A review of autonomous navigation technology for orchard robots based on visual SLAM

Abstract

As the global population grows and urbanization accelerates, agricultural production faces challenges such as labor shortages, limited resources, and an aging population. The application of agricultural automation and intelligent technology has become an important means to improve production efficiency and reduce labor dependence. As an important area of agricultural production, the demand for labor is particularly significant. In recent years, the rapid development of real-time localization and mapping (Simultaneous Localization and Mapping) technology has provided technical support for autonomous navigation of agricultural robots. In this paper, the research background, research status, technical principles and development, application case analysis, challenges and future prospects of autonomous navigation technology for orchard robots based on visual SLAM at home and abroad are reviewed. Based on the analysis of relevant literature, this paper summarizes the application status of visual SLAM technology in orchard robot navigation and delves into its future development direction. Moreover, a well-defined and comprehensive conclusion is presented at the end to encapsulate the key insights and implications of the research.

**Keyword：**orchard robots; autonomous navigation; visual SLAM; agricultural automation; Smart agriculture

Introduction

As the global population continues to grow and urbanization accelerates, agricultural production is facing increasing challenges, including labor shortages, limited resources, and an aging population. Agricultural automation is developing rapidly around the world as an important means of addressing these challenges. In agricultural production, the application of mechanization and intelligent technology not only improves production efficiency, but also effectively reduces the dependence on labor. As an important area of agricultural production, the demand for labor is particularly significant. According to statistics [1], the planting area of orchards in China will reach 1.3010×10⁷ hm² in 2023, but the comprehensive mechanization rate is only 25.88%, far lower than the level of more than 80% in European and American countries. Some developed countries have used intelligent equipment to realize the fine management of orchards, which further highlights the urgent need to improve the level of mechanization and intelligence of orchards in China [2]. In recent years, the rapid development of Simultaneous Localization and Mapping (SLAM) technology has provided technical support for autonomous navigation of agricultural robots. SLAM technology uses sensors (such as depth cameras and IMUs) to obtain environmental information to realize real-time positioning and path planning of robots. As a typical semi-structured environment, the orchard has complex terrain and irregular distribution of obstacles, and the traditional navigation methods are difficult to meet the actual needs. Due to its advantages of low cost and high resolution, visual SLAM technology has gradually become a hot spot in the research of agricultural robot navigation. In particular, open-source SLAM algorithms such as RTAB-Map (Real-Time Appearance-Based Mapping) can achieve efficient mapping and accurate positioning, providing technical support for orchard operations. The purpose of this paper is to review the research status and development trend of autonomous navigation technology for orchard robots based on visual SLAM, and to provide reference for related research.

Background:

Challenges to agricultural production include labor shortages, limited resources, and an ageing population. The application of agricultural automation and intelligent technology has become an important means to improve production efficiency and reduce labor dependence. As an important area of agricultural production, the demand for labor is particularly significant. The mechanization rate of orchards in China is low, which is much lower than that of European and American countries. Some developed countries have used intelligent equipment to realize the fine management of orchards, which further highlights the current situation that the mechanization and intelligence level of orchards in China need to be improved urgently. SLAM technology provides technical support for autonomous navigation of agricultural robots.

**1.2 Research status at home and abroad**

Due to its good environmental adaptability, orchard mobile robots have become an important tool to solve complex orchard operation scenarios. In recent years, with the rapid development of intelligent robot research, scholars at home and abroad have gradually shifted their research focus to orchard mobile robots, and developed a variety of robot systems applied to orchard environments, such as spraying robots and picking robots. However, due to the need to improve the level and stability of intelligence, coupled with the high cost of equipment, the orchard mobile robot has not yet been applied on a large scale.

Autonomous navigation technology, as the key to the intelligence of orchard mobile robots [3], can realize functions such as precise positioning, path planning, and trajectory tracking control through the perception of the environment. The core elements of a navigation system include navigation sensors, data processing algorithms, and navigation control decisions. This section reviews the research progress of autonomous navigation technology of orchard mobile robots, analyzes the advantages and disadvantages of different navigation technologies, and looks forward to the future development direction in terms of dynamic environment adaptability and cost optimization.

**1.2.1 Research status of agricultural mobile robots**

Agricultural mobile robots play an important role in the development of smart agriculture, especially in unstructured environments such as orchards. Developed countries such as Japan and the United States began to explore orchard mobile robots as early as the 80s of the 20th century, and developed mature equipment such as picking robots, weeding robots, and spraying robots [4] [5]. These robots are usually based on mobile platforms and carry robotic arms or spraying equipment to perform specific tasks, which is of great significance in improving the level of agricultural mechanization and intelligence[6]. However, compared with developed countries, China started late in terms of intelligence, work efficiency and stability of orchard mobile robots.

In the late 90s of the 20th century, China gradually began to pay attention to the development of agricultural robot technology. In 1998, China Agricultural University established the "China Agricultural University Precision Agriculture Research Center", marking the official launch of China's precision agriculture research. In the same year, Wang Maohua put forward the core concept of precision agriculture development and technological innovation, which laid a theoretical foundation for the early development of agricultural robot technology[7]. In 2001, Qin Jianglin proposed a technical support system for precision agriculture with Chinese characteristics, which promoted the research of agricultural robots in China to move towards a more systematic and standardized direction [8].

At the beginning of the 21st century, with the acceleration of urbanization and the reduction of agricultural population, China's agricultural robot research has gradually shifted to practical applications. In order to cope with the rising labor costs, the government has introduced a series of support policies to promote the research and development and application of agricultural automation equipment. In recent years, with the expansion of market demand and technological progress, the research of agricultural mobile robots has shown a diversified development trend, especially autonomous navigation technology has become the key to realize the intelligence of mobile robots. Through multi-sensor fusion, SLAM algorithm optimization and path planning technology improvement, the researchers have significantly improved the intelligence level of orchard mobile robots.

In 2013, Mousazadeh et al. [9] examined the challenges of driving vehicles in traditional agricultural operations to ensure smooth and evenly spaced paths, while monitoring paths and adjusting machine settings, highlighting the need for agricultural robot navigation. In 2015, Rovira et al. [10] proposed the application of GNSS technology in agricultural robot navigation, which can improve navigation efficiency and resource utilization in open environments. However, in 2017, de Ponte et al.[11] pointed out the disadvantages of GNSS-based navigation systems: they are susceptible to changes in environmental factors, such as the physical structure of the environment, obstruction by obstacles, bad weather, and signal interruptions. As a result, it is difficult to provide long-term robust and reliable navigation information in unstructured agricultural environments. Subsequently, Higuti et al. [12] also demonstrated through research that the LiDAR navigation system has higher stability in the orchard environment compared to the GNSS navigation system. Experiments have been conducted to verify the feasibility of using low-cost 2D LiDAR sensors to achieve autonomous navigation.

In 2018, Malavazi et al. [13]proposed an autonomous agricultural robot navigation algorithm based on LiDAR data to enable autonomous navigation between crop rows without the need for a priori crop information, such as row spacing or width. In this study, the PEARL method is improved, and the straight line extraction ability of 2D point cloud is optimized through outlier penalty, model elimination, new model search and geometric constraints. Experimental results show that the proposed method is superior to the traditional PEARL and RANSAC methods in crop detection and navigation performance. In addition, the algorithm has been successfully verified on the Oz weeding robot developed by Naio Technologies in France in Figure 1.

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| **Fig.1. Oz weeding robot** |

In 2021, Wang et al. [14] proposed a lidar point cloud map construction and navigation method suitable for orchard environment. In this method, a mobile mapping system based on LiDAR-IMU is designed to realize the construction of high-precision point cloud map of orchard environment. In terms of navigation, a robot relocation method based on 3D prior feature point map and a local path planning method based on TEB algorithm are also proposed, and the experimental results show that the method has good performance in the path planning and navigation of orchard robots.

Although LiDAR has the advantages of high resolution and large field of view, it can provide accurate position information for target detection and localization by sensing the position of objects in the surrounding environment [15]. However, the cost of LiDAR sensors is too high for large-scale deployment of agricultural vehicles. In view of this situation, in 2017, Alsalam et al. [16] explored a more cost-effective alternative, vision-based autonomous navigation systems. The system uses computer vision technology to perceive the environment through the images captured by the camera to realize target detection and positioning. Although vision solutions may not be as accurate as LiDAR in some respects, their lower costs and evolving technology make them an attractive option in the field of agricultural robotics. In 2018, Meng et al. [17] used visual image processing to realize crop row recognition and navigation guide line detection, which effectively improved the navigation ability of agricultural mobile robots in complex farmland environments. In 2019, Huang Peichen et al. [18] studied a crawler robot orchard navigation system based on the combination of machine vision and satellite system in an orchard environment. At the same time of developing the navigation system, a linear path tracking method of the crawler robot based on the pre-aiming point was proposed, and the linear tracking function of the crawler robot forward and reverse was realized. In view of the complex system structure caused by traditional navigation methods, an end-to-end orchard automatic driving system based on monocular vision and deep learning was designed, which greatly simplified the degree of human participation and realized the automatic navigation in the orchard, and effectively improved the operation efficiency and navigation accuracy of agricultural robots. Subsequently, Kanagasingham et al. [19] in 2020 demonstrated the integration of machine vision, global navigation satellite systems (GNSS). and Compass, an autonomous navigation system for weeding robots in rice fields was developed. The system not only precisely guides the robot along the crop rows, but also maintains an accuracy of less than 100 millimeters in different environmental conditions, such as weed intensity, plant growth stage, and weather conditions. The experimental results show that the system performs well at low weed concentrations, with a heading compensation accuracy of less than 2.5°and an average deviation of only 45.9 mm from the ideal path. Even when weed concentrations increase, the system can effectively navigate the robot and avoid serious damage to the plants. In the same year, Xu Yaoxin et al. [20] designed a multi-sensor fusion positioning scheme based on the improved volumetric Kalman filter algorithm by improving the genetic ant colony algorithm and combining the Lyapunov function to construct the trajectory tracking control law, which optimized the motion control of the orchard robot and improved the degree of operation automation and production efficiency. Subsequently, Samwel et al. [21] investigated a pivot-based machine vision technique for autonomous path tracking and navigation of orchard robots by converting the raw color images captured by the on-board camera into grayscale images and extracting texture features using a Gabor filter.

In 2021, Krul et al. [22] compared two open-source visual SLAM algorithms, LSD-SLAM and ORB-SLAM, which further verifies the feasibility and effectiveness of the vision-based autonomous navigation system in the indoor agricultural environment. Studies have shown that visual SLAM technology not only shows significant advantages in terms of cost-effectiveness and object detection and localization, but also demonstrates excellent practicability and reliability in real-world agricultural applications. This achievement proves the potential of vision-based autonomous navigation in the agricultural field, lays a technical foundation for the realization of the development of precision navigation and smart agriculture of agricultural robots in the future, and makes vision-based autonomous navigation possible. Subsequently, in 2023, Zhang et al. [23] and Zhou et al. [24] respectively discussed the application of the combination of lidar and vision in complex navigation scenarios. Zhang et al. [23] proposed a high-precision navigation system that fuses lidar and visual positioning, and realized accurate environmental map construction and navigation through a two-stage strategy: in the first stage, SLAM algorithm was used to combine lidar and IMU for environmental map construction and flexible navigation; In the second stage, visual recognition technology is used for high-precision positioning, and the accuracy is improved to less than 10 mm. Experiments show that the system exhibits excellent navigation performance in indoor environments, which verifies the potential of laser and vision fusion. At the same time, Zhou et al. [24] improved the ORB-SLAM2 algorithm, proposed a hybrid mapping scheme based on dense point cloud and octree map by combining laser SLAM and visual SLAM, and designed a hybrid path planning algorithm (A\* combined with DWA). Experimental results show that the proposed method can not only effectively cope with the needs of real-time obstacle avoidance, but also improve the efficiency of path planning in dynamic scenes, and provide technical support for navigation in complex outdoor environments.

To sum up, visual navigation technology is gradually expanding from indoor scenes to outdoor complex environments. By combining lidar and vision sensors, researchers have provided new ideas for real-time navigation and environmental adaptability. However, in the face of challenges such as changing outdoor lighting conditions and dynamic obstacles, navigation technology still needs to be further optimized to achieve more efficient and reliable autonomous navigation capabilities of agricultural mobile robots.

**1.2.2 Research status of visual SLAM**

With the proposal and development of real-time localization and mapping (Simultaneous Localization and Mapping) technology, its application in mobile robot navigation has received extensive attention. In 1986, Smith et al. [20] first proposed the concept of SLAM and used it to realize simultaneous localization and mapping of robots [21], which is mainly used to solve the problems of "where am I", "where am I going", and "how am I going" [22]. After nearly 40 years of development, SLAM technology has made breakthrough research progress [23-24]. Depending on the sensor that obtains environmental information, SLAM technology can be divided into laser SLAM [25] and visual SLAM [26]. Among them, visual SLAM has been widely studied in agriculture, indoor navigation, unmanned driving and other fields due to its low cost, high resolution and rich ability to obtain environmental information. The main sensors of visual SLAM are monocular cameras [27], binocular cameras [28], RGB-D cameras [29], and event cameras [30].

In recent years, with the development of camera technology, products such as monocular cameras, binocular cameras and RGB-D cameras have promoted the rapid development of visual SLAM. According to the different image data processing methods, visual SLAM technology can be divided into visual SLAM based on feature points, visual SLAM based on direct method, and visual SLAM based on semi-direct method. Real-Time Appearance-Based Mapping (RTAB-Map) based on feature point method has become one of the important frameworks in the field of visual SLAM due to its excellent performance in real-time loop detection and graph optimization. RTAB-Map not only supports a variety of sensors such as RGB-D cameras and stereo cameras, but also significantly reduces cumulative errors through graph optimization in large-scale scenes, making it especially suitable for long-term navigation tasks. Compared with feature point algorithms such as ORB-SLAM, RTAB-Map pays more attention to global mapping and long-term consistency, which provides strong technical support for autonomous navigation in complex scenarios such as agricultural robots.

In 2007, Davison et al. [31] first proposed a monocular visual SLAM method called MonoSLAM. It uses the EKF algorithm to establish a map of environmental feature points, which is stable enough to solve the problem of monocular feature initialization, although it has certain limitations. In addition, due to the sparse map established by this method, the problem that the robot cannot complete the positioning task when more environmental details are needed is gradually exposed. For this reason, the UKF method [32] and an improved UKF method [33] have been developed to address the linear uncertainty of visual SLAM. The PF-based monocular SLAM method proposed by Sim et al. [34] can construct more accurate mappings, but the computational complexity of the algorithm is too high to be applied in large-scale environments. In the same year, Klein et al. [35] devised a keyframe-based SLAM method for monocular vision PTAM (Parallel Tracking and Mapping). This method improves the problem that MonoSLAM cannot work stably in large-scale scenes for a long time, and the tracking and mapping of the algorithm are divided into two parallel tasks. The core idea of keyframe extraction technology, that is, to optimize the map and motion trajectory through the concatenation of several key images, thus avoiding the processing of the details of each image, is to realize the tracking and map construction of the camera at the same time through parallel threads, so as to improve the ability of visual positioning and map construction in large-scale environments [36].

In 2015, Raul Mur-Artal et al. [37] proposed a new real-time visual SLAM method ORB-SLAM. This method is a monocular SLAM based on the feature method, which adds a loopback detection module on the basis of PTAM dual threading, and uses ORB (Oriented FAST and Rotated BRIEF) to estimate the 3D feature position and reconstruct the environment map in real time, and its feature calculation has good rotation, scale invariance and high positioning accuracy. However, this method will make the CPU computing burden large, resulting in the generated map can only be used for positioning requirements, and cannot be used for navigation and obstacle avoidance requirements. To this end, Mur-Artal et al. [38] proposed an improved ORB-SLAM algorithm ORBSLAM2 in 2017, which introduced a new feature point selection and descriptor matching strategy to improve the accuracy of feature point matching, and also added the loopback detection algorithm of the bag-of-word model to improve the robustness of the ORB-SLAM system in large-scale scenarios. In 2021, Campos et al. proposed ORB-SLAM3 [39] is a visual SLAM algorithm that supports a variety of cameras, and he has optimized it at all stages: it has excellent performance in terms of operation efficiency and composition accuracy, but the ORB-SLAM series algorithms rely particularly on environmental features, which is also a common problem of many feature point method SLAM: in low-texture scenes (corridors, etc.) are difficult to detect enough feature points for extraction, resulting in reduced robustness and accuracy of the system. To this end, Jiang [40] used line features as supplementary features in the visual odometry part, and then improved the line feature reprojection error model to construct a constraint based on point-line affine invariance.

Dense Tracking and Mapping in Real-Time(DTAM) [41] is a visual SLAM algorithm based on the direct method proposed in 2011. DTAM has a relatively stable mapping effect, but it consumes a lot of computing resources. LSDSLAM [42] is a semi-dense visual SLAM algorithm based on the direct method proposed by Jakob Engel et al. in 2014, which achieves photometric consistency through continuous image frames, and the constructed map is semi-dense, that is, a part of the map points is retained to improve the computational efficiency. In the same year, Forster et al. proposed that Semi-direct monocular Visual OdometrySVO [43] is a sparse direct visual odometry, and it should be noted that there are elements related to the feature point method in SVO. In SVO, it is also detected in the image frame

Some feature points, but these feature points are different from the feature points extracted by SIFT and SURF, which are directly obtained by detecting image pixels and texture information. SVO looks for the features of sparse maps and does not need to calculate descriptors, so it runs quickly, and SVO is relatively lightweight compared to other SLAM systems, making it suitable for low-cost embedded systems. After that, Jakob Engel proposed the Direct Space Odometry(DSO) [44], which is a visual odometry based on the sparse direct method, in which the DSO uses the calibration results of geometric and photometric cameras for high-precision estimation, but strictly speaking, the DSO is not a complete SLAM, and it has no loopback detection like the SVO, so it is inevitable that there will be cumulative errors.

VINS-MONO [45] (Visual-Inertial Navigation System for Monocular Camera) is a visual inertial navigation system based on a monocular camera and an inertial measurement unit (IMU).VINS-MONO is tightly coupled with the imu module, which provides inertial measurements and visual data for more robust mapping, which performs well in dynamic environments and scenes with large lighting changes.

In addition, with the development of deep learning technology, visual SLAM is gradually integrated into deep learning models, which enhances feature extraction, matching, and environmental understanding capabilities [46-47], and deep learning is also often used to improve loopback detection [48].It makes the SLAM system better handle the dynamic environment and improves the stability of the long-term operation of the system. Since Kendall et al. proposed the introduction of deep learning methods into visual odometry in 2015, after nearly a decade of development, the framework of visual SLAM system based on deep learning has become increasingly mature [49]. The CNN-SLAMH [50], developed by Tateno et al. under the framework of LSD-SLAM, is a combination of the traditional monocular vision SLAM framework and the introduction of CN Progressive Prediction to predict depth information from images, which can generate dense depth maps in real time and then be integrated into SLAM map construction and pose estimation to improve positioning and accuracySimilarly, CNNs are used to obtain depth information such as CodeSLAM [51] and D3VO [52]. The development of these technologies enables visual SLAM to better cope with the complexity of dynamic environments, laying a solid foundation for the application of agricultural robots in diverse scenarios. A comparison of some classical visual SLAM methods is shown in Table 1 below:

**Table 1** Classical visual SLAM methods

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | MoonSLAM | PATM | ORB-SLAM | DATM | LSD-SLAM | VINS | RTAB-MAP |
| The type of algorithm | Sparse feature points | Keyframe-based | Feature points | Dense direct method | Semi-dense direct method | Vision + IMU | Feature point + loopback detection |
| Applicable sensors | Monocular | Monocular and binocular (RGB-D). | Monocular | RGB-D | Monocular | Monocular + IMU | RGB-D, binocular and multi-sensor fusion |
| Real-time | real time | real time | highly efficient | highly efficient | medium | Medium-high | highly efficient |
| robustness | Lower | medium | Excellent, but dependent on feature points | Excellent, but affected by light | Excellent, suitable for low-texture scenes | high, adaptable to dynamic environments | High, supports long-term navigation and global optimization |
| Loopback detection | Not supported | Not supported | In the tank | Not supported | In the tank | In the tank | In the tank |
| Environmental adaptability | Low-texture performance is limited | Ideal for small-scale static scenes | Underrepresented dynamic/low-texture scenes | Dense indoor scenes perform well | Outdoor low-texture performance is better | Adapt to dynamic and lighting changing environments | Excellent performance in both indoor and outdoor and dynamic static environments |
| Map type | Sparse maps | Sparse maps | Sparse maps | Dense map | Semi-dense map | Sparse maps | Sparse and dense maps |
| Computing power requirements | Lower | Lower | Higher | high | medium | Higher | Medium, suitable for embedded applications |

2. Challenges and Prospects

2.1 Challenges

The current challenges of autonomous navigation technology for orchard robots are as follows:

Accuracy of Environmental Perception: In orchard environments, factors such as varying lighting conditions, complex tree structures, and dynamic obstacles can affect the accuracy of environmental perception. Ensuring precise detection and localization of obstacles, fruits, and other relevant objects is crucial for safe and efficient navigation.

Real-time Nature of Path Planning: Orchard robots need to quickly process sensory information and generate optimal paths in real-time to avoid obstacles and reach target locations. However, complex environments and large amounts of data can pose challenges to the real-time performance of path planning algorithms.

Multi-robot Collaboration: Coordinating multiple orchard robots to work together efficiently requires effective communication and task allocation mechanisms. Ensuring smooth collaboration and avoiding conflicts between robots is a significant challenge.

2.2 Future Outlook

To address these challenges and better meet the needs of agricultural operations in complex orchard environments, future research should focus on the following directions:

Optimization of Navigation Algorithms: Further refine and optimize navigation algorithms to improve the accuracy, efficiency, and robustness of autonomous navigation systems. This includes enhancing environmental perception algorithms, developing more efficient path planning strategies, and improving multi-robot coordination mechanisms.

Sensor Fusion: Integrate different types of sensors, such as cameras, LiDAR, IMUs, and GPS, to leverage their complementary strengths and achieve more reliable and comprehensive environmental perception. Sensor fusion can help overcome the limitations of individual sensors and improve the overall performance of the navigation system.

Application of Artificial Intelligence Technology: Utilize artificial intelligence techniques, such as deep learning and reinforcement learning, to enhance the intelligence and adaptability of orchard robots. AI can enable robots to learn from experience, make better decisions in complex situations, and improve their ability to handle dynamic environments.

Multi-robot Collaboration: Develop advanced multi-robot collaboration frameworks and protocols to enable efficient and coordinated operation of multiple orchard robots. This includes improving communication systems, designing effective task allocation algorithms, and ensuring safe and seamless interaction between robots.

**2.3 Conclusion**

This paper has comprehensively reviewed the research background, current status, technical principles and development, application cases, challenges, and future prospects of autonomous navigation technology for orchard robots based on visual SLAM both domestically and internationally. Through an in-depth analysis of relevant literature, the application status of visual SLAM technology in orchard robot navigation has been summarized, and potential future development directions have been identified. The findings of this review suggest that future research should focus on optimizing navigation algorithms and enhancing the stability and adaptability of the system to better cope with the complex and dynamic nature of agricultural

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