Herding Animals through Social Integration of Robots and Leader-Follower Formation Control

Qizhan Tam
Department of Mechanical Engineering
Stanford University
Stanford, U.S.A
qtam@stanford.edu

***Abstract*—There has been extensive studies into flocking behavior of herd animals and the strategies to use robots to herd the animals. The motivation is to alleviate the labor-intensive agriculture sector through automation. This paper builds upon the cow herding model of Schwager et al. [11], and utilizes the concept of social integration of robots into animals introduced by Halloy et al. [9,10]. The goal of the paper is to devise a leader-follower formation control method that will have the leaders (robots) move the followers (herd) from an initial starting position to a final position, avoiding certain regions regarded as dangerous for the followers, while incentivizing leader exploration of the path ahead. Three variations of leader-follower formation control methods were introduced, the first two methods using robot leaders to guide the herd through a path, while the third method uses potential field path navigation. Simulations of all three methods were presented.**

I. Introduction

The goal of this study is to analyze the behaviors of herd animals under the influence of socially integrated robots and the different possible control policies used to move the herd animals to a target location.

The landmark study on using robots to control herd animals by Vaughan [1] demonstrated the potential of automated agents to reduce the workload of farmers. There has since been studies on the different ways to control the movements of herd animals using electronic devices such as virtual fencing [2, 3] and using a single or multiple robot herders [4, 5, 6] in a robot pursuer-evader game. Most of the robot herding methods rely on stress factors to drive the animals to the desired location. For example, the use of virtual fencing in [2] requires a number of the herd members to be induced with stress when they cross the fence boundaries, with differential electric shock as the suggested method. As there are no other sensory cues, the herd animals will have to continuously experience stress for them to move to the target location. This may have negative consequences on the quality of the eventual animal products. It has been shown in dairy cows [7] that being in stressful situations resulted in physiological and behavioral changes, among which is reduced milk yield. This also extends to other herd animals such as cattle, sheep and pigs where stress results in lower quality of meat [8].

The proposed method of this study instead relies on the collective behavior of the herd to self-organize using socially integrated robots, as demonstrated on cockroaches by Halloy et al. [9,10]. They showed that a small number of robots were able to influence the cockroaches into choosing shelters of relative brightness [9], followed by their design of robots with a suit of sensors that were able to be integrated into a swarm cockroach using cockroach pheromones [10]. Having a robot to be accepted into the herd by more intelligent animals such as cows is expected to be more difficult than just masking them with pheromones of their target animals. With the advances made in all-terrain four-legged robots, such as Boston Dynamics' SpotMini, it is likely in the near future that a robot that can be accepted by the herd as a member of their own.

This paper introduces three variations of leader-follower formation control methods. The "leader" may consist of multiple robots and the "followers" are fixed to a herd of 30 cows. The first proposed method uses a fixed gain controller which maintains a certain separation distance between the leader and followers. The leader follows a path and attempts to guide the followers along the path. The second method is similar, with the gain being variable, changing in response to how closely the herd is following the path. The final method uses potential field path navigation in which the leader attempts to guide the followers along an artificial potential field. Simulation results of the three controllers were presented in each of their respective sections.

II. Herd Model

A. Follower (Herd) Dynamics

The herd model used in this paper is the model first developed by Schwager et al. [11] and used by Correll et al. [2] for their work on cow herding behavior with minor modifications. The state space of each agent $i \in \{1, \dots, m\}$ at each point in time τ is represented by:

$$x_i{}^{\tau} = [p_i{}^{\tau}, \dot{p_i}{}^{\tau}]^T,$$

where $p_i \in \mathbb{R}^2$ is a row vector of herd agent i's cartesian coordinates and $\dot{p}_i \in \mathbb{R}^2$ is its velocity vector. The dynamics of the agents are:

$$x_i{}^{\tau+1} = \begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & a_i & 0 \\ 0 & 0 & 0 & a_i \end{bmatrix} x_i{}^{\tau} + \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \left(\frac{1}{m} \sum_{j=1, j\neq i}^{m} f_{ij}\left(p_i{}^{\tau}, p_j{}^{\tau}\right) + \omega_i{}^{\tau} \right)$$

$\omega_i{}^\tau \in \mathbb{R}^2$ is a vector of zero-mean gaussian white noise parameterized by covariance matrix, Σ with a variance of $1.22e^{-2}$. $a_i = .9294$ is the velocity damping factor. $f_{ij} \in \mathbb{R}$ is the interaction force exerted by agent j on agent i which is dependent on the distance and unit direction vector between agents. This force is summed over all agents and the mean is found by dividing the total force with the total number of agents, m.

$$f_{ij}(p_i, p_j) = \left(\theta_1 - \frac{\theta_2}{\| p_j - p_i \|}\right) n_{ij}$$

$$n_{ij} = \frac{p_j - p_i}{\| p_j - p_i \|}$$

$\theta_1 = .0225$ and $\theta_2 = .0732$ are calibration parameters for the model based on actual herd data [Schwager]. Originally specified for each unique pair of agents, for this paper the averaged parameters were used as was done in [Correll].

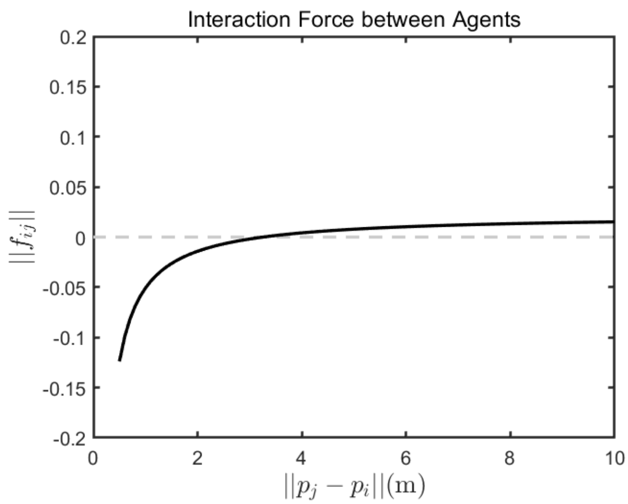

Fig. 1. Force magnitude experienced between 2 agents at various separation distances.

B. Leader (Robot) Model

We model the leader as a robot with single-integrator dynamics, with $u_i{}^\tau$ denoting the control input:

$$\dot{p_i}^\tau = u_i{}^\tau$$

$$p_i{}^{\tau+1} = p_i{}^\tau + \dot{p_i}^\tau \cdot \Delta t$$

As a group of robots may be used to lead the herd, a formation controller will be required for such a situation. For convenience, an individual robot is chosen as the overall leader and the rest of the robots will be following the overall leader using a similar potential field model as the herd:

$$p_i{}^{\tau+1} = p_i{}^\tau + f_{i1}(p_i{}^\tau, p_1{}^\tau) \cdot \Delta t$$

The force term is only dependent on the robot's and the robot leader's positions, with the calibration parameters remaining the same as the herd model's.

III. Problem Formulation

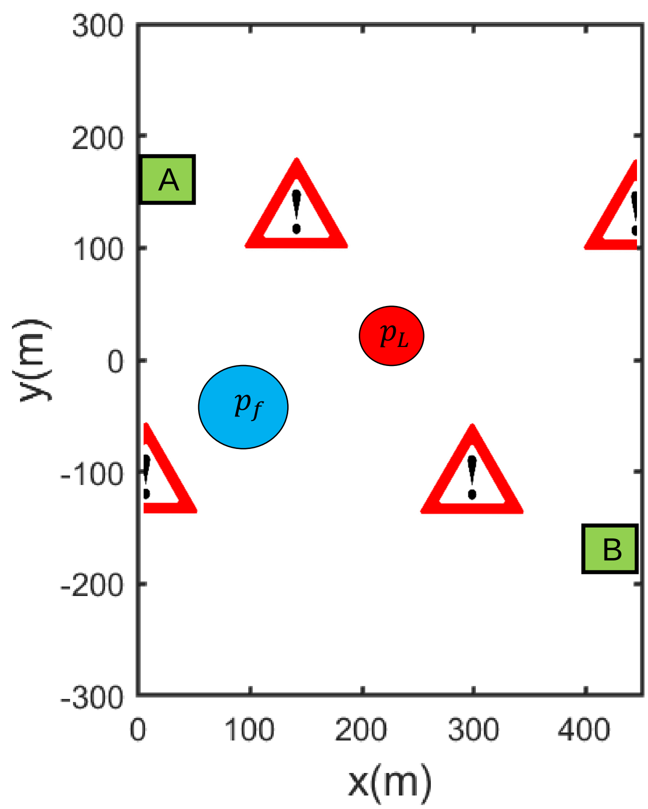

Fig. 2. An illustration of the map where the leaders, p_L and followers, p_f have to traverse, with the danger signs signalling the regions where the herd should be driven away from.

The scenario is a 600m x 400m area where the leaders and followers must traverse, with dangerous regions known beforehand (marked in Fig. 2). The primary goal is to move the herd from point A to point B while avoiding the marked regions. The secondary goal is for the leaders to be able to move ahead of the herd as far as possible to scout the terrain so that any changes to the navigation path can be made before the herd gets too close.

IV. Method 1: Fixed Gain Controller

A. Setup

There are additional parameters in the problem formulation that is required for this method. A herd of 30 animals from point A to point B while staying within the bounds of a distance normal to the path, specified by b_+ and b_-:

$$b_+ \coloneqq \{r(x) + n(x) * d_+,\ x\epsilon R\}$$

$$b_+ \coloneqq \{r(x) - n(x) * d_-,\ x\epsilon R\}$$

The mean position of the herd, p_f is used as a measure of the herd's location, and the robot leader's position is denoted as p_L. In this case, the distances of the upper and lower bounds are equivalent, $d = d_+ = d_-$.

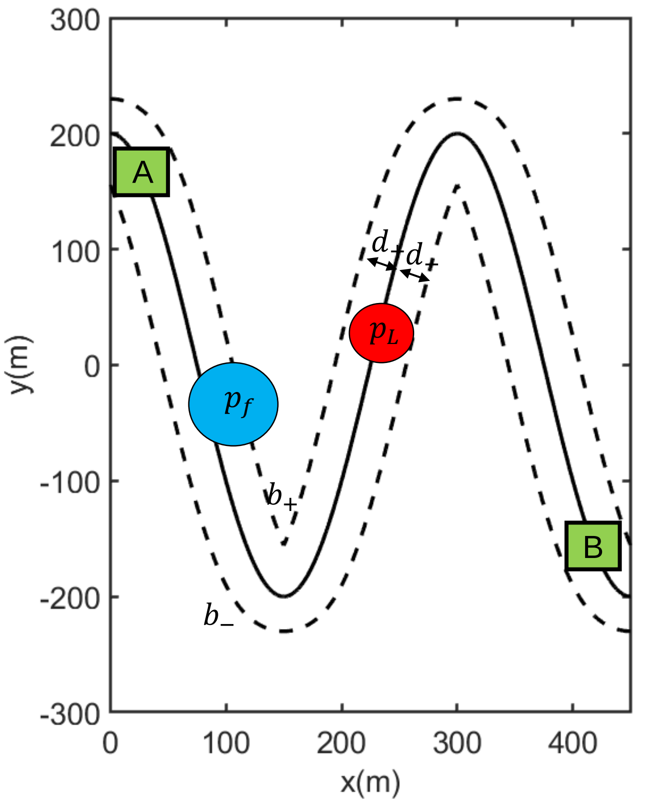

Fig. 3. The same illustration as in Part III but with additional details included for Method 1's controller.

B. Controller

The leader's controller of this method uses artificial potential fields between the leader and follower where the equilibrium separation distance ($u = 0$) between the herd and leader is k_L.

$$u = \dot{p_L} = \frac{k_L}{\| p_L - p_f \|} T(p_L)$$

$$T(p_L) = \frac{r'(p_L)}{\| r'(p_L) \|}$$

$r'(p_L)$ represents the gradient of the path, $r(p_L)$, where the leader is currently positioned, p_L. This means that $T(p_L)$ is the unit tangent vector of the path where the leader is located. Using this controller, the leader attempts to maintain a distance k_L from the herd while moving along the path.

C. Simulation Results

At low gains, the herd manages to stay within the boundaries, but the leader maintains a close distance. At high gains, the leader is further from the herd, but at the turns (Fig 4), the herd strays outside of the boundaries. Ideally, the leader will be able to venture further down the path along the straight portions but stay closer to the herd when it is required to guide the herd along steep curves.

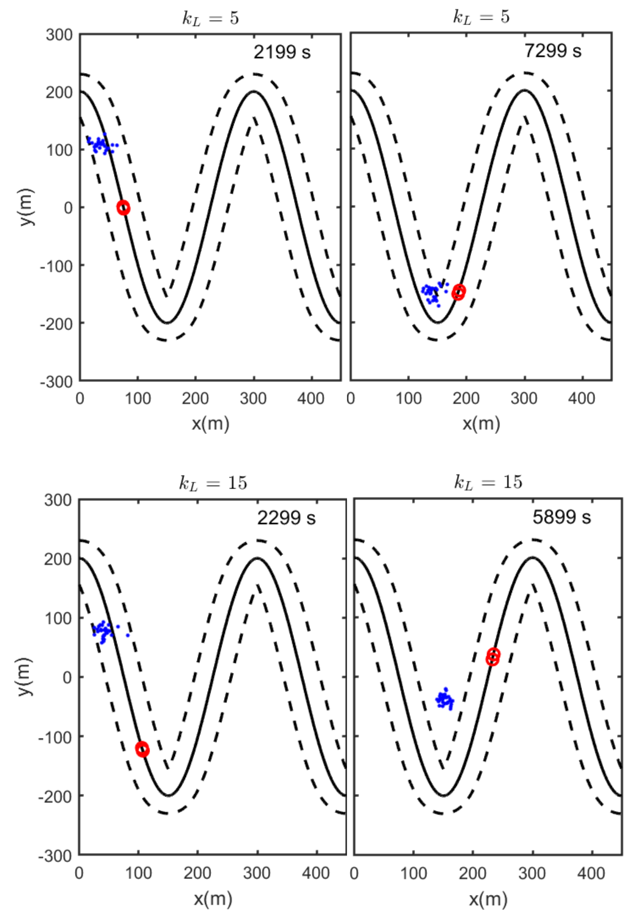

Fig. 4. (Top) At low gains, $k_L \leq 5$, the herd manages to stay within the boundaries. (Bottom) At high gains, $k_L > 5$, the herd strays away from the boundaries.

V. Method 2: Adaptive Gain Controller

This controller has a gain that is variable, which changes according to how close the herd is from crossing the boundaries. It takes advantage of both the increased exploration provided by a higher gain and the safer herding behavior provided by a lower gain. However, a prediction model of the herd's future trajectory is required.

A. Herd Trajectory Prediction Model

5 leaders were held stationary while the followers were allowed to approach the leader. The change in separation distance with time was tracked and plotted in Fig. 5. The average separation distance was modeled as having a linear relationship with time until the followers got close (~20m) to the leaders. It was observed that, on average, the herd's center moved in a straight direction towards the leaders.

By taking the slope of the average separation distance over time, a velocity magnitude, v_5, for a 30-member herd following 5 leaders can be found. Thus, the herd's center velocity, $\dot{p_{fL}}^{\tau}$, can be described by:

$$\dot{p_{fL}}^{\tau} = v_n \frac{{p_L}^{\tau} - {p_f}^{\tau}}{\|{p_L}^{\tau} - {p_f}^{\tau}\|}$$

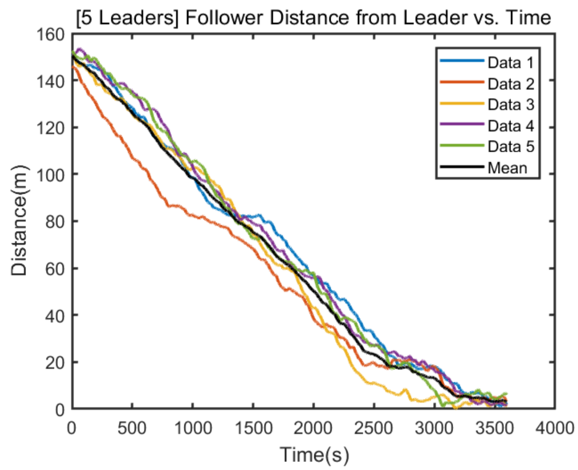

Fig. 5. The separation distance over time data for 5 separate iterations with the same simulation parameters. The herd member positions were generated randomly about a point with a 25 m radius.

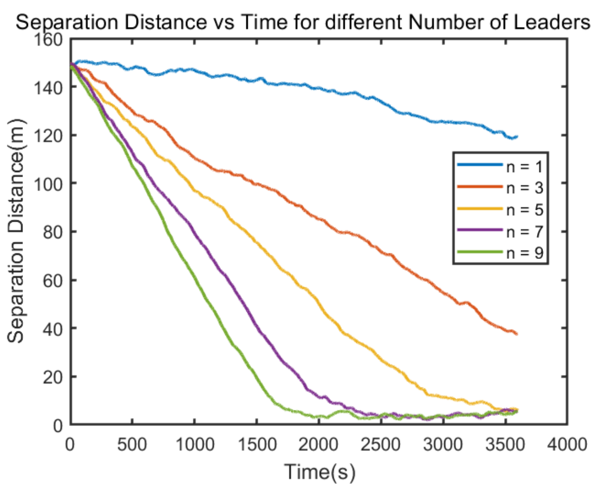

Fig. 6. Mean separation distance over time for different number of leaders, each averaged over 5 iterations of simulation.

When the average separation distance vs. time data is plotted for various number of leaders, a linear trend emerged which is made clear in Fig, 7. A general model can be used to describe the relationship between the follower speed and the number of leaders:

$$v_n = 0.0102n - 0.0013$$

v_n is the velocity magnitude of n leaders for a herd of 30 followers.

As such, the follower velocity model can be described by the formula:

$$\dot{p_{fL}}^{\tau} = v_n \frac{{p_L}^{\tau} - {p_f}^{\tau}}{\left\| {p_L}^{\tau} - {p_f}^{\tau} \right\|}$$

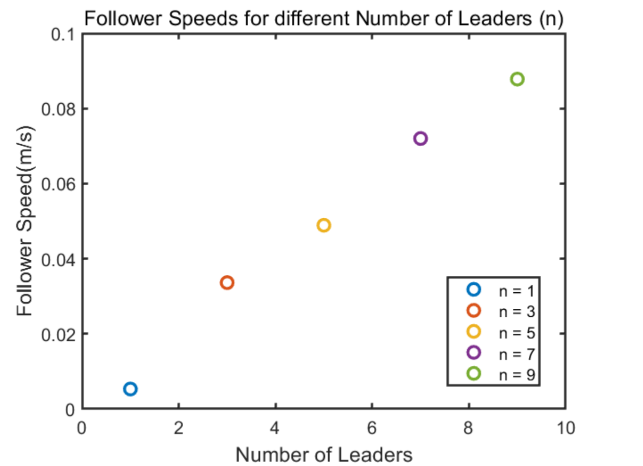

Fig. 7. Follower speeds for different number of leaders which show a linear trend.

B. Setup

The setup is almost identical with the setup in Method 1, with the addition of extra vectors that are required for the herd trajectory prediction.

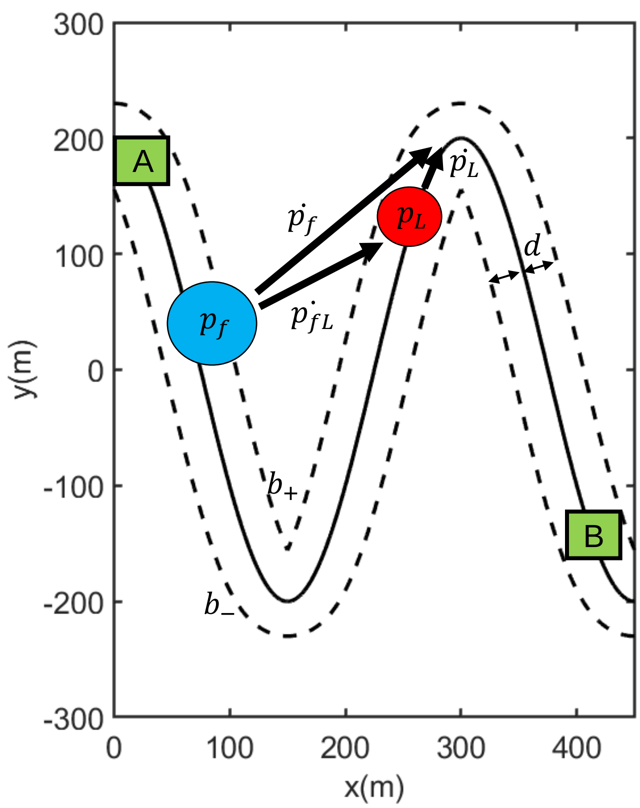

Fig. 8. The same illustration as in Method 1 with additional vectors.

Introducing new terms, $\dot{p_L}$ represents the leader's velocity, $\dot{p_{fL}}$ represents the follower velocity (assuming stationary leader) described in the previous section, and $\dot{p_f}$ is the instantaneous follower velocity which takes the leader's velocity into account:

$$\dot{p_f} = \dot{p_{fL}} + \dot{p_L}$$

C. Controller

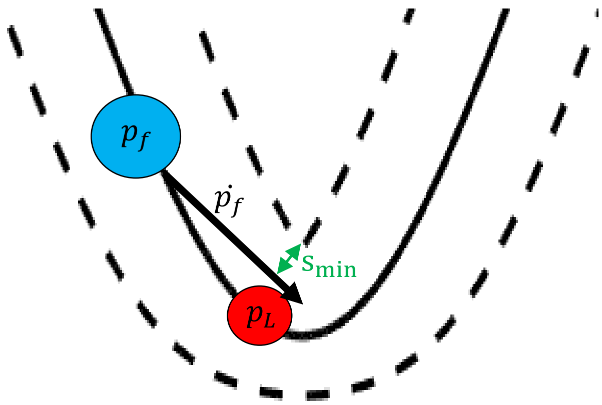

Fig. 9. A close-up of the illustration with the minimum distance of the predicted herd trajectory from the boundaries, s_{min}, shown.

The leader's controller is similar to the fixed gain method's controller with the difference being the gain which varies with how close the predicted herd trajectory is to the boundaries.

$$u = \dot{p_L} = \frac{k_L(s_{min})}{\| p_L - p_f \|} * T(p_L)$$

$$T(p_L) = \frac{r'(p_L)}{\| r'(p_L) \|}$$

s_{min} is the minimum distance of the predicted herd trajectory from the boundaries. It is normalized by d, the normal distance of the boundaries from the path and scaled by α, a constant. As $s_{min} \to d$, $k_L \to \alpha$ which leads to maximum separation distance. Conversely, as $s_{min} \to 0$, $k_L \to 0$ which stops the leader.

$$S_{min} = \min\{dist(p_f \pm \dot{p_f} \cdot t,\ b_\pm)\}$$

$$k(s_{min})_L = \alpha \cdot \frac{s_{min}}{d}$$

D. Simulation Results

The leader is a lot more aggressive in exploring ahead of the heard with increasing α values, similar to Method 1's behavior when increasing k_L. However, at the corners, when the predicted herd trajectory gets increasingly closer to the boundaries, resulting in a decreasing s_{min} and hence a smaller $k(s_{min})_L$, the controller input goes to 0 and the leader slows down until the follower is no longer in danger of straying away from the boundaries.

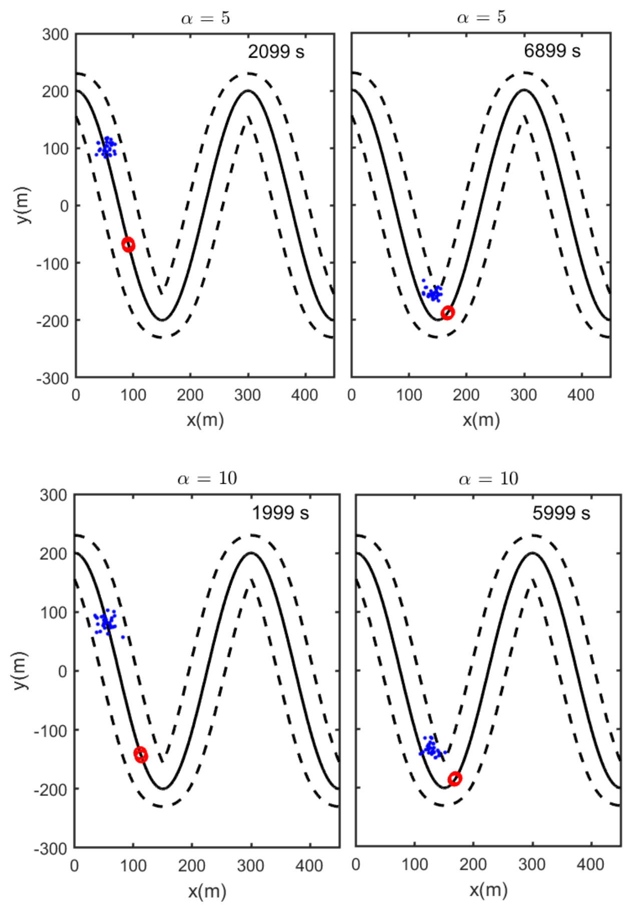

Fig. 10. (Top) The leader is more conservative in exploration at smaller α values. (Bottom) The leader is a lot more aggressive in exploration at higher α values. For all α values, the leader slows down at the turns to wait for the followers to catch-up.

VI. METHOD 3: POTENTIAL FIELD PATH NAVIGATION

Thus far a path has been pre-defined and the leader was able to guide the follower to its destination safely. However, the assumption that underpins the previous controllers is that the herd behavior is predictable and does not deviate from the model. In reality, other external influence or just the random behaviors of the herd members may lead to the herd straying away from the boundaries and the leader unable to keep track of them.

A common, more flexible alternative is path navigation using artificial potential fields. Such potential fields were already used for the interaction between the leader and followers, but now they will be extended towards the environment.

A. Setup

Each dangerous region $i \in \{1,2,3,4\}$ denoted in Fig. 2 is treated as an obstacle to be avoided, represented by a repulsive potential field, $U_{rep,i}(p_f)$ which exerts a repulsive force, $F_{rep,i}(p_f)$, on the herd's center.

$$U_{rep,i}(p_f) = \frac{1}{2} k_{obst,i} \left(\frac{1}{d_{obst,i}(p_f)} - \frac{1}{r_i} \right)^2$$

$$F_{rep,i}(p_f) = -\nabla U_{rep,i}(p_f)$$

$$= k_{obst,i} \left(\frac{1}{d_{obst,i}(p_f)} - \frac{1}{r_i} \right) \frac{p_f - p_{obst,i}}{d^3_{obst,i}(p_f)}$$

$k_{obst,i}$ is a scaling constant and $d_{obst,i}(p_f)$ is the distance of p_f from the obstacle centered at $p_{obst,i}$ with radius r_i.

$$d_{obst,i}(p_f) = \|p_f - p_{obst,i}\|$$

The goal, which is Point B in Fig. 2, is represented by an attractive conical potential field, $U_{att}(p_f)$, which exerts an attractive force, $F_{att}(p_f)$, on the herd's center.

$$U_{att}(p_f) = k_{goal} \|p_f - p_{goal}\|$$

$$F_{att}(p_f) = -\nabla U_{att}(p_f)$$

$$= -k_{goal}(p_f - p_{goal})$$

The total potential field, $U_{tot}(p_f)$, and the resulting force, $F_{tot}(p_f)$, experienced by the herd is shown in Fig. 12 and can be expressed as:

$$U_{tot}(p_f) = U_{att}(p_f) + \sum_{i=1}^{4} U_{rep,i}(p_f)$$

$$F_{tot}(p_f) = F_{att}(p_f) + \sum_{i=1}^{4} F_{rep,i}(p_f)$$

B. Controller

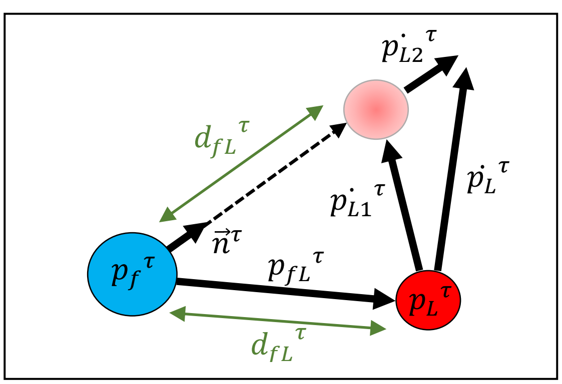

Fig. 11. A close-up of the illustration with the minimum distance of the predicted herd trajectory from the boundaries, s_{min}, shown.

The requirement for the controller is to guide the herd in a way such that the herd's center moves according to the gradient descent of the total potential field. As the leader has only minimal control over the follower's speed, only the potential field force's unit directional vector is taken into consideration by the controller.

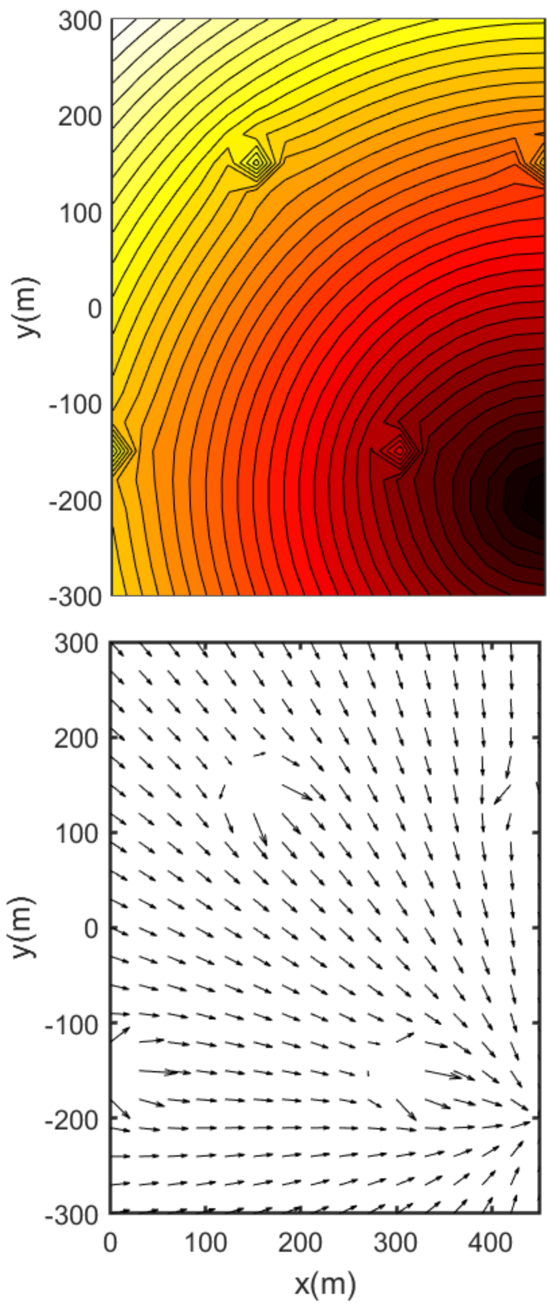

Fig. 12. (Top) The total potential field with the darker colors representing lower potential energy. (Bottom) The negative gradient of the potential field.

From Fig. 11, p_{fL} is the directional vector from the follower to the leader that has magnitude $d_{fL}{}^{\tau}$. $\vec{n}^{\tau}$ is the unit directional vector of the total force from the virtual potential fields. The control input drives the leader's position such that its next position, $p_{fL}{}^{\tau+1}$ is collinear with the current time-step's $\vec{n}^{\tau}$. The distance $d_{fL}{}^{\tau+1}$ is determined in the same manner as in the previous methods.

To find $\dot{p_{L1}}$, which aligns the leader with $\vec{n}$:

$$\dot{p_{L1}}^{\tau} = \frac{d_{fL}{}^{\tau} \cdot \vec{n}^{\tau} - p_{fL}{}^{\tau}}{\Delta t}$$

The second required component is $\dot{p_{L2}}$, which regulates the separation distance between the follower and leader:

$$\dot{d_{fL}}^{\tau} = \frac{k_L}{\| p_L - p_f \|}$$

$$\dot{p_{L2}}^{\tau} = \dot{d_{fL}}^{\tau} \cdot \Delta t \cdot \vec{n}^{\tau}$$

This leads to the controller:

$$u = \dot{p_L}^{\tau} = \dot{p_{L1}}^{\tau} + \dot{p_{L2}}^{\tau}$$

C. Simulation Results

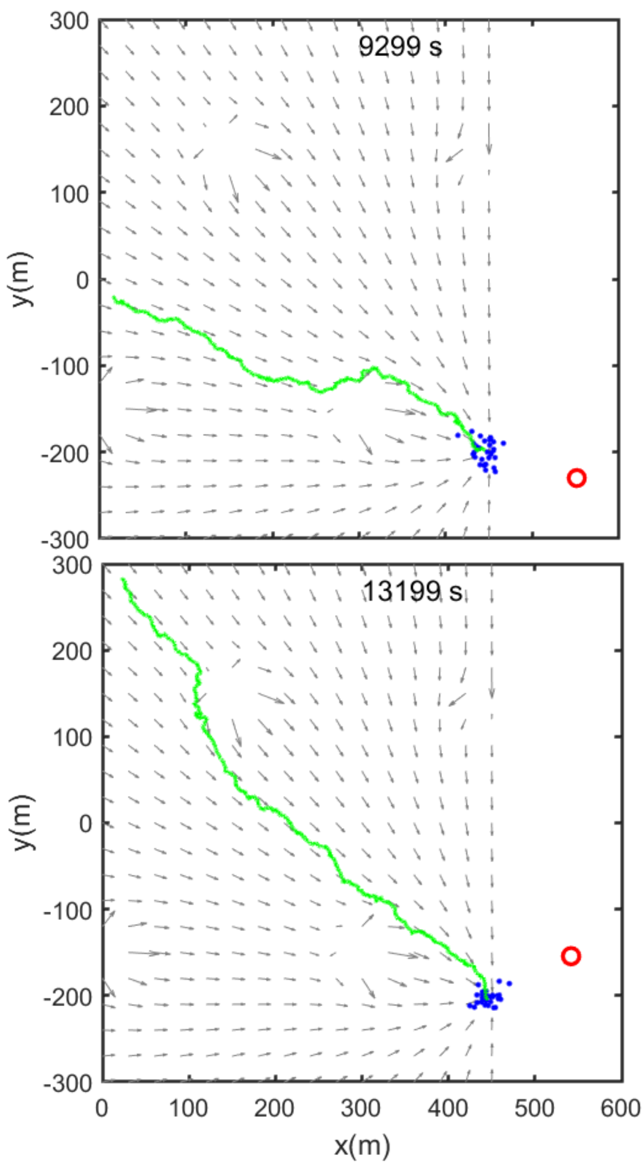

Fig. 13. The path taken by the herd is in green. Paths with 2 different starting locations are shown to illustrate the versatility of using potential field navigation.

The potential field path navigation allows for more flexible herding paths and it is more robust to herd behavior deviations which the other methods do not take into account. In its current form, the controller does not allow the leader to venture further ahead when the herd is away from the danger regions.

VII. Discussion

Method 1's fixed gain controller is the simplest of all the controllers in this paper but offers no guarantees that the herd will avoid the dangerous regions. Method 2's variable gain controller balances the exploration along the straight path segments and the safety of the herd by slowing down when the herd is in danger of straying away from the safe boundaries. However, the leaders using the controllers of Methods 1 and 2 would not be able to react under the situation when the herd deviates from its modeled behavior or when there is external influence that repels or attracts the herd.

Method 3 provides a more flexible approach to navigation as the entire map is already mapped with paths following the gradient descent of the surrounding's potential field.

Methods 1 and 2 also require a separate path planning algorithm, such as A* or dRRT to determine the trajectory of the herd, which will incur increased computational costs compared to Method 3.

VIII. Conclusion

This paper has demonstrated three variations of leader-follower formation control methods for a socially integrated robot in a herd of cows. For future work, unicylce dynamics and velocity limitations on varying terrain should be taken into account to provide a more realistic robot model. Method 3's potential field path navigation method can be extended to account for robot exploration when the herd is away from the danger regions.

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https://stanford.box.com/s/f4iyu4tjnxc6ald5h63g791czeb8o5ue