Phase Transition Model between Swarm Behavior and Territorial Behavior

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Abstract

Swarm behavior is collective behavior of creatures moving with their neighbors, such as a flock of birds or a school of fishes. From the system optimization standpoint of view, there have been a number of "bio-inspired" models proposed to apply the swarm behavior to organize complex systems and/or to incorporate robustness and flexibility. Territorial behavior is another group form of homogeneous individuals in which each one lives in a separate region (territory) from each other. For system optimization, The most notable application is coverage control.

There are some creatures which exhibit either swarm behavior and territorial behavior according to their circumstances and conditions. However, as far as we know, there is no attempt toward any model or algorithm to combine both the swarm behavior and territorial behavior to make systems adapt to the change of circumstances and conditions.

This paper proposes a phase transition model to combine swarm behavior and territorial behavior. The model is expected to apply to network optimization in dynamic environments, especially transition between cloud computing and edge computing. Through simulation-based experiments, we verify the convergence behavior of the model.

Keywords: Swarm behavior, Territorial Behavior, dynamic transition.

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1 Introduction

This paper proposes a phase transition model to combine swarm behavior and territorial behavior.

Swarm behavior is collective behavior of creatures which typically consists of homogeneous individuals moving with their neighbors. A flock of birds or a school of fishes is a typical example. It is generally thought that they pretend to be a single big individual to protect themselves against predators. Another example is a colony of ants or bees in which they collaborate with each other to perform some tasks, sometimes in a social and complex manner [1].

Territorial behavior is another group form of homogeneous individuals in which each one lives in a separate region (territory) from each other to avoid any conflict [2, 3].

An interesting observation is that there are some creatures which exhibit either swarm behavior and territorial behavior according to their circumstances and conditions. Some species of fish such as *oryzias latipes* changes their group behavior according to the width of their living area and density [4]. It is thought that if the area is small or survival of the group matters, they exhibit the swarm behavior, whereas if the area is large or conflict among members matters, they exhibit the territorial behavior.

There have been some computation models proposed to imitate and mimic swarm behavior. Boid model [5] and Vicsek model [6] are early and famous examples. From the system optimization standpoint of view, there have been a number of attempts made to apply such kinds of biological collective behavior to organize complex systems and/or to incorporate robustness and flexibility. In the study area of multiagent systems in particular, various "bio-inspired" models and algorithms have been proposed to investigate and apply the swarm behavior and the territorial behavior respectively. The former is called "Swarm Intelligence" [7].

Swarm intelligence includes many kind of meta-heuristic optimization algorithms inspired by the swarm behavior: Particle Swarm Optimization (PSO) [8] and Artificial Bee Colony Algorithm (ABC) [9] to name a few. A group of problem solving agents moving here and there in a search space tries as a whole to find the global optimal solution [7, 10].

Regarding the territorial behavior, the most notable application is coverage control [11]. It is a mathematical model utilizing the characteristics of territory, and agents in a group moves around in the given space to solve the optimal placement problem.

As far as we know, there is no attempt toward any model or algorithm to combine or integrate both the swarm behavior and territorial behavior to make systems adapt to the change of circumstances and conditions although there really are some creatures in nature as mentioned above.

What me have in mind is network optimization in dynamic environments. Cloud computing is a form of network for concentration. All the computation resources and storage are virtually centralized in a single large place called cloud for performance and convenience, and all the tasks are executed there. On the other hand, Edge computing, or sometimes called Fog computing, is a form of network for decentralization [12]. Computation resources and storage are distributed over many small places called edges for load distribution, and tasks are executed on any of them considering load balancing.

In a mobile network in particular, the network topology, load pattern, task scheduling, and various constraints regarding throughput, latency, etc. change dynamically. Dynamic task allocation is a complex and difficult issue, and we expect that swarm behavior, territorial behavior, and their combination must bring us some useful insight toward solving this issue. In this case, a task is interpreted as an individual creature, and load concentration is interpreted as density of the individuals.

This paper proposes a new self-propelled particle model in which members in a group, or a particle, change their behavior between swarm behavior and territorial behavior depending on the population, or density, surrounding each of them.

The rest of this paper is organized as follows: Section 2 describes some backgrounds, and Section 3 proposes our model. Section 4 presents simulation-based experiments to verify our model, and Section 5 discusses experiment results. Section 6 contains some concluding remarks.

2 Background

2.1 Swarn intelligence

Swarm intelligence includes many kind of meta-heuristic optimization algorithms inspired from social behavior of creatures such as a swarm of social insects, a flock of birds and a school of fish [7].

SI algorithms can solve complex optimization problems. Particle Swarm Intelligence (PSO) and Artificial Bee Colony Algorithm (ABC) are the most popular SI algorithms in which agents move in the given search space by cooperating with each other and find a global optimal (maximum or minimum) solution.

2.2 Coverage control

Covering control is a category of algorithms for arranging some agents moving autonomously at a desired position. The most basic example is Cortés' method [11], which defines the following control rule:

$$u_i(t) = -k(x_i(t) - \mathcal{C}(\mathcal{V}_i x(t))) \tag{1}$$

$$\mathcal{C}(\mathcal{V}_i(x(t))) = \frac{\int_{\mathcal{V}_i(x)} \phi(q)dq}{\int_{\mathcal{V}_i(x)} q\phi(q)dq} \tag{2}$$

where $u_i(t)$ is control input for agent i, k is a gain which a designer gives appropriately, $x_i(t)$ is coordinate of agent i, $\mathcal{V}_i(x(t))$ is a voronoi region of agent i, $\mathcal{C}(\mathcal{V}_i(x(t)))$ is the center of gravity of the i's Voronoi region.

In this way, the agents, such as mobile sensors, partition the given space into non-overlapping areas so that the given space can solve an optimal placement problem which minimizes the following evaluation function:

$$J(x_1, ..., x_n) = \sum_{i=1}^{n} \int_{\mathcal{V}_i(x)} h(||q - x_i||)\phi(q)dq \tag{3}$$

where $h(x) = x^2$ is performance function, and $\phi(q)$ is importance function.

3 Model

We propose a model which exhibits phase transition phenomenon of swarm behavior and territory behavior depending on a discount strength d. In this model, the gain of each agent is discounted as the number of its neighbors increases. This is based on an idea that the more neighbors are, the less the agent obtains its gain. This is inspired by the behavior of some species of fish such as *oryzias latipes*. Each agent follows the processes below:

1) Initialization

N self-driving agents are placed randomly in the given search space $f(\vec{x})$.

2) Observing neighbors

Each agent i observes agents within its recognition radius R as i's neighbors set N_i, and the agents within the radius $R_{\mathrm{av}}(< R)$ as the set of i's neighbors to avoid collision N_i^{av} .

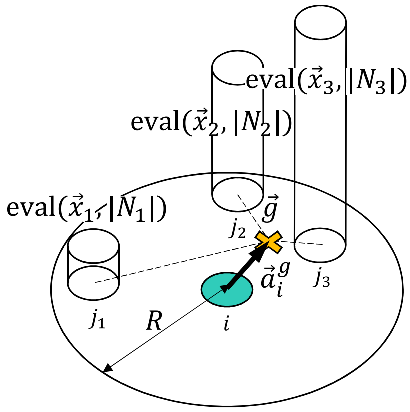


Figure 1: Acceleration towards the center of mass $\vec{a}_i^g$

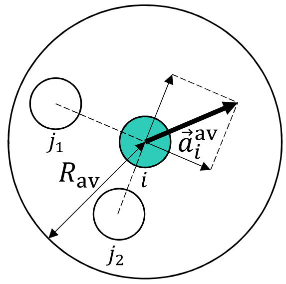


Figure 2: Acceleration to avoid collision $\vec{a}_i^a$

$$N_i = \{j \neq i \mid |\vec{x}_j - \vec{x}_i| < R\} \tag{4}$$
$$N_i^{\text{av}} = \{j \neq i \mid |\vec{x}_j - \vec{x}_i| < R_{\text{av}}\} \tag{5}$$

3) Evaluation of a given search space

The value of the search space $f(\vec{x})$ is converted to the positive gain $g(\vec{x})$ using the following expression:

$$g(\vec{x}) = \begin{cases} \dfrac{1}{1+f(\vec{x})}, & f(\vec{x}) \geq 0 \\ 1 + \text{abs}(f(\vec{x})), & f(\vec{x}) < 0 \end{cases} \tag{6}$$

This is the same as the evaluation expression used in Artificial Bee Colony Algorithm (ABC). Using $g(\vec{x})$ value, the evaluation value $\text{eval}(\vec{x}_i, |N_i|)$ for the coordinates $\vec{x}_i$ is calculated as following expression:

$$\text{eval}(\vec{x}, n) = \frac{w}{(n+1)^d} \cdot g(\vec{x}) \tag{7}$$

where n is the number of neighbors, $w > 0$ is the weighting factor, and $d \geq 0$ is the discount strength of the gain. This evaluation function is based on an idea that the more its rival is, the less the agent obtains the resource in the environment.

4) Movement

To obtain a higher gain, Each agent i generates acceleration $\vec{a}_i^g$ to the center of mass of its neighbors' evaluation values (Fig. 1). it also generates acceleration $\vec{a}_i^{\mathrm{av}}$ to avoid collisions to neighbors (Fig. 2). Each acceleration is normalized with the coefficients c_g, c_{av} and i's velocity in the next step $\vec{v}_i^{\mathrm{next}}$ is calculated by adding the linear sum of these acceleration $\vec{a}_i$ to its current velocity $\vec{v}_i$.

The overspeed is prohibited using the function $\vec{V}(\vec{v})$ as below.

$$\vec{a}_i^g = \frac{\sum_{j \in N_i} \mathrm{eval}(\vec{x}_j, |N_j|) \cdot \vec{x}_j}{\sum_{j \in N_i} \mathrm{eval}(\vec{x}_j, |N_j|)} - \vec{x}_i \tag{8}$$

$$\vec{a}_i^{\mathrm{av}} = \sum_{j \in N_i^{\mathrm{av}}} \frac{\vec{x}_j - \vec{x}_i}{|\vec{x}_j - \vec{x}_i|} \tag{9}$$

$$\vec{a}_i = \frac{c_g}{|\vec{a_i^g}|} \vec{a_i^g} + \frac{c_{\mathrm{av}}}{|\vec{a_i^{\mathrm{av}}}|} \vec{a_i^{\mathrm{av}}} \tag{10}$$

$$\vec{v}_i^{\mathrm{next}} = \vec{V}(\vec{v}_i + \vec{a}_i) \tag{11}$$

$$\vec{V}(\vec{v}) = \min\left(\frac{V_{\max}}{|\vec{v}|}, 1\right) \cdot \vec{v} \tag{12}$$

$$\vec{x}_i^{\mathrm{next}} = \vec{x}_i + \vec{v}_i^{\mathrm{next}} \tag{13}$$

5) Termination

If the termination condition is satisfied, the program is terminated. Otherwise, return to 2).

4 Simulation

We conducted three experiments based on simulation to observe the differences in behavior of agents under the various parameters and to confirm that agents could exhibit phase transition between swarm behavior and territorial behavior depending on the value of discount strength d.

Common values for the simulation parameters are set as listed in Table 1.

Table 1: The parameters of the simulations.

parameter	description	typical values
total number of agents	N	200
maximum speed	$V_{\max}$	0.05
radius of local recognition	R	2.0
radius of avoiding	R_{av}	0.2
weighting factor	w	100000
strength to the center of mass	c_g	5
strength of avoiding force	c_{av}	10
search range		$[-5.12, 5.12]^2$
number of steps		10000

A: Swarm Behavior and Characteristic of Optimization

The first experiment was executed under $d = 0$ (i.e. the gain of each agent does not depend on the surrounding population), to observe the agents exhibiting swarm behavior for the parameter $R = 1.0, 1.5, 2.0$, respectively.

We used four test functions listed in Table 2 used by Shi and Eberhart [13] for benchmarks.

Table 2: Characteristics of the test functions

function	fomula
Sphere	$f_1(\vec{x}) = x_1^2 + x_2^2$
Rosenbrock	$f_2(\vec{x}) = 100(x_2 - x_1^2)^2 + (x_1 - 1)^2$
Rastrigin	$f_3(\vec{x}) = x_1^2 + x_2^2 - 10(\cos 2\pi x_1 + \cos 2\pi x_2) + 20$
Ackley	$f_4(\vec{x}) = 20 + e - 20e^{-0.2\sqrt{\frac{1}{2}(x_1^2+x_2^2)}} - e^{\frac{1}{2}(\cos 2\pi x_1 + \cos 2\pi x_2)}$

function	modality	global minimum
Sphere	uni-modal	$f_1(0,0) = 0$
Rosenbrock	uni-modal	$f_2(1,1) = 0$
Rastrigin	multi-modal	$f_3(0,0) = 0$
Ackley	multi-modal	$f_4(0,0) = 0$

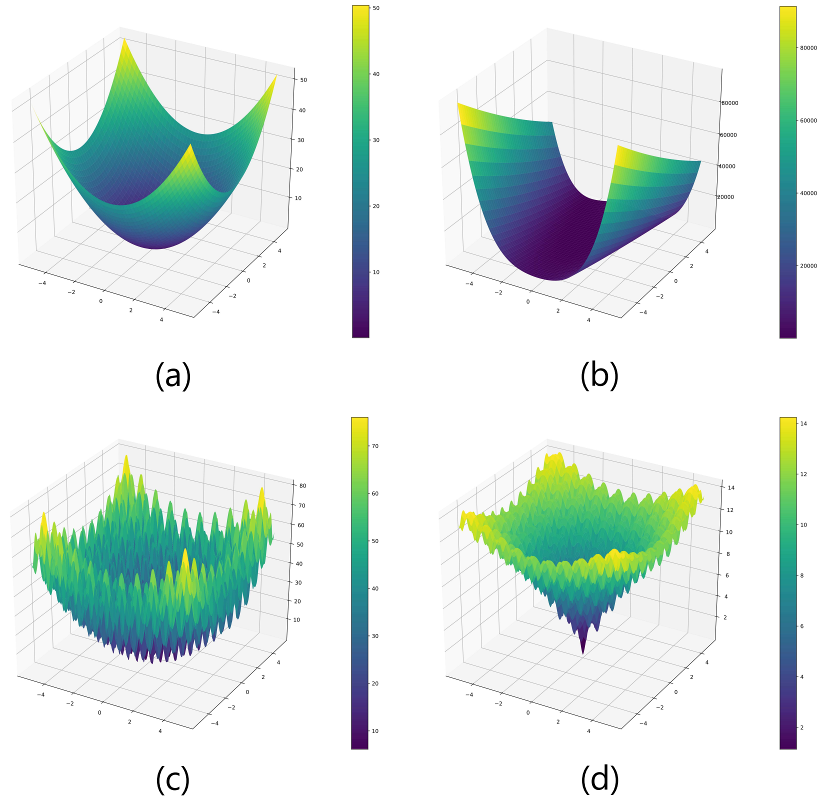


Figure 3: Overview of four test functions. (a) Sphere, (b) Rosenbrock, (c) Rastrigin, (d) Ackley

B: Territorial behavior and Characteristic of Space Partition

The second experiment was executed under $d > 0$ (i.e. the gain of each agent depends on the surrounding population) to observe the agents exhibiting territorial behavior. To simplify, we used the sphere function f_1 for the search space. We conducted three simulations as below.

B-1: The Characteristic under Change of d

First, the simulation was executed under the discount strength $d = 5, 10, 15, 20, 50$, respectively.

B-2: The Characteristic under Change of R

Second, the simulation was executed under each of the recognition range as $R = 5, 10, 15, 20, 50$ while keeping $d = 5$, respectively.

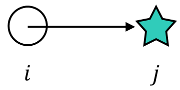


Figure 4: Directed edge between agents. Round represents agent and star represents representative agent

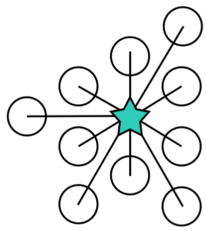


Figure 5: Topology of a cluster. One 'best' agent is in the center of each cluster

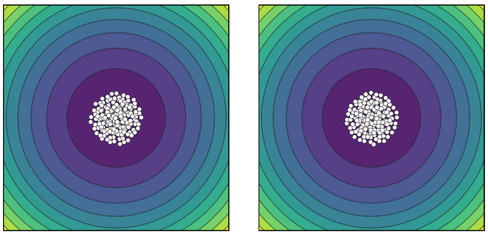
B-3: Topology of the Clusters

Third, the topology of the clusters in B-1. was visualized as follows: for each agent i, the agent which had the highest evaluation value $eval(\vec{x}_j, |N_j|)$, which was called the 'best' agent, was selected in itself and its neighbors $j \in N_i$, and each agent and its 'best' are connected by a directed edge as shown Figure 4.

C : Phase Transition between Swarm Behavior and Territorial Behavior

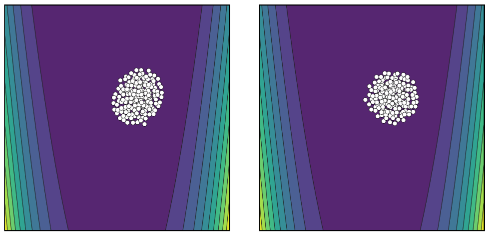
In the third experiment, d was changed in the interval $[0, 20]$ with the step size of 0.25, while in the interval $[1, 2]$ the step size is 0.1, to confirm that agents could exhibit phase transition between swarm behavior and territorial behavior.

From the result of B-3, it was empirically confirmed that the each cluster had topology as shown in Figure 5, which had the structure consisted of one 'best' and some other agents. We defined the number of clusters as the number of 'best' agents.



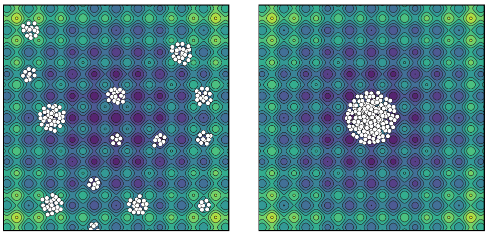
(a) $R = 1.0$ (b) $R = 2.0$

Figure 6: Sphere



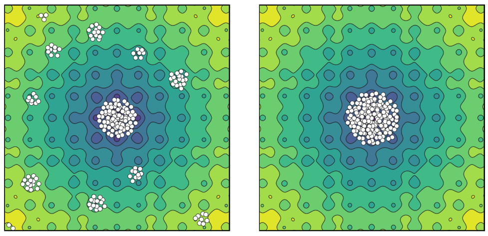
(a) $R = 1.0$ (b) $R = 2.0$

Figure 7: Rosenbrock



(a) $R = 1.0$ (b) $R = 2.0$

Figure 8: Rastrigin



(a) $R = 1.0$ (b) $R = 2.0$

Figure 9: Ackley

5 Results and Discussion

A: Optimization Characteristics of Swarm Behavior

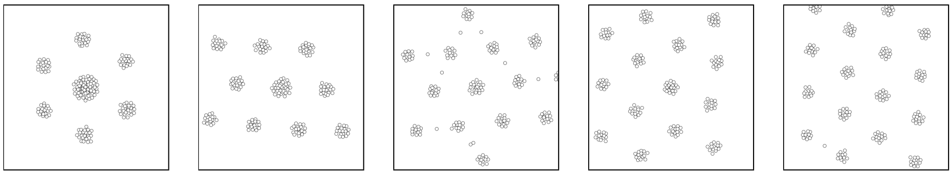
Figure 6, 7, 8 and 9 show the final states of agents in the cases of $R = 1.0, 2.0$ in simulation A using Sphere, Rosenbrock, Rastrigin and Ackley, respectively.

In all the cases of uni-modal functions (Figure 6 and 7), the agents found the global optimum solution. In the cases of multi-modal functions (Figure 8 and 9), however, the agents stuck to a local optimal solution when the R value was small. This is because they could not recognize an agent which had a higher gain.

B: Territorial behavior and Characteristic of Space Partition

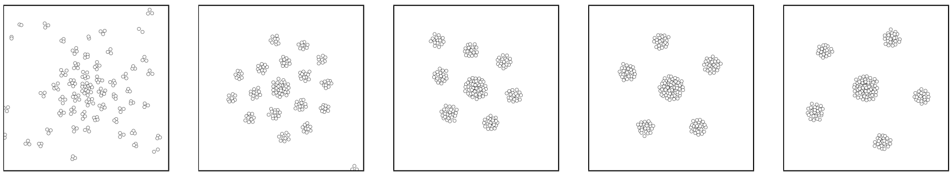
B-1: The Characteristic under Change of d

Figure 10 is the steady-state agents in the cases in a certain trial of simulation B-1.



(a) $R = 5$ (b) $R = 10$ (c) $R = 15$ (d) $R = 20$ (e) $R = 50$

Figure 10: Area partition characteristics by discount strength d



(a) $R = 5$ (b) $R = 10$ (c) $R = 15$ (d) $R = 20$ (e) $R = 50$

Figure 11: Area partition characteristics by recognition range R

It shows the characteristic of area partition, and the larger the discount strength d was, the more clusters were created.

The agents formed multiple clusters around the global optimal solution, each of which boundary of the area was polygon-like. This is similar to some animals' territory patterns in nature [2].

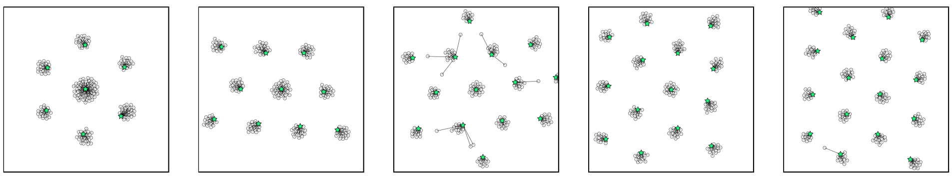
B-2: The Characteristic under Change of R

Figure 11 is the steady-state agents in the cases in a certain trial of simulation B-2.

It shows the larger recognition ranges R of the agents were, the larger gaps between clusters were.

B-3: Topology of the Clusters

Figure 12 is topology of the clusters of the result of simulation B-1.



(a) (b) (c) (d) (e)

Figure 12: clusters topology of the simulation A result (Figure 10))

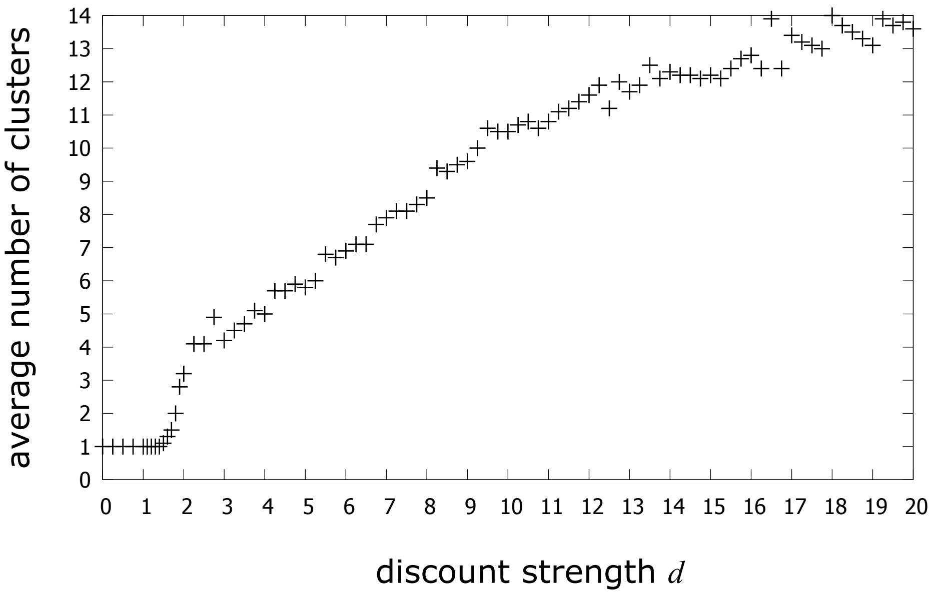


Figure 13: Phase transition between swarm behavior and territorial behavior

We observe that each cluster has one best agent, which is represented as a colored star in the figures. In addition, it is confirmed that the network in the cluster has a structure in which all agents in the cluster hang from one representative agent. Thus, we can assume that each generated cluster has a star topology of which the best agent is at the center.

C : Phase Transition between Swarm Behavior and Territorial Behavior

Figure 13 is the result of simulation C.

The agents exhibited swarm behavior which formed a single cluster with d in $[0, 1.5]$, while territorial behavior which partition the area with d larger than 1.5. Thus, we can assume that this is phase transition for which the threshold is $d_0 = 1.5$.

6 Concluding remarks

This paper proposes a new self-propelled particles model in which agents can transit between swarm behavior and territorial behavior according to a parameter depending on the population surrounding each of them. The model is a combination of swarm behavior and territorial behavior, or in other words, augmentation of a swarm behavior model to include territorial behavior as well.

The results are summarized as below:

(1) If a discount strength for the gain of each agent is larger than a threshold, agents exhibit territorial behavior to partition the search space, otherwise they exhibit swarm behavior to optimize in the search space.

(2) Under gradual change of the discount strength, we observe phase transition between swarm behavior and territory behavior.

We have already obtained some preliminary, yet promising results in applying this model to dynamic network optimization. Future study includes:

(1) To improve the optimization ability of the swarm behavior in this model.

(2) To modify the territorial behavior in this model toward application to coverage control algorithms, and to analyze what kind of evaluation function is optimized by the territorial behavior in this model.

(3) To explore possible applications of the phase transition characteristic between concentration and distribution (e.g. load balancing or routing control in the field of computer networks).

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