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# Review of Wheeled Mobile Robots' Navigation Problems and Application Prospects in Agriculture

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**ABSTRACT** Robot navigation in the environment with obstacles is still a challenging problem. In this paper, the navigation problems with wheeled mobile robots (WMRs) are reviewed, the navigation mechanism of WMRs is analyzed in detail, the methods of solving the sub problems such as mapping, localization and path planning which all both related to robot navigation are summarized and the advantages and disadvantages of the existing methods are expounded. Especially in the agricultural field, the precise navigation of robots in the complex agricultural environment is the prerequisite for the completion of various tasks. This paper is aimed at the special complexity of the agricultural environment, prospected the application of the solution to the navigation problem of WMRs in agricultural engineering, put forward the research direction to solve the problems of precise navigation in agricultural environments.

**INDEX TERMS** WMRs, navigation, mapping, localization, path planning, agriculture.

## I. INTRODUCTION

In recent years, the robots have been used to replace humans in many fields, and then accurate navigation of mobile robots are very important in some tasks. With the popularization of robot application, many researchers get their focus on the study of robot navigation. The main issue of the robot navigation is that how the robots move to the destination from the starting place following the projected route by using the localization and environment information which obtained from the sensors on the robots. Success in navigation requires success at the four building blocks of navigation: perception, localization, cognition and motion control [1]. The key issues involved are mapping, localization, path planning, etc. With the long-term in-depth study and the experimental demonstration, a large number of technical methods have been proposed to help solve the problems of accurate navigation.

In the 1980s, the precision agriculture [2] was proposed as a new concept in the agriculture. In the precision agricultural system, the cultivated land resources need to be better utilized, the labor cost of productions needs to be reduced, and the crop yield and quality need to be further improved. Furthermore, the operators need to make the most appropriate management decision more reasonably and use robot and other advanced mechanics to execute decisions more frequently. Some existing theories and methods for navigation problems are mostly verified and applied in general urban environments. Restricted by working spaces and conditions, some of them have not been applied in the agricultural environment, such as the unstructured complex farmland and the facility environment. Nevertheless, all the methods and theories have great reference values for the robot navigation research in agricultural environment. In this review, we selectively summarized the research on the key problems in the navigation of wheeled mobile robots (WMRs) in the past three decades and prospected their application in the agriculture field.

## II. THE NAVIGATION MECHANISM OF WMRs

### A. THE STURCTURAL FEATURES OF WMRs

Among the many well-developed mature robots, WMRs are the most widely used robot. The common WMRs chassis is mainly composed of the body, the wheels and the supporting mechanism of the wheel and the wheel drive mechanism [3]. According to the number of wheels on the chassis, the chassis can be divided into two-wheel, three-wheel and four-wheel structures. These structures are commonly used. The four-wheel chassis is one of the most used structures. In the field of agricultural engineering, the chassis with such a structural configuration is used as the mobile platform of mobile robots. Sometimes due to the complexity of the terrain structure, and to ensure a stable driving ability, it is necessary to consider adding a buffer suspension device [3] on the site, the one of the typical Agricultural WMRs chassis is shown in Figure 1.

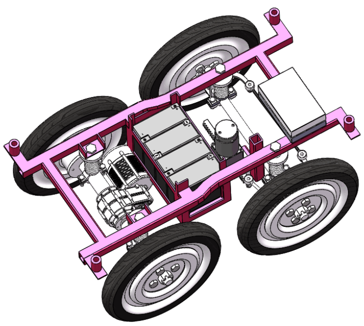

**FIGURE 1.** A four-wheeled agricultural WMRs chassis.

In order to guarantee the stability of the motion plane and simplify the operation process, the driving mode of almost all the four-wheeled chassis are used two-wheeled differential driving and front-wheeled synchronous steering.

The advantages of two-wheeled differential driving are simple, low cost and better obstacle avoidance performance. Besides, in the development of WMRs, three-wheeled omni-directional driving is also the one of the common driving methods. However, no matter what kind of chassis driving mode, the chassis needs to be kinematically modeled during the navigation process. The simple Kinematic models of two-wheeled differential chassis and three-wheeled omnidirectional chassis [3] are shown in Figure 2 and Figure 3.

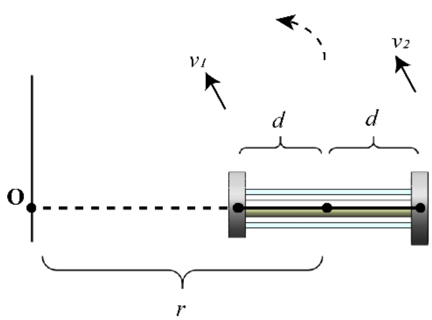


**FIGURE 2.** Kinematic models of Two-wheeled differential chassis [3].

Set the chassis to move in a circular motion at a point along the plane of the center of the chassis. $v$, $w$ are the linear velocity and angular velocity of the center of the chassis, respectively. $v_1$ is the left-wheeled speed, $v_2$ is the right-wheeled speed, d is the vertical distance from the center of the wheel to the center of the chassis, and r is the distance from the point of the chassis plane to the center of the chassis. According to the model, it can be calculated:

$$\frac{v_1}{r-d} = \frac{v_2}{r+d}$$

it can be obtained:

$$r = \frac{(v_2 - v_1)d}{(v_2 - v_1)}$$

And due to $\omega = \frac{v_2}{r+d}$, it can be calculated

$$\omega = \frac{v_2 - v_1}{2d}$$

At this point, it can be adjusted the corresponding speed of the left and right wheels according to the required $v$ and $w$.

Set the line speeds of the three wheels of the chassis are $v_1$, $v_2$ and $v_3$ respectively. The distance between the centers of the three wheels in the center of the chassis is $d$, and the angle between the axles is 120°. According to the model calculation, it can be calculated:

(1) The chassis translates the linear velocity $v_x$ along the x-axis

$$\begin{cases} v_1 = 0 \\ v_2 = -sin60^\circ \times v_x \\ v_3 = sin60^\circ \times v_x \end{cases}$$

(2) The chassis translates the linear velocity $v_y$ along the y-axis

$$\begin{cases} v_1 = v_y \\ v_2 = -cos60^\circ \times v_y \\ v_3 = -cos60^\circ \times v_y \end{cases}$$

(3) Rotating angular velocity $\omega$ of chassis along the center of the chassis

$$v_1 = v_2 = v_3 = \omega d$$

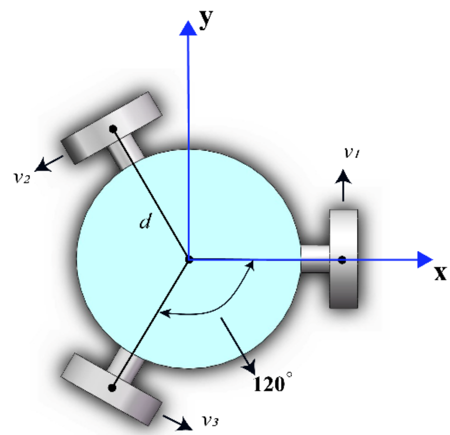


**FIGURE 3.** Kinematic models of Three-wheeled omnidirectional chassis [3].

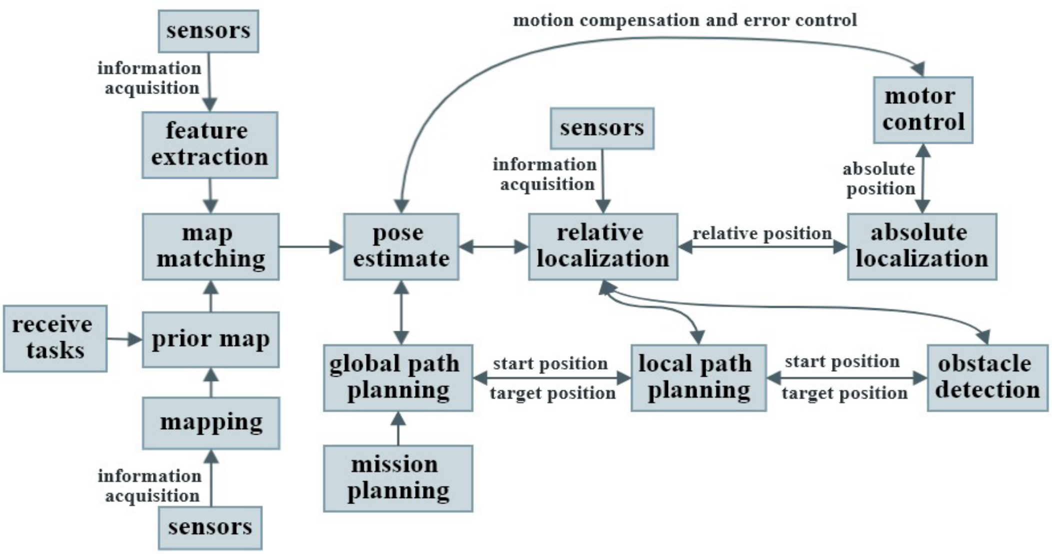


**FIGURE 4.** The navigation structure of WMRs.

After synthesis, it can be obtained

$$\begin{bmatrix} v_1 \\ v_2 \\ v_3 \end{bmatrix} = \begin{bmatrix} 0 & 1 & d \\ -sin60^\circ & -cos60^\circ & d \\ sin60^\circ & -cos60^\circ & d \end{bmatrix} \begin{bmatrix} v_x \\ v_y \\ \omega \end{bmatrix}$$

From the above calculation results, when using a three-wheel omnidirectional chassis, the above matrix relationship can be used for calculation.

### B. NAVIGATION CONTROL OF WMRs

The navigation accuracy of mobile robots mainly depends on its working environment. In recent years, through a large number of scientific research, summary and demonstration, whether in the outdoor environment or the indoor environment, researchers have partly solved the problems related to robot navigation. Nowadays, the several mainly methods which achieve robots navigation include global navigation satellite system(GNSS) [4], laser navigation [5], inertial navigation [6], electromagnetic navigation [7], radio navigation [8], visual navigation [9] and beacon navigation [10], etc. In the meantime, the methods of combining various navigation technologies are also common used. These methods utilize the complementary principle of various types of sensors to reduce the localizing error and improve navigation accuracy. In the outdoor environment, the GNSS [4] has been widely used and it is supported by mature technologies, among which the most widely used is the global positioning system(GPS). Currently, the opening level of GPS is civilian. With the improvement of the accuracy of the atomic clock, the existing ranging accuracy is between 2.93 m and 29.3m [11]. But its accuracy does not meet the demands in most scenarios. In order to obtain higher localizing accuracy, some improved methods have been proposed, the localizing accuracy can reach the centimeter level or even higher. Besides, The GPS is greatly affected by the environment, such as bad weather, obstruction of obstacles, etc., and there will be large errors in localizing. In the indoor environment, the influence of the irreversible factors such as more obstacles and faster attenuation of satellite signals will make it more difficult to realize accurate position.

For WMR, accomplish all the various tasks of the accurate navigation process in the complex environment, it needs to rely on each part of a robots to fully coordinate the work, and its navigation control structure is shown as Figure 4.

The navigation structure of the WMRs includes four parts: mapping, localization, path planning, and obstacle avoidance control. After receiving the navigation task, the robots firstly need to estimate the position and pose combined with the map features. If the prior map is known, the robots use the sensors to perceive the surrounding environment, and then the robots will analyze and process the information obtained by the sensors, and extract points, lines, and other features to determine the position and pose. If it is not known, the robots must extract, process and integrate the environmental information through the sensors before estimating the pose, so as to build local map information and update the global map information in real time. In the process of mapping, the robots need to acquire its position in the global map in real time, acquire the environment features according to the map, and next step is map matching, the robots will combine the odometry and other sensors to estimate the pose. After completing the map construction, the robots need to plan the path of the navigation. Path planning needs to solve three problems, i.e., determination of starting position and the target position, movement of robots, dealing with obstacles. In practice application, the starting position and target position need to be distinguished. About the path planning, the global path planning is required first and then the local path planning is followed, both of them need to get the starting position and the target position. The starting position $(X_0, Y_0, Z_0)$, target position $(X, Y, Z)$ of the global path planning and starting position $(\hat{X}_0, \hat{Y}_0, \hat{Z}_0)$, target location $(\hat{X}, \hat{Y}, \hat{Z})$ of local path planning all need the support of the current map environment, so the accuracy of the map construction is the prerequisite for completing the path planning. However, the global path planning is more complex, but it is roughly the same with the local path specification method. As long as the local path planning is done, the correctness of the global planning can be guaranteed. Another problem that needs to be solved in path planning is obstacle avoidance. In this case, sensors such as ultrasonic sensors are required to detect the obstacles, and the pose is estimated and adjusted in real time so as to guide the robots bypass the obstacles to complete the obstacle avoidance control. Throughout the navigation process, localization is robots must have done at any moment, and it is also the important complement of the path planning. The localization of the WMRs is roughly divided into two steps: relative localization [12] and absolute localization [13]. The relative localization cannot be used alone because the wheels will slide during movement. Absolute localizing refers to the measurement system based on external distance, such as GPS. In practical applications, the WMRs estimate their positions and poses based on the odometer firstly and obtain their relative position coordinate $(\hat{X}, \hat{Y}, \hat{Z}, \hat{\theta})$, and then get their global positions $(X, Y, Z, \theta)$ through an external measurement system. Whether in the indoor environment or outdoor environment, the localization of the robots is extremely important, and the correct localization is the prerequisite for the efficient completion of all work. WMRs also need to complete real-time motion control, mainly depend on controlling wheel rotation movement. In various environments, there are both flats and bumpy roads that contact the wheels, and unstable slippage may occur, causing errors to accumulate, resulting in inaccurate navigation.

The navigation structure shown in Figure 4 is suitable for the general environment. When the robots are in an agricultural environment, special issues need to be noted except for the mentioned work flows. The first problem is sensor selection and calibration. Unlike the structured of the urban environment, the agricultural environment is not a regular one. This imposes higher requirements on the accuracy of robot sensors. It requires sensors with sufficiently higher sensitivity and smaller delay, and then it must be combined with the environment to calibrate the sensors to ensure accurate environmental information can be captured in practical applications. Only in this way it can provide security for subsequent navigation. The next step is how to achieve obstacle avoidance. Because the morphology of crops is different at each growth stage, the obstacle avoidance problem in agricultural environment is more difficult to handle than the urban environment. Not only do robots need to steer clear of the relatively fixed obstacles in the way of navigation, they also need to avoid the crops. Thirdly, safety issues are also very important. In the agricultural environment, the safety of robots and crops needs constant attention. When navigating, the operator must ensure that the robots are controllable. If the robots are out of control, it should be able to stop all actions of the robots in time and switch to the hibernate mode to prevent the robots from damaging the crop. Especially when working outdoors with large robots, safety issues must be considered first.

## III. ENVIRONMENTAL MAPPING

Environment mapping is the primary task in the robot navigation. At first, the continuous representation methods [1] were widely used. But they were not conductive to the robot high efficiency operation. Therefore, some simple decomposition strategies [1] have been proposed. The discrete representation method is a typical method based on these strategies and facilitates the construction and presentation of environment maps. In general, environment maps are represented by topological maps [14], feature maps [15], grid maps [16], and appearance based methods [17]. These methods are commonly used in robots mapping, but each has obvious deficiencies. Moreover, as robots are increasingly used in complex environments, the accuracy of navigation and localizing is subjected to great challenges. Using the traditional representation methods, the constructed maps will not be satisfactory in some details. They may cause a large gap between the actual environment, leading to the deviations and even the robots kidnapped problem [18] during navigation. In order to deal with the problems caused by many aspects, except for working to ameliorate these mentioned methods, some relatively advanced representation methods have been proposed. These methods can provide robots with more reliable environmental information to some extent.

### A. TRADITIONAL MAP REPRESENTATION

There are mainly three types of traditional map: scale map [15], [16], topological map [14], and hybrid map [19]. Each point in the scale map can be represented by coordinates. Common scale maps include feature maps and grid maps. Topological maps use nodes to represent specific locations, and then use edges to connect adjacent points. The hybrid map representation is a combination of the advantages and disadvantages of scale maps and topological maps to generate more flexible and robust maps.

The feature map extracts certain feature quantities such as points, lines, and surfaces, etc. to represent the environment map. González-Baños and Latombe [20] used sensors to extract line features and constructed polygons to represent maps. Lee and Chung [21] have improved the methods, in which two images were used for environmental feature matching to extract feature maps. After verified, the feature matching failure rates of these methods were 0, but the errors of directly extracting features using sensors were relatively large. Therefore, these methods are often used only for the description of the indoor structured environment, and two-dimensional maps do not restore environmental information. However, since the visual sensor is adopted and the multi-sensor fusion method is applied, it becomes much simpler to realize the three-dimensional feature map construction of the environment. Auat *et al.* [22] used a combination of laser and video camera to realize the rapid construction of three-dimensional maps, capable of visually displaying environmental features, and providing more reliable support for the subsequent navigation work. Lepej and Rakun [23] used two laser sensors to extract features and estimate the robots' position to suit a complex field environment. Chebrolu *et al.* [24] and others used 3D Lidar sensors to build 3D scan to better determine the surroundings for robots.

The grid map first was proposed by Moravec and Elfes [25] was using a plurality of sonar sensors to decompose the environment space into multiple units and simply describe them according to whether they were occupied or not. Later, it was successfully applied. Liu *et al.* [26] proposed a triangular mesh map to simplify the planar area into several simple triangles to improve the efficiency of meshing in 2008 and proposed a reconnaissance algorithm based on a laser scanner to better perform the triangular mesh decomposition, and combined the method of the feature map with the grid diagram to fully improve the accuracy [27]. In order to improve the processing speed of the computer, Klaser *et al.* [28] and others proposed an octree data structure to handle camera noise. This method can also detect obstacles more accurately and calculate the space gap for collision avoidance. After the presentation of grid method, Matthies and Elfes [29] proposed the concept of occupancy grid map, the basic idea was to mesh two values, simply indicate whether each grid was occupied or not. This method can greatly reduce the computational burden and increase the efficiency. Occupancy grid map is currently widely used to represent three-dimensional environmental maps and have achieved very good results. Mun *et al.* [30] generated dynamic and static 3D grid maps in the environment, the dynamic used to detect obstacles, and the static used for robots localizing. However, to ensure the accuracy and stability of the occupancy grid map, the computational cost and error rates must be reduced as much as possible. Oh and Kang [31] proposed a fast-occupying grid filtering method that speeded up computation by 38.9% and accuracy by 12%. Tabib *et al.* [32] and others used multiple sensor observations to infer and determine mesh information to improve accuracy, and the results were satisfactory.

Topological maps are ubiquitous in the real world. The generalized Voronoi diagram [33] is a more general representation method. Due to the small storage capacity space required, they can more efficiently conduct location estimation and target recognition. Also, the construction process does not require fine processing of the position between two nodes. Therefore, the selection of nodes is an important issue to consider when constructing a topology map. Ramachandran *et al.* [34] used robots to construct topological maps with uncertain position data obtained during random detection. Maria *et al.* [35] proposed a skeleton topology extraction method to represent maps.

In order to better reduce the errors in the construction of the environment map, integrating the advantages of the traditional map representation method, a hybrid map representation method can be used. After constructing a grid map, Zhou *et al.* [36] and others established a topological map of the indoor environment. The combination of the two maps can better describe the information about the environment and make the constructed map more robust. Sung-Hyeon *et al.* [37] proposed a hybrid mapping method that used grid maps and feature maps to represent the environment around the robots, providing guarantees for subsequent design algorithms, improving the accuracy of the algorithm and reducing the computational complexity degree.

Table 1 shows the advantages, limitation and application scenarios of these map representation methods. These three methods for constructing maps have their own advantages and disadvantages. Although researchers are constantly ameliorating and optimizing, they still can't make one of them completely and efficiently model the environment. Fortunately, the use of hybrid map representation can reduce the problems associated with single map representations to a certain degree. Such as using the geometric-topological representation mentioned earlier, the topological map can guarantee the global coherence, and the geometric map can help localization of the robots. At present, the traditional map representation method is still the most used in the robot mapping. As the increasing demand, researchers are still making continuous improvements to these methods in order to be able to represent the environmental information more efficiently for subsequent localizing and path planning.

Most of the traditional map representation methods are used in some structured environments where the surface texture of the terrain is uniform and the environmental information is known. When describe the unstructured environments such as farmland, we should pay attention to some issues. In the feature map representation, the first consideration is whether it is practical or not. Feature map is generally used in indoor highly structured environments, where information on the characteristics of objects in the environment is obvious. Although the environment of agricultural facilities belongs to the indoor environment, due to the diverse morphology traits and intensive growth of crops, the edge characteristics may not be obvious, and some feature information is easy to overlap. Three-dimensional grid representation [38] is needed to be introduced in the agriculture field, it can help describe the environment a lot. Because of their complexity, the problem of correcting parallax images [39] in agricultural environments and the density of point cloud images [40] is more complex than the general environment. In topology representation, every crop and all kinds of machinery and other obstacles are considered as nodes, but when there are two very similar places in the environment, the topological map method will be difficult to determine whether it is the same node. In the path planning, the application of the topology diagram has its limitations. In summary, it can be seen that although these map representations are applied in various

**TABLE 1.** **Traditional map representations.**

| Cartographic representation | Advantages | Limitation | Application scenarios |
|---|---|---|---|
| Scale map[15, 16] | Feature map - used for obstacle recognition and self-pose estimation.<br>Grid map - easy to create and maintain in a small and simple environment. | Feature map - the sensors are susceptible to noise and more suitable for highly structured indoor environments.<br>Grid map in a large environment or when fine meshing is required, the amount of calculation will increase, and it is not conducive to robots processing and maintenance. | Mapping，Localization, Simultaneous Localization and Mapping（SLAM） |
| Topological map[14] | A high degree of abstraction.<br>It can facilitate path planning and greatly reduce computational complexity in a large and simple environment. | The characteristics of the nodes in the topological map are required to be sufficiently obvious, and they also depend on the accuracy of the information processed by the sensors. They cannot be judged whether all the information in the environment is traversed or not. | Path Planning |
| Hybrid map | Reduce the problems caused by single map presentation. | It's difficult to achieve in practical application | All above |

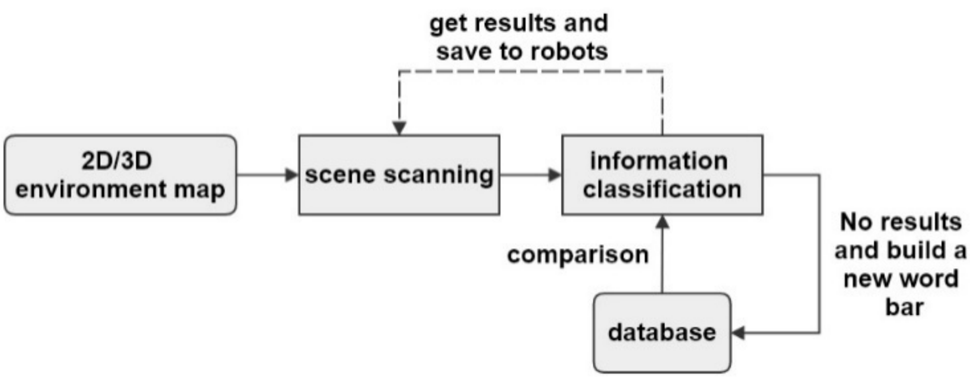


**FIGURE 5.** **The construction of the simple semantic map.**

fields, the situation in agriculture is the most special. In order to deal more efficiently with the problem of constructing environmental map on the navigation of agricultural robots, more research and exploration should be conducted for the structured representation of hybrid map.

### B. SEMANTIC MAP REPRESENTATION

Each location, road, or obstacle in a semantic map [41] are represented by a tag, which is then grouped together. Haspelmath [42] and Haan [43] described in detail how to draw classical semantic maps and some technical problems. In the field of robots, semantic map attracted people's attention in recent years. It can help robots to understand what is happening in the real world, Figure 5 shows the construction of the simple semantic map. Its main idea is to decompose the information obtained by the sensors into characters that can be understood by the computer, and then the computer can combine these characters and perform query matching on the combined results in the database and use the found results to describe the map information. When robots navigate, the introduction of semantic maps can improve navigation and localizing accuracy to some extent. Dabeer *et al.* [44] used semantically significant landmarks (such as traffic signs, etc.) to navigate in 3D map, and improved the accuracy of the distances to the corners of landmarks within 20 cm. Murali *et al.* [45] proposed a new method for integrating semantic information based on vision-based vehicle navigation, which improved the sub-meter accuracy achieved by using visual navigation about 20%. Semantic maps can also be used in conjunction with traditional map representations and are a great improvement over traditional map representation methods. Li *et al.* [46] constructed a collaborative multi-level semantic map and combined it with a two-dimensional grid map to support autonomous parking. The experimental results show that this scheme can improve navigation localizing accuracy and prove the feasibility of indoor autonomous parking.

If only employing the traditional map representation, or just improving the traditional map representation, the robots only know whether there are obstacles in front of it during the actual operation and cannot accurately determine the type of obstacles. However, in the agricultural environment, robots need to have a clear understanding of the precise environmental information, and semantic map can provide great help. Semantic map allows robots to know exactly where they are, what obstacles are around, and what they see. They can provide guidance for follow-up operations, especially the precise operation of robots under the precision agriculture system. When the robots navigate in the agricultural environment, if the prior map of the localization and path planning is optimally constructed and represented, such as the introduction of a semantic map for accurately representing the specific environment, the subsequent navigation of the robots will be more efficient and convenient. However, due to the technical limitations, there are still many difficulties to construct the semantic map of the entire space concept. It requires people to carry out further exploration and research. It is certain that the semantic map is a development direction of the map representation and localizing of agricultural robots.

### C. DIGITAL TERRAIN MODEL REPRESENTATION

Digital Terrain Model representation(DTM) [47] is a method of depicting surface relief patterns. This type of map representation can either digitize an existing topographic map, that is establishing a traditional grid map, or rely on the satellites, drones, and other collecting images used for map construction and presentation, and then transmitting images to the robots. The digital terrain model representation is usually based on Fourier series and gaussian polynomials to perform uniform fitting reconstruction or image representation, digital terrain map is one of the better ways to restore real terrain, and they can improve obstacle detection and localization performance to a certain extent.

The digital terrain model representation is one of the commonly used methods for surveying and mapping. It is suitable for some outdoor terrain environments. It can restore real scenes more quickly and accurately than traditional map representations. Although this method is rarely used in robot map representations, researchers have applied it to the robotics field based on their special advantages. Reinoso *et al.* [48] used digital drones to construct a digital terrain map with a 3D composition error of only 12 cm. Kim *et al.* [49] used synthetic aperture radar (SAR) technology to construct a digital terrain model, which reduced the composition error by 23% and improved the localizing accuracy by 16%. Wang *et al.* [50] used an interferometric synthetic aperture radar sensor to construct a digital terrain model that can identify obstacles more accurately. However, the error of this method is related to the number and size of sampling points. To obtain a small error, the requirements for sampling equipment and fitting methods are high. With the increasing number of sampling points, the cost will also increase. In the agricultural environment, sometimes there is no need for complicated map representations. The robots can accurately know the key information in the environment during navigation. The digital terrain model representation can be constructed into a regular grid model, which is similar to the main idea of traditional map representation methods. According to its unique advantages of describing the surface relief conditions, this method is worth learning when we navigate in farmland and other environments

### D. OTHER MAP REPRESENTATIONS

Besides these mapping methods, there are some other methods that have been successfully implemented. The radar representation is based on an observation node and describes the environmental map by scanning the morphological characteristics of the surrounding obstacles. In some outdoor natural environments, if data is collected using optical sensors, it may be subject to large errors due to environmental changes. Rouveure *et al.* [51] used the millimeter-wave radar's rotating fan beam antenna for simulation and used radar data to construct and represent a two-dimensional environment. However, this method can only create a two-dimensional image of the environment and cannot obtain the target height. In order to construct and represent three-dimensional images of the environment, Foesselbunting [52] developed a radar sensor model that can be used as a vector sensor. They proposed rules for signal interpretation of radar phenomena and signal processing of frequency-modulated continuous-wave signal. Then used these rules to obtain the height of the target to construct a three-dimensional environmental image. This method has strong robustness, and it can express high-fidelity environmental maps due to the great anti-interference ability. However, it is not widely used and promoted because of its high cost and its vulnerability to interference from other frequency bands. The solar map representation is an energy estimation map collected by solar panels, and Plonski *et al.* [53] etc. measured solar energy through the robot's position to obtain a better energy-saving route. Interpolation mapping method [54] uses the method of interpolation to describe the situation of two workspaces in order to identify the robots' range of motion.

These methods are some of the typical map representation methods proposed by people in constant scientific research. Although some methods are only practiced in special fields, we can explore some representations suit for the outdoor field environment with complex terrains and indoor facility environment where there are many obstacles, based

**TABLE 2. The common methods of robot localization.**

| Type | Method | Description | Limitation |
|---|---|---|---|
| Dead-reckoning[55] | Odometry[58] | Measure MWRs wheels' rotational speed, calculate the move distance and estimate position. | Start position needs to know and the errors will increase with time. |
| | INS[6] | Gyroscope to get the angular acceleration, accelerometers to get the linear acceleration, estimate angular and position. | |
| Beacon[10] | RFID[59] | Recognize the specific target, obtain the relevance data, to judge the robot's current position and region. | Only short and small distance available, widely be used in indoor environment |
| | QR-code[60] | Large data memory, based on RFID technique, get the robot's current position and region. | Only one simple can be recognized at one time, high cost of scanning equipment, and low sensitivity. |
| GPS[11] | GPS(civil grade)[11] | Satellite communications to test and range, obtain the robot's position. | Low precision and limited in indoor environment. |
| Map-matching[56] | Visual[9] | Cameras to get the information of characteristic points, match with prior map and know the robot's position. | High cost of computing, limited by light, bad real-time performance. |
| | Laser[5] | Calculate the launch and reflects' time difference to know the distance and angular. | High cost. |
| | Infrared[61] | Working principle is same as Laser. | Easily Interfered by environment, disabled to detect the black and transparent substances, short measure distance. |
| | Ultrasound[62] | Working principle is same as Laser. | Easily Interfered by environment, disabled to measure the surface roughness and irregular substances, short measure distance and slow acquisition speed |
| | Wireless sensors[63] | Receive or detect the nodes' position and reckon own position. | Nodes' positions random, and their coordinates need to be known, rely on algorithm's performance |
| Probabilistic localization [57] | Markov[64] | Obtain the trust-degree in grid map, estimate position by probability theory | Need the grid map and critically trust-degree to calculate. |
| | Kalman filter[65] | Exceptional circumstance of Markov localization, use weighted between observation results and prediction results to know the results | Observation results need other technique to get, prediction results need speculation of human, large errors. |

on its related theories and advantages, such as penetration of electromagnetic waves, anti-jamming, etc.

## IV. ENVIRONMENTAL LOCALIZATION

The localization of WMRs in the environment is an extremely critical work, if the robots could get their positions of the global coordinates and current poses, they would make the next behavior plans, and it can be seen as the prerequisites of the path planning. The robots' poses acquisition is mainly processed by relative localization technology, but the errors will increase with time, it's not good to use the relative localization technology alone to realize the robot accuracy localization. The global position estimate is mainly dependent on absolute localization, but now all the global localization technologies are sensitive to the environment, they are severely limited in some working spaces. Many technologies are widely used in outdoor localization, such as the GNSS, but in the indoor environment, the GNSS is limited, it needs

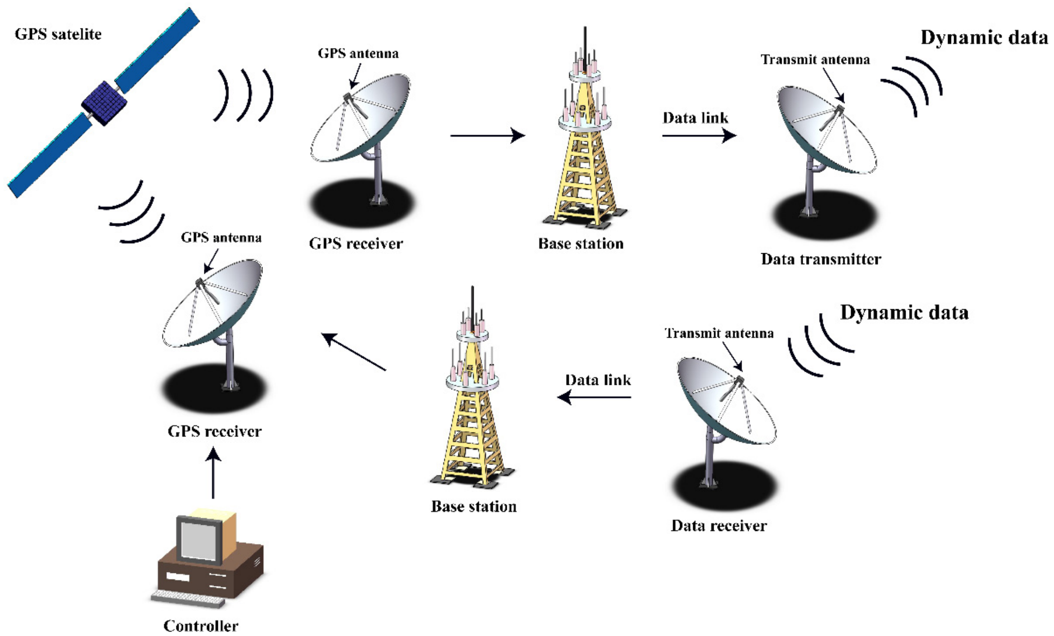


**FIGURE 6.** **DGPS sketch map [66].**

the other sensors to achieve the robot localization. Although there is no idea to give the most accuracy position information to robots, researchers have conducted a significant amount of research on robot localization optimization treatment. With some technical bottlenecks are broken through, in some scenarios, the more accuracy robot localization is basically actualized. In robot localization field, dead-reckoning [55] could be used as relative localization, and absolute localization generally includes beacon localization [10], global position system(GPS) [11], map-matching localization [56], probabilistic localization [57] and etc. The common methods of robot localization are lists in Table 2.

These common methods of robot localization are based on distance measurements, it could perform more accurate localization precision than others. But these methods also have some obviously chief objections, such as some methods give rough precision, easily interfered by environment and humans. In order to improve this situation, with many experiments, researchers made some progress, and some better methods are also proposed. All these methods' feasibility proves, this would help to offer the new research directions of robot localization in the future. In agricultural field, these traditional methods of localization are now widely used, dead-reckoning [55] and GPS [11] are used the most in the farmland environment, but due to the effect of the roughness of the ground, wheels' rotational speed is not accurate, Measurement results of sensors such as gyroscopes and accelerometers are prone to bias, errors will be enlarged; GPS [11] (civil grade) is not tally with the precision agriculture, it may damage the crops and it's irreversible, so it needs to be improved. Beacon localization method [10] always won't be used, because of the crops dense growth and uneven surface of the ground, the beacons can't be tiled very tidily, the robots are unable to recognize and localize. Among the map-matching localization [56] methods, some of these methods are considering to use, the visual method [9] can be employed to research on robot navigation, the laser [5], infrared [61] and ultrasound [62] and wireless sensors [63] methods need to fully consider the obstacles, these obstacles may prevent the signal. In addition, probabilistic localization [57] methods have some good algorithms to decrease the errors during the localizing process, so it's applicable to agriculture. General localization should be thought about carefully when they are used in agriculture, some ideas are not meeting the requirements, and others need to be improved before used.

### A. DIFFERENTIAL GPS

General civilian GPS receivers' localizing accuracy is not satisfactory, it has large errors, and at the end of the 20th century, GPS affected by some policies, the errors are further increased. In order to solve this problem, researchers combined the differential technique and the GPS technique together, improved the localizing accuracy. The Differential GPS (DGPS) includes differential position GPS (P-DGPS), differential pseudo range GPS(PR-DGPS) and differential carrier phase GPS(RTK-DGPS) [66], the DGPS work principle as shown in Figure 6. The PR-DGPS and RTK-DGPS are popularized used.

PR-DGPS is to set some high precision receivers in the accurate position, serve as the datum station, to make use of the true distance of each satellite to the reference station to correct the pseudo distance and to guide the correction of the nearby receivers to improve the precision.

Liu *et al.* [67] apply the PR-DGPS technology to remote control vehicles, and verify that the localizing accuracy will continue to decrease with the distance increasing from the base station. Liu and Yang [68] use the pseudo distance differential technique to improve the single point localizing accuracy. It shows that the mean and variance of the pseudo range differential positioning error is obviously smaller than the mean and variance of the single point localizing error in the same condition, but the error of the pseudo distance differential will increase with the distance increasing from the base station. Shen *et al.* [69] propose an improved pseudo range differential positioning method, which reduces the error by 50% and reduces the variance by two orders of magnitude. PR-DGPS positioning accuracy is not too high. If the robots use PR-DGPS, this technique needs to be improved, the existing receiver's hardware can be updated or optimized, but this will improve the cost.

RTK-DGPS is a technology that uses the differential method to process the carrier phase between observation stations in time to improve the measurement error of GPS. The technology principle is the same as the PR-DGPS, which transmits the observation results and coordinate information of the observation station to the user station in time from the observation station. RTK technology has been applied in many fields. Because of its high localizing precision, it has also been widely used in agricultural production in recent years. Bakker *et al.* [70] designed an automatic navigating system based on RTK-DGPS, and combined with the related technology of machine vision to map the crop rows, finally achieved the goal of the robot localization. The localizing accuracy of this method is very high and the error range is within 5cm. Pérez-Ruiz *et al.* [71] studied a path control system for weed control knives, which ensured the non-destructive weeding of crops and achieved 0.8 cm localizing accuracy. Xue *et al.* [72] studied a variable visual navigation system, it's located by RTK technology and reaches 1.58 cm localizing accuracy, then combined with other navigation techniques to ensure the stability of the navigation process. Yue *et al.* [73] improved RTK-DGPS and proposed a GPS/INS integrated navigation algorithm based on time/satellite carrier phase difference, the experiments proved that the method improved the localizing accuracy by more than 50%. RTK localizing accuracy is very high, and it can be used for real-time data processing, but the basic requirements are too high, except for the high cost, narrow available range and other shortcomings, it will also have a great challenge to the hardware. In RTK technology, the carrier wave length is long, so the frequency can reach very high frequency or UHF range. At present, there are still many problems that haven't been overcome in the field of high frequency, so there are also many problems need to be solved in popularizing this technology.

The differential GPS is the improvement of the GPS. The researchers now are able to realize the localizing accuracy around 1cm, which is sufficient in agriculture, especially in outdoor fields, it is better to be used in plain areas, but in some non-plain areas, the growth environment of crops is surrounded by mountains and hills. This environment will cause difficulties for the erection of the receiver and the signal transmission between the receivers because of the working principle of PR-DGPS and RTK-GPS, which is one of the reasons for the failure of the large-scale promotion at present. Therefore, how to further improve DGPS has become the research difficulty of farmland robot navigation and location in non-plain areas.

### B. SOUND SOURCE LOCALIZATION

The robot sound source localization [74] means that the robots can capture the sound information of the environment through the sensor or the audio array, and then judge the location of the sound source by the fusion processing of the information, thus providing the condition for estimating self-location. Although speech recognition technology has been developed and applied for a long time, it is rarely used in human-machine interaction [75] in robotics. Rucci *et al.* [76] simulated the hunting behavior of the owl, constructed a robot head measurement system with two sided microphone and one camera, and successfully realized the sound source localization. The general model of sound source localization is shown in Figure 7.

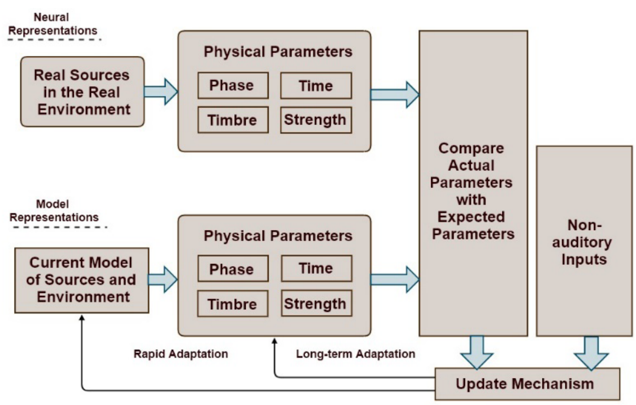


**FIGURE 7. The general model of sound source localization [74].**

In order to improve localizing accuracy of the sound source localization, the most important thing is to design optimization algorithm. Cui and Song [77] proposed an acoustic location algorithm based on ten variables stereo array, the average localizing error is within 0.01 meters. Pavlidi *et al.* [78] proposed a multi-source sound source localization and counting method, the CPU processing time is reduced by 55%, and the localizing error of each speaker of the sound source is controlled under 2.5 degrees. In addition, the noise needs to be considered, in order to reduce the influence of the system noise, Gu *et al.* [79] proposed an auditory system based on microphone array, which successfully suppressed noise and made the system have good robustness and a shorter waiting time. There are also some researchers who integrate some other methods with microphone arrays, this can also achieve good sound source localization. Su *et al.* [80] proposed

**TABLE 3.** The common solutions of SLAM.

| Method | Description | Limitation |
|---|---|---|
| MonoSLAM[83] | The core of the approach is online creation of a sparse but persistent map of natural landmarks within a probabilistic framework. | Less landmarks and sparse points are easy to lose |
| PTAM[84] | Split tracking and mapping into two separate tasks, processed in parallel threads on a dual-core computer. | Tracking can only proceed when the FAST corner detector fires, so the feature points are easy to lose |
| LSD-SLAM[85] | A direct (feature-less) monocular SLAM algorithm which allows to build large-scale, consistent maps of the environment. | Sensitive to camera parameters and it is easy to lose when it moves fast. |
| ORB-SLAM[86] | A feature-based monocular SLAM system that operates in real time, in small and large indoor and outdoor environments. | Waste a lot of time because of feature extraction and it is hard to transplant to embedded system. |
| SVO[87] | A semi-direct monocular visual odometry algorithm that is precise, robust, and faster than current state-of-the-art methods. | Less feature points and they are easy to lose |
| LIDAR-SLAM[88] | An efficient method of acquiring as-built floors by using LIDAR and SLAM. | Affected by laser detection range and accuracy |

a method for audio tracking using a laser rangefinder and a microphone array, the reflection of sound and blocking of obstacles are considered, the sound source is successfully detected, the error is controlled to 0.1138 meters. Escudero *et al.* [81] used FPGA to locate the sound source, tested it under 1KHZ, 2.5KHZ and 5KHZ, this idea not only improved the processing speed, but also controlled the measured average angle error around 2.32 degrees. Sun *et al.* [82] proposed a localization algorithm based on the probabilistic neural network, the results showed that the average azimuth error and elevation error are only 4.6 degrees and 3.1 degrees respectively.

Therefore, the sound source localization is to use the robot's position to detect the sound source. In order to obtain the positions of the robots, the sound source can be placed in an accurate position, the positions of the robots are calculated according to the position coordinates of the sound source and the distance between the robots and the sound source. If it needs to locate the sound source in a complex environment such as the agricultural environment, it is necessary to pay attention to the frequency of the sound source, the interference of the noise, the obstruction of the obstacle and the errors of the microphone. But sometimes there maybe appear a variety of mixed sound sources with similar frequencies, in this case, accurately identifying the correct sound source is also a difficult problem to overcome in the future.

### C. SIMULTANEOUS LOCALIZATION AND MAPPING

Simultaneous localization and mapping (SLAM) means that robots use their sensors to localize and map at the same time in unknown environments. This technology was proposed at the end of the 1980s. During scores of year's developments, SLAM can be roughly divided into two categories: visual SLAM and laser SLAM. Table 3 lists some common SLAM solutions.

SLAM is the focus of research in the robotic field. The researchers have successfully solved some localizing problems in practical application by using these solutions or improving these solutions. Lee *et al.* [89] proposed a new method of high efficiency SLAM using a forward-looking monocular vision sensor, the pose of the camera and the location of the beacons can be corrected according to the local map, when the robots are walking on the road of 774 meters long, comparing with the unimproved SLAM solution, the absolute localization error is reduced to 0.71 meters. Endo *et al.* [90] applied LSD-SLAM to the visually impaired people's navigation system, using a wearable camera to estimate the position of the visually impaired people and it successfully was experimented in a real environment, it can help the visually impaired people avoid obstacles during walking. Xiao *et al.* [91] proposed an improved ORB-SLAM system, which is compared with the method of laser scanner using triangulation algorithm, it showed that the error within the range of 12 meters is only 35cm, and can get more accurate scale of the real environment. Santos *et al.* [92] proposed a hybrid SLAM with the low cost landmark based on the two-dimensional extended Kalman filter algorithm SLAM (EKF-SLAM), which improves the localizing accuracy of the robots in the steep slope environment and also has the ability to deal with mixed maps of natural and man-made landmarks.

Although some SLAM solutions have been successfully applied and commercialized, there are still many problems need to be solved. For example, the SLAM assumes that the map is static and the application scene is generally indoor environment. In the establishment agricultural environment, it is different from the general indoor environment, there are more obstacles exists in the process of robot navigation, and the multi-sensor fusion technology needs to be used. However, there are still some bottlenecks in how to use multi-sensor fusion technology in SLAM, and the advantages of various sensors are not fully performed. Many research experiments showed that it did not really realize the autonomous and high precision localizing of the robots in the general indoor environment. Besides, most of the maps in SLAM are feature maps, the previous article has mentioned that outdoor environment can be used to construct feature maps, it is also necessary to think about whether SLAM technology can be used in an outdoor environment. In general, SLAM can be applied in theory, but few researchers have done research in this area so far. And in agricultural environments, especially in outdoor environments, many objects are moving, the dynamic SLAM technology is needed, although there are some researchers such as Lee *et al.* [93] has done some research on dynamic feature extraction, some problems have also been solved, the dynamic SLAM is still considered as the one of the most difficult problems in the SLAM field. By the way, the SLAM optimization algorithm also needs to be considered under the precision agriculture conditions. In a word, all these problems will bring great challenges to the SLAM research of agricultural robots, and they also will become the focus of SLAM research in an agricultural robot field.

### D. FUSION LOCALIZATION

The robot fusion localization mainly uses the fusion of multiple localization methods to locate the robots, give full play to the advantages of various methods, realize the information complementation, and maximize the localizing accuracy. Yang *et al.* [94] used sensors to scan corners and adopted the idea of feature map construction, to extract corner features to locate robots, the localizing accuracy is around 10cm. Li *et al.* [95] proposed a hybrid location model based on the least square method and Kalman filter for high precision GPS localization and wireless mobile localization, it is proved that the model has a higher localizing accuracy than ordinary pseudo range differential localizing. Yang and Scherer [96] combined visual localization with odometer localization, in order to get the better geometric edge and reduce the attitude estimation error by more than 50%. Tsuno *et al.* [97] used the laser rangefinder and the extended Kalman filter to verify that the root mean square error (RMS) of the location was raised to less than 2mm.

The Fusion localization technology is similar to multi-sensor fusion technology, which combines the advantages of multiple technologies to form a set of solutions to overcome the shortcomings of a single technology. It is especially suitable for some high precision required localizing scenes and can also solve the problems of location in some complex scenes. In agriculture, this kind of method can be considered, but it may be more affected by the influence of various factors, such as the environment state, the characteristics of each sensor, the establishment of the fusion model and the allocation of resources. Although the realization of the technology is simple, how to improve the precision will be a big problem.

## V. ENVIRONMENTAL PATH PLANNING

The path planning problem of robots is a hot issue of the composition strategy to research the starting and ending path, while the algorithm of path planning is to realize avoiding obstacles by finding the optimal path. Hence, the optimum degree of the algorithm directly determines the efficiency of path planning. It becomes simple to plan a path for the wheeled mobile robots because of its low-speed operating environment and negligible dynamic problems, often the algorithm is biased to simple approximatively [1], and this is different with industrial robots. Here, we make some discussion and analysis for the common search algorithms of path planning and obstacle avoidance problem.

### A. PATH PLANNING SEARCH ALGORITHM

It is similar to graph traversal, the path planning search algorithm is to find the target node according to the initial conditions and certain rules, and the search algorithm generally has two broad categories: exact algorithm and approximation algorithm. The breadth-first search algorithm (BFS) [98] and depth-first search algorithm (DFS) [99] both belong to the exact algorithm, and Dijsktra algorithm [100] is one application of the breadth-first search algorithm, while the approximate algorithm the A* algorithm [101] and D* algorithm [102] is relatively mature. These four algorithms are based on the clear map which generally uses a topology representation [14], additionally the researchers find the RRT [103] algorithm can also be used to path planning when without the clear map, and the common algorithms are demonstrated in Table 4.

The BFS algorithm [98] traverses from the starting point and nodes adjacent to it, and spreads out without considering the optimum. The DFS algorithm [99] can estimate the cost of a node to the target point to quickly reach it. The Dijkstra algorithm [100] focuses on the shortest path from the starting point to all the other points and can get the optimum. A* algorithm [101] introduces the heuristic idea with information of the surrounding nodes around the starting and the target nodes, focusing on the shortest path from the starting point to a certain point, so it can be seen as the improved Dijsktra algorithm [100]. RRT algorithm [103] is a tree structure expanding out from the starting point with its expansion direction determined by random sampling in the planning space.

These algorithms which have about four kinds of applications in agriculture: DFS algorithm [99], Dijkstra algorithm [100], A* algorithm. [101] and RRT algorithm [103]. Because the BFS algorithm [98] consumes too much computing resources and greatly increases the application cost, it is not practical in agricultural environments, D* algorithm [102]

**TABLE 4.** Common research algorithm.

| Algorithm | Description | Limitation |
|---|---|---|
| BFS[98] | Breadth-first algorithm, thoroughly searches the whole map without consideration the possible results until succeeding. | Occupying too much memory. |
| DFS[99] | Depth-first search algorithm fastest find the optimal approximate solution without traversing all nodes. | Slow speed, can find the optimal solution under certain circumstances. |
| Dijkstra[100] | Static path algorithm，expands outward from the starting point until succeeding, local optimal of each expansion and not necessary the global optimal. | Traverse all points, low efficiency, high time and space complexity. |
| A*[101] | Static path algorithm，a deep priority search algorithm, from the start point, focusing the shortest path point to point. | Introduce a large amount of redundant data, resulting in slower speed. |
| D*[102] | Dynamic path algorithm，can be regarded as dynamic A* algorithm, moving to the target point, focusing on the change of the next node or adjacent node in the shortest path. | Low speed and high complexity. |
| RRT[103] | A sampling based path planning algorithm， simple to build and can quickly traverse the unexplored areas, and solve complex problems under high dimension. | Large randomness, lack of smoothness and repeatability of planning for the same task. |

**TABLE 5.** The improved search algorithm.

| Original Algorithm | Improvement Algorithm | Description | Limitation |
|---|---|---|---|
| A*[101] | IDA*[106] | Iterative deepening search algorithm, the parameters of record depth are added to the depth first algorithm return when getting the corresponding depth. | The evaluation function is not easy to set. |
| | LPA*[107] | A* algorithm is used for the first time, and then calculates the changed path by previous information. | Local smoothness is not good, which is not conducive to practical application. |
| | Bidirectional A*[108] | Bidirectional A* algorithm, conducting from the beginning point to end point until coinciding with the search point. | The collection of forward and backward search needs to be constrained. |
| D*[102] | Focussed D*[109] | D* expansion algorithm，mainly focuses on reducing the subsequent computing cost. | Difficult to calculate load distribution. |
| | D* Lite[102] | Improvement on LPA*, the optimal path search by reverse search, starting point changes with time while target point fixed. | All nodes are initialized with high complexity, and it is not optimal to judge the priority list nodes by traversing the entire table. |
| | Field D*[110] | The method to calculate the shortest boundary point with the key to compute the path consumption of each node. | High time complexity, the operation time is much longer than D* and D* Lite. |

is not suitable for establishment environment. The algorithm is mainly to solve the optimal path problem in a dynamic environment, so it can be applied in field environment. However, as far as the current research, it is rare to use this algorithm for outdoor environmental path planning in the field of agricultural robotics. We can see from table 4, these relatively mature search algorithms have some limitations in the general environment and have been improved afterward. In recent years, new algorithms such as Theta$*$ [104] and Phi$*$ [105] have been proposed which has developed the original approximation algorithm and improved the accuracy of path planning to some extent. Table 5 lists some improved search algorithms and Table 6 shows the novel search algorithms proposed in recent years.

**TABLE 6.** The new search algorithms.

| Algorithm | Description | Limitation |
|---|---|---|
| Theta*[104] | A Mutation algorithm of A*, propagating information along the edge of the grid, does not constrain the path to the grid edge, fast and can find the short path. | There is no guarantee to find the true shortest path and the parent of each node must be adjacent to it. |
| AP Theta*[104] | A Mutation algorithm of A*, propagating information along the edge of the grid and discussing the propagation Angle when extending the vertex. | Not fast speed and the slightly longer path. |
| Lazy Theta*[111] | A Mutation algorithm of Theta*, performs sight line inspection for each extension point, which can be used in a 3D grid environment. | The default sight line is always true, and the parent is set according to Theta*. |
| Phi[105] | A version of Theta* that can be incrementally manipulated. | Can only repeat single execution when re-computing any Angle path. |
| Incremental Phi*[105] | With the expansion of Theta*, the extended vertex is reduced, and the longer path can be searched when repeat calculating any Angle path, which makes the speed approximately one order of magnitude faster than Theta*. | The time that may appear to extend at each vertex is inconsistent. |

At present, these improved algorithms and new search algorithms almost have been rarely applied in agriculture, but after making the summary and analysis of the characteristics of the above algorithms, meanwhile, we combined with the complexity in the agricultural environment, and give some prospects in the future agriculture application. The three types of algorithms improved based on A∗ [101] are practically applicable in the facility environment. The IDA* algorithm [106] combines the advantages of A∗ [101] and DFS [99] to find the optimal path faster. The LPA* algorithm [107] has not good ability in handling the path smoothing, but it can be used for local path planning which is extremely important in the facility environment. The Bidirectional A* [108] can improve the speed and reduce the algorithm complexity. We can also consider combining this algorithm with the advantages of IDA∗ [106]. By constructing a two-way depth search A* algorithm [101], we can greatly improve the speed and accuracy of the A* algorithm [101], and this is also needed in such complex agricultural environment. The three types of improved algorithms for D∗ [102] can be temporarily ignored in agricultural applications. After all, although the field environment is dynamic, its dynamic target is not too much, and the general D∗ [102] algorithm can be competent, so we should focus on the promotion and application of D* algorithm [102]. As for the new search algorithms Theta∗ [104] and Phi∗ [105], which have been proposed in the last decade and have not yet been maturely applied in the general environment. However, these algorithms can be applied in agriculture via their characteristics in the future. Firstly, the mutation algorithms based on the A* algorithm [101] can be applied to all environments applicable to the A* algorithm [101] theoretically, and then they can solve the edge and angle problem of the map that the original path search algorithm cannot handle well in practical applications, this can greatly reduce the error of improving the path planning. Finally, these algorithms are not so complex, and the computational complexity is much lower than original. These advantages all indicate that they have good application prospects in agricultural environments. Besides the advantages of these improved algorithms and new search algorithms, their shortcomings are also very obvious. To reduce or avoid these shortcomings in the application, it is also a matter for future researchers in the field of agricultural robots.

### B. OBSTACLE AVOIDANCE

The obstacle avoidance control of robots is a sub-problem that needs to be addressed in the path planning. And the obstacle avoidance problem can be regarded as a link in the local dynamic path planning problem. In order to ensure crop and body safety, robots need to make quickly obstacle avoidance decisions on the perception of the surrounding environment timely because the local environment is constantly changing. When solving the obstacle avoidance problem, the obstacles must firstly be detected and then the obstacle avoidance control should be performed. The basic requirement is to estimate the distance to avoid the obstacles in conjunction with its own movement speed and posture and determine the minimum avoidance distance and the maximum avoidance angle. In terms of obstacle avoidance control, combined with current research status, the commonly used algorithms include BUG algorithm [112], Visibility method [113], Artificial

**TABLE 7. The common algorithm of obstacle avoidance control.**

| Algorithm | Description | Limitation |
|---|---|---|
| BUG[112] | Only use tactile sensors to get local information about the surroundings without having to understand the global situation. | The turning radius of the robots is not fully considered and the path is not smooth. |
| Visibility method [113] | Combine the vertices of the robots, the target point, and the polygonal obstacle, and the connected straight line is regarded as an arc, which is regarded as a "forbidden zone". | The robots stop moving and perform data acquisition, which is greatly affected by the sensor accuracy. |
| Artificial potential field method[114] | Create a virtual force to estimate the position of the robots and control the movement by the force of the obstacle on the robots. | Cannot plan paths between nearby obstacles. |
| VFH[115] | The surrounding environment is decomposed into binary grid maps, and the histogram is used to characterize the influence of the robot's surroundings on its motion direction. | It has the disadvantages of grid map representation. |
| Dynamic window method[116] | Sampling according to the speed range and better simulating the trajectory of the robots. | The sampling space is limited by the robot's acceleration and deceleration performance. |

potential field method [114], VFH [115], Dynamic window method [116], etc. As shown in Table 7.

People also did a lot of research on these five methods and achieved good results, Xu *et al.* [117] used the BUG algorithm to solve the obstacle avoidance problem in navigation under unknown static conditions. Souidi *et al.* [118] also improved the BUG algorithm to make optimal use of sensor data and reduce the length of the path to the target. Tran Quoc *et al.* [113] used the viability method to optimize the path planning scheme in a two-dimensional space with obstructions, which greatly reduced the planning time. In addition, Babic *et al.* [119] proposed a method of constructing the visible map in three-dimensional space which simplifies the complicated construction, and shows that the construction of the three-dimensional visible map can be completed without using a professional computer or a supercomputer. Shi *et al.* [120] analyzed the inadequacies of the artificial potential field method and proposed an improvement method to develop the smoothness of the planning path; Kumar and Kaleeswari [121] successfully used the VHF method to implement obstacle avoidance control for the wheeled robots, and completed the obstacle avoidance path planning when the robot's distance to the obstacle was more than 20cm. Xie *et al.* [122] extended the dynamic window method to maximize efficiency in avoiding obstacles and other local path planning. Henkel *et al.* [123] also extended the dynamic window method to estimate energy consumption and found that the energy consumption is reduced by 9.79% compared to the original dynamic window method.

It is not difficult to find that the five methods have their unique advantage through the series work of the researchers, while table 7 also lists the limitations of each method. This is only an application in the general environment, for the obstacle avoidance problem in the agricultural environment, the dynamic window method has been mentioned and used [28], this method is to sample the speed within a certain period of time. The difficulty when used in the agricultural environment is the speed calculation problem because the odometry and inertial measurement unit will produce errors over time, which will increase the difficulty to use the dynamic window method. The application of BUG method and visible image method of agriculture has certain prospects, but if they are to be applied, some problems need to be considered. Due to the dense growth of crops, the working space of agricultural robots is not large. When obstacle avoidance is needed, obstacles need to be avoided as much as possible, the robots need to keep relatively close distances with the obstacles and then bypass the obstacles, so the accuracy of the sensor and the selection requirements of decision points for returning to the normal path after detouring is very high. This directly affects the efficiency of path planning. The principle of the artificial potential field method determines that this method is not suitable for use in agricultural environments, and the dense obstacles will not allow the robots to plan a better path. While the VHF method can be used, it primarily carries out the representation of the environmental map by the thought of occupying the grid to represent the relationship between the obstacle and the robots to guide the robot's movement to avoid obstacles, once the requirements become strict, such as the number of obstacles is increasing or the accuracy is improving, it will impose a great burden on the calculation, and this is a problem should be fully considered. In a word, although some obstacle avoidance algorithms have not been applied in agriculture, but their good performance characteristics in the general environment also provide direction for researchers to bring them into agriculture.

## VI. APPLICATION PROSPECT OF AGRICULTURAL WMRs RESEARCH

Since 1980s, a lot of scientific research on the navigation of agricultural WMRs has been carried out, and there has been made a breakthrough in the key technology. But there are still many problems, such as high cost, large site impact and low intelligence, which still face difficulties that can't be widely promoted and applied. Therefore, combined with the current research status of the key problems in the field of robot navigation, the future research on the navigation of the agricultural WMRs should start from the following aspects:

(1) Mapping in agricultural environments. There are numerous existing methods for mapping, but a lot of problems still need to be done. Although the map which we constructed is static by default, minor changes in the agricultural environment may cause changes on the map structure or shape in actual agricultural operations. While the solution to dynamic obstacle avoidance, as reported by Zhu [124], based on a hidden Markov model is developed, in most cases, the positional change of the obstacle will still bring a lot of difficulties to the follow-up navigation work. Simultaneous localization and mapping (SLAM) technology provides related solutions, but currently SLAM technology can only be accurately solved in a simple environment, which will greatly reduce the efficiency if it is used in a complex agricultural environment. The studies of dynamic environment map by Jeong *et al.* [125] and Awashima *et al.* [126] deserve summarization and consideration.

(2) The obstacle avoidance control problem in the agricultural environment. Obstacle avoidance is a problem that must be solved by mobile robots. In urban environments, obstacles often refer to certain types of movable or fixed relatively regular objects. Because the ground is flat, it is only necessary to divert the robots around the obstacles. However, in the agricultural environment, especially in the field environment, ground protrusions caused by terrain undulations are regarded as obstacles, except for the movable objects. In this situation, not all of the obstacles should be made a detour, sometimes only adjust the pitch angle of the robots and pass over them. These special obstacles make the problem of obstacle avoidance control in the agricultural environment more complicated. In the detection of obstacles, it is still necessary to determine the types of obstacles, and then make decisions on the obstacle avoidance control based on actual conditions.

(3) Motion control problem of robots in agricultural environment. It is relatively simple for the general small-scale operation robot movement control. But agricultural WMRs which used in the outdoor operation are mostly bulky, slow-moving machinery, its movement control during the operation is particularly important, especially the turning problem. For example, the combine harvester, when moving in the field, should make turning at the farmland boundary. In this situation, it is necessary to consider the size of the harvester and the turning radius. Although Ackermann steering linkage [127] can solve most of the wheeled vehicle turning problems, there are still many issues that need to be solved for the motion control of the robots which have numerous wheels and complex structure. Lim *et al.* [128] simulated the extremely complex environment in the preparation of the robotics challenge, and completed machine manipulation, movement, localization, etc. in the environment, Zhang *et al.* [129] and Wei *et al.* [130] also have done some research in navigation and control of agricultural machinery, both of them would provide some research directions for motion control of robots in the complex agricultural environment.

(4) Multi-robot collaboration in agricultural environment. At present, in order to adapt to demand and reduce labor costs, multiple robots will work together in the same area to form a multi-robots system [131]. At this time, the localization problem between them needs to be given sufficient attention. Each of them needs to estimate its status and position by self-detect, and communicate with other robots in real time, and exchange data correctly and rapidly to ensure that it will not collide with other robots during follow-up path planning. Some related theories of signal estimation and detection, such as Bayesian criteria and Kalman filtering [65], help robots finish these tasks, reduce errors in the process, and provide basic support for collaborative precision localizing among multiple robots. However, as these mentioned things, the agricultural environment is a complex and changeable environment, exploration and improvement must be carried out in light of actual conditions.

(5) Multi-sensor fusion problems in agricultural environments. Multi-sensor fusion is a critical technology for accurate navigation of agricultural WMRs, such as the use of laser scanners for environmental feature extraction, visual sensors or ultrasonic sensors for obstacle distance measurement, and inertial measurement unit for real-time monitoring and correction of vehicle speed and steering. The use of any single sensor alone can't satisfy the requirements of precise navigation. Accordingly, the use of the redundancy and complementarity of multiple sensor data collection to fuse various information can obtain more accurate data and information. It should be noted that visual sensors have been applied more and more in the field of robot navigation in addition. The visual navigation and localizing technology can provide a better 3D environment and better simulate the real environment. From the perspective of recent developments,

robot navigation works will be bound up with visual technology in the future.

(6) The issue of SLAM in agricultural environment. SLAM is a research hotspot in the field of mobile robots. Many WMRs using SLAM technology have been used and promoted in the field of home services. However, in complex environment fields such as agriculture, there are few applications. The first difficult problem needs to be solved is computed. If the environment becomes larger and more complex, the time complexity and space complexity of data processing will be extremely increased. These adverse factors lead to the inability to meet the demands of high-efficiency precision agriculture. The second is a dynamic environmental issue. The map should be updated in real time under changing circumstances. If the map is updated incorrectly, then the follow-up will happen with vicious iterations, leading to navigation failure. Thirdly, many researchers are currently accustomed to constructing some simple and ideal environments to obtain some good data when conducting experimental research, but they are extremely unfavorable for the application of robots in complex environments. These are some of the open problems in the SLAM research field, and these are also the great challenges for further research in this area in the future.

(7) Navigation costs in agricultural environment. This is a problem that all agricultural workers are concerned about. WMRs are high-cost consumable products. If the robot navigation technology which has applied in other fields are directly introduced into agricultural engineering, it is bound to make higher costs of agricultural robots. Meanwhile, in the actual production, the output and the benefit value will be influenced. Therefore, researchers need to research how to take these advanced technologies into the field of agricultural robots with low cost, and how to satisfy the people's requirements for accurate navigation of agricultural robots.

## VII. CONCLUSION

This paper is the review of the navigation problems of agricultural wheeled mobile robots. In this paper, we have described the background of WMRs research, proposed the navigation mechanism of WMRs, and given a detailed introduction of mapping, localization, and path planning in navigation. In the section of mapping, we have summarized the traditional map representations and the improved methods of semantic map representation, digital terrain model representation and other special map representations. In the section of localization, we have described the differential global localizing systems, sound source localization, SLAM, and fusion localization methods. In the section of path planning, we have summarized some common algorithms and analyzed their advantages and disadvantages, and the new algorithms proposed in recent years were also introduced. The development of agricultural WMRs is relatively backward. And some problems and methods are needed to be further researched. For the complexity of the agricultural environment and deficiencies found in the practical applications, researchers need to improve the existing methods or propose the new ones and verify the practicability and effectiveness of the new methods in time. Techniques and methods that have been successfully applied in other fields can provide ideas for the agricultural robot research. In addition. The robot navigation needs to consider the cost, all the process need to meet the requirements of low cost and high efficiency.

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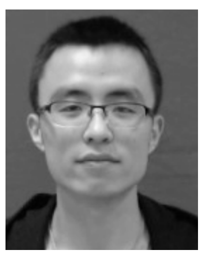

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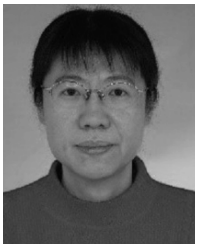

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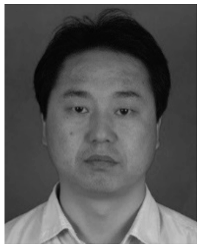

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