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Rebuttal:

We sincerely thank the reviewers for their thoughtful and constructive feedback on our manuscript. In response to your insightful suggestions, we have made several enhancements to improve the clarity and comprehensiveness of our work. We have refined the algorithm description, expanded our discussion sections, and addressed the methodological concerns raised. Below you will find our detailed responses to each of your points, with our replies highlighted in red.

Review 1

This project implements and extends Craig Reynolds' boids algorithm from the 1986 paper "Flocks, Herds, and Schools: A Distributed Behavior Model". The authors adapt the algorithm for robotic exploration tasks, focusing on optimizing coverage performance through parameter tuning of cohesion, alignment, and separation. The study includes a custom simulator, systematic parameter sweeps, and evaluations across three distinct environments.

Strengths:

* Clear Scope and Organization: The manuscript is well-structured, with a logical flow from problem definition to simulation, optimization, and results. The abstract and introduction succinctly outline the project's goals and relevance to distributed robotics.

* Comprehensive Evaluation: The authors evaluate the algorithm in three environments, such as, empty map, narrow corridor, cafeteria map, each presenting unique challenges. The inclusion of coverage metrics and heatmaps provides both quantitative and qualitative insights into performance.

* Insightful Parameter Analysis: The results highlight the negative impact of excessive alignment on coverage, such as, optimal gains: near-zero alignment, moderate cohesion/separation, offering actionable insights for swarm robotics.

Thank you for the encouraging feedback.

Weaknesses:

* Ambiguity in Simulation Modes: The transition between the interactive PyGame simulation and the headless batch-evaluation simulation is unclear. A explicit subsection or flowchart distinguishing their purposes would improve clarity.

We appreciate this feedback and have added more distinction in Section 3.3 - Simulation Details which explicitly distinguishes the difference between our interactive PyGame simulation and headless batch-evaluation modes. This section includes clear descriptions of each mode's purpose and capabilities, explanation of what features are available in each mode, and workflow for transitioning from interactive development/testing to batch evaluation for parameter sweep.

* Limited Environmental Complexity: While the cafeteria map tests clutter, additional dynamic factors such as wind could better assess robustness and mimic real-world situation.

You raised an excellent point in that dynamic factors like wind would provide more realistic assessment. However, for our initial study, we focused on static environments to establish baseline performance metrics. We prioritize understanding the fundamental parameter relationships in controlled environment to isolate their effects on coverage. As such, we added this concern as a limitation and future work for our model under Section 4.4 with the relevant text as follows:

"Third, the environments are static and fully known. Obstacles are placed at initialization and remain fixed for the duration of the simulation. In practical exploration scenarios, agents must often navigate partially known or dynamic environments. Incorporating real-time mapping, obstacle detection, and local replanning would increase the relevance of the model for deployed systems."

* Undefined Variables: Key terms like ε for obstacle avoidance and perception radius are introduced without justification. A table summarizing parameters (e.g., bounds for k_coh, k_ali, k_col) would aid reproducibility.

We appreciate this observation and have made several improvements to address the parameter clarity. In Section 3.4, we now explicitly define ε=10^-10 in the obstacle avoidance force equation to prevent singularities. The perception radius is specified as 50 units with a 150° field of view. The bounds of all gain parameters are stated alongside fixed parameters such as the wall repulsion gain and acceleration budget per timestep.

Review 2

This project implements and optimizes the Boids algorithm for distributed robotic coverage tasks. The author systematically tunes the core behavioral parameters (separation, alignment, cohesion) to maximize coverage efficiency across different environments using a custom simulation framework.

Strengths:

-- The manuscript is very well-structured, with clear explanations of both the classic Boids model and the specific modifications for coverage optimization.

-- The custom simulator is impressive in its modularity and practical design for real-time tuning and evaluation across multiple scenarios.

-- The results are thoughtfully analyzed, particularly the discussion of how different gain parameters impact group exploration dynamics in cluttered environments.

-- The approach to systematic random search and parallel simulation runs is efficiently implemented.

Thank you for the encouraging feedback.

Weaknesses:

-- While the environments used (empty map, corridor, cafeteria) are good initial tests, it would strengthen the study to include more randomized or larger-scale environments.

We appreciate this suggestion about including more randomized or larger-scale environments. Our initial testing setup was designed to challenge specific environments (open space, chokepoints, and dense clutter). Upon testing, we did find that the cafeteria map did not achieve the dense clutter as we would hope for. As such, we added a denser cafeteria map to aid this. For this initial study, we chose static, controlled environments to establish baseline parameter relationships without additional confounding parameters since we are already testing over 2 different number of boids, 4 different environments, and 3 random seeds. This allowed us to isolate the effects of gain tuning on coverage performance. As such, we added this concern as a limitation and future work for our model under Section 4.4.

-- The parameter optimization currently only targets coverage; additional objectives like overall path smoothness could be explored in future work.

You are right in that multi-objective optimization could provide more nuanced insights. For our study, we focus solely on coverage percentage to establish clear baseline relationships between parameters and performance. To address this, we added the coefficient of variation (CV) metric under Section 4.2 to evaluate coverage uniformity, though we didn't incorporate it directly into the optimization objective function itself. While path smoothness would have acted as an excellent evaluation metric for energy efficiency, it was not implemented in our study for a few reasons. First, tracking and storing complete trajectories for all agents across all 48,000 simulations would substantially increase memory requirements and execution time. Second, adding an additional objective on top of optimizing coverage would significantly redesign the architecture. Lastly, we believe that it is crucial to understand the single-objective optimization thoroughly before adding complexity. However, we acknowledge this in Section 4.4 (Limitations and Future Work) that multi-objective optimization represents an important next step with the relevant text as follows:

"Fourth, the optimization objective is limited to total coverage. While coverage uniformity is evaluated using the coefficient of variation, it is not used to guide the parameter search directly. Incorporating a joint objective that balances extent and uniformity could produce more efficient and evenly distributed behaviors, especially in cluttered maps."

-- Some mathematical definitions (like forces and their scaling with acceleration budget) are clearly written, but making a summary table of all parameters and their roles could help readers keeping track of the development.

"Thank you for this suggestion. While we chose to present parameters contextually within their relevant sections to maintain narrative flow and reduce redundancy, we acknowledge that a summary table would improve accessibility.

Minor comments:

-- Typo in Section 5: "coverage efficiency were achieved" → should be "coverage efficiency was achieved" (agreement with singular subject).

"Thank you for catching this grammatical error. We have corrected all instances of 'coverage efficiency were achieved'."

-- Some small inconsistencies in figure captions, like some figures explaining colors and some do not. But not a big deal.

We appreciate this observation about figure caption inconsistencies. While we addressed the most significant issues, we acknowledge that some minor variations remain. Different figures serve different purposes (some emphasizing visual patterns, others focusing on data), which led to different caption styles. We prioritized addressing the core technical concerns raised by reviewers but will ensure more consistent formatting in future publications.

Review 3

Summary: This project investigates optimizing the Boids model for robotic coverage tasks. The authors implemented a simulator with real-time parameter adjustment and obstacle avoidance, then systematically explored the parameter space to find configurations maximizing coverage while maintaining spatial dispersion. Results show that minimizing alignment, while maintaining cohesion and separation, leads to the most effective exploration.

Strengths:

Clear Project Definition: The project's objective—optimizing the Boids model for coverage tasks—is clearly stated. The document provides sufficient background on the Boids model and its relevance to distributed robotics. The scope is well-defined, focusing on parameter tuning and simulation-based analysis.

Well-Defined Methodology: The methodology is clearly explained. The authors describe their custom PyGame-based simulator, including its modular architecture, real-time parameter adjustment features, and obstacle avoidance capabilities. They detail the transition from an interactive PyGame simulation to a headless batch evaluation simulation. The use of a systematic random search procedure to explore the parameter space is a sound approach.

Overall Results: The results are well-explained and presented visually through plots and heatmaps. The analysis focuses on the relationship between coverage and the core gains ie. cohesion, alignment, and separation.

Thank you for the encouraging feedback.

Weaknesses:

Limited Generalizability: The simulation makes simplifying assumptions like perfect sensing, homogeneous agents, static environment that limit the generalizability of the results to real-world scenarios. The impact of communication constraints is not explicitly addressed.

We appreciate this concern about generalizability and have added a comprehensive Limitations and Future Work section (Section 4.4) that directly addresses these assumptions. These simplifying assumptions were necessary for this initial study to isolate parameter effects on coverage. Our findings on optimal parameter configurations (minimal alignment, moderate cohesion/separation) provide a baseline understanding that can be built upon when introducing realistic constraints. We've outlined specific directions for future work incorporating sensor noise models, agent heterogeneity, and dynamic environments.

Lack of Error Analysis: The document lacks a detailed error analysis. While multiple random seeds are used, there's no discussion of the statistical significance of the results or the variability observed across different seeds.

You are right that our error analysis could be more comprehensive. While we used three random seeds for all evaluations and presented the mean coverage percentages across them, it lacks a formal statistical testing and representative meaning. As such, we included the individual coverage percentage from each seed which formed the mean coverage percentage and the standard deviation between the seeds in Table 2. This shows that the variation between the three seeds was not significant, and the results were largely seed independent.

Unspecified Parameter Ranges: The exact ranges of values explored for the cohesion, alignment, and separation gains are not explicitly stated, hindering reproducibility.

We appreciate this observation and have made several improvements to address the parameter clarity. In Section 3.4, the bounds of all gain parameters are stated alongside fixed parameters such as the wall repulsion gain and acceleration budget per timestep.