[FFR120] Decision Making in Collective Motion

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Collective motion in animal groups emerges from local interactions between individuals and enables efficient information transfer without centralized control. In this study, an agent-based model is implemented to investigate how informed individuals influence group-level decision-making. Two numerical experiments are performed. First, the relationship between the proportion of informed agents and the group's ability to follow a preferred direction is examined. The accuracy of information transfer is quantified using the alignment between the group's direction and the informed preference. Second, collective decisions under conflicting preferences are studied by introducing multiple groups of informed agents with different desired directions. The results demonstrate that a small fraction of informed individuals can effectively guide large groups, while conflicts between information sources lead either to consensus or to an averaging of directions depending on their relative strength.

Project Topic: P - Collective Dynamics in Agent-Based Systems

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I. INTRODUCTION

Collective behavior in animals, such as flocking in birds, shoaling in fish, and swarming in insects, is a well-studied phenomenon in complex systems and self-organization [1]. Although each individual in the group follows relatively simple local rules, the interaction between individuals can give rise to coordinated movement patterns and efficient information transfer at the group level. Understanding such mechanisms is not only of biological interest, but also has applications in, for example, robotics, optimization, and distributed computing [1].

A central question in the research field concerns how information is propagated and can influence the group when only a subset of the individuals carry external information, for example about a migration route or food source in animal groups. [2] presented an influential agent-based model that shows how a group can make collective decisions without explicit leaders, solely through local interactions between individuals. The aim of this project is to implement and analyze a variant of their model, which will be referred here to as the Couzin model, through numerical simulations.

The project investigates the following research questions:

1. How does the proportion of informed individuals relative to the total group size affect the accuracy of information dissemination and the resulting collective direction of movement?

2. How does the presence of conflicting information sources, represented by multiple informed subgroups with different preferred directions, influence collective decision making and collective movement, and how is this affected by the feedback mechanism proposed by [2]?

Special attention is paid to identifying under which conditions the group reaches consensus on a common direction, and when the competing signals instead lead to a averaging of the direction of movement. Through comparisons with previous results, especially [2], the work aims to illustrate the mechanisms that enable robust collective decisions in the absence of central control.

II. OVERVIEW

In this section, two alternative models for investigating decision making and collective motion are discussed together with the chosen model. The section is summarized in Table I.

The weighted voter model. The weighted voter model describes collective decision making as an opinion dynamics process, where agents repeatedly update their discrete preferences by copying neighbors, with update rates weighted by the perceived quality of alternatives [3]. Decision accuracy emerges from this weighting mechanism, as higher-quality options bias the stochastic dynamics toward correct consensus even under conflicting initial preferences. However, the model operates at an abstract level and does not explicitly represent agents' spatial positions, motion, or interaction geometry. As a result, it is well suited for studying accuracy and consensus formation in opinion space, but less appropriate for investigating how information is transferred through local interactions coupled to collective movement and spatial coordination.

The (modified) Vicsek model. The Vicsek model describes collective motion through local alignment interactions, where agents update their direction based on the average heading of nearby neighbors with added noise [4]. Although the original formulation does not include informed individuals or explicit preferences, it can be modified by introducing directional biases to a subset of agents, making it possible to study information transfer accuracy in a simplified setting. Conflicting preferences can likewise be represented by assigning different preferred directions to different subgroups and examin-

TABLE I. **Overview of simulation models**.

Method / Model	**Use case scenario**	**Features**	**Suitable for the project?**
The weighted voter model	Collective decision making with discrete alternatives, where agents must reach consensus under uncertainty and potentially conflicting preferences.	Opinion-based stochastic update rule; Weighted influence reflecting option quality or confidence; Supports analysis of accuracy and consensus time; No explicit spatial motion or interaction geometry	Not really, since it lacks spatial coordination and movement dynamics central to this project.
The (modified) Vicsek model	To study collective motion emerging from local alignment interactions, commonly used to study clustering, alignment and phase transitions in systems of self-propelled agents.	Local alignment with neighboring agents; Stochastic update rule with noise; Can be extended with directional biases; Less biologically relevant (than the chosen model)	Only partially, since it captures collective motion well, but only allows simplified studies of information transfer and decision accuracy.
The Couzin model	Collective motion and decision making in moving groups, where coordination emerges from local interactions without explicit signaling or leadership.	Zone-based local interaction rules; Explicit spatial motion and coordination; Supports informed agents and conflicting preferences; Couples movement dynamics with information transfer	Yes, it forms the main inspiration and modeling framework for the project.

ing the resulting collective alignment. However, due to its minimal and abstract interaction rules, the extent to which such extensions capture underlying decision-making mechanisms remains limited and is not explicitly addressed in the original model.

The Couzin model. The Couzin model describes collective motion through explicitly defined zones of repulsion, alignment, and attraction, enabling coordinated group movement based solely on local interactions. By allowing a subset of agents to be informed and biased toward a preferred direction, the model provides a natural framework for studying accuracy of information transfer in moving groups. Conflicting preferences can be represented by multiple informed subgroups with different directional biases, making it possible to investigate collective decision making under disagreement.

III. METHOD

The project is based on an agent-based model of collective movement, inspired by [2], where each individual is represented by a point agent moving in the plane with constant velocity. Each agent is described at time t by its position vector $c_i(t)$ and its velocity vector $v_i(t)$. The interactions of the agents are governed by two concentric zones: a repulsion zone with radius α, and a larger zone for orientation and attraction with radius ρ, see Fig 1. Unlike other agent based models of collective motion, like the Vicsek model [4] or the so called "boids model" introduced by [5], in which combined influences are averaged on to decide on direction, this model uses priority. This property, argues [2], makes the model more biologically relevant. Each agent will, in case there are neighboring agents j, inside its repulsion zone, prioritize to steer away from them. The desired direction then becomes

$$\mathbf{d}_i(t+\Delta t) = -\sum_{j\neq i} \frac{\mathbf{c_j}(t)-\mathbf{c_i}(t)}{|\mathbf{c_j}(t)-\mathbf{c_i}(t)|}.$$

If there are no neighboring agent in the repulsion zone but some in the orientation/attraction zone, those agents, j, will influence agent i:

$$\mathbf{d}_i(t+\Delta t) = \sum_{j\neq i} \frac{\mathbf{c_j}(t)-\mathbf{c_i}(t)}{|\mathbf{c_j}(t)-\mathbf{c_i}(t)|} + \sum_{j=1} \frac{\mathbf{v_j}(t)}{|\mathbf{v_j}(t)|}.$$

So far, the agents don't "want" to move in any certain direction, as long as they follow the above rules. Now, a proportion of the agents – so called informed agents – have some preferred direction $\mathbf{g}$, which will influence its desired direction, in addition to the previous rules:

$$\mathbf{d'}_i(t+\Delta t) = \frac{\hat{\mathbf{d}}_i(t+\Delta t)+\omega\hat{\mathbf{g}}}{|\hat{\mathbf{d}}_i(t+\Delta t)+\omega\hat{\mathbf{g}}|}.$$

The factor $\omega \in [0,1]$ weighs the preferred direction of the informed agent. Subsequently, the position vectors are updated according to

$$\mathbf{x_i}(t+\Delta t) = \mathbf{x_i}(t) + v\hat{\mathbf{d}}_\mathbf{i}(t+\Delta t)\Delta t$$

where the scalar v is a constant speed and Δt the length of the timestep. A final important detail is the parameter θ_{max} which limits the maximum turning angle (in radians) per timestep.

The first experiment examines how the group's ability to follow an external information signal (i.e. a preferred direction) depends on the proportion of informed individuals $p = \frac{N_{informed}}{N}$. For every combination of N and p, 100 simulations are run and their final group direction $\mathbf{h}$ is computed as the vector pointing from the

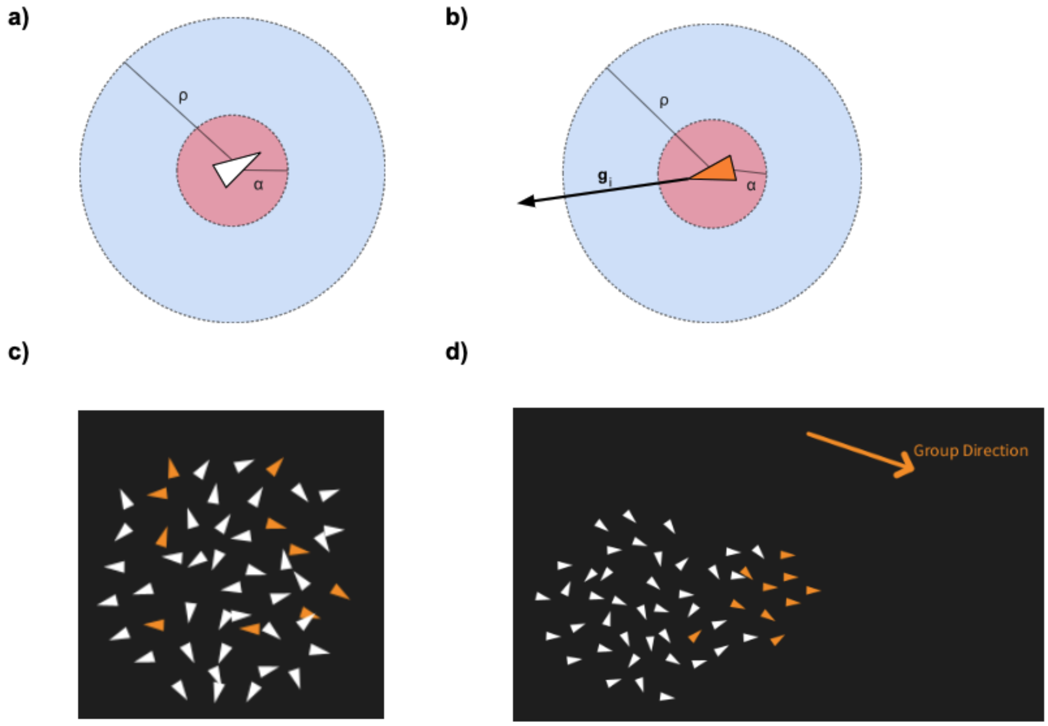

FIG. 1. **Method employed.** a) A regular agent with a repulsion zone (red) and a orientation/attraction zone (blue). b) An informed agent with preferred velocity $\mathbf{g_i}$. c) Agents are initialized with random position and velocity close to each other. d) Final direction (orange arrow) is calculated at the end of the simulation.

group centroid (center of mass) at 250 timesteps previous to the final timestep, to the group centroid at the final timestep. From these vectors $\mathbf{h}$, the accuracy with respect to the preferred direction $\mathbf{g}$ is computed as the mean angular deviation from $\mathbf{g}$ and normalised so that accuracy 0 corresponds to no information transfer and accuracy 1 corresponds to perfect alignment with $\mathbf{g}$. The second experiment studies collective decision-making under conflicting preferences. The informed agents are divided into two groups with different preferred directions of movement $\mathbf{g_1}$ and $\mathbf{g_2}$. The number of informed agents with respective preferred direction will be varied to investigate how this asymmetry affects the final direction of the group. Multiple simulations are carried out for varying differences in direction, each time recording the final direction of the group. In order to allow for better agreement on one direction, in contrast to having the group move in an average direction (between $\mathbf{g_1}$ and $\mathbf{g_2}$), a feedback mechanism is implemented for the informed agents. Informed agents will increase their weight (now initially ω_{init}) by $\omega_{\mathbf{inc}}$ up to some $\omega_{\mathbf{max}}$ if they find themselves pointing within 20 degrees to their own preferred direction. Otherwise they will decrease ω by $\omega_{\mathbf{dec}}$ down to 0. The second experiment will also investigate the effect of this feedback mechanism.

IV. RESULTS AND DISCUSSION

This section is structured as follows. First, the results of the two experiments are presented. These are then discussed in relation to the findings of [2], followed by a discussion of methodological choices and limitations of the chosen approach.

The first experiment shows that the group accuracy increases rapidly with the proportion of informed individuals p, after which it saturates at a value close to 1. Furthermore, a smaller fraction of informed individuals is required to achieve high accuracy as the group size N increases. For the largest group sizes, a slight temporary decrease in accuracy is observed around $p = 0.15$ and $p = 0.25$.

In the second experiment, we first observe that in the absence of feedback (left-hand panels in Fig. 3), the final group direction lies close to the mean of the two conflicting preferred directions for conflict angles up to approximately 125 degrees. Beyond this threshold, the group typically selects one of the two preferred directions. In these cases, the first preferred direction $\mathbf{g}_1$ is chosen more frequently when it is supported by a larger number of informed individuals ($n_1 > n_2$). When the feedback mechanism is introduced in the case $n_1 > n_2$, this asymmetry in directional choice becomes more pronounced,

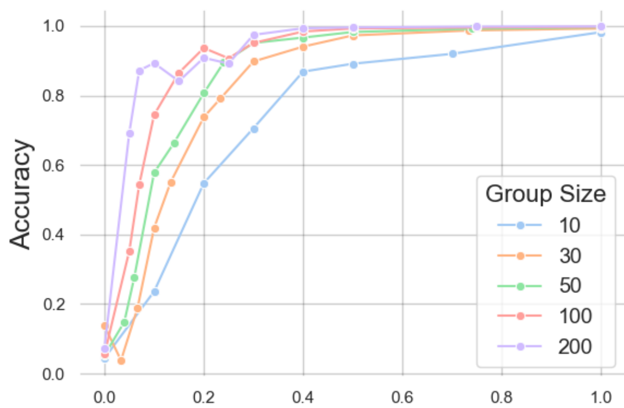

FIG. 2. **Accuracy and group elongation vs p.** The proportion of informed agents needed to achieve high accuracy is less for larger groupsizes N. Parameters used were $\omega = 0.3$, $\alpha = 24$, $\rho = 230$, $\theta_{max} = 0.3$, $v = 1$. Simulations were run for 2500 time steps with 200 runs for each $p - N$ pair.

particularly for conflict angles larger than 125 degrees. Applying the feedback mechanism to the symmetric case ($n_1 = n_2$) results in final group directions that lie slightly closer to the two preferred directions than in the absence of feedback, for larger conflict angles.

For conflict angles below 125 degrees, the feedback mechanism also influences the group direction by increasing the spread towards the two preferred directions, while the mean direction remains centered between them. This effect is visible in the right-hand panels of Fig. 3 as a broader band of outcomes around the mean direction.

We can initially conclude that the model successfully achieves information transfer across the group through purely local interactions and without any explicit signaling or leadership. The qualitative relationship between group accuracy and the proportion of informed individuals closely matches that reported by [2], with accuracy increasing rapidly for small values of p and saturating at high values.

For the first experiment, the main deviation from the results of [2] is the temporary reduction in accuracy observed for certain intermediate values of p at large group sizes. Visual inspection of the simulations for these parameter values reveals that this decrease is associated with a loss of group cohesion, where the group partially or fully fragments instead of maintaining a single coherent flock. In such cases, the definition of a single, well-defined group direction becomes less meaningful, which naturally leads to a reduction in measured accuracy.

This lack of stability provides a unifying explanation for several observations across both experiments. In the second experiment, the effect of the feedback mechanism on collective decision-making is present but less pronounced than in [2], particularly for larger conflict angles. A plausible explanation is that increased instability makes the group more susceptible to fragmentation or internal fluctuations (group pending between directions), which in turn weakens the reinforcement effect of feedback on a single dominant direction.

In a highly stable flock, small asymmetries—such as differences in the number of informed individuals preferring a given direction—can be consistently amplified through social interactions. By contrast, when stability is reduced, the group direction becomes less well-defined, and the amplification of directional preferences is correspondingly weaker. This interpretation is consistent with the observed variability in final group directions and the reduced clarity of directional outcomes compared to [2].

The primary challenge of the project was therefore not the implementation of the model itself, but the identification of parameter values that yield sufficiently stable group dynamics. The relatively large number of interacting parameters made this task non-trivial. In particular, the balance between the repulsion radius, the orientation radius, and the preference strength ω was found to be crucial for maintaining cohesion while still allowing informed individuals to influence the group. However, achieving stability also required careful fine-tuning of additional parameters, highlighting how sensitive the model is to their combined effects.

The approach used to identify suitable parameter values relied primarily on manual inspection of visualized simulations combined with iterative adjustment of parameters. While this method was sufficient to produce qualitatively reasonable behavior, it is neither systematic nor efficient. A more robust approach would involve automated parameter sweeps combined with quantitative stability metrics, such as measures of group cohesion or automatic detection of group splitting events. Implementing such automated stability detection would furthermore make it possible to distinguish between genuine decision-making effects and artifacts arising from unstable group dynamics, thereby strengthening the interpretation of the results.

V. CONCLUSIONS AND OUTLOOK

This project has demonstrated that collective decision making and effective information transfer can emerge in moving groups through purely local interactions, without centralized control or explicit signaling. The qualitative dependence of group accuracy on the proportion of informed individuals is in good agreement with the findings of [2], supporting the robustness of the underlying mechanism. However, fully reproducing the quantitative results of the original study proved challenging, highlighting the inherently complex and sensitive nature of the system. Small changes in parameter values were found to significantly affect group stability, cohesion, and the amplification of directional preferences, underscoring the model's strong dependence on coupled nonlinear interactions. Besides seeing these difficulties only as shortcomings of the method, one should also recognize

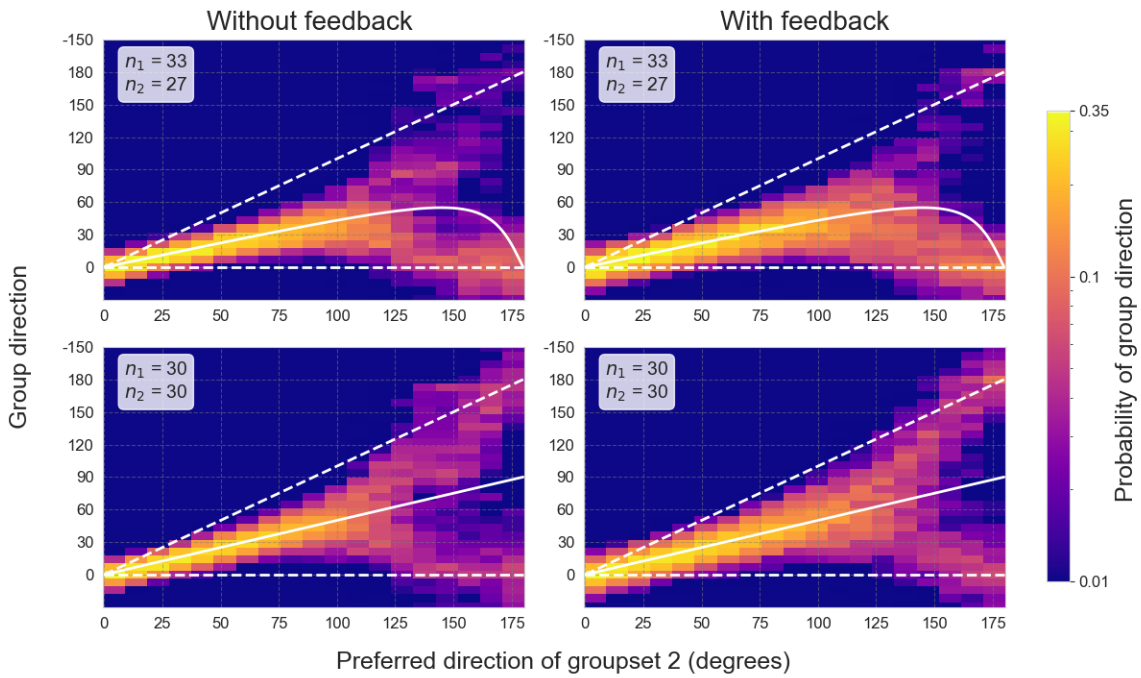

FIG. 3. **Results for 2nd experiment** The diagonal dashed line corresponds to the conflicting $\mathbf{g}_2$ direction and the horisontal dashed line corresponds to $\mathbf{g}_1$ which is held constant and equal to zero. Meanwhile, the solid line is the average direction, with consideration to the number of informed agents holding the different preferred directions. For each of the four configurations, $\mathbf{g}_2$ was varied in intervals of 10 degrees with 500 runs carried out for each interval totaling 9500 runs for each configuration. The parameters used were the same as in experiment 1 with the addition: $\omega_{init} = 0.1, \omega_{inc} = 0.008, \omega_{dec} = 0.0006$.

them as characteristic features of complex systems, where emergent behavior is strongly dependent on finely tuned conditions. Future work could focus on systematic parameter exploration and the development of quantitative stability metrics to better distinguish genuine decision-making dynamics from artifacts caused by loss of cohesion and fragmentation.

VI. CONTRIBUTIONS

The author of this report is the sole contributor to the project and this report.

VII. CONFLICT OF INTEREST

The author declares no conflict of interest.

VIII. DATA AND CODE AVAILABILITY

All source code are made publicly available at https://github.com/ViggoS/couzin-collective-motion.

[1] T. Vicsek and A. Zafeiris, Collective motion, Physics Reports **517**, 71 (2012), collective motion.

[2] I. D. Couzin, J. Krause, N. R. Franks, and S. A. Levin, Effective leadership and decision-making in animal groups on the move, Nature **433**, 513 (2005), this study introduces the idea of a few informed individuals who control the collective movement of the group. It is also the results in this article that the project aims to reproduce.

[3] G. Valentini, H. Hamann, and M. Dorigo, Self-organized collective decision making : the weighted voter model, in *AAMAS '14 : Proceedings of the 2014 international conference on Autonomous agents and multi-agent systems*, edited by A. Bazzan and M. Huhns (ACM, New York, NY, 2014) pp. 45–52, used as an alternative model and discussed in the overview.

[4] T. Vicsek, A. Czirók, E. Ben-Jacob, I. Cohen, and O. Shochet, Novel type of phase transition in a system of self-driven particles, Physical Review Letters **75**, 1226–1229 (1995), the original article presenting the "Vicsek model". Used in the overview.

[5] C. W. Reynolds, Flocks, herds and schools: A distributed behavioral model, SIGGRAPH Comput. Graph. **21**, 10.1145/37402.37406 (1987), craig Reynolds 1987 article introducing a model for the simulation of animal flocks, which would later be called the "boids model". Used in the method for comparison with the method in the project.