Self-organized swarm control using neural principles of spatial phase coding

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Introduction

Recently, Monaco *et al.*[1] discovered a new class of neurons, coined "phaser cells," revealing an internal timing code that can localize a rodent based on activation relative to the hippocampal theta oscillation (6–10 Hz) during locomotion.

Swarmalators[2](sw), a recently formulated mathematical model consisting of distributed agents that 'sync and swarm,' augment the spatial states of agents in the swarm with auxiliary phase states that are coupled to each other in the vein of the Kuramoto oscillator model.[3] This coupling of spatial and phase states introduces novel swarming behaviors due to mobilization controlled by phase-dependent attraction/repulsion (eq. 1) and distance-dependent phase-synchronization (eq. 2).

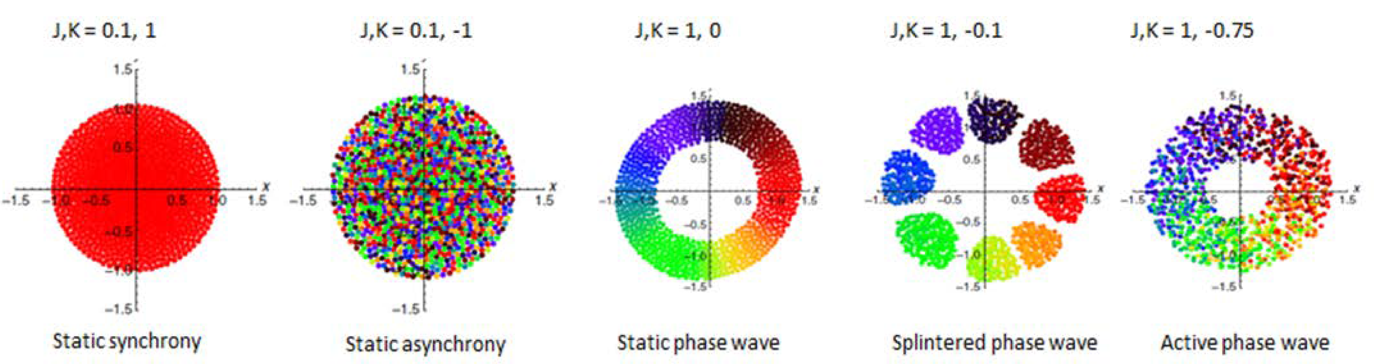


Figure adapted from O'Keeffe KP, Hong H & Strogatz SH. Nature Communications 8, 1504 (2017).

(1) $$\dot{\mathbf{x}}_i = \mathbf{v}_i + \frac{1}{N}\sum_{j=1}^{N}\left[\mathbf{I}_{\mathrm{att}}(\mathbf{x}_j - \mathbf{x}_i)F(\theta_j - \theta_i) - \mathbf{I}_{\mathrm{rep}}(\mathbf{x}_j - \mathbf{x}_i)\right]$$

(2) $$\dot{\theta}_i = \omega_i + \frac{K}{N}\sum_{j=1}^{N}H_{\mathrm{att}}(\theta_j - \theta_i)G(\mathbf{x}_j - \mathbf{x}_i)$$

Motivating questions:

1. Can brain-inspired use of phase states improve swarming?
2. Can (generalized) auxiliary states produce elegant swarm control solutions that maintain stigmergic flavor of swarms?

Hypothesis: Bottom-up, self-organized control based on neural algorithms enables swarms to execute spatial tasks not achievable using state-of-the-art decentralized control mechanisms.

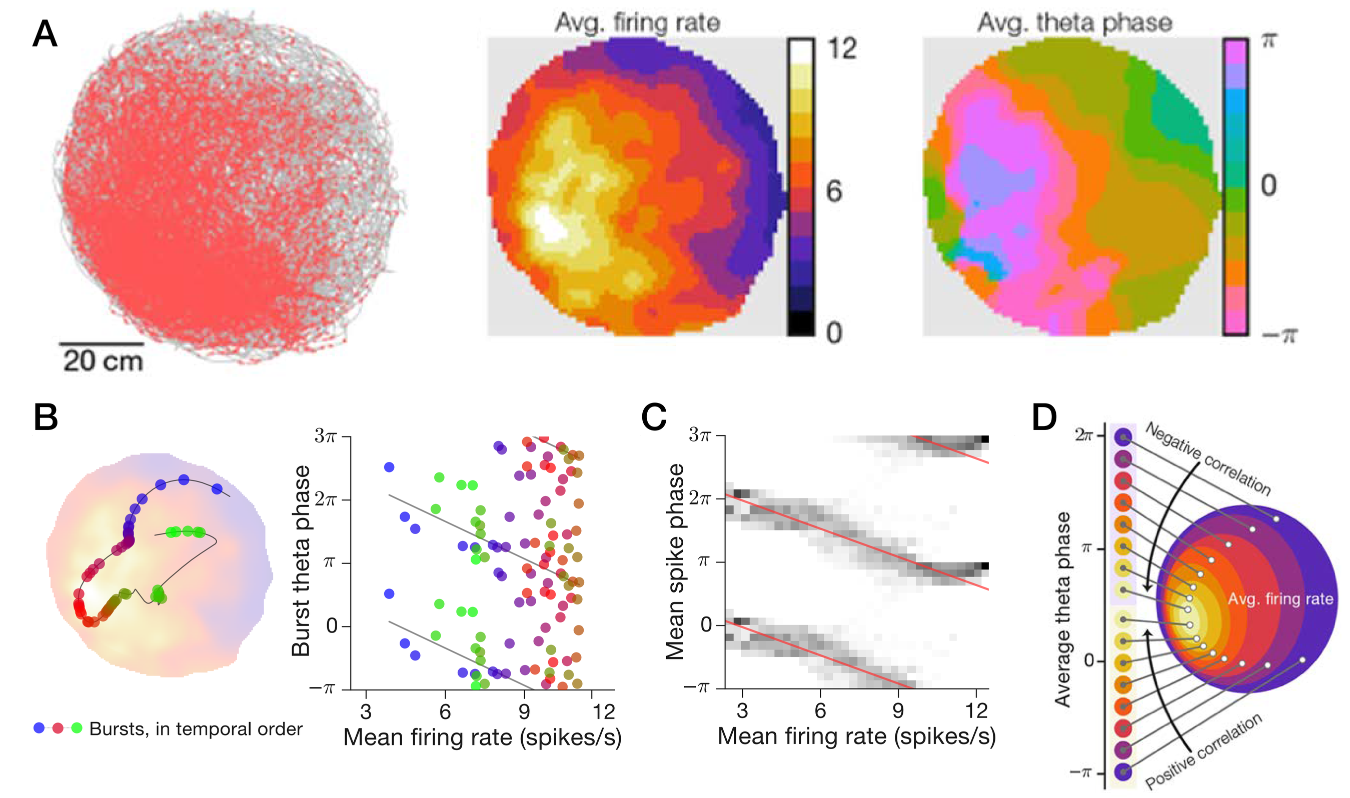
Methods

For $i = 1, \ldots, N$, where N is the population size, $x_i = (x_i, y_i)$ is the position of the i-th swarmalator, and θ_i, ω_i, and v_i are its phase, natural frequency, and self-propulsion velocity. The functions $\mathbf{I}_{att}$ and $\mathbf{I}_{rep}$ refer to the spatial attraction and repulsion between swarmalators. The phase interaction is represented by $\mathbf{H}_{att}$. The function ***F*** in Eq. (1) measures the influence of phase similarity on spatial attraction. Function ***G*** in Eq. (2) measures the influence of spatial proximity on the phase attraction. J is the amplitude of ***F***. When J > 0, swarmalators are attracted to the same phase; J < 0, swarmalators are attracted to the opposite phase; J = 0, sw are phase agnostic. K represents the phase coupling strength such that when $K > 0$, the phase coupling between swarmalators tends to converge in phase. In contrast, when $K < 0$, phases tend to diverge. The auxiliary phase states θ_i provide an interface to neural coding mechanisms based on temporal coordination through shared oscillations.

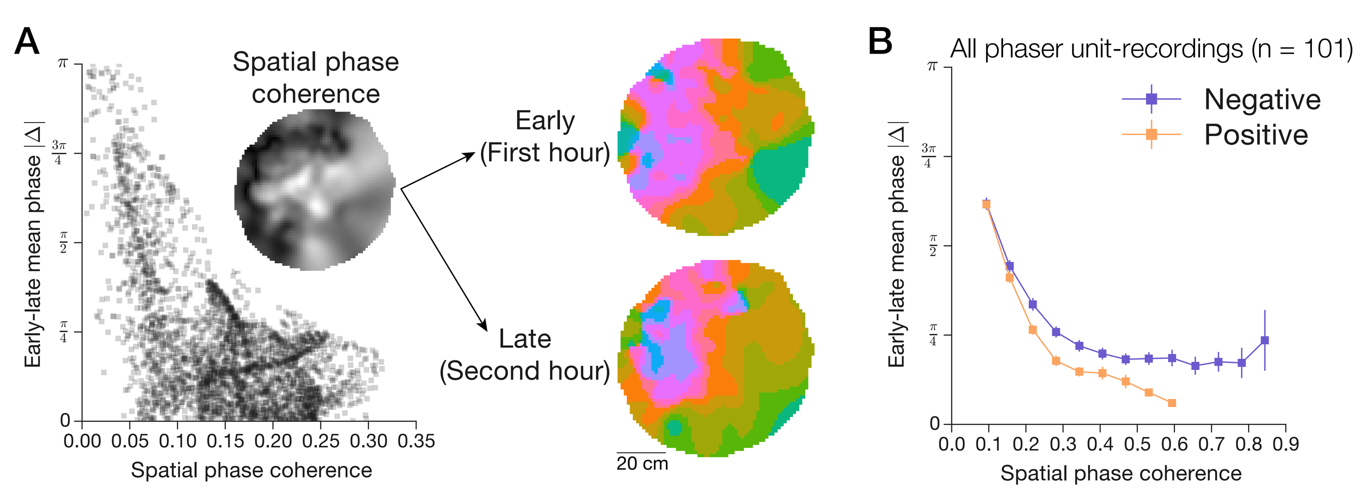
We exploited the auxiliary phase states in the sw formalism to provide an interface to neural coding mechanisms based on spatial patterns of temporal coordination using phaser cell dynamics. We demonstrated how sw agents can be used to model spatial navigation tasks in simple and real-world complex environments.

Phaser Cell Characteristics

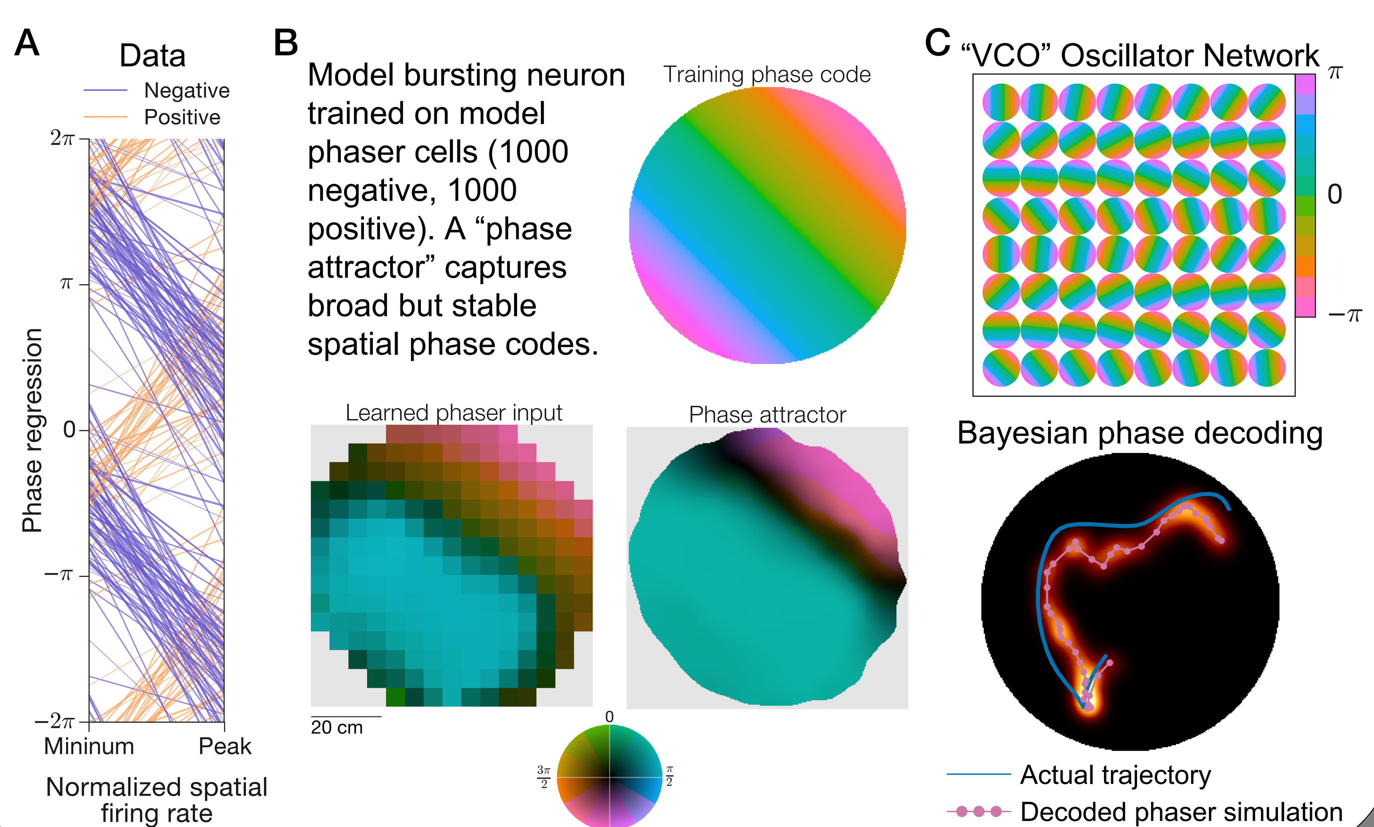
Phaser cell populations collectively provide spatial patterns of synchrony that directly localize the spatial map to an allocentric reference frame. An example cell from lateral septum (A, left to right): spikes and trajectory; firing ratemap; mean phase map.



In individual phaser cells, the phase variance of burst timing reduces spatial phase information that can be decoded instantaneously. However, mean phase values are stable over hours of recordings at particular locations in the environment.

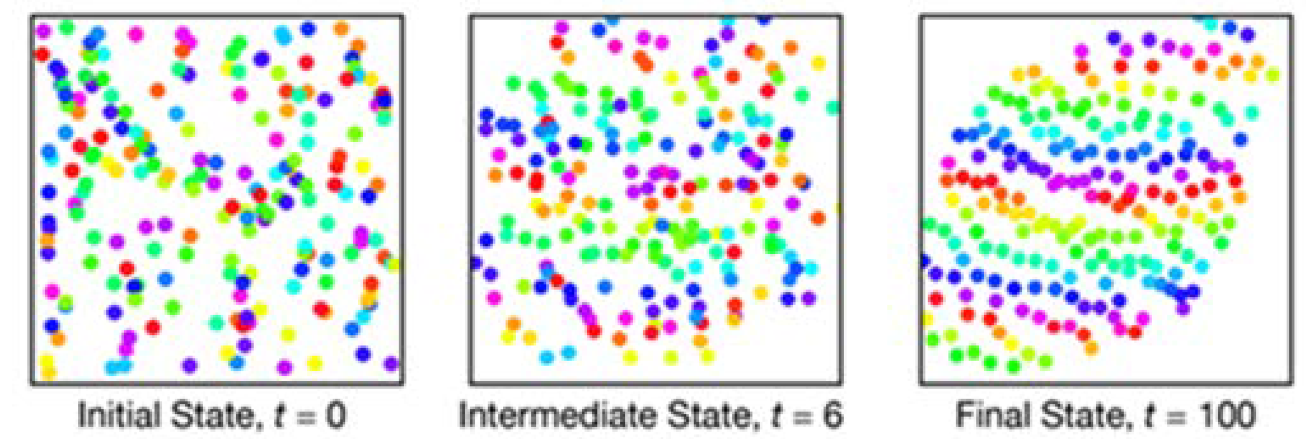


In 5 rats, 101 recordings with phaser cells were made, including 45 "negative" phase-shifting cells and 24 "positive" phasers. In theory, phaser cell populations with diverse spatial profiles and locations of high phase coherence will collectively encode a strong spatial signal in population-level phase synchrony.

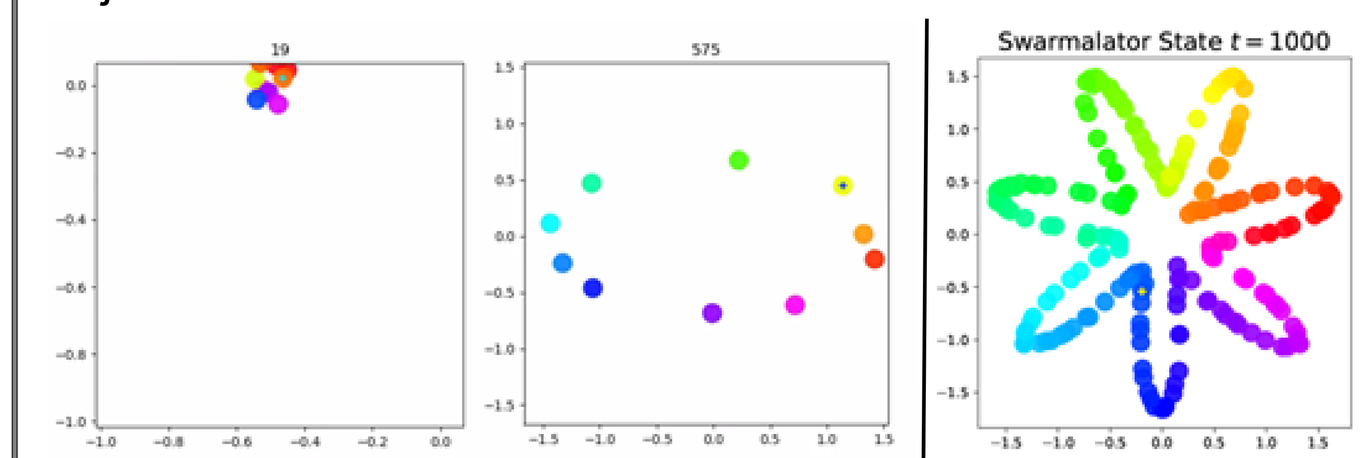


Phaser-inspired Swarmalators

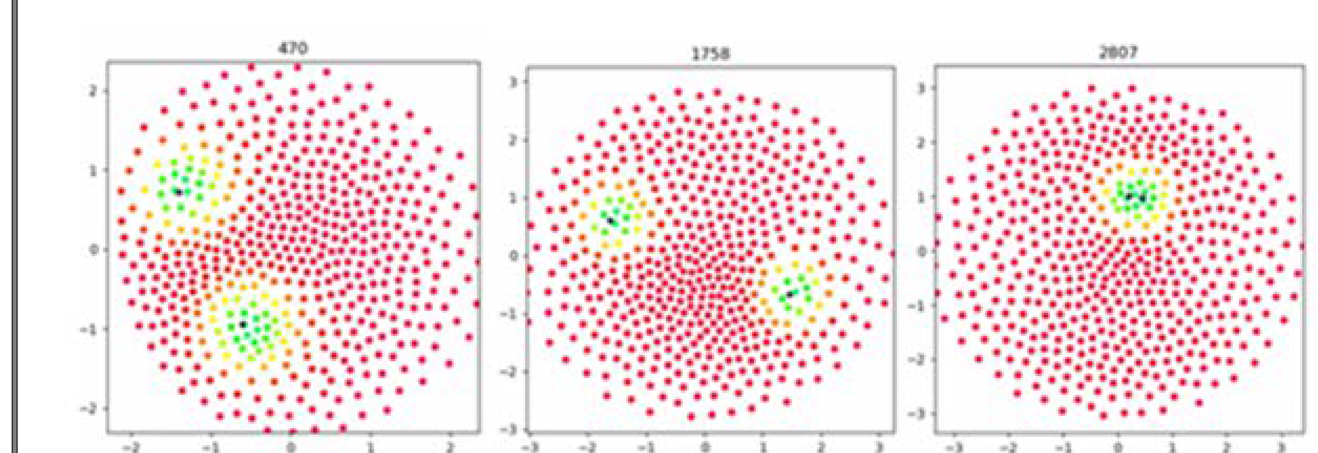
Swarmalators combine phase (color coding) and spatial dynamics to enable emergent behaviors among swarms of mobile oscillators. Each dot represents a robotic agent.



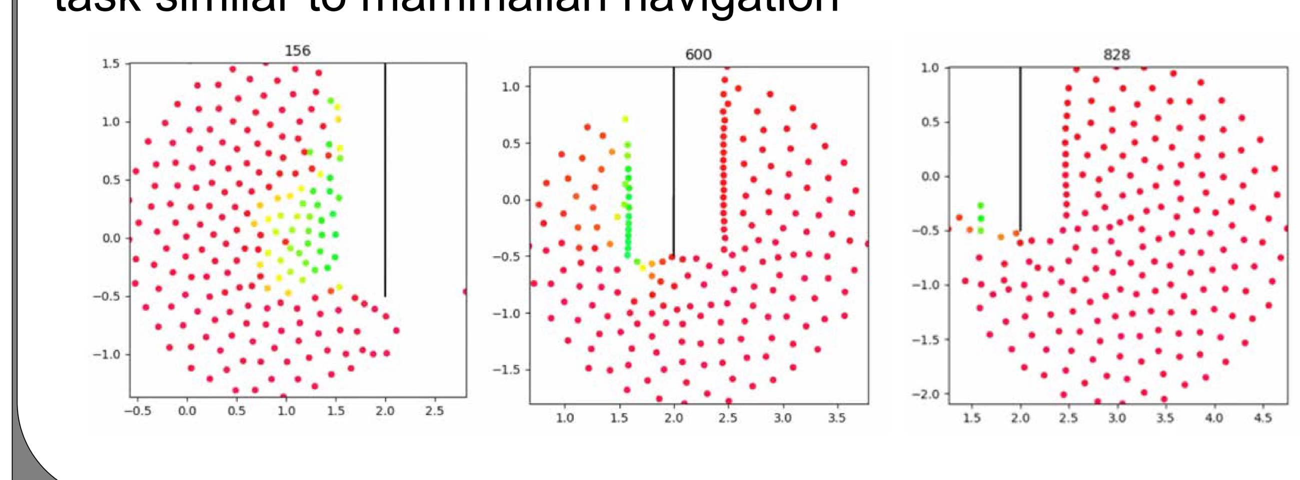
A phase-based control field can spatially guide the evolution of a swarm and simulate patrol behavior along parametric trajectories



A phase-based control field can spatially guide the evolution of a target-tracking swarm and simulate bump-like control similar to hippocampal place fields

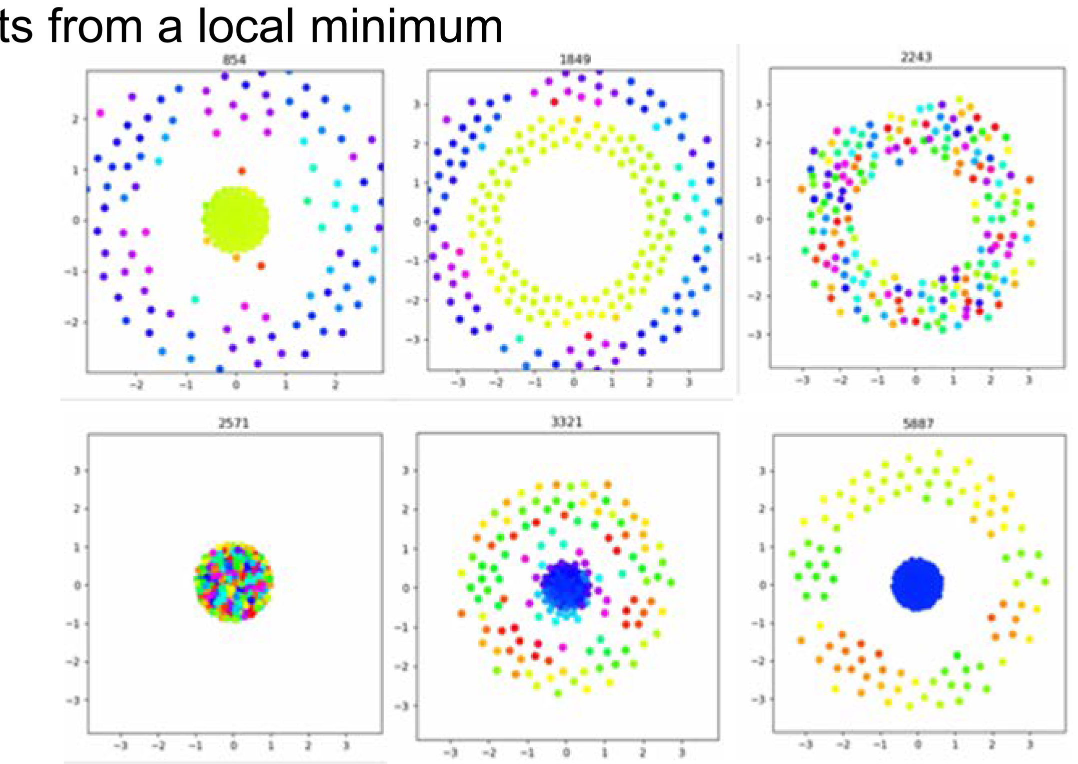


Swarms of agents avoiding an obstacle in a computational task similar to mammalian navigation

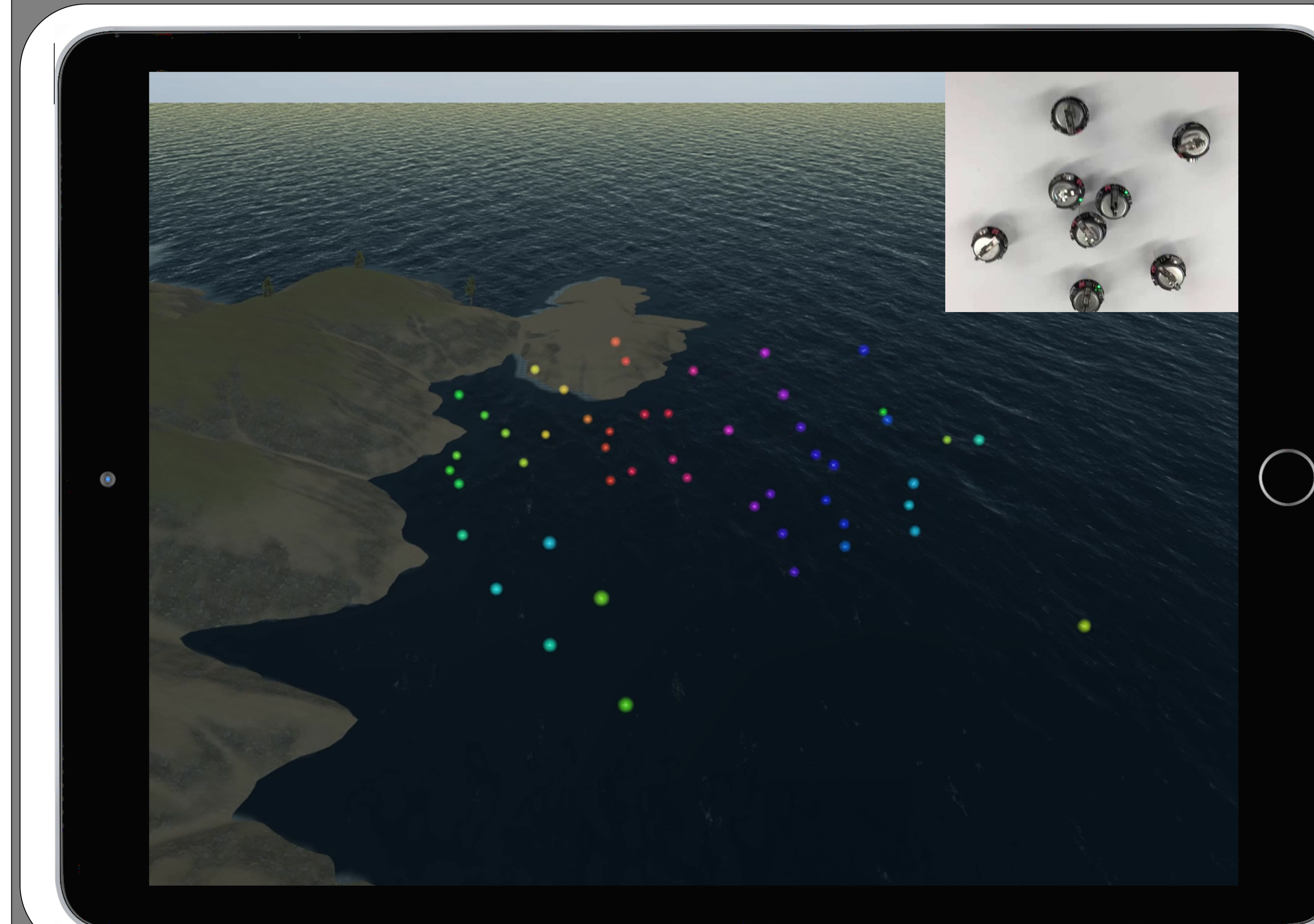


Neuro-inspired Metacontroller

Goal: A novel metacontroller that relinquishes swarmalator agents from a local minimum



Note: This simulation is illustrative



Conclusions

- Neural inspired dynamics can be applied through the sw formalism to elicit useful swarming behaviors, such as to track targets, avoid obstacles, and patrol assets
- Future work includes
  1) Generalization of metacontroller to enable dynamic replanning that relinquishes swarmalator agents from a local minimum
  2) Identify existing models of neural computation that would benefit swarm behaviors
  3) Exploit paradigms that are unhindered by the constraints of biology to inspire future swarm designs

Bibliography

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3. Kuramoto, Y. Self-entrainment of a population of coupled non-linear oscillators. 420–422 (Springer, 1975).

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