Spatiotemporal Dynamics of Food Exchange Networks in Honeybees

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Computer Science

Introduction

- *Trophallaxis*, the direct transfer of food among nestmates serves not only as a feeding mechanism but also as a medium for information exchange among workers, helping them coordinate their activities within the hive [1].
- Using an integrated experimental-modeling approach, we aim to study the dynamics of food distribution among honeybees.

Question of Interest

What is the mechanism behind food exchange interactions?

Approaches

- Build a model that reproduces the food exchange dynamics
- Use topology to characterize phase changes in the collective behavior
- Study the communication mechanism among bees

Behavioral Experiments

- Six different colonies of honeybees Apis *mellifera* L. were divided into two groups.
- One group was *deprived* of food for 24 hours before each experiment, while others had constant access to food.
- These *fed* bees, which comprised $\sim 10\%$ of the whole population in each experiment, were carefully marked with a pink dot on their thorax.



Model rules

- 1. Check immediate r –neighborhood, If $d \leq 2r$, then agents will move one step toward each other at the next timestep (attraction parameter r)
- Modify heading by $\Delta \theta$ drawn from a uniform distribution and take a random walk step (angle parameter θ^*)
- Check for encounter (distance parameter d) 3.
- Excl
- 5. Loop until the food distribution is uniform (variance threshold)
 - Convergence: $\sigma^2(t) \leq \sigma^2_{threshold}$
- The values of some model parameters such as trophallaxis duration are drawn from the experiments.

Findings

- Short-range attractions foster aggregation, which in turn increases the efficiency of food distribution.
- Comparing the cluster sizes across real and simulated bees show We then correlate those events with the spatiotemporal density of bees by treating the positions $(S_{i,t}^p)$ and that model with attraction is a better match to the natural behavior directions $(S_{i,t}^d)$ vectors as a set of gradients that define a minimal surface of height f(x, y, t). of the bees [2].



- [1] Greenwald *et al. Scientific Reports*, 2015. [2] Gharooni Fard *et al. MIT Press*, 2020. [3] Ulmer *et al. PLOS ONE*, 2019. [4] Gharooni Fard *et al.* To appear in *Npj Complexity*, 2024.

- [5] Nguyen *et al. PNAS*, 2020.

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Agent-Based Model

hange food:
$$f_i(t+1) = f_i(t) \pm \frac{\Delta f(t)}{2}$$

$$\sigma^2(t+1) - \sigma^2(t) \le \Delta \sigma_{threshold}^2$$





References



Topological Data Analysis

- Our experimental analysis described in [2] suggests that bees aggregate to share food.
- We use TDA, a framework from applied mathematics, to analyze the morphology of the group.
- the value of β_0 (*i.e.*, the number of connected components).
- slices to detect any possible regime shift.



Findings

- Feeding the time-series data of the ℓ^2 norm of the CROCKER plots to two different clustering algorithms, we successfully detect the change in the group dynamics soon after the fed bees are introduced.
- This method works both on experimental and simulated data [4].

Outlook: Communication for Aggregation

- We train a machine-learning algorithm [5] to identify the positions and directions of scenting events which honeybees use to communicate — in our experiments.
- We compute the value of normalized mutual information $MI\langle f \rangle_t$ between the attractive surface (f) and the density of the bees (ρ), averaged over 10 minutes after the introduction of the fed bees.

 $MI(f(x, y, t); \rho(x, y, t))$

Preliminary Findings

Our preliminary results confirm that there is positive correlation, $MI\langle f \rangle_t = 0.44$, between scenting events and the location of the food exchange aggregations.







$$) = \sum_{f_i \in f} \sum_{\rho_i \in \rho} P_{(f,\rho)}(f_i,\rho_i) \log \frac{P_{(f,\rho)}(f_i,\rho_i)}{P_{(f)}(f_i)P_{(\rho)}(\rho_i)}$$

