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Review

A Comprehensive Review of Path Planning for Agricultural Ground Robots

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Citation: Chakraborty, S.; Elangovan, D.; Govindarajan, P.L.; ELnaggar, M.F.; Alrashed, M.M.; Kamel, S. A Comprehensive Review of Path Planning for Agricultural Ground Robots. *Sustainability* **2022**, *14*, 9156. https://doi.org/10.3390/su14159156

Academic Editors: Mahyar Amirgholy, Mehdi Nourinejad and Jidong J. Yang

Received: 2 June 2022
Accepted: 22 July 2022
Published: 26 July 2022

Abstract: The population of the world is predicted to reach nine billion by 2050, implying that agricultural output must continue to rise. To deal with population expansion, agricultural chores must be mechanized and automated. Over the last decade, ground robots have been developed for a variety of agricultural applications, with autonomous and safe navigation being one of the most difficult hurdles in this development. When a mobile platform moves autonomously, it must perform a variety of tasks, including localization, route planning, motion control, and mapping, which is a critical stage in autonomous operations. This research examines several agricultural applications as well as the path planning approach used. The purpose of this study is to investigate the current literature on path/trajectory planning aspects of ground robots in agriculture using a systematic literature review technique, to contribute to the goal of contributing new information in the field. Coverage route planning appears to be less advanced in agriculture than point-to-point path routing, according to the finding, which is due to the fact that covering activities are usually required for agricultural applications, but precision agriculture necessitates point-to-point navigation. In the recent era, precision agriculture is getting more attention. The conclusion presented here demonstrates that both field coverage and point-to-point navigation have been applied successfully in path planning for agricultural robots.

Keywords: path planning; agriculture; ground robot; automation; algorithms

1. Introduction

Every day, roughly 240,000 individuals join the global population, which is anticipated to reach 8.18 billion by 2025 and 9.7 billion by 2050. Even though cultivated land is nearing its limit, estimations suggest that food production would need to expand by 70% by 2050 if global peace is to be maintained [1]. Producing enough food to fulfill the ever-increasing need of this growing population is thus a tremendous issue for civilization. We must construct more efficient—yet sustainable—food production technologies, farms, and infrastructures to achieve this critical goal. Precision agriculture (PA)—a collection of strategies and techniques for precisely managing field fluctuations to boost crop yield, company profitability, and ecosystem sustainability—has provided some astonishing solutions to achieve that goal. Precision agriculture has already been recognized as a critical strategy for optimizing crop management methods and improving field product quality while also guaranteeing environmental safety [2]. Cropland monitoring and management may be a difficult process in particularly large fields and/or in fields located in mountainous terrain, necessitating the use of automated devices [3]. As the number of agricultural laborers continues to diminish throughout the world, the use of multi-robots for agricultural activities is becoming increasingly widespread on large-scale farms with fewer personnel [4]. For successful and effective implementation of PA, unmanned ground vehicles (UGVs) play a vital role. Many agricultural products are perishable in nature and require special considerations throughout the supply chain operations to prevent their decay. Truck scheduling for cross-docking of fresh products [5], intermodal freight network design for transport of perishable products [6], optimized truck scheduling at a cold-chain cross-docking terminals [7–9], and vessel scheduling in liner shipping [10] are some important research areas of supply chain operations to prevent the decay of agricultural products. Through the application of UGV in the agricultural field, the decay of agricultural products at the farm field can be avoided to some extent. The path planning of UGV for the agricultural field is the one of the most important areas in development of agricultural UGVs.

UGVs serve a critical role in boosting agricultural efficiency, such as optimizing fertilizer usage or performing precise weed control [11,12]. The productivity of farming families and the yield per unit area are improving as a result of job division and cooperation among multi-robot systems (MRS). A growth in related research has boosted the possibility for utilization, as tasks can be done more efficiently [13]. UGVs are now being used in agriculture for mapping [14,15], seeding, sensing [16], and pesticide spraying, among other things. To uninterruptedly execute the aforementioned tasks in the agricultural field, UGVs should have a high level of automation with the least amount of human intervention [17]. Navigation, detection, action, and mapping are the four most significant automation characteristics of autonomous agricultural robots [18]. Navigation is critical, and detection and mapping are frequently used [19]. Path planning is the most important and integral part for navigating UGVs. The vehicle/robot must construct a path between preset target locations without colliding with obstacles in order to navigate autonomously [20]. The robot then follows the course calculated by the path planning algorithm. Furthermore, the robot must cope with unknowns and unanticipated scenarios that may occur in real-time, such as unexpected impediments, unplanned tasks, and so on. Despite their widespread usage, GPS systems have limits and downsides in situations where high precision navigation is required or when the satellite signal is low, such as in covered areas, greenhouses, or unusual mountainous locations [21]. Due to wheel slippage on sloping terrains, which is common in various crops such as vineyards, UGV motion prediction via wheel odometry has severe limits in agricultural applications [22].

Robotic platforms will increase farm efficiency, according to the strategic European research agenda for robotics [23]. Even though this field is becoming more popular in research [24], only a few commercial solutions are available [25]. Planting, harvesting, monitoring, spraying, and trimming are just a few of the agricultural chores that have been automated. Autonomous robot navigation is required for all of these procedures. This stage, which is a crucial aspect of autonomous robot navigation: localization, mapping, motion control, and path planning are the four prerequisites. Path planning for a robot requires a series of calculations for the translation and rotational motions of the robot to avoid obstacles from the initial point to the end point in the operating environment [26]. Agricultural areas provide a number of difficulties for robotic navigation. Agrarian fields, unlike interior surroundings, are complex, unstructured, and unpredictable. Path planning tactics that are well suited for indoor areas may not be suitable for agricultural needs, necessitating the development of sophisticated agricultural path planning strategies. Path planning for UGVs is drawing a lot of attention owing to the Industry 4.0 revolution and exponential growth in machine learning. There are various publications on this topic in the literature, with the first originating in 1989 when Palmer et al. [27] proposed a problem with efficient field paths around an obstruction prompted by agricultural sector concerns. Bochtis et al. [28] presented research on agricultural machinery improvements, with path planning algorithms for farm area coverage being one of the topics covered. A smart farm should rely on autonomous decision-making to ensure (i) system efficiency, (ii) better product quality, (iii) lower costs, (iv) improved product safety and environmental sustainability, (v) reduced consumer delivery time, and (vi) increased market share and profitability while stabilizing the labor force. When the robot detects an unexpected obstacle, it is forced to change course. To safely avoid the barrier, the robot must either design a short-term time-dependent trajectory and subsequently return to the original path or compute a new path and follow it autonomously. In UGV navigation, route planning is critical for finding the best path between destination sites while avoiding obstacles. Based on the environmental data utilized to calculate an optimum path, this issue may be divided into global route planning and local trajectory planning. The purpose of global path planning is to find the most efficient route using a global geographical map. Local trajectory planning, on the other hand, uses sensor data from the surrounding environment to create a real-time, collision-free trajectory. As a result, to correctly complete various activities and minimize obstructions, both global route planning and online local trajectory planning are required [29].

To the best of our knowledge, path planning applications in agriculture do not receive a systematic and detailed assessment. As a result, this research examines the many techniques of path planning that have been used over time in various agricultural areas.

The methodology for this review is detailed in Section 2. The notion of path planning and its many approaches are briefly explained in Section 3. In Section 4, we look at the works that have been recognized as being related to agricultural path planning and Section 5 summarizes the revision's findings.

2. Methodology

This study used a 'systematic literature review' method to examine the existing literature on the path/trajectory planning features of ground robots in agriculture, with the goal of providing new information in the area [30]. To organize and assess the available literature in an area, a systematic literature review necessitates a more rigorous and well-defined technique [31]. Using the scientific search engine Google Scholar, a list of more relevant literature was compiled. Number of publications and percent of review papers found in Google Scholar for the last five years is presented in Figure 1, when searched with "path planning for agricultural ground robots".

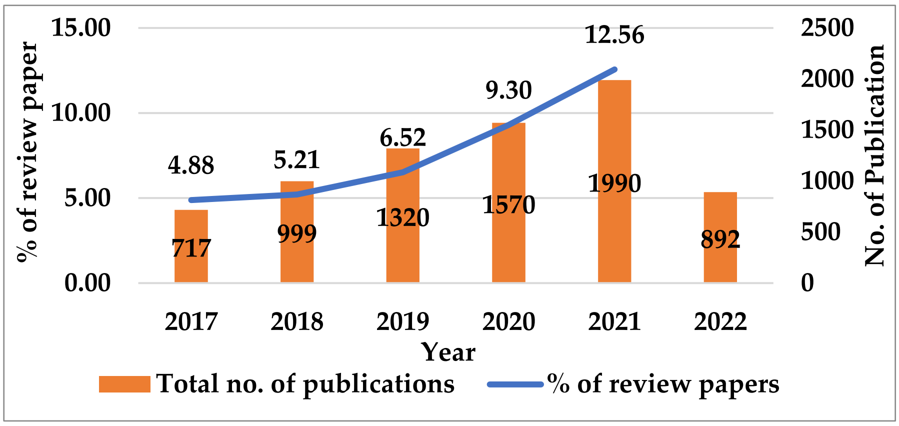

Figure 1. No of publications and % of review paper in a broad search.

Figure 1 shows that in the last five years the interest on the topic is increasing exponentially. While investigating in-depth about those literatures it was observed that most of them focused on aerial vehicles instead of ground vehicles. It can also be seen that the percentage of review papers on the field is increasing with time. A number of important publications from peer-reviewed scientific journals were chosen, which assisted in the identification of key authors and additional research pertinent to the issue of path planning agricultural robots. In this paper, we use the word "locomotion planning" to refer to the phrases "motion planning," "route planning," and "path planning," which are commonly used interchangeably in the literature when it comes to robotics-assisted automated activities. The level of abstraction of the solution domain can be used to make a broad distinction between these words. The phrase "motion planning" refers to the process of developing efficient trajectories for mobile robot systems, especially when kinematic restrictions, dynamic constraints, object coordination, and other factors are present. Furthermore, from a topological perspective, the term "route planning" refers to calculating the optimal sequence (permutation) for visiting the nodes in a graph and is equivalent to the problem of the complete traversal of a graph [32,33].

In contrast, "path planning" refers to the challenge of identifying a collision-free path linking a predetermined start and a target point [34], whether in a topological, geometrical, or a trajectory sense. Any route planning approach for ground robots in the agricultural field was studied, and papers from a variety of agricultural fields were picked. The purpose of this review of relevant work is to address the following questions:

1. What agricultural task is it performing?
2. Which path planning technique is used?
3. On-line capabilities?
4. Dynamic or static?
5. Path optimality?
6. Geometry characteristics?
7. Optimization criteria?
8. Constraints of the robot?
9. Limitations?
10. Computational complexity and processing time?
11. Field testing conditions?

3. Path Planning

Automatic ground vehicle guiding is now implemented using either local positioning systems (vision or laser-based sensors) or global positioning systems (GPSs) as shown in Figure 2.

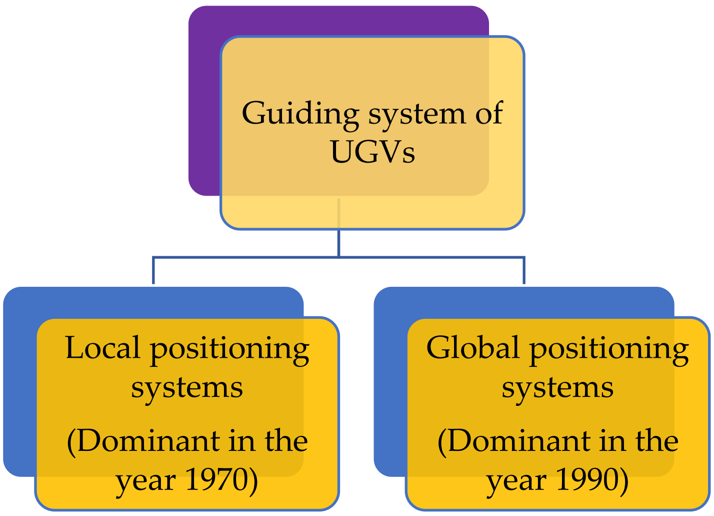

Figure 2. Guiding system of automatic ground vehicle.

Since the 1970s, local positioning systems have been employed in autonomous applications [35,36]. Although they are inexpensive to adopt, their primary downside has been observed to be susceptibility to light conditions in outdoor locations [37]. Recent advancements in satellite technology have resulted in a rise in the latter's use, which has progressively displaced the former, which was dominant in the 1990s [38,39]. The use of real-time kinematic (RTK)-GPS with centimeter precision [40] has allowed for extensive agricultural vehicle research. Agricultural vehicles with GPSs provide several advantages, including relieving the driver of the arduous duty of precisely directing the vehicle, improving trajectory tracking accuracy, and the ability to operate at night or in foggy conditions.

The configuration space (C-space) technique is an important method for articulating and finding a solution to the hindrance in path planning. It is a crucial notion to represent the robot as a single point. The complications are expanded in proportion to the robot's size to compensate for the robot's smaller size [41]. Potential fields, sampling-based techniques, cell decomposition, and nature-inspired algorithms like the genetic algorithm (GA), particle swarm optimization (PSO), and ant colony optimization (ACO) are all examples of path planning approaches. It's possible to divide path routing into two categories: path routing based on point-to-point and coverage path routing.

3.1. Point-to-Point Routing

The goal of mobile robot point-to-point path planning is to discover a collision-free path from a starting point to a destination point while minimizing time, distance, and energy consumption. In this approach the robot behaves like a single particle in a potential field, with the destination point representing an attraction point and the impediments representing a repulsion point. The agricultural open space is divided into tiny areas known as a cell by cell breakdown method [42] in this path planning approach. An approach for calculating the restrictions on an object's position caused by the existence of other objects is provided in [42]. Their strategy is based on creating an object's position and orientation as a single point in a configuration space, where each coordinate denotes a degree of flexibility in the object's position or orientation. Local minima arises when the algebraic sum of all the potentials is null, which is a common occurrence in this approach. This situation may make it difficult for the robot to achieve its goal which has been addressed in [43]. Results from the experiment conducted in [43], with research prototype rovers show that the planner enables real-time performance while allowing exploitation of the complete vehicle mobility envelope in difficult terrain.

When the outer perimeter of the obstacle zone is not utilized, the overall travel time of a mobile robot is shortened. To reduce processing time, Goto et al. [44] suggested an A* algorithm-based solution. The trip distance of the path and difficulty is used as the objective functions by Castillo et al. [45] in the multi-objective genetic algorithm method. RRT stands for "rapidly exploring random tree" and is a well-known sampling-oriented method for randomly exploring pathways. RRT favors unexplored territory. The RRT's vertices have a uniform distribution. Even though there are few edges, the procedure is rather straightforward, and RRTs always remain interconnected. These planners are simple, but they are inefficient, and they prefer to create courses with sharp bends [46]. RRT-Connect, also known as bi-directional RRTs, uses a heuristic to connect two RRTs—one at the beginning point and the other at the target position. This method works well for issues without differential constraints. One tree is enlarged during each iteration, and the new vertex is linked to the nearby vertex of the other tree. The roles are then switched, with both trees now exploring the open configuration space. For planning movements of a robotic arm with several degrees of freedom, this approach is appropriate [47]. A road map of the investigated region and an associated Safe Region (SR) are constructed in Sensor-based Random Trees (SRTs) [48,49]. The sensors are able to identify the Local Safe Region (LSR). Each node of the SRT is made up of a Local Safe Region and a free configuration. All Local Safe Regions make up the Safe Region. It is a projection of the open area around the robot in a certain configuration. The LSR's form is determined by the robot's sensor properties, such as its angular resolution. A ball or a star are two possible LSR shapes. Experimental evidence shows that the star shaped LSR exploration approach is more accurate [48]. Karaman et al. [50] introduced RRT*, a technique that converges to a near-optimal solution. Masehian and Sedighizadeh [51] used PSO with a probability road map to achieve shortness and smoothness as goals. Multi-objective PSO (MOPSO) algorithms, on the other hand, have been developed for over two decades and have made significant progress in solving multi-objective optimization problems [52]. MOPSO's suitability varies greatly depending on the complexity and dimensionality of the issues under consideration. In path planning, several of the researchers used the multi-objective decision-making (MODM) technique. The analytic hierarchy process (AHP) was used by Kim and Langari [53] to create an ideal path for a mobile robot. Buniyamin et al. developed the Point Bug method to reduce the usage of an obstacle's outside perimeter (obstacle border) by searching for a few key spots on the obstacle's outer perimeter that may be used as a turning point to the target, and then generating a full path from source to target [54].

Masehian and Sedighizadeh [55] used particle swarm optimization with a probability road map to achieve brevity and smoothness as goals. Ahmed and Deb [56] modified the non-dominated sorting genetic algorithm to account for travel distance, safety, and path smoothness all at the same time. Ahmed and Deb [56] improved the non-dominated sorting genetic algorithm to account for travel distance, safety, and path smoothness at the same time. MOPSO was used in [57] to design robot routes and create Pareto optimum pathways. To limit the robot to its maximum turning rate, Fernandes et al. [58] employ cell decomposition using A*. In the subject of path planning, nature-inspired algorithms have gotten a lot of attention. In the literature, GA, PSO, and ACO are frequent study areas with promising findings for robot path planning. These nature-inspired path planning algorithms are described in detail and reviewed by Mac et al. [59]. GA is a natural genetics-based optimization method that makes use of procedures including natural selection of samples, crossover among them, and mutation [59]. For mobile robot motion planning, a method combining the Voronoi diagram (VD) and the modified Ant Colony Optimization (M-ACO) algorithm is proposed [60]. In the obstacle-filled space, the Voronoi diagram generates edges and vertices, and M-ACO chooses the nodes to safely build the shortest path using point to point motion planning. Elhoseny et al. [61] applied a modified GA in a dynamic field, for a path planning approach. Ma et al. [62] proposed a dynamic augmented multi-objective particle swarm optimization algorithm for the path planning problem of an unmanned surface vehicle (USV), in which the goal was to find the shortest, smoothest, most economical, and safest path in the presence of obstacles and currents, while keeping collision avoidance, motion boundaries, and velocity constraints in mind.

Xiong et al. [63] recently employed an ACO algorithm to design numerous autonomous maritime vehicles' paths. By integrating the benefits of the A* algorithm and the fuzzy analytic hierarchy process (FAHP), Kim et al. [64] proposed an optimum path planning module. Numerical simulations were used to test the performance of the suggested motion control approach and path planning algorithm. By performing a point-to-point movement task, circular route tracking job, and randomly moving target tracking task, it was proven that the suggested motion controller outperforms current controllers such as PID. Furthermore, A*–FAHP was used to assess the performance of the suggested route planning algorithm on the omni-wheel mobile robot, and it was simulated utilizing static, dynamic, and autonomous ballet parking circumstances. The results of the simulation showed that the suggested method produces the best path in a short amount of time. Although the suggested method contains qualities that make it acceptable for a dynamic working environment, it must be verified and improved through tests on difficulties that may arise in a real robot's driving environment. Reference [65] also presented multi-objective consideration path planning algorithms more recently. The purpose is to use the vacant spaces in the cell graph to find a collision-free route. The availability of each cell is indicated in each cell. The cell decomposition approach is frequently used with search algorithms such as A* or Dijkstra to find a path

[65]. When utilizing A*, the procedure always creates the best path based on the criteria. This method, however, has increased the computing difficulty.

3.2. Coverage Routing

The job of establishing a path that travels through all points of an area or volume while avoiding obstacles is known as coverage path planning (CPP). The following conditions for a coverage operation were specified by Cao et al. [66]:

(1) The robot must be able to cover the entire region.
(2) The robot must completely occupy the area without any overlap.
(3) The processes must be continuous and sequential, with no pathways being repeated.
(4) All impediments must be avoided by the robot.
(5) Make use of basic motion trajectories.
(6) In the given circumstances, an "optimal" approach is sought.

In complicated situations, however, it is not always possible to meet all of these needs. As a result, prioritization is essential. Depending on the assurance, these algorithms can be characterized as heuristic or comprehensive, regardless of whether they are classified on-line or off-line. Many coverage strategies, whether implicitly or explicitly, use cellular breakdown to assure coverage. Approximate, semi-approximate, and accurate approaches are all available [67].

Cell grid-based approaches, which split the map into a regular grid of cells and draws a route across all of them, are another sort of coverage algorithm. To identify a coverage path, Zelinsky et al. [68] used the standard wavefront approach. The wavefront algorithm creates a wavefront from the goal to the start by defining a beginning and a goal cell. Before approaching the target further, cells in equidistant level groups of these wave fronts are visited. Although not ideal, randomization is a low-cost solution for tiny robots functioning in constrained environments. The primary benefit of a random technique, according to Choset et al. [69], is that no localization sensors or sophisticated path planning algorithms are required. This is impossible in the case of agricultural field needs, as specific agricultural activities involve specialized methods that cannot be provided by random operations. Furthermore, the platform's operating costs would be significantly higher. Huang [70] recommended rotating the sweep line or cells for ideal boustrophedon patterns. Methods of precise cellular breakdown split free space into distinct sections (cells). To cover the free cells, simple movements are utilized. As specimen, all the vacant cells may be covered by a pattern like zigzag. The widely used boustrophedon cell decomposition [71] is a cell breakdown approach that uses a simple back-and-forth motion within the created cells. Acar et al. [72] demonstrated path generation with flawless cellular breakdown.

The spanning tree approach [73] divides open space into mega cells and builds a spanning tree that encompasses all of them. There are four smaller cells inside the mega cells that may be reached by travelling the spanning tree. Both approaches ensure coverage, although the movement patterns are rather unpredictable. Acar et al. [74] explore coverage route design in demining applications. Two coverage methods are used in this study's omnidirectional vehicle: accurate cellular breakdown with back-and-forth mobility and a probabilistic methodology. Yang et al. [75] proposed a neural network method for dealing with path routing challenges in dynamic conditions, which might be useful in cleaning robots. The neural network-based coverage route planner [75], which treats all cells as neurons and determines which cell to visit next depending on the activation status of surrounding cells in the network, is a biologically inspired approach for covering a cell grid. Wong and MacDonald [76] extended the discovery of important cell breakdown sites to any type of topological landmark. Chibin et al. [77] used the ACO method to tackle a comprehensive coverage path planning problem. Galceran and Carreras [78] have summarized and discussed the majority of the significant work in the topic of coverage path planning.

Schafle et al. [79] developed an energy-optimized coverage path design utilizing GA. Kouzehgar et al. [80] proposed a simple additive weighting (SAW)-based path planning technique for a cleaning robot, with area coverage and energy consumption as considerations. Zoto et al. [81] proposed a process that uses high-resolution pictures taken from UAV to automatically develop a coverage path plan for a UGV. The experimental findings demonstrate that the work as a whole makes a substantial contribution to UGV coverage path planning in difficult environments such as mountainous vineyards, which can help farmers manage agricultural activities. However, when dealing with environments that vary considerably from one vineyard area to another, there are certain flaws.

The traditional accurate cellular decomposition techniques [67,82,83], the Morse-based cellular decomposition methods [72], and the landmark-based cell decomposition algorithms [76] are among the ways that split the original map into smaller units that may be covered by a simple motion pattern. Unlike traditional precise cellular decompositions, which rely on polygonal structures and impediments, Morse-based decompositions do not have this constraint.

4. Application of Routing in Agriculture

Applications of path planning in agriculture cover a wide range of topics and applications, as evidenced by the fact that we found a good number of publications for this study. Some articles in this collection discuss point-to-point path planning techniques, while some discuss coverage path planning issues. Agricultural applications include navigation in vineyards, orchards, greenhouses, and wheat farms, among others. Monitoring, targeted spraying, and harvesting are only some of the uses for navigation. Some authors, on the other hand, propose a path planning algorithm that is tailored for agricultural areas and/or machinery but does not apply to a specific purpose. For agriculture applications, there is no widely used path planning algorithm, with different methods for each job, whether in 2D/3D surroundings. The works reviewed in this section are tabulated in Tables 1 and 2, which includes a list of all the articles chosen and brief replies to the questions of Section 2.

The first paper listed in point-to-point route planning is from 1997 [84], and it provides a GA for building a path for robots used in the agricultural field, while taking into account the limits of the location. Linker et al. [85] released a paper in 2008 with a modified cell decomposition utilizing the A* method for orchard navigation. They took into account the limits that are unique to the vehicle and environment, such as a limited steering angle, a restricted range of pitch and roll degrees, a preference for forward motion, and reluctance for frequent turning. Although the claim by authors indicates that the path they have devised is the best, some of the limitations may lead to a less-than-ideal path. Santos et al. [86] employed a similar technique considering the center of mass of the robot, for safe navigation in a steep slope vineyard, in which the algorithm limits roll, pitch, and yaw angles. They took into account the limits that are unique to the vehicle and environment in question, such as a limited steering angle, a restricted range of pitch and roll degrees, a preference for forward motion, and reluctance for frequent turning. Other characteristics, such as soil compaction and automated recharge systems, are taken into account in certain variants of this technique. Another work uses D* cell decomposition, that is built based on A* but incorporates robot dynamics. The goal of this work is to navigate around an unknown oil palm plantation [87]. In an unstructured 3D terrain, an artificial potential field planner is used for energy optimization [88], and Mai et al. [89] employs multi-point measurement in potato cultivation using ACO. The authors differ on which approach to employ for point-to-point path routing, despite the fact that cell decomposition is marginally preferred. Point-to-point routing approach in agricultural field is tabulated in Table 1.

Table 1. Agricultural applications of point-to-point routing.

Ref. No.	Year	Application in Agricultural Field	Path Planning Approach	Dynamic or Static Environment	On-Line or Off-Line	Geometry Features: 2D/3D	Geometry Features: Terrain Configuration	Optimization Criteria	Robot Restrictions	Limitations	Tested in Real Scenario	Computational Complexity/Processing Time
[84]	1997	Create a suboptimal path for a mobile agricultural robot and use it to solve various nonlinear agricultural control issues.	GA	Static	Off-line	2D	NA	data	– Car-like vehicle -maximum steer angle of 40 degrees – maximum steer rating of 7 degrees per second – velocity range: 0.4–1.2 m per second	NA	No	Complex/100 s
[85]	2008	For choosing the best routes for car-like vehicles that operate in orchards	Modified Cell Decomposition with A*			3D	Parallel rows and random generated obstacles	Shortest path that – Avoids excessive roll and pitch angles; – Prevents soil compaction.	Car-like vehicle: – limited steer angle; – limited pitch and roll; – forward motion preferable;	Preference of forward motion may generate a suboptimal path. (Longer path and processing time)		Medium High/-average: 8.0 s; -best case: 1.39 s; -worst case: 24.84 s
[87]	2017	Navigation through oil palm plantation	Cell Decomposition with D* Lite	Partially dynamic	On-line	2D	Unstructured tree plantation	Shortest path	Differential robot	Robot can't exactly follow the path	Yes	Medium High/NA
[90]	2018	A multilevel system is suggested to keep track of a vineyard robot's autonomy,	Modified Cell Decomposition with A*	Static	Off-line	3D	Irregular curved vine rows with high slopes at	Shortest path with minimum energetic cost	Differential robot	Algorithm may need to run for hours in the first	No	Medium High/90 min. to generate all the possible paths

		plan the robot's off-line journey to the closest charging station, and dock the robot there while taking into account visual tags.				the edges			time execution		
[88,91]	2018	An optimized path over straight-line path has been proposed for a field operated agricultural rover to save energy and prolong the battery life.	Artificial Potential Field			Unstructured 3D simulated terrain without obstacles	Optimize energy consumption avoiding uphill	NA	NA	No	Simple/NA
[92]	2018	Navigation in steep slope vineyards aware of soil compaction				Irregular curved vine rows with high slopes at the edges	Shortest path while avoiding soil compaction	Differential robot; Tricycle robot; Tracks robot;	Processing time increases to avoid the compaction when many paths are produced at the same location	No	Medium High/Differential: [0.05, 0.6] s Tricycle: [0.05, 0.4] s Tracks: [0.1, 0.2] s
[93]	2019	Navigation in steep slope vineyards aware of vegetation wall distance	Modified Cell Decomposition with A*			Irregular curved vine rows with high slopes at the edges	Shortest path maintaining the distance to the vegetation	data	It is impossible to ensure an accurate distance over the entire trip	No	Medium High/NA
[86]	2019	Navigation in steep slope vineyards aware robot's center of mass		Partially dynamic	On-line	Irregular curved vine rows with high slopes at the edges	Shortest safe path – avoiding excessive roll and pitch angles; – Controlling	Differential Robot: – limited pitch and roll according center of mass; – limited	Heavy in terms of computational memory for big dimension terrains	Yes	Medium High / 0.06 s to 0.26 s

								orientation and limiting maximum robot turn rate;	maximum turn rate;			
[89]	2019	Multi-point measurement in potato ridge cultivation	ACO	Static	Off-line	2D	Parallel rows of potatoes	Shortest distance	NA	No direct application to any real robot	No	Complex/NA
[94]	2020	For automated tractor steering control in greenfield farming, an online path planning algorithm is suggested.	Model proposed by the authors	N/A	On-line		NA	NA	Tractor with trailer: – limited steer angle; – limited steer rating;	The swath distance from the pickup center approaches 1 m	Yes	NA

An analysis of Table 1 shows that point-to-point path routing approach is mainly tested in a static environment rather than the practical field condition of agricultural land as shown in Figure 3.

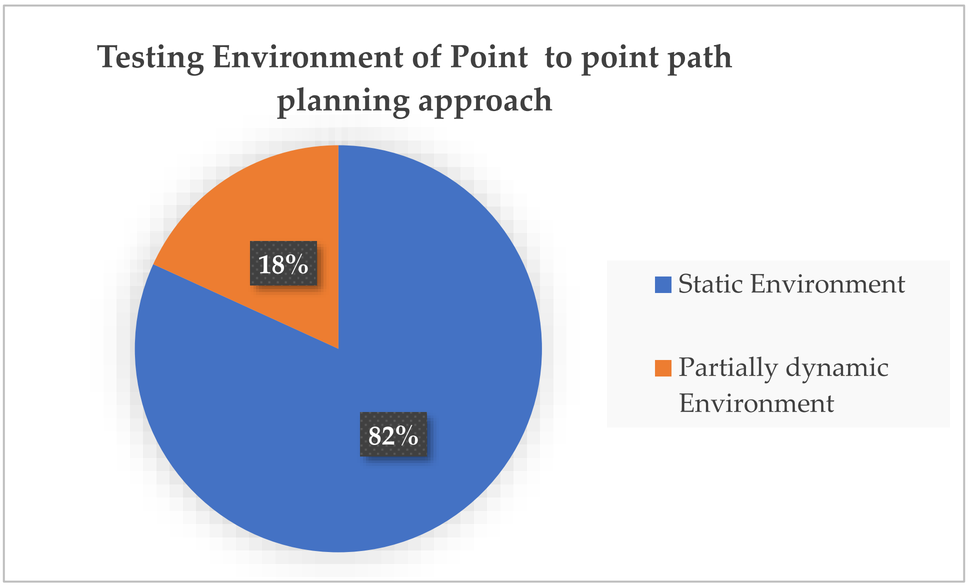

Figure 3. Testing environment of point-to-point path routing approach.

The methods used in coverage path planning issues differ throughout the literature. The total covering of irregularly shaped terrains is a typical objective in this field. In 2006, the earliest selected study presented a Hamiltonian Graph exploration to cover irregular-shaped areas with the least amount of overlaps and maneuvers [95]. In 2009, Oksanen et al. [67] presented a greedy technique for covering curve-shaped fields that included a heuristic algorithm. Hameed et al. [96] presented a GA-based technique for predicting the best driving route for agricultural equipment to minimize fuel consumption five years later.

The authors say that their method is optimal or near-optimal or provides a sub-optimal alternative. Only two point-to-point [86,87] and two coverage path planning [97,98] studies offer an online solution in dynamic situations, showing that the majority of the approaches are static off-line path planners. Only a few point-to-point techniques are included in this category, hence fewer than half of the authors claim to have conducted experiments in a genuine setting. Furthermore, some works do not even identify the qualities of the robot. Coverage routing application in agricultural field is tabulated in Table 2.

Table 2. Agricultural applications of Coverage routing.

Ref. No.	Year	Application in Agricultural Field	Path Planning Approach	Dynamic or Static Environment	On-Line or Off-Line	Geometry Features		Optimization Criteria	Robot Restrictions	Limitations	Tested in Real Scenario	Computational Complexity/Processing Time
						2D/3D	Terrain Configuration					
[95]	2006	Coverage field farm with agricultural machines	Hamiltonian Graph exploration based approach	Static	Off-line	2D	Irregular shaped polygons	Minimize overlapping and number of maneuvers	Farm Tractor: – limited steer angle; – limited steer rate;	NA	No	NP-complete/NA
[67]	2009	Coverage fields with autonomous or human-driven agricultural machine	Greedy algorithms for division of area into sub-areas and Heuristic algorithm for selection driving direction	Static	Off-line	2D	Complex shaped fields	– Fuel refilling path consideration; -Cost function weighted with: the relative efficiency (operated area divided by total time); the normalized distance (travelled distance in a sub-area excluding the travelled distance in the headland area) and the normalized area (the area of a created sub-area divided by the remaining area)	NA	It is possible to find cases in where this method fails to offer a solution	No	NP-hard/4 min
[96]	2014	Intelligent coverage for agricultural robots	2D/3D GA-based approach	Static	Off-line	both	Complex and irregular shaped fields	Optimal driving direction which minimizes energy	NA	Can result in coverage plans that	No	Complex/NA

		and autonomous machines						consumption (fuel);		require increased operational time		
[99]	2016	Rural Postman Coverage in steep slope vineyard	A* and Dijkstra search in graphs	Static	Off-line	3D	Irregular curved vine rows in terraces with high slopes at the edges	Find optimal permutation of tracks to ensure coverage;	Farm tractor is used for testing, where U-turn maneuvers not possible;	No. of wicker may require for repetition of a specific path, and that's against the principles of most CPP problems	Yes	NP-hard/NA
[100]	2016	Side-to-side coverage for agricultural robots	Grid-based 2D coverage projection on 3D terrain with cylindrical approach for optimization to the topography	Static	Off-line	3D	Accepts all topographical types os terrain	Minimize skip/overlap areas between swaths	NA	Cylindrical approach cannot differentiate between skips and overlaps	Yes	NA
[101]	2016	Coverage for a fleet in an agricultural environment	Mix-opt (developed by authors)—a mix of various permutation operators	Static	Off-line	2D	Parallel Rows	A set of n tracks and m vehicles are predecided, determine a set of routes such that each track is covered exactly once by any of the involved vehicles while minimizing the total cost of covering all the tracks	Farm Tractor: -limited steer angle; -limited steer rate;	It is presented just as a route planning tool; the authors defend the implementation using a more concise language.;	No	NA
[102]	2016	UGV to measure ground p properties of greenhouses	Back and forth strategy	Static	Off-line	2D	Parallel rows of vegetation	The path must travel through all of the points in the shortest feasible time and with the shortest possible longitude	Differential Robot	NA	Yes	NA
[97]	2016	Agricultural robot swarm for seeding task	Developed by authors (algorithm not specified)	Dynamic	On-line	2D	Irregular polygons on plain agricultural areas	- Find a path that will allow you to cover the full sow-	Limited supply of energy and seeds;	System tested with a small number of	Yes	NA

							ing area;—Find uniform workload distribution between robots;—Find optimized overall path length considering limited availability of energy and seed on-boar;		robots; In the early demonstrations, switching from large machines to swarm robots may not be well accepted;		
[98]	2018	Precision pollination in greenhouse	Voronoi Graphs with Dijkstra search and Dynamic windows approach for local obstacles	Dynamic	On-line	2D	Parallel rows of plants in greenhouse	Cover all pollinization points minimizing	Differential Robot with arm manipulator	The problem has to be reformulated to generate paths which ensure flowers near the end of their pollinization are reached sooner	Yes	Medium-Low/N/A
[92]	2018	Coverage Path Planning for ground robot with aerial imagery	A* algorithm search in graphs with gradient Descent optimization for smoothing the trajectory	Static	Off-line	2D	Hilly Vineyards with parallel vine rows	Cover all of vineyards' rows while minimizing distance	NA	In UAV imagery, there are non-continuous rows of path labels.;—Weakness as environments deviate significantly from one parcel to another	Yes	Medium/N/A
[103]	2019	Optimize harvesting area of a robot combine harvester of wheat or paddy	N-polygon algorithm to determine optimum harvesting area (Developed by authors)	Static	Off-line	2D	Convex and concave polygon fields	Cover area without overlaps or skips in the	Big dimension agricultural tracks machine	NA	No	N/A/5 min
[104]	2020	Intelligent irriga-	ant colony algo-	Static	Off-line	3D	rugged and nar-	capability of ex-	In the steering gear	The control	Yes	Complex/40 s

	tion robot is designed for multipurpose	rithm based on Bayesian theory		row environment	panding the working area and reduction in the water waste - opts for the shorter path under the premise where more information can be obtained.	control system, the turning radius of the mobile robot is 0.5 m and the maximum forward/backward speed is 0.7 m/s.	between software and robots as well as the irrigation device has not been fully automated

An analysis of Table 2 indicates that in 83% of cases the coverage path planning approach is tested in a static environment whereas in 17% of cases it has been tested in a dynamic environment as shown in Figure 4.

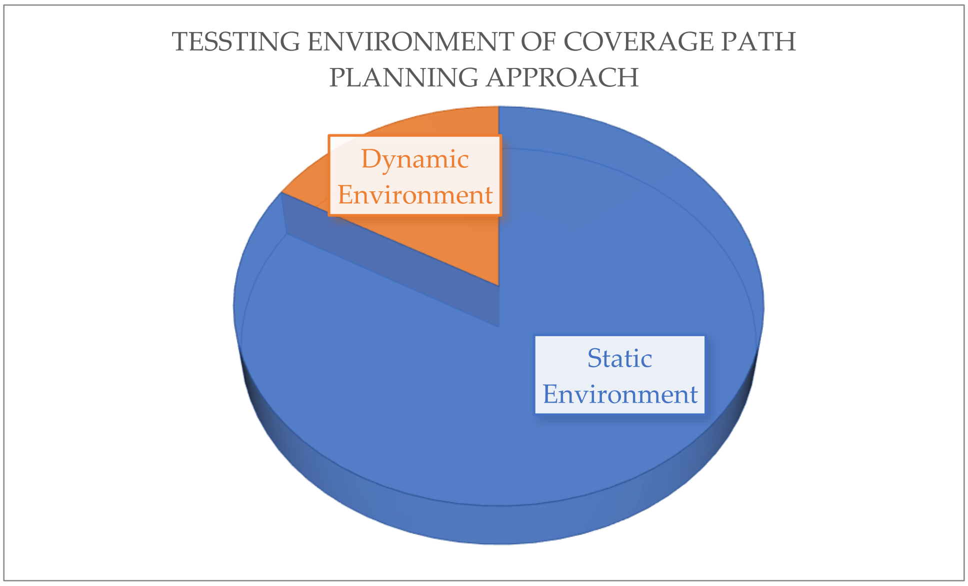

Figure 4. Testing environment of coverage path planning approach.

The computational complexity was studied without any formal measurements because most authors are unable to provide appropriate facts on this topic, including computational requirements and temporal demands in some cases. Some articles characterize their coverage route planning approach as nondeterministic polynomial-time complexity, known as a level of complexity used to classify decision-making challenges [105].

This review study concludes that route planning is commonly used in industry and the interior environment, but it is rarely used in ground robotics in agricultural contexts. Coverage route planning is substantially more sophisticated in farming since it is a common problem. Point-to-point planners, on the other hand, are perfect for precision agricultural tasks requiring an autonomous job to be performed on a certain number of plants. When cutting plants, for example, the robot must just visit those that have been chosen, rather than the entire field. To summarize, agricultural path routing research is essential for implementing agricultural automation on the right "track". Further research should focus on validating and optimizing the suggested methodologies through extensive testing in real-world agricultural settings

5. Conclusions

The current study provided a detailed analysis of a path routing approach in agricultural for ground robots. It studied the application in the agricultural field and discussed the constraints enforced by the robot setup or the terrain type in the agricultural field. This work describes the path routing methodology, the kind of outdoor environment, the terrain geometry characteristics, the optimization criteria, the method's restriction, the computation complexity, and the implementation of testing in an actual scenario.

- The study categorized path routing approaches into two classes: point-to-point and coverage path routing.
- The analysis suggests that in agriculture, coverage path routing is less progressed than point-to-point path routing. This is owed to the fact that coverage path routing

is commonly required for agricultural applications in broader view, while point-to-point path routing is required for recently advancing precision agriculture.

- In 83% of cases the coverage path planning approach is tested in a static environment whereas in 17% of cases it has been tested in a dynamic environment.
- Point-to-point path routing approach is tested in a static environment in 82% of cases and has only been tested in a partially dynamic condition in 18% of cases.

The authors used a variety of path planning approaches in the review, therefore, it can be concluded that the best path planning approach depends on the particular task of the agricultural field. Only around half of the writers claimed to have used real-world scenarios in their research. As a result, future research should focus on optimization and validation through thorough testing in real-world agricultural settings, as well as making new agricultural field data sets available to the research community, for effective integration in the automation of agricultural activities. In this literature review only the path planning approach required for UGVs used particularly for in field task at agricultural land is focused. Application of UGVs for other farming tasks such as egg collection at farm, phenotyping, sorting and packing at utility platforms can be considered as our future work.

Author Contributions: Conceptualization, S.C.; methodology, S.C.; formal analysis, S.C.; investigation, S.C.; resources, D.E., M.F.E. and M.M.A.; data curation, P.L.G. and M.M.A.; writing—original draft preparation, S.C.; writing—review and editing, S.K., M.F.E. and M.M.A.; visualization, S.K.; supervision, D.E., M.F.E. and M.M.A. All authors have read and agreed to the published version of the manuscript

Funding: This research is funded by Prince Sattam Bin Abdulaziz University, grant number IF-PSAU-2021/01/18921.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: The authors extend their appreciation to the Deputyship for Research & Innovation, Ministry of Education, Saudi Arabia, for funding this research work through the project number (IF-PSAU-2021/01/18921).

Conflicts of Interest: The authors declare no conflict of interest.

References

1. CEMA–European Agricultural Machinery. Available online: https://www.cema-agri.org/ (accessed on 20 May 2022).
2. Delavarpour, N.; Koparan, C.; Nowatzki, J.; Bajwa, S.; Sun, X. A Technical Study on UAV Characteristics for Precision Agriculture Applications and Associated Practical Challenges. *Remote Sens.* **2021**, *13*, 1204. https://doi.org/10.3390/rs13061204.
3. Comba, L.; Biglia, A.; Ricauda Aimonino, D.; Gay, P. Unsupervised Detection of Vineyards by 3D Point-Cloud UAV Photogrammetry for Precision Agriculture. *Comput. Electron. Agric.* **2018**, *155*, 84–95. https://doi.org/10.1016/j.compag.2018.10.005.
4. Kim, J.; Kim, S.; Ju, C.; Son, H.I. Unmanned Aerial Vehicles in Agriculture: A Review of Perspective of Platform, Control, and Applications. *IEEE Access* **2019**, *7*, 105100–105115. https://doi.org/10.1109/access.2019.2932119.
5. Pan, F.; Fan, T.; Qi, X.; Chen, J.; Zhang, C. Truck Scheduling for Cross-Docking of Fresh Produce with Repeated Loading. *Math. Probl. Eng.* **2021**, *2021*, 5592122. https://doi.org/10.1155/2021/5592122.
6. Dulebenets, M.A.; Ozguven, E.E.; Moses, R.; Ulak, B.M. Intermodal Freight Network Design for Transport of Perishable Products. *Open J. Optim.* **2016**, *5*, 120–139. https://doi.org/10.4236/ojop.2016.54013.
7. Theophilus, O.; Dulebenets, M.A.; Pasha, J.; Lau, Y.-Y.; Fathollahi-Fard, A.M.; Mazaheri, A. Truck Scheduling Optimization at a Cold-Chain Cross-Docking Terminal with Product Perishability Considerations. *Comput. Ind. Eng.* **2021**, *156*, 107240. https://doi.org/10.1016/j.cie.2021.107240.
8. Zheng, F.; Pang, Y.; Xu, Y.; Liu, M. Heuristic Algorithms for Truck Scheduling of Cross-Docking Operations in Cold-Chain Logistics. *Int. J. Prod. Res.* **2021**, *59*, 6579–6600. https://doi.org/10.1080/00207543.2020.1821118.
9. Qi, C.; Hu, L. Optimization of Vehicle Routing Problem for Emergency Cold Chain Logistics Based on Minimum Loss. *Phys. commun.* **2020**, *40*, 101085. https://doi.org/10.1016/j.phycom.2020.101085.
10. Dulebenets, M.A.; Ozguven, E.E. Vessel Scheduling in Liner Shipping: Modeling Transport of Perishable Assets. *Int. J. Prod. Econ.* **2017**, *184*, 141–156. https://doi.org/10.1016/j.ijpe.2016.11.011.

11. Utstumo, T.; Urdal, F.; Brevik, A.; Dørum, J.; Netland, J.; Overskeid, Ø.; Berge, T.W.; Gravdahl, J.T. Robotic In-Row Weed Control in Vegetables. *Comput. Electron. Agric.* **2018**, *154*, 36–45. https://doi.org/10.1016/j.compag.2018.08.043.
12. Asefpour Vakilian, K.; Massah, J. A Farmer-Assistant Robot for Nitrogen Fertilizing Management of Greenhouse Crops. *Comput. Electron. Agric.* **2017**, *139*, 153–163. https://doi.org/10.1016/j.compag.2017.05.012.
13. Zhang, C.; Noguchi, N. Development of a Multi-Robot Tractor System for Agriculture Field Work. *Comput. Electron. Agric.* **2017**, *142*, 79–90. https://doi.org/10.1016/j.compag.2017.08.017.
14. Roldán, J.; Garcia-Aunon, P.; Garzón, M.; de León, J.; del Cerro, J.; Barrientos, A. Heterogeneous Multi-Robot System for Mapping Environmental Variables of Greenhouses. *Sensors* **2016**, *16*, 1018. https://doi.org/10.3390/s16071018.
15. Potena, C.; Khanna, R.; Nieto, J.; Siegwart, R.; Nardi, D.; Pretto, A. AgriColMap: Aerial-Ground Collaborative 3D Mapping for Precision Farming. *IEEE Robot. Autom. Lett.* **2019**, *4*, 1085–1092. https://doi.org/10.1109/lra.2019.2894468.
16. Gonzalez-de-Santos, P.; Ribeiro, A.; Fernandez-Quintanilla, C.; Lopez-Granados, F.; Brandstoetter, M.; Tomic, S.; Pedrazzi, S.; Peruzzi, A.; Pajares, G.; Kaplanis, G.; et al. Fleets of Robots for Environmentally-Safe Pest Control in Agriculture. *Precis. Agric.* **2017**, *18*, 574–614. https://doi.org/10.1007/s11119-016-9476-3.
17. van Henten, E.J.; Bac, C.W.; Hemming, J.; Edan, Y. Robotics in Protected Cultivation. *IFAC Proc. Vol.* **2013**, *46*, 170–177. https://doi.org/10.3182/20130828-2-sf-3019.00070.
18. Bonadies, S.; Gadsden, S.A. An Overview of Autonomous Crop Row Navigation Strategies for Unmanned Ground Vehicles. *Eng. Agric. Environ. Food* **2019**, *12*, 24–31. https://doi.org/10.1016/j.eaef.2018.09.001.
19. García-Santillán, I.D.; Montalvo, M.; Guerrero, J.M.; Pajares, G. Automatic Detection of Curved and Straight Crop Rows from Images in Maize Fields. *Biosyst. Eng.* **2017**, *156*, 61–79. https://doi.org/10.1016/j.biosystemseng.2017.01.013.
20. Ghaleb, F.A.; Zainal, A.; Rassam, M.A.; Abraham, A. Improved Vehicle Positioning Algorithm Using Enhanced Innovation-Based Adaptive Kalman Filter. *Pervasive Mob. Comput.* **2017**, *40*, 139–155. https://doi.org/10.1016/j.pmcj.2017.06.008.
21. Ericson, S.K.; Åstrand, B.S. Analysis of Two Visual Odometry Systems for Use in an Agricultural Field Environment. *Biosyst. Eng.* **2018**, *166*, 116–125. https://doi.org/10.1016/j.biosystemseng.2017.11.009.
22. Bechar, A.; Vigneault, C. Agricultural Robots for Field Operations: Concepts and Components. *Biosyst. Eng.* **2016**, *149*, 94–111. https://doi.org/10.1016/j.biosystemseng.2016.06.014.
23. EuRobotics. Strategic Research Agenda for Robotics in Europe. 2013. Available online: http://relaunch.eu-robotics.net/eurobotics/activities/eurobotics-alliances/ (accessed on 29 May 2022).
24. Roldán, J.J.; Cerro, J.D.E.L.; Garzón-Ramos, D.; Garcia-Aunon, P.; Garzón, M.; León, J.D.E.; Barrientos, A. Robots in Agriculture: State of Art and Practical Experiences. In *Service Robots*; CRC: Boca Raton, FL, USA, 2018. ISBN 9789535137221.
25. dos Santos, F.N.; Sobreira, H.; Campos, D.; Morais, R.; Paulo Moreira, A.; Contente, O. Towards a Reliable Robot for Steep Slope Vineyards Monitoring. *J. Intell. Robot. Syst.* **2016**, *83*, 429–444. https://doi.org/10.1007/s10846-016-0340-5.
26. Mac, T.T.; Copot, C.; Tran, D.T.; De Keyser, R. Heuristic Approaches in Robot Path Planning: A Survey. *Rob. Auton. Syst.* **2016**, *86*, 13–28. https://doi.org/10.1016/j.robot.2016.08.001.
27. Liu, G.; Palmer, R.J. Efficient Field Courses around an Obstacle. *J. Agric. Eng. Res.* **1989**, *44*, 87–95. https://doi.org/10.1016/s0021-8634(89)80073-3.
28. Bochtis, D.D.; Sørensen, C.G.C.; Busato, P. Advances in Agricultural Machinery Management: A Review. *Biosyst. Eng.* **2014**, *126*, 69–81. https://doi.org/10.1016/j.biosystemseng.2014.07.012.
29. Peralta, F.; Arzamendia, M.; Gregor, D.; Reina, D.G.; Toral, S. A Comparison of Local Path Planning Techniques of Autonomous Surface Vehicles for Monitoring Applications: The Ypacarai Lake Case-Study. *Sensors* **2020**, *20*, 1488. https://doi.org/10.3390/s20051488.
30. Baumeister, R.F.; Leary, M.R. Writing Narrative Literature Reviews. *Rev. Gen. Psychol.* **1997**, *1*, 311–320. https://doi.org/10.1037//1089-2680.1.3.311.
31. Hammersley, M. On "Systematic" Reviews of Research Literatures: A "narrative" response to Evans & Benefield. *Br. Educ. Res. J.* **2001**, *27*, 543–554.
32. Bochtis, D.D.; Sørensen, C.G. The vehicle routing problem in field logistics: Part I. *Biosyst. Eng.* **2009**, *104*, 447–457.
33. Bochtis, D.D.; Sørensen, C.G. The vehicle routing problem in field logistics: Part II. *Biosyst. Eng.* **2010**, *105*, 180–188.
34. Hirayama, M.; Guivant, J.; Katupitiya, J.; Whitty, M. Path planning for autonomous bulldozers. *Mechatronics* **2019**, *58*, 20–38.
35. Julian, A.P. Design and Performance of a Steering Control System for Agricultural Tractors. *J. Agric. Eng. Res.* **1971**, *16*, 324–336. https://doi.org/10.1016/s0021-8634(71)80024-0.
36. Reid, J.; Searcy, S. Vision-Based Guidance of an Agriculture Tractor. *IEEE Control Syst.* **1987**, *7*, 39–43. https://doi.org/10.1109/mcs.1987.1105271.
37. Hiremath, S.A.; van der Heijden, G.W.A.M.; van Evert, F.K.; Stein, A.; ter Braak, C.J.F. Laser Range Finder Model for Autonomous Navigation of a Robot in a Maize Field Using a Particle Filter. *Comput. Electron. Agric.* **2014**, *100*, 41–50. https://doi.org/10.1016/j.compag.2013.10.005.
38. GPS Applications in General Aviation. In *Global Positioning System: Theory and Applications, Volume II*; American Institute of Aeronautics and Astronautics: Washington, DC, USA, 1996; pp. 375–395. ISBN 9781563471070.
39. Bell, T. Automatic Tractor Guidance Using Carrier-Phase Differential GPS. *Comput. Electron. Agric.* **2000**, *25*, 53–66. https://doi.org/10.1016/s0168-1699(99)00055-1.

40. Bevly, D.M.; Parkinson, B. Cascaded Kalman Filters for Accurate Estimation of Multiple Biases, Dead-Reckoning Navigation, and Full State Feedback Control of Ground Vehicles. *IEEE Trans. Control Syst. Technol.* **2007**, *15*, 199–208. https://doi.org/10.1109/tcst.2006.883311.
41. Raja, P. Optimal Path Planning of Mobile Robots: A Review. *Int. J. Phys. Sci.* **2012**, *7*, 1314–1320. https://doi.org/10.5897/ijps11.1745.
42. Lozano-Pérez, T. Spatial Planning: A Configuration Space Approach. In *Autonomous Robot Vehicles*; Springer: New York, NY, USA, 1990; pp. 259–271. ISBN 9781461389996.
43. Pivtoraiko, M.; Knepper, R.A.; Kelly, A. Differentially Constrained Mobile Robot Motion Planning in State Lattices. *J. Field Robot.* **2009**, *26*, 308–333. https://doi.org/10.1002/rob.20285.
44. Goto, T.; Kosaka, T.; Noborio, H. On the Heuristics of A* or A Algorithm in ITS and Robot Path-Planning. In Proceedings of the 2003 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2003) (Cat. No.03CH37453), Las Vegas, NV, USA, 27–31 October 2003.
45. Castillo, O.; Trujillo, L.; Melin, P. Multiple Objective Genetic Algorithms for Path-Planning Optimization in Autonomous Mobile Robots. *Soft Comput.* **2006**, *11*, 269–279. https://doi.org/10.1007/s00500-006-0068-4.
46. Rodriguez; Tang, X.; Lien, J.-M.; Amato, N.M. An Obstacle-Based Rapidly-Exploring Random Tree. In Proceedings of the 2006 IEEE International Conference on Robotics and Automation, Orlando, FL, USA, 15–19 May 2006.
47. Kuffner, J.J.; LaValle, S.M. RRT-connect: An efficient approach to single-query path planning. In Proceedings of the 2000 ICRA. Millennium Conference, IEEE International Conference on Robotics and Automation, Symposia Proceedings (Cat. No. 00CH37065), San Francisco, CA, USA, 24–28 April 2000; Volume 2, pp. 995–1001.
48. Oriolo, G.; Vendittelli, M.; Freda, L.; Troso, G. The SRT method: Randomized strategies for exploration. In Proceedings of the IEEE International Conference on Robotics and Automation, ICRA '04, New Orleans, LA, USA, 26 April–1 May 2004; Volume 5, pp. 4688–4694.
49. Yiping, Z.; Jian, G.; Ruilei, Z.; Qingwei, C. A SRT-based path planning algorithm in unknown complex environment. In Proceedings of the 26th Chinese Control and Decision Conference (2014 CCDC), Changsha, China, 31 May–2 June 2014; pp. 3857–3862.
50. Karaman, S.; Walter, M.R.; Perez, A.; Frazzoli, E.; Teller, S. Anytime Motion Planning Using the RRT. In Proceedings of the 2011 IEEE International Conference on Robotics and Automation, Shanghai, China, 9–13 May 2011.
51. Masehian, E.; Sedighizadeh, D. A Multi-Objective PSO-Based Algorithm for Robot Path Planning. In Proceedings of the 2010 IEEE International Conference on Industrial Technology, Via del Mar, Chile, 14–17 March 2010.
52. Goh, C.K.; Tan, K.C.; Liu, D.S.; Chiam, S.C. A Competitive and Cooperative Co-Evolutionary Approach to Multi-Objective Particle Swarm Optimization Algorithm Design. *Eur. J. Oper. Res.* **2010**, *202*, 42–54. https://doi.org/10.1016/j.ejor.2009.05.005.
53. Kim, C.; Langari, R. Analytical Hierarchy Process and Brain Limbic System Combined Strategy for Mobile Robot Navigation. In Proceedings of the 2010 IEEE/ASME International Conference on Advanced Intelligent Mechatronics, Montreal, QC, Canada, 6–9 July 2010.
54. Buniyamin, N.; Ngah, W.W.; Sariff, N.; Mohamad, Z. A simple local path planning algorithm for autonomous mobile robots. *Int. J. Syst. Appl. Eng. Dev.* **2011**, *5*, 151–159.
55. Masehian, E.; Sedighizadeh, D. An Improved Particle Swarm Optimization Method for Motion Planning of Multiple Robots. In *Springer Tracts in Advanced Robotics*; Springer: Berlin/Heidelberg, Germany, 2013; pp. 175–188. ISBN 9783642327223.
56. Ahmed, F.; Deb, K. Multi-Objective Optimal Path Planning Using Elitist Non-Dominated Sorting Genetic Algorithms. *Soft Comput.* **2013**, *17*, 1283–1299. https://doi.org/10.1007/s00500-012-0964-8.
57. Zhang, Y.; Gong, D.-W.; Zhang, J.-H. Robot Path Planning in Uncertain Environment Using Multi-Objective Particle Swarm Optimization. *Neurocomputing* **2013**, *103*, 172–185. https://doi.org/10.1016/j.neucom.2012.09.019.
58. Fernandes, E.; Costa, P.; Lima, J.; Veiga, G. Towards an Orientation Enhanced Astar Algorithm for Robotic Navigation. In Proceedings of the 2015 IEEE International Conference on Industrial Technology (ICIT), Seville, Spain, 17–19 March 2015.
59. Karur, K.; Sharma, N.; Dharmatti, C.; Siegel, J.E. A Survey of Path Planning Algorithms for Mobile Robots. *Vehicles* **2021**, *3*, 448–468. https://doi.org/10.3390/vehicles3030027.
60. Habib, N.; Purwanto, D.; Soeprijanto, A. Mobile Robot Motion Planning by Point to Point Based on Modified Ant Colony Optimization and Voronoi Diagram. In Proceedings of the 2016 International Seminar on Intelligent Technology and Its Applications (ISITIA), Lombok, Indonesia, 28–30 July 2016.
61. Elhoseny, M.; Tharwat, A.; Hassanien, A.E. Bezier Curve Based Path Planning in a Dynamic Field Using Modified Genetic Algorithm. *J. Comput. Sci.* **2018**, *25*, 339–350. https://doi.org/10.1016/j.jocs.2017.08.004.
62. Ma, Y.; Hu, M.; Yan, X. Multi-Objective Path Planning for Unmanned Surface Vehicle with Currents Effects. *ISA Trans.* **2018**, *75*, 137–156. https://doi.org/10.1016/j.isatra.2018.02.003.
63. Xiong, C.; Chen, D.; Lu, D.; Zeng, Z.; Lian, L. Path Planning of Multiple Autonomous Marine Vehicles for Adaptive Sampling Using Voronoi-Based Ant Colony Optimization. *Rob. Auton. Syst.* **2019**, *115*, 90–103. https://doi.org/10.1016/j.robot.2019.02.002.
64. Kim, C.; Suh, J.; Han, J.-H. Development of a Hybrid Path Planning Algorithm and a Bio-Inspired Control for an Omni-Wheel Mobile Robot. *Sensors* **2020**, *20*, 4258. https://doi.org/10.3390/s20154258.
65. Chen, Z.; Wu, H.; Chen, Y.; Cheng, L.; Zhang, B. Patrol Robot Path Planning in Nuclear Power Plant Using an Interval Multi-Objective Particle Swarm Optimization Algorithm. *Appl. Soft Comput.* **2022**, *116*, 108192. https://doi.org/10.1016/j.asoc.2021.108192.

66. Cao, Z.L.; Huang, Y.; Hall, E.L. Region Filling Operations with Random Obstacle Avoidance for Mobile Robots. *J. Robot. Syst.* **1988**, *5*, 87–102. https://doi.org/10.1002/rob.4620050202.
67. Oksanen, T.; Visala, A. Coverage Path Planning Algorithms for Agricultural Field Machines. *J. Field Robot.* **2009**, *26*, 651–668. https://doi.org/10.1002/rob.20300.
68. Zelinsky, A.; Jarvis, R.A.; Byrne, J.C.; Yuta, S. Planning Paths of Complete Coverage of an Unstructured Environment by a Mobile Robot. In Proceedings of International Conference on Advanced Robotics, Tokyo, Japan, 1–2 November 1993.
69. Choset, H. Coverage for robotics—A survey of recent results. *Ann. Math. Artif. Intell.* **2001**, *31*, 113–126. Available online: https://link.springer.com/article/10.1023/A:1016639210559 (accessed on 29 May 2022).
70. Huang, W.H. Optimal Line-Sweep-Based Decompositions for Coverage Algorithms. In Proceedings of the 2001 ICRA, IEEE International Conference on Robotics and Automation (Cat. No.01CH37164), Seoul, Korea, 21–26 May 2001.
71. Choset, H.; Acar, E.; Rizzi, A.A.; Luntz, J. Exact Cellular Decompositions in Terms of Critical Points of Morse Functions. In Proceedings of the 2000 ICRA, Millennium Conference, IEEE International Conference on Robotics and Automation, Symposia Proceedings (Cat. No.00CH37065), San Francisco, CA, USA, 24–28 April 2000.
72. Acar, E.U.; Choset, H.; Rizzi, A.A.; Atkar, P.N.; Hull, D. Morse Decompositions for Coverage Tasks. *Int. J. Rob. Res.* **2002**, *21*, 331–344. https://doi.org/10.1177/027836402320556359.
73. Gabriely, Y.; Rimon, E. Spiral-STC: An on-Line Coverage Algorithm of Grid Environments by a Mobile Robot. In Proceedings of the 2002 IEEE International Conference on Robotics and Automation (Cat. No.02CH37292), Washington, DC, USA, 11–15 May 2002.
74. Acar, E.U.; Choset, H.; Zhang, Y.; Schervish, M. Path planning for robotic demining: Robust sensor-based coverage of unstructured environments and probabilistic methods. *Int. J. Robot. Res***. 2003**, *22*, 441–466.
75. Yang, S.X.; Luo, C.A. Neural Network Approach to Complete Coverage Path Planning. *IEEE Trans. Syst. Man Cybern. B Cybern.* **2004**, *34*, 718–725. https://doi.org/10.1109/tsmcb.2003.811769.
76. Wong, S.C.; MacDonald, B.A. A Topological Coverage Algorithm for Mobile Robots. In Proceedings of the 2003 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2003) (Cat. No.03CH37453), Las Vegas, NV, USA, 27–31 October 2003.
77. Chibin, Z.; Xingsong, W.; Yong, D. Complete Coverage Path Planning Based on Ant Colony Algorithm. In Proceedings of the 2008 15th International Conference on Mechatronics and Machine Vision in Practice, Auckland, New Zealand, 2–4 December 2008.
78. Galceran, E.; Carreras, M. A Survey on Coverage Path Planning for Robotics. *Rob. Auton. Syst.* **2013**, *61*, 1258–1276. https://doi.org/10.1016/j.robot.2013.09.004.
79. Schafle, T.R.; Mohamed, S.; Uchiyama, N.; Sawodny, O. Coverage Path Planning for Mobile Robots Using Genetic Algorithm with Energy Optimization. In Proceedings of the 2016 International Electronics Symposium (IES), Denpasar, Indonesia, 29–30 September 2016.
80. Kouzehgar, M.; Rajesh Elara, M.; Ann Philip, M.; Arunmozhi, M.; Prabakaran, V. Multi-Criteria Decision Making for Efficient Tiling Path Planning in a Tetris-Inspired Self-Reconfigurable Cleaning Robot. *Appl. Sci.* **2018**, *9*, 63. https://doi.org/10.3390/app9010063.
81. Zoto, J.; Musci, M.A.; Khaliq, A.; Chiaberge, M.; Aicardi, I. Automatic Path Planning for Unmanned Ground Vehicle Using UAV Imagery. In *Advances in Service and Industrial Robotics*; Springer International Publishing: Berlin/Heidelberg, Germany, 2020; pp. 223–230. ISBN 9783030196479.
82. Latombe, J.-C. Exact Cell Decomposition. In *Robot Motion Planning*; The Springer International Series in Engineering and Computer Science; Springer: Berlin/Heidelberg, Germany, 1991; Volume 124, pp. 200–247. Available online: http://link.springer.com/chapter/10.1007/978-1-4615-4022-9 (accessed on 25 May 2022).
83. Choset, H.; Pignon, P. Coverage Path Planning: The Boustrophedon Cellular Decomposition. In *Field and Service Robotics*; Springer: Berlin/Heidelberg, Germany, 1998; pp. 203–209. ISBN 9781447112754.
84. Noguchi, N.; Terao, H. Path Planning of an Agricultural Mobile Robot by Neural Network and Genetic Algorithm. *Comput. Electron. Agric.* **1997**, *18*, 187–204. https://doi.org/10.1016/s0168-1699(97)00029-x.
85. Linker, R.; Blass, T. Path-Planning Algorithm for Vehicles Operating in Orchards. *Biosyst. Eng.* **2008**, *101*, 152–160. https://doi.org/10.1016/j.biosystemseng.2008.06.002.
86. Santos, L.; Santos, F.; Mendes, J.; Costa, P.; Lima, J.; Reis, R.; Shinde, P. Path Planning Aware of Robot's Center of Mass for Steep Slope Vineyards. *Robotica* **2019**, *38*, 684–689. https://doi.org/10.1017/s0263574719000961.
87. Juman, M.A.; Wong, Y.W.; Rajkumar, R.K.; H'ng, C.Y. An Integrated Path Planning System for a Robot Designed for Oil Palm Plantations. In Proceedings of the TENCON 2017–2017 IEEE Region 10 Conference, Penang, Malaysia, 5–8 November 2017.
88. Yan, X.-T.; Bianco, A.; Niu, C.; Palazzetti, R.; Henry, G.; Li, Y.; Tubby, W.; Kisdi, A.; Irshad, R.; Sanders, S.; et al. The AgriRover: A Reinvented Mechatronic Platform from Space Robotics for Precision Farming. In *Reinventing Mechatronics*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 55–73. ISBN 9783030291303.
89. Mai, T.; Shao, S.; Yun, Z. The Path Planning of Agricultural AGV in Potato Ridge Cultivation. *Ann. Adv. Agric. Sci.* **2019**, *3*, 21–30. https://doi.org/10.22606/as.2019.32003.
90. Santos, L.; Santos, F.N.D.; Mendes, J.; Ferraz, N.; Lima, J.; Morais, R.; Costa, P. Path planning for automatic recharging system for steep- slope vineyard robots. In *ROBOT 2017: Third Iberian Robotics Conference*; Ollero, A., Sanfeliu, A., Montano, L., Lau, N., Cardeira, C., Eds; Springer: Berlin/Heidelberg, Germany, 2018; pp. 261–272.

91. Niu, C.; Yan, X. Energy optimization path planning for battery- powered agricultural rover. In *MATEC Web of Conferences*; EDP Sciences: Ulys, France, 2018; Volume 173, p. 02001.
92. Santos, L.; Ferraz, N.; Neves dos Santos, F.; Mendes, J.; Morais, R.; Costa, P.; Reis, R. Path Planning Aware of Soil Compaction for Steep Slope Vineyards. In Proceedings of the 2018 IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC), Torres Vedras, Portugal, 25–27 April 2018.
93. Santos, L.; Santos, F.N.; Magalhaes, S.; Costa, P.; Reis, R. Path Planning Approach with the Extraction of Topological Maps from Occupancy Grid Maps in Steep Slope Vineyards. In Proceedings of the 2019 IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC), Porto, Portugal, 24–26 April 2019.
94. Pichler-Scheder, M.; Ritter, R.; Lindinger, C.; Amerstorfer, R.; Edelbauer, R. Path Planning for Semi-Autonomous Agricultural Vehicles. In *Reinventing Mechatronics*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 35–53. ISBN 9783030291303.
95. Taïx, M.; Souères, P.; Frayssinet, H.; Cordesses, L. Path Planning for Complete Coverage with Agricultural Machines. In *Springer Tracts in Advanced Robotics*; Springer: Berlin/Heidelberg, Germany, 2006; pp. 549–558. ISBN 9783540328018.
96. Hameed, I.A. Intelligent Coverage Path Planning for Agricultural Robots and Autonomous Machines on Three-Dimensional Terrain. *J. Intell. Robot. Syst.* **2014**, *74*, 965–983. https://doi.org/10.1007/s10846-013-9834-6.
97. Blender, T.; Buchner, T.; Fernandez, B.; Pichlmaier, B.; Schlegel, C. Managing a Mobile Agricultural Robot Swarm for a Seeding Task. In Proceedings of the IECON 2016-42nd Annual Conference of the IEEE Industrial Electronics Society, Florence, Italy, 23–26 October 2016.
98. Ohi, N.; Lassak, K.; Watson, R.; Strader, J.; Du, Y.; Yang, C.; Hedrick, G.; Nguyen, J.; Harper, S.; Reynolds, D.; et al. Design of an Autonomous Precision Pollination Robot. In Proceedings of the 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Madrid, Spain, 29 August 2018.
99. Contente, O.; Lau, N.; Morgado, F.; Morais, R. A Path Planning Application for a Mountain Vineyard Autonomous Robot. In *Advances in Intelligent Systems and Computing*; Springer: Berlin/Heidelberg, Germany, 2016; pp. 347–358. ISBN 9783319271453.
100. Hameed, I.A.; la Cour-Harbo, A.; Osen, O.L. Side-to-Side 3D Coverage Path Planning Approach for Agricultural Robots to Minimize Skip/Overlap Areas between Swaths. *Rob. Auton. Syst.* **2016**, *76*, 36–45. https://doi.org/10.1016/j.robot.2015.11.009.
101. Conesa-Muñoz, J.; Pajares, G.; Ribeiro, A. Mix-Opt: A New Route Operator for Optimal Coverage Path Planning for a Fleet in an Agricultural Environment. *Expert Syst. Appl.* **2016**, *54*, 364–378. https://doi.org/10.1016/j.eswa.2015.12.047.
102. Ruiz-Larrea, A.; Roldán, J.J.; Garzón, M.; del Cerro, J.; Barrientos, A. A UGV Approach to Measure the Ground Properties of Greenhouses. In *Advances in Intelligent Systems and Computing*; Springer: Berlin/Heidelberg, Germany, 2016; pp. 3–13. ISBN 9783319271484.
103. Rahman, M.M.; Ishii, K.; Noguchi, N. Optimum Harvesting Area of Convex and Concave Polygon Field for Path Planning of Robot Combine Harvester. *Intell. Serv. Robot.* **2019**, *12*, 167–179. https://doi.org/10.1007/s11370-018-00273-4.
104. Chen, M.; Sun, Y.; Cai, X.; Liu, B.; Ren, T. Design and Implementation of A Novel Precision Irrigation Robot Based on an Intelligent Path Planning Algorithm. *arXiv* **2020**, arXiv: 2003.00676.
105. Cook, S.A. The Complexity of Theorem-Proving Procedures (1971). In *Ideas That Created the Future*; The MIT Press: Cambridge, MA, USA, 2021; pp. 333–338. ISBN 9780262363174.