Integrating Artificial Intelligence with SLAM Technology for Robotic Navigation and Localization in Unknown Environments

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Chao Fan
Trine University

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Chao Fan 1*

Information Science,Trine University,Phoenix, AZ, USA

*Corresponding author: chao.fan.yaqin@gmail.com

Zihan Li 1.2

Computer Science,Northeastern University,San Jose, CA, USA

zihanli1997@gmail.com

Weike Ding 2

Electrical and Computer Engineering,University of Illinois at Urbana-Champaign,Champaign, Illinois,USA

victorccding@gmail.com

Huiming Zhou 3

Computer Science, Northeastern University, CA, USA

zhouhuiming2021@gmail.com

Kun Qian 4

Business Intelligence,Engineering School of Information and Digital Technologies,Villejuif, France

kunqian06@gmail.com

Abstract

In the era of advancing technology, unmanned inspection robots have become indispensable for their efficiency, precision, and safety. Key to their autonomous operation is Simultaneous Localization and Mapping (SLAM) technology, which allows robots to navigate and create maps of unknown environments in real-time. This article explores the integration of SLAM with artificial intelligence, highlighting its role in robotic navigation, localization, and obstacle avoidance. Specifically, we delve into SLAM's principles, its implementation with LiDAR technology, and its application in autonomous robot localization. Furthermore, we introduce a collaborative mapping algorithm based on ORB-SLAM3, enhancing map construction efficiency and real-time performance. Through our exploration, we illustrate the transformative potential of SLAM technology, paving the way for safer and more efficient robotic inspection systems across various industries.

key words :

SLAM technology;Unmanned inspection robots;Autonomous navigation;LiDAR integration;ORB-SLAM3

1 INTRODUCTION

With the continuous advancement of technology, the wave of intelligence and automation is sweeping across various industries. In this era, unmanned inspection robots have emerged as the new favorite in the field of inspection, thanks to their efficient, precise, and safe characteristics. [1]The advent of unmanned inspection robots has brought revolutionary changes to inspection work. Leveraging their efficient, precise, and safe features, they play a significant role in various sectors such as electricity, petrochemicals, and manufacturing.

Within the technical system of unmanned inspection robots, positioning and navigation technology are the key to achieving autonomous operation. Simultaneous Localization and Mapping (SLAM) technology, in particular, is an important innovation in the positioning and navigation technology of unmanned inspection robots. Today, let us unveil the mysterious veil of SLAM [2]technology and explore its applications and advantages in unmanned inspection robots.

In this article, we delve into the intricacies of SLAM technology, its integration with artificial intelligence, and how it facilitates robotic navigation and localization in environments where the terrain is unknown. We will discuss its role in enabling robots to create maps of their surroundings in real-time, while simultaneously determining their own position within those maps. Additionally, we will explore how SLAM technology enhances the adaptability and reliability of unmanned inspection robots, allowing them to navigate complex and dynamic environments with ease.

Through this exploration, we aim to shed light on the [3]transformative potential of integrating artificial intelligence with SLAM technology, paving the way for safer, more efficient, and more autonomous robotic inspection systems across industries.

2 RELATED WORK

2.1 Simultaneous Localization And Mapping (SLAM)

SLAM, short for Simultaneous Localization And Mapping, was first proposed by Hugh Durrant-Whyte and John J.Leonard in 1988. SLAM is more of a concept than an algorithm. It is defined to solve the problem of "starting from an unknown location in an unknown environment, the robot locates its own position and posture through repeated observed map features (such as corners, columns, etc.) in the process of movement, and then incrementally builds a map according to its own position. To achieve simultaneous positioning and map construction of the purpose of the "problem method." The principle of SLAM technology is to use cameras, [4-6]liDAR or sensors such as vision sensors, inertial measurement units, to collect environmental information, and then use algorithms to fuse this information to determine the location of the robot in an unknown environment and build a map of the environment.

The core principle of SLAM technology is to estimate the location of the robot and the map of the environment at the same time, without knowing the environment of the robot in advance. This process involves constantly updating the robot's location estimates and map construction. One of the key challenges of SLAM is to accurately estimate the robot's state in the face of uncertainty and sensor noise. Therefore, the SLAM problem can be formalized as a Bayesian filtering problem, where the robot's state and map features are modeled as probability distributions. Common SLAM algorithms include methods based on [7]Extended Kalman filter (EKF-SLAM), particle filter, and graph optimization. These algorithms use different mathematical tools to solve SLAM problems, the specific choice depends on the application scenario and the availability of computing resources.

SLAM technology is critical to the ability of a robot or other agent to move and interact, because it represents the basis for that ability: knowing where it is, knowing what its surroundings are like, and then knowing how to act autonomously next.

The entire visual SLAM process consists of the following steps:

1. Read the sensor information. The main purpose of visual SLAM is to read and preprocess camera image information.

2. Visual Odometry (VO). The task of the visual odometer is to estimate the motion of the camera between adjacent map images and what the local map looks like. [8]VO is also known as the preceding segment.

3. Back-end Optimization. The back end receives the camera position and attitude measured by the visual odometer at different times and the information of the loop detection, and optimizes them to get a globally consistent trajectory and map. Since it is connected after VO, it is also called the back end.

4. Check the Loop Closing. Loop detection determines whether the robot has reached the previous position. If a loop is detected, it provides the information to the back end for processing.

5. Mapping. Based on the estimated trajectory, he builds a map corresponding to the mission requirements.

2.2 LIDAR

Implementing SLAM requires two types of techniques. One type of technology is sensor signal processing (including front-end processing), which depends largely on the sensor used. Another type of technology is pose optimization (including back-end processing), which is sensor-independent. Therefore, although SLAM is an algorithm technology, the basis for the application of SLAM is a sensor with excellent performance (LiDAR or image sensor). Depending on the sensor choice, there are currently two schools of technology: visual V-SLAM and liDAR SLAM[9].

Among them, laser SLAM uses laser radar (LiDAR) as the main sensor for positioning and mapping. Lidar can measure the distance of a target by sending out laser pulses and measuring the time of the reflected signal. Lidar is divided into single line, multi-line, 2D Lidar, 3D Lidar and so on. Multi-line LiDAR can acquire multiple scanning lines at the same time, which improves the efficiency and accuracy of data acquisition. [10]2D LiDAR and [11]3D LiDAR: 2D LiDAR can only acquire two-dimensional information about the environment, such as distance and Angle, and is commonly used for plane navigation and obstacle avoidance. 3D Lidar can obtain three-dimensional information about the environment, including height, for building three-dimensional maps and conducting three-dimensional navigation.

Lidar's ability to provide accurate distance measurements makes LaserSLAM excellent in indoor and other environments. However, laser SLAM is somewhat dependent on the structure of the environment, which can cause problems if the environment structure is complex or difficult to detect. The multi-line LiDAR 3D SLAM technology can theoretically build a 3D point cloud map of a million square meters of large scenes, and the perceived environmental information features are rich, and the positioning and matching are stable, which is suitable for most scenes. Why theoretical? Because the premise is that the sensor is good enough to generate a dense point cloud.

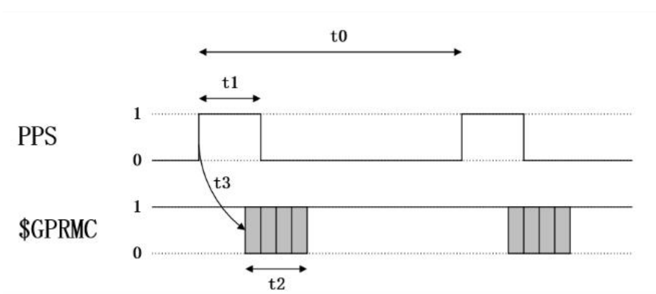

Figure 1. Transmission architecture of Lidar implemented by sdk protocol

Therefore, in the Figure 1,in the realization of robot self-positioning and navigation, according to the sensor configuration given by the laser God intelligence, the 16-line 3D [12]Lidar uses the leading core signal processing ASIC chip and advanced multiple echo detection technology and data calibration technology, and the point cloud output can reach 320,000 points/second, which is the leading point cloud performance in the entire industry. With this level of composition, the outdoor measurement accuracy can reach ±3cm and the indoor measurement accuracy can reach ±2cm.

2.3 Robot autonomous localization

SLAM technology can realize autonomous localization and navigation of inspection robots by integrating sensor data and map information. The robot uses lidar, vision sensors and other devices to collect data to estimate its position and update the map in real time. The robot can accurately navigate in the unknown environment and complete the inspection task. In the visual navigation and positioning system for autonomous positioning of robots, the navigation method of installing vehicle cameras in robots based on local vision is widely used at home and abroad. In this navigation mode, control equipment and sensing devices are loaded on the robot body, and [14]high-level decisions such as image recognition and path planning are completed by the on-board control computer.

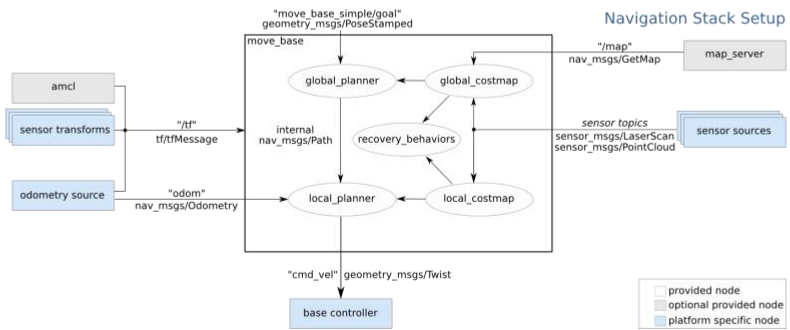

Figure 2. Multi-modal path architecture of robot autonomous navigation and positioning

In Figure 2, move_base function package realizes optimal path planning in robot navigation, and amcl realizes robot positioning in two-dimensional map. In order to realize the robot's global optimal path planning and real-time obstacle avoidance path planning, move_base needs to subscribe to depth sensor information (sensor_msgs/LaserScan or sensor_msgs/PointCloud) and Odometry information published by the robot, At the same time, the complete TF coordinate transformation is also an important basis for path planning. The final output of the navigation frame is the control robot's velocity instruction (geometry_msgs/Twist)[15-17], which requires the robot control node to have the ability to analyze the center line velocity and angular velocity of the control instruction, and control the robot to complete the corresponding motion.

The core of robot autonomous positioning and navigation in an independent environment is closely related to slam technology. The steps for robot autonomous navigation and positioning are as follows:

1. Build an environment map

The core idea of the inspection robot using SLAM technology to build an environment map is to identify and record the location of landmarks and obstacles in the environment through sensor data and feature extraction. The location information of these landmarks and obstacles is then integrated into a map, providing the robot with a visual representation of the environment.

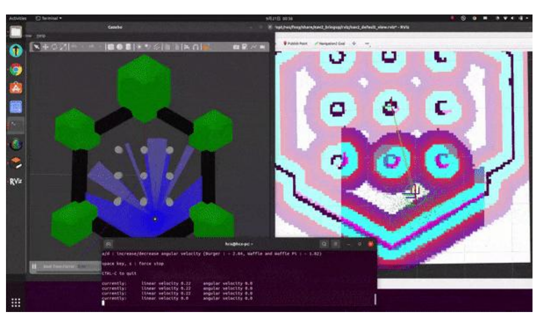

figure 3. The robot independently constructs a multimodal navigation map

After the initial pose is constructed (FIG. 3), AMCL[18] will randomly sprinkle some particles around the robot. With the movement of the robot, each particle will update the pose in real time along with the speed of the robot. When the environmental state around the particle is much different from that of the robot, it will be gradually eliminated. In this way, the particles are concentrated in the robot's position where the probability is high, that is, the result of positioning.

SLAM technology is relevant here because it allows robots to simultaneously locate and build maps in unknown environments, thus making the process of building maps closely related to the autonomous navigation of robots. With SLAM technology, the robot can constantly update the map based on sensor data, thereby improving the accuracy and efficiency of operations such as path planning and obstacle avoidance.

2. Detect and avoid obstacles

SLAM technology enables inspection robots to detect obstacles in the environment in real time, and make path planning and obstacle avoidance according to map information. By analyzing LiDAR or vision sensor data, the robot can identify the position and shape of obstacles, so as to plan a safe navigation path and ensure the smooth progress of inspection. SLAM technology is relevant because it provides a map of the environment the robot needs and allows the robot to navigate and avoid obstacles while updating the map in real time. Through SLAM technology, the robot can detect and avoid obstacles more accurately, thus improving the safety and efficiency of inspection.

3. Environment awareness and data association

SLAM technology associates the robot's perception data with map information through data association technology to realize the perception and understanding of the environment. The robot can perform positioning and attitude estimation by matching sensor data with map features. This allows the robot to accurately sense changes in the environment and provide reliable navigation and inspection data. SLAM technology is relevant here because it allows the robot to update the map based on real-time perception data and combine the perception data with map information through data association technology. Through SLAM technology, robots can better understand the environment and improve the accuracy and reliability of navigation and inspection.

In this section, we've delved into critical technologies essential for robotic navigation and localization, namely Simultaneous Localization and [19]Mapping (SLAM), LiDAR technology, and robot autonomous localization. SLAM facilitates the simultaneous estimation of robot position and map construction in unknown environments, LiDAR technology provides precise distance measurements crucial for environment mapping, and robot autonomous localization integrates SLAM with sensor data to enable autonomous navigation. Together, these technologies empower robots to navigate effectively and interact autonomously, paving the way for advancements in robotics and automation.

3 METHODOLOGY

Completing complex tasks in large-scale complex scenes is a challenging task for robots, especially the need to build dense point cloud maps to provide more effective information, and the need for efficient composition. However, the traditional multi-robot SLAM algorithm often has some problems such as high computational complexity, low efficiency and poor real-time performance when constructing global maps. To address these challenges, a multi-robot collaborative map building algorithm based on ORB-SLAM3[20-23] is proposed. The algorithm enables the cooperative robots to build a local dense point cloud map based on the same world coordinate system, and obtain the pose estimation relationship between the local maps through the keyframe tracking model, so as to realize the construction of a real-time global dense point cloud map. Through the collaborative method, the algorithm significantly improves the efficiency of map construction, while maintaining high real-time and positioning accuracy, showing a good development prospect.

3.1 ORB-SLAM3

Visual SLAM is a SLAM system based on visual sensors. Compared with laser sensors, visual sensors have the advantages of low cost, preserving environmental semantic information, and can be combined with deep learning. ORB-SLAM series algorithms are the most widely concerned and applied algorithms in visual SLAM. The ORB-SLAM3 is a visual, visual + INS, hybrid mapping SLAM system that can operate with pinhole or fisheye models on monocular, binocular, and RGB-D cameras. In large/small scenes, indoor/outdoor, ORB-SLAM3 can be robust real-time operation, is widely used in commercial products.

Compared to the ORB-SLAM-VI and ORB-SLAM-VI, its biggest highlights are:

Feature-based tightly integrated Visual Inertial SLAM system (maximum a posteriori estimate MAP for IMU initialization, etc.)

Multi-map SLAM System (New Location Recognition Method)

In the initialization stage of IMU, MAP idea is introduced, which improves the initialization speed, greatly improves the robustness, and significantly improves the accuracy.

Multiple submap systems greatly improve system recall, and ORBSLAM3 is more robust when visual information is lacking or even lost. When the target is lost, a submap is rebuilt and merged with the previous inactive map during the loop closing process. Therefore, ORB-SLAM3 is the first system that can reuse the information obtained by all the algorithms in the history, which means that previous co-view keyframes can also be used together (both the co-view keyframes of active and inactive maps in the Atlas).

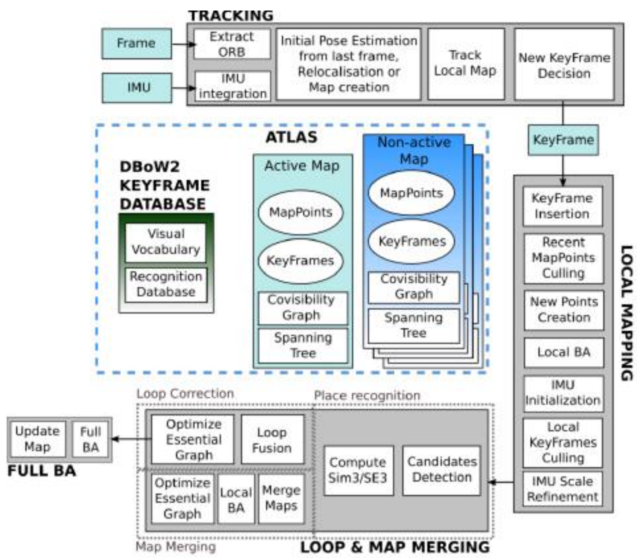

Figure 4.ORB-SLAM3 architecture diagram

As shown in the figure,tlas consists of a multi-map representation of a series of separate maps (including active map and non-active-map). An active map represents the map that is currently located, and the racking thread passes frames into it, which are continuously optimized by the local mapping and scaled up by the addition of new keyframes. The map is active-map, and the DBOW library is used to merge with the map.

3.2 Robotic ORB-SLAM3 cloud map construction

Because ORB-SLAM3 generates a sparse point cloud map, and the sparse point cloud map has relatively little information, which is difficult to meet the needs of the robot's subsequent navigation and path planning, so the dense point cloud map of a single robot is constructed.

The RGB-D camera output image frame, using ORB-SLAM3 to select key frames in the image frame, convert the RGB-D data of key frames into point clouds, register according to the corresponding camera pose, and then filter the point clouds on the map, and finally realize the construction of dense point cloud map.

The process of dense point cloud map construction is as follows:

Step 1: With the help of the mathematical formula (1) of the camera model in 1.1, each pixel of the RGB image frame is iteratively calculated to generate a key frame point cloud, and points with invalid depth values are omitted.

Step 2: Transform the point cloud generated by the keyframe KFi into the base coordinate system of the initial frame KF0 through the corresponding camera pose.

Step 3: Statistical filter is used to calculate the distribution of distance values between each point on the map and its neighboring N points. After obtaining the corresponding distance mean, the points with closer mean value are retained, and the points with too large mean value are discarded, so as to eliminate the isolated points.

Step 4: Use the voxel filter to downsample the three-dimensional space to ensure that there is only one point in the constant size cube to avoid a large number of similar points in the overlapping area under multiple perspectives, thus effectively saving storage space.

Step 5: The dense point cloud map is obtained after filtering the global map.

In order to obtain a higher recall rate, for each new active key frame, the system queries several similar key frames in Atlas in the DBoW2 database. In order to achieve 100% accuracy, each candidate keyframe is geometrically validated in several steps. The basic operation of all geometry validation steps is to check whether there are ORB feature points in the image window whose descriptors match the ORB descriptors of the mapping points, and to use the Hamming distance threshold between them.

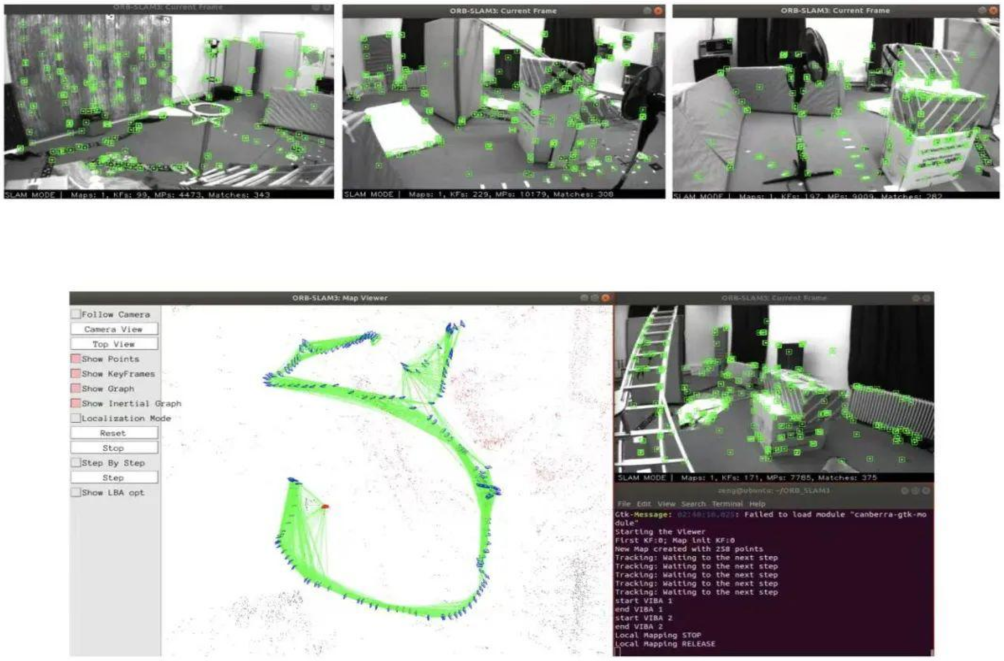

Figure 5. Procedure diagram for constructing and locating the ORB-SLAM3 multimodal map

3.3 Robotic autonomous positioning results

In pure vision, the multi-map system adds robustness to fast motion by creating a new map when tracking is lost, which is later merged with the global map. This can be seen in the sequences V103 monocular and V203 Binocular 11,ORB-SLAM2 cannot solve these problems, and our system successfully solves these problems in most implementations. Precisely because of its faster feature initialization, binocular vision is more robust than monocular vision and has the added advantage of estimating true proportions.

However, a huge leap in robustness was achieved with our novel Visual Inertial SLAM system, in both monocular and binocular configurations. Binocular inertial systems have a very small advantage, especially in the most challenging V203 sequences. We can conclude that inertial integration not only improves accuracy and reduces median ATE error compared to purely visual solutions, but also gives the system excellent robustness and more stable performance.

3.4 Result discussion

Therefore, an open-source library for visual-inertial and multi-session SLAM, supporting monocular, stereo, RGB-D, pinhole, and fisheye cameras, has been developed. Apart from the integrated libraries themselves, our primary contributions include rapid and accurate initialization techniques for inertial measurement units and multi-session map merging functionalities. These functionalities rely on a novel position recognition technique with improved recall rates, rendering ORB-SLAM3 highly suitable for long-term and large-scale SLAM applications.

The experimental results demonstrate that ORB-SLAM3 is the first system capable of effectively utilizing short-term, medium-term, long-term, and multi-map data associations in visual and visual-inertial systems, achieving precision levels beyond what existing systems can achieve. Furthermore, our results indicate that, in terms of accuracy, the ability to associate all these types of data surpasses other alternatives, such as using direct methods instead of features or performing keyframe marginalization on local bundle adjustment rather than assuming a set of external static keyframes.

Regarding robustness, direct methods may exhibit greater robustness in low-texture environments but are limited to short-term and medium-term data associations. On the other hand, matching feature descriptors successfully addresses long-term multi-map data associations but seems less robust than using Lucas-Kanade tracking.

4 CONCLUSION

SLAM has been a hot research topic in the field of intelligent vehicles for the past three decades. The first principle study of this method was initially focused on the autonomous control of mobile robots. SLAM applications have been used for a wide range of topics such as augmented reality (AR)[24] visualization, computer vision modeling, and self-driving cars. In recent years, SLAM has been used as an intelligent technology for building 3D maps of environments using sensor fusion algorithms. With the increasing level of automotive/semi-automatic vehicle control, much of the latest research work is focused on applications in the automotive industry. This paper mainly discusses the application and research progress of SLAM in the field of intelligent vehicle. It introduces the basic principles and methods of SLAM, including graph structure models, filters such as Kalman filters and particle filters, and 3D maps of environments built based on sensor fusion algorithms. The paragraph also mentions different types of SLAM methods, such as vision-based SLAM (V-SLAM) and direct methods, as well as related algorithms and techniques, such as [25]ORB-SLAM, [26]DTAM, LSD-SLAM, DSO, etc. In addition, path integration, visual association and competing attractor processes in SLAM are covered, as well as tight coupling methods using IMUs and inertial measurement units.

In robotics, map building in SLAM usually refers to building a map that is geometrically consistent with the environment. The topological map established in the general algorithm only reflects the connection relationship of various points in the environment, and can not build a geometrically consistent map. Therefore, these topological algorithms cannot be used in SLAM.Direct representation is similar to satellite maps in that it is built directly from sensors (usually image sensors). This method has the largest redundancy of information, which is a great challenge for data storage. At the same time, it takes a lot of trouble for robots to extract useful data from it, so direct representation method is rarely used in practical applications.

In conclusion, we have introduced the pivotal role of SLAM technology in the advancement of robotic inspection systems. Leveraging SLAM's capabilities, robots can navigate, localize, and create maps of unknown environments autonomously. We have discussed the integration of SLAM with LiDAR technology, enabling precise environment mapping crucial for obstacle avoidance. Additionally, we presented a collaborative mapping algorithm based on ORB-SLAM3, enhancing map construction efficiency and real-time performance. Our findings demonstrate the transformative potential of SLAM technology, promising safer, more efficient, and more autonomous robotic inspection systems across industries. Through continued research and development, SLAM technology is poised to revolutionize robotic applications, driving further advancements in automation and intelligence.

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