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COMPARING COLLECTIVE FORAGING WITH INTERACTIONS INSPIRED BY PHEROMONES AND SONAR

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ABSTRACT

Communication inspired by animals is a timely topic of research in the modeling and control of multi-agent systems. Examples of such bio-inspired communication methods include pheromone trails used by ants to forage for food and echolocation used by bats to orient themselves and hunt. Source searching is one of many challenges in the field of swarm robotics that tackles an analogous problem to animals foraging for food. This paper seeks to compare two communication methods, inspired by sonar and pheromones, in the context of a multi-agent foraging problem. We explore which model is more effective at recruiting agents to forage from a found target. The results of this work begin to uncover the complicated relationship between sensing modality, collective tasks, and spontaneous cooperation in groups.

INTRODUCTION

Collective behavior describes the coordinated actions of a large group of social animals working together to the benefit of accomplishing a common goal [1, 2]. Among these animal groups, an impressive example is ants, which are known to cooperate for collective transport, and building structures [3, 4]. As ants forage for food, a number of methods may be used based on the size of the colony and species of ant [3]. For example, the Argentine ant (*Linepithema humile*) uses the "mass recruitment" strategy, where scouts are sent out to locate food and, upon finding a source, they return to the colony laying a chemical trail in the form of pheromones. This trail between the source and colony causes other members to be recruited to the foraging effort and is strengthened over time as more members drop their own pheromone [5]. Depending on the species of ant, this pheromone trail can be controlled or continuously dropped and in both cases evaporates withing a couple of hours of being laid [6]. Even with evaporation and sensing distance limitations, pheromones are a useful method of indirect communication as they do not require a colony member to be in contact with another to understand where to go. In this way, it acts as an efficient communication method allowing members to continue to work and communicate with others asynchronously based on spatial locations.

Emergence of collective behavior in bats is qualitatively different from ants and most other social animals due to their unique way of sensing the environment. Many species of bats use echolocation for object detection and navigation [7]. Echolocation is a form of active sensing in which the sensor emits a signal in the environment and gathers information by intercepting its echo. In contrast, in passive sensing, the sensor relies on signals generated by the environment. Sonar, radar and LiDAR are examples of active sensors, while microphones and cameras are examples of passive sensors. The use of active sensing by individuals provides a unique opportunity for communication, as sensing signals can be eavesdropped and interpreted by peers in a group. Some studies suggest that bats can detect their conspecific's echolocation signal during group flight. For example, bats are able to identify each other and family members by listening to their echolocation [8]. In addition, the work by Barclay

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shows that little brown bats exploit eavesdropping in their search for food, night roosts, nursery colonies and mating/hibernation sites [9]. Another reason for eavesdropping can be related to signal jamming. A study by Chiu, et al. shows that, when a pair of bats is flying together, one bat may stop echolocation presumably to avoid signal jamming [10]. From a competitive point of view, a study on wild bats shows that individuals may intentionally jam each other during the competition over food [11].

Engineers take inspiration from animal collective behavior in many application areas, like swarm robotics. Large groups of simple robots with sufficient communication can lead to complex interactions between agents and their environment. All coordination requires some type of sensing and communication, and the hardware used to accomplish this is frequently inspired by nature [12–15]. Using bio-inspired sensing and communication provides engineers with potentially robust solutions to common problems faced in designing how agents will interact in autonomous multi-agent systems to perform a task collectively. Examples of such tasks include aggregation / dispersion, collective movement and transport of objects, and collaborative source searching [16]. Towards this goal, modeling group behaviors using novel communication systems is an important step in the design of multi-agent systems, as it allows us to predict if such systems would be effective in the physical world.

In this paper, we seek to compare collective behavior between groups of agents using three bio-inspired communication models in a random foraging problem. These models, two of which are inspired by pheromone communication and the other by sonar eavesdropping in bats, are compared to find which is a more effective communication strategy in terms of recruiting agents to forage from a nearby target. Our main findings suggest that eavesdropping is a more effective recruitment strategy that is easily implemented with any sufficiently loud sonar compared to our pheromone model.

MODELING

We define three agent-based models to test foraging recruitment effectiveness of the sonar- and pheromone-based communication. In all models, agents initialize their positions at a home and search for a foraging target. Once agents have found the target, they try to recruit others to the path between target and home. Two models, inspired by ants, were designed with agents communicating through pheromone trails dropped over their previously traveled positions. The third model, inspired by the echolocation used by bats, was designed with agents using sound as their communication method, where a "found target" signal is emitted when an agent arrives at the target.

In all three discrete-time models, agent i has a two-dimensional position and velocity $\vec{x}_i(t) \in \mathbb{R}^2$ and $\vec{v}_i(t) \in \mathbb{R}^2$, respectively, at time step $t \in \mathbb{N}$ for $i = 1, 2, \ldots, N$. The N agents are initialized to leave home at time $t = 0$ with velocities assigned randomly in $\mathbb{R}^2$ with a uniform distribution. In line with [6], the agents have a constant speed $s \in \mathbb{R}^+$. The home is a two-dimensional point $\vec{H}$ and the target is a circle with center $\vec{T}$ and radius r_T. If the agent senses the target or a signal from a peer (either through pheromone trails or eavesdropping), then the agent updates its velocity and position according the models below. We call this action "gathering", since it results in traveling repeatedly on the path between the target and home. Otherwise, they perform a random walk; we call this action "foraging". To avoid agents traveling too far from the target without finding it, a "return home" tag is introduced at intervals of t_r for all agents that are foraging. At these times, foraging agents return home and emerge with randomly assigned velocities. This periodic process acts as a virtual boundary and shortens the time to convergence.

Ant-inspired model

The first two models are inspired by ants, which forage and gather as a group by simultaneously walking and dropping an attractive pheromone, which acts as to recruit other foragers. As stated in the introduction, our inspiring system is the Argentine ant which drops pheromone almost continuously [6, 17]. We define a "continuous drop" model, in which the agents drop units of pheromone that attract others who encounter it. However, the Argentine ant is unusual in this continuous deposition of pheromone; most ant species opt to only drop pheromone on salient paths, such as when a food source has been found [17]. This motivates our second "targeted drop" model, which seeks to capture the dynamics of a species where an agent only drops pheromone once the target location is found. These two models can be compared to see if either mode of pheromone communication is more effective than echolocation.

In both the continuous and targeted pheromone models, agents initially forage by performing a random walk until they encounter a pheromone trail or the target (called points of interest). Sensing of a point of interest occurs when the point of interest is within a circle of radius ρ_p centered at the agent's position $\vec{x}_i$ and when the angle between the agent's velocity $\vec{v}_i$ and the point of interest relative to $\vec{x}_i$ is less than some angular threshold θ.

When a point of interest is sensed, agents update their velocity according to whether they sense either the target or a pheromone trail. If the point of interest is a pheromone trail, agents will turn in the direction of highest concentration of pheromone in its sensing space, see Figure 1. That is,

$$\vec{v}_i(t+1) = s\mathbf{N}\left[\sum_{j \in \mathcal{N}_i(t)} \mathbf{N}[\vec{p}_j(t) - \vec{x}_i(t)]\right] \tag{1}$$

where $\mathbf{N}[\vec{u}] = \vec{u}/\|\vec{u}\|$, $\vec{p}_j(t)$ is the position of a pheromone deposit j existing at time step t, and $\mathcal{N}_i(t)$ is the set of indices of

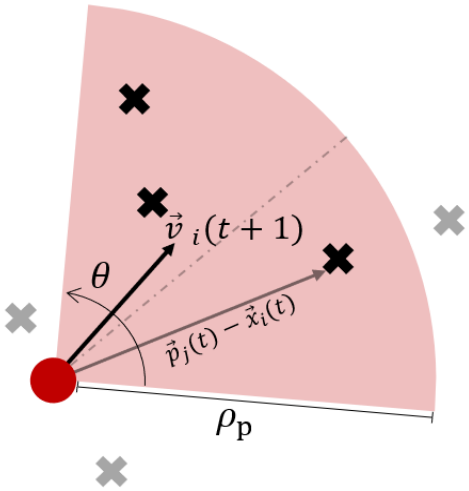

FIGURE 1. A schematic of the sensing space of the agent with position $\vec{x}_i(t)$ and how it locates each pheromone deposit (shown as black x's) and updates its velocity $\vec{v}_i$ based on a center of mass calculation. The agent's sensing space is shaded in pink, with linear range ρ_p and angular range θ. Pheromone deposits which are present but not sensed by the agent are shown as gray x's.

pheromone deposits that can be sensed by agent i. We note that this model is deterministic, unlike others in the literature which use the pheromone distribution to define a random variable is sampled to define the agent's turn rate and direction [6, 17]. If the point of interest is the target $\vec{T}$, agents turn toward the home position $\vec{H}$ and follow this path alternating between $\vec{H}$ and where the historical path intersected $\vec{T}$ indefinitely. That is,

$$\vec{v}_i(t+1) = \begin{cases} s\mathbf{N}[\vec{H} - \vec{x}_i(t)] \text{ if } i \text{ has most recently visited } \vec{T} \\ s\mathbf{N}[\vec{T} - \vec{x}_i(t)] \text{ if } i \text{ has most recently visited } \vec{H}. \end{cases} \tag{2}$$

Agents using this update are considered to be gatherers. Cartoons illustrating how the two pheromone models work are given in Figure 2.

As the models update, agents create a pheromone trail at their positions, which we label $\vec{p}_j(t)$. The distinction between the two pheromone models is that the continuous model augments the set of points $\vec{p}_j$ with all agent positions at all time steps, while the targeted model only adds points to the set of $\vec{p}_j$ when the conditions to use the update (2) have been satisfied. In other words, agents using the targeted model only start making a pheromone trail continuously *after* they have first encountered the target. For both models, points on the pheromone trail are set to decay at a fixed rate d, so that $\vec{p}_j(t-d)$ is no longer sensed by agents for times greater than t.

For both pheromone models, agent i's new position is found with the updated velocity following

$$\vec{x}_i(t+1) = \vec{x}_i(t) + \vec{v}_i(t+1). \tag{3}$$

Bat-inspired model

As it is reported in [18], bats use different types of echolocation calls when engaged in searching or foraging versus the final stage of attacking prey. It has been shown that other bats nearby may eavesdrop on these calls to infer behavior, allowing them to actively compete with conspecifics for food [11]. In this model, we build an interaction based on such eavesdropping, but we design agents which collaborate for collective foraging, rather than competing.

Similar to the ant-inspired models, an agent using the bat-inspired model leaves the nest and forages via a random walk to find the target. When an agent finds the target, it will forage, alternating between $\vec{H}$ and $\vec{T}$ following the velocity update rule expressed in (2). However, instead of dropping pheromone, the gathering agents broadcast a "found target" signal analogous to the feeding buzz used by bats. This signal is assumed to be audible within a circle of radius ρ_s centered at the gatherer's position. Therefore, all the agents within this circle can "eavesdrop" and infer the gatherer's intention, and move towards it. In other words, agent i will update its velocity at time t based on

$$\vec{v}_i(t+1) = s\mathbf{N}[\vec{x}_g(t) - \vec{x}_i(t)] \tag{4}$$

when $\|\vec{x}_i - \vec{x}_g\| < \rho_s$ where $g \in \{1, 2, \ldots, N\}$ is the index of the gatherer. When an agent eavesdrops on a group of gathering agents, it randomly selects one of the gatherers using a uniform distribution. This agent keeps following the randomly-selected gatherer until it finds the target. At this time, it becomes a gathering agent itself and follows the update rule in (2) to alternate between home and target while broadcasting a found target signal. When the velocity of each agent at the next time step is found, the position of each agent updates by (3). A cartoon illustrating how the eavesdropping model is given in Figure 2.

Foraging behavior

If an agent is not using either the pheromone or the eavesdropping model above, it forages by performing a random walk defined by the discrete-time update

$$\vec{x}_i(t+1) = \vec{x}_i(t) + \alpha\vec{v}_i(t+1) + (1-\alpha)\vec{v}_i(t). \tag{5}$$

Here, $\alpha \in [0, 1]$ is a weight on a two-time-step filter that smooths the agent's trajectory.

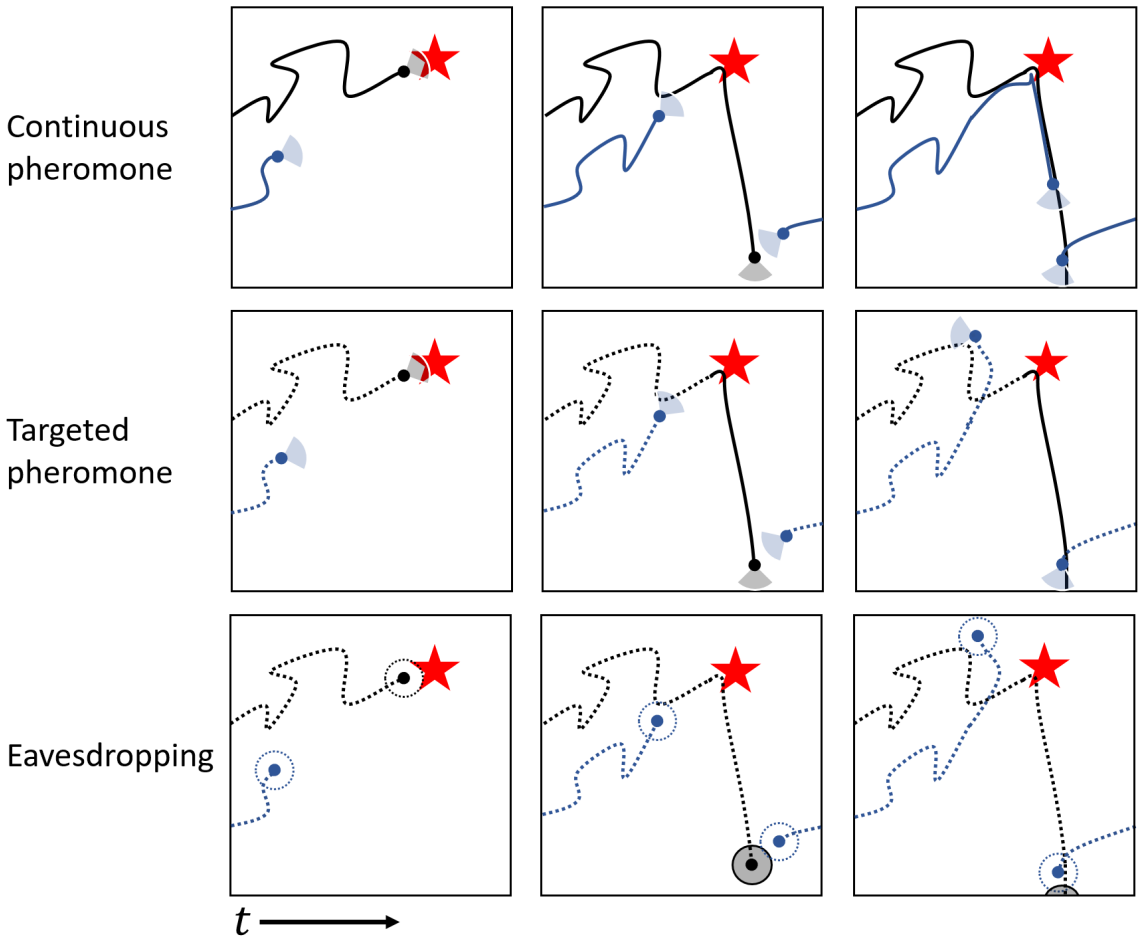

FIGURE 2. Time lapse of model dynamics for (top row) continuous pheromone model in which agents drop pheromone continuously, (middle row) targeted pheromone model that agents only drop pheromone when they found the target, and (bottom row) eavesdropping model in which agents listen to agents close by. Agent positions are shown as dots and the target is shown as a red star. Agents path histories are shown by dotted lines and pheromone trails are shown by solid lines (black and blue) and sensing spaces by shaded circular sections. For the eavesdropping model, sensing space and eavesdropping range are shown by the circles around agent positions. Once an agent reaches the target using the eavesdropping model, the sensible range for the found target signal is shown by the shaded gray circle.

Recruitment metric

We define a metric to assess the success of each model in enabling recruitment of agents gathering between the target and home. Since a gathering agent is successfully performing foraging between target and home, the percentage of gathering agents at each time step demonstrates the success of the model at that time. Therefore, we record the number of gathering agents $R(t)$ using update (2) over time as a metric to compare the models.

SIMULATIONS

Parameters

All simulations were performed using MATLAB version R2018a. Using experimental data found by [6], each agent has a constant speed $s = 0.02$ m/s. The simulation space is dimensional in meters, with home $\vec{H}$ being set at the origin and target $\vec{T}$ placed at $(0.5, 0.5)$. Each simulation was performed with $N = 100$ agents. All models were simulated for 3600 time steps, with the time step being 1 s, and 50 repetitions were performed. Both ant-inspired models follow the same parameters for sensing and following pheromone, with a sensing range and angle of $\rho_p = 0.02$ m and $\theta = 90^\circ$ angle, respectively [6]. We use a pheromone decay rate of $d = 1000$ s. The bat-inspired model is simulated with an eavesdropping range ρ_s between 0.01 m and 0.03 m at intervals of 0.002 m. For the random walk, we define $\alpha = 0.25$ by qualitatively comparing the smoothness of ant trajectories in [6] with those generated by the model with a range of values for α. In preliminary simulations, we observed foraging

TABLE 1. SIMULATION PARAMETERS

Variable	Symbol	Value
Length of simulations	t	3600 s
Simulation replicates	-	50
Number of agents	N	100
Speed of agents	s	0.02 m/s
Smoothing variable	α	0.25 s
Pheromone decay rate	d	1000 s
Eavesdropping ranges	ρ_s	[0.01,0.03] m
Pheromone sensing range	ρ_p	0.02 m
Pheromone sensing angle	θ	90°
Return home time interval	t_r	600 s
Target center location	$\vec{T}$	(0.5,0.5) m
Target radius	r_T	0.1 m
Home location	$\vec{H}$	(0,0) m

agents effectively losing the intended target. To avoid this, we defined the "return home" tag to be at 600 s intervals. The tag acts as a virtual boundary, stopping agents from becoming effectively lost. A summary of these simulation parameters is shown in Table 1.

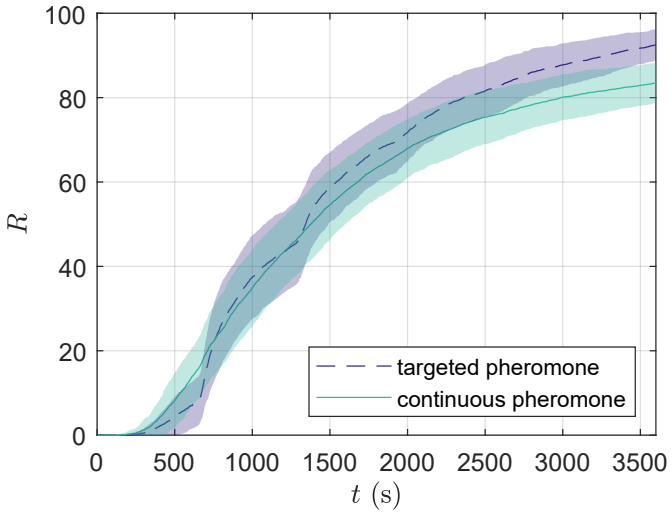

FIGURE 3. Recruitment of continuous and targeted pheromone models over time. Shaded areas indicate mean ± one standard deviation computed over 50 simulation replicates.

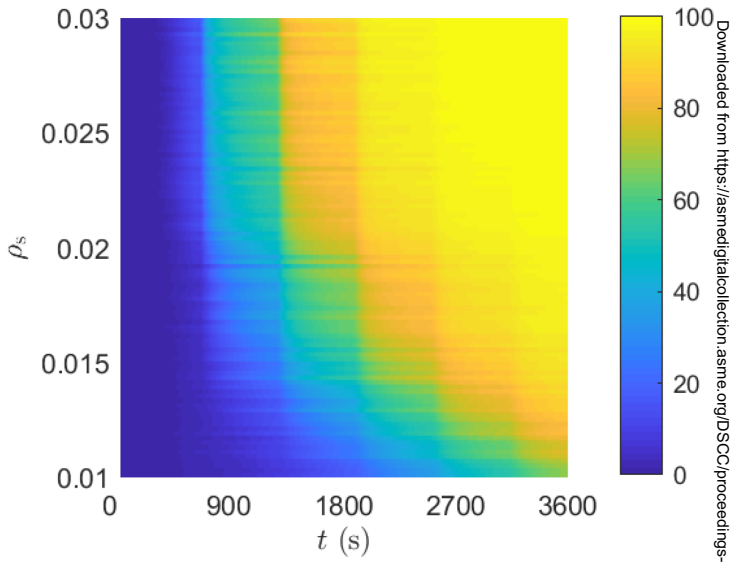

FIGURE 4. Mean recruitment for the eavesdropping model over time as ρ_s is varied.

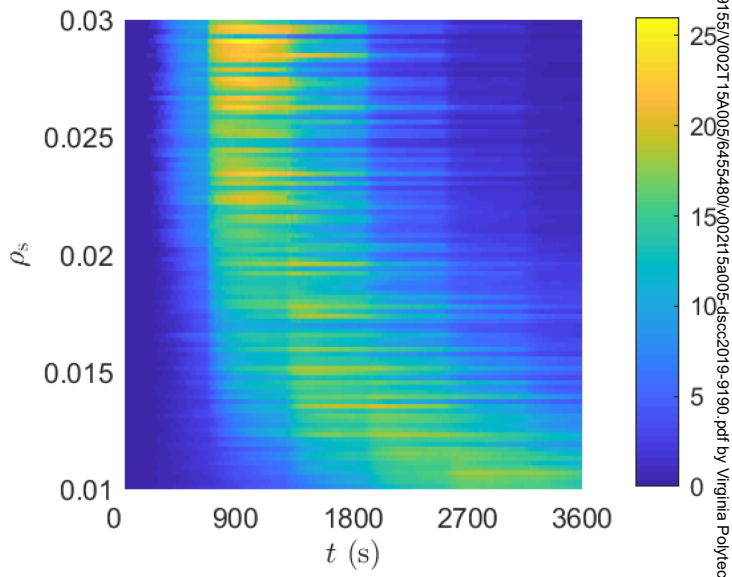

FIGURE 5. Standard deviation of recruitment for the eavesdropping model over time as ρ_s is varied.

Results

Figure 3 presents the time-series for foraging recruitment for the two ant-inspired models, with mean and standard deviation over the 50 replicates shown. Comparing these models, we see that both models are generally equivalent during the transient, though they converge to different final values at $t = 3600$ s, see Figure 3. We performed a Kolmogorov-Smirnov test in MATLAB and found that the differences in the final distributions are

statistically significant with a p-value of 0.05 [19].

Figures 4 and 5 show the mean and standard deviation of the recruitment time-series in the eavesdropping model as a heat map, where the vertical axis varies the eavesdropping range used in the model and statistics are computed over the 50 replicates. In Figure 4, we see that the pattern for each value of ρ_s is the same as the ant-inspired model, going from a zero to a value near 100 as time increases. However, the recruitment converges sooner as the eavesdropping range increases, saturating once $\rho_s > 0.022$ m. The larger eavesdropping range increases the likelihood that an agent is recruited when foraging. In addition, we note that the standard deviation of the recruitment peaks during the transient, since R varies the most between replicates in this phase.

To compare the performance of the bat- and ant-inspired models, we can find where the recruitment time series from the eavesdropping model best matches the continuous and targeted pheromone in two ways. First, we find the value of ρ_s for which the norm of the difference between the entire time series from the eavesdropping and pheromone models is minimized. Next, we find the value of ρ_s for which the absolute difference between the final recruitment values from the eavesdropping and pheromone models is minimized. Plots comparing these values are shown for the continuous and targeted models in Figures 6 and 7, respectively. For both models, we see that the eavesdropping model that best fits the pheromone models converges to a higher recruitment value at $t = 3600$ s. In addition, the eavesdropping model that best matches the final values lies entirely under the recruitment curves for the pheromone models.

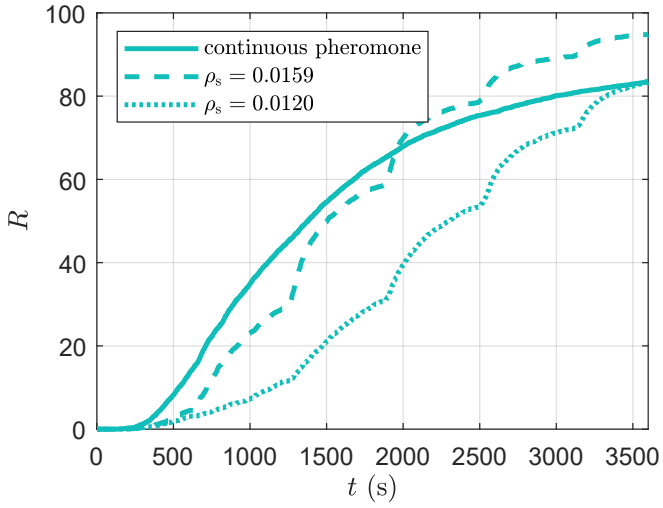

FIGURE 6. Continuous pheromone time series compared to the best fit eavesdropping range, with both time series averaged over 50 replicates. The solid line shows the pheromone model, while the dashed and dotted lines show best fits for the entire time series and the final value, respectively.

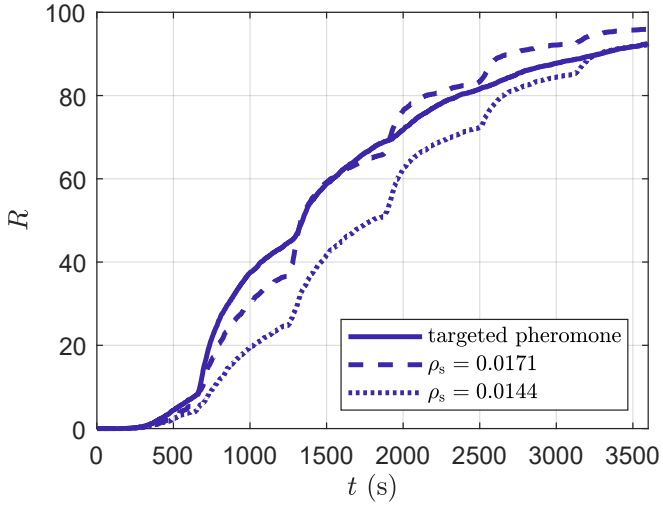

FIGURE 7. Targeted pheromone time series compared to the best fit eavesdropping range, with both time series averaged over 50 replicates. The solid line shows the pheromone model, while the dashed and dotted lines show best fits for the entire time series and the final value, respectively.

DISCUSSION

These results suggest that the targeted pheromone model is able to recruit more individuals than the continuous pheromone model, as it converges to a statistically higher value in the simulated time. A reason for this difference in performance could be that, even when pheromone decays quickly as it does in these models, there is still a large amount of pheromone surrounding $\vec{H}$ in the continuous drop model. This pheromone distribution, corresponding to recently visiting agents that are not necessarily coming from the target direction, may lead agents away from the trail towards $\vec{T}$ when they re-emerge from $\vec{H}$. By comparison targeted pheromone dropping creates a clear trail towards $\vec{T}$, increasing the chance that an agent randomly leaving $\vec{H}$ can pick up the correct travel direction towards the target. In fact, we can see a discrete jump in recruitment at 600 s intervals when the foraging agents all return home, which allows for comparatively more agents to be recruited by those that are already gathering. These jumps are less noticeable in the continuous pheromone model, which supports the explanation of behavior above.

Comparing Figures 3 and 4, eavesdropping can perform much better or worse than either pheromone model, with the majority of tested eavesdropping ranges easily out performing the pheromone. The eavesdropping model performs equivalently to the pheromone model at about $3/4$ of the range of pheromone sensing ($\rho_s = 0.012$ m and 0.0144 m, see Figures 6 and 7, compared to $\rho_p = 0.02$ m). If values were scaled to be more practical

for actual use in a robotic system, sonar would have to be extremely quiet to perform equivalently. Since most sonar sensors can be operated at a higher intensity than the parameters used here, sonar may be a preferable sensing scheme to pheromone when designing a foraging robotic swarm. However, this conclusion neglects the existence of potentially negative or confounding interference as a result of eavesdropping. In systems which use much higher sonar intensity, this consideration would have to be taken into account.

While the sonar model does generally outperform the pheromone model in the simulated time, it is observed that the pheromone models may converge in a faster time as seen by the steep slope in Figures 6 and 7. We believe this is due to the fact that pheromone trails are semi-permanent and, once established, are continuously being strengthened. This is in contrast to eavesdropping, which requires an agent to be in the vicinity of another agent which is already on the trail to gain the necessary information to follow. In fact, when the the decay rate of the pheromone is 1 time step, the targeted pheromone model and the eavesdropping model are equivalent. If the decay rate is increased from 1, we expect the faster convergence of recruitment with pheromone.

CONCLUSION AND FUTURE WORK

In this paper, we compared three models from two different bio-inspired communication methods to test their recruitment effectiveness in a collective foraging problem. We found that continuous dropping of pheromone can lead to less efficient recruitment and, through eavesdropping, agents can recruit large numbers of other agents to assist in foraging from a known target.

Continuing to expand on these ideas, we hope to use the findings in [3] to model different behaviors shown in variable sized colonies using bio-inspired communication in the future. We would like, in addition, to investigate the performance of pheromone-based sensing with other sensing mechanisms in a multi-agent team of robots.

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