Self-Organization for Multi-Agent Groups

Dong Hun Kim

Abstract: This paper presents a framework for the self-organization of swarm systems based on coupled nonlinear oscillators (CNOs). In this scheme, multiple agents in a swarm self-organize to flock and arrange themselves as a group using CNOs, which are able to keep a certain distance by the attractive and repulsive forces among different agents. A theoretical approach of flocking behavior by CNOs and a design guideline of CNO parameters are proposed. Finally, the formation scenario for cooperative multi-agent groups is investigated to demonstrate group behaviors such as aggregation, migration, homing and so on. The task for each group in this scenario is to perform a series of processes such as gathering into a whole group or splitting into two groups, and then to return to the base while avoiding collision with agents in different groups and maintaining the formation of each group.

Keywords: Coupled oscillators, formation, self-organization, swarm system.

1. INTRODUCTION

The field of cooperative mobile agents or robots offers an incredibly rich application domain, integrating a huge number of fields that are distinct from the social sciences and engineering. That so many theories have been brought to bear on "cooperative robotics" clearly shows the energy and allure of the field. Yet, cooperative robotics is still an emerging area with open directions. It is generally believed that proper organization of swarms of cooperating mobile agents provides significant benefits over single unit approaches for various missions. For specific tasks, cooperating agents do not need to be sophisticated or expensive to compete with their advanced independent counterparts. In addition, the integrated multi-agent systems facilitate increased mobility, survivability, sensor coverage and information flows.

A swarm is a distributed system with a large number of autonomous agents [1]. In [2], many simple agents occupied one or two dimensional environments and were able to perform tasks such as pattern generation and self-organization. Self-organization in a swarm is the ability to distribute itself "optimally" for a given task, e.g., via geometric pattern formation or structural organization. The mechanisms for self-organization in swarms are studied in [1,3].

Multi-agent systems are becoming more and more significant throughout industrial, commercial and scientific applications [4,5]. The number of agents currently being used in industrial projects is rapidly increasing. The rate of scientific and industrial development has made way for the use of robots in many fields [9]. Numerous solutions to problems including path planning [20], obstacle avoidance [21] and target-following [18,19] have been proposed and tested. However, the increased cost for each unit and the complications accompanying the escalating number of group members are the two major factors limiting those system-theoretic efforts.

Some research has been performed to investigate flocking by autonomous mobile agents [16,17]. [16] presented a simple flocking task and described a leaderless distributed flocking algorithm. However, off-line optimization is required to optimize the leaderless performance. [12] and [13] show that simple behaviors like avoidance, aggregation and dispersion can be combined to create an emergent flocking behavior. Other recent related papers on formation control include [14] and [15]. [15] simulates robots in a line-abreast formation navigating past way points to a final destination. Using the terminology introduced in this article, agents utilize a leader-referenced line formation. Although several attempts have been made to study various groups of formations or behaviors, there exists no developed study on the formation and migration among multi-agent groups. On the other hand, over the past few years much attention has been attracted to the behavior-based reactive systems [22]. Behavior-based intelligences are motivated by natural species and can show great adaptability and robustness to the time-

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Dong Hun Kim is with the School of Information Science and Technology, the University of Tokyo, 7-3-1 Hongo, Bunkyo-ku, Tokyo 113-8656, JAPAN (e-mail: dhkim@axis.t.u-tokyo.ac.kr).

varying environment with relatively simple algorithms, as well as correspondingly low computation costs during real-time operations [6].

Recent research results indicate that a variety of nonlinear systems can exhibit self-organization, reactive behavior to external stimulus and pattern formation [7,8]. More specifically, CNOs have been extensively studied for their simplicity to implement and exhibit a wide variety of novel and complex spatiotemporal behaviors. In [10], it was reported that by using a nonlinear oscillator scheme a sequence of basic behavior such as random walking, obstacle avoidance and light following could be coordinated in a single robot to achieve more complicated behavior. However, these behavior-based computational organizations lack insightful comprehension to the problems and sometimes exhibit unpredicted and undesirable performances. They require a great deal of time to be trained for selection of proper parameter values in different working environments [10]. These schemes should be combined in a certain trade-off and might be employed at various levels of different scenarios for a future hierarchically architectural and multi-strategy adaptive intelligent system consisting of a swarm of inhomogeneous mobile agents.

In this paper, a self-organized scheme based on CNOs for a swarm agent system is proposed and explored. This scheme shows that mobile agents flock using attractive force, and arrange using both attractive and repulsive force. As well, swarm behavior ensures safe separation between swarm members while enforcing the level of cohesion. The purpose of this study is to determine the theoretical approach of flocking behavior by CNOs for multi-agent groups and to propose design guidelines of CNOs parameters. In addition, it is specifically to obtain global behaviors with flexibility and scalability by using simple local individual rules. This scheme, aided by the relative distance of the nearest agent in the same group, does not require that each agent is aware of the distance from the farther agent in the same group. Moreover it is extended to introduce self-organization in multi groups unlike previous studies dealing with self-organization in a single group.

2. THE PROPOSED ALGORITHM

In this section, a self-organized swarm system controlled by CNOs is presented for the group formation. The method for group migration is also described and the virtual zone is developed to avoid conflict between agents.

2.1. The swarm model

Suppose the point mass model in which the individuals move based on Newton's law $m_{ij}a_{ij} = F_{ij}$ where subscripts i and j are defined as the i th group and the j th agent respectively, and m_{ij}, a_{ij}, and F_{ij} are the mass and acceleration of the agent and the force acting to cause the agent's acceleration respectively. This gives rise to the system of motion equations

$$\begin{aligned} \dot{\mathbf{y}}_{ij} &= \mathbf{v}_{ij}, \\ m_{ij}\dot{\mathbf{v}}_{ij} &= u_{ij}, \end{aligned} \tag{1}$$

where $\mathbf{y}_{ij}$ is the position of the j th agent in the i th group, and $u_{ij} = F_{ij}$ is total force acting on the individual agent. Now, suppose there is a velocity damping term of the form $-k_v\mathbf{v}_{ij}$ in u_{ij}, where $k_v > 0$. In other words, assume that we have

$$u_{ij} = -k_v\mathbf{v}_{ij} + \bar{u}_{ij}. \tag{2}$$

Now, note that for organisms such as bacteria we have m_{ij}, which is very small (i.e., we have $m_{ij} \approx 0$) and the viscosity of the environment for them is high. Therefore, we can take $m_{ij} = 0$. Substituting this in the above system of equations we obtain

$$\dot{\mathbf{y}}_{ij} = \frac{1}{k_{ij}}\bar{u}_{ij}. \tag{3}$$

If we consider with $k_v = 1$ and $\bar{u}_{ij} = -\nabla U_{ij}$, we have the equation of motion of each individual i described by

$$\dot{\mathbf{y}}_{ij} = -\nabla U_{ij}, \tag{4}$$

where U is the artificial potential energy in the system and is given by Section 2.

For a planar formation on multiple vehicles, similar dynamics are used in [11]. Note that the controller $\bar{u}_{ij}$ is an energy minimization controller of the form $\bar{u}_{ij} = -\nabla U_{ij}$. Therefore, each of the individuals in the swarm moves in such a way as to minimize the total artificial potential energy in the system.

The agent model is based on the premise that in the near future technology will allow the production and deployment of large-scale masses of agents. The agents will be small. They will likely possess only basic capabilities and mission specific sensors. Direct communication between agents may or may not exist. The environment model is very "object-oriented" in its approach to agent construction. Sensors and behaviors are encapsulated when possible. This approach allows individual components to be added and removed from the model as if the corresponding physical component were being added to or removed from an actual agent. We restrict the workspace to two-dimensional space. The robot moves in $[xy]$ plane. The proposed method could also be extended to a more complex three-dimensional space later on.

One drawback of the model here is that each individual needs to be aware of the nearest agent in the group. In biological swarms, often each individual can only see (or sense) the individuals in its neighborhood because the ranges of their senses are limited. Therefore, in nature the attraction depends only on the individuals that it can sense. Therefore, the final behavior of the swarms described here may not be in perfect harmony with actual biological swarms. Moreover, in engineering applications the sensing limitations of the agents can be overcome with technologies such as GPS (Global Positioning System). The proposed swarm model can be thought of as a group of agents that know the position of the nearest agent and the position of a target. Nevertheless, the analysis here is first to apply CNOs and deal with theoretical treatments of the stability for self-organization of swarms.

The formation and maintenance of coherent group movement has long been studied in natural systems, and more recently efforts have been made to reproduce this type of behavior in artificial systems. The first such work appeared in the context of computer animation, and since then this behavior has been extensively studied in simulation [24]. It has successfully synthesized bird behaviors such as collision avoidance, velocity matching and flock centering. To avoid collision with other birds and obstacles, birds use the steer-to-avoid rule. However, theoretical treatments or analysis of flocking behavior have not been presented. Such a model is only used as a computer model of coordinated animal motion such as bird flocks and fish schools for simulating visually satisfying flocking and schooling behaviors for the animation industry. The model was based on three dimensional computational geometry of the sort normally used in computer animation or computer aided design. As such, the generic simulated flocking creatures became known as boids. Other experiments by the same author [24] have been conducted by evolving groups of artificial creatures. [30] evolved the control system of a group of creatures placed in an environment with static obstacles and a manually programmed predator for the ability to avoid obstacles and predation. Despite the fact that the results described in the paper are rather preliminary, some evidences indicate that coordinated motion strategies were beginning to emerge. The problem is how to get the developed boid system to satisfy the theoretical analysis of flocking behavior. In the next Section, a *self-organized* swarm system based on CNOs is

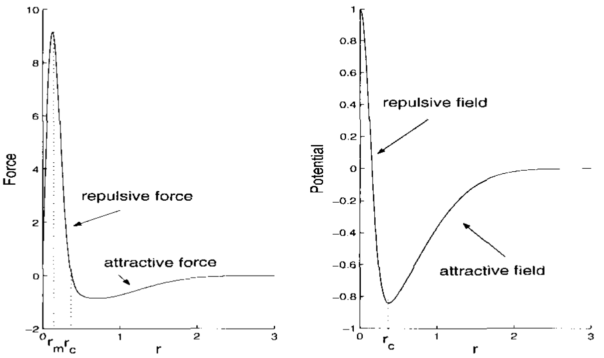


Fig. 1. The force and potential between two agents.

proposed and explored.

2.2. To maintain the group formation

Artificial potential methods have been previously used for obstacle-avoidance path planning [25-27]. In the last decade, they have been extended to group behaviors such as swarming and aggregation of autonomous mobile agents. However, most of the previous studies deal with multiple agents that belong to only one group, not multiple groups. In this study, the interaction of group behaviors in multi groups are dealt with and the virtual zone is proposed to avoid conflict among the agents of different groups. Previous studies have used artificial potential functions within restricted relative distance among agents [28,29] because their corresponding attractive force also increases as the relative distance increases. For this reason, saturated maximal attractive force or restricted distance in implementation was needed.

The CNO that has simple interaction potential operates among the self-organization agents to keep the group formation. It is modeled as follows.

$$U_{ij} = c_{ir} e^{(-\|\mathbf{y}_{ij} - \bar{\mathbf{y}}_{ij}\|^2 / l_{ir})} - c_{ia} e^{(-\|\mathbf{y}_{ij} - \bar{\mathbf{y}}_{ij}\|^2 / l_{ia})}, \quad (5)$$

where c_{ia}, c_{ir}, l_{ia}, and l_{ir} are the strengths and correlation distances of the attractive and repulsive force respectively, and $\bar{\mathbf{y}}_{ij}$ is the position of the nearest agent from the j th agent in the i th group. From (5) we obtain corresponding force

$$\begin{aligned} F_{ij} = -\nabla U_{ij} &= 2\frac{c_{ir}}{l_{ir}} e^{(-\|\mathbf{y}_{ij} - \bar{\mathbf{y}}_{ij}\|^2 / l_{ir})} (\mathbf{y}_{ij} - \bar{\mathbf{y}}_{ij}) \\ &\quad -2\frac{c_{ia}}{l_{ia}} e^{(-\|\mathbf{y}_{ij} - \bar{\mathbf{y}}_{ij}\|^2 / l_{ia})} (\mathbf{y}_{ij} - \bar{\mathbf{y}}_{ij}). \end{aligned} \quad (6)$$

Fig. 1 shows the attractive and repulsive force between two agents where $r = \|\mathbf{y}_{ij} - \bar{\mathbf{y}}_{ij}\|$, $r_c = \sqrt{\frac{l_{ir} l_{ia}}{l_{ia} - l_{ir}} \ln \frac{c_{ir} l_{ia}}{c_{ia} l_{ir}}}$, and ∇U_{ij} and U_{ij} signify the force and potential, respectively. r_c is the minimum distance in order to maintain a distance between two agents.

Each time, the individual agent evaluates its potential profile and decides its force using the gradient descent method. Attraction is modeled by an attractive field, which draws the charged agent towards the nearest agent. The agent simply moves downhill in the direction provided by the local field gradient in Fig. 1. Then it maintains constant distance r_c by a repulsive field.

Remark 1: The following issue may be raised. The attractive force in Fig. 1 decreases as the distance increases over a particular range of distance. Also, the repulsive force decreases as the distance decreases under a particular range of distance. In the proposed CNO scheme, in order to control the relative distance between two agents, there should be a negative sign for attractive force and a positive sign for repulsive force, respectively. Thus, unless attractive force converges to zero as relative distance increases, its potential function based on the gradient decent method is not constituted. For this reason, it is not possible for the entire region to increase the attractive force as the distance increases, in terms of the configuration of a potential function. Such a behavior based on CNOs could be a drawback. However, from a biological aspect, the behavior of the agent to move slowly over a long relative distance and the behavior of the agent to move quickly over a short relative distance, when the relative distance is longer than r_c, corresponds to the swarming process of collective behavior in nature. When it comes to the decreasing repulsive force under a particular distance range, because it is applicable to the agents initially positioned at less than the relative distance r_m between two agents, it is not an important issue. Also, small l_{ir} can be used to reduce the region of decreasing repulsive force.

Now let us analyze swarm cohesion and investigate how to set the design guidelines of their scaling factors in CNOs satisfying such a swarm behavior, based on Lyapunov stability.

Theorem 1: For formation force (6), $\mathbf{y}_{ij}(t) \to \mathbf{B}_\varepsilon(\mathbf{y}_{ij}^c)$ as $t \to \infty$, where

$$\mathbf{B}_\varepsilon(\mathbf{y}_{ij}^c(t)) = \{\mathbf{y}_{ij} : \| \mathbf{y}_{ij} - \mathbf{y}_{ij}^c \| \le \frac{1}{2} r_c\} \tag{7}$$

and the center of two agents is defined as $\mathbf{y}_{ij}^c = \frac{1}{2}(\mathbf{y}_{ij} + \overline{\mathbf{y}}_{ij})$.

Proof: We define the distance between $\mathbf{y}_{ij}$ and $\mathbf{y}_{ij}^c$ as $\mathbf{e}_{ij} = \mathbf{y}_{ij} - \mathbf{y}_{ij}^c$. From the definition of the center of two agents, we have $\mathbf{y}_{ij} + \overline{\mathbf{y}}_{ij} = 2\mathbf{y}_{ij}^c$. Subtracting from both sides $2\mathbf{y}_{ij}$ we obtain

$$(\mathbf{y}_{ij} - \overline{\mathbf{y}}_{ij}) = 2(\mathbf{y}_{ij} - \mathbf{y}_{ij}^c) = 2\mathbf{e}_{ij}. \tag{8}$$

The error equation can be written as

$$\begin{aligned}\dot{\mathbf{e}}_{ij} &= -\nabla U_{ij} + \frac{1}{2}\sum_{j=1}^{2} \nabla U_{ij} = -\nabla U_{ij} \\ &= 2\frac{c_{ir}}{l_{ir}} e^{(-\|\mathbf{y}_{ij} - \overline{\mathbf{y}}_{ij}\|^2 / l_{ir})} (\mathbf{y}_{ij} - \overline{\mathbf{y}}_{ij}) \\ &\quad -2\frac{c_{ia}}{l_{ia}} e^{(-\|\mathbf{y}_{ij} - \overline{\mathbf{y}}_{ij}\|^2 / l_{ia})} (\mathbf{y}_{ij} - \overline{\mathbf{y}}_{ij}) \\ &= 4\frac{c_{ir}}{l_{ir}} e^{(-4\|\mathbf{e}_{ij}\|^2 / l_{ir})} \mathbf{e}_{ij} - 4\frac{c_{ia}}{l_{ia}} e^{(-4\|\mathbf{e}_{ij}\|^2 / l_{ia})} \mathbf{e}_{ij}\end{aligned} \tag{9}$$

since we obtain $\frac{1}{2}\sum_{j=1}^{2} \nabla U_{ij} = 0$ which follows from the fact that

$$2\frac{c_{ir}}{l_{ir}} e^{(-\|\mathbf{y}_{ij} - \overline{\mathbf{y}}_{ij}\|^2 / l_{ir})} (\mathbf{y}_{ij} - \overline{\mathbf{y}}_{ij}) - 2\frac{c_{ia}}{l_{ia}} e^{(-\|\mathbf{y}_{ij} - \overline{\mathbf{y}}_{ij}\|^2 / l_{ia})} (\mathbf{y}_{ij} - \overline{\mathbf{y}}_{ij}) + 2\frac{c_{ir}}{l_{ir}} e^{(-\|\mathbf{y}_{ij} - \overline{\mathbf{y}}_{ij}\|^2 / l_{ir})} (\overline{\mathbf{y}}_{ij} - \mathbf{y}_{ij}) - 2\frac{c_{ia}}{l_{ia}} e^{(-\|\mathbf{y}_{ij} - \overline{\mathbf{y}}_{ij}\|^2 / l_{ia})} (\overline{\mathbf{y}}_{ij} - \mathbf{y}_{ij}) = 0.$$

Defining a Lyapunov function as $V_{ij} = \| \mathbf{e}_{ij} \|^2 / 2 = \mathbf{e}_{ij}^T \mathbf{e}_{ij} / 2$ and using (9), we obtain

$$\dot{V}_{ij} \le -4 \| \mathbf{e}_{ij} \|^2 \left[\frac{c_{ia}}{l_{ia}} e^{(-4\|\mathbf{e}_{ij}\|^2 / l_{ia})} - \frac{c_{ir}}{l_{ir}} e^{(-4\|\mathbf{e}_{ij}\|^2 / l_{ir})}\right]. \tag{10}$$

For the right-side to be negative definite, $\frac{c_{ia}}{l_{ia}} e^{(-4\|\mathbf{e}_{ij}\|^2 / l_{ia})} > \frac{c_{ir}}{l_{ir}} e^{(-4\|\mathbf{e}_{ij}\|^2 / l_{ir})}$. Using the natural logarithm function $4\| \mathbf{e}_{ij} \|^2 > \frac{l_{ir} l_{ia}}{l_{ia} - l_{ir}} \ln(\frac{c_{ir} l_{ia}}{c_{ia} l_{ir}})$ gives

$$\| \mathbf{e}_{ij} \| > \frac{1}{2}\sqrt{\frac{l_{ir} l_{ia}}{l_{ia} - l_{ir}} \ln(\frac{c_{ir} l_{ia}}{c_{ia} l_{ir}})}, \tag{11}$$

that is, $r > 2\| \mathbf{e}_{ij} \| > r_c$. There exists a constant r_c such that for $r > 2\| \mathbf{e}_{ij} \| > r_c$ we obtain $\dot{V}_i < 0$. Thus, it is guaranteed that in that region $\| \mathbf{e}_{ij} \|$ is decreasing and eventually $\| \mathbf{e}_{ij} \| \le \frac{1}{2} r_c$ is achieved. □

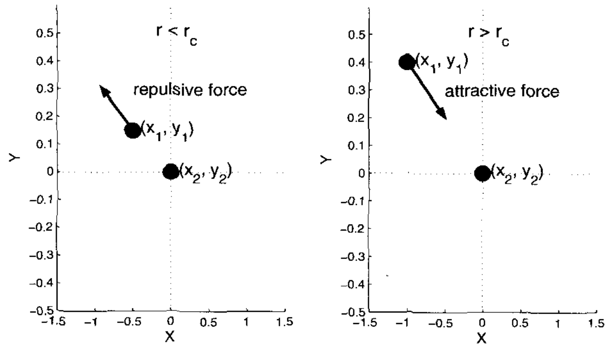


Fig. 2. The repulsive and attractive forces between two agents.

Theorem 2: For $l_{ia} > l_{ir}$ and $(\frac{c_{ir} l_{ia}}{c_{ia} l_{ir}})^{\frac{l_{ir} l_{ia}}{l_{ia} - l_{ir}}} > 1$ in (5), each agent can maintain its distance from the other agents by repulsive and attractive forces.

Proof: 1) Repulsive force

In Fig. 2, we suppose that $\mathbf{y}_{ij}$ and $\bar{\mathbf{y}}_{ij}$ are located in (x_1, y_1) of the top-left plane and (x_2, y_2) of (0,0), respectively. Here (x_2, y_2) is the position of the nearest agent from $\mathbf{y}_{ij}$. If we assume $r < r_c$, (x_1, y_1) of $\mathbf{y}_{ij}$ gets a repulsive force to $-\nabla_x U_{ij} < 0$ and $-\nabla_y U_{ij} > 0$.

Considering x and y separately in (6) gives

$$\begin{aligned}
-\nabla_x U_{ij} &= -2\frac{c_{ia}}{l_{ia}} e^{-(x_1 - x_2)^2 / l_{ia}} (x_1 - x_2) \\
&\quad + 2\frac{c_{ir}}{l_{ir}} e^{-(x_1 - x_2)^2 / l_{ir}} (x_1 - x_2) < 0, \\
-\nabla_y U_{ij} &= -2\frac{c_{ia}}{l_{ia}} e^{-(y_1 - y_2)^2 / l_{ia}} (y_1 - y_2) \\
&\quad + 2\frac{c_{ir}}{l_{ir}} e^{-(y_1 - y_2)^2 / l_{ir}} (y_1 - y_2) > 0.
\end{aligned} \tag{12}$$

$x_1 - x_2 < 0$ and $y_1 - y_2 > 0$ give $\frac{c_{ir}}{l_{ir}} e^{-(x_1 - x_2)^2 / l_{ir}} > \frac{c_{ia}}{l_{ia}} e^{-(x_1 - x_2)^2 / l_{ia}}$ and $\frac{c_{ir}}{l_{ir}} e^{-(y_1 - y_2)^2 / l_{ir}} > \frac{c_{ia}}{l_{ia}} e^{-(y_1 - y_2)^2 / l_{ia}}$, respectively. Using natural logarithm function give $\frac{l_{ir} l_{ia}}{l_{ia} - l_{ir}} \ln(\frac{c_{ir} l_{ia}}{c_{ia} l_{ir}}) > (x_1 - x_2)^2$, $\frac{l_{ir} l_{ia}}{l_{ia} - l_{ir}} \ln(\frac{c_{ir} l_{ia}}{c_{ia} l_{ir}}) > (y_1 - y_2)^2$, respectively. Combining both equations gives

$$\sqrt{\frac{l_{ir} l_{ia}}{l_{ia} - l_{ir}} \ln(\frac{c_{ir} l_{ia}}{c_{ia} l_{ir}})} > \| \mathbf{y}_{ij} - \bar{\mathbf{y}}_{ij} \| \tag{13}$$

, i.e. $r_c > r$. Thus, when $r < r_c$, (x_1, y_1) of $\mathbf{y}_{ij}$ gets the repulsive force between two agents of (x_1, y_1) and (x_2, y_2). Using the identical procedure, it can be proved whether (x_1, y_1) of $\mathbf{y}_{ij}$ is located on the top-right, bottom-left or bottom-right plane.

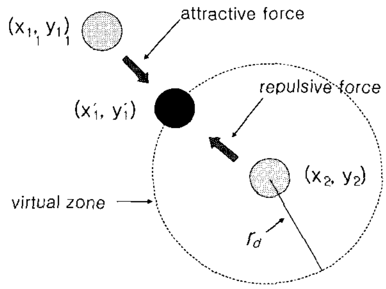


Fig. 3. Virtual zone.

2) Attractive force

If we assume $r > r_c$, (x_1, y_1) of $\mathbf{y}_{ij}$ gets an attractive force to $-\nabla_x U_{ij} > 0$ and $-\nabla_y U_{ij} < 0$. Considering x and y separately gives

$$\begin{aligned}
-\nabla_x U_{ij} &= -2\frac{c_{ia}}{l_{ia}} e^{-(x_1 - x_2)^2 / l_{ia}} (x_1 - x_2) \\
&\quad + 2\frac{c_{ir}}{l_{ir}} e^{-(x_1 - x_2)^2 / l_{ir}} (x_1 - x_2) > 0, \\
-\nabla_y U_{ij} &= -2\frac{c_{ia}}{l_{ia}} e^{-(y_1 - y_2)^2 / l_{ia}} (y_1 - y_2) \\
&\quad + 2\frac{c_{ir}}{l_{ir}} e^{-(y_1 - y_2)^2 / l_{ir}} (y_1 - y_2) < 0.
\end{aligned} \tag{14}$$

$x_1 - x_2 < 0$ and $y_1 - y_2 > 0$ gives $\frac{c_{ir}}{l_{ir}} e^{-(x_1 - x_2)^2 / l_{ir}} < \frac{c_{ia}}{l_{ia}} e^{-(x_1 - x_2)^2 / l_{ia}}$ and $\frac{c_{ir}}{l_{ir}} e^{-(y_1 - y_2)^2 / l_{ir}} < \frac{c_{ia}}{l_{ia}} e^{-(y_1 - y_2)^2 / l_{ia}}$, respectively. Using natural logarithm function gives $\frac{l_{ir} l_{ia}}{l_{ia} - l_{ir}} \ln(\frac{c_{ir} l_{ia}}{c_{ia} l_{ir}}) < (x_1 - x_2)^2$, $\frac{l_{ir} l_{ia}}{l_{ia} - l_{ir}} \ln(\frac{c_{ir} l_{ia}}{c_{ia} l_{ir}}) < (y_1 - y_2)^2$, respectively. Combining both equations gives

$$\sqrt{\frac{l_{ir} l_{ia}}{l_{ia} - l_{ir}} \ln(\frac{c_{ir} l_{ia}}{c_{ia} l_{ir}})} < \| \mathbf{y}_{ij} - \bar{\mathbf{y}}_{ij} \|, \tag{15}$$

that is, $r_c < r$. Thus, when $r < r_c$, (x_1, y_1) of $\mathbf{y}_{ij}$ gets the attractive force between two agents of (x_1, y_1) and (x_2, y_2). Using the identical procedure, in the same manner it can be proved whether (x_1, y_1) of $\mathbf{y}_{ij}$ is located on the top-right, bottom-left or bottom-right plane. □

Thus, if one agent is far from another agent on the basis of r_c, the agent is drawn to another agent by attractive force. On the other hand, if the distance between individual agents is too close on the basis of r_c, they are able to keep a certain distance as a result of repulsive force. Thus, each agent possesses the characteristic of flocking to keep the formation while ensuring safe separation between swarm agents.

The nonlinear paradigm of CNOs allows for smooth transitions between behaviors, giving a high degree of control over robot performance, unlike [28,29] giving unsmooth transition. Moreover it does not need to saturate attractive forces compulsively in the case of a large relative distance, neither does it require restricted relative distance, unlike in quadratic potential functions [28,29]. As for planar functions, their corresponding forces are constants as relative distance increases, signifying the same force for any relative distance and allowing the switching phenomenon near a desired relative distance. As for quadratic functions, their corresponding forces proportionally increase as relative distance increases, which is not practically implementable over the complete relative distance range and also requires saturated attractive forces over a long relative distance.

Remark 2: There is a primary difference between the work of C. Reynolds (boid model) [24] and our work. Reynolds' boid system does not encompass theoretical treatments or the analysis of formation behavior. However, the proposed study shows the theoretical approach of flocking behavior by CNOs, artificial potential functions based on gradient descent method, and also proposes the design guideline of CNO parameters as shown in Section 2.2. As a result, the proposed scheme using CNOs is completely different from that of his work merely illustrating visual simulating motion satisfying a flocking behavior for the animation industry.

2.3. To avoid conflict between agents and to maintain the group migration

The worst-case scenario is that the agent of one group may conflict with the agent of another group. Thus, an additional algorithm is required. The virtual zone is proposed to avoid conflict among the agents of different groups. If one agent located in (x_1, y_1) approaches near enough to conflict with the agent of a different group located in (x_2, y_2), the agent located in (x_1, y_1) keeps its distance r_d as follows

$$x_1' = x_1 + r_d \frac{(x_1 - x_2)}{r_o} - (x_1 - x_2),$$
$$y_1' = y_1 + r_d \frac{(y_1 - y_2)}{r_o} - (y_1 - y_2), \tag{16}$$

where x_1' is the new value of x_1, y_1' is the new value of y_1, r_d is the radius of the virtual zone, i.e., a desired distance between the centers of the two agents, and $r_o = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$.

Fig. 3 illustrates that the agent located in (x_1, y_1) cannot be closer than (x_1', y_1') when it approaches the other agent located in (x_2, y_2). In the next chapter, the worst-case scenario is dealt with.

The behavior of migration in this study is distinct from that of formation control (e.g. [23]), because the goal of migration is simply to achieve and maintain coherent group movement rather than to govern well organized inter-agent position relationships. Also, formation control is not an end in itself, but rather can be used as a component of a multi-agent system, organizing the nodes of a distributed sensing system.

The PD type controller is used for group migration.

$$V_{ij} = K_p \mathbf{e}_{ij}^t + K_d \frac{d\mathbf{e}_{ij}^t}{dt}, \tag{17}$$

where K_p and K_d are the proportional and derivative gains, $\mathbf{e}_{ij}^t = \mathbf{y}_{ij} - \mathbf{y}_i^t$ and $\mathbf{y}_i^t$ is the desired positions of the agents in i th group.

The approach taken for formation does not require a central controller, which is an important characteristic of a self-organizing system. Instead, an assumption is needed that each agent can detect signals from the others. Each agent determines the positions of its peers by direct perception of the other agents. When communication between agents is demanded, the agents transmit their current position in world coordinates.

Remark 3: Note that we are not attempting to solve possible oscillatory or unstable motion of the agents for potential function configuration in narrow passages or in the presence of obstacles. We shall restrict our attention to propose the formulation of CNOs for swarm behavior in single groups and multiple groups, and for the design guideline of their scaling factors in CNOs satisfying such a swarm behavior.

3. FORMATION OF THE SELF-ORGANIZED SWARM USING CNOS

Use of CNOs to keep a formation has a great deal of flexibility. While maintaining the swarm characteristics, the agent can wander about flexibly, i.e. it has a nature of self-organized flocking allowing it to make a formation dynamically without explicit reorganization contrary to [23]. Because the proposed approach does not explicitly use the alignment of other group members, the individual agent is not commanded to be located in a certain position for alignment. Moreover, this approach has a good scalability that adds or removes any number of agents easily. Simulations running this algorithm have provided very satisfactory results. Some of the results are shown in Figs. 4-7. Fig. 4 illustrates flocking at $(0,0)$ when $r_c = 0.3707$. The small dots indicate the initial configuration of agents and the big dots indicate the configuration of the group after $t = 2$. Randomly initialized 30 agents flock by attractive force, and then arrange by attractive and repulsive forces. The standard deviation value for the distance between an agent and centered-agents is 0.2663.

Consider the sample run. Fig. 5 shows that the randomly initialized 7 agents on the left side of the frame immigrate into the right side of the frame. Fig. 6 illustrates agents moving in for a 90^o turn. In Fig. 6, the agents were randomly initialized on the top-left side of the simulation environment, then directed to proceed to the lower center of the frame. After the formation was established, a 90^o turn to the right was initiated. Fig. 6 depicts that each agent moved flexibly without fixed formation. In the existence of a group of obstacles, 25 agents are illustrated in Fig. 7. The agents start on the left side of the field and move to the right around a group of obstacles in the middle of the field. After the formation splits around an obstacle, each agent comes together. This example shows that the proposed algorithm ensures safe separation and good cohesion performance among the agents.

Consider the worst-case scenario in which two groups having 7 agents each move across, i.e., the agents of one group conflict with the agents of the another group. Fig. 8 shows the intersection of the two groups. Two agent groups were randomly initialized on the top-left and bottom-left side of the simulation environment and then directed to proceed to the bottom-right and top- right side of the frame, respectively. Accordingly, they conflict with each other in the middle of the simulation environment. Though each agent maintains a distance against the other agents within its own group by the CNOs, it could potentially conflict with the agents of the other group. In this case, the virtual zone is effective. Fig. 9 is the snap shot of Fig. 8 in the middle of the simulation environment. It shows that all of the agents keep their distance without bumping into one another due to the virtual zone.

4. FORMATION SCENARIO FOR COOPERATIVE MULTI-AGENT GROUPS

The proposed formation scenario for cooperative multi-agent groups shows basic group behaviors such as aggregation, dispersion and migration, and also complex group behaviors such as homing, flocking and arranging. It is supposed that, in this scenario, there are four multi-agent groups in which each group

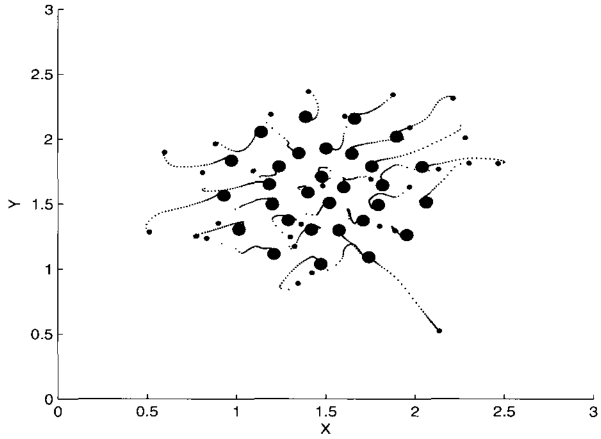


Fig. 4. Flocking when $r_c = 0.3707$.

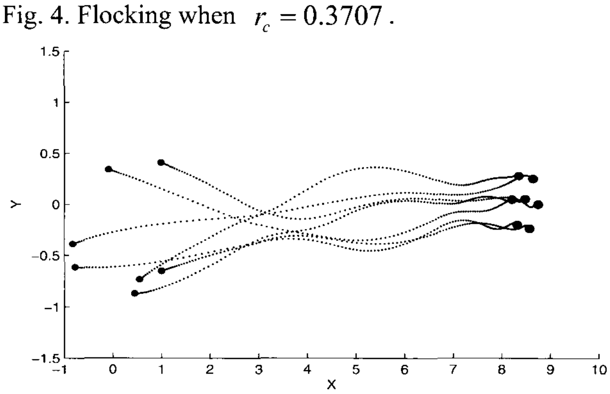


Fig. 5. Following.

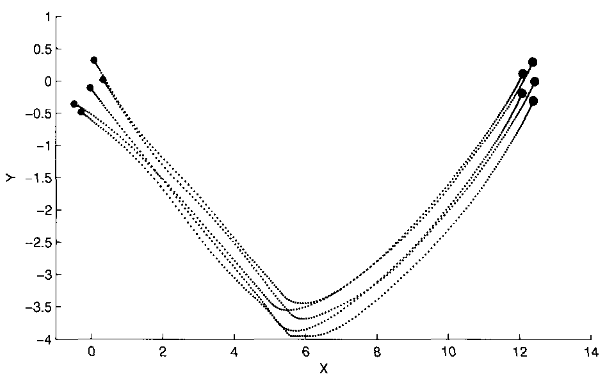


Fig. 6. Following for a 90^o turn.

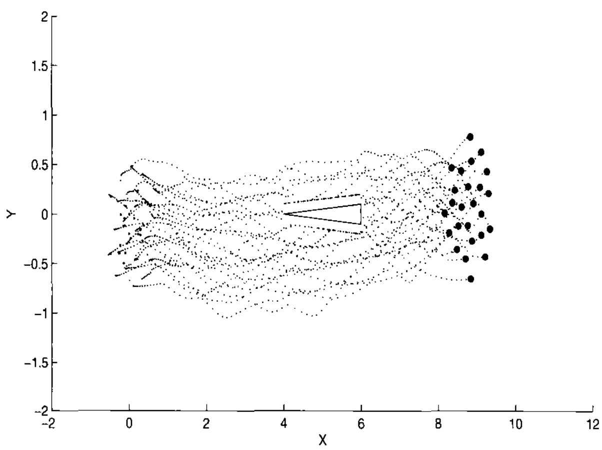


Fig. 7. 25 agents negotiating a group of obstacles in the middle of the field.

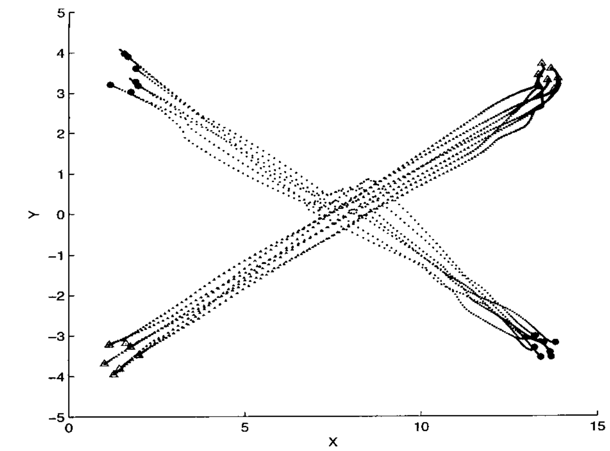


Fig. 8. Intersection of two groups (dot: A group, triangle: B group).

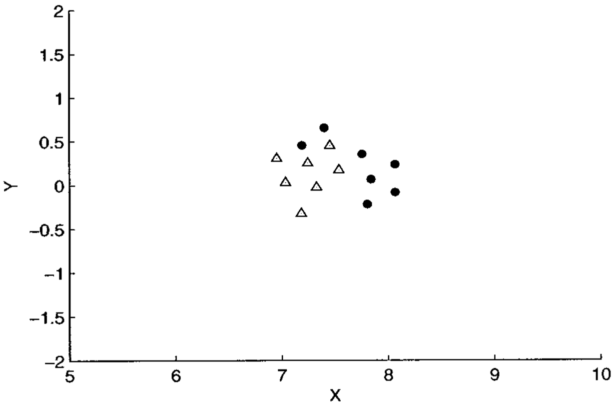


Fig. 9. Snap shot of Fig. 8 (dot: A group, triangle: B group).

is composed of 7 agents. The purpose of this scenario is to obtain the characteristics of aggregation and separation among multi-agent groups intentionally and randomly. Its procedure is presented below.

- Procedure

a. Four multi-agent groups are randomly initialized on the left and center side of the simulation environment. ⇒ Fig. 10(a)

b. Each agent group flocks at a certain point and then arranges into a large group. ⇒ Fig. 10(b)

c. The large group immigrates to the right side. ⇒ Fig. 10(c)

d. The large group is separated into two groups by random selection. ⇒ Fig. 10(d)

e. Each agent is segregated from the two groups in order to return to the base located in the left and center side of the simulation environment. ⇒ Fig. 10(e)

f. Each agent joins together in its original group and then comes together in a group arrangement. ⇒Fig. 10(f)

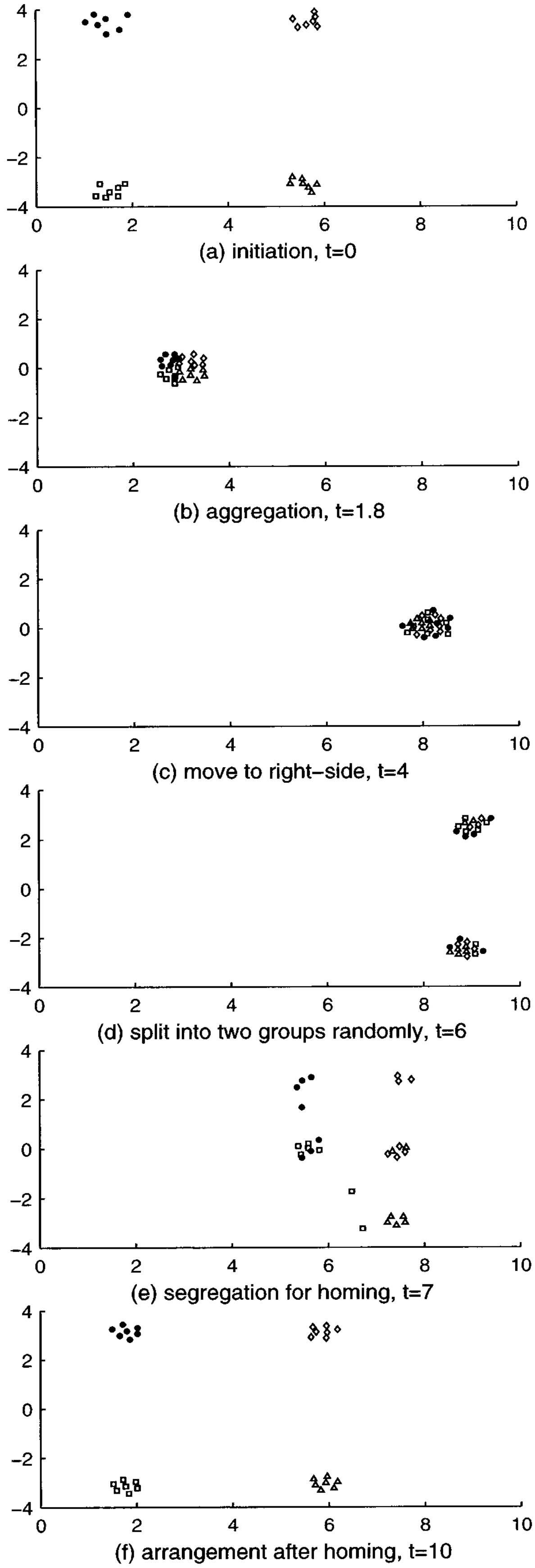


Fig. 10. Formation Scenario for Cooperative Multi-Agent groups.

This mission also includes avoiding collision with other agents and maintaining a formation, typically in the context of a higher-level mission scenario. It is very similar to the group characteristics of birds, i.e. a series of process (flocking, aggregation, migration and homing) [24].

Each agent from every group is physically and functionally identical. Therefore, new agents can be added to the team whenever necessary. The proposed approach is designed for a broad range of tasks, not for a specific task in current multi-agent systems. They can be adapted to various tasks with minimal structural changes. Individually, agents have limited capabilities and limited knowledge of the environment. However, as a swarm, they can exhibit "intelligent behavior". Simple individual behavior will result in an intelligent swarm behavior provided that some type of direct or indirect communication between agents exists. Examples from possible military applications for multiple groups through various maneuvers include swarm bombs or troop agents. In particular, it is highly effective for swarm bombs that have come out of their shell and need to self-organize to the specified region containing its individual group that is different from the region for the other groups in the same bomb.

5. CONCLUSIONS

This paper presents a design framework based on CNOs for multi-agent groups. An analytical approach to self-organization for multi-agents and design guidelines has been proposed and studied. In this scheme, flexible formation based on CNOs and the virtual zone makes each agent in a swarm split against collision with agents of the other groups while migrating, and then allows it to flock to each individual group. Thus, the proposed approach does not require specified formation and each agent is self-organized according to the given environment by flexible and simple formation for an individual group. Global behaviors such as formation and migration among multi-agent groups can be obtained by using the simple local individual interactive rules. The framework is fully scalable for the distributed control that operates independently of the size of the group. As well, initial arrangement for the formation is not required since each agent tries to flock after it is positioned randomly at initial state. The proposed CNO is applicable to the entire relative distance between the agents, without restricting the distance or requiring any compulsively saturated distance. Although self-organization for multi-agent groups in two-dimensional environment has just been studied, the method could be extended to a more general scenario in three-dimensional space. With the proposed concept and system structure, further scenarios including cooperation with group agents and migration in more complicated environments can be additionally studied.

REFERENCES

[1] K. Jin, P. Liang, and G. Beni, "Stability of synchronized distributed control of discrete swarm structures," *Proc. of IEEE Int. Conf. on Robotics and Automation*, pp. 1033-1038, 1994.

[2] G. Beni, "The concept of cellular robotic system," *Proc. of IEEE Int. Symp. on Intelligent Control*, pp. 57-62, 1998.

[3] P. Liang and G. Beni, "Robotic morphogenesis," *Proc. of IEEE Int. Conf. on Robotics and Automation*, pp. 2175-2180, 1995.

[4] C. R. Carignan and D. L. Akin, "Autonomous formation flight," *IEEE Control System Magazine*, vol. 20, no. 6, pp. 34-44, 2000.

[5] D. J. Stilwell and B. E. Bishop, "Platoons of underwater vehicles," *IEEE Control System Magazine*, vol. 20, no.6, pp. 45-52, 2000.

[6] G. T. Anderson and M. R. Clark, "Navigation of autonomous robots with an intelligent Oscillator Controller," *Proc. of the IEEE/ASME Int. Conf. on Advanced Intelligent Mechatronics*, pp. 1003-1007, 1999.

[7] A. Mogilner and L. Edelstin-Keshet, "Spatio-angular order in population of self-aligning objects: Formation of oriented patches," *Physica D*, vol. 89, pp. 346-367, 1996.

[8] H. Levine, W. Rappel, and I. Cohen, "Self-organized in systems of self-propelled particles," *Physical Review E*, vol. 63, 2001.

[9] R. A. Alejandro and P. V. Vicente, "Adaptive control with impedance of cooperative multi-robot system," *Proc. of the IEEE Int. Conf. on Robotics & Automation*, pp. 1522-1527, 1998.

[10] M. R. Clark and G. T. Anderson, "Coupled Oscillator control of autonomous mobile robots," *Autonomous Robots*, no. 9, pp. 189-198, 2000.

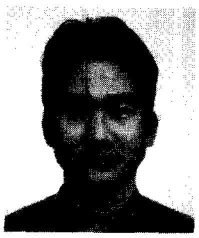
[11] R. Olfati-Saber and R. M. Murray, "Distributed cooperative control of multiple vehicle formations using structural potential functions," *In IFAC World Congress, Barcelona, Spain*, to appear, 2002.

[12] M. J. Mataric, "Designing emergent behaviors: from local interactions to collective intelligence," *Proc. of Int. Conf. Simulation of Adaptive Behavior: From Animals to Animats*, pp. 432-441, 1992.

[13] M. J. Mataric, "Minimizing complexity in controlling a mobile robot population," *Proc. of IEEE Int. Conf. Robot. Automat.*, pp. 830-835, 1992.

[14] T. Balch and R. C. Arkin, "Behavior-based formation control for multi-robot teams," *IEEE Trans. on Robotics and Automation*, pp. 926-939,

1998.
[15] L. E. Parker, "Designing control laws for cooperative agent teams," *Proc. of IEEE Int. Conf. Robot. Automat.*, pp. 582-587, 1993.
[16] A. T. Hayes and P. D. Tabatabaei, "Self-organized flocking with agent failure: off-line optimization and demonstration with real robots," *Proc. of the IEEE int. Conf. on Robotics & Automation*, pp. 3900-3905, 2002.
[17] R. Vaughan, N. Sumpter, J. Henderson, A. Frost and S. Cameron, "Robot control of animal flocks," *Proc. of the IEEE ISIC/CIRA/ISAS Joint Conference*, pp. 277-282, 1998.
[18] L. E. Parker, "Cooperative robotics for multi-target observation," *Intelligent Automation and Soft Computing, special issue on Robotics Research at Oak Ridge National Laboratory*, vol. 5, no. 1, pp. 5-19, 1999.
[19] B. B. Werger and M. J. Mataric, "Broadcast of local eligibility for multi-target observation," *Proc. on Distributed Autonomous Robotic Systems*, 2000.
[20] Y. Zhong, J. Liang, G. Guochang, R. Zhang, and H. Yang, "An implementation of evolutionary computation for path planning of cooperative mobile robots," *Proc. on Intelligent Control and Automation*, 2002.
[21] K. Macek, I. Petrovic, and N. Peric, "A reinforcement learning approach to obstacle avoidance of mobile robots," *Int. Workshop on Advanced Motion Control*, pp. 462 -466, 2002.
[22] S. Nolfi and D. Floreano, *Evolutionary Robotics*, The MIT Press, 2000.
[23] T. Balch and M. Hybinette, "Behavior-based coordination of large-scale robot formations," *Proc. of Fourth Int. Conf. on Multi Agent Systems*, pp. 363-364, 2000.
[24] C. W. Reynolds, "Flocks, herds and schools: a distributed behavioral model," *Computer Graphics*, vol. 21, no. 4, pp. 25-34, 1987.
[25] S. S. Ge and Y. J. Cui, "New potential functions for mobile robot path planning," *IEEE Trans. on Robotics and Automation*, vol. 16, no. 5, pp. 615-620, 2000.
[26] V. Prahlad, C. Kay, and M. Wang, "Evolutionary artificial potential fields and their application in real time robot path planning," *Congress of Evolutionary Computation*, San Diego, California, pp. 256-263, 2000.
[27] E. Rimon and D. E. Koditschek, "Exact robot navigation using artificial potential functions," *IEEE Trans. on Robotics and Automation*, vol. 8, no. 5, pp. 501-518, 1992.
[28] C. Unsal and J. S. Bay, "Spatial self-organization in large populations of mobile robots," *IEEE International Symposium on Intelligent Control*, Columbus, Ohio, pp. 249-254, August 1994.
[29] J. S. Baras, X. Tan, and P. Hovareshti, "Decentralized control of autonomous vehicles," *Prof. of 42nd IEEE Conference on Decision and Control*, Maui, Hawaii, CD-ROM, 2003.
[30] C. W. Reynolds, "An evolved vision-based behavioral model of coordinated group motion," In Jean-Arcady Meyer, Herbert L. Roiblat, and Stewart Wilson, editors, *From Animals to Animals 2*, MIT Press, pp. 384-392, 1992.



Dong Hun Kim received his B.S., M.S., and Ph.D. degrees from the Department of Electrical Engineering, Hanyang University, Korea, in 1995, 1997, and 2001, respectively. From 2001 to 2003, he was a Research Associate under several grants in the Department of Electrical and Computer Engineering at Duke University, NC, USA. He was a Visiting Assistant Professor under several grants in the Department of Aerospace and Mechanical Engineering at Boston University, MA, USA in 2003. He is currently engaged in post-doctoral research at the School of Information Science and Technology, the University of Tokyo, Japan. His research interests include self-organization of swarm systems, mobile robot path planning, decentralized control of autonomous vehicles, intelligent control, and adaptive nonlinear control.