Self-organization of Swarm Systems by Association

Dong Hun Kim

Abstract: This paper presents a framework for decentralized control of self-organizing swarm systems based on the artificial potential functions (APFs). The framework explores the benefits by associating agents based on position information to realize complex swarming behaviors. A key development is the introduction of a set of association rules by APFs that effectively deal with a host of swarming issues such as flexible and agile formation. In this scheme, multiple agents in a swarm self-organize to flock and achieve formation control through attractive and repulsive forces among themselves using APFs. In particular, this paper presents an association rule for swarming that requires less movement for each agent and compact formation among agents. Extensive simulations are presented to illustrate the viability of the proposed framework.

Keywords: Cooperative motion, multi-agents, navigation, path planning.

1. INTRODUCTION

Potential field methods have been studied extensively for the path planning of autonomous mobile robots in the past decade [1-5]. In this method, a robot is modeled as a moving particle inside an artificial potential field that is generated by superposing an attractive potential that pulls the robot to a goal configuration and a repulsive potential that pushes the robot away from obstacles.

Recent years have witnessed a rapidly increasing interest in managing the group behaviors of swarm systems, in particular, the coordinated movement of vehicular swarms, i.e., systems of multiple autonomous and semi-autonomous vehicles. The effort to develop engineered swarms has been inspired by common swarming behaviors in nature such as insects, birds, fish, or mammals. It is envisioned that the outcomes of swarm research can impact a wide variety of applications such as the deployment of unmanned ground and air vehicles for both military and civil missions, satellite formations, and large scale cooperative mobile sensor and device networks, to name a few. Though a large number of techniques have been studied in the literature [6-10], it remains a challenge to offer a general framework that is able to realize various swarm behaviors in complex environments and yet at the same time simple enough for analytical treatment and practical implementation.

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Other recent related papers on formation control include [11-13]. [13] 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. In the studies, a fixed formation is needed to attain their object. On the other hand, the proposed association rules employ a flexible formation for swarming and immigration. Much attention has not been given to a flexible formation for self-organization of swarm systems by association, which is based on local connectivity rather than global. This paper continues the work of [16] and represents a modest attempt to offer a simple and effective framework for coordinating the group behaviors of swarm systems by association.

The control objective is the coordinated movement of a group of agents in the presence of multiple and possibly moving obstacles. There are a number of essential requirements for swarm movement. First, there should be no collision among the agents as well as between agents and obstacles. Secondly, the swarm should move in a formation or flocking mode. Lastly, there may be additional optimality type requirements. In [16], the authors presented a set of analytical guidelines for designing potential functions to avoid local minima for a number of representative scenarios. Specifically the following cases are addressed: 1) a non-reachable goal problem (a case that the potential of the goal is overwhelmed by the potential of an obstacle, 2) an obstacle collision problem (a case that the potential of the obstacle is overwhelmed by the potential of the goal), 3) an obstacle collision problem in swarm (a case that the potential of the obstacle is overwhelmed by the potential of other robots in a group formation), and 4) an inter-robot collision problem (a case that the potential of the robot in a formation is overwhelmed by the potential of the goal).

In this paper, the framework explores the benefits by associating agents based on position information to realize complex swarming behaviors based on the same APFs used in [16]. A key development is the introduction of a set of flocking by APFs that effectively deal with a host of swarming issues such as flexible and agile formation. In this scheme, multiple agents in a swarm self-organize to flock and achieve formation control through attractive and repulsive forces among themselves using APFs. The framework enables agents to maintain a flexible formation, while migrating as a group and avoiding any obstacles. Different from previous studies on swarming strategies [18-23], the purpose of this study is to explore a set of associations among agents for swarming that requires less movement for each agent and compact formation among agents.

This paper is organized as follows. Section 2 discusses the environment and agent model and introduces the problem statement. In Section 3, we present a progressive sequence of scenarios involving designing potential force laws to maintain group migration and formation and avoid obstacles. In Section 4, a set of methods for association among agents to realize swarming behaviors are presented. In Section 5, simulations of group behaviors using the proposed methods are carried out to compare total movements and compactness. Finally, concluding remarks are collected in Section 6.

2. SWARM MODEL, NOTATION AND PROBLEM STATEMENT

2.1. Environment and agent model

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. There have been extensive simulation studies [22] that have led to successful synthesis of birds' behaviors such as collision avoidance, velocity matching, and flock centering. Other experiments by the author of [22] involved evolving groups of artificial creatures. In [21] it studied the evolving 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. Though the results described in the paper were rather preliminary, evidences indicate that coordinated motion strategies began to emerge.

The phenomena of swarming in nature has inspired the interest to engineer large-scale artificial swarms. A typical artificial swarm system is a large-scale fleet of cooperative robots. Each robot in such a robotic swarm can be viewed as an agent. The omni-directional robot without non-holonomic constraints can be one of such prototype agent model [23]. They will likely possess only basic capabilities and mission specific sensors. Direct communication between agents may or may not exist. In this paper, the model of a swarm agent is constructed by building upon an autonomous agent object. In abstract programming terms it may also be thought as an object with some general capabilities. The basic agent possesses only locomotion as an innate capability. Neighbor position information may be used for group behaviors such as flocking and migration. In engineering applications the sensing limitations of the agents can be overcome with technologies such as GPS (Global Positioning System), which is a typical assumption in swarm systems [6-10].

2.2. Notations

In this section, we introduce the notations used in this paper.

ψ	relative position vector
U	potential function
F	force corresponding to potential function
c	strength distance for exponential function
l	correlation distance in exponential function
d	positive constant for distance

Superscripts

$\mathbf{P}$	position of agent
g	group migration
o	obstacle avoidance
og	general configuration for group migration and obstacle avoidance
ogg	proposed configuration for group migration and obstacle avoidance
f	group formation
$oggf$	proposed configuration for group formation, migration and obstacle avoidance
th	farthest

Subscripts

i	individual agent index
j	obstacle index
k	other individual agent index
g	group migration
o	obstacle avoidance
c	center position
r	repulsion between two agents
a	attraction between two agents
f	group formation

2.3. Problem statement

The analysis that the authors made propositions for APFs in [16] is the first step towards dealing with theoretical treatments of several situations that may happen in self-organization of swarms. In [16], each

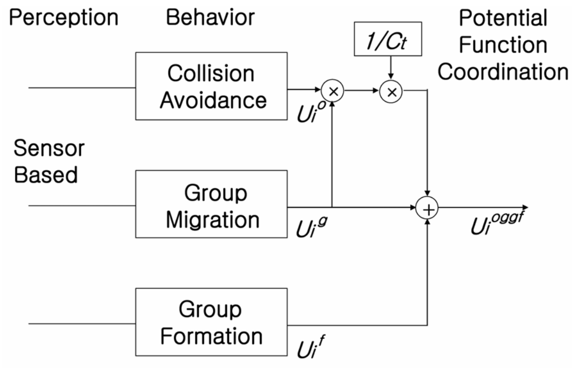


Fig. 1. Behavior architecture.

agent makes self-organization using the position information of all neighbors to get successive group behaviors. However, such a scheme requires more data acquisition followed by time consumption. Besides, the greater the agents composed in a swarm system, the heavier the burden required to get position information by correspondence. We propose a more simple and effective algorithm that embeds each agent to only attempt to maintain association depending on a small number of neighbors, that is, not depending on all neighbors, which is conventionally used in [7-9] and [16-23]. In this scheme, the association of an agent with its neighbors changes with the movement of the swarm as well as its environment.

The behavior of the swarm system in the proposed algorithm is largely divided into three parts: group migration, collision avoidance, and group formation as shown in Fig. 1. We deal with global behaviors, not separate behaviors by subsumption coordination based on priority in [19]. We describe several artificial potential field techniques satisfying such behaviors. Path planning using artificial potential fields is based on an intuitive analogy. The agent is treated as a particle acting under the influence of a potential field U, which is modulated to represent the structure of free space [24]. Typically, obstacles are modeled as carrying electrical charges, and the resulting potential field is used to represent the free space. Each of the individuals in the swarm moves so as to minimize the total artificial potential energy in the system. In this paper, localized distributed controls based on APFs are utilized throughout group behaviors such as group migration, formation, and obstacle avoidance.

3. GROUP BEHAVIORS

In this section, a self-organized swarm system controlled by APFs is presented for the group migration, obstacle avoidance, and group formation. The behavior of migration in this study is distinct from that of formation control (e.g., [17]), since 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 system.

3.1. APFs for group migration and obstacle avoidance

Before we describe artificial potential fields, relative position vectors between the agents and the goal are defined as

$$\psi_i^g = \mathbf{P}_i - \mathbf{P}_{goal}, \tag{1}$$

where $\mathbf{P}_{goal}$ is the goal position.

This relative position vector physically means that the formation is independent of the absolute position of the group. That is why each agent controls its position based on its relative position to the others and it never has any reference point in its working environment.

Attraction towards the goal is modeled by attractive fields, which draws the charged agent towards the goal in the absence of obstacles. The simple APF for group migration is modeled as follows.

$$U_i^g = c_g(1 - e^{-\frac{\|\psi_i^g\|^2}{l_g^2}}), \tag{2}$$

where c_g and l_g are the strength and correlation distance for group migration. The second term c_g in the right side of (2) acts to make U_i^g zero when ψ_i^g =0.

Its corresponding force is then given by the negative gradient of (2).

$$F_i^g = -\nabla U_i^g = -\frac{2c_g\psi_i^g}{l_g^2}e^{-\frac{\|\psi_i^g\|^2}{l_g^2}}. \tag{3}$$

Relative position vectors between the agents and the obstacles are defined as

$$\psi_j^o = \mathbf{P}_i - \mathbf{O}_j, \tag{4}$$

where $\mathbf{O}_j$ is the position of obstacle j which is a neighbor of agent i.

Collision between the obstacles and the agent is avoided by the repulsive force between them, which is simply the negative gradient of the potential field. The simple APF for obstacle avoidance is modeled as follows.

$$U_i^o = \sum_{j \in N_{oi}} \{c_o e^{-\frac{\|\psi_j^o\|^2}{l_o^2}}\}, \tag{5}$$

where c_o and l_o are the strength and correlation distance for obstacle avoidance. N_{oi} denotes the set of labels of those obstacles which are neighbors of agent i.

Its corresponding force is then given by the negative gradient of (5).

$$F_i^o = -\nabla U_i^o = \sum_{j \in N_{oi}} \{ \frac{2c_o \psi_j^o}{l_o^2} e^{-\frac{\|\psi_j^o\|^2}{l_o^2}} \}. \tag{6}$$

3.2. Total APFs for path planning

The total potential of conventional configuration in which the potential for group migration and the potential for obstacle avoidance are combined together has an additive structure as follows.

$$\begin{aligned} U_i^{og} &= U_i^o + U_i^g \\ &= \sum_{j \in N_{oi}} \{ c_o e^{-\frac{\|\psi_j^o\|^2}{l_o^2}} \} - c_g e^{-\frac{\|\psi_i^g\|^2}{l_g^2}} + c_g. \end{aligned} \tag{7}$$

Its corresponding force is

$$\begin{aligned} F_i^{og} &= -\nabla U_i^o - \nabla U_i^g \\ &= \sum_{j \in N_{oi}} \{ \frac{2c_o \psi_j^o}{l_o^2} e^{-\frac{\|\psi_j^o\|^2}{l_o^2}} \} - \frac{2c_g \psi_i^g}{l_g^2} e^{-\frac{\|\psi_i^g\|^2}{l_g^2}}. \end{aligned} \tag{8}$$

If the above potential and force are used, each agent has common problems [14] such as a narrow passage between closely spaced obstacles and a non-reachable goal with obstacles nearby. For this reason, the authors proposed the following configuration for total potential to overcome such local minimum problems [15]. The total potential has a multiplicative and additive structure between the potential for group migration and the potential for obstacle avoidance.

$$\begin{aligned} U_i^{ogg} &= \frac{1}{c_g} U_i^o \cdot U_i^g + U_i^g \\ &= \sum_{j \in N_{oi}} \{ c_o e^{-\frac{\|\psi_j^o\|^2}{l_o^2}} \} (1 - e^{-\frac{\|\psi_i^g\|^2}{l_g^2}}) \\ &\quad - c_g e^{-\frac{\|\psi_i^g\|^2}{l_g^2}} + c_g. \end{aligned} \tag{9}$$

Its corresponding force is

$$\begin{aligned} F_i^{ogg} &= -\nabla U_i^{ogg} \\ &= \sum_{j \in N_{oi}} \{ \frac{2c_o \psi_j^o}{l_o^2} e^{-\frac{\|\psi_j^o\|^2}{l_o^2}} \} (1 - e^{-\frac{\|\psi_i^g\|^2}{l_g^2}}) \\ &\quad + \sum_{j \in N_{oi}} \{ c_o e^{-\frac{\|\psi_j^o\|^2}{l_o^2}} \} (-\frac{2\psi_i^g}{l_g^2} e^{-\frac{\|\psi_i^g\|^2}{l_g^2}}) \\ &\quad - \frac{2c_g \psi_i^g}{l_g^2} e^{-\frac{\|\psi_i^g\|^2}{l_g^2}}. \end{aligned} \tag{10}$$

In [15] by the author, the comparison of simulation results between using (7) and (9) and their analysis were presented. Now let us consider APFs for group formation.

3.3. APF for group formation

The group formation behavior seeks to establish a specific relationship between adjacent neighbors. A swarm system composed of N number of agents is considered. Relative position vectors among the agents are defined as

$$\psi_k^f = \mathbf{P}_i - \mathbf{P}_k. \tag{11}$$

Agents flock together and arrange their formation through attractive and repulsive forces among themselves using APFs. The potential function of each agent for group formation is designed as follows.

$$U_i^f = \sum_{k \in N_{fi}} \{ c_r e^{-\frac{\|\psi_k^f\|^2}{l_r^2}} - c_a e^{-\frac{\|\psi_k^f\|^2}{l_a^2}} + c'_a \| \psi_k^f \|^2 + c_f \}, \tag{12}$$

where N_{fi} denotes the set of labels of those agents which are neighbors of agent i. c_r, c_a, l_r, and l_a are the strengths and correlation distances of the repulsive and attractive forces, respectively. c'_a is the strength of the auxiliary attractive force.

$$c_f = -c_r e^{-\frac{c'_f}{l_r^2}} + c_a e^{-\frac{c'_f}{l_a^2}} - c'_a c'_f, \tag{13}$$

where $c'_f = \frac{l_r^2 l_a^2}{l_r^2 - l_a^2} ln \frac{c_a c'_a l_r^2}{c_r l_a^2}$. c_f acts to make the minimum of the potential function zero. The distance between two agents at the point where $U_i^f(k)$ is minimum is $d^f = \sqrt{c'_f}$.

The corresponding force is then given by the negative gradient of (12)

$$F_i^f = -\nabla U_i^f = \sum_{k \in N_{fi}} \{ \frac{2c_r \psi_k^f}{l_r^2} e^{-\frac{\|\psi_k^f\|^2}{l_r^2}}$$

$$-\frac{2c_a\Psi_k^f}{l_a^2}e^{-\frac{\|\Psi_k^f\|^2}{l_a^2}}-2c'_a\Psi_k^f\}. \quad (14)$$

See Proposition 3 in [16] for the proof of cohesive behavior for the above potential function and force.

3.4. APFs for group formation, migration, and obstacle avoidance

Total potential for group formation, migration, and obstacle avoidance is

$$\begin{aligned} U_i^{oggf} &= \frac{1}{c_g}U_i^o \cdot U_i^g + U_i^g + U_i^f \\ &= \sum_{j\in N_{oi}}\{c_o e^{-\frac{\|\Psi_j^o\|^2}{l_o^2}}\}\cdot(-e^{-\frac{\|\Psi_i^g\|^2}{l_g^2}}+1) \\ &\quad - c_g e^{-\frac{\|\Psi_i^g\|^2}{l_g^2}} + c_g + \sum_{k\in N_{fi}}\{c_r e^{-\frac{\|\Psi_k^f\|^2}{l_r^2}} \\ &\quad - c_a e^{-\frac{\|\Psi_k^f\|^2}{l_a^2}} + c'_a\|\Psi_k^f\|^2 + c_f\}. \end{aligned} \quad (15)$$

Its corresponding force is

$$\begin{aligned} F_i^{oggf} &= -\nabla U_i^{oggf} \\ &= \sum_{j\in N_{oi}}\{\frac{2c_o\Psi_j^o}{l_o^2}e^{-\frac{\|\Psi_j^o\|^2}{l_o^2}}\}(-e^{-\frac{\|\Psi_i^g\|^2}{l_g^2}}+1) \\ &\quad + \sum_{j\in N_{oi}}\{c_o e^{-\frac{\|\Psi_j^o\|^2}{l_o^2}}\}(-\frac{2\Psi_i^g}{l_g^2}e^{-\frac{\|\Psi_i^g\|^2}{l_g^2}}) \\ &\quad -\frac{2c_g\Psi_i^g}{l_g^2}e^{-\frac{\|\Psi_i^g\|^2}{l_g^2}} + \sum_{k\in N_{fi}}\{\frac{2c_r\Psi_k^f}{l_r^2}e^{-\frac{\|\Psi_k^f\|^2}{l_r^2}} \\ &\quad -\frac{2c_a\Psi_k^f}{l_a^2}e^{-\frac{\|\Psi_k^f\|^2}{l_a^2}} - 2c'_a\Psi_k^f\}. \end{aligned} \quad (16)$$

See [16] for analysis of the collision problems that the proposed APFs may raise in the process of group formation, migration, and obstacle avoidance. [16] showed that our formulation of the APFs for group formation can solve possible local minimum and collision problems in potential function configuration. Use of the APFs to keep a formation has a great deal of flexibility. While maintaining the characteristics of swarm, each agent wanders about flexibly, i.e. it has a nature of self-organized flocking that each agent makes a formation dynamically without explicit reorganization contrary to [17].

4. ASSOCIATION FOR SWARMING

The agents in the paper would also have the following characteristics: All agents are physically and functionally identical. Therefore, they can be manufactured inexpensively in large numbers, which would be the case. Furthermore, new agents can be added to the team whenever necessary. 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 communications among agents exists.

4.1. A set of association rules

The full connectivity assumption that each agent makes self-organization using position information of all neighbors to get successive group behaviors has been a popular scheme in the flocking control of a swarm system. Such a scheme tends to maintain a cohesive formation among agents.

We propose a simpler and more effective algorithm that embeds each agent to only attempt to maintain association with a small number of neighbors, that is, not depending on all neighbors, as is conventional in [7-9] and [16-23].

A basic idea to organize the interactions for swarming is to utilize the mutual attractive and repulsive effects between the nearest neighbor. We refer to such an association rule as *min-1*. Such a scheme for swarming can be extended to the case with multiple nearest neighbors by using relative distances. Association rules considering the two and three nearest neighbors are referred to as *min-2* and *min-3*, respectively. Fig. 2 shows an example of a min-2 association rule at a step, where each agent has two interactions between its neighbors. However, separation may happen in those cases, where agents flock in several groups, rather than in a single group, as shown in Fig. 2.

Consideration of the nearest and farthest neighbors can be used to make an association rule for swarming.

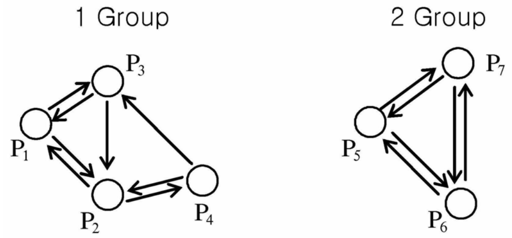


Fig. 2. An example of a min-2 association rule at a step.

We refer to such an association rule as *min-max* that enables agents to flock into a single group. However, the association of an agent with its farthest neighbor for swarming requires movements that are too excessive for all agents. In addition, an agent that associates with its nearest and farthest neighbors usually could change the selection of its nearest and farthest neighbors to excess on a frequent basis. The phenomenon may cause an agent to go this way and that. So another association rule that combines the nearest neighbor and the farthest neighbor together appropriately would be required.

An association rule that switches the neighbor for swarming depending on the relative distance to the farthest neighbor is suggested in order not to cause an agent to go this way and that. We refer to such an association rule as *min-max hybrid*. Before we describe *min-max hybrid*, relative position vectors between the agent and the farthest neighbor are defined as

$$\psi_i^{th} = \mathbf{P}_i - \mathbf{P}_i^{th}, \tag{17}$$

where $\mathbf{P}_i^{th}$ is the position of the farthest neighbor.

In the association rule of *min-max hybrid*, an agent approaches only its nearest neighbor if ψ_i^{th} is smaller than threshold value d_{th}. Otherwise, an agent approaches only the farthest neighbor for swarming. In the initial state where all agents scatter in the distance, an agent would approach its farthest neighbor. Then, if the relative distance between an agent and its farthest neighbor is within a certain area, that is, $\psi_i^{th} < d_{th}$, the agent would adopt the association rule of *min-1*.

To simplify the interactions among the agents, association rules based on local connectivity are employed, namely, each agent dynamically associates itself with only other chosen agents. The *min-max hybrid* association rule includes the nearest neighbor and the farthest neighbor when the relative distance between an agent and its farthest neighbor is out of a certain area. On the other hand, when the relative distance between an agent and its farthest neighbor is within a certain area, the *min-max hybrid* association rule includes only the nearest neighbor. Thus, except the case that distance between two agents is farther than designated distance in initial state, association rule *min-1* is employed.

The resulting *min-max hybrid* association rule enjoys two important interrelated benefits. Firstly, it simplifies the interactions in swarm systems. Secondly, the simplicity of the *min-max hybrid* rule is advantageous for practical implementations.

4.2. Simulation of group formation via association

Simulation results are given to investigate the effectiveness of each association rule and to compare it. Ten agents are used in the simulations. The initial positions of all the agents can be randomly generated as shown in Table 1, but to facilitate comparison they are chosen to be the same for all the simulations. Design parameters are set to $l_o = 1/5$, $l_g = 2$, $l_a = 1/2$, $l_r = 1$, $c_o = 3$, $c_g = 1$, $c_a = 1/2$, and $c_r = 1/3$.

Those simulations deal with only group formation for swarming, not including group migration and obstacle avoidance. Fig. 3 presents trajectories of swarming for the algorithms of *min-1*, *min-2*, *min-3*, *min-max*, and *min-max hybrid*, respectively. Table 2 shows total movements and compactness for each association given in Fig. 3. Total movements means total distances that all agents moved for all steps. Compactness for an association rule is computed as follows:

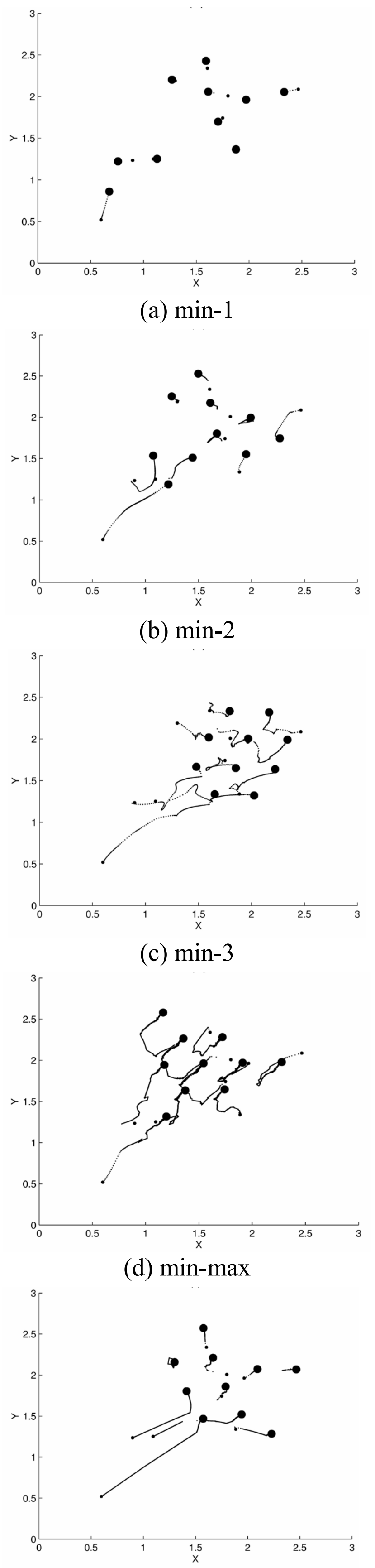
$$Compactness = \sum_{i=1}^{n} \{P_c - P_i\} \text{ for every step,} \tag{18}$$

where P_c is the center position of all agents and n is the number of agents.

In the case of *min-1*, each agent does not flock together at all as shown in Fig. 3(a). Thus, the value of compactness, 6.4531 in Table 2 is too high. In this simulation environment, the value less than 5.0 guarantees a swarm behavior in the view of a swarming form. Each agent by the association rule of *min-2* swarms in Fig. 3(b) which makes the formation connectible but not satisfactory. Formation by the association rule of *min-3* shows a satisfactory result in Fig. 3(c). However, it does not guarantee coherence in the case of a swarm system composed of more swarm agents that requires more connection among neighbors in order to flock to a single group. The association rule of *min-2* is the same as this. In the case of *min-max*, some agents go back the way that they have gone, as indicated in Fig. 3(d), which brings out the high value of total movements. Thus, the value of total movements, 23.433 in Table 2 is so high that it requires lots of energy consumption. Fig. 3(e) shows trajectories of swarming using the association rule of *min-max hybrid*. The association rule guarantees

Table 1. The initial positions of all agents.

Agent	Position	Agent	Position
A_1	(1.0948, 1.2518)	A_2	(0.5983, 0.5198)
A_3	(1.8864, 1.3397)	A_4	(1.8002, 2.0073)
A_5	(2.4660, 2.0877)	A_6	(1.6053, 2.3399)
A_7	(1.3001, 2.1894)	A_8	(0.8976, 1.2355)
A_9	(1.7504, 1.7416)	A_{10}	(1.9667, 1.9626)



(a) min-1

(b) min-2

(c) min-3

(d) min-max

(e) min-max hybrid

Fig. 3. Trajectories of Swarming. (*small dot*: initial position, *large dot*: final position).

Table 2. Total movements and compactness for each association.

	Total movements	Compactness
min-1	1.085	6.4531 (too high)
min-2	4.951	4.9347
min-3	9.040	4.1727
min-max	23.433 (too high)	4.4000
min-max-hybrid	6.422	4.7259

coherence and does not cause the agents to separate. As well, the value of total movement is very satisfactory. Communication burden can be resolved somewhat on account that each agent follows the association rule of *min-1* after flocking to a single group.

Next, consider group behaviors including migration, formation and obstacle avoidance.

5. SIMULATION OF GROUP BEHAVIORS

As the well-known collective behavior of ants attacking a larger insect than them with cooperation, self-organized swarm agents are designed as agents who migrate to a designated place while keeping a formation. The task is due to motivations related to the biological inspirations behind cooperative systems. Each agent in this task migrates to a goal while avoiding obstacles, avoiding collision with other agents and maintaining a formation.

In this section, simulation results are given to illustrate the effectiveness of the algorithms discussed in the proceeding sections.

Figs. 4-8 illustrate the different snapshots of a migration process of ten agents to a goal using *min-1*, *min-2*, *min-3*, *min-max*, and *min-max hybrid*, respectively. Each agent is randomly initialized on the left side of $x = -2$ as shown in Table 3. The goal is initialized on (0,0). For all the simulations, there are three circular obstacles centered at $(-0.80.8)$, (-1.50), and $(-0.8-0.8)$ with radius 0.2.

In Figs. 4-8, the swarm agents spontaneously divide into several parts by themselves to surpass the

Table 3. The initial positions of all agents.

Agent	Position	Agent	Position
A_1	(-3.2, 1.2)	A_2	(-4.3, 1.5)
A_3	(-3, 1)	A_4	(-3.5, 0.5)
A_5	(-4, 0)	A_6	(-3.5, -0.5)
A_7	(-3, -1)	A_8	(-3.5, -1.5)
A_9	(-4.5, -1.2)	A_{10}	(-3, -0.3)

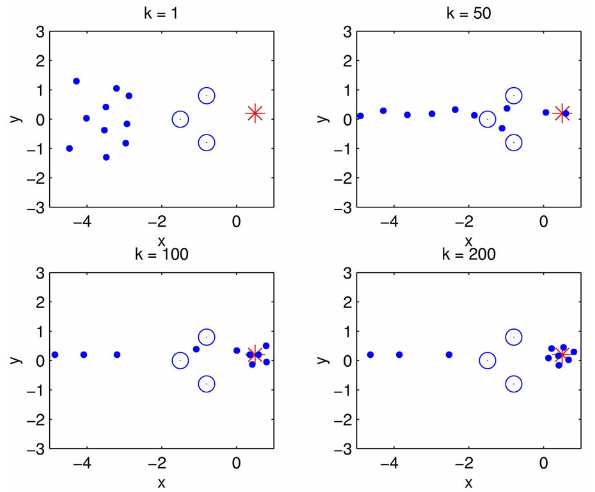


Fig. 4. Snapshots of migration by the association rule of *min-1* (*dot*: agent, *astral mark*: moving target, *circle*: obstacle).

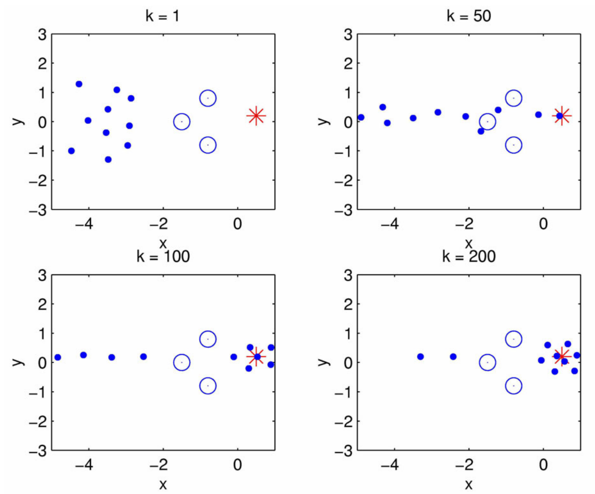


Fig. 5. Snapshots of migration by the association rule of *min-2* (*dot*: agent, *astral mark*: moving target, *circle*: obstacle).

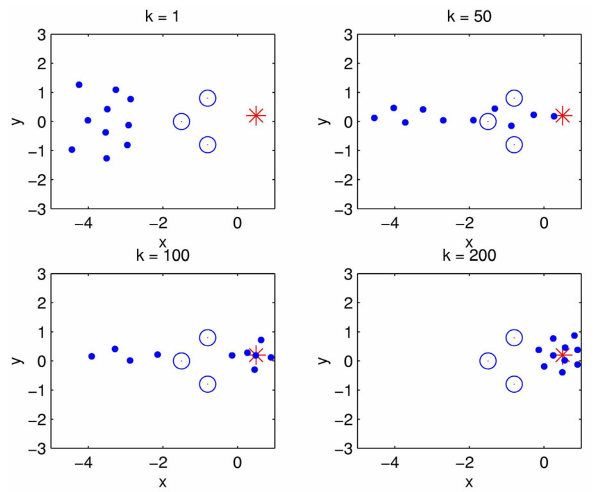


Fig. 6. Snapshots of migration by the association rule of *min-3* (*dot*: agent, *astral mark*: moving target, *circle*: obstacle).

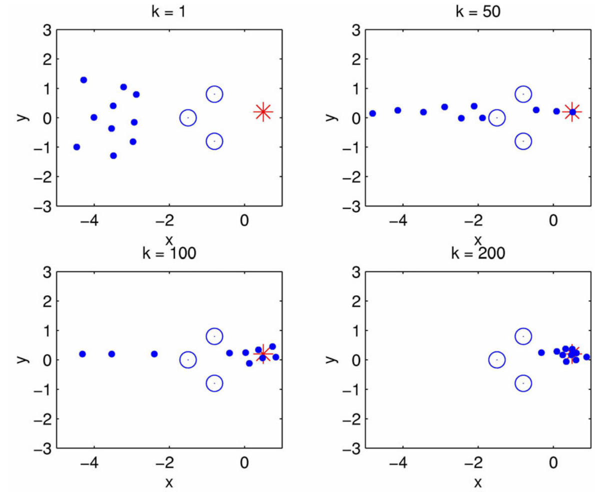


Fig. 7. Snapshots of migration by the association rule of *min-max* (*dot*: agent, *astral mark*: moving target, *circle*: obstacle).

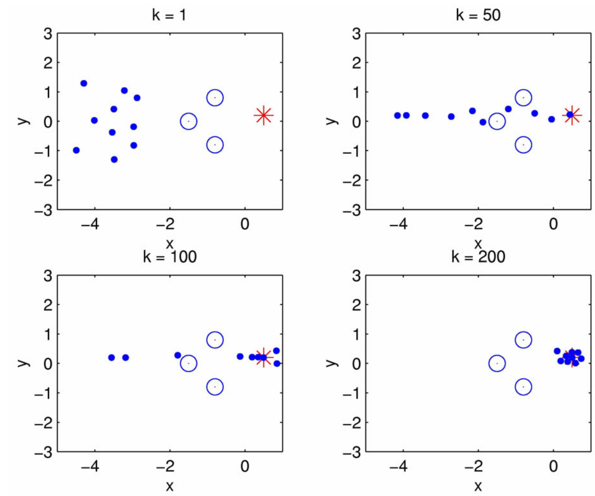


Fig. 8. Snapshots of migration by the association rule of *min-max hybrid* (*dot*: agent, *astral mark*: moving target, *circle*: obstacle).

Table 4. Total movements and compactness for each association.

	Total movements	Compactness
1-4 min-1	60.913	17.4444
min-2	63.247	11.2952
min-3	33.278	4.9032
min-max	74.713	2.9401
min-max-hybrid	65.059	2.0613

blocking area when meeting the obstacle, and finally form a certain kind of group pattern at the neighborhood of the goal.

Association rule *min-1* in Fig. 4 indicates the slowest migration compared with the other association rules, as a case of the previous swarming behavior. Association rule *min-3* in Fig. 6 shows better migration performance than association rule *min-2* in Fig. 5. Association rule *min-max* in Table 4 indicates somewhat high total movements, but in Fig. 7, it reveals better migration performance than association rule *min-2* in Fig. 5. Association rule *min-max hybrid* in Fig. 8 presents the best migration performance in terms of migration speed and lower total movements than association rule *min-max*. Note that each agent in association rule *min-max hybrid* scheme adopts the association rule of association rule *min-1* after the relative distance between an agent and its farthest neighbor is within a certain area.

The relative distances among agents in the process of formation are adjusted by the selection of design parameters c_r, c_a, l_r, l_a in Section 3.3. As for the collision with inter-agents, the author guaranteed their coherence and made a set of propositions for the design parameters in [16].

6. CONCLUSIONS

In this paper, we present a framework for decentralized control of self-organizing swarm systems based on the APFs. The framework explores the benefits by associating agents based on position information to realize complex swarming behaviors. A key development is the introduction of an association rule by APFs that effectively deal with a host of swarming issues such as flexible and agile formation. The association rule *min-max hybrid* for swarming that requires less movement for each agent and compact formation among agents is presented and compared with other possible association rules. The framework enables the agents in a swarm to maintain a flexible formation, while migrating as a group and avoiding any obstacles, as shown in the paper. Extensive simulation studies coupled with preliminary analysis [16] illustrate the comparative effectiveness of association rules. Research is underway for both in-depth analysis of the proposed framework and micro-robot based experiments.

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