**Integrating computational science with biology to study collective animal behavior**

**Introduction and Problem Statement**

Biologists have spent decades studying collective animal behavior due to its important implications for social intelligence, collective cognition, and its potential applications in automated control of distributed systems1. Of the numerous forms of collective animal behavior, swarming behavior is one of the most striking examples observed in nature. Since the long generation times in swarming animals makes studying the evolution of swarming behavior difficult3, I developed a computational model that simulates digital organisms with evolving behaviors. Using this model, I determined that the *confusion* *effect*, where swarming prey confuse and thereby reduce the attack efficiency of their predators, provides a sufficient (but not necessary) selective advantage to evolve and maintain swarming behavior in prey5. Ioannou et al.(2012) designed an innovative study where hand-coded, simulated prey were projected onto the side of a fish tank containing a single predatory fish, allowing a highly controlled study of what aspects of prey swarming behavior affect predator hunting behavior. Here I propose to extend this experiment by allowing the simulated prey behaviors to *evolve* in response to selective pressures applied by the biological predator. This will enable me to address hypotheses about swarm behaviors in response to biological predators on an *evolutionary* scale, as opposed to studying swarming behavior at a fix point in evolutionary time.

**Research Hypotheses, Methods, and Expected Outcomes**

Using my computational model, I will examine the predator-prey dynamics between swarming water fleas (*Daphnia magna*) and predatory three-spined sticklebacks (*Gasterosteus aculeatus L.*), addressing the following three hypotheses:

**Hypothesis I:** *Swarming behavior decreases predator attack efficiency*. Previous work has suggested that Daphnia swarming behavior decreases the attack efficiency of predatory three-spined sticklebacks4. Here I will first seek to confirm this hypothesis in my system by projecting groups of 50 simulated prey with evolving behaviors onto the side of a fish tank containing a single stickleback. I expect prey that swarm to experience fewer successful attack attempts from the predator than prey that move around randomly. All experiments will be repeated 30 times, measuring the number of attacks (capture attempts on the simulated prey) and the latency to the first attack by the stickleback on the simulated prey. I will compare the mean attack efficiency (# successful attacks / total # attacks) and time to first attack attempt to detect if there are significant differences in the predator’s response to the experimental prey behaviors.

**Hypothesis II**: *Larger swarms reduce predator attack efficiency moreso than smaller swarms*. Next, I will repeat the first experiment with pre-evolved cohesive swarms and vary the number of simulated prey in the swarm (swarm sizes from [3]: 5, 15, 25, 50, 100). This hypothesis predicts that the sticklebacks will perform fewer successful attacks and take longer to attack larger swarms (size 25, 50, and 100) than smaller swarms (size 5 and 15). If this prediction holds, it indicates that larger swarms increase the difficulty of predator attacks on individual prey, which is likely the result of the confusion effect. Alternatively, if there is no significant difference in predator response between experiments, then this would provide further evidence that predators that feed on swarming prey are not affected by the confusion effect. Lastly, if predators instead prefer to attack larger swarms than smaller swarms, then this would indicate that the confusion effect is not magnified by swarm size, and attacking larger swarms is advantageous for predators because there are more prey to potentially be captured per attack.

**Hypothesis III**: *The structure of the predator’s visual system plays a significant role in the efficacy of the confusion effect*. Lastly, I will test the hypothesis proposed in my previous work that the efficacy of the confusion effect as a defensive mechanism can be reduced if the predator evolves a more focused visual system5. The stickleback has two species variations that exhibit significantly different foraging behavior: *limnetics* typically feed on plankton in clear water near lake surfaces, whereas *benthics* feed on small invertebrates in the cloudy water on the lake floor6. As in previous experiments, I will project 50 simulated prey onto the side of fish tanks containing separate species. This hypothesis predicts that the limnetics will exhibit significantly higher attack efficiency and shorter attack latencies than the benthics due to the limnetic’s specialized, focused visual system for hunting agile prey in clear water. If this prediction holds, predators that feed on swarming prey could have a selective advantage by evolving a narrow, focused retina to reduce the efficacy of the confusion effect.

**Intellectual Merit**

This interdisciplinary research advances the field of behavioral science by merging a biological system with an evolving computational system, offering behavior researchers unprecedented experimental control over predator-prey dynamics and the ability to test hypotheses about the *evolution* of behavior in response to predation. Michigan State University offers the necessary facilities for this research, including Dr. Jenny Boughman’s stickleback research lab; Dr. Chris Adami’s computational lab studying evolutionary processes and evolving animal behavior; and support from zoologist Dr. Fred Dyer and the NSF BEACON Center, an interdisciplinary research collaboration between biologists and computer scientists. My previous research has prepared me to design and complete these experiments, and will be published in venues such as ALife XIII, SwarmFest 2012, and journals such as the Proceedings of the National Academy of Sciences.

**Broader Impacts**

This work develops a platform for directly interfacing biological and computational research, and increasing understanding of collective cognition and decision-making in animals. Research in this area has applications in behavioral science, Artificial Intelligence, Artificial Life, Robotics, distributed control systems, and many other fields that seek to understand how individual behaviors can result in emergent phenomena1. In addition, research in digital evolution and animal behavior is readily accessible to broad populations, and I will continue to share this research and my passion for science with college undergraduates and K-12 audiences through the NSF BEACON Center, local science fairs and volunteering at the local museum.

**References**

[1] Couzin, ID (2009) Collective cognition in animal groups. *Trends in Cognitive Sciences* 13:35-43.

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[5] Olson RS, Hintze A, Dyer FC, Knoester DB, Adami C (2012) Predator confusion is sufficient to evolve swarming. *In review.* Preprint: http://arxiv.org/abs/1209.3330

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