WOLF-SAR: Wolf Pack Logic Framework for Search and Rescue

Anonymous CVPR submission

Paper ID

Abstract

WOLF-SAR, standing for Wolf Pack Logic Framework for Search and Rescue, represents an innovative approach in robotic motion planning tailored for search and rescue (SAR) operations. Drawing inspiration from the strategic hunting behaviors of wolf packs, WOLF-SAR aims to enhance SAR effectiveness through biomimetic principles and advanced cooperative behavior algorithms. The core of WOLF-SAR is built around the Rapidly-exploring Random Tree (RRT) algorithm, a key methodology in modern robotics for static path planning. This algorithm underpins the system's ability to plot efficient routes through challenging environments, resembling the tactical movements of wolves. While WOLF-SAR's current implementation focuses on static scenarios, its foundation allows for potential future adaptations towards dynamic and unpredictable environments typical in SAR missions. Central to WOLF-SAR's design is the concept of role allocation, where each robotic agent is assigned specific tasks within the SAR operation, akin to the role differentiation observed in natural wolf packs. This structured approach is crucial for methodical area coverage and thorough search operations in static environments. WOLF-SAR's potential in SAR applications is highlighted through its emphasis on cooperative strategies, where multiple robotic agents work in unison to cover extensive areas. Although the current version does not include real-time adaptability to moving targets or changing environments, its structured path planning provides a solid basis for systematic search efforts in predefined areas. Extensively validated in simulated environments, WOLF-SAR showcases the effectiveness of applying biomimetic strategies to robotic systems for SAR purposes. The project illustrates the feasibility of using static path planning algorithms in a cooperative, multi-agent context, laying the groundwork for more complex, dynamic adaptations in future iterations. As a conceptually strong model, WOLF-SAR contributes significantly to the field of SAR robotics, offering a framework that combines biomimicry with technological innovation. It serves as a promising platform for further development towards adaptable, real-time SAR operations, bridging the gap between static planning and dynamic environmental challenges.

1. Introduction

Path planning plays a crucial role in guiding robots through environments from a starting point to a destination, focusing on optimal routes and specific constraints. This area has seen significant research and practical application in the past ten years, benefiting sectors like manufacturing, automotive, healthcare, and more. In terms of mapping, environments can be represented through discrete or continuous spaces, depending on the available information. The complexity of these environments varies with the presence of dynamic and dynamic obstacles, as well as other robots sharing the space. The methods used by robots to reach their objectives based on environmental data can be divided into local and global path-planning challenges. Global path planning, also referred to as offline planning, involves predetermining a safe trajectory from start to finish before the robot begins its journey. Conversely, local path planning, or online planning, entails robots navigating incrementally, making decisions at each step toward their goal.

Various techniques have been applied to address motion and path planning challenges. Classic methods include roadmap, cell decomposition, potential field, and mathematical programming. In the roadmap approach, the navigable space and possible movements are simplified into paths connecting the start and end points in this space. The visibility graph and Voronoi diagram are two notable examples of roadmap strategies. The potential field method combines attraction and repulsion forces to guide the robot toward its destination. Mathematical programming tackles trajectory planning as a numerical optimization issue, with the MILP method being a case in point. However, classical methods sometimes struggle with issues like high dimensionality, time complexity, and getting stuck in local minima. This led to the development of probabilistic approaches. Probabilistic road maps (PRM) and rapidly-exploring random trees (RRT) are key examples of sampling-based motion planning algorithms, known for their effectiveness in complex, high-dimensional environments.

In this landscape, WOLF-SAR emerges as an innovative robotic motion planning system designed for the demanding requirements of search and rescue (SAR) operations. WOLF-SAR stands for Wolfpack Logic Framework for Search and Rescue, a system inspired by the intricate and coordinated hunting behaviors of wolf packs. WOLF-SAR leverages biomimetic principles to enhance SAR operation efficiency, applying advanced cooperative behavior algorithms and role allocation strategies.

At the heart of WOLF-SAR is the utilization of the RRT algorithm, tailored to meet the challenges of SAR scenarios. This approach enables the system to map out efficient routes through unpredictable and hazardous environments, echoing the tactical acumen of wolves in the wild. WOLF-SAR's unique contribution lies in its capability to dynamically assign roles and adapt strategies in real-time, mirroring the adaptive hunting strategies found in nature. This adaptability is especially valuable in SAR contexts, where conditions can change rapidly and unpredictability is a constant.

Through extensive simulation and validation, WOLF-SAR demonstrates its potential as a state-of-the-art tool in autonomous robotics, offering dynamic and efficient solutions in complex SAR operations. By harnessing the power of biomimicry and integrating it with advanced robotic technologies, WOLF-SAR sets a new benchmark for SAR robotics, offering a scalable and adaptable framework for future real-world applications in SAR and beyond.

2. Related Work

The development of multi-robot systems that exhibit collective behaviors akin to natural organisms has been an area of substantial interest in robotics. Duncan et al. studied lek behavior as a model for multi-robot systems, highlighting the importance of spatial distribution and behavioral roles in achieving complex group objectives[5]. While this provides a framework for understanding multi-robot interactions, it does not fully capture the dynamic role-switching and adaptive coordination required in SAR operations, which is a critical aspect of WOLF-SAR. Observations of wolves in natural settings have yielded significant insights into the strategies and dynamics of group hunting [11], [10]. Smith's documentation of wolves chasing prey provides real-world behavioral patterns that inform the design of WOLF-SARS' cooperative algorithms[11]. However, these insights alone do not translate into the autonomous decision-making algorithms necessary for robotic SAR applications. Weitzenfeld et al. further extended this understanding by developing a wolf pack hunting model for multiple robots, laying the groundwork for algorithmic role allocation and task execution in robotic systems [17]. WOLF-SAR builds upon these models by incorporating real-time environmental feedback and agent state information to adaptively reassign roles among SAR robots, an area not fully developed in Weitzenfeld's model. Research into the effects of group size on predatory success by MacNulty et al. suggests nonlinear relationships that could impact the design of cooperative multi-robot systems [10]. These findings inform the scaling aspects of WOLF-SAR, which must ensure effectiveness regardless of the number of robots deployed. Holling's exploration of predator-prey dynamics provides a foundational understanding of the functional responses required for effective bio mimetic emulation in robotic systems [7].

The ethogram proposed by MacNulty et al. for large-carnivore predatory behavior offers a detailed framework for the programming of behavioral sequences in robotic predators like those in WOLF-SAR [9]. This detailed behavioral lexicon, however, requires translation from biological to mechanical agents, a process that involves considerable innovation to maintain relevance in a SAR context. Abrantes' study on the evolution of canine social behavior and the comprehensive work on wolf ecology and conservation by Mech and Boitani provide in-depth insights into the social and environmental factors influencing wolf behavior [1], [13]. These works contribute to the socio-biological underpinnings of WOLF-SARS' behavioral algorithms but do not address the technical implementation of such behaviors in robotic systems. The robotics field has also seen significant developments in mission specification and execution for multi-agent systems. The work by Georgia Tech's Mobile Robotics Laboratory on MissionLab, and MacKenzie et al.'s research on multiagent mission specification, establish methods for defining and executing complex behaviors in robotic teams [8]. WOLF-SAR enhances these methods by allowing for a higher degree of autonomy and dynamic reactivity within each agent, a necessity for the unpredictable nature of SAR environments. Arkin's contributions to behavior-based robotics and motor schema-based navigation provide seminal methodologies for the design of autonomous robots [3], [2].

Rossi et al.'s made a comprehensive survey and application-focused review of collective behavior coordination algorithms for multi-agent systems. The paper classifies these algorithms based on their underlying mathematical structures and examines their scalability, bandwidth use, and demonstrated maturity. It serves as a guide to various mathematical techniques and identifies their applicability to multi-agent coordination tasks, offering insights valuable for the development of efficient and scalable multi-agent systems[15]. David Mechs' insights into the social and hunting behaviors of wolves have been instrumental in informing robotic systems that mimic these natural strategies, particularly in the context of cooperative algorithms and group dynamics[12]. Gerky et al explored how roles can be dynamically allocated among groups of robots. Their research often addresses how robotic agents can autonomously decide who should do what task, enhancing efficiency and adaptability in collaborative scenarios[6]. D. Couzin delves into the dynamics of collective decision-making in animal groups, such as swarming ants, schooling fish, and flocking birds. The paper emphasizes how group-level behaviors emerge from the interactions of individuals, highlighting the role of social interactions, individual state, and environmental factors in shaping collective action. Couzin draws parallels between collective animal behavior and neuronal processes, suggesting that understanding animal group dynamics can offer insights into the principles of cognitive science, particularly in the context of collective decision-making and information processing[4]. Rodriguez et al introduce a variation of the Rapidly-exploring Random Tree (RRT) algorithm that specifically focuses on efficiently navigating around obstacles. This obstacle-based RRT method enhances the standard algorithm's ability to plan paths in complex environments by prioritizing exploration in regions near obstacles, improving both the efficiency and effectiveness of path planning in scenarios where obstacles are a significant concern. The study demonstrates its utility through simulations, showing improved performance in navigating challenging environments[14]. Cumhur et al proposed the use of Rapidly-exploring Random Trees (RRT) as a method for testing automated vehicles. This approach focuses on creating diverse and challenging scenarios for vehicle testing, enhancing the robustness and reliability of automated vehicle systems. By employing RRT algorithms, the study aims to systematically and efficiently explore possible driving scenarios, including edge cases, to better validate and improve the safety and performance of autonomous vehicles[16].WOLF-SAR adopts and extends these principles, integrating them with bio mimetic strategies to form a cohesive system capable of intelligent, autonomous SAR operations.

3. Methodology

3.1. Wolf Hierarchy System

The wolf pack hierarchy system as shown in **Fig 1** is an important aspect of the WOLF-SAR methodology, as it mimics the social structure of real-world wolves to improve the coordination and efficiency of search and rescue (SAR) operations conducted by autonomous agents. The WOLF-SAR draws inspiration from the complex social structure of wolf packs in nature. Wolves are known for their intricate social hierarchy, which dictates the roles each member plays within the pack. This hierarchical structure ensures efficient hunting, territory defense, and pack unity.

In WOLF-SAR, each robotic agent (wolf) is assigned a role reflective of this hierarchy, which influences its behavior within the SAR operation:

Alpha Wolves: These are the lead agents responsible for decision-making and determining the overall strategy of the SAR operation. They guide the pack and are often the first to respond to dynamic changes in the operation.

Beta Wolves: Acting as the lieutenants, betas support the alpha in strategic planning and may take over the lead if an alpha is compromised. They are often involved in complex tasks that require a higher level of decision-making.

Delta Wolves: These agents carry out specialized roles such as scouts, trackers, or communicators. They provide essential support to the alpha and beta wolves by relaying information and executing specific tasks vital to the mission's success.

Omega Wolves: Typically the last in the hierarchy, omegas serve as the workforce of the operation. They follow the strategic directions set by the higher-tier wolves and perform the bulk of the search tasks within the designated areas.

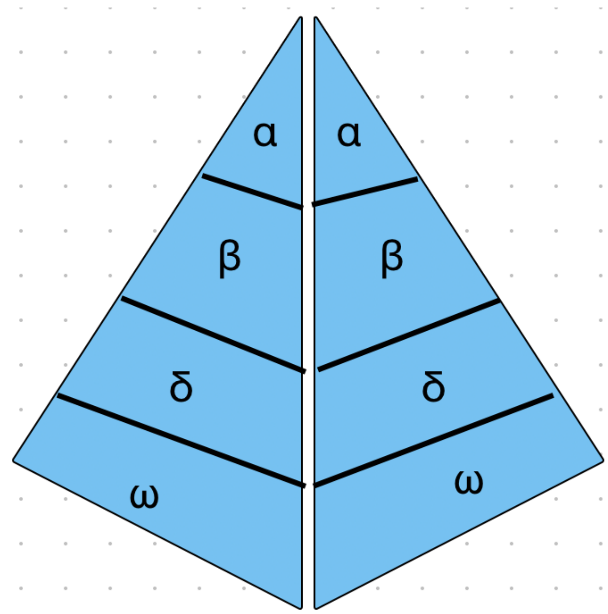

Figure 1. Hierarchy System in a pack of Wolves.

3.2. Environment

3.2.1 Environment Specifications

The environment is a 200 by 200 unit square, representing a confined area in which the robots must operate. This size is large enough to simulate a variety of scenarios while being manageable for computational simulations.

3.2.2 Levels of Difficulty

Easy Terrain (Level A): An open area with no obstacles, allowing for straightforward navigation and task execution. Ideal for baseline testing of path planning efficiency and task allocation.

Medium Complexity (Level B): Features minimal obstacles scattered throughout the grid. It introduces both rectangular and circular obstacles. These obstacles create more complex navigation challenges, requiring more advanced path-finding and obstacle avoidance strategies as shown in Figure 2.

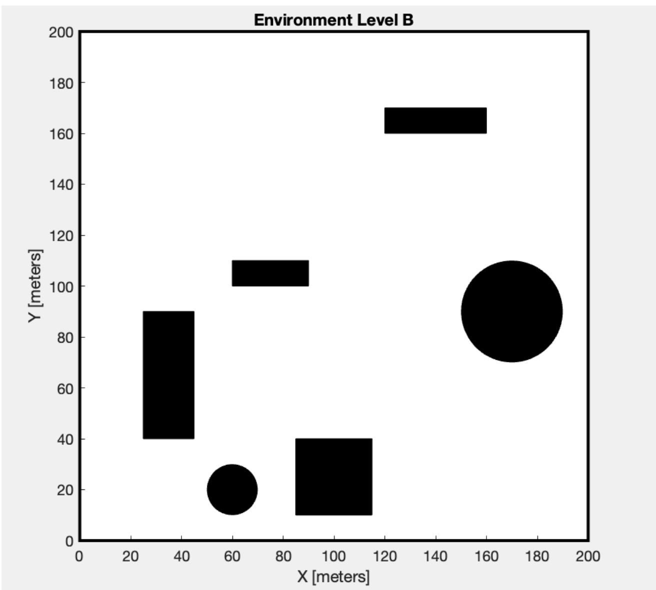

Figure 2. Environment Level B

Hard Terrain (Level C): Characterized by a high density of obstacles, simulating challenging and unpredictable environments like disaster zones or dense forests. This level tests the system's capability to handle complex navigation and task execution under restrictive conditions as shown in Figure 3.

Each level progressively increases in complexity, offering a comprehensive assessment of the WOLF-SAR system's performance in varying scenarios.

3.3. Initialization

The initialization process of the agents within WOLF-SAR is performed through two primary methods. Creating a function which designed to encapsulate the path information into an individual wolf agent. It serves the purpose of translating the RRT-generated path, which may be in a cell array format, into a consistent matrix form for easier manipulation and evaluation. The initialization of the wolf's fitness to infinity indicates that until an actual path is evaluated, the wolf's efficiency is considered to be undefined or

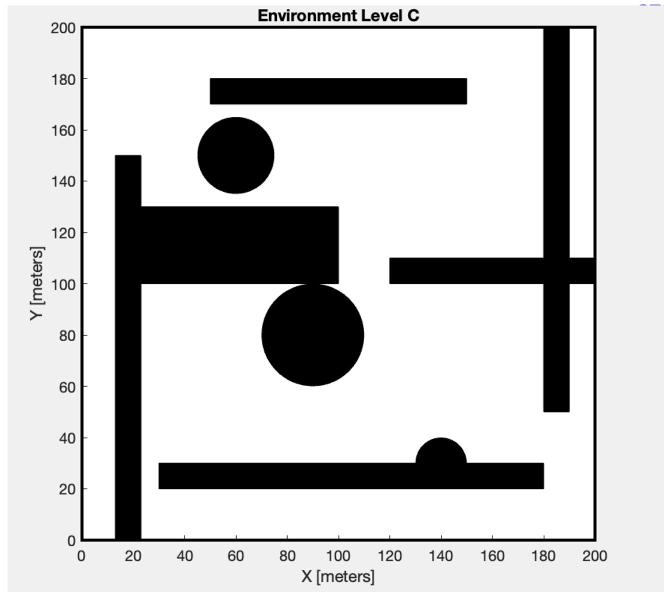

Figure 3. Environment Level C

the worst possible.

Implementing a function that iterates over a collection of paths provided by the RRT algorithm, creating a wolf agent for each path. This function allows the application of above mentioned function to each element of the RRT path array, resulting in an array of wolf agents, each with its associated path and initial fitness score.

3.4. Rapidly Exploring Random Trees(RRT)

The WOLF-SAR system employs the Rapidly-exploring Random Tree (RRT) algorithm as its core path planning strategy, fundamental to the system's operational efficiency in search and rescue (SAR) scenarios. RRT is a prominent algorithm in the field of robotics for its proficiency in navigating complex and high-dimensional spaces. RRT works by randomly building a space-filling tree that grows towards unexplored regions of the search space. It starts from an initial node (usually the starting position of the robot) and extends the tree by adding new nodes, aiming to rapidly and uniformly explore the space.

The methodological foundation of RRT is relatively straightforward but powerful. It begins with the creation of a tree rooted at the starting position. From here, the algorithm iteratively extends the tree by generating random nodes within the search space and connecting these to the nearest existing node in the tree. This process is underpinned by calculating the Euclidean distance as shown in (1) where q represents a node in the tree, and q_{rand} is the newly sampled point.

$$d(q, q_{\text{rand}}) = \sqrt{(q_{\text{rand}}.x - q.x)^2 + (q_{\text{rand}}.y - q.y)^2}$$

(1)

Then a new node q_{new} is generated towards q_{rand} from the node q_{near} using the step size Δq as mentioned in (2):

$$q_{\text{new}} = q_{\text{near}} + \Delta q \cdot \frac{(q_{\text{rand}} - q_{\text{near}})}{\|q_{\text{rand}} - q_{\text{near}}\|} \tag{2}$$

This ensures that the new node is within a reachable distance from q_{near}.Then collision check is done to ensure if the path segment between q_{near} and q_{new} is free of obstacles and ensuring safe navigation. If no collision is detected, q_{new} is added to the tree. This process repeats until the tree approaches the goal within an acceptable margin.

Our WOLF-SAR is integrated with the RRT to heighten the effectiveness of SAR operations. In this system, each robotic agent, akin to a wolf, initializes its own RRT, thereby simulating the potential paths a wolf would take during a coordinated hunt. This bio-mimetic adaptation of RRT extends beyond mere path generation; it imbues the agents with roles reflective of a wolf pack's structure, such as scouts and hunters, each with their unique responsibilities within the SAR mission.

3.5. Fitness-Score

A function is created to calculate the fitness score which mirrors the efficiency and effectiveness of a wolf pack's movement across a landscape. In SAR operations, just as a wolf pack must efficiently traverse terrain while avoiding hazards, the WOLF-SAR system evaluates paths for robotic agents based on length and safety. Paths that are shorter and avoid obstacles are akin to a wolf pack choosing efficient hunting routes while steering clear of potential threats. Within WOLF-SAR, the path length is analogous to a wolf pack's travel distance during a hunt. The function assesses the cumulative distance that a robotic agent would cover, seeking to minimize it, much like a pack would opt for the most direct, energy-conserving path to their prey. Obstacles in the environment represent potential dangers to both wolves and robots alike. a function is created in WOLF-SAR which is a strategic component that imposes penalties for paths leading too close to obstacles, much as a wolf would instinctively avoid unnecessary risks while navigating the wild.

The weighted fitness score, which combines path length and obstacle penalty, reflects the hierarchical decision-making process of a wolf pack. In WOLF-SAR, different weights can represent the varying roles within the pack, such as scouts prioritizing path safety over speed, or hunters favoring the quickest route to the target. These supporting functions are crucial for maintaining the pack's integrity, ensuring that each member — or in this case, each robotic agent — maintains a safe distance from potential hazards. This cooperation is vital in SAR scenarios, where the collective success of the mission depends on the individual safety and effectiveness of each agent.

3.6. Simulation

The core of the methodology lies in the innovative use of the Rapidly-exploring Random Tree (RRT) algorithm, which provides a stochastic yet structured approach to navigating through diverse terrains. This simulation focuses on emulating the adaptive strategies that wolves employ during a hunt, applying these to robotic agents in a SAR context. The simulation unfolds in a predefined environment with varying levels of difficulty, where rectangular and circular obstacles are strategically placed to mimic real-world impediments. Each agent, represented as a 'wolf' in the simulation, initiates an RRT from its starting position, exploring the environment by extending a tree towards random points. The algorithm prioritizes growth towards the goal, or 'prey,' while avoiding collisions with obstacles. The 'fitness' of each path is determined by a combination of its length and proximity to obstacles, encouraging not only the shortest route but also the safest. Adhering to the hierarchical structure of wolf packs, the agents are assigned roles such as Alpha, Beta, Delta and Omega, dictating their responsibilities and influence within the simulation. Alphas lead the pack, Betas support in decision-making, and Omegas act according to the directives, ensuring a coordinated effort in the SAR operation. This structured approach allows for a methodical and comprehensive coverage of the search area. Upon reaching the prey, the simulation backtracks to determine the most efficient path taken by the agent, optimizing the route for future iterations. Additionally, the simulation can adapt to changes in real-time, a feature that, while not currently implemented, is anticipated in the evolution of WOLF-SAR to enhance its applicability in dynamic and unpredictable SAR scenarios.

4. Results

In the execution of the WOLF-SAR algorithm the results are depicted in a visual representation, where each line traces the path taken by the corresponding wolf agent, classified into roles such as Alpha, Beta, Delta, and Omega, based on their path lengths and fitness scores. The WOLF-SAR system's simulation on various complexity levels of the environment—denoted as A, B, and C—provided insightful data into the system's performance and the efficacy of the Rapidly-exploring Random Tree (RRT) path planning algorithm.

In environment Level A, characterized by its lack of obstacles, the performance metrics indicate an efficient pathfinding with minimal deviation. The Alpha Wolf, leading the pack, demonstrates a path length of 130 units and a corresponding fitness score that reflects the least hindrance and a direct approach towards the objective. The paths generated for the Alpha, Beta, Delta, Omega1, Omega2, Omega3, and Omega4 wolves were evaluated for their length and fitness scores, with the Alpha wolf achieving a path length of 130 units and a corresponding fitness score of 130. This indicates a direct and obstacle-free path to the target, exemplifying the Alpha's role in leading the pack. As anticipated, the Beta and Delta wolves followed with marginally longer paths of 140 units, reflecting their support roles in the search operation. The Omega wolves, designated as the last tier in the hierarchical structure, displayed longer path lengths ranging from 150 to 190 units. These results validate the hierarchical path planning strategy embedded within WOLF-SAR, where leadership roles are clearly delineated, and the division of tasks is apparent through the path lengths and associated fitness scores. The Figures 4, 5 illustrates the path taken by the wolves during exploration and exploitation and their final paths. The Figure 6 shows the path lengths and fitness scores.

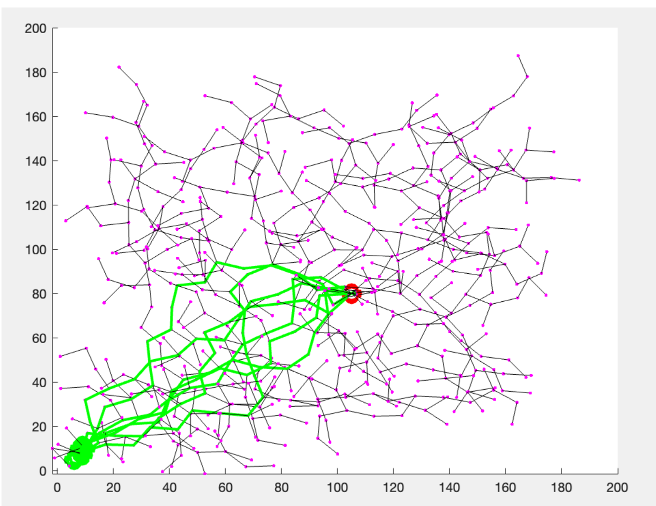

Figure 4. Paths of each Wolf during the tree exploration of Map-A

Map B introduced a higher complexity environment with a denser distribution of obstacles. The Alpha wolf's path length increased to 230 units with a fitness score of 255.23, suggesting more intricate navigation was required. The Beta, Delta, and Omega wolves demonstrated increased path lengths and fitness scores, with the Omega4 wolf's path length reaching 320 units and a fitness score of 460.95. The increased path lengths and fitness scores for Map B are indicative of the adaptability of WOLF-SAR's algorithms to more challenging environments. The fitness scores, which account for both path length and obstacle avoidance, show a direct correlation with the complexity of the terrain, confirming that the WOLF-SAR system maintains its search efficiency even as environmental challenges escalate. In

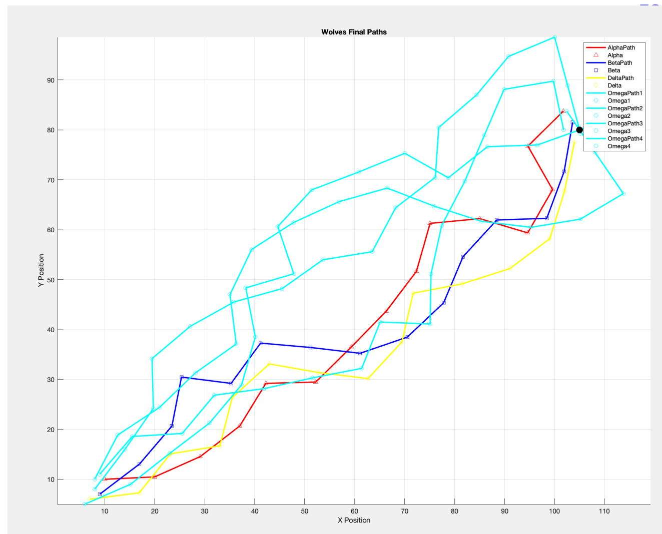

Figure 5. The final Paths(Map-A)

```
Alpha Wolf Path Length: 140.000000
Alpha Wolf Fitness Score: 140.000000
Beta Wolf Path Length: 140.000000
Beta Wolf Fitness Score: 140.000000
Delta Wolf Path Length: 140.000000
Delta Wolf Fitness Score: 140.000000
Omega1 Wolf Path Length: 150.000000
Omega1 Wolf Fitness Score: 150.000000
Omega2 Wolf Path Length: 150.000000
Omega2 Wolf Fitness Score: 150.000000
Omega3 Wolf Path Length: 160.000000
Omega3 Wolf Fitness Score: 160.000000
Omega4 Wolf Path Length: 160.000000
Omega4 Wolf Fitness Score: 160.000000
```

Figure 6. Path Lengths and Fitness Scores(Map-A)

Environment Level B, the system faced increased challenges with the introduction of scattered obstacles. Here, the strategic allocation of roles within the wolf pack became evident. The Alpha wolf maintained its lead, though with a lengthier path due to necessary detours. Notably, the Beta and Delta wolves demonstrated the system's adaptive capabilities, altering their paths responsively. The fitness scores in this environment reflected the additional complexity, with slightly elevated values indicating the system's efforts to negotiate the obstacles while still prioritizing path efficiency.The Figures 7, 8 illustrates the path taken by the wolves during exploration and exploitation and their final paths. The Figure 9 shows the path lengths and fitness scores.

The most complex terrain, Environment Level C, put the WOLF-SAR system to a rigorous test. The intricate web

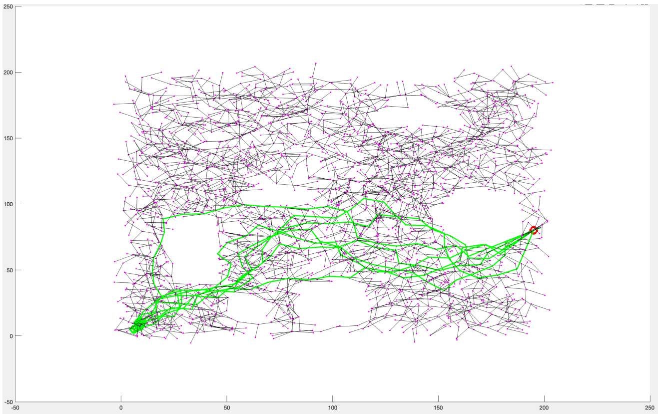

Figure 7. Paths of each Wolf during the tree exploration of Map-B

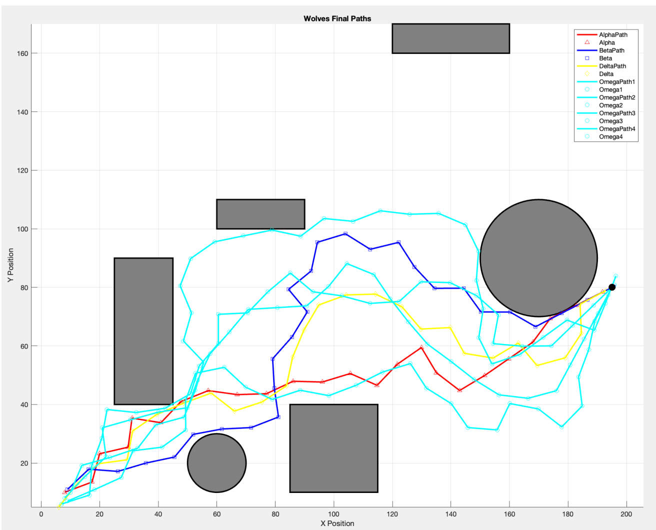

Figure 8. The final Paths(Map-B)

```
Alpha Wolf Path Length: 230.000000
Alpha Wolf Fitness Score: 255.235428
Beta Wolf Path Length: 270.000000
Beta Wolf Fitness Score: 280.699134
Delta Wolf Path Length: 260.000000
Delta Wolf Fitness Score: 289.074484
Omega1 Wolf Path Length: 270.000000
Omega1 Wolf Fitness Score: 294.028704
Omega2 Wolf Path Length: 270.000000
Omega2 Wolf Fitness Score: 298.166228
Omega3 Wolf Path Length: 270.000000
Omega3 Wolf Fitness Score: 349.313694
Omega4 Wolf Path Length: 320.000000
Omega4 Wolf Fitness Score: 460.954330
```

Figure 9. Path Lengths and Fitness Scores(Map-B)

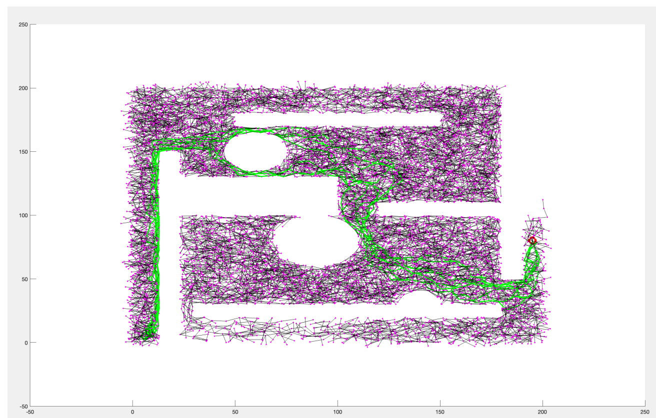

Figure 10. Paths of each Wolf during the tree exploration of Map-C

of paths generated by the RRT algorithm showed an intensive search pattern. Despite the dense array of obstacles, the Alpha wolf's path remained the most direct, although significantly lengthier than in simpler environments. The increase in fitness scores across the pack was indicative of the heightened difficulty, with the Omega wolves displaying the largest paths and corresponding fitness values. This environment underscored the system's dynamic path planning and obstacle avoidance capabilities, crucial for real-world SAR operations. The Figures 10, 11 illustrates the path taken by the wolves during exploration and exploitation and their final paths. The Figure 12 shows the path lengths and fitness scores.

5. Conclusion

The WOLF-SAR simulation represents a significant stride in the application of bio-inspired algorithms for search and rescue (SAR) operations. Through the emulation of wolf pack tactics and the integration of Rapidly-exploring Random Tree (RRT) algorithms, WOLF-SAR has demonstrated notable success in pathfinding across a spectrum of environmental complexities. The system's performance in simulations of varying difficulty levels, from open terrains to obstacle-dense environments, underscores its adaptability and robustness. The Alpha wolf, indicative of the lead SAR unit, consistently found efficient paths to the objective, albeit with increased path lengths and fitness scores in more complex scenarios. This mirrors the expected behavior in real-world SAR operations, where the leading units often have to navigate through the most challenging conditions. Despite the promising outcomes, there remains room for improvement in WOLF-SAR's design. Currently, the system operates under the assumption of a static prey or target location. In a real-world context, SAR operations frequently involve dynamic elements, such as moving individuals or shifting hazards. Future iterations

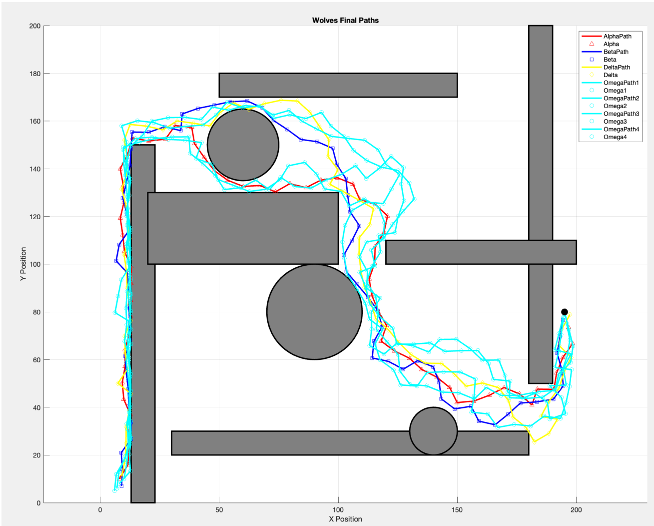

Figure 11. The final Paths(Map-C)

```
Alpha Wolf Path Length: 462.000000
Alpha Wolf Fitness Score: 1365.273178
Beta Wolf Path Length: 483.000000
Beta Wolf Fitness Score: 1381.749260
Delta Wolf Path Length: 504.000000
Delta Wolf Fitness Score: 1408.063949
Omega1 Wolf Path Length: 483.000000
Omega1 Wolf Fitness Score: 1417.394523
Omega2 Wolf Path Length: 539.000000
Omega2 Wolf Fitness Score: 1543.133455
Omega3 Wolf Path Length: 490.000000
Omega3 Wolf Fitness Score: 1544.450104
Omega4 Wolf Path Length: 525.000000
Omega4 Wolf Fitness Score: 1688.536521
```

Figure 12. Path Lengths and Fitness Scores(Map-C)

of WOLF-SAR could benefit from incorporating algorithms that account for such dynamics, enabling a more realistic and practical application of the system.

Furthermore, the current model could be expanded to include more nuanced behaviors observed in natural wolf packs, such as stealth and ambush tactics, which may translate into more strategic SAR approaches in environments with varying visibility or accessibility.Another avenue for development is the optimization of computational resources. As SAR operations may involve extensive search areas, scaling WOLF-SAR to efficiently cover vast terrains without taxing computational resources could make the system more viable for large-scale deployment.Additionally, integration with real-time data sources, such as satellite imagery and drone reconnaissance, could provide WOLF-SAR with up-to-the-minute environmental information, enhancing its real-time decision-making capabilities.The prospects of machine learning and artificial intelligence also offer transformative potential for WOLF-SAR. By learning from past simulations and actual SAR missions, the system could evolve to predict obstacles, identify the most likely areas where survivors may be located, and even adapt to different SAR scenarios autonomously. In conclusion, WOLF-SAR stands as a testament to the power of bio-inspired computational models in addressing complex real-world problems. With continued development and integration of advanced computational methods, the future scope of WOLF-SAR is not only to match but to exceed the capabilities of its biological counterparts, offering a valuable asset in the critical domain of SAR operations.

References

[1] R. Abrantes. *Evolution of canine social behavior*. Dogwise Publishing, 2004.

[2] R. C. Arkin. Motor schema—based mobile robot navigation. *The International journal of robotics research*, 8(4):92–112, 1989.

[3] R. C. Arkin. *Behavior-based robotics*. MIT press, 1998.

[4] I. D. Couzin. Collective cognition in animal groups. *Trends in cognitive sciences*, 13(1):36–43, 2009.

[5] B. A. Duncan, P. D. Ulam, and R. C. Arkin. Lek behavior as a model for multi-robot systems. In *2009 IEEE International Conference on Robotics and Biomimetics (ROBIO)*, pages 25–32. IEEE, 2009.

[6] B. P. Gerkey and M. J. Matarić. A formal analysis and taxonomy of task allocation in multi-robot systems. *The International journal of robotics research*, 23(9):939–954, 2004.

[7] C. S. Holling. The functional response of predators to prey density and its role in mimicry and population regulation. *The Memoirs of the Entomological Society of Canada*, 97(S45):5–60, 1965.

[8] D. C. MacKenzie, R. C. Arkin, and J. M. Cameron. Multiagent mission specification and execution. *Robot colonies*, pages 29–52, 1997.

[9] D. R. MacNulty, L. D. Mech, and D. W. Smith. A proposed ethogram of large-carnivore predatory behavior, exemplified by the wolf. *Journal of Mammalogy*, 88(3):595–605, 2007.

[10] D. R. MacNulty, D. W. Smith, L. D. Mech, J. A. Vucetich, and C. Packer. Nonlinear effects of group size on the success of wolves hunting elk. *Behavioral Ecology*, 23(1):75–82, 2012.

[11] J. D. Madden, R. C. Arkin, and D. R. MacNulty. Multi-robot system based on model of wolf hunting behavior to emulate wolf and elk interactions. In *2010 IEEE International Conference on Robotics and Biomimetics*, pages 1043–1050. IEEE, 2010.

[12] L. D. Mech. Alpha status, dominance, and division of labor in wolf packs. *Canadian journal of zoology*, 77(8):1196–1203, 1999.

[13] L. D. Mech and L. Boitani. *Wolves: behavior, ecology, and conservation*. University of Chicago Press, 2019.

[14] Rodriguez, X. Tang, J.-M. Lien, and N. Amato. An obstacle-based rapidly-exploring random tree. In *Proceedings 2006 IEEE International Conference on Robotics and Automation, 2006. ICRA 2006.*, pages 895–900, 2006.

[15] F. Rossi, S. Bandyopadhyay, M. T. Wolf, and M. Pavone. Multi-agent algorithms for collective behavior: A structural and application-focused atlas. *arXiv preprint arXiv:2103.11067*, 2021.

[16] C. E. Tuncali and G. Fainekos. Rapidly-exploring random trees for testing automated vehicles. In *2019 IEEE Intelligent Transportation Systems Conference (ITSC)*, pages 661–666, 2019.

[17] A. Weitzenfeld, A. Vallesa, and H. Flores. A biologically-inspired wolf pack multiple robot hunting model. In *2006 IEEE 3rd Latin American Robotics Symposium*, pages 120–127. IEEE, 2006.