Robust Mitigation Strategy for Misleading Pheromone Trails in Foraging Robot Swarms

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Abstract. This study advances the security of swarm robotics by examining the resilience of stigmergic communication in foraging robot swarms against deceptive strategies. We specifically investigate the swarm's vulnerability to attacks via misleading pheromone trails laid by detractor robots, which significantly hinder foraging performance. Through simulations, we evaluated the adverse effects of such attacks on resource collection and forager capture rates, highlighting a notable decline as the percentage of detractors increases. To counter these threats, we implement a robust defense mechanism utilizing DBSCAN for density-based clustering of pheromone trails, complemented by a cluster grouping method that effectively isolates batches of detractors early in the simulation. This approach incorporates an adaptive timing mechanism to discern and counteract misleading trails, substantially mitigating forager captures and enhancing swarm foraging efficiency. Furthermore, we extend our analysis by introducing obstacles in the simulation environment to test the defense's robustness under varied and complex conditions. These experiments demonstrate that our defense strategy remains effective, maintaining operational stability even when faced with additional environmental challenges. This research not only underscores critical security vulnerabilities in pheromone-based foraging algorithms but also sets the foundation for developing more secure and resilient swarm robotics systems for real-world applications where robustness against both deceptive strategies and environmental complexities is essential.

Keywords: Swarm Robotics · Intrusion Detection · Autonomous Robots

1 Introduction

Drawing inspiration from natural systems like ants, termites, and birds, current research in swarm robotics spans behaviors such as self-organization [13,19],

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aggregation [3,4], object sorting [31,32], and foraging [14,15,18,21,25]. However, these tasks are all optimized for benign environments, assuming no malicious activity. This paper aims to address the less explored aspects of security and reliability [16], particularly focusing on the vulnerabilities of pheromone-based foraging robot swarms to security threats like the ant mill phenomenon [8,9] and intrusion attacks that exploit virtual pheromone trails to deceive robots [5,27]. These vulnerabilities are crucial as they impact real-world applications in environmental monitoring, search and rescue, disaster recovery, and military operations, demanding more robust and reliable swarm robotics technologies [2,20,22,36]. Our research dives into stigmergic communication, where the environment is a medium for interaction, enhancing collective adaptability but also exposing inherent vulnerabilities [5,27,29,35]. We investigate the impact of detractors-hijacked robots laying misleading pheromone trails leading to forager capture and removal, which hampers foraging efficiency. Our proposed defense employs an enhanced Density-Based Spatial Clustering of Applications with Noise (DBSCAN) alongside an isolation strategy to effectively remove multiple detractors from the environment at once [12]. This novel application of DBSCAN not only mitigates specific vulnerabilities but also broadens the security protocols in swarm robotics and stigmergic communication.

The paper proceeds to detail past work on swarm robotics vulnerabilities (Sect. 2), the central-placed foraging model (Sect. 3), the methodology for addressing pheromone trail exploits (Sect. 4), our experimental setup (Sect. 5), and the evaluation of our experiments (Sect. 6). We conclude with a summary of our contributions and directions for future work (Sect. 7).

2 Related Work

Insect colonies utilize pheromone-based communication for coordination, which, while effective, has vulnerabilities that various organisms exploit, leading to evolutionary arms races [1,6,7,11,17,30,35]. A notable example is the “ant mill” or “army ant syndrome,” where ants are trapped in a deadly loop [8]. Despite evolved defensive strategies, ants remain susceptible due to their inability to override instinctual responses to pheromone trails, highlighting inherent fragilities in stigmergic communication [26,28,33].

Similarly, virtual pheromone trails in robotic swarms facilitate efficient coordination but introduce vulnerabilities exploitable through signal manipulation [14,15,18,21,23,25]. Emergent behaviors like the ant mill can undermine foraging algorithms, suggesting that current systems are prone to dysfunction and manipulation by malicious entities, known as “detractors,” who mislead robots with indistinguishable false trails [5,9,27].

This paper builds on previous work by exploring how malicious robots may disrupt stigmergic communication, assessing the broader implications for swarm robotics security and proposing strategies to mitigate these risks. This focus addresses the gap in research where the resilience of pheromone trails and their susceptibility to interference in artificial systems have been minimally explored.

3 Central-Placed Foraging

Central-placed foraging (CPF) is a well-established model where a nest acts as a central collection zone within the search space, and robots exhibit four major behavioral states [14]:

Departing: Robots leave the center, searching randomly or returning to previously successful locations using site fidelity or pheromone waypoints. Upon reaching a target, robots transition to *Searching*.

Searching: Robots search using random walk [10]. Successful searches lead to *Surveying*, while unsuccessful ones may end with a return to the center, determined by a probability p_r.

Surveying: Robots assess local resource density within a search radius r_{search} (Table 1), recording the count k of resources.

Returning: Robots carry resources back to the center. The density of resources λ_{lp} is taken into account to generate a probability (see Eq. 1) of laying a new pheromone waypoint. The robots then restart the cycle from *Departing*.

Behavioral parameters like λ_{sf} (site fidelity rate) and λ_{lp} (pheromone waypoint rate) are managed by a Poisson Cumulative Distribution Function (CDF) [15]:

$$\textsc{Pois}(k, \lambda) = e^{-\lambda} \sum_{i=0}^{[k]} \frac{\lambda^i}{i!} \tag{1}$$

Decisions to act are triggered if $\textsc{Pois}(c, \lambda_{sf}) > \mathcal{U}(0, 1)$ or $\textsc{Pois}(c, \lambda_{lp}) > \mathcal{U}(0, 1)$, leading to the use of site fidelity or the laying of a new pheromone waypoint.

The pheromone waypoints have an initial strength of 1 and decay exponentially over time by $w = e^{-t\lambda_{pd}}$. Waypoints below a threshold γ are removed, maintaining only the most relevant paths.

4 Methodology

Attack Strategy. We introduce a scenario where malicious agents, known as detractors, disrupt the foraging process by distributing misleading pheromone trails. These trails lead benign foragers to designated capture sites, effectively removing them from the foraging task as shown in Fig. 1. Detractors mimic benign foragers to avoid detection, but instead of reporting actual resource locations, they report coordinates within the vicinity of capture sites. This deceptive strategy is inspired by historical hunting techniques such as buffalo jumping, where the prey is pushed to fatal traps [34]. The attack's effectiveness is measured by tracking the number of foragers misled to capture sites, and the rate of their capture, providing insights into the impact of these tactics on overall swarm efficiency.

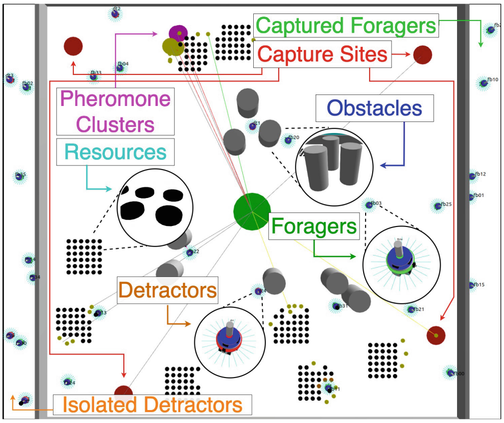


Fig. 1. A mid-simulation phase depicting the foraging scenario in ARGoS.

4.1 Defense Strategy

To counteract threats from detractors, our defense employs the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm to analyze and cluster pheromone trails. This method helps identify clusters formed by similar pheromone trail patterns, distinguishing between those laid by genuine foragers and detractors.

DBSCAN Implementation: We apply DBSCAN to the spatial coordinates given by the pheromone trail waypopints. We configure DBSCAN with a search radius ϵ equal to the robots' search radius for spatial relevance. The minimum points threshold $minPts$ is set to 2, due to the expected data sparsity in small-scale swarm scenarios.

Cluster Grouping: Post-DBSCAN clustering, we construct a graph to link clusters based on common creator IDs. The nodes represent individual clusters, and the edges are formed between the nodes if their associated pheromone trails share at least one common creator ID. Using this graph model depicted in Fig. 2, we create larger cluster groupings to facilitate the identification robots who are exhibiting similar trail laying behavior.

Travel Time Estimation and Adjustment: In order to detect and flag misleading trails, we incorporate a travel-time estimation strategy. Each pheromone trail laid by robots includes an estimated travel time calculated based on the distance to the destination and the robot's average speed. When a robot follows a trail, the actual time taken to travel is recorded and compared against the estimated time. Significant deviations suggest potential misleading trails, triggering an isolation event for the trail creator and other robot's associated with the flagged trail's cluster group.

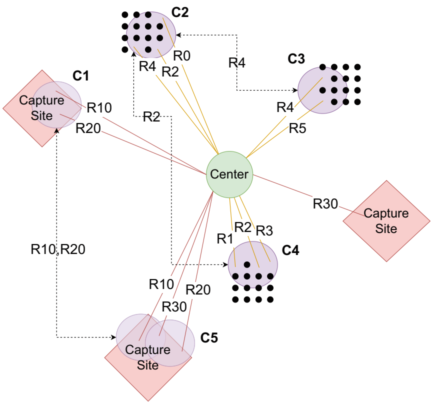


Fig. 2. A graphical representation of cluster connectivity based on common creator IDs.

This strategy involves updating our understanding of trail legitimacy continuously: If the actual travel time consistently exceeds the estimated by a significant margin, it suggests the presence of a misleading trail. However, obstacles and collisions can affect travel time and must be taken into account. Therefore, we update the estimated travel-time using a simple feedback loop taking into consideration the measured travel time when a robot returns. The estimate is only updated when a robot returns after the current estimated travel time of the trail.

Isolation and Reintegration: A 'strike' is given to all robots associated with a cluster group when a robot does not return within the estimated travel time of one of the trails within the group. Accumulating a predefined threshold of five strikes (determined empirically) results in the robot's temporary isolation from the swarm to prevent further disruption of foraging activities. This threshold ensures a balance between prompt response to threats and the minimization of false positives, essential for maintaining swarm integrity.

However, if a forager returns on a trail within a flagged cluster group after its estimated travel time, the trail creator and other robots associated with the trail's cluster group are reintegrated (if isolated) or have a 'strike' removed. This addresses false positives, allowing dynamic adaptation to new information and maintaining operational efficiency.

5 Experiment Setup

We utilize the ARGoS multi-robot simulator to conduct our experimental studies [24]. The experiments are designed to evaluate the impact of detractor behaviors and the effectiveness of our proposed defense mechanisms under various scenarios, with experimental parameters detailed in Table 1. Conducted under controlled settings with consistent arena sizes, resource clusters, and robot numbers, our experiments ensure repeatability and reliability. Key assumptions include uniform robot capabilities, randomized resource distribution, and specific detractor behaviors to isolate the effects of variable parameters on the foraging efficiency and defense effectiveness.

Experiment 1 - Pheromone Trail Dynamics: The first experiment investigates how the rate of laying pheromone trails, denoted as λ_{fg} for foragers and λ_{dt} for detractors, affects the foraging performance and susceptibility to attacks. We aim to determine the most impactful settings on resource collection efficiency and forager capture rates, setting the stage for robust testing of our defense strategies in subsequent experiments.

Experiment 2 - Detractor Impact Analysis: In Experiment 2, we assess the resilience of our defense strategy by varying the number of detractors (n_{dt}) and adjusting the pheromone lay rates for both foragers and detractors. This setup allows us to observe the direct effects of increased detractor presence on the foraging process and the efficacy of our defense mechanisms under escalated threat conditions.

Experiment 3 - Obstacle Dynamics: Additionally, a third experiment introduces environmental obstacles to evaluate the robustness of our defense under more complex and realistic conditions. We manipulate the obstacle density (n_{obs}) and distribution patterns (d_{obs}), either randomly or in an annular configuration, to test how physical barriers affect the foraging algorithms and the defense system's capability to adapt and maintain effectiveness.

Table 1. Consolidated Experimental Parameters

Parameter	Exp. 1	Exp. 2	Exp. 3	Description
D_{arena}	(10,10,1)			Foraging area dimensions (x, y, z)
$D_{cluster}$	(6,6)			Resource cluster size (l, w)
n_{fg}	24			# of foragers
n_{dt}	25%	10%,20%,30%,40%,50%	25%	# of detractors based on n_{fg}
n_{cl}	8			# of resource clusters
n_{obs}	N/A		0, 4, 8, 12, 16	Density of obstacles
r_{center}	0.25			Radius of the center
$r_{resource}$	0.05			Radius of resource
r_{search}	$4 \cdot r_{resource}$			Foot-bot search radius
r_{cs}	$r_{center}/2$			Capture site radius
λ_{fg}	1, 4, 8, 12	4		Lay rate of pheromone trails for foragers
λ_{dt}	1, 4, 8, 12	1		Lay rate of pheromone trails for detractors
d_{obs}	N/A		Random, Annular	Obstacle & resource distribution
ϵ	r_{search}			DBSCAN cluster neighborhood radius
$minPts$	2			DBSCAN minimum points per cluster

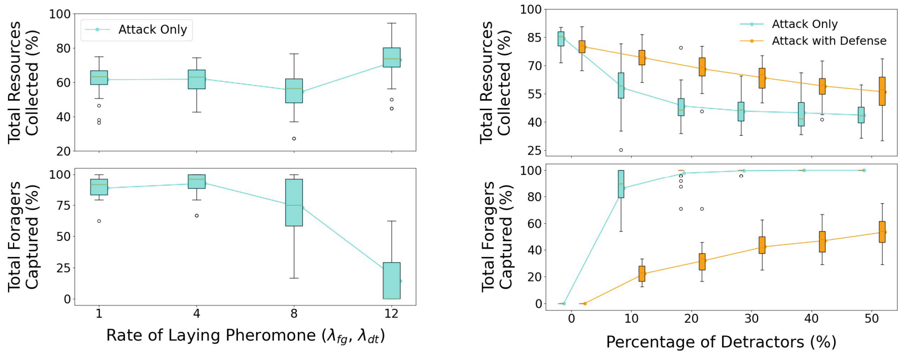
6 Results

6.1 Experiment 1: Evaluation of Pheromone Trail Dynamics

The first experiment focused on varying the rates of laying pheromone trails, λ_{fg} and λ_{dt}, and their effects on foraging performance. Figure 3a illustrates the impact on resource collection efficiency and forager capture rates over 50 runs. The tested rates were 1, 4, 8, and 12, with the smaller values indicating a higher frequency of trail laying.

Key findings include: 1) At $\lambda_{fg}, \lambda_{dt} = 1$, resource collection was at 61.61%, and the forager capture rate was high at 88.75%. 2) Increasing the rate to 4 resulted in a slight increase in resource collection to 61.82% and the highest capture rate of 92.50%. 3) At a rate of 8, the resource collection decreased to 54. 71%, and the forager capture rate decreased to 72.92%. 3) The 12 rate showed an increase in resource collection to 73.19% and a significant reduction in forager captures to 14.31%.

These results underscored the risk associated with higher trail laying frequencies, with a rate of 4 selected for further testing in Experiment 2 due to its pronounced impact on forager captures.



(a) (b)

Fig. 3. (a) The foraging performance and foragers captured across different rates of laying pheromones while under attack. (b) Detractor Isolation Rates.

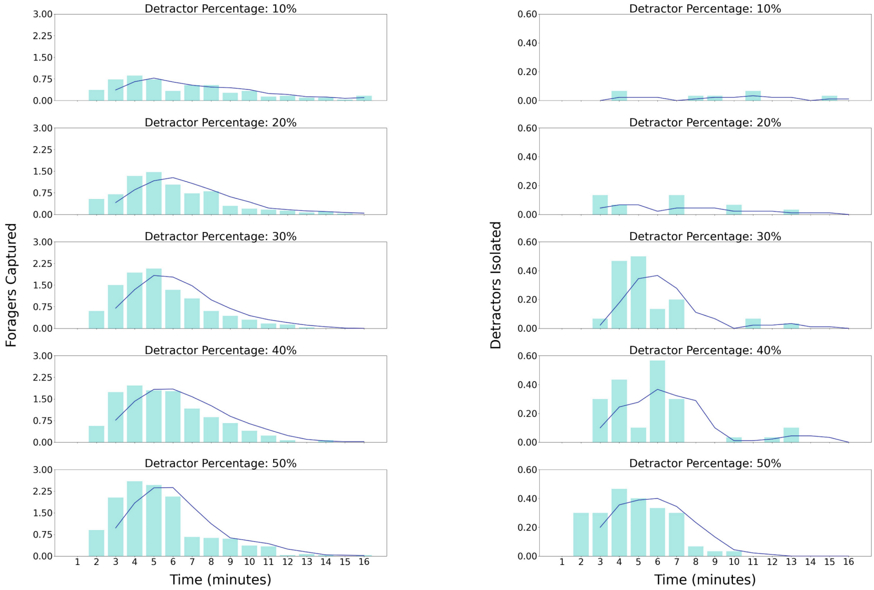
6.2 Experiment 2: Evaluation of the Defense Strategy

Experiment 2 assessed the defense strategy against varying levels of detractors, from 10% to 50% of the swarm. Figure 3b presents the performance of the foraging system with and without the defense mechanism.

The findings of Experiment 2 include: 1) Without detractors, the baseline foraging efficiency was approximately 85%. 2) With detractors, efficiency decreased to 57.92% at 10% detractors and further to 43.66% at 50% detractors. 3) The defense improved foraging performance by 16.06% at 10% detractors and by 12.33% at 50% detractors. 4) Capture rates reduced significantly with the defense, especially noticeable at higher detractor levels.

The defense showed substantial effectiveness in mitigating detractor impacts, confirming its capability to adapt and counteract increasing threats.

Forager Capture Dynamics: Figure 4a presents the fluctuating rates of forager captures per minute under various detractor levels, highlighting the defense mechanism's responsiveness. Notable points include: 1) Forager captures peak early but reduces to near-zero levels beyond minute 16, indicating effective threat neutralization. 2) At 10% detractors, the capture rate peaks at 0.866 per minute by minute 4, then decreases steadily to 0.033 by minute 15. 3) At 50% detractors, the capture rate reaches a higher peak of 2.6 per minute by minute 4, then drops sharply to nearly 0.0 by minute 16.



(a) Forager Capture Rates (b) Detractor Isolation Rates

Fig. 4. Dynamics of foragers captured and detractors isolated over time in Experiment 2.

Detractor Isolation Dynamics: Figure 4b shows the frequency of detractor isolation events per minute, demonstrating the precision and efficiency of the defense strategy: 1) Isolation events decrease to virtually none after minute 16, showcasing the prompt efficacy of the defense. 2) At 10% detractors, isolation rates are minimal, peaking only at 0.066 at minute 11. 3) Increased percentages of detractors lead to higher isolation rates, with 20% peaking at 0.133 by minute 7 and 30% reaching a peak of 0.5 by minute 5, indicating a scaled response to greater threats.

6.3 Experiment 3: Robustness of Defense in Varied Environments

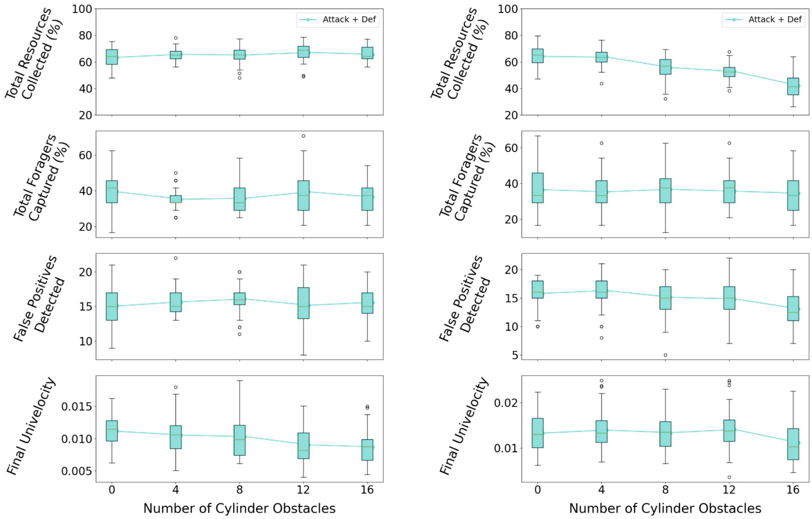
In Experiment 3, the robustness of the defense was challenged by introducing environmental obstacles, which tested the system's adaptability to physical changes that could impact navigation and the effectiveness of pheromone trails. The defense mechanism proved resilient across various obstacle densities, effectively maintaining foraging efficiency and minimizing forager captures.

The performance in environments with different obstacle densities showed no significant degradation in the defense's ability to protect the foragers. This indicates that the system is not only effective under direct attacks but also adaptable to complex operational conditions that include physical barriers. This resilience is crucial for real-world applications where environmental unpredictability is common.

These findings emphasize the defense's proficiency in maintaining operational stability and highlight its potential for deployment in dynamic and challenging real-world scenarios where both security threats and environmental obstacles are prevalent.

Figure 5 shows 1) a peak in "Total Resources Collected" at 66.26% with a standard deviation of 7.78 when faced with sixteen obstacles, suggesting a resilient adaptation to navigational challenges. 2) "Total Foragers Captured" remained relatively stable despite increased obstacle density, with minimal mean capture rates fluctuating slightly, demonstrating the defense's effectiveness under varied conditions. 3) The "False Positives Detected" metric was stable across different obstacle densities, indicating that the defense system maintained accuracy in threat detection even with environmental complexity. 3) The 'final Univelocity' exhibited minor variations, reflecting the system's ability to adapt to increased navigational challenges posed by obstacles.

These findings underscore the defense mechanism's robustness, not only in terms of managing detractor threats but also in handling environmental factors that might complicate navigation and communication within the swarm. The detailed results of Experiment 3 provide critical insight into defense capabilities, strengthening its effectiveness and adaptability under complex and dynamically changing conditions, confirming the readiness of the system for deployment in real-world scenarios where natural and artificial obstacles are present.



(a) Random Distribution (b) Annular Distribution

Fig. 5. Performance metrics under different obstacle distributions: Random and Annular. Demonstrates how environmental complexity affects foraging efficiency and defense effectiveness.

7 Conclusion

This study substantially advances the field of swarm robotics by addressing vulnerabilities in foraging algorithms exposed to deceptive strategies such as misleading pheromone trails. Our investigations were articulated through a series of experiments.

In Experiment 1, we observed that different pheromone trail laying rates significantly affected foraging efficiency and forager capture rates (Fig. 3a). The most notable findings were at the lay rates of 4 and 12, which represented the extremes in forager capture rates and resource collection efficiency, respectively. Experiment 2 demonstrated the effectiveness of our defense mechanism, which significantly mitigated the impact of attacks at various detractor levels (Fig. 3b). The defense strategy effectively improved foraging performance by up to 16.07% and reduced forager capture rates by up to 65.69%, even as the detractor percentage increased. This highlights the defense's adaptability and robustness in maintaining swarm functionality under attack scenarios (Fig. 4a and Fig. 4b).

Experiment 3 tested the defense's resilience against environmental challenges and showed that while obstacles affected foraging efficiency, they did not compromise the defense's effectiveness (Fig. 5a and Fig. 5b). This indicates the defense mechanism's capability to operate effectively in complex environments.

These results not only underline the efficacy of our defense mechanism in rapidly and efficiently isolating detractors but also emphasize the importance of designing swarm robotics systems that are secure, resilient, and adaptable to various operational threats. The manipulation of virtual pheromone trails poses significant challenges; however, our approach offers a potent countermeasure, establishing a foundational strategy for enhancing the robustness of foraging algorithms against pheromone-based attacks. This research contributes to a broader understanding of the integration of safety and security measures into swarm robotics at the developmental stage, ensuring that these systems are prepared to face real-world operational challenges. Future work will focus on enhancing the scalability and efficiency of our defense mechanisms, exploring applications in more dynamic environments, and possibly integrating advanced machine learning techniques to further refine adaptability and threat detection capabilities.

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