Intelligent Control of a Swarm of Reconnaissance Robots for Terrain Monitoring Tasks

Abzal E. Kyzyrkanov[1,2], Sabyrzhan K. Atanov[2], Shadi A. Aljawarneh[3] and Nazira A. Tursynova[2]

[1] *Astana IT University, Astana, 010000, Kazakhstan*
[2] *L.N. Gumilyov Eurasian National University, Astana, 010000, Kazakhstan*
[3]*Jordan University of Science and Technology, Irbid, 22110, Jordan*

Abstract

This paper introduces an algorithm developed for the intelligent control of a swarm of reconnaissance robots tasked with terrain monitoring. At its core, the algorithm harnesses fuzzy logic to significantly enhance decision-making in terms of optimal direction selection and velocity adjustments. These features are vital for the effective exploration and monitoring of diverse terrains. The algorithm is designed to achieve several key objectives: maintaining a specific formation, avoiding obstacles with precision, and optimizing power usage for extended operations. A distinctive aspect of this approach is the incorporation of a leader-follower dynamic, directed by a virtual leader, which allows for adaptable and cohesive movement coordination within the swarm. Moreover, the algorithm integrates strategies for energy conservation, including the selective deactivation of Lidars, thus striking a balance between efficient obstacle detection and power management. This innovative algorithm stands as a significant advancement in the realm of reconnaissance robotics, showcasing the transformative impact of fuzzy logic in refining movement coordination and enhancing the operational efficiency of robots engaged in terrain monitoring tasks.

Keywords

Swarm robotics, terrain monitoring, reconnaissance robots, fuzzy logic, intelligent control systems, obstacle avoidance, autonomous navigation, energy efficiency in robotics, leader-follower dynamics, lidar technology

1. Introduction

The advancement of robotics has been pivotal in revolutionizing both industrial processes [1] and day-to-day activities [2], penetrating areas where human involvement is difficult or impracticable, such as combat [4], deep-sea [5], and space exploration [6].

Throughout its evolution, robotics has seen an array of methodologies aimed at augmenting the efficacy of robots. For instance, work [7] has developed optimal control models for automobile transport, while others have considered the challenges of IoT communications in 5G networks [8]. With the dawn of new 6G/IoE technology [9] and the proposal of lightweight cryptography systems for IoT devices using DNA [10], the field continues to expand. Additionally, the exploration into the advantages and limitations of educational portals with blockchain technology elements in higher education institutions has been noted [11].

Group robotics, where multiple robots are deployed for intricate tasks, stands out in this landscape. This approach has been a central focus of research for a considerable time, allowing multiple simple robots to solve a single complex problem.

Swarm robotics, a subset of group robotics, which emerged approximately three decades ago [12], has garnered considerable focus. This paradigm, inspired by the behavior of social creatures like ants [13] and bees [14], encompasses not only conventional-sized robots but also more

DTESI 2023: Proceedings of the 8th International Conference on Digital Technologies in Education, Science and Industry, December 06–07, 2023, Almaty, Kazakhstan
kyzyrkanov.abzal@astanait.edu.kz (A.E. Kyzyrkanov); atanov5@mail.ru (S.K. Atanov); saaljawarneh@just.edu.jo (Sh.A. Aljawarneh); ntursynova000@gmail.com (N.A. Tursynova)
0000-0002-8817-8617 (A.E. Kyzyrkanov); 0000-0003-2115-7130 (S.K. Atanov); 0000-0003-3972-5300 (Sh.A. Aljawarneh); 0000-0002-1857-9028 (N.A. Tursynova)

innovative domains like nanorobots, which are on par with molecular dimensions [15], and aerial entities like drones [16].

A primary challenge within swarm robotics lies in developing algorithms that permit autonomous robots to collaborate efficiently. This entails overcoming hurdles like collision avoidance, with extensive research dedicated to addressing these challenges [17, 18].

Incorporating fuzzy logic into robotics, especially within the swarm robotics context, offers a promising avenue forward [19]. Fuzzy logic's ability to process ambiguous and uncertain data makes it apt for intricate decision-making scenarios in robotics, facilitating more intuitive reasoning in unpredictable environments. Moreover, formation control stands as an area where fuzzy logic can be pivotal, aiming at directing a group of robots to adopt specific patterns and move cohesively.

Furthermore, energy conservation is paramount in robotic swarms, especially during prolonged terrain monitoring missions [20]. The algorithm proposed in this paper acknowledges this need, meticulously modulating the power consumption of individual robots, thereby enhancing their operational longevity and efficiency.

Conclusively, this paper introduces an innovative algorithm for the coordinated movement of reconnaissance robots for terrain monitoring tasks. Grounded in the principles of fuzzy logic and energy efficiency, this algorithm signifies a marked advancement in the domain of swarm robotics, enriching the broader discourse on the integration of fuzzy logic and energy-saving measures in robotics, underscoring their value in refining algorithm development and control strategies for complex, real-world endeavours.

2. Problem formulation and background

In the realm of autonomous robotics, one significant challenge is developing an intelligent control system for a swarm of reconnaissance robots designated for terrain monitoring tasks. This complex problem encompasses several key aspects that are crucial for the successful deployment and operation of the robotic swarm.

The foremost issue is the coordination and control of multiple autonomous agents. Each robot within the swarm possesses unique capabilities and operates under specific constraints. The control mechanism needs to ensure that all robots function cohesively, understanding their individual roles and responding appropriately to environmental stimuli and the actions of their peers.

Additionally, the swarm must navigate through diverse terrains while maintaining a specified formation. This formation is critical for maximizing coverage and data collection efficiency. Maintaining formation isn't just about geometric positioning; it also involves dynamic adjustments in response to environmental changes and unforeseen obstacles.

Obstacle avoidance is another significant aspect of this problem. The robots must be able to identify obstacles in their path and adjust their movements accordingly, without compromising the mission objectives or the formation integrity. This requires sophisticated sensing and decision-making capabilities embedded within each unit of the swarm.

Energy conservation is a crucial factor in the design of the control system. Operating a swarm of robots can be energy-intensive, especially when considering the power needed for movement, sensing, and communication. An intelligent control system must optimize energy usage, ensuring the longevity of the mission and minimizing the frequency of recharging or refuelling intervals.

Finally, the system must be capable of handling real-time data processing and decision-making. With the swarm being deployed in dynamic environments, the control mechanism needs to rapidly process sensory data, make informed decisions, and adjust the behaviour of the robots accordingly. This requires a robust and flexible algorithm capable of adapting to changing conditions and optimizing the swarm's performance.

In conclusion, the control of a swarm of reconnaissance robots for terrain monitoring involves addressing challenges in coordination, formation maintenance, obstacle avoidance, energy conservation, and real-time decision-making. The solution to this problem would significantly enhance the capabilities and efficiency of robotic swarms in various monitoring and exploration applications.

2.1. Efficient power management through selective rangefinder activation

Contemporary rangefinders have the capability to identify obstacles from extensive distances, with some able to detect objects many times the swarm's overall size. Despite their impressive range, these devices consume substantial amounts of power, posing a challenge for prolonged missions.

To mitigate this challenge and conserve energy, an approach is proposed where robots intermittently switch off their rangefinders and instead rely on the spatial orientation and movements of their adjacent peers. Robots situated centrally or towards the back of the group, for example, can effectively navigate by mirroring the actions of those leading the formation.

The approach described in this paper integrates this concept of intermittent rangefinder activation. Rangefinders are activated selectively, predominantly by the robots in front or in situations necessitating acute obstacle detection. This judicious use of rangefinders plays a pivotal role in reducing energy consumption, thereby boosting the endurance and operational effectiveness of the swarm.

2.2. Leader-follower approach

The essence of the leader-follower model hinges on the followers consistently maintaining a predetermined distance from the leader. In this context, both the leader and the followers are conceptualized as points on a plane, and their respective positions enable the calculation of the distance between them. This measured distance becomes the targeted spacing that the followers aim to uphold (Figure 1).

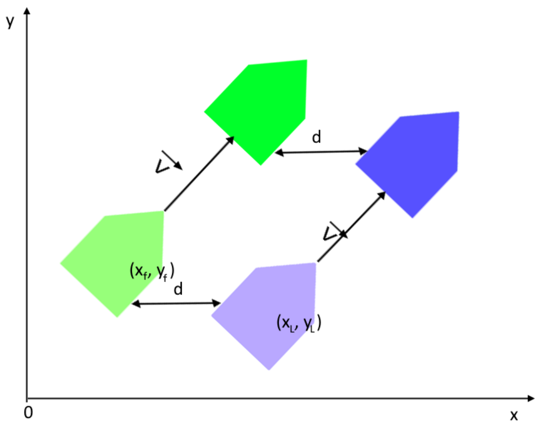

Figure 1: Leader-follower approach

However, designating a physical robot as the leader introduces a potential vulnerability. If the leader encounters any malfunction, it could jeopardize the functionality of the entire swarm. To circumvent this issue, the concept of a virtual leader is introduced. Unlike a physical leader, the virtual leader's position is typically centralized within the swarm, providing a reference point for the followers. This virtual leader strategy enhances the resilience of the swarm by eliminating dependence on a single, potentially fallible, physical leader. It ensures continuity of operation even in the face of individual robot failures, thereby bolstering the stability and robustness of the swarm's coordinated movements.

2.3. Integration of Fuzzy Logic for Enhanced Decision Making

Fuzzy logic plays a pivotal role in refining the decision-making process within the swarm. By incorporating fuzzy logic systems, the swarm's response to environmental variables and internal parameters is significantly enhanced. This logic system operates on the principle of degrees of truth rather than the conventional binary true or false. This nuanced approach allows for more flexible and adaptive responses to a variety of situations.

In the context of swarm robotics, fuzzy logic is utilized to determine the optimal direction and velocity for the robots. This involves processing a multitude of inputs such as proximity to obstacles, alignment with the virtual leader, and the positions of neighbouring robots. The fuzzy logic system interprets these inputs, which often contain uncertainties and imprecisions, and computes the most suitable course of action.

This approach is particularly beneficial in terrain monitoring tasks, where the environment can be unpredictable and full of uncertainties. The fuzzy logic system enables the swarm to navigate effectively through such terrains by making real-time adjustments based on the sensory data it receives.

Moreover, the adoption of fuzzy logic contributes to the overall efficiency of the swarm. It allows for smoother coordination and movement, reducing the likelihood of abrupt or erratic manoeuvres that could disrupt the formation or lead to increased energy consumption. By ensuring more consistent and harmonious movements within the swarm, fuzzy logic not only enhances operational effectiveness but also contributes to energy conservation.

3. Design of algorithm

The algorithm initiates with the swarm embarking towards the predetermined goal. Within the swarm, the robots perpetually adjust their velocity at regular intervals. The motion's velocity vector can be conceptualized as a pair (v, w), where 'v' signifies the linear velocity, measured in meters per second, and 'w' denotes the rotation angle.

As per the algorithm outlined in this paper, the linear velocity remains constant throughout; it's the direction that undergoes alterations. The initial step involves calculating the virtual leader's position using specific formulas. Subsequently, based on the motion's direction, the robots equipped with active lidars, termed as observers, are identified. All other robots in the swarm deactivate their lidars to optimize power consumption. Typically, activating the lidars of only three observer robots suffices the central leading robot, identified as the middle observer, and two flank robots, labelled as the left and right observers. When altering direction, the rangefinders on the left and right are slightly angled to prevent encountering obstacles. The selection of these observer robots is contingent on the swarm's directional orientation.

To calculate the angular velocity, Fuzzy Logic is employed. This method assesses the proximity to any detected obstacle by the operational rangefinders and the target's location. The incorporation of Fuzzy Logic facilitates a more nuanced and adaptable calculation of angular velocity, enabling the swarm to respond dynamically to varying environmental conditions.

This section delves into a detailed explanation of each step within the algorithm.

3.1. Determination of the virtual leader's position and observer identification

The virtual leader's coordinates are determined by the arithmetic mean of the group robots' coordinates. By recentering the coordinate system to the virtual leader's position and rotating the X-axis towards the swarm's direction, the identification of observer robots becomes straightforward.

This new coordinate system is depicted in Figure 2, where (x_i, y_i) represents the ith robot's position, (x_L, y_L) indicates the virtual leader's position, w is the moving direction, and (x'_i, y'_i) are the ith robot's coordinates in the adjusted system.

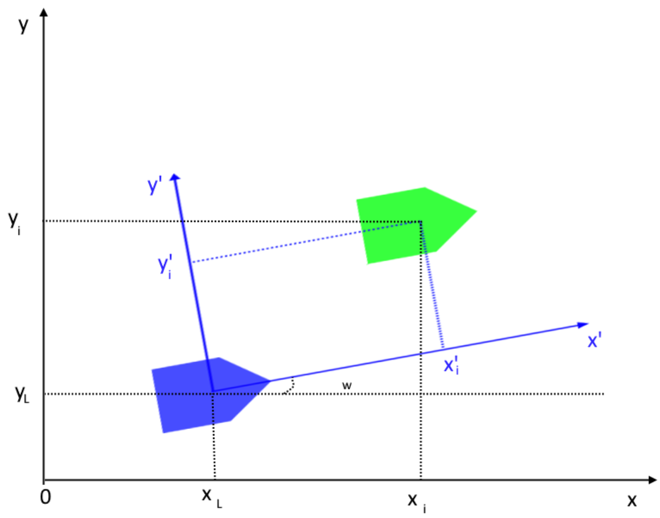

Figure 2: Switching coordination

As an illustrative example, Fig. 4 demonstrates the process of observer definition. The central rangefinder is activated on the robot that is foremost in the motion direction. In other words, the average observer is the robot with the maximum x' value in the new coordinate system.

The identification of the left and right observers follows a similar rationale. These robots are selected based on their maximum distance from the middle, i.e., from the x-axis. The robot with the highest y' value activates the rangefinder on the left, while the robot with the lowest y' value activates the rangefinder on the right.

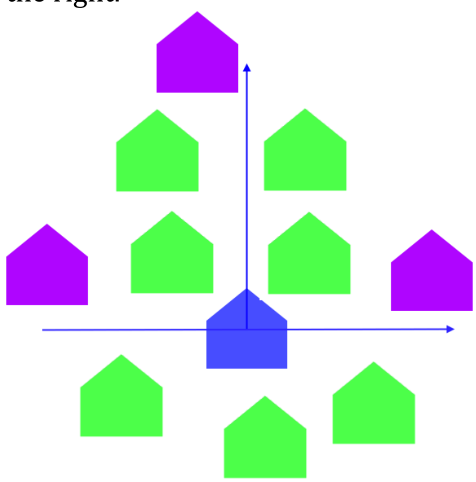

Figure 3: Selecting observers. Virtual leader is shown as blue and observers are shown as purple

3.2. Calculation of the angular velocity using fuzzy logic

The determination of angular velocity in the swarm of autonomous robots employs a sophisticated fuzzy logic system. This system takes into account various inputs to ascertain the optimal angular velocity for the swarm.

The inputs and the output are represented using membership functions, which define the degree to which a particular input or output belongs to a fuzzy set. Inputs to the Fuzzy Logic Controller are:

- Range of Lidars: The ranges detected by the lidars of the three observers are crucial inputs. These ranges are categorized as close, far, or not detected.
- Current Angular Velocity: The present state of angular velocity is also an input, which is classified into categories like sharp left, left, straight, right, or sharp right.

- Goal Position Relative to Current Velocity: The relative positioning of the goal with respect to the current velocity of the swarm is another significant input. This position could be to the left, directly in front, or to the right of the swarm.

The system uses a set of fuzzy rules that map the inputs to an output. These rules are formed based on expert knowledge and the specific dynamics of the swarm.

The output from this fuzzy logic system is a suggested adjustment to the angular velocity. This suggested adjustment is a fuzzy set comprising potential adjustments such as turning left (an adjustment of minus 15 degrees), maintaining the current direction (an adjustment of 0 degrees), or turning right (an adjustment of plus 15 degrees).

To convert the fuzzy output into a precise angular velocity adjustment, the centroid defuzzification process is employed. The centroid defuzzification is determined using the equation:

$$V_{adjust} = \frac{\sum V_{possibility} * \mu(V_{possibility})}{\sum \mu(V_{possibility})} \tag{1}$$

Where V_{adjust} represents the angular velocity adjustment calculated by the defuzzification process, $V_{possibility}$ denotes the possible angular velocity adjustments, namely minus 15, 0, and plus 15 degrees, $\mu(V_{possibility})$ signifies the membership degree for each potential adjustment in the fuzzy output set.

In this equation, each potential angular velocity adjustment is multiplied by its corresponding membership degree in the fuzzy output set. This product is then summed and divided by the sum of all the membership degrees, resulting in the weighted average that gives the precise adjustment to be made to the angular velocity.

The value V_{adjust}, obtained from the centroid defuzzification process, is added to the current angular velocity (V_{old}) of the swarm. This ensures coordinated and efficient movement, as the adjustment is based on a thorough analysis of the current conditions and objectives of the swarm, encompassing the intricate dynamics of motion and obstacle avoidance.

$$V_{new} = V_{old} + V_{adjust} \tag{2}$$

Where V_{new} represents the new angular velocity to be applied uniformly across all members of the swarm.

4. Experiments

In order to validate the effectiveness of the proposed algorithm, an experimental study was conducted using a custom-built simulator. This simulator was designed using the Python programming language and augmented with functionalities from the Pygame module. The objective of these experiments was to closely monitor the behaviour of the swarm under various conditions and to evaluate the performance of the developed algorithm in a controlled environment.

The experimental setup is visualized in Figure 4, which captures the initial state of the simulation. This representation includes.

- Robots: Nine autonomous robots are depicted as green circles, positioned to commence their navigational task.
- Virtual Leader: The pivotal component of the swarm, the virtual leader, is represented by a blue star, guiding the collective movement of the robots.
- Obstacles: To assess the obstacle avoidance capability of the algorithm, four obstacles are introduced in the simulation environment, depicted as black rectangles.

Goal Position: The target destination for the swarm is indicated by a red circle, serving as the focal point for the swarm's movement.

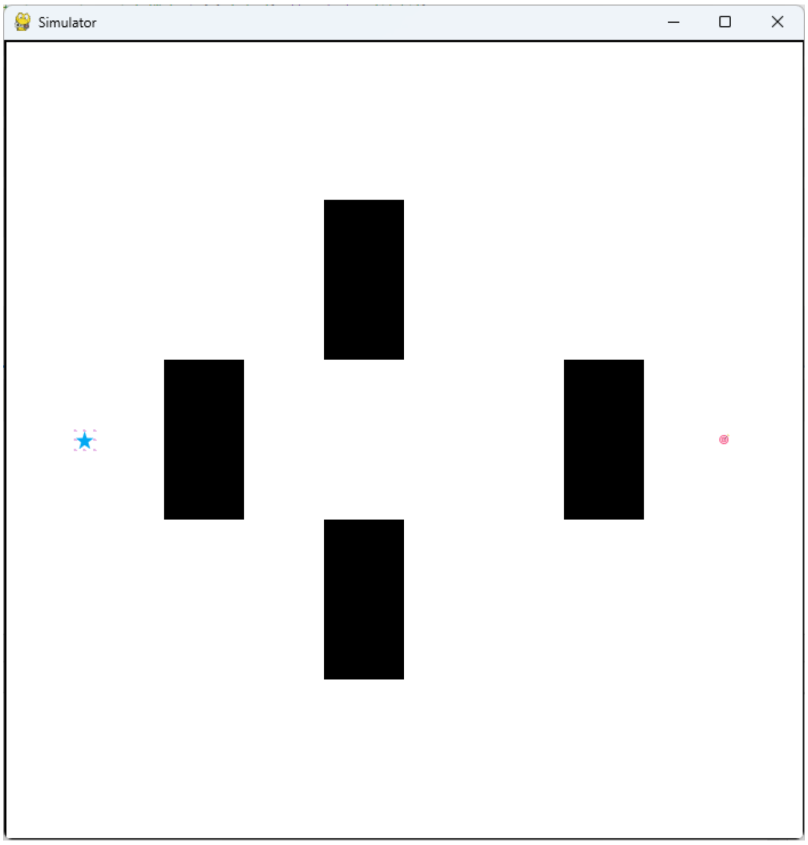

Figure 4: Initial state

In this simulation, the lidars' range was standardized at 20 units. To comprehensively assess the algorithm's performance, the linear velocity of the robots was varied between 0 and 10, with incremental steps of 0.1. This allowed for a detailed examination of the algorithm's response to different speeds.

The number of steps taken by the swarm to reach the goal side was meticulously recorded. The variations in this metric over different velocities are illustrated in Figure 5.

.

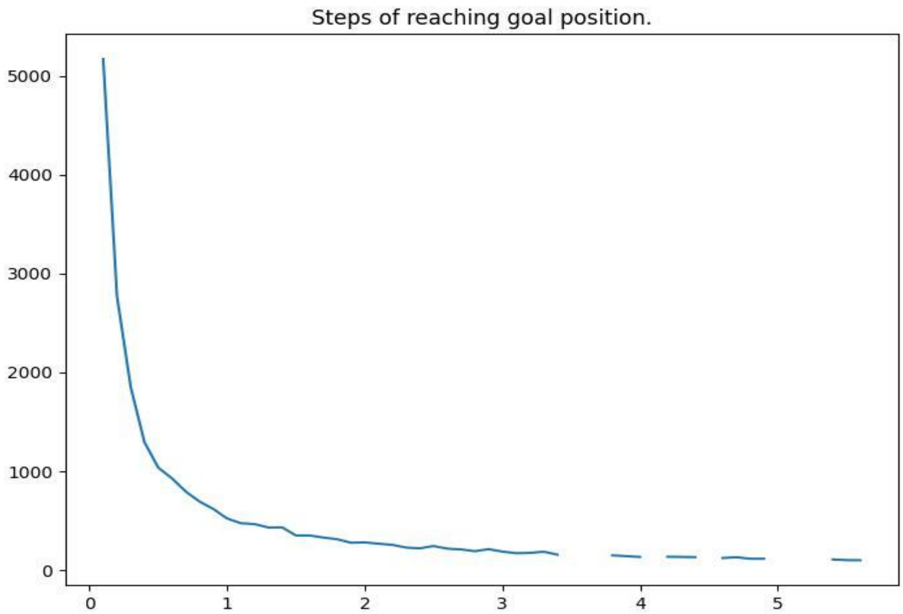

Figure 5: Steps of reaching goal position

A vital aspect of the algorithm's success is its ability to prevent collisions. Therefore, the count of robots that collided during the navigation process was carefully observed. The trend in collision occurrences across different velocities is depicted in Figure 6.

.

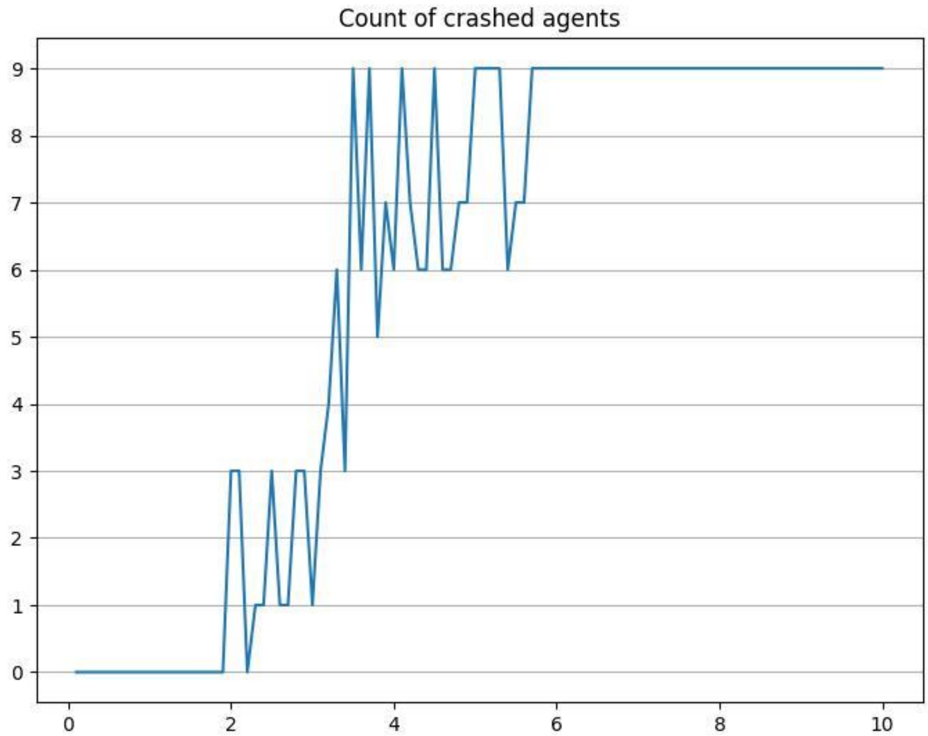

Figure 6: Count of crashed agents

Through these experiments, the research aimed to not only validate the algorithm's ability to guide the swarm to the target but also to ensure safe passage by effectively avoiding obstacles and preventing collisions among the robots. The results and discussions derived from these experiments are expected to provide valuable insights into the strengths and potential areas for improvement in the developed algorithm.

5. Discussion

In this section, we examine the emergent behaviors of the agents in relation to their velocity parameters, using a series of illustrative figures that map their trajectories. The observed patterns provide insights into the optimization strategies that the algorithm adopts under different scenarios, highlighting both its strengths and potential limitations.

Figure 5 offers a foundational perspective, showcasing the trajectories at a basic operational level. Here, the agents navigate through the environment by identifying and avoiding obstacles. The plotted paths indicate that the algorithm prioritizes safety and precision, a fundamental requirement for any navigational system.

Progressing to Figure 6, when multiple agents are introduced to the environment, the dynamics change noticeably. The trajectories shed light on how individual agents navigate collectively, emphasizing the algorithm's effectiveness in managing multiple entities safely.

Figure 7, with a velocity parameter of v=1.0, presents trajectories that are straightforward. Agents are consistent in their approach, even at this basic speed. The overall behavior suggests that even at modest speeds, the algorithm is adept at ensuring efficient and safe navigation.

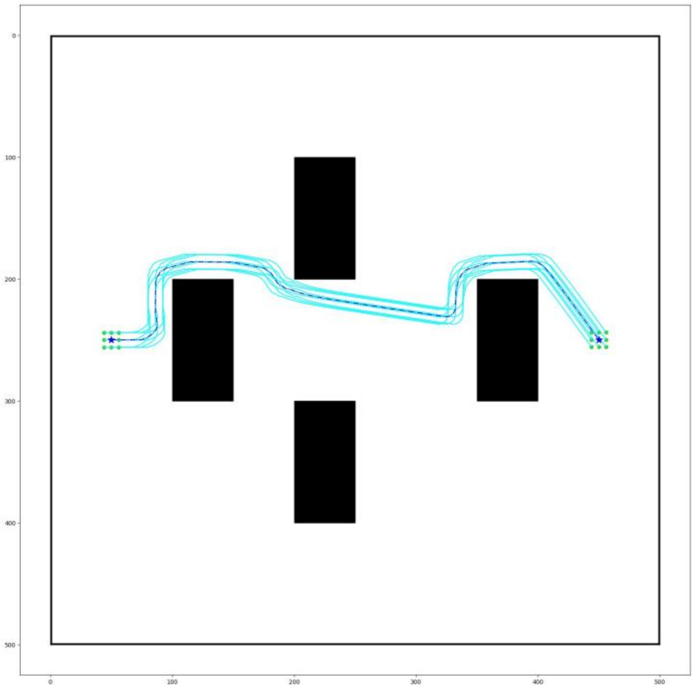

Figure 7: Trajectory of the agents when linear velocity is 1.0

The plot thickens with Figure 8, set at v=8.5. Interestingly, while agents at other velocities, ranging from 0.1 to 2.4, typically navigate through the midst of obstacles, at this particular velocity, they seem to find a unique path that skirts the obstacles. This deviation from the norm is striking and suggests that at specific velocities, the agents might discover unconventional yet effective paths. It's a testament to the algorithm's ability to adapt and optimize based on varying parameters.

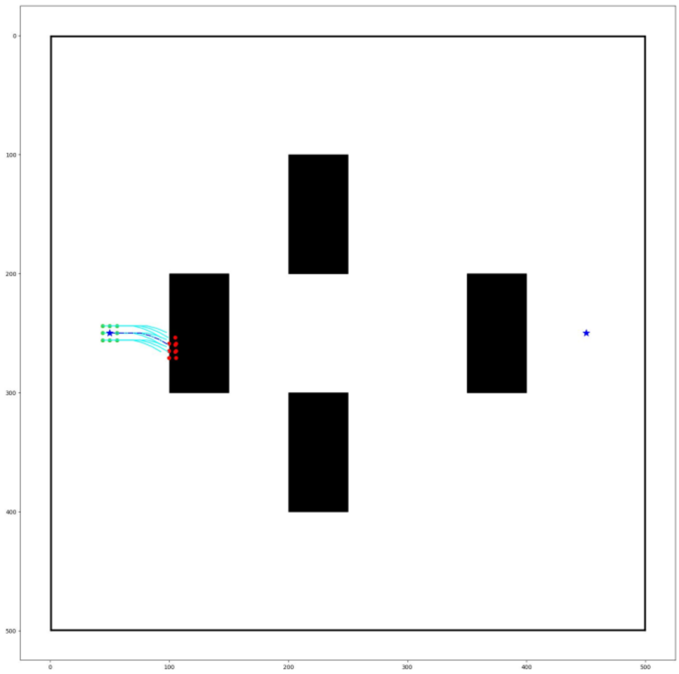

Figure 8: Trajectory of the agents when linear velocity is 8.5

In Figure 9, operating at v=1.4, the agents exhibit a notable shift in behavior. Contrary to their behavior at other velocities, they manage to navigate around the periphery of the obstacles, effectively finding a way out. This particular behavior underscores the algorithm's flexibility, indicating that there might exist sweet spots in velocity parameters where agents can unlock more efficient paths.

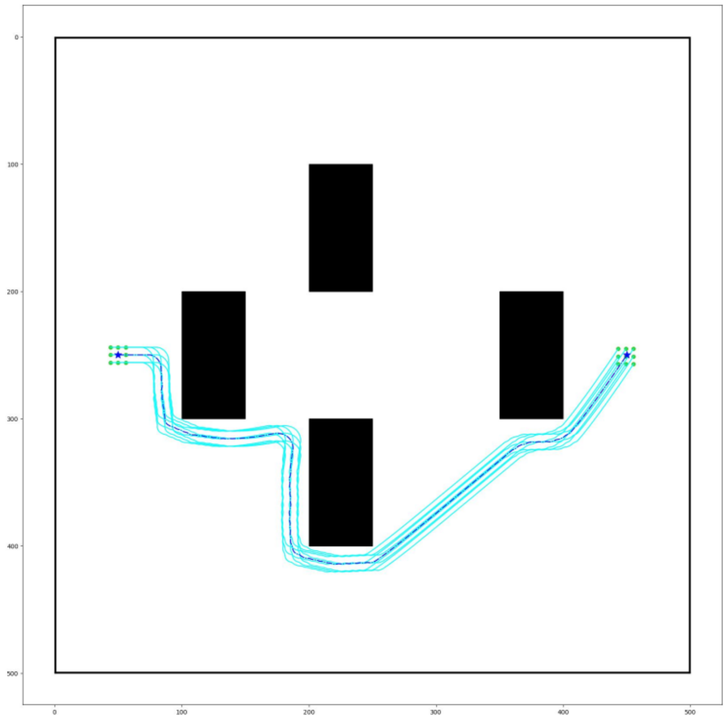

Figure 9: Trajectory of the agents when linear velocity is 1.4

However, Figure 10 introduces a challenge. At v=2.0, for the first time, agents start to crash. This observation is pivotal. It denotes that there's a threshold velocity, somewhere close to v=2.0, beyond which the agents' safety mechanisms are compromised, leading to collisions. This insight is crucial for setting operational boundaries for the algorithm in practical applications.

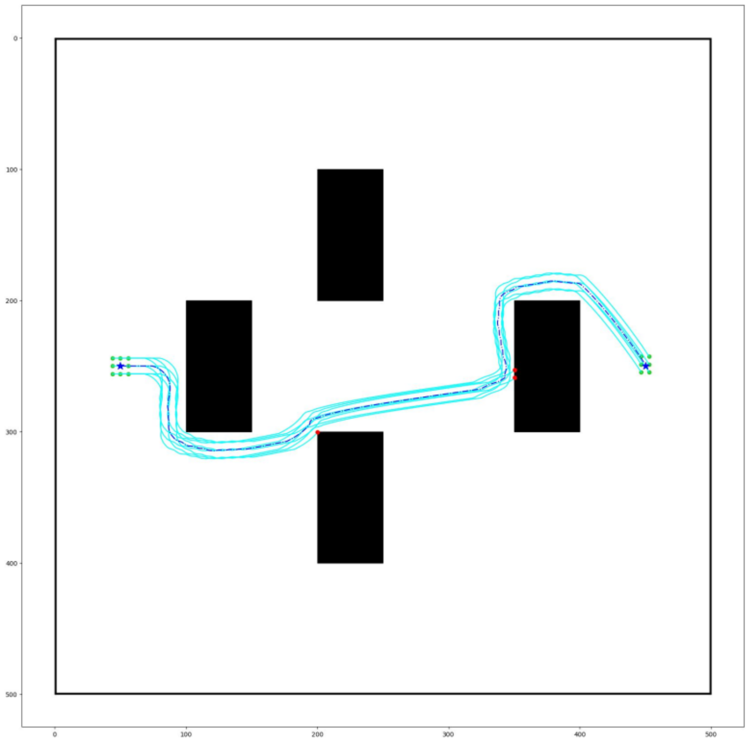

Figure 10: Trajectory of the agents when linear velocity is 2.0

In summary, the varying trajectories across different velocities emphasize the nuanced and adaptive nature of the algorithm. While it excels under certain conditions, finding innovative paths like in Figures 8 and 9, it also has its limitations, as seen in Figure 10. This analysis serves as a roadmap for future improvements, guiding efforts to refine and bolster the algorithm's robustness and efficiency.

6. Conclusion

In the realm of robotics, where adaptability and efficiency form the cornerstone of successful deployments, the algorithm presented in this paper stands as a significant milestone. Leveraging the robust capabilities of fuzzy logic, we have showcased a methodological framework for the proficient management of reconnaissance robot swarms engaged in terrain monitoring.

Our algorithm, unique in its design and functionality, excels in maintaining desired formations, skillfully avoiding obstacles, and optimizing power consumption. These accomplishments are paramount, particularly in dynamic terrains where swift adaptability is a necessity. The incorporation of a leader-follower dynamic, underpinned by a virtual leader, ensures seamless and adaptable coordination within the swarm, lending credence to the algorithm's robustness.

Furthermore, our innovative approach to energy conservation, through measures like selective Lidar deactivation, paves the way for longer, more efficient missions. Such energy-saving initiatives not only extend the operational duration of the swarm but also set a precedent for future robotic endeavours where resource management is paramount.

The comprehensive experiments, insightful discussions, and the results delineated in the paper unequivocally underscore the transformative potential of our algorithm. Through this study, we have illuminated the myriad possibilities that lie at the confluence of fuzzy logic and robotics.

In summary, the innovative algorithm detailed herein marks a pivotal progression in reconnaissance robotics. It sets forth a vision for the future where robotic swarms, armed with advanced algorithms, venture into terrains with unmatched efficiency, precision, and intelligence, pushing the boundaries of what is possible in the realm of robotic exploration.

7. Acknowledgements

This research is funded by the Committee of Science of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Project No. AP19677508).

8. References

[1] Brogårdh T. (2007). Present and future robot control development—An industrial perspective, Annual Reviews in Control, vol. 31(1), pp. 69-79.

[2] Rawassizadeh R. et al. (2019). Manifestation of virtual assistants and robots into daily life: Vision and challenges, CCF Transactions on Pervasive Computing and Interaction, vol. 1, pp. 163-74.

[3] Jahanshahi H. et al. (2019). Robot motion planning in an unknown environment with danger space, Electronics, vol. 8(2), p. 201.

[4] Budiharto W. et al. (2020). Design of object tracking for military robot using PID controller and computer vision," ICIC Express Letters, vol. 14(3), pp. 289-94.

[5] Mazzeo A. et al. (2022). Marine robotics for deep-sea specimen collection: A systematic review of underwater grippers, Sensors, vol. 22(2), p. 648.

[6] Arm P. et al. (2019). Spacebok: A dynamic legged robot for space exploration. International Conference on Robotics and Automation (ICRA), pp. 6288-6294.

[7] Baimukhamedov M.F., Moldamurat K., Akgul M.K. (2019). Optimal control model of the automobile transport. pp. 1312–1316.

[8] Yassein M. B., Aljawarneh S., Al-Sadi A. (2017). Challenges and features of IoT communications in 5G networks. 2017 International Conference on Electrical and Computing Technologies and Applications (ICECTA), pp. 1-5.
[9] Mardini W., Aljawarneh S., Al-Abdi A. (2021). Using Multiple RPL Instances to Enhance the Performance of New 6G and Internet of Everything (6G/IoE)-Based Healthcare Monitoring Systems. Mobile Netw Appl, vol. 26, pp. 952–968.
[10] Al-Husainy M.A., Al-Shargabi B., Aljawarneh S. (2021). Lightweight cryptography system for IoT devices using DNA. Computers & Electrical Engineering, vol. 95, p. 107418.
[11] Sakhipov A., Yermaganbetova M. (2022). An educational portal with elements of blockchain technology in higher education institutions of Kazakhstan: opportunities and benefits," Global Journal of Engineering Education, vol. 24(2), pp. 149 – 154.
[12] Karpov V. E. (2016). Modeli sotsial'nogo povedeniya v gruppovoy robototekhnike [Models of Social Behavior in Group Robotics]. UBS, vol. 59, pp. 165–232.
[13] Miao C. et al. (2021). Path planning optimization of indoor mobile robot based on adaptive ant colony algorithm," Computers & Industrial Engineering, vol. 156, p. 107230.
[14] Gleadow R., Hanan J., Dorin A. (2019). Averting robo-bees: why free-flying robotic bees are a bad idea," Emerging Topics in Life Sciences, vol. 3(6), pp. 723-9.
[15] Li J. et al. (2022). Ultrasonically propelled micro-and nanorobots," Advanced Functional Materials, vol. 32(5), p. 2102265.
[16] Yemelyev A. K., Moldamurat Kh., Seksenbaeva R. B. (2021). Development and Implementation of Automated UAV Flight Algorithms for Inertial Navigation Systems. 2021 IEEE International Conference on Smart Information Systems and Technologies (SIST), pp. 1-5.
[17] Kyzyrkanov A. E., Atanov S., Aljawarneh S. (2021). Formation control and coordination of swarm robotic systems. The 7th International Conference on Engineering & MIS.
[18] Kyzyrkanov A., Atanov S., Aljawarneh S. (2021). Coordination of movement of multiagent robotic systems," 2021 16th International Conference on Electronics Computer and Computation (ICECCO), pp. 1-4.
[19] Anabeza, Christian C., and Argel A. Bandala. (2023). Fuzzy Logic Controller for Autonomous Environment-Based Drone Swarm Formation. In 2023 IEEE Region 10 Symposium (TENSYMP), pp. 1-5. IEEE.
[20] Toibazarov, Daulet, Gani Baiseitov, Abzal Kyzyrkanov, Shadi Aljawarneh, and Sabyrzhan Atanov. (2023). DEVELOPMENT OF CONTROL SOFTWARE FOR SELFORGANIZING INTELLIGENT MOBILE ROBOTS. Eastern-European Journal of Enterprise Technologies, 122(9).