Inferring Swarm Models Using a Single Monitoring Robot

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Abstract

Infiltrating a swarm of artificial or living agents using a single monitoring robot could allow for the assessment of their swarm rules and parameters without the need for any external infrastructure. The inferred swarm model could then be used to control these swarms, for example to guide them to safe areas. In this study we introduce a scheme for autonomous artificial agents to extract knowledge about the interactions within a swarm of interest. By infiltrating the swarm of interest with a monitoring robot and constantly measuring the distance between the infiltrator and its nearest neighbour, the repulsion radius of the swarm agents can be estimated. Though this method works for a range of tested parameters, it is still limited to a specific model of interaction.

Introduction

Understanding the rules that give rise to an observed emergent behaviour typically takes many iterations, either through trial and error or using automatic tools such as machine learning (Hauert et al., 2014). Most important, such studies typically require an external telemetry system that can track the position of all agents in the swarm over time (Puckett et al., 2014; Li et al., 2016). In contrast, our aim is to send a single monitoring robot into a swarm to extract its rules and parameters. As a first step we show in simulation how a robot injected into a swarm moving according to a flocking model based on Couzin et al. (2002) can extract the repulsion radius of the swarm using only local observations. Flocking was chosen as it is a well studied swarm algorithm (Fine and Shell, 2013). In the future, we aim to use the information learned by the robot, to control the swarm, for example by moving it in space.

Methodology

In order to simplify the problem, the following assumptions are made. First, the general structure of the swarm of interest's interaction rules is known. Second, the unknown part of the swarm of interest's interaction rules is the actual parameter of the rules. Thus, the task of the monitoring agent is reduced to inferring the unknown parameter's value.

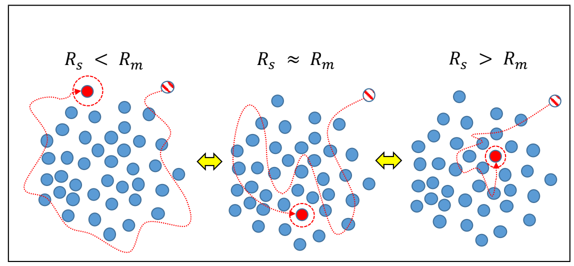

Figure 1: The different areas which the monitoring agent (red) frequents according to the relative size of R_s and R_m.

This study is conducted through custom-made computer simulations. In general, a swarm of 50 identical agents are initiated in a 2D-simulated space. Then, a monitoring agent is deployed into the same space to interact with the swarm and collect data. Each simulation is terminated after a fixed time of 500 simulation seconds.

The behaviours of each agent, including the monitoring agent, are governed by a modified version of the interaction rules from Couzin et al. (2002); we neglect the zone of orientation from that theory. The swarm agents are set to react to the monitoring agent the same way they react to their conspecifics. The repulsion radius of the swarm agents, R_s, which is selected as the unknown parameter, is fixed for a set of simulations, while the monitoring agent's repulsion radius, R_m, is varied.

Results

Observation of simulated flocks suggests found that the monitoring agent travels in different area w.r.t. the swarm as R_m varies (see Figure 1). When $R_s < R_m$, the monitoring agent tends to stay outside of the swarm, while, when $R_s > R_m$, the monitoring agent tends to stay in the center of the swarm. When $R_s \approx R_m$, the monitoring agent's position is more ambiguous compared with the previous two extreme cases. Figure 2 shows the histogram of the distance between the monitoring agent and the centroid of the swarm, which agrees with the qualitative description above. Thus,

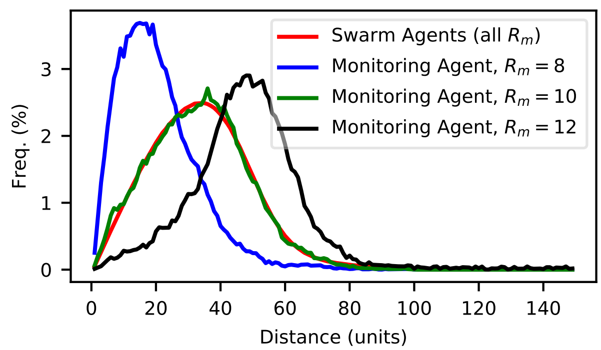

Figure 2: Distributions of the distances from the centroid of the swarm to the monitoring and swarm agent when $R_s = 10$ and R_m is varied.

(a) (b)

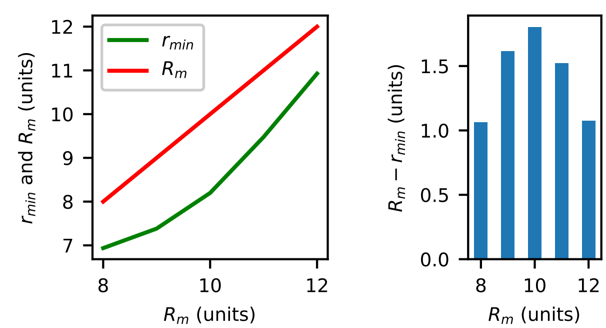

Figure 3: (a) Plots comparing r_{min} and R_m as a function of R_m (b) $R_m - r_{min}$ as a function of R_m, which is maximised when $R_m = R_s$. ($R_s = 10$ in both panels.)

it is possible to estimate R_s by varying R_m and monitoring the area that the monitoring agent frequents. However, this method requires a global view of the system in order to measure the distance between the monitoring agent and the swarm's centroid. Therefore, we instead investigate local measurements–the measurement which the monitoring agent is able to perform.

One of the monitoring agent's local measurements that is affected by the value of R_m is the average distance from the monitoring agent to the nearest swarm agent, r_{min}. Figure 3(a) shows that r_{min} and R_m increase at a different rate. When R_m is lower than R_s, the increment rate of r_{min} is lower than that of R_m. In contrast, when R_m is higher than R_s, r_{min} is increasing at a higher rate than R_m. As a result, the difference between r_{min} and R_m is maximised when R_m is equal to R_s, see Figure 3(b). Therefore, R_s can be estimated by varying R_m until the difference between r_{min} and R_m is maximised.

This method of estimating R_s works for a range of R_s

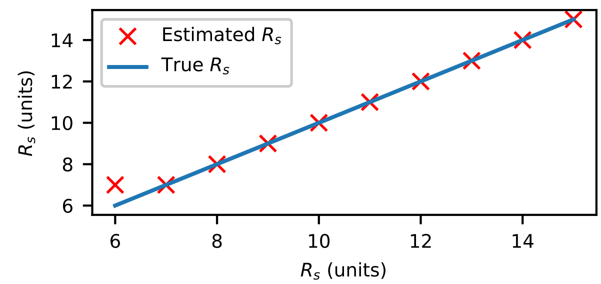

Figure 4: Estimated R_s as a function of true R_s

values. Figure 4 shows that the method introduced is capable of correctly guessing R_s in the range of 7 to 15 units. When $R_s < 7$, the measurements of r_{min} are more noisy, affecting the accuracy of the method.

Conclusions

This study suggests that it is possible to study the interactions between agents in a swarm of interest by infiltrating the swarm with a robot instead of monitoring the swarm with an external system. In the case of the model selected in this work, the repulsion radius of the swarm agent can be estimated by varying the repulsion radius of the monitoring agent until a specific targeted value is maximised.

However, the conditions in which this method was tested are limited, and there are many issues to address before a practical implementation would be possible. Firstly, it was tested in the selected model of interaction. Also, the swarm agents have to perceive the monitoring agent as one of their own. In the future, we aim to expand the parameters and rules that can be inferred by the monitoring agent, as well as expanding to swarm behaviours behind flocking. We also hope to study the benefits of applying the information gained to manipulate the swarm of interest.

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