Incentive for Self-Protection in a Collective System: a Swarm Robotics Case Study

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Designing controllers for agents of a collective system is challenging. The challenge lies in the nonlinearity between the behavior of the individuals and the emerging patterns in the collective. A branch of ongoing research in collective systems, e.g., in swarm robotics, concerns with discovering mechanisms that lead to specific collective behaviors indirectly, i.e., the effects of incentives in the emergence of interesting collective patterns. Various intrinsic motivations have been suggested as the drivers of pattern development in natural and artificial collective systems. An example is the development of pathways to provide easier access to currents that flow through a system (Bejan and Zane, 2012; Zahadat, 2019). Another example is the emergence of collective motion as a result of intrinsic motivation for maximization of potential future states (Charlesworth and Turner, 2019). By getting inspiration from the principle of free energy minimization in biological systems (Friston et al., 2010), predictability of the future states have also been used as an intrinsic motivation, resulting in a number of collective formations. It demonstrated the tendency of agents to locate themselves in the positions that are less prone to changes in their surrounding (Zahadat et al., 2015; Kaiser and Hamann, 2019). The current paper presents early investigations of the agents' incentive for avoiding the surrounding environment by locating themselves between their peers, i.e., an incentive for self-protection. The swarm behavior resulted from this intrinsic motivation leads to formation of aggregates with high mobility of agents within them (Fig. 2A)[1]. The behavior is loosely similar to the huddling behavior of emperor penguins (Waters et al., 2012), where the birds self-organize to take turn in locating themselves inside the crowd to stay protected from the wind. The behavior appears to show a relatively low sensitivity to the swarm density.

Setup

Agents model The collective system contains $N = 50$ agents in a toroidal area of size 1000×780 pixels. Figure 1A-B, depicts an agent and its related parameters. An agent has a radius of r_a and eight sensors all around. The sensors visibility distance is r_f. The sensor's output is 2, 1, and 0, respectively for detecting something in a close vicinity ($< r_c$), farther away ($\geq r_c$), or no detection. In every time step, each agent performs one of the five possible actions: stand still, move forward with normal speed ($v = v_0$), move forward fast ($v = 2v_0$), turn left, or turn right with angle $\Delta\theta = \Delta\theta_0$ (Fig. 1A). The agents are controlled by identical artificial neural networks (ANNs). The inputs of the ANNs are the current and previous values of the sensors and the speed and rotation of the agent according to their previous actions (Fig. 1C). The ANNs are feed-forward with two hidden layers of size 20 and 10 nodes. Softmax classifier is used for the output layer to choose one of the five actions and other layers use ReLU activation function.

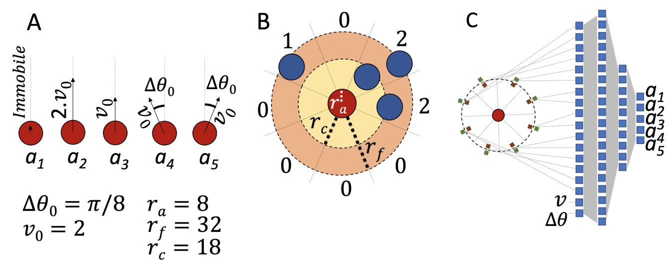

Figure 1: Setup of the collective system: A) actions, B) sensors, C) structure of the ANN controller.

Evolutionary setup The identical controllers of agents are designed by evolving a population of 50 ANNs for 200 generations. A genetic algorithm was used with elitism of one genome and a mutation of the others with a stepsize $\mathcal{N}(0, 0.2)$. Every evolutionary experiment is repeated for 10 independent runs. The fitness is evaluated after 1000 time-steps. To evaluate controllers for the incentive for self-protection, a protection level is defined for every agent i as
$P_i = \frac{1}{|S|} \arg\max_t |S_{near}(t)|,\ t_c - \tau \leq t \leq t_c$
where S is the set of all sensors, $S_{near}(t)$ is the set of sensors that detect a near neighbor at time-step t, t_c is the current time-step, and $\tau = 50$ is the validity period of protection. The function yields the maximum number of closely

[1] See a video at https://vimeo.com/523444449

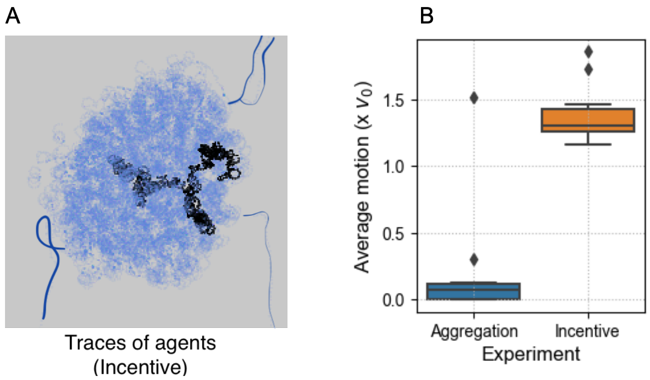

Figure 2: A) Agents' traces in a given time period in an example aggregate. The black line indicates the trace of a focal agent moving through the aggregate, the blue lines represent the traces of the other agents. The solid blue lines outside the aggregate are manually highlighted for better visibility. B) Agents' mobility at the end of the experiments.

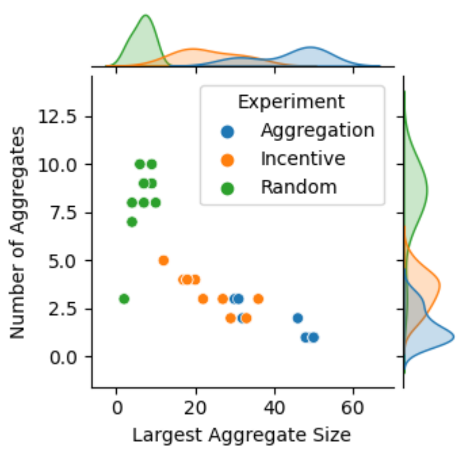

Figure 3: Number of aggregates vs. number of agents in the largest aggregate.

occupied sensors in the past τ time-steps. τ allows the agents to take turns in their relative positionings. The overall fitness is calculated by averaging the protection level of the agents in the swarm, as $F_{Incentive} = \frac{1}{N}\sum_{i=0}^{N} P_i$, where N is the swarm size. To get a quantitive evaluation of the behavior, we compare the results with ANN controllers directly evolved for an aggregation behavior. The fitness function for the aggregation experiments is defined as $F_{Aggregation} = L/N$, where L is the size of the largest aggregate normalized by N (swarm size). All the other evolutionary parameters are identical to the above experiments.

Results

In the following, the behavior of the best controllers evolved for the *Incentive* and *Aggregation* are investigated. In each

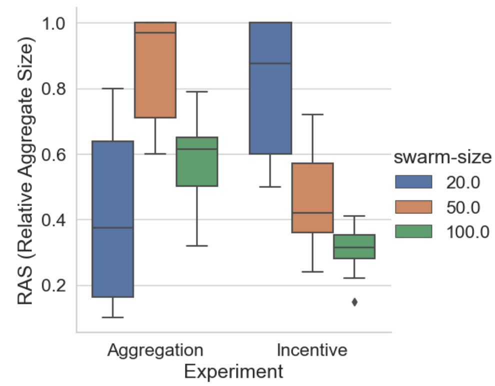

Figure 4: RAS in different swarm sizes.

experiment, the state of the swarm after 5000 time-steps is observed. The experiments are repeated for 10 independent runs. Figure 3 represents the number of aggregates vs. the size of the largest aggregate. The values are shown for both *Incentive* and *Aggregation* experiments, as well as 10 randomly generated ANN controllers. A statistical evaluation (Student's t-test) indicates that the aggregation formation in the *Incentive* experiment is significantly different than random ($p < 0.01$). Figure 2B compares the mobility of the agents for the *Incentive* and *Aggregation* experiments. As the figure indicates, the behavior resulted from evolution for *Aggregation* leads to relatively immobile agents, while the evolution for *Incentive* results in dynamic aggregates with agents that move within the aggregate. Figure 2A depicts example traces of agents. The agents swirl within the aggregate and occasionally relocate between the inside and border regions. The solid blue lines in the figure indicate that the agents move relatively straight once outside the aggregates. As stated above, the controllers are evolved with a swarm size of $N = 50$. Here we use the same controllers in smaller and larger swarms and observe the resulted aggregates. Figure 4 compares the Relative Aggregate Size (RAS) formed by the controllers of *Incentive* and *Aggregation* experiments for three different swarm sizes. RAS is defined as the size of the largest aggregate normalized by the swarm size. As the figure represents, for swarm size $N = 50$, the aggregation-based controller leads to $RAS \simeq 1$, meaning that a single aggregate is formed consisting of the whole swarm, whereas with the incentive-based controller, RAS is closer to 0.5 meaning that the swarm is split into, presumably two, local aggregates. For a larger swarm where the agent density is high, RAS drops for both the *Incentive* and *Aggregation* experiments, indicating the formation of more local aggregates in both cases. For a smaller swarm, RAS drops significantly for *Aggregation* controller, while it shows a big raise up to 1 for the *Incentive* controller. It suggests that the aggregation formation behavior resulted as a side effect of the incentive for self-protection is less sensitive to the swarm density.

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