

# Influencing Flock Formation in Low-Density Settings

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## ABSTRACT

Flocking is a coordinated collective behavior that results from local sensing between individual agents that have a tendency to orient towards each other. Flocking is common among animal groups and might also be useful in robotic swarms. In the interest of learning how to control flocking behavior, recent work in the multiagent systems literature has explored the use of influencing agents for guiding flocking agents to face a target direction. 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 lower density environments. The source of this ineffectiveness is that the influencing agents explored in prior work tended to face directions optimized for maximal influence, but which 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 influencing agent behaviors, which we dub “follow-then-influence”; agents act like normal members of the flock to achieve positions that allow for control and then exert their influence. This strategy overcomes the difficulties posed by low density environments.

## KEYWORDS

Ad hoc teamwork; flocking; influence maximization; collective behavior; algorithms; simulation studies

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## 1 INTRODUCTION

Flocking behavior can be found in a variety of species across nature, from flocks of birds to herds of quadrupeds, schools of fish, and swarms of insects. Researchers have argued that flocking as a collective behavior emerges from simple, local rules [22]. It is therefore natural to imagine placing externally-controlled artificial agents into flocks to influence them. Yet it remains an open question whether such techniques are actually effective. Previous work [3–9] has explored the use of influencing agents to guide flocking agents to face a target direction in small and toroidal<sup>1</sup> settings, but in such settings, agent density is high, so interactions are common, and flock formation is rapid.

In the present 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. 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. Our work may also have implications for coordination in low-density swarms of robotic multi-agent systems, where control may be imperfect, such as RoboBees [1]. More broadly, flocking has implications for consensus in animal groups [2, 23, 27] and in human social networks [13]. Flocking algorithms have also been used to simulate multivariate timeseries and human movement [18, 20]. In all these cases, agent density may vary greatly, so it is important to understand influencing agent dynamics in both low density and high density settings.

To study flocking in lower density environments, we introduce two new test settings. 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 [12] in this setting, but is much less rapid, so we study whether influencing agents can speed up flock formation. In the second setting, similar to existing “sheep herding” tasks [15], we use a non-toroidal simulation space and start the flocking agents inside a circle in the center. Since this space is non-toroidal, flock formation is not guaranteed, so we study whether influencing agents

<sup>1</sup>In a toroidal environment, agents that exit the simulation space from one side immediately re-appear on the other side.

can instigate flocking behavior by keeping the flocking agents in a pre-defined area, or by moving them all in a certain direction.

We find that results from the existing literature are not robust in these environments with low agent density, since agent interactions are more rare. In particular, with less frequent local interactions between agents, maintaining a connection to the flock becomes a key factor in the efficacy of influencing agent behaviors. Simple behaviors such as “face the goal direction” are often superior to more complex behaviors that try to optimize for speed of convergence. We experiment with a number of new strategies and find that a multi-stage approach of “follow-then-influence” is most effective in low-density environments. In this approach, influencing agents start out by participating as normal members of the group, embedding themselves inside small, naturally-forming flocks. After some time, the influencing agents start pushing their neighbors to face a given goal direction.

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 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 the flocking model we use and the new test settings. §3 describes the role of influencing agents and formalizes agent behaviors. §4 describes our experimental setup and the experiments we run to evaluate agent behaviors in the new test settings, and §5 presents the results. 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 [17] to model the flock. In this simplified model, also proposed independently by Vicsek and collaborators [25], 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  $i$  moves with constant speed  $s = 0.7$  and has orientation  $\theta_i(t)$  with position  $p_i(t) = (x_i(t), y_i(t))$ . At timestep  $t$ , agent  $i$  updates its position based on its alignment:  $x_i(t) = x_i(t - 1) + s \cos(\theta_i(t))$  and  $y_i(t) = y_i(t - 1) + s \sin(\theta_i(t))$ . 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 neighborhood radius  $r$  of agent  $i$ , not including agent  $i$  itself. At timestep  $t$ , each agent updates its orientation to turn towards the average of its neighbors’ orientations:

$$\theta_i(t + 1) = \theta_i(t) + \frac{1}{2} \frac{1}{|N_i(t)|} \sum_{j \in N_i(t)} (\theta_j(t) - \theta_i(t))$$

The factor of  $\frac{1}{2}$  in the second term reflects a “momentum” factor.

### 2.2 New Settings

Previous work has studied influencing agents in a small toroidal  $150 \times 150$  grid, with neighborhood radius  $r = 20$  [7, 8]. In this work, we study low-density dynamics by introducing two new settings

that are more adverse to flock formation; we call these new settings the *large* setting and the *herd* setting. In these settings, we set the neighborhood radius to  $r = 10$ .

In the *large* setting, non-influencing agents are randomly placed in a toroidal  $1,000 \times 1,000$  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, convergence to a single direction is still provably guaranteed, so we are primarily interested in studying the length of time to convergence in this case [12]. In the *herd* setting, non-influencing agents are placed randomly in a circle of radius 500 whose origin lies at the center of a  $5,000 \times 5,000$  non-toroidal grid. When agents reach the edge of the grid, they move off-world; in this way, agents can get “lost” from the rest of the flock. As a result, convergence to a single flock is not guaranteed. Therefore, we are interested in studying how well influencing agents can keep the non-influencing agents from getting lost.

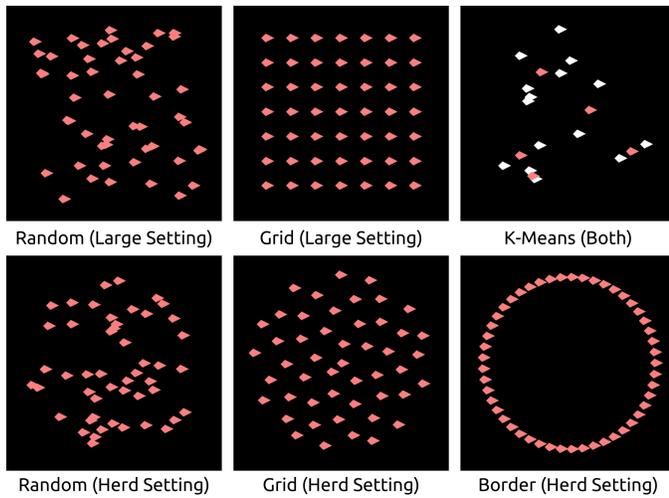
## 3 INFLUENCING AGENTS

We can change flock dynamics by introducing influencing agents that we control. We refer to non-influencing agents as Reynolds-Vicsek agents. We do not give the influencing agents any special control over the Reynolds-Vicsek agents; we simply let them interact with influencing agents using the same local sensing rules as with any other agent. We also limit the influencing agents to have the same speed as Reynolds-Vicsek agents, both to help the influencing agents “blend in” in real applications and to be consistent with the related prior work. We let the influencing agents have a sensing radius of twice the normal neighborhood radius. This allows the influencing agents to see their neighbors’ neighbors, allowing for more complex algorithms. In some cases, the influencing agents can communicate with each other, but they do not need a global view.

### 3.1 Placement

Each influencing agent algorithm we use is decomposed into two parts: a placement strategy and an agent behavior. Except for slight modifications to make some of these strategies work in a circular environment, the placement strategies we use are drawn from the literature [3, 9]. The placement strategies we use in this work 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].

We use three placement strategies for the *large* setting: *random*, *grid*, and *k-means*. 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-Vicsek agents in the simulation space. This strategy finds a cluster for each influencing agent



**Figure 1: The different placement strategies we explore in this paper. Red agents are influencing agents, and white agents are Reynolds-Vicsek agents. Note that *k-means* is the only placement strategy where the placement of influencing agents depends on placement of Reynolds-Vicsek agents.**

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 the *herd* setting, with some slight modifications. 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 [19]. 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  $\phi$  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 circular placement strategy, inspired from the border strategies used in prior work [9]. This strategy places agents on the circumference of the circle of radius  $r$  around the origin  $O$ . We refer to the circular strategies as *circle-random*, *circle-grid*, and *circle-border*, respectively.

### 3.2 Behaviors

Once we have placed the influencing agents, we still need to design how they will work together to influence the flock. We call this aspect of the design “agent behaviors.” In the present work we focus on decentralized “ad-hoc” algorithms for the influencing agents, since this class of algorithms has been the focus of the existing multiagent systems literature on this topic [3, 6, 7]. A summary of the behaviors we investigate is shown in Table 1.

**Table 1: Summary of the behaviors we investigate**

Setting	Goal Type	Name	Description
Large		<i>Face</i>	Always face goal direction
		<i>Offset Momentum</i>	Offset last average velocity
		<i>One-Step Lookahead</i>	Simulate one step, choose best
		<i>Coordinated</i>	Pair off and coordinate
		<i>Multistep</i>	<b>Follow-then-influence</b>
Herd	Traveling	<i>Face</i>	(As above)
		<i>Offset Momentum</i>	(As above)
		<i>One-Step Lookahead</i>	(As above)
		<i>Coordinated</i>	(As above)
		<i>Circle</i>	Trace circle around agents
	Stationary	<i>Polygon</i>	Trace polygon around agents
		<i>Multicircle</i>	<b>Follow-then-influence</b>

### 3.3 Large Setting

For the *large* setting, we study four behaviors drawn from prior work [7–9], and one new *multistep* behavior.

In previous work, Genter and Stone have introduced baselines *face* and *offset momentum* behaviors, as well as more sophisticated *one-step lookahead* and *coordinated* behaviors. Each of these behaviors aims to turn Reynolds-Vicsek agents to a pre-set goal angle  $\theta^*$ . Influencing agents using the *face* behavior always face the angle  $\theta^*$ . With the *offset momentum* behavior, influencing agents calculate the average velocity vector of the agents in their neighborhood, and align to a velocity vector that, when added to the average velocity vector, sums to the vector pointing in direction  $\theta^*$ . We note that such a vector always exists; if the average velocity vector is  $(x, y)$ , and  $\theta^*$  is represented by vector  $(x', y')$ , then the agents align to vector  $(x' - x, y' - y)$ . A *one-step lookahead* 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  $\theta^*$  among all its neighbors. Finally, with the *coordinated* behavior, each agent pairs with another and runs a one-step lookahead to minimize the average difference in angle from  $\theta^*$  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].

The *multistep* behavior is a novel contribution and adopts what we call a “follow-then-influence” behavior. In the initial stage, influencing agents simply behave like normal Reynolds-Vicsek agents; as a result, they easily join flocks and become distributed throughout the grid. At the same time, each influencing agent estimates how many Reynolds-Vicsek agents are path-connected to it; 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. An accurate calculation of path-connectedness requires a global view from every influencing agent, since paths may extend arbitrarily far away from the influencing agent. In our algorithm, we only consider Reynolds-Vicsek agents that are within the sensing radius of the influencing agents. Given their local estimates, the influencing agents compute a global sum of all their estimates; once that sum passes over some threshold  $T$ , the influencing agents calculate the average angle  $\bar{\theta}$  among all the agents that are locally connected to influencing agents, and from there adopt the *face* behavior with goal direction  $\bar{\theta}$ .

We also explore some variations of the *multistep* behavior by noticing that once the sum of connected agents passes the threshold  $T$ , any of the other behaviors studied can be used to turn the Reynolds-Vicsek agents towards the final goal direction  $\bar{\theta}$ . In other words, the *multistep* behavior can be paired with any other behavior. We study these pairings to see how effective they are.

### 3.4 Herd Setting

For the *herd* setting, we divide the behaviors into two categories: traveling behaviors and stationary behaviors. As a reminder, in the *herd* setting, the simulation space is non-toroidal, and all the Reynolds-Vicsek 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-Vicsek agents to stay in the center (stationary behaviors), or we can let the influencing agents direct the Reynolds-Vicsek agents away from their initial starting position (traveling behaviors). Since all the agents have a constant speed, the former is much more difficult than the latter, so we must evaluate them separately.

For the traveling behaviors, we can use all the behaviors used in the *large* setting, except for the *multistep* behavior. Since the world is non-toroidal, it is not guaranteed that the number of connected agents will ever pass the threshold  $T$ ; in this case, the influencing agents would simply wander forever.

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-Vicsek agents to enter their neighborhood. Once they detect Reynolds-Vicsek agents in their neighborhood, they adopt a “following” behavior where they act like Reynolds-Vicsek 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.

## 4 EXPERIMENTAL SETUP

We extended the MASON simulator to run the experiments [14]. 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 understand 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  $1,000 \times 1,000$  grid and vary the number  $N$  of Reynolds-Vicsek agents from 50 to 300 in increments of 50. We run these simulations for 6,000 time steps. In the *herd* setting, we use a  $5,000 \times 5,000$  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 6,000 time steps.

### 4.2 Influencing Agents

To evaluate the contributions of influencing agents in the *large* setting, we measure time to convergence. We define convergence as having half the Reynolds-Vicsek agents face the same direction, since full convergence takes much longer.

We test the *random*, *grid*, and *k-means* placement strategies, along with the full suite of behaviors in the *large* setting. We place 300 Reynolds-Vicsek agents on the grid and vary the number of influencing agents from 10 to 100 in intervals of 10.

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 behaviors (traveling behaviors vs. stationary behaviors), the number of agents facing the same direction is irrelevant. The stationary behaviors rotate the agents around the origin (in fact, if the Reynolds-Vicsek agents are all facing the same goal direction, the stationary behavior has failed). Instead, we measure the number of Reynolds-Vicsek agents that are connected to influencing agents at 15,000 time steps; at this point in time, all the agents have travelled out of the grid, and no new interactions occur. As a result, this quantity measures sustained influence over the Reynolds-Vicsek agents over time.

In the *herd* setting, we examine the three circular placement strategies—*circle-border*, *circle-random*, and *circle-grid*—with two placement radii, 500 and 750, along with the *k-means* placement strategy. We split our examination of behaviors between the traveling behaviors (the same behaviors as used in the *large* setting, minus the *multistep* behavior) and three stationary behaviors—*circle*, *polygon*, and *multicircle*. We use a polygon with ten sides (a decagon) for the *polygon* behavior, and we vary the final radius for the *multicircle* behavior 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 1,100. We place 300 Reynolds-Vicsek agents on the grid and again vary 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-Vicsek 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 the 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, so the number of flocks increases. In the second stage, these small flocks that formed collide with one another and join together to form larger flocks, so the number of flocks decreases. 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 lone 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. One small artifact in the metric is 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 report on the efficacy of the behaviors in the *large* setting. The average times for 50% convergence with different placement strategies and the five behaviors are shown in Figure 3. We show graphs for 300 Reynolds-Vicsek agents and 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, and when there are fewer influencing agents, convergence happens slower). Note that smaller is better in these graphs.

The most immediately striking finding is that, in less dense settings, the *one-step lookahead* and *coordinated* behaviors significantly underperform the “baseline” *face* and *offset momentum* behaviors, irrespective of placement strategy. This is an opposite result from Genter and Stone’s findings on smaller simulation spaces [3, 7], which found that the *one-step lookahead* and *coordinated* behaviors

outperform the *face* and *offset momentum* 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-Vicsek 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 red, adopts an orientation that turns neighboring Reynolds-Vicsek agents towards the goal direction. Even though this action does turn Reynolds-Vicsek agents towards the goal direction, the influencer cannot successfully turn all the agents in a single step; as a result, the influencing agent 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-Vicsek agents, causing the agent to lose influence. Once the influencing agent has lost influence, the agent has difficulty catching up with the same flock, since influencing agents travel at the same speed<sup>2</sup> as Reynolds-Vicsek agents. As a result, the influencing agent is not actively influencing the direction of any Reynolds-Vicsek agents until it encounters another group of Reynolds-Vicsek 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-Vicsek agents very quickly. As a result, the gains from the smarter local algorithm still outweigh the negative effects from losing influence.

The *multistep* behavior does not suffer from the same problem; it can both maintain influence and effectively turn Reynolds-Vicsek agents and so outperforms all the other behaviors by a couple hundred steps. When the *multistep* behavior is paired with the other behaviors, though, it magnifies their inability to maintain influence. The bottom graph of Figure 3 shows variations on the *multistep* behavior, wherein influencing agents adopt different behaviors after the number of Reynolds-Vicsek agents under control passes  $T$ . Note that the variations that pair the *multistep* behavior with the *offset momentum*, *one-step lookahead*, and *coordinated* behaviors perform almost an order of magnitude worse than the *multistep-face* behavior. What is the root cause of this difference? The *multistep* 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 difficulty changing the orientation of existing flocks quickly before losing influence. As a result, the *multistep* behavior takes an order of magnitude longer to reach convergence when paired with the other behaviors.

Finally, we note that the effect of placement behaviors on convergence time are almost non-existent. When the density is lower,

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

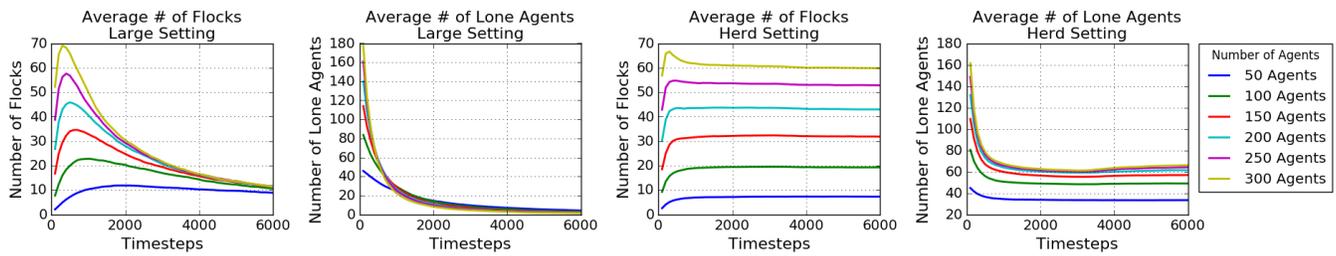


Figure 2: Average flock counts and lone agent counts over time for the *large* and *herd* settings with no influencing agents, varying the number of Reynolds-Vicsek agents.

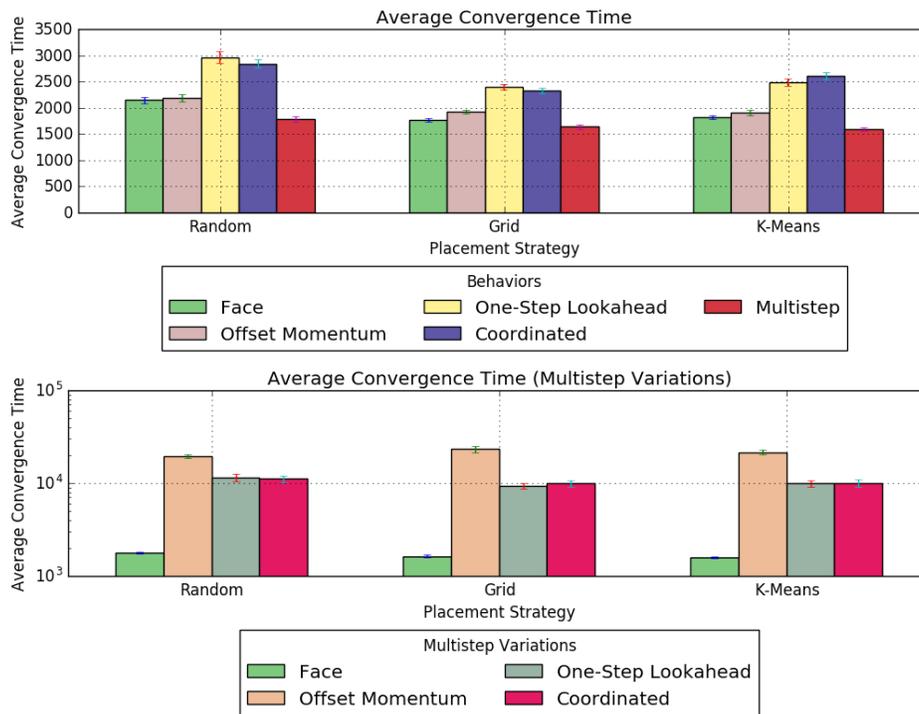


Figure 3: Average times to 50% convergence for 300 Reynolds-Vicsek agents with 50 influencing agents in the *large* setting under different placement strategies and behaviors. Top: The five main behaviors for the *large* setting. Bottom: Variations on the *multistep* behavior, in log scale. Smaller is better. Error bars show standard error of the mean.

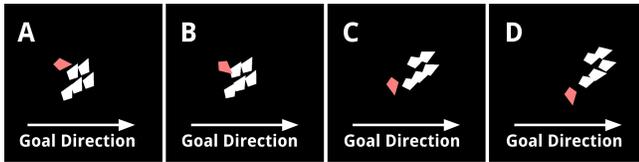
there is a much smaller chance that any influencing agent will start out with more than one Reynolds-Vicsek agent in its neighborhood, even with the *k-means* placement behavior. As a result, even the best clustering approach is almost the same as starting out randomly or in a grid.

### 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-Vicsek agents in one place if they are facing the same direction. Instead, we exclusively measure the number of Reynolds-Vicsek 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-Vicsek agents. The average number of agents in such local flocks after 15,000 time steps is given in Figure 5 for both the traveling and stationary behaviors. We find that the traveling behaviors vastly outperform any of the stationary behaviors. However, there may be environments in reality for which the traveling behaviors are not applicable (suppose it is strictly necessary to keep a flock in one place, for instance). Thus, we analyze the traveling behaviors separately from the stationary behaviors.

5.3.1 *Traveling.* Again, we find that the *face* behavior tends to outperform the *offset momentum*, *one-step lookahead*, and *coordinated* behaviors; we attribute this to the tendency of the *offset momentum*, *one-step lookahead*, and *coordinated* behaviors to lose



**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-Vicsek agents are shown in white. In A, the influencing agent first encounters the flock of Reynolds-Vicsek 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-Vicsek agents. This changes the orientation of the Reynolds-Vicsek agents, but the influencing agent has started to travel away from the flock by D.**

influence over time. We note that the effect is not as pronounced here as in the *large* experiments, since each influencing agent has to control fewer agents.

In contrast to the *large* experiments, we find that here the placement strategy has a major impact on the efficacy of the traveling behaviors. 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-Vicsek agents slip through the “holes.” Furthermore, by the time the Reynolds-Vicsek agents reach the border, they have already formed flocks, and it is more difficult for the influencing agents to point them in the right direction. This effect is less pronounced for *Grid 750* and almost non-existent for *Random 750*, since these strategies place influencing agents within the circle, and not simply along its circumference. As a result, the Reynolds-Vicsek 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-Vicsek 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-Vicsek agents.

**5.3.2 Stationary.** Among the stationary behaviors, the *multi-circle* behavior achieves the best outcomes, but its performance depends on its paired placement strategy. The *multicircle* behavior slightly underperforms the *circle* behavior when paired with the *Border* placement strategies; slightly overperforms when paired with the *k-means*, *Random*, and *Grid 500* placement strategies; and performs the same as *circle* in the *Grid 750* strategy. What drives these trends? Once the *multicircle* behavior 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-Vicsek 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-Vicsek agents and induce a circling behavior in the final stage.

Finally, we note that *Border 750* is the worst placement strategy, similar to when it is used in the traveling behaviors. Also, the *polygon* behavior tends to underperform or match the performance of *circle*, which tells us that adopting occasional sharper turns can sometimes be detrimental.

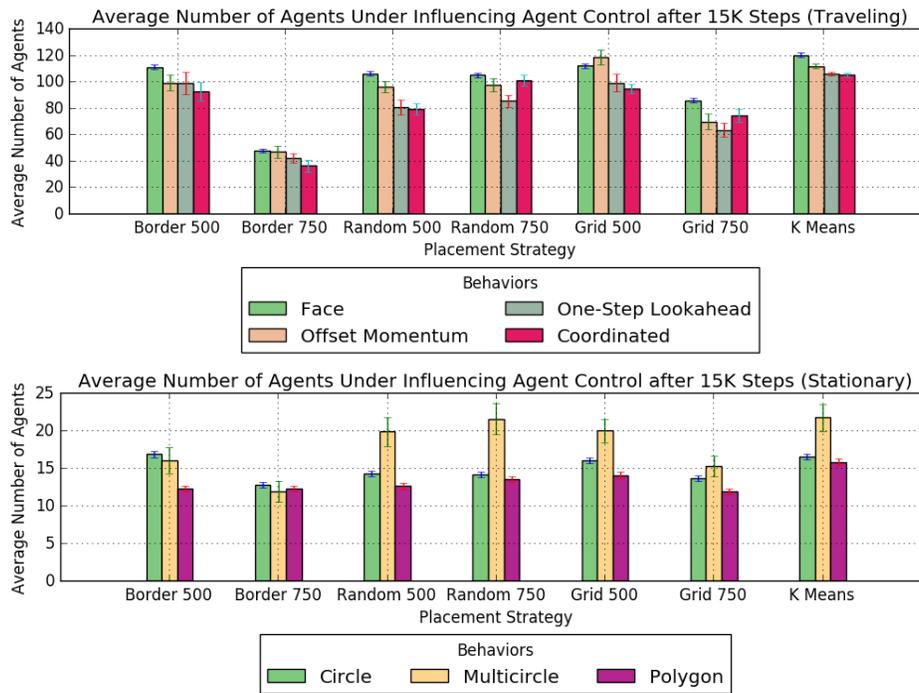
## 6 RELATED WORK

Our work builds upon a series of papers by Genter and Stone examining ways to use external agents to influence flocking [4–9]. This prior work 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 also presented results from simulations with different implementations of Reynolds’s flocking model, as well as physical experiments with these algorithms in a small RoboCup setting [3]. This prior work almost exclusively studied small environments, where density of agents is high, and quick flock formation was virtually guaranteed. We study two new low-density environments and introduce behaviors to adapt to the difficulties presented by these new environments.

Jadbadaie et al. [12] studied Reynolds-Vicsek agents from an analytical perspective. Two strong results from this work were that a group of Reynolds-Vicsek agents in a toroidal setting will eventually converge regardless of initial conditions, and that in the presence of a single agent with fixed orientation (analogous to a single influencing agent), all the agents will converge to that fixed agent’s orientation. This theory provides important context for Genter and Stone’s work and the work that we present here: when the setting is toroidal, convergence is guaranteed, so the interesting question is how fast we can reach convergence.

Couzin et al. [2] studied the design of influencing agents for flocking as well, albeit with a slightly different flocking model. They proposed an influencing behavior wherein influencing agents adopt orientations “in between” their desired goal orientation and the orientations of their neighbors, in order to still influence their neighbors while not adopting orientations so extreme that they have no chance of being effective in the long term. This is similar in spirit to the motivation behind the multistep algorithm. We adapted Couzin’s algorithm to the new settings, but do not present the results in this text for space reasons. The adaptation did not perform as well as the new *multistep* behavior or the *face* behavior, but it did outperform the *one-step lookahead* behavior.

Han et al. [11] published a series of papers showing how to align a group of agents in the same direction. This work assumed a single influencing agent with infinite speed, and 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-Vicsek 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-Vicsek agents to prevent the use of behaviors like this, in hopes that our results will be more relevant to real applications; we suspect that influencing agents that act similarly to real agents will be more successful in real applications.



**Figure 5: Average number of agents under influencing agent control after 15,000 steps with 300 Reynolds-Vicsek agents and 50 influencing agents in the *herd* setting under various placement strategies and influencing agent behaviors. The traveling behaviors attempt to control the direction of the Reynolds-Vicsek agents, while the stationary behaviors keep the influencing agents near the goal area using circling techniques. Larger is better. Error bars represent standard error of the mean.**

Su et al. [21] studied the question of flock formation and convergence, but in the context of the Olfati-Saber flocking model [16]. 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, 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-Vicsek agents.

Researchers of collective animal behavior have begun using replica conspecifics in order to influence animal groups across a range of species, from fish to ducks to cockroaches [10, 24, 26]. Halloy et. al. used robotic influencing agents to control groups of cockroaches; they exploited the cockroaches’ inability to differentiate between real cockroaches and robotic influencing agents. Vaugahn et. al. used robotic influencing agents to herd a flock of ducks (on the ground) to a goal position in a small caged area; their approach used robot agents to “push” the ducks from a distance, like a dog herding sheep.

## 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 novel control behaviors for these settings. In addition to 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 found that a multi-stage 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.

Although we did not present results from using the multi-stage approach in the smaller simulation environments from previous work, preliminary experiments suggest that, in the smaller environments, it is not as effective as algorithms that optimize for rapid convergence. Future work could try to find an algorithm that works well in all settings.

It could also explore how to aggregate small flocks into one larger flock. Many 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. A successful algorithm would have to change the direction of the flock without losing individual Reynolds-Vicsek agents on the edges of the flock.

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