A Bottom-Up Approach to the Evolution of Swarming

Randal S. Olson[1,3,5], Christoph Adami[2,5], Fred C. Dyer[3,4,5] and Arend Hintze[1,2,5]

[1]*Department of Computer Science and Engineering,* [2]*Department of Microbiology and Molecular Genetics,*
[3]*Ecology, Evolutionary Biology, and Behavior Program,* [4]*Department of Zoology,*
[5]*BEACON Center for the Study of Evolution in Action, Michigan State University, East Lansing, MI 48823, USA*

Extended Abstract

One of nature's most evident examples of self-organization is the formation of swarms, schools, or flocks of animals. These groups of individuals coordinate their movement on an individual basis to form self-organized collectives. It has been hypothesized that these aggregations of individuals improve mating success (Diabate et al., 2011), or may be an adapted defense against predators by confusing the potential predator (Krause and Ruxton, 2002; Jeschke and Tollrian, 2007). In the past, these ostensibly complex swarming behaviors have been explained by the swarm members adhering to three simple rules: 1) Move in the same direction as your neighbors; 2) Remain close to your neighbors; and 3) Avoid collisions with your neighbors (Reynolds, 1987). We characterize this model as a top-down approach, where the behavior of the group is explained by simple rules that were conceived ad hoc and work only when applied to that particular system. Generally, this approach requires knowledge about the position and motion vector of nearby agents and therefore requires complex mathematical computations to determine the motion of each agent in the swarm (Oboshi et al., 2002; Chen and Fang, 2006; Hemelrijk and Hildenbrandt, 2011).

We find it implausible that biological creatures in swarms are performing complex computations, such as determining the relative position and motion vector of nearby conspecifics, every millisecond to make a decision about where to move next. We suggest instead that there must be a simpler, more computationally tractable mechanism (for biological organisms) that is guiding swarming behavior in nature. In this abstract we present a bottom-up approach, where each agent in the swarm is controlled individually by a Markov network brain (Edlund et al., 2011) as opposed to genetic programming (Reynolds, 1993) or neural networks (Kwasnicka et al., 2007). The information provided to each swarm agent is limited to the information that the agent's retina conveys, and every agent's actions depend only on a combination of the swarm agent's current sensory input (e.g., eyes and ears) and the state of internal nodes in the swarm agent's Markov brain (i.e., memory). We suggest that this is a more realistic model of swarms observed in nature, since the information provided to the brain is simple to compute and decisions are made on an individual basis rather than by a top-down controller. This evolutionary agent-centered approach enables us to examine the environmental conditions that are conducive for swarming, and how these conditions influence the evolution of swarming behavior.

In nature, we observe two varieties of swarming behavior: insect swarms which remain at one location during their breeding period to facilitate mating (Diabate et al., 2011), and flocks of birds or schools of fish that roam while still maintaining a coherent swarm. Swarm coherence is believed to be influenced by the rate of predation (Beauchamp, 2004), thus some swarming behaviors can be understood as a group effort to deter potential predators (Krause and Ruxton, 2002; Jeschke and Tollrian, 2007). Examples of anti-predator swarming behavior can be observed in nature, such as in flocks of starlings (Feare, 1984). While predation is believed to be the key selection pressure causing the difference between stationary and roaming swarms, there is little evidence to support this (Beauchamp, 2004). Evolutionary experiments on natural swarms are inconvenient and time-consuming, while our bottom-up approach of evolving agent controllers allows these questions to be addressed in an experimental model system.

Every swarm agent has its own retina consisting of two rows of 12 pixels covering a range of 180° facing forward. Each of the 12 pixels covers a 15° segment and indicates if at least one other swarm agent is within viewing range within that segment. The second row of pixels functions identically to the first, but instead indicates the presence of a predator. Each swarm agent is controlled by its own Markov network brain, defined by a network of Markov variables that are connected by stochastic logic gates (as in Edlund et al. 2011), except that we also allow deterministic along with stochastic gates. We evolve the Markov network brains with a standard Genetic Algorithm, where mutations alter the brain by adding or removing connections between input, output, and memory nodes, or modifying the logic of one of the brain's Markov gates. The swarm agents have the choice every update to travel straight ahead at a speed of 1 unit (normal speed), to travel straight ahead at a speed of 2 units (rushing speed), or to travel a distance of 1 unit and turn left or right by 8° (turning), for a total of 4 possible actions. In the experiments where we study the effects of predation on swarm behavior, we include a hand-designed predator that performs swooping attacks on the swarm. The predator has a retina covering 40° in front of it and targets agents in its field of view with a probability of $\frac{1}{d}$ where d is the agent's distance from the predator, such that closer agents are more likely to be targeted for predation. In simulation, the predator moves at a constant speed of 1.5 units and has a 25% chance of successfully killing any swarm agent that gets within 3 units of it.

We used three different fitness functions to evolve the swarms: rewarding coherence, rewarding avoidance of the predator, and rewarding avoidance of the predator while also maintaining coherence. The fitness of a swarm being rewarded for coherence is $W_s = \sum_{t=0}^{t_{\max}} \sum_{i=1}^{n} \frac{1}{r_i}$, where n is the number of agents alive in the swarm (here, $n = 20$), $t_{\max}$ is the total number of updates for which the swarm is evaluated, and r is the distance of the agent to the center of the swarm at update t. The fitness of a swarm under predation is computed as $W_p = \sum_{t=0}^{t_{\max}} \sum_{i=1}^{n} d$, where d is defined as the distance between agent and predator. Dead agents have a distance of 0 to the predator. If both selection pressures for coherence and predation are applied, the total fitness is the sum of both components: $W_s + \frac{1}{4} W_p$. Each of the three selection regimes were tested in 100 replicate experiments with a standard Genetic Algorithm with fitness proportional selection, 1% per-gene mutation rate, 5% gene duplication, and 2% deletion rate, and no cross-over.

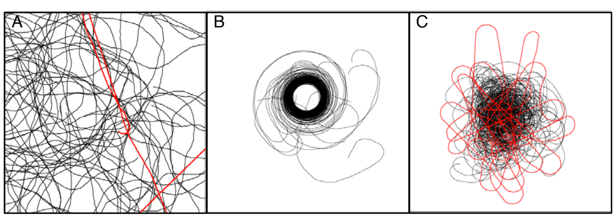

Figure 1: Trajectories of individuals in swarms with only predation (A), with only rewarding coherence (B), and with predation and rewarding coherence (C). Swarming agent paths in black, predator paths in red. All three figures have the same scale.

Selecting only for predator avoidance results in complete dissipation of the swarm (Figure 1A), and shows that predation alone is insufficient for driving swarming behavior in this system. On the other hand, selecting for coherence alone results in agents that aggregate but move in small, predictable circles that do not roam (Figure 1B). When selecting for predation avoidance and coherence at the same time, some swarms show similar behavior than those evolved without predation, but we also find several swarms that actively avoid the predator and roam unpredictably (Figure 1C), similar to predated swarms observed in nature. Taken together, these results demonstrate that realistic swarming behavior can be evolved in an agent-based model with minimal information provided to each agent, suggesting that more complex models (e.g., models that require processing of relative positions and motion vectors) are not proper models of natural swarms. Our results suggest that a bottom-up approach using Markov brains represents a promising new platform that can be used to study the evolution of swarming behaviors in an experimental system.

References

Beauchamp, G. (2004). Reduced flocking by birds on islands with relaxed predation. *Proceedings of the Royal Society London Series B*, 271(1543):1039–1042.

Chen, S. and Fang, H. (2006). Modeling and control of scalable engineering swarm. In *The Sixth World Congress on Intelligent Control and Automation*, pages 526 –530, Piscataway, N.J. IEEE Press.

Diabate, A., Yaro, A., Dao, A., Diallo, M., Huestis, D., and Lehmann, T. (2011). Spatial distribution and male mating success of Anopheles gambiae swarms. *BMC Evolutionary Biology*, 11(1):184.

Edlund, J. A., Chaumont, N., Hintze, A., Koch, C., Tononi, G., and Adami, C. (2011). Integrated information increases with fitness in the evolution of animats. *PLoS Comput Biol*, 7(10):e1002236.

Feare, C. (1984). *The starling*. Shire natural history. Oxford University Press, USA.

Hemelrijk, C. K. and Hildenbrandt, H. (2011). Some causes of the variable shape of flocks of birds. *PLoS ONE*, 6(8):e22479.

Jeschke, J. M. and Tollrian, R. (2007). Prey swarming: which predators become confused and why? *Animal Behaviour*, 74(3):387 – 393.

Krause, J. and Ruxton, G. (2002). *Living in groups*. Oxford University Press, USA.

Kwasnicka, H., Markowska-Kaczmar, U., and Mikosik, M. (2007). Open-ended evolution in flocking behaviour simulation. In *Proceedings of the International Multiconference on Computer Science and Information Technology*, pages 103–120.

Oboshi, T., Kato, S., Mutoh, A., and Itoh, H. (2002). Collective or scattering: evolving schooling behaviors to escape from predator. In Standish, R. K., Bedau, M. A., and Abbass, H. A., editors, *Proceedings of the 8th International Conference on Artificial Life*, pages 386–389, Cambridge, MA, USA. MIT Press.

Reynolds, C. W. (1987). Flocks, herds and schools: A distributed behavioral model. In *Proceedings of the 14th annual conference on Computer graphics and interactive techniques*, SIGGRAPH '87, pages 25–34, New York, NY, USA. ACM.

Reynolds, C. W. (1993). An evolved, vision-based behavioral model of coordinated group motion. In *From animals to animats 2*, pages 384–392, Cambridge, MA, USA. MIT Press.