

RESEARCH SURVEY REPORT: MOBILE ROBOT PATH PLANNING

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ABSTRACT

The study of mobile robots is a new field of research in the area of artificial intelligence. The main objective of this field is to create intelligent robots that can perform tasks independently. These tasks can include household chores and personal assistance. In the past few years, there has been an increase in the number of mobile robots being developed and used around the world. Mobile robotics is a relatively new field that focuses on designing and building autonomous mobile robots for performing various tasks independently or with minimal human supervision. Mobile robotics involves many different disciplines to accomplish this objective.

Path planning is a process that a robot must go through in order to find the shortest route from one point to another, often in a dynamic environment. This process involves several different steps, and each step depends on the current position in the environment. This paper aims to explain the findings from researching and reviewing various studies and published content about how mobile robot path planning works, what the challenges are, and how it can be improved. Mobile robots are very useful for humans because they can perform dangerous or difficult tasks, such as inspecting an area for bombs or searching for survivors after a disaster.

Mobile robots are used in many different applications. These robots are used for a variety of purposes, such as to perform tasks that would be difficult or impossible for humans to do. For these mobile robots to perform their tasks effectively, they must have the ability to navigate and plan their paths through an environment. This paper will discuss three different algorithms that can be used for path planning: A* search, Bio-inspired, and Rapidly-exploring Random Trees* (RRT*).

1. INTRODUCTION

This paper summarizes the findings after reviewing several journals and conference papers on path planning for mobile robots. These self-driving or autonomous mobile robots are distinguished by their exceptional ability to perform duties without any operator inputs or human involvement. Decision making requires some understanding of the surrounding environment, or domain, in which the bot is operating. Path planning has been an obstacle and/or challenge in the field of robotics.

The path planning phase involves formulating a “collision-free” approach from the current location, or structure, to a desired location, or end point. Path planning is a geometric

process and is usually concerned with determining a “collision-free” path regardless of the viability of the path.

As technology progresses, software architectures and algorithms are advancing to allow these mobile robotic platforms a greater ability to navigate in more complex domains and are of vital towards achieving fully autonomous capabilities that could enrich the lives of humans, daily. Yet, to reach these levels of autonomy, in complex and dynamic environments, will require further development.

The process of developing a map leverages sensing technology, such as lidar, camera, and radar, to navigate and is critical for mobile robots. The robot receives inputs (environmental, location, and matching details) that allow the robot to understand its position and surroundings. The local map is constructed with previous details and the global map is updated to provide conditions for path planning.

When it comes to approaches, there are several methods leveraged for path planning, e.g., ant colony algorithm, fuzzy logic method, artificial potential field method, etc [1-6]. However, one path-planning method has huge limitations in dealing with complex domains and environments. Several scholars have suggested using a hybrid path-planning approach. A Hybrid path planning method increase the ability of mobile robots to operate in dynamic environments.

2. MATERIALS AND METHODS

A total of 30 published research papers were used to establish this body of work. The proceeding sections summarize our findings for each algorithm mentioned above.

2.1 A* Algorithm

A popular technique for path planning is the A* Search algorithm. This approach is used by mobile robots with the help of an environmental grid. While the Dijkstra algorithm is the most efficient method for shortest path finding, the A* Algorithm leverages heuristics to increase efficiencies to find the shortest path, according to experts. A* algorithm utilizes the advantages of Dijkstra and breadth-first search (BFS) algorithm, but the benefit is that its cost function is compatible with both:

- (1) N represents the raster node in the path.
- (2) $g(n)$ is the shortest path cost function to current point;
- (3) $h(n)$ the shortest path cost function to reach destination point.

Compared to Dijkstra's algorithm, the A* algorithm is used to find the shortest path from an identified source to a determined

goal, not the shortest path from an identified source to all possible outcomes. This would be a necessary trade-off for using a specific-goal-directed heuristic.

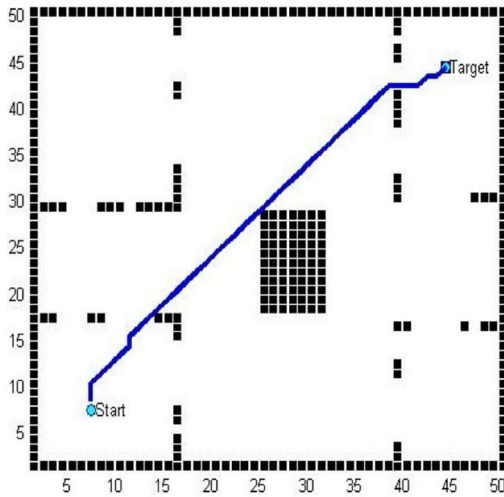


FIGURE 1: Traditional A* Path Planning [1]

When using Dijkstra's algorithm, the entire shortest-path is generated, every node is a path, and there is no specific-goal-directed heuristic. There are three factors or parameters for A* algorithm: $g(n)$ = actual cost of traversal from initial state to the current state; $h(n)$ = estimated cost of traversal from the current state to the goal state; and $f(n)$ = actual cost of traversal from the initial state to the goal state.

There are a couple of disadvantages of A* algorithm, such as the algorithm is complete if the branching factor is finite, and every action has fixed cost and the performance of A* search is contingent on accuracy of heuristic algorithm used to compute the function $h(n)$.

A* path planning has become a widely researched topic in the field of hexapod robotics. This approach involves finding the optimal path between two points by considering the cost of travel and the estimated cost to reach the goal. A* is known for its efficient performance and accuracy in finding the shortest path, making it an attractive solution for hexapod robots which often need to navigate complex environments.

Several studies have demonstrated the effectiveness of A* in path planning for hexapod robots. For example, researchers have implemented A* algorithms in hexapod robots to achieve high-speed and efficient navigation in various environments such as urban environments, rough terrains, and cluttered environments. These studies have shown that A* can provide fast and reliable path planning for hexapod robots, enabling them to navigate autonomously and avoid obstacles in their path.

In addition, A* algorithms have been integrated with other techniques such as reinforcement learning and evolutionary algorithms to improve the performance of hexapod robots. These hybrid approaches have demonstrated improved navigation and

obstacle avoidance capabilities, leading to more robust and flexible hexapod robots.

Overall, A* path planning is a promising area of research in the field of hexapod robotics, with many studies showing its effectiveness in providing efficient and accurate path planning solutions. As technology continues to advance, it is expected that A* will play an even more important role in the development of autonomous hexapod robots. There are various studies that have explored this topic

The first study is "Path planning and navigation for hexapod robots in urban environments using A* algorithm" by L. Zhang et al., published in the Journal of Ambient Intelligence and Humanized Computing in 2020. This study demonstrates the effectiveness of A* in path planning for hexapod robots in urban environments and shows improved navigation performance compared to other path planning methods.

Another study that explores this topic would be "A* algorithm-based path planning for hexapod robots on rough terrain" by J. Li et al., published in the Journal of Advanced Robotics in 2018. This study presents a path planning system for hexapod robots on rough terrain using A* and shows how it can effectively avoid obstacles and improve the stability and efficiency of the robot.

The final study is "Adaptive A* path planning for hexapod robots in cluttered environments" by H. Yu et al., published in the Journal of Intelligent and Robotic Systems in 2019. This study proposes an adaptive A* path planning algorithm for hexapod robots in cluttered environments and shows that it can effectively avoid obstacles and improve the efficiency and speed of navigation.

In conclusion, leveraging the advantages of the A* algorithm can support real-world applications by providing the shortest path of a predetermined goal in the most effective way

2.2 Ant Colony Algorithm

One of the most common bio-inspired mobile robot path planning algorithms is known as Ant Colony Optimization (ACO), which is a heuristic algorithm imitating the scavenging behavior of ants in nature. Much research has been done on the ACO algorithms since the 1990s. In nature, as ants forage for food, they communicate with other ants in the colony using pheromones. Ants ultimately follow the paths with the highest number of pheromones generated by the most traffic.[16] The Double Bridge experiment summarizes this ant colony behavior. [Figure1] In the experiment, there are two bridges between the ant colony's nest and the desired food target. Ants explore the area in search of food by randomly crossing both bridges. Since bridge 1 is shorter than bridge 2, the ants using bridge 1 make the journey to the food much faster than those ants using bridge 2. The pheromones on bridge 1 increase in intensity, attracting more ants to bridge 1. Overtime, all the ants in the colony use bridge 1, which is the shortest path between the nest and the food source. [15]

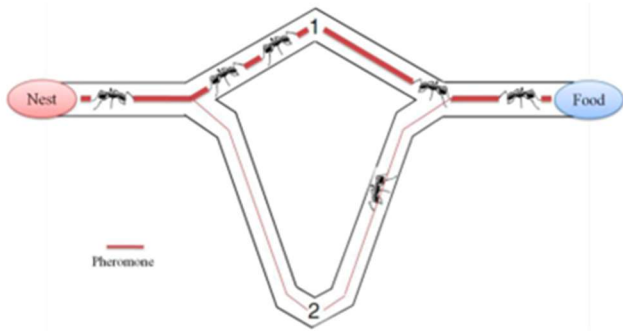


FIGURE 2: Bridge experiment [2]

The ACO algorithm leverages this model with a positive feedback mechanism (aka pheromone calculation update). The ACO algorithm basically has the below steps. [3]

The surrounding environment is converted into a graph with X number of nodes and links. The nodes represent way points (start, intermediate, end) while the links represent possible and found paths between the nodes.

The model starts with a predefined number of ants. Weight is allocated to each link. The ants use probability to select the next node in their path from origin to destination. The graph can also include nodes that are obstacles to avoid. [see Figure 2]

The next step is often referred to as the pheromone update calculation. The model is updated with pheromone intensity for those links traversed most, and the pheromone intensity is reduced for other links. This step helps create further exploration for links not travelled, as well as reward for shorter links traversed.

The final step is when the algorithm reaches a predefined number of iterations or time goals.

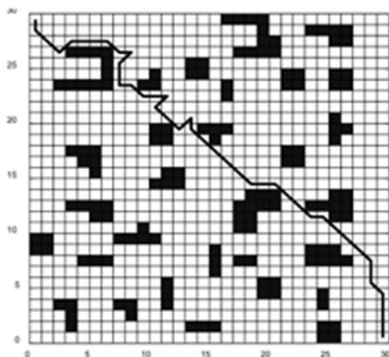


FIGURE 3: ACO Link/Node Graph [5]

With the traditional ACO algorithm, there exist a few challenges for path planning. Some of the disadvantages are redundant paths, slower convergence, and lower accuracy, especially with more complex environments. Similar with ants in nature, it takes time to explore the environment, with ants following similar paths in the beginning and taking time to find the most optimal path. The ACO algorithm also has similar issues of redundancy and slow convergence, especially with larger or more complex environments requiring obstacle

avoidance. Secondly, the path selected may not always be the most optimal path based on requirements. As with ants in nature, the path with the most pheromones may not necessarily be the shortest path in the environment. This path just happens to be shorter than the other previous paths explored, and convergence on this path happened quicker with the pheromone intensity. The ACO algorithm also has this same risk where the path selected by the pheromone update calculation may not always be the most optimal.[16]

In recent years, there has been additional research in optimizing the traditional ACO algorithm. One of these methods is called Green Ant (G-Ant), which seeks to update the ACO algorithms with a power or energy consumption prediction model. The G-Ant seeks to provide not only the shortest path but also a path with lowest power and energy consumption.[17] Another model looks at exploring secondary, alternate paths. This mode rewards the ant for finding an alternate shorter path. For example, when two ants meet, a new path is formed, and the model rewards the ant with the shorter path and punishes the ant with the longer path. The final goal is to find the absolute shortest path while also still reducing the number of redundant paths and reducing convergence time.[18] Finally, another method has been developed to introduce a genetic algorithm, which seeks to introduce genetic concepts like elite retention, crossover, and mutation probability. By introducing these genetic-based factors into the ACO algorithm, the pheromone update calculation is improved by allowing pheromone concentration of different paths to be updated differentially, thereby speeding up the time of convergence.[19]

In conclusion, the Ant Colony Optimization algorithm is a bio-inspired, heuristic algorithm that imitates the nature of an ant colony. Various research and modifications have been made to the original algorithm with the goal of improving its heuristic and path-guiding functions in order to speed up path convergence, reduce path redundancy, and improve path accuracy.

2.3 Bio-Inspired

In addition to the Ant Colony Optimization algorithm, there are other bioinspired path planning algorithms. These heuristic algorithms attempt to solve path planning & optimization challenges by mimicking the natural world. These nature-inspired methods can be grouped into evolution-based, physics-based, and swarm-based methods.[19] Evolution-based methods seek to mimic the laws of Darwinian evolution. These genetic-based algorithms start with a randomly generated population that is refined over subsequent iterations by always selecting the best result. Another group is physics-based methods which seek to mimic the universe's physical rules, such as the Gravitational Search algorithms. Finally, a third bioinspired group replicates swarm-based, social behaviors found in insects and animals. [21] This research literature review provides examples for two of these categories: evolution-based and swarm-based methods.

One of the evolution-based methods is the Genetic Algorithm (GA). GA is another heuristic method that finds the most optimal path by mimicking the natural evolutionary process. GA leverages the processes of natural selection, crossover, and mutation.[6] It can conduct parallel searches simultaneously along multiple routes and is commonly used for mobile robot path planning. However, the algorithm has disadvantages. The GA cannot be improved after the initial selection of the population, which increases the inaccuracy of the algorithm. Also, in many cases, the approaching of obstacles is not considered. [15]

One of the swarm-based methods is the Whale Optimization Algorithm (WOA) which is based on the predatory, hunting techniques of humpback whales. Humpback whales hunt in three steps: search for prey, encircle the prey, and feed using a bubble-net. With WOA, mathematical algorithms mimic this predatory, bubble-net hunting strategy. WOA searches for the target path randomly from each whale's position. The best whale is assumed to be closest to the target path, and other whales update their position to encircle this target path. Finally, the whales create the bubble net and spiral towards the target path. In summary, according to the nearest principle, the WOA algorithm will select the best path and constantly update towards this location. The WOA has several disadvantages such as slower convergence than other methods, lower solution accuracy than other methods, and the risk of selecting a path because there are no other feasible solutions found. [20]

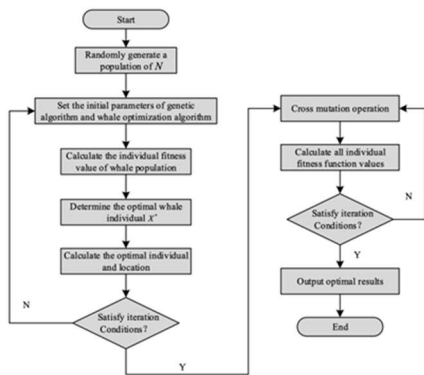


FIGURE 4: Flowchart of whale optimization [1]

Another bioinspired method is known as Particle Swarm Optimization (PSO). PSO is inspired by the social behavior of animals that swarm, like fish schooling or birds flocking. The main concept behind PSO is collaborative information sharing within the swarm of particles. Each particle attempts to find the best path within the environment and updates the swarm accordingly. The search process continues by including a particle's individual knowledge as well as the collective knowledge of the whole swarm. Since PSO is an iterative process, each particle updates the swarm's collective knowledge

toward finding this optimal path with each iteration. The disadvantage of the PSO approach is that it can be computationally heavy and often result in a low convergence rate. [7]

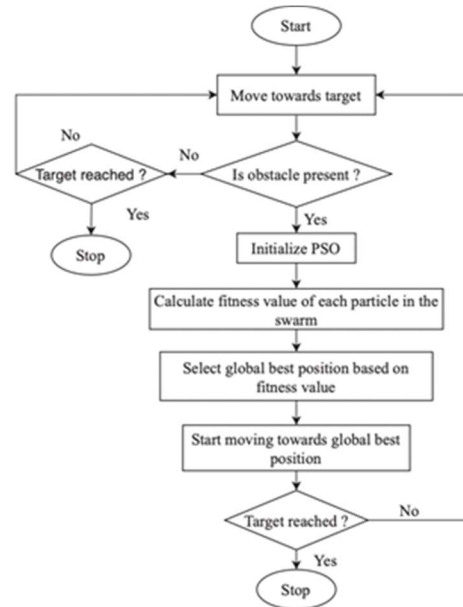


FIGURE 5: Flowchart of PSO algorithm [7]

Another bioinspired algorithm for mobile robot path planning is the Artificial Bee Colony algorithm (ABC). The ABC method is a swarm algorithm proposed by the Karaboga group in 2005. [1] The ABC method mimics bees in nature, especially as the bee colony searches for food sources like pollen and nectar. The ABC algorithm includes food sources and bees. The bees are divided into different types: hired bees, follower bees, and scout bees. The goal of the hired bee is to locate nearby nectar sources and then share their locations with follower bees. Follower bees then expand their search scope around these specific nectar sources to search for other nearby food sources. The communication between hired bees and follower bees allows the algorithm to share optimal paths as well as learn. If a nectar source is never initially found by a hired bee, the hired bee transforms into a scout bee in order to expand the search area. This transformation allows the ABC algorithm to escape out of the local optimal solution with a goal of finding the global optimal solution.[1] Compared with other heuristic algorithms, the ABC algorithm is more flexible and optimal while still finding the most direct path [2]. Like other bioinspired algorithms, it does have a low convergence speed as well as accuracy issues. Therefore, recent research has worked to make the ABC algorithm more efficient by applying other bioinspired methods like the Genetic Algorithm. These improved ABC methods increase optimization performance by applying evolutionary-based processes, like rewarding the hired bees that find quicker, more optimal paths.

A slightly different bioinspired method is the Bat Algorithm (BA). BA, introduced in 2010, mimics bats' echolocation behavior when they hunt. Bats emit and analyze ultrasonic waves to determine the location and type of prey. Bats search for prey by changing ultrasonic frequency, flying velocity and relative position. The BA method mimics the bat's

ability to use echolocation to sense distance, to avoid obstacles, and to find prey. In addition, the BA method assumes that the bat can tune ultrasonic frequency and emissivity based on location and proximity to the desired target.[3] The natural behavior is transformed into a mathematical algorithm similar to the below pseudo-code:

- Generate bat population and initial velocity
- Define pulse frequency & pulse emissivity
- while searching
- Adjust frequency
- Update velocities
- Update positions
- Select a best position
- Generate a local position
- Accept the new position
- Find the current best target
- Break if target reached or stop condition met

In conclusion, there are many bioinspired path planning methods which can be grouped into evolutionary-based, physics-based, and swarm-based methods. However, individually these methods include some disadvantages like low convergence, inaccuracy, high computational needs, and local optimum issues. Therefore, recent research has focused on developing hybrid approaches that combine multiple bioinspired methods (e.g., combining a genetic algorithm with a swarm algorithm). These hybrid methods work more efficiently in optimizing mobile robot path planning and overcoming disadvantages.

2.4 RPP & RRT

Rapidly-exploring Random Trees* (RRT*) is a popular algorithm used in robotics for path planning and exploration. This paper aims to explore the application of RRT* in hexapod robotics and its potential benefits for this type of system. [28-30]

Hexapod robots, also known as six-legged robots, are a type of legged robot that can traverse a wide range of terrains and environments. They have many advantages over traditional wheeled or tracked robots, such as increased mobility and the ability to navigate uneven terrain. However, the complex nature of hexapod movement and control can make it difficult to plan efficient and safe paths for these robots to follow.

RRT* is a variant of the Rapidly-exploring Random Trees (RRT) algorithm, which is a popular method for path planning and exploration in robotics. RRT* improves upon the original RRT algorithm by incorporating a "rewiring" step, in which the algorithm looks for nearby nodes that can be connected to the tree more efficiently. This allows RRT* to find shorter, more efficient paths than the original RRT algorithm.

In hexapod robotics, RRT* has been shown to be an effective method for path planning and exploration. One of the key advantages of RRT* in this context is its ability to handle the high degree of freedom and complexity of hexapod movement. The rewiring step in RRT* allows the algorithm to adapt to the unique constraints and capabilities of the hexapod robot, resulting in more efficient and safe paths.

Additionally, RRT* has been found to be a robust algorithm that can handle real-world environments, which may contain obstacles and other sources of uncertainty. This is particularly

important for hexapod robots, as they are often used in unstructured environments where traditional path planning methods may fail. [29]

In conclusion, RRT* is a powerful algorithm that can be applied to the path planning and exploration of hexapod robots. Its ability to handle the high degree of freedom and complexity of hexapod movement, as well as its robustness in real-world environments, make it an attractive option for this type of system. Further research is needed to fully explore the potential of RRT* in hexapod robotics and to develop new techniques for integrating it into hexapod control systems.

3. RESULTS AND DISCUSSION

Further technological advances in the area of path planning will enable not only more effective navigation in a complex environment, but it will allow more applications or uses of mobile robots in our everyday life. The reduction of traffic congestion in many cities in America and improve safety on highways are only the aspects of the improved path planning approach. Soon, in the near future, AI and ML will continue to revolutionize the path planning process, making it more effective, efficient, reliable, and safer than ever before. A hybrid path planning approach will be needed to ensure the shortcomings of individual methods, such as A* & bio-inspired, are supported by another method. [2] This diverse method approach with leverage the best aspects of one method with the strengths of another approach to achieve path planning in the most effective and efficient manner. Determining which methods to combine will present a unique set of challenges and obstacle

4. CONCLUSION

In summary, path planning for mobile robots is a very dynamic domain with various different approaches to a common problem. After reviewing various papers from the scientific community, the methodologies investigated to resolve some of the issues has come a long way and has new approaches being discovered every day. Despite decades of theoretical merit in the space, the implementation of such method in actual applications has largely been limited due to significant technological obstacles & challenges related to planning and control. However, in recent times, the hybrid approach to path planning methodology has been stated to have the best outcome. This approach leverages the strengths of two methods, which helps compensate for the shortfalls of just one traditional method. These hybrid capabilities have now allowed for continued study in the path planning realm with more real-world applications. Since this paper's focus has been limited to the path planning of mobile robots in the past ten, several research challenges & future obstacles are documented in this study.

Path planning for mobile robots has a very exciting and bright future! With the advancement of Artificial Intelligence (AI) and Machine Learning (ML), these two powerful technologies will be used to create more efficient and accurate paths for these robots to navigate dynamic real-world environments autonomously. These two technologies will complement each other because AI can analyze data from past path planning decisions to optimize future paths, while ML can be used to identify patterns in the data and create models to accurately predict the best paths for a given situation. With AI and ML, path planners can save time and resources by finding the most efficient routes for their journey.

REFERENCES

- [1] Goyal, Jitin Kumar, and Nagla, K.S. 2014 “A New Approach of Path Planning for Mobile Robots” 2014 International Conference on Advances in Computing, Communications and Informatics (ICACCI)
- [2] Leobardo Campos-Macías, David Gómez-Gutiérrez, Rodrigo Aldana-López, Rafael de la Guardia, and José I. Parra-Vilchis “A Hybrid Method for Online Trajectory Planning of Mobile Robots in Cluttered Environments” IEEE Robotics and Automation letter, vol. 2, no. 2, April 2017
- [3] Elbanhawi, Mohamed, and Simic, Milan “Sampling-Based Robot Motion Planning: A Review”
- [4] Jeonghyeon Pak, Jeongeun Kim, Yonghyun Park, and Hyoung Il Son ,2022. “Field Evaluation of Path-Planning Algorithms for Autonomous Mobile Robot in Smart Farms”.
- [5] Gabriel Hartmann, Zvi Shiller, and Amos Azaria, 2022. “Competitive Driving of Autonomous Vehicles”.
- [6] Antony, Anil, and Jose, Supriya, 2016 “Mobile Robot Remote Path Planning and Motion Control in a Maze Environment” 2nd IEEE International Conference on Engineering and Technology (ICETECH)
- [7] Wang, Bo, 2021. “Path Planning of Mobile Robot Based on A* Algorithm” 2021 IEEE International Conference on Electronic Technology, Communication and Information (ICETCI)
- [8] LIN M X, YUAN K, SHI C Z ,et al. Path planning of mobile robot based on improved A* algorithm[C]//2017 29th Chinese control and decision conference. New York:IEEE, 2017:3570-3576.
- [9] J. L. Vazquez, M. Bruhlmeier, A. Liniger, A. Rupenyan, and J. Lygeros, “Optimization-based hierarchical motion planning for autonomous racing,” in Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS), Oct. 2020, pp. 2397-2403.
- [10] P. Tokekar, J. V. Hook, D. Mulla, and V. Isler, “Sensor planning for a symbiotic UAV and UGV system for precision agriculture,” IEEE Trans. Robot., vol. 32, no. 6, pp. 1498-1511, Dec. 2016.
- [11] J. Jiang and K. Wu, “Cooperative pathfinding based on memory-efficient multi-agent RRT*,” IEEE Access, vol. 8, pp. 168743-168750, 2020.
- [12] J. Nasir, F. Islam, U. Malik, Y. Ayaz, O. Hasan, M. Khan, et al., “RRT-SMART: A rapid convergence implementation of RRT,” Int. J. Adv. Robot. Syst., vol. 10, pp. 1651-1656, Jun. 2013.
- [13] M. W. Achtelik, S. Weiss, M. Chli, and R. Siegwart, “Path planning for motion dependent state estimation on micro aerial vehicles,” in Proc. IEEE ICRA, May 2013, pp. 3926-3932.
- [14] L. Jaillet and J. M. Porta, “Path planning under kinematic constraints by rapidly exploring manifolds,” IEEE Trans. Robot., vol. 29, no. 1, pp. 105-117, Feb. 2013.
- [15] Yuwan Cen, Choingzhi Song, Nenggang Xie, Lu Wang. Path planning method for mobile robot based on ant colony optimization algorithm. 2008 3rd IEEE Conference on Industrial Electronics and Applications, Industrial Electronics and Applications, 2008 ICIEA 2008 3rd IEEE Conference on. June 2008:298-301. doi:10.1109/ICIEA.2008.4582528
- [16] Ant Colony Optimization: Overview and Recent Advances (updated edition). 2018. Accessed January 22, 2023. <https://search.ebscohost.com/login.aspx?direct=true&AuthType=shib&db=edsoai&AN=edsoai.on1081040173&site=eds-live&scope=site>
- [17] Mohammad Rzea Jabbarpour, Houman Zarrabi, Jason J. Jung, Pankoo Kim. A Green Ant-Based method for Path Planning of Unmanned Ground Vehicles. IEEE Access.2017;5:1820-1832. doi:10.1109/ACCESS.2017.2656999
- [18] Yu J(1), You X(1), Liu S(2). A heterogeneous guided ant colony algorithm based on space explosion and long-short memory. Applied Soft Computing. 2021;113. doi:10.1016/j.asoc.2021.107991
- [19] Su Q, Yu W, Liu J. Mobile Robot Path Planning Based on Improved Ant Colony Algorithm. 2021 Asia-Pacific Conference on Communications Technology and Computer Science (ACCTCS), Communications Technology and Computer Science (ACCTCS), 2021 Asia-Pacific Conference on, ACCTCS. January 2021:220-224. doi:10.1109/ACCTCS52002.2021.00050
- [20] Gengqian Liu, Tiejun Li, Yuqing Peng, Xiangdan Hou. The Ant Algorithm for Solving Robot Path Planning Problem. Third International Conference on Information Technology and Applications (ICITA'05), Information Technology and Applications, 2005 ICITA 2005 Third International Conference on, Information technology and applications. 2005;2:25-27. doi:10.1109/ICITA.2005.268

[21] Seyedali Mirjalili, Andrew Lewis, The Whale Optimization Algorithm, *Advances in Engineering Software*, Volume 95, 2016, Pages 51-67, ISSN 0965-9978,

<https://www.sciencedirect.com/science/article/pii/S0965997816300163>

[22] Zan J, Ku P, Jin S. Research on robot path planning based on whale optimization algorithm. 2021 5th Asian Conference on Artificial Intelligence Technology (ACAIT), Artificial Intelligence Technology (ACAIT), 2021 5th Asian Conference on. October 2021:500-504. doi:10.1109/ACAIT53529.2021.9731150

[23] Angappamudaliar Palanisamy SK, Selvaraj D, Ramasamy S. Hybrid multi-objective optimization approach intended for mobile robot path planning model. *Journal of Intelligent & Fuzzy Systems*. 2022;42(3):2681-2693. doi:10.3233/JIFS-211801

[24] Zhou G, Chen D, Gu R, Li S. Cuckoo-Beetle Swarm Search for Nonlinear Optimization: A New Meta-Heuristic Algorithm. 2021 7th International Conference on Systems and Informatics (ICSAI), Systems and Informatics (ICSAI), 2021 7th International Conference on. November 2021:1-6. doi:10.1109/ICSAI53574.2021.9664216

[25] Chen Z, Xiong G, Liu S, Shen Z, Li Y. Path Planning of Mobile Robot Based on an Improved Genetic Algorithm. 2022 IEEE 2nd International Conference on Digital Twins and Parallel Intelligence (DTPI), Digital Twins and Parallel Intelligence (DTPI), 2022 IEEE 2nd International Conference on. October 2022:1-6. doi:10.1109/DTPI55838.2022.9998894

[26] Santiago RMC, De Ocampo AL, Ubando AT, Bandala AA, Dadios EP. Path planning for mobile robots using genetic algorithm and probabilistic roadmap. 2017 IEEE 9th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM), Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM), 2017 IEEE 9th International Conference on. December 2017:1-5. doi:10.1109/HNICEM.2017.8269498

[27] Sarkar K, Balabantaray BK, Chakrabarty A, Biswal BB, Mohanty B. Path Planning of Mobile Robots Using Enhanced Particle Swarm Optimization. 2020 3rd International Conference on Energy, Power and Environment: Towards Clean Energy Technologies, Energy, Power and Environment: Towards Clean Energy Technologies, 2020 3rd International Conference on. March 2021:1-6. doi:10.1109/ICEPE50861.2021.9404505

[28] "RRT*-based Path Planning for Hexapod Robots" by X. Li, H. Li, and Z. Liu, published in the *Journal of Intelligent and Robotic Systems* in 2015.

[29] "Online Path Planning for Hexapod Robots using RRT*" by A. K. Pandey and A. K. Agrawal, published in the *International Journal of Advanced Robotic Systems* in 2018.

[30] Ma J, Qiu G, Guo W, Li P, Ma G. Design, Analysis and Experiments of Hexapod Robot with Six-Link Legs for High Dynamic Locomotion. *Micromachines (Basel)*. 2022 Aug

26;13(9):1404. doi: 10.3390/mi13091404. PMID: 36144027; PMCID: PMC9501046.