An Analysis of Collective Movement Models for Robotic Swarms

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***Abstract*—A swarm is defined as a set of two or more independent homogeneous or heterogeneous agents acting in a common environment, in a coherent fashion, and which generates emergent behavior. The creation of artificial swarms or robotic swarms has attracted many researchers in the last two decades. Many studies have been undertaken using practical approaches to swarm construction such as investigating the navigation of the swarm, task allocation and elementary construction. This paper examines aggregations that emerge from three different movement models of relatively simple agents. The agents only differ in their maximum turning angle and their sensing range.**

***Keywords*—swarm robotics, emergence, self organization.**

I. Introduction

Aggregation patterns that can be observed in nature and biology have always been of great fascination to researchers, *e.g.* flocks of birds, schools of fish, social insects foraging and attacking *etc.* These patterns are evident in countless other examples of animal and insect migrating behaviors such as great herds of antelopes and wildebeests thundering across the savannah, and Monarch butterflies migrating south into remote mountain tops in central Mexico towards the end of the summer season. In all these cases, it is fascinating to observe how coordinated and synchronized these natural group behaviors are.

It would be fair to think that animals, like birds and fish, achieve these movement patterns by having leaders to keep them organized, *e.g.* the bird at the front of the flock leads and the others follow. On the contrary, most bird flocks and fish schools are leaderless, in fact the movements of the flocks and schools are determined by the instantaneous decisions of individual birds or fish. These may include maintaining a fixed distance between local neighbors [1] or the reaction to fluid flow around an individual [2].

Orderly flock patterns arise when each bird follows simple rules in response to dynamic interactions with neighbours in the flock. Such movements are a prime example of emergent behavior and self organization.

By understanding the movement model of biological swarms, roboticists can develop and build more complex organization mechanisms for large multi-robot systems.

A. *Self-organization*

The main feature of self-organization is that a system's organization or movement does not explicitly depend on external control factors. In other words, the organization emerges solely due to the local interactions between individuals and their environment [3].

The organization can evolve dynamically either in time or space and can maintain some kind of stable form or can show transient phenomena. An example of such a system is that of a colony of ants sorting eggs without any particular ant knowing the sorting algorithm itself [4].

Many social insect societies exhibit interesting complex behaviors in organizing themselves to perform specific activities such as foraging and nest building. Cooperation amongst individuals arises through an indirect communication mechanism, called stigmergy [5] and by interacting through their environment.

B. *Emergence*

Like the word *Intelligence*, the definition of *Emergence* (or *Emergent Behavior*) has attracted some attention by researchers.

Taylor [6] asserts that the emergent properties are collections of units at a lower level of organization and, through their interaction, often give rise to properties that are not the mere superposition of their individual contributions.

Steels [7] s that "emergent functionality means that a function is not achieved directly by a component or hierarchical system of components, but indirectly by the interactions of more primitive components among themselves and with the world."

Mataric [8] defines emergent behavior for swarm intelligence as follows: emergent behaviors is apparent by global states which are not explicitly programmed in, but it results from local interactions amongst individuals. It is considered interesting based on some metric established by the observer.

Despite several differences in the definition of emergence, one common theme connects all these definitions in the AI (Artificial Intelligence) community, *i.e.* emergent behavior occurs as a result of local interactions amongst individuals and between individuals and their environment.

In recent times, many researchers have shown an increasing interest in building multi-robot systems or, on a much larger scale, robot swarms. Unlike other studies on multi-robot systems in general, swarm robotics emphasizes self-organization and emergence behavior in a large number of agents promoting scalability, flexibility and robustness by only using limited local communication. This also requires the use of relatively simple robots, equipped with limited communication mechanisms, localized sensing capabilities and the exploration of decentralized control strategies.

In this paper, we use the idea of flocking from [9][10] and we add an artificial potential field (AFP) to the arena. We then describe the simulation procedures and methodology. Finally, we present our results and offer some conclusions.

II. Simulation Setup

A. Working Arena

In this study, the NetLogo simulation tool has been used. NetLogo was developed by Uri Wilensky in 1999 [10] as a programmable modeling environment for simulating natural and social phenomena. NetLogo is well suited for modeling time dependent complex systems and literally allows users to give instructions to hundreds or thousands of independent agents operating concurrently. This makes it possible to explore the connection between micro-level individual behavior and macro-level patterns that emerge from the interactions of individuals.

The working arena in the simulation is based on patches. In these simulations an arena size of 201 by 201 patches was chosen. We then applied APF to attract all agents to the center of the arena with a radius of 63 unit patches from the center, as shown in Fig. 1; the white background represents the area which is not affected by the applied field.

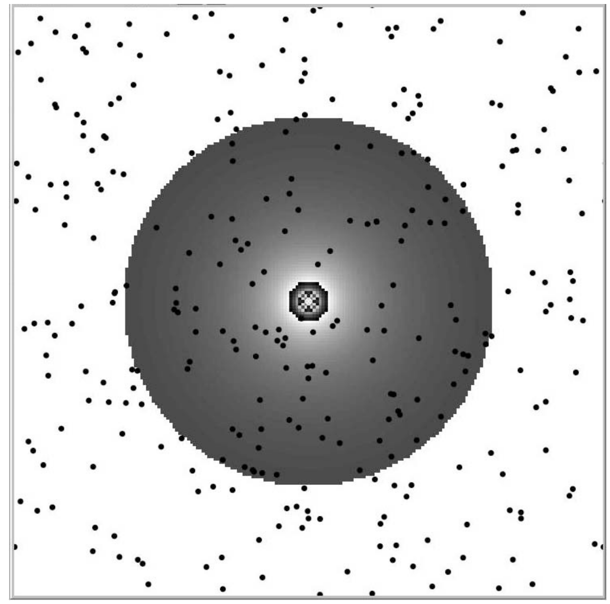


Fig. 1. Working Arena with 300 agents

B. Movement Models

In designing the aggregation behavior of artificial swarms, several approaches have been proposed, which can be simply divided into two classes: physicomimetics and biomimetics [11].

Physicomimetics is a general description for engineering systems which gain inspiration from physical systems such as fluid flow analyses, Newtonian analyses and kinetic analyses. The research in Physicomimetics is focused on swarm behaviors that are similar to that shown by solids, liquids and gases [11]. As an example of Physicomimetics, Spears and Gordon [12] showed how swarms of micro-air vehicles (MAVs) are controlled and self organizes into a hexagonal lattice, which create a distributed sensing grid with a fixed spacing between MAVs [13].

On the other hand, biomimetics is a general description for engineering methods or systems that mimic biological systems or systems found in nature. Biomimetics is also known as bionics, biognosis, biomimicry and has a varied field of application from business studies to political sciences.

In the field of swarm engineering, Reynolds was one of the first to simulate behavioral control animation [9]. He developed a system to model flocking behavior and coordinated movements seen in birds and fish in which he named the creatures “boids”. The basic Reynolds' flocking model is based on three simple steering behaviors, namely *Separation*, *Alignment* and *Cohesion*, which describes how an individual boid should change its heading or direction and velocity based on the positions and velocities of its nearby neighbors or flockmates.

Fig. 2 shows three basic strategies of Reynolds' flocking rules. On the left is the cohesion strategy where the red boid feels the urge to steer towards the average position of flockmates in its vicinity, resulting in the boids staying close to one another. The green boid in the center of Fig. 2 exhibits the separation strategy; this strategy is to ensure that the boid is maintaining a safe distance from its flockmates and encourages the boid population to avoid crowding the neighborhood. Finally, the blue boid on the

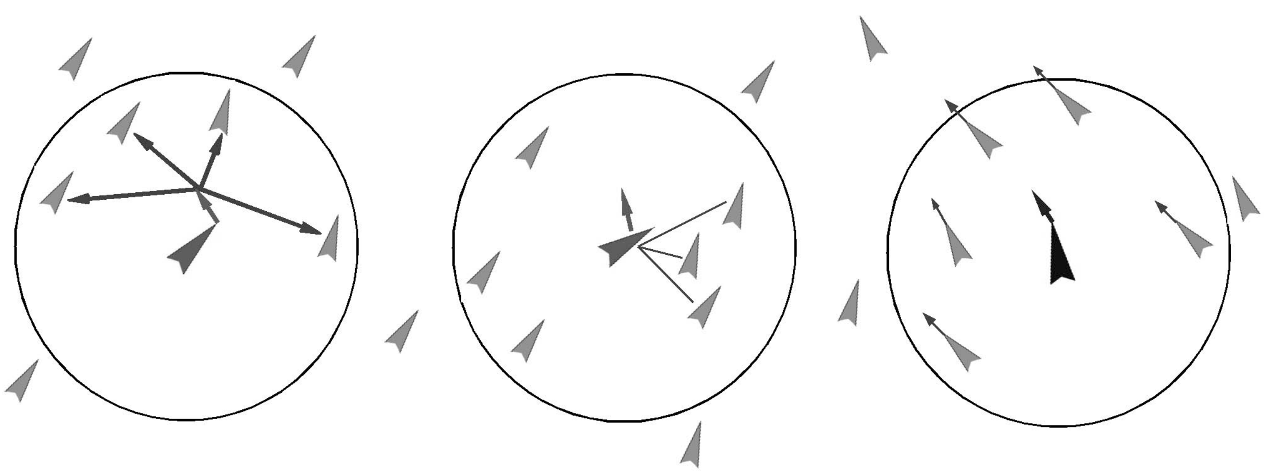


Fig. 2. Reynolds [9] primitive flocking rules; from left to right: *Cohesion*, *Separation* and *Alignment* strategy.

right demonstrates the alignment strategy which sometimes is referred to as the *velocity matching* strategy. This rule encourages the boid to move with a similar heading and velocity as its flockmates.

In this study, three different movement models, namely fish-like, mosquito-like and firefly-like have been modeled. These are governed by rules as represented in the flowchart in Fig. 3.

The agent has been modeled so that each agent can sense or "see" others within its neighbourhood in 360-degrees, as shown in Fig. 4. The difference between each movement model consists of the *visibility range* and the *movement span*.

Visibility range is the variable where we define how far each agent can see from its position; while the *movement span* is a set of maximum angles that are available for the agent to change its direction either to the left or right for its next movement. As shown in Table I, *Visibility range* and *movement span* for the fish-like model have been set to 10 unit-patches and 10-degrees; for the mosquito-like model 7 unit-patches and 45-degrees, while for the firefly-like model they are 5 unit-patches and 90-degrees, respectively.

TABLE I.
VARIABLES FOR MOVEMENT MODELS

Movement model	Movement span	Visibility range
Fish-like	10	10
Mosquito-like	45	7
Firefly-like	90	5

Fig. 5 shows some sample trajectories for each model after we apply the movement span. From Fig. 5 we can clearly see the differences between the trajectories of each movement model. Fig. 5(a) shows fish-like motion where the movement is like fish motion with a *calm* turning angle. Fish-like motion is useful for scanning large areas of the arena in a short time period. Fig. 5(b) and Fig. 5(c) show the trajectories of the mosquito-like and the firefly-like movement model, respectively. As we can see from the trajectories, firefly-like motion allows the agent to move around scanning in a small local area, and this can be useful for searching for small objects in a small area, while the mosquito-like movement appears to scan a wider area in the arena as well as its own neighborhood area.

C. Simulation Methodology

For this study, Wilensky's [10] flocking model has been adopted and adapted. We extended the model by adding an APF originating from the center of arena as defined by equation (1). The strength of the field is subjected to the patch's *distance* from the origin and the circular area of the field is subject to a variable, *fieldRadius,* that is set to 63.

$$field = \left\{ \begin{array}{ll} 1, & distance \geq fieldRadius \\ \dfrac{fieldRadius}{distance}, & otherwise \end{array} \right\} \quad (1)$$

The number of agents in the simulations has been set to 300. At the beginning of the simulation, agents are randomly distributed in the arena, which are represented as small black dots as shown in the Fig. 1. As the simulation starts, each agent goes into a *wander* phase if the agent is outside the APF or a *wander inside field* phase if the agent is inside the APF area, as shown in the flowchart in Fig. 3. Each agent then examines the position where they were at; if that particular position is affected by the APF, or having *field* value of larger than one (*field* > 1), the agent is then attracted to the field.

The agent then looks around, within its *visibility range,* for flockmates. If any mate is found, the agent flocks with the flockmates, otherwise it continues roaming. While inside the *field*, the aforementioned rules were used with added attraction to the center of the *field*, so that agents did not leave the *field*.

As we are extending Wilensky's model of flocking [10], three more variables from the model needed to be assigned; *max-align-turn*, *max-cohere-turn* and *max-separate-turn.* These variables are the maximum angles that each agent can turn through during the *alignment*, *cohesion* and

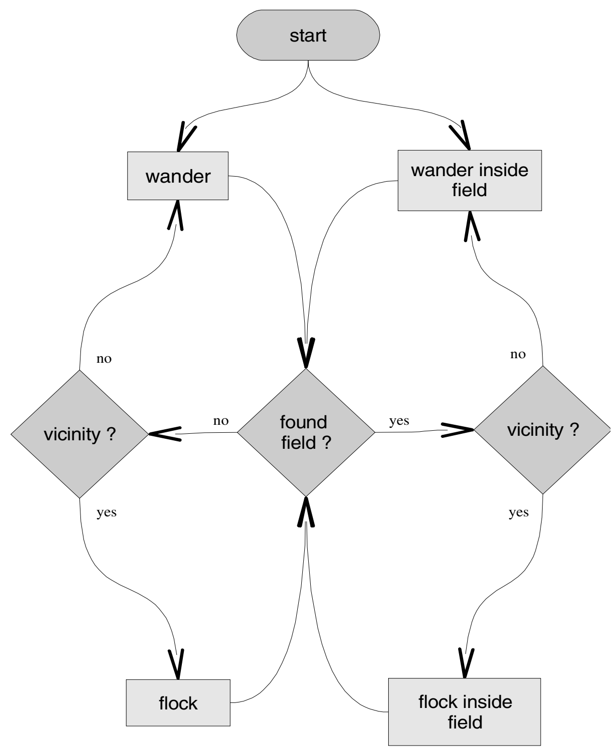


Fig. 3. Flowchart of movement models.

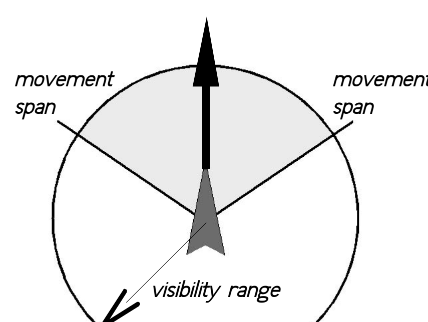


Fig. 4. Representation of an individual agent

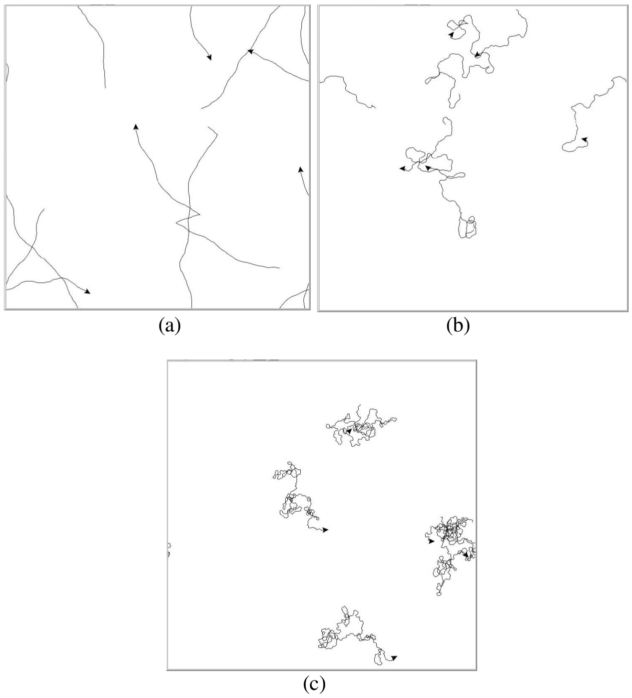


Fig. 5. Agents motion trajectories for each movement model: (a) fish-like, (b) mosquito-like, (c) firefly-like.

separation rules respectively. For the simulations, we decided to have the three angles relying on the *movement span* angle. The value for *max-align-turn* is set to half of the *movement span* angle, and *max-cohere-turn and max-separate-turn* to one-third of the *movement span.*

D. Pre-simulation Setup

In pre-simulation experiments, we tested each movement model without an APF added to the arena to analyze the emergent global behavior. We started the experiments with

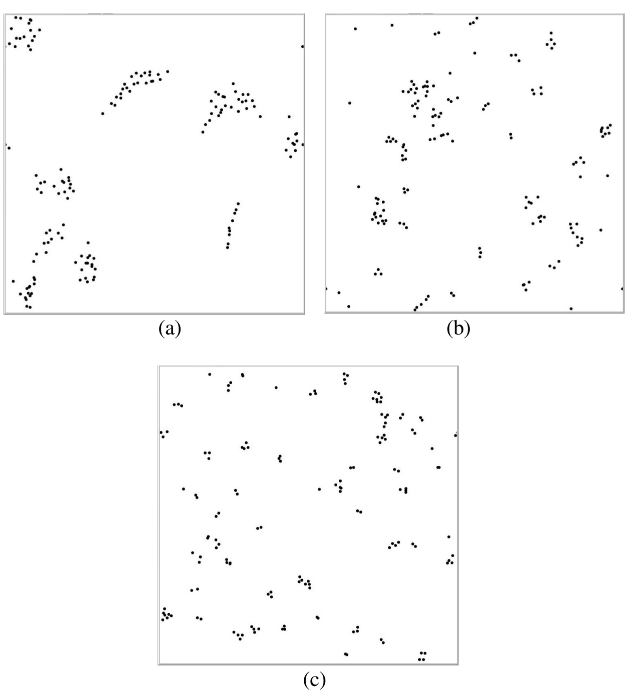


Fig. 6. Agents position at t = 7000 time steps of three movement models: (a) fish-like, (b) mosquito-like, (c) firefly-like.

200 agents randomly distributed in the arena and allowed the simulations to run for 7,000 time steps. Figs. 6(a), 6(b) and 6(c) show the aggregation of the fish-like, mosquito-like and firefly-like swarms movement models, respectively. For the fish-like movement model, the agents aggregate in large numbers in several groups. The firefly-like movement model, on the other hand, shows that agents formed several clusters with a small number of agents in each cluster. Using the mosquito-like movement model, fig. 6(b) shows that the agents aggregate in several large and small groups. This behavior is similar to what Ikawa and Okabe [14] suggested, that mosquitoes do not remain at a single swarming site but repeatedly enter and leave the sites. For this reason, mosquitoes aggregate with large and small numbers in each group; hence, the name mosquito-like movement model.

III. Simulations and Results

As previously mentioned, 300 agents were used in these simulations. All simulations used a square arena of size 201 by 201 patches, such as the one shown in Fig. 1. Thirty runs are made for each movement model, as stated before, with random initial placement of the agents in the arena. The performance was evaluated at the end of the simulation and all runs were executed for 7,000 simulation time steps to give enough time for all agents to aggregate towards the field. The data for analysis was recorded at every 100 time steps during the simulation.

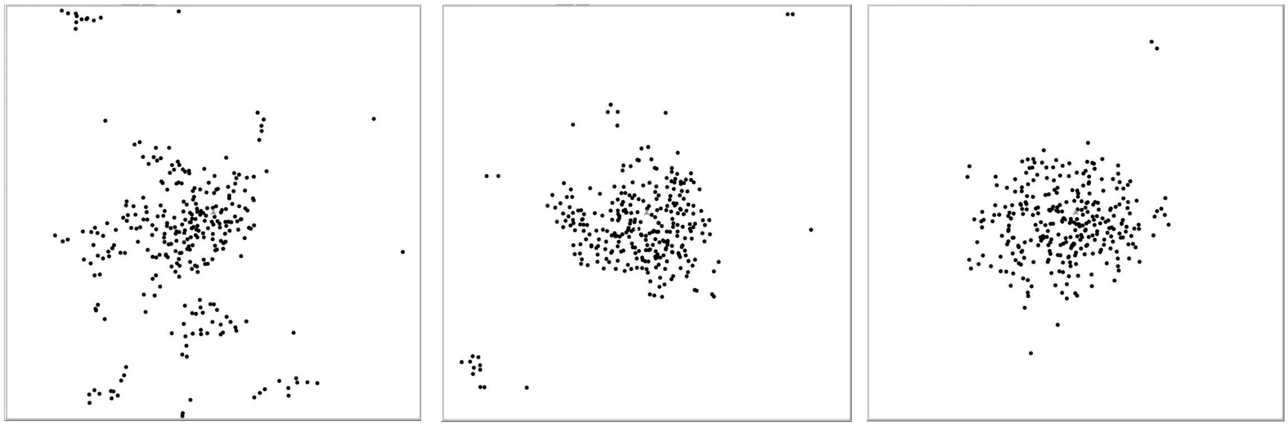
A. Evaluating the fish-like movement model

In evaluating each movement models, first we counted the number of agents within the circular area starting from the center of the field, in our case, from the patch at (0,0). As the number of agents in the simulations was fixed at 300 agents and the working arena at 201 by 201 patches, increasing from zero, we can expect that the number of agents should reach 300 when the radius of the circular area originating from the the center of *field* reaches 141, as it would completely cover the arena. The reason we counted the number of agents within the circular area was to see how close these agents are to the center of APF.

As stated previously, for the fish-like movement model, we set the *movement span* to 10-degrees and *visibility range* to 10 patches. Fig. 7 shows the agent's location from one of the simulations at three different simulation time steps; 150, 330 and 500 time steps, respectively. It is clear that as early as 150 time steps, more than half the number of agents have already converged towards the center of the arena.

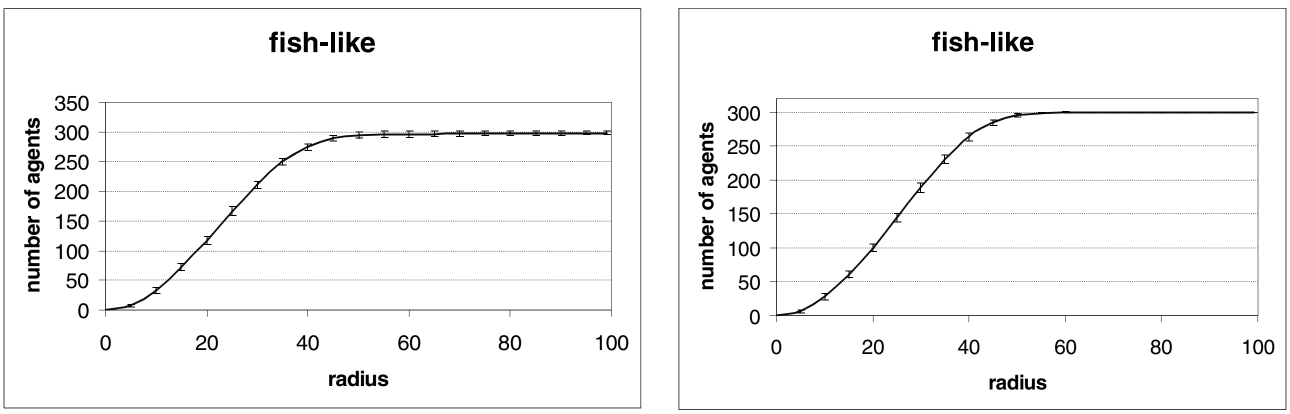
During the *flock inside field* phase, the flocking agents exhibited a smooth circling behavior concentrated on the origin of the APF; in this case, the center of the arena. The overall direction of the flow appears to be random, sometimes clockwise and sometimes anti-clockwise. The reason for this is because as soon as an agent enters the *field* it will look around for flockmates. If any is found, it will change its direction to match the majority of its flockmates in either a clockwise or anti-clockwise direction, resulting in the aforementioned emergent behavior inside the *field.*

Fig. 8(a) and 8(b) are plots of the number of agents within the circular area from the center of the APF, at simulation time steps of 500 and 5000, respectively. The results show that, at 500 simulation time steps, almost all the agents are already inside the field; in other words, almost all of the 300 agents have already converged



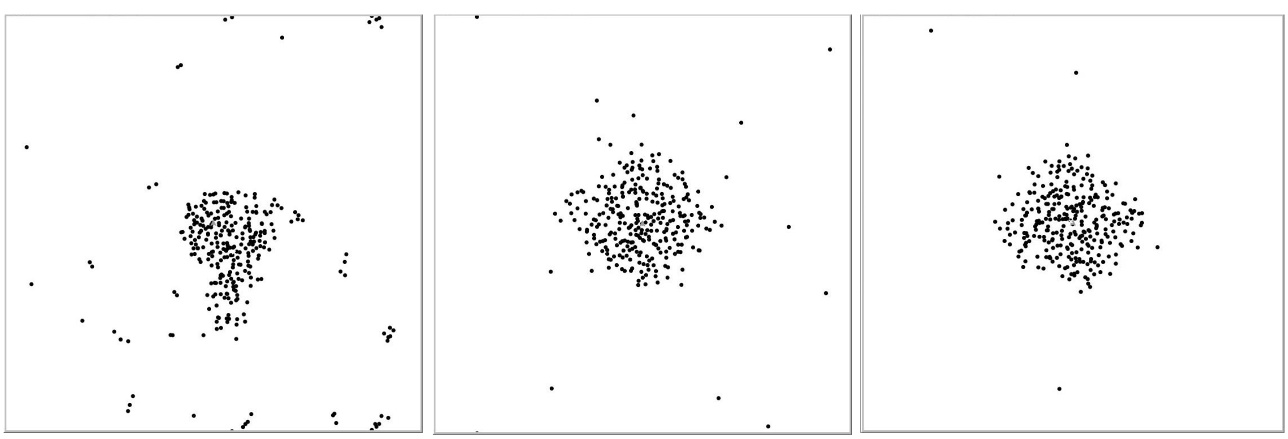
(a) (b) (c)

Fig. 7. Positions of agents in the arena at different time steps for the fish-like movement model; (a) at 150 time steps, (b) at 330 time steps, (c) at 500 time steps.



(a) (b)

Fig. 8. Number of agents for the fish-like movement model within circular area from the center of APF; (a) at 500 simulation steps, (b) at 5000 simulation steps.



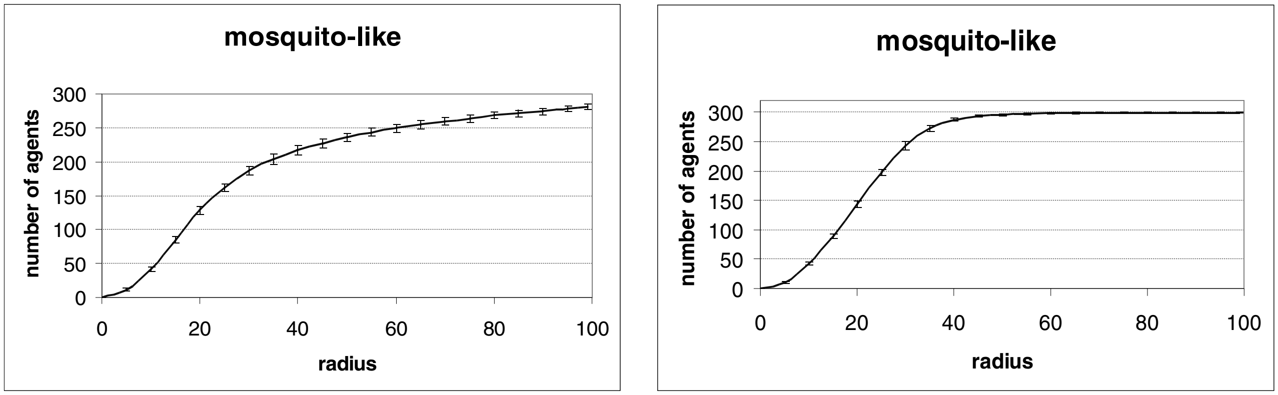
(a) (b) (c)

Fig. 9. Positions of agents in the arena at different time steps for the mosquito-like movement model; (a) at 500 time steps, (b) at 1000 time steps, (c) at 1500 time steps.

towards the field of radius 63, with small variances. Fig. 8(b) shows that, by 5000 simulation time steps, all the agents are converged inside the field with no or negligible variance.

B. Evaluating the mosquito-like movement model

As mentioned above, for the mosquito-like movement model, we set the *visibility range* and *movement span* to 7 patches and 45-degrees, respectively. In this movement



(a) (b)

Fig. 10. Number of agents for the mosquito-like movement model within circular area from the center of APF; (a) at 500 simulation steps, (b) at 5000 simulation steps.

model, without the *field* agents appear to be forming several clusters of varying size as shown in Fig. 6(b)

Fig. 9 shows the snapshots of one of the simulation runs for the mosquito-like movement model at three different time steps: 500, 1000 and 1500 time steps, respectively. At t = 500, we can notice that more than two-third of the agents are already converged towards the center of arena, at t = 1000, the number of agents is increasing and at t = 1500 almost all the agents have found the field and aggregate near the center.

During the *flock inside field* phase, the flocking behavior appears to be circulating the origin of the *field*, but not as smoothly as that exhibited by the fish-like movement model. In this case the agents tend to stay a little bit closer to their flockmates, thus limiting the circulating movement.

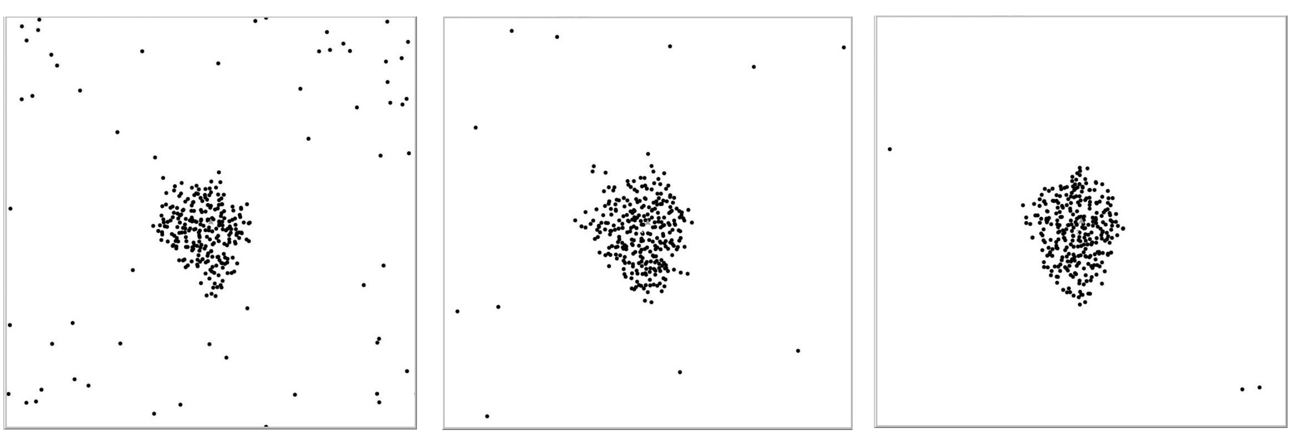
Figs. 10(a) and 10(b) show the plot of the number of agents within a particular radius of the center of the *field*, at simulation time steps of 500 and 5000, respectively. From fig. 10(a), it can be clearly seen that at t = 500, around 250 agents are flocking inside the field with a variance around 10 agents. At 5000 simulation time steps, all the 300 agents have converged towards the center of the field with a small standard deviation of 1.21.

C. *Evaluating the firefly-like movement model*

For the firefly-like movement, we fixed the *visibility range* to 5 patches and *movement span* 90-degrees. Fig. 11 shows one of the simulation runs for the firefly-like movement model at 1000, 2000 and 3000 time steps, respectively. At t = 1000, even though some of the agents are already converged towards the center of arena, we can clearly see that a great number of agents are still in the *wander* or *flock* phase; in other words, agents are roaming in the arena looking for flockmates or flocking outside the *field.* At t = 2000, the number of agents outside the *field* seems to decrease significantly compared to t = 1000. At t = 3000, almost all the agents are in the *wander inside field* phase or have already converged towards the *field.*

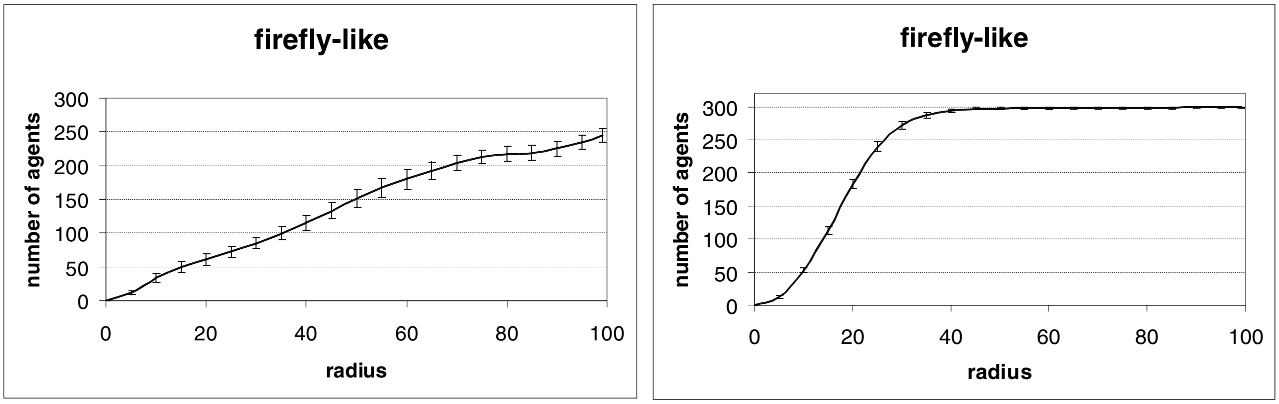
During the *flock inside field* phase, unlike the previous two movement models, instead of agents circulating the origin of the APF, the agents seem to only converge to the center of the field and move around only within their small local area.

Figs. 12(a) and 12(b) show the plot of number of agents within a particular radius of the origin of the APF, at simulation time steps of 500 and 5000, respectively. From fig. 12(a), we can see that at t = 500, the number of agents increases almost linearly with radius, this shows that the agents are still evenly distributed across the arena; while at



(a) (b) (c)

Fig. 11. Positions of agents in the arena at different time steps for the firefly-like movement model; (a) at 1000 time steps, (b) at 2000 time steps, (c) at 3000 time steps.



(a) (b)

Fig. 12. Number of agents for the firefly-like movement model within circular area from the center of APF; (a) at 500 simulation steps, (b) at 5000 simulation steps.

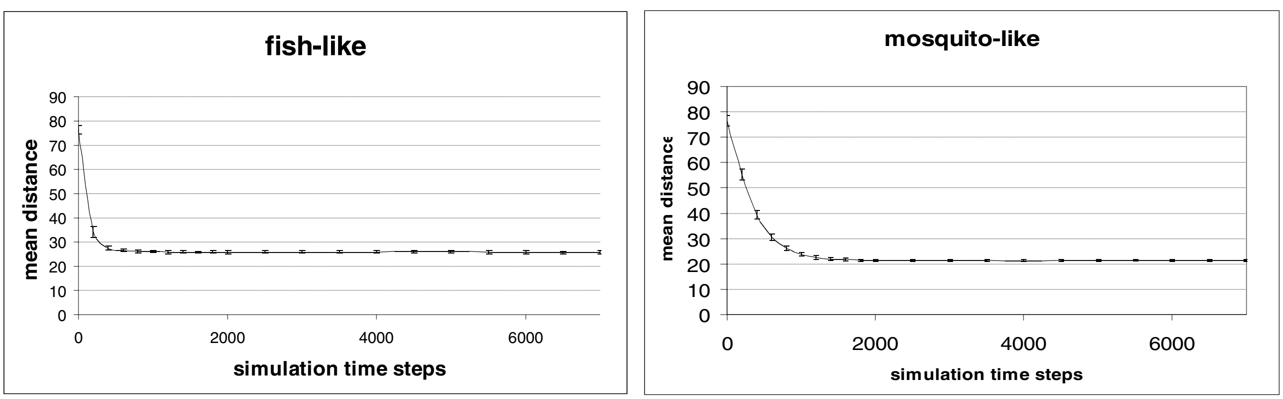
$t = 5000$, all the 300 agents have converged towards the center of the field with a small standard deviation of 1.87.

D. Evaluating mean distance

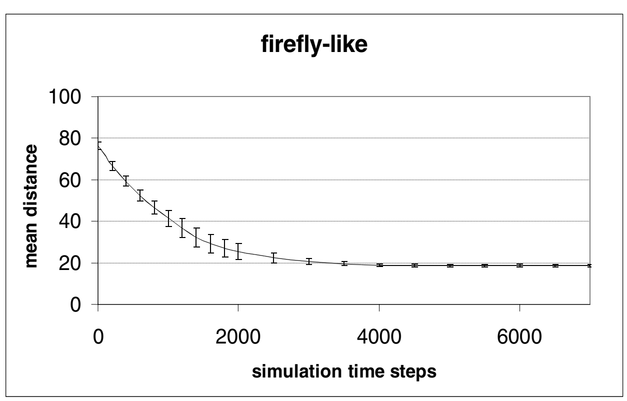
In order to further understand how the swarm converges, we then computed the mean distance, D of each agent towards the center of APF at each time step during the simulations as in (2); where x_a and y_a are the x-coordinate and y-coordinate of agent a, and n is the number of agents in the simulation.

$$D = \frac{\sum_{a=1}^{n} \sqrt{(x_a^2 + y_a^2)}}{n} \tag{2}$$

Fig. 13 shows the plots of mean distance D, against time for each movement model. Fig. 13(a) and 13(b) show plots for the fish-like and the mosquito-like movement models. As can be observed from the plots, the variance of D over 30 runs reaches to about 5 prior to convergence; while for the firefly-like movement model fig. 13(c) has a higher variance of around 10 prior to convergence.



(a) (b)



(c)

Fig. 13. Convergence of mean distance, D during simulations; (a) fish-like, (b) mosquito-like, (c) firefly-like movement models.

Fig. 13 also shows the significant difference in convergence rates between the three movement models. The graphs clearly show that the fish-like movement model converges faster than the other two; while the firefly-like movement model is the slowest. This can be explained by the fact that for the fish-like movement model, with a small *movement span* of 10 degrees, agents can cover a wide area in a short time; while in the firefly-like movement model, with a wider *movement span* of 90 degrees, the agents are more likely to scan within their local area.

From the fig. 13(c), it can be seen that the mean distance, *D,* for the firefly-like movement model is the smallest at around 18 units; while the fish-like model in fig. 13(a), has the largest at around 27 units.

From fig. 7(c) for fish-like, fig. 9(c) for mosquito-like and fig. 11(c) for firefly-like movement models, it can be seen that when the systems converged, they form loose, medium and tight clusters, respectively. It is the innate tendency to form these kinds of clusters that affects the mean distance *D* values in the plot of fig. 13.

IV. Conclusions

In this paper, we have selected several individual behaviors in terms of single-agent movement models and studied their effect in a macroscopic swarm.

Results show that by changing the limits of the angle through which an agent can turn, *i.e. movement span*, various swarming behaviors can be achieved. Several emergent behaviors are achieved and these behaviors affect the convergence rate in performing an aggregation task.

Future directions of this work will include investigation on how the population density in the arena affects the performance and the convergence rate. Also, further work will be carried out in scenarios with more than one attraction field with varying strengths and the effect this will have on an agent's trajectory and the group behavior of the swarm. Several types of obstacles will also be modeled in order to understand the emergent behaviors that obstructions may produce.

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