Association Rules for a Swarming Behavior of Multiple Agents

Hahmin Jung, Dong Hun Kim *

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.**

Keywords: swarm systems, group behavior, potential functions, association.

1 Introduction

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 [1]-[6], 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.

Other recent related papers on formation control include [4]-[5]. [5] 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 one. This paper continues the work of [10] 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 [10]. 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 [11], 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. The behavior of migration in this study is distinct from that of formation control (e.g. [7]), 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.

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2.1 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 following.

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

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 following.

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

where c_o and l_o are the strength and correlation distance for obstacle avoidance. $\mathcal{N}_{oi}$ 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).

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

2.2 Total APFs for path planning

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

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

If the above potential and force are used, each agent has common problems [6] such as a narrow passage between closely spaced obstacles and a non-reachable goal with obstacles nearby. For this reason, the authors proposed following configuration for total potential to overcome such local minimum problems [9]. The total potential has a multiplicative and additive structure between the potential for group migration and the potential for obstacle avoidance.

$$\begin{aligned} U_i^{ogg} &= \frac{1}{c_g}U_i^o \cdot U_i^g + U_i^g \\ &= \sum_{j\in\mathcal{N}_{oi}}\{c_o e^{-\frac{\|\psi_j^o\|^2}{l_o{}^2}}\}(1 - e^{-\frac{\|\psi_i^g\|^2}{l_g{}^2}}) \\ &\quad - c_g e^{-\frac{\|\psi_i^g\|^2}{l_g{}^2}} + c_g. \end{aligned} \tag{8}$$

In [9] 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.

2.3 APF for group formation

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

$$\psi_k^f = \mathbf{P}_i - \mathbf{P}_k. \tag{9}$$

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 following.

$$U_i^f = \sum_{k\in\mathcal{N}_{fi}}\{c_r e^{-\frac{\|\psi_k^f\|^2}{l_r{}^2}} - c_a e^{-\frac{\|\psi_k^f\|^2}{l_a{}^2}} + c_a'\|\psi_k^f\|^2 + c_f\} \tag{10}$$

where $\mathcal{N}_{fi}$ 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 force, respectively. c_a' is the strength of the auxiliary attractive force.

$$c_f = -c_r e^{-\frac{c_f'}{l_r{}^2}} + c_a e^{-\frac{c_f'}{l_a{}^2}} - c_a'c_f' \tag{11}$$

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 (10)

$$F_i^f = -\nabla U_i^f = \sum_{k \in \mathcal{N}_{fi}} \{ \frac{2c_r \psi_k^f}{{l_r}^2} e^{-\frac{\|\psi_k^f\|^2}{{l_r}^2}} - \frac{2c_a \psi_k^f}{{l_a}^2} e^{-\frac{\|\psi_k^f\|^2}{{l_a}^2}} - 2c'_a \psi_k^f \}. \quad (12)$$

See *the proposition 3* in [10] for the proof of cohesive behavior for the above potential function and force.

2.4 APFs for group formation, migration, and obstacle avoidance

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

$$\begin{aligned} U_i^{oggf} &= \frac{1}{c_g} U_i^o \cdot U_i^g + U_i^g + U_i^f \\ &= \sum_{j \in \mathcal{N}_{oi}} \{ c_o e^{-\frac{\|\psi_j^o\|^2}{{l_o}^2}} \} \cdot (-e^{-\frac{\|\psi_i^g\|^2}{{l_g}^2}} + 1) \\ &\quad - c_g e^{-\frac{\|\psi_i^g\|^2}{{l_g}^2}} + c_g + \sum_{k \in \mathcal{N}_{fi}} \{ c_r e^{-\frac{\|\psi_k^f\|^2}{{l_r}^2}} \\ &\quad - c_a e^{-\frac{\|\psi_k^f\|^2}{{l_a}^2}} + c'_a \|\psi_k^f\|^2 + c_f \}. \end{aligned} \quad (13)$$

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], [10]-[11].

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*

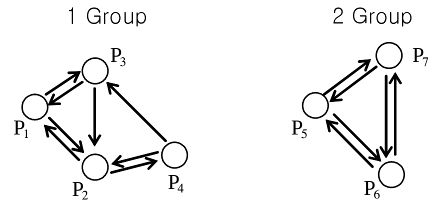

Figure 1: An example of a min-2 association rule at a step

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

$$\psi_i^{th} = \mathbf{P}_i - \mathbf{P}_i^{th} \quad (14)$$

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 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*

Tab. 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)

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.

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. 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. 2 is 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 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:

$$Compactness = \sum_{i=1}^{n} \{P_c - P_i\} \text{ for every step} \qquad (15)$$

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. 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.

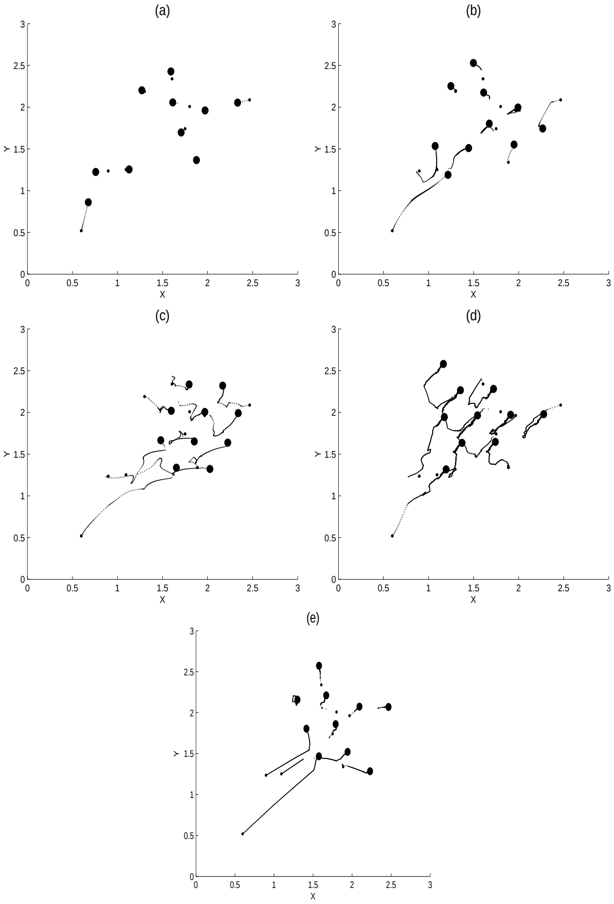

Figure 2: Trajectories of Swarming (a) min-1, (b) min-2, (c) min-3, (d) min-max, and (e) min-max hybrid ; (*small dot*: initial position, *large dot*: final position)

Tab. 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

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

4 Simulation of Group Behaviors

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

Figure 3-5 illustrate the different snap shots of a migration process of ten agents to a goal using *min-3*, *min-max*, and *min-max hybrid*, respectively. Each agent is randomly initialized on the left side of $x = -2$. 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 Fig. 3-5, the swarm agents spontaneously divide into several parts by themselves to surpass the blocking area when meeting the obstacle, and finally form a certain kind of group pattern at the neighborhood of the goal.

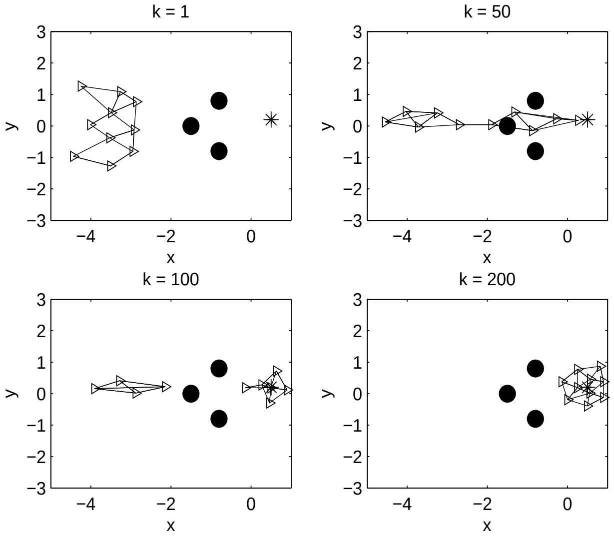

Figure 3: Snap shots of migration by the association rule of *min-3* (*dot*: agent, *astral mark*: moving target, *circle*: obstacle)

Tab. 3 Total movements and compactness for each association

	total movements	compactness
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

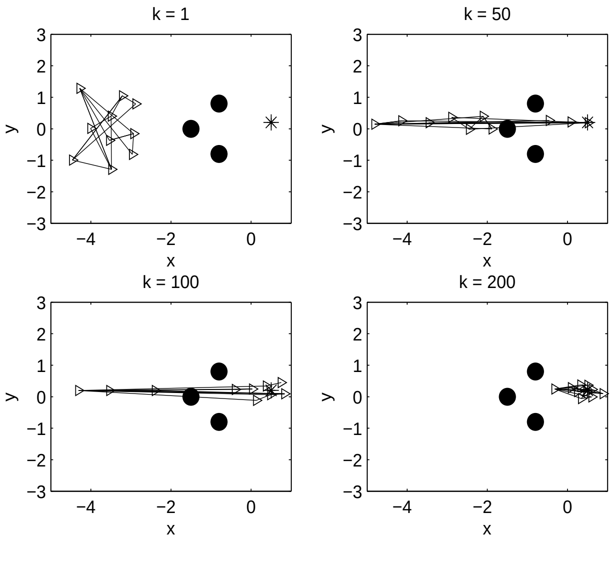

Figure 4: Snap shots of migration by the association rule of *min-max* (*dot*: agent, *astral mark*: moving target, *circle*: obstacle)

Association rule *min-max* in Tab. 3 indicates somewhat high total movements. Association rule *min-max hybrid* in Fig. 5 shows 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 2.3. As for the collision with inter-agents, the author guaranteed their coherence and made a set of propositions for the design parameters in [10].

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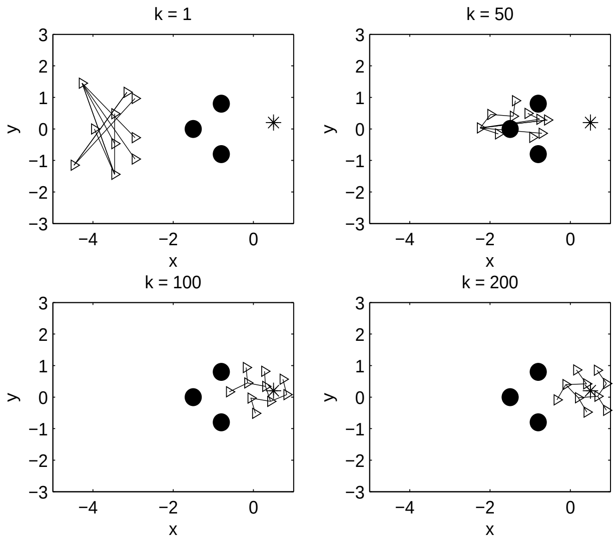

Figure 5: Snap shots of migration by the association rule of *min-max hybrid* (*dot*: agent, *astral mark*: moving target, *circle*: obstacle)

5 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 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 [10] 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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