연합방법을 이용한 다개체 에이전트들의 무리짓기 행동제어

김동헌*, 한병조**, 김응석***, 김홍필****, 양해원**
경남대*, 한양대**, 한라대***, 경일대****

Swarming Behavior of Multiple Agents by Association

Dong Hun Kim*, Byung Jo Han**, Eung-Suk Kim***, Hong-Pil Kim****, and Hai-Won Yang**
Kyungnam University*, Hanyang University**, Halla University***, and Kyungil University****

Abstract - This paper presents a framework for decentralized control of self-organizing swarm agents 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 particular, this paper presents an association rule for swarming that requires less movements for each agent and compact formation among agents. Extensive simulations are presented to illustrate the viability of the proposed framework.

1. Introduction

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 one. This paper continues the work of \cite{Kim1} and represents a modest attempt to offer a simple and effective framework for coordinating the group behaviors of swarm systems by association.

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 [1]. 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 \cite{bib:Spears}, the purpose of this study is to explore a set of association among agents for swarming that requires less movements for each agent and compact formation among agents.

2. APFs for Group Behaviors

In this section, a self-organized swarm system controlled by APFs is presented for the group migration, obstacle avoidance, and group formation. 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.

See [1] for the APFs of group behaviors presented by the authors!

3. Association for Swarming

3.1 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 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 small number of neighbors, that is, not depending all neighbors which is conventionally used in [1]-[3].

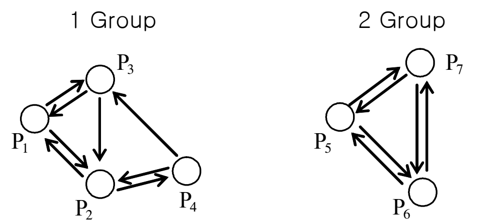
A basic idea to organize the interactions for swarming is to utilize the mutual attractive and repulsive effects between the nearest neighbor. We refer such an association rule as *min-1*. Such a scheme for swarming can be extended to the case with multiple nearest neighbors by using relative distances. Association rules considering the two and three nearest neighbors are referred as *min-2* and *min-3*, respectively. Figure 1 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 flocks in several groups not in a single group, as shown in Fig. 1.

Consideration of the nearest and farthest neighbors can be taken to make an association rule for swarming. We refer such an association rule as *min-max* that enables agents flock into a single group. However, the association of an agent with its farthest neighbor for swarming requires too excessive movements 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 frequently to excess. 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 a relative distance to the farthest neighbor is suggested in order not to cause an agent to go this way and that. We refer 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

$$\psi_i^{th} = \mathrm{P_i} - \mathrm{P}_i^{th} \tag{1}$$

where P_i is the position of i-th robot, and P_i^{th} is the position of the farthest neighbor.



<Figure 1> An example of a min-2 association rule at a step

In the association rule of *min-max hybrid*, an agent approaches only its nearest neighbor if ψ_i^{th} is smaller than a thresh hold 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 approached 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 association rule *min-max hybrid* 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 association rule *min-max hybrid* 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 association rule *min-max hybrid* enjoys two important interrelated benefits. First, it simplifies the interactions in swarm systems. Secondly, the simplicity of the *min-max hybrid* rule is advantageous for practical implementations.

<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)

3.2 Simulation of group formation via association

Simulation results are given to investigate the effectiveness of each association rule and compare it. Ten agents are used in the simulations. The initial positions of all the agents can be randomly generated as shown in Tab. 1, but to facilitate comparison they are chosen to be the same for all the simulations.

Those simulations deal with only group formation for swarming, not including group migration and obstacle avoidance. Fig. 2 is trajectories of swarming f or 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 shown in Fig. 2. Total movements means total distances that all agents moved around for all steps. Compactness for an association rule is computed as follows:

$$Compactness = \sum_{i=1}^{n} \mathrm{P_c} - \mathrm{P_i} \quad \text{for every step} \qquad (2)$$

where $\mathrm{P_c}$ 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. 2 (a). Thus, the value of compactness, 6.4531 in Tab.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. 2 (b) which makes the formation connectible but not satisfactory. Formation by the association rule of *min-3* shows a satisfactory result in Fig. 2 (c). However, it does not guarantee coherence in the case of a swam 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 it has gone, as shown in Fig. 2 (d), which brings out the high value of total movements. Thus, the value of total movements, 23.433 in Tab. 2 is so high that it requires lots of energy consumption. Figure 2 (e) shows trajectories of swarming using the association rule of *min-max hybrid*. The association rule guarantees 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.

<Table 2> Total movements and compactness for each association

association rule	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

4. 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. The association rule *min-max hybrid* for swarming that requires less movements 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 is shown in the paper. Extensive simulation studies coupled with preliminary analysis [1] illustrate the comparative effectiveness of association rules. Research is underway for both in-depth analysis of the proposed framework and micro-robot based experiments.

[References]

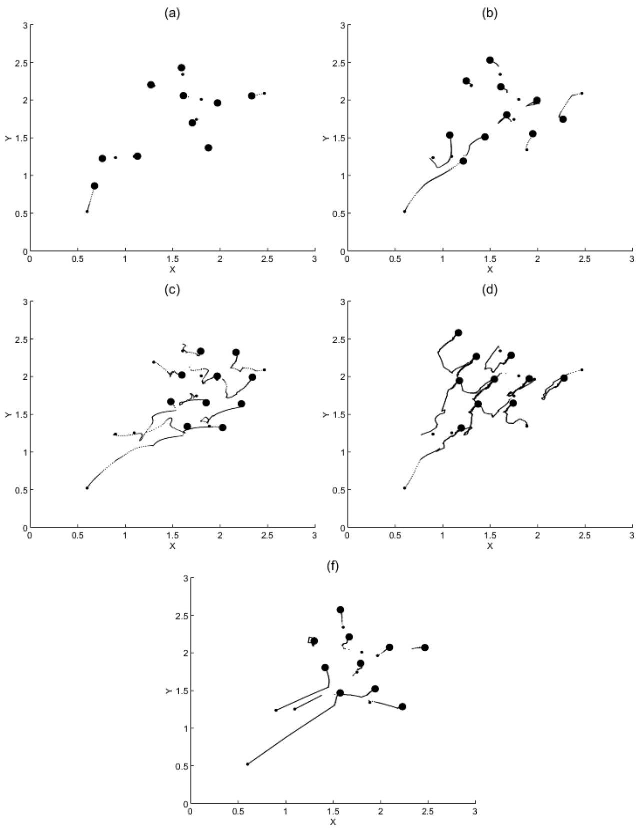
[1] D. H. Kim, H. O. Wang, and S. Shin, ''Decentralized Control of Autonomous Swarm Systems Using Artificial Potential Functions : Analytical Design Guidelines,'' *Int. Journal of Intelligent and Robotic Systems*, vol. 45, no. 4, pp. 369-394, 2006.

[2] T. Balch and M. Hybinette, ''Behavior-based coordination of large-scale robot formations,'' *Proc. Fourth Int. Conf. on Multi Agent Systems*, pp. 363-364, 2000.

[3] W. Spears, D. Spears, J. Hamann, and R. Heil, ''Distributed, physics-based control of swarms of vehicles,'' *Autonomous Robots*, vol. 17 no. 2-3, pp. 137-162, 2004.

[4] Y. Koren and J. Borenstein, ''Potential field methods and their inherent limitations for mobile robot navigation,'' *Proc. of the IEEE int. Conf. on Robotics & Automation*, pp. 1398-1404, 1991.

[5] D. H. Kim and S. Shin, ''Local Path Planning Using a New Artificial Potential Function Configuration and Its Analytical Design Guidelines,'' *Advanced Robotics,* vol. 20, no. 1, pp. 115-135, 2006.



<Figure 2> Trajectories of Swarming (a) min-1, (b) min-2, (c) min-3, (d) min-max, and (e) min-max hybrid ; (small dot: initial position, large dot: final position)