{\alpha,2} \ldots u_{\alpha,\tau}$, where

$$u_{\alpha,i} = \begin{cases} 1, & \text{if an } \alpha\text{ - type object was encountered at i - th step,} \\ 0, & \text{otherwise.} \end{cases}$$

Deneubourg [5], proposed a memory register model consisting in a shift register of fix length with equal weight. As the time passes, the whole record is shifted one place, the older (less significant) record is removed, and on the first (most significant) place enters the new record. Recently, Oprisan et al. [1,8,13,14] proposed a more efficient memory register model that uses a first order recurrence to define the actual state of the cellular automata (CA). The main advantages are its computational efficiency, reflected in a very economic memory allocation, and long (temporal) correlation, reflected by a complete Markov chain.

In our weighted memory register, every object-type is characterized, at any instant τ, by a weighted frequency: $f_\alpha(\tau) = \sum_{i=1}^{\tau} w(i) u_{\alpha,i} \left(\sum_{i=1}^{\tau} w(i) \right)^{-1}$ where $w(i)$ is an appropriate weighting function. The weighting function is $w(i) = 1/r^{i-1}$, and indicates that for $r >> 1$ the contribution of the τ-th step (with $\tau >> 1$) to present decision is quite insignificant (short-type memory). The limit case $r = 1$ corresponds to an infinite and equally weighted record whereas for $r < 1$ the contribution of older steps become significant [1,8]. This type of memory function, that enhances the effect of past history, was suggested as a possible microscopic mechanism in a model of oncogenesis [1,13,14,15]. The above definition of the memory register leads to a first order recursive for the weighted memory associated to every object-type [14]. Numerical simulations have shown that the memory radius, r, should depend on the cluster dimension (i.e. aggregation stage) in order to optimize the computational effort [13,14]. We proved that the clustering process occurs for any $r > 1$ [13,14,15]. Here we are interested in optimizing the aggregation speed. Extensive numerical simulations indicate that the memory radius must depends on the cluster dimension (i.e. aggregation stage) in order to optimize the computational effort [13,14,15] (see Figure 1).

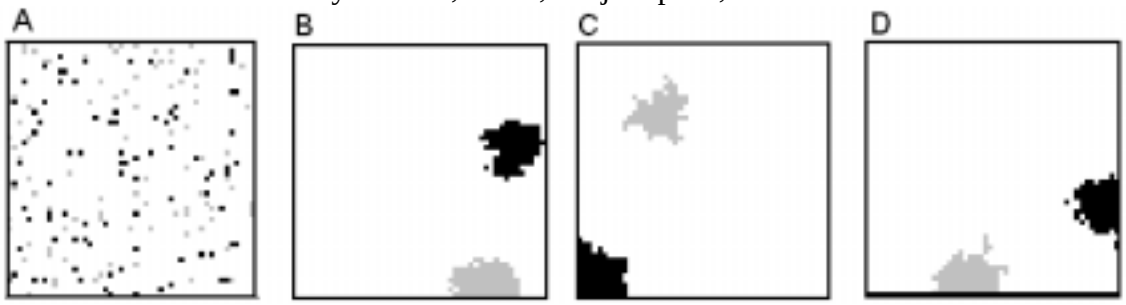

Figure 1. Starting with an arbitrary initial configuration (A) and with 30 RLA, N_a = 100, N_b = 100, in a 50 X 50 two-dimensional rectangular lattice clusters appear for r =1.1 after 2.5 10^5 steps (B), r =1.3 after 6.5 10^5 steps (C), r = 1.5 after 10^6 steps (D). Extensive numerical simulations suggested the idea that an appropriate time-dependent memory radius can optimize the algorithm.

3. THE RESULTS

3.1 The intermediate steady-states hypothesis: a theoretical approach on memory registers optimization.

Our main hypothesis in theoretical derivation of the optimized relationship between memory radius r and the simulation time step is that the aggregation process takes place progressively. Starting with a random distribution, the first step is to grow only two-objects clusters. The next step is to destroy some of the two-objects clusters to form three-objects clusters and so forth. To simplify the analysis we concentrate only on two object-types (α and β) environment without loosing the generality of the method. Assuming that between *n*-th and *n+1*-th computational time step the system increases the α-type cluster with one unit then the relationship between the weighting frequencies are: $f_\alpha^n < f_\beta^n$ and $f_\alpha^{n+1} > f_\beta^{n+1}$. In the limit of large memory, $\tau \to \infty$, the above conditions gives $\frac{r(2-r)}{2(r-1)} < f_\alpha^n < \frac{r}{2(r-1)}$. For instance, after *n*-th computational step, a two-objects cluster appears if the memory radius satisfies $r \in (2^{1/2}, 2)$. For three-objects clusters the memory radius must satisfies $r \in (2^{1/3}, 2^{1/2})$. Generally, it is straightforward that transition from p-objects clusters steady state to (p+1)-objects clusters requires $r \in (2^{1/(p+1)}, 2^{1/p})$. To correlate the cluster dimensions with the simulation time step we proposed as a conventional measure of iteration time steps needed to switch between *p* and *p+1*-objects steady clusters a quantity proportional with the sum of the corresponding mean-free distance between the clusters (λ). The above measure determines the theoretically derived optimized relationship between the memory radius, *r*, and the computational time step *N*: $r \propto e^{\frac{\lambda \ln 2}{2N}}$.

3.2. Numerical results and the annealing rule

The functional self-organization algorithm above described (see also [1,8,13,14,15] for details) requires a well-defined measure of the aggregation stage. Our choice is a texture analysis using features, which considers that texture-context information is contained in the overall spatial relationship between its gray tones [9]. Let *p(i,j)* denote the normalized matrix of relative frequencies with which two cells, separated by distance *d*, occur on the image, one with gray tone *i* and the other with gray tone *j*. A relevant feature is the contrast, which represents a measure of the amount of local variations present in the

image. In a homogeneous image this feature has a great values and decrease if the texture become less homogeneous (texture with different clusters): $Contrast = \sum_{n=0}^{N_g-1} n^2 \sum_{|i-j|=n} p(i,j)$, where N_g is the number of gray levels present in the image under investigation. Numerical simulations demonstrate that the above-defined feature is sensitive to aggregation stages and offers a quantitative meaning of this fuzzy concept (see Figure 2). Based on the above-defined global measure, we performed extensive numerical simulations to find the optimal time-dependence of the memory radius, r, in order to validate the theoretical derived relationship ($r \propto e^{\frac{\lambda \ln 2}{2N}}$) and its background hypothesis - the intermediate steady states assumption. We found that at the very beginning of the numerical simulations there is a quasi-linear relationship between the slope of the feature and the time step (see Figure 2).

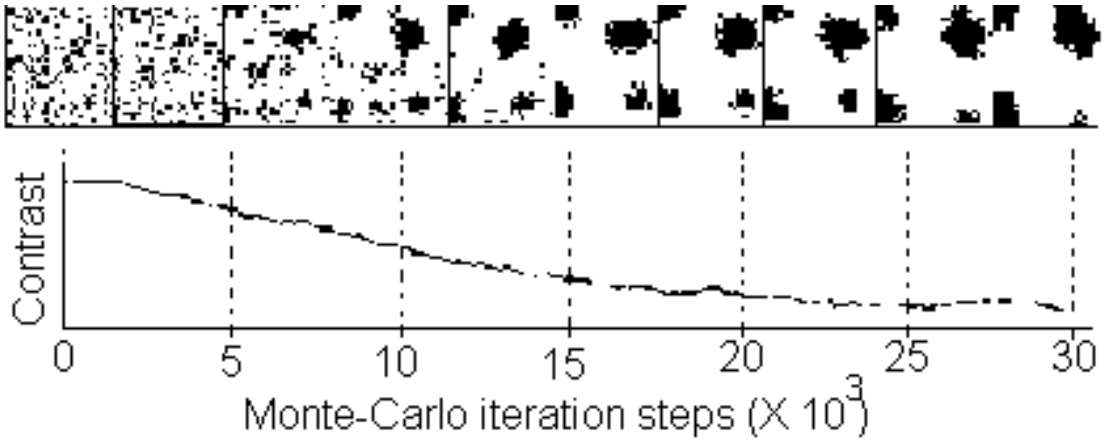

Figure 2. Qualitative picture of the environment (upper panel) and the corresponding quantitative measure (lover panel). The environment is a two-dimensional periodic lattice with 100 X 100 sites and 10 % black objects' concentration. The task was performed by 40 RLAs with memory radius r = 1.1.

Our optimization strategy combines the high speed of the features decreases for initial high memory radius with the lowest quasi steady state at the end of linear region for low memory radius. For this purpose, we recorded the slope of the contrast feature for that specific memory radius value and the simulations were started over for another value of r. Figure 3A summarize the computationally derived optimal relationship between the slope of the contrast feature and the memory radius in order to ensure a minimum computational time. Once the relationship between microscopic control parameter (memory radius r) and the macroscopic measure of aggregation stage (the contrast feature) was established we get practical instrument to optimize the aggregation process. The plot of the optimally controlled memory radius against the iteration step (see Figure 3B) shows that the interpolation curve (continuous line) agrees with our theoretically derived time-dependent memory radius ($r \propto e^{\frac{\lambda \ln 2}{2N}}$).

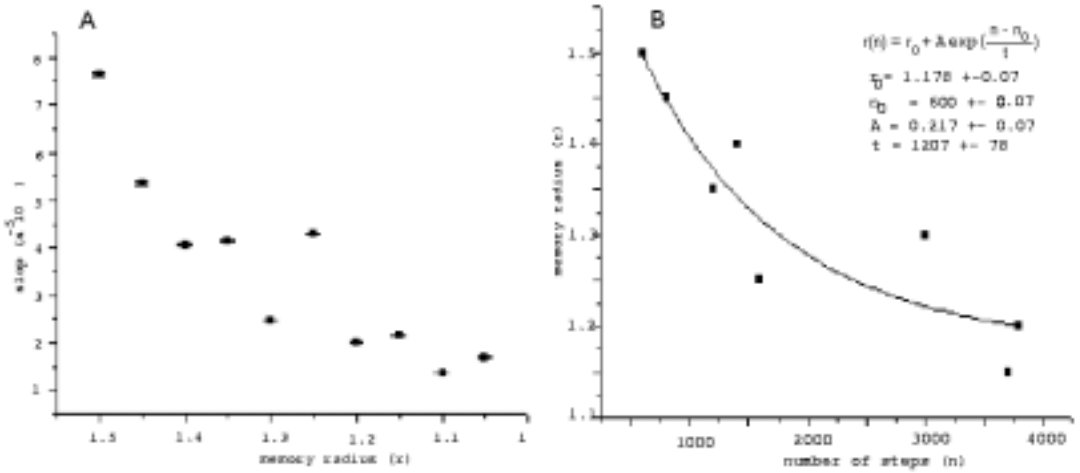

Figure 3. The plot of the steady slope of contrast feature against the memory radius *r* (A). The environment is a rectangular 100 X 100 lattice, with 10 % black objects' concentration and 40 RLAs. The chosen slope of the features maximizes the linear correlation coefficient and, therefore, is an indication that the steady state was reached. The plot of the memory radius (*r*) against the time step (*n*) when the sorting steady state was reached (B). The best fit is an exponential decaying function with the indicated parameters.

4. CONCLUSIONS

Previous studies suggested that a realistic approach on the problem of local decision in the aggregation process performed by a team of mobile agents is the first order recurrent memory function [1,8,13,14,15]. The present study analyses the dynamical aspects of the memory feature, particularly, its correlation length or {\it memory radius}. Based on {\it intermediate steady state} hypothesis we derived a theoretical time-dependent memory radius that leads to a minimum aggregation time. The intuitive idea behind our approach is that each two-, three-, four-, etc. clusters are metastable and the inherent stochastic behavior of the robot-like-ants (RLA) is the mechanism that drives the systems from intermediate (metastable) steady states to a final (stable) steady state. Once we found a time-dependent memory radius, which we thought to be the optimum, the next step was to check our finding using numerical simulation.

On the other hand, using a swarm of robots inspired from social insects behavior has some drawbacks. For example, stagnation is one: because of the lack of a global knowledge, a group of robots may find itself in a deadlock, where it cannot make any progress. Another problem is to determine how these so-called "simple" robots should be programmed to perform user-designed tasks. The pathways to solutions are usually not predefined but emergent, and solving a problem amounts to finding a trajectory for the system and its environment so that the states of both the system and the environment constitute the solution to the problem: although appealing, this formulation does not lend itself to easy programming. Until now, we implicitly assumed that all robots were identical units: the situation becomes more complicated when the robots have different characteristics, respond to different stimuli, or respond differently to the same stimuli, and so forth; if the body of theory that roboticists can use for homogeneous groups of robots is limited, there is virtually no theoretical guideline for the emergent design and control of heterogeneous swarms.

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