Robotica (2023), **41**, pp. 2079–2104
doi:10.1017/S0263574723000322

CAMBRIDGE UNIVERSITY PRESS

RESEARCH ARTICLE

A comprehensive review of the latest path planning developments for multi-robot formation systems

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Received: 15 November 2022; **Accepted:** 15 February 2023; **First published online:** 31 March 2023

Keywords: path planning, multi-robot, formation control, leader–follower, virtual formation, behavior-based formation, dynamic formation, entralized decision, decentralized decision, distributed decision, hybrid decision

Abstract
There has been a continuous interest in multi-robot formation systems in the last few years due to several significant advantages such as robustness, scalability, and efficiency. However, multi-robot formation systems suffer from well-known problems such as energy consumption, processing speed, and security. Therefore, developers are continuously researching for optimal solutions that can gather the benefits of multi-robot formation systems while overcoming the possible challenges. A backbone process required by any multi-robot system is path planning. Thus, path planning for multi-robot systems is a recent top research topic. However, the literature lacks a recent comprehensive review of path planning works designed for multi-robot systems. The aim of this review paper is to provide a comprehensive assessment and an insightful look into various path planning techniques developed in multi-robot formation systems, in addition to highlighting the basic problems involved in this field. This will allow the reader to discover the research gaps that must be solved for a better path planning experience for multi-robot formation systems. Finally, an illustrative comparative example is presented at the end of the paper to show the advantages and disadvantages of some popular path planning techniques.

1. Introduction

Robots are considered to be a central pillar of the fourth industrial revolution. Within the last few decades, robots have been widely involved in important tasks across various fields, including transportation, healthcare, and the military. However, the developer's ambitions were high aiming to maximize the exploitation of robots and involve them in more sophisticated tasks. It has been noticed that some complicated missions cannot be achieved by a single robot. This had led to propose robotic systems which consist of multiple robots collaborating together as a fleet in formation to achieve certain tasks. However, the idea of collaborative robotic systems was thought of as an impractical theoretical approach for several decades due to the lack of computing capabilities, especially in networking. Today, the recent advancements in computing capabilities have caused a great interest in the development of multi-robot formation systems.

The idea of formation is inspired by the behavior of natural creatures such as fish schooling and bird flocking where a number of animals utilize specific formations to provide protection from predators. In a similar manner, a number of robots can operate in formation to achieve complex missions and provide higher levels of autonomy. One of the first attempts to implement a multi-robot formation system was conducted by Fukuda and Nakagawa in the late 1980s. The work was a reconfigurable robot in which its formation shape can be modified based on the mission requirement [1]. Another remarkable project was released by the Institute of Physical and Chemical Research in Japan. The project named the actor-based robots and equipments synthetic system. This was a system architecture to enable different robots to jointly fulfill missions [2].

There are several advantages to adopting multi-robot formation systems. Efficiency is the main advantage of multi-robot systems. Since several robots are operating in parallel, it is expected that the task can be achieved quicker. Another advantage is the robustness where single-point failure is avoided. If a robot fails, other robots can take over, and the task can still be completed. Moreover, some tasks cannot be achieved with a single robot, and a combination of heterogeneous collaborative robots is required to accomplish the mission. For example, a robotic system consists of unmanned aerial vehicles (UAVs) and unmanned ground vehicles (UGVs) can be used to achieve an efficient surveillance task where the UAVs can first scan the area to search for a specific ground object and then guide the UGVs to reach the object. The importance of multi-robot systems has also emerged in the military sector. A report produced by the Department of Defense (DoD) in the United States have planned a roadmap for Unmanned Integrated Systems for the period within the years between 2011 to 2036. The report has clearly emphasized the importance of increasing the use of unmanned vehicles in the future battlefield. The report indicated that a considerable percentage of the budget of DoD department has already been allocated to develop advanced unmanned vehicle systems. There is also a vision by the DoD department to develop seamless integration of unmanned vehicle systems with conventional military assets.[1] Moreover, the Ministry of Defence in the United Kingdom has also shown increasing interest in unmanned vehicles. The UK Ministry of Defence has proposed the Unmanned Warriors project which involved more than 50 robots working in various environmental domains. The Unmanned Warriors project aimed to showcase the benefits of such technology to the future battlefield [3].

A backbone process required by an autonomous robotic system is path planning [4, 5]. Path planning is the problem of finding an obstacle-free path to the desired destination. In contrast with trajectory planning, a path planning problem ignores the temporal evolution of motion which means neither velocities nor acceleration is taken into account [6]. There are several indicators for a good path planning algorithm. Some well-known indicators are the path length, the computational speed, the smoothness of the path, the energy cost, and the safety. A good path planning algorithm should be able to produce a high-quality path in terms of the length and the smoothness within the least energy cost and the shortest execution time possible. However, improving these metrics at once is not a trivial process. A common practice within path planning algorithms is to operate in an iterative manner. The more the iterations, the shorter and smoother the obtained path. Another factor is the resolution of the map. Higher map resolutions can help produce higher-quality paths. However, high-resolution maps will contain a substantial amount of data, and therefore, the processing time required is expected to increase.

The previously described trade-off problem between execution speed and path quality is expected to be more challenging for multi-robot systems. The reason is that adding more robots to the system will naturally increase the processing efforts within the system, and therefore, the processing time will automatically increase. Therefore, the path planning problem for robotic systems is a top research topic in state-of-the-art robotics-related research problems [7–11].

There are several attempts to produce a review on path planning techniques designed for multi-robot systems. However, the reviews published recently in the literature were limited to either reviewing only a specific robot type such as UAV-based systems [12], and UGV-based systems [13], or neglecting the formation control system which is an essential factor for multi-robot systems [13–15]. To the best of the author's knowledge, the literature lacks the presence of a recent study on the state-of-the-art path planning techniques designed for multi-robot formation systems. Therefore, this paper presents a comprehensive review of the latest works in path planning techniques for multi-robot systems. In this paper, the main focus is to classify multi-robot based on the formation type. There are different formation configurations for multi-robot systems, including the leader–follower approach, the virtual approach, the behavior-based approach, and the dynamic approach. However, some multi-robot systems do not follow a specific formation. The goal of this paper is to list as much as multi-robot systems presented lately in

[1]US Military, Unmanned System Integrated Roadmap, FY2011-2036. Technical report, US Department of Defense (DoD), 2011.

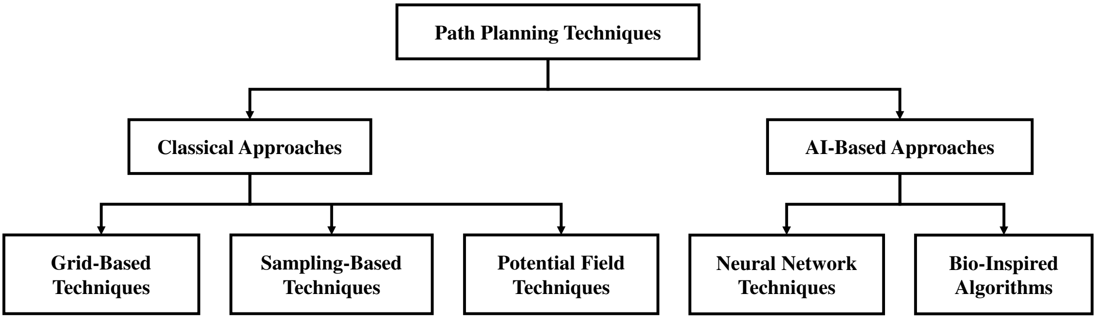

Figure 1. *General classification of path planning techniques.*

the literature. Therefore, a more-general classification system based on "decision-making" is presented to be able to list more techniques. Based on "decision-making," multi-robot systems can be classified generally into centralized, decentralized, distributed, and hybrid systems.

The remaining of the paper is presented as follows. Section 2 introduces different path planning techniques. Section 3 presents the latest path planning works published in the literature based on the formation type adopted. Recent multi-robot papers based on the more-general classification system, the decision-making, are presented in Section 4. Experimental analysis using different multi-robot path planning techniques is presented in Section 5. Finally, the conclusion appears in Section 6.

2. Path planning techniques classification

Path planning is a computational problem that aiming to obtain sequential obstacle-free configurations to the goal point. The most basic path planning scenario is to calculate an obstacle-free path from a specified starting configuration to the goal configuration. In such a scenario, other "disturbances" or complications such as terrain are neglected. The geometry of objects including the robot and obstacles is presented in a two-dimensional or three-dimensional workspace.

Configuration space, obstacle-free space, goal space, and obstacle space are some well-known path planning concepts. The configuration space represents the total set of all possible configurations (poses). If the robot is treated as a sample point in a 2D map, then the pose of the robot can be expressed with two parameters (x, y), and thus, the configuration space is a plane. On the other hand, if the orientation of the robot is important to be addressed, then the robot must be presented as a 2D shape that can rotate and translate. Therefore, the pose of the robot, in this case, should be expressed using three parameters (x, y, θ). The configuration space will be $R^2 \times OT(2)$, where OT(2) is the special orthogonal group of 2D rotations. Finally, for UAVs, six parameters are used to describe the pose of the UAV (x, y, z) to specify the location and the Euler angles (α, β, γ) to describe the orientation. The configuration space for UAVs is $R^3 \times OT(3)$.

The obstacle space is the set of configurations that are located within an obstacle or restricted area. The complement of the obstacle space is the obstacle-free space which is the set of configurations located within free space areas that the robot can safely navigate through. Finally, the goal space, which is a subspace of the free space represents the desired configuration.

Path planning techniques can be divided mainly into classical approaches and artificial intelligence (AI) approaches as shown in Fig. 1. Table I summarizes the advantages and disadvantages of popular path planning techniques.

2.1. Classical approaches

It has been observed that some classical path planning approaches do not guarantee obtaining an obstacle-free path. These methods are considered least desirable for real-time implementation, since

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Table I. *Advantages and disadvantages of popular path planning techniques.*

Technique	Category	Advantages	Disadvantages
A*, D*	Grid-based	Can always find a path if exists	Can be time-consuming, consumes a lot of memory
RRT	Sampling-based	Can be fast	No shortest path guarantees
PRM	Sampling-based	Probabilistically optimal	Narrow corridor problem
Fast marching	Potential field	Execution speed	Local minima problem
Recurrent neural network	Neural network	Scalable	Requires huge computing resources
Genetic algorithm	Bio-inspired techniques	Can work for large and complex maps	Computationally expensive

their main disadvantage is their high computational cost and inability to respond to environmental uncertainty [16]. In this paper, the classical approaches will be classified into grid-based techniques, sampling-based techniques, and artificial potential field techniques (APF).

2.1.1. Grid-based techniques

Grid-based approaches use multi-resolution grid data structures where object space is quantized into a finite number of cells. Necessary operations are then performed on the quantized space [17]. Fast processing time is a significant advantage of grid-based methods. However, the processing speed varies based on the number of cells in each dimension of quantified space [18]. A* and D* algorithms are two examples of grid-based path planning techniques [19].

A* algorithm is a well-known path search algorithm that was first introduced in 1963 [20]. It is an extension of the Dijkstra technique with additional heuristic calculations to improve the performance [21]. Although the A* algorithm is successfully implemented on 2D robotic systems, its implementation on 3D robotic systems is still challenging [22]. The main drawback of this algorithm is that it requires a long computational time to find the shortest path [6]. Figure 2 illustrates an example of finding an obstacle-free path using A* algorithm. D* algorithm is another grid-based approach that was first proposed in 1994 as an improvement over the classical A* algorithm [23]. The abbreviation D stands for "Dynamic" since it is similar to the A* algorithm except it is the dynamic variant of the A* algorithm. The algorithm can be used to solve path planning problems in unknown environments [23]. On the other hand, the time it takes to do a simulation increases as the problem becomes more complex [24]. Modified versions such as D*-Lite and Focussed D* have significantly replaced the conventional D* algorithm due to the fast execution capabilities [25, 26].

2.1.2. Sampling-based techniques

Sampling-based algorithms select sample points randomly from the entire space. Whenever the line separating two samples does not intersect with an obstacle, and the distance between these samples does not exceed the predetermined maximum distance, the samples will be interconnected. After that, the shortest path will be selected as the final path [27]. Rapidly exploring random trees (RRT) and probabilistic RoadMap (PRM) are two of the most well-known sampling-based techniques [28].

The PRM algorithm generates the probable path in a short amount of time, which enables it to be used in more reactive situations. However, it lacks smooth navigation since it wastes a lot of time preparing paths that will never be used. [29]. Figure 3 shows an example of finding a feasible path using PRM technique. On the other hand, the RRT approaches are widely used to solve single-query path planning

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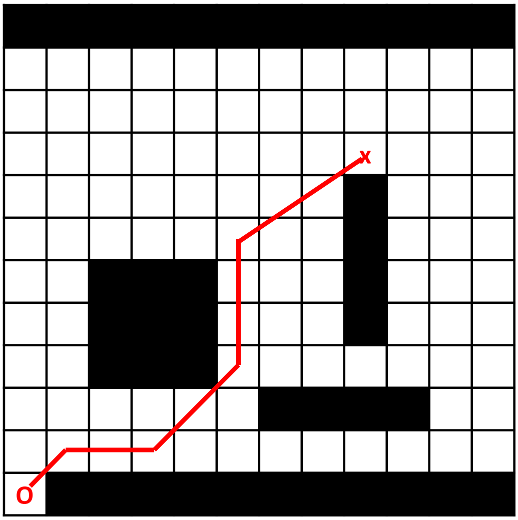

Figure 2. *Finding the obstacle-free path using the A* grid-based technique.*

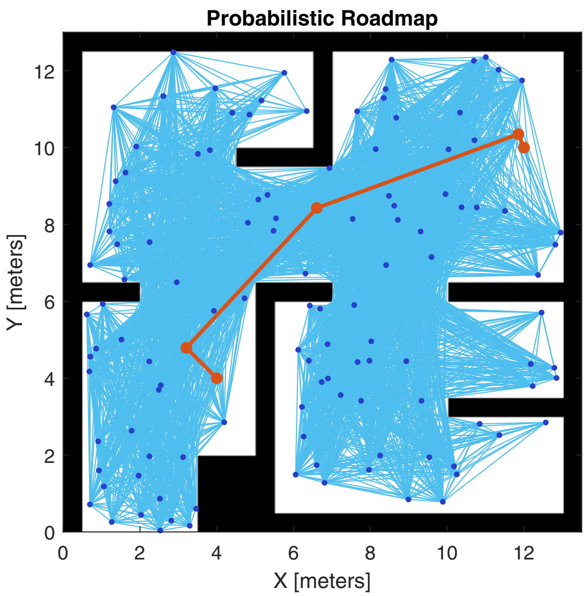

Figure 3. *Finding the obstacle-free path using a PRM planner.*

problems. However, producing paths on huge dynamic maps remains a challenge for these approaches [30]. The RRT*N algorithm is presented in ref. [31]. The objective of this modified algorithm is to improve the RRT algorithm's processing speed. The RRT*N algorithm was successfully expanded to operate in a three-dimensional environment, demonstrating its ability to work with both dynamic and static obstacles. Additionally, in order to solve the problem of high computation cost, various modifications of RRT have been proposed such as RRT-Connect algorithm [32], RRT* algorithm [33], and Bi-RRT algorithm [34].

2.1.3. Potential field techniques

The APF algorithm is used to reach the target point and avoid obstacles by modeling the robot as a charge point that is affected by the attractive force provided by the target point and repulsive forces

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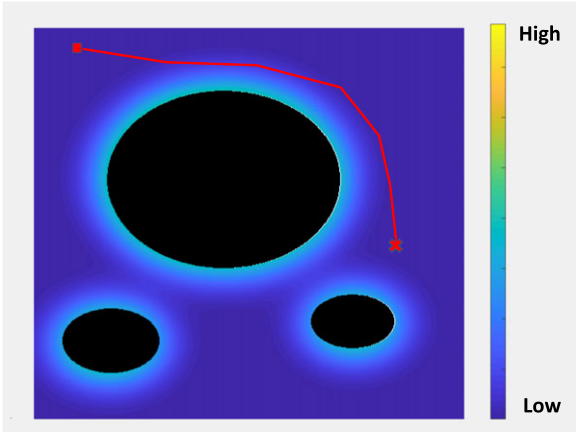

Figure 4. *Finding the obstacle-free path using the potential field method.*

caused by obstacles [35]. The main advantage of this algorithm is its rapid convergence, as it may get the final path with fewer computations than grid-based and sampling-based approaches [36]. Figure 4 illustrates an example of a path planning process using potential field method. However, since APF methods are based on optimization techniques, they suffer from the local minima problem. The authors in ref. [37] proposed a modified APF approach for multi-UAV systems. The suggested approach used a distance factor and jump methodology to address common challenges such as unreachable goals in a 3D multi-UAV environment.

2.2. AI-based techniques

AI is a field of computer science and engineering that aims to create machines and systems that can perform tasks that typically require human intelligence, such as visual perception, speech recognition, decision-making, and language understanding. AI is widely used in robotic path planning to enable robots to navigate through complex environments and complete tasks autonomously. AI is achieved through a combination of techniques such as machine learning, computer vision, natural language processing, and knowledge representation. Machine learning, in particular, is a method of teaching computers to learn from data, without being explicitly programed. In other words, learning is the process of automatically modifying an algorithm based on previous experiences without the need for human intervention [38]. AI techniques including machine learning and computer vision are often used to help robots identify and avoid obstacles, as well as to make decisions about which path to take. For example, a robot equipped with AI might use machine learning algorithms to learn from previous experiences and optimize its path planning over time. Additionally, computer vision algorithms can be used to give the robot a sense of its environment, allowing it to detect and avoid obstacles in real time.

A well-known machine learning approach is the artificial neural networks (ANNs). A neural network is a type of machine learning model inspired by the structure and function of the human brain. It is composed of interconnected layers of artificial neurons that process and transmit information, allowing the network to learn and make decisions based on input data. AI is not explicit to mimicking human behavior. For example, the bio-inspired techniques are a set of methodologies that take inspiration from nature to design and develop new technologies and systems. These techniques aim to mimic the behavior, structure, and function of natural systems, such as the human body, animals, and plants, to solve problems in fields such as robotics, computer science, and engineering. In this paper, the AI-based approaches will be subdivided into ANN-based algorithms and the bio-inspired algorithms.

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2.2.1. ANN-based algorithms

ANN is an operating model made up of a huge number of nodes that are connected to each other. Each node represents an activation function, which is considered a specific output function. Each link between two nodes represents a weighted value for the signal that passes through the connection, which is equivalent to an ANNs memory [21]. Some of the characteristics that make ANN-based systems valuable in the field of mobile robotic navigation are their ability to generalize, distributed representation, enormous parallelism, fault tolerance, and learning ability [16]. However, ANN-based techniques have the disadvantage of being time-consuming, and the learning method may not be able to ensure convergence with the optimal solution. Therefore, different methods are utilized with ANN models as a hybrid mechanism to produce the optimum result during the robotic navigation process [39].

2.2.2. Bio-inspired techniques

Bio-inspired techniques, also known as biomimicry, are a set of methodologies that take inspiration from nature to design and develop new technologies and systems. These techniques aim to mimic the behavior, structure, and function of natural systems, such as the human body, animals, and plants, to solve problems and improve performance in fields such as robotics, computer science, and engineering. For example, bio-inspired robots can be designed to mimic the movement and sensory capabilities of animals, such as snakes or insects, to improve their ability to navigate through difficult terrains. For path planning, bio-inspired algorithms can be used to improve the efficiency and robustness of optimization and search algorithms.

Population search optimization methods (PSOMs) are examples of bio-inspired techniques. A PSOM technique uses multiple agents during each run to enhance the candidate agents so that better agents can be produced for each iteration of improvements. Although these searching approaches are effective at identifying encouraging spots in huge areas, they do not effectively exploit the search space's vast expanses [40]. Some examples of PSOM include particle swarm optimization (PSO) algorithm [41], Bat algorithm [42], and genetic algorithm (GA) [43].

3. Formation control-based path planning

In this section, various recent path planning techniques are listed based on the adopted formation. The advantages of each formation technique will be addressed in the corresponding section. Section 3.1 discusses the latest path planning techniques using leader–follower formation. Section 3.2 presents the virtual formation path planning techniques. Behavior-based formation path planning techniques are discussed in Section 3.3. Finally, dynamic formation path planning techniques are presented in Section 3.4.

3.1. Leader–follower formation path planning

In the leader–follower approach, a single robot called the leader has full access to the navigation information. Therefore, this leader moves along the predefined trajectory and the followers (the other robot) follow the leader to the desired location. These followers don't have any information about the path and the final destination [3]. The advantages of the leader–follower approach are that: it is easy to be designed and implemented, can be analyzed using standard control technique, efficient with respect to communication within the system (fewer communication channels), and energy-saving mechanism. The disadvantage of the leader–follower approach is that it is centralized control approach. Thus, it lacks robustness where leader's fault can penalize the whole formation and feedback from followers to a leader is generally not applied in this approach [77, 78].

Leader–follower formation has been applied for various robotic systems including USVs, UAVs, UGVs, and manipulators. Table II lists briefly various leader–follower techniques published recently in the literature. For USV systems, the works in refs. [44, 45] have used fast marching (FM) as a path

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Table II. Summary of the works done based on the formation type.

Formation type	Robot type	Paper	Year	Technique	Exp/Sim	Comment
Leader–follower	USV	[44], [45]	2015, 2016	Potential field	Sim	Efficient computational time. Cluttered environment.
		[46]	2016	Grid-based	Exp	Jellyfish removal.
		[47]	2022	Potential field	Sim	Used adaptive fuzzy logic sliding mode control method.
	UAV	[48], [49]	2015, 2021	Potential field	Sim	Used fast marching square method.
	UGV	[50]	2012	Grid-based	Both	Localization in uncertain environments.
		[51], [52], [53]	2014, 2013, 2019	Potential field	[51] Both, [52, 53] Sim	[51] Used ARO optimization. [52] Voroni fast marching.
		[54], [55], [56], [57], [58]	2022, 2019, 2021, 2016, 2022	AI-based	[55] Exp, [54, 56–58] Sim	Q-Learning algorithm. [55] Integer programming. [56] Bayesian optimization and Monte Carlo. [57] Artificial immune network. [58] Ant colony optimization (ACO).
		[59], [60], [61]	2002, 2012, 2015	Other	[59, 60] Exp, [61] Sim	[59] Kmodynamic randomized motion planner. [60] Wifi-based positioning. [61] Adversarial formation.
	Manipulator	[62]	2022	Potential field	Both	Grasping application.

Table II. *Continued.*

Formation type	Robot type	Paper	Year	Technique	Exp/Sim	Comment
Virtual	UAV	[63]	2015	Potential field	Sim	–
	UGV	[64]	2021	Grid-Based	Exp	Parcel moving in warehouses.
		[65]	2019	Other	Both	Circle-packing algorithm.
Behavior	UGV	[66]	2010	Potential field	Both	Assist the firefighters.
		[67]	2017	Grid-based	Sim	Basic Theta* and LIAN for smart relocation tasks.
		[68]	2021	AI-based	Sim	Used reinforcement learning
Dynamic	Heterogeneous	[69]	2017	Sampling-based	Both	Used constrained optimization method. Static and moving obstacles.
	UGV	[70]	2014	Sampling-Based	Both	Clutter environment.
		[71]	2005	Grid-Based	Both	Dynamic environment.
		[72]	2013	Potential field	Both	Static and dynamic obstacles in uncertain conditions.
		[73]	2016	AI-based	Both	Used PSO for dynamic obstacles.
		[74]	2014	AI-based	Sim	Artificial immune algorithm.
		[75]	2019	Other	Sim	Configuration of a multifunctional modular robot.
	UAV	[76]	2014	Potential field	Sim	Virtual leader and behavioral approach.

"Exp/Sim" column refers to "Experimental/Simulation."

Figure 5. *A leader–follower experiment conducted in ref. [145].*

planning technique, while in ref. [46] Theta* technique has been used. In ref. [44], the FM proposed algorithm has achieved efficient computational time compared to competitive path planning systems. Another potential filed technique was proposed in ref. [47]. In ref. [46], the authors have utilized Theta* as a path planning technique for the proposed robotic system with the objective of extracting jellyfish from the sea. The authors have proposed a new mechanism named angular rate-constrained path planning system to solve the problem of minimum turning radius which is a known drawback of leader–follower approaches. The jellyfish removal process was successfully tested at Masan Bay in South Korea.

On the other hand, the works in refs. [48, 49] have implemented leader–follower UAV systems using potential field methods. UAV systems operate in a 3D environment which requires more processing time due to the huge amount of data to be processed. Therefore, the works in refs. [48, 49] have adopted potential field techniques which are known for fast execution. In ref. [48], the authors have used the fast marching square (FM^2) algorithm which is a potential field technique.

Finally, the literature has shown a larger number of papers proposing UGV leader–follower systems compared to USV and UAV systems. Variety path planning techniques were applied, including grid-based [50], potential field [51–53], optimization and machine learning [54–58], and other techniques [59–61]. Examining localization tasks in uncertain environments is the objective of the authors in ref. [50]. They have used both simulations and experiments in order to check the performance of the proposed technique. On the other hand, the proposed leader–follower techniques in refs. [51–53] have used the potential field method as a path planning technique. In addition to the potential field method, the asexual reproduction optimization method has been used in ref. [51] to enhance the performance of the proposed path planning system, while in ref. [52], Voronoi FM method was proposed as a path planning technique. Another path planning category used in leader–follower UGV systems is the optimization and machine learning methods [54–57]. Q-Learning algorithm was utilized by the authors of [54], while the Integer Programming method was used in ref. [55]. Moreover, the work in ref. [56] implemented the Bayesian optimization and Monte Carlo simulations to achieve the path planning tasks. Finally, artificial immune networks were used in ref. [57] as a path planning technique. The literature has shown other path planning techniques adopted by leader–follower UGV systems such as Kmodynamic randomized motion planner (MP) algorithm [59], Wifi-based positioning algorithm [60], and adversarial formation algorithm [61]. Fig. 5 shows a leader–follower experiment. In ref. [62], the fingers of an end effector of a manipulator were treated as stand-alone robots. Therefore, a leader–follower approach based on FM^2 was implemented on UR3 robot to achieve grasping application.

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3.2. Virtual formation path planning

The formation design in the virtual structure approach considers all the N number of robots in the formation as a single rigid structure. Each robot in the formation is provided with the desired trajectories. Then a control scheme works on maintaining the formation by minimizing the error between the virtual structure and the current robot position. The advantage of this approach is that its structure depends on the feedback of the position of each robot. Thus, it is capable of identifying the faulty robots in the formation unlike the leader–follower approach. The disadvantage in this approach is that the obstacle avoidance mechanism is not easy to be implemented [78, 79].

Virtual formation path planning has been used in UAV [63] and UGV [64, 65] systems. As shown in Table II, a limited number of works have focused on virtual formation techniques. In ref. [63], the APF method integrated with the extra control force is proposed. In order to solve the multi-UAV formation path planning issue, the virtual target point and the virtual velocity rigid body were presented based on this approach. The simulation results proved the path planning method's efficiency and the availability of realistic path following. On the other hand, virtual formation path planning has been used in [2, 3] for UGV systems. In ref. [64], a graph-based approach for moving cooperative rectangular parcels in a warehouse utilizing unicycle robots is introduced. After the box has been securely fastened and moved, a virtual formation leader is created in the middle of the box, which eliminates the requirement for individual robot path planning. Experimental results have shown that the proposed approach is time-efficient and user-friendly. In ref. [65], an arbitrarily shaped control strategy is introduced for avoiding obstacles problem in a tough unknown environment. To avoid narrow paths and corners, a swarm-like architecture is established by creating an arbitrarily shaped virtual region followed by a series of packed circles. Simulation and experimental results have been presented to show the performance of the suggested controllers.

3.3. Behavior-based formation path planning

The behavior-based approach utilizes numerous behaviors for each robot. A final control action takes place based on the weighting of the relative importance of each behavior. The importance of each behavior is identified based on sensory inputs such as obstacle avoidance, goal-seeking, and formation keeping [79, 80]. The main advantages of this approach is that it is capable of dealing with multi-task missions. Furthermore, the approach is suitable to be used in an unknown or dynamic environment. The main disadvantages of the approach are related to the difficulty in mathematically expressing the system behavior. Moreover, it is difficult to prove and guarantee the system stability [3].

Behavior-based formation path planning is typically used to fulfill multi-task missions in unknown or dynamic environments. However, the main drawback is that it is difficult to prove and guarantee system stability. Therefore, the behavior-based formation has been mostly implemented within UGV systems [66–68]. Table II summarizes numerous behavior-based techniques that have been recently discussed in the literature. In ref. [66], a group of autonomous assistant mobile robots has been developed to help firefighters in scouring the warehouse in the case of a fire. The robots assist firefighters on the scene by pointing out potential obstructions and preserving communication links. Therefore, robots must be able to fulfill particular behaviors such as remaining in a group. The potential field method is adopted here to control the generated model. On the other hand, the behavior-based technique proposed in ref. [67] utilized a grid-based method to solve the smart relocation task for UGV systems. The authors used basic Theta* and limited angle algorithms as path planning techniques to produce smooth paths. Finally, a machine learning path planning method based on reinforcement learning is proposed in ref. [68]. As part of the robot path planning process in an unknown environment, reinforcement learning is used to apply the robot's behavioral decisions and to improve its predictive abilities. A visual simulation platform has been developed in order to enable researchers to test multi-robot motion control algorithms.

3.4. Dynamic formation

The dynamic formation refers to the robotic systems that modify its formation type during operation due to some special needs. The dynamic formation is used to improve the efficiency and reliability of

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the formation. The dynamic concept signifies the robustness of the formation. Although the dynamic formation is widely used in UGVs, it is also very useful for UAVs and heterogeneous robotic systems. Table II lists a number of dynamic formation techniques that have been recently addressed in the literature. For example, the work in ref. [69] presented a team of UAVs and mobile manipulators that collaboratively carry an object. The performance of the proposed object transport approach was tested experimentally and through simulations. A sampling-based and nonlinear optimization technique have been applied in 2D and 3D environments to avoid static and moving obstacles. In addition, the authors in ref. [76] proposed a dynamic formation path planning for UAV systems using the hybrid virtual and behavioral approach schema. The proposed formation control strategy was based on the potential field method to solve the local minima problem.

More works have been focused on UGV dynamic formation systems [70–75]. In order to achieve the intended formation goal, several path planning techniques have been applied. In ref. [70], RRT algorithm was used as a path planning technique for mobile robots in order to operate autonomously in a cluttered environment. The proposed method has successfully addressed collision avoidance and formation forming problems through simulations and experiments. In addition, some works have applied a path planning technique in a dynamic environment containing static and moving obstacles using simulations and experiments such as A^* algorithm [71] and FM square [72]. Some dynamic formation systems have adopted meta-heuristic optimization techniques such as PSO [73] and artificial immune algorithm [74]. Finally, the robotic system proposed in ref. [75] had successfully implemented a dynamic formation system for a group of modular robots. Modular robots are self-reconfigurable robots with variable morphology. They are made up of distinct modules to form a kinematic structure. Their flexible design enables such robots to adjust their shape to be able to fulfill the task. The challenge is to form the required kinematic structure in real time. The work in ref. [75] addressed the time problem and aimed to reduce the time required for the formation of the modular robot configuration using analytical geometry methods.

4. Decision-making-based path planning

The previous section has listed the latest multi-robot path planning systems based on the adopted formation style. However, some multi-robot systems do not consider a specific formation style. To have a comprehensive review paper of the latest multi-robot path planning techniques published in the literature, a more-general classification method is adopted in this section based on the decision-making approach. Based on the decision-making approach, multi-robot systems can be classified into centralized, decentralized, distributed, and hybrid decision-making approaches. The basis of this classification strategy is the determination of the entities that are mainly responsible to process and control the multi-robot system. In the centralized approach, a central processing unit which can be a stand-alone computer or a robot is the responsible entity for controlling the system. On the other hand, within a decentralized strategy, each robot has its own controller and acts based on its own processed data. In the distributed decision approach, the robots are involved in the planning process of the system, but there is no central agent to compute the plans. Finally, the hybrid decision-making approach refers to the robotic systems that apply multiple decision-making approaches at once. Using such a classification approach, any multi-robot system can be classified into one of the decision-making approaches.

However, there is still a reasonable connection between formation-based classification and decision-making-based classification. Since the decision-making-based classification is a more-general classification strategy, different formation styles can be classified as a certain decision-making approach, but not vice versa. Therefore, all of the techniques listed in Section 3 can be classified in this section into one of the decision-making approaches. In general, the leader–follower formation style can be considered a centralized decision-making approach, since the plans and the control of the system are performed in a centralized entity which is the leader robot. The virtual formation style in which the robots are treated as a moving rigid body can be considered a distributed decision-making approach, since the universal plan of the system is determined by a collaborative mechanism performed by the individual

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robots. The behavior-based formation style can be considered as a decentralized approach, since each robot plans individually according to a specific behavior such as line following, wall following, avoiding obstacles, and goal following. Finally, the dynamic formation style can be naturally mapped to the hybrid decision-making strategy. On the other hand, not all multi-robot systems that adopt a certain decision-making approach are committed to a specific formation style. Thus, this section aims to list recent multi-robot techniques that do not adhere to a known formation style and classify them based on the decision-making approach.

In this section, recent decision-making-based path planning techniques are listed. Section 4.1 discusses the latest path planning techniques based on the centralized-based decision. Section 4.2 presents the decentralized decision path planning techniques. Distributed decision path planning techniques are discussed in Section 4.3. Finally, hybrid decision-making path planning techniques are presented in Section 4.4. The main path planning works done based on the decision type is given are summarized in Table III.

4.1. Centralized decision path planning

Centralized architectures contain a central control agent which can be a stand-alone computer or a robot. The control agent has global information about the environment as well as the information of every robot. This enables the central agent to communicate with all robots. The main advantage of the centralized architecture is that the central control agent has a global view of the world, whereby globally optimal plans can be produced. On the other hand, this architecture is typical for a small number of robots and ineffectual for large teams with a high number of robots. In addition, it is not robust in relation to dynamic environments or failures in communications and other uncertainties. In the case of a malfunction of the central control agent, a new agent must be available, or else the entire team will be disrupted [77].

Based on the aforementioned drawbacks, centralized decision-making has been applied to a limited number of works related to UGV systems [81–88]. In ref. [81], the task allocation was performed using a GA, and the path planning was performed using the A^* algorithm. The authors in ref. [82] proposed a hybrid algorithm to discover the optimal trajectory of the path for multi-mobile robots in a cluttered environment using improved particle swarm optimization (IPSO) and differentially perturbed velocity (DV) algorithm. According to the experimental and simulation findings, the suggested IPSO-DV outperforms IPSO and DE in terms of optimal trajectory path length and arrival time. However, the works in refs. [83, 84] proposed a centralized architecture for trajectory planning in a dynamic environment based on the APF technique. An approach that relies on an external path planner for general configuration spaces was proposed in ref. [85]. The approach decoupled the problem into a set of sub-problems whose solutions can be sequentially executed. The implementation showed that the algorithm is able to solve problems with many robots and a low degree of coupling. Finally, the literature has shown other path planning techniques adopted by centralized decision path planning for UGV systems such as centralized decoupled algorithm [86], PUSH-AND-SWAP approach [87], and two-level partition-based algorithm [88].

4.2. Decentralized decision path planning

In the decentralized control strategy, each robot makes its own decisions based on its measurements. Thus, several independent controllers are used to control the robots rather than a single centralized control scheme. Consequently, this strategy provides higher robustness than the centralized strategy to be used with large-scale systems. The disadvantages of this strategy are related to the coordination difficulty that might occur [77, 141, 142].

A large base of decentralized decision path planning research has been focused on UGVs rather than UAVs. For UAV systems, the authors in ref. [89] proposed a potential field path planning technique that constructs closed pathways for any coverage task such as environmental mapping or surveillance

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Table III. *Summary of the path planning works done based on the decision type.*

Decision type	Robot type	Paper	Year	Technique	Exp/Sim	Comment
Centralized	UGV	[81]	2016	Grid-based	Sim	A* was the main algorithm. GA has been used for task allocation.
		[82]	2016	Hybrid algorithm	Both	IPSO and DV algorithm.
		[83], [84]	2012, 2020	Potential field	Sim	Dynamic environments.
		[85], [86], [87], [88]	2009, 2011, 2011, 2013	Other	Sim	[85] Optimal decoupling into sequential plans, [86] centralized decoupled algorithm, [87] PUSH_AND_SWAP approach, [88] two-level partition-based algorithm.
Decentralized	UAV	[89]	2014	Potential field	Both	Voronoi-based cost function
	UGV	[90], [91], [92]	2012, 2020, 2021	AI-based	[90, 91] Sim and [92] Both	[90] Genetic algorithm. [91] CNN and GNN. [92] DCCP and CBF-CLF.
		[93], [94], [95], [96], [97], [98]	2016, 2017, 2020, 2005, 2016, 2006	Potential field	[93, 96] Both, [94, 95] Sim, and [97, 98] Exp	[93] Vector field method. [94] Used the decentralized approach. [96] Switched local potentials. [97] MSFM technique. [98] Vector field algorithm.
		[99], [100]	2011, 2019	Grid-based	Both	CA method.

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Table III. Continued.

Decision type	Robot type	Paper	Year	Technique	Exp/Sim	Comment
		[101], [102]	2015, 2013	Hybrid technique	[101] Both and [102] Sim	[101] Repulsive function (potential field method), A* algorithm, and UKF. [102] Potential-based genetic algorithm.
		[103]	2011	Sampling-based	Both	Decentralized multi-agent rapidly exploring random tree (DMA-RRT) algorithm.
		[104], [105], [106]	2010, 2013, 2009	Other	Sim	[104] Rough mereological theory. [105] Artificial moments. [106] Dynamic priority strategy.
Distributed	UAV	[107], [108], [109], [110]	2020, 2017, 2019, 2019	AI-based	[107, 109] Sim and [108, 110] Exp	[107] Military and civilian tasks. [108] Surveillance, inspection, and rescue tasks. [109] Formation for reconnaissance and attack. [110] Fleet formation control and target tracking.
		[111], [112]	2018, 2013	Optimization	[111] Exp [112] Sim	[111] Lin–Kernighan–Helsgaun heuristic algorithm. [112] Hierarchical control structure.
		[113]	2020	Grid-based	Sim	MCPP-MLCT method.
		[114]	2016	Other	Sim	Tangent circle method.
	UGV	[115], [116]	2019, 2014	Potential field	Sim	[115] Static and dynamic obstacles. [116] Used the rotational vector field method.
		[117], [118]	2002, 2018			[117] A* algorithm. [118] Used CGD algorithm.

Table III. *Continued.*

Decision type	Robot type	Paper	Year	Technique	Exp/Sim	Comment
		[119], [120], [121], [122]	2016, 2013, 2020, 2017	Grid-based	[117], [118], [119] Both, [120–122] Sim	[119] Bellman–Ford algorithm. [120] Rescue missions. [121] SaG algorithm.
		[123], [124], [125]	2008, 2017, 2018			[123] Parallel differential evolution algorithms. [124, 125] Artificial bee colony algorithm.
		[126], [127], [128], [129]	2017, 2016, 2017, 2016	AI-based	[123], [124], [125], [126, 128, 129] Sim, [127] Both	[126, 128] D2PSO algorithm. [127] Also used improved gravitational search algorithm (IGSA). [129] Also used bacterial foraging (BFOA).
	Heterogeneous	[130], [131], [132], [133]	2015, 2019, 2020, 2015	AI-based	Sim	[130] Kernel sequence enumeration (KSE) algorithm. [131] Modified ant colony optimization (MACO) and genetic algorithm (GA). [132] Improved dragonfly algorithm (DA). [133] Simulated annealing algorithm.
		[134]	2017	Other	Exp	SLAM.
Hybrid decision	Satellite	[135]	2020	AI-based	Sim	Used genetic algorithm.
	UGV	[136]	2010	AI-based	Both	Static and dynamic obstacles.
		[137]	2019	Grid-based	Sim	Complex and crowded environments.
		[138], [139]	2022, 2014	Other	[138] Sim, [139], Exp	[138] Autonomous driving application. [139] Any-Com ISS algorithm.
	WSN	[140]	2014	Other	Sim	(HADCC) algorithm. Energy efficient.

using gradient descent of a Voronoi-based cost function. However, in order to minimize the uncertainty of localization, the authors in ref. [143] proposed an optimization path planning algorithm called the online optimization perceptual strategy. On the other hand, different decentralized decision path planning techniques have been applied to UGV systems, including optimization and machine learning [90–92], potential field [93–98], cellular automaton (CA) method [99, 100], hybrid algorithms [101, 102], sampling-based [103], and other techniques [104–106].

Several optimization and machine learning techniques were proposed such as GA [90], convolutional neural network, graph neural network algorithm [91], datagram congestion control protocol, and control barrier and Lyapunov function [92]. Potential field-based techniques were implemented to a number of works with different algorithms such as vector field algorithm [93, 98], switched local potentials [96], and multi-stencils FM technique [97] to deal with the path planning task. The main objective in ref. [94] is to ensure the safety of robots while they interact with each other. The UGV formation system is considered as a network with a decentralized architecture. Each robot performs path planning based on a potential field approach. In addition, the work in ref. [95] focused on combining a decentralized architecture with an APF technique to coordinate the motion of the robots. CA method was proposed in refs. [99, 100] to solve the path planning problem in a cooperative robotic team. The proposed method was implemented and tested in a real system using mobile robots.

Furthermore, the work in refs. [101, 102] utilized decentralized decision path planning using a hybrid technique. In ref. [101], a composite local path planning method was proposed using a repulsive function, A^* algorithm, and unscented Kalman filter (UKF). The repulsive function in the potential field method was used to avoid collisions between robots and obstacles. On the other hand, the A^* algorithm assisted the robots to find the optimal path. Moreover, an error estimator based on UKF was used to ensure that each robot's path deviation during navigation is kept to a minimum. In addition, another hybrid technique for a UGV swarm system was proposed in ref. [102] using a potential-based GA. The proposed algorithm consists of a global path planner (GPP) and a MP. The GPP searches for a path that the swarm robots should follow from the start to the goal within a Voronoi diagram of the workspace. The MP is developed using a GA algorithm based on artificial potential models. The potential functions are used to keep robots away from obstacles and to keep the robotic swarm within a certain distance from each other. In ref. [103], an algorithm based on a sampling-based method called decentralized multi-agent RRT algorithm was presented to handle the path planning for a multi-agent system in a complex environment. Finally, there are different path planning techniques adopted by decentralized decision strategy for UGV system such as rough mereological theory [104], artificial moments method [105], and dynamic priority strategy [106].

4.3. Distributed decision path planning

The distributed control strategy is a modified version of the decentralized control strategy. The only difference is the communication channel between each robot in the formation. This structure overcomes the difficulty in coordination but requires a high amount of communication [77, 144].

Several robotic systems have adopted the distributed decision path planning strategy ranging from UAVs [107–114], UGVs [115–129], and even heterogeneous (UAV-UGV) systems [130–134]. The PSO algorithm was commonly used as a path planning tool for several UAV applications for distributed decision systems such as military and civilian tasks [107], surveillance, inspection, and rescue tasks [108], formation for reconnaissance and attack [109], and fleet formation control and target tracking [110]. Other optimization algorithms were also adopted such as Lin–Kernighan–Helsgaun heuristic algorithm [111] and hierarchical control structure [112]. In ref. [113], a grid-based algorithm named multi-robot coverage path planning-multiple land cover types method was proposed to develop a distributed decision path planning system.

On the other hand, the literature has shown that UGV systems have intensively focused on distributed systems [115–129]. In ref. [115], the authors utilized the APF method to navigate through an environment with static and dynamic obstacles. The authors in ref. [116] have also used an APF-based technique

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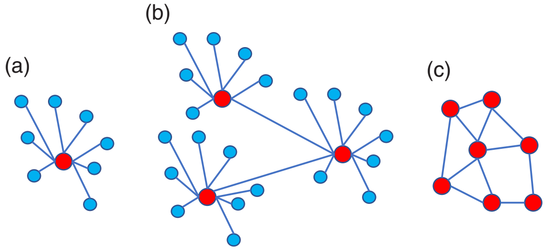

Figure 6. *A comparison between (a) centralized, (b) decentralized, and (c) distributed robotic systems.*

named the rotational vector field method. Grid-based path planning algorithms were also adopted to create a distributed decision system, including A* algorithm [117] and chessboard-shaped grid division algorithm [118]. Graph-based algorithms were also adopted such as Bellman–Ford algorithm [119] and SplitAndGroup (SaG) algorithm [121]. However, most proposed systems have integrated some optimization and machine learning algorithms as part of the pathfinding process [123–129]. The most successful optimization technique was the PSO algorithm [126–129]. The reason can be attributed to the fast execution speed of the algorithm, which is highly recommended for distributed systems. In refs. [126, 128], a variation of the PSO algorithm named dynamic distributed PSO algorithm was utilized in a distributed system. Other optimization and machine learning techniques were also implemented within other works such as parallel differential evolution algorithms [123] and artificial bee colony algorithm [124, 125]. Figure 6 shows a comparison between centralized, decentralized, and distributed robotic systems.

4.4. Hybrid decision-making

Hybrid decision-making refers to the robotic systems that apply multiple decision-making approaches at once. Hybrid decision-making has been applied to a limited number of works. Some types of robots that have used hybrid decision systems are satellites [135], UGVs [136–139], and wireless sensor networks (WSNs) [140]. The work in ref. [135] compared centralized and decentralized approaches to spacecraft formations during reconfiguration. It was developed under the paradigms of cluster autonomy and safe maneuverability. The GA was used as a path planning approach. As a result, while decentralized architecture helps the algorithm to run faster, it also means that inter-satellite communication traffic is increased.

Regarding UGV systems, the authors in ref. [139] experimentally evaluated a distributed centralized multi-robot path planning algorithm called Dynamic Team Any-Com ISS. They aimed to develop solutions to a multi-robot path planning problem that are guaranteed to be complete, resilient to communication failure, and flexible enough to accommodate different team sizes. In ref. [136], a path planning approach was presented to coordinate UGVs in an environment with static and dynamic obstacles. The pathfinding problem was modeled as a constrained optimization problem, and the motion plan to avoid dynamic obstacles was implemented through an online technique. In ref. [137], the D* Lite algorithm was proposed to deal with complex and crowded environments. A new hybrid-based formation robotic system has been proposed in ref. [140]. The new technique named hybrid advance distributed centralized clustering (HADCC) algorithm was proposed as an energy-efficient path planning technique for WSN networks in ref. [140]. The proposed HADCC is based on hybrid cluster head selection algorithm. Moreover, an advance network topology is implemented to execute the proposed model.

5. Illustrative example

This section presents multi-robot path planning tests on four different maps using A*, RRT, and PRM techniques. Figures 7, 8 and 9 show the paths that were obtained using A* and PRM, respectfully.

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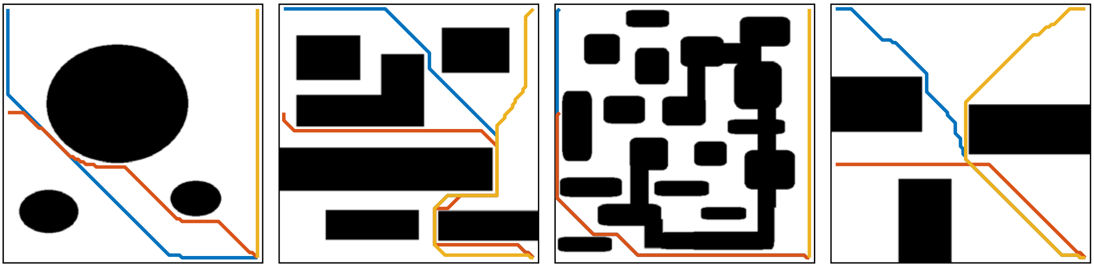

Figure 7. *A* paths obtained under different maps.*

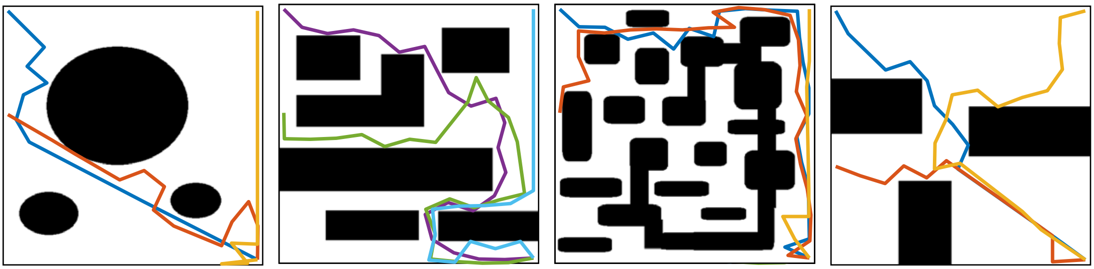

Figure 8. *RRT paths obtained under different maps.*

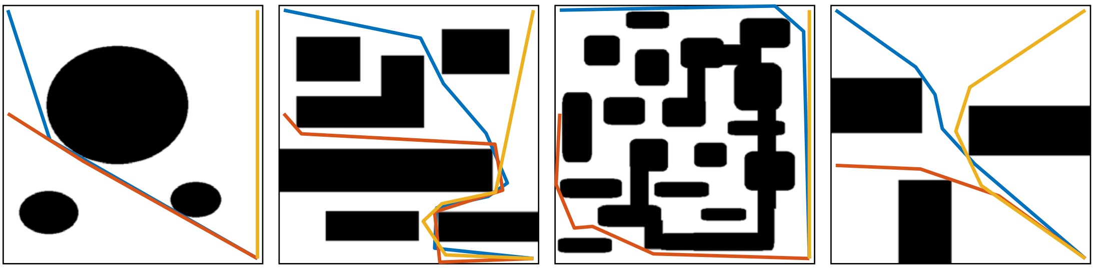

Figure 9. *PRM paths obtained under different maps.*

Table IV shows a comparative study between A* and PRM in terms of the average path length and the processing time. It is widely known in the path planning community that there is a critical trade-off problem between path length and the quality of the path. The quality of an obstacle-free path is examined using two attributes, the path length, and the smoothness of the path. It is challenging to obtain a smooth short path in a real-time manner.

Table IV shows the time quality results obtained using different parameters. The time quality trade-off is clear in the table. Shorter paths need a longer execution time. For example, the shortest path obtained in Table IV is 98.2 meters when adopting PRM. This record has also achieved the longest processing time of 4.20 s. For A*, the parameter G refers to the resolution of the grid to be used. It is expected that increasing the grid resolution will result in obtaining higher quality paths, however, with the cost of increased processing time. The reason is that higher-resolution maps will contain more points to be processed, and therefore, the time is expected to increase. This fact is valid based on Table IV. Increasing the resolution size from $100x100$ to $250x250$ increases the processing time from 0.51 to 2.56 s. On the other hand, the length of the path has decreased from 104.5 meters to 100.4 meters. For RRT, the parameter S refers to the step size of the planner. Based on Table IV, the step size parameter does not affect the processing time of the technique.

The PRM technique has a critical parameter which is the number of samples denoted by N in Table IV. Increasing the number of samples will increase the probability to obtain a shorter path, but with a cost of

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Table IV. *Comparative study between A*, RRT, and PRM in terms of the average path length and the average processing time.*

Map	Technique	Parameter	AVG. path length (m)	AVG. processing time (s)
Map 4	A*	G = 100x100	104.5	0.51
		G = 150x150	102.1	0.94
		G = 200x200	101.2	1.22
		G = 250x250	100.4	2.56
	RRT	S = 20	135.3	0.23
		S = 30	130.20	0.20
		S = 40	129.40	0.20
		S = 50	124.31	0.20
	PRM	N = 50	120.5	0.42
		N = 100	119.6	1.50
		N = 150	99.3	2.65
		N = 200	98.2	4.20

increased execution time. Based on Table IV, increasing the number of samples from 50 to 200 decreases the length of the obtained path from 120.5 to 98.2 meters. However, the execution time required increases from 0.42 to 4.20 s.

Table IV shows that the RRT technique has achieved the best processing speed. However, it is known that RRT path is not as smooth as the paths obtained using A* (Fig. 7) and PRM (Fig. 9). Smoothness is an important attribute, especially for controllers. After obtaining an obstacle-free path, a controller is responsible for tracking the path of the robot. It is easier for a controller to track a smooth path than a non-smooth path such as the path obtained by RRT.

6. Conclusions

This paper has presented a comprehensive review of the latest path planning techniques proposed for multi-robot systems. First, a general introduction to path planning techniques was presented. Then, the latest path planning works were presented based on the formation control strategy. After that, state-of-the-art decision-making-based path planning techniques including centralized and decentralized techniques were listed. Finally, some path planning simulations were presented to provide a quick comparison between different path planning techniques. This research has highlighted that there are a few number of recent works done in the area of virtual and behavior formation systems, especially for UAV systems. In addition, the literature shows a lack in the number of robotic systems that proposed heterogeneous systems. Mentioning such research gaps in the field of path planning for multi-robot systems is critical for future development and enhancement.

Supplementary materials. To view supplementary material for this article, please visit https://doi.org/10.1017/S0263574723000322.

Author contributions. Conceptualization: Saif Sinan, Raouf Fareh, Mohammed Baziyad and Maamar Bettayeb. Writing: Nour Abujabal, and Mohammed Baziyad. Literature Review and classification: Saif Sinan, Mohammed Baziyad, and Nour Abujabal.

Financial support. This research received no specific grant from any funding agency, commercial or notfor-profit sectors.

Conflicts of interest. The authors declare no conflicts of interest.

Ethical standards. Not applicable

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Cite this article: N. Abujabal, R. Fareh, S. Sinan, M. Baziyad and M. Bettayeb (2023). "A comprehensive review of the latest path planning developments for multi-robot formation systems", Robotica **41**, 2079–2104. https://doi.org/10.1017/S0263574723000322