

RESEARCH ARTICLE

WILEY

# A hybrid model for simulating grazing herds in real time

Jure Demšar<sup>1</sup>  | Will Blewitt<sup>2</sup> | Iztok Lebar Bajec<sup>1</sup>

<sup>1</sup>Faculty of Computer and Information Science, University of Ljubljana, Ljubljana, Slovenia

<sup>2</sup>School of Computing, Electronics and Maths, Coventry University, Coventry, UK

## Correspondence

Jure Demšar, Faculty of Computer and Information Science, University of Ljubljana, SI-1000 Ljubljana, Slovenia.  
Email: jure.demsar@fri.uni-lj.si

## Funding information

Slovenian Research Agency (ARRS), Grant/Award Number: P2-0395

## Abstract

Computer simulations of animal groups are usually performed via individual-based modelling, where simulated animals are designed on the level of individuals. With this approach, developers are able to capture behavioural nuances of real animals. However, modelling each individual as its own entity has the downside of having a high computational cost, meaning that individual-based models are usually not suitable for real-time simulations of very large groups. A common alternative approach is flow-based modelling, where the dynamics of animal congregations are designed on the group level. This enables researchers to create real-time simulations of massive phenomena at the cost of biological authenticity. A novel approach called hybrid modelling tries to mix the best of both worlds—precision of individual-based models and speed of flow-based ones. An unknown surrounding hybrid model is the question of their biological authenticity and relevance. In this study, we develop a hybrid model for the simulation of herds of grazing sheep. Through Bayesian data analysis, we show that such an approach can encompass several aspects of real-world sheep behaviour. Our hybrid model is also extremely efficient, capable of simulating herds of more than 1,000 individuals in real time without resorting to graphics processing unit execution.

## KEYWORDS

animal groups, collective animal behaviour, crowd simulation, hybrid model, sheep herds

## 1 | INTRODUCTION

The phenomenon of collective animal behaviour can be commonly observed in nature in the form of flocks of birds, schools and shoals of fish, swarms of insects, human crowds, herds of ungulates, etc. Because it appears on many different scales in many different forms, it is interesting for researchers coming from various scientific fields—from biology, physics, and medicine to social studies, control theory, and computer science.<sup>1–4</sup> Computer scientists usually focus on the development of computer models that can reproduce and visualize the dynamics and patterns of these natural phenomena.

Over the last couple of years, computer models have become an important tool for either studying the behaviour of animal groups<sup>3,5–10</sup> and their evolution,<sup>11–15</sup> or generating spectacular animations for use in computer games and movies.<sup>16–19</sup> Roughly, computer models of collective behaviour can be classified into three groups—individual-based models, flow-based models, and hybrid models.<sup>16,19</sup>

In individual-based models, also microscopic models,<sup>16,20</sup> each individual in the crowd is simulated as an intelligent and autonomous agent. The focus is, thus, on the individual—modelling its perception of the virtual world, the decision process, and the actions by means of which it interacts with other individuals and the world. Because of this, individual-based

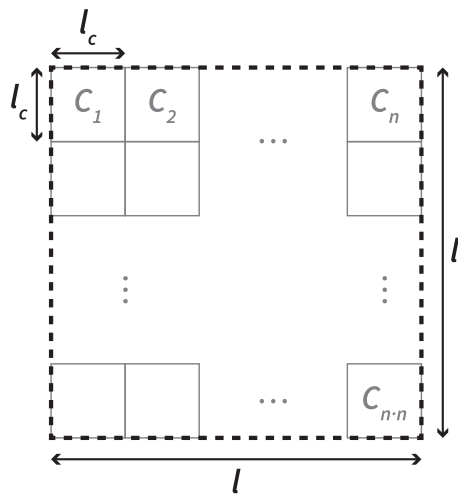
models are able to capture all the intricate details of collective behaviour on the lowest level (level of an individual), and result in computer models that can recreate behaviours that are very similar to the behaviour of animals in nature. In other words, the biological accuracy and relevance of individual-based models are high. Indeed, individual-based modelling is the most common approach when computer models are used for studying the phenomenon of collective behaviour from a biological perspective.<sup>2</sup> However, simulating at the level of an individual has its downside; the computational complexity is much higher than with alternative approaches, especially when the numbers of simulated agents are significant.<sup>16</sup> The computational complexity arises from at least three different but interconnected factors—the simulation update step, the simulation of the perception system, and the sheer volume of intelligent agents to be simulated. To alleviate the issues that arise from the computational complexity and increase processing speed, several approaches have been suggested. Some researchers reduced the computational workload by decreasing the update frequency (an increase in reaction time) of each individual,<sup>21</sup> others focused on the optimization or change of the perception and interaction system,<sup>21–24</sup> but as individual-based models are very suitable for parallel execution, many researchers adapted techniques from highly parallel processing.<sup>21,23,25</sup> The latter is most commonly achieved via general-purpose computing on graphics processing units (GPGPU). Unfortunately, if the simulation is to be used in a computer game, this kind of processing is not always available, with mobile games as the most known example—a vast majority of mobile phones at the time of this writing do not support GPGPU.

Flow-based models<sup>19,26–28</sup> (sometimes also called macroscopic<sup>16,20</sup>) are traditionally used for simulations of large crowds, where researchers are interested mostly in the high-level patterns of the crowd and not in the low-level interactions between individuals. In a way, these models resemble the dynamics of fluids or particles in physics.<sup>16,19,20,26</sup> Flow-based approaches have a much lower computational complexity than individual-based approaches and are as such capable of simulating much larger crowds in real time. They are most commonly used in computer games and movies where the patterns displayed by massive crowds are usually more appreciated than an extremely high degree of biological accuracy. Traditionally flow-based models are used for simulating behaviour of human crowds,<sup>26–28</sup> but the technique can also be used for the simulation of groups of animals.<sup>29</sup> However, even when used for the simulation of groups of animals, the principal goal is the production of animations of massive collective behaviour events to be used in computer games and movies, and the biological accuracy and relevance remains in the background.

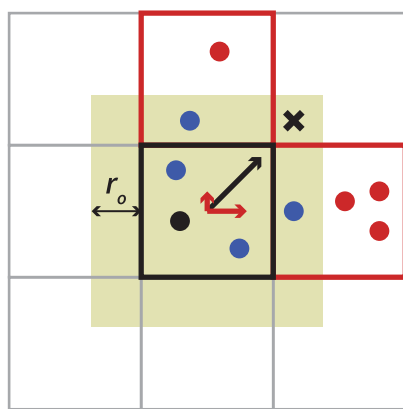
Hybrid models are a cross between individual-based models and flow-based models. They are a relatively novel approach that tries to combine the best of both worlds.<sup>16,30</sup> Hybrid models use techniques from flow-based modelling to simulate the high-level motion of groups and techniques from individual-based modelling for simulating the interactions between individual agents that form the groups. This allows one to simulate large crowds (but not as large as with flow-based modelling alone) where the intelligent agents are able to interact with each other on the level of individuals and thus achieve a higher biological accuracy than flow-based models. While hybrid and flow-based models have already been used for simulating behaviour of human crowds,<sup>16,30–32</sup> there have been only few applications when it comes to the simulation of animal group behaviour.<sup>31,33</sup> Note that, in these latter cases, the principal focus was not the optimization for real-time performance but an expansion of possible questions the model can be used to answer. As a consequence, the question if hybrid models, when the principal focus is real-time performance, can create simulations that visualize biologically accurate and relevant behaviour remains unanswered.

Among the many fascinating examples of animal group behaviour, there are cases that alternate between various behavioural states or regimes. Some species of fish, for example, transit between a swarming state and a polarized state.<sup>34,35</sup> In some behavioural states or regimes, the individuals intensively interact with each other, whereas in others, there is a very little low-level interaction. A typical example are herds of sheep, which alternate between the packing and dispersing regime.<sup>36</sup> In the dispersing regime grazing sheep form small polarized groups that slowly spread out over the foraging field. When sheep get too dispersed or endangered by an imminent predator, an avalanche-like packing event occurs. During this global packing event a dispersed herd quickly coalesces into a tight and compact group. This type of behaviour is not exclusive to sheep, for example, musk oxen are also known for forming tight groups, which protect weaker individuals from predators.<sup>37,38</sup> This interplay between local interactions and global events seems like an ideal case for an investigation about the suitability of hybrid modelling for the purpose of simulating groups of animals.

In 2015, Ginelli et al.<sup>36</sup> developed an individual-based model suitable for simulating herds of grazing ungulates (Merino sheep). The main purpose of their computer model were biological studies and not real-time simulations. As a consequence, the model is computationally quite complex, suitable only for simulating small groups of individuals. In nature, however, ungulate groups are commonly composed from thousands of individuals.<sup>39</sup> In this work, we present a hybrid model suitable for simulating herds of grazing ungulates in real time. We show that our model is capable of simulating large herds while retaining behaviour similar to behaviour in a biologically accurate model.



**FIGURE 1** The living area, a square with side length  $l$ , is bounded by a fence (dashed black line). Small grey squares visualize the division of the living area into a regular grid of square cells with side length  $l_c = l/f_p$ . The grid is used for both the optimization of the perception system and the implementation of the hybrid model



**FIGURE 2** Simulation of attractive flow (black arrow) during packing events. Circles represent individuals and the black cross depicts the position of the global centre of mass ( $\mathbf{g}'$ ). The black circle is the observed individual and the cell marked with a black square is its corresponding cell. Blue circles are metric neighbour candidates, individuals that are located in the same cell as the observed individual or in the nearby vicinity of that cell—yellow-colored area. Red circles are sheep located in neighbour cells (red squares). Neighbour cells are used for calculating local cohesion, and the red arrows represent the calculated local cohesion vectors

## 2 | METHODS

### 2.1 | Environment

In our model, the simulated sheep are represented by point like agents that reside inside a square living area with a side length of 200 m that is surrounded by a fence (Figure 1). At the beginning of each simulation,  $N$  sheep are spawned at random locations inside a circular area in the middle of the living area. To prevent spawning an unrealistically tight group, the radius of the circular area is set to  $\sqrt{N} \text{ m}^2$ .

We use grid-based spatial partitioning, a method that in most, but the densest of scenarios significantly speeds up the process of searching for neighbours.<sup>21,24</sup> More precisely, we place a regular grid over the living area and keep track of the agents located in each cell. By facilitating this information, we do not have to search the whole sheep population when searching for neighbours of a particular individual but can instead sift only through a usually small subset of agents. In our case, this subset includes the individuals that are located in the same cell as the observed individual and those individuals that are located in adjacent cells (closer than interaction distance,  $r_o$ , of the observed individual's cell, see also Figure 2).

### 2.2 | The model

The basis of our implementation is the individual-based model developed by Ginelli et al.<sup>36</sup> Let the  $i$ th sheep at time step  $t$  be represented by its position  $\mathbf{p}_i^t$ , its orientation  $\theta_i^t$ , and its behavioural state  $q_i^t \in \{0, 1, 2\}$ , coding idle, walking, and running states, respectively. In our model, sheep move according to

$$\mathbf{p}_i^{t+\Delta t} = \mathbf{p}_i^t + \Delta t v_i^{t+\Delta t} \mathbf{h}_i^{t+\Delta t}, \quad (1)$$

where  $v_i^t$  is the speed,  $\mathbf{h}_i^t = (\cos \theta_i^t, \sin \theta_i^t)$  is the orientation of the sheep, and  $\Delta t$  is the elapsed time since the previous update—see Equations (3), (4), and (7) for details.

**TABLE 1** The model's parameters

Parameter	Description	Value
$\Delta t$	Update step	Dynamic
$N$	Number of sheep	100–5,000
$r_s$	Spawn area radius	$\sqrt{N}m^2$
$l$	Size of the living area	200 m
$f_p$	Flow precision	40
$l_c$	Grid cell length	5 m
$v(0)$	Speed when idle	0 m/s
$v(1)$	Speed when walking	0.15 m/s
$v(2)$	Speed when running	1.5 m/s
$\beta$	Attraction/repulsion factor	0.9
$\eta$	Grazing noise factor	0.13
$\omega$	Running noise factor	10
$r_o$	Interaction radius	1
$r_e$	Equilibrium radius	1
$\epsilon$	Local group attraction factor	0.9
$v_\Delta$	Maximum speed change	0.1
$\theta_\Delta$	Maximum orientation change	0.1
$\gamma$	Fence repulsion factor	0.1
$r_f$	Fence repulsion radius	10
$\alpha$	Mimicking factor	15
$\alpha_0$	Stopping mimicking factor	0.5
$\alpha_2$	Running mimicking factor	2
$\tau_{0 \rightarrow 1}$	Idle to walking coefficient	24
$\tau_{1 \rightarrow 0}$	Walking to idle coefficient	8
$A_2$	Running threshold	14
$d_0$	Stopping threshold	0.8

Due to a low update step (1s), the manoeuvrability of sheep in Ginelli et al.'s model is unbounded, and as a result, each individual sheep always moves in its desired direction with its desired speed. For example, even if a modelled sheep wants to perform a complex manoeuvre, say a U-turn, it can perform it instantly (in a single update step). Visually this produces choppy turns and accelerations, unwanted features in real-time simulations intended to be used for computer games. To introduce smoothness of motion, we, in our model, limited the change of speed and orientation per update frame and the orientation and speed of an individual sheep are, thus, updated as

$$v_i^{t+\Delta t} = v_i^t + \Delta t \left( v(q_i^{t+\Delta t}) - v_i^t \right)_{\perp -v_\Delta \cdot \Delta t}^{\top v_\Delta \cdot \Delta t} \quad (2)$$

$$\theta_i^{t+\Delta t} = \theta_i^t + \Delta t \left( \theta(q_i^{t+\Delta t}) - \theta_i^t \right)_{\perp -\theta_\Delta \cdot \Delta t}^{\top \theta_\Delta \cdot \Delta t}, \quad (3)$$

where  $(a)_{\perp b}^{\top c} = \min(\max(a, b), c)$ ,  $v(q)$  represents the speed associated with behavioural state  $q$ , and  $\theta(q)$  the desired orientation when the observed individual is in behavioural state  $q$ . Idle sheep ( $q_i^t = 0$ ) remain stationary, emulating resting on the ground, taking a nap, that is,  $v(0) = 0$  and  $\theta(0) = \theta_i^t$ . Walking sheep ( $q_i^t = 1$ ) have a desired speed of 0.15 m/s and their desired orientation is calculated with Equation (4). Running sheep ( $q_i^t = 2$ ) have a desired speed of 1.5 m/s and their desired orientation is calculated with Equation (7). See Table 1 for a complete list of the model's parameters and their values. Our hybrid model uses techniques from individual-based modelling to simulate interactions between walking sheep and techniques from flow-based modelling to simulate the packing events of running sheep. Walking sheep, while trying to keep away from fences, interact with all sheep closer to the observed individual than the interaction distance  $r_o$ ; this set of sheep are called metric neighbours ( $\mathbf{M}_i^t$ ). More specifically, they try to align their movement direction with these individuals and keep them at a safe enough distance.

$$\theta(1) = \text{Arg} \left[ \gamma a(d_{if}^t) \mathbf{a}_i^t + \sum_{j \in \mathbf{M}_i^t} \mathbf{h}_j^t + \beta s(d_{ij}^t) \mathbf{e}_{ij}^t \right] + \psi_i^t. \quad (4)$$

This tendency to align while maintaining a safe distance is modelled with the second part of the Equation (4), where  $\mathbf{e}_{ij}^t$  is a unit vector pointing from the observed individual  $i$  to its neighbour  $j$ ,  $d_{ij}^t$  is the metric distance between these

two individuals,  $s(d_{ij}^t) = \min(0, (d_{ij}^t - r_o)/r_o)$  the separation strength, and  $\beta$  the attraction/repulsion factor. Fence effects are modelled by the first part of the equation, where  $\mathbf{a}_i^t$  is a unit vector pointing from the observed individual  $i$  towards the centre of the living area,  $d_{if}$  is the metric distance of the observed individual to the closest fence segment,  $r_f$  the fence repulsion radius,  $a(d_{if}) = r_f/d_{if}$  the repulsion strength, and  $\gamma$  the fence repulsion factor. Random grazing patterns of walking sheep are emulated with the noise component ( $\psi_i^t$ )—a random angle chosen from a uniform distribution  $[-\eta\Pi, \eta\Pi]$ . Note that, in Ginelli et al.'s original model,<sup>36</sup> the separation force of walking sheep is not explicitly modelled for the sake of simplicity. Neither are the fence effects due to the negligible role of the fence in their experiments. In their model, a certain degree of separation is achieved with noise alone. Because our preliminary simulation runs showed that sheep quite often overlap each other in physical space, possibly due to the reduced integration interval, we, as a consequence, amended the original equation to include an explicit separation force. Equation (4) leads to the formation of small subgroups of grazing sheep that disperse diffusively throughout the living area.

The behaviour of running sheep is, on the other hand, implemented with a flow-based approach. Here, we used the spatial partitioning grid of cells to implement attractors that direct the flow of sheep. This is also the main difference with respect to Ginelli et al.'s model, where the behaviour of running sheep is based on the first shell of Voronoi neighbours.<sup>40</sup>

Based on Ginelli, et al.'s analysis, the behaviour of sheep is characterised as an intermittent collective dynamic where long dispersion phases (during which grazing sheep slowly spread out) are punctuated by fast packing events, triggered by an individual-level behavioural shift.<sup>36</sup> During packing events, the previously spread out group quickly regroups into a tight pack. These events are typically triggered when an individual located at the group periphery starts running towards the centre of the group, recruiting more and more sheep into a compact, fast-moving herd before finally stopping almost synchronously, leaving a rather dense herd that then resumed grazing.<sup>36</sup>

The centre of the group of sheep at time step  $t$  can be computed as

$$\mathbf{g}^t = \frac{1}{N} \sum_{i \in \mathbf{C}} \mathbf{c}_i n_i^t, \quad (5)$$

where  $\mathbf{C}$  denotes the set of indices of cells that constitute the grid-based spatial partitioning of the living area,  $\mathbf{c}_i$  the centre of the cell with index  $i$ , and  $n_i^t$  the number of individuals that are at time step  $t$  located in the cell with index  $i$ .

A packing event could be simulated by simply forcing running sheep to head for the centre of the group, but the end result where all sheep run towards the exact centre of the group would look rather synthetic. To solve this issue, sheep are attracted towards a slightly displaced centre of group and towards local sheep subgroups. Position of local sheep along with the randomized global centre of sheep group at the current time step define an attractive flow over the entire living area. The attractive flow is computed on a cellular level as

$$\mathbf{f}_i^t = (1 - \epsilon) \mathbf{g}_i^t + \epsilon \frac{\sum_{j \in \mathbf{G}_i} \mathbf{c}_{ij} n_j^t}{n^t}, \quad (6)$$

where  $\epsilon$  is the factor that determines the strength of attraction towards local groups,  $\mathbf{G}_i$  is a set of indices of cells that contain at least one individual and are immediately adjacent to cell  $i$  (cells marked red in Figure 2),  $\mathbf{c}_{ij}$  is a unit vector pointing from the centre of cell  $i$  to the centre of cell  $j$ , and  $n^t$  is the number of individuals currently in the cell  $i$  and its immediate adjacent cells. To remove the undesired synthetic look where sheep always coalesce to the exact centre of the herd sheep,  $\mathbf{g}_i^t$  is a unit vector pointing from the centre of cell  $i$  to a slightly displaced centre of the sheep group— $\mathbf{g}_i^t = \mathbf{g}^t + \omega^t \mathbf{r}^t$ . Here,  $\omega^t$  is a uniform random number from the interval  $[0, \omega]$ , and  $\mathbf{r}^t$  a unit vector pointing in a random direction. The group centre displacement is updated every second.

Finally, in our hybrid model, the behaviour of running sheep ( $q_i^t = 2$ ) is governed by Equation (7), where the first part of the equation models the fence effects, the middle part repulsion from metric neighbours and alignment with running metric neighbours, and the last part the flow of running sheep due to a packing event. Here,  $\mathbf{f}_i^t$  denotes a unit vector in the direction of the attractive flow of the grid cell inside of which the observed individual  $i$  is located.

$$\theta(2) = \text{Arg} \left[ \gamma a(d_{if}^t) \mathbf{a}_i^t + \sum_{j \in \mathbf{N}_i} \left( \delta_{2,q_j^t} \mathbf{h}_j^t + \beta s(d_{ij}^t) \mathbf{e}_{ij}^t \right) + \mathbf{f}_i^t \right] \quad (7)$$

Transitions between states (idle, walking, and running) are determined by transition rates. The transition rate between walking and idle state and vice versa is computed as

$$p_{0 \rightarrow 1}^t = \frac{1 + \alpha n_{i,1}^t}{\tau_{0 \rightarrow 1}}, \quad p_{1 \rightarrow 0}^t = \frac{1 + \alpha n_{i,0}^t}{\tau_{1 \rightarrow 0}}, \quad (8)$$

where  $n_{i,1}^t$  and  $n_{i,0}^t$  are the number of walking and idle metric neighbours of the observed individual  $i$ ,  $\alpha$  the strength of mimetic effects, and  $\tau_{0 \rightarrow 1}$  and  $\tau_{1 \rightarrow 0}$  transition coefficients.

The transition from idle to running and from walking to running is calculated as

$$p_{0,1 \rightarrow 2}^t = e^{\mathcal{A} - \mathcal{A}_2} (1 + \alpha n_{0,1 \rightarrow 2}^t), \quad (9)$$

where  $\mathcal{A}$  is the area of the convex hull surrounding the cells that contain sheep,  $\mathcal{A}_2$  is the running threshold, and  $n_{0,1 \rightarrow 2}^t$  is the number of sheep that started running (transitioned from idle or walking to a running state) in the previous update step.

Hence, the transition rate from running to idle is calculated as

$$p_{2 \rightarrow 0}^t = \frac{1}{e^{\mathbf{d}_i^2 - d_0}} (1 + \alpha n_{2 \rightarrow 0}^t), \quad (10)$$

where  $\mathbf{d}_i^t$  is distance from individual's position to the displaced centre of the sheep group ( $\mathbf{g}_r^t$ ),  $[\cdot]$  is the stopping threshold, and  $n_{2 \rightarrow 0}^t$  is the number of sheep that stopped (transitioned from running to idle) in the previous update step.

Whether an individual will change its state is determined by switching probabilities

$$P_{a \rightarrow b}^t = 1 - e^{-p_{a \rightarrow b}^t}, \quad (11)$$

where  $a$  is the current state of the observed individual,  $b$  is its potential new state, and  $p_{a \rightarrow b}^t$  is the particular transition rate calculated based on Equations (8), (9), and (10). For every individual, the model first tests the transition from idle to walking or vice versa; next, it tests the transition to running, and finally, the transition from running to idle. A certain transition triggers if a uniform random number from the interval  $[0, 1]$  is higher than the calculated switching probability. Transition calculations are triggered once per second.

To summarize, each update step we calculate the new position of each simulated sheep (Equation 1) by using its current speed (Equation 2) and orientation (Equation 3). The behaviour of each sheep depends on its current state (idle, walking, or running), which changes through time (Equations 8, 9, 10, and 11). Idle sheep stand still and do not change their speed or orientation. Walking sheep form small grazing herds that slowly spread over the living area (Equation 4). Sheep switch to the running state during packing events when large dispersed herds coalesce into small compact ones (Equations 5, 6, and 7).

## 2.3 | Statistical analysis

To compare the behaviour of sheep between the individual-based model and the hybrid model, we performed a Bayesian data analysis. Bayesian data analysis is an approach that is gaining momentum in the 21st century and seems to be slowly but steadily replacing the more common frequentist statistics.<sup>41,42</sup>

The main goal of our experiments was to investigate how the means of various measured metrics in our hybrid model compare with Ginelli et al.'s model or with empirical data.<sup>36</sup> The experiments are not deterministic; they are stochastic in nature, and therefore, a source of (random) measurement error. To estimate and account for this, our simulations consisted of  $n = 5$  different runs (iterations). We used the following Bayesian hierarchical model to estimate the mean values of measured metrics:

$$\begin{aligned} y_i &\sim \mathcal{N}(\mu_i, \sigma_i), \\ \mu_0 &\sim \mathcal{N}(\mu_p, \sigma_p), \\ \sigma_0 &\sim \mathcal{U}(u_{\text{low}}, u_{\text{hi}}), \\ \mu &\sim \mathcal{N}(\mu_0, \sigma_0), \end{aligned} \quad (12)$$



where  $y_i$  are the metric measurements for the  $i$ th iteration. That is, we model each iteration with its own distribution with potentially different means  $\mu_i$  and standard deviations  $\sigma_i$ . These means are assumed to be drawn from a population of means, with the grand mean  $\mu_0$ , and a standard deviation  $\sigma_0$ . The grand mean  $\mu_0$  is the parameter we are interested in estimating. According to Gelman,<sup>43</sup> we set a uniform prior distribution of variance hyperparameters. Weakly informative priors were set on educated guesses.

To draw samples from the posterior distribution, we used the Stan tool for Bayesian inference.<sup>44</sup> Each model was run for 1,000 warm-up and 5,000 sampling iterations, which was sufficient to reduce approximation errors to negligible levels.

### 3 | RESULTS

Ginelli et al.<sup>36</sup> already showed that the simulations of sheep herds in their individual-based model are a valid representation of natural sheep behaviour. To validate that the same holds for the developed hybrid model, we compared the behaviour of sheep in our hybrid model with Ginelli et al.'s model and empirical data.

There are two distinct regimes observable in herds of grazing sheep in nature and in computer models—the dispersing or grazing regime and the packing regime. During the grazing regime, sheep slowly disperse through the field while feeding, following the grazing regime is the packing regime, where sheep quickly coalesce into a single dense group. Meaning that a dispersing event is followed by a packing event, which is again followed by a dispersing event.

Each simulation run lasted until we recorded 50 events (25 dispersing and 25 packing events). To reduce the impact of randomness, the whole process was repeated five times for each of the two models.

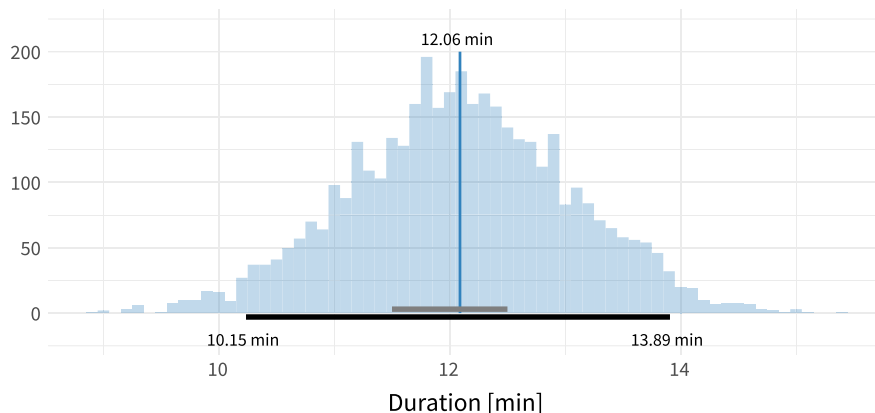
First, we analysed the behaviour of sheep during dispersing events where sheep graze the grass and slowly spread around the living area. Because the behaviour of sheep in our model uses the same equations and parameters as in Ginelli et al.'s case it was expected to present similar results. Indeed, the ratio between walking and idle sheep during dispersing events is with both models around five to one.<sup>36</sup>

Next, we compared the duration of dispersing events in our model with the empirical data gathered by Ginelli et al.—in nature dispersing events last approximately 12 min (there are approximately five pairs of long dispersing events and short packing events per hour).<sup>36</sup> Precise values of these measurements are presented in the middle column of Table 2. To determine the similarity, we performed two tests. First, we calculated whether the duration of dispersing events in our case is likely to be 12 min. Hence, next, we determined if the most likely duration of dispersing events in our case falls within the—region of practical equivalence—the ROPE interval.<sup>42</sup> Figure 3 is based on Bayesian data analysis of dispersing event duration. The duration of 12 min measured for dispersing events in nature is inside the 95% CI, in other words, the duration of 12 min is one of the 95% most likely outcomes. Furthermore, the most probable duration (12.06 min) is inside the ROPE interval, which we here set to 30 s. Based on this, we can assume that there is no major difference in terms of dispersing event duration between our model and empirical data.

Finally, we compared the area that the sheep cover after packing events in our model and Ginelli et al.'s model (rightmost column in Table 2). The area was calculated as the area of the convex hull surrounding the sheep at the end of a packing

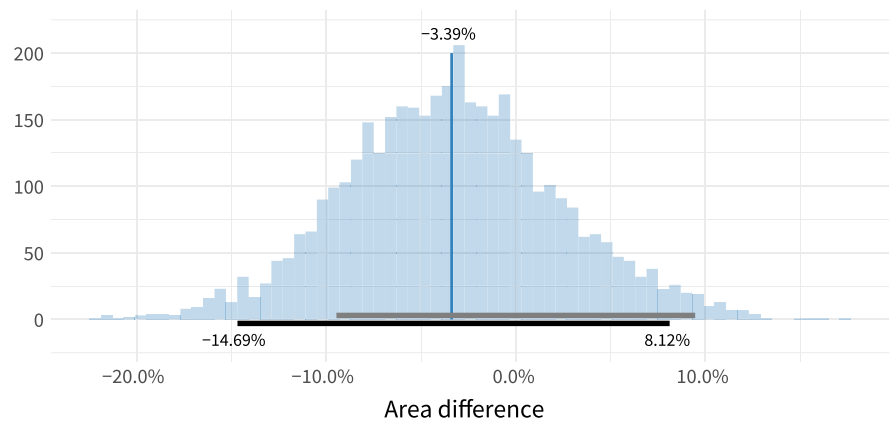
	Duration of dispersing events	Area after packing events
Ginelli et al.	12 min	528.18 m <sup>2</sup> , [476.38 m <sup>2</sup> , 586.11 m <sup>2</sup> ]
Our model	12.06 min, [10.17 min, 13.92 min]	546.06 m <sup>2</sup> , [524.98 m <sup>2</sup> , 569.33 m <sup>2</sup> ]

**TABLE 2** Comparison of results between our model and Ginelli et al.'s model based on empirical data. Values in square brackets represent 95% confidence intervals



**FIGURE 3** Statistics for the dispersing event duration. As the duration of 12 min is inside the 95% CI (black line just under the x-axis), and the most likely difference (blue vertical line) is inside the region of practical equivalence (ROPE) interval (grey line just above the x-axis), we can assume the duration of dispersing events in our model is comparable to empirical data

**FIGURE 4** A comparison of packing events for the individual-based model and the hybrid model. Visualized is the difference in area after packing events between both models. As the difference of zero is in both cases inside the 95% CI (black line just under the x-axis), and the most likely difference (blue vertical line) is inside the region of practical equivalence (ROPE) interval (grey line just above the x-axis), we can assume there is no major difference between the two behaviours in terms of packing events



**FIGURE 5** A screenshot of a simulation visualized with our model

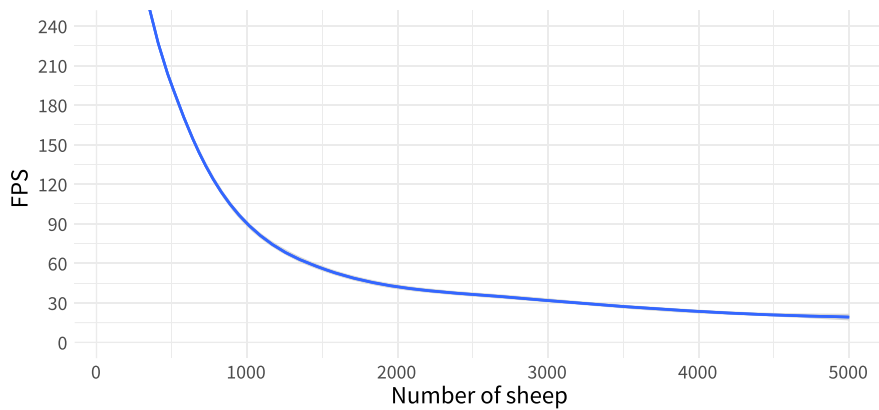
event. Figure 4 visualizes the comparison of packing events. As you can see, the difference of zero is inside the 95% CI for both the area and duration. As the most likely difference between the models is also inside the region of practical equivalence (ROPE) interval (here set to 25 m<sup>2</sup>). Based on this, we can also assume there is no major difference in the area of packing events between our model and Ginelli et al.'s model.

Because our model was built for real-time applications, we also measured its performance. The model was developed and tested in Unity Engine.<sup>45</sup> The computer on which the tests were performed housed an Intel Core i7-870 2.93 GHz CPU, 8 GB RAM, and NVIDIA GeForce GTX 460 display adapter. When measuring the frame rate, the graphics settings were set to low (no shading and antialiasing) in order to achieve maximum possible frame rate. A sample screenshot of these simulations can be seen on Figure 5.

To analyse the computational performance of the hybrid model, we measured its frame rate. Frame rate represents the maximal amount of update steps our model could calculate in 1 s and is measured in frames per second (FPS). We measured the frame-rate on herds of sheep consisting from 50 to 5,000 individuals. For each group size, we ran the simulations and measured the FPS every 6 s; we stopped the simulation when we executed 300 measurements. First 50 measurements were discarded in order to prevent the initial artificially generated state from influencing the results. Figure 6 visualizes the performance of our hybrid model.

The holy grail of processing for the purpose of real-time applications in video games or movies is to achieve a consistent frame rate of 60 FPS<sup>46</sup>; when this rate is not obtainable, a frame rate of 30 FPS is also deemed acceptable as it results in decently smooth motion. Our model is capable of simulating herds consisting of up to 1,400 individuals with 60 FPS and up to 3,100 with 30 FPS. Note here that the presented results were not obtained from processing on highly parallel platforms (e.g., GPGPU). We decided against that as we believe that our results and models are more general (cross-platform) if we develop them by means of classic, nonparallel, programming. Because both individual-based models,<sup>21,23,25</sup> and spatial partitioning<sup>21</sup> are well suited for parallel approaches similar techniques could be used to greatly increase performance of the developed hybrid model.





**FIGURE 6** Graph visualizing the speed of simulations in our hybrid model. Visualized is the mean frame-rate along with the 95% CI. FPS = frames per second

## 4 | CONCLUSION

Here, we built on Ginelli et al.'s sheep herding individual-based model<sup>36</sup> and developed a hybrid model that is suitable for simulating large herds of sheep in real time. To this point, hybrid models were predominantly used for computer simulations of human crowds. To our knowledge, this is the first adoption for real-time simulations of groups of animals, for example, schools of fish, flocks of birds, herds of ungulates, and swarms of insects. To ease the comparison of the developed model with Ginelli et al.'s<sup>36</sup> simulated sheep in our model also reside on a flat, two-dimensional field. However, all of the developed methods would also work perfectly fine in a three-dimensional world. Note here, though, that putting a uniform two-dimensional grid over a three-dimensional world results in nonuniform division of space, so the speed up achieved by spatial partitioning would be suboptimal.

Ginelli et al.'s<sup>36</sup> main purpose was to develop a model, which reproduces biologically relevant motion of sheep herds. Thus, in their case, the emphasis was on the comparison between the tracking data gathered on real sheep and the motion of sheep produced by the model. Because the real world data about sheep motion used in their research was sampled once per second, their individual-based model used a fixed update step of 1 s. This is unsuitable for most games and real-time applications, as by updating the behaviour of the simulated animals only once per second typically results in an unresponsive, unnatural, and choppy motion. In real-time simulations, smoothness of motion and fast reactions to changes in the environment are of paramount importance, and to achieve this, developers usually do not set a strict update frequency but instead strive for the highest possible update frequency. We achieved this via our hybrid model.

By comparing the developed hybrid model with empirical data and Ginelli et al.'s individual-based model inspired on empirical research, we showed that hybrid models are capable of retaining a certain degree of biological accuracy. This finding is important because it shows that hybrid models are not only suitable for use in games and movies but can also be potentially used for biological studies where scientists investigate the whys and hows surrounding the behaviour of large animal groups.

## ACKNOWLEDGEMENTS

We would like to thank Uroš Prosenik for designing the 3D models used in our visualizations of sheep herds. This work was funded in part by the Slovenian Research Agency (ARRS) through the Pervasive Computing research programme (P2-0395).

## DATA AVAILABILITY

The source code behind all of the simulations presented in this manuscript can be found at <https://github.com/demsarjure/SheepHerding>. The videos of simulations can be seen at <https://bit.ly/2t8GSp4>. The movement of sheep in the videos is sped up by a factor of 60.

## ORCID

Jure Demšar  <https://orcid.org/0000-0001-6080-149X>

## REFERENCES

- Deisboeck TS, Couzin ID. Collective behavior in cancer cell populations. *BioEssays*. 2009;31(2):190–197.
- Demšar J. Evolution of fuzzy animats in a competitive environment [PhD thesis]. Ljubljana, Slovenia: Faculty of Computer and Information Science, University of Ljubljana; 2017.
- Lebar Bajec IL, Heppner FH. Organized flight in birds. *Animal Behaviour*. 2009;78(4):777–789.
- Sumpter DJT. The principles of collective animal behaviour. *Philos Trans Royal Soc B Biol Sci*. 2006;361(1465):5–22.
- Couzin ID, Krause J, James R, Ruxton GD, Franks NR. Collective memory and spatial sorting in animal groups. *J Theor Biol*. 2002;218(1):1–11.
- Demšar J, Lebar Bajec I. Simulated predator attacks on flocks: a comparison of tactics. *Artificial Life*. 2014;20(3):343–359.
- Demšar J, Hemelrijk CK, Hildenbrandt H, Lebar Bajec I. Simulating predator attacks on schools: evolving composite tactics. *Ecological Modelling*. 2015;304:22–33.
- Heppner FH, Grenander U. A stochastic nonlinear model for coordinated bird flocks. In: Krasner S, editor. *The ubiquity of chaos*. Washington, DC: AAAS Publications, 1990; p. 233–238.
- Hildenbrandt H, Carere C, Hemelrijk CK. Self-organized aerial displays of thousands of starlings: a model. *Behavioral Ecology*. 2010;21(6):1349–1359.
- Vicsek T, Czirók A, Ben-Jacob E, Cohen I, Shochet O. Novel type of phase transition in a system of self-driven particles. *Phys Rev Lett*. 1995;75(6):1226–1229.
- Demšar J, Štrumbelj E, Lebar Bajec I. A balanced mixture of antagonistic pressures promotes the evolution of parallel movement. *Scientific Reports*. 2016;6:39428.
- Demšar J, Lebar Bajec I. Evolution of collective behaviour in an artificial world using linguistic fuzzy rule-based systems. *PLOS ONE*. 2017;12(1):1–20.
- Hein AM, Rosenthal SB, Hagstrom GI, Berdahl A, Torney CJ, Couzin ID. The evolution of distributed sensing and collective computation in animal populations. *eLife*. 2015;4:1–43.
- Olson RS, Hintze A, Dyer FC, Knoester DB, Adami C. Predator confusion is sufficient to evolve swarming behaviour. *J Royal Soc Interface*. 2013;10(85).
- Olson RS, Knoester DB, Adami C. Evolution of swarming behavior is shaped by how predators attack. *Artificial Life*. 2016;22(3):299–318.
- Ijaz K, Sohail S, Hashish S. A survey of latest approaches for crowd simulation and modeling using hybrid techniques. *Proceedings of the 17th UKSIM-AMSS International Conference on Modelling and Simulation*; 2015 Mar 25–27; Cambridge, UK. Washington, DC: IEEE Computer Society; 2015. p. 111–116.
- Lind J. *MASSIVE: software engineering for multiagent systems*. 1999.
- Reynolds C. Flocks, herds, and schools: a distributed behavioral model. *ACM SIGGRAPH Comput Graph*. 1987;21(4):25–34.
- Zhou S, Chen D, Cai W, et al. Crowd modeling and simulation technologies. *ACM Trans Model Comput Simul*. 2010;20(4). Article No. 20.
- Xu M-L, Jiang H, Jin X-G, Deng Z. Crowd simulation and its applications: recent advances. *J Comput Sci Technol*. 2014;29(5):799–811.
- Reynolds C. Big fast crowds on PS3. *Proceedings of the 2006 ACM SIGGRAPH Symposium on Videogames (Sandbox '06)*; 2006 Jul 30–31; Boston, MA. New York, NY: ACM; 2006. p. 113–121.
- de Lima Bicho A, Rodrigues RA, Musse SR, Jung CR, Paravisi M, Magalhães LP. Simulating crowds based on a space colonization algorithm. *Comput Graph*. 2012;36(2):70–79.
- Da Silva AR, Lages WS, Chaimowicz L. Boids that see: using self-occlusion for simulating large groups on GPUs. *ACM Comput Entertain*. 2009;7(4). Article No. 51.
- Vermeulen JL, Hillebrand A, Geraerts R. A comparative study of *k*-nearest neighbour techniques in crowd simulation. *Comput Animat Virtual Worlds*. 2017;28:e1775.
- Husselmann AV, Hawick KA. Simulating species interactions and complex emergence in multiple flocks of Boids with GPUS. *Proceedings of the IASTED International Conference on Parallel and Distributed Computing and Systems*; 2011 Dec 14–16; Dallas, TX. Anaheim, CA: Acta Press; 2011. p. 100–107.
- Treuille A, Cooper S, Popović Z. Continuum crowds. *ACM Trans Graph*. 2006;25(3):1160–1168.
- Hughes RL. The flow of human crowds. *Annu Rev Phys Chem*. 2003;35(1):169–182.
- Morini F, Yersin B, Maim J, Thalman D. Real-time scalable motion planning for crowds. *Proceedings - 2007 International Conference on Cyberworlds (CW'07)*; 2007 Oct 24–26; Hannover, Germany. Piscataway, NJ: IEEE; 2007. p. 144–151.
- Wang X, Jin X, Deng Z, Zhou L. Inherent noise-aware insect swarm simulation. *Comput Graph Forum*. 2014;33(6):51–62.
- Park SI, Cao Y, Quek F. Large scale crowd simulation using a hybrid agent model. *Motion Games*. 2011.
- Bayazit OB, Lien JM, Amato NM. Better group behaviors in complex environments using global roadmaps. In: *Artificial life VIII: Proceedings of the Eighth International Conference on Artificial Life*. Cambridge, MA: MIT Press, 2002. p. 362–370.
- Golas A, Narain R, Curtis S, Lin MC. Hybrid long-range collision avoidance for crowd simulation. *IEEE Trans Vis Comput Graph*. 2014;20(7):1022–1034.
- Goodwin RA, Nestler JM, Anderson JJ, Weber LJ, Loucks DP. Forecasting 3-D fish movement behavior using a Eulerian-Lagrangian-agent method (ELAM). *Ecological Modelling*. 2006;192(1–2):197–223.
- Becco C, Vandewalle N, Delcourt J, Poncin P. Experimental evidences of a structural and dynamical transition in fish school. *Phys A Stat Mech Appl*. 2006;367:487–493.
- Tunstrøm K, Katz Y, Ioannou CC, Huepe C, Lutz MJ, Couzin ID. Collective states, multistability and transitional behavior in schooling fish. *PLOS Comput Biol*. 2013;9(2).

36. Ginelli F, Peruani F, Pillot M-H, Chaté H, Theraulaz G, Bon R. Intermittent collective dynamics emerge from conflicting imperatives in sheep herds. *PNAS*. 2015;112(41):12729–12734.
37. Freedman HI, Wolkowicz GSK. Predator-prey systems with group defence: the paradox of enrichment revisited. *Bull Math Biol*. 1986;48(5–6):493–508.
38. Tener JS. Muskoxen in Canada: a biological and taxonomic review. Department of Northern Affairs and National Resources, Canadian Wildlife Service. 1965.
39. Creel S, Winnie JA Jr. Responses of elk herd size to fine-scale spatial and temporal variation in the risk of predation by wolves. *Animal Behaviour*. 2005;69(5):1181–1189.
40. Aurenhammer F. Voronoi diagrams — a survey of a fundamental data structure. *ACM Comput Surv*. 1991;23(3):345–405.
41. Kruschke JK. Bayesian estimation supersedes the *t* test. *J Exp Psychol*. 2013;142(2):573–603.
42. Kruschke JK. *Doing Bayesian data analysis: A tutorial with R, JAGS, and Stan*. 2nd ed. Cambridge, MA: Academic Press; 2014.
43. Gelman A. Prior distribution for variance parameters in hierarchical models. *Bayesian Analysis*. 2006;1(3):515–533.
44. Carpenter B, Lee D, Brubaker MA, et al. Stan: a probabilistic programming language. *J Stat Softw*. 2017;76(1).
45. Unity Technologies. *Unity - Game Engine*. 2017.
46. Andreev D. Real-time frame rate up-conversion for video games: or how to get from 30 to 60 Fps for free. *Proceedings of the ACM SIGGRAPH 2010 Talks*; 2010 Jul 26–30; Los Angeles, CA. New York, NY: ACM; 2010. Article No. 16.

## AUTHOR BIOGRAPHIES



**Jure Demšar** is an Assistant Professor at the Faculty of Computer and Information Science, University of Ljubljana. His main areas of research are data analysis, collective behaviour, crowd simulations and game development. He obtained his PhD degree in Computer Science from University of Ljubljana in 2017.



**Will Blewitt** is a Lecturer at Coventry University, and the Course Director for Coventry University's Games Technology degree programme. His main areas of research interest are game-focused AI and heterogeneous computing. He obtained his PhD in Computer Science from De Montfort University in 2012, before participating in post-doctoral research in rehabilitative gaming at Newcastle University.



**Iztok Lebar Bajec** received his BSc (2000), MSc (2002) and PhD (2005) at the University of Ljubljana, from the Faculty of Computer and Information Science. Currently he holds the position of Associate Professor at the same institution. His research interests are fuzzy logic, modelling and simulation of collective behaviour, and multivalued logic in quantum-dot cellular automata.

**How to cite this article:** Demšar J, Blewitt W, Lebar Bajec I. A hybrid model for simulating grazing herds in real time. *Comput Anim Virtual Worlds*. 2019;e1914. <https://doi.org/10.1002/cav.1914>