Simulation of the collective behaviour of flocking sheep to a herding dog

Mark Loboda and Klemen Plestenjak

Collective behaviour course research seminar report

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Iztok Lebar Bajec | associate professor | mentor

This project investigates collective behaviour in sheep flocks interacting with a herding dog. We reimplement the model from Collective responses of flocking sheep (Ovis aries) to a herding dog (border collie) in Python, supported by a visual simulation of flock–dog dynamics. After reproducing the published results, the model is extended with support for real-time target setting, herding using two dogs, and environmental obstacles. Additional experiments are done to test how our two-dog herding strategy compares to the original results and how well each of them scales with the number of sheep.

Sheep Flocking | Herding Dog | Simulation | Collective Behaviour

Collective behaviour is a common phenomenon in animal groups, where individuals coordinate their actions to form patterns that appear guided by collective intelligence emerging at the group level. This project focuses on the interaction between a flock of sheep and a herding dog, where the dog displays elements of predatory behaviour while the sheep, responding as prey, move collectively to maintain cohesion and avoid perceived threats. Our work is based on the paper by Jadhav et al. [1], which we reimplement in Python and extend with real-time interactive visualization of the simulated behaviour state.

Related work

Research on collective behaviour in animal groups can be broadly grouped into three types of models: **agent-based models** simulate each individual separately, **continuum (hydrodynamic) descriptors** treat the group as a fluid-like medium described as density and velocity fields, and **control-theoretic approaches** are where groups are modeled and analyzed using principles of feedback and optimization.

Jadhav et al. [1] introduces an agent-based model in which a flock of sheep collectively reacts when being herded by a trained dog. Even though the dog approaches the flock from behind, the analysis of real trajectories shows that sheep at the front tend to initiate directional changes and that these changes then propagate backwards through the group. On longer time scales, the dog adapts its motion to the collective movement of the flock rather than tracking single individuals.

Other studies explore different aspects of the shepherding problem. Strömbom et al. [2] proposes a minimal rule-based model based on switching between collecting dispersed individuals and driving a cohesive group. Liu et al. [3] extend such rule-based methods and apply them to robotic shepherding, guiding a swarm of agents. Nalepka et al. [4] look at humans performing a simplified shepherding task in a virtual environment. Instead of coding rules, they study patterns that emerge when pairs of two people try to herd moving agents together.

To conclude, these studies outline three complementary perspectives on shepherding: minimal rule sets that capture core behavioural patterns, planning-based strategies for challenging environments, and human-in-the-loop approaches that highlight how people naturally coordinate in herding tasks.

Methods

The model contains two types of agent: sheep and a steering agent (the dog). Sheep interact through short-range avoidance, longer-range attraction, and local alignment with a limited set of neighbours. The dog applies an effective repulsive pressure from behind the flock while moving laterally, which generates the zigzag driving motion described in the paper [1].

Quantification of the flock. Consider the group barycenter (or centroid) of the sheep flock by:

$$\vec{r}_B(t) = \frac{1}{N}\sum_{i=1}^{N}\vec{r}_i(t)$$

where $\overrightarrow{r}_i(t)$ is the sheep's position at a given moment. Then, we define group cohesion C and group polarization P as:

$$C(t) = \frac{1}{N}\sum_{i=1}^{N} d_{Bi}, \qquad P(t) = \frac{1}{N}\left\|\sum_{i=1}^{N}\frac{\overrightarrow{v}_i(t)}{\mathrm{v_i(t)}}\right\|$$

where $\overrightarrow{v}_i(t)$ is the velocity vector, $\mathrm{v}_i(t) = \| \overrightarrow{v}_i(t) \|$ the speed of an individual i and $d_{\mathrm{B}i} = \| \overrightarrow{r}_i(t) - \overrightarrow{r}_B(t) \|$ the distance between the barycenter and i.

The sheep. At a given time t^n the sheep i is located at $\overrightarrow{r}_i^{\,n}$ and moves to $\overrightarrow{r}_i^{\,n+1}$ given by

$$\overrightarrow{r}_i^{\,n+1} = \overrightarrow{r}_i^{\,n} + l\,\overrightarrow{e}(\phi_i^{n+1})$$

where $\overrightarrow{e}(\phi_i^{n+1})$ is the unit vector in the direction of ϕ_i^{n+1} and l is the length travelled during this period. The sheep's heading angle during a $n+1$-th step ($\overrightarrow{U}_i^{\,n+1}$) is modeled with a weighted additive combination of the previous time step vector director ($\overrightarrow{e}(\phi_i^n)$), an additive noise ($\overrightarrow{N}_i^{\,n}$) and the vectors corresponding to the external social interaction ($\overrightarrow{S}_{\mathrm{social}}^{\,i,n}$) between sheep and the repulsion from the dog ($\overrightarrow{R}_{\mathrm{dog}}^{\,i,n}$).

$$\overrightarrow{U}_i^{\,n+1} = \alpha\,\overrightarrow{e}(\phi_i^n) + \overrightarrow{S}_{\mathrm{social}}^{\,i,n} + \overrightarrow{R}_{\mathrm{dog}}^{\,i,n} + \epsilon\overrightarrow{N}_i^{\,n}$$

The sheep's social interactions are modeled by finding a limited number of its nearest neighbours (k) within a limited distance, where only a random few of those have an impact on the sheep's behaviour. The social interaction is then modeled by randomly choosing (n_{Att}) of these neighbours, which contribute equally to the strength of attraction (S^i_{Att}), and a number $n_{Ali} \le n_{Att}$, sampled randomly from the n_{Att} attracting ones, which act on the alignment of the sheep (S^i_{Ali}), each with the same intensity. Finally, the sheep is repulsed by every sheep closer than a distance d_{Rep} with the same intensity. We define each social interaction as follows:

$$\overrightarrow{S}_{\mathrm{Att}}^{\,i} = \frac{w_{\mathrm{Att}}}{n_{\mathrm{Att}}}\sum_{j=1}^{n_{\mathrm{Att}}}\frac{\overrightarrow{r}_j - \overrightarrow{r}_i}{\|\overrightarrow{r}_j - \overrightarrow{r}_i\|}$$

$$\overrightarrow{S}_{\mathrm{Ali}}^{\,i} = \frac{w_{\mathrm{Ali}}}{n_{\mathrm{Ali}}}\sum_{j=1}^{n_{\mathrm{Ali}}}\overrightarrow{e}_j$$

$$\overrightarrow{S}_{\mathrm{Rep}}^{\,i} = -\frac{w_{\mathrm{Rep}}}{n_{\mathrm{Rep}}}\sum_{j=1}^{n_{\mathrm{Rep}}}\frac{\overrightarrow{r}_j - \overrightarrow{r}_i}{\|\overrightarrow{r}_j - \overrightarrow{r}_i\|}$$

where $w_{Att}, w_{Ali}, w_{Rep}$ are corresponding positive weights.

When the dog is closer than a distance R_D, the sheep is repulsed by:

$$\overrightarrow{R}_{\mathrm{dog}}^{\,i} = -w_{\mathrm{dog}}\frac{\overrightarrow{r}_{\mathrm{dog}} - \overrightarrow{r}_i}{\|\overrightarrow{r}_{\mathrm{dog}} - \overrightarrow{r}_i\|}$$

where w_{Dog} is a positive weight, $\overrightarrow{r}_{Dog}$ the dog's position, and $\overrightarrow{r}_i$ the sheep's position.

The dog. At each time step, the dog's position is updated towards a point P_{drive} such that the flock's barycenter B lies between P_{drive} and the herding target T. If an individual sheep S_i separates from the flock by more than a distance l_{sep}, the dog has to make it return to the group by moving the P_{drive} in the same way but considering the flock's barycenter as the target and S_i the sheep to be driven. We can define the point P_{drive} as:

$$\overrightarrow{r}_{P_{\mathrm{drive}}} = \begin{cases} \overrightarrow{r}_B - l_{\mathrm{drive}}\dfrac{\overrightarrow{r}_T - \overrightarrow{r}_B}{\|\overrightarrow{r}_T - \overrightarrow{r}_B\|}, & \text{if } R \le l_{\mathrm{sep}}, \\ \overrightarrow{r}_{i^*} - l_{\mathrm{drive}}\dfrac{\overrightarrow{r}_B - \overrightarrow{r}_{i^*}}{\|\overrightarrow{r}_B - \overrightarrow{r}_{i^*}\|}, & \text{if } \|\overrightarrow{r}_{i^*} - \overrightarrow{r}_B\| > l_{\mathrm{sep}}. \end{cases}$$

where i^* is the most distant sheep from the barycenter.

Two-dog. Dog collaboration was implemented by splitting the flock into two groups. This is done by first computing the midpoint between the two dogs and defining a direction line from this midpoint toward the flock barycenter. A splitting line is then constructed perpendicular to this direction line and passing through the midpoint. Sheep are assigned to one of the two groups based on which side of the splitting line they lie on, as shown in figure 1. Each dog is then responsible for driving and collecting its assigned group. This approach prevents both dogs from selecting the same sheep and ensures that each dog operates on a distinct subset of the flock, improving the collection and driving time, especially for larger groups.

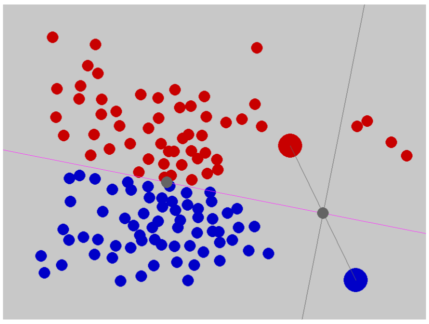


Figure 1. Splitting lines used for two-dog collaboration simulation. Sheep are divided into two groups, shown in red and blue, and each dog is indicated by a larger circle. The lines illustrate how the flock is split between the two dogs.

Environment obstacles. Obstacles are modeled as static, axis-aligned bounding boxes (AABB), defined by their rectangular bounds $[x_{\min}, x_{\max}, y_{\min}, y_{\max}]$.

For an agent located at position $\vec{r} = (x, y)$, the closest point $\vec{r}_c$ on the obstacle is computed as

$$\vec{r}_c = \big(\text{clip}(x, x_{\min}, x_{\max}), \text{clip}(y, y_{\min}, y_{\max})\big),$$

Let $d = \vec{r} - \vec{r}_c$.

If the agent lies outside the obstacle and $d \geq d_{\text{obs}}$, no obstacle interaction occurs. Otherwise, the obstacle induces a repulsive force

$$\vec{R}_{\text{obs}} = -w_{\text{obs}} \left(\frac{d_{\text{obs}} - d}{d_{\text{obs}}} \right)^2 \frac{\vec{d}}{\|\vec{d}\|}, \qquad 0 < d < d_{\text{obs}},$$

where w_{obs} is the obstacle repulsion strength and d_{obs} is the obstacle interaction range.

The quadratic decay produces a smooth increase in repulsion as the agent approaches the obstacle boundary.

Vision Limit. At each time step sheep interaction is restricted to sheep that lie within a fixed perceptual (vision) range. This introduces a vision constrait that reduces unrealistic long-range interactions that are present in the original model. For a local sheep i at position $\vec{r}_i$, the set of perceived neighbours $\mathcal{N}_i$ is defined as:

$$\mathcal{N}_i = \{ j \neq i \mid \|\vec{r}_j - \vec{r}_i\| \leq R_{\text{vis}} \}.$$

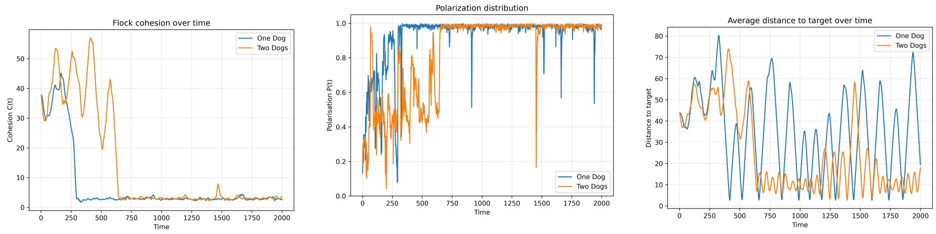
where R_{vis} is the sheep sight range.

Idle state. We introduced an idle state in which each sheep enters idle behaviour when a dog is farther away than a predefined threshold. In this state, the social interactions and noise are further downscaled, creating the effect of sheep calmly grazing when no threat is detected.

Results

To compare one-dog and two-dog herding under identical conditions, we ran two simulations with the same initial state and parameters, differing only in the number of dogs. The simulation uses the original parameter values reported by Jadhav et al. [1], with the addition of new parameters required by our extensions (explicit target, obstacles, sheep neighbour range, and two-dog coordination).

We simulated $N = 14$ sheep, matching the group experiments in the reference study. Both runs use the same random seed ($\texttt{SEED} = 42$) so that sheep initial positions and noise realizations are comparable across one-dog and two-dog conditions.



Distribution of cohesion. | Distribution of polarization. | Average distance to target.

Figure 2. Temporal evolution of cohesion, polarization and distance to target of the flock.

Figure 2 shows the temporal evolution of cohesion, distance to target, and polarization for one-dog and two-dog herding.

Cohesion decreases over time in both cases as the flock transitions from an initially dispersed state to a collected configuration. In the two-dog condition, cohesion exhibits larger early fluctuations during the collection phase but ultimately converges to a compact state comparable to the single-dog case. The average distance to the target decreases in both configurations; however, one-dog herding shows stronger oscillations, whereas two dogs keep the flock closer to the target on average.

Polarization increases over time as the flock organizes into coherent motion. Both configurations reach highly aligned states, but the two-dog case displays greater variability during early collection, reflecting transient coordination dynamics between dogs.

To evaluate how this performs with an increasing number of sheep, we measured the number of required ticks for the flock to reach a cohesive state. Once a flock reaches a cohesion threshold of 15, it is considered to be in a cohesive state. For each flock size, results were averaged over 20 independent runs with different random seeds to ensure statistical stability.

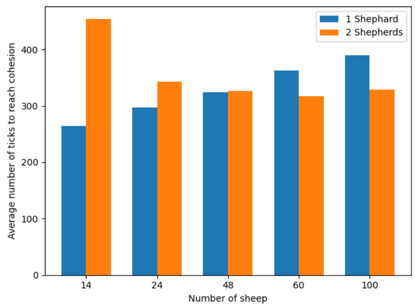


Figure 3. Average number of ticks required for flock to reach good cohesion.

As shown in figure 3, for small flocks ($N = 14$), single-dog herding achieves cohesion faster than two-dog herding. In this mode, the flock remains relatively compact, and the presence of a second dog does not improve collection efficiency. Due to limited coordination between the dogs, each dog tends to act independently, attempting to collect nearby sheep rather than jointly cooperating to enclose and merge the flock.

To support development and analysis, we implemented a real-time visualization tool that renders all agents on a grid-based environment.

Discussion

The main goal of the project was successfully accomplished: we reimplemented the original paper and introduced several modifications and improvements. Some of the originally planned improvements were revised. In particular, dog obstacle avoidance was not implemented, as we consider it a pathfinding problem rather than a collective behaviour one, and because real-life shepherds are typically guided by a human.

For future improvements, we propose a more robust method for handling obstacles. The model should redirect sheep and dogs around obstacles rather than simply deflecting them. This would also address issues we encountered when attempting to split the group into two sections upon encountering an obstacle.

The entire source code with the implementation and other resources is available at https://github.com/markloboda/collectivebehaviour2025.

CONTRIBUTIONS. Both authors worked on the implementation and report.

Bibliography

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