

# Bottom-up models of swarming and the entropy of visual states

H. L. Devereux<sup>1</sup> and M. S. Turner<sup>2,3</sup>

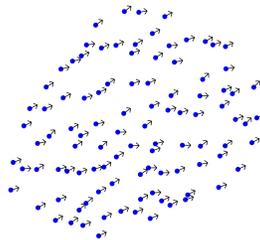
<sup>1</sup> Department of Mathematics and

<sup>2</sup> Department of Physics, University of Warwick, Coventry CV4 7AL, UK

<sup>3</sup> Department of Chemical Engineering, University of Kyoto, Kyoto 615-8510, Japan

M.S.Turner@warwick.ac.uk,

WWW home page: <http://homepages.warwick.ac.uk/~phscz/>



**Fig. 1.** Snapshot of dynamics generated by self-propelled agents that use vision to sense each other. The agents chose a re-orientation move in each discrete time step so as to maximise the configurational entropy of visual states accessible to them over all possible subsequent re-orientations out to a time horizon of  $\tau$  timesteps; here  $\tau = 6$  and  $N = 50$  agents.

## Abstract

We study a “bottom-up” model for swarming in discrete time. Moving agents re-orientate themselves in each timestep so as to **maximise the entropy associated with visual states accessible to them in the immediate future**. The relative positions and orientations of all agents in the future, and this entropy, is therefore contingent on their current reorientation move of each agent, selected accordingly. We refer to this mechanism as Future State Maximisation (FSM) and argue that it should confer evolutionary fitness for a number of reasons that, in more general settings, would include resource acquisition and risk avoidance. Here we pose FSM dynamics in terms of a genuine configurational entropy, here that of the sensor array analogous to the retina. These sensors can register 1 if one or more other unit-radius agents lie in their angular field of view, otherwise 0. The entropy is calculated from the distribution of visual states over all accessible future re-orientation sequences, explicitly enumerated. The dynamics depends primarily on an integer parameter  $\tau$ , the future time horizon

for the states entering the configurational entropy. Simulations generated from this model at high values of  $\tau \gtrsim 5$  gives rise to co-aligned, cohesive swarms even though no other interactions of any kind are present, i.e. co-alignment, attraction or repulsion. The swarms are characterised by high polar order. We further investigate the role of visual occlusion in which the entropy is computed only over the (visual projection of) those agents that are visible to another agent in the present timestep. We find no qualitative changes in the behaviour when occlusion is incorporated. For smaller values of  $\tau$  we observe swarm fragmentation. We use a clustering algorithm to measure the rate of fragmentation and the co-alignment in the ordered sub-clusters. We discuss possible extensions of our work from 2D to 3D.

## Background

Collective motion occurs in many natural systems from swimming bacteria [1], bioconvecting phytoplankton [2] and swarming krill [3] to flocks of starlings [4] and herds of sheep [5]. Models that seek to reproduce this motion often introduce explicit co-alignment, attraction and repulsion [5, 6]. We consider this to be a “top-down” approach, in which the key empirical behaviour, here alignment and cohesion, is coded into the model at the outset. We instead see bottom-up models as those that seek to explore how these properties might emerge naturally from some underlying principle or cognitive strategy. We believe our work represents such a bottom-up approach in the sense that it starts with the principle of Future State Maximisation. This is an evolutionarily and behaviourally plausible mechanism, working directly on visual input. It spontaneously gives rise to aligned swarms in which agents retain control of their visual environment in the sense that they have the freedom to explore the most varied environments in the future. In earlier work [7] we showed how neural networks operating directly on the visual input could mimic similar dynamical states. Such neural networks provide a mechanism for real-time execution of what is otherwise a time-consuming algorithm as well as providing a simple toy model for the evolutionary adoption of FSM.

This work represents several significant advances on earlier work [7]. Firstly, FSM is posed in terms of a *bona fide* configurational entropy, rather than a more algorithmic definition involving a count over distinct (non-degenerate) states. This may be important if we are ever to develop analytical models for FSM in the future, e.g. based on field theories. Secondly, we demonstrate that visual occlusion does not limit the ability of the agents to generate cohesive swarms that fragment rarely, if at all. Finally, we have employed a clustering algorithm to study the flock fragmentation that occurs when  $\tau$  is too small. In this case fragmentation may arise because agents are not able to perceive re-orientation moves far enough in the future to be able to target trajectories that avoid fragmentation. In the limit  $\tau \rightarrow \infty$  we speculate that FSM would lead to swarms that are robustly cohesive under any perturbation or choice of initial conditions.

## References

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