Design of Influencing Agents to Aid Flock Formation in Low-Density Settings

Paper #494

ABSTRACT

Flocking is a coordinated collective behavior that results from local sensing between individual agents who have a tendency to orient towards each other. Flocking is common amongst animal groups and could also be useful in robotic swarms. In the interest of learning how to control flocking behavior, several pieces of recent work in the multiagent systems literature have explored the use of influencing agents for guiding flocking agents to face a target direction. However, the existing work in this domain has focused on simulation settings of small areas with toroidal shapes. In such settings, agent density is high, so interactions are common, and flock formation occurs easily. In our work, we study new environments with lower agent density, wherein interactions are more rare. We study the efficacy of placement strategies and influencing agent behaviors drawn from the literature, and find that the behaviors that have been shown to work well in high-density conditions tend to be much less effective in the environments we introduce. The source of this ineffectiveness is a tendency of influencing agents explored in prior work to face directions intended for maximal influence that actually separate the influencing agents from the flock. We find that in low-density conditions maintaining a connection to the flock is more important than rushing to orient towards the desired direction. We use these insights to propose new placement strategies and influencing agent behaviors that overcome the difficulties posed by our new environments. The best influencing agents we identify act like normal members of the flock to achieve positions that allow for control, and then exert their influence. We dub this strategy "follow-then-influence."

1 INTRODUCTION

Across nature, flocking behavior can be found in a variety of species, from flocks of birds, to herds of quadrupeds, schools of fish, or swarms of insects. In such species, groups exhibiting collective behavior emerge from simple, local rules [18]. An open question is whether externally-controlled influencing agents can be used to affect the behavior of flocks. For example, environmental engineers might want to steer flocks of birds away from windmills, or steer a school of fish away from critical dam infrastructure.

Previous work has explored the use of influencing agents to guide flocking agents to face a target direction in small and toroidal settings. In such settings, agent density is high, so interactions are common, and flock formation is rapid. In this work, we focus on lower-density settings where interactions are rarer and flock formation is more difficult. We study how influencing agent priorities must change in these settings to be successful and propose new influencing agent strategies to adapt to the challenges posed by these settings.

For our work, we draw heavily from a recent series of studies of this problem by Genter and Stone [3–9]. Genter and Stone study influencing agent placement and behavior in small, toroidal environments.[1] In such environments, agents are bound to a small space and have unlimited opportunities to re-enter the screen and join a flock; flock formation is rapid.

We study this question in a more adverse environment by proposing two new test settings with lower agent density. In one setting, we keep the simulation space toroidal but increase the size of the space by several factors, greatly decreasing agent density. Flock formation is still provably guaranteed in this setting, but is much less rapid, so we study whether influencing agents can speed up flock formation. In the other setting, we make the simulation space non-toroidal but start the flocking agents in a circle in the center. Since this space is non-toroidal, flock formation is not guaranteed, so we study whether influencing agents can instigate flocking behavior by keeping the flocking agents in a pre-defined area, or move them all in a certain direction.

Low-density settings are important to study because they capture dynamics in situations where flocking may not occur naturally, but where we might want to instigate flocking behavior; imagine a herd of buffalo that is currently grazing, or a spooked flock of birds where individual agents fail to coordinate. It may also have implications for coordination in low-density swarms of robotic multi-agent systems, where control may be imperfect, such as RoboBees [1].

To help organize our analysis, we consider three different aspects of influencing agent design: placement strategy, local behaviors, and global behaviors. Placement strategies refer to the initial placement of influencing agents in the simulation space and their placement relative to flocking agents. Local behaviors dictate how an influencing agent attempts to influence local neighbors to face a given goal direction. Global behaviors, on the other hand, dictate how influencing agents determine their goal direction. For example, we might program all the influencing agents to have a pre-determined goal direction such as East or South, or we might program a global behavior that picks a goal direction after some time based on the initial dynamics of the simulation.

We find that in environments with low agent density, agent interactions are rare, so results from experiments in smaller settings do not translate well to larger settings. In particular, when agent interactions are rare, maintaining a connection to the flock becomes a key factor in the efficacy of influencing agent behaviors. As a result, simple local behaviors such as "face the goal direction" are often superior to more complex local behaviors that try to optimize for speed. We also experiment with a number of new strategies

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[1]In a toroidal environment, agents that exit the simulation space from one side immediately re-appear on the other side

and find that a multi-stage approach of "follow-then-influence" can be effective in certain situations. In this approach, influencing agents start out by obeying the flocking rules, embedding themselves inside small, naturally-forming flocks. After some time, the influencing agents start influencing their neighbors to face a given goal direction. Finally, we find that reasonable placement strategies are often interchangeable, and that more complex strategies often perform similarly to random strategies.

The main contributions of this work are:

- An investigation of two new low-density flocking settings, where flock formation is more difficult.
- The introduction of new placement strategies and influencing agent behaviors to adapt to the difficulties presented by these new settings.
- Analysis of the major differences in influencing agent priorities in low-density vs. high-density settings.

The rest of this paper is organized as follows: §2 describes our formal flocking model and our new test settings. §3 describes the role of influencing agents and formalizes concepts of placement strategies and behaviors. §4 describes our experimental setup and the experiments we run to evaluate our placement strategies and behaviors in our test settings. We discuss the results and their implications in §5. In §6, we discuss related work and other approaches. Finally, we conclude and discuss future work in §7.

2 PROBLEM DESCRIPTION

2.1 Flocking Model

Like other studies in the literature, we use a simplified version of Reynold's Boid algorithm [15] to model the flock. In this simplified model, also proposed independently by Vicsek and collaborators [20], agents change their alignment at every step to be similar to the average alignment of other agents in their neighborhood. At each time step, each agent a_i moves with constant speed $s = 0.7$, has orientation $\theta_i(t)$, and position $p_i t) = (x_i(t), y_i(t))$. At timestep t, a_i updates its position based on its alignment: $x_i(t) = x_i(t-1) + scos(\theta_i(t))$ and $y_i(t) = y_i(t-1) - ssin(\theta_i(t))$. At the same time, the agents change their orientation based on the alignments of neighboring agents. Let the neighbors $N_i(t)$ be the set of agents at time t that are within radius r of a_i, not including a_i itself; in our simulations, this radius is 10 units. At timestep t, each agent updates its orientation to be the average of their neighbors' orientations:

$$\theta_i(t+1) = \theta_i(t) + \frac{1}{n_i(t)} \Sigma_{a_j \in N_i(t)} \text{calcDiff}(\theta_j(t), \theta_i(t)),$$

where calcDiff computes the difference in angle between two orientations [8].

2.2 New Settings

Previous work has studied influencing agents in small toroidal 300x300 and 600x600 grids [7, 8]. In this work, we introduce two new settings that are more adverse to flock formation; we call these new settings the *large* setting and the *herd* setting. Before discussing these settings in detail, we note that our *herd* setting is unrelated to Genter and Stone's 2014 herd experiment [6].

In the *large* setting, non-influencing agents are randomly placed in a toroidal 1000x1000 grid with random initial orientations. The larger grid size results in lower agent density; as a result, agents start out much farther away from other agents' neighborhoods, and interactions are much rarer. However, since the simulation space remains toroidal, flock formation is still provably guaranteed, so we are primarily interested in studying the amount of time to convergence in this case. In the *herd* setting, non-influencing agents are placed randomly in a circle of radius 500 whose origin lies at the center of a 5000x5000 non-toroidal grid. In this setting, flock formation is not guaranteed, since the space is non-toroidal. As a result, we are interested in studying how well influencing agents can keep the non-influencing agents from getting lost.

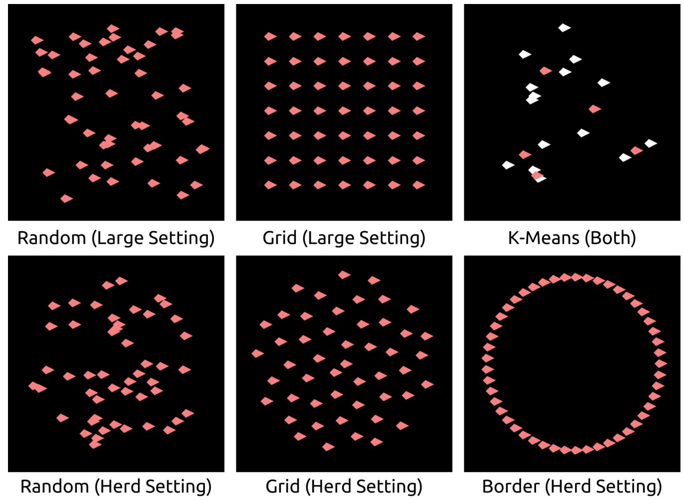


Figure 1: The different placement strategies we explore in this paper. Red agents are influencing agents, and white agents are Reynolds-Viscek agents.

3 INFLUENCING AGENTS

We can change flock dynamics by introducing influencing agents that we control. We refer to non-influencing agents as Reynolds-Viscek agents. Influencing agents do not have any special control over Reynolds-Viscek agents, which simply interact with influencing agents using the same local sensing rules as with any other agent. However, influencing agents can induce different behaviors in the flock by adopting different strategies and exerting influence over their neighbors. Open questions include where best to place these agents for maximum influence and what behaviors influencing agents should adopt. In this work, we force the influencing agents to have the same speed as the Reynolds-Viscek agents to conform to the Genter and Stone experiments. In a real application, having a similar speed to animals in a flock may assist in the influencing agents' ability to blend in with the animals. We briefly address approaches that do not conform to this constraint in §6.

3.1 Placement

In this work, we study a number of different placement strategies. Our different placement strategies are shown in Figure 1. We note that the question of how to maneuver influencing agents to reach the positions given by these placement strategies is important, but out of scope for this paper. For a discussion of this question, we refer the reader to Genter and Stone [3, 8].

For the *large* setting, we study three placement strategies adopted from the literature: *random*, *grid*, and *k-means* [3, 9]. The random placement strategy, as its name suggests, places influencing agents randomly throughout the grid. The grid placement strategy computes a square lattice on the grid and places influencing agents on the lattice points. This strategy ensures regular placement of influencing agents throughout the grid. The k-means placement strategy uses a k-means clustering algorithm on the positions of Reynolds-Viscek agents in the simulation space. This strategy finds a cluster for each influencing agent by setting k equal to the number of influencing agents, and then places an influencing agent at the center of each cluster.

We develop similar placement strategies for our herd setting, with some differences. To adapt the strategies to a circular arrangement of agents, we define each strategy in terms of some radius r about an origin O, except for the *k-means* strategy, which remains the same. We modify the *random* placement strategy to randomly distribute agents within the circle of radius r about the origin O, instead of the entire simulation space. We adapt the grid placement strategy to a circular setting using a sunflower spiral [16]. In polar coordinates relative to O, the position of the n-th influencing agent in a sunflower spiral is given by $(c\sqrt{n}, \frac{2\pi}{\phi^2}n)$, where ϕ is the golden ratio, and c is a normalizing constant such that the last influencing agent has distance r from O. We also introduce a circle border placement strategy, inspired from the border strategies from [9]. This strategy places agents on the circumference of the circle of radius r around the origin O.

3.2 Behaviors

Once we have placed our influencing agents, we still need to design how they will work together to influence the flock. We call this aspect of the design influencing agent behaviors. In the present work we focus on decentralized "ad-hoc" algorithms for our influencing agents since this class of algorithms has been the focus of the existing multiagent systems literature on this topic [3, 6, 7].

To help organize our analysis, we split behaviors into local and global components; each influencing agent behavior is composed of a local and global component. The local component takes a desired orientation as an argument and dictates which direction an influencing agent will face to try to influence its neighbors towards the goal orientation. The global component, on the other hand, dictates the desired orientation to feed to the local component and how the influencing agents might coordinate to decide on a desired orientation. For example, one behavior might be for the influencing agents to circle around the center of a grid and get the Reynolds-Viscek agents to circle with them. The global component would compute the desired orientation necessary at each step to maintain the circling behavior, and the local component would compute which exact direction to face to get the Reynolds-Viscek agents to face the desired orientation at that step. For grammatical sanity, we will refer to different candidates for local and global components as "local behaviors" and "global behaviors" throughout the rest of this paper; however, it is important to recognize that any actual behavior must have a local and global component.

Table 1: Summary of global behaviors we investigate

Setting	Type	Name	Description
Large		*Direct*	Influence neighbors or face goal
		Random	Influence neighbors or face random
		Multistep	***Follow-then-influence***
Herd	Net	*Direct*	Influence neighbors or face goal
	Stationary	*Circle*	Trace circle around agents
		Polygon	Trace polygon around agents
		Multicircle	***Follow-then-influence***

Local Behaviors. Like our placement strategies, we draw on Genter and Stone for many of our local behaviors [7–9]. In previous work, they have introduced baseline behaviors *face* and *offset momentum*, as well as more sophisticated behaviors *one step lookahead* and *coordinated*. Each of these behaviors requires a goal angle θ^*. In *face*, influencing agents always face the angle θ^*. In *offset momentum*, influencing agents calculate the average velocity vector of the agents in their neighborhood, and take on a velocity vector that, when added to the average velocity vector, sums to the vector pointing in direction θ^*. In *one step lookahead*, each influencing agent cycles through different angles and simulates one step of each of its neighbors if it were to move in that angle. It adopts the angle that results in the smallest average difference in angle from θ^* among all its neighbors. Finally, in *coordinated*, each agent pairs with another and runs a one step lookahead to minimize the average difference in angle from θ^* among both their neighbors. For a more detailed explanation of these behaviors, especially the *coordinated* behavior, we direct the reader to Genter and Stone [7].

Global Behaviors. The global behaviors we investigate are listed in Table 1. We have three global behaviors for the *large* setting: *direct*, *random*, and *multistep*. As its name suggests, the *direct* global behavior has each influencing agent use a local behavior to directly influence its neighbors towards the goal angle θ^*. When an influencing agent has no neighbors, it simply faces the goal direction.

The *random* global behavior is very similar, but it directs influencing agents in a random direction when they have no Reynolds-Viscek neighbors. We introduced this behavior as a response to interactions where an influencing agent is almost successful in changing the direction of a group of Reynolds-Viscek agents, but gets separated before it is completely successful. In these cases, the Reynolds-Viscek agents are left on a trajectory that is almost parallel to the goal direction; as a result, further interactions with influencing agents are rare.

The *multistep* behavior adopts what we call a "follow-then-influence" behavior. In the initial stage, influencing agents simply behave like normal Reynolds-Viscek agents; as a result, they easily join flocks and become distributed throughout the grid. At the same time, the influencing agents perform a global calculation of the total number of Reynolds-Viscek agents that are path-connected to influencing agents. Here, we define two agents as being path-connected if there is a path between them, where edges are created by two agents being in each other's neighborhood. Once that number passes some threshold T, the influencing agents calculate the average angle $\overline{\theta}$ among all the agents that are locally connected to influencing agents, and from there adopt the *direct* behavior with goal $\overline{\theta}$. We choose $\overline{\theta}$ to minimize the amount that each influencing agent needs to turn its flock on average. To the best of our knowledge, this is a novel behavior not studied in the existing literature.

For the *herd* setting, we divide our global behaviors into two categories: a *net* behavior, and a set of *stationary* behaviors. As a reminder, in the *herd* setting, the simulation space is non-toroidal, and all the Reynolds-Viscek agents start in a circle in the center. In this setting, flock formation is not guaranteed, so we are interested in using influencing agents to instigate flocking behavior. There are two different choices we can make; we can either try to force the Reynolds-Viscek agents to stay in the center (*stationary* behaviors), or we can let the influencing agents direct the Reynolds-Viscek agents away from their initial starting position. Since all our agents have a constant speed, the former is much more difficult than the latter, so we must evaluate them separately.

The *net* behavior is equivalent to the *direct* behavior; there is a single pre-determined goal direction, and the influencing agents try to direct the Reynolds-Viscek agents towards the goal direction. We call it a net behavior because it looks as if the influencing agents are "catching" the Reynolds-Viscek agents in a net.

We study three *stationary* behaviors: *circle*, *polygon*, and *multicircle*. The *circle* and *polygon* behaviors have each influencing agent trace a circle or polygon around the origin. For placement strategies where influencing agents have different distances to the origin, the influencing agents simply trace circles and polygons of different radii.

The *multicircle* behavior is analogous to the *multistep* behavior from *large*. The influencing agents start out by circling around the origin and wait for Reynolds-Viscek agents to enter their neighborhood. Once they detect Reynolds-Viscek agents in their neighborhood, they adopt a "following" behavior where they act like Reynolds-Viscek agents to integrate into a small flock. They continue this following stage until reaching a final radius r_F, at which point they again adopt a circling behavior. In addition to building influence by following before influencing, this behavior also makes maintaining influence easier; since the final radius is larger than the original radius, the final path turns less sharply than if the influencing agents had stayed at their original radius. To the best of our knowledge, this is the first presentation of such a multi-stage behavior to induce circling behavior under the Reynolds-Vicsek model in the literature.

Besides the above global behaviors, we also explored a few more variations on the *net* behavior and the *multicircle* behavior. One variation of the *net* behavior was equivalent to the *random* global behavior from the large setting. The other was similar to the the stationary *circle* behavior; influencing agents would trace a circle until encountering Reynolds-Viscek agents, whereupon they would influence the Reynolds-Viscek agents towards the goal direction. The variations on the *multicircle* behavior included different final radii from those presented in §5, as well as a variation that introduced a transitional period between the initial following state and the final circling state. These additional variants added few qualitative insights, so we do not report them for simplicity of exposition.

4 EXPERIMENTAL SETUP

We extended the MASON simulator to run our experiments.[13] We used the default parameters for the Flocking simulation that is included with the MASON simulator, except without any randomness, cohesion, avoidance, or dead agents. We sampled all metrics every 100 time steps and ran all experiments for 100 trials.

4.1 No Influencing Agents

Previous literature compared new influencing agent behaviors with baseline influencing agent behaviors, but did not compare to settings with no influencing agents. In order to observe the marginal contribution of influencing agents in future experiments, we start our investigation of the *large* and *herd* settings by studying flock formation in those environments without any influencing agents. We use two metrics to evaluate flock formation: average number of flocks formed and average proportion of lone agents at each time step.

In the *large* setting , we test on a $1000x1000$ grid and vary the number N of Reynolds-Viscek agents from 50 to 300 in increments of 50. We run these simulations for 6000 time steps. In the *herd* setting, we use a $5000x5000$ grid, position the herd in the center of the grid with radius 500, and vary N from 50 to 300 in increments of 50. We run these simulations for 6000 time steps.

4.2 Influencing Agents in the Large Setting

Next, we evaluate the contributions of influencing agents. To evaluate the contributions of influencing agents in the *large* setting, we measure the time required for half of the Reynolds-Viscek agents to face the same direction. Unlike in previous work, which has limited the goal direction to a single pre-determined goal direction, here we open up the possibility to convergence to any direction to match the goal of our multi-step behavior.

We test the *random*, *grid*, and *k-means* placement strategies, along with global behaviors *face*, *random*, and *multistep*, each paired with local behaviors *fact*, *offset momentum*, *one step lookahead*, and *coordinated*. We place 300 Reynolds-Viscek agents on a $1000x1000$ grid, with 300 Reynolds-Viscek agents and vary the number of influencing agents from 10 to 100 in intervals of 10.

4.3 Influencing Agents in the Herd Setting

To evaluate the contributions of influencing agents in the *herd* setting we measure a slightly different metric. Since we have two qualitatively different categories of global behaviors (net behaviors vs. stationary behaviors), the number of agents facing the same direction is irrelevant, since the stationary behaviors rotate the agents around the origin (in fact, if the Reynolds-Viscek agents are all facing the same goal direction, the stationary behavior has failed). Instead, we measure the number of Reynolds-Viscek agents that are connected to influencing agents at 15000 time steps; this is a measure of sustained influence over the Reynolds-Viscek agents over time.

We examine three circular placement strategies, *border*, *random*, and *grid*, with two placement radii, *500* and *750*, along with the *k-means* placement strategy. We split our examination of global behaviors between the *net* behavior (analogous to *face*) and three stationary behaviors - namely *circle*, *polygon*, and *multicircle*. We use a polygon with ten sides (a decagon) for our *polygon* experiments, and we vary the final radius for multicircle based on the initial placement radius. When the placement radius is *500*, we set the final radius to *900*; when the placement radius is *750*, we set the final radius to *1100*. Finally, we pair the *face*, *offset momentum*, *one step lookahead*, and *coordinated* local behaviors with all the global behaviors and placement strategies. We place 300 Reynolds-Viscek agents inside a circle of radius 500 at the center of a $5000x5000$ grid, varying the number of influencing agents from 10 to 100 in intervals of 10.

5 RESULTS

5.1 No Influencing Agents

First, we briefly characterize the flocking behavior of a group of Reynolds-Viscek agents without influencing agents in the *large* and *herd* settings. We measure the number of clusters of agents that are path-connected and facing the same direction; each of these clusters forms a small flock. We also measure the number of lone agents (the number of agents with no neighbors). Figure 2 shows graphs of these values over time for our two settings.

In the *large* setting, there are two qualitative stages of convergence: initial flock formation and flock unification. In the first stage, individual agents collide with each other and form small flocks. In the second stage, these small flocks that formed collide with one another and join together to form larger flocks. In Figure 2, the first stage is represented by the initial increase in the average number of flocks, and the second stage is represented by the following decrease in the average number of flocks. This behavior is reflected in the continually decreasing number of lone agents; since the number of lone agents continues to decrease over time, we know that the decrease in the total number of flocks is due to flock convergence. Note that when there are more total agents, the absolute number of lone agents decreases faster and reaches a similar value to the other cases by the end of the simulation. In other words, the *ratio* of lone agents to total agents hits a lower value when there are more agents, but the final absolute number of total agents is still similar to the other cases.

The two stages of convergence also occur somewhat in the *herd* setting, but the second stage is cut off by the non-toroidal nature of the setup. As flocks leave the starting area, the chances of interacting with other flocks vastly decreases, so most of the flocks formed from the first stage never end up merging with other flocks. This is reflected in the plateaus of both the total number of flocks and the total number of lone agents. Some small artifacts in the graphs are worth mentioning; since the agents start off in a much smaller area than in the *large* setting, many of the agents start out with a non-zero number of neighbors. This causes the initial value of the average number of flocks to be non-zero, and the average number of lone agents to be less than the total number of agents.

5.2 Influencing Agents in the Large Setting

Next, we study the efficacy of various behaviors and placement strategies in the *large* setting. The average times for 50% convergence under different combinations of placement strategies with global and local behaviors are shown in Figure 3. We show graphs for 50 influencing agents only, since the trends for the other numbers of influencing agents were similar (the major difference being that when there are more influencing agents, convergence happens faster). Note that smaller is better in these graphs. The most immediately striking finding is that, in our more adverse setting, the *one step lookahead* and *coordinated* local behaviors significantly underperform the *face* behavior irrespective of global behavior and also underperform *offset momentum* for the *face* and *random* global behaviors. This is an opposite result from Genter and Stone's findings on smaller simulation spaces [3, 7], which found that *one step lookahead* and *coordinated* outperform *face* and *offset momentum* (the latter of which are in fact presented as "baseline" behaviors). This finding is also rather counterintuitive; why should the "smarter" behaviors underperform the simpler behaviors?

The answer is that, when agent interactions are rare, it is more important for influencing agents to *maintain influence* than it is for them to quickly change the direction of neighboring Reynolds-Viscek agents. The *one step lookahead* and *coordinated* behaviors underperform here because they tend to send influencing agents away from neighboring agents. An example of this phenomenon is shown in Figure 4. The influencing agent, shown in black, adopts an orientation that turns neighboring Reynolds-Viscek agents towards the goal direction. Even though this does turn Reynolds-Viscek agents towards the goal direction, it cannot successfully turn all the agents in a single step; as a result, it must maintain that orientation for future steps. However, as long as the neighboring agents are not facing the goal direction, the influencing agent's chosen orientation takes it away from the center of the flock of Reynolds-Viscek agents, causing it to lose influence. Once the influencing agent has lost influence, it is difficult to catch up to the same flock, since influencing agents travel at the same speed[2] as Reynolds-Viscek agents. As a result, the influencing agent is not actively influencing the direction of any Reynolds-Viscek agents until it encounters another group of Reynolds-Viscek agents.

Note that this effect also happens on a smaller simulation space, but it is not nearly as pronounced; when interactions are very frequent, influencing agents that have lost influence can find another group of Reynolds-Viscek agents very quickly. As a result, the gains from the smarter local algorithm still outweigh the negative effects from losing influence.

This effect is more pronounced for the *multistep* behaviors. First, we note that the *multistep* global behavior paired with the *face* local behavior seems to slightly outperform the *direct* and *random* global behaviors, but the *multistep* global behavior paired with the other local behaviors drastically underperform anything else. What is the root cause of this difference? The *multistep* global behavior starts out by creating many local flocks, some of which have influencing agents in them. When interactions are rare, the *offset momentum*, *one step lookahead*, and *coordinated* behaviors have difficulties changing the orientation of existing flocks quickly before losing influence. As a result, the *multistep* behavior takes an

[2] There are some approaches which remove this speed constraint from influencing agents [11]. However, this allows for unrealistic behaviors wherein influencing agents travel to one Reynolds-Viscek agent and a time and change the direction of the individual Reynolds-Viscek agent before moving on to the next one. This results in Reynolds-Viscek agents that are all facing the same direction, but that are often not path-connected.

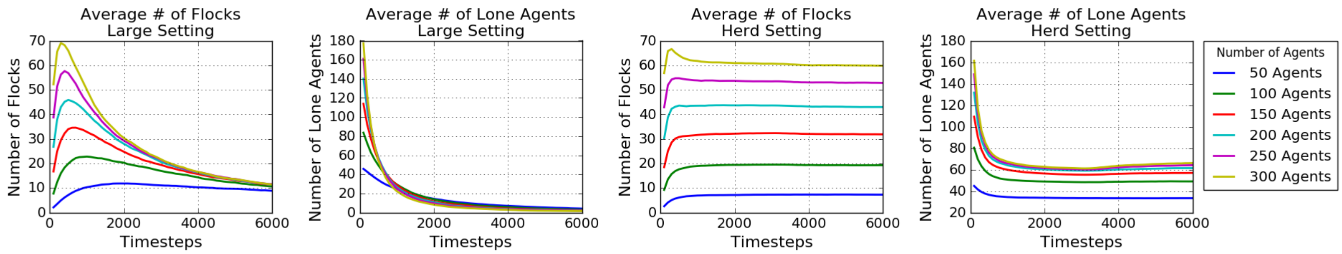


Figure 2: Average flock counts and lone agent counts over time for the *large* and *herd* settings with no influencing agents, varying the number of Reynolds-Viscek agents.

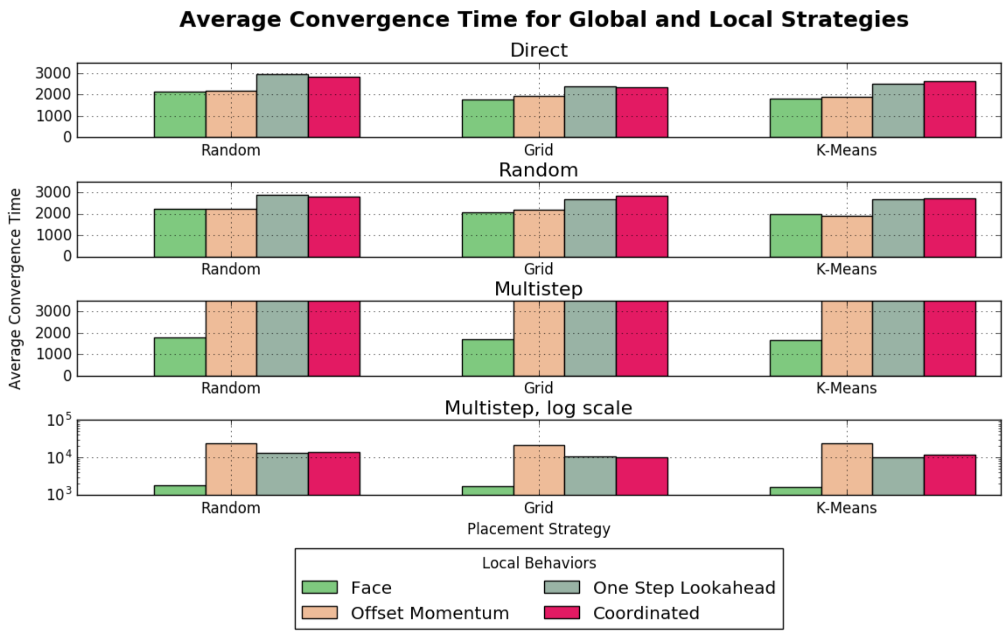


Figure 3: Average times to 50% convergence for 300 Reynolds-Viscek agents with 50 influencing agents in the *large* setting under different placement strategies, paired with various global and local behaviors. Smaller is better.

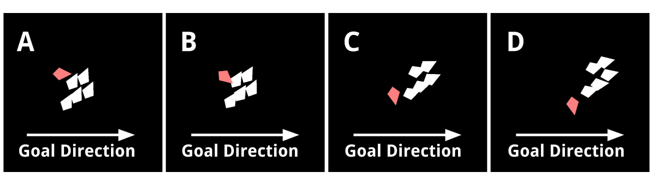


Figure 4: An example of an influencing agent losing influence under the *one step lookahead* behavior. The influencing agent is shown in red, and the Reynolds-Viscek agents are shown in white. In A, the influencing agent first encounters the flock of Reynolds-Viscek agents. In B-D, the influencing agent takes on directions that are oriented away from the goal direction to try to rapidly influence the Reynolds-Viscek agents. This changes the orientation of the Reynolds-Viscek agents, but the influencing agent has started to travel away from the flock by D.

order of magnitude longer to reach convergence when paired with the other local behaviors.

Finally, we note that the effect of placement behaviors on convergence time are almost non-existent. When the density is lower, there is a much smaller chance that any influencing agent will start out with more than one Reynolds-Viscek agent in its neighborhood, even with the *k-means* placement behavior. As a result, even the best clustering approach is almost the same as starting out randomly or in a grid.

5.3 Influencing Agents in the Herd Setting

Next, we evaluate results for our experiments in the *herd* setting. In many cases, measuring the number of agents facing the same direction is not interesting here, since it is impossible to keep Reynolds-Viscek agents in one place if they are facing the same direction. Instead, we exclusively measure the number of Reynolds-Viscek agents that are path-connected to influencing agents and facing the same direction as the influencing agent. This is a measure of "control" of the Reynolds-Viscek agents. The average number of agents in such local flocks after 15000 time steps is given in Figure 5 for both the net and stationary behaviors. We find that the net behavior vastly outperforms any of the stationary behaviors. However, there may be environments in reality for which the net behavior is not applicable (suppose it is strictly necessary to keep a flock in one place, for instance). Thus, we analyze the net behaviors separately from the stationary behaviors.

Net. Again, we find that the *face* local behavior tends to outperform the *offset momentum*, *one step lookahead*, and *coordinated* local behaviors. Again, we attribute this to the tendency of the *offset momentum*, *one step lookahead*, and *coordinated* behaviors to lose influence over time. We note that the effect is not as pronounced here as in our *large* experiments, since each influencing agent has to control fewer agents.

In contrast to the *large* experiments, we do find that the placement strategy has a major effect on the efficacy of the net behavior. Again, this has to do with density of influencing agents. For example, notice that *Border 750* (place the influencing agents in a circle about the origin with radius 750) vastly underperforms the other placement strategies. The larger radius results in a lower density of influencing agents, so a greater number of Reynolds-Viscek agents slip through the "holes" in the net. Furthermore, by the time the Reynolds-Viscek agents reach the border, they have already formed local flocks, and it is more difficult for the influencing agents to point them in the right direction. This effect is less pronounced for *Random 750* and *Grid 750*, since these strategies place influencing agents within the circle, and not simply along its circumference. As a result, the Reynolds-Viscek agents still encounter influencing agents before reaching the circumference of the circle.

Finally, we note that *k-means* outperforms all other placement strategies by a few agents. Again, the main driving factor behind this is agent density. When an influencing agent starts out in a clustered area, it has at least one other Reynolds-Viscek agent in its neighborhood. As a result, its effective area of influence is slightly larger than with the other placement strategies. This helps it pick up more Reynolds-Viscek agents in the net.

Stationary. For the stationary behaviors, we found that any local behavior except for *face* was almost completely ineffective; the average number of agents under influencing agent control after 15000 steps across 100 trials was almost 0. Again, this is a result of the inability of the *offset momentum*, *one step lookahead*, and *coordinated* local behaviors to maintain influence over time. Each of the stationary behaviors requires the influencing agents to keep the Reynolds-Viscek agents rotating about the origin in some way. Without consistent influence, this is impossible.

Beyond that, we find that the *multicircle* behavior slightly underperforms the *circle* behavior when paired with the *Border* placement strategies, but slightly overperforms when paired with the *k-means*, *Random*, *Circle*, and *Grid* placement strategies, and performs the same as *circle* n the *Grid* strategies. What drives these trends? Once *multicircle* reaches the final stage, it is tracing a larger circle than the *circle* behavior traces on its own. As a result, it is easier to maintain influence and turn the Reynolds-Viscek agents over time in the final stage. Before that, however, the influencing agents are in a following stage. When the influencing agents start out inside the circle, they have more time to infiltrate small flocks of Reynolds-Viscek agents and induce a circling behavior in the final stage.

Finally, we note that *Border 750* is the worst placement strategy, for reasons similar to the reasons for the net behaviors, and *polygon* tends to underperform or match the performance of *circle*. This tells us that adopting occasional sharper turns can sometimes be harmful, but not always.

6 RELATED WORK

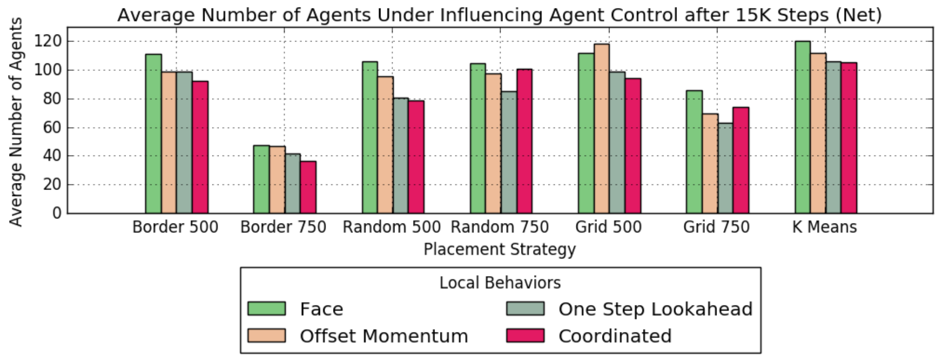
Our work builds mainly upon the work of Genter and Stone, who have recently published a series of papers on the best way to influence an existing flock to change direction [4–9]. This prior literature has studied a number of placement strategies and influencing agent behaviors, including questions of how best to join or leave a flock in real scenarios. Genter's PhD thesis also presents results from simulations with a slightly different implementation of Reynold's flocking model, as well as physical experiments with these algorithms in a small RoboCup setting. This prior literature has almost exclusively studied small environments, where density of agents is high, and quick flock formation is virtually guaranteed. In our work, we study two new low-density environments and introduce new placement strategies and influencing agent behaviors to adapt to the difficulties presented by these new environments.

Han et. al. have [11] published a series of papers showing how to align a group of agents in the same direction. This literature has assumed a single influencing agent with infinite speed, and has used this property to construct a behavior that has the influencing agent fly around and correct the orientation of agents one at a time. The result is that the Reynolds-Viscek agents all eventually converge to the target direction, but are not connected to each other. In our work, we limit the speed of influencing agents to be the same as the Reynolds-Viscek agents to prevent the use of behaviors like this, and in hopes that our results will be more applicable to real applications; we suspect that influencing agents that act similarly to real birds will be more successful in real-world applications.

Jadbadbaie et. al. [12] have studied variations on the Reynolds flocking model from an analytical perspective, with no influencing agents. A strong result from this literature is that a group of Reynolds-Viscek agents in a toroidal setting will eventually converge regardless of initial conditions. However, there has been less analytical work on the speed of flock formation, and very little on the use of influencing agents to speed up flock formation or to force flocks to face given directions.

Su. et. al. [17] have also studied the question of flock formation and convergence, but have studied the question in the context of the Olfati-Saber flocking model [14]. This model assumes the existence of a single virtual leader that non-influencing agents know about. The virtual leader plays the role of an influencer here, but has special control over the other agents based on its status. In our work, we assume that influencing agents do not have any special interaction rules with Reynolds-Viscek agents.

Couzin et. al. [2] have studied this question with a slightly different formulation, and with a different model of flocking behavior.



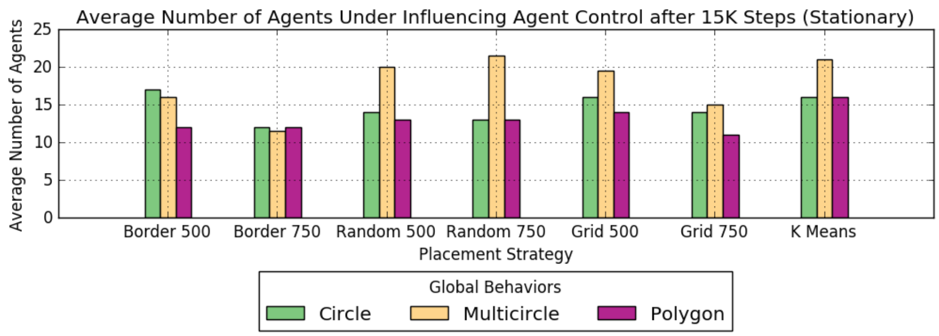


Figure 5: Average number of agents under influencing agent control after 15000 steps with 300 Reynolds-Viscek agents and 50 influencing agents in the *herd* setting under for various placement strategies and influencing agent behaviors. The net behavior moves the influencing agents and their Reynolds-Viscek agents off-screen, while the stationary behaviors keep the influencing agents near the goal area using some sort of circling technique. For the stationary behaviors, we found the only effective local behavior was *face*, so that is the only local behavior displayed. Larger is better.

In their model, flocking behavior is achieved by maintaining distance between neighbors, and they cast the problem as one of informed individuals (analogous to influencing agents) trying to change the trajectory of the flock. The informed individuals are not externally-controlled; they simply have information about the "correct" orientation. In particular, the informed individuals can be wrong or have different opinions than other individuals, so information transfer is key. This differs from the settings we study, where influencing agents are completely autonomous and agree on a goal direction.

Other researchers have tackled this question with real flocking agents. Halloy et. al. [10] have used robotic influencing agents to move cockroaches to areas they would otherwise avoid. Cockroaches display flocking behavior, but with very different models from the one that we study. In this case, Halloy et. al. have exploited the cockroaches' inability to differentiate between real cockroaches and the robotic influencing agents.

Vaughan et. al. [19] have used robotic influencing agents to herd a flock of ducks (on the ground) to a goal position in a small caged area. The approach here largely uses the robot agents to "push" the ducks from a distance, like a dog herding sheep. The dynamics in this case are very different from the models we study; when the ducks are on the ground, they can stand still, for instance, and the fence limits the ducks' behavior.

7 CONCLUSION

We have studied the problem of controlling flocks using influencing agents under two new, more adversarial environments with lower agent density, and have introduced some novel behaviors and placement strategies for these settings. Besides these new algorithms, we have found that, in low-density environments it is more important for influencing agents to *maintain influence* than it is for them to rapidly turn their neighbors towards the correct destination. As a result, earlier results from smaller simulation environments often do not hold in the environments we introduce. We have found that a multistage approach that first embeds influencing agents in small flocks before attempting to steer these flocks to the goal direction can be effective in addressing some of these shortcomings.

Future work could explore the design space of placement strategies and agent behaviors by applying machine learning techniques to this problem. Future work could also explore how to aggregate small flocks into one larger flock. Many of our behaviors result in multiple small flocks clustered around influencing agents that have converged in the sense that they are all facing the same direction, but remain disconnected from each other. An interesting challenge would be develop algorithms to merge small flocks that start out with the same orientation, while maintaining flock composition. For this challenge, a successful algorithm for an influencing agent must change the direction of the flock without losing individual Reynolds-Viscek agents on the edge of the flock.

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