Maximization of Transfer Entropy leads to Evolution of Functional Differentiation of Swarms

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Abstract

We aimed to investigate the principle of emerging interactions between swarms using the functional differentiation theory of the brain. We propose a heterogeneous swarms model, where two swarms having different parameters evolve to maximize transfer entropy between them. In our simulation, we found the emergence of heterogeneous behavior among the swarms, and the appearance of several interaction patterns depending on the degree of the transfer entropy. Our results imply that the same principle of functional differentiation may underlie both the brain and swarms, leading to a novel design of brain-inspired swarm intelligence.

Introduction

Diverse types of interactions between swarms, e.g., prey-predator and leader-follower, are observed in organisms' behavior. In such collective behavior, swarms have varying roles, i.e., they are functionally differentiated. This heterogeneity is reportedly a key in the emergence of interactions and pattern formation (Sayama, 2009).

In mathematical neuroscience, Yamaguti and Tsuda (2015) proposed self-organization with constraints as a principle of functional differentiation in the brain. They showed that maximizing the transfer entropies between neural modules allows the modules to have different dynamics and to interact with each other.

In this paper, we hypothesize that the principle of functional differentiation can also be applied to multi-swarm interactions. We extend the conventional boids model (Reynolds, 1987) to a heterogeneous swarms model and maximize the transfer entropies between the swarms using a genetic algorithm. Consequently, functional differentiation in the swarms is expected to emerge as in the brain.

Model

We propose a heterogeneous swarms model (Fig. 1), in which two swarms have different boid parameters. In a typical boids model, the velocity of the ith agent is updated based on its neighbor agents:

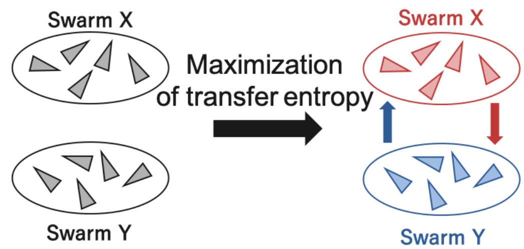

Figure 1: Heterogeneous swarms model. In an initial generation (left), all agents have the same parameters, and the labels of swarms, X or Y, are randomly assigned to agents. Agents belonging to a swarm have the same parameters which can be different from those of the other swarm. Then, the parameters for swarms X and Y are optimized to maximize transfer entropies between them. Consequently, the parameters become heterogeneous and the swarms begin to interact, suggesting that their functions have now differentiated.

$$\Delta \vec{v_i} = w_{\mathrm{s}} \sum_{j \in S_{\mathrm{s}}} \frac{\vec{x_i} - \vec{x_j}}{|\vec{x_i} - \vec{x_j}|} + w_{\mathrm{a}} \left(\vec{v_i} - \frac{\sum_{j \in S_{\mathrm{a}}} \vec{v_j}}{n_{\mathrm{a}}} \right) + w_{\mathrm{c}} \left(\vec{x_i} - \frac{\sum_{j \in S_{\mathrm{c}}} \vec{x_j}}{n_{\mathrm{c}}} \right) + \epsilon(t). \quad (1)$$

where $\vec{x_i}$ and $\vec{v_i}$ denote the position and velocity of the ith agent, respectively. The parameters, w_{s}, w_{a}, and w_{c} denote the weights for separation, alignment, and cohesion among agents, respectively. S_{s}, S_{a}, and S_{c} denote the set of neighboring agents for each rule, and v_{a} and v_{c} indicate the number of the neighboring agents. Noise $\epsilon(t)$ is added so as to make behavior complex.

Our model assumes two swarms, labeled as X and Y. They have different weights while all agents have the same weights in the typical model. For example, the weight for separation, W_{s}, consists of weights for the inter-swarms, $w_{X \to Y}$ and $w_{Y \to X}$, and weights for the intra-swarms,

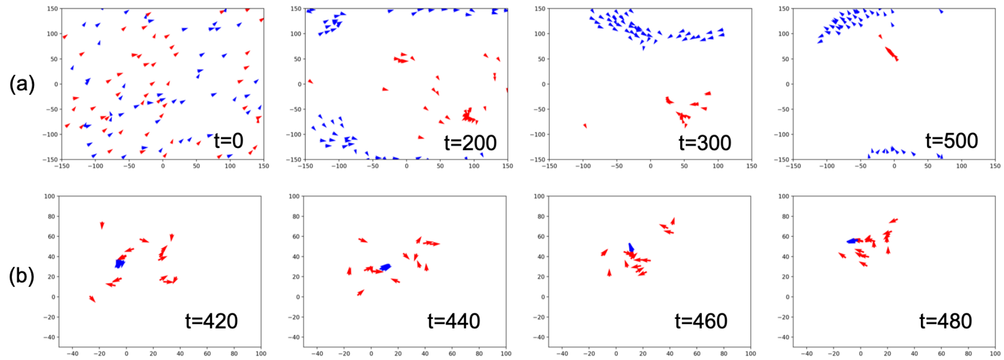

Figure 2: Behavior of the optimized heterogeneous swarms. (a): prey-predator like dynamics when the fitness was higher. (b): rotating leader dynamics when the fitness was lower.

$w_{X \to X}$ and $w_{Y \to Y}$:

$$W_s = \begin{bmatrix} w_{s_{X \to X}} & w_{s_{X \to Y}} \\ w_{s_{Y \to X}} & w_{s_{Y \to Y}} \end{bmatrix}. \quad (2)$$

The weights for alignment and cohesion are defined in the same manner.

The twelve weight parameters in total are optimized using a standard genetic algorithm. The fitness is defined as the product of transfer entropies between the averaged series of the velocity of the swarms: $T_{X \to Y} * T_{Y \to X}$, where $T_{X \to Y}$ denotes the transfer entropy from swarm X to swarm Y, and $T_{Y \to X}$ denotes vice versa. In the initial generation, the labels of swarms are randomly assigned to agents, and they have the same weight parameters. Then, the weights are optimized to maximize the transfer entropies through elite selection.

Results

We constructed a 2D simulator of 100 agents, in which a swarm consisted of 50 agents. The population in a generation was 96. The history length and delay for transfer entropy were 1.

Simulation results showed that the fitness converged in two values: approximately 0.3 and 0.04. Fig. 2 (a) and (b) illustrate behavior of the swarms when the consequent fitnesses were high and low, respectively. In both cases, the swarms had different parameters and seemed to have different functions. In Fig. 2 (a), the blue swarm appears to be escaping from the red swarm, which looks like prey-predator interaction. In Fig. 2 (b), the blue swarm appears to rotate and the red swarm loosely follows it.

Discussion

In this study, we proposed a heterogeneous swarms model, where two swarms with different parameters evolve to maximize transfer entropy between them. Our simulation showed that functional differentiation and interactions between heterogeneous swarms were developed by maximizing the transfer entropy. The interaction patterns of the swarms varied depending on the fitness, suggesting that the same principle may underlie function differentiation in swarms and the brain. We suppose that the interaction between heterogeneous swarms is the foundation of division of labor, which is ubiquitously observed in biological systems, especially in social insects (Duarte et al., 2011). In addition to the conventional explanation that division of labor is due to efficient foraging, our model suggests that such an evolutionary process might involve an increase in information transfer or communication between swarms. In future, we plan to develop our model further by imposing tasks on the swarms to investigate the contribution of the functional differentiation to task performance, adaptability, and robustness.

Acknowledgements

This work was supported by JST CREST Grant Number JPMJCR17A4, Japan.

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